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Review Article

A review of tunnelling caused ground surface settlement prediction with artificial intelligence method

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Abstract: The accuracy of surface settlement predictions, which aim to limit theoretical, numerical and experimental simulation errors, is influenced by several factors, including parameter values, assumption conditions and other limitations. However, the recent introduction of machine learning (ML) and deep learning (DL) has provided new ideas for surface settlement prediction. In this paper, the advances of ML and DL in surface settlement prediction are systematically reviewed. The classification of surface settlement prediction methods is first conducted based on the principles of commonly used ML and DL algorithms, including maximum surface settlement prediction and surface settlement time series prediction. Existing studies are then analysed, and common methods for improving prediction accuracy are presented. Finally, the performance of common ML and DL algorithms in predicting surface settlement is compared using the Kunming dataset. The study then draws conclusions based on the results of the comparative studies and literature research, highlighting the impact of dataset quality and feature selection on the generalisation ability of prediction models and the real-time prediction ability of existing studies.

Keywords: Tunneling, Settlement prediction, Machine learning, Deep learning

1. Introduction

The release of unbalanced ground stresses during the process of excavation frequently results in surface settlement [14,45,57]. Surface settlements caused by excavations for tunnels commonly result in the impairment of surface structures. This may potentially undermine the load-bearing capacity of beams and columns, while also adversely affecting the structural stability of the whole structure [2,40]. A plethora of theories have been formulated by researchers, including continuum theory and stochastic medium theory [43,45,49]. Based on these theories, traditional prediction methods – including, but not limited to, fitting formulas(e.g.,using the gap parameter to define the equivalent ground loss parameter [28], theoretical calculations(e.g.,Fourier series-based displacement function for circular shallow tunnels [29], numerical simulations(e.g.,Finite Element Method [32], Discrete element modelling [33]), and model estimation [18] – can be utilised for predicting surface settlement.

However, the conventional surface settlement prediction methodologies outlined above are predominantly founded upon simplified assumptions [56] or empirical formulae [55], impeding the capacity to predict surface settlement with precision. The mechanical properties of soil are influenced by multiple factors, such as geological conditions, groundwater, and construction methods, which interact with each other in complex ways. To improve

Received: Jan.25, 2025; Revised: Mar.13, 2025; Accepted: Jul.1, 2025; Published: Nov.4, 2025

DOI: https://doi.org/10.55976/cer.1202513572-20

the prediction accuracy of surface settlement, machine learning (ML) and deep learning (DL) algorithms have been introduced. Compared to traditional prediction methods, ML and DL have the capacity to discern intricate non-linear correlations from surface settlement data, thereby identifying more nuanced patterns and trends. In recent studies, Back-Propagation (BP) [4], Radial Basis Function (RBF) [3-4], Long Short-Term Memory (LSTM) [21,30,37,52], Gated Recurrent Unit (GRU) [51], eXtreme Gradient Boosting (XGBoost) [21,53], Generalized Regression Neural Network (GRNN) [4], Support Vector Machine (SVM) [21,30,38,52-53] and Extreme Learning Machine (ELM) [12,22], are frequently used for surface settlement prediction.

However, these ML and DL algorithms also have certain limitations. For instance, factors such as the computational resources available, and the quality of the datasets can influence the accuracy of the predictions and the generalisability of the models [60-61]. In order to enhance the efficacy and performance of machine learning (ML) and deep learning (DL) algorithms, the utilisation of optimised parameters (e.g.,modified standard penetration tests [4]) or advanced algorithms (e.g.,Particle Swarm Optimization (PSO) [22,58]) has been demonstrated in related studies. This has led to a substantial improvement in the generalisation capability and precision of SS predictions [4,12,14-15,18,21-22,29,33,41-42,55-56,58,59].

This paper provides a comprehensive overview of recent advancements in the application of machine learning (ML) and deep learning (DL) algorithms for predicting surface settlement.Specifically, the review addresses the following key questions: (i) What are the commonly used ML and DL algorithms in surface settlement prediction, and what are their underlying principles? (ii) How can surface settlement problems be formulated as ML and DL tasks, and how should they be categorized? (iii) What critical challenges must be addressed in future research to advance the use of ML- and DL-based surface settlement prediction methods? The structure of this paper is organized as follows. Section 2 begins with a brief introduction to the core principles of commonly used ML and DL algorithms. This section also highlights the applications of these algorithms in areas of civil engineering. In Section 3, we discuss how DL and ML algorithms can be utilized to predict surface settlement and categorize surface settlement problems into the following types:Maximum Surface Settlement (MSS) prediction and Surface Settlement Time Series (SSTS) prediction. Subsequently, Section 4 compares and analyzes the performance of commonly used ML and DL algorithms in surface settlement prediction tasks using the Kunming dataset. Based on the research findings and a review of the literature, Section 5 provides a critical discussion of the main issues addressed in the study and offers insights into future directions for development. Finally, the paper concludes with some concluding remarks.

2. Overview of AI method in surface settlement prediction

The application of machine learning and deep learning algorithms in surface settlement prediction caused by tunnel excavation has significantly improved prediction accuracy and generalization ability. These algorithms are clearly categorized into two main types: machine learning algorithms and deep learning algorithms, based on their algorithmic structure and learning approaches. Machine learning algorithms, such as Random Forest (RF), Support Vector Machine (SVM), and Extreme Learning Machine (ELM), primarily rely on constructing mathematical models to extract features from historical data and make predictions. The advantage of these algorithms lies in the high interpretability of their prediction models. Deep learning algorithms, particularly Recurrent Neural Networks (RNN) and their variants, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), excel in automatically learning complex features and temporal dependencies in data by constructing multi-layer neural network structures. These algorithms perform exceptionally well when dealing with large-scale, high-dimensional data, though their model interpretability tends to be weaker. Both types of algorithms offer unique advantages in surface settlement prediction, contributing to the continuous improvement in the accuracy and efficiency of prediction models.

We have summarized 5 commonly used ML algorithms and 2 DL algorithms in the field of regression prediction, elucidated their core principles, and provided examples of their applications within the realm of civil engineering.

2.1 Machine learning methods

2.1.1 Support Vector Machine (SVM)

Support Vector Machines [8] (SVM) have been extensively studied and applied in the field of machine learning and have become a crucial tool for solving classification and regression problems. In regression prediction tasks, SVM aims to find a function model that accurately fits the data samples, minimizing the deviation between predicted and actual values. In recent studies, Min-Yuan Cheng et al.[7] utilized the SVM algorithm to predict trends in building prices. Similarly, Bonsang Koo et al. [23] applied the SVM algorithm to examine the semantic integrity of the mapping between Building Information Modeling (BIM) elements and Industry Foundation Classes (IFC). Furthermore, Anna Hoła et al. [16] employed SVM for the non-destructive identification of brick wall moisture.

The core principle of SVM lies in identifying an optimal hyperplane in the feature space to perform regression prediction tasks. This process involves maximizing the margin between the support vectors and the hyperplane to enhance the model's generalization capability. Additionally,

by introducing kernel functions, SVM can handle nonlinear problems, making it applicable to more complex data scenarios. Finally, optimization algorithms are employed to solve the quadratic programming problem, thereby determining the precise position of the optimal hyperplane. In order to find the optimal hyperplane, researchers often assume a specific form for the hyperplane regression function. Building on this foundation, subsequent steps involving solution and optimization are performed to finalize the model parameters:

$$f(x) = w^T \phi(x) + b$$

Here, w represents the weight matrix, b is the bias term, and Φ(x) denotes the kernel mapping function, which maps the input x to a higher-dimensional feature space. For simplicity of representation, the high-dimensional feature vectors are projected onto a two-dimensional plane, as illustrated in Figure 1.

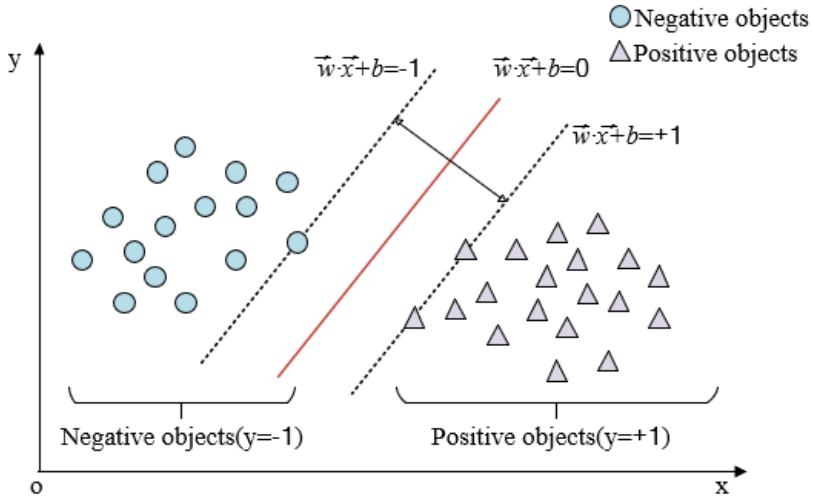

Figure 1. SVM feature space

The optimization interval is governed by Eq below, where represents the maximized margin between the two support vectors, as shown in the interval between the two dashed lines in the figure:

$$\rho(\mathbf{w}, b) = \min_{\{\mathbf{x}\cdot\mathbf{y}=1\}} \frac{\mathbf{x}\cdot\mathbf{w}}{|\mathbf{w}|} - \max_{\{\mathbf{x}\cdot\mathbf{y}=-1\}} \frac{\mathbf{x}\cdot\mathbf{w}}{|\mathbf{w}|}$$

Thus, for regression prediction problems, the prediction function can be expressed as:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x) + b$$

Here, a_i, a_i^* are the Lagrange multipliers of the support vectors, where a_i corresponds to negative errors and a_i^* corresponds to positive errors, x represents the input feature vector, x_i denotes the feature vector of the i-th training sample, $K(x_i,x)$ is the kernel function used to compute the similarity between the new input x and the support vectors.

