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Review article

Comprehensive review of machine learning in geotechnical reliability analysis: Algorithms, applications and further challenges

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A R T I C L E I N F O

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A B S T R A C T

Geotechnical reliability analysis provides a novel way to rationally take the underlying geotechnical uncertainties into account and evaluate the stability of geotechnical structures by failure probability (or equivalently, reliability index) from a probabilistic perspective, which has gained great attention in the past few decades. With the rapid development of artificial intelligence techniques, various machine learning (ML) algorithms have been successfully applied in geotechnical reliability analysis and the number of relevant papers has been increasing at an accelerating pace. Although significant advances have been made in the past two decades, a systematic summary of this subject is still lacking. To better conclude current achievements and further shed light on future research, this paper aims to provide a state-of-the-art review of ML in geotechnical reliability analysis applications. Through reviewing the papers published in the period from 2002 to 2022 with the topic of applying ML in the reliability analysis of slopes, tunneling, and excavations, the pros and cons of the developed methods are explicitly tabulated. The great achievements that have been made are systematically summarized from two major aspects. In addition, the four potential challenges and prospective research possibilities underlying geotechnical reliability analysis are also outlined, including multisensor data fusion, time-variant reliability analysis, three-dimensional reliability analysis of practical cases, and ML model selection and optimization.

Contents

Abbreviations: ML, Machine learning; MCS, Monte Carlo simulation; ANN, Artificial neural network; SVM, Support vector machine; RVM, Relevant vector machine; PSO, Particle swarm optimization; ELM, Extreme learning machine; MARS, Multivariate adaptive regression splines; XGBoost, Extreme gradient boosting; CNN, Convolutional neural network; AI, Artificial intelligence; BPNN, Back-propagation neural network; 2D, Two-dimensional; 3D, Three-dimensional; RBF, Radial basis function; GPR, Gaussian process regression; BF, Basic function; GCV, Generalized cross-validation; SVR, Support vector regression; SLFN, Single hidden layer feed-forward neural network; FS, Safety factor; P_f, Failure probability; RLEM, Random limit equilibrium method; RFEM, Random finite element method; RSM, Response surface method; RV, Random variable; RF, Random field; LSF, Limit state function; GA, Genetic algorithm; FEM, Finite element method; LS-SVM, Least squares support vector machine; PCE, Polynomial chaos expansion; ASVM, Adaptive support vector machine; ARVM, Adaptive relevant vector machine; CSRSM, Collocation-based stochastic response surface method; BCS, Bayesian compressive sampling

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1. Introduction

The safety of geotechnical structures has gained increasing attention in geotechnical engineering practice because their failure may cause significant casualties and economic losses, such as the catastrophic Qianjiangping landslide (e.g., [1]) and Shenzhen landslide [2]. Evaluating the stability of geotechnical structures reasonably is an important prerequisite for disaster prevention and reduction, and geotechnical reliability analysis provides a novel way to explicitly consider the underlying various geotechnical uncertainties (e.g., the inherent variability of geomaterial properties, transformation uncertainty, and measurement error) (e.g., [3,4]) and quantify the safety margin of geotechnical structures by failure probability (or equivalently, reliability index) from a probabilistic perspective. Generally, the evaluation of failure probability is not a trivial task in geotechnical reliability analysis since the complicated implicit performance functions are commonly encountered in engineering practice, leading to the unavailability of analytical solutions. In such a case, the brute-force Monte Carlo simulation (MCS) method has gained popularity in reliability analysis by virtue of its simplicity, flexibility, and easy to use for geotechnical engineers. Nonetheless, it suffers from a known criticism of extensive computational efforts and poor efficiency (e.g., [5–7]). The MCS needs to repeatedly invoke geotechnical software (e.g., Abaqus, FLAC, and GeoStudio) to perform a large number of deterministic analyses so as to reach the desired accuracy, which may be a computationally expensive task in practical applications.

With the rapid development of artificial intelligence technologies, many researchers have contributed to the integration of ML and geotechnical reliability analysis for improving computational accuracy and efficiency, which gives rise to a lot of successful applications (e.g., [5,8–16]). The basic idea of ML in aiding geotechnical reliability analysis is to reconstruct the high-dimensional implicit performance function through learning from the prepared data which mainly contains the input random variables or random field samples of geomaterial properties (e.g., cohesion, friction angle, and saturated hydraulic conductivity) as well as the corresponding quantity of interest (e.g., the factor of safety) that is generally calculated from the geotechnical software. As the ML-based reliability analysis model reaches the desired performance after sufficient training and proper validation, it can be conveniently used to estimate the failure probability of geotechnical structures with reasonable accuracy and efficiency.

Until now, various ML algorithms and their variants have been successfully applied in the geotechnical reliability analysis, such as artificial neural network (ANN) (e.g., [17]), support vector machine (SVM) (e.g., [18]), relevant vector machine (RVM) (e.g., [15]), particle swarm optimization (PSO) (e.g., [19]), extreme learning machine (ELM) (e.g., [20]), multivariate adaptive regression spline (MARS) (e.g., [10,21]), extreme gradient boosting (XGBoost) (e.g., [11,22,23]), and convolutional neural network (CNN) [7,13,14,24,25]. These ML algorithms greatly enhance the computational efficiency in the geotechnical reliability analysis, allowing engineers and researchers to focus more on the engineering problems without being compromised by the prohibitively computational tasks in practical applications. Furthermore, benefiting from the great development of ML, the free and open-source packages of the above-mentioned ML algorithms are widely available today from the Internet, such as the open-source packages of the XGBoost and CNN are shared in the well-known GitHub website and can be downloaded for users freely. This open and friendly environment has greatly accelerated the development of ML-based geotechnical reliability analysis methods. Through retrieving from the Web of Science database, a total of 306 papers have been published in the period from 2002 to 2022 concerned with applying ML in the reliability analysis of slopes, tunneling, and excavations. In the past two decades, more and more geotechnical practitioners have been devoted to the application of ML in geotechnical reliability analysis, and this research topic is expected to have great prospects.

Although significant advances have been made in geotechnical reliability analysis in the past two decades, a systematic summary on this subject is still lacking. To the best of the authors' knowledge, this paper is the first comprehensive survey of recent progress in ML-based geotechnical reliability analysis. The main contributions of this review can be summarized as follows: (1) It systematically reviews 306 papers with the topic of applying ML in the geotechnical reliability analysis of slopes, tunneling, and deep excavations, and the pros and cons of the developed methods are explicitly tabulated using three tables; (2) It provides insights into the previous research from two important aspects, namely the input geotechnical parameter characterization and output failure probability evaluation in geotechnical reliability analysis; (3) It outlines four crucial but unsolved problems in geotechnical reliability analysis, as well as novel challenges and promising research directions.

This paper aims to present a review of ML in geotechnical reliability analysis applications. The remainder of this paper starts with a brief introduction of failure probability evaluation in Section 2. In Section 3, several commonly used ML algorithms and their applications in the geotechnical reliability analysis are systematically outlined. Besides, the insights from previous works are also outlined in Section 4. In Section 5, the potential challenges and prospective research possibilities are presented. Finally, the primary conclusions drawn from this review are summarized in Section 6.

2. Failure probability evaluation

In geotechnical reliability analysis, the failure probability $\mathrm{P_f}$ (or reliability index β) is frequently used to measure the safety margin of geotechnical structures from a probabilistic perspective, which can be defined as (e.g., [4]):

$$\mathrm{P_f} = P[\mathrm{g}(\Theta) < 0] = \int \cdots \iint_{\mathrm{g}(\Theta)<0} f(\Theta) d\Theta \tag{1}$$

where Θ denotes geotechnical parameters that are commonly regarded as random variables or random field variables; $g(\Theta)$ is the performance function concerning geotechnical parameters

Θ; P[g(Θ) < 0] is the possibility of $g(\Theta)$ less than zero; $f(\Theta)$ denotes joint probability density function for Θ. Besides, the reliability index β of interest can be conveniently obtained by:

$$\beta = \Phi^{-1}(1 - P_f) \tag{2}$$

where Φ^{-1} denotes the inverse of the cumulative distribution function of the standard normal distribution.

Generally, it is difficult to solve the P_f analytically by integrating the performance function over the failure zone. This is because the performance function is usually implicit and highly nonlinear in geotechnical engineering. In such a case, it is preferable to calculate the P_f approximately by MCS due to its conceptual simplicity and easy implementation for geotechnical engineers. Taking the slope reliability analysis for example, the P_f can be calculated by:

$$P_f = \frac{1}{N_{MCS}} \sum_{i=1}^{N_{MCS}} I\left[FS_i < 1\right] \tag{3}$$

where N_{MCS} is the total number of MCS; FS_i denotes the safety factor (FS) based on the ith realization of random variables or random fields; $I[\cdot]$ is an indicator function for judging whether the slope failure occurs or not. If FS_i is less than the threshold value (i.e., 1), $I[\cdot] = 1$; otherwise, $I[\cdot] = 0$. As indicated by Eq. (3), it is a cumbersome task to calculate P_f which involves a large number of deterministic slope stability analyses. In such a case, an increasing number of ML algorithms have been integrated into geotechnical reliability analysis to improve computational efficiency, as discussed in the next section.

3. Applications of ML in geotechnical reliability analysis

From the statistical data retrieved from the Web of Science database, the main applications of ML in the reliability analysis of geotechnical structures focus on slopes, tunneling, and excavations. Fig. 1 depicts the proportion of ML applications in these three fields. It is obvious that most ML applications are devoted to the slope (i.e., 48%) in the past two decades, followed by excavation, and tunneling accounts for the smallest proportion. If 'machine learning', 'slope', and 'reliability' are used as keywords in a search engine of the Web of Science database, the annual number of published papers for 'slope' relating to 'machine learning' and 'reliability' can be obtained, as shown in Fig. 2(a). It can be seen that the application of ML in slope reliability analysis shows a dramatic increase in 2019 and 2021. Similarly, the number of publications in tunneling and excavation can also be obtained as shown in Fig. 2(b) and (c), respectively. As expected, the ML application in the reliability analysis of these two geotechnical structures has an increasing trend. Thus, this section will focus on previous studies related to reliability analysis of the three main geotechnical structures (i.e., slopes, tunneling, and deep excavations) based on ML techniques.

3.1. Some typical machine learning algorithms

Artificial intelligence (AI) tends to build intelligent systems that learn, adapt, mimic and even exceed human intelligence. In the past few decades, AI methods have been commonly used for solving scientific, engineering, economic and medical problems. These methods are considered as useful tools to address practical problems, as they can exploit and capture complex, dynamic, and non-linear relationships hidden in data. Currently, AI is used in a wide range of applications, including data mining, pattern recognition, natural language processing, self-driving, and so on. ML is seen as a primary component of AI and it is proposed to solve problems that cannot be explicitly programmed.

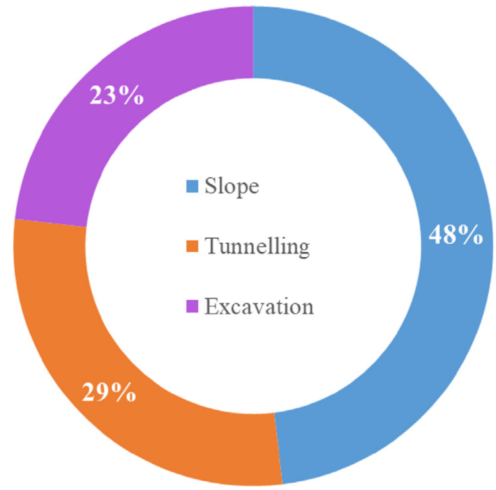


Fig. 1. Proportion of ML in the reliability analysis of geotechnical structures.

The key principle of ML is to learn from historic experience automatically and rationally through computer algorithms, and then apply what it has learned to new problems, as known as the generalization ability. Until now, ML has been widely used in the realm of geotechnical engineering because it provides a versatile tool to reveal and handle uncertainty and randomness (e.g., [26–33]), which are frequently faced by geotechnical engineers and researchers. This subsection will provide a brief introduction of several presentative ML algorithms popularized in the geotechnical reliability analysis.

3.1.1. Radial basis function (RBF)

The RBF is an important kind of feed-forward neural network, which is designed based on localized basis functions and iterative function approximation networks. The RBF neural network consists of three layers, i.e., input, hidden, and output layers (Fig. 3). Like other ANNs, the input layer takes input and the output layer provides the target value. The main feature of RBF lies in its hidden layer, where neurons process information with the application of the nonlinear transformation from the input space to the output space. More specifically, each neuron in the hidden layer uses the radial basis function as a non-linear activation function whose outputs are inversely proportional to the distance from the center of the neuron [34]. Therefore, the neuron center, the distance scale, and the shape of the radial function are the model parameters. For jth output, $y_j(i)$ can be expressed as follows:

$$y_j(i) = \sum_{k=1}^{K} w_{jk}\Phi[x(i), c_k, \sigma_k],\ \ j = 1, 2, \ldots, n\ i = 1, 2, \ldots, N \tag{4}$$

where w_{jk} denotes connection weight, $\Phi[x(i), c_k, \sigma_k]$ is the specific RBF used, $\sigma_k \in R^m$ and $c_k \in R^m$ are the width value vector and the center value vector of RBF, respectively, and K denotes the number of RBFs used. $c_k = [c_{k1}, c_{k2}, \ldots, c_{km}]^T \in R^m, k = 1, 2, \ldots, K$ and $\sigma_k = [\sigma_{k1}, \sigma_{k2}, \ldots, \sigma_{km}]^T \in R^m, k = 1, 2, \ldots, K$.

