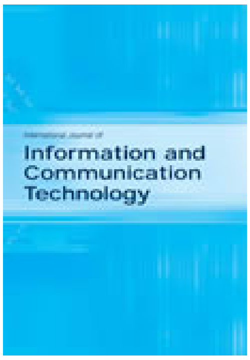


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

AI-driven hybrid deep learning for real-time excavation risk assessment in deep foundation pit engineering

Xuhui Luo

DOI: 10.1504/IJICT.2025.10071437

Article History:

Received:	24 March 2025
Last revised:	16 April 2025
Accepted:	16 April 2025
Published online:	13 June 2025

AI-driven hybrid deep learning for real-time excavation risk assessment in deep foundation pit engineering

Xuhui Luo

Central and Southern China Municipal Engineering Design and Research Institute Co, Ltd.,
Hube, Wuhan, 430010, China
Email: lxhxftg202@163.com

Abstract: Excavation of the deep foundation pit is a challenging organisation due to unstable soil, groundwater seepage, and structural failures. Traditional risk assessments are useful but computationally expensive and inflexible to real-time conditions. This study then proposes a hybrid deep learning model that integrates CNN, LSTM and transformer architectures for improving excavation risk prediction. FEM data are used to capture spatial features, LSTM models sequential deformations, and the transformer incorporating multi-source geotechnical data. The model was validated on a Shanghai excavation project with an RMSE of 2.90 mm, which outperforms FEM, CNN-LSTM and transformer only. In addition, it achieved 94.5% F1 score for failure detection and had reduced inference time to 1.4 seconds. The accuracy and speed of these results provides confidence in the model to be deployed in real-time for safety monitoring and AI based geotechnical risk management.

Keywords: deep foundation pit engineering; excavation risk prediction; hybrid deep learning; DL; finite element method; FEM; multi-source data fusion; real-time geotechnical monitoring.

Reference to this paper should be made as follows: Luo, X. (2025) 'AI-driven hybrid deep learning for real-time excavation risk assessment in deep foundation pit engineering', *Int. J. Information and Communication Technology*, Vol. 26, No. 19, pp.57–78.

Biographical notes: Xuhui Luo is affiliated with the Central and Southern China Municipal Engineering Design and Research Institute Co., Ltd., Wuhan. His research interests include municipal engineering, smart city planning, and environmental infrastructure systems. He actively participates in regional and national projects related to urban development and water management.

1 Introduction

Modern urban infrastructure construction requires a subway system, underground tunnel, basement, and high-rise building foundation, all essential for deep foundation pit engineering (Jiang et al., 2024; Cui et al., 2020. The excavation, however, has geotechnical risks such as soil instability, excessive ground deformation, groundwater seepage, and retaining wall failure, posing a danger to the retaining wall, structure beneath, other nearby structures, immediate and remote users, as well as the underground, and resulting in catastrophic structural collapse, economic loses, and loss of life (Zhang and Liu, 2022; Niu et al., 2023; van Adrichem and Adnan, 2001). These risks are further escalated in more complex soil conditions, such as urban environments with adjacent structures, high groundwater tables, or varying environmental factors like rainfall and seismic effects.

Accurate risk assessment and real-time monitoring are the two main ways to mitigate these risks. Until now, empirical models, statistical methods, and numerical simulation (e.g., the finite element method, FEM) have been used by traditional geotechnical engineers to assess excavation stability. The detailed stress-strain analysis to be given by FEM simulations and its valuable insights to soil–structure interaction will be discussed (Aldosary et al., 2018; Yoonirundorn et al., 2024; Yin et al., 2017). However, FEM-based approaches are computationally expensive and depend on manually calibrated input parameters, and they are not easy to adapt to real-time excavation conditions (Ninić and Meschke, 2015). In addition, they do not effectively use one of the critical features, namely sensor-based monitoring information, to assess dynamic changes in soil and structural behaviour during excavation.

Over the last few years, machine learning (ML) and deep learning (DL) techniques have been marching far surpassing human intelligence's capabilities (Painuli and Bhardwaj, 2022; Manta-Costa et al., 2024), thus initiating new methods of automated prediction of excavation risks. DL models can be fed large-scale geotechnical datasets for the first time, identify hidden patterns in excavation risks, and predict them accurately (Li et al., 2023; Liu et al., 2022; Baghbani et al., 2022). Nevertheless, the current DL models either do spatial analysis (convolutional neural networks (CNNs)) for available data or forecast temporal change (long short-term memory networks (LSTMs)) without integrating multi-source data. Based on this, the study presents a hybrid DL model integrating CNNs, LSTMs, and Transformers into a holistic, real-time excavation risk assessment system, taking advantage of the superior temporal and spatial location learning properties to improve prediction accuracy and adaptability.

1.1 Problem statement

A significant source of constant challenges in excavation safety is excavation failure. While much work has been done to improve the reliability of geotechnical risk prediction, this continues to be hindered by the limitations of conventional stress models. We can summarise the significant shortcomings of the existing risk assessment techniques.

- Real-time adaptability – all of the simulations based on FEM are manually re-calibrated for different excavation conditions and cannot automatically adapt to real-time sensor data (e.g., inclinometer, piezometer, and strain gauge) data coming from the excavated area.
- The inability of multi-source data integration – traditional models do not provide for FEM outputs, sensor reading, geotechnical parameters, and environmental conditions together effectively; hence doesn't offer the best risk assessments.
- Most ML/DL models are not sufficiently accurate in predicting failures: either they do not include spatial features (using CNNs on FEM data) or temporal trends

(LSTMs on sensor data), or they cannot provide a comprehensive and multi-source risk assessment.

A hybrid AI-based approach that models the spatial, temporal, and multimodal excavation risk factors has been designed to solve these issues. Using the actual test results from resort excavation, this study extends the hybrid DL model to advance excavation risk forecasting, enhance real-time adaptability, and accurately predict potential failures.

1.2 Objectives of the study

The study aims to construct and validate a hybrid DL framework for excavation risk assessment in deep foundation pit engineering. The specific objectives are:

- For the analysis of the limitations of conventional risk assessment methods, empirical models, FEM simulations, and existing DL models for predicting excavation-induced deformations and failures.
- A hybrid DL model integrating CNN embedding for spatial feature extraction, LSTM for sequential risk prediction, and transformer for multi-source data fusion to develop a comprehensive excavation risk assessment framework.
- The proposed model was evaluated using a real-world deep excavation project in Shanghai, which considers sensor readings, FEM-generated stress-strain data, and environmental parameters.
- CNN-LSTM models and transformer-based models are used to compare the hybrid model's performance to standalone FEM simulations and to demonstrate improvements in prediction accuracy, real-time adaptability, and computational efficiency.
- It contributes to proposing a real-time deployment strategy for the hybrid model to be integrated into geotechnical monitoring systems, with which excavation safety management and risk mitigation strategies would be feasible in an automated manner.

Aiming to revolutionise excavation risk assessment by introducing an AI-driven, real-time, highly accurate decision support system for geotechnical engineers, this research accomplished these goals.

1.3 Significance of the study

The significance of this research is based on its findings, which have significant implications for geotechnical engineering, excavation safety, and AI-driven construction monitoring. The proposed hybrid DL model addresses several key challenges.

- Better excavation risk prediction accuracy: with the integration of CNNs, LSTMs, and Transformers, better prediction accuracy is achieved at an enhanced tolerance for prediction failure regarding ground deformations, lateral wall movements, and groundwater risks.

