Early Warning Model Construction for Deformation Monitoring and Management of Deep Foundation Pit Project Combined with Artificial Intelligence

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***Abstract*—In various engineering construction projects, construction safety problems caused by pit deformation continue to be solved. The existing early warning model for pit deformation management cannot effectively meet the needs of actual construction for complex pit projects. Artificial intelligence technology has more obvious advantages in foundation pit deformation detection due to its wide applicability, flexibility, and other characteristics. This study uses Gaussian regression analysis model to construct a corresponding deep foundation pit deformation monitoring and management warning model. The purpose is to better monitor and manage the deformation of deep foundation pits, ensuring the smooth and stable development of the entire construction project. In the experimental analysis, different performance indicators were used to verify the effectiveness of the research method, including different error indicators, precision, recall rate, F1 score, etc. MAE can effectively evaluate the deviation between predicted values and actual values, which indicates that the model is closer to the true value. Precision, recall, and F1 score can better evaluate the proportion of correctly classified samples and demonstrate the model's discriminative ability. These indicators comprehensively measure the performance of the model from different perspectives. In specific construction projects, the results showed that the proposed method had an RMSE of 0.012 and a MAE of 0.015, both significantly lower than the comparative methods, indicating better performance. The precision, recall, and F1 score of GRGA were 92.37%, 47.52%, and 0.17, respectively. In the comparison of existing foundation pit deformation monitoring methods BPNN, CNN, and GM, the precision was 90.52%, 90.03%, and 89.95%, respectively, the recall was 34.20%, 32.01%, and 29.67%, respectively, and the F1 score was 0.10, 0.13, and 0.14, respectively. The research method has more obvious advantages. The results demonstrate that the early warning model is an effective method for analyzing and predicting the deformation of deep foundation pits. The combination of Gaussian regression and genetic algorithm for deep excavation management can model and predict nonlinear deformation data, optimize the parameters of Gaussian regression process, and improve prediction accuracy. Compared with existing warning methods, the method proposed in this study utilizes Gaussian regression process to better model and analyze the deformation process of foundation pits, thus accurately analyzing the detailed changes of foundation pits.**

Keywords*—Deep foundation pit; deformation; Gaussian regression analysis; management warning; artificial intelligence

I. Introduction

In recent years, there has been a notable increase in the number of engineering projects, both large and small, that are being undertaken as a result of the continuous deepening of infrastructure construction. The construction of underground space has become a topic of significant research interest. In the construction process, deep foundation pit becomes a construction problem that must be solved. Influenced by factors such as geology, topography, climate, and construction forces, there are various risks and safety problems in deep foundation pits [1-2]. Common pit deformations are mainly categorized into surface settlement, enclosure deformation, and base elevation and deformation. Prediction of pit deformation can provide effective guidance for on-site construction and reduce potential risks that may occur during construction [3]. Enclosure works of the pit need to be stable enough to ensure the safety of foundation construction. In the specific construction process, the prediction of deep pit deformation is mainly based on the competent judgment of artificial experience, which has strong subjectivity and low accuracy. For example, a collapse accident occurred at a subway construction site in Hangzhou in 2008. The accident caused the nearby river to breach its banks and the river water to flow backwards. 11 vehicles driving on the road fell into a deep pit, and multiple workers were killed. A series of chain damage effects such as damage to nearby residential buildings and underground pipelines. The progressive integration of artificial intelligence and intelligent monitoring in engineering management has paved the way for the development of an effective early warning model for the management of deep foundation pit deformation [4-5]. However, although the deep excavation deformation warning model based on neural networks and grey models has achieved certain research success, there are still shortcomings. The existing methods mainly rely on manual operation, which is time-consuming and labor-intensive, and the monitoring efficiency is limited, making it difficult to detect small deformations. In addition, they have limited coverage in the monitoring process, which can easily lead to blind spots in inspection and monitoring, further increasing safety hazards. At the same time, such methods face difficulties in determining thresholds and large parameter quantities during the calculation process. Gaussian regression, a relatively novel artificial intelligence technology, has emerged as a prominent topic in intelligent learning, with successful applications spanning diverse domains such as engineering construction and intelligent prediction. Based on the advantages of Gaussian regression modeling in early warning analysis, a deep excavation deformation management early warning model based on Gaussian process regression is studied and constructed. Meanwhile, in the calculation process, genetic computing is

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used to determine the optimal parameters in the foundation pit modeling process, thereby reducing the number of parameters and optimizing the calculation process. It is expected to better realize the deformation problem of the deep foundation pit construction process, reduce the potential safety problems, and ensure the smooth and stable progress of the overall construction.