The most commonly used function $\Phi[\cdot]$ is the Gaussian form, which can be expressed as follows:

$$\varphi[x_i, c_{ki}, \sigma_{ki}] = \exp(\frac{-(x_i - c_{ki})^2}{2\sigma_{ki}^2}) \tag{5}$$

Therefore, the jth output in Eq. (4) can be calculated as follows:

$$y_j(i) = \sum_{k=1}^{K} w_{jk} \exp\left\{-\sum_{i=1}^{m}[(x_i - c_{ki})^2/2\sigma_{ki}^2]\right\} \tag{6}$$

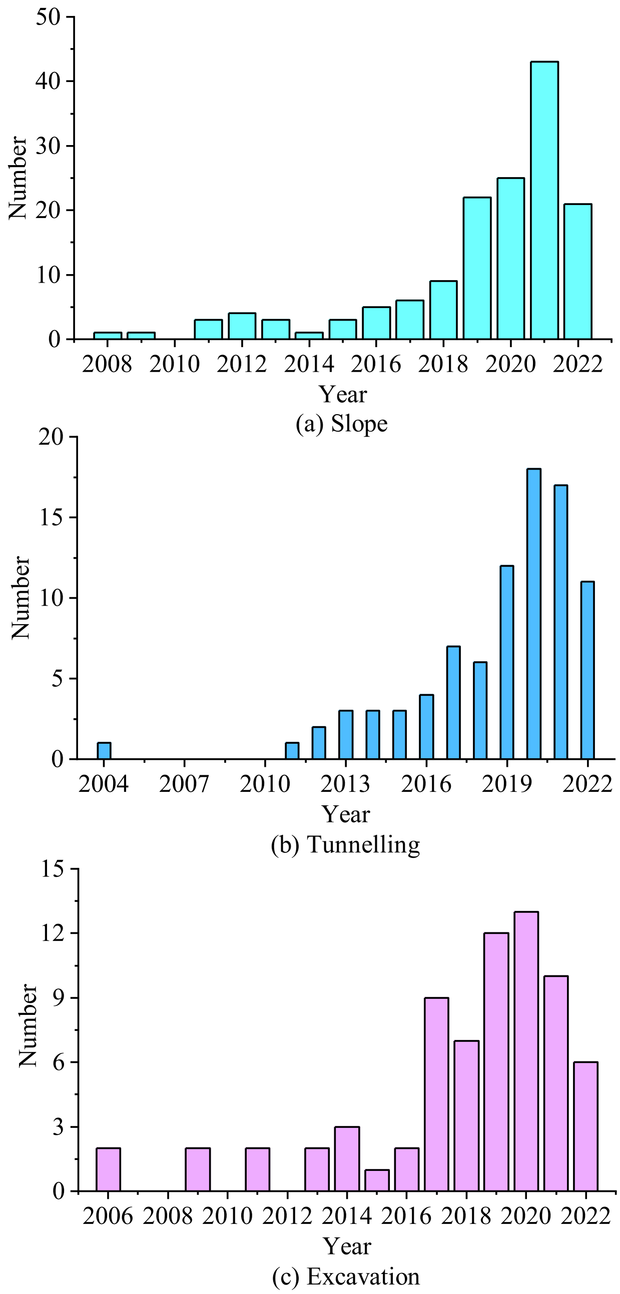


Fig. 2. Annual number of published papers relating to the ML application in reliability analysis of different geotechnical structures (Retrieved in August 2022).

where c_{ki} is the center of the Gaussian function and σ_{ki} denotes the Gaussian function spread. One of the selection methods for σ_k is expressed as follows:

$$\sigma_k^2 = \frac{1}{m_k} \sum_{x \in \theta_k} \|x - c_k\| \tag{7}$$

where m_k is the number of sample data in the kth cluster, and θ_k is the kth cluster of the training set.

3.1.2. Convolutional Neural Network (CNN)

The CNN was first proposed by Fukushima and Miyake [36], and it has been successfully used for the classification, segmentation, and recognition of images over the past two decades. Compared with traditional methods, CNN has proven its superiority in both accuracy and efficiency. The core feature of CNN lies in the building block which is composed of many layers that are interconnected with each other using a set of shared weights and biases. The architecture of a typical CNN (Fig. 4) consists of convolutional, pooling, and fully connected layers.

Convolution is a powerful tool used for extracting features. For an input image, a square convolutional kernel with weights is usually used to traverse each pixel. Each input pixel and the corresponding area of the convolution kernel are multiplied by the corresponding weights of the convolution kernel, which is also called the filter bank. The result of this product is then summed again, adding the bias of the convolution kernel. Finally, this process results in a pixel in the output image, which can be expressed as follows:

$$y_i = \sum_i x_i \times w_{ij} + b_i \tag{8}$$

where x_i denotes the input of each channel, w_{ij} is the corresponding weight of each convolutional kernel, b_i is the bias of the convolutional kernel, and y_i represents the final output. Generally, the results of this procedure are then passed through a nonlinear function, such as *Relu* and *tanh*. This approach not only effectively solves the disappearing gradient problem, but also has high execution speed and precision.

Pooling is a down-sampling operation, which selects spatial invariance by reducing the resolution of the feature map. Usually, the unit in a pooling layer receives the maximum of a local patch of units in one feature map, and there are two main types of pooling operations. The max-pooling operator selects the maximum value from an image array's subarrays. By contrast, the average pooling operator selects the mean value.

Fully connected layers are followed behind the convolution and pooling procedure. They are the traditional multi-layer perceptron neural network, which is one of the most popular ANNs. The term 'fully connected' implies that all units in the feature maps are concatenated together into a form of a vector.

3.1.3. Multivariate adaptive regression splines (MARS)

The MARS proposed by Friedman [38] is a nonlinear, nonparametric data-driven method to capture the underlying relationship between dependent variables and input variables without any specific assumption about the functional form. The word 'splines' in MARS means these splines are smoothly connected. According to Friedman [38], these curves are named as basic functions (BFs), where the interface points to connect any two adjacent pieces which are named as knots. These knots symbolize the beginning of some data in one specific region and the end of the data from another region, where the candidate knots are randomly set. Generally, the procedure to construct a MARS model contains two parts, named as the forward phase and the backward phase. To be specific, the forward phase is to add functions and determine the underlying knots to improve the prediction accuracy, and the least effective terms for MARS will be deleted in the backward phase.

MARS builds up the implicit functional relationship via BFs, including piecewise linear and piecewise cubic functions. For simplicity, only the piecewise linear function is demonstrated. Piecewise linear functions are in the form of $\max(0, x - t)$ corresponding to a knot at the value of t, which means only the positive part will be adopted, otherwise it will be given a value of zero:

$$\max(0, x - t) = \begin{cases} x - t, \textit{if } x \geq t \\ 0, \textit{otherwise} \end{cases} \tag{9}$$

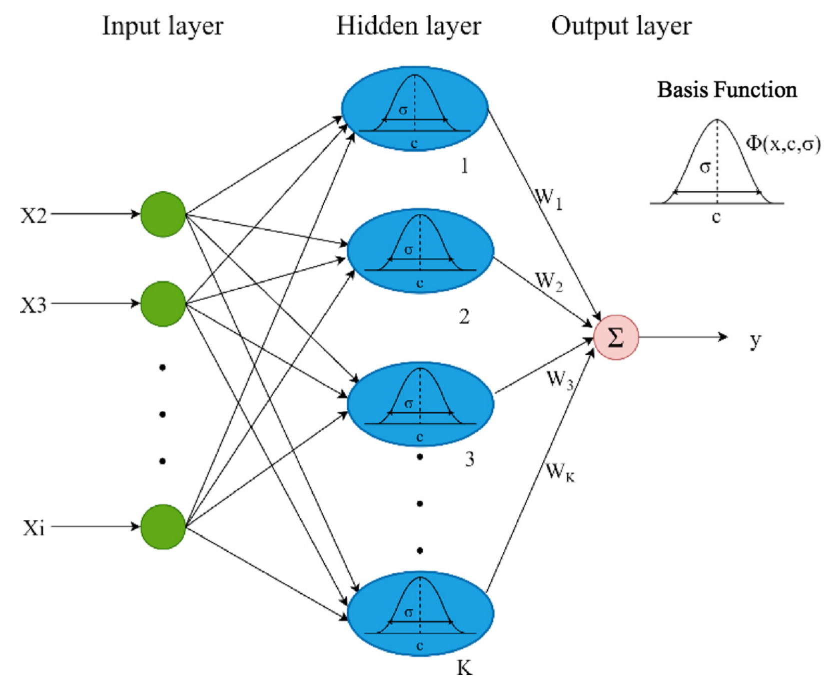


Fig. 3. A typical structure of RBF neural network.
Source: Adapted from Qasem et al. [35].

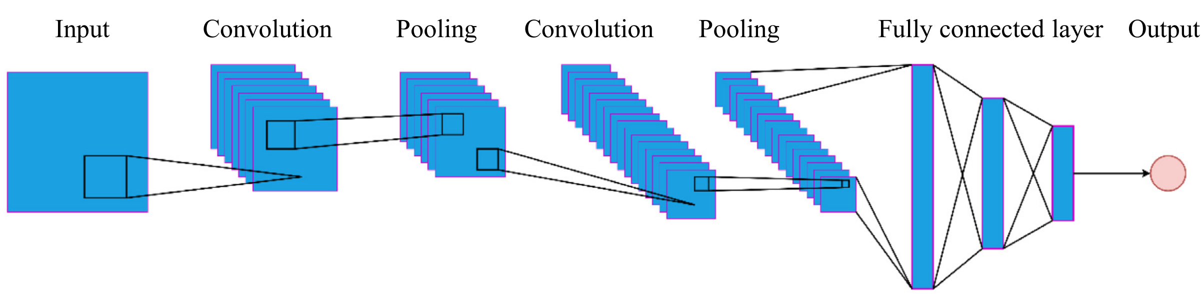


Fig. 4. A typical structure of CNN.
Source: Adapted from Li et al. [37].

Then, the MARS model will be built up of a linear combination of BFs and their interactions as follows:

$$f(\mathrm{X}) = \beta_0 + \sum_{i=1}^{m} \beta_i \lambda_i(\mathrm{X}) \tag{10}$$

in which each $\lambda_i(x)$ is a basis function in the form of a spline function, or the product of two or more spline functions already contained in the model. The constant coefficients β can be estimated via the least-squares method. In order to obtain the model in Eq. (10), a forward selection procedure is first conducted with the training data. Considering a current model with m basis functions, the next pair is added to the model in the form:

$$\hat{\beta}_{m+1}\lambda_i(X)\max(0, X_j - t) + \hat{\beta}_{m+2}\lambda_i(X)\max(0, t - X_j) \tag{11}$$

Similarly, each β is evaluated via the least square method. When a basic function is added to the MARS model, the interactions between any two pre-existing BFs in the model have been considered. BFs will be continually considered until the optimal model is obtained without underfitting or overfitting.

To reduce the number of terms, a procedure named backward deletion follows. This procedure aims to find a close to optimal model by removing the superfluous variables. In this phase, the algorithm prunes the model by deleting the BFs with the lowest contribution to the model until it finds the best sub-model. Model subsets are compared using the less computation-consuming method of Generalized Cross-Validation (GCV) to avoid overfitting. Interesting readers can refer to Zhang and Goh [39,40] for more details on the calculation of the GCV. Generally, MARS is an adaptive procedure because the selection of BFs and the variable knot locations are data-based and dependent on the specific problem.

3.1.4. Extreme learning machine (ELM)

The ELM is a computer algorithm proposed by Huang et al. [41] and it can be described as a least square-based single hidden layer feed-forward neural network (SLFN). Fig. 5 shows a typical architecture of ELM. For a single hidden layer ELM model with N samples $\{x_i, y_i\}$, where $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$ and $y_i = [y_{i1}, y_{i2}, \ldots, y_{ik}]^T \in R^k$, the standard SLFN with $\tilde{N}$ hidden neurons and the activation function $g(x)$ can be expressed as follows:

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i x_j + b_i) = o_j,\ \ j = 1, 2, \ldots, N \tag{12}$$

where $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ is the input weight of ith hidden layer neuron; $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{ik}]^T$ is the output weight of ith hidden layer neuron; b_i is the bias of ith hidden layer neuron; $w_i x_j$ is the inner product of w_i and x_j; $o_j = [o_{j1}, o_{j2}, \ldots, o_{jk}]^T$ is the output parameter of the jth input parameter.