- Continuous sensor data inclinometer, piezometer, and strain gauge networks are available, which are processed by the hybrid model continuously and hence allow for re-al-time risk monitoring, a feature not available with the traditional FEM models.
- Modelling of FEM stress strain data, real-time sensor readings, and environmental parameters results in a multi-source data fusion approach that offers a holistic risk assessment and hence, improves decision-making for excavation projects.
- Practical feasibility and computational efficiency – FOR the model to be easily implemented in real-world excavation projects without extensive process delays, it must achieve high prediction accuracy while maintaining computational efficiency.

This study presents a new AI-based approach that improves excavation risk evaluation, and as a result, the excavation will be safer and more efficient.

1.4 Contribution of the research

This study introduces several novel contributions of excavation risk assessment and geotechnical AI.

- A hybrid DL model – a CNN-LSTM-transformer hybrid model is developed to develop an all-encompassing, multi-source excavation risk assessment framework.
- Higher spatial feature extraction – the CNN part is more effective in analysing FEM-generated stress-strain heatmaps to pinpoint high-risk excavation zones in a more specific way than could have been achieved by human methods.
- LSTM component further develops time-series forecasting by learning the sequences of excavation-induced de-formation better to estimate the lateral wall movement and settlement trends.
- The transformer part incorporates geotechnical factors, real-time sensor readings, and environmental factors to deliver a multimodal holistic risk assessment.
- Real-world case study validation – the hybrid model is validated through a deep excavation project in Shanghai, where it surpasses the accuracy of traditional FEM and standalone DL models.
- Real-time deployment capability – the research suggests deploying the hybrid model in IoT-based excavation monitoring systems with the capability of real-time safety monitoring on active construction sites.

1.5 Organisation of the paper

The rest of this paper is organised as follows: In Section 2: literature review, state-of-the-art risk assessment approaches – FEM, ML, and DL – are explored, and a gap in research is identified that is the focus of the proposed hybrid model. Section 3: deep foundation pit risk assessment using CNN-LSTM-transformer architecture describes the proposed CNN-LSTM-transformer architecture and discusses how it can be used in excavation risk prediction. Case study and preparation of the dataset is described in Section 4: experimental section, which also entails model training and validation. The results and analysis presented in Section 5 involve testing the hybrid model against other approaches in terms of quantitative and qualitative evaluations. In Section 6, the discussion interprets the findings with a discussion of model accuracy, computational efficiency, and practical implications. Section 7: future work outlines potential future work in AI-driven excavation risk assessment. The conclusion in Section 8 summarises the study's contributions, key findings, and practical significance.

2 Literature review

Engineering bottomless foundation pit requires geotechnical processes to correct these problems: soil deformation, groundwater change, and structural instability (Xu et al., 2023), which must be assessed and executed through real-time risk assessment methods. Previous geotechnical risk assessment methods relied on empirical models, numerical simulations, and statistical approaches, which can be computationally inefficient and non-adaptive for real-time excavation conditions. The ability to integrate multi-source data is limited. In the last few years, cutting-edge ML and DL methods have also demonstrated promise in filling these limitations, so they should be able to provide much more accurate, automated, and real-time excavation risk predictions. This section examines the relevant studies on excavation risk assessment methods, their limitations, and how the proposed hybrid DL model with CNNs, LSTM networks, and Transformers will bridge the gap.

2.1 Traditional risk assessment approaches

The excavation risks have been widely predicted by empirical models relying on simplified assumptions and pre-existing geotechnical datasets. Classical theories, such as Rankine and Coulomb's earth pressure models, estimate lateral earth pressure acting on retaining walls (Galvin, 2016; Zhao, 2023; Askaripour et al., 2022). Terzaghi's bearing capacity theory and Meyerhof's settlement equations are analytical soil stability and settlement solutions (Mohamed, 2014). Assumptions are oversimplified because they do not reflect complex on-site behaviour due to soils. Insufficiency to adapt to site-specific variations and the need for manual calibration for each excavation project (Carter and Barnett, 2022). It is limited in dynamic excavation conditions by its inability to capture real-time monitoring data, which affects its effectiveness (Rao et al., 2022). However, these limitations lead researchers to complete empirical models with additional numerical simulations, such as the FEM (Kudela and Matousek, 2022), to provide more accurate predictions of excavation risks.

Soil structure interaction problems in deep excavation projects can be solved using a numerical method, i.e., FEM-based geotechnical modelling (Maleki et al., 2022; Gu et al., 2024). Predictors of stress-strain behaviour, lateral wall displacements, and the seepage effects under various excavation scenarios are typically software like PLAXIS, ABAQUS, and FLAC3D (Lin et al., 2023; Lohar et al., 2024). FEM has been successfully applied to excavation risk assessment (Bozkurt and Akbas, 2023). However, there are several challenges associated with it, such as computation cost – FEM models for engineering large excavation projects require a high computational cost. Dependency on manually calibrated parameters, such as soil cohesion, internal friction angle, and permeability coefficients and their uncertainties (Ou, 2016). Once a FEM simulation is complete, the model is not adaptable to actual real-time conditions, which include inclinometers, piezometers, and strain gauges (Kumar et al., 2024). These limitations reveal the necessity of data-driven approaches such as ML and DL that can be used alongside FEM simulations to offer real-time risk prediction and flexibility in reproducing conditions at the site.

2.2 Machine learning and deep learning in geotechnical engineering

Automate risk assessment and predictions of excavation failure. ML has often been applied in geotechnical engineering (Firoozi, 2023; Phoon and Zhang, 2023; Fan et al., 2025). Standard ML techniques include SVM, which is used for soil classification, slope stability analysis, and excavation failure prediction (Mahmoodzadeh et al., 2022). The prediction of landslide occurrence, ground settlement, and excavation deformations are made with random forest (RF) and gradient boosting machines (GBMs) (Ali et al., 2024). We can get better predictions from the ML models, but not without limitations, which our method also has. Inability to process high dimensional geotechnical data, e.g., FEM stress tensors, multifold sensor readings, and environmental parameters. It is subject to dependence on manually selected features such that engineers can choose which geotechnical parameters affect excavation stability, possibly leading to bias. Less able to capture sequential dependencies in the excavation behaviour and thus less effective for the time series forecasting of soil deformation trends. Due to these limitations, DL models have become a more robust alternative for excavation risk assessment.

The performance of the DL approaches in geotechnical risk assessment is superior to previous approaches by automating feature extraction, revealing complex spatial and temporal dependencies, and aggregating data from multiple excavation sources (Pan et al., 2024; Zhou et al., 2024; Zhou et al., 2023). Some of the most used DL architectures are process FEM-generated stress-strain heat maps, site imagery, and deformation maps, and analysing spatially distributed excavation risks with CNNs. By extracting localised excavation risk features, CNNs enhance the ability of landslide high-risk zones to be identified in retaining walls and soil layers (Su et al., 2024; Morgenroth et al., 2019; Pu et al., 2025). However, CNNs do not absorb the temporal risks of excavation; therefore, they are insufficient for sequential excavation monitoring. The LSTM networks are a type of neural network that is effective for working with time series data (Song et al., 2020; Sherstinsky, 2020; Lindemann et al., 2021) and have been applied for analysing deformations caused by excavation over time in geotechnical applications. Sensor readings, including inclinometer, piezometer, and strain gauge, are processed sequentially by LSTMs to predict ground displacement and structural stability trends. LSTM demonstrates its strength in time-dependent risk prediction (Wengang et al., 2023; Li et al., 2020; He et al., 2024). Still, they cannot integrate multiple data sources when predicting excavation risks, hence being unable to correlate the risks among different geotechnical parameters. Due to self-attention mechanisms, Transformers previously developed for natural language processing (NLP) are effective in multimodal applications for excavation risk assessment (Liu et al., 2024; Amel et al., 2024; Zhang et al., 2022). Unlike CNNs and LSTMs, transformers can process FEM outputs, real-time sensor data, and other environmental inputs in parallel. Determine relationships between complicated geotechnical properties, excavation-induced stress changes, and external factors (such as rainfall seismic activity) (Fang et al., 2024; Garakani et al., 2024). Implementation of long-range dependency learning helps forecast excavation risk beyond short-range trends.