2.1.2 Random Forest (RF)

The Random Forest algorithm(Random Forests) (RF) has gained widespread application and recognition in data mining and machine learning due to its remarkable robustness against outliers and noise, as well as its resilience to overfitting. Xiong Wang et al. [44] integrated the RF algorithm to develop an innovative risk management system for deep foundation pits. This system enhances the accuracy of risk prediction and improves the intelligence level of the system through real-time data interaction and inversion. On the other hand, Xianguo Wu et al. [46] proposed a novel framework that leverages the RF algorithm to accurately predict the impact of foundation pit construction on the deformation of existing tunnels.

The core principle of using the RF algorithm for regression prediction lies in constructing multiple decision trees to form the regression model. During the tree construction process, an element of "randomness" is cleverly introduced. This randomization introduces diversity among the decision trees, which effectively enhances the model's generalization ability, as illustrated in Figure 2. Specifically, when constructing each decision tree, the RF algorithm employs the bootstrap method to randomly sample subsets from the original dataset as training data. Additionally, during the splitting process at each node, the algorithm randomly selects features for splitting, further enhancing the model's diversity and robustness.

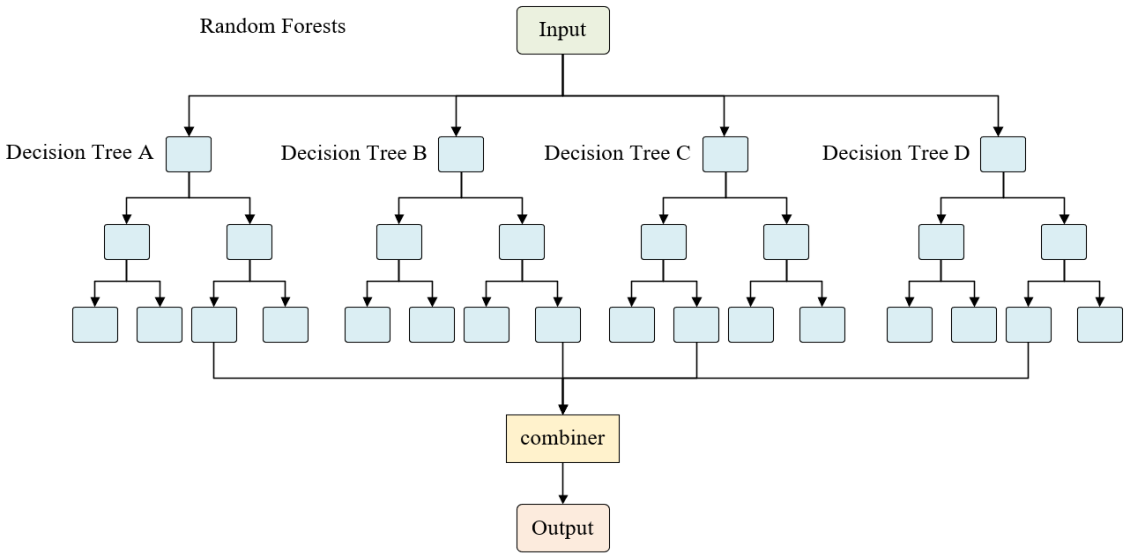

Figure 2. RF Decision tree construction

For regression prediction problems, assume that the random forest consists of T decision trees, and each decision tree outputs a predicted value $\hat{y}_i$ for the input sample x. The final predicted value $\hat{y}$ of the random forest is obtained by averaging the predicted values of all trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

2.1.3 Extreme Learning Machine (ELM)

Extreme Learning Machine [13] (ELM) algorithm is primarily used to enhance the training efficiency of neural networks and optimize the learning process through a randomized approach, addressing the computational complexity issues in traditional neural network training. ELM has been widely applied to binary classification and multi-class classification problems. Due to its high computational efficiency, it is particularly suitable for handling large-scale datasets. Giulio Mariniello et al.[31] developed an automated damage assessment method based on ELM (LA-ELM), focusing on the prestressed tendon failure problem in prestressed concrete bridges. Qiubing Ren et al.[38] proposed an online learning model based on SOS-ELM, which enables real-time monitoring of dam displacement behavior.

The core idea of the ELM algorithm is to randomize the parameters of the hidden layer nodes (i.e., input weights and biases), and then calculate the output layer weights using the least squares method. This approach reduces the iterative process typically required in traditional neural network training, as shown in Figure 3.

First, the parameters of the hidden layer nodes are randomly generated, and the output of each input sample in the hidden layer is calculated using an activation function (such as Sigmoid, ReLU, etc.):

$$H = \begin{bmatrix} h_1(\mathbf{x}_1) & h_2(\mathbf{x}_1) & \cdots & h_L(\mathbf{x}_1) \\ h_1(\mathbf{x}_2) & h_2(\mathbf{x}_2) & \cdots & h_L(\mathbf{x}_2) \\ \vdots & \vdots & \ddots & \vdots \\ h_1(\mathbf{x}_N) & h_2(\mathbf{x}_N) & \cdots & h_L(\mathbf{x}_N) \end{bmatrix}$$

Where $h_j(x_i)$ represents the output of the i-th sample after passing through the activation function of the j-th hidden node. The output layer weights β are then directly solved using the least squares method:

$$\beta = (H^T H)^{-1} H^T \mathrm{T}$$

Where T is the target value matrix of the training samples. Based on the computed hidden layer weights and biases, as well as the output layer weights, the predicted result can be calculated:

$$\hat{\mathbf{y}} = H(\mathbf{x})\beta$$

2.1.4 eXtreme Gradient Boosting (XGBoost)

eXtreme Gradient Boosting [6] (XGBoost) is an efficient implementation of the Gradient Boosting Decision Tree (GBDT) algorithm. By improving the underlying algorithm, XGBoost enhances both training speed and

concrete, thereby reducing uncertainties in experimental results.

The core idea of XGBoost is to optimize the model's prediction capability by integrating multiple weak classifiers, typically decision trees, as shown in Figure 4.

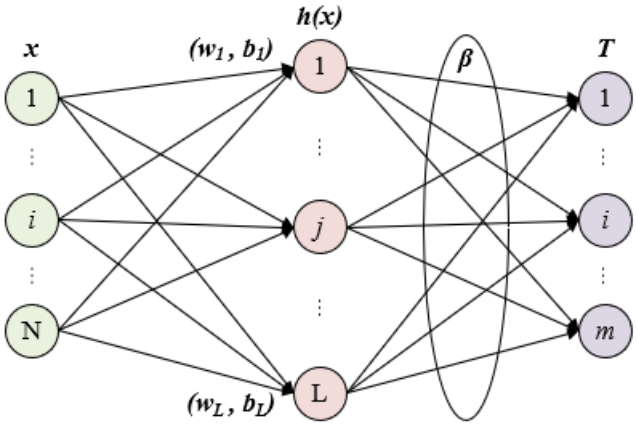

Figure 3. ELM operating mechanism

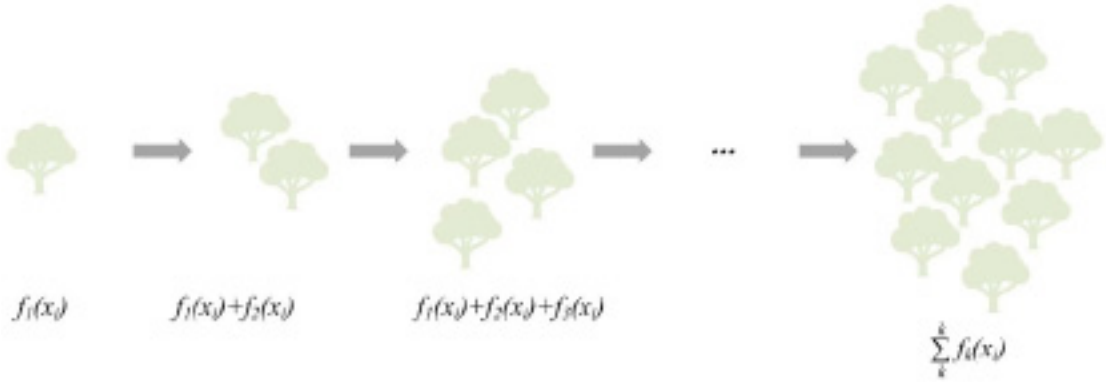

Figure 4. XGBoost Model optimization

The prediction formula of XGBoost can be expressed as:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

Here, $\hat{y}_i$ is the predicted value for sample i, K is the total number of weak learners (trees), $f_k(x_i)$ is the predicted value for sample x_i from the K-th tree.

The goal of XGBoost is to learn the model parameters by optimizing the objective function, which consists of the loss function and the regularization term:

$$\mathrm{L}(\theta) = \sum_{i=1}^{N} \log(y_i, \hat{y}_i) + \Omega(f)$$

Where y_i is the true value of sample i, and $\Omega(f)$ is the regularization term:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{k=1}^{T} f_k^2$$

Where T is the number of leaves in the tree, f_k represents the weights of the tree leaves, λ and γ are the regularization parameters.

2.1.5 Back-Propagation (BP)

The Back Propagation Neural Network [39] (BPNN) is a classic artificial neural network model. Yang Liu et al. [27] used a BP neural network to analyze the spatial vulnerability of rural settlements in the hilly areas of Sichuan, identifying the main influencing factors and their distribution characteristics. Sheng-Hua Xiong et al. [48] employed the BP neural network to process and predict SAR data for runway settlement issues at airports.