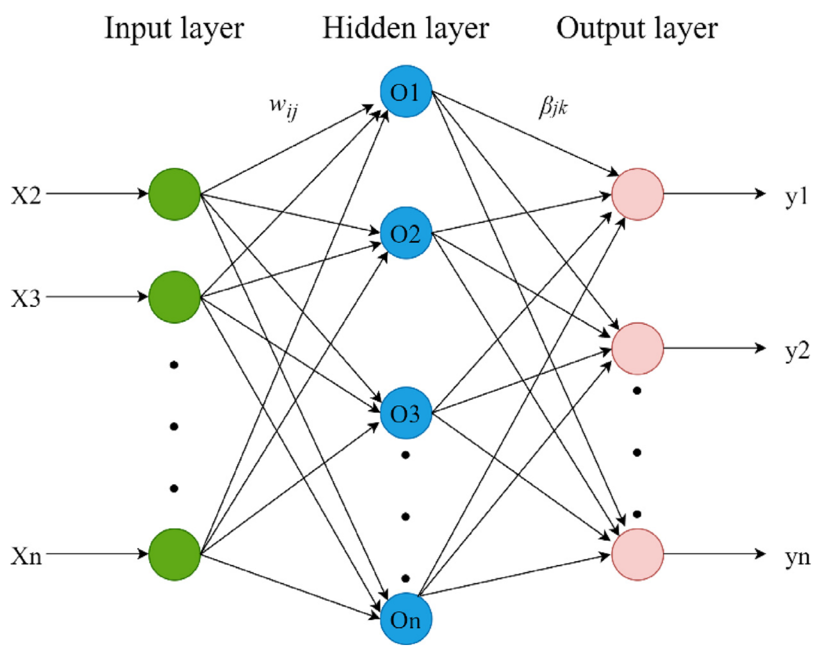


Fig. 5. A typical structure of ELM.

The model can be continuously improved by minimizing the errors between output and actual value, which can be expressed as:

$$\sum_{j=1}^{N} \left\| o_j - y_j \right\| = 0 \tag{13}$$

Eq. (12) is known as the cost function and it can be transformed into:

$$\sum_{i=1}^{\widetilde{N}} \beta_i g(w_i x_j + b_i) = y_j,\ \ j = 1, 2, \ldots, N \tag{14}$$

And it can be expressed in a simplified way:

$$H\beta = Y \tag{15}$$

where $H = \begin{bmatrix} g(w_1 x_1 + b_1) & \cdots & g(w_{\widetilde{N}} x_1 + b_{\widetilde{N}}) \\ \vdots & \ddots & \vdots \\ g(w_1 x_N + b_1) & \cdots & g(w_{\widetilde{N}} x_N + b_{\widetilde{N}}) \end{bmatrix}_{N\times\widetilde{N}}$ is the output matrix of the hidden layer, $\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\widetilde{N}}^T \end{bmatrix}_{\widetilde{N}\times k}$ is the output weight, and $Y = \begin{bmatrix} Y_1^T \\ \vdots \\ Y_N^T \end{bmatrix}_{N\times k}$ is the target matrix. H is usually obtained by the gradient descent method. The input weights w_i and hidden bias b_i can be randomly generated at the beginning of the training stage, and can be fixed during the training procedure. The output weight β_i can be determined by solving the least square solution of the linear system $H\beta = Y$:

$$\hat{\beta} = H^{\dagger} Y \tag{16}$$

where $H^{\dagger}$ is the Moore–Penrose generalized inverse of the matrix H.

3.1.5. Extreme gradient boosting (XGBoost)

The XGBoost was proposed as an alternative method to predict a response variable given certain covariates [42]. It uses a gradient boosting framework and is also a decision-tree-based ensemble method. The core principle of this method is that it builds classification or regression trees one by one, and then the residuals of the previous tree are used to train the subsequent model. In the training process, this method can integrate values of the previously trained trees to achieve a better outcome. It can use the pruning procedure to avoid over-fitting, which reduces the size of a decision tree by removing decision nodes that contribute little to target values. Fig. 6 shows the schematic diagram of the computational process of XGBoost and the prediction is calculated as:

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{17}$$

where $\hat{y}_i^{(t)}$ denotes the final tree model; $\hat{y}_i^{(t-1)}$ is the previous tree model; $f_t(x_i)$ is the newly generated tree model, and t is the total number of base tree models.

To achieve optimal model performance, it is important to select appropriate values of depth and number of trees. The objective function is defined as:

$$Obj^{(t)} = \sum_{i=1}^{t} L(y_i, \hat{y}_i^{(t)}) + \sum_{i=1}^{t} \Omega(f_i) \tag{18}$$

where y_i is the actual value; $\hat{y}_i^{(t)}$ is the predicted value; $L(y_i, \hat{y}_i^{(t)})$ is the loss function and $\Omega(f_i)$ is the regularization term.

Substituting Eq. (17) into Eq. (18) and then following some deduction steps (seen in [42]), Eq. (18) can be obtained as:

$$Obj^{(t)} = \sum_{i=1}^{t} L(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) + constant \tag{19}$$

Following Chen and Guestrin [42], the objective function can be transformed into the form of the following equation:

$$Obj^{(t)} = \sum_{i=1}^{t} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{20}$$

where $g_i = \partial y_i^{(t-1)} L(y_i, y_i^{(t-1)})$ and $h_i = \partial^2 y_i^{(t-1)} L(y_i, y_i^{(t-1)})$ are the first and second-order gradient statistics on the loss function.

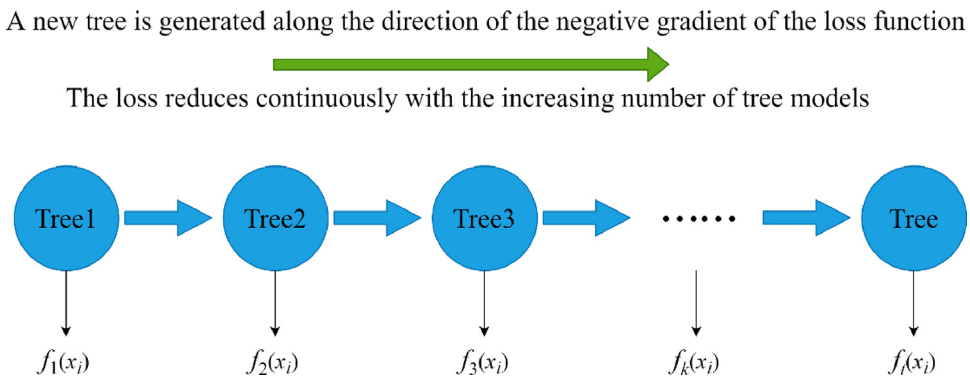


Fig. 6. The schematic diagram of XGBoost algorithm.
Source: Adapted from Mo et al. [43].

The regularization term $\Omega(f_t)$ is expressed by Eq. (21) and it is used to reduce model complexity and avoid over-fitting, enhancing the generalization ability.

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda \|w\|^2 \tag{21}$$

where T is the number of leaves; w is the corresponding weights of the leaf; λ and γ are coefficients, and the default values are 1 and 0, respectively.

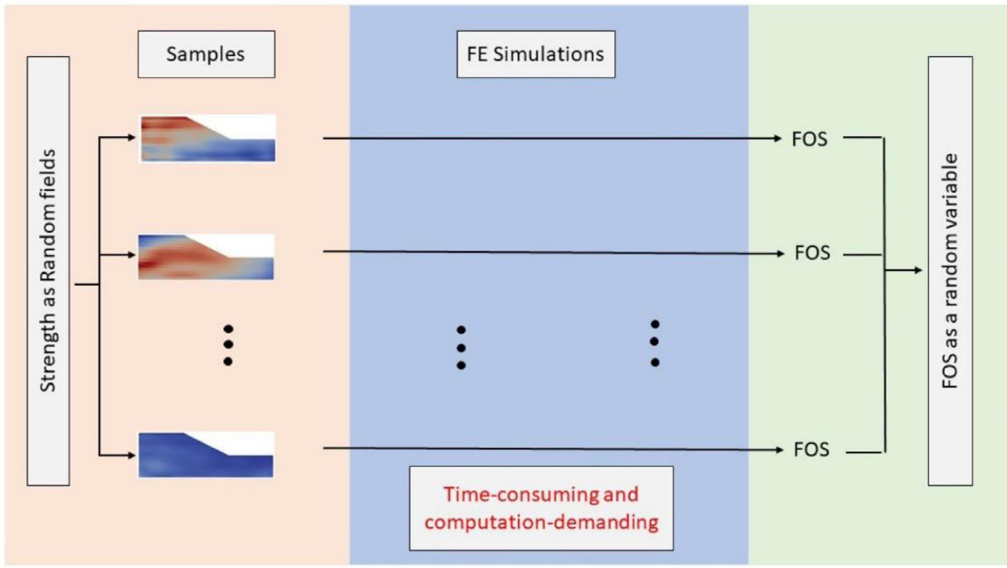
3.2. Slopes

With the increasing population, mountain areas are gradually being used, and more and more infrastructures are built near slopes to alleviate the pressure of the limited land resources [44]. In these areas, landslide hazards are widespread, thus fatalities and economic losses often occur. For disaster prevention and mitigation, slope stability analysis is often performed. In the traditional deterministic analysis, the FS measures whether a slope is safe, which is calculated via the limit equilibrium method, finite element limit analysis, or strength reduction method. Actually, the geotechnical parameters are rarely homogeneous by nature, e.g., soil properties in one site are different from those in another site due to various deposition conditions or loading histories [3]. The spatial variability of soil properties will be ignored by the aforementioned deterministic methods when assessing the slope stability and it is assumed that the soil parameters from different soil layers are all constant. To improve the accuracy of the slope stability assessment, the spatial variability of soil properties is considered and reliability analysis methods are adopted to estimate the slope stability with a widely-used indicator of P_f via the brute-force MCS method, which may be seriously computation-consuming. To be specific, the spatial variability of soil parameters is characterized via the random field theory, then each FS corresponding to a specific random field will be calculated. Based on the obtained FSs via the MCS, the P_f can be calculated. In the field of risk assessment for slopes in the geotechnical engineering, the aforementioned method to calculate the P_f is named as random limit equilibrium method (RLEM) and random finite element method (RFEM) correspondingly.

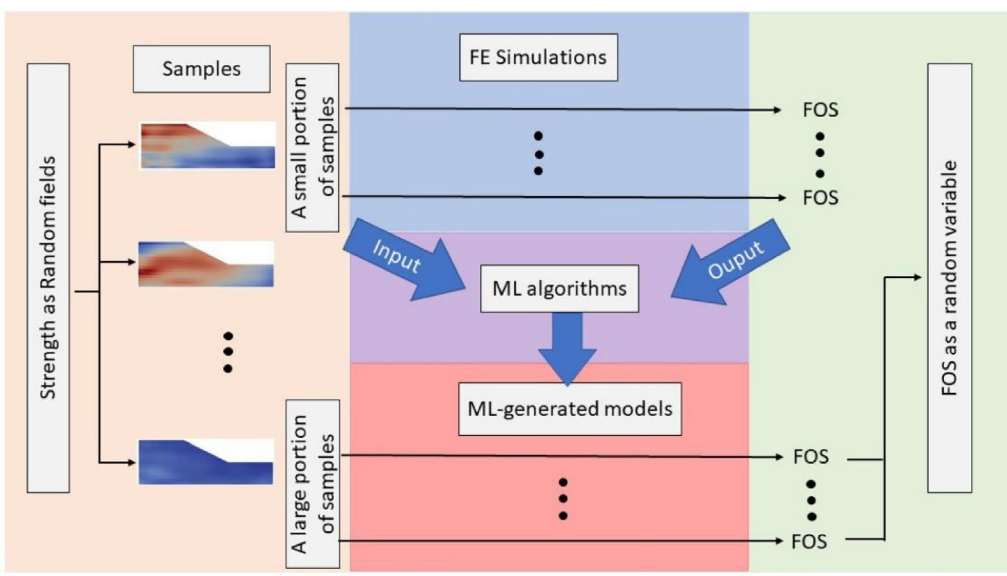
In order to improve the computation efficiency, some efficient methods named response surface method or surrogate models are proposed, i.e., the quadratic polynomial function. With the development of artificial intelligence technologies, a more efficient method named ML-aided reliability analysis is gradually used in the reliability analysis of slope stability considering the spatial variability of soil properties. Such an ML-aided method is similar to the 'surrogate models' method. The main procedures for the establishment of the ML-aided method contain the following parts: (1) A number of random variables or random field samples of geotechnical soil properties are firstly generated via MCS; (2) RFEM/RLEM is subsequently performed to calculate all the corresponding FSs; (3) Consider these random variable samples or random field samples as input, and the calculated FSs as the output. After the procedure of training and validation with a specific ML algorithm, the target model is established to capture the potential relationship between the input random variable/random field samples and the output FSs; (4) Through the obtained ML-based model, the FSs corresponding to another large number of random field samples can be calculated efficiently and accurately. To enhance the understanding of the ML-aided method, Fig. 7 describes the differences between the traditional reliability analysis and the ML-based reliability analysis of slope stability, where the uncertainty of soil parameters is characterized under the random field theory framework. It is noted that the abbreviation FOS in Fig. 7 is the same as the FS mentioned in this paper.

The remaining part of this subsection is to illustrate the applications of some typical ML algorithms in the reliability analysis of slope stability, especially for high dimensional or highly nonlinear response surface method (RSM) (e.g., [14,44,45]).