However, Transformers have obvious advantages; they need large and computationally expensive training datasets, which makes their real-time deployment problematic.

2.3 Research gaps

Although DL has significantly improved the prediction of excavation risk, the following challenges remain.

- FEM models are not real-time adaptable and must be manually re-calibrated for different excavation conditions.
- High-dimensional geotechnical datasets challenge ma-chine learning models that select destructive features in their implementations.
- For example, CNNs cannot process time series data, LSTMs cannot fuse multiple data sources, and Trans-formers require high computational resources.

These gaps support the need for a hybrid DL model by integrating the strengths of CNNs, LSTMs, and Transformers as part of an improved Exodus risk assessment modelling.

3 Hybrid deep learning approach

The risk assessment of the excavation-induced failure requires a comprehensive and adaptive approach for integrating multi-source geotechnical data to predict excavation-induced failures accurately, as shown in Figure 1. However, FEM based stress-strain analyses employ high accuracy but are time-consuming and not real-time adaptable. Single DL architectures, however, can process sensor-based time series data and learn about past excavation failures. Still, they only capture the spatial and temporal dependencies to a limited extent. To address these limitations, this study suggests a hybrid DL model that combines CNNs, LSTM networks, and Transformers. With FEM-generated data to extract the temporal stress strain, the LSTM component on real-time sensor data learns the sequential deformation trends; the Transformer component enables the extraction from multi-source data, in the end, to predict failure more effectively. Investigating the synergistic use of analytical and numerical methods for deep excavation risk assessment yields a hybrid approach that provides improved predictive accuracy, real-time adaptability, and computational efficiency, and this approach promises to be suitable for such an undertaking.

3.1 Data collection and pre-processing

As part of the model training and validation dataset, multi-source geotechnical data is gathered from a real-world deep excavation project in Shanghai. Over the internet of things (IoT) based sensor networks deployed in modern excavation sites constantly monitor excavation stability. It can help measure the lateral displacement of the retaining walls to detect the lateral displacements caused by the excavation. Seepage shape dynamics are controlled by groundwater pressure fluctuations and their effects on soil stability. Identify stress variations in retaining walls and bracing systems and sense of failures. To do structural integrity analysis on bracing elements, measure forces acting on bracing elements. The sensor readings belong to a time-series dataset that, in further experiments, is fed into the LSTM and transformer models.

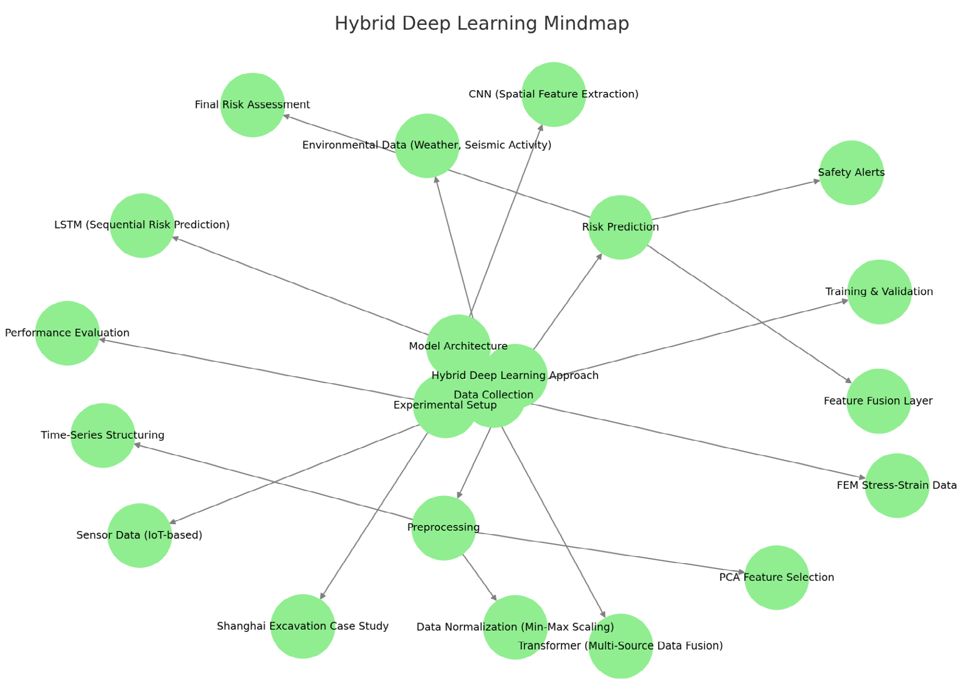
Subsurface soil conditions depend highly on the excavation stability and require thorough geotechnical investigation. Data for which hydraulic data is collected from borehole logs and laboratory tests includes:

- Influences slope stability: soil cohesion (c).
- Internal friction angle (ϕ): determines shear resistance.
- Unit weight (γ): affects vertical stress distribution.
- Permeability coefficient (k): governs groundwater seep-age.

The stress-strain maps of excavation sites are high precision generated by FEM simulations. The key outputs from PLAXIS 3D-based FEM model are:

- Displacement field (u_x, u_y, u_z): tracks ground movement in different directions.
- Stress components (σ_{xx}, σ_{yy}, σ_{xy}): represent forces within soil masses.

Figure 1 A structured mindmap of a hybrid deep learning approach for excavation risk assessment integrating the multi-source geotechnical data, pre-processing techniques (see online version for colours)



Notes: The deep learning architecture (CNN, LSTM, and transformer), risk prediction process, and experimental validation.

The excavation stability mainly depends on external environmental factors, particularly climate changes and seismic activity. The collected ecological parameters include:

- Rainfall (R_t): increases soil water content, affecting slope stability.
- Temperature (T_t): impacts thermal expansion/contraction of excavation structures.
- Seismic activity (S): triggers additional lateral forces on retaining walls.

Several pre-processing steps on the raw excavation dataset are needed to ensure consistent, scalable, and high performance of the DL:

- All numerical features (sensor readings, FEM outputs, geotechnical parameters) are scaled to the range [0, 1] using min-max scaling; data normalisation.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

- Principal component analysis (PCA) is applied to FEM outputs to feature select and extract stress-strain dominant features.
- Sensor data are structured into fixed-length overlapping windows suitable for sequential analysis with LSTM networks.

3.2 Model architecture

Based on this, the hybrid DL model has three major components: CNNs for spatial feature extraction, LSTMs for sequential risk prediction, and Transformers for multi-source data fusion. FEM-generated stress-strain heatmaps are processed with CNNs to detect high-risk excavation zones. The application of a filter f over the FEM stress matrix X is a convolutional layer.

$$h_{i,j} = \sum\nolimits_m \sum\nolimits_n f_{m,n} X_{i-m,j-n} + b \tag{2}$$

where $h_{i,j}$ represents the extracted feature at the position (i, j). $f_{m,n}$, denotes the convolutional kernel. After being supplied with the CNN extracted localised stress patterns, the Transformer model has multi-source risk prediction.