The reasons for choosing Gaussian regression in the study are as follows. The Gaussian process regression model can effectively handle nonlinear and high-dimensional deformation data of foundation pits. During the solving process, Gaussian regression can infer unknown data by assuming the distribution relationship between data points, which has stronger flexibility and data prediction performance. The innovation of the research is as follows: Gaussian process regression is used to model the deformation problem of foundation pits, aiming to develop a more accurate model and conduct a more comprehensive analysis of the deformation process of foundation pits. Subsequently, a genetic algorithm is employed to optimize the intricate parameter calculations undertaken during the modeling process. This is done with the objective of attaining the optimal parameters for modeling the deformation of the foundation pit and thereby facilitating a more precise analysis of the deformation of the foundation pit.

Most existing research is focused on the deformation of foundation pit structures and the resulting collapse issues. The research on early warning management of deformation problems during the construction process of deep foundation pits is relatively insufficient. Especially for the nonlinear changes in the deformation process of foundation pits, existing research has not achieved more accurate simulation. Therefore, in order to better capture the detailed changes in the deformation process of foundation pits and address issues such as settlement and collapse, a Gaussian regression-based foundation pit deformation modeling method was developed to analyze nonlinear deformation data. The contributions of the research are as follows. This study first used Gaussian regression to model the deformation of foundation pits, and optimized Gaussian regression using genetic algorithms to obtain a prediction method for foundation pit deformation. The method was validated through experiments, and better prediction results for foundation pit deformation were obtained than existing research methods. At the same time, the error results obtained were also within a reasonable range, providing effective evidence support for the prediction of foundation pit deformation.

The study is divided into many sections. Section II reviews the current status of industry research on deep foundation pit deformation problems and Gaussian regression distributions. Section III designs a deep foundation pit deformation warning model based on Gaussian regression distributions. Section IV validates the performance of the designed method. The paper is concluded in Section V.

II. RELATED WORK

With the economic development, all kinds of infrastructure construction are increasing. In the project construction, all kinds of pit work develop in the direction of depth and large-scale. The deformation of foundation pits in the construction process has gradually received widespread attention. Many scholars have studied the causes of pit deformation and the monitoring and early warning. Kim T et al. observed the lateral deformation of excavation support walls in foundation pits. The study used inverse analysis techniques to conduct inverse analysis on excavation sites and summarized the evolution process of excavation deformation under different soil conditions [6]. Discontinuities or imbalances in the cambered support structure might lead to collapse, which may result in damage and casualties. Therefore, Nam et al. used a three-dimensional numerical model to convex corners of retaining walls in deep foundation pits. It was found that connecting two discrete longitudinal rows at the convex corner could effectively improve the stability [7]. Cui et al. used on-site monitoring and numerical simulation methods to explore the changes during excavation of foundation pits. The results indicate that excavation of the inner pit reduces the passive earth pressure, and setting up support structures or bottom plates in the step area can effectively suppress the deformation of the outer support structure, thereby reducing the deformation of the foundation pit [8]. Mao Z et al. used the finite element software Midas GTS NX (2019) to analyze the effects of different support types (pile anchor support and double row pile support) on the excavation of tunnel foundation pits near subway stations. The displacement of the foundation pit increases continuously from a distance away from the excavation to a distance closer to the excavation. This study can provide reference for related engineering projects to ensure the safety and stability of subway structures [9]. Shi established a finite element model for the damage caused by water inflow and seepage in foundation pits, and analyzed the effects of the depth of the confined water level and groundwater level on the deformation of the foundation pit. The results indicate that changes in groundwater level have a significant impact on the deformation of foundation pits [10].

With the development of artificial intelligence technology, various advanced artificial intelligence technologies are widely used for monitoring the deformation of foundation pits. Cui et al. constructed a PSO-GM-BP foundation pit deformation prediction model based on PSO-optimized GM(1,1) model and BP network model. A small amount of measured data during the excavation process of the bottomless foundation pit at Changsha Metro Station was used to validate the model. The method could accurately predict the deformation of a foundation pit with reliable precision and applicability, thereby providing effective guidance for the construction of the foundation pit [11]. Zhang et al. developed a 3D model based on FLAC3D for numerical simulation of excavation deformation at a subway station in Jinan city as a project. The horizontal displacement of the supporting structure, axial force of the support, and vertical displacement of the columns were compared with the data collected on site. The results indicated that during excavation of the foundation pit, the maximum deformation of the support structure gradually decreased from the top and increased gradually, with a final maximum deformation of about 17 meters deep [12]. Pan et al. proposed a new Probabilistic Deep Reinforcement Learning (PDRL) framework to optimize monitoring of deep excavation projects, aiming to minimize costs and risks caused by excavation. Firstly, a Bayesian bidirectional generalized regression neural network was established to describe the relationship and role between foundation pit ground settlement and the safety status of adjacent buildings. Subsequently, a dual deep Q-network method was trained for continuous learning of monitoring strategies. The findings indicated that this approach could address the inherent ambiguity within the environmental context and the model itself, thereby facilitating the optimization of monitoring strategies, the attainment of cost-effectiveness, and the mitigation of risk [13]. The summary of related work is shown in Table I.

