

Deep Learning-based Prediction of Tunnel Face Stability in Layered Soils using Images of Random Fields

Zheming Zhang, S.M.ASCE¹, Ze Zhou Wang, PhD, Aff.M.ASCE², Siang Huat Goh, PhD³, Jian Ji, PhD, M.ASCE⁴

¹PhD Candidate, Key Laboratory of Ministry of Education for Geomechanics and Embankment Engineering, Hohai University, Nanjing, China; Department of Civil and Environmental Engineering, National University of Singapore, Singapore. Email: e1092645@u.nus.edu; millionzhang77@gmail.com

²Marie Skłodowska-Curie Fellow, Faculty of Engineering, University of Cambridge, United Kingdom. Email: wangzz@u.nus.edu

³Associate Professor, Department of Civil and Environmental Engineering, National University of Singapore. Email: gohsianghuat@nus.edu.sg

⁴Professor, Key Laboratory of Ministry of Education for Geomechanics and Embankment Engineering, Hohai University, Nanjing, China. (Corresponding Author). Email: ji0003an@e.ntu.edu.sg

Abstract

The stability analysis of tunnel faces in multilayered soils presents challenges due to the inherent variability in natural soils. While the random field finite-element method offers a reliable approach to address such variability, its heavy computational demands have been a significant drawback. To overcome this limitation, this study presents a novel deep learning-based method for efficient tunnel face stability analysis in layered soil with spatial variability. By combining the power of Convolutional Neural Networks (CNNs) and U-Net, this method trains surrogate models using a small but sufficient number of random field images to effectively learn high-level features that encompass the spatial variabilities, which significantly enhances computational efficiency. In particular, the U-Net generates precise displacement field images based on random field images, enabling the discrimination of tunnel face collapse failure modes. To validate the effectiveness of this proposal, a comprehensive case study involving layered soils with spatial variabilities is conducted. The remarkable agreement between the outputs of CNNs and U-Net and the predictions of finite-element simulations underscores the promising potential of employing deep-learning models as the surrogate for analyzing the stability of tunnel faces in spatially variable layered soils. Last but not least, the key innovation of this work lies in the pioneering application of U-Net within the geotechnical reliability analysis domain.

Author keywords: Tunnel face stability; Spatial variability; Convolutional neural networks; U-Net; Geotechnical reliability; Collapse failure mode

38 Introduction

39 Ensuring the stability of tunnel faces is crucial during the tunnel boring process, particularly in
40 challenging geological conditions. To prevent collapse, it is necessary to apply a critical support
41 pressure, traditionally determined under the assumption of isotropic and homogeneous soils. However,
42 natural soils often exhibit significant variability in properties due to complex geological processes over
43 time (Griffiths et al. 2009; Phoon and Kulhawy 1999; Wang et al. 2016). In addition, the driving of
44 tunnels in multilayered soils is common in practical engineering, especially with larger shield
45 diameters, which can result in different collapse (failure) modes. Therefore, the stability analysis of
46 tunnel faces should consider the interactive effects of spatial variabilities and geological stratigraphy
47 (Shi and Wang 2023).

48 Over the years, various analytical models have been proposed to address the stability of tunnel face
49 in layered soils, these being primarily based on the limit equilibrium method and the limit analysis
50 method. The first limit equilibrium failure mechanism was proposed by Horn (1961), who adopted the
51 wedge-silo stability model to derive the critical support pressure using the limit equilibrium equations.
52 Building upon this, numerous improved models (Broere 2002; Hu et al. 2012; Li et al. 2022; Qarmout
53 et al. 2019) have been proposed to address the stability of tunnel faces in more complex geological
54 scenarios.

55 Among the limit analysis methods, Mollon et al. (2011) proposed a three-dimensional rotational
56 mechanism with a spatially discretized failure surface to calculate the ultimate support pressure using
57 the upper and lower limit theory (Tu et al. 2023). Based on this approach, many researchers have
58 proposed improved models to assess support pressures and failure modes of tunnel face in layered

soils. Ibrahim et al. (2015) studied tunnel face stability in frictional layered ground using an upper bound solution based on the three-dimensional rotational failure mechanism. The findings were validated through finite-element simulations, which showed good agreement with the proposed mechanism with regards to the collapse pressure and failure modes. Senent and Jimenez (2015) modified the three-dimensional rotational failure mechanism, considering the entire tunnel area and incorporating the possibility of partial collapse in stratified ground. In addition to providing practical insights for this commonly encountered situation, they also emphasized the importance of further research focusing on scenarios where multiple strata intersect at the tunnel face. Li et al. (2021) further integrated the three-dimensional rotational failure mechanism with a random field to perform probabilistic stability analysis of tunnel faces.

Sloan (2013) conducted a comparative analysis of analytical solutions in geotechnical problems, highlighting their distinct characteristics. The study concluded that while analytical methods excel in defining solution ranges and addressing complex loading and boundary conditions, they have limitations when it comes to handling intricate soil models and accurately predicting soil-structure interaction during tunneling. Consequently, numerical modelling has emerged as the preferred approach in such cases.

In the existing literature (Chen et al. 2023; Cheng et al. 2019; Ji et al. 2021; Mollon et al. 2013), the primary numerical simulation tools currently used for assessing tunnel face stability include discrete-element method (DEM), finite-difference method (FDM) and finite-element method (FEM), among others. Numerical simulations offer several advantages, such as the ability to handle complex structures and loading conditions, provide higher precision and accuracy through discretization, and

offer flexibility in simulating different scenarios. Furthermore, numerical simulations allow for the visualization of the failure zone of the tunnel, providing comprehensive information on various aspects, including but not limited to stress distribution, displacement fields, and deformation. This wealth of information facilitates a deeper understanding of the stability issues associated with tunnel faces and serves as a comprehensive basis for the safety assessment of tunneling projects. However, the modelling and calculations in numerical simulations impose significant demands on computing resources and are time-consuming (Guo et al. 2022).

In recent years, machine learning techniques have gained widespread popularity in geotechnical reliability analysis, the key objective being to enhance computational efficiency (Wang et al. 2022; Wu et al. 2022; Zhang et al. 2021; Zhao et al. 2023). Deep learning, a subset of machine learning, incorporates "thinking" or "decision-making" capabilities that mimic the structure and functionality of neural networks in human brains. Deep learning models can learn from training data, enabling them to uncover intricate relationships and patterns that may not be readily discernible through traditional analytical methods.

In geotechnical engineering, the convolutional neural network (CNN) is a powerful deep learning model widely used for capturing the topology of images, particularly in the context of random field images that contain valuable information about spatially variable soil parameters. By automatically linking the features extracted from random field images to the output quantities of the finite-element model, CNN can replace costly finite-element simulations. In a series of studies (Ji et al. 2022; Wang 2022; Wang et al. 2021), the application of CNN to geotechnical engineering problems such as slope stability, retaining wall analysis and surface footing design was demonstrated. Zhang et al. (2021)

employed CNN to assess the safety factor against tunnel face deformation with confidence intervals in spatially variable soils. The highly promising performance of CNN in regression problems demonstrates its suitability for predicting the critical support pressure at the tunnel face.

On the other hand, the failure mode or mechanism of a geosystem is also vital for the analysis, design and management of the system. The above-mentioned studies, however, did not focus on this aspect. Hsiao et al. (2022) mentioned that, although a traditional CNN can be trained and adopted as a classifier to predict failure modes and the companion probability value, it failed to delineate specific failure zones, thus limiting the understanding and visualization of the failure mechanism of a geosystem. Consequently, there is still a significant research gap to be addressed in leveraging deep learning techniques to study the failure mechanism of geosystems.

In light of recent advancements in artificial intelligence (AI) image-generation capabilities, this study introduces the pioneering application of U-Net, an advanced Convolutional Neural Network architecture (Ronneberger et al. 2015), in the field of geotechnical engineering. The architecture of U-Net was modified and extended to handle limited training images and generate more accurate localization and segmentations.

In the present study, U-Net is further adapted to enhance the prediction of tunnel face collapse modes through establishing a connection between the features of random field images and the high-dimensional output quantities of the finite-element model. Specifically, U-Net is modified and employed to predict the displacement fields of tunnel faces and their surrounding soil mass. By analyzing the contours of the displacement fields, the collapse modes can be effectively identified and predicted. The key contribution of this study lies in pioneering the application of U-Net within the

geotechnical reliability analysis domain to construct surrogate models involving high-dimensional inputs and high-dimensional outputs. This innovation sets it apart from existing studies that employed traditional CNN architecture to predict single or low-dimensional outputs (such as safety factors) based on random field images.

In essence, a deep-learning methodology that involves the combination of two machine learning models, one CNN and one U-Net, is proposed in the present study to serve as advanced surrogate models for random field finite-element analysis of tunnel face stability. Besides predicting the critical support pressure in the presence of multiple soil layers by CNN, the collapse modes based on different realizations of the random fields are also identified by U-Net. The proposed deep-learning methodology serves as an efficient tool for providing valuable insights into comprehending the complex collapse modes observed in tunnel excavation face, thus contributing to improved risk control in practical tunnel engineering.

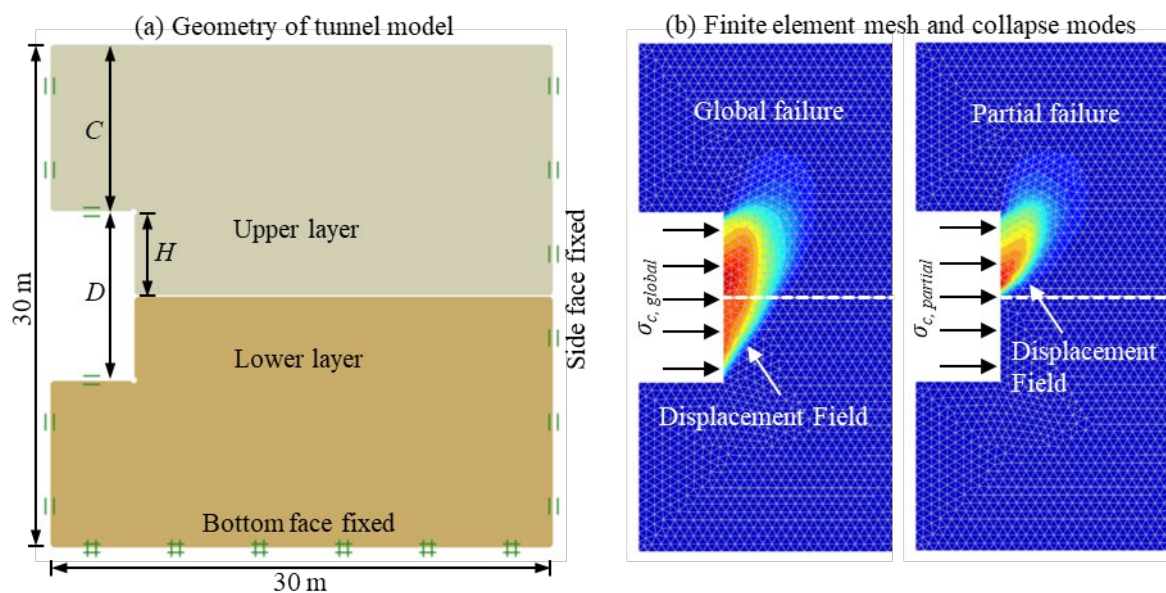


Fig. 1. Schematic diagram of the model depicting the tunnel face stability analysis.

Illustrative Tunnel Face Stability Example

The finite-element limit analysis (FELA) method combines the strengths of finite-element modelling and classic limit analysis methods, making it particularly suitable for analyzing geotechnical stability problems. In this study, the finite-element software Optum G2 (Krabbenhøft and Lyamin 2014) was employed to perform the limit analysis calculations and evaluate the stability of tunnel faces.

Following the hypothetical example documented by (Cheng et al. 2019; Senent and Jimenez 2015), a plane strain model was constructed to simulate the tunnel face stability in a two-layered ground, where the upper layer weaker compared to the lower layer. As shown in Fig. 1(a), the tunnel is modeled with a diameter (D) of 10 m and a cover (C) of 10 m. The height (H) represents the vertical distance from the crown of the tunnel to the interface between the upper and lower layers. The constitutive behavior of the materials was characterized by the Mohr–Coulomb model. To minimize boundary effects, a domain measuring 30 m $\times$ 30 m was utilized.

The boundary conditions of the model are clearly depicted in the figure. The left and right boundaries of the model are supported by vertical rollers. The top boundary (ground surface) and excavation face of the tunnel are free to deform, while the model base is fully restrained. The top and bottom tunnel liners are modeled using rigid elements which are constrained against any vertical deformation. These boundary conditions have been proven effective for stability analysis purposes (Augarde et al. 2003).

The simplified two-dimensional model of the tunnel allows for a practical assessment of tunnel face stability and provides a reasonable approximation of the actual conditions (Yamamoto et al. 2011). While it may lead to an overestimate of the critical collapse pressure compared to three-dimensional

models. It is important to note that the energy dissipation is primarily influenced by the failure surface area within the upper bound limit analysis framework (Cheng et al. 2019). Hence, the plane strain model is suitable for evaluating the range of failure zones. Moreover, in certain cases, it is easier to visualize differences in the failure mechanisms. Thus, the utilization of a simplified two-dimensional tunnel model offers a valid approach to evaluate tunnel face stability.