The evolution of excavation deformations over time makes it an iterative problem, and the corresponding sequential risk prediction models are necessary. An LSTM network processes sensor data sequences; output is obtained as future ground movement patterns. At each time step, the hidden state h_t is updated as:

$$h_t = o_t \odot \tanh(c_t) \tag{3}$$

where o_t is the output gate and the memory cell state. The early warning of ground instability with LSTMs is made possible by capturing the long-term excavation trend.

FEM outputs, real-time sensor readings, and environmental conditions are integrated using self-attention mechanisms where the Transformer based encoder is used.

$$A = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

It is what is an attention mechanism in the Transformer model that has the input matrices Q(query), K(key), and V(value), and d_k scaling factor. The model's ability to make this correlation across the range of geotechnical parameters is enhanced using this mechanism, which increases overall prediction accuracy. Finally, the final risk score was generated by CNN, LSTM, and Transformer model outputs being combined in a fully connected fusion layer:

$$R = \sigma\left(W_c\left[h_{CNN}, h_{LSTM}, h_{Transformer}\right] + b_c\right) \tag{5}$$

where W_c, represents learnable weights. Safety recommendations with appropriate actionability are given at the low, moderate, or high-risk level.

3.3 Advantages of the hybrid model

The proposed hybrid DL model has significantly improved the excavation risk. CNNs take FEM stress maps and return high-risk excavation zones. LSTMs capture long-term excavation-induced deformations accurately. Transformer promotes integrated resource use (geotechnical, environmental, and sensor-based) to improve prediction robustness in the presence of comprehensive multi-source data fusion. The model processes continuous data from model excavation monitoring and generates safety alerts in real-time. A DL architecture has been optimised to balance accuracy and inference speed, making it computationally efficient for real-time deployment on active construction sites. It describes the hybrid approach as offering a breakthrough in using AI in geotechnical engineering for safer, more innovative, and more efficient excavation.

4 Experimental setup

The experimental setup that is used to test the proposed hybrid DL model to evaluate excavation risk is described in this section. The experiment is conducted on a real-world case study of a deep excavation project in Shanghai and structured model training and validation. The case study is an actual excavation around which accompanying sensor readings, FEM-generated stress-strain outputs, and environmental conditions exist. The hybrid CNN-LSTM-Transformer model is rigorously evaluated regarding prediction accuracy, computational efficiency, and real-time adaptability using the training and validation process.

4.1 Case study: deep excavation project in Shanghai

For the sake of validating the effectiveness of the hybrid model, a deep excavation project in Shanghai was selected. This site is subject to challenging geotechnical conditions such as soft to very soft silty clay and a high groundwater table with high lateral soil movement risks. The bracing system was constructed as a diaphragm wall and used to excavate; continuous monitoring was necessary to avoid instability and failure of the structure. Key specifications of the excavation site are summarised, as shown in Table 1.

The high moisture content and low shear strength of silty clay increase risks such as groundwater seepage, lateral wall deformation, and soil instability. As such, these challenges make the site an appropriate case study for evaluating the performance of the hybrid DL model.

Table 1 Site specifications.

Parameter	*Value /description*
Excavation depth	15 metres
Soil type	Silty clay with a high groundwater table
Retaining structure	Diaphragm wall with a bracing system
Excavation duration	6 months
Monitoring period	Continuous monitoring during excavation

4.2 *Model training and validation*

The dataset was divided into three subsets to train and evaluate the hybrid model, as shown in Table 2.

Table 2 Dataset partitioning

Dataset	*Percentage*	*Purpose*
Training set	70%	Used for model learning and parameter optimisation
Validation set	20%	Used for hyperparameter tuning and overfitting prevention
Testing set	10%	Evaluate model performance on unseen data

However, since excavation failures are rare, the synthetic minority over-sampling technique (SMOTE) was also used to balance the number of failures versus non-failure samples to ensure the model was balanced and without bias. To enhance the hybrid DL model efficiency and optimise the training parameters. The model was trained using MSE as the loss function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{6}$$

where y_i is the actual excavation-induced deformation $\hat{y}_i$, is our predicted deformation, and is the total number of data points. Adam optimiser was chosen to achieve efficient convergence. The updated rules are:

$$m_t = \beta_1 m_{t-1} + \left(1 - \beta_1\right) g_t \tag{7}$$

$$v_t = \beta_2 v_{t-1} + \left(1 - \beta_2\right) g_t^2 \tag{8}$$

$$\theta_t = \theta_{t-1} - \frac{\alpha m_t}{\sqrt{v_t} + \in} \tag{9}$$

In other words, the gradient of the loss function is g_t moment estimates v_t, and the learning rate is α. This adaptive learning rate keeps the network from overfitting and converges the network faster. The trained model was evaluated using three key metrics, as shown in Table 3:

Then, this real-world excavation site in Shanghai was used to validate the hybrid DL model in this experimental study. Integration of FEM data, sensor readings, and AI-based predictive modelling led to high accuracy and efficiency in the model. Experimental results and the model performance analysis are presented in the next section.

Table 3 Performance evaluation metrics

Metric	*Description*
RMSE	Measures the deviation between predicted and actual deformations
F1-score	Evaluates the model's ability to detect excavation failures
Computation time	Assesses model efficiency in real-time deployment

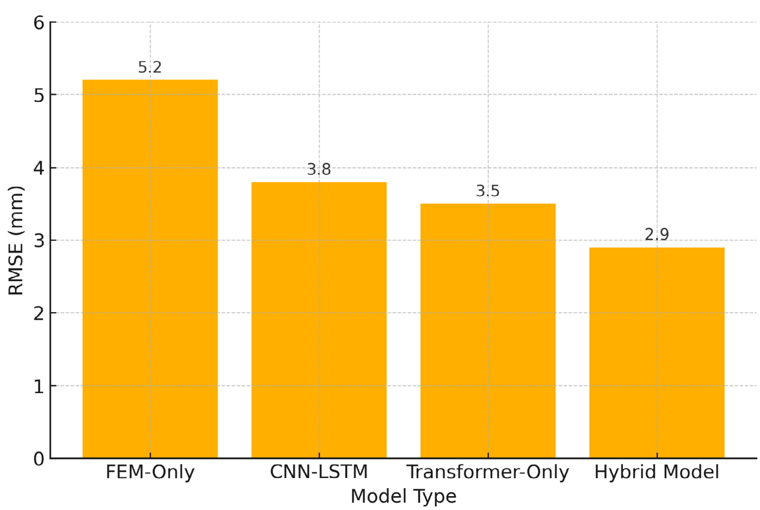
5 Results and analysis

This section presents the experimental results by applying the hybrid DL model to the Shanghai deep excavation case study. The RMSE, F1 score and computation time were evaluated on the model's performance. The model prediction of excavation-induced deformations, lateral wall displacements, and groundwater seepage risk is demonstrated by analysing the results. The improvements in accuracy, adaptability, and efficiency are compared against FEM simulations, individual DL models (CNN-LSTM, transformer), and hybrid models (CNN + LSTM + transformer).

5.1 Predictive accuracy of the hybrid model

The RMSE values of the hybrid model were compared to those of FEM-only simulations, CNN-LSTM models, and transformer-only models to assess prediction accuracy. Table 4 and Figure 2 encompass the results.

Figure 2 Compared to fem-only simulations, the hybrid model outperforms other models and reduces the prediction errors in excavation risk prediction by about 44.2% (see online version for colours)



The predictions obtained from these results for excavation-induced deformations are lower (minimum RMSE = 2.90 mm) than any other method, and the hybrid model outperforms the different methods in predicting these deformations. It was found that manual parameter calibration and computational limitations do not allow the FEM-only model to reach the highest prediction error (5.20 mm). Another model, CNN-LSTM and transformer, reduces the prediction errors. Still, they fail to perform optimally and rely on multi-source data fusion and sequential risk prediction.