The core idea of the BP algorithm is to propagate information forward through the network and then use the chain rule (chain differentiation) to backpropagate the error from the output layer to the input layer. The weights and biases of the network are then updated using gradient descent. The BP network typically consists of three main layers: the Input Layer, Hidden Layer, and Output Layer, as shown in Figure 5:

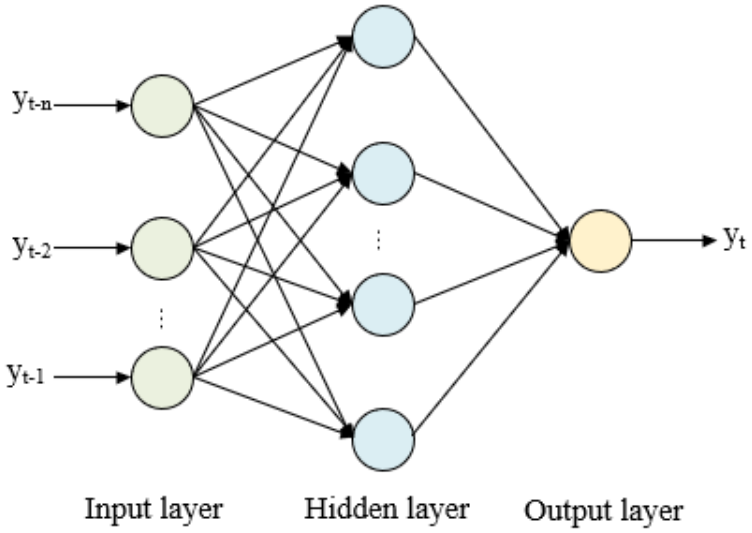

Figure 5. BP framework

The mathematical relationship(Dong et al. 2018) of the propagation process in these three layers can be expressed as:

From the input layer to the hidden layer:

$$y_j = f_l\left(\mu_j + \sum_{m=t-n}^{t-1} \mu_{jm} y_m\right)(0 \le \mu_j, \mu_{jm} \le 1)$$

From the hidden layer to the output layer:

$$y_t = f_o\left(\lambda_o + \sum_{j=1}^{I} \lambda_{oj} y_j\right)(0 \le \lambda_o, \lambda_{oj} \le 1)$$

Where y_m and y_j represent the inputs to the input layer and the hidden layer, y_t represents the predicted value at point t, μ_{jm} and λ_{oj} represent the network weights between the output layer and the hidden layer, μ_j and λ_o are the thresholds of the hidden layer and the output layer, n and Idenote the number of nodes in the input layer and hidden layer, respectively, f_l and f_o represent the activation functions of the hidden layer and the output layer.

2.2 Deep learning methods

2.2.1 Recurrent Neural Network (RNN)

In time series forecasting, numerous algorithms are employed, including Deep Belief Networks (DBN), Support Vector Machines (SVM) or Support Vector Regression (SVR), Convolutional Neural Networks (CNN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Recurrent Neural Networks (RNN). Compared to other algorithms, the nodes between the hidden layers of RNN are not disconnected, but rather connected. The input to the hidden layers includes not only the output from the input layer, but also the output from the previous time step of the hidden layer. Long Short-Term Memory [36] (LSTM) and Gated Recurrent Unit [7,23] (GRU) are both variants of Recurrent Neural Networks [16] (RNNs).

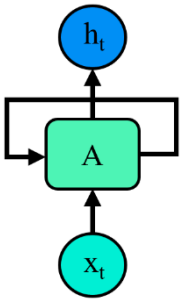

Figure 6. RNN unit

Figure 6 shows an RNN unit x_t where A represents the neural network module, denotes the input at the current time step, and h_t represents the hidden state at the current time step. By combining the input sample weights, the previous hidden state h_{t-1}, the output sample weights V,t he input data bias vector b , and the output data bias vector c, the current hidden state h_t and the output y_t can be determined based on the input data x_t, as follows:

$$h_t = f(Ux_t + Wh_{t-1} + b)$$
$$y_t = Soft\max(Vh_t + c)$$

In this context, f represents the activation function for the input, *Soft*maxrepresents the activation function for the output. In RNN, U, W and b are shared, which is different from LSTM and GRU. However, RNNs face issues such as vanishing and exploding gradients, making

it difficult to handle long-term dependencies. To address these problems, LSTM networks were introduced. LSTM introduces a gating mechanism, consisting of the input gate, forget gate, and output gate, to control the flow of information. These gates allow for selective updating and forgetting of information, enabling better capture of long-term dependencies. Additionally, LSTM introduces a cell state to store and transfer information.

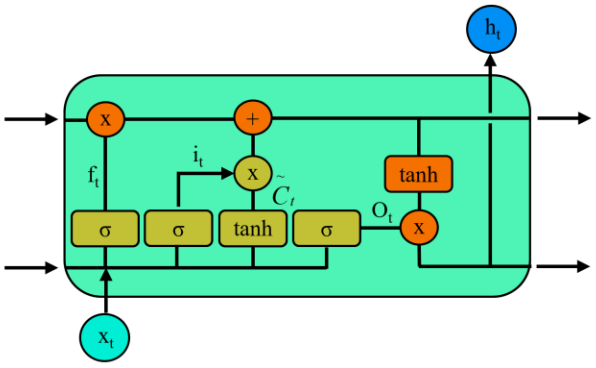

Figure 7. LSTM Unit

In the forget gate and input gate, the sigmoid function is used to transform x_t and h_t into a vector of values between 0 and 1, where 0 indicates forgetting and 1 indicates storing:

$$f_t = \sigma(\mathrm{Wf} \cdot [h_{t-1}, x_t] + b_f)$$

Subsequently, the input gate determines whether to add new information to the cell state:

$$\mathrm{i_t} = \sigma(\mathrm{W_i} \cdot [\mathrm{h_{i-1}}, \mathrm{x_t}] + \mathrm{b_i})$$

$$\tilde{C}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right)$$

Next, the previously discarded information is combined with the newly retained information to update the cell state:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Finally, the output gate regulates the amount of information extracted from the cell state and generates the new output using the tanh activation function:

$$\mathrm{o_t} = \sigma\left(\mathrm{W_o} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_o}\right)$$

$$h_t = o_t * \tanh(C_t)$$

Here, b represents the bias vector, and W denotes the weight matrix for each gate.

To enhance the LSTM structure and reduce the number of parameters, the Gated Recurrent Unit (GRU) was developed. The GRU simplifies the LSTM structure by merging the forget gate and input gate into a single update gate, effectively combining the cell state and hidden state. This reduction in parameters enables the GRU to achieve comparable accuracy with improved computational efficiency, making it particularly well-suited for resource-constrained environments.

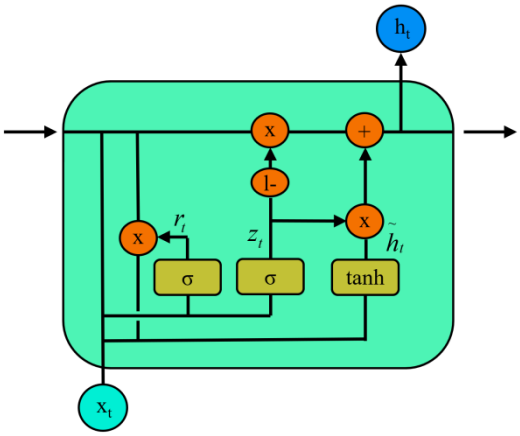

Figure 8. GRU Unit

The reset gate determines how new input information is combined with previous memory:

$$\mathrm{r_t} = \sigma(W_r \cdot [h_{t-1}, \mathrm{x_t}])$$

The update gate determines how much of the previous memory is retained and combined with the new input:

$$Z_t = \sigma(W_z \cdot [\mathrm{h_{z-1}}, x_t])$$

The hidden state can be obtained using the following formula:

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

The LSTM and GRU networks, by incorporating forget gates and update gates, effectively capture long-term dependency information, demonstrating widespread applications and excellent performance in fields such as time series forecasting, pattern recognition, and signal processing. The application of RNN-based algorithms provides new solutions for predicting complex problems in the field of civil engineering. Qing Kang et al. [20] combined the attention mechanism with the LSTM model to predict the posture and position of the tunnel boring machine, improving prediction accuracy. The average R-squared value increased from 0.625 to 0.736, while the average root mean square error (RMSE) decreased from 3.31 to 2.24. Iman Ranjbar et al. [36] developed two architectures based on the LSTM network to assess the distributed damage of concrete, including a classification model and a regression model. They used time-series ultrasound response signals as input, which outperformed manually extracted features.

2.2.2 Convolutional Neural Network (CNN)

CNN has become a competitive method in time series prediction due to its efficiency, flexibility, and feature learning capability. Compared to traditional time series

algorithms, CNN can quickly train on large-scale data by sharing convolution kernel parameters and performing parallel computation. It also automatically learns complex features from the data without relying on manually designed features. CNN is particularly effective at capturing periodicity and local trends, making it especially proficient in handling time series data with short-term fluctuations. Additionally, CNN has strong generalization capabilities(Zhang et al. 2024) , allowing it to handle both univariate and multivariate time series data. It can also be combined with other models(Huang et al. 2024; Bai et al. 2025), to further improve performance. In contrast, while RNN and LSTM can capture long-term dependencies, their training efficiency is lower, and they are less effective at extracting local features compared to CNN.