Zhang et al. [46] proposed a Kriging-based RSM to conduct the system reliability analysis for soil slopes, where the undrained shear strength was modeled as random variables. Compared with the traditional RSM method, the Kriging-based RSM performs the global approximation, which can evaluate the system reliability of soil slopes more accurately. Kang et al. [47] adopted a novel machine learning method called v-support vector machine to construct the surrogate model for FS prediction, which can achieve an accurate evaluation of the system failure probability. Ji et al. [48] performed the slope system reliability analysis via surrogate models, which were based on the least-squares support vector machine regression. Results showed that the developed model could guarantee robust and accurate estimations of the stability for spatially variable slopes. Chivata Cardenas [49] proposed a meta-modeling approach based on Bayesian networks to explore the influences of uncertainties on slope stability. Liu et al. [8] further extended the MARS-based RSM to evaluate the reliability of slopes in spatially variable soils. Based on their study, it could be found that the proposed method could evaluate the P_f of the slopes considering the spatial variability of soil properties with enough efficiency and accuracy. He et al. [44] employed neural networks and SVM as surrogate models to accelerate computational efficiency. Results showed that the required time for calculating the failure probability with predefined accuracy can be significantly reduced. Wang et al. [11] carried out the reliability analysis of the earth dam slope with the aid of XGBoost. It was found that this novel method could evaluate the P_f rationally and



(a) Traditional reliability analysis for slope stability



(b) ML-aided reliability analysis of slope stability

Fig. 7. Illustration of main procedures for traditional/ML-aided reliability analysis.
Source: From He et al. [44].

efficiently. Moreover, the coefficient of variation, the scale of fluctuation, and the auto-correlation function may significantly affect the reliability analysis results. Wang and Goh [14] developed a novel method based on CNNs to accelerate the process of reliability analysis. They took a two-layer slope as an example and found that CNNs combined with MCSs could deal with uncertain events with low failure probability. Compared with other metamodel-based methods, i.e., single/multiple stochastic response surface method, CNNs-based RSM are more efficient. Recently, Wang and Goh [7] further combined the maximum entropy method with CNN-based surrogate model to estimate a multi-layered slope stability, where the accuracy and efficiency are guaranteed at the same time.

The researches mentioned above are all two-dimensional (2D) problems to simplify the calculation. In nature, most landslides are in three-dimensional (3D) space. Thus, 3D slope reliability analysis can more accurately evaluate the true slope stability. 2D reliability analysis is inherently time-consuming, therefore 3D reliability analysis may consume much more time. In order to successfully perform the 3D slope reliability analysis, it is necessary to extend the idea of 2D ML-based RSM to 3D problems. Recently, Song et al. [45] adopted the RBF to construct the RSM and then performed the 3D slope reliability analysis. In their study, the strength parameters (i.e., cohesion and friction angle) were considered as random variables. It is found that the 2D slope reliability analysis is too conservative and may overestimate the P_f, and the RBF-based RSM can guarantee accuracy, feasibility, and

Table 1
Summary of ML-based reliability analysis of slopes.

Dimension	Parameter characterization	ML algorithms	Advantages	Limitations	References
2D	RV	ANN	High accuracy; Parallel distributed processing; Strong robustness	Requiring a large number of initial parameters; Consuming a long time during model training	Cho [17]
2D	RV	Kriging	Predominant fitting performance in highly nonlinear problems	Only valid within the range of calibration data	Zhang et al. [46]
2D	RV	*v*-SVM	Good generalization capability; Adaptable for high-dimensional problems;	Unable to provide sequential prediction; Single prediction outputs	Kang et al. [47]
2D	RV	LS-SVM	Computationally efficient; Good generalization capability; Adaptable for high-dimensional problems	Unable to provide sequential prediction; Single prediction outputs	Ji et al. [48]
2D	RV	Bayesian networks	Graphical representation; Use of prior knowledge; Relevant variables identification; Propagation of uncertainty; Inference enabled; Use of incomplete observations	Requiring the known prior information; Sensitive to the format of the input data	Chivata Cardenas [49]
2D	RF	MARS	No need to deal with a large amount of data and high dimension data	Unable to provide sequential prediction; Single prediction outputs	Liu et al. [8]
2D	RF	ANN, SVM	Good generalization capability; Adaptable for high-dimensional problems	Unable to provide sequential prediction; Single prediction outputs	He et al. [44]
2D	RF	XGBoost	High accuracy; Parallel distributed processing; Strong robustness	Requiring large memory	Wang et al. [11]
2D	RF	CNN	Adaptable for high-dimensional problems; High performance in feature classification	Large number of samples required	Wang and Goh [7,14]
3D	RF	RBF	Better nonlinear fitting ability	Unexplainable	Song et al. [45]
3D	RV	RVM	Adaptable for high-dimensional non-linear problems; Accurate and efficient	Time-consuming	Li et al. [15]
2D	RV	GWO-MKELM	Strong fitting and generalization	Poor readability and interpretability; No sequential prediction ability; Single output prediction	Ling et al. [5]

superiority. Li et al. [15] developed active learning relevant vector machine combined with MCS to perform the reliability analysis for rock slopes. It is found that the proposed method could avoid overfitting in the period of model training and ensure enough calculation efficiency. Furthermore, it is verified that this combined method slightly outperforms some previously online methods, especially for high non-linear problems. Ling et al. [5] combined the strength reduction method, multi-kernel-based extreme learning machine, and multi-objection gray wolf optimization to form a novel reliability analysis method. In their study, the cohesion and friction angle were considered as random variables. Results showed that the developed method could evaluate slope stability with sufficient accuracy and efficiency. Moreover, it is found that this proposed method has the potential to calculate P_f for slopes with the consideration of the coefficients of variation and correlation of different soil properties. More details about the applications of ML in the reliability analysis of deep excavations are presented in Table 1.

3.3. Tunneling

Nowadays, with the development of the city, the tunnel plays an increasingly important role in linking different places. During construction, several problems will be faced, such as surface settlement, shield machine performance, and stability of excavation face. In addition, due to the complexity of geological conditions and the limitation of investigation technique, the geological conditions in front of the cutter head are often unknown and change with the advanced process, which also will pose great threats to the safety of equipment and personnel life. Therefore, how to overcome these problems to improve the safety, efficiency, and construction quality of shield tunnels is necessary.

In the past, deterministic analysis was the main analysis measure, while it did not take the uncertainty of parameters into consideration, which might not be realistic. Therefore, nowadays, reliability-based design is becoming more and more prevalent in the geotechnical engineering community. In addition, conventional reliability is mainly based on intensive numerical simulation, which requires expensive computational cost, especially for complex geotechnical structure systems. Limit state function (LSF) describes the engineering behaviors, while it generally cannot be known explicitly, which brings lots of difficulties for reliability analysis. As ML is good at capturing the complex nonlinear and multivariate relationship between the target and features, ML is gradually incorporated into reliability analysis to improve computational efficiency and accuracy.

Due to excavation, the stress field around a tunnel will change so that the squeezing deformation may happen, which can result in instability of the tunnel and pose a great challenge to later maintenance. Therefore, it is necessary to evaluate the reliability of surrounding rock deformation. Qi et al. [50] first established a reliability evaluation model by combining the commonly used numerical simulation technique and reliability theory. This reliability evaluation model is a constraint solving problem and beyond the capability of the conventional analytical method, and hence, genetic algorithm (GA) is incorporated into it as GA is good at finding global optimization.

Currently, the reliability-based method is being paid more and more attention in geotechnical engineering, such as tunnel engineering. In engineering practice, the LSF of an engineering structure is not known explicitly but can be known implicitly with aid of numerical simulation technique, which means that conventional reliability analysis needs a large number of iterative calculations [51]. The RSM is a practical method in reliability analysis in geotechnical engineering, because it makes use of the merit of the finite element method (FEM) and can reduce the number of numerical simulations. However, traditional polynomial-based RSMs are frequently unable to approximate the true LSF. To overcome this problem, ANN-based and SVM-based RSM were presented [52]. ANN has several shortcomings: a low convergence rate, easily falling into local minimum, and overfitting problem. In view of those problems, SVM-based RSM has a better performance in practice. Inspired by pioneering works, SVM has been devoted to multiple reliability analysis and is proven that it has a satisfying performance (e.g., [53]).

As an ML algorithm, SVM involves several hyper-parameters, and generally, the optimal hyper-parameters can build the best SVM model for a specific problem. As a result, sequential minimum optimization-based SVM algorithm was previously utilized to construct the SVM model. Considering that the calculation process is time-consuming, Zhao et al. [51] proposed least squares support vector machine (LS-SVM) and further integrate it with RSM to build an LS-SVM-based RSM. Compared with traditional RSM and other methods, LS-SVM-based RSM can reach the final target using fewer iterations. Li et al. [54] developed a hybrid model by integrating an experimental design called uniform design with SVM, where the uniform design is utilized to generate sampling points and SVM is applied to build a response surface approximating the true implicit LSF. Through three examples, the presented method is proven that it has a powerful potential for probabilistic assessment of tunnel stability involving an inexplicit LSF.

For reliability analysis, Bai et al. [55] found that RBF is capable of constructing LSF with high accuracy and good performance. Therefore, Wang et al. [56] applied three RBFs to construct metamodels of LSF. Two tunnel examples were taken into consideration for validation of three RBFs in tunnel reliability analysis, and the results prove that the metamodel based on RBFs can effectively and efficiently perform reliability for complex engineering systems with lower computational cost than traditional RSM.

Metamodel-based Monte Carlo method is also a useful tool in the reliability analysis community, several strategies have been put forward to build a suitable metamodel for a specific problem, including polynomial chaos expansion (PCE), Kriging model, and ANN. PCE is easily subjected to the 'curse of dimensionality', and the drawbacks of ANN have been discussed above. As prementioned, SVM has several merits, and for example, it can avoid overfitting problems and is capable of high dimension and highly nonlinear problems. Pan and Dias [57] developed a reliability system by combining adaptive SVM (ASVM) and MCS, in which system ASVM adopts an active learning strategy. Four examples, including nonlinearity, high dimension, and implicit limit state function problems (i.e. stability analysis of a tunnel face), are used to validate the applicability of the proposed ASVM-MCS, whose results indicate that this presented approach can effectively capture the nonlinear and high dimension characteristic of LSF.

Actually, besides RSM, the variance reduction technique is another method to reduce computational cost, such as importance sampling, directional simulation, Latin hypercube sampling, and subset simulation. It is found that these two methods can be combined to perform the reliability analysis with high efficiency and accuracy [57].

Based on previous research, Cui and Ghosn [58] proposed a subset simulation–Kriging & K-means method, in which the Kriging algorithm is employed to build surrogate models for each cluster of data points representing a potential failure mode as identified via the K-means algorithm. Therefore, besides the high efficiency, this method can also identify different failure modes in the structure system, which can provide more reference to engineers. If this method is devoted to tunnel engineering, it will produce some promising works.

In view of building metamodel for reliability analysis, Samui et al. [59] have studied the application of RVM in reliability analysis, which indicates that can predict the implicit LSF. Therefore, in terms of the metamodel technique, Li et al. [15] presented a new reliability analysis method combining an adaptive relevant vector machine (ARVM) and MCS, in which the stability of the surrounding rock of a circular tunnel is taken into consideration for validation of the presented method. The results show that the simulated limit state surface by ARVM-MCS is rather close to the true limit state surface, indicating that the presented method has good performance.

To study the settlement and bending moment of a shallow buried circular tunnel in a soil mass, Hamrouni et al. [60] adopted RSM to analyze the serviceability of this tunnel in view of reliability. Considering the expensive computational time, GA is introduced to find the optimal solutions, and the results show that GA eliminates the successive iterative method utilized by the classical RSM method and saves much computation time. It is easy to understand that several types of geological conditions may exist in one section of the tunnel, and hence, Zhou et al. [61] investigated the effect of a weak interlayer on the stability of the tunnel face, where an active learning method combining Kriging and MCS was employed for the reliability analysis, whose flowchart is illustrated in Fig. 8. At the same time, the relative importance of each soil property is evaluated by integrating global sensitivity analysis. Compared with conventional approaches, the proposed method is capable of providing multiple interesting results, including the probability of failure, model response statistics and sensitivity index with a relatively lower computational cost.

Nowadays, the numerical simulation technique is a useful tool in geotechnical engineering. Proper selection of geomechanical parameters is a key component in geotechnical numerical simulation. To this end, parameter inversion is adopted. In the early period, displacement back-analysis is often used to identify the mechanical parameters of the surrounding rock mass of a tunnel [62]. Later, RSF or modified RSF by ANN has been put forward to perform mechanical parameter inversion. In light of the drawbacks of ANN, SVR is gradually incorporated into RSF. To obtain the best SVR model, two optimization algorithms (i.e., GA and PSO) can be utilized to achieve good results. However, GA often has a low convergence rate, and PSO easily falls into local minimum and also has relatively lower accuracy. As a result, Zhuang et al. [63] adopted a new multi-strategy artificial fish swarm algorithm to find the best SVR model.