Table 4 RMSE comparison for different models

Model type	*RMSE (mm)*
FEM-only	5.2
CNN-LSTM	3.8
Transformer-only	3.5
Hybrid model	2.9

5.2 *Excavation failure classification performance*

Besides RMSE, the model's performance in correctly classifying the excavation failures was evaluated based on the F1-score, which is the arbitration between the precision (correctly predicted failures) and recall (actual failures detected). In Table 5, the models' F1-score values are shown.

Figure 3 The hybrid model's steeper precision-recall curve validates its ability to accurately identify excavation risks, eliminating false alarms and failure to catch (see online version for colours)

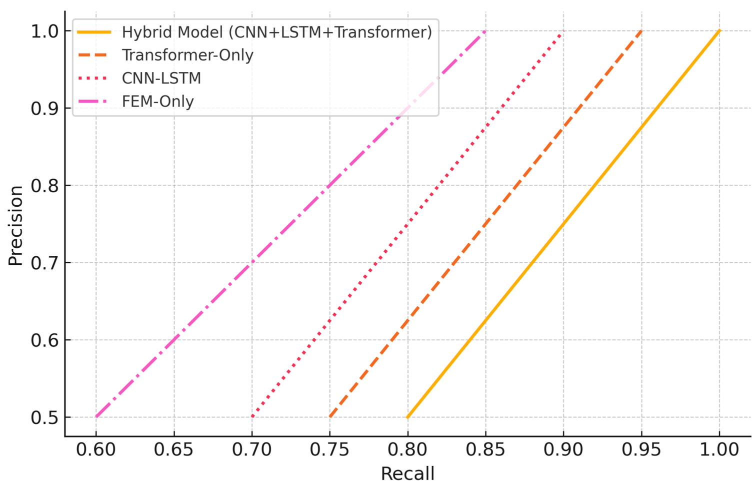


Table 5 F1-score comparison for failure prediction

Model type	*F1-score (%)*
FEM-only	81.4
CNN-LSTM	89.7
Transformer-only	91.2
Hybrid model	94.5

Although the performance for the FEM-only model is 81.4%, it is significantly outperformed by the hybrid model (94.5%). The results of this improvement further imply that DL models can be combined with multiple sources of geotechnical data and precision-recall curves shown in Figure 3.

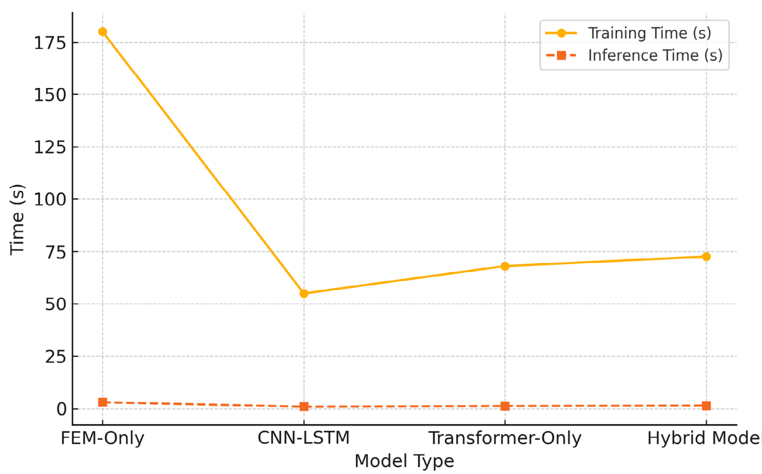
5.3 Computational efficiency analysis

Excavation risk prediction should be performed in near real-time for real-world applications so that proactive decisions can be made. The training was conducted on an NVIDIA Tesla V100 GPU with 32GB memory, and inference was tested on an NVIDIA RTX 3080 GPU with 10GB memory. Table 6 and Figure 4 compare the computation time for training and inference.

Table 6 Computation time comparison

Model type	*Training time (s)*	*Inference time (s)*
FEM-only	180.0	3.0
CNN-LSTM	55.0	0.9
Transformer-only	68.0	1.2
Hybrid model	72.5	1.4

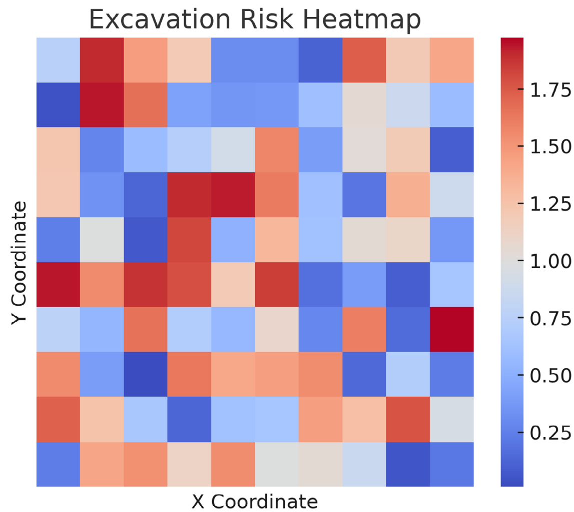
Figure 4 The hybrid model achieves optimal trade-off between inference speed and extraordinarily high prediction accuracy, a plausible solution for monitoring excavation risk (see online version for colours)



5.4 Visualisation of risk predictions

Finally, predicted ground deformation values from the hybrid model were used to visualise the excavation risk predictions on heatmaps in Figure 5.

Figure 5 The hybrid model predicts high-risk zones (red) that coincide with recorded excavation failures, giving evidence of the reliability of the hybrid model in predicting instability patterns (see online version for colours)



5.5 Results summary

Results indicate that the hybrid DL model performs much better than FEM simulations alone and standalone DL models. The key findings are:

- Improves excavation risk prediction precision: the hybrid model has an RMSE of 2.90 mm.
- Improved F1: the hybrid model leads to an improved precision of 94.5%.
- Inference times: the model has an inference time of 1.4 s, which is sufficiently low for real-time monitoring.
- Practical effectiveness: the hybrid model's excavation risk heatmaps follow practical failure events.

The profound foundation pit risk assessment results indicate that CNN + LSTM + transformer can achieve higher accuracy, reliability, and computational efficiency than other hybrid DL models (CNN + LSTM + GRU or CNN + LSTM + BiGRU). It reduces prediction errors, helps classify excavation failure, and can be applied to real-time monitoring. The results validate the model's ability as an advanced decision-support tool in geotechnical engineering.

6 Discussion

The study's main findings are provided in this section, and the advantages of the hybrid DL model in deep foundation pit risk assessment are discussed. It has been found that integrating CNNs, LSTMs, and Transformers brings substantial accuracy improvement, real-time adaptability, and computational efficiency in predictive accuracy. In addition, this section incorporates the limitations of the proposed approach, such as the computational complexity, data dependency, and model interpretability.

6.1 Key findings

Analysing complex stress-strain distributions in excavation sites is one of the main challenges of the excavation risk assessment. FEM simulations traditionally produce high-resolution stress maps, but engineers must tediously pore over those results to find the high-risk zones. The hybrid model automates this process by incorporating CNNs. Critical spatial features from FEM-generated stress-strain heatmaps can then be extracted. Estimating the probability of the stress transfer zone resulting in high deformation. Learning patterns of soil structure interaction for enhancing spatial awareness. Using the stress tensors, soil displacement field, and retaining wall deformation map, the CNN component can successfully process the excavation risk analysis and is more data-driven and automated.