TABLE I. SUMMARY OF RELATED WORK

Author	Method	Advantage	Shortcomings
He et al. [6]	A compensated excavation method	Verify the scientific validity and feasibility of the compensatory excavation method	Not applied in other projects
Nam et al. [7]	A three-dimensional numerical mode	Can effectively improve the stability	Not applied in practical scenarios
Cui et al. [8]	An on-site monitoring and numerical simulation method	Can effectively suppress the deformation of the outer support structure	Accuracy needs further optimization
Xu et al. [9]	A construction safety method for water-rich soft soil deep foundation pits	Identify potential safety hazards and implement appropriate control measures	High computational complexity
Shi [10]	A finite element model for the damage in foundation pits	The change in groundwater level has a significant impact on the deformation of foundation pits	Other complex factors were not taken into account
Cui et al. [11]	A PSO-GM-BP foundation pit deformation prediction model	Accurately predict the deformation with reliable precision and applicability	Not applied in other projects
Zhang et al. [12]	A 3D model based on FLAC3D	The maximum deformation of the support structure gradually decreased	Large deformation
Pan et al. [13]	A new Probabilistic Deep Reinforcement Learning (PDRL) framework	Address the inherent ambiguity within the environmental context	High computational complexity

The deformation problem of deep foundation pits has been the subject of extensive attention and research by industry scholars. However, the majority of existing studies have focused on the deformation of the foundation pit structure and the subsequent collapse problem. However, most of the existing researches are about the deformation of foundation pit structure and the resulting collapse problem. There is a relative lack of research on the early warning management of the deformation problem of deep foundation pits in the construction process. Based on this, this study combines the advantages of Gaussian regression analysis in data warning management and constructs a corresponding deep excavation deformation pre-management model. It aims to provide timely and effective solutions to the deformation problem of deep foundation pits in engineering projects, ensuring the smooth progress of the overall construction of the project.

III. EARLY WARNING MODEL CONSTRUCTION OF DEEP FOUNDATION PIT DEFORMATION BASED ON OPTIMIZED GAUSSIAN REGRESSION MODEL

In recent years, with the continuous acceleration of urbanization construction, the safety problems caused by deep foundation pit deformation in various engineering projects occur frequently. The study addresses this problem by adopting Gaussian regression model to design the corresponding deep foundation pit deformation early warning model. Then, the model is utilized to design and monitor the specific deep foundation pit deformation for early warning.

A. Deep Foundation Pit Deformation Engineering Design

The early warning of deformation management of foundation pit denotes the timely monitoring of deep foundation pits in engineering projects through a variety of technical methods and means, aiming to implement early warning treatments in accordance with the statistical analysis of monitored data. This approach is of paramount importance for ensuring the safe and stable development of the project. The deformation of deep foundation pit is mainly reflected in the deformation of foundation pit enclosure structure, pit uplift, and surface settlement. There is a significant relationship between the deformation of the foundation pit and the surface morphology change of the periphery of the foundation pit, which roughly meets the change curve shown in Fig. 1 [14].

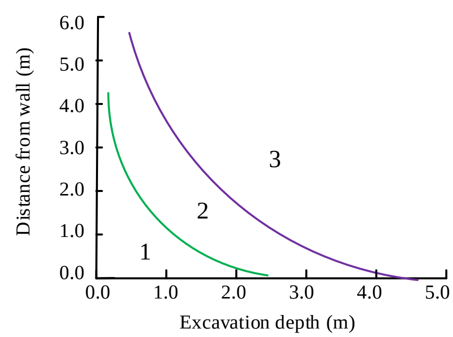


Fig. 1. Surface subsidence relationship.

There are many factors affecting the deformation of deep foundation pit, including climate, topography, construction program, and construction technology, etc. Its impact is also a process of qualitative change from quantitative change, therefore, its early warning management is a relatively difficult process. To better analyze the deformation of the deep foundation pit, the study takes the deep foundation pit in the project of a certain place as an example, and designs the monitoring layout design for the deep foundation pit project. The study selects a pit project in S city. The total area is 12,431 m2, of which the basement floor area is 3,716.29 m2, the shape of the pit is similar to the quadrilateral, and the excavation depth of the pit bottom is 6.43m. The soil conditions from the surface layer downwards are miscellaneous fill soil, sandy silt, silty clay, and clay [15-16]. The existing amount of buildings around the surface are mainly large-scale hotels, commercial buildings, etc., and the underground layer belongs to the garage and the human defense. The specific schematic diagram is shown in Fig. 2 [17-18].