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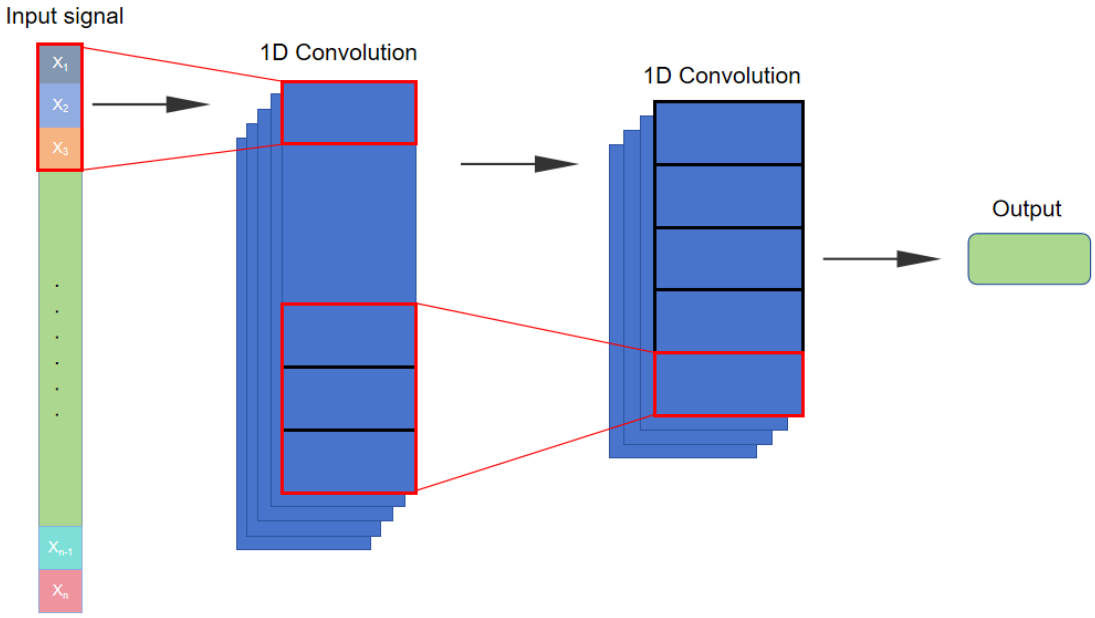


Figure 9. CNN 1D Convolution

The key characteristic of time series is its sequentiality and temporal correlation. CNN can extract the local features between consecutive time steps using one-dimensional convolution (1D Convolution). A typical CNN algorithm consists of several layers, including input layer, convolutional layer, activation layer, pooling layer, fully connected layer, and output layer. The core structure includes:

Input layer: Suppose the length of the input time series is T, and the data dimension at each time step is d. The input data can be represented as a two-dimensional matrix, where the rows correspond to time steps, and the columns correspond to the features at each time step.

Convolutional layer: The convolutional layer is the core component of CNN, primarily responsible for capturing local patterns and features in the sequence through sliding window operations. In 1D convolution, the convolutional layer uses a filter (or kernel) that slides over the input time series, computing the weighted sum of the filter and the local time window at each position. The convolutional kernel is a fixed-length small window with size $k \times d$, which slides within the time window of size k to extract the local features of each time step. The kernel size d is chosen to match the dimensionality of the input features. The convolution operation is defined by the following formula:

$$y_i = \sum_{k=1}^{K} w_k \cdot x_{i+k-1}$$

Here, x_i is the input sequence, y_i is the output sequence,

w_k are the parameters of the convolution kernel, and K is the size of the convolution kernel.

Activation Layer: The activation layer is a key component in neural networks, as it introduces non-linearity, allowing the network to learn complex patterns and mappings from the features output by the convolutional layer. In CNN, this layer is typically placed after each neuron's output and uses a non-linear function to transform the network's output. Common activation functions include ReLU, Sigmoid, Tanh, and Leaky ReLU, among others. For example, using the ReLU activation function:

$$Z_t = \mathrm{ReLU}(y_t) = \max(0, y_t)$$

In this case, y_t represents the value input into the activation function. The activation function enables the network to capture more complex patterns, enhances the model's non-linear expression ability, and improves its predictive performance.

Pooling layer: The pooling layer is a crucial component of CNN, typically placed after the convolutional layer, and serves to reduce the dimensionality and summarize the features extracted by the convolutional layer. The main purpose of the pooling layer is to decrease the spatial dimensions (i.e., the width and height of the image or feature map), thus reducing the computational load and number of parameters, while retaining the essential features. In time series processing, max pooling is commonly used:

$$Z_t = \max(x_t, x_{t+1}, \ldots, x_{t+k-1})$$

or average pooling:

$$z_t = \frac{1}{k}\sum_{i=0}^{k-1} x_{t+i}$$

Where z_t represents the pooling result corresponding to the current time step t, and $x_t, x_{t+1}, \ldots, x_{t+k-1}$ represents the values from the input data sequence. These values come from the original time series data, containing the input values from t for k consecutive time steps.

CNN, when handling time series data, significantly reduces the model's parameter count through parameter sharing, improving computational efficiency and reducing the risk of overfitting. By stacking multiple convolutional layers or adjusting the convolution kernel size, CNN can flexibly extract features at different scales, balancing both local and global patterns, thus adapting to a wide range of task requirements. The application of CNN algorithms provides a new approach to solving complex prediction problems in the field of civil engineering. Furkan Elmaz et al. [11] proposed a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) architecture for indoor temperature prediction. This architecture outperformed both the Multi-Layer Perceptron (MLP) and standalone LSTM models across all prediction ranges, demonstrating superior robustness. Shuting Chen et al. [5] combined the CNN algorithm to extract local patterns related to the spatial characteristics of pavement deformation basins, providing high-quality features for subsequent LSTM time series modeling. This approach enabled high-precision prediction of the pavement deformation basin area (DBA).

3. AI methods in surface settlement prediction

Traditional surface settlement prediction methods mainly rely on empirical formulas, analytical methods, and numerical simulations. However, these approaches have limitations in prediction accuracy and applicability. In contrast, machine learning (ML) and deep learning (DL) methods are capable of processing large and complex datasets, automatically learning the nonlinear relationships between input features and surface settlement, without relying heavily on physical assumptions. The advantages of ML/DL methods lie in their high flexibility and adaptability, enabling them to capture complex factors that are difficult to model with traditional methods, thus improving prediction accuracy. However, these methods require high-quality data and have relatively poor model interpretability.

3.1 Transformation of the surface settlement prediction problem

Surface settlement prediction based on ML/DL methods is inherently a regression prediction problem. In surface settlement prediction, multivariate regression and time series forecasting methods are commonly used. Multivariate regression forecasting utilizes multiple independent variables (features) to predict a dependent variable (target value). In surface settlement prediction, this may include various independent variables such as geological conditions, tunnel parameters, construction factors, etc. The advantage of this approach lies in its ability to comprehensively consider various factors, thereby improving the overall accuracy of the prediction. However, the model complexity is relatively high, which may lead to overfitting. On the other hand, time series forecasting predicts based on data arranged in chronological order, considering the trend of data changes over time. In surface settlement prediction, monitoring data that changes over time can be used to forecast future settlement. The advantage of this approach lies in its ability to capture dynamic changes over time. However, it requires high temporal consistency and completeness of the data and may be influenced by seasonal and cyclical factors. To better utilize ML/DL methods, it is necessary to transform and analyze the surface settlement prediction problem to some extent.

3.1.1 Maximum Surface Settlement (MSS) prediction

When using multiple regression prediction, it is necessary to first identify key factors that influence settlement as

independent variables, such as tunnel depth, diameter, geological conditions, construction methods, etc., with surface settlement as the dependent variable. By collecting a large amount of data samples containing these independent and dependent variables, a multiple regression model is constructed. Finally, machine learning algorithms (such as random forests, gradient boosting trees, etc.) are used to automatically learn the complex relationships between the independent and dependent variables, thereby enabling accurate prediction of the Maximum Surface Settlement (MSS).

3.1.2 Surface Settlement Time Series (SSTS) prediction

When using time series forecasting, settlement monitoring data should be arranged in chronological order to construct a time series model. Considering the changing trends and seasonality of settlement data over time, deep learning algorithms (such as Long Short-Term Memory networks, LSTM, and Gated Recurrent Units, GRU) are employed to capture long-term dependencies and dynamic changes within the time series. By training the model to learn temporal patterns from historical settlement data, future settlement trends (SSTS) can be predicted. This method is particularly suitable for scenarios where settlement data evolves continuously over time with periodicity, as well as for long-term automated monitoring of surface settlement.

3.2 ML and DL based surface settlement prediction

Through a search in the Web of Science (WOS) database, 256 articles related to surface settlement prediction published from 2016 to 2025 were found. These articles were processed using Citespace software to generate the keyword clustering distribution map shown in Figure 10, which illustrates the clustering of keywords from relevant research papers. The different colors of the clusters and labels represent different research topics or groups of keywords. Figure 10 indicates that recent research has mainly focused on construction parameters and machine learning studies. Additionally, techniques from computer science and statistics, such as machine learning and Bayesian methods, are increasingly being applied in the field of surface settlement prediction. The application of numerical models and imaging technologies in surface settlement prediction can help researchers more accurately simulate and forecast surface settlement. However, a single method is often insufficient to address the complex problem of surface settlement. The integrated use of multiple methods and technologies, such as combining machine learning with numerical models, is a key focus of future research. This suggests that with the advancement of big data, computational power, and the interdisciplinary integration of surface settlement prediction with the field of computer science, machine learning techniques are playing an increasingly important role in tackling complex surface settlement problems.

By analyzing 21 high-quality articles, as shown in Tables 1 and 2, recent research in the field of surface settlement prediction has primarily focused on the application of new algorithms, the adoption of new optimization methods, and feature engineering. Through the introduction of new algorithms, parameter tuning, and feature selection and construction, the goal has been to improve the accuracy and robustness of prediction models.

Table 1 shows that SVM, LSTM, and RF are the most frequently used algorithms in surface settlement prediction. Researchers have explored various algorithms, ranging from traditional machine learning techniques to deep learning methods. This suggests that no single algorithm is universally optimal, as different algorithms perform differently across various scenarios and datasets. Additionally, only six related studies involve surface settlement time series prediction (SSTS), indicating that this approach is rarely adopted in current research. However, some studies on maximum surface settlement prediction still employ algorithms that are more suited for time series prediction tasks related to surface settlement. In Mahmoodzadeh's study [30], LSTM was used, and its prediction accuracy was only surpassed by DNNS. In the articles related to surface settlement time series prediction, the R2 values for SSTS predictions were all greater than 0.95, which is higher than the average R2 value of 0.9 in MSS predictions. This indicates that surface settlement time series prediction (SSTS) holds significant potential.

In Table 2 , T stands for tunnel excavation parameters, G denotes geometric parameters, and S signifies shield parameters, Table 2 shows that some studies use a single type of feature for prediction, while others, such as STF-Network and 3D-ResUnite, combine multiple features to enhance prediction accuracy. Some studies focus particularly on feature engineering, for example, using Karst boundary and cave features, indicating that well-chosen features can significantly improve model performance. Additionally, current research incorporates various optimization strategies, including the introduction of new algorithms, parameter tuning, and feature selection. Combining these strategies often results in better prediction outcomes.