Soil movements, wall deformations, and structural loads increase over weeks and months in excavation projects, significantly impacting the project's timing and success. Delayed failure detection is the biggest issue with traditional models, as they cannot incorporate the sequential excavation phase data. The hybrid model integrates LSTM networks. It learns from the historical inclinometer and piezometer readings to predict future excavation-induced deformations. It identifies the recurring instability trends and warns early of excessive lateral wall movements. It enhances the temporal resolution of risk assessments by forecasting deformation trends before failure. It allows engineers to make proactive decisions, such as adjusting bracing systems to avoid structural damage before it occurs, which only requires analysing sequential excavation data by the LSTM component.

The excavation risk is a function of multiple interdependent factors like the geotechnical properties, real-time sensor readings, and environmental conditions. However, these existing DL models cannot incorporate these dissimilar datasets well. The transformer component of the hybrid model processes multiple sensor readings while obtaining real-time risk assessment. The environmental variation (e.g., rainfall intensity, seismic activity) is correlated with the excavation-induced stress variation. Weigh the importance of each geotechnical parameter used in long-term risk prediction with a self-attention mechanism. The transformer component integrates a wide range of geotechnical datasets in a more complete excavation risk assessment framework than the analysis of the single source datasets.

The result is an AI-driven risk assessment model that is adaptive, scalable, and highly accurate, a product of the combination of CNNs, LSTMs, and transformers. The hybrid model was compared with the traditional. It achieves a considerable RMSE reduction to 2.90 mm and thus improves deformation prediction accuracy. It achieves an F1-score of 94.5% compared to the previous F1-score of 55.4% during the classification of excavation failure. It keeps an inference time of 1.4 seconds, is computationally efficient, and is capable of real-time applications. It verifies that the hybrid model outperforms FEM-only simulations and standalone DL procedures, making the excavation risk assessment safer and more reliable.

6.2 imitations

The hybrid model substantially improves over traditional excavation risk assessment methods but notes its few limitations. Training and running the real-time deployment of DL models, especially transformers, takes many computational resources. FEM stress-strain tensors, multi-sensor source input, and environmental data are all used as high-dose input. Increase the number of trainable parameters (DL layers, like CNN, LSTM, transformer, and so on), which have longer training times compared to simpler ML models, as shown in Table 7.

Table 8 Computational complexity across models

Model type	*Training time (s)*	*Inference time (s)*	*Hardware requirements*
FEM-only	180.0	3.0	High CPU usage
CNN-LSTM	55.0	0.9	Medium GPU usage
Transformer-only	68.0	1.2	High GPU usage
Hybrid model	72.5	1.4	High GPU/TPU usage

The generalisation of DL models mainly relies on large-scale, labelled datasets. The history of excavation failures is rare, so obtaining sufficient training data from real-world excavation failures is challenging. Suitable datasets that comprise standardised geotechnical data with labelled stress-strain outputs. Measurable multi-source sensor data (i.e., inclinometer readings or piezometer data). For these challenges, this study used data augmentation techniques, using the SMOTE. Future work needs to concentrate on building open-access geotechnical datasets for generalisation.

A significant obstacle with DL models lies in their opacity, as they function as black boxes, and it is impossible to explain why a particular excavation risk prediction was made. Interpretability of promising engineering decision-making, where interpretability is required to validate predictions. Such as regulatory compliance in which a preferred construction risk assessment can be derived from explainable models. To resolve this problem, XAI techniques ought to be embedded into future versions of the hybrid model. CNN visualisation highlights what stress-strain regions contribute to risk predictions using gradient weighted class activation mapping (Grad-CAM). Attention heat maps for Transformer models should be examined to find which geotechnical parameters strongly influence the excavation failure forecasts. Neural networks (NNs) are augmented with hybrid AI + physics-informed neural networks (PINNs) to guarantee physically consistent outputs.

7 Future work

The proposed hybrid DL model dramatically improves the accuracy of excavation risk assessment. Nevertheless, there are opportunities for further research and development to improve the efficiency and make the model more valuable in the real world. Future work will have to optimise computational efficiency, expand dataset availability, enhance model interpretability, and develop a real-time monitoring system for automated excavation safety management. However, the computational complexity of CNN, LSTM, and Transformer architectures in deploying DL models makes it one of the key challenges for geotechnical risk assessment. Future work is the exploration of the use of lightweight neural network architectures (such as quantised neural networks (QNNs), knowledge distillation, and edge AI for (on-site) excavation monitoring at low-power devices. Most existing methods are based on historical and real-time sensor data, while limited and non-standardised labelled excavation failure datasets exist. Future research should aim to develop multi-source sensor readings, excavation failure case studies, and standardised stress-strain data to enhance model generality and robustness. Model interpretability is a second critical gap, especially in DL models, often black-box predictors that engineers do not quickly validate. Future work will integrate explainable AI (XAI) frameworks, such as attention-based visualisation techniques for transformers, Grad-CAM for CNN feature mapping, and feature attribution methods for time-series predictions, to address the issue of transparency and trust regarding the AI-driven risk assessment. Secondly, PICC can be integrated with DL models to ensure that the predictions can be consistent with the geotechnical engineering principle for model reliability in real-world applications. Finally, the proposed hybrid model can include a time IoT-based sensor network for automated excavation risk monitoring. It is suggested that future work should be focused on further developing an AI-driven digital twin of excavation sites, where real-time sensor data continues to be fed into the hybrid model, providing continuous risk assessment, early warning alerts, and predictive maintenance recommendations. This research utilises cloud-based AI analytics and wireless sensor networks to enable autonomous excavation risk management systems to increase safety, reduce project delays, and increase construction efficiency.

8 Conclusions

In this study, a DL hybrid model using CNNs, LSTMs, and Transformers is presented to reduce errors in the probabilistic predictiveness and enhance real-time adaptability and multi-source data fusion for excavation risk assessment in deep foundation pit engineering. FEM simulations are valuable to assess the stress-strain distribution and soil-structure interaction. Still, they pay high computational costs, are manually dependent on parameters, and lack flexibility in real-time excavation conditions. However, existing DL models also have disadvantages when applied separately. CNNs rely on spatial feature extraction, and LSTMs only know the time series. Transformer is excellent for combined multi-source data but requires large-scale datasets and a lot of computational capacity.

This study presents a hybrid AI-driven risk assessment framework to overcome these challenges, utilising CNNs for stress-strain feature extraction from FEM simulation, LSTMs for predicting the sequential excavation-induced deformations, and Transformers for integrating available geotechnical, sensor-based, and environment risk factors. The model was validated using a real-world deep excavation project in Shanghai using an inclinometer, piezometer, strain gauge readouts, and FEM-generated stress-strain data. The experiment results in an RMSE of 2.90 mm, which is much smaller than the RMSE of traditional FEM-only simulations (5.20 mm RMSE), CNN-LSTM models (3.80 mm RMSE), and Transformer models (3.50 mm RMSE). The model also has a 94.5% failure classification F1 score, which proves that the model can correctly classify the excavation instability with greater accuracy than current methods. The hybrid model can be computed in real-time (inference time of 1.4s), and its computational efficiency also makes it suitable for real-time deployment in excavation safety monitoring systems.