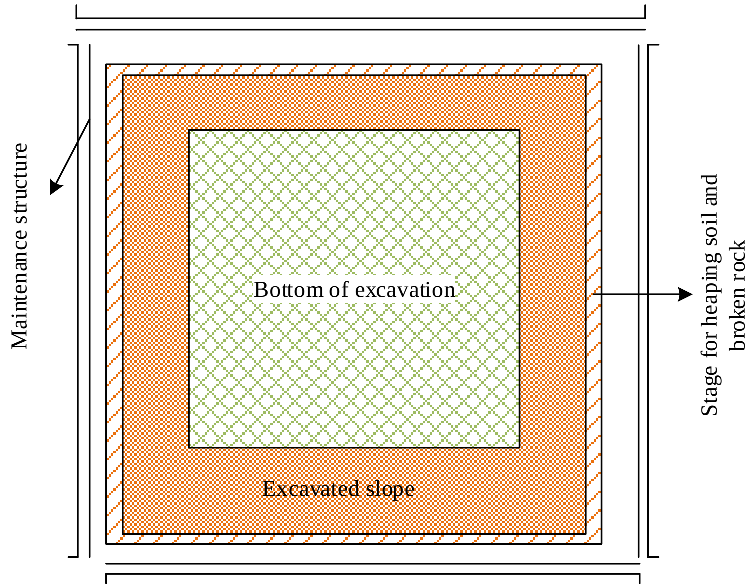


Fig. 2. Schematic diagram of foundation pit structure.

In this pit monitoring site, the placement of measuring instruments in the pit monitoring project, and the subsequent generation of a report for the surveyor, are carried out through the setting of various types of data acquisition instruments to obtain the corresponding sample data. However, there is an error between the study of the introduction of visual measurement technology for pit monitoring in the image acquisition, and the actual measured target object [19-20]. Visual measurement can be a single imaging multi-point observation, close-up photography in the target, and the measured object line into target points, from the shooting image to get the exact location of multiple target points, that is, the center of the target point. Then Gobor technique is used to process the acquired pit deformation sample images. The area around the key point is divided into L（$L \le 50$） sub-windows of $N \times N$, and then each sub-window is Gabor-transformed, and the 2D Gabor filter is defined in Eq. (1).

$$\sigma = \sqrt{2\ln 2}\left(\frac{2\phi+1}{2\phi-1}\right) \tag{1}$$

In Eq. (1), σ denotes the bandwidth of the 2D Gabor filter and ϕ denotes the half-peak bandwidth in octave. The image feature extraction of 2D Gabor is shown in Eq. (2).

$$P_{u,v}(x,y) = G(x,y) * C_{u,v}(x,y) \tag{2}$$

In Eq. (2), $P_{u,v}(x,y)$ denotes the Gabor features of the image when the scale is u and the direction is v. $G(x,y)$ denotes the gray scale of the input image. $*$ denotes the convolution factor. $C_{u,v}(x,y)$ denotes the 2D Gabor kernel function. The computed local correlation features are shown in Eq. (3).

$$R_{\mu n} = \frac{1}{L-n}\sum_{i=1}^{L-n}\mu_i\mu_{i+n} \qquad (n = 1, 2m) \tag{3}$$

To facilitate the subsequent pit deformation early warning analysis, it is necessary to obtain and analyse sample data on pit deformation. This will inform the design of the corresponding pit deformation early warning management model.

B. Construction of a Deformation Warning Model

In the construction of engineering projects, the construction complexity, comprehensiveness, and technical requirements of deep foundation pit engineering are higher. Foundation pit engineering is actually a kind of protective engineering project. The main role is to provide corresponding support space for the overall construction of engineering structure to ensure the stability of the surrounding soil and the smooth progress of the construction project. In the construction of deep foundation pit, it is usually necessary to excavate to the surrounding to set up the corresponding protective structure and measures. However, in the specific construction process, the construction difficulty of deep foundation pits and potential risk factors are not effectively controlled. In particular, the deformation monitoring of various protective structures directly affects the construction of the main structure and the progress of the overall project. The traditional pit deformation monitoring models are time series-based monitoring model and gray system-based monitoring model. In addition, the existing phase change monitoring methods for foundation pits mainly rely on manual operation, which is not only time-consuming and labor-intensive, but also has limited monitoring efficiency, making it difficult to detect small deformations. Overall, existing single point monitoring methods often have difficulty covering the entire area in various excavation projects, resulting in monitoring blind spots and increasing safety hazards. Other advanced monitoring technologies, such as 3D laser scanning technology, although have higher coverage, their corresponding costs also increase [21]. With the continuous development of artificial intelligence technology, it has a more significant role in risk prediction of all kinds of engineering projects. Accordingly, the study introduces artificial intelligence technology to monitor and warn the deformation problems occurring in deep foundation pit projects. Gaussian regression model is a kind of artificial intelligence analysis method based on statistical knowledge for data processing. Gaussian regression captures complex nonlinear relationships through a specified kernel function. Modeling can be carried out based on the specific data characteristics of excavation deformation, in order to more accurately describe the changing patterns of excavation deformation. In addition, deformation monitoring of foundation pits involves multiple different variables, such as time, spatial location, historical deformation data, etc. Gaussian process regression can handle inputs and outputs of any dimension, making it suitable for multivariate regression problems. Therefore, it has good flexibility and applicability, allowing for the development of timely and effective measures to ensure the safety of foundation pit construction.