For the tunneling work, the tunnel roof is also a key part that should be paid attention to. If the tunnel is shallowly buried, the significant tunnel roof defection can lead to ground settlement

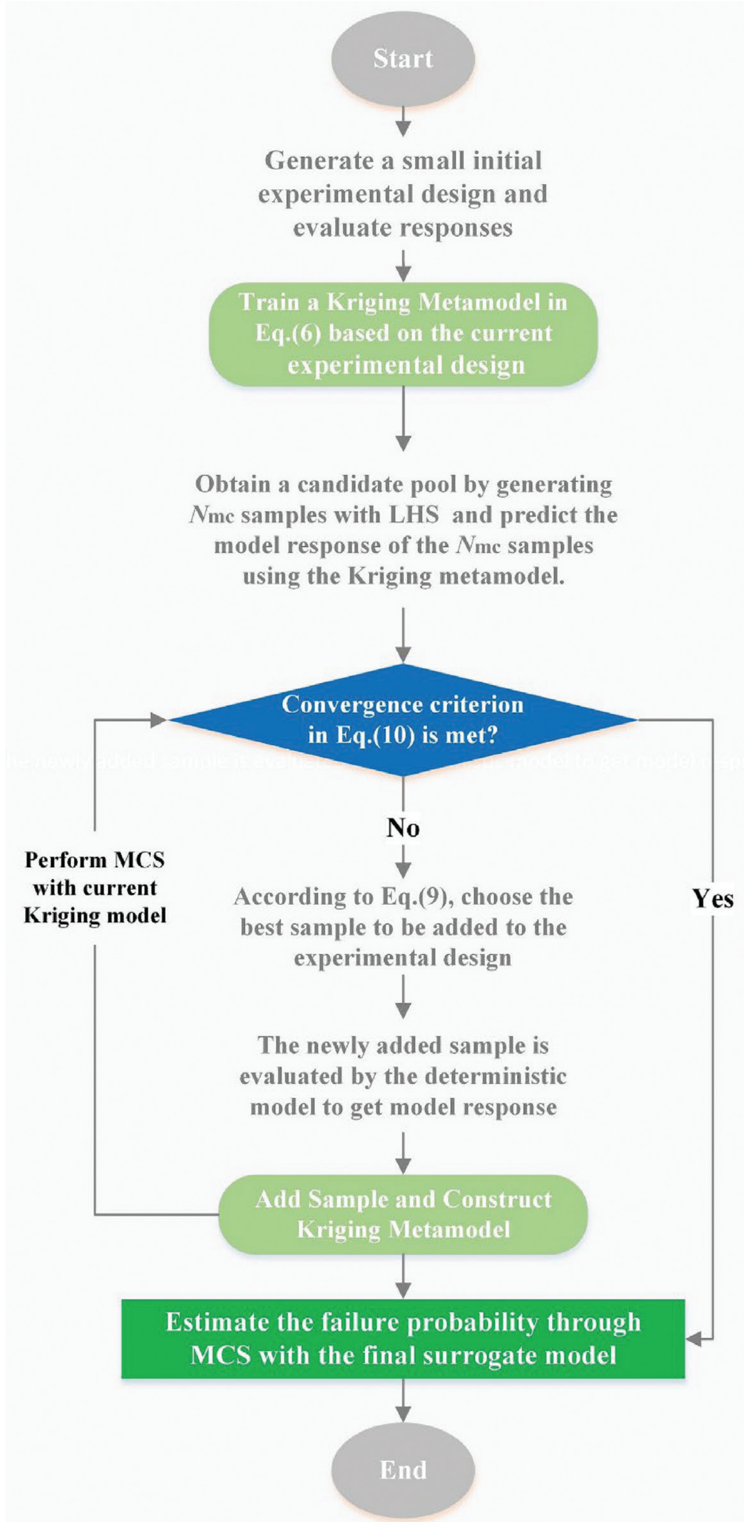


Fig. 8. Flowchart of an active learning method based on Kriging and MCS.
Source: From Zhou et al. [61].

or even ground subsidence. While the conventional 3D numerical simulation can be used to assess the reliability of tunnel roof, the estimation cannot be in real-time due to its expensive computational cost. To this end, Zhou et al. [64] did a study to combine the conventional numerical simulator and ML algorithms. In the work of Zhou et al. [64], according to the actual project information, FLAC 3D is employed to generate the synthetic database about maximum tunnel roof defection, and ANN is used to establish the surrogate model about the maximum tunnel roof defection, and at last, a simplified approach is further proposed to estimate the exceedance probability of tunnel roof defection. Similarly, Verma et al. [65] also established three surrogate models to represent the limit state function of tunneling using three ML algorithms including collocation-based stochastic response surface method

Table 2
Summary of ML-based reliability analysis of tunneling.

Dimension	Parameter characterization	ML algorithms	Advantages	Limitations	References
2D	RV	SVM	(1) The current approach combining uniform design and SVM can be used successfully for their reliability analyses involving the implicit LSF; (2) Suitable for small number of sampling points.	(1) It is difficult to use the analysis of variance for data analysis; (2) The spatial variability of soils cannot be considered.	Li et al. [54]
2D	RV	RBF	(1) Accurate estimations of the failure probability; (2) Less computational effort.	(1) A low convergence rate; (2) easily falling into local optimum; (3) The spatial variability of soils cannot be considered.	Wang et al. [56]
2D	RV	ASVM	(1) Be capable of handling issues involving nonlinearity, high-dimension, and implicit limit state function; (2) The errors of the estimated failure probabilities by the proposed ASVM-MCS are under control and rather small.	(1) The proposed method is only applicable for the assessment of failure probability, and hence, it cannot provide other results related to probabilistic analysis; (2) The current method cannot deal with the issue of small failure probability; (3) The spatial variability of soils cannot be considered.	Pan and Dias [57]
2D	RV	Kriging & K-means	(1) The proposed method can identify the important failure modes; (2) With the aid of Subset Simulation, it can estimate the system reliability and solve nonlinear problems with low probabilities of failure.	(1) The K value in K-means should be specified before; (2) K-means is sensitive to the center of cluster and outliers; (3) K-means is not suitable for classification of non-convex shapes; (4) The spatial variability of soils cannot be considered.	Cui and Ghosn [58]
2D	RV	GA	The unknown parameters in the performance function can be optimized by GA.	The spatial variability of soils cannot be considered.	Hamrouni et al. [60]
3D	RV	Kriging	Good accuracy and less computational cost.	(1) The spatial variability of soils cannot be considered so that the $P_f$may be over-estimated slightly; (2) The positive correlation between the weak layer soils and the nearby soils.	Zhou et al. [61]
2D	RV	ARVM	(1) Avoid the over-fitting problems; (2) Suitable for high-dimensional and non-linear problems with less computational costs.	The spatial variability of soils cannot be considered.	Li et al. [15]
3D	RV	ANN	It is computational efficiency and makes the probabilistic analysis computationally viable.	(1) The correlations among the input random variables are not considered well, especially for the site-specific database; (2) ANN has several shortcomings: a low convergence rate, easily falling into local minimum, and overfitting problem.	Zhou et al. [64]
2D	RF	CNN	(1) Less computational costs; (2) The nonlinear pattern between the random field of soil property input and the factor of safety of tunnel target can be deserted; (3) The confidence interval of predicted results can be produced.	The determination of hyper-parameters in CNN is complex.	Zhang et al. [66]
2D	RV	CSRSM, MARS	(1) Less computational costs; (2) The epistemic uncertainty can be considered; (3) CSRSM and MARS both are found appropriate for both the normal and non-normal random variables.	The results from MARS fall on the conservative side as compared to the CSRSM and it produces more unexpected scenarios which need to be considered.	Verma et al. [65]

(CSRSM), multi-gene genetic programming, and MARS, and in conjunction with the MCS, the failure probability of tunnel is also estimated accurately and efficiently. The results also show that the computational cost is evidently reduced, and the CSRSM and MARS can incorporate the epistemic uncertainty very well. Compared with regular ML algorithms, Zhang et al. [66] applied the CNN to predict the tunnel performance, in which the basic framework is similar, that is, numerical simulation considering the spatial variability of soils is used to produce the synthetic database for training and testing, and then, a surrogate model about tunnel performance is built by CNN architecture. The novelty in the work of Zhang et al. [66] is that the presented method can obtain the results with the confidence interval. Additionally, more details about the applications of ML in the reliability analysis of tunneling are tabulated in Table 2.

3.4. Deep excavations

In recent years, many researchers majored in applications of ML in evaluating key parameters during deep excavation, such as determining the deflection of support wall and ground settlement or basal heave displacement via polynomial regression, MARS, ANN (e.g., [67–69]). Additionally, more and more studies also concentrated on geotechnical reliability analysis via random field theory. Different from deterministic analysis, reliability analysis usually needs more computational effort since the complicated implicit performance functions are commonly encountered in engineering practice.

Huang and Wang [70] applied ANN in the reliability analysis of braced excavation. The mechanical and physical properties of soil were regarded as input layers and the deformation and safety factors were regarded as output layers. ANN model was adopted to determine the limit state functions so that the reliability index can be obtained. Cao et al. [71] applied the SVM in the system reliability analysis of foundation excavation. The SVM model was adopted to establish response surface equations and the Pearson correlations analysis was adopted to evaluate the correlations of multiple failure modes. Zhang et al. [68] combined the Back-propagation neural network (BPNN) and the optimized gray discrete Verhulst model to predict the foundation pit settlement. The results showed that the proposed model inherited the advantages of the two models, which could satisfactorily describe the settlement monitoring projects. Kumar and Samui [20] proposed the ELM-based and MARS-based first-order second-moment methods for the reliability analysis of pile foundations, which significantly reduces the computational pains and memory requirements in the reliability analysis. It was found that the MARS model performed much better than the ELM model in their research. He et al. [72] evaluated the failure probability in braced excavation using Bayesian networks with integrated model updating, which overcomes the limitation of the complex likelihood function and enables failure probabilities to be determined with real-time result updating. Ray et al. [9] adopted three different ML algorithms to study the shallow foundation reliability based on settlement criteria, in which the soil parameters were taken as input variables while the settlement of shallow foundations was regarded as output. Wang et al. [13,24] proposed a new method that can decrease computing efforts underlying the reliability analysis of braced excavations and shallow foundations. In their study, the random fields were treated as images in the CNN, and the predictions of FEM can be regarded as output layers that contain information about the random variabilities in both spatial distribution and intensity, as described in Fig. 9. Similarly, Wu et al. [25] applied the CNN to predict the wall deflection of braced excavation considering the spatial variability of soil parameters, and compared its predictive performance with the XGBoost model.

On the other hand, ML methods also played an important role in taking good use of the information of in-site investigation data for soil parameter characterization. For example, in conditional random field modeling, the assumptions based on historical statistical information were regarded as prior information, and the in-site investigation information will update the prior model and obtain the posterior model. For example, Juang et al. [73] conducted probabilistic inverse analysis of wall deformations and ground settlement induced by excavations via the Bayesian updating method. Luo and Hu [74] expanded the Bayesian method to update multiple soil parameters using field data on wall deflections and ground surface settlement from braced excavations. Leung et al. [75] proposed a novel conditional random field modeling method and discussed the optimal arrangement of boring holes in project sites. More details about the applications of ML in the reliability analysis of deep excavations are listed in Table 3.

4. Insights from previous works

After reviewing the research contributed by previous researchers, great achievements have been made in geotechnical reliability analysis with the aid of ML, which are summarized from two important aspects in this section.

4.1. Input geotechnical parameter characterization

Probabilistic characterization of the spatially variable geotechnical parameters is a significant prerequisite in geotechnical reliability analysis. It is known that the measured data obtained from various in-situ and/or laboratory tests are relatively sparse and limited, which poses great difficulty in rationally characterizing the geotechnical parameters due to the unavailability of statistical information (e.g., means, standard deviations, and probability distribution). Such statistical information obtained from classical statistical analyses generally requires a considerable amount of test data so as to generate statistically meaningful results. To address this issue, machine learning provides a rational way to portray the spatially variable geotechnical parameters based on limited site-specific data. Wang et al. [76] proposed a Bayesian machine learning method called Bayesian compressive sampling (BCS) method to directly simulate the random field samples from sparsely measured data. Hu et al. [77] further applied the BCS method for generating 2D isotropic or anisotropic random field samples from sparse measurements. Wang et al. [78] optimized the BCS for simulating random field samples with a linear or nonlinear trend directly from sparse measurements without detrending. Thus, it can be seen that the newly developed BCS method provides a versatile tool for generating the random field samples directly from the limited measurement data, which is able to simulate the non-stationary non-Gaussian random field and random field with unknown trend function. Besides, inspired by the powerful ability of CNN in the field of image recognition, Zhang et al. [79,80] developed an efficient CNN-based approach for estimating the horizontal scale of fluctuation and vertical scale of fluctuation based on the limited cone penetration test data. Compared with the BCS method that generates random field samples directly from sparse measurements, the CNN-based approach first quantifies the critical parameters required in the autocorrelation functions (e.g., the single exponential autocorrelation) and then uses them for random field characterization. Both the BCS method and CNN-based method offer a rational approach for probabilistically characterizing the spatially variable geotechnical parameters, addressing the bottleneck of sparse and limited site-specific data that are frequently encountered in geotechnical engineering practice.