4. A case for time series prediction of surface settlement

4.1 Brief introduction of dataset

In this study, a 267-metre-long and 80-metre-wide section of the tunnel through the airport was selected to predict surface settlement. This section contains 159 monitoring points that were measured with the MS60 3D scanning robot. The measurement robot works with continuous measurement, the target search mode is super search, the

scanning frequency is 30 KHz, the standard deviation of angle measurement is 1, the standard deviation of distance measurement is 2 mm + 1.5 ppm, and the standard deviation of the elevation measurement is 2.0 mm. The spacing of the measurement points along the tunnel excavation direction was maintained to coincide with the construction progress. 159 monitoring sites were observed and 287,297 samples were obtained, with an average collection interval of 3.85 hours and 290 d of continuous monitoring.

By employing the MATLAB resampling function, the signals from 1,792 (equals to 7×2^8) resample points were obtained. Then, a combination of the MATLAB filloutlier function and medfilt function was used for data outliers. The filloutlier function detects outliers using the 'Generalized Extreme Studentized Deviate (GESD)' method, a statistically robust approach for identifying data points that significantly deviate from the rest of the dataset, and replaces them with spline interpolation to estimate values based on the overall trend of the data, ensuring smoothness and continuity. Simultaneously, the medfilt function applies median filtering, calculating the median value within a sliding window of eight sample lengths around each data point to effectively remove noise and outliers while preserving the data's essential features. The combination of these two methods—filloutlier for outlier detection and replacement, and medfilt for noise reduction—ensures the data is consistent, reliable, and free from distortions, providing a high-quality foundation for accurate analysis and robust modeling. This preprocessing step is crucial for enhancing data integrity and supporting subsequent computational tasks.

The ML algorithms introduced in this paper are support vector machine (SVM), random forest (RF), extreme learning machine (ELM), and back propagation (BP). Deep learning algorithms include convolutional neural networks (CNN), long short-term memory networks (LSTM), and gated recurrent units (GRU).

During training, the dataset was divided into small batches. To optimize GPU performance and prevent variations in data batch fluctuations from affecting the loss, the resampled signals must contain integer multiples of the minimum batch size, chosen as a power of 2 due to hardware limitations. The minimum batch size is a hyperparameter whose optimal value is determined through experimentation. In this study, the author determined the minimum batch size as 32. Additionally, a dynamic validation set was used to maintain sample size and validation features, preventing overfitting and ensuring model reliability. Validation iterations depended on batch and simplex sizes.

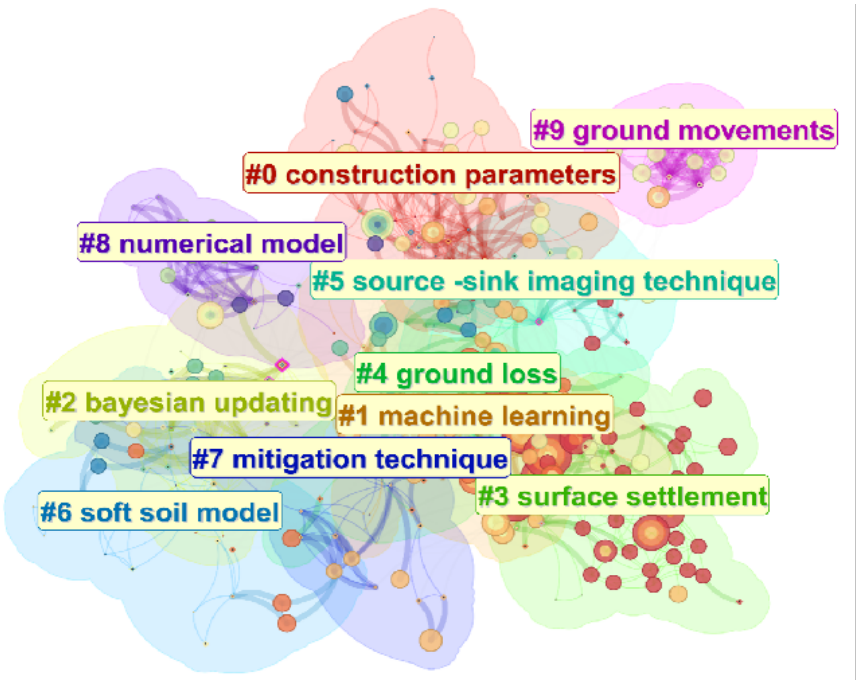


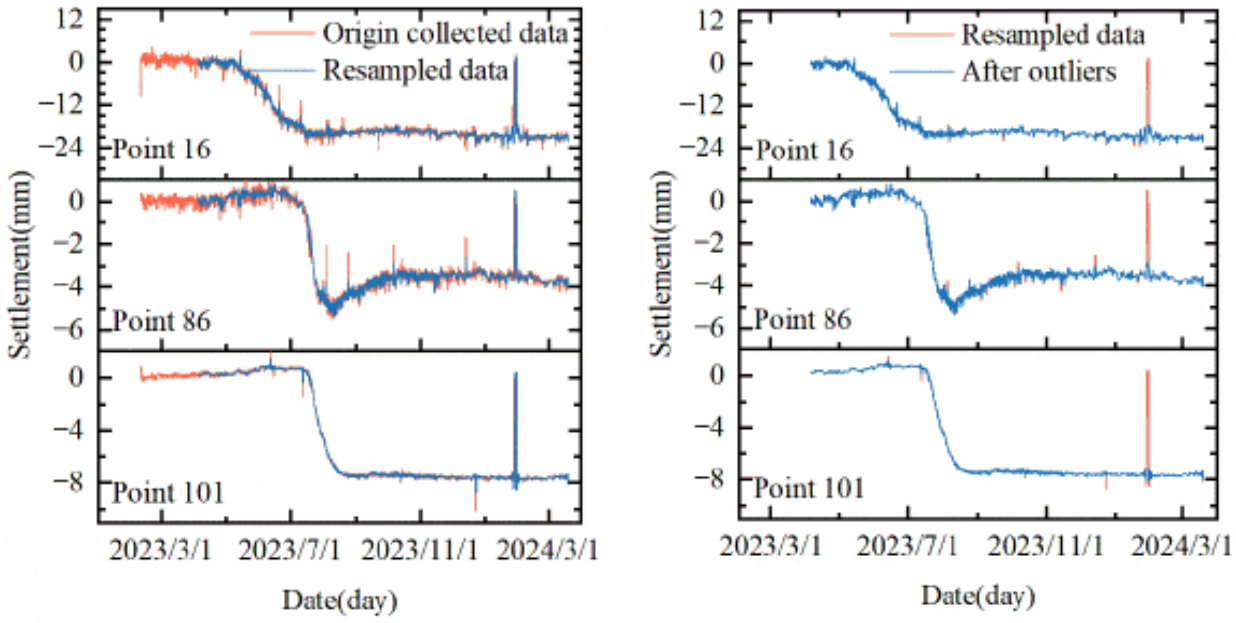
Figure 10. Keyword clustering distribution map

Table 1. Algorithm statistics table

Researcher	Algorithms	Number of features	Prediction type
Mahmoodzadeh	LSTM, DNNS, KNN, GPR, SVR, DT, LR	6	MSS
Mohammadi. F	MR, MLP, BP	6	MSS
V. R. Kohestani	RF, ANN	9	MSS
Jingsheng Shi	BPNN, MNN	11	MSS
Abouzar Darabi	AANN, BPNN	19	MSS
Santos Jr.	ANN	14	MSS
Da Hu	BP, PSO, PSO-BP, AWPSO-BP, PWPSO-BP	12	MSS
A. Pourtaghi	ANN, Wavenet, BP	9	MSS
Hasanipanah	ANN, PSO, PSO-ANN	5	MSS
Qing Kang	Attention-LSTM	9	SSTS
Ning Zhang	LSTM, GRU and Conv1d	18	SSTS
Dongku Kim	SVR, RF, GBM, XGB and LGBM	32	MSS
Chen, L.	STF-Network, 3D-ResUnit	/	MSS
Chen, R.-P	BP, RBF, GRNN	10	MSS
Kumar, A	LSTM	1	SSTS
Ren, M	DTW, GRA, ARM, SVR	1	SSTS
Zhang, P	LSTM, RF, PSO, GRG	13	Both
Zhang, W.G	XGBoost, ANN, SVM, MARS	7	MSS
Hai-ying Fu	BP, RF	4	MSS
Fu-Chao Kong	PSO-ELM	7	SSTS
Chao Zhou	RF	10	MSS

Table 2. Parameter types and optimisation tables

Researcher	T	G	S	Special parameter	Optimization approach
Mahmoodzadeh	Yes	Yes	Yes	None	Algorithm Comparison
Mohammadi. F	Yes	Yes	None	None	New Algorithm
V. R. Kohestani	Yes	Yes	None	None	New Algorithm
Jingsheng Shi	Yes	Yes	None	None	New Algorithm
Abouzar Darabi	Yes	Yes	None	None	Algorithm Comparison
Santos Jr.	Yes	Yes	None	None	Feature Selection
Da Hu	Yes	Yes	None	None	New Algorithm
A. Pourtaghi	Yes	Yes	None	None	New optimizer
Hasanipanah	Yes	Yes	None	None	New optimizer
Qing Kang	Yes	Yes	Yes	None	New Algorithm
Ning Zhang	Yes	Yes	None	Karst cave features	Extended model, new indicators
Dongku Kim	Yes	Yes	Yes	None	New optimizer
Chen, L.	None	None	None	None	New Algorithm
Chen, R.-P	Yes	Yes	Yes	None	improved indicators
Kumar, A	None	None	None	Only settelment	New Algorithm
Ren, M	None	None	None	Only settelment	New Algorithm
Zhang, P	Yes	Yes	Yes	anomalies parameters	Feature Selection, New optimizer
Zhang, W.G	Yes	Yes	Yes	None	Feature Selection
Hai-ying Fu	None	None	None	Karst boundary	New indicators
Fu-Chao Kong	None	Yes	Yes	None	New Algorithm
Chao Zhou	Yes	Yes	Yes	None	Algorithm Comparison



(a) Resampling processing (b) Outlier processing

Figure 11. Typical monitoring points' data preprocessing

4.2 Evaluation of different AI methods

The most commonly utilised metrics for the evaluation of predictive model performance encompass R-squared (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute percentage Error (MAPE).