The Gaussian regression process is a stochastic process that involves a sample function that obeys a Gaussian distribution. The mathematical definition of the Gaussian distribution process is shown in Eq. (4).

$$\{g(x), x \in X\} \tag{4}$$

In Eq. (4), X is the set parameter set, and any point x belongs to X. Eq. (4) is a stochastic process defined on the probability space M. At this point, there exists a random variable x_i corresponding to it, that is, the stochastic process. Gaussian regression process is a collection of random variables that conform to a Gaussian distribution. Taking a specific observation data x as an example, the Gaussian regression process is shown in Eq. (5).

$$g(x) = \{GP(f(x), w(x,x))\} \tag{5}$$

In Eq. (5), x is any observation data. $f(x)$ represents the mean function of the observed data. $w(x,x)$ represents the covariance function of the observed data. GP stands for Gaussian distribution process. Gaussian regression analysis is then based on the Gaussian regression process to perform specific data regression analysis. Regression analysis lies in determining the functional relationship that exists between two variables and is widely used in various scientific data analysis. The mathematical definition of the data regression problem is shown in Eq. (6).

$$Z = R(x) + \varepsilon \tag{6}$$

$R(x)$ denotes the functional relationship between any two variables, and ε denotes the observation noise vector that independently obeys Gaussian distribution. Gaussian regression process needs to preprocess the initial data when constructing the objective function. If a and b constitute the observation data set of deep foundation pit deformation $E\{(a_s, b_s) | (s = 1,2,...,n)\}$, a^* is the set of results to be predicted, and b^* is the set of samples to be predicted. According to the Gaussian distribution property, the joint prior distribution relationship between a^* and b^* is shown in Eq. (7).

$$\begin{bmatrix} b \\ b^* \end{bmatrix} = \left(0, \begin{bmatrix} w(a,a) + \sigma^2 I_n \\ w(a^*, a) \end{bmatrix}\right) \tag{7}$$

In Eq. (7), $w(a,a)$ denotes the covariance function of the sample data a. σ^2 denotes the noise variance. I_n denotes the unit matrix. After obtaining the dataset E, according to the Gaussian distribution, the posterior distribution of b^* is shown in Eq. (8).

$$p(b^* | E, a^*) = [m(b), w(b^*, b^*)] \tag{8}$$

In Eq. (8), $m(b)$ denotes the corresponding output of x to be predicted, and $w(b^*, b^*)$ denotes the posterior variance of the predicted output value. The Gaussian distribution regression process actually describes the distribution of the function from the probability space dimension of the function. However, in some high-dimensional models, more sample points are required in the calculation process [22]. According to the above process, the prediction model construction of Gaussian distribution regression can be realized, and the construction of Gaussian regression model is shown in Fig. 3.

The mean of the predicted values is a linear combination of the kernel function $w(b^*, b^*)$. The data with nonlinear relationship can be mapped to the feature space to complete the linear relationship transformation, thus simplifying the complexity of solving the nonlinear problem. Different covariance functions can be used in the Gaussian process. The commonly used covariance function is shown in Eq. (9).

$$k(x_i, x_j) = \sigma^2 \exp(-\frac{1}{2l^2} r^2) + \sigma_n^2 \varsigma_{ij} \tag{9}$$

In Eq. (9), σ^2 denotes the covariance signal, l denotes the moderating parameter, and ς_{ij} denotes the Kronecker value. The larger the value, the less significant the correlation between the inputs and outputs of the sample data.