The critical support pressure (σ_c) for tunnel face stability is determined using the load multiplier function provided by Optum G2. Specifically, the internal support pressure gradually increases from a small initial value until the governing equations of the upper bound stress-displacement relationships are satisfied. The pressure applied then represents the critical support pressure, which is numerically equal to the prescribed initial value of the support pressure multiplied by the final value of the multiplier.

The presence of a weaker soil layer in the upper section of the tunnel face can significantly influence the collapse pressure. The existence of this weaker layer introduces the possibility of a partial collapse of the tunnel face. Fig. 1(b) illustrates two potential collapse modes for the tunnel excavation face in layered soils. The collapse mode can be identified based on the displacement fields. A global failure is one in which the displacement field extends to the bottom of the excavation face, as shown on the left subplot of Fig. 1(b). Otherwise, it is a local or partial failure, as shown on the right subplot.

In order to simulate the variability of soil layers encountered in tunnel excavations, this research draws upon the same case study conducted by (Cheng et al. 2019; Senent and Jimenez 2015), but with consideration of four representative soil layer scenarios. These scenarios encompass a homogeneous soil layer and three different layered soil configurations. The layered soil configurations differ in the

depth of the layer interface, with the ratio H/D equal to 0.25, 0.5 and 0.75 as illustrated in Fig. 2. Table 1 summarizes the statistics of the parameters involved in this problem.

Table 1 Statistical parameters of soil properties.

Layers	Unit Weight (kN/m ³)	Cohesion c (kPa)			Friction angle φ (°)			Autocorrelation distances (for both c and φ)	
		Mean	COV	Distribution	Mean	COV	Distribution	l_h (m)	l_v (m)
Upper layer	20	2	0.2	Lognormal	25	0.2	Lognormal	20	2
Lower layer	25	15	0.2	Lognormal	40	0.2	Lognormal	20	2

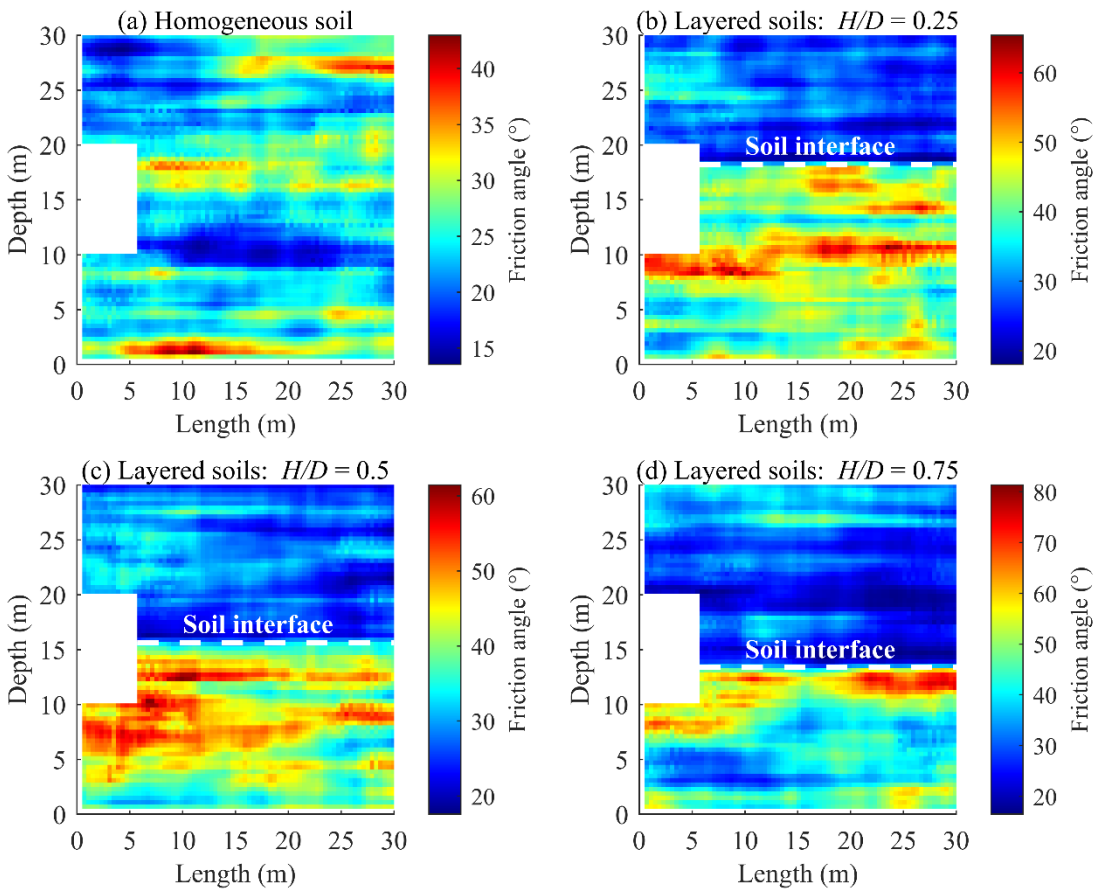


Fig. 2. Samples of digitally generated random fields friction angle φ for different H/D values.

Optum G2 is equipped with a built-in engine that utilizes the KL expansion for generating random fields. To ensure accuracy, a total of 1,000 expansion terms was employed to generate the random fields. These generated random fields were then mapped onto the finite-element mesh by the software. It is important to note that the element size of the discretized random field plays a significant role in capturing the variation of the soil parameters. As demonstrated by (Ching and Phoon 2013), smaller elements are necessary to achieve acceptable accuracy. Following their recommendations, the ratio of the mesh size to the auto-correlation distance is set as lower than 0.2 in this study.

It is noteworthy that, in the absence of spatial variability, the predominant failure mechanism caused by a significant strength disparity between the upper and lower homogeneous soil layers is that of a partial failure, confined solely to the stronger soil above the layer interface (Alagha and Chapman 2019; Senent and Jimenez 2015). However, as will be shown in the later parts of this paper, upon incorporating the spatial variability of the soil strength parameters, the results of the Monte Carlo simulations show that both partial and global failures are possible, depending on the random fields generated for the individual realization. In other words, the partial failure zones do not develop solely in the upper weaker layer, but in some realizations can penetrate into the underlying stronger layer.

In the subsequent parts of this paper, the methodology and analyses will be explained and discussed with reference to the preceding tunnel face stability example. This example will serve as a guiding framework to explain the steps and procedures involved in the study, with the aim of providing a clear and comprehensive understanding of the proposed methodology and the analyses conducted.

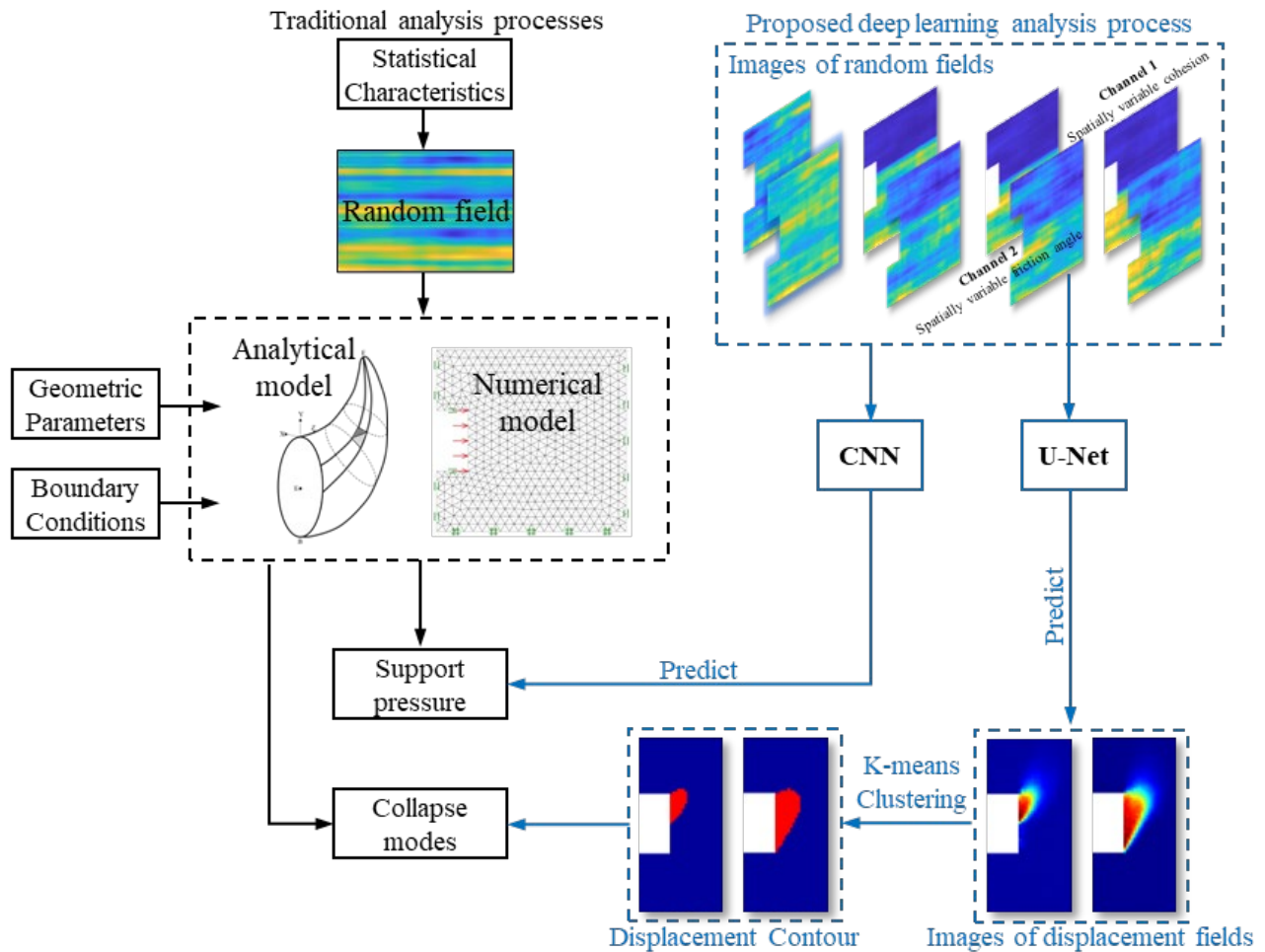


Fig. 3. Comparison of the traditional analysis process with the proposed deep learning analysis process.

The Proposed Methodology

Fig. 3 provides a visual representation of the proposed deep learning analysis process, with a comparison made with the traditional approach for predicting and evaluating tunnel face stability considering the spatial variability of soil parameters. The traditional process involves several steps. Initially, statistical characteristics of soil parameters are used to generate realizations of the random fields that are statistically consistent with the desired spatial variability. These random fields are then incorporated into an analytical or numerical model, which is constructed based on predetermined

geometric parameters and boundary conditions. By performing Monte Carlo simulations, the critical support pressure and collapse mode are determined for each realization of the random field. The traditional analysis process, however, has certain drawbacks. Analytical models, while computationally fast, often rely on simplifying assumptions and approximations, such as rigid block mechanisms (Qarmout et al. 2019), rotational failure mechanisms (Mollon et al. 2013), etc., which may limit the accuracy of the results. On the other hand, numerical models can capture the complexity of real engineering scenarios more realistically but require significant computational resources and time.

In contrast, the proposed deep learning analysis process employs a different approach. It begins by generating random field images that reflect the soil parameter variabilities. These images are then fed into a CNN model, which utilizes regression analysis to predict the critical support pressure after proper training. The proposed methodology further advances the fusion of deep learning and tunnel face stability analysis through employing the U-Net model to further interpret random field images and predict the corresponding high-dimensional outputs depicting the images of displacement fields. The displacement fields output will not only allow engineers to obtain predictions of the tunnel face and surrounding soil mass, but also visualize and interpret the collapse modes and mechanisms more accurately. For example, the K-means Clustering method (Huang et al. 2013; van den Eijnden and Hicks 2017) can be employed to delineate the contours of failure zones, enabling the identification of collapse modes and mechanisms. By leveraging image-based representations of random fields, coupled with proper training, the proposed approach can effectively capture and recognize intricate spatial patterns and variations of the material parameters. This leads to a quicker and more efficient prediction

of the critical support pressure and the ability to visualize the displacement fields and failure zones.

In the following section, details pertaining to the key components that make up the proposed methodology will be explained.