The value of R^2 ranges from 0 to 1, with a closer proximity to 1 indicating a superior model fit:

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\bar{y}_i - y_i)^2}$$

RMSE is a common measure of the discrepancy between an observed value and a true value. A lower RMSE value indicated a smaller deviation between the observed and true values:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_i (y_i - \hat{y}_i)^2}$$

MAE and MAPE were calculated as the mean of the absolute value of the difference between the predicted and actual values. Additionally, MAE and MAPE were calculated as the mean of the absolute value as a proportion of the actual value. It is desirable for these values to be as small as possible:

$$MAE = \frac{1}{n}\sum_i \left| \hat{y}_i - y_i \right|$$

$$MAPE = \frac{100\%}{n}\sum_i \left| \frac{\hat{y}_i - y_i}{y_i} \right|$$

Table 3 presents the four evaluation indices of the predicted value of the surface settlement for each algorithm, including the original and improved algorithms. As shown in Table 3, the mean R^2 of each original algorithm is 0.9938, the root mean square error is 0.2162 mm, the mean error is 0.1449, and the mean error percentage is 8.536 %. RF and ELM performed best in the surface settlement time series prediction task with high prediction accuracy and low error. While BP performs relatively average, other algorithms such as CNN, Bi-GRU, Bi-LSTM, PSO-LSTM and PSO-GRU perform moderately well, each with certain application scenarios and values. However, this assessment is specifically targeted at the Kunming dataset, the generalizability of these models to other datasets remains uncertain due to potential region-specific biases and limitations in the dataset's diversity. For instance, preprocessing techniques and features optimized for Kunming's geological and environmental conditions may not translate well to datasets from other regions with differing characteristics. Additionally, the dataset may overrepresent certain conditions, leading to overfitting and reduced performance on new data. To enhance generalizability, future work should incorporate diverse datasets, employ adaptive preprocessing methods, and identify universal features relevant across various scenarios. Cross-dataset validation is also essential to ensure the models' robustness and applicability beyond the Kunming dataset.

Table 3. R2, RMSE, MAE and MAPE using ATD model algorithm

Algorithm	R2	RMSE	MAE	MAPE
SVM	0.99365	0.327	0.269	20.02%
RF	0.99943	0.098	0.043	2.78%
ELM	0.99962	0.080	0.040	2.67%
BP	0.98278	0.539	0.341	14.40%
CNN	0.99876	0.145	0.085	5.43%
BI-GRU	0.99666	0.237	0.197	10.29%
BI-LSTM	0.99896	0.132	0.094	4.20%
PSO-LSTM	0.99669	0.236	0.116	7.99%
PSO-GRU	0.99800	0.184	0.135	9.04%

5. Discussion

Current research mainly focuses on the application of artificial intelligence methods, particularly machine learning and deep learning algorithms, to predict surface settlement induced by tunnel excavation. These studies encompass not only the prediction of Maximum Surface Settlement (MSS) but also the prediction of Surface Settlement Time Series (SSTS), offering a more comprehensive understanding of the dynamic changes in surface settlement. Algorithms play a pivotal role in the current landscape of surface settlement prediction.

However, many AI models, function as "black boxes" , making it challenging to interpret how predictions are generated. This lack of transparency can hinder their adoption in engineering applications, where understanding the underlying mechanisms is essential. Additionally, training advanced AI models, especially DL models, demands substantial computational resources (e.g., GPUs or TPUs) and time, which can pose a significant barrier to practical implementation, particularly in resource-constrained environments. Furthermore, AI models trained on specific datasets often struggle to generalize to different geological conditions or construction scenarios. Variations in soil properties, groundwater levels, or construction methods can significantly reduce prediction accuracy when applied to new environments.

Traditional methods, such as the convergence-confinement method, are grounded in well-established physical principles and offer clear interpretability. However, they often rely on simplified assumptions and may fail to fully capture the complexity of soil behavior. In contrast, AI models excel at learning intricate patterns from data but typically lack physical interpretability. Similarly, the Finite Element Method (FEM) is highly versatile and capable of simulating complex geotechnical conditions with high accuracy. Nevertheless, FEM demands significant expertise and computational resources for model setup and analysis. While AI models are data-driven and adept at handling nonlinearity and large datasets, they do not inherently incorporate physical laws, which can lead to less reliable predictions in scenarios where physical constraints are critical. In summary, traditional methods are more interpretable and physically grounded but are often constrained by their assumptions and computational demands. On the other hand, AI models excel in processing complex data but may suffer from a lack of transparency and struggle with extrapolation beyond their training data.

In terms of feature engineering, specific methods often cannot be directly applied to other engineering scenarios. This is because the selection and optimization of feature engineering approaches are highly dependent on the specific research context and data characteristics. For instance, methods that utilize unique parameters such as Karst boundaries and cave features may yield significant results in regions with similar geological conditions but may not be applicable in areas with different geological settings. Similarly, prediction methods based on time series data may perform exceptionally well in scenarios where the data exhibits strong temporal characteristics. However, their effectiveness may diminish in cases of missing data or when temporal features are less pronounced. Consequently, a single feature engineering approach lacks generalizability. To enhance the accuracy and robustness of predictive models, it is essential to select and optimize feature engineering methods tailored to the specific research context and data characteristics.

High-quality, labeled datasets for ground surface settlement are often scarce due to the high cost and complexity of data collection. Limited datasets can result in overfitting and poor generalization of AI models, compromising their effectiveness. Additionally, datasets may be biased toward specific geological conditions or construction methods, causing models to perform well only in similar contexts and limiting their applicability to diverse scenarios. Furthermore, data preprocessing steps, such as normalization and feature selection, play a critical role in model performance. Inadequate preprocessing choices can introduce noise or discard essential information, ultimately reducing prediction accuracy.

Therefore, in current research, both the application and improvement of algorithms coexist, with a stronger

emphasis on the improvement of algorithms. This is because the diversity and complexity of data in surface settlement prediction make it challenging to directly apply existing algorithms and achieve ideal results. As a result, researchers tend to experiment with various algorithms to identify the most suitable solution for specific scenarios and datasets. Based on the literature review and example analysis, in surface settlement prediction, the most recommended algorithms are Long Short-Term Memory (LSTM) networks or their variants, such as Gated Recurrent Units (GRU). The reason for this is that LSTM and GRU excel at handling time-series data and can effectively capture long-term dependencies within the data, which is crucial for surface settlement time-series prediction. Nevertheless, as research progresses, there has been an increasing focus on algorithm optimization and improvement, such as introducing new function optimizers to enhance training efficiency and prediction accuracy, or conducting feature engineering to select and optimize input parameters, further boosting the performance of prediction models. Moreover, these algorithms have been shown to exhibit high prediction accuracy and robustness in several studies. For example, Qing Kang et al.(Kang et al. 2023) combined an attention mechanism with the LSTM model to predict the posture and position of a shield machine, significantly improving prediction accuracy.

Currently, significant progress has been made in predicting surface settlement caused by tunnel excavation using artificial intelligence methods, particularly machine learning and deep learning algorithms. These algorithms have not only improved prediction accuracy but also expanded the scope of predictions, ranging from maximum surface settlement to surface settlement time series, providing strong support for engineering practice.

In the future, research on surface settlement prediction could integrate the physical mechanisms underlying surface settlement to further improve prediction accuracy and reliability. Surface settlement is a complex physical process involving various factors, such as soil compression, deformation, and changes in pore water pressure. By gaining a deeper understanding of these physical mechanisms, more accurate predictive models can be developed, capable of capturing the interactions and dynamic changes among different factors. For example, numerical simulation methods can be incorporated to simulate the development of surface settlement under various construction parameters and geological conditions, providing machine learning algorithms with richer training data and features. Additionally, advancements in automated monitoring technologies enable researchers to obtain more accurate geological and construction parameter information, offering more reliable inputs for predictive models. This approach—integrating physical mechanisms with machine learning algorithms—holds the potential not only to improve prediction accuracy and generalization but also to deepen the understanding of the complex processes of surface settlement. Such an approach can provide more scientific guidance for engineering practices. While this research direction is promising, it requires interdisciplinary collaboration and in-depth investigation. Moreover, ML and DL algorithms can also be utilized to improve dataset quality, thereby enhancing prediction accuracy. For example, data augmentation can be employed to generate diverse samples [47], auto-labeling and semi-supervised learning can reduce the cost of manual annotation [25], data cleaning techniques can repair noise and missing values [34] and generative adversarial networks (GANs) [35] can create high-quality synthetic data to compensate for data scarcity. These methods, when combined, can significantly enhance the quality, scale, and diversity of datasets, ultimately improving model performance and generalization capabilities.

6. Conclusion

In this review, we systematically summarize the progress made in the application of machine learning (ML) and deep learning (DL) to land subsidence prediction. We introduce the core principles of commonly used ML and DL algorithms for land subsidence prediction. The land subsidence problem is categorized into the following types: maximum land subsidence (MSS) prediction and land subsidence time series (SSTS) prediction. Using the Kunming dataset, we validate the effectiveness of various algorithms, including SVM, RF, ELM, BP, CNN, BI-GRU, BI-LSTM, PSO-LSTM, and PSO-GRU, in land subsidence prediction. Additionally, we discuss the advantages and limitations of ML and DL algorithms compared to traditional prediction methods.

This paper offers an in-depth analysis of the current use and effectiveness of machine learning and deep learning algorithms in this field. The study highlights the limitations of traditional prediction methods, which often struggle to meet the demands of complex and dynamic engineering scenarios due to challenges in parameter determination and reliance on empirical values. In contrast, machine learning and deep learning algorithms, such as Support Vector Machines (SVM), Random Forests (RF), Extreme Learning Machines (ELM), XGBoost, and Recurrent Neural Networks (RNN), have shown significant improvements in prediction accuracy and generalization capabilities by automatically learning complex features and temporal dependencies within data.

In particular, recurrent neural networks (RNN) and their variants, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have demonstrated exceptional performance in handling time-series data, offering innovative solutions for surface settlement time-series prediction. Through a thorough literature review and case analysis, this paper highlights the varying performance of different algorithms across diverse scenarios and datasets, underscoring the critical importance of algorithm selection and optimization.

However, ML and DL also face significant limitations in engineering applications: lack of transparency, making it difficult to interpret prediction processes; training requires substantial computational resources and time; scarce and biased datasets for ground surface settlement often lead to overfitting, poor generalization, and reduced AI model accuracy. While AI models excel at handling complex data, they fall short in transparency, generalization, and physical consistency. Current research faces several challenges, such as the need for targeted algorithm improvements and the generalizability of feature engineering methods. Future studies should integrate the physical mechanisms of surface settlement to further enhance the accuracy and reliability of predictive models. For example, combining numerical simulations with field monitoring data can provide richer training data and features for machine learning algorithms, thereby enabling the construction of more accurate predictive models. Furthermore, interdisciplinary collaboration and in-depth research will be key drivers for advancing this field. In summary, with the increase in big data and computational capabilities, artificial intelligence methods will play an increasingly important role in predicting surface settlement induced by tunnel excavation.

Credit author statement

ZeKun Zhu: Writing-Original draft preparation, Conceptualization, Methodology, Software. Chang Liu: Conceptualization, Data curation, Writing - Review & Editing, Funding acquisition.

Conflicts of interests

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

References

[1] Bai W, Zheng G, Mu Y, Ma H, Han Z, Xue Y. Cooperative spectrum sensing method based on channel attention and parallel CNN-LSTM. *Digital Signal Processing*. 2025 Mar 1;158:104963. doi: 10.1016/j.dsp.2024.104963.

[2] Boscardin MD, Cording EJ. Building response to excavation-induced settlement. *Journal of Geotechnical engineering*. 1989 Jan;115(1):1-21.

[3] Chen L, Hashiba K, Liu Z, Lin F, Mao W. Spatial-temporal fusion network for maximum ground surface settlement prediction during tunnel excavation. *Automation in Construction*. 2023 Mar 1;147:104732. doi: 10.1016/j.autcon.2022.104732.

[4] Chen RP, Zhang P, Kang X, Zhong ZQ, Liu Y, Wu HN. Prediction of maximum surface settlement caused by earth pressure balance (EPB) shield tunneling with ANN methods. *Soils and Foundations*. 2019 Apr 1;59(2):284-95. doi: 10.1016/j.sandf.2018.11.005.

[5] Chen S, Cao J, Wan Y, Huang W, Abdel-Aty M. A novel CPO-CNN-LSTM based deep learning approach for multi-time scale deflection basin area prediction in asphalt pavement. *Construction and Building Materials*. 2025 Jan 10;458:139540. doi: 10.1016/j.conbuildmat.2024.139540.

[6] Chen T, Guestrin C. Xgboost: A scalable tree boosting system. InProceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining 2016 Aug 13 (pp. 785-794). doi: 10.1145/2939672.2939785.

[7] Cheng MY, Hoang ND, Wu YW. Hybrid intelligence approach based on LS-SVM and Differential Evolution for construction cost index estimation: A Taiwan case study. *Automation in Construction*. 2013 Nov 1;35:306-13. doi: 10.1016/j.autcon.2013.05.018.

[8] Cortes C, Vapnik V. Support-vector networks. *Machine learning*. 1995 Sep;20:273-97. doi: 10.1007/BF00994018.

[9] Dong W, Huang Y, Lehane B, Ma G. XGBoost algorithm-based prediction of concrete electrical resistivity for structural health monitoring. *Automation in Construction*. 2020 Jun 1;114:103155. doi: 10.1016/j.autcon.2020.103155.

[10] Dong X, Lian Y, Liu Y. Small and multi-peak nonlinear time series forecasting using a hybrid back propagation neural network. *Information Sciences*. 2018 Jan 1;424:39-54. doi: 10.1016/j.ins.2017.09.067.

[11] Elmaz F, Eyckerman R, Casteels W, Latré S, Hellinckx P. CNN-LSTM architecture for predictive indoor temperature modeling. *Building and Environment*. 2021 Dec 1;206:108327. doi: 10.1016/j.buildenv.2021.108327.

[12] Fu HY, Zhao YY, Ding HJ, Rao YK, Yang T, Zhou MZ. A novel intelligent displacement prediction model of karst tunnels. *Scientific Reports*. 2022 Oct 10;12(1):16983. doi: 10.1038/s41598-022-21333-x.

[13] Huang GB, Zhu QY, Siew CK. Extreme learning machine: a new learning scheme of feedforward neural networks. In2004 IEEE international joint conference on neural networks (IEEE Cat. No. 04CH37541) 2004 Jul 25 (Vol. 2, pp. 985-990). Ieee. doi: 10.1109/IJCNN.2004.1380068.

[14] Guo Y, Jia X, Li X, Wang Y, Kumar R, Sharma R, Swaminathan M. Extrapolation With Range Determination of 2-D Spectral Transposed Convolutional Neural Network for Advanced Packaging Problems. *IEEE Transactions on Components, Packaging and Manufacturing Technology*. 2023 Sep 22;13(10):1533-44. doi: 10.1109/TCPMT.2023.3317851.

[15] Hasanipanah M, Noorian-Bidgoli M, Jahed Armaghani D, Khamesi H. Feasibility of PSO-ANN model for predicting surface settlement caused by tunneling.

Engineering with Computers. 2016 Oct;32:705-15. doi: 10.1007/s00366-016-0447-0.

[16] Hoła A, Czarnecki S. Random forest algorithm and support vector machine for nondestructive assessment of mass moisture content of brick walls in historic buildings. *Automation in Construction*. 2023 May 1;149:104793. doi: 10.1016/j.autcon.2023.104793.

[17] Huang H, Wang Z, Liao Y, Gao W, Lai C, Wu X, Zeng Z. Improving the explainability of CNN-LSTM-based flood prediction with integrating SHAP technique. *Ecological Informatics*. 2024 Dec 1;84:102904. doi: 10.1016/j.ecoinf.2024.102904.

[18] Huang M, Zhou X, Yu J, Leung CF, Tan JQ. Estimating the effects of tunnelling on existing jointed pipelines based on Winkler model. *Tunnelling and Underground Space Technology*. 2019 Apr 1;86:89-99. doi: 10.3390/app12073342.

[19] Jia P, Zhao W, Khoshghalb A, Ni P, Jiang B, Chen Y, Li S. A new model to predict ground surface settlement induced by jacked pipes with flanges. *Tunnelling and Underground Space Technology*. 2020 Apr 1;98:103330. doi: 10.1016/j.tust.2020.103330.

[20] Kang Q, Chen EJ, Li ZC, Luo HB, Liu Y. Attention-based LSTM predictive model for the attitude and position of shield machine in tunneling. *Underground Space*. 2023 Dec 1;13:335-50. doi: 10.1016/j.undsp.2023.05.006.

[21] Kim D, Kwon K, Pham K, Oh JY, Choi H. Surface settlement prediction for urban tunneling using machine learning algorithms with Bayesian optimization. *Automation in construction*. 2022 Aug 1;140:104331. doi: 10.1016/j.autcon.2022.104331.

[22] Kong F, Lu D, Ma Y, Tian T, Yu H, Du X. Novel hybrid method to predict the ground-displacement field caused by shallow tunnel excavation. *Science China Technological Sciences*. 2023 Jan;66(1):101-14. doi: 10.1007/s11431-022-2079-8.

[23]Koo B, La S, Cho NW, Yu Y. Using support vector machines to classify building elements for checking the semantic integrity of building information models. *Automation in Construction*. 2019 Feb 1;98:183-94. doi: 10.1016/j.autcon.2018.11.015.

[24] Kumar S, Kumar D, Donta PK, Amgoth T. Land subsidence prediction using recurrent neural networks. Stoch Environ Res Risk Assess [Internet]. 2022 Feb [cited 2024 Sep 7];36(2):373–88. doi: 10.1007/s00477-021-02138-2.

[25] Liu H, Chen H, Du J, Xie C, Zhou Q, Wang R, Jiao L. Auto-adjustment label assignment-based convolutional neural network for oriented wheat diseases detection. *Computers and Electronics in Agriculture*. 2024 Jul 1;222:109029. doi: 10.1016/j.compag.2024.109029.

[26]Liu Y, Liu L, Yang L, Hao L, Bao Y. Measuring distance using ultra-wideband radio technology enhanced by extreme gradient boosting decision tree (XGBoost). *Automation in Construction*. 2021 Jun 1;126:103678. doi: 10.1016/j.autcon.2021.103678.

[27] Liu Y, Shu B, Chen Y, Zhang H. Spatial vulnerability assessment of rural settlements in hilly areas using BP neural network algorithm. *Ecological Indicators*. 2023 Dec 15;157:111278. doi: 10.1016/j.ecolind.2023.111278.

[28] Loganathan N, Poulos HG. Analytical prediction for tunneling-induced ground movements in clays. *Journal of Geotechnical and geoenvironmental engineering*. 1998 Sep;124(9):846-56. doi: 10.1061/(ASCE)1090-0241(1998)124:9(846).

[29] Lu D, Kong F, Du X, Shen C, Gong Q, Li P. A unified displacement function to analytically predict ground deformation of shallow tunnel. *Tunnelling and Underground Space Technology*. 2019 Jun 1;88:129-43. doi: 10.1016/j.tust.2019.03.005.

[30] Mahmoodzadeh A, Mohammadi M, Daraei A, Ali HF, Al-Salihi NK, Omer RM. Forecasting maximum surface settlement caused by urban tunneling. *Automation in Construction*. 2020 Dec 1;120:103375. doi: 10.1016/j.autcon.2020.103375.

[31] Mariniello G, Pastore T, Asprone D, Cosenza E. Layout-aware extreme learning machine to detect tendon malfunctions in prestressed concrete bridges using stress data. *Automation in Construction*. 2021 Dec 1;132:103976. doi: 10.1016/j.autcon.2021.103976.

[32] Olsen PC. Evaluation of triangular plate elements in rigid-plastic finite element analysis of reinforced concrete. *Computer methods in applied mechanics and engineering*. 1999 Aug 1;179(1-2):1-7. doi: 10.1016/S0045-7825(99)00038-9.

[33] O'Sullivan C. Particulate discrete element modelling: a geomechanics perspective. CRC Press; 2011 Apr 6.

[34] Peng J, Shen D, Nie T, Kou Y. RLclean: An unsupervised integrated data cleaning framework based on deep reinforcement learning. *Information Sciences*. 2024 Nov 1;682:121281. doi: 10.1016/j.ins.2024.121281.

[35] Qian C, Tang W, Wang Y. RGAnomaly: Data reconstruction-based generative adversarial networks for multivariate time series anomaly detection in the Internet of Things. *Future Generation Computer Systems*. 2025 Feb 10:107751. doi: 10.1016/j.future.2025.107751.

[36] Ranjbar I, Toufigh V. Deep long short-term memory (LSTM) networks for ultrasonic-based distributed damage assessment in concrete. *Cement and Concrete Research*. 2022 Dec 1;162:107003. doi: 10.1016/j.cemconres.2022.107003.

[37] Ren M, Cheng G, Zhu W, Nie W, Guan K, Yang T. A prediction model for surface deformation caused by underground mining based on spatio-temporal associations. *Geomatics, natural hazards and risk*. 2022 Dec 31;13(1):94-122. doi: 10.1080/19475705.2021.2015460.

[38] Ren Q, Li M, Kong T, Ma J. Multi-sensor real-time monitoring of dam behavior using self-

adaptive online sequential learning. *Automation in Construction*. 2022 Aug 1;140:104365. doi: 10.1016/j.autcon.2022.104365.

[39] Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. *Nature*. 1986 Oct 9;323(6088):533-6. doi: 10.1038/323533a0.

[40] Shen SL, Cui QL, Ho CE, Xu YS. Ground response to multiple parallel microtunneling operations in cemented silty clay and sand. *Journal of Geotechnical and Geoenvironmental Engineering*. 2016 May 1;142(5):04016001. doi: 10.1061/(ASCE)GT.1943-5606.0001441.

[41] Swaminathan M, Bhatti OW, Guo Y, Huang E, Akinwande O. Bayesian learning for uncertainty quantification, optimization, and inverse design. IEEE *Transactions on Microwave Theory and Techniques*. 2022 Oct 6;70(11):4620-34. doi: 10.1109/TMTT.2022.3206455.

[42] Tang XW, Gan PL, Liu W, Zhao Y. Surface settlements induced by tunneling in permeable strata: a case history of Shenzhen Metro. *Journal of Zhejiang University-Science A*. 2017 Oct 1;18(10):757-75. doi: 10.1631/jzus.A1600522.

[43] Wang F, Du X, Li P. Predictions of ground surface settlement for shield tunnels in sandy cobble stratum based on stochastic medium theory and empirical formulas. *Underground Space*. 2023 Aug 1;11:189-203. doi: 10.1016/j.undsp.2023.01.003.

[44] Wang X, Pan Y, Chen J. Digital twin with data-mechanism-fused model for smart excavation management. *Automation in Construction*. 2024 Dec 1;168:105749. doi: 10.1016/j.autcon.2024.105749.

[45] Wei G, Zhang XH, Xu YF, Wang Z. Prediction of ground settlement due to excavation of a quasi-rectangular shield tunnel based on stochastic medium theory. *Geotechnical and Geological Engineering*. 2019 Oct;37:3605-18. doi: 10.1038/s41598-024-74164-3.

[46] Wu X, Feng Z, Liu J, Chen H, Liu Y. Predicting existing tunnel deformation from adjacent foundation pit construction using hybrid machine learning. *Automation in Construction*. 2024 Sep 1;165:105516. doi: 10.1016/j.autcon.2024.105516.

[47] Xia Y, Cheng X, Hu X. Soil organic matter content prediction in tobacco fields based on hyperspectral remote sensing and generative adversarial network data augmentation. *Computers and Electronics in Agriculture*. 2025 Jun 1;233:110164. doi: 10.1016/j.compag.2025.11016.

[48] Xiong SH, Wang ZP, Li G, Skibniewski MJ, Chen ZS. Prediction of airport runway settlement using an integrated SBAS-InSAR and BP-EnKF approach. *Information Sciences*. 2024 Apr 1;665:120376. doi: 10.1016/j.ins.2024.120376.

[49] Xu Q, Lei S, Zhu Y, Zhao W, Wang C, Wang D. Theoretical prediction model for surface settlement caused by the excavation of new tunnels undercrossing existing tunnels based on modified stochastic medium theory. KSCE *Journal of Civil Engineering*. 2022 Sep;26(9):4136-45. doi: 10.1007/s12205-022-1911-6.

[50] Zhang J, Xu M, Cui M, Xin Y, Wang H, Su P. Prediction of ground subsidence caused by shield tunnel construction under hidden karst cave. *Geotechnical and Geological Engineering*. 2022 Jul;40(7):3839-50. doi: 10.1007/s10706-022-02136-3.

[51] Zhang N, Zhou A, Pan Y, Shen SL. Measurement and prediction of tunnelling-induced ground settlement in karst region by using expanding deep learning method. *Measurement*. 2021 Oct 1;183:109700. doi: 10.1016/j.measurement.2021.109700.

[52] Zhang P, Wu HN, Chen RP, Dai T, Meng FY, Wang HB. A critical evaluation of machine learning and deep learning in shield-ground interaction prediction. *Tunnelling and Underground Space Technology*. 2020 Dec 1;106:103593. doi: 10.1016/j.tust.2020.103593.

[53] Zhang WG, Li HR, Wu CZ, Li YQ, Liu ZQ, Liu HL. Soft computing approach for prediction of surface settlement induced by earth pressure balance shield tunneling. *Underground Space*. 2021 Aug 1;6(4):353-63. doi: 10.1016/j.undsp.2019.12.003

[54] Zhang Y, Fang Z, Fan J. Generalization analysis of deep CNNs under maximum correntropy criterion. *Neural Networks*. 2024 Jun 1;174:106226. doi: 10.1016/j.neunet.2024.106226.

[55] Zhang Z, Zhang M. Mechanical effects of tunneling on adjacent pipelines based on Galerkin solution and layered transfer matrix solution. *Soils and Foundations*. 2013 Aug 1;53(4):557-68. doi: 10.1016/j.sandf.2013.06.007.

[56] Zhang Z, Zhang M, Jiang Y, Bai Q, Zhao Q. Analytical prediction for ground movements and liner internal forces induced by shallow tunnels considering non-uniform convergence pattern and ground-liner interaction mechanism. *Soils and Foundation*s. 2017 Apr 1;57(2):211-26. doi: 10.1016/j.sandf.2017.03.004.

[57]Zheng Y, Yan J, Su R, Ma S, Li Y, Wang X, Zheng J, Zhu Y, Yu Y. Investigation of the settlement mechanism and control measures of a super-large section tunnel in a giant karst cave using ultra-thick backfill method. *Tunnelling and Underground Space Technology.* 2023 Jul 1;137:104956. doi: 10.1016/j.tust.2022.104956.

[58] Zhou J, Shi X, Du K, Qiu X, Li X, Mitri HS. Feasibility of random-forest approach for prediction of ground settlements induced by the construction of a shield-driven tunnel. *International Journal of Geomechanics*. 2017 Jun 1;17(6):04016129. doi: 10.1061/(ASCE)GM.1943-5622.0000817.

[59] Zhou Z, Ding H, Miao L, Gong C. Predictive model for the surface settlement caused by the excavation of twin tunnels. *Tunnelling and Underground Space Technology.* 2021 Aug 1;114:104014. doi: 10.1016/j.tust.2021.104014

[60] Zhang SG, Zhang XD, Li YJ. Prediction of ground surface settlement around foundation pits using artificial

neural networks. *Journal of Liaoning Technical University* (Natural Science Edition). 2001;(6):767–769.Available from: https://kns.cnki.net/kcms2/article/abstract?v=VcTOyLYtvEx7KQBwCECrXCf46qv1kGBL4W9c7gnW7MuY4IXa-5BNIgUZe84NtInqpsZg70XdiLKC3wP8jQrDkahGOQgKmKupbYkpT3dJUaUKP_bxouFXenoP2FpGXQ4KFOpf_rFBvACRJPE83_zJl7Azfk_kvClC9sogtnXqO7rbfPtgQPmsuo7h_6vuQzrS&uniplatform=NZKPT&language=CHS.

[61] Li WX, Zhai SH, Qiao JL. Analysis of ground surface subsidence caused by tunnel excavation and its effects. Chinese *Journal of Rock Mechanics and Engineering*. 2004;(S2):4752–4756. Available from: https://kns.cnki.net/kcms2/article/abstract?v=VcTOyLYtvEwz84YR8dZn92dNrvWdPyVewqlcbm2_772xAoQCVL3L4Kf8E96jKsB1G8Gnr9zyGwI49_79oBeDEA5UIDFOi6Pie_s5IBgRgdfgQaYAF8gxYBI75zHKD84brNDMpmnKz7SvYwr1C_2AU89oVsCnRr0e0fyyZn9jLkrNsfslJpk06aq_TcdpFoTZ&uniplatform=NZKPT&language=CHS.