The study also presents several limitations, such as a higher computational resource demand, the dependency on the preceded labelling of the excavation failure dataset, and the lack of interpretability of the DL architectures. Future research should inspect lightweight AI architectures, explainable AI (XAI) frameworks, and PINN integration to enhance the model efficiency, transparency, and generality. In addition, integrating IoT-based real-time excavation monitoring systems and cloud-based AI analytics in the practical deployment of the AI-based excavation risk assessment in any substantial project is also possible.

Finally, a hybrid deep-learning model establishes a new benchmark for AI-derived excavation safety, predictive accuracy, and real-time adaptability. This research will pave the road for safer, smarter, and more efficient excavation projects by integrating DL with geotechnical monitoring systems. It will lead to the next generation of AI geotechnical engineering solutions.

Declarations

The author declares that he has no conflict of interest.

References

Aldosary, M., Wang, J. and Li, C. (2018) 'Structural reliability and stochastic finite element methods', *Engineering Computations*, Vol. 35, No. 6, pp.2165–2214, DOI: 10.1108/EC-04-2018-0157.

Ali, N. et al. (2024) 'integrating machine learning ensembles for landslide susceptibility mapping in Northern Pakistan', *Remote Sensing*, Vol. 16, No. 6, p.988, https://doi.org/10.3390/rs16060988.

Amel, O., Siebert, X. and Mahmoudi, S.A. (2024) 'Comparison analysis of multimodal fusion for dangerous action recognition in railway construction sites', *Electronics*, Vol. 13, No. 12, p.2294, https://doi.org/10.3390/electronics13122294.

Askaripour, M., Saeidi, A., Rouleau, A. and Mercier-Langevin, P. (2022) 'Rockburst in underground excavations: A review of mechanism, classification, and prediction methods', *Underground Space*, Vol. 7, No. 4, pp.577–607, https://doi.org/10.1016/j.undsp.2021.11.008.

Baghbani, A., Choudhury, T., Costa, S. and Reiner, J. (2022) 'Application of artificial intelligence in geotechnical engineering: a state-of-the-art review', *Earth-Science Reviews*, Vol. 228, p.103991, https://doi.org/10.1016/j.earscirev.2022.103991.

Bozkurt, S. and Akbas, S.O. (2023) 'Finite element-based geotechnical risk analysis for anchor-supported deep excavations', *Arabian Journal of Geosciences*, Vol. 16, No. 8, p.470, https://doi.org/10.1007/s12517-023-11463-5.

Carter, T.G. and Barnett, W.P. (2022) 'Improving reliability of structural domaining for engineering projects', *Rock Mechanics and Rock Engineering*, Vol. 55, No. 5, pp.2523–2549, https://doi.org/10.1007/s00603-021-02544-6.

Cui, Z-D., Zhang, Z-L., Yuan, L., Zhan, Z-X. and Zhang, W-K. (2020) 'Design of open caisson structures', in Cui, Z-D., Zhang, Z-L., Yuan, L., Zhan, Z-X. and Zhang, W-K. (Eds.): *Design of Underground Structures*, pp.493–552, Springer Singapore, Singapore.

Fan, H., Li, L., Zhou, S., Zhu, M. and Wang, M. (2025) 'Prediction and risk assessment of lateral collapse in deep foundation pits using machine learning', *Automation in Construction*, 3 January, Vol. 171, p.106011, https://doi.org/10.1016/j.autcon.2025.106011.

Fang, R., Deng, L., Fan, W., Yang, G., Tang, D. and Mohammad, A. (2024) 'Research on response characteristics of loess slope and disaster mechanism caused by structural plane extension under excavation', *Scientific Reports*, Vol. 14, No. 1, p.28700, https://doi.org/10.1038/s41598-024-80016-x.

Firoozi, A.A. (2023) 'Application of machine learning in geotechnical engineering for risk assessment', in *Machine Learning and Data Mining Annual*, Vol. 2023, IntechOpen, London, UK.

Galvin, J. (2016) 'Fundamental principles for ground engineering', in *Ground Engineering-Principles and Practices for Underground Coal Mining*, pp.13–80, Springer, Algeria.

Garakani, A.A., Pirjalili, A., Yoosefi, S. and Khoshghalb, A. (2024) 'Assessing the stress–deformation and safety factor against sliding in reinforced deep urban excavations in unsaturated soils', *International Journal of Geomechanics*, Vol. 24, No. 7, p.4024130, https://doi.org/10.1061/ijgnai.gmeng-9052.

Gu, G., Zhang, Z., Huang, X., Li, Y. and Lei, Q. (2024) 'A finite element-based dynamic simulation method for modeling shield-ground interactions: 3D numerical simulations with comparison to physical experiments', *Computers and Geotechnics*, Vol. 169, p.106262, https://doi.org/10.1016/j.compgeo.2024.106262.

He, C., Wang, C., Peng, J., Jiang, W. and Liu, J. (2024) 'SVD-LSTM-based rainfall threshold prediction for rainfall-induced landslides in Chongqing', *Geomatics, Natural Hazards and Risk*, Vol. 15, No. 1, p.2424423, https://doi.org/10.1080/19475705.2024.2424423.

Jiang, Z., Zhu, S., Que, X. and Ge, X. (2024) 'Deformation effects of deep foundation pit excavation on retaining structures and adjacent subway stations', *Buildings*, Vol. 14, No. 8, p.2521, DOI: https://doi.org/10.3390/buildings14082521.

Kudela, J. and Matousek, R. (2022) 'Recent advances and applications of surrogate models for finite element method computations: a review', *Soft Computing*, Vol. 26, No. 24, pp.13709–13733, https://doi.org/10.1007/s00500-022-07362-8.

Kumar, P.R., Muthukkumaran, K. and Sharma, C. (2024) 'Technological advancements and sustainable practices in rock slope stability–critical review', *Physics and Chemistry of the Earth*, Parts A/B/C, p.103699, https://doi.org/10.1016/j.pce.2024.103699.

Li, X., Li, Y., Lu, X., Wang, Y., Zhang, H. and Zhang, P. (2020) 'An online anomaly recognition and early warning model for dam safety monitoring data', *Structural Health Monitoring*, Vol. 19, No. 3, pp.796–809, https://doi.org/10.1177/1475921719864265.

Li, X., Pan, Y., Zhang, L. and Chen, J. (2023) 'Dynamic and explainable deep learning-based risk prediction on adjacent building induced by deep excavation', *Tunnelling and Underground Space Technology*, Vol. 140, p.105243, https://doi.org/10.1016/j.tust.2023.105243.

Lin, Q., Cao, P., Dong, T., Liu, J., Zhao, Q. and Zhu, W. (2023) 'Numerical simulation of flood control levee deformation by shield tunnel excavation through the liuyang river: a case study', *Geofluids*, Vol. 2023, No. 1, p.8925891, https://doi.org/10.1155/2023/8925891.

Lindemann, B., Müller, T., Vietz, H., Jazdi, N. and Weyrich, M. (2021) 'A survey on long short-term memory networks for time series prediction', *Procedia Cirp*, Vol. 99, pp.650–655, https://doi.org/10.1016/j.procir.2021.03.088.

Liu, L., Zhou, W. and Gutierrez, M. (2022) 'Effectiveness of predicting tunneling-induced ground settlements using machine learning methods with small datasets', *Journal of Rock Mechanics and Geotechnical Engineering*, Vol. 14, No. 4, pp.1028–1041, https://doi.org/10.1016/j.jrmge.2021.08.018.

Liu, T. et al. (2024) *The Role of Transformer Models in Advancing Blockchain Technology: A Systematic Survey*, arXiv preprint arXiv:2409.02139, https://doi.org/10.2139/ssrn.5059646.

Lohar, G.K., Kumar, A. and Roy, N. (2024) 'Numerical assessment of time-dependent deformation of a road tunnel – a case study', *Transportation Infrastructure Geotechnology*, Vol. 11, No. 2, pp.447–469, https://doi.org/10.1007/s40515-023-00290-6.

Mahmoodzadeh, A., Mohammadi, M., Farid Hama Ali, H., Hashim Ibrahim, H., Nariman Abdulhamid, S. and Nejati, H.R. (2022) 'Prediction of safety factors for slope stability: comparison of machine learning techniques', *Natural Hazards*, pp.1–29, https://doi.org/10.1007/s11069-021-05115-8.

Maleki, J., Pak, A., Yousefi, M. and Aghakhani, N. (2022) 'A comprehensive FE study for design of anchored wall systems for deep excavations', *Tunnelling and Underground Space Technology*, Vol. 122, p.104340, https://doi.org/10.1016/j.tust.2021.104340.

Manta-Costa, A., Araújo, S.O., Peres, R.S. and Barata, J. (2024) 'Machine learning applications in manufacturing-challenges, trends, and future directions', *IEEE Open Journal of the Industrial Electronics Society*, https://doi.org/10.1109/ojies.2024.3431240.

Mohamed, F.M.O. (2014) *Bearing Capacity and Settlement Behaviour of Footings Subjected to Whom it May Concern: Static and Seismic Loading Conditions in Unsaturated Sandy Soils*, Université d'Ottawa/University of Ottawa.

Morgenroth, J., Khan, U.T. and Perras, M.A. (2019) 'An overview of opportunities for machine learning methods in underground rock engineering design', *Geosciences*, Vol. 9, No. 12, p.504, https://doi.org/10.3390/geosciences9120504.

Ninić, J. and Meschke, G. (2015) 'Model update and real-time steering of tunnel boring machines using simulation-based meta models', *Tunnelling and Underground Space Technology*, 1 January, Vol. 45, pp.138-152, DOI: https://doi.org/10.1016/j.tust.2014.09.013.

Niu, Y., Zou, L., Wang, Q. and Ma, F. (2023) 'Study on deformation characteristics of retaining structures under coupled effects of deep excavation and groundwater lowering in the affected area of fault zones', *Sustainability*, Vol. 15, No. 10, p.8060, DOI: https://doi.org/10.3390/su15108060.

Ou, C-Y. (2016) 'Finite element analysis of deep excavation problems', *Journal of Geoengineering*, Vol. 11, No. 1, pp.1–12, https://doi.org/10.1139/t94-026.

Painuli, D. and Bhardwaj, S. (2022) 'Recent advancement in cancer diagnosis using machine learning and deep learning techniques: a comprehensive review', *Computers in Biology and Medicine*, Vol. 146, p.105580, https://doi.org/10.1109/ojies.2024.3431240.

Pan, Y., Qin, J., Hou, Y. and Chen, J-J. (2024) 'Two-stage support vector machine-enabled deep excavation settlement prediction considering class imbalance and multi-source uncertainties', *Reliability Engineering and System Safety*, Vol. 241, p.109578, https://doi.org/10.1016/j.ress.2023.109578.

Phoon, K-K. and Zhang, W. (2023) 'Future of machine learning in geotechnics', *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, Vol. 17, No. 1, pp.7–22, https://doi.org/10.1080/17499518.2022.2087884.

Pu, Y., Chen, J., Apel, D.B. and Shang, X. (2025) 'Real-time identification of rock failure stages using deep learning: a case study of acoustic emission analysis in rock engineering', *Rock Mechanics and Rock Engineering*, pp.1–17, https://doi.org/10.1007/s00603-025-04423-w.

Rao, A.S. et al. (2022) 'Real-time monitoring of construction sites: sensors, methods, and applications', *Automation in Construction*, Vol. 136, p.104099, https://doi.org/10.1016/j.autcon.2021.104099.

Sherstinsky, A. (2020) 'Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network', *Physica D: Nonlinear Phenomena*, Vol. 404, p.132306, https://doi.org/10.1016/j.physd.2019.132306.

Song, X. et al. (2020) 'Time-series well performance prediction based on long short-term memory (LSTM) neural network model', *Journal of Petroleum Science and Engineering*, Vol. 186, p.106682, https://doi.org/10.1016/j.petrol.2019.106682.

Su, C., Hu, Q., Yang, Z. and Huo, R. (2024) 'A review of deep learning applications in tunneling and underground engineering in China', *Applied Sciences*, Vol. 14, No. 5, p.1720, https://doi.org/10.3390/app14051720.

van Adrichem, W.P. and Adnan, S. (2001) 'Innovative solution to prevent coiled tubing operational failures caused by human errors', in *SPE/ICoTA Coiled Tubing Roundtable*, SPE/ICoTA Coiled Tubing Roundtable, SPE-68427-MS, https://doi.org/10.2118/68427-MS.

Wengang, Z., Hanlong, L., Lin, W., Xing, Z. and Yanmei, Z. (2023) *Application of Machine Learning in Slope Stability Assessment*, Springer Nature, Turkey.

Xu, Z., Xu, W., Zhou, P., Zhu, Z., Zhao, J. and Gao, P. (2023) 'Research on coal mine goaf restoration based on stability of overlying rocks and numerical simulation analysis: a case study of Jingmen Garden Expo Park', *Sustainability*, Vol. 15, No. 2, p.1464, https://doi.org/10.3390/su15021464.

Yin, Z.Y., Jin, Y.F., Shen, J.S. and Hicher, P.Y. (2017) 'Optimization techniques for identifying soil parameters in geotechnical engineering: comparative study and enhancement', *International Journal for Numerical and Analytical Methods in Geomechanics*, 7 July, Vol. 42, No. 1, pp.70–94, DOI: 10.1002/nag.2714.

Yoonirundorn, K., Senjuntichai, T., Keawsawasvong, S., Ngamkhanong, C. and Wijeyewickrema, A.C. (2024) 'Stability analysis of multiple unsupported excavations in cohesive-frictional soils using finite element limit analysis (FELA) and an artificial neural network (ANN)', *Modeling Earth Systems and Environment*, 1 April, Vol. 10, No. 2, pp.1589–1598, DOI: 10.1007/s40808-023-01857-5.

Zhang, L., Wang, J., Wang, Y., Sun, H. and Zhao, X. (2022) 'Automatic construction site hazard identification integrating construction scene graphs with BERT based domain knowledge', *Automation in Construction*, Vol. 142, p.104535, https://doi.org/10.1016/j.autcon.2022.104535.

Zhang, W. and Liu, H. (2022) 'Excavation failure cases and analysis', in *Design of Deep Braced Excavation and Earth Retaining Systems Under Complex Built Environment: Theories and Case Studies*, pp.383–416, Springer Singapore, Singapore.

Zhao, J. (2023) *Numerical Modeling and Uncertainty Analysis of Tunneling-and Deep Excavation-Induced Structural Damage*, University of California, Berkeley.

Zhou, C., Gao, X., Chen, E.J., Ding, L. and Qin, W. (2023) 'Deep learning technologies for shield tunneling: challenges and opportunities', *Automation in Construction*, Vol. 154, p.104982, https://doi.org/10.1016/j.autcon.2023.104982.

Zhou, X., Pan, Y., Qin, J., Chen, J-J. and Gardoni, P. (2024) 'Spatio-temporal prediction of deep excavation-induced ground settlement: a hybrid graphical network approach considering causality', *Tunnelling and Underground Space Technology*, Vol. 146, p.105605, https://doi.org/10.1016/j.tust.2024.105605.