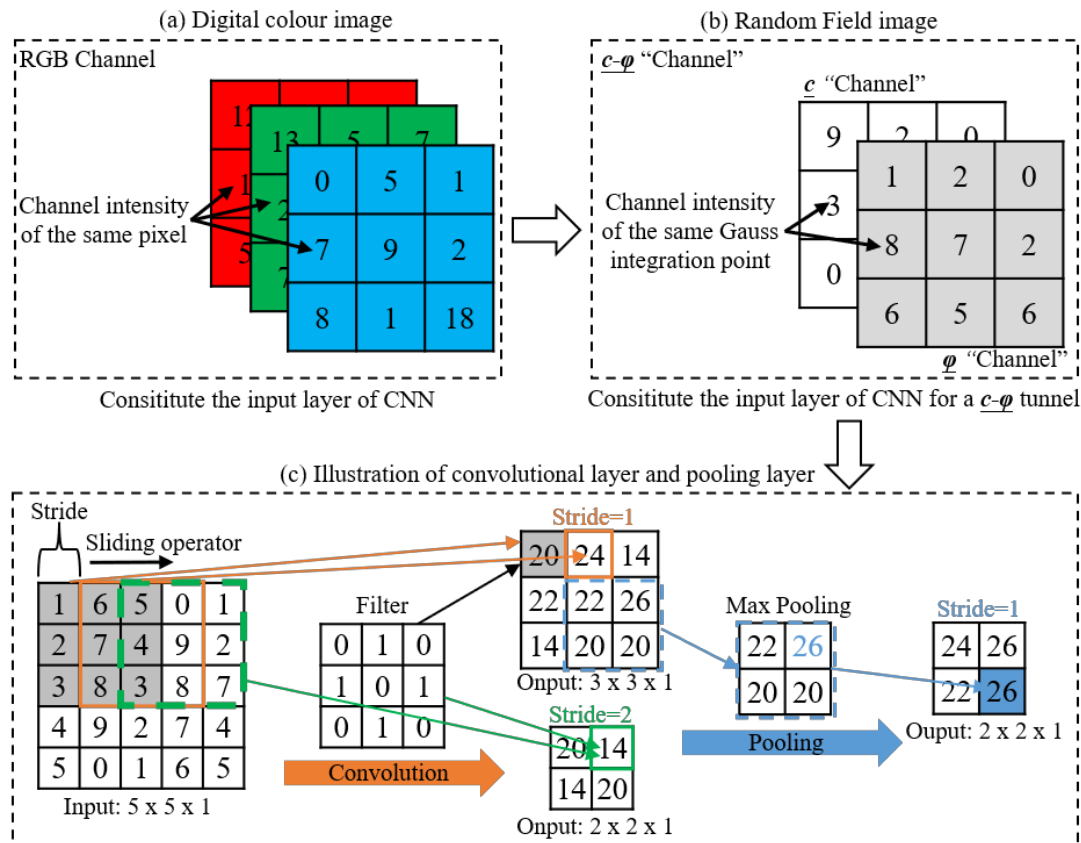


Fig. 4. Representation of channel information and learning process in CNNs.

Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) commonly consist of several key components, including convolutional layers, pooling layers, activation layers and normalization layers. These layers are typically followed by a fully-connected layer, a dropout layer and an output layer, forming the architecture of the CNN, as depicted in Fig. 5. In this study, the MATLAB Convolutional Neural

245 Networks Toolbox (Vedaldi and Lenc 2015) was employed for all the deep learning tasks. All
 246 computations were performed on a computer equipped with an NVIDIA GeForce RTX 3060 GPU.

247 The configuration of the CNN input layer for FELA differs from the traditional approach employed
 248 in processing color digital images. A typical color digital image is composed of pixels, each featuring
 249 three channels representing the primary colors: red, green, and blue. As a result, each pixel is
 250 characterized by three values corresponding to the intensities of these channels. In Fig. 4(a), the CNN
 251 input layer for conventional image processing depicts an image with dimensions of $3 \times 3 \times 3$. Here,
 252 the first two "3"s denote the width and height of the image in pixels, while the third "3" indicates the
 253 presence of three channels (red, green, and blue).

254

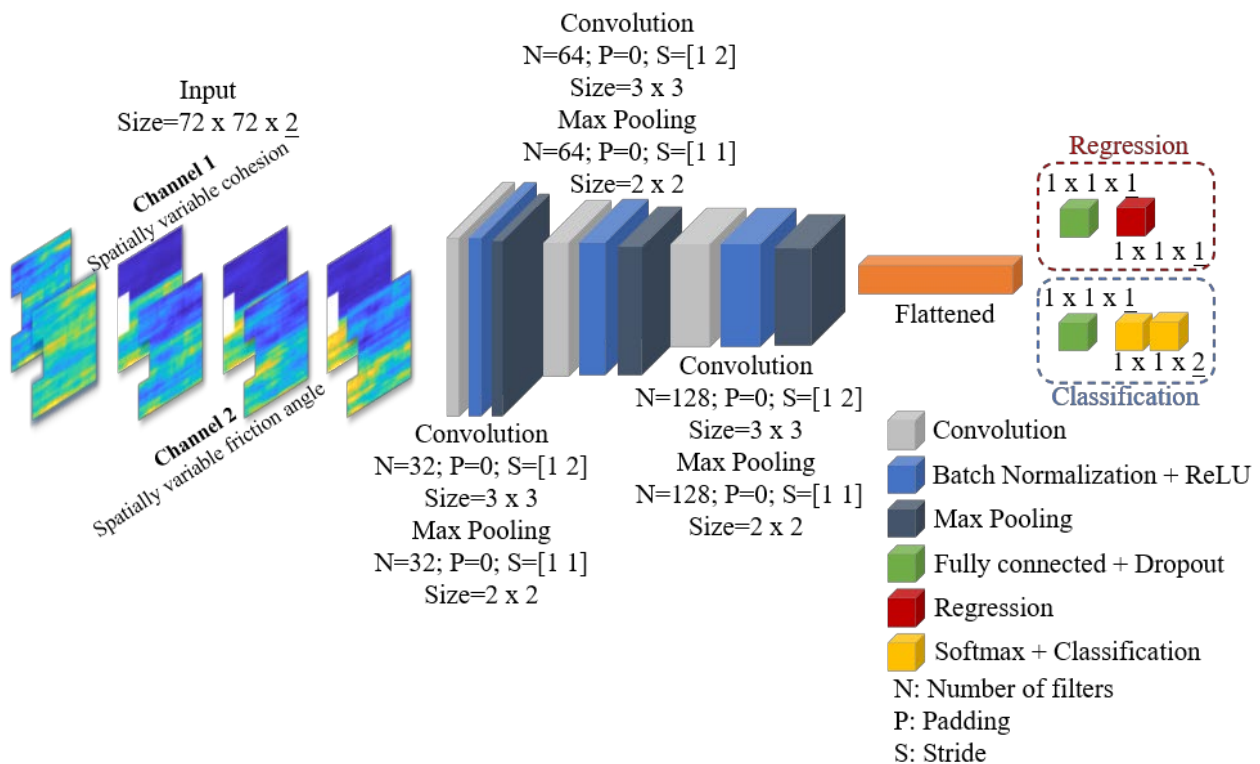


Fig. 5. Architecture of the CNN.

255

In finite element analysis, the material parameter values are assigned to the gauss integration points within each finite element. When using CNNs to interpret random fields, the Gauss integration points in the discretized mesh can be considered analogous to pixels in traditional image processing. As illustrated in Fig. 4(b), similar to the RGB three-channel setup in traditional images, each random field representation of a variable property can be considered as a "channel." The value of the property at a Gauss integration point corresponds to the "channel intensity" of a "pixel". For instance, in the case of a soil layer with varying cohesion (c) and friction angle (ϕ), each finite-element realization involves two random fields. As a result, the input layer of the CNN consists of a two-channel "image" comprising the " c " channel and the " ϕ " channel, representing the values of cohesion and friction angle, respectively. This configuration allows the two random fields to be processed in a manner similar to a two-channel image using CNNs. This is further illustrated in Fig. 5, in which the input random field image has a size of $72 \times 72 \times 2$. The two "72" refer to the number of Gauss integration points along the width and height of the 2D model domain, while the "2" denotes the two random variables involved, i.e., c and ϕ .

Fig. 4(c) provides insights into how CNNs learn from random field image-based inputs. Convolutional and pooling layers are two important components of the CNN structure used to learn image features and reduce data dimensionality. A fundamental component integral to the convolutional layer is the filter or kernel. The convolutional layer adheres to the processes outlined in Fig. 4(c). Employing a sliding window operator with a user-defined step size known as the stride (S), the filter traverses horizontally and vertically across the entire input image. A dot product operation is executed on each pair of filters and subarrays of the input image, both of which share the same dimensions as

the filter. The resultant dot product values are aggregated to yield the entries in the output matrix. For instance, if the stride is set to 1, the sum of the dot product involving the first subarray of the image and the filter is 20, representing the value in the first cell of the output matrix with dimensions of $3 \times 3 \times 1$. Subsequently, the filter shifts one stride to the right, initiating a similar operation resulting in 24, which forms the value in the second cell of the output matrix. If the stride is set to 2, the values in the first and second cells of the output matrix are 20 and 14, respectively, and the output matrix dimensions become $2 \times 2 \times 1$. The pooling layer can enlarge the receptive field and aggregate global information by reducing the spatial resolution. There are two typical types of pooling operators, i.e., max-pooling and average-pooling. This study adopted a max-pooling operator for analyses. With a sliding window, max-pooling chooses the maximum value in the subarray of the input matrix. Thus, key image features, such as edges, can be somewhat invariant to translation, which is important for feature extraction and description. Following the example in Fig. 4(c), with a window size of 2, the maximum number in the first subarray is 26, which is the value assigned to the first cell of the output matrix obtained with the max-pooling operator. A pooling layer often is placed after a convolutional layer, which produces multiple input matrices for the pooling layer.

Convolutional layers and pooling layers are typically stacked alternately to form the backbone structure of CNNs. The repeated stacking of these layers allows the gradual learning of higher-level features, thereby enhancing the model's capability for image understanding and recognition. This hierarchical structure can be flexibly designed for various image learning tasks by adjusting parameters such as the size and number of convolutional kernels and the strategy for pooling operations. While convolutional layers and pooling layers are pivotal components for CNNs to learn image features, the

entire network also encompasses other layers, including fully connected layers and activation functions, and among others. These layers collaborate to achieve the learning of advanced features in images.

Referring to Fig. 5, the feature extraction component of the CNN used for the illustrative tunnel face stability example consists of three pairs of convolutional layers, batch normalization layers, max pooling layers and ReLU layers. The outputs from the convolutional layers, which employ filters of size 3×3 , a padding of 0, and a stride of 1 and 2 in the two principal directions, are then passed through the ReLU layer and subsequently processed by the max pooling layer with a size of 2×2 , a padding of 0, and a stride of 1 in both principal directions. The numbers of filters used in the three pairs are 32, 64, and 128, respectively. Finally, depending on the nature of the problem, a regression or classification is performed to predict the support pressure or collapse mode based on the outputs of the fully-connected layer. To reduce overfitting, a dropout rate of 50% is prescribed in the dropout layer.

During the training of the CNN, the stochastic gradient descent algorithm (sgdm) is employed to optimize the filter weights and biases. For regression-based predictions, the accuracy of the training and validation phases is evaluated by calculating the root mean square errors (RMSE) between the CNN-predicted support pressures and the corresponding support pressures calculated using FELA. Similarly, for classification-based predictions, the accuracy of the training and validation phases is assessed based on the classification accuracy of the CNN-predicted collapse mode compared to the actual collapse mode determined through FELA. The configurable hyper-parameters used in the trainings of the CNN in this study are summarized in Table 2.

319

Table 2 Configurable hyper-parameters of the CNN.

Learning rate	Momentum	Minimum batch size	Maximum epoch	L2-regularization parameter	Validation Frequency	Accuracy
0.00001	0	64	1000	0.00001	1	RMSE

320

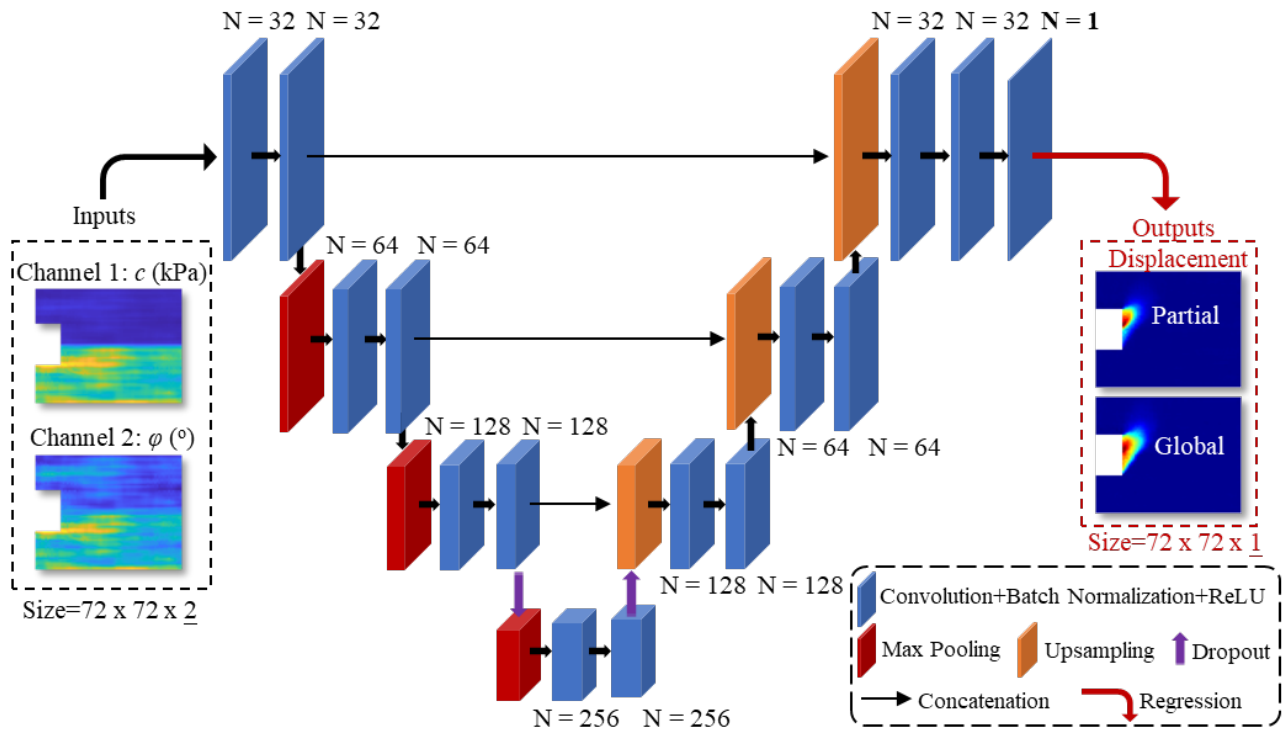


Fig. 6. Architecture of the U-Net.