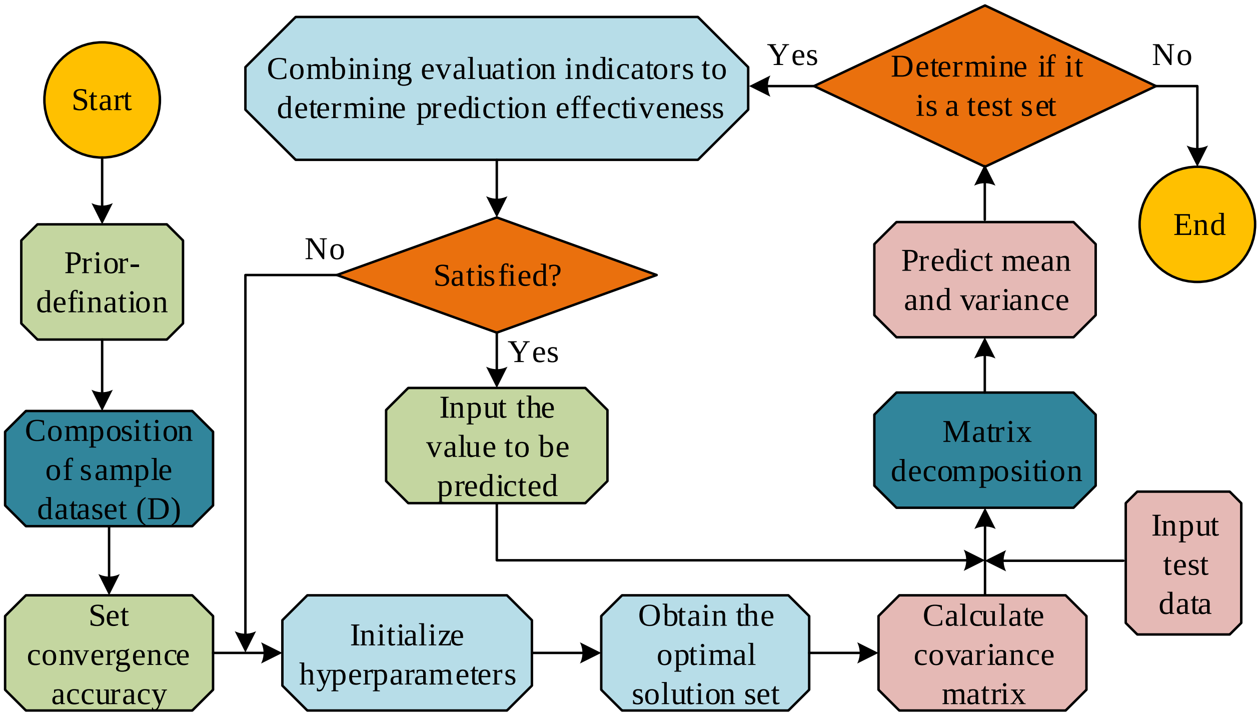


Fig. 3. Gaussian regression process.

C. Early Warning Model Construction of Deep Foundation Pit Deformation Based on Optimized Gaussian Regression Model

In the Gaussian regression process, the study uses the conjugate gradient method to solve the optimal hyperparameters. However, in the actual application process, the method gets unsatisfactory results. Accordingly, the study uses genetic algorithm to optimize it. Genetic algorithm, as an optimal algorithm as bionic, has a weak dependence of its objective function on the initial value and the global optimum. It has been widely used in computing multi-parameter and multi-variable problems [23]. Therefore, the study constructs an improved Gaussian regression model based on genetic algorithm to determine the optimal parameters. In the optimization process, firstly, chromosome coding is used by code conversion to transform the form of target parameters to be solved in the Gaussian regression process into the form of genetic code strings. The fitness function is selected for evaluating the fitness of the individual, and the higher the value of the function obtained, the better the solution effect. Taking individual P as an example, in the calculation process of genetic algorithm, the fitness function of P is expressed as Eq. (10).

$$E(P_i)=\frac{1}{2}\sum_{k=1}^{N}\left(y_{ki}-o_{ki}\right)^2 \tag{10}$$

In Eq. (10), N represents the population size. P_i represents the node i of individual P. o_{ki} represents the expected output value of node i on chromosome k. y_{ki} is the actual output value. Finally, the selection of individuals in a population generally adopts proportional selection, which is based on the ratio of individual fitness to the sum of fitness of all individuals. This way, every individual has the possibility of being selected. If n is used to represent the size of the population, i represents the individual. F_i is the individual fitness which can be obtained. The probability of i being selected in shown in Eq. (11).

$$P_i=\frac{F_i}{\sum_{i=1}^{n}F_i} \tag{11}$$

After the initial selection is completed, the optimal strategy is used to further select the optimal value, i.e., the optimal value is determined by searching for the individuals with the two extreme values of the highest and the lowest fitness. Accordingly, the pit deformation prediction model is constructed based on the optimized Gaussian regression network of genetic algorithm to predict the pit deformation, and the inverse normalization results are output in MATLAB [24]. The implementation process of the improved Gaussian regression model based on genetic algorithm is shown in Fig. 4.