4.2. Output failure probability evaluation

The evaluation of failure probability (or equivalently, reliability index) is a major concern in geotechnical reliability analysis, which quantifies the safety margin of geotechnical structures from a probabilistic perspective. Although the MCS method has been widely used in reliability analysis due to the advantages of simplicity and flexibility, it is known that the MCS method generally requires extensive computational efforts and is often criticized for poor efficiency. As a promising alternative, various ML algorithms and their variants have been successfully applied in the past two decades for facilitating the evaluation of failure probability, such as MARS, XGBoost, CNN, and so on. These ML algorithms significantly improve computational efficiency and boost the application of geotechnical reliability analysis methods in solving practical engineering problems (e.g., reliability-based design), allowing engineers and researchers to concentrate more on practical engineering problems without being compromised by the prohibitively computational tasks in practical applications. Actually, the key idea of ML in aiding geotechnical reliability analysis is to approximate the high-dimensional implicit performance function through learning from a preparatory database, which contains the input geotechnical parameters (e.g., shear strength parameters and hydraulic parameters) and the output quantity of interest (e.g., the FS for slopes). As the established ML models achieve a desired performance after sufficient training and rational validation, they can be conveniently used to estimate the failure probability of geotechnical infrastructures.

It can be seen that the calibration of ML models plays a significant role in ML-aided geotechnical reliability analysis methods,

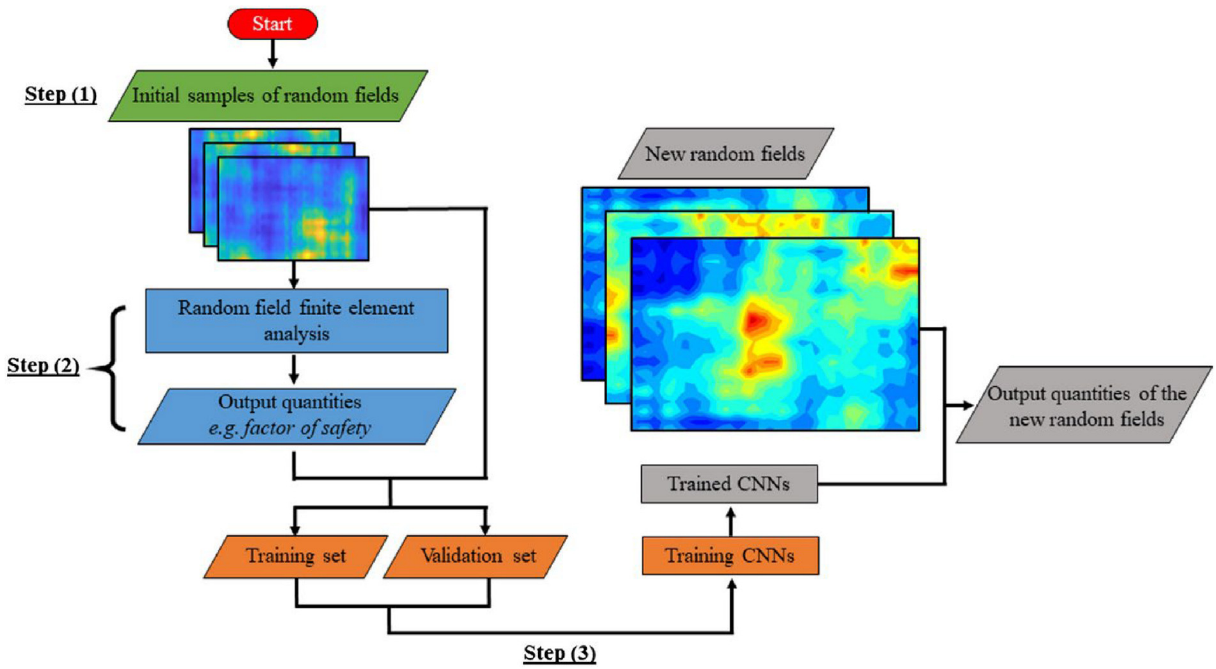


Fig. 9. Framework of CNN model.
Source: From Wang et al. [13].

Table 3
Summary of ML-based reliability analysis of deep excavations.

Dimension	Parameter characterization	ML algorithms	Advantages	Limitations	References
2D	RV	MARS	Simple and explicit expression	Single output prediction; Number of basic functions is hard to determine	Zhang and Goh [40], Kumar and Samui [20]
2D	RV	BPNN	Multiple output prediction; Low computational cost	Poor readability	Zhang et al. [68]
2D	RV	SVM	Simple and explicit expression	Poor nonlinear mapping ability	Cao et al. [71]
2D	RV	ANN	Simple and explicit expression	Single output prediction; Poor nonlinear mapping ability	Huang and Wang [70]
2D	RV	ELM	Higher learning efficiency; Higher generalization ability	More computational cost; More nodes will lead to overfitting	Kumar and Samui [20]
2D	RV	Bayesian updating	Available for sparse data; Available for multidimensional monitoring data	Single output prediction	Juang et al. [73], Luo and Hu [74]
2D	RV	PSO	Low computational cost	Poor generalization ability	Ray et al. [9]
2D	RF	CNN	Low computational cost; Available for multiple input data	Only available for input data with matrix type	Wang et al. [13], Wang et al. [24], Wu et al. [25]
3D	RV	Bayesian network	The real-time updated failure probabilities in the excavation process are available	Prior distribution must be defined reasonably	He et al. [72]
3D	RF	Bayesian updating	Available for sparse data; Considering both prior information and in-site investigation data	Posterior model also depends on prior information	Leung et al. [75]

which highly depend on the preparatory database. Compared with the computational efforts in the preparation of a database that generally necessitates a large number of deterministic analyses through repeatedly invoking geotechnical software, the computational cost of the established ML models in the estimation of failure probability can be negligible. For example, Wang et al. [11] took about 3 h and 20 min on a personal desktop computer to prepare a database with a total of 2198 samples, while just about 15 s were consumed in predicting the failure probability of 10,000 testing samples when using the established XGBoost model. If we extend the 2D model analyzed in Wang et al. [11] to 3D reliability analysis, the computational efforts may increase significantly. Thus, preparing a training database becomes a computationally expensive and time-consuming task in geotechnical reliability analysis, which emphasizes the necessity of developing new ML-aided geotechnical reliability analysis methods that require fewer training samples.

5. Challenges and future directions

Benefited from the great development of AI technologies, more and more ML algorithms including several commonly used ML algorithms and some latest advanced ML methods (e.g., XGBoost and CNN) have been applied to the geotechnical reliability analysis in the past decades, which gives rise to a lot of ML-based reliability analysis methods and greatly facilitates the implementation of reliability analysis in geotechnical engineering practice. Although great achievements have been obtained, there still exist many remaining issues needed to be further explored, as summarized in Fig. 10.

Firstly, most of the available applications were concentrated on time-invariant reliability analysis, and the time-variant reliability analysis has been rarely reported. The time-variant reliability analysis generally focuses on the evaluation of failure probability during a given period, in contrast, the time-invariant reliability analysis pays attention to the failure probability at a specified time point of interest which is unable to consider the effects of geomaterial properties and external loading may be varying with time. For example, it is well recognized that the reservoir slope stability is significantly affected by the periodic reservoir water level fluctuation and seasonal rainfall (e.g., [81,82]), leading to the reservoir slope reliability varying with the external environment. Besides, as a key component of tunneling engineering, the lining structure is frequently subjected to groundwater seepage which may cause material deterioration with service time, potentially threatening the serviceability and safety of the tunneling [83]. Thus, the time-variant reliability analysis of geotechnical structures with the aid of ML is recommended in future research.

Secondly, we discuss how to select an appropriate ML algorithm among numerous candidates and rationally determine the associated hyper-parameters. Until now, many open-source packages of ML algorithms are available on the Internet and can be downloaded freely for scientific research, such as the packages of the XGBoost and CNN which are shared in the well-known open-source website called GitHub. This open and friendly environment allows researchers and engineers to have more choices when they want to perform geotechnical reliability analysis with the aid of the ML algorithm, enabling the possibility of addressing the same engineering problem using different ML algorithms. The associated hyper-parameters can be determined through optimization strategies [84]. It is undeniable that each ML algorithm has its own merits and shortages, and thus no single or particular model can be always regarded as the most appropriate one in solving geotechnical problems. Thus, it is advisable to choose an appropriate ML algorithm according to the computational efficiency, memory consumption, and prediction performance in practical applications.

Furthermore, previous research mainly focused on simplified models and lacked realistic geotechnical case applications. Through reviewing the published research on slope reliability analysis using ML algorithms, the idealized simple slopes have been widely studied, which may be far away from the realistic situation. Compared with the commonly used 2D slope model, the reliability analysis of slope stability in 3D space not only can reflect the stability state accurately, but also reveals the deformation and mechanical behaviors from a more practical perspective. Therefore, it is necessary to extend the ML-based reliability analysis methods to 3D cases. Similarly, many works related to tunneling and deep excavations simply consider a single circular tunnel or a simple deep excavation model in 2D space without any adjacent building, tunnel, or deep excavation. Under the current complex building environment, especially in urban areas with high densities of buildings, the existing infrastructures may be affected by adjacent construction, such as the existing piles which can be influenced by adjacent deep excavations, and the existing tunnels which can be affected by a new tunnel. These works are far away from the true nature of the current city. Thus, future research should focus more on the reliability analysis of realistic geotechnical cases with the aid of ML.

Finally, the monitoring information was rarely incorporated into the geotechnical parameter characterization when compared with the measured data obtained from various in-situ and/or laboratory tests. In the past few decades, previous researchers have contributed a lot to probabilistically characterize the spatially variable geotechnical parameters based on sparse and limited site-specific data. It is well known that more and more advanced sensors are installed onto geotechnical infrastructures. MegaByte or even GigaByte of monitoring data are produced each hour, which would be transferred by the fifth-generation (5G) mobile network. Therefore, the requirement for making the best use of these valuable monitoring data in geotechnical reliability analysis is even more demanding.

6. Summary and conclusions

This paper reviewed previous studies on the applications of ML in different geotechnical reliability analysis problems in the past two decades. The evaluation of failure probability is a primary concern in the geotechnical reliability analysis and the direct MCS method usually requires extensive computational efforts to ensure the desired accuracy. With the great development of ML in the past few decades, many researchers have contributed to the evaluation of failure probability by incorporating ML algorithms, such as MARS, XGBoost, CNN, and so on. These ML-based reliability analysis methods provide a powerful tool to calculate the failure probability with higher accuracy and efficiency, allowing geotechnical engineers to concentrate more on engineering problems rather than the prohibitively computational tasks in practical applications.

By reviewing the published research in the field of geotechnical reliability analysis, it is evident that ML algorithms and their variants have been successfully applied in the reliability analysis of geotechnical structures including slopes, tunneling, and deep excavations. Each ML algorithm has its own merits and shortages, and thus it is advisable to select an appropriate ML algorithm according to the computational efficiency, memory consumption, and prediction performance in practical applications since no single or particular model can be always regarded as the most appropriate one in solving different geotechnical problems.

Although remarkable progress has been achieved in the application of ML in geotechnical reliability analysis, there still exist many challenges that need further attention in future studies. Most of the available studies were concentrated on time-invariant reliability analysis which pays attention to the failure probability at a specific time point of interest and is unable to consider the effects of geomaterial deterioration and external loading variation with time. In addition, previous research mainly focused on simplified models or two-dimensional reliability analysis, leading to the lack of realistic geotechnical case applications. Furthermore, the computational efficiency needs to be further improved because preparing a training dataset is generally computationally expensive and time-consuming in geotechnical reliability analysis which needs to repeatedly conduct a large number of deterministic analyses. Thus, future research is recommended to introduce some advanced ML algorithms or ensemble/hybrid models that require fewer training samples, so as to reduce the computational burden in geotechnical practical applications. In addition, the future study reviewing of machine learning methods for 5G data and their application in geotechnical reliability analysis, is desirable.