321

U-Net Configuration

322

As shown in Fig. 6, the architecture of the U-Net shares similarities with the CNN. The U-Net learns

323

image features in exactly the same way as CNN. The main distinction lies in the arrangement of

324

convolutional layers in the U-Net, which forms a u-shaped structure consisting of two main paths: the

325

contracting path known as the Encoder, and the symmetric expansive path being referred to as the

326

Decoder. This symmetrical design enables the U-Net to perform “image-to-image” function which, in

327

the context of the present study, involves the prediction of the “high-dimensional output displacement

328

field images” from the “high-dimensional input random field images”. In this study, the MATLAB

Deeping Learning Toolbox was employed, and all training tasks were performed on a single GPU workstation with an NVIDIA GeForce RTX 3060 GPU.

The input layer of U-Net is the same as that of the CNN, consisting of random field images of size $72 \times 72 \times 2$. The encoder is responsible for capturing the contextual information from the input images, employing a stack of convolutional and max pooling layers to extract high-level features. The architecture of the encoder follows a typical CNN structure, with each step consisting of two 3×3 convolutions with a stride of 1 in both principal directions, a ReLU layer, and a 2×2 max pooling layer with a stride of 2 in both principal directions. The max pooling layer facilitates downsampling, and the number of feature channels doubles at each downsampling step. In this study, the number of feature channels were 32, 64, 128 and 256. A 50% dropout rate was applied in the dropout layer to reduce overfitting.

On the other hand, the decoder plays a crucial role in enabling precise localization by utilizing transposed convolutions. The decoder path receives the encoded features from the encoder and gradually increases the spatial resolution of the feature maps through the transposed convolutions or upsampling operations. This expansion process aids in recovering the spatial details lost during the contraction path. In this study, each step in the expansive path consists of an upsampling of the feature map followed by a 2×2 convolution (“up-convolution”) with a stride of 2 in both directions that halves the number of feature channels, concatenation with the corresponding cropped feature map from the contracting path, and two 3×3 convolutions with a stride of 1 in both directions, each followed by a ReLU layer. Cropping is necessary to account for the loss of border pixels in every convolution. Through this process, the number of feature channels is halved from 256 to 128, 64 and 32. At the final

layer a 1×1 convolution is employed to map each 32-component feature vector. Finally, a $72 \times 72 \times$
1 image of the displacement field is generated through regression. Table 3 shows the configurable
hyperparameters used in the trainings of the U-Net.

Table 3 Configurable hyper-parameters of the U-Net.

Initial learn rate	Momentum	Minimum batch size	Maximum epoch	L2- regularization parameter	Validation Frequency	Accuracy
0.0001	0	32	1000	0.0001	1	RMSE

Implementation Procedures

The implementation flowchart of the proposed method to efficiently predict the critical support
pressures and collapse modes of tunnel face in layered spatially variable soils is shown in Fig. 7. The
methodology consists of the following five main steps:

Step 1: After constructing the FELA models of the tunnel, a set of X random fields is generated
based on the statistical properties of the variables involved in the study. Random field FELAs are then
performed on these samples to obtain the critical support pressures and collapse modes.

Step 2: The generated X samples of random fields and their corresponding results are divided into
two subsets: a training set and a validation set. In this study, 70% of the X dataset is allocated for
training, while the remaining 30% is used for validation.

Step 3: Following the establishment of the appropriate architecture for the CNN and U-Net, the
training and validation datasets are utilized to train the models.

368 Step 4: Once sufficient training and validation have been performed, the trained CNN and U-Net
 369 models are employed to replace the FELA model. These models are utilized for predicting the critical
 370 support pressures and displacement fields corresponding to the random fields generated through
 371 additional Monte Carlo simulations.

372 Step 5: The K-means Clustering method is used to delineate the displacement contours based on
 373 the predicted displacement fields to identify and classify different collapse modes.

374

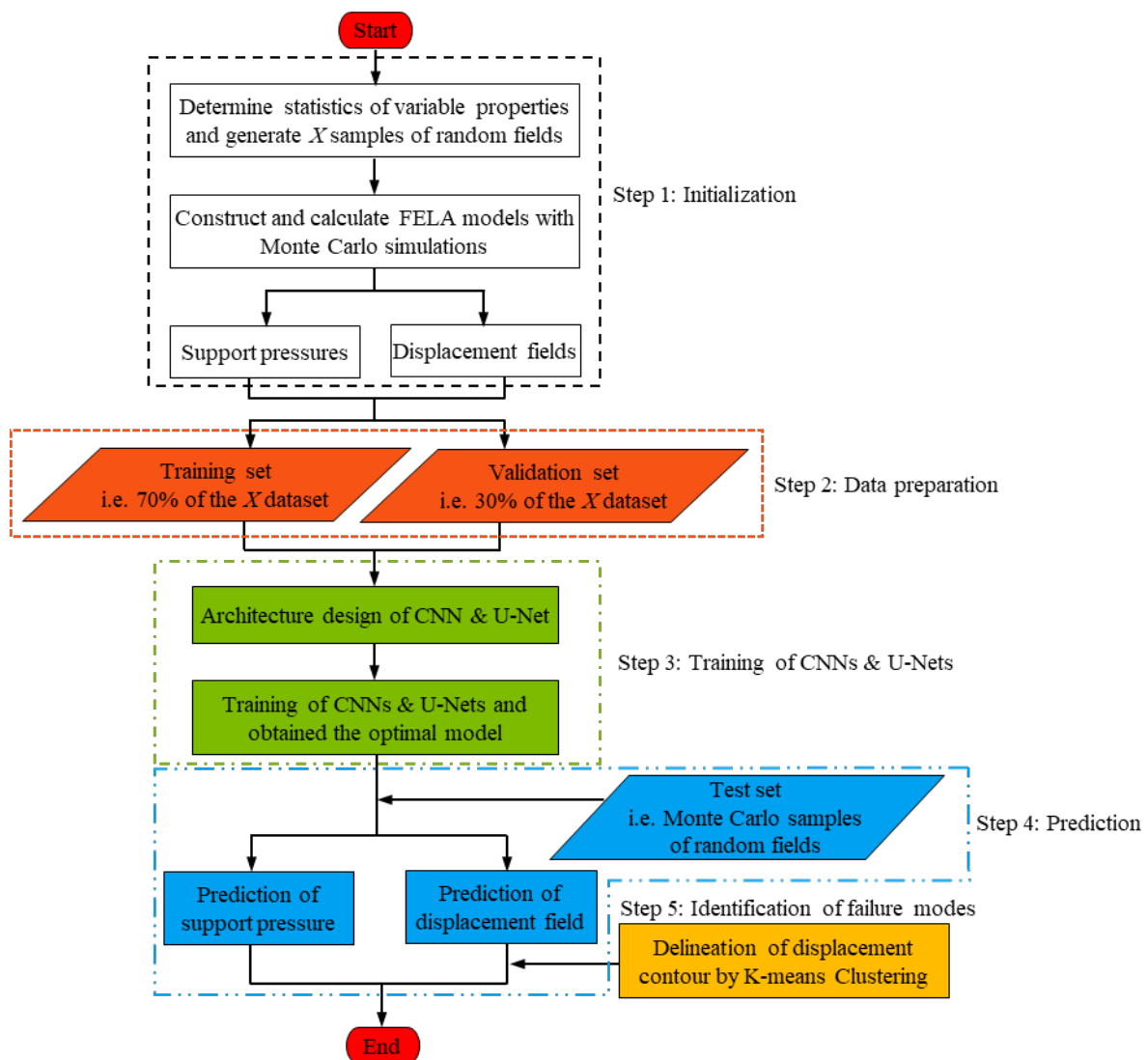


Fig. 7. Implementation procedure for the proposed methodology.

Analysis Results using the Proposed Methodology

Regression-based prediction of critical support pressures

During the training process, 450 number of samples which involved the four scenarios ($H/D = 0.25, 0.5, 0.75, 1.0$) were generated as the training set. The combined dataset for four representative soil layer scenarios is then used to train a CNN model with the architecture shown in Fig. 5. The trained CNN model has the capability to predict critical support pressures for all four scenarios, setting it apart from other methods that require the construction of individual models for each scenario due to technical limitations. Fig. 8 illustrates the training process of CNN. The loss value decreases gradually with the number of iterations, showing region smoothness with fluctuations due to the dropout layer. A lower loss function value indicates better model performance and accuracy.

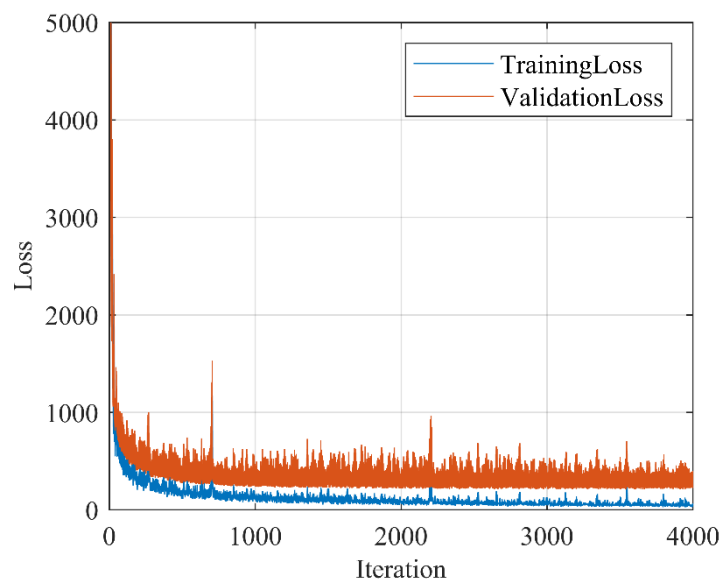


Fig. 8. Training progress of CNN model.

After the model is trained, an additional set of 4000 Monte Carlo simulations is generated independently to be utilized to perform random field finite-element limit analyses (FELAs). These simulations are carried out for four representative soil layer scenarios ($H/D = 0.25, 0.5, 0.75, 1.0$), with each scenario consisting of 1000 MCS. The critical support pressures obtained from these 4000 MCS simulations serve as the benchmark dataset for assessing the accuracy of the trained CNN models.

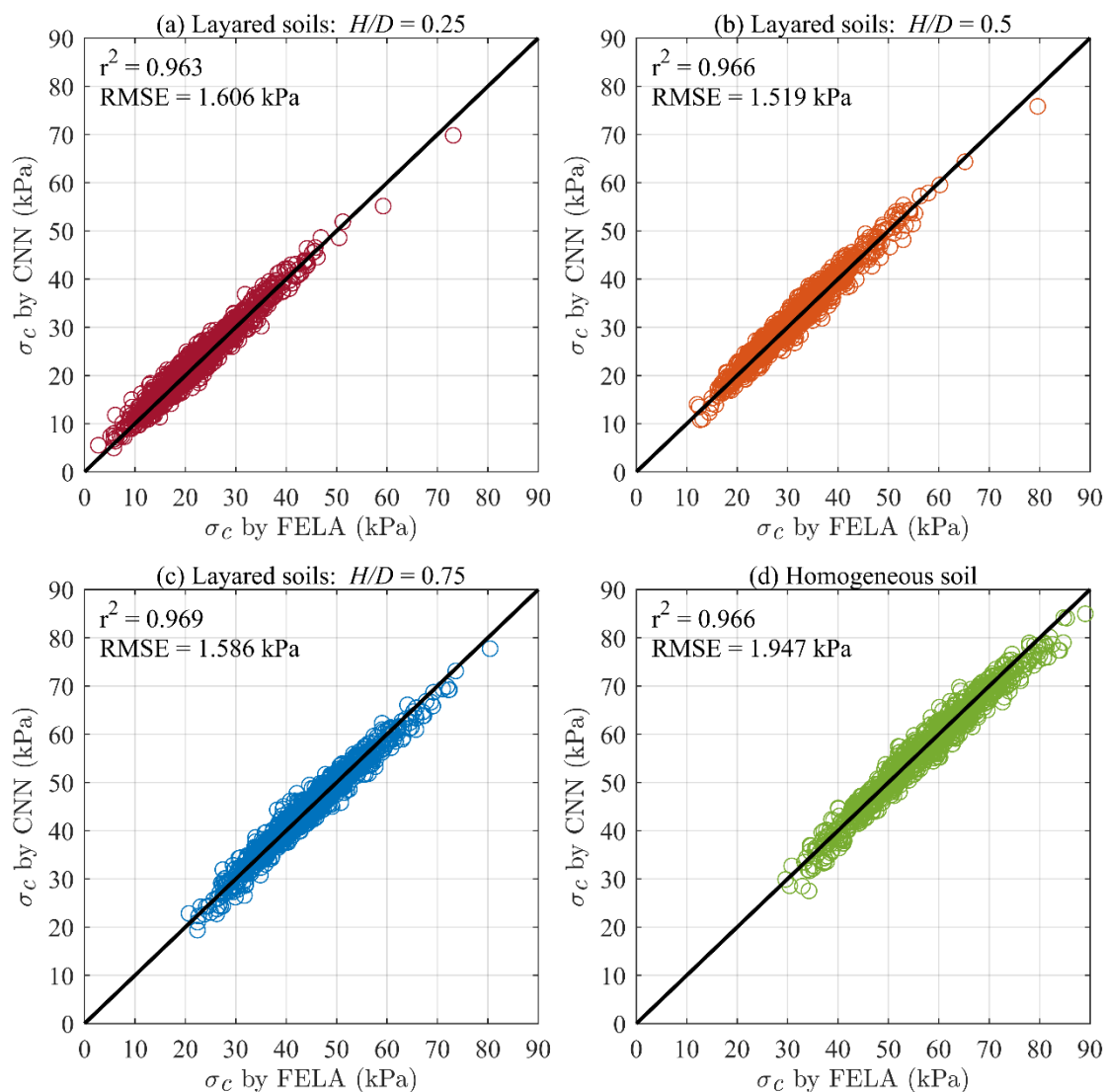


Fig. 9. FELA versus CNN-predicted support pressures for different H/D values.