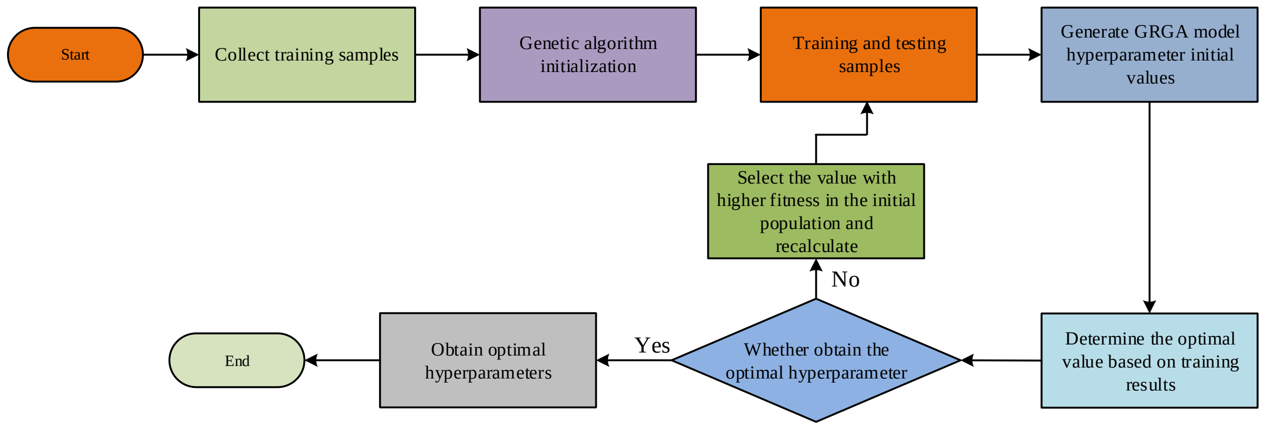


Fig. 4. Improved Gaussian regression process based on genetic algorithm.

In Fig. 4, when using an improved Gaussian regression model based on genetic algorithm for predicting excavation deformation, data samples are first collected and the genetic algorithm and Gaussian regression model are initialized. Then, the data samples are trained to generate parameter values for the GRGA model. Determine the optimal parameter values based on the training results. If the optimal value can be obtained from the training results, the process can be ended by outputting the optimal value. If the optimal value cannot be obtained from the training results, select a higher fitting value for sample training again. The Gaussian regression model has relatively few parameters in the modeling process, and the model hyperparameters can effectively avoid the data bias that occurs when manually assigning values by adaptive solving. The new Gaussian regression model is obtained by improving the Gaussian regression process using the above process. In the Gaussian regression process, the arbitrary variables are mutually independent Gaussian stochastic processes. Therefore, the established Gaussian regression process model is shown in Eq. (12).

$$g(x^*) = \sum_{i}^{n} K(x, x^*) \tag{12}$$

In Eq. (12), $K(\cdot)$ represents the combination function, which is the covariance matrix between the input sample x and the input value x^* to be predicted. $g(x^*)$ represents the Gaussian regression process of the input value x^* to be predicted. In accordance with the principle of "systematic, economical, convenient, and intuitive," the suitable monitoring location is determined based on the geological, climatic, and hydrological conditions in the vicinity of the foundation pit. Subsequently, a model is established based on the genetic algorithm to predict the horizontal deformation displacement of the foundation pit from both horizontal and vertical perspectives. The acquired monitoring sample data are normalized and then trained in MATLAB. The genetic algorithm is initialized first to determine the initial weights and thresholds, and then the corresponding training parameters are input to train genetic algorithm. The training is terminated when the training error is less than the established thresholds or when the search training reaches the preset value. The normalized values are outputted. Finally, the trained network is simulated on the prediction samples, and the final prediction results are obtained after the inverse normalization. The specific process is shown in Fig. 5.

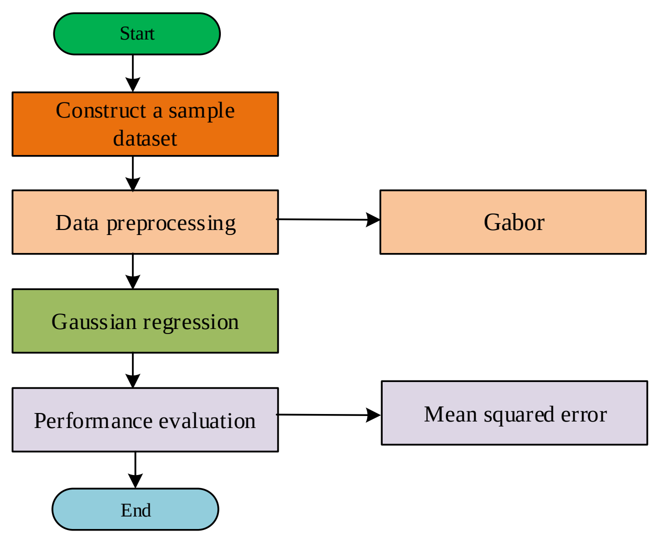


Fig. 5. Gaussian regression analysis process.

This study trained and tested the research method using the AI Earth - A Map of China's Surface Deformation (2022) dataset. This dataset covers the national surface deformation situation, with over 300 map views. To ensure data quality, the sample data is first preprocessed by adjusting the pixel values of the image to a specific range (usually between 0 and 1), which speeds up model training and improves model accuracy. Scale the images based on the average and standard deviation of the image dataset to ensure that the feature distributions have similar distributions. The two datasets are divided into a training set and a testing set in a 7:3 ratio to train the model.

IV. Experimental Analysis of Deep Foundation Pit Deformation Warning Model Based on Optimized Gaussian Regression Model

Based on the Gaussian regression warning model, the study introduces a genetic algorithm to optimize it and constructs a corresponding pit deformation warning model. In this section, the study verifies the performance and application effect of the proposed method, and at the same time introduces relevant comparison methods to verify its performance.

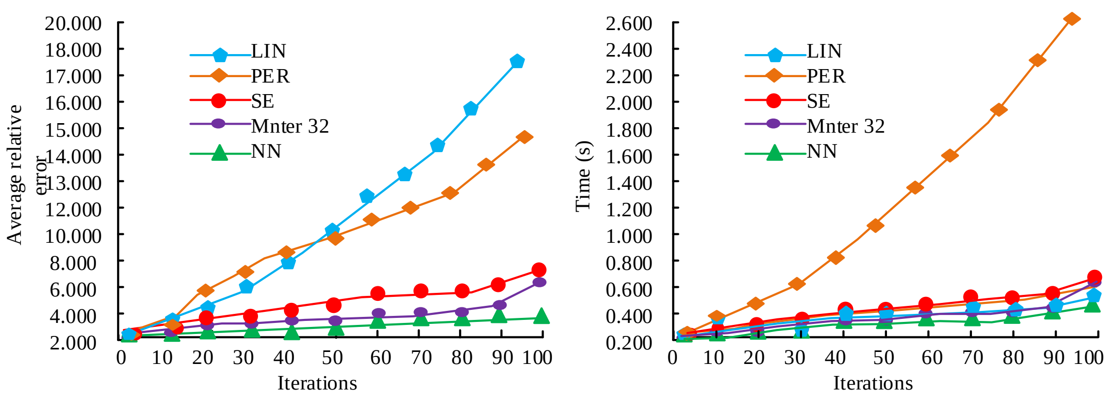
A. *Performance Analysis of Early Warning Model for Deep Foundation Pit Deformation*

To verify the performance effect of the early warning model, the corresponding experiments were designed to analyze it. In genetic algorithms, the population size determines the size of the model's search space. Appropriate population size can effectively solve complex problems while avoiding premature maturity. The crossover probability and mutation probability determine the search capability of the model. Both too high and too low can affect the diversity of the population. Therefore, based on existing research results, the parameters of the genetic algorithm used in the study are set as follows. The population size was set to 20, the crossover probability was set to 0.9, and the mutation probability was set to 0.05. This study uses the number of iterations of the algorithm as the convergence criterion. To ensure consistency in the experimental environment, the number of iterations is set to 100. The study first set the parameters of the genetic algorithm. The pre-set genetic algorithm was used for parameter optimization to obtain the optimal parameter combination for foundation pit deformation modeling and prediction. The optimal parameter combination obtained through multiple experiments is shown in Table II. The number of hidden layers determines the complexity and learning ability of the model, and this parameter range can explore the performance changes from shallower models (16 layers) to deeper models (128 layers) to obtain the optimal value. Dropout can explore different regularization effects. A lower Dropout rate may not be sufficient to effectively reduce overfitting, while a higher Dropout rate may lead to insufficient model learning. The Batch-size range is designed to find a balance between training speed and stability. 100 iterations is a relatively common choice that allows the model enough time to learn features from the data while avoiding excessively long training time.

TABLE II. PARAMETER VALIDATION

Optimal parameters	Initial value	Optimal value
Number of hidden layers in the network	[16, 128]	81
Dropout	[0.01, 0.5]	0.078
Bach-size	[16, 128]	41
Maximum number of iterations	100	100

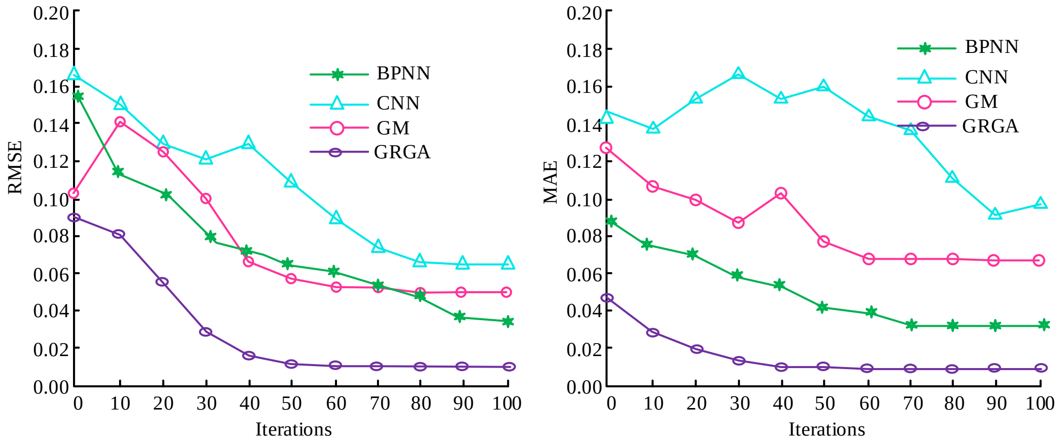
The optimal parameters obtained through multiple experiments are used for subsequent model validation. In the Gaussian regression