Benefiting from the rapid development of ML, a large number of open-source packages are available on the Internet and can be downloaded freely for scientific research, allowing researchers and engineers to address practical engineering problems using different algorithms of interest. This open and friendly environment can not only stimulate the growing tendency of applying

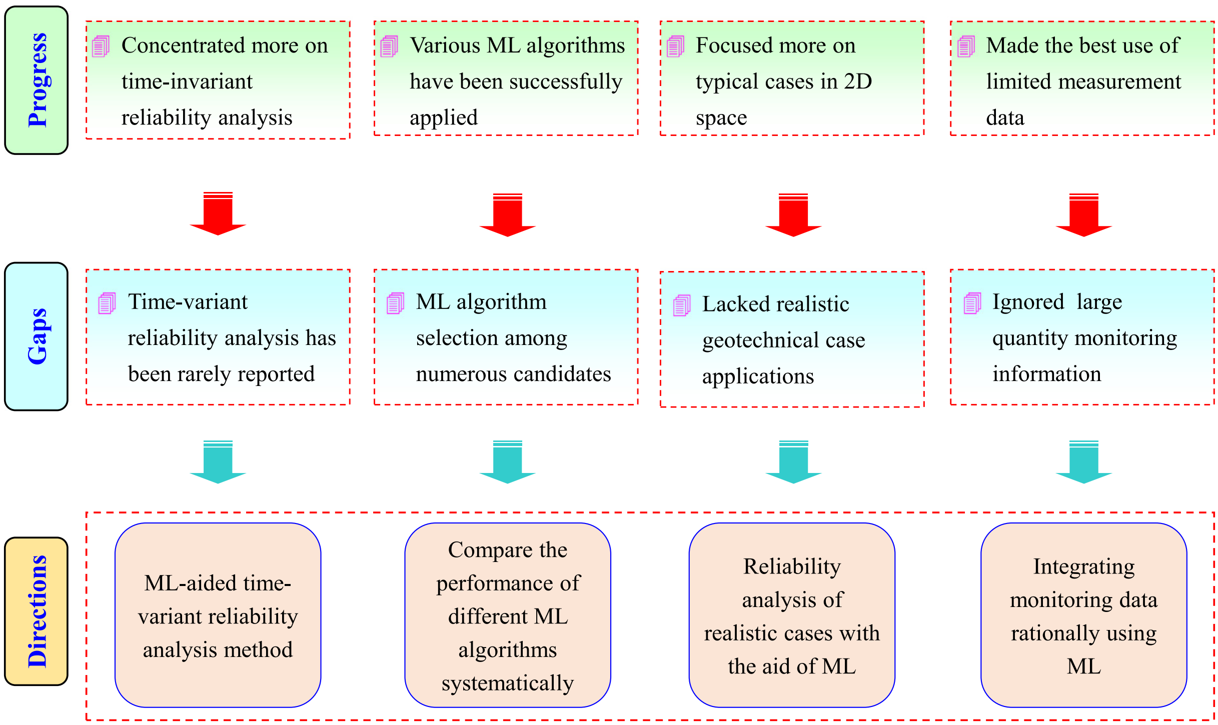


Fig. 10. Research progress, gaps, and future directions.

ML in geotechnical engineering, but also accelerate the development of ML-based reliability analysis methods. In the near future, the above-mentioned challenges including time-variant reliability analysis, three-dimensional reliability analysis of realistic geotechnical cases, and more efficient reliability analysis approaches, are expected to be successfully conquered with the aid of ML.

Declaration of 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.

Data availability

Data will be made available on request.

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References

[1] F.W. Wang, Y.M. Zhang, Z.T. Huo, X.M. Peng, S.M. Wang, S. Yamasaki, Mechanism for the rapid motion of the Qianjiangping landslide during reactivation by the first impoundment of the Three Gorges dam reservoir, China. Landslides 5 (4) (2008) 379–386, http://dx.doi.org/10.1007/s10346-008-0130-7.

[2] L.T. Zhan, Z. Zhang, Y.M. Chen, R. Chen, S. Zhang, J. Liu, A.G. Li, The 2015 Shenzhen catastrophic landslide in a construction waste dump : Reconstitution of dump structure and failure mechanisms via geotechnical investigations, Eng. Geol. 238 (2018) 15–26, http://dx.doi.org/10.1016/j.enggeo.2018.02.019.

[3] K. Phoon, Z. Cao, J. Ji, Y.F. Leung, S. Najjar, T. Shuku, C. Tang, Z.Y. Yin, Y. Ikumasa, J. Ching, Geotechnical uncertainty, modeling, and decision making, Soils Found 62 (5) (2022) 101189, http://dx.doi.org/10.1016/j.sandf.2022.101189.

[4] S.H. Jiang, J. Huang, D.V. Griffiths, Z.P. Deng, Advances in reliability and risk analyses of slopes in spatially variable soils: A state-of-the-art review, Comput. Geotech. 141 (2022) http://dx.doi.org/10.1016/j.compgeo.2021.104498.

[5] Q. Ling, Q. Zhang, Y. Wei, L. Kong, L. Zhu, Slope reliability evaluation based on multi-objective grey wolf optimization-multi-kernel-based extreme learning machine agent model, Bull. Eng. Geol. Environ. 80 (2021) 2011–2024, http://dx.doi.org/10.1007/s10064-020-02090-5.

[6] J.Z. Li, S.H. Zhang, L.L. Liu, L. Huang, Y.M. Cheng, D. Dias, Probabilistic analysis of pile-reinforced slopes in spatially variable soils with rotated anisotropy, Comput. Geotech. 146 (2022) 104744, http://dx.doi.org/10.1016/j.compgeo.2022.104744.

[7] Z.Z. Wang, S.H. Goh, A maximum entropy method using fractional moments and deep learning for geotechnical reliability analysis, Acta Geotech. 17 (4) (2022) 1147–1166, http://dx.doi.org/10.1007/s11440-021-01326-2.

[8] L. Liu, S. Zhang, Y. Cheng, L. Liang, Advanced reliability analysis of slopes in spatially variable soils using multivariate adaptive regression splines, Geosci. Front. 10 (2) (2019) 671–682, http://dx.doi.org/10.1016/j.gsf.2018.03.013.

[9] R. Ray, D. Kumar, P. Samui, L.B. Roy, A.T.C. Goh, W. Zhang, Application of soft computing techniques for shallow foundation reliability in geotechnical engineering, Geosci. Front. 12 (1) (2021) 375–383, http://dx.doi.org/10.1016/j.gsf.2020.05.003.

[10] L. Wang, C. Wu, X. Gu, H. Liu, G. Mei, W. Zhang, Probabilistic stability analysis of earth dam slope under transient seepage using multivariate adaptive regression splines, Bull. Eng. Geol. Environ. 79 (6) (2020) 2763–2775, http://dx.doi.org/10.1007/s10064-020-01730-0.

[11] L. Wang, C. Wu, L. Tang, W. Zhang, S. Lacasse, H. Liu, L. Gao, Efficient reliability analysis of earth dam slope stability using extreme gradient boosting method, Acta Geotech. 15 (11) (2020) 3135–3150, http://dx.doi.org/10.1007/s11440-020-00962-4.

[12] H. Wang, L. Zhang, K. Yin, H. Luo, J. Li, Landslide identification using machine learning, Geosci. Front. 12 (1) (2021) 351–364, http://dx.doi.org/10.1016/j.gsf.2020.02.012.

[13] Z.Z. Wang, C. Xiao, S.H. Goh, M.X. Deng, Metamodel-based reliability analysis in spatially variable soils using convolutional neural networks, J.

Geotech. Geoenviron. Eng. 147 (3) (2021) 04021003, http://dx.doi.org/10.1061/(asce)gt.1943-5606.0002486.
[14] Z.Z. Wang, S.H. Goh, Novel approach to efficient slope reliability analysis in spatially variable soils, Eng. Geol. 281 (1) (2021) 105989, http://dx.doi.org/10.1016/j.enggeo.2020.105989.
[15] T.Z. Li, Q. Pan, D. Dias, Active learning relevant vector machine for reliability analysis, Appl. Math. Model. 89 (2021) 381–399, http://dx.doi.org/10.1016/j.apm.2020.07.034.
[16] Q.J. Pan, Y.F. Leung, S.C. Hsu, Stochastic seismic slope stability assessment using polynomial chaos expansions combined with relevance vector machine, Geosci. Front. 12 (1) (2021) 405–414, http://dx.doi.org/10.1016/j.gsf.2020.03.016.
[17] S.E. Cho, Probabilistic stability analyses of slopes using the ANN-based response surface, Comput. Geotech. 36 (2009) 787–797, http://dx.doi.org/10.1016/j.compgeo.2009.01.003.
[18] S. Li, H.B. Zhao, Z. Ru, Slope reliability analysis by updated support vector machine and Monte Carlo simulation, Nat. Hazards 65 (1) (2013) 707–722, http://dx.doi.org/10.1007/s11069-012-0396-x.
[19] P. Yi, K. Wei, X. Kong, Z. Zhu, Cumulative PSO-Kriging model for slope reliability analysis, Probab. Eng. Mech. 39 (2015) 39–45, http://dx.doi.org/10.1016/j.probengmech.2014.12.001.
[20] M. Kumar, P. Samui, Reliability analysis of pile foundation using ELM and MARS, Geotech. Geol. Eng. 37 (4) (2019) 3447–3457, http://dx.doi.org/10.1007/s10706-018-00777-x.
[21] H. Shen, J. Li, S. Wang, Z. Xie, Prediction of load–displacement performance of grouted anchors in weathered granites using FastICA-MARS as a novel model, Geosci. Front. 12 (1) (2021) 415–423, http://dx.doi.org/10.1016/j.gsf.2020.05.004.
[22] M.X. Wang, D.R. Huang, G. Wang, D.Q. Li, SS-XGBoost: A machine learning framework for predicting newmark sliding displacements of slopes, J. Geotech. Geoenviron. Eng. 146 (9) (2020) 04020074, http://dx.doi.org/10.1061/(asce)gt.1943-5606.0002297.
[23] W.G. Zhang, C.Z. Wu, L.B. Tang, X. Gu, L. Wang, Efficient time-variant reliability analysis of Bazimen landslide in the Three Gorges Reservoir Area using XGBoost and LightGBM algorithms, Gondwana Res. (2022) http://dx.doi.org/10.1016/j.gr.2022.10.004.
[24] Z.Z. Wang, S.H. Goh, W. Zhang, Reliability-based design in spatially variable soils using deep learning: An illustration using shallow foundation, Georisk 1 (2022) 1–15, http://dx.doi.org/10.1080/17499518.2022.2083178.
[25] C. Wu, L. Hong, L. Wang, R. Zhang, S. Pijush, W. Zhang, Prediction of wall deflection induced by braced excavation in spatially variable soils via convolutional neural network, Gondwana Res. (2022) http://dx.doi.org/10.1016/j.gr.2022.06.011.
[26] T. Zhao, Y. Wang, Interpolation and stratification of multilayer soil property profile from sparse measurements using machine learning methods, Eng. Geol. 265 (2020) 105430, http://dx.doi.org/10.1016/j.enggeo.2019.105430.
[27] J. Li, P. Li, D. Guo, X. Li, Z. Chen, Advanced prediction of tunnel boring machine performance based on big data, Geosci. Front. 12 (1) (2021) 331–338, http://dx.doi.org/10.1016/j.gsf.2020.02.011.
[28] Z. Liu, G. Gilbert, J.M. Cepeda, A.O.K. Lysdahl, L. Piciullo, H. Hefre, S. Lacasse, Modelling of shallow landslides with machine learning algorithms, Geosci. Front. 12 (1) (2021) 385–393, http://dx.doi.org/10.1016/j.gsf.2020.04.014.
[29] P. Zhang, Z.Y. Yin, Y.F. Jin, T.H.T. Chan, F.P. Gao, Intelligent modelling of clay compressibility using hybrid meta-heuristic and machine learning algorithms, Geosci. Front. 12 (1) (2021) 441–452, http://dx.doi.org/10.1016/j.gsf.2020.02.014.
[30] R.H. Zhang, C.Z. Wu, A.T.C. Goh, T. Bohlke, W.G. Zhang, Estimation of diaphragm wall deflections for deep braced excavation in anisotropic clays using ensemble learning, Geosci. Front. 12 (1) (2021) 365–373, http://dx.doi.org/10.1016/igsf.2020.03.003.
[31] W. Zhang, H. Li, Y. Li, H. Liu, Y. Chen, Application of deep learning algorithms in geotechnical engineering: A short critical review, Artif. Intell. Rev. 54 (8) (2021) 5633–5673, http://dx.doi.org/10.1007/s10462-021-09967-1.
[32] S. Zheng, Y.X. Zhu, D.Q. Li, Z.J. Cao, Q.X. Deng, K.K. Phoon, Probabilistic outlier detection for sparse multivariate geotechnical site investigation data using Bayesian learning, Geosci. Front. 12 (1) (2021) 425–439, http://dx.doi.org/10.1016/j.gsf.2020.03.017.
[33] J. Ching, I. Yoshida, K. Phoon, Comparison of trend models for geotechnical spatial variability: Sparse Bayesian learning vs. Gaussian process regression, Gondwana Res. (2022) http://dx.doi.org/10.1016/j.gr.2022.07.011.
[34] A. Karkevandi-Talkhooncheh, A. Rostami, A. Hemmati-Sarapardeh, M. Ahmadi, M.M. Husein, B. Dabir, Modeling minimum miscibility pressure during pure and impure CO2 flooding using hybrid of radial basis function neural network and evolutionary techniques, Fuel 220 (2018) 270–282, http://dx.doi.org/10.1016/j.fuel.2018.01.101.
[35] S.N. Qasem, I. Ebtehaj, H. Bonakdari, Potential of radial basis function network with particle swarm optimization for prediction of sediment transport at the limit of deposition in a clean pipe, Sustain. Water Resour. Manag. 3 (2017) 391–401, http://dx.doi.org/10.1007/s40899-017-0104-9.
[36] K. Fukushima, S. Miyake, Neocognitron: A Self-Organizing Neural Network Model for a Mechanism of Visual Pattern Recognition, Competition and Cooperation in Neural Nets, Springer, 1982, pp. 267–285, http://dx.doi.org/10.1007/978-3-642-46466-9_18.
[37] B. Li, K.C.P. Wang, A. Zhang, E. Yang, G. Wang, Automatic classification of pavement crack using deep convolutional neural network, Int. J. Pavement Eng. 21 (2020) 457–463, http://dx.doi.org/10.1080/10298436.2018.1485917.
[38] J.H. Friedman, Multivariate adaptive regression splines, Ann. Statist. 19 (1991) 1–67, http://dx.doi.org/10.1214/aos/1176347963.
[39] W.G. Zhang, A.T.C. Goh, Multivariate adaptive regression splines for analysis of geotechnical engineering systems, Comput. Geotech. 48 (2013) 82–95, http://dx.doi.org/10.1016/j.compgeo.2012.09.016.
[40] W.G. Zhang, A.T.C. Goh, Multivariate adaptive regression splines and neural network models for prediction of pile drivability, Geosci. Front. 7 (1) (2016) 45–52, http://dx.doi.org/10.1016/j.gsf.2014.10.003.
[41] G.B. Huang, Q.Y. Zhu, C.K. Siew, Extreme learning machine: A new learning scheme of feedforward neural networks, in: 2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No. 04CH37541), Ieee, 2004, pp. 985–990, http://dx.doi.org/10.1109/IJCNN.2004.1380068.
[42] T. Chen, C. Guestrin, Xgboost: A scalable tree boosting system, in: Proceedings of the 22nd Acm Sigkdd International Conference on Knowledge Discovery and Data Mining, 2016, pp. 785–794, http://dx.doi.org/10.1145/2939672.2939785.
[43] H. Mo, H. Sun, J. Liu, S. Wei, Developing window behavior models for residential buildings using XGBoost algorithm, Energy Build. 205 (2019) 109564, http://dx.doi.org/10.1016/j.enbuild.2019.109564.
[44] X. He, H. Xu, H. Sabetamal, D. Sheng, Machine learning aided stochastic reliability analysis of spatially variable slopes, Comput. Geotech. 126 (2020) http://dx.doi.org/10.1016/j.compgeo.2020.103711.
[45] L. Song, X. Yu, B. Xu, R. Pang, Z. Zhang, 3D slope reliability analysis based on the intelligent response surface methodology, Bull. Eng. Geol. Environ. 80 (2021) 735–749, http://dx.doi.org/10.1007/s10064-020-01940-6.
[46] J. Zhang, H.W. Huang, K.K. Phoon, Application of the kriging-based response surface method to the system reliability of soil slopes, J. Geotech. Geoenviron. Eng. 139 (2013) 651–655, http://dx.doi.org/10.1061/(asce)gt.1943-5606.0000801.
[47] F. Kang, Q. Xu, J. Li, Slope reliability analysis using surrogate models via new support vector machines with swarm intelligence, Appl. Math. Model. 40 (2016) 6105–6120, http://dx.doi.org/10.1016/j.apm.2016.01.050.
[48] J. Ji, C. Zhang, Y. Gui, Q. Lue, J. Kodikara, New observations on the application of LS-SVM in slope system reliability analysis, J. Comput. Civ. Eng. 31 (2017) http://dx.doi.org/10.1061/(asce)cp.1943-5487.0000620.
[49] I. Chivata Cardenas, On the use of Bayesian networks as a meta-modelling approach to analyse uncertainties in slope stability analysis, Georisk-Assess. Manag. Risk Eng. Syst. Geohazards 13 (2019) 53–65, http://dx.doi.org/10.1080/17499518.2018.1498524.
[50] C. Qi, R. Xu, J. Wu, J. Yu, Reliability analysis of rock mass deformation in tunnel excavation based on genetic algorithm, J. Eng. Geol. 16 (2) (2008) 258–262, (In Chinese).
[51] H. Zhao, Z. Ru, X. Chang, S.D. Yin, S.J. Li, Reliability analysis of tunnel using least square support vector machine, Tunn. Undergr. Space Technol. 41 (2014) 14–23, http://dx.doi.org/10.1016/j.tust.2013.11.004.
[52] C. Bucher, T. Most, A comparison of approximate response functions in structural reliability analysis, Probab. Eng. Mech. 23 (2–3) (2008) 154–163, http://dx.doi.org/10.1016/j.probengmech.2007.12.022.
[53] A. Roy, S. Chakraborty, Support vector regression based metamodel by sequential adaptive sampling for reliability analysis of structures, Reliab. Eng. Syst. Saf. 200 (2020) http://dx.doi.org/10.1016/j.ress.2020.106948.
[54] X. Li, X. Li, Y. Su, A hybrid approach combining uniform design and support vector machine to probabilistic tunnel stability assessment, Struct. Saf. 61 (2016) 22–42, http://dx.doi.org/10.1016/j.strusafe.2016.03.001.
[55] Y.C. Bai, X. Han, C. Jiang, J. Liu, Comparative study of metamodeling techniques for reliability analysis using evidence theory, Adv. Eng. Softw. 53 (2012) 61–71, http://dx.doi.org/10.1016/j.advengsoft.2012.07.007.
[56] Q. Wang, H. Fang, L. Shen, Reliability analysis of tunnels using a metamodeling technique based on augmented radial basis functions, Tunn. Undergr. Space Technol. 56 (2016) 45–53, http://dx.doi.org/10.1016/j.tust.2016.02.007.
[57] Q. Pan, D. Dias, An efficient reliability method combining adaptive support vector machine and Monte Carlo simulation, Struct. Saf. 67 (2017) 85–95, http://dx.doi.org/10.1016/j.strusafe.2017.04.006.
[58] F. Cui, M. Ghosn, Implementation of machine learning techniques into the subset simulation method, Struct. Saf. 79 (2019) 12–25, http://dx.doi.org/10.1016/j.strusafe.2019.02.002.
[59] P. Samui, T. Lansivaara, D. Kim, Utilization relevance vector machine for slope reliability analysis, Appl. Soft Comput. 11 (5) (2011) 4036–4040, http://dx.doi.org/10.1016/j.asoc.2011.03.009.

[60] A. Hamrouni, D. Dias, B. Sbartai, Probability analysis of shallow circular tunnels in homogeneous soil using the surface response methodology optimized by a genetic algorithm, Tunn. Undergr. Space Technol. 86 (2019) 22–33, http://dx.doi.org/10.1016/j.tust.2019.01.008.

[61] S. Zhou, X. Guo, Q. Zhang, D. Dias, Q.J. Pan, Influence of a weak layer on the tunnel face stability - Reliability and sensitivity analysis, Comput. Geotech. 122 (2020) http://dx.doi.org/10.1016/j.compgeo.2020.103507.

[62] N. Moreira, T. Miranda, M. Pinheiro, P. Fernandes, D. Dias, L. Costa, J. Sena-Cruz, Back analysis of geomechanical parameters in underground works using an evolution strategy algorithm, Tunn. Undergr. Space Technol. 33 (2013) 143–158, http://dx.doi.org/10.1016/j.tust.2012.08.011.

[63] D.Y. Zhuang, K. Ma, C.A. Tang, Z.Z. Liang, K.K. Wang, Z.W. Wang, Mechanical parameter inversion in tunnel engineering using support vector regression optimized by multi-strategy artificial fish swarm algorithm, Tunn. Undergr. Space Technol. 83 (2019) 425–436, http://dx.doi.org/10.1016/j.tust.2018.09.027.

[64] M. Zhou, M. Shadabfar, Y. Xue, Y. Zhang, H. Huang, Probabilistic analysis of tunnel roof deflection under sequential excavation using ANN-based Monte Carlo simulation and simplified reliability approach, ASCE-ASME J. Risk Uncertain. Eng. Syst. A 7 (4) (2021) 1–14, http://dx.doi.org/10.1061/ajrua6.0001170.

[65] A.K. Verma, A. Pain, E. Agarwal, D. Pradhan, Reliability assessment of tunnels using machine learning algorithms, Indian Geotech. J. 52 (2022) 780–798, http://dx.doi.org/10.1007/s40098-022-00610-6.

[66] J. Zhang, K.K. Phoon, D. Zhang, H. Huang, C. Tang, Deep learning-based evaluation of factor of safety with confidence interval for tunnel deformation in spatially variable soil, J. Rock Mech. Geotech. Eng. 13 (2021) 1358–1367, http://dx.doi.org/10.1016/j.jrmge.2021.09.001.

[67] Y. Zhou, S. Li, C. Zhou, H. Luo, Intelligent approach based on random forest for safety risk prediction of deep foundation pit in subway stations, J. Comput. Civ. Eng. 33 (1) (2019) http://dx.doi.org/10.1061/(asce)cp.1943-5487.0000796.

[68] C. Zhang, J.Z. Li, Y. He, Application of optimized grey discrete Verhulst-BP neural network model in settlement prediction of foundation pit, Environ. Earth Sci. 78 (15) (2019) 15, http://dx.doi.org/10.1007/s12665-019-8458-y.

[69] W. Zhang, R. Zhang, C. Wu, A.T.C. Goh, S. Lacasse, Z. Liu, H. Liu, State-of-the-art review of soft computing applications in underground excavations, Geosci. Front. 11 (4) (2020) 1095–1106, http://dx.doi.org/10.1016/j.gsf.2019.12.003.

[70] F.K. Huang, G.S. Wang, ANN-based reliability analysis for deep excavation, in: EUROCON 2007 - The International Conference on Computer as a Tool, 2007, pp. 2039–2046, http://dx.doi.org/10.1109/EURCON.2007.4400328.

[71] J. Cao, C.N. Sun, H.M. Liu, Application of SVM to reliability analysis of foundation excavations system, Adv. Mater. Res. 859 (2014) 315–321, http://dx.doi.org/10.4028/www.scientific.net/AMR.859.315.

[72] L.X. He, Y. Liu, S.F. Bi, L. Wang, M. Broggi, M. Beer, Estimation of failure probability in braced excavation using Bayesian networks with integrated model updating, Undergr. Space (2020) http://dx.doi.org/10.1016/j.undsp.2019.07.001.

[73] C.H. Juang, Z. Luo, S. Atamturktur, H.W. Huang, Bayesian updating of soil parameters for braced excavations using field observations, J. Geotech. Geoenviron. Eng. 139 (3) (2013) 395–406, http://dx.doi.org/10.1061/(ASCE)GT.1943-5606.0000782.

[74] Z. Luo, B. Hu, Bayesian model and parameter calibration for braced excavations in soft clays, Mar. Georesour. Geotechnol. 38 (10) (2020) 1235–1244, http://dx.doi.org/10.1080/1064119X.2019.1673855.

[75] Y.F. Leung, W. Liu, Y. Lei, S.C. Hsu, Quantifying cost-effectiveness of subsurface strata exploration in excavation projects through geostatistics and spatial tessellation, Autom. Constr. 90 (2018) 243–252, http://dx.doi.org/10.1016/j.autcon.2018.02.032.

[76] Y. Wang, T.Y. Zhao, K.K. Phoon, Direct simulation of random field samples from sparsely measured geotechnical data with consideration of uncertainty in interpretation, Can. Geotech. J. 55 (6) (2018) 862–880, http://dx.doi.org/10.1139/cgj-2017-0254.

[77] Y. Hu, T.Y. Zhao, Y. Wang, C. Choi, C.W.W. Ng, Direct simulation of two-dimensional isotropic or anisotropic random field from sparse measurement using Bayesian compressive sampling, Stoch. Environ. Res. Risk Assess. 33 (8–9) (2019) 1477–1496, http://dx.doi.org/10.1007/s00477-019-01718-7.

[78] Y. Wang, T.Y. Zhao, Y. Hu, K.K. Phoon, Simulation of random fields with trend from sparse measurements without detrending, J. Eng. Mech. 145 (2) (2019) 1–12, http://dx.doi.org/10.1061/(ASCE)EM.1943-7889.0001560.

[79] J.Z. Zhang, K.K. Phoon, D.M. Zhang, H.W. Huang, C. Tang, Novel approach to estimate vertical scale of fluctuation based on CPT data using convolutional neural networks, Eng. Geol. 294 (2021) 106342, http://dx.doi.org/10.1016/j.enggeo.2021.106342.

[80] J.Z. Zhang, D.M. Zhang, H.W. Huang, K.K. Phoon, C. Tang, G. Li, Hybrid machine learning model with random field and limited CPT data to quantify horizontal scale of fluctuation of soil spatial variability, Acta Geotech. (2021) http://dx.doi.org/10.1007/s11440-021-01360-0.

[81] D. Huang, D.M. Gu, Y.X. Song, D.F. Cen, B. Zeng, Towards a complete understanding of the triggering mechanism of a large reactivated landslide in the Three Gorges reservoir, Eng. Geol. 238 (2018) 36–51, http://dx.doi.org/10.1016/j.enggeo.2018.03.008.

[82] W. Zhang, L. Tang, H. Li, L. Wang, L. Cheng, T. Zhou, X. Chen, Probabilistic stability analysis of Bazimen landslide with monitored rainfall data and water level fluctuations in Three Gorges reservoir, China, Front. Struct. Civ. Eng. (2020) http://dx.doi.org/10.1007/s11709-020-0655-y.

[83] C. Wang, Reliability-based design of lining structures for underground space against water seepage, Undergr. Space (2020) http://dx.doi.org/10.1016/j.undsp.2020.03.004.

[84] W.G. Zhang, C.Z. Wu, H.Y. Zhong, Y.Q. Li, L. Wang, Prediction of undrained shear strength using extreme gradient boosting and random forest based on Bayesian optimization, Geosci. Front. (2021) http://dx.doi.org/10.1016/j.gsf.2020.03.007.