Fig. 9 compares the critical support pressure (σ_c) predicted by the trained CNN against the critical support pressure obtained from FELA for the four representative soil layer scenarios. Each subplot contains 1000 points representing test samples. The coefficient of determination (r^2) and root-mean square error (RMSE) are separately calculated for each scenario, as shown in Fig. 9(a-d).

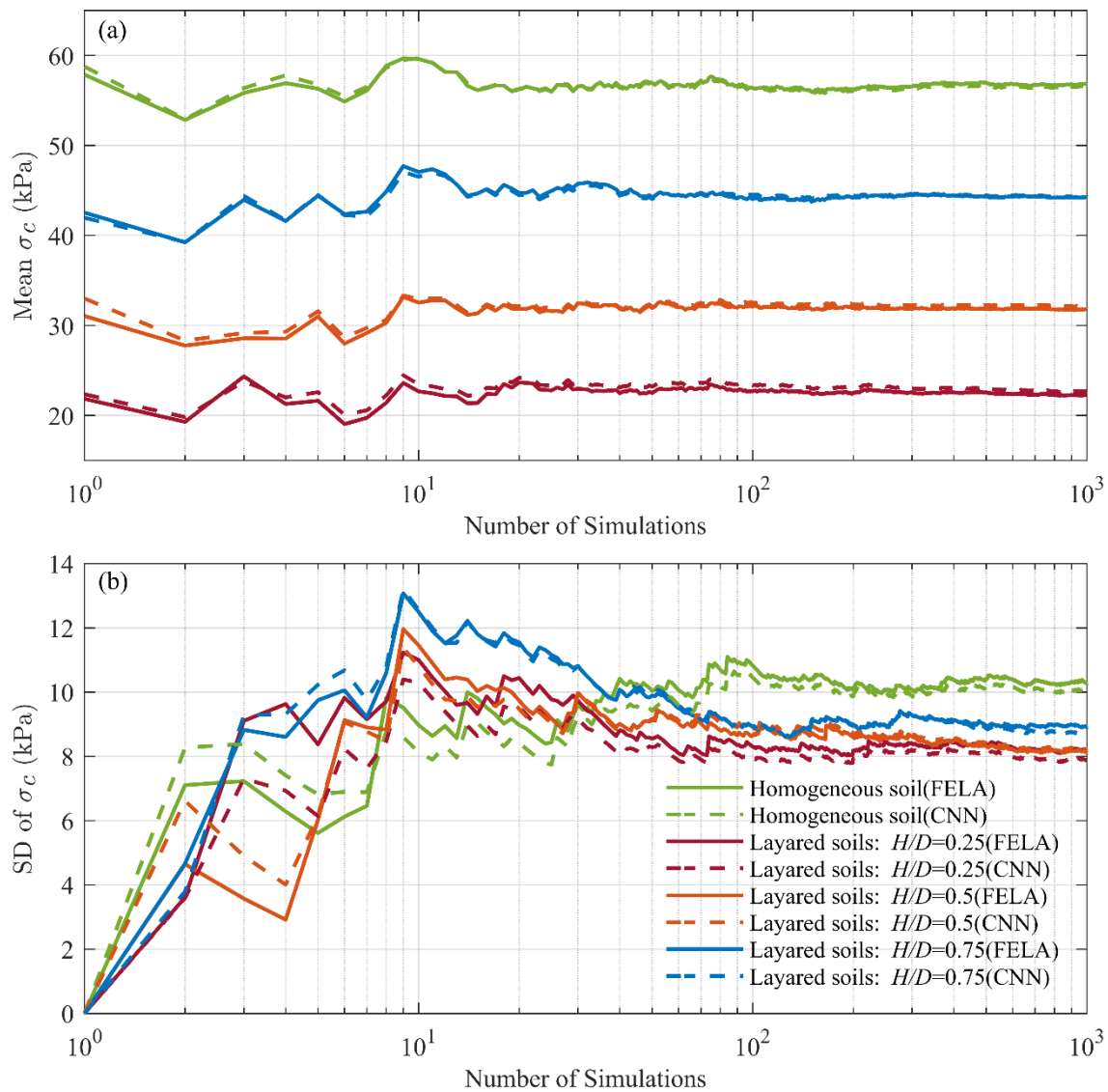


Fig. 10. Convergence of mean and the standard deviation of support pressures for CNN and FELA for different H/D values.

In all four subplots, it is evident that the predictions generated by the trained CNN model exhibits a high level of agreement with the FELA predictions. The coefficients of determination for all scenarios exceed 0.95, indicating a strong correlation between the predicted values from the CNN model and the FELA. In addition, the RMSE values are below 1.95 kPa, indicating that the deviations between the CNN and FELA predictions are small.

Fig. 10 plots, for each scenario, the convergence trends of the mean and standard deviation of the CNN and FELA predicted support pressures with the number of simulations. The results show that, in all cases, convergence of the mean and standard deviation is achieved after the initial 100 Monte Carlo simulations. Hence, the 4000 simulations conducted in this study (1000 for each soil layer scenario) are sufficient to obtain reliable results. Moreover, the good agreement between the convergence trends of the CNN and FELA results provides further evidence that the CNN can serve as a good surrogate model for the random field finite-element model.

To investigate the influence of training sample size on the accuracy of the CNN model, four different sample sizes are examined: 150, 300, 450, and 600. Fig. 11 presents a bar chart illustrating the accuracy of the trained CNN models in terms of r^2 and RMSE for the predicted pressures across the different training sample sizes.

In Fig. 11(a) and (b), the four sets of bars represent the mean values of r^2 and RMSE, respectively, obtained from 20 CNNs trained using the same sample size but different data. Each set of bars corresponds to one of the four representative soil layer scenarios. The error bars depict the range between the maximum and minimum values observed across the 20 sets, providing a visual representation of the variability in the performance of the CNN models.

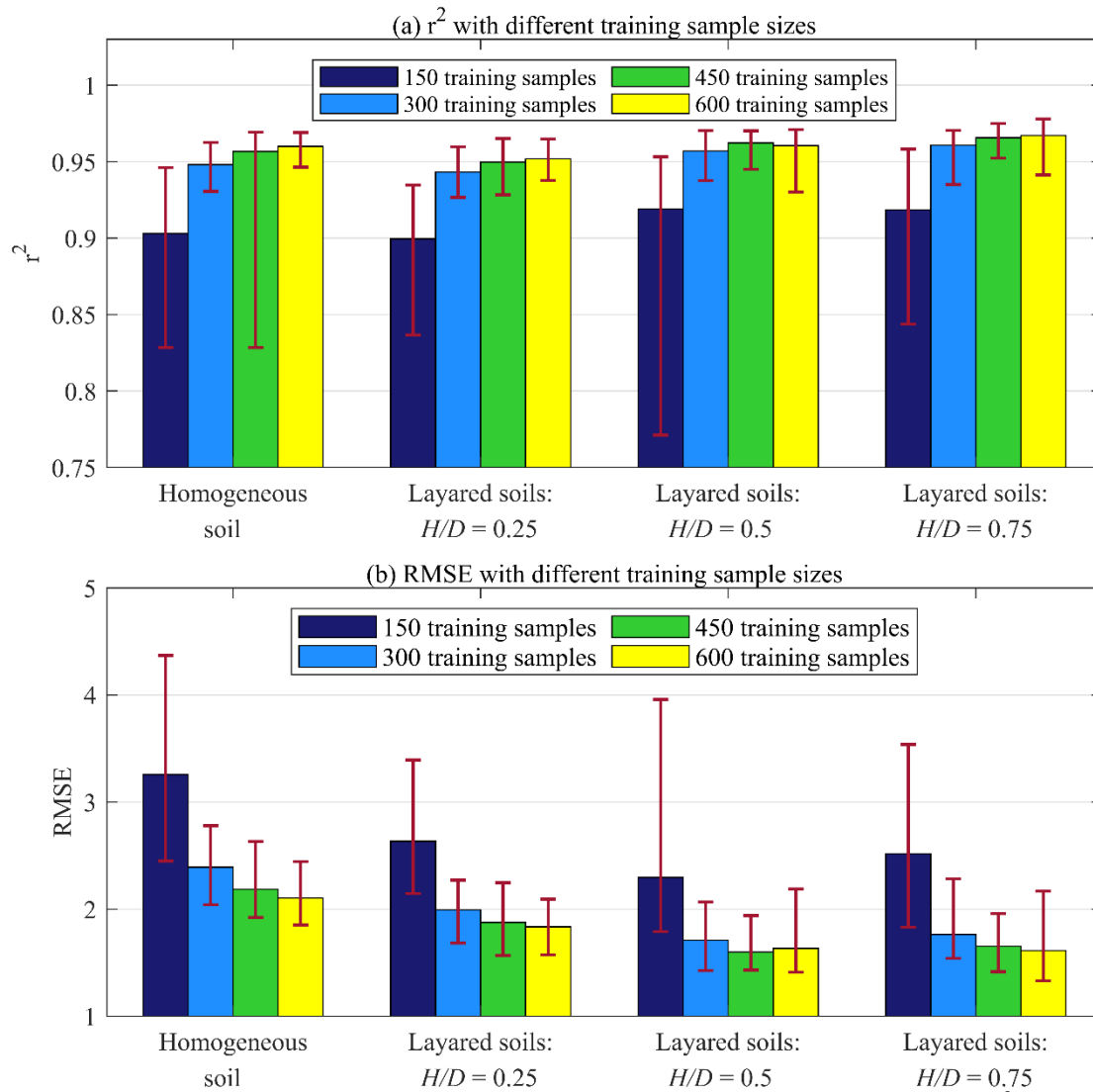


Fig. 11. Influence of training sample size on the (a) coefficient of determination (r^2) and (b) root-mean square errors (RMSE) of the CNN-predicted support pressures.

424 As the training sample size increases, a notable trend emerges: the mean r^2 values tend to increase
 425 while the mean RMSE values decrease. This trend signifies that the larger training sample size leads
 426 to improved predictions by the CNN models. With a larger sample size, the CNN can effectively
 427 capture and learn additional features related to the intensity and spatial variation of the random
 428 properties, leading to enhanced predictive performance.

429 To ensure the robustness of the CNN predictions, it is important to compare the results obtained

using different CNN models trained with distinct datasets. Each dataset contains the same number of training samples, but with different realizations of random fields that are generated independently using the same statistical and spatial parameters. To achieve this, 20 different and independent sets of samples are generated for each training sample size, and 20 separate CNN models are trained using these 20 sample sets. For instance, in the case of a training sample size of 300, 20 sets of 300 training random fields are generated, leading to the creation of 20 individual CNN models. This approach is implemented to avoid reliance on a single set of training samples, which could yield biased results due to an overly favorable or non-favorable sample set.

Fig. 11 provides insights into the relationship between the training sample size and the differences between the maximum and minimum values. Notably, when the training sample size is limited to 150, significant discrepancies exist between the maximum and minimum values. However, as the training sample size increases, the differences between the maximum and minimum values decrease. This trend suggests that a larger training sample size is instrumental in reducing prediction uncertainty and enhancing the robustness of the trained CNN model. It is important to highlight that once the training sample size surpasses 450, the improvements in both accuracy and robustness become marginal. Consequently, for the cases in this study, a minimum of 450 sets of training samples is recommended to ensure reliable and accurate predictions of support pressures.

Prediction of collapse modes (Regression and Classification)

To accurately identify the collapse modes, the case with a H/D ratio of 0.5 is adopted for an in-depth study. Fig. 12 illustrates three representative tunnel face failure modes, based on both the FELA and

U-Net computed displacement fields. To determine the collapse modes of the tunnel face, it is necessary to accurately delineate the contours of the displacement field computed using the FELA model. However, due to the cloud-like nature of the displacement fields (e.g., Fig. 12), the contour edges are often unclear, making it challenging to visually identify the collapse mode accurately, especially in certain realizations. To address this issue and achieve a more precise contour delineation, the K-means Clustering is employed.

