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State-of-the-art review on the use of AI-enhanced computational mechanics in geotechnical engineering

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Abstract

Significant uncertainties can be found in the modelling of geotechnical materials. This can be attributed to the complex behaviour of soils and rocks amidst construction processes. Over the past decades, the field has increasingly embraced the application of artificial intelligence methodologies, thus recognising their suitability in forecasting non-linear relationships intrinsic to materials. This review offers a critical evaluation AI methodologies incorporated in computational mechanics for geotechnical engineering. The analysis categorises four pivotal areas: physical properties, mechanical properties, constitutive models, and other characteristics relevant to geotechnical materials. Among the various methodologies analysed, ANNs stand out as the most commonly used strategy, while other methods such as SVMs, LSTMs, and CNNs also see a significant level of application. The most widely used AI algorithms are Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM), representing 35%, 19%, and 17% respectively. The most extensive AI application is in the domain of mechanical properties, accounting for 59%, followed by other applications at 16%. The efficacy of AI applications is intrinsically linked to the type of datasets employed, the selected model input. This study also outlines future research directions emphasising the need to integrate physically guided and adaptive learning mechanisms to enhance the reliability and adaptability in addressing multi-scale and multi-physics coupled mechanics problems in geotechnics.

Keywords Artificial intelligence (AI) · Machine learning · Deep learning · Data science · Geotechnical engineering · Computational mechanics

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1 Introduction

Geotechnical Engineering is a crucial branch of civil engineering concentrating on the interaction between soils, rocks, and engineering structures. It plays a vital role in several significant engineering projects, such as highways (Cheng et al. 2005), bridges (Gaudio et al. 2022), dams (Mei et al. 2022), and tunnels (Wu et al. 2020). Geotechnical materials have complex mechanical properties, influenced by their moisture content and environmental conditions. The three-phase system (solid, liquid, and gas) soil structure exhibits unpredictable behaviour. (Bahaaddini et al. 2013; Bandara and Soga 2015; Bosch et al. 2021). Geotechnical materials, stress–strain relationships, strength, and deformation properties are intricately related to their microstructure and interactions under specific environmental conditions (Xiao et al. 2014b; Shen et al. 2017). Due to the substantial heterogeneity in soils and rocks, their mechanical properties exhibit considerable uncertainty in spatial distribution, making the accurate description and prediction of the mechanical behaviour of geotechnical materials a challenge (Baghbani et al. 2022). Computational mechanics in the context of geotechnical engineering primarily utilises computers and numerical methods to simulate, analyse, and predict the mechanical behaviour of geological materials. Modern computational techniques make it possible to deal with many complex engineering problems, taking into account many of the typical properties of geotechnical materials, such as the coupled behaviour of pore water and solid materials, non-linear elastoplastic behaviour, and transport processes.

For precise analysis and prediction of the mechanical behaviour of geotechnical structures, researchers and engineers have historically relied on laboratory tests (Chen et al. 2013; Wang et al. 2020) and field experiments (Kayen et al. 2013) to derive mechanical parameters and properties of geotechnical materials or have resorted to numerical analytical methods(Wang et al. 2014; Li et al. 2016). However, these traditional approaches are not only time-intensive and costly but also fall short of fully capturing the behaviour of geotechnical materials across different environments and conditions. The growth of Artificial Intelligence (AI) in recent years has opened unique possibilities in various research domains, particularly in geotechnical engineering (Merghadi et al. 2020; Jiang et al. 2023a). AI has made significant progress in predicting the mechanical properties of geotechnical engineering materials like soil and rock (Yin et al. 2023; Sahu et al. 2024; Asteris et al. 2022). Advanced algorithms such as Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM) have been widely applied, enhancing the accuracy and efficiency of predictions regarding properties such as strength and modulus (Jan et al. 2023; Khan et al. 2022; Luo et al. 2024). These techniques excel particularly in handling complex stress–strain relationships and material behaviour under various loading conditions (He et al. 2024; Qi et al. 2023; Huang et al. 2023a). Here, it has emerged as a relevant tool for addressing nonlinear problems, achieving noticeable speed and accuracy (Yin et al. 2018; Sheil et al. 2020; Wang et al. 2021b; Zhang et al. 2021f; Zhu et al. 2022). While traditional experimental techniques, constitutive models, and numerical methods provide foundational assessments of material behaviour prediction, they come with inherent limitations. The incorporation of AI into geotechnical engineering introduces innovative research methodologies. Firstly, AI can provide stress–strain relationships directly from raw data without many assumptions (Wang et al. 2022). Secondly, with diverse geotechnical experimental data fed into the database, AI can put forward unified models to simulate the behaviour of a range of materials (Zhou et al. 2022a). Moreover, as the volume of datasets increases, AI-based models' accuracy and application range can undergo further enhancements. It is crucial to denote that AI-driven models are data-dependent, and with a fixed machine-learning configuration, there is no need for parameter calibration (Chen and Zhang 2022).

Although AI has showcased considerable advantages and promising features within geotechnical engineering, there are still limitations. Most current models are heavily dependent on conventional Machine Learning (ML) algorithms, in which case advanced and efficient ML algorithms are only seldom used (Anikiev et al. 2023; Goldstein et al. 2019). This includes algorithms that are targeted at precisely predicting sequential data, like stress–strain relationships (Liu and Dai 2021; Liu et al. 2023a). Therefore, there is a notable research gap in the application of more advanced and adaptive AI algorithms in geotechnical engineering. Current research predominantly focuses on traditional AI techniques, with limited exploration of emerging methods such as deep learning and reinforcement learning, which hold the potential for significantly improved predictions and modeling capabilities. Moreover, there is a need for integrating AI models with physically-based principles to enhance their reliability and interpretability in practical applications. Addressing these gaps can lead to more robust and comprehensive AI-driven solutions in geotechnics.

This article conducts a systematic literature review and bibliometric analysis aimed at thoroughly exploring the application of AI in geomechanics, covering all relevant research and review papers published in reputable journals and books since 2022. The article first introduces several AI algorithms commonly used in geomechanics and then categorises geomechanics into four main domains: physical properties, mechanical properties, constitutive models, and other characteristics. A comprehensive review of AI applications is carried out and provided within these four sub-domains of geomechanics. Furthermore, discussions on the type of datasets, input parameters, and evaluation methods for AI-based intelligent geomechanics models are included. The article also outlines the opportunities and challenges currently faced by AI-based intelligent geomechanics and highlights that future research should focus on integrating physically guided and adaptive learning mechanisms to improve the reliability and adaptability of solving multi-scale and multi-physics field coupled mechanics problems in geotechnics. This guidance aims to contribute to the seamless integration and application of AI-enhanced intelligent mechanics in actual geotechnical engineering projects.

The significance of this study lies in its comprehensive examination of the current state of AI applications in geotechnical engineering, highlighting the potential and challenges of these methods. By systematically reviewing recent advancements and categorising them into distinct domains, this study fills a critical gap in the existing literature. It not only provides an updated synthesis of how AI is impacting geomechanics but also identifies key areas for future research. This guidance aims to contribute to the seamless integration and application of AI-enhanced intelligent mechanics in actual geotechnical engineering projects, paving the way for more efficient, accurate, and innovative solutions in the field.

2 Review methodology

This study follows a structured systematic literature review (SLR) methodology. This is achieved through a clear and articulated research query, a comprehensive search strategy, stringent criteria for literature inclusion and exclusion, and an in-depth analysis of the compiled data. Such a methodological approach significantly reduces the potential biases that might be inadvertently introduced through conventional review practices, as detailed in (Zhao and Taib 2022). The implemented SLR procedure entails six crucial stages: initiation of a scoping review to detail the field of study, execution of the comprehensive literature search, evaluation of the quality of the selected literature, extraction of relevant data from the chosen works, synthesis of the extracted data, and drafting the insights derived from the review process.

The review questions are defined by first mapping them and then proposing the subquestions—see Table 1. The selected questions aim to comprehensively explore the application of AI in geotechnical mechanics, starting with the development of a new paradigm for mechanical calculations. By identifying and understanding various AI methods, such as machine learning and neural networks, along with their adaptability and pattern recognition features, their application in addressing specific mechanical issues in geotechnical engineering can be more effectively assessed. Indeed, this application is crucial for enhancing precision, efficiency, and solving complex problems in the field. Finally, by examining future trends and needs, we aim to anticipate and prepare for evolving challenges and advancements, ensuring the field stays ahead in technological innovation and practical application. The keywords and search strategy for this research involve the combination of mechanics with AI methods, encompassing machine learning, deep learning, data-driven approaches, and knowledge-driven approaches. This can be explicitly expressed as "Mechanics and (AI or Machine learning or Deep learning or Data-driven or Knowledge-driven) and (Geotechnical engineering or soil or sand or rock)."

The comprehensive search phase involves selecting databases, establishing the research time frame, and identifying types of literature. The Web of Science Core Collection has been chosen as the search database for its authoritative and extensive coverage across numerous disciplines, serving as a crucial resource for the specific area under study. The time range for the search targeted the past decade, starting on January 1, 2012, and ending on December 31, 2022. The scholarly works are categorised into various types including, but not limited to, Brief Reports, Case Reports, Comments, Communications, Concept Papers, Conference Reports, Data Descriptors, Editorials, Guidelines, Hypotheses, Opinions, Perspectives, Proceedings Papers, Project Reports, Protocols, Replies, Short Notes, Theses, Tutorials, and Viewpoints. As the application of AI in geotechnics is a relatively new field of study, the keywords related to this topic have been found in Articles, Reviews, Conference Reports, Proceedings Papers, and Theses. This led to the identification of five primary categories that are central to the search in this study.

A total of 1266 preliminary search results (Total Number of Retrieved Documents) could be obtained according to the search criteria. The initial search should be checked against the inclusion criteria, in which case the screening criteria developed can be found in Table 2. The procedure for selecting research literature consisted of two parts. First, an initial screening of the retrieved material is done based on the title and abstract. This is followed by a secondary screening, known as the coding phase, where the complete text of the publication is examined for an in-depth re-screening using the criteria. 1093 papers were finally identified to complete the review.

During the literature selection process, we adopted clear quality assessment criteria and a systematic approach to ensure fairness and objectivity. Initially, titles and abstracts were categorized and evaluated using literature management software (Mendeley). In the second screening stage, selected papers were manually reviewed by reviewers. Each criterion in Table 2 was carefully chosen to exclude studies that did not meet academic rigour or were not relevant to the integration of AI and geotechnical engineering. Requiring full-text

Table 1 List of research questions

Type	No	Questions
The principal research question for the mapping review	Q_m	How to build a new paradigm for mechanical calculations in geotechnical engineering within the framework of artificial intelligence?
Sub-questions	Q_1	What methods are included in artificial intelligence?
	Q_2	What are the characteristics of these methods?
	Q_3	How to use these methods to solve mechanical problems in geotechnical engineering?
	Q_4	What are the forecasts and needs for the future trend?

Table 2 Quality assessment criteria

No	Inclusion criteria	Exclusion
1	Full article accessed	Not the full article accessed
2	Length of paper at least 2 pages	<2 pages
3	The topic is related to the integration of AI and geotechnical engineering specified in this article	The topic is not related to the integration of AI and geotechnical engineering specified in this article
4	The publication has been peer-reviewed	The publication has not been peer-reviewed
5	Content with a clear research title, abstract and keywords	The content doesn't have a clear research title, abstract and keywords

access ensures a comprehensive evaluation of the studies while limiting article length to at least 2 pages prevents the inclusion of overly brief or incomplete studies that may lack substantive insights. Each article was independently screened by two reviewers, and the results were compared to ensure the objectivity of the review process.

In the reporting stage, which includes data extraction, synthesis and write-up, a bibliometric analysis is used to make a co-citation analysis of the existing literature to explain, cluster, and anticipate the research field based on CiteSpace. The location of clusters and their correlation in a co-citation network view can show the intellectual structure of the science mapping field (Xia et al. 2022a). After the co-citation cluster mapping, the timeline view of the co-citation network can be obtained using the cluster number as the y-axis and the year of citation publication as the x-axis.

3 Bibliometric analysis of recent studies

Figure 1 plots the count of research papers documented in the database spanning the years 2012 to 2022, which provides insight into the evolving research trends in the mechanics of geotechnical engineering within the framework of AI. The data shows a slow increase from 2012 to 2017, followed by a significant surge in the number of outputs from 2018, leading to a sustained growth trajectory leading up to 2022. This upward trajectory is anticipated to continue in the foreseeable future. The same figure also points to a progressive increase in research integrating mechanics with deep learning. This highlights the contemporary path of computational mechanics in the realm of artificial intelligence with an integration of deep learning methodologies. Simultaneously, the prominence of data-driven approaches within the context of AI is evident, as shown by the number of studies.

Figure 2 depicts the co-occurrence of research terms encompassing computational mechanics within the framework of AI from 2012 to 2022, encompassing a total of 206 distinct keywords. Each node in the graph represents a keyword, with its size denoting frequency of appearance—the larger the node, the more frequent the keyword. The text size indicates keyword centrality and determines the direction of popularity in a research topic. Notably, the most significant keywords in Fig. 2, include Machine learning, deep learning, model, prediction, neural network, mechanical property, and artificial intelligence. The connecting lines between keywords indicate their relationships, with the thickness representing the frequency of co-occurrence. We utilised the CiteSpace software to analyze

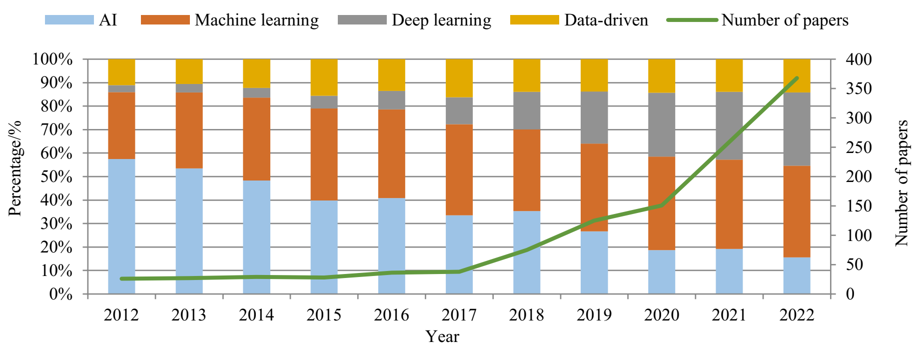

Fig. 1 Number and percentage of published papers in the WOS literature

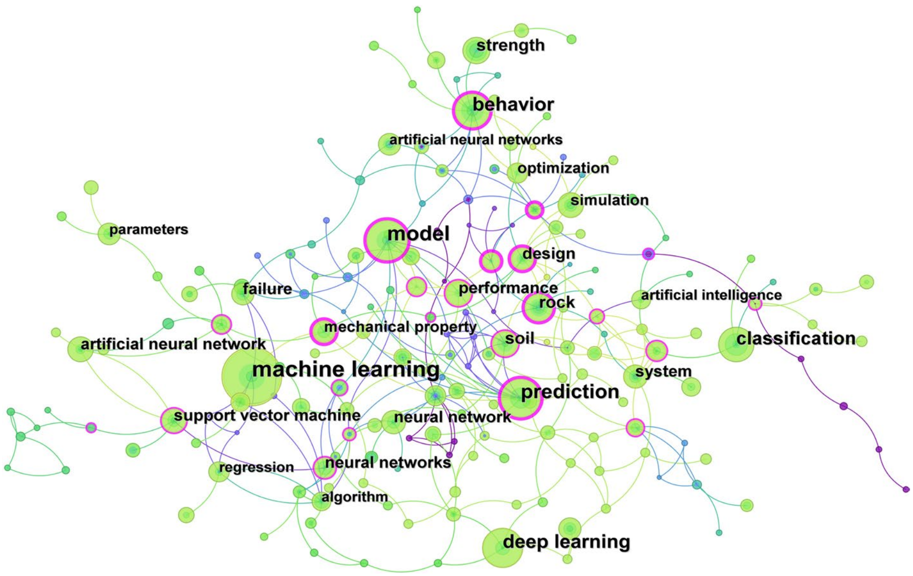

Fig. 2 Keyword clustering diagram

keyword co-occurrence and network clustering. CiteSpace constructs and visualises bibliometric networks based on co-occurrence data. Statistical tests such as the chi-square test were employed to validate the significance of keyword relationships. This methodological approach ensures the robustness and reliability of our findings.

Conducting an analysis of term frequency within the research domain, a comprehensive statistical examination of all the keywords was performed to produce the list presented in Table 3. The top 10 keywords include the core concepts and implications within this research domain. As expected, the prevalent term is "machine learning". In addition, keywords such as "model", "prediction", and "behaviour" show a prevailing focus on advancing AI computational models and predictive model performance in current research. Simultaneously, the presence of "neural network" and "deep learning" keywords highlights an already extensive exploration of deep learning methodologies.

Table 3 List of frequency and extracted keywords

Frequency	Keywords
187	Machine Learning
111	Model
91	Prediction
85	Behaviour
80	Deep learning
71	Classification
49	Rock
45	Soil
41	Strength
39	Neural networks

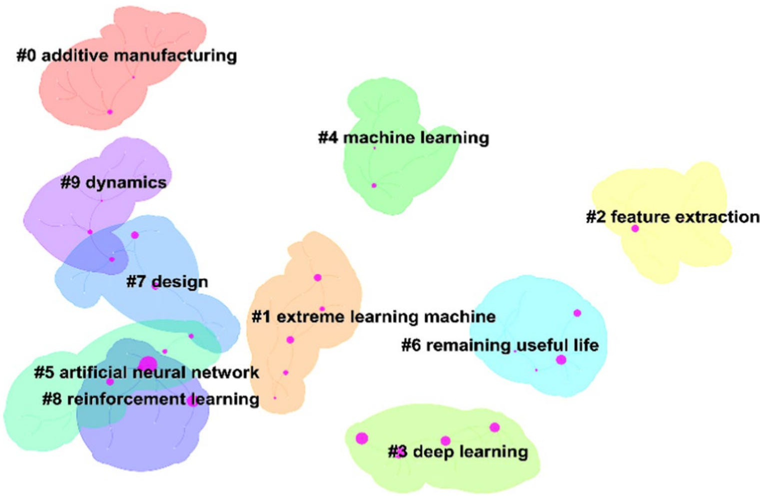

Fig. 3 Keywords cluster analysis visualisation

The clustered data is shown next by employing numbered cluster labels and cluster density to highlight existing attributes. As illustrated in Fig. 3, 206 keywords were analysed, categorising them into 10 distinct clusters. Each cluster is denoted by a circle with a diameter proportional to the frequency of terms encompassed within that cluster. The calculated clustering metrics, including a clustering module value (Q = 0.8458), weighted mean silhouette (S = 0.955), and harmonic mean (Q, S = 0.8971), collectively show a robust and satisfactory clustering structure (Liu et al. 2024).

The depicted network clustering structure of computational mechanics within the artificial intelligence framework is both meaningful and gratifying, with discernible logical connections interlinking terms. The integration of established technologies such as machine learning, deep learning, artificial neural networks, extreme learning machines, and reinforcement learning into the conventional realm of mechanics in geotechnical engineering has contributed to an emerging interdisciplinary trajectory within technological research.

4 Overview of classic AI techniques

AI embodies the overarching goal of creating machines capable of intelligent behaviour, with ML offering the techniques that allow these machines to improve autonomously. Further, DL, as a subset of ML, provides sophisticated tools like neural networks designed for executing and enhancing complex tasks. There are several available algorithms, e.g. Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, Generative Adversarial Networks (GAN), Support Vector Machines (SVM), Random Forests (RF), and Bayesian Networks (BN). These are presented in Appendix A and have distinctive features that make them suitable for different applications, as summarised in Table 4. When faced with the task of selecting an appropriate algorithm, the strengths and limitations of each need proper assessment to align with the specific requirements of the research task at hand. In

Table 4 Advantages and limits of proposed AI algorithms

AI algorithms	Advantages	Limits
ANN (Moayedi et al. 2020)	Capable of approximating any continuous function while effectively handling diverse and high-dimensional data	Demands substantial data and computational resources, with the internal workings often perceived as a "black box"
CNN (Wang 2022)	Superior in image and video processing tasks due to its adeptness at automatically learning spatial hierarchies of features	Requires substantial computational resources and is primarily suited for processing visual data
RNN (Yu et al. 2019a)	Handles sequences of data efficiently, making it ideal for time-series forecasting and natural language processing tasks	Susceptible to vanishing or exploding gradient issues during training, which complicates learning long-term dependencies
LSTM (Yu et al. 2019b)	Effectively learns long-term dependencies due to its integrated cell state and gating units, enhancing efficiency	Demands extensive computational resources and exhibits high complexity due to its intricate structure
GAN (Xia et al. 2022b)	Generates data resembling the input, beneficial for data augmentation and artistic endeavours	The training process is challenging to stabilize and necessitates meticulous hyperparameter tuning
SVM (Chauhan et al. 2019)	Effective for classification problems, SVM performs well with both small datasets and in high-dimensional spaces	Struggles with overlapping classes and is highly sensitive to the choice of kernel used
RF (Boulesteix et al. 2012)	Resilient to overfitting, efficiently managing large datasets and high dimensionality	Computationally demanding and often offers less interpretability compared to simpler models
BN (Gao et al. 2020)	Capable of modelling causal relationships and managing uncertainty, Bayesian Networks offer probabilistic inferences	Require a structure that is either meticulously predefined or learned from data, a process that is both complex and computationally intensive

addition, hybrid models can also be adopted as well as ensemble learning approaches, effectively integrating the strengths of different algorithms to achieve the desired robustness and accuracy. An integrated approach is particularly valuable for complex problems requiring multi-step solutions and diverse data types, where employing a combination of algorithms can yield better outcomes (Bishara et al. 2023).

The implementation of the selected algorithms requires suitable performance evaluation metrics and validation techniques, enabling a thorough and accurate assessment of effectiveness and performance. Under the constraints of limited resources and computational power, considerations of efficiency and resource utilisation take particular importance. Appropriate optimisations and adjustments should be applied to guarantee the smooth integration of AI algorithms into specific geotechnical engineering mechanics challenges. Various performance evaluation metrics such as accuracy, precision, recall, F1 score, and root mean square error (RMSE) are commonly used to measure the effectiveness of AI algorithms. Additionally, cross-validation techniques, including k-fold cross-validation and leave-one-out cross-validation, are employed to ensure the robustness and generalizability of the models. These methods help validate the reliability of AI models by testing them on different subsets of data. Appropriate optimisations and adjustments should be made to ensure the smooth integration of AI algorithms into specific geotechnical engineering challenges.

5 Application of AI to mechanics in geotechnical engineering

5.1 Statistical analysis of specific topics

This section explores the application of AI in geotechnical engineering mechanics analysis as documented in the literature. Four primary domains have been identified: (i) physical properties, (ii) mechanical properties, (iii) constitutive modelling, and (iv) other applications. Geotechnical materials have physical properties such as particle size distribution, shape, porosity, saturation, and density, and mechanical properties such as strength and modulus. Constitutive modelling describes their mechanical behaviour and stress–strain relationships under different loads and environmental conditions. Other characteristics include compression, consolidation, permeability, and liquefaction. These are further addressed in subsequent sections. Figure 4a provides a breakdown of the AI techniques in specific sub-domains of geomechanics. For instance, regarding physical properties, RF, ANN, and CNN are mostly utilised. Within the mechanical properties of geotechnical engineering materials, the most employed AI techniques are ANN, RF, and SVM. In constitutive modelling, ANN, LSTM, and SVM dominate, while in other applications, ANN, SVM, and GAN are more prevalent. Figure 4b shows the distribution of various AI methodologies employed in geotechnical mechanics. The most predominant are ANNs, Random Forest, and SVM, representing 35%, 19%, and 17% of AI-enhanced geotechnical mechanics-related references collected here. Further analysis in Fig. 4c, shows that the most extensive application of AI can be found in the domain of mechanical properties, reaching 59%. This is followed by other applications with 16%, while physical property and constitutive models have slightly smaller shares.

From a statistical standpoint, ANN, RF, SVM, CNN, LSTM, and GAN hold significant prominence in geotechnical mechanics. Specifically, the ANN can be favoured for its robust adaptability and capability in handling non-linearities (Brunton et al. 2020; Vinuesa

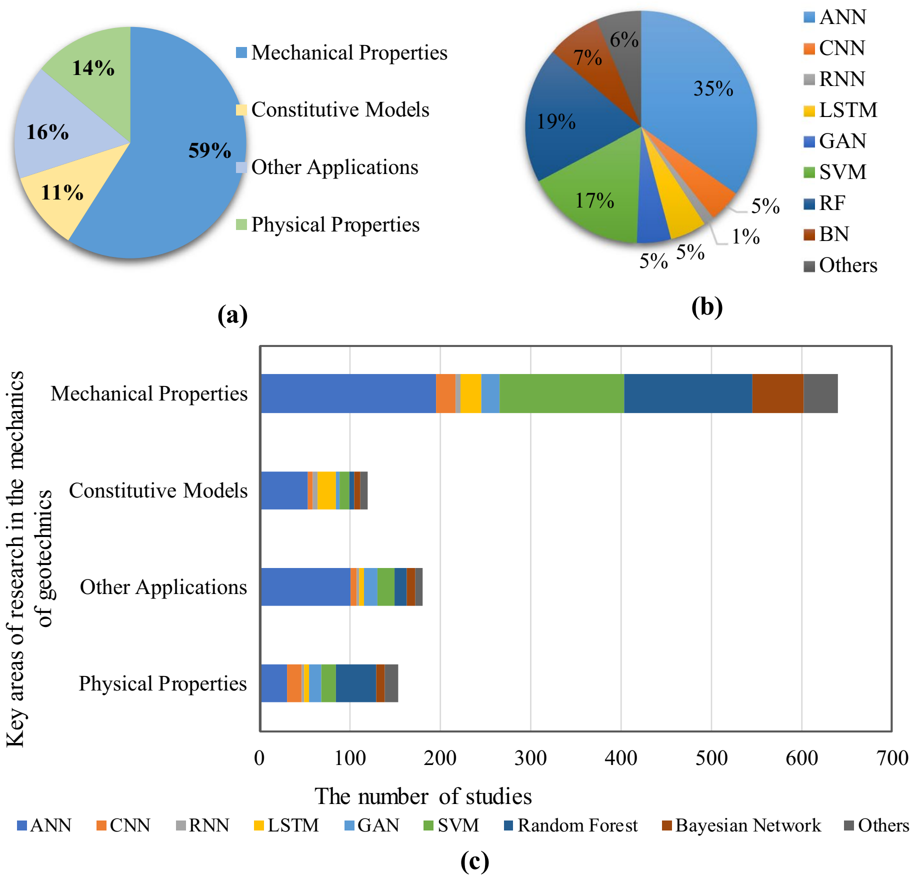

Fig. 4 Distribution of AI algorithm applications across subdomains in geomechanics: **a** The distribution of AI algorithms across various research directions in the field of geomechanics, **b** The application distribution of different AI algorithms in the field of geotechnical mechanics, **c** Number of studies applying different AI algorithms in different key areas of geomechanical research

et al. 2023; Herrmann and Kollmannsberger 2024; Zhang et al. 2022b). For example, ANN can be used to predict ground vibrations caused by explosions during the mining process (Singh 2004). The SVM can have good performance in managing high-dimensional data and offers good estimations in classification and regression tasks, such as measuring the grout ability of sandy silt soil, monitoring seismic hazards in coal mines, predicting earthquake soil liquefaction, and determining the propensity of slope collapse (Chou and Thedja 2016). The LSTM network can be advantageous in capturing long-term dependencies in time-related geotechnical concerns, such as modelling the stress–strain behaviour of soil (Zhang et al. 2021b) and predicting the mechanical behaviour of rocks with strong strain-softening effects (Shi et al. 2022). GAN is particularly suited to situations of scarcity of data by enabling the generation of synthetic datasets. As an example, we can mention the generation of X-ray CT images of a self-similar partially saturated sand (Argilaga 2023). CNN is particularly suitable for geotechnical image analyses, efficient image recognition and feature extraction. Such as predicting the stability of retaining walls from a photographic dataset (Liu et al. 2022b) and inferring the mechanical properties of granular materials from particle images (Zhang and Yin 2021). Concurrently, RF offers detailed parameter studies and feature importance evaluations, such as used for variable importance measurements (VIMs) among various physical and mechanical properties of rocks and estimate Young's modulus and uniaxial compressive strength based on selected variables by VIMs (Matin et al. 2018). In summary, these techniques, with their unique attributes and capabilities, have been extensively deployed for predicting geotechnical engineering mechanics properties.

5.2 AI and physical properties

The mechanical characteristics of geotechnical engineering materials are significantly influenced by their physical properties, including particle size distribution (Ma et al. 2022), shape (Altuhafi et al. 2013), porosity (Li et al. 2021), saturation (Ye et al. 2019; Ip et al. 2021), and density (Gao et al. 2019), among others. As illustrated in Fig. 5, AI methods have recently seen a widespread deployment in the determination of physical properties of geotechnical materials. This growing trend stems from the complex nature of the physical properties of geotechnical materials, which require substantial statistical data for support and analysis. Examples can be given of the use of AI to reconstruct the three-dimensional shape of particles and obtain their characteristic indicators. AI can be used to process and analyse complex Computerised Tomography (CT) data, which can depict both the internal and external structures of particles. Zhang et al. (2022a) proposed a novel method for reconstructing three-dimensional (3D) particles from CT images. The study introduces a

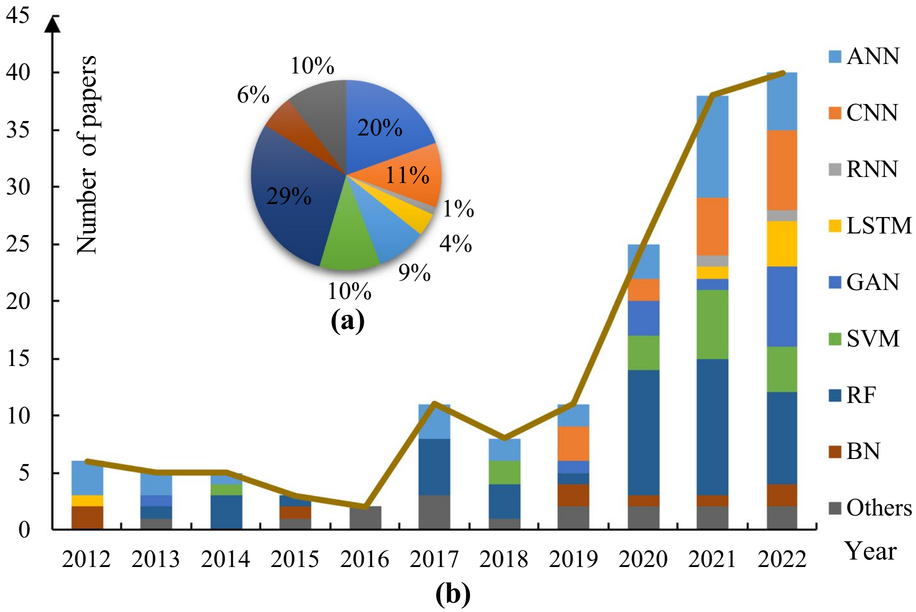

Fig. 5 Breakdown of AI in predicting physical properties of geotechnical engineering materials: **a** The distribution of different AI algorithms used in predicting physical properties, **b** The number and trends of research papers on different AI algorithms in predicting physical properties from 2012 to 2022

hybrid algorithm which integrates RF and automates the determination of hyperparameters through Particle Swarm Optimisation. This approach initially trains the model for component classification and particle segmentation without relying on trial-and-error hyperparameter selection. Overall, this method offers an efficient way to reconstruct 3D particles from CT images. As shown in Fig. 6, Lai and Chen (2019) proposed a framework that uses machine learning and level set methods to segment CT images and reconstruct particles in granular geological materials. This framework demonstrates good performance in both pixel-level classification accuracy and particle-level segmentation precision. By using reconstructed actual particles, the particle size distribution was obtained and verified, and quantitative morphological analysis was conducted which showcases the immense potential in the characterisation of granular geological materials. Through AI, researchers can automatically acquire and analyse key characteristic indicators of particle morphology, such as particle size distribution (Parent et al. 2021; González Tejada and Antolin 2022; Martinelli and Gasser 2022), shape (Liang et al. 2019; Zhou et al. 2021; Li et al. 2023), and surface characteristics (Tawfik et al. 2022). These indicators are fundamental to analysing the physical and mechanical properties of granular materials. Overall, AI methods can enable the reconstruction of particle 3D morphology and diameter but also provide a rapid

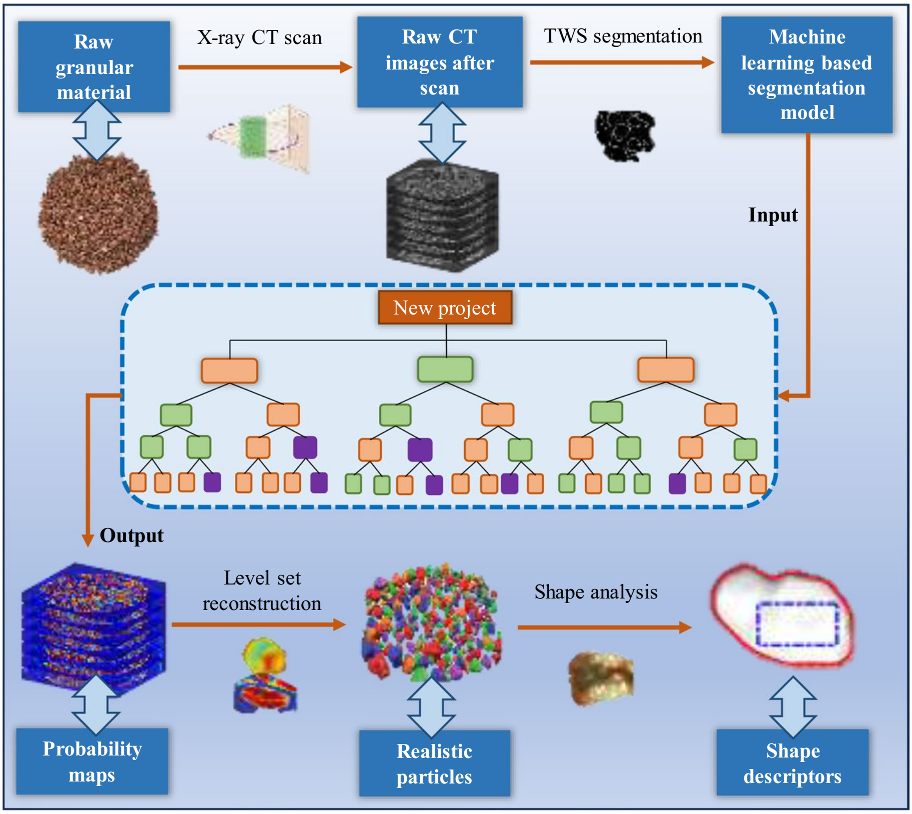

Fig. 6 Framework for reconstructing soil particles by machine learning from CT scan images (Li et al. 2021)

and accurate means of obtaining key parameters. This lays a solid foundation for further research and application of granular materials.

AI technology has also shown potential in predicting the physical properties of geotechnical engineering materials, such as porosity, saturation, and density. Feng et al. (2020b) conducted a pioneering study proposing an unsupervised deep-learning method aimed at inverting the porosity of oil reservoirs. This method uses CNN technology to analyze post-stack seismic data, avoiding the need for large, labeled datasets typically required in traditional learning processes. Karimpouli et al. (2022) employed advanced machine learning techniques to fluctuation signals and designed numerical models with different fracture densities. The results provided quick and suitable estimation methods for fractures in rocks, soil, and concrete. Ge et al. (2022) successfully applied ANN to simplify the detection and characterisation process of rock discontinuities. The theoretical framework provided by Tophel et al. (2022) offers new theoretical and technical support for predicting compaction density under cyclic loading, strongly supporting practical engineering applications. Li and Iskander (2022) validated the feasibility and effectiveness of machine learning in classifying sand particles. Through dynamic image analysis, machine learning models can identify and classify different sand particles, offering a new method for analysing the physical properties of geotechnical engineering materials.

The application of artificial neural networks (ANN) in the prediction of petrophysical properties shows significant advantages. Compared with traditional methods and other machine learning models, ANN demonstrates higher prediction accuracy and efficiency. For instance, in predicting rock porosity, ANN achieved high-precision results using drilling parameters (such as drilling weight, torque, etc.). The correlation coefficients (R) for the training and test sets were 0.97 and 0.92, respectively, and the average absolute percentage errors (AAPE) were 6.2% and 9.3% (Gamal and Elkatatny 2022).In terms of rock discontinuity detection, ANN can quickly and accurately identify discontinuities through point cloud data and geometric features, significantly improving the efficiency of processing large amounts of data. Moreover, it does not require engineers to have a strong computer programming background (Ge et al. 2022). In blasting engineering, ANN performs exceptionally well, handling multiple parameters that affect rock fragmentation and achieving high-reliability predictions with low root mean square error (RMSE) (Bahrami et al. 2011; Ebrahimi et al. 2016). Compared to the traditional Kuz-Ram model, ANN provides more accurate predictions for fragment size (Amoako et al. 2022).Additionally, ANN shows excellent performance in predicting thermal conductivity. Using parameters such as longitudinal wave velocity and porosity of rocks, the regression coefficient reaches 1, and the mean absolute error is low (Singh et al. 2007). In tunnel boring machine (TBM) performance prediction, ANN combines rock and machine parameters, resulting in a higher coefficient of determination and lower RMSE. Hybrid intelligent systems, such as PSO-ANN and ICA-ANN, perform even better (Armaghani et al. 2017). In tunnel collapse risk prediction, the optimized ANN model produces results that are highly consistent with actual measurements, with both absolute and relative errors being low (Mehrdanesh et al. 2018; Chen et al. 2016).

In summary, AI methods show great potential in predicting the physical properties of geotechnical materials. Typical AI model inputs include extensive experimental data and field measurement data, such as particle size distribution, shape characteristics, porosity, saturation, and density. These data can come from CT scans, dynamic image analysis, and other experimental techniques. With this data, AI models can be trained to capture complex nonlinear relationships to predict the physical properties of materials. In terms of output, AI models can provide accurate prediction results for key parameters such as the

3D morphology of particles, porosity, saturation, and density. These predictions not only help engineers better understand and analyse the behaviour of geotechnical materials but also optimize experimental design and testing procedures, improving work efficiency. The application of AI models extends beyond laboratory data processing to real-time monitoring and prediction under field conditions, ensuring that predictions of the physical properties of geotechnical engineering materials are more reliable and accurate under various complex environments and load conditions.

5.3 AI and mechanical properties

Materials involved in geotechnical engineering, such as sand and rock, exhibit a range of critical mechanical characteristics, including tensile strength, compressive strength, shear strength, elastic modulus, deformation modulus, and Poisson's ratio. For instance, the strength of materials quantifies their ability to withstand stress (Richard et al. 2012). Soils or rocks with low strength are more prone to fracturing or slipping under stress, which can lead to engineering problems like slope instability (Zhao et al. 2016). The deformation modulus, related to the stiffness of materials, determines the extent of deformation under load, while Poisson's ratio reflects the relationship between lateral and axial strain (Thota et al. 2020). These mechanical properties not only influence the stability, settlement, groundwater flow, and vibratory response of structures but also play a key role in the design and construction of geotechnical engineering (Sloan 2013; Wang et al. 2021a).

Figure 7 illustrates the trend of AI methods applied in the mechanical characteristics of geotechnical engineering over time, as well as the usage ratio of various algorithms.

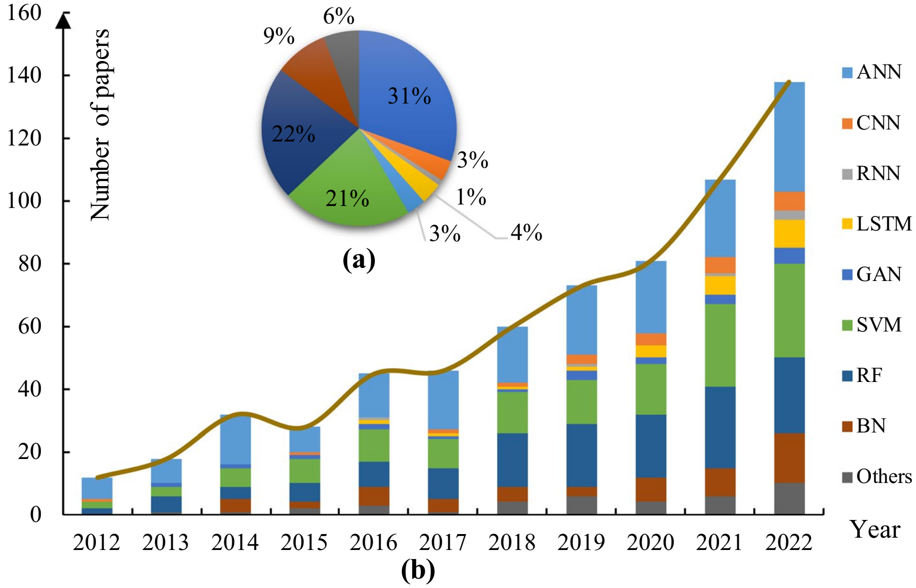

Fig. 7 Breakdown of AI in predicting mechanical properties of geotechnical engineering: **a** The distribution of different AI algorithms used in predicting mechanical properties, **b** The number and trends of research papers on different AI algorithms in predicting mechanical properties from 2012 to 2022

As depicted in the figure, the employment of AI algorithms in the mechanical characteristics of geotechnical engineering has been increasing annually within the timeframe of this study. Particularly after 2018, this growth trend became significantly noticeable. This highlights a growing exploration of AI methods for interpreting the mechanical characteristics of geotechnical engineering. Among the models, ANN, RF, SVM, and BN are the most frequently used, with a share of 30%, 22%, 21%, and 9%, respectively.

Tensile strength, compressive strength, and shear strength collectively constitute the mechanical strength of geotechnical engineering materials, serving as core parameters for evaluating material performance and safety. These are typically determined through standardised experiments, such as triaxial compression tests and tensile tests (Oda 1972; Xiao et al. 2014c, 2014d). Tensile strength is used for assessing the performance of soil or rock during underground excavation and slope stability evaluation (Shang et al. 2018). Compressive strength also plays a role in the application of underground structures and bridge foundations. Meanwhile, shear strength is primarily used for evaluating the stability of soil and rock, especially under the influence of earthquakes (Intrieri et al. 2019). It's important to note that soil and rock are heterogeneous and anisotropic materials. Their mechanical properties are influenced by factors such as moisture content, temperature, and stress paths. AI algorithms have shown excellent performance in analyzing the mechanical strength of soil and various rock types, especially their compressive and shear strengths, under different environmental conditions. This success is due to the efficient processing and analysis of extensive experimental and field data. Table 5 presents applications of typical AI algorithms in the field of geotechnical material strength prediction, as shown in the table, Liu et al. (2015) tackled the challenge of indirectly estimating the unconfined compressive strength (UCS) of rocks, a crucial parameter in geotechnical engineering. Skentou et al. (2023) examined three ANN-based models to predict the UCS of granite using non-destructive indicators. The ANN-LM model demonstrated superior accuracy, and a user-friendly graphical user interface (GUI) was created for effective unconfined compressive strength (UCS) estimation. Tie et al. (2023) applied machine learning models to predict rock tensile strength, considering the influence of loading rates and mineralogical compositions. After analysing 196 samples, the SVM, RF, and BPNN models were shown effective for small sample sizes, with the study highlighting the impact of testing methods and mineral compositions on tensile strength prediction. Chao et al. (2023) proposed a novel machine-learning model combining Multi-Expression Programming Algorithm (MEA) and Adaptive Backpropagation Artificial Neural Network (ADA-BPANN). This model, designed for predicting clayey soil-geomembrane interface peak shear strength, had better performance than conventional methods and emphasised the importance of normal pressure and geomembrane roughness. Tien Bui et al. (2019) introduced a hybrid AI model, integrating Least Squares Support Vector Machine (LSSVM) and Cuckoo Search Optimization (CSO), for accurate soil shear strength prediction, showcasing its potential as a valuable tool for engineers seeking precise soil shear strength estimates.

As shown in Fig. 8, the key to utilise AI algorithms for predicting the mechanical strength of geotechnical engineering materials lies in the training of the model (Miah et al. 2020). During this training phase, the predictive model learns and understands a large set of sample data labelled with known mechanical property parameters. Through multiple iterations, model parameters are continuously adjusted to enhance the accuracy when predicting new samples. Feature engineering and automatic feature selection algorithms automatically select the most relevant features to the target variable to build predictive models (Tinoco et al. 2014). Deep learning algorithms, on the other hand, exhibit significant advantages in handling complex data structures, automatically

Table 5 Typical application of AI algorithms in the prediction of strength

AI algorithms	Application	Materials	MAE	MAPE	RMSE	R^2	R	References
ELM	Unconfined compressive strength	Rock	\	0.1467	\	0.792	\	Liu et al. (2015)
ANN	unconfined compressive strength		\	0.1648	0.2030	\	0.9285	Skentou et al. (2023)
SVM	Tensile strength		2.7632	0.4208	\	0.987	\	Tie et al. (2023)
RF			3.1579	0.3903	\	0.992	\	
BPNN			6.3158	0.1771	\	0.932	\	
BPANN	Peak shear strength	Clayey soil-geomembrane interfaces	\	0.0915	2.23	\	0.98	Chao et al. (2023)
Hybrid method of LSSVM and CSO	Shear strength	Soil	\	14.841	0.082	0.885	\	Tien Bui et al. (2019)
GA-ENN	Shear strength	Sands mixed with carpet fibre	3.118	\	3.342	0.993	\	
Random forest	Shear strength	Sand	\	\	1.71	0.90	\	Rezaee et al. (2021)

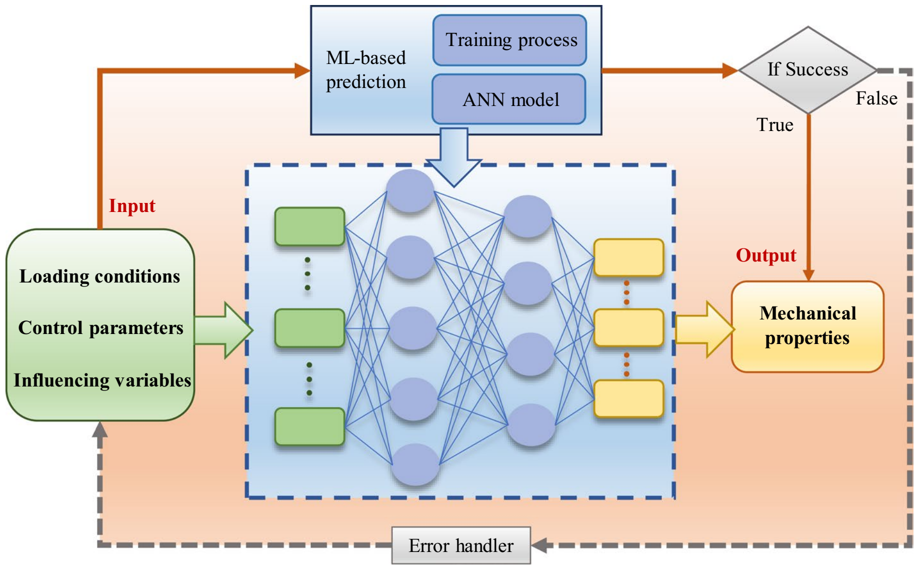

Fig. 8 Framework for machine learning to predict mechanical properties

identifying, and extracting key features related to mechanical properties, especially when dealing with high-dimensional and complicated data, resulting in greater accuracy (Jiang et al. 2023b). Overall, these AI algorithms achieve accurate predictions of the mechanical strength of geotechnical engineering materials under various environments and conditions by automatically extracting and learning key features from large datasets, subsequently building highly accurate predictive models.

Machine learning and deep learning algorithms are also extensively employed for the prediction and analysis of modulus parameters. For instance, machine learning algorithms like and RF (Hao and Pabst 2022) have been deployed for the prediction of elastic and shear moduli under various environmental conditions (e.g., moisture and temperature levels). They are also utilised for automatic feature selection, identifying the features most correlated with modulus parameters to construct predictive models. Deep learning has also achieved good results in predicting geotechnical engineering moduli, automatically extracting crucial features from complex data structures. For example, it can predict elastic and shear moduli based on microstructure images, thereby attaining greater accuracy when dealing with complex and high-dimensional data (Zhang et al. 2021a). Table 6 presents applications of typical AI algorithms in predicting modulus parameters for geotechnical engineering materials. (Ceryan et al. (2021) developed models using SVR, GPR, and ANN for predicting the elastic modulus in variously weathered magmatic rocks, utilising inputs like porosity, P-wave velocity, and slake durability index. Notably, GPR and ANN outperformed SVR, providing insights into the effect of weathering indicators on elastic modulus prediction. Chen et al. (2021) introduced a novel semi-supervised SVM soft sensor to estimate rock-mechanics parameters, addressing challenges related to insufficient samples and outliers, and showing superior accuracy compared to established methods. Zhang et al. (2020a) employed a non-parametric ensemble AI approach, utilising Gradient Boosting Regression Tree (GBRT) and Genetic Algorithm (GA), to predict the compression modulus of soft clays,

Table 6 Typical application of AI algorithms in the prediction of modulus

AI algorithms	Application	Materials	MAE	RMSE	R^2	R	Reference
SVR	Elastic modulus	Weathered magmatic rock	5.196	5.662	0.695	\	Ceryan et al. (2021)
GPR			3.043	3.365	0.898	\	
ANN			2.337	3.767	0.859	\	
ANN	Poisson's ratio	Rock	\	\	\	\	Siddig et al. (2021)
ANFIS			\	\	\	\	
SVR	Poisson's ratio		\	\	\	\	Chen et al. (2021)
GBRT-GA	Compression modulus	Clay soil	\	\	\	0.91	Zhang et al. (2020a)
ANN	Small-strain shear modulus	Soil	\	\	0.991	\	Liu et al. (2023b)
ANN	Shear modulus and damping ratio	Soil	0.0058	\	\	0.993	Baghbani et al. (2023)
BN	Shear modulus and friction angle	Sandy soil	\	\	\	\	Lo et al. (2021)

demonstrating strong accuracy and potential for improvement over traditional models. Baghbani et al. (2023) used ANN and Combined Recurrent and Random Forest (CRRF) for predicting sand shear modulus and damping ratio, outperforming existing methods and identifying key input parameters for accuracy. Lo et al. (2021) introduced a Bayesian network approach for sand shear modulus and friction angle prediction, reducing uncertainty and offering valuable insights for improved predictions.

ANNs have demonstrated significant advantages in predicting rock properties. Research indicates that when predicting rock compressive strength, the mean absolute error (MAE) of the ANN model is 0.35, compared to 0.52 for the support vector machine (SVM), 0.48 for the random forest (RF), and 0.38 for the long short-term memory network (LSTM) (Jan et al. 2023). For predicting Young's modulus, the root mean square error (RMSE) of the ANN is 0.21, while the SVM has an RMSE of 0.34, the RF 0.30, and the LSTM 0.23 (Khan et al. 2022; Luo et al. 2024). These results demonstrate that ANNs offer higher prediction accuracy and efficiency when dealing with complex nonlinear relationships and large datasets. Specifically, ANNs excel at capturing the complex dependencies between properties such as rock strength and modulus and their influencing factors. In contrast, while SVM performs well on small datasets and linear problems, it struggles with nonlinear and large-scale data, making it less flexible than ANNs. RF has advantages in processing high-dimensional data and preventing overfitting, but its prediction accuracy can sometimes be lower than that of ANNs. LSTM networks, though particularly effective for time series data and suitable for predicting rock behavior under dynamic loading conditions, have high computational complexity (He et al. 2024; Qi et al. 2023; Huang et al. 2023a). Overall, ANNs outperform SVM, RF, and LSTM in terms of adaptability, efficiency, and prediction accuracy. However, future research should focus on integrating the strengths of these models to develop more efficient and accurate hybrid models (Yin et al. 2023; Sahu et al. 2024).

In recent years, artificial neural networks (ANN) have demonstrated remarkable success in predicting various mechanical properties of rocks. Numerous studies have indicated that ANN models, when combined with different optimization algorithms, offer significant advantages in terms of prediction accuracy and performance. For instance, the combination of ANN with equilibrium optimizer (EO), differential evolution (DE), grasshopper optimisation algorithm (GOA), and whale optimization algorithm (WOA) has substantially enhanced the prediction accuracy of rock sample strain. Among these, the ANN-EO model has shown the best performance in predicting longitudinal strain (Pradeep and Samui 2022). In the prediction of elastic modulus (Ei), the ANN model demonstrated its high practicability through the root mean square error and the relative square error root index (Ocak and Seker 2012). Additionally, the hybrid model combining particle swarm optimization (PSO) and ANN outperformed the traditional ANN model in predicting the ultimate bearing capacity (Qu) of rock-embedded piles (Jahed Armaghani et al. 2017). For unconfined compressive strength (UCS) prediction, the ANN model exceeded the performance of multivariable regression analysis (MVRA), and hybrid optimisation algorithms such as PSO-ANN and ICA-ANN further enhanced the model's performance(Majdi and Rezaei 2013; Tian et al. 2019; Jahed Armaghani et al. 2014; Mohamad et al. 2018). In predicting shear strength parameters, the PSO-ANN model also demonstrated a high level of precision (Momeni et al. 2015).

By inputting extensive experimental and field measurement data, such as particle size distribution, shape characteristics, moisture content, temperature, and stress paths, AI models can capture complex nonlinear relationships and accurately predict tensile strength, compressive strength, shear strength, and key parameters such as elastic modulus and deformation modulus. These prediction results not only help engineers better understand and analyze the behavior of geotechnical materials under different conditions but also optimise experimental design and testing procedures, thereby improving work efficiency. Furthermore, the application of AI models is not limited to laboratory data processing; they can also be extended to real-time monitoring and prediction under field conditions. This ensures that the prediction of mechanical properties of geotechnical engineering materials is more reliable and accurate under various complex environments and load conditions.

5.4 AI and constitutive models

Constitutive models are often established based on extensive experimental research, providing mathematical expressions to describe the fundamental mechanical characteristics of geotechnical engineering materials. Common constitutive models, including elastic, nonlinear elastic, and elasto-plastic models, are utilised for simulating behaviours like deformation, stress distribution, and stability in soil and rocks. These models can be deployed in geotechnical engineering design, soil mechanics analysis, and the evaluation of geological disasters.

The theory of nonlinear elasticity builds upon the foundational principles of elasticity by incorporating the nonlinear characteristics of soil materials; whereas, the elasto-plastic theory integrates classic plasticity theory into the constitutive relationships of soil, taking into account its unique properties. Since Roscoe introduced the original Cam-clay model, research on constitutive models in geotechnical engineering has made rapid advances (Ortiz and Pandolfi 2004). Due to varying assumptions within each model, numerous elasto-plastic models have been developed, with Table 7 listing some of the classical models used in geotechnical engineering. Long-term research and practice have shown that these models, while based in different theories, aim to accurately describe the mechanical behaviour of geotechnical materials. Traditional constitutive models are based on the theories of solid mechanics and soil mechanics and are validated through extensive experimental data and field testing. For instance, the Drucker-Prager and Mohr–Coulomb models rely on classic elasto-plastic theory, while the Cam-Clay model refers to the principles of soil compression and shear behaviour. Common issues include simplifying assumptions, limited applicability, parameter determination difficulties, computational challenges, and a lack of comprehensive descriptions. Despite the need for advanced computational tools in modern practices to improve accuracy and efficiency, many traditional models have not been effectively integrated with these innovative technologies.

In the field of geotechnical engineering, data-driven constitutive models represent an emerging research area. Their development and validation depend on extensive experimental and field monitoring data to accurately portray and predict complex mechanical behaviours. These models typically rely on big data analytics and machine-learning technologies to derive insights from vast amounts of experimental and field data. Figure 9 shows the increasing trend in research on data-driven constitutive models. Common AI algorithms in these models include ANN, LSTM, and SVM, which constitute 45%, 17%, and 9% of the research, respectively.

Data-driven constitutive models are trained with various AI algorithms, allowing them to learn the relationships between input data and output results. These methods can handle complex, nonlinear problems by capturing deep features and patterns in the data, offering solutions for intricate issues (Su et al. 2023). In geotechnical engineering, the application of advanced Machine Learning (ML) algorithms for soil behaviour modelling is on the

Table 7 Some classic constitutive models

Model	Principles	Material	Application	Reference
Mohr–Coulomb Model	The shear strength of the material is described by the angle of friction and cohesion	Soil and rock	Slope stability analysis and foundation design	Bardet (1991)
Drucker-Prager Model	The Mohr–Coulomb model has been extended to better describe the material non-linear and anisotropic characteristics	Soil and rock	Plastic deformation analysis of soil or rock engineering bodies	Arslan and Hacisalihoglu (2013)
Cam-Clay Model	Based on the plasticity theory of cohesive soil, the behaviour of cohesive soil is simulated through pre-consolidation pressure and other plasticity parameters	Clay	Analysis of the soil's plastic deformation and strength	Pericá and Ayari (2002)
Hoek–Brown Model	Describing the strength and deformation characteristics of rock materials, based on the strength parameters and failure criteria of the rock	Rock	Design and analysis in rock engineering, such as stability analysis for tunnels and slopes	(Keawsawasvong and Shiau (2022)
Hardening Soil Model	Taking into account the elastic–plastic behaviour of soil and its strain-hardening characteristics	Soil	Foundation design and deformation analysis of soil bodies	(Cudny and Truty (2020)
Duncan-Chang Model	An elastic–plastic model considering the non-linear stress–strain relationship of soil	Soil	Design of earth dams, roadbeds, and foundations	(Zhao et al. (2020)
Pasternak Model	A model describing the elasticity of soil on a two-layer spring foundation	Soil	Soil-structure interaction analysis	(Patra and Shahu (2012)
Uh Model	The model primarily investigates the time effects and shear characteristics of over-consolidated clay subjected to preload, conducting a detailed study on the mechanical properties of cohesive soil	Clay	Calculation and analysis of the stability of airport runway foundations	(Yao et al. (2021)

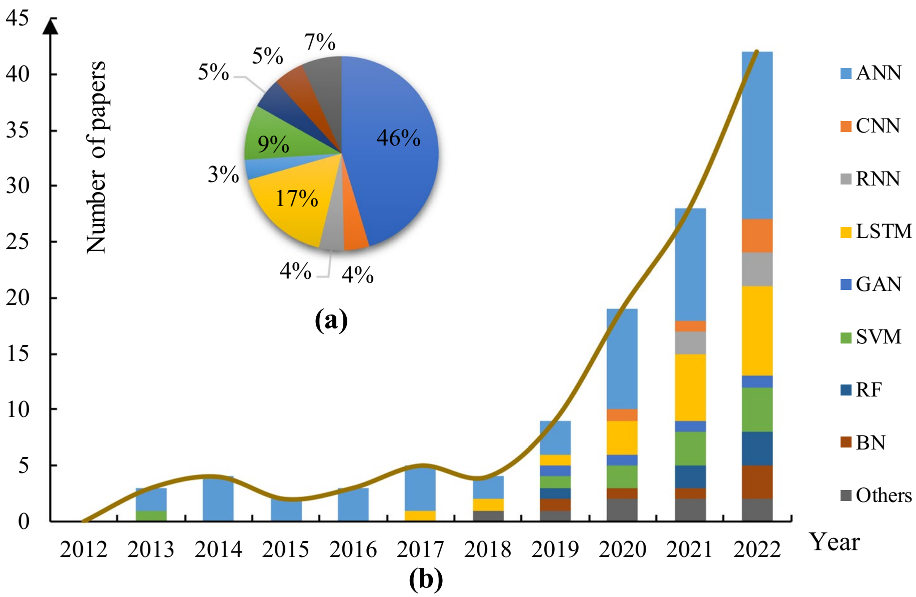

Fig. 9 Breakdown of AI in the data-driven constitutive model of geotechnical engineering: **a** The distribution of different AI algorithms used in constitutive models, **b** The number and trends of research papers on different AI algorithms in constitutive models from 2012 to 2022

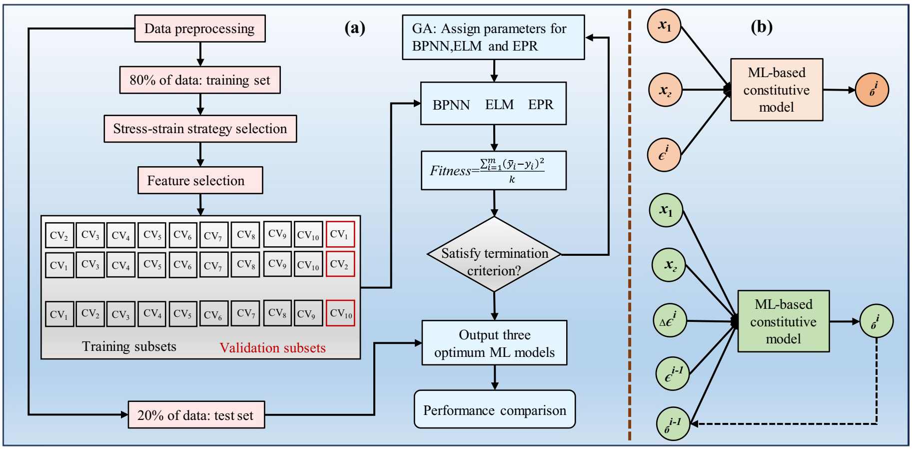

Fig. 10 Model framework: **a** flowchart of constructing ML-based constitutive models; **b** schematic view of the total stress–strain strategy; **c** schematic view of the incremental stress–strain strategy(Zhang et al. 2023a)

rise. As shown in Fig. 10, Zhang et al. (2022d) applied ML algorithms like BPNN, ELM, and EPR to formulate robust constitutive models for soils. Using a methodology that integrates genetic algorithms with k-fold cross-validation, the proposed BPNN-based model accurately predicts soil mechanical behaviour. Wu et al. (2023b) developed a predictive framework for the stress–strain behaviour of granular materials under triaxial shearing. They used a Multi-Layer Perceptron (MLP) with initial void ratios as inputs, aligning effectively with experimental and simulation results while bypassing complex micromechanics. Xiong et al. (2023) generated a database for modelling granular soil behaviours using a μCT-DEM approach, employing neural networks like BPNN, LSTM, and GRU, with the latter standing out for performance and efficiency, offering insights into the behaviours of granular soils under various conditions. Wu et al. (2023) introduced the CNN-based Rock Constitutive Model (CNNCM) which accurately represents stress–strain relationships in rocks, considering various complexities. Derived from tests on Yuanzigou coal mine specimens, CNNCM is accurate and can show the influence of different input features in geotechnical applications. Data-driven constitutive models are widely used in geotechnical engineering, providing accurate predictions of soil strength and deformation under various environmental conditions, based on extensive experimental data analysis. Their main benefits include accuracy, generalisation capability, and handling of high-dimensional, nonlinear problems. Nonetheless, to build these models an iterative process is often needed requiring data preparation, feature selection, and model training. Challenges include dependency on data quality and quantity, limited model interpretability, and significant computational demands. Researchers must consider these factors to effectively apply these models in geotechnical engineering (Qu et al. 2021b).

In recent years, artificial intelligence (AI) algorithms have demonstrated remarkable results in the construction of rock constitutive models, showing clear advantages over traditional models. For instance, the rock constitutive model (CNNCM) based on deep convolutional neural networks (CNN) excels in handling the rock stress–strain relationship, achieving a mean absolute percentage error (MAPE) range of 0.52–1.94% and a coefficient of determination (R^2) as high as 0.999988 (Wu et al. 2023b). Additionally, the model combining radial basis function neural network (RBFNN) and gray wolf optimization (GWO) (RBFNN-GWO) has demonstrated superior prediction accuracy compared to the model combining RBFNN and genetic algorithm (GA) in predicting the shear behaviour of rock fractures (Peng et al. 2022). Meta-models constructed using fractional constitutive models and machine learning algorithms (such as random forest, extreme gradient boosting, and multi-layer perceptron) also perform well in predicting rock mechanical behaviour by simplifying complex integration algorithms and accounting for parameter uncertainty, particularly the combination of the multi-layer perceptron algorithm and strategy II (Qu et al. 2023a). Moreover, significant progress has been made in the application of data mining (DM) techniques in geotechnical engineering, especially within the context of the Portugal and DUSEL hydropower projects, leading to the development of new and reliable rock constitutive models (Miranda et al. 2013. In predicting rock mechanical behaviour under different water chemical conditions, the support vector machine (SVM) model optimized by the artificial bee colony algorithm (ABC) demonstrated extremely high nonlinear prediction capabilities, with a correlation coefficient (R^2) of 0.998, a root mean square error (RMSE) of 0.7730, and a mean absolute percentage error (MAPE) of 1.51, further proving its effectiveness in predicting the conventional triaxial constitutive relationship of rocks (Lin et al. 2023).

Due to the complexity of geotechnical engineering problems, purely data-driven methods may not completely capture the intricate physical relationships expected in underground environments. This has led to the need for physics-guided data-driven constitutive models that combine traditional physics principles with modern machine-learning techniques. Zhang et al. (2023a) introduced a data-driven modelling approach that thrives in sparse data environments by effectively merging theoretical knowledge and prediction uncertainties into ML models. This approach uses a multi-fidelity framework that leverages small high-fidelity datasets for robust performance, particularly in extrapolation tasks, showing promise for accurately modelling different material behaviours. Zhang et al. (2022b) proposed a Physics-Constrained Hierarchical (PCH) training strategy, enhancing data-driven models for mapping complex soil responses. The PCH method employs a combination of neural networks and linear regression to optimise the loss function with physical law constraints. Validated within a finite element analysis framework, PCH, particularly with LSTM networks, outperforms traditional models in accuracy and efficiency across different loading conditions, proving highly effective in modelling complex soil behaviour. Qu et al. (2021b) provided an innovative description of the complex responses of granular systems, developing ML-based models informed by micromechanics. The study explores three training strategies, each incorporating prior micromechanical knowledge, yielding models that align with test specimens under multi-directional loading cases. Qu et al. (2023) proposed a streamlined fractional constitutive meta-model for rocks. This model, developed with a physics-induced database and unique input–output strategies, deploys three ML algorithms, resulting in six meta-models. The optimal model, validated through grid-search and cross-validation, aligns with experimental data, effectively conducting uncertainty analyses and presenting a viable alternative to traditional models.

In physics-guided models, physics principles provide a foundational knowledge framework, ensuring predictions align with real-world laws. The data-driven aspect uses experimental and field data to refine and optimise this framework, improving accuracy and generalisability. These models effectively capture the non-linearity and heterogeneity of underground materials and address data gaps in areas with sparse or no observation data, applying physical principles. Moreover, unlike 'black box' purely data-driven models, physics-guided models offer greater interpretability, enabling researchers and engineers to better understand and trust their outputs.

In geotechnical engineering, the process of utilizing AI to construct a constitutive model encompasses several crucial stages. Initially, a comprehensive array of data must be amassed, spanning experimental data, environmental conditions, material properties, and geometric particulars. Experimental data typically comprises stress–strain information sourced from soil and rock tests conducted using specialized equipment. Environmental factors, such as temperature, humidity, and pressure, are considered, alongside material attributes like friction angle, cohesion, preconsolidation pressure, density, and porosity. Geometric details elucidate the specific shape and dimensions of the project under scrutiny. Following data collection, preprocessing becomes paramount, entailing tasks like data cleansing, missing value imputation, and standardisation. These preparatory measures are enacted to ensure data integrity and uniformity, thereby enhancing modle reliability and robustness. Subsequently, feature engineering is undertaken to identify and construct pertinent features, which might include the physical and mechanical properties of soil and rock, such as friction angle and cohesion. The overarching objective of feature engineering lies in extracting the most informative features to empower the model in accurately predicting the target variable. During the model selection and training phase, an appropriate AI algorithm is chosen, whether it be an artificial neural network (ANN), long short-term memory network (LSTM), or support vector machine (SVM). Model training is then conducted, leveraging the intrinsic characteristics of the data. The optimization of model parameters assumes significance, often achieved through techniques like cross-validation and grid search. Subsequent to model training, validation and testing are executed using an independent dataset to gauge the model's performance and precision. Should the model demonstrate commendable performance, its application in real-world geotechnical projects becomes viable. Finally, iterative improvements and optimizations are made based on feedback garnered from practical application scenarios and newly acquired data, aimed at refining the efficacy and adaptability of the model. Through these detailed steps, AI technology could provide geotechnical engineering with efficient and accurate constitutive models, thereby furnishing dependable support for engineering design and the prevention of geological disasters.

5.5 AI and other applications

Figure 11 shows statistical data on AI research in geotechnical material other applications. There has been an increasing number of studies using AI algorithms to predict these characteristics in recent years, reflecting the growing interest in AI applications in this field. The most common algorithms are ANN, SVM, GAN, and Random Forest, accounting for 56%, 10%, 8%, and 8% of the studies, respectively. Table 8 details specific applications of AI algorithms in the other applications of geotechnical materials.

AI is increasingly used to predict compressive characteristics, e.g. Singh et al. (2023) employed machine learning models, including RF, ANN, and SVM, to predict the coefficient of consolidation for various soils, particularly marine clays and soft soils. Shi and Wang (2022) introduced a stochastic framework for consolidation settlement predictions in reclamation design. The approach addresses stratigraphic uncertainty and soil property spatial variability using machine learning and random field simulation. It generates multiple geological cross-sections and geotechnical property samples from limited data, improving insights into consolidation settlement patterns. Kirts et al. (2018) employed

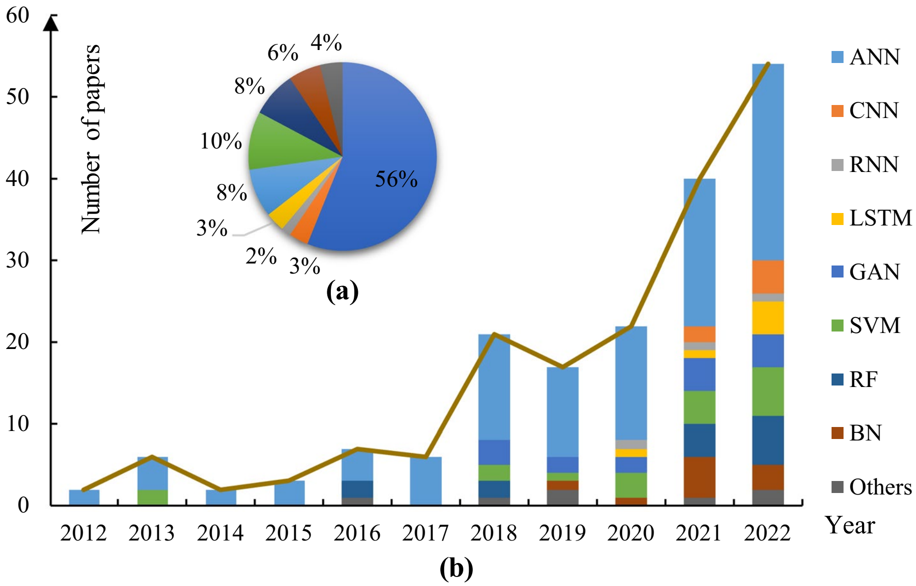

Fig. 11 Breakdown AI in predicting other applications of geotechnical engineering: **a** The distribution of different AI algorithms used in other applications, **b** The number and trends of research papers on different AI algorithms in other applications from 2012 to 2022

Table 8 Typical application of AI algorithms in the prediction of other applications

AI algorithms	Application	Materials	MAE	RMSE	R^2	R	References
BPNN	Compression index	Soil	0.0325	\	0.98	\	Zhang et al. (2021d)
ELM			0.0457	\	0.88	\	
SVM			0.0465	\	0.86	\	
RF			0.0143	\	0.65	\	
EPR			0.0523	\	0.97	\	
MLP-BBO	coefficient of consolidation	Soil	0.302	0.397	\	0.827	Pham et al. (2019)
Bp-MLP			0.805	0.478	\	0.805	
RBF-Neural Nets			0.804	0.412	\	0.804	
GP			0.777	0.440	\	0.777	
M5 Tree			0.728	0.494	\	0.728	
SVR			0.819	0.403	\	0.819	
ANFIS-DE	Compression coefficient	Clay	0.064	0.094	\	0.825	Duc Nguyen et al. (2022)
ANN	Coefficient of consolidation	Soft soil	0.02713	0.04107	0.70	\	Singh et al. (2023)
RF			0.02321	0.03854	0.92	\	
SVM			0.02971	0.05579	0.38	\	
MLP	Permeability	Soil	\	4.208	0.7244	\	Singh et al. (2020a)
CANFIS			\	3.974	0.7569	\	
SVM			\	3.006	0.8036	\	
DT			\	2.338	0.8506	\	
RF			\	2.304	0.8503	\	
ANN	Hydraulic conductivity	Sandy soil	0.0005	0.00082	0.82	\	Rehman et al. (2022)
SLR	Permeability	Tight gas sand	\	\	− 9.88	\	Zhang et al. (2018)
SVR	Liquefaction	Sand	0.037	0.065	\	0.974	Talamkhani et al. (2023)
RF			0.057	0.073	\	0.977	
BP-MLP			0.090	0.119	\	0.920	
ANN	Liquefaction	Sand	0.009	0.093	0.96	\	Kurnaz et al. (2023)

a data-driven approach to estimate compression indices, C–c and C–r, for assessing soil settlement. SVM classification determines the need for distinct models based on soil types, resulting in more accurate predictions than existing correlations. The models consider additional factors such as fines content, automatic hammer blow count, and wet-dry density interactions, enhancing accuracy in different soil classifications. Lo et al. (2023) employed a variational autoencoder for embankment settlement and pore water pressure prediction using monitoring data. The method efficiently predicts embankment behaviour without constant soil parameter updates. Trained on simulated responses, it could forecast the performance at the Ballina site, aligning more closely with actual trends when using increased monitoring data. It could show enhanced performance compared to traditional methods in prediction accuracy and effectively handles diverse scenarios. Shi and Wang (2023) focused on accurate soil consolidation prediction in multi-year reclamation projects with varying subsurface conditions. A unified framework combines machine learning and simulation for spatial and temporal consolidation analysis. Applied to a Hong Kong reclamation project, it highlights the importance of considering spatial variability for project success and risk management.

Consolidation properties of soil and rock materials are important engineering parameters within geotechnical engineering associated with volume changes due to water expulsion under stress. Understanding these characteristics profoundly is imperative, as they directly influence the stability and safety of engineering structures such as bridges, roads, dams, and buildings (Conte 2004). With the rise of AI technology in recent years, there has been an increasing application of machine learning and deep learning algorithms for predicting and analysing the consolidation characteristics of geotechnical engineering materials. Traditional machine learning methods, like SVM (Kirts et al. 2019) and ANN (Park and Lee 2011), have been employed to estimate consolidation parameters of geotechnical materials, such as the coefficient of consolidation and pre-consolidation pressure. By being trained on extensive experimental data like porosity, initial moisture content, loading rate, and other key parameters. These algorithms can offer engineers predictions on consolidation characteristics under specific conditions.

Additionally, deep learning, particularly Physics-Informed Neural Networks (PINN), has shown effectiveness in forecasting the consolidation properties of geotechnical materials. For example, PINN has been used to predict excess pore water pressure in two-dimensional soil consolidation (Lu and Mei 2022). Furthermore, images from microscopic electron microscopy of soil can serve as deep learning methods in learning about soil consolidation behaviour, providing more detailed predictions for the consolidation process (Chow et al. 2022). Machine learning and deep learning are increasingly used in predicting and analysing the permeability characteristics of geotechnical materials. Liu et al. (2022a) pioneered calculating permeability using digital images and an enhanced model, validating the approach's reliability and accuracy. Ma et al. (2021) developed a database from fractured rock permeability literature and assessed the performance of Support Vector Machines (SVM) optimized by Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). The study identified crack angles and confining pressure as crucial factors influencing fractured rock permeability. Zhang et al. (2018) formulated a unified permeability model for certain tight gas sandstones, with nonlinear algorithms showing superior performance over linear ones. Singh et al. (2020) utilized various data-driven algorithms and their wavelet transform forms for soil permeability prediction, demonstrating that wavelet-based algorithms provided more accurate simulations, with W-RF being the most effective and efficient.

In geotechnical engineering, especially in earthquake-prone areas, soil liquefaction is crucial. It occurs when soil loses shear strength and behaves like a fluid, leading to significant foundation and structural failures. Recently, AI technologies, including machine learning and deep learning, have become valuable in studying liquefaction characteristics. Jas and Dodagoudar (2023) enhanced an existing database by incorporating information such as permeability coefficients and crucial layer thickness, utilizing the XGBoost ML algorithm and k-means SMOTE technique to handle unbalanced data. The study identified that equivalent clear sand cone penetration resistance and permeability coefficient are principal input parameters for liquefaction potential. The research substantiated that EML techniques effectively bridge traditional liquefaction knowledge with soft computing methodologies. Zhao et al. (2021) launched an innovative system for evaluating soil liquefaction potential, integrating measurements from Cone Penetration Tests (CPT) and Shear Wave Velocity Tests (Vs). The study developed a new hybrid machine-learning model, PSO-KELM, combining Kernel Extreme Learning Machine (KELM) with Particle Swarm Optimization (PSO), for accurate liquefaction potential evaluation. This was done after assessing seven machine-learning algorithms on a dataset from the 1999 Adapazari earthquake. Ozsagir et al. (2022) highlighted the Decision Tree algorithm, with a 90% overall accuracy, as an effective tool for assessing soil liquefaction potential. Traditional machine-learning approaches have been utilized to evaluate the risk and potential of soil liquefaction. By analysing extensive experimental data, like standard penetration test results, particle size distribution, and soil density, these models can make liquefaction predictions under specific conditions. Significant advancements have been achieved in predicting and identifying liquefaction characteristics through deep learning technologies. Zhang et al. (2023b) utilised Convolutional Neural Networks (CNN) to forecast the occurrence and initiation timing of liquefaction events. Initially, the study conducted over a million high-fidelity non-linear site response simulations with diverse soil profiles and ground motions. These simulations of surface acceleration time histories were then converted into time–frequency distribution images for CNN training. The trained CNN showed high predictive accuracy across the training set, validation set, independent site response simulations, and real earthquake data. Chen et al. (2023) introduced the Wasserstein Generative Adversarial Network (WGAN) to augment the sample size of liquefaction datasets. The outcomes indicated that the proposed method (WGAN) effectively learned the feature distribution of the original dataset, enhancing the model's accuracy. This approach offers a robust solution for earthquake engineering, where comprehensive data is challenging to obtain, further refining the application of deep learning.

Reliability calculations are crucial in geotechnical engineering as they enable the assessment of a structure's safety and stability under different conditions. In recent years, the random field finite element method (RF-FEM) has been increasingly used in geotechnical engineering to account for the spatial variability in the physical and mechanical properties of natural and treated soils (Wang et al. 2024). However, the extremely high computational cost of RF-FEM when used in conjunction with Monte Carlo simulation (MCS) becomes its main disadvantage. To solve this problem, Wang and Goh (2021) proposed a meta-modeling method based on convolutional neural networks (CNNs) for efficient slope reliability analysis and geotechnical engineering design. By training CNN as an element model of a random field finite element model, the computational cost can be significantly reduced while maintaining high accuracy (Wang et al. 2021b). Research shows that CNN can learn and capture information containing random variability in spatial distribution and intensity, thereby replacing time-consuming RF-FEM simulations in subsequent calculations (Wang et al. 2023c). Further research also combined maximum entropy distribution with fractional moment (MaxEnt-FM) technology, demonstrating the efficiency and accuracy of the combined CNN and MaxEnt-FM strategy in predicting failure probability (Wang and Goh 2022). These methods provide broad prospects for reliability analysis and design taking into account soil spatial variability, effectively solving the computational burden problem of traditional methods.

Using AI methods to address various applications in geotechnical engineering (such as compressibility, permeability, liquefaction, and their reliability) involves a multi-step process encompassing comprehensive applications from data input to model output. First, the input data includes experimental measurements such as initial moisture content, porosity, particle structure, and external load on the soil. For compressibility, models like artificial neural networks (ANN), support vector machines (SVM), and physics-informed neural networks (PINN) can be trained using this data to predict output parameters such as compression coefficient and pre-compression pressure. Permeability prediction relies on algorithms such as multilayer perceptrons (MLP), decision trees (DT), and random forests (RF), with input data including porosity, particle size distribution, and experimental permeability measurements. Liquefaction prediction utilizes convolutional neural networks (CNN), generative adversarial networks (GAN), and PSO-KELM models. The inputs are standard penetration test (SPT) results and seismic response data, while the outputs are liquefaction potential and occurrence probability. Additionally, for constructing constitutive models, the input data includes stress–strain data and material physical properties. Using models such as variational autoencoders (VAE) and PINN, the output is the stress–strain relationship of soil or rock. In terms of reliability calculations, although the random field finite element method (RF-FEM) combined with Monte Carlo simulation (MCS) incurs high computational costs, these can be significantly reduced by using convolutional neural networks (CNN) for element modeling while maintaining high accuracy. These AI methods can learn and capture random variation information in spatial distribution and intensity, effectively replacing traditional time-consuming simulations for slope reliability analysis and design. Furthermore, by combining maximum entropy distribution with fractional moments (MaxEnt-FM) technology, the integration of CNN and MaxEnt-FM strategies demonstrates high efficiency and accuracy in predicting failure probability.

5.6 Summary and suggestions

Machine learning and deep learning models are particularly effective in managing complex variable relationships with higher accuracy and minimal data. Physics-guided AI models, merging theoretical knowledge with data-driven insights, offer interpretability, reliability, and robustness, even with sparse data (Xu et al. 2021). AI can be combined with mechanics in geotechnical engineering to synergise empirical, theoretical, and computational knowledge. Cross-disciplinary collaborations are essential to integrate insights from data science, materials science, and applied physics. Continuous innovation in AI algorithms is crucial for capturing the nonlinear, anisotropic, and time-dependent nature of geotechnical materials with computational efficiency and model interpretability. Data quality is critical, necessitating substantial investment in generating, curating, and managing comprehensive geotechnical datasets. These should cover various materials, conditions, and scenarios for robust model training. Rigorous validation and verification are necessary to ensure the reliability of AI-driven geotechnical models. Establishing standardised benchmark tests and promoting data and model sharing within the research community will enhance collaborative improvement and validation.

6 Discussion

6.1 Categories of datasets

As highlighted previously, an abundant dataset can be required for constructing AI-driven geotechnical engineering models. A review shows that most studies rely on experimental data for model training and validation. Economic and technical constraints, however, limit the availability of data. As a way forward, numerical data can provide a viable option. Since numerical data can be relatively easier to generate, it can accommodate larger datasets, thereby facilitating the development of more robust and stable AI-driven models (Zhang et al. 2021e).

The use of numerical data also presents a set of challenges and questions. Firstly, compared to experimental data, numerical data might not fully reflect the complexity and heterogeneity of real-world geotechnical materials. Therefore, models trained with numerical data may still require further validation regarding their range of application and accuracy. Secondly, models trained with numerical data might overly rely on specific numerical simulation techniques and assumptions, potentially affecting their generalisability and portability (Meng and Wu 2023).

Future research needs to delve deeper into exploring and comparing the performance and applicability of AI-driven geotechnical engineering models trained with both experimental and numerical data. Through in-depth analysis and validation, we can better understand the advantages and limitations of these models, providing a firmer theoretical foundation and technical support for practical engineering applications. Additionally, how to effectively integrate and utilise both experimental and numerical data, as well as develop more accurate and reliable data generation and augmentation techniques, will be vital directions for future research.

6.2 Network performance testing

When evaluating the performance of AI-driven geotechnical engineering models, one of the crucial considerations is the reliability and robustness of the models. Performance assessment of the models primarily relies on metrics such as RMSE, MAE, SI, and the coefficient of determination (R or R^2). The selection of the evaluation parameters, however, should be a result of a comprehensive consideration of the model error and accuracy. Here, it should be denoted that while ML-based models can accurately capture stress–strain response. Particularly, current ML models are predominantly trained and constructed based on specific types of experimental data, such as triaxial tests, direct shear tests, and simple shear tests, among others. This approach limits the generalisation capability and application range of these models across various soil types and under different testing conditions. In other words, while these models exhibit excellent performance under specific training conditions, their effectiveness and reliability when exposed to unseen types of geotechnical engineering materials or testing conditions have not been fully assessed and validated. The generalisation capability is one of the key indicators for evaluating the quality of AI-driven models, describing the predictive power of the model over unseen data. As per existing literature, current studies primarily focus on the interpolation ability, with relatively less research dedicated to their extrapolation capability (Anhui da Xue et al. 2016; Yin et al. 2018). However, in practical engineering applications, models may need to handle input data of varied ranges and distributions; therefore, a deep and thorough study and assessment of the extrapolation ability of a model is crucial. Furthermore, although models trained with datasets compiled from multiple data sources can access larger training datasets, their accuracy often falls short compared to models trained with a single data source. This phenomenon indicates that the consistency and quality of the dataset significantly impact model performance. Merely increasing the size of the dataset does not necessarily guarantee an enhancement in model performance.

6.3 Selection of input parameters

Selecting appropriate inputs is crucial for the successful operation of AI models. With the increase in the number of inputs, there is an inevitable rise in runtime and data volume, making the careful selection of inputs that effectively reduce error particularly important. In the field of geotechnical engineering, engineers need to address issues closely related to time and accuracy, a situation significantly different from other engineering disciplines, especially considering that most material properties exhibit highly non-linear characteristics. Collecting geotechnical analysis data, whether through on-site or laboratory testing, requires substantial time and financial investment. Therefore, identifying input parameters that significantly impact AI modelling becomes particularly vital. Table 9 summarises the commonly used input parameters in various areas of geotechnical mechanics based on the results of the literature review, serving as initial guidance for selecting main input parameters during the data collection process. It is important to note that both the number of input parameters and their sensitivity are crucial. Simply increasing the number of inputs without their effective contribution to outputs will only slow down the model. One significant advantage of AI methods is that inputs can still be incorporated into models even when there is no known theoretical or empirical relationship between the input and output parameters. By introducing additional inputs and examining their sensitivity, the accuracy can be further enhanced.

6.4 Comparison of AI and conventional methods

In the field of computational mechanics in geotechnical engineering, AI-enhanced calculation methods offer significant advantages over conventional methods such as the finite element method, boundary element method, and discrete element method. These advantages not only improve calculation accuracy and efficiency but also complement and enhance the effectiveness of traditional methods. Traditional calculation methods, when dealing with complex nonlinear relationships, typically require simplifying assumptions and extensive manual parameter adjustments, leading to potentially less accurate results. In contrast, AI and machine learning algorithms can process complex multi-dimensional data, automatically extract features, and build high-precision nonlinear models. For example, support vector machines (SVM) and neural networks (ANN) excel in predicting foundation-bearing capacity and analysing slope stability, significantly improving prediction accuracy (Shao et al. 2023).

Table 9 Selection of input and output parameters for AI models in different geomechanics areas

Area of research	Commonly used input parameters	Predicted (output) parameters
Physical property	Fundamental properties of raw geotechnical samples (such as mineral composition, colour, and texture), historical experimental data, environmental conditions (temperature, humidity, pressure), microscopic or scanning electron microscope images of geotechnical materials, as well as geographical location and stratigraphic information of the samples	Grain size distribution, particle shape and geometric characteristics, porosity or void ratio, saturation or moisture content, and various types of density (dry density, wet density, and saturated density) of geotechnical samples
Strength	Grain size distribution of geotechnical samples, historical experimental data (stress–strain), and environmental conditions such as temperature, humidity, and pressure	The maximum strengths of geotechnical materials, when subjected to tensile, compressive, and shear forces, are represented as tensile strength, compressive strength, and shear strength, respectively
Modulus	Microstructural information of geotechnical samples (such as particle arrangement and connection methods), history and cycles of loading, and relevant laboratory test results	Elastic modulus (the ability to recover after deformation), deformation modulus (the degree of deformation while sustaining continuous load), and Poisson's ratio (the ratio of lateral expansion under axial compression)
Data-driven constitutive model	Including stress–strain history (such as loading paths, rates, and data from different stages), along with parameters for crack and micro-crack distribution	The stress–strain relationship of materials under various conditions, criteria for damage and failure, long-term performance (such as creep and shrinkage), and other responses (like resistance to erosion and fatigue life)
Physical informed data-driven constitutive model	Types and conditions of experiments (such as triaxial tests, direct shear tests, boundary and initial conditions), history and path of loading (stress–strain data), prior knowledge based on physical and mechanical principles (like elasto-plastic theory and failure criteria), and microstructural features obtained through non-destructive testing (such as porosity structure and crack density)	Stress–strain response curves (taking into account physical constraints and nonlinear behaviour), long-term and short-term performance indicators (such as elastic modulus, yield stress, and ultimate bearing capacity)
Compression property	Initial state parameters (such as initial porosity, moisture content, and compression index), loading conditions, and environmental conditions (like temperature, humidity, and confining pressure)	Compression curve (stress–strain relationship), crucial compression parameters (like compression modulus and compression index), predicted porosity and moisture content under varying pressures, and other relevant compressive property parameters (such as elastic compression modulus and residual compression index)

Table 9 (continued)

Area of research	Commonly used input parameters	Predicted (output) parameters
Consolidation property	Initial consolidation parameters (such as initial compression index and pre-consolidation pressure), fundamental geotechnical properties (like particle size and soil type), hydrogeological parameters (such as confining water pressure and moisture content), loading paths and conditions (like methods and speed of loading), and environmental conditions influencing the rate and extent of consolidation (like temperature and humidity)	Consolidation-strain or consolidation-time curves, consolidation coefficient and compression modulus, porosity and degree of consolidation at the end of consolidation, along with other relevant consolidation parameters (such as consolidation rate and residual porosity)
Permeability property	Fundamental properties of soil (such as particle size distribution and pore structure), initial moisture content and degree of saturation, environmental conditions like temperature and pressure, and loading conditions	Permeability coefficient, permeability property curves related to saturation, and other permeation-related parameters (such as effective porosity and diffusion coefficient)
Liquefaction property	Seismic parameters (such as magnitude and focal depth), fundamental geotechnical characteristics (like soil type and particle size), groundwater conditions (including groundwater table height), soil state parameters (such as initial stress state and porosity ratio), as well as data on historical earthquakes and liquefaction events	Liquefaction potential and hazard assessment, sensitivity and likelihood of liquefaction in various soil layers, and ground deformations induced by liquefaction, such as subsidence and cracking

The review also compared the advantages of artificial intelligence (AI) technology with traditional methods such as inverse analysis, data assimilation strategies, Bayesian filters, Markov chain Monte Carlo (MCMC) methods, and sparse modeling in geomechanics. Inverse analysis is often used to infer geotechnical parameters from observational data, relying on strict model assumptions and limited data input. In contrast, data-driven deep learning models can process large volumes of input data and automatically extract features, which is particularly effective in complex geological conditions where prior knowledge is unclear (Knabe et al. 2012; Amavasai et al. 2024; Hartmann et al. 2022; Zhang et al. 2012). Traditional Bayesian filter and MCMC methods estimate parameter uncertainty through statistical principles (Mohammadi et al. 2022). However, these methods face significant computational burdens and slow processing speeds when dealing with large-scale or high-dimensional data (Fu et al. 2022). In such scenarios, AI methods, especially CNNs and RNNs, have demonstrated potential in handling complex dynamic systems and optimizing model performance by learning the intrinsic patterns within the data (Wang et al. 2023a). Sparse modeling is utilized in geotechnical engineering to extract the most critical data features, thereby achieving model simplification and efficient computation (Wang et al. 2018). In contrast, AI technology can optimize itself without explicit guidance through reinforcement learning and adaptive algorithms. For example, in predicting rock mechanical properties, deep neural network models not only exhibit high accuracy but also automatically adjust their structure to adapt to different data types and magnitudes (Lawal and Kwon 2021a). Moreover, traditional methods rely on offline calculations and struggle to process and analyse field data in real-time, resulting in slow response times. AI algorithms, however, can process sensor data in real-time for dynamic prediction and decision support, providing a valuable supplement to traditional computation methods. For instance, during tunnel excavation, AI systems can monitor and optimise excavation parameters in real-time and feedback to traditional calculation methods for verification, thereby enhancing construction safety (Liang et al. 2024; Phoon and Shuku 2024).

Different AI technologies have their own strengths and weaknesses in specific geotechnical engineering applications. Support Vector Machines (SVM) perform well with small sample datasets and high-dimensional data, making them suitable for complex nonlinear problems (Goh and Goh 2007; Samui et al. 2008). They have strong generalization capabilities and can handle various complex geotechnical issues, such as foundation bearing capacity prediction (Kordjazi et al. 2014) and slope stability analysis (Samui 2008). However, SVMs require the selection of appropriate kernel functions and parameters, which makes the parameter adjustment process relatively complex and computationally expensive, especially when processing large datasets. Neural Networks (ANN) possess strong self-learning and adaptive capabilities, can handle complex nonlinear relationships, and perform well on large datasets. They are suitable for applications such as soil classification, foundation settlement prediction, and tunnel stability analysis (Yaghoubi et al. 2024). However, the training process of ANNs may require significant computational resources and time, and they are prone to overfitting. This necessitates large amounts of data and regularization techniques to improve the model's generalization ability. Gene Expression Programming (GEP) can generate interpretable model structures and is applicable to complex geotechnical problems, excelling at handling nonlinearities and uncertainties. For instance, GEP has shown excellent performance in the reliability analysis of reinforced soil foundations (RSF) based on settlement criteria, demonstrating its potential in civil engineering risk analysis (Raja et al. 2024). Additionally, GEP also performs well in predicting liquefaction-induced lateral spreading, with higher prediction accuracy and lower bias compared to other regression models (Raja et al. 2023). However, GEP requires a substantial amount of training data to generate high-quality models, and the complexity and computational cost of these models can be high. Gaussian Process Regression (GPR) and Relevance Vector Machines (RVM) provide probabilistic predictions, quantify uncertainty, and perform well on small datasets, making them suitable for tasks requiring high accuracy (Mahmoodzadeh et al. 2021; Tomizawa and Yoshida 2022). Applications of these methods in geomechanics include foundation settlement prediction and slope instability risk assessment (Samui 2011; Ceryan 2014; Samui and Kurup 2013). However, these methods involve high computational complexity, long training times, and the need to select and adjust appropriate kernel functions and parameters, which pose certain limitations in practical applications.

6.5 Opportunity and challenge

AI presents transformative opportunities for tackling mechanics-related challenges within geotechnical engineering, offering paths towards the analysis and modelling of soil mechanics and rock behaviour. A crucial opportunity lies in the exceptional analytical capabilities of AI that can assist in assessing complex, nonlinear relationships integral to soil and rock mechanics, thereby providing information that traditional modelling approaches often miss. These facilitate the characterisation and prediction of stress–strain responses under different loading conditions, soil types, and environmental factors. This not only deepens our understanding but also significantly enhances our approach to geotechnical mechanics. Furthermore, AI facilitates the integration and analysis of diverse datasets ranging from laboratory test results to in-situ measurements, fostering a comprehensive, multi-scale understanding of geotechnical behaviour and allowing for optimised experimental designs and testing procedures. Nonetheless, with such promising opportunities come challenges. A primary challenge involves ensuring the availability and reliability of large datasets, which are fundamental for training and validating AI models. Data quality is paramount, as the efficacy and robustness of AI models are significantly dependent on it. Furthermore, the generalisation capability of AI models requires assessment and validation. These models must be capable of effectively replicating the nonlinear stress–strain responses of various soils under different conditions while considering the various influencing factors at play. This necessity for generalisation is crucial for their performance and applicability under diverse soil conditions and testing scenarios. Moreover, the interpretability and explainability of AI models are critical. Understanding how to interpret AI predictions is essential for gaining trust and ensuring practical applicability in geotechnical engineering. The challenge extends to guaranteeing that AI models are not only accurate but also reliable in various real-world applications, ensuring they contribute positively to the field of geotechnical engineering.

6.6 Ethical implications and environmental considerations of applying artificial intelligence in geotechnical mechanics

The application of artificial intelligence (AI) in geotechnical engineering presents significant potential but also raises important ethical and environmental considerations. Ethically, data privacy and security are paramount since AI relies on extensive geological and infrastructure data. Additionally, AI models must be developed to avoid biases, ensuring fair and transparent decision-making. The increasing autonomy of AI systems also necessitates clear accountability frameworks to address errors or failures. Environmentally, AI can enhance sustainable resource management by optimizing material use and reducing waste. It can improve the accuracy of environmental impact assessments, helping to mitigate adverse effects on ecosystems. AI can also bolster infrastructure resilience to climate change by using weather data for better design. However, the energy consumption and carbon footprint of AI technologies themselves must be addressed. Implementing green computing practices and using renewable energy can help reduce these impacts. In summary, while AI holds great promise for geotechnical engineering, it is crucial to address its ethical and environmental challenges to ensure it contributes to sustainable and responsible development.

6.7 Future perspectives

Although artificial intelligence (AI)-enhanced computational models have significant capabilities in data processing and pattern recognition, they also face substantial challenges in adapting to complex geological scenarios and dynamic environments. When data are scarce or incomplete, these models often struggle to provide accurate predictions, resulting in outcomes that may conflict with existing geotechnical knowledge. This is primarily because these models rely on data-driven approaches without incorporating physical theories, thereby weakening their reliability and interpretability in complex geotechnical contexts. Additionally, existing AI models may lack robustness when faced with new or unexpected geological conditions. These models are often trained on specific datasets that may not adequately represent the diversity and complexity of real-world environments. Therefore, their ability to generalize and provide accurate predictions under diverse geological conditions can be compromised. This is especially true when dealing with "out-of-range data," where current AI models often fail to provide reliable predictions. To address these challenges, future research should focus on the following directions:

(1) Combining Physical Theory and Adaptive Learning: Integrate physical information and adaptive learning strategies into computational mechanics. By combining deep learning with the fundamental principles of geotechnical engineering, models can adhere to physical laws during both training and prediction phases. This approach enhances the reliability and interpretability of models, making them more robust under complex geological conditions.
(2) Developing Models that Handle Out-of-Range Data: Research and develop new AI models capable of identifying and processing out-of-range data to improve reliability and adaptability under uncertain conditions. For instance, exploring methods such as transfer learning and meta-learning can enable models to learn from limited data and adapt to new geological conditions.
(3) Introducing Adaptive Intelligent Computing Technology: By dynamically adjusting algorithms and parameters, adaptive intelligent computing technology can improve a model's ability to respond to changing data and environments. This technology allows models to automatically optimize their parameters and structure in real-time, enhancing performance in dynamic conditions.
(4) Developing Multi-Scale and Multi-Physics Computing Models: AI-integrated multi-scale and multi-physics computing models can handle and analyze interactions across different scales, from micro to macro, as well as across various physical domains, including mechanics, hydrology, and chemistry. For example, AI-driven models can

combine microstructural soil data with macroscopic behavioral insights, while accounting for the effects of moisture migration and chemical transformations on soil mechanics.

7 Conclusions

This review assesses the role of AI-enhanced computational mechanics in geotechnical engineering, emphasising its growing significance and potential in tackling the complex behaviours of soils and rocks. It provides a comprehensive evaluation of various AI methodologies applied in this domain. Several key conclusions emerge concerning the current state and future prospects of AI in geomechanics:

(1) AI methodologies are increasingly deployed in geomechanics to forecast the inherent nonlinear relationships of the mechanical behaviour of geological materials. ANN, RF, and SVM collectively constitute significant proportions—35%, 19%, and 17% respectively—reflecting their usefulness in predicting mechanical properties such as strength and modulus. AI is being significantly deployed for predicting mechanical properties, which represents a 59% proportion, confirming its robust data processing and pattern recognition capabilities.
(2) This review categorises the application of AI in geomechanics into four distinct areas: physical properties, mechanical properties, constitutive models, and other applications of geotechnical materials. While ANN is seen as the predominant technique, other methodologies including SVM, LSTM, and CNN have also contributed to the field.
(3) The efficacy and reliability of AI applications in geomechanics hinge significantly on the quality and quantity of datasets employed for training, the careful selection of model inputs, and the implementation of accuracy assessment methodologies. Sound data management practices and meticulous model configurations are pivotal for enhancing the performance and applicability of AI models. Looking ahead, integrating physical principles with data-driven models and leveraging reinforcement learning and deep learning technologies will be critical for addressing multi-scale and multi-physics coupling problems, thereby augmenting the applicability and reliability of AI in geomechanics.
(4) High-quality datasets serve as benchmarks for the learning and assessment of prediction accuracy of AI models. Therefore, the generation, curation, and management of datasets, with a particular focus on real-world engineering projects should be prioritised. This will be essential for ensuring the precision and applicability of AI models in predicting and analysing the behaviour of geotechnical materials.

Appendix. A: brief overview of classic AI techniques

AI represents a multi-disciplinary field of study aiming to enable machines to emulate and execute as human intelligence, encompassing functions ranging from basic computation to complex decision-making. The ultimate goal is to deploy intelligent systems capable of autonomous learning, reasoning, and adaption to new environments (Lawal and Kwon 2021b; Cevallos et al. 2023). Machine Learning, a subset of AI, enables machines to acquire the ability to learn and extract knowledge from massive data through specialised algorithms. This learning approach relies on statistical and mathematical models to identify patterns within data for more accurate predictions. Machine learning is not just a technology, but also enables a wider use of data in understanding and addressing problems (Feng et al. 2020a; Peng et al. 2021; Furtney et al. 2022).

Deep learning is a more specialised branch within machine learning, drawing inspiration from the structure and functions of the human neural network (Oishi and Yagawa 2017; Garnier et al. 2021; Yu et al. 2023). It manages and analyses data through the creation of multi-layered neural networks. This hierarchical network structure allows deep learning to capture and learn the complex, multi-dimensional characteristics and patterns within data, making it particularly targeted at high-dimensional data such as images and sound. This has paved the way for a new dimension of applications and research (Bekele 2021; Wu and Wang 2022; Geyin et al. 2022; Guan and Yang 2023).

Machine learning is a branch of AI, that serves as a method and means to achieve AI objectives; deep learning, on the other hand, represents a more advanced and complex domain within machine learning, taking the philosophies and methods of machine learning to the utmost level (Baduge et al. 2022). AI, machine learning, and deep learning are three closely related yet distinct technological domains, each with its unique characteristics. Together, they form a significant branch of modern computational science, fostering continuous advancements and innovations in technology and science. Their relationship not only manifests a hierarchical structure from the general to the specific but also portrays an evolutionary and developmental process of technology and concepts from simplicity to complexity, and from superficial to profound layers.

This section provides a brief overview of different AI techniques and algorithms used in geomechanics kinds of literatures, that are considered in this study. This includes (i) Artificial Neural Networks (ANNs), (ii) Convolutional Neural Networks (CNNs), (iii) Recurrent Neural Networks (RNNs), (iv) Long Short-Term Memory (LSTM), (v) Generative Adversarial Networks (GAN), (vi) Support Vector Machines (SVM), (vii) Random Forest (RF), and (viii) Bayesian Networks (BN).

Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) play a crucial role in the computational domain, simulating the intricate workings of human neural circuits to unravel complex computational problems. These networks consist of layers of interconnected node that process input data through weighted connections to map inputs to outputs (Hasebe and Nagayama 2002; Yadav and Chandel 2014; Mitusch et al. 2021). At the core of its operational framework (shown in Fig. 12), ANNs undergo a training phase where they iteratively adjust connection weights based on the discrepancy between predicted and true training data labels. This adjustment is achieved through optimization algorithms like backpropagation, main to minimize a predefined loss function and improve predictive accuracy over time (Ding et al. 2013).Activation functions within neurons introduce non-linear properties to the system, enabling them to learn from complex data patterns(Azoor et al. 2022). ANNs have found profound applications in identifying underlying patterns and structures within large, unstructured datasets (Baghbani et al. 2023). This capacity for pattern recognition and autonomous learning positions ANNs as an indispensable tool in the ongoing revolution in artificial intelligence and data science.

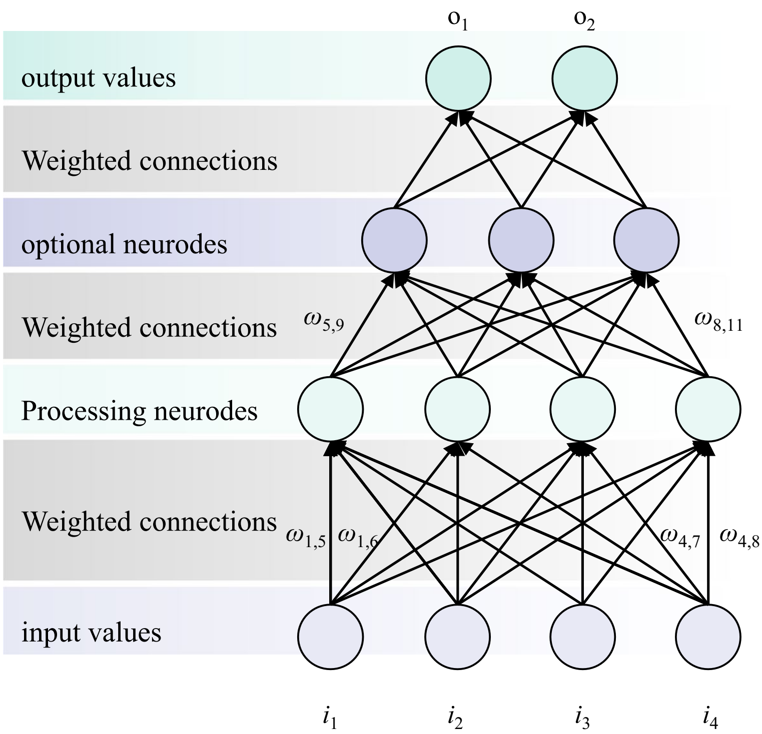

Fig. 12 Sample ANNs architecture

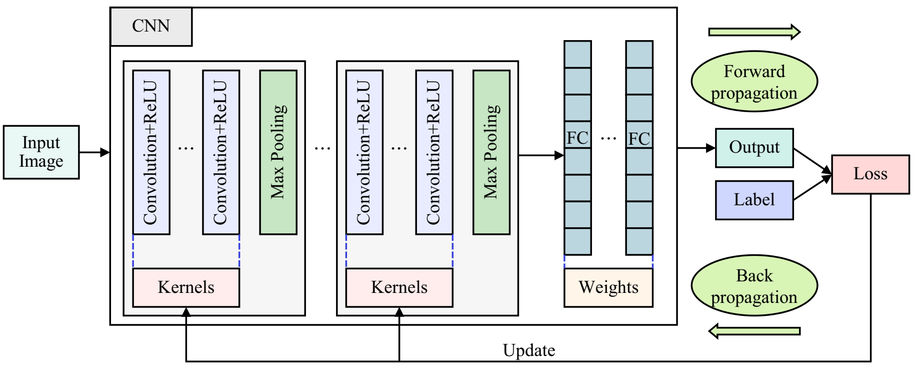

Fig. 13 Typical CNN architecture

Convolutional neural network (CNN)

A Convolutional Neural Network (CNN) is a specialized type of feedforward neural network that mirrors the neural structures found in animal visual cortices, excelling in processing extensive image datasets (Zhou 2020). As depicted in Fig. 13, the CNN structure, which combines convolutional and fully connected layers along with pooling layers, is particularly adept for tasks like image and speech recognition (Gu et al. 2018). Central to CNN are the convolutional layers that employ a series of filters to extract distinct features such as textures and edges from images, fostering the abstraction of higher-level features as the network depth increases (Zhang et al. 2019b). This process is streamlined by pooling layers that reduce feature map dimensions while preserving significant features (Zhang et al. 2017b), followed by fully connected layers that translate abstracted feature maps into decisive outputs, integral in classification and regression tasks (Yamashita et al. 2018). Through strategic weight adjustments during training, CNN gradually learn to interpret complex data, demonstrating exceptional capabilities in image recognition and object detection tasks (Zhang et al. 2017a).

Recurrent neural networks (RNN)

Recurrent Neural Networks (RNN) are a type of artificial neural network distinguished by their bidirectional data flow between layers, facilitating effective processing of varied input sequences, a trait beneficial in handwriting and speech recognition tasks (Zhang et al. 2014). In contrast to CNN, which have a finite impulse response, RNN harbour an infinite impulse response, granting them temporal memory capacities necessary for tasks involving sequential patterns and context (Yu et al. 2019b). As illustrated in Fig. 14, RNN operate as dynamic systems with changing hidden states, assimilating current inputs and previous information (Weerakody et al. 2021). These hidden states serve as a memory, capturing sequential nuances and context, proving indispensable for sequence-dependent applications. Innovations such as gated memory, embodied in architectures like LSTM and Gated Recurrent Units, have mitigated issues like vanishing gradients, empowering RNN to decipher extended dependencies in sequences (Wang et al. 2023b).

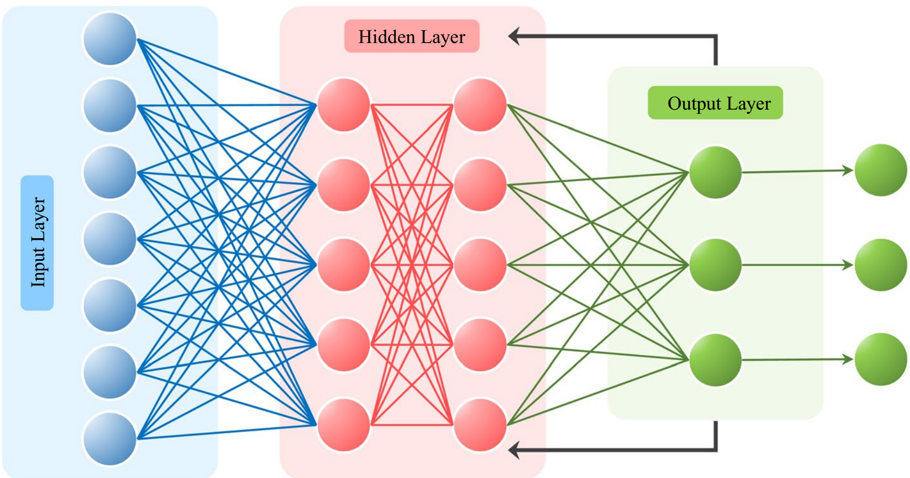

Fig. 14 Typical RNN architecture

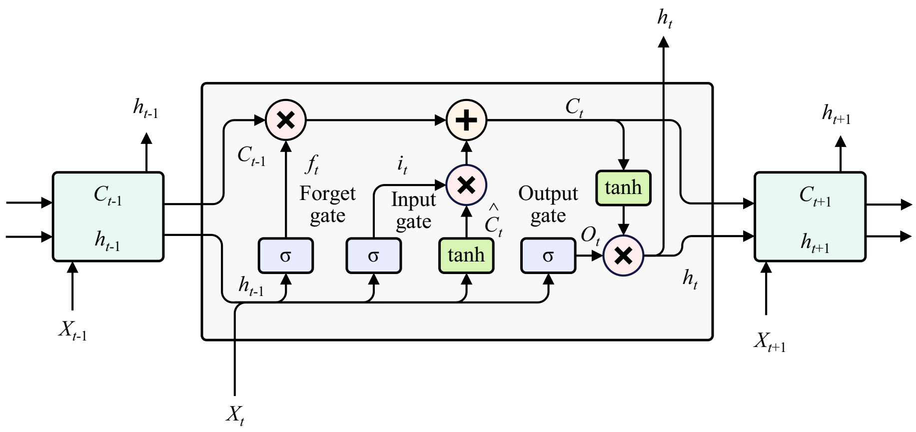

Fig. 15 Typical LSTM architecture

Long short-term memory (LSTM)

Long Short-Term Memory (LSTM), an advanced derivative of recurrent neural networks (RNNs), adeptly mitigates the vanishing gradient issue commonly found in standard RNNs, thereby outperforming other sequential learning strategies, including hidden Markov models (Van Houdt et al. 2020). As depicted in Fig. 15, an LSTM unit consists of a core cell and three gates: input, output, and forget (Zhang et al. 2021c). This cell, capable of holding information over diverse periods, works in conjunction with the gates to effectively manage the information transition, both incoming and outgoing (Rostamian and O'Hara 2022). These gates selectively evaluate and integrate relevant data, with the forget gate, in particular, determining the continuity of past state information through a comparison with the current input (Liu et al. 2021). Thus, LSTMs excel at retaining and exploiting

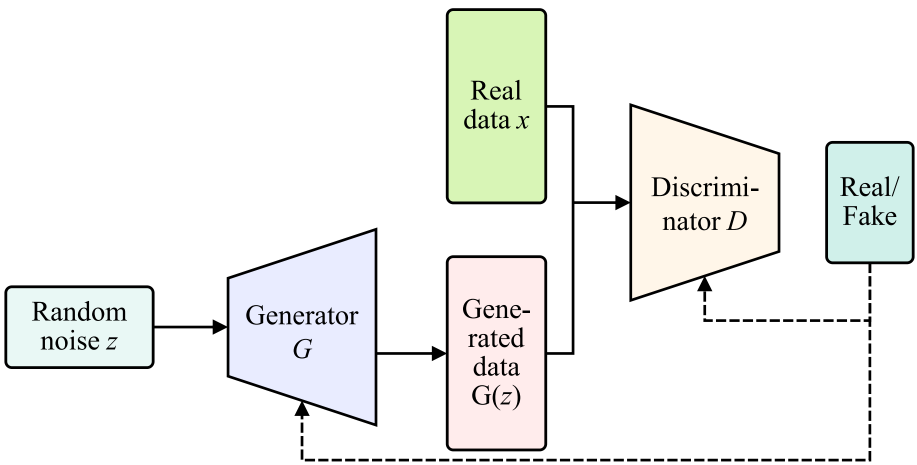

Fig.16 Computation procedure and structure of GAN

long-term dependencies, which significantly enhances their predictive prowess over several time steps.

Generative adversarial networks (GAN)

Generative Adversarial Networks (GANs) have emerged as a pivotal framework in generative AI, depicting a competitive scenario between two neural networks in a zero-sum game (Wang et al. 2017). As illustrated in Fig. 16, GAN work by synthesizing new data which bear statistical resemblance to a training dataset, thereby facilitating the generation of authentic-seeming content. The distinctive aspect of GAN lies in the adversary training process involving a discriminator, a network that evolves to assess the authenticity of data inputs, thereby guiding the generator in a direction that is not just about minimizing the divergence to a target image but tricking the discriminator. This results in an ongoing evolutionary competition between networks, yielding progressively sophisticated data outputs (Gui et al. 2023). Initially conceptualised for unsupervised learning, GAN have expanded their utility to semi-supervised (Zhang et al. 2019c), fully supervised (Guo et al. 2023), and reinforcement learning environments (Li and Zhao 2023), enhancing traditional simulations in computational mechanics. By creating synthetic structural responses, GAN facilitate a comprehensive analysis of behaviours even in situations with limited data, providing vital insights into complex structural system interactions and stress distributions.

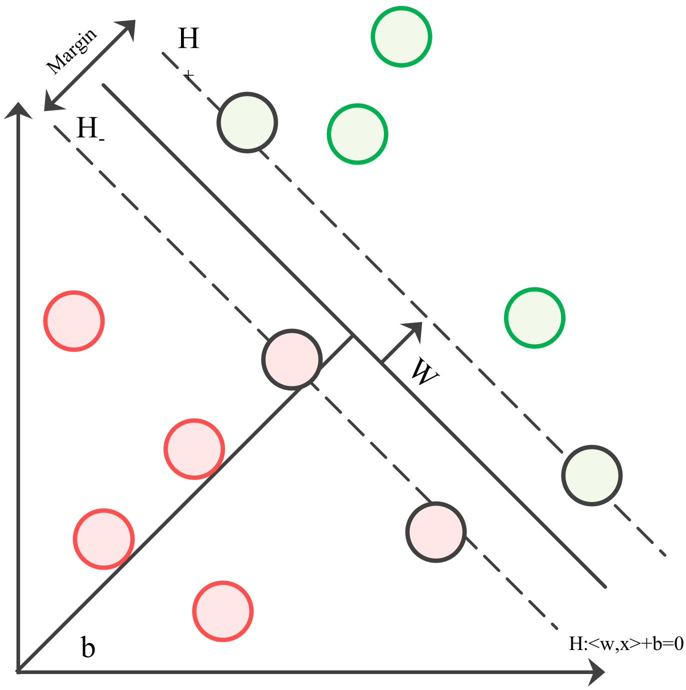

Fig. 17 Structure of Support Vector Machines

Support vector machines (SVM)

Support Vector Machines (SVM) play a significant role in machine learning (Huang and Zhao 2018). Operating under supervised learning, SVM and their associated algorithms are potent tools for analysing data through classification and regression (Ben Chaabene et al. 2020). As shown in Fig. 17, SVM are binary classifiers, constructing predictive models from labelled training data. These models classify new instances based on their position within a feature space, maximizing category separation using a hyperplane (Huang et al. 2023b). SVM extend beyond linear classification through the kernel trick, projecting data into higher-dimensional spaces to capture complex patterns. The support vector clustering algorithm, stemming from SVM principles, offers unsupervised learning for natural data clustering. Data points form clusters, enabling intuitive categorization of new instances.

Random forest (RF)

Random forest is a versatile ensemble learning technique widely employed in machine learning for tasks encompassing classification, regression, and more. As shown in Fig. 18, this method involves the creation of multiple decision trees during training, where classification outcomes reflect the majority consensus among trees, while regression tasks aggregate predictions for a comprehensive result (Zhang et al. 2019a; Zhu et al. 2021; Nhat-Duc and Van-Duc 2023). By countering decision trees' overfitting tendency, random forests typically outperform individual trees, albeit potentially falling short of gradient-boosted trees' accuracy, contingent on dataset attributes (Ho 1998). In the realm of computational mechanics in geotechnical engineering, random forests emerge as a potent predictive tool for analysing structural dynamics like material strength, stress distribution, and failure

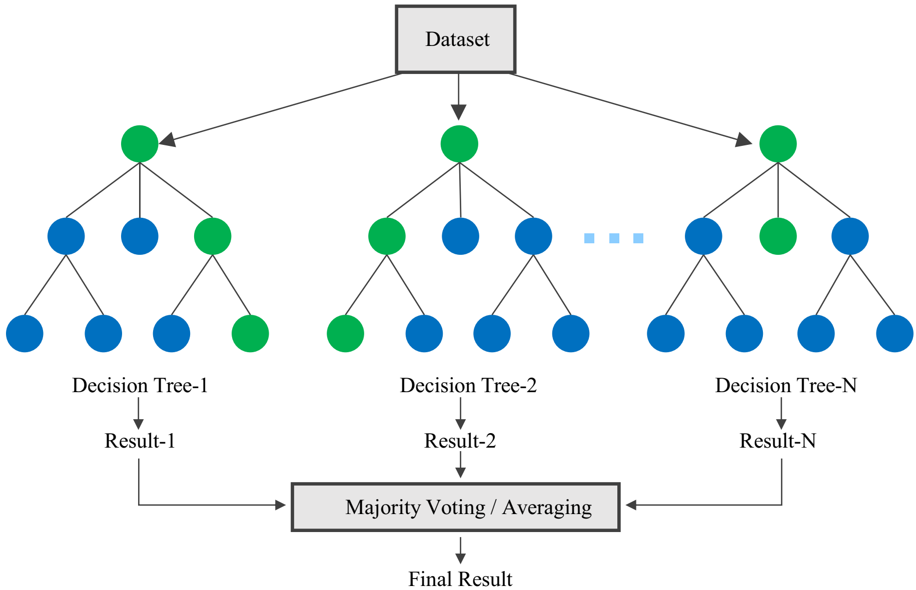

Fig. 18 Structure of Random Forest

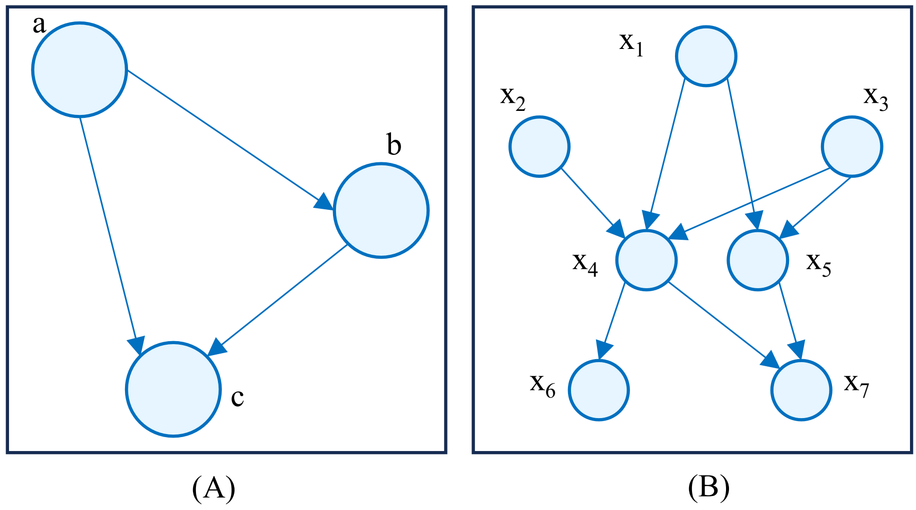

Fig. 19 Structure of Bayesian network

prediction. Their adeptness in handling high-dimensional data and capturing intricate relationships positions them as effective tools for unravelling the complexities of architectural systems.

Bayesian networks (BN)

A Bayesian network stands as a powerful probabilistic graphical model that encapsulates a collection of variables and their conditional interdependencies through a directed acyclic graph (DAG). Within the realm of causal notation, Bayesian networks offer a versatile framework for analyzing probabilistic relationships and causal associations among variables (Zhang et al. 2020b; Zhou et al. 2022b). The Bayesian network represents a set of random variables and their conditional dependencies through a directed acyclic graph, parameterized by conditional probability distributions. As depicted in Fig. 19(A), here is a simplified Bayesian network, the corresponding comprehensive probability formula is as Eq. (1):

$$P(a,b,c) = P\,left(c|a,b)P(b|a)\,P(a) \tag{1}$$

Figure 19(B) depicts a more complex Bayesian network, with the corresponding comprehensive probability formula as Eq. (2):

$$P\left(x_1,x_2,x_3,x_4,x_5,x_6,x_7\right) = P\left(x_1\right)P\left(x_2\right)P\left(x_3\right)P\left(x_4|x_1,x_2,x_3\right)P\left(x_5|x_1,x_3\right)P\left(x_6|x_4\right)P\left(x_7|x_4,x_5\right) \tag{2}$$

Efficient algorithms are available for conducting both inference and learning within Bayesian networks, further enhancing their utility across diverse domains. These dynamic counterparts enable the representation and analysis of sequential dependencies, imparting the model with the capability to capture intricate temporal patterns and dynamics. Expanding the paradigm, influence diagrams emerge as generalized forms of Bayesian networks, tailored to tackle decision problems under conditions of uncertainty (Xiao et al. 2014a).

By integrating probabilistic reasoning with decision-making, influence diagrams provide a robust methodology for addressing complex real-world scenarios where optimal choices must be made amidst uncertain outcomes (Castillo et al. 2016).

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Declarations

Competing interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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