This method divides nodes into K_{cl} clusters based on the differences in their average displacements relative to their respective clusters. In this study, K_{cl} is set as two clusters, one cluster consisting of nodes that make up the failure region (i.e., nodes with relatively larger average displacements), while the other cluster comprises nodes outside the failure region (i.e., nodes with relatively smaller average displacements). This approach helps to differentiate between the failure and non-failure regions in the displacement fields.

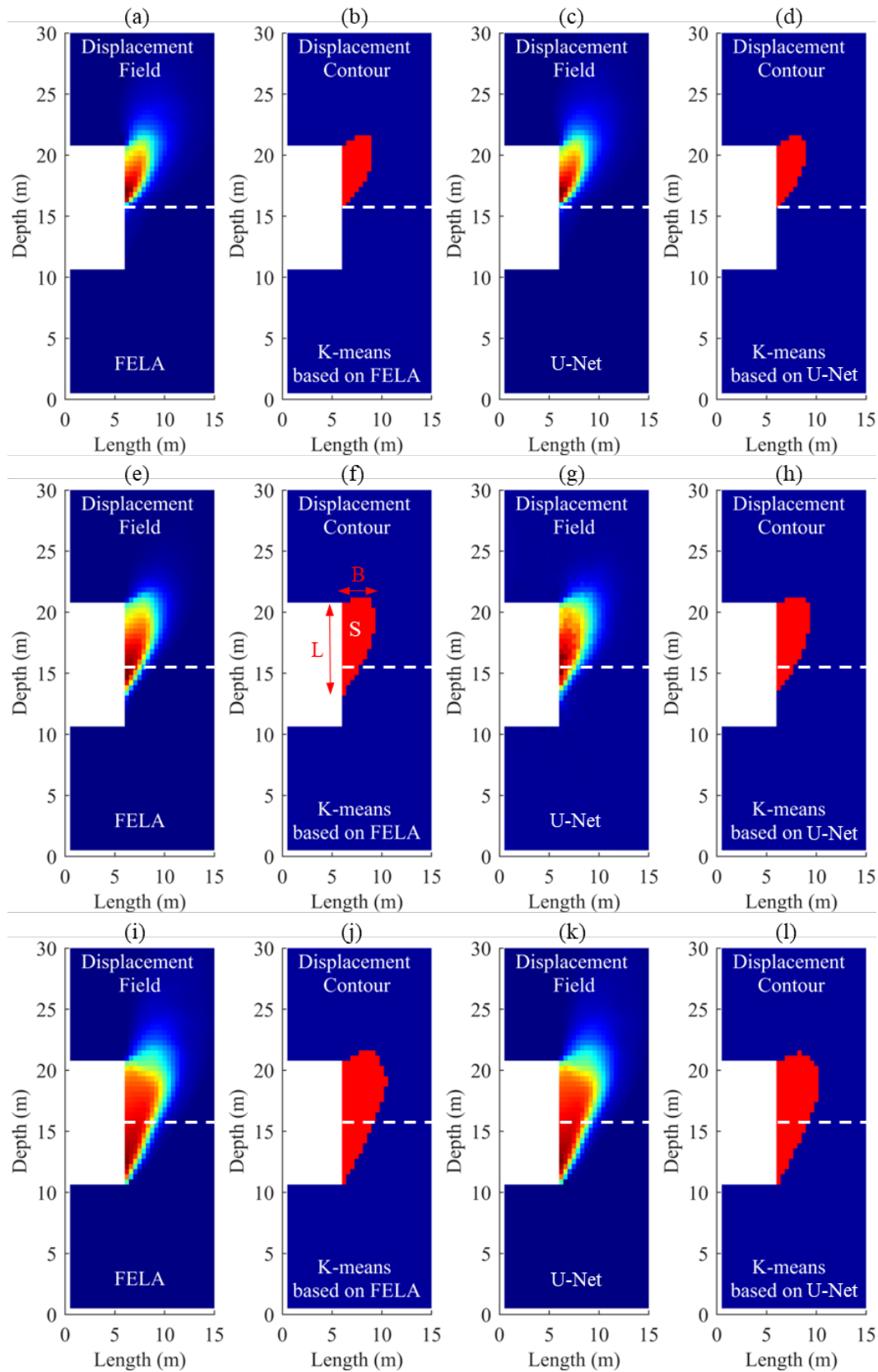


Fig. 12. FELA versus U-Net-predicted displacement field delineation of displacement contour for different collapse mode.

Fig. 12 shows three representative failure cases associated with (i) the corresponding random fields images, (ii) the displacement fields computed by the FELA model, (iii) the displacement fields predicted by the U-Net model, and (iv) the displacement contours obtained by applying the K-means Clustering method on (ii) and (iii). It is observed that, when the spatial variability is considered, partial collapse modes in which the failure zone in the upper weaker layer extends partially into the lower stronger layer can occur for certain realizations of the random fields, as shown in Fig. 12(b1) and (b3). In this study, a global failure is defined as one in which the zone of significant soil movements extends all the way to the bottom of the excavation face, as shown in Fig. 12(c1) and (c3). All other cases, in which the failure surface does not reach the bottom of the excavation face, are classified as partial failures. It is worth mentioning that the support pressures under different collapse modes can be obtained by importing the corresponding random field images into the CNN model trained in this study.

A total of 5000 Monte Carlo simulations were conducted to perform the random field finite element limit analyses (FELAs) in this part of the study. From these 5000 FELAs, the collapse modes were categorized as global or partial according to the previously defined criteria, thus creating a benchmark dataset for assessing the accuracy of the trained U-Net model. Fig. 13 plots the relationship between the percentage of each collapse mode (global or partial) and the number of simulations. It is noted that the percentage of the two collapse modes generally converged within the first 1000 Monte Carlo simulations. Specifically, the percentage of partial collapse cases stabilized at 63.04% while the percentage of global collapse cases stabilized at 36.96%. This convergence indicates that the 5000 simulations conducted in this study were sufficient to capture the behavior and variability of the collapse modes.

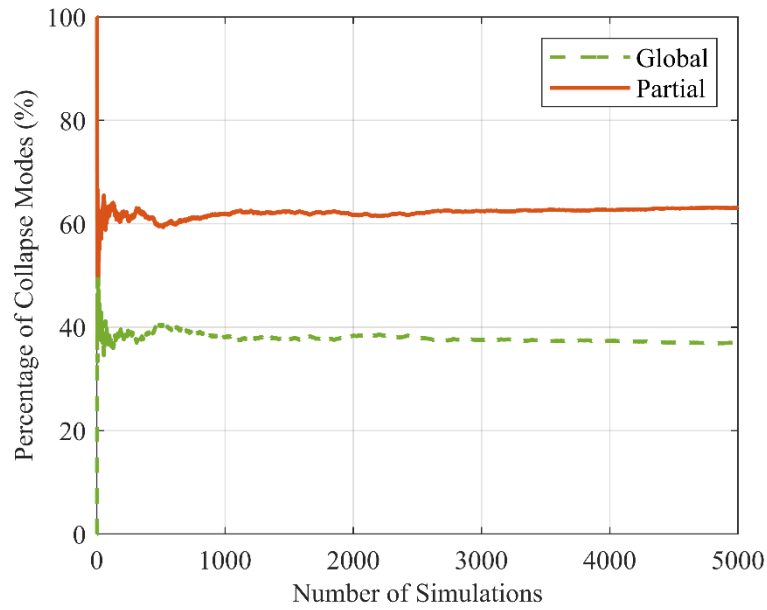


Fig. 13. Convergence of percentage of collapse modes for different sample sizes.

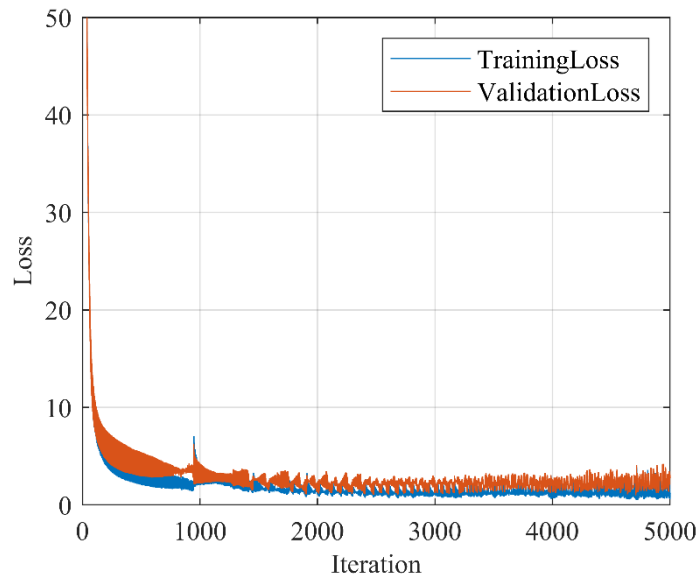


Fig. 14. Training progress of U-Net model

Accuracy of the trained U-Net

From the images shown on Fig. 12, it is evident that the displacement fields computed by FELA and predicted by U-Net are nearly identical, with slight variations observed at the edges of the

displacement contours generated by K-means Clustering. These variations do not significantly impact the overall accuracy of the predictions. More detailed discussions regarding the prediction accuracy and the improved performance of the U-Net will be presented in the subsequent sections.

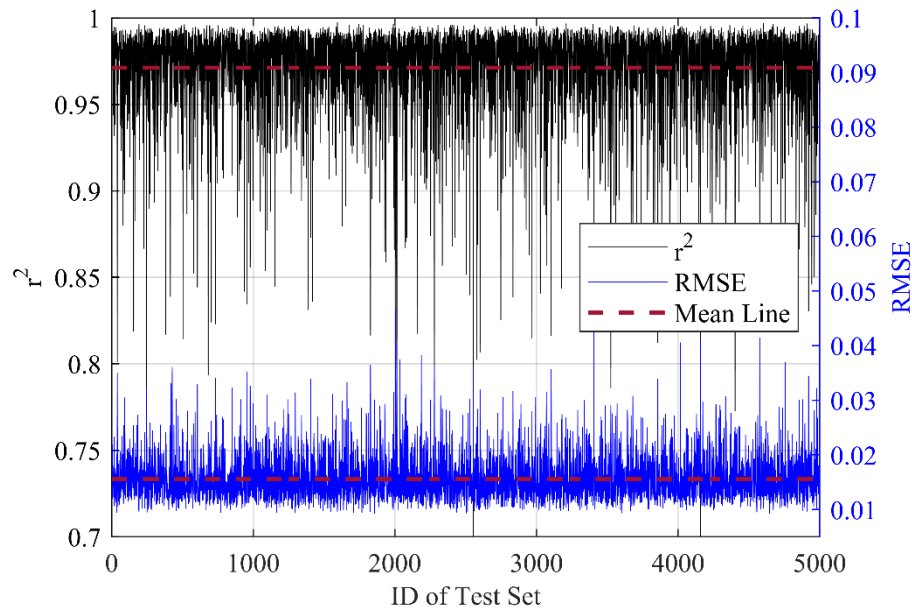


Fig. 15. RMSE and r^2 of U-Net predictions of displacement field.

The training process of U-Net model is shown as Fig. 14. It can be seen that the loss values for both training and validation sets were progressively decreased and converged with iteration. The accuracy of the predicted displacement field image can also be evaluated by comparing the pixel values between the original image from FELA and the U-Net predicted image using metrics such as RMSE and r^2 . For example, for each image, all pixel values in the original image can be compared with the values in the predicted image, from which the r^2 and RMSE values can be computed. Fig. 15 presents the accuracy of the predicted displacement field images for each sample in the test set. The r^2 values are plotted on the left vertical axis while the RMSE values are plotted on the right vertical axis. It is observed that the r^2 values fluctuates around a mean of 0.971, while the RMSE fluctuates around a

mean of 0.016m. These metrics strongly suggest that the displacement field images predicted by the U-Net exhibit a high level of accuracy.

Comparison with CNN classification

To further demonstrate the advantages of using the proposed U-Net model in predicting collapse modes, it is compared with the traditional CNN-based classification technique in this section. Referring to Fig. 5, when traditional CNN is used to for this task, the training is based on input random fields and output collapse modes, either partial or global. The trained CNN can only make binary predictions, partial vs global, with regard to the classification of the collapse mode, and does not predict the shape and extent of the failure zone. On the other hand, the proposed U-Net approach not only classifies whether the failure mode is partial or global, but also predicts the displacement fields which are then further processed using K-means Clustering to arrive at the collapse modes.

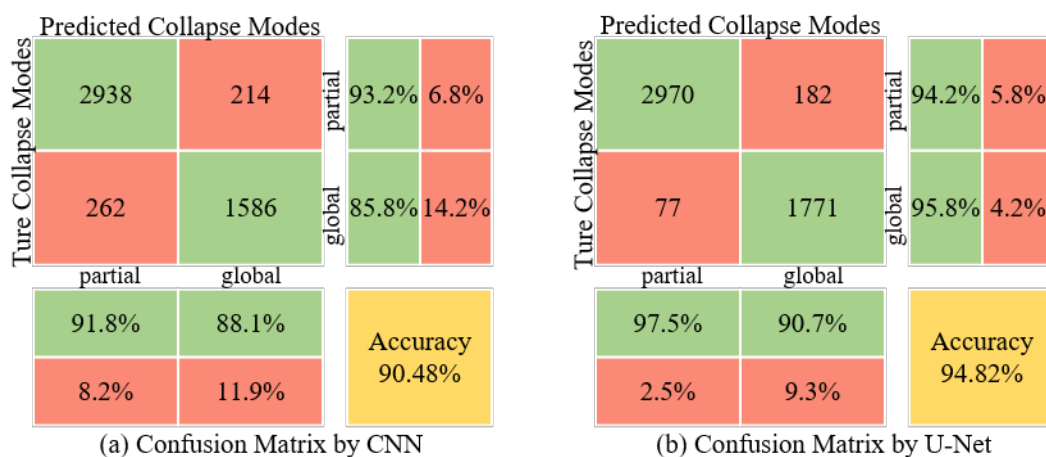


Fig. 16. Comparison of the confusion matrix of CNN and U-Net.

Fig. 16 shows the confusion matrix generated by the CNN and U-Net models, which was used to evaluate the accuracy of collapse mode predictions. The confusion matrix by U-Net provides the following results: True Positives (TP) of 2970, False Positives (FP) of 182, True Negatives (TN) of 1771, and False Negatives (FN) of 77. The overall accuracy of the U-Net model was 94.82%. When compared to the CNN confusion matrix, the U-Net model achieves a higher TP count (2970) compared to the CNN model (2938), which demonstrates its superior ability to correctly identify partial collapse modes. Furthermore, the U-Net model also yields a lower FP count (182) compared to the CNN model (214), indicating fewer instances where the model incorrectly classified global collapse as partial collapse. Moreover, the U-Net model exhibits a higher TN count (1771) compared to the CNN model (1586), which suggests improved accuracy in identifying global collapse. Additionally, the U-Net model has a lower FN count (77) compared to the CNN model (262), indicating a smaller number of cases where partial collapse was misclassified as global collapse. These improvements in TP, FP, TN, and FN values contribute to a higher overall accuracy of 94.82% for the U-Net model, surpassing the accuracy of 90.48% achieved by the CNN model.

Indeed, the improved performance of the U-Net model can be attributed to its ability to first predict the displacement field, before performing an autonomous classification of the collapse mode. This sequential approach gives U-Net a certain error correction capability that the CNN model lacks. By predicting the displacement field and subsequently analyzing it, U-Net can identify and minimize any inaccuracies or inconsistencies in the predicted collapse modes, resulting in improved accuracy. This unique feature of U-Net enables it to effectively capture and analyze complex patterns within the displacement field, which has proven to be advantageous in accurately classifying partial and global

collapse modes. As a result, the U-Net model emerges as a valuable tool in the field of collapse mode prediction.

The U-Net and traditional CNN-based classification is further compared in terms of robustness. For each training sample size, 20 distinct and independent sets of training samples were generated. These sets are used to train 20 separate U-Net models, and each model was then employed to determine the collapse modes for the same 5000 random field samples.

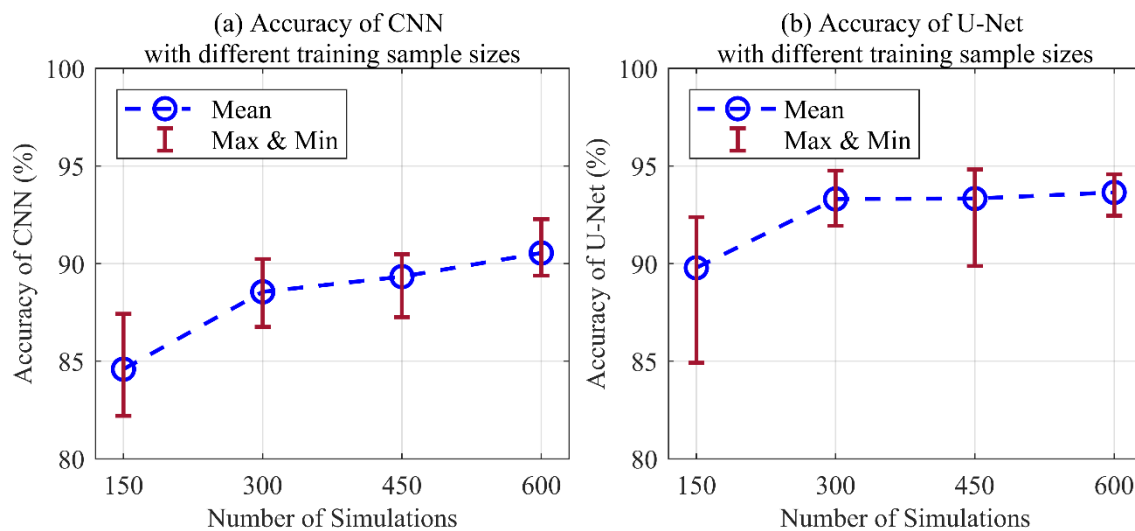


Fig. 17. Comparison of the accuracy of CNN and U-Net with different training sample sizes.

Fig. 17 evaluates the robustness of the trained CNN and U-Net models by plotting the accuracy of the failure mode prediction associated with the four different training sample sizes. The four blue hollow circles represent the mean accuracy obtained from the 20 trained CNN and U-Net models for each training sample size, while the error bars indicate the maximum and minimum values across the 20 sets. It can be observed that the average accuracy increases with the training sample size. The overall accuracy of the U-Net model is approximately 4% higher compared to that of the CNN model.

This trend indicates that the utilization of a larger training sample size allows the U-Net model to learn additional features related to the intensity and spatial variation of the random properties, thereby improving its predictive capabilities. When the training sample size exceeds 300, the average accuracy of U-Nets stabilizes at around 94%.

However, as the sample size increases, there is no observable reduction in the range bounded by the maximum and minimum values of the percentage accuracy. This can be attributed to the inherent variability and complexity of the data. With a larger sample size, the random field realizations would still inevitably contain diverse and extreme strength values, which may in turn lead to more complex failure patterns, the net effect of which is that there is no significant reduction in the range of prediction accuracy.

Geometric characterization of the failure zone

In practical engineering, engineers are particularly concerned with the failure of tunnel excavation faces as it is crucial for safety assessments and control measures. Therefore, it is important to be able to estimate the geometry of the failure region as accurately as possible. In this section, the use of the proposed U-Net model in predicting the failure region is demonstrated.

The geometry of the failure zone can be characterized using three parameters, as shown in Fig. 12(b2): the length (L), width (B), and area (S) of the displacement contour. The length L refers to the vertical extent of the failure zone on the excavation face and can serve as a potential indicator of ground settlement. A longer length may imply a larger area of ground subsidence, which can adversely affect the serviceability and/or stability of nearby facilities. The width B refers to the transverse or horizontal

extent of the failure zone behind the excavation face. A larger failure width B would mean that stronger support structures are required to maintain excavation face stability. The area S in 2-D is indicative of the overall volume of the failure zone in 3-D space. A larger area S would typically result in more severe damage and greater engineering risks, and may necessitate the implementation of more precise and robust support measures to safeguard excavation face stability.

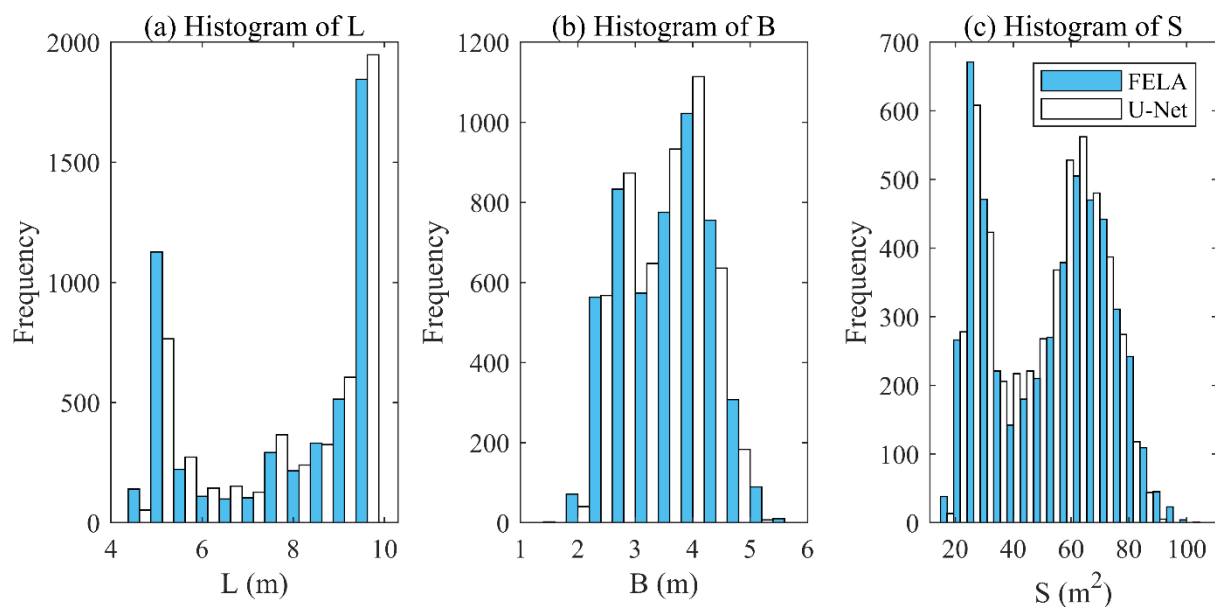


Fig. 18. Histogram of geometric parameters.

Fig. 18 presents the histograms of the length L , width B , and area S based on the 5000 Monte Carlo simulations. **Fig. 18(a)** shows that the distribution is multi-modal, with the mean length L being approximately 7.92m and the two modes occurring at 5m and 10m. The results indicate that the two most common modes of tunnel face failure involves the failure zone terminating at (i) the interface between the two soil layers ($L = 5\text{m}$) and (ii) the tunnel invert level ($L = 10\text{m}$), which is consistent with the patterns observed in layered soils without considering random fields (Senent and Jimenez

2015). Fig. 18(b) shows that the width B ranges from 1.7m to 5.8m, with a mean value of approximately 3.72m. Additionally, Fig. 18(c) demonstrates that the area S is more sensitive to the length L and therefore also follows a multi-modal distribution, with the two modes occurring at 30m² and 70m², and a mean value of approximately 53.62m². These observations also indicate that conventional engineering practices that assume a normal distribution may not be applicable to this case and may result in biased interpretations, which further highlights the importance of numerical modelling in the current task.

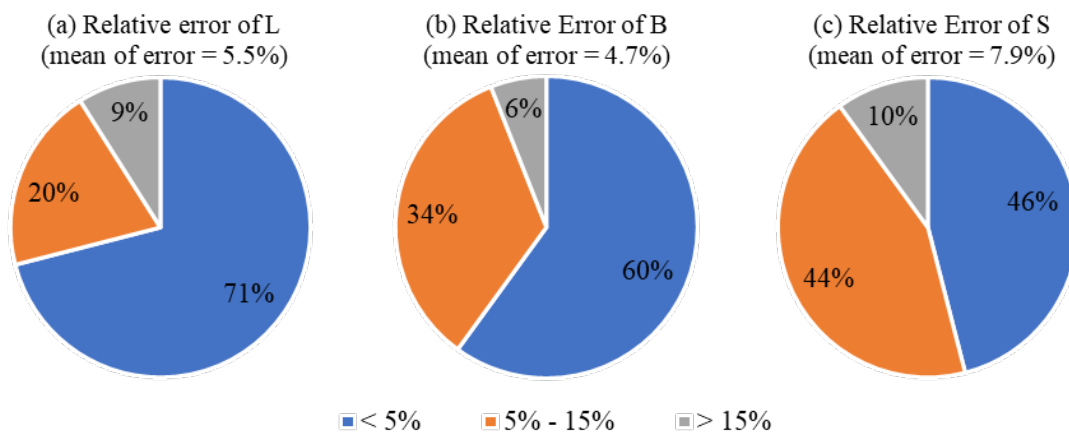


Fig. 19. Relative errors of the geometric parameters predicted by U-Net.

The relative errors ($| \text{Predicted value} - \text{True value} | / \text{True value}$) associated with the predictions of parameters L , B and S are shown in Fig. 19. The accuracy of the predictions is categorized into three levels, corresponding to relative errors of (i) less than 5% (blue sector), (ii) between 5% and 15% (orange sector), and (iii) greater than 15% (grey sector). In general, for all the three parameters, the largest category is associated with the relative errors of less than 5%. In addition, for relative errors less than

15%, the U-Net predictions are unlikely to yield predictions with large error. Furthermore, the mean of relative errors is less than 8%, which support the effectiveness of the U-Net in capturing the underlying patterns and characteristics of the failure zones. These findings demonstrate U-Net's ability to accurately estimate the geometric parameters of the failure zones.

Discussions

This study has demonstrated the advantages of using U-Net for predicting the collapse modes of tunnel face in a two-layer soil based on random field images. Compared to conventional CNNs, U-Net exhibits superior "image-to-image" prediction capabilities, thus enabling more accurate identification of the tunnel face collapse modes. This ability gives U-Net a distinct advantage in terms of error correction, leading to higher classification accuracy compared to CNNs. Furthermore, U-Net can very quickly provide useful information on the type/range of failure mechanisms that may be encountered, and hence allow engineers to undertake rapid response measures, instead of having to spend a lot of time running Monte Carlo finite element simulations. The Monte Carlo simulations (5000 FELAs) requires about 18 hours of computational time while the U-Net, after approximately 35 minutes of training, only takes 30 seconds to complete predictions. All computations were performed on a single GPU workstation with an NVIDIA GeForce RTX 3060 GPU.

While this study demonstrated promising performance of CNN and U-Net in predicting critical support pressure and failure modes of the tunnel face, there are several limitations. Firstly, the tunnel face model and ground random field used in this study are two-dimensional, thus neglecting the three-dimensional effects of support structures, boundary conditions and constraints and the parameter

variability and deformation in the plane-strain direction. Secondly, this study focuses on a few typical and simple layered soil scenarios, limiting the applicability of the trained models to tunnels involving more complex stratigraphy. Lastly, although U-Net improves the accuracy in predicting excavation face failure modes compared to CNN, there is room for improvement in accuracy for certain extreme samples, such as those on the verge of two failure modes.

Looking ahead, the potential of U-Net extends beyond displacement field predictions. It can be leveraged to predict stress and strain fields, among other quantities, thus enabling a more multifaceted analysis of tunnel face stability. By encompassing these other key indicators of tunnel performance, U-Net has the potential to play an important role in safety control enhancements in real-world engineering problems, making it a promising tool for future research and applications in the field. Furthermore, the two-dimensional model employed in this study can be viewed as a slice of a three-dimensional model. In the future, there is a promising opportunity to extend the proposed deep learning framework to the three-dimensional domain, allowing for more realistic and comprehensive predictions. This expansion to the three-dimensional space could provide a more accurate representation of the complex deformation behaviors in tunnel excavation, enhancing the applicability of the developed model for practical engineering scenarios. Such an advancement would contribute to a more holistic understanding of tunnel stability and safety, further solidifying the potential of U-Net in advancing the state-of-the-art in machine-learning-based tunneling research and applications.

Conclusion

This study proposes a deep learning framework for analyzing tunnel face stability in layered soils considering spatial variability. It demonstrates the use of properly-trained CNN and U-Net as surrogate models for identifying high-level features that capture the spatial distribution and intensity of randomly varying strength parameters, thus enabling high-quality predictions of both collapse modes and critical support pressures of tunnel faces. Through appropriate training and validation, deep learning models can replace computationally demanding Monte Carlo simulations in random field finite element limit analysis, offering improved efficiency. Furthermore, the study demonstrates that U-Net outperforms CNN in accuracy and efficiency for classification tasks involving spatially variable soils. The key findings can be summarized as follows:

(1) Both CNN and U-Net are effective in learning and capturing information pertaining to the random variabilities in spatial distribution and intensity, while requiring only a relatively small number of training samples, which is less than 500 in this study. Noted that the number of training samples required may vary if a third soil layer is present, or if the geological condition changed.

(2) CNN can effectively predict critical support pressures for a tunnel face traversed by a two-layer soil system, each of which is treated as a spatially variable random field.

(3) U-Net, through its "image-to-image" predictive capability, is capable of accurately predicting displacement field images when 'fed' with random field images of the spatially varying soil parameters. This approach endows U-Net with some degree of error correction capability, resulting in higher accuracy in classification compared to CNN.

(4) Both partial and global collapse are possible modes of tunnel face failure mechanisms in

layered soils, when the spatial variability of the soils is considered. The depth to which the failure surface in a partial collapse may extend varies, depending on the specific realization of the random fields, and may penetrate into the stronger underlying layer with or without reaching the tunnel face invert level.

(5) By making use of the U-Net predicted displacement fields, the potential tunnel face failure mechanisms, taking into consideration spatial variability, can be quickly identified. This makes it possible to undertake rapid response measures and other safety precautions to minimize tunnel failure risks in the field.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgements

This work is supported by the Natural Science Foundation of China [NSFC Grant Nos. U22A20594, 52079045], the Fundamental Research Funds for the Central Universities [B230205028]. Zheming Zhang would like to thank China Scholarship Council for providing a scholarship [Grant No. 202206710106] in Singapore, and Ze Zhou Wang would acknowledge his research funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101034337.

Zhang, Z. M., Wang, Z. Z., Goh, S. H., & Ji, J.* (2024). "Deep Learning-based Prediction of Tunnel Face Stability in Layered Soils using Images of Random Fields". *Journal of Geotechnical and Geoenvironmental Engineering*, 150(8), 04024065. <https://doi.org/10.1061/JGGEFK.GTENG-12109>

684 Supplemental Materials

685 Pseudocodes for the implementation of CNN and U-Net are available online in the ASCE Library
686 (www.ascelibrary.org).

687

688 References

- 689 Alagha, A. S. N., and Chapman, D. N. (2019). "Numerical modelling of tunnel face stability in
690 homogeneous and layered soft ground." *Tunn. Undergr. Space Technol.*, 94.
- 691 Augarde, C. E., Lyamin, A. V., and Sloan, S. W. (2003). "Stability of an undrained plane strain heading
692 revisited." *Comput. Geotech.*, 30(5), 419-430.
- 693 Broere, W. (2002). "Tunnel face stability and new CPT applications."
- 694 Chen, X., Hu, Y., Zhang, L., and Liu, Y. (2023). "3D large-deformation modelling on face instability
695 and sinkhole formation during tunnelling through non-uniform soils." *Tunn. Undergr. Space
696 Technol.*, 134.
- 697 Cheng, H., Chen, J., Chen, R., and Chen, G. (2019). "Reliability study on shield tunnel face using a
698 random limit analysis method in multilayered soils." *Tunn. Undergr. Space Technol.*, 84, 353-
699 363.
- 700 Cheng, H., Chen, J., Chen, R., Huang, J., and Li, J. (2019). "Three-dimensional analysis of tunnel face
701 stability in spatially variable soils." *Comput. Geotech.*, 111, 76-88.
- 702 Ching, J., and Phoon, K.-K. (2013). "Effect of element sizes in random field finite element simulations
703 of soil shear strength." *Comput. Struct.*, 126, 120-134.
- 704 Griffiths, D. V., Huang, J., and Fenton, G. A. (2009). "Influence of Spatial Variability on Slope
705 Reliability Using 2-D Random Fields." *J. Geotech. Geoenviron. Eng.*, 135(10), 1367-1378.
- 706 Guo, X., Dias, D., Carvajal, C., Peyras, L., and Breul, P. (2022). "Three-dimensional probabilistic
707 stability analysis of an earth dam using an active learning metamodeling approach." *Bull. Eng.
708 Geol. Environ.*, 81, 1-20.
- 709 Horn, N. (1961). "Horizontal earth pressure on the vertical surfaces of the tunnel tubes." *Proceedings
710 of the National Conference of the Hungarian Civil Engineering Industry* Budapest.
- 711 Hu, X., Zhang, Z., and Kieffer, S. (2012). "A real-life stability model for a large shield-driven tunnel
712 in heterogeneous soft soils." *Frontiers of Structural and Civil Engineering*, 6, 176-187.
- 713 Huang, J., Lyamin, A. V., Griffiths, D. V., Krabbenhoft, K., and Sloan, S. W. (2013). "Quantitative risk
714 assessment of landslide by limit analysis and random fields." *Comput. Geotech.*, 53, 60-67.
- 715 Ibrahim, E., Soubra, A.-H., Mollon, G., Raphael, W., Dias, D., and Reda, A. (2015). "Three-
716 dimensional face stability analysis of pressurized tunnels driven in a multilayered purely
717 frictional medium." *Tunn. Undergr. Space Technol.*, 49, 18-34.
- 718 Ji, J., Jiang, Z., Yin, X., Wang, T., Cui, H., and Zhang, W. (2022). "Slope reliability analysis based on
719 deep learning of digital images of random fields using CNN." *Chinese Journal of Geotechnical*

Zhang, Z. M., Wang, Z. Z., Goh, S. H., & Ji, J.* (2024). "Deep Learning-based Prediction of Tunnel Face Stability in Layered Soils using Images of Random Fields". *Journal of Geotechnical and Geoenvironmental Engineering*, 150(8), 04024065. <https://doi.org/10.1061/JGGEFK.GTENG-12109>

Engineering, 44(8), 1463-1473.

Ji, J., Zhang, Z., Wu, Z., Xia, J., Wu, Y., and Lü, Q. (2021). "An efficient probabilistic design approach for tunnel face stability by inverse reliability analysis." *Geosci. Front.*, 12(5), 101210.

Krabbenhøft, K., and Lyamin, A. (2014). "Optum G2." *Optum Computational Engineering*.

Li, T., Gong, W., and Tang, H. (2021). "Three-dimensional stochastic geological modeling for probabilistic stability analysis of a circular tunnel face." *Tunn. Undergr. Space Technol.*, 118, 104190.

Li, W., Zhang, C., Zhang, D., Ye, Z., and Tan, Z. (2022). "Face stability of shield tunnels considering a kinematically admissible velocity field of soil arching." *J. Rock Mech. Geotech. Eng.*, 14(2), 505-526.

Mollon, G., Dias, D., and Soubra, A. H. (2011). "Rotational failure mechanisms for the face stability analysis of tunnels driven by a pressurized shield." *Int. J. Numer. Anal. Methods Geomech.*, 35(12), 1363-1388.

Mollon, G., Dias, D., and Soubra, A. H. (2013). "Range of the safe retaining pressures of a pressurized tunnel face by a probabilistic approach." *J. Geotech. Geoenviron. Eng.*, 139(11), 1954-1967.

Phoon, K.-K., and Kulhawy, F. H. (1999). "Characterization of geotechnical variability." *Can. Geotech. J.*, 36(4), 612-624.

Qarmout, M., König, D., Gussmann, P., Thewes, M., and Schanz, T. (2019). "Tunnel face stability analysis using Kinematical Element Method." *Tunn. Undergr. Space Technol.*, 85, 354-367.

Ronneberger, O., Fischer, P., and Brox, T. "U-net: Convolutional networks for biomedical image segmentation." *Proc., Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III* 18, Springer, 234-241.

Senent, S., and Jimenez, R. (2015). "A tunnel face failure mechanism for layered ground, considering the possibility of partial collapse." *Tunn. Undergr. Space Technol.*, 47, 182-192.

Shi, C., and Wang, Y. (2023). "Data-driven sequential development of geological cross-sections along tunnel trajectory." *Acta Geotech*, 18(4), 1739-1754.

Sloan, S. W. (2013). "Geotechnical stability analysis." *Geotechnique*, 63(7), 531-571.

Tu, S., Li, W., Zhang, C., and Chen, W. (2023). "Effect of inclined layered soils on face stability in shield tunneling based on limit analysis." *Tunn. Undergr. Space Technol.*, 131.

van den Eijnden, A. P., and Hicks, M. A. (2017). "Efficient subset simulation for evaluating the modes of improbable slope failure." *Comput. Geotech.*, 88, 267-280.

Vedaldi, A., and Lenc, K. "Matconvnet: Convolutional neural networks for matlab." *Proc., Proceedings of the 23rd ACM international conference on Multimedia*, 689-692.

Wang, X., Li, Z., Wang, H., Rong, Q., and Liang, R. Y. (2016). "Probabilistic analysis of shield-driven tunnel in multiple strata considering stratigraphic uncertainty." *Struct. Saf.*, 62, 88-100.

Wang, Y., Shi, C., and Li, X. (2022). "Machine learning of geological details from borehole logs for development of high-resolution subsurface geological cross-section and geotechnical analysis." *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, 16(1), 2-20.

Wang, Z. Z. (2022). "Deep Learning for Geotechnical Reliability Analysis with Multiple Uncertainties." *J. Geotech. Geoenviron. Eng.*, 148(4), 06022001.

Zhang, Z. M., **Wang, Z. Z.**, Goh, S. H., & Ji, J.* (2024). "Deep Learning-based Prediction of Tunnel Face Stability in Layered Soils using Images of Random Fields". *Journal of Geotechnical and Geoenvironmental Engineering*, 150(8), 04024065. <https://doi.org/10.1061/JGGEFK.GTENG-12109>

Wang, Z. Z., Xiao, C., Goh, S. H., and Deng, M.-X. (2021). "Metamodel-Based Reliability Analysis in Spatially Variable Soils Using Convolutional Neural Networks." *J. Geotech. Geoenviron. Eng.*, 147(3), 04021003.

Wu, C., Hong, L., Wang, L., Zhang, R., Pijush, S., and Zhang, W. (2022). "Prediction of wall deflection induced by braced excavation in spatially variable soils via convolutional neural network." *Gondwana Research*.

Yamamoto, K., Lyamin, A. V., Wilson, D. W., Sloan, S. W., and Abbo, A. J. (2011). "Stability of a circular tunnel in cohesive-frictional soil subjected to surcharge loading." *Comput. Geotech.*, 38(4), 504-514.

Zhang, J., Phoon, K. K., Zhang, D., Huang, H., and Tang, C. (2021). "Deep learning-based evaluation of factor of safety with confidence interval for tunnel deformation in spatially variable soil." *J. Rock Mech. Geotech. Eng.*, 13(6), 1358-1367.

Zhao, C., Mahmoudi, E., Luo, M., Jiang, M., and Lin, P. (2023). "Unfavorable geology recognition in front of shallow tunnel face using machine learning." *Comput. Geotech.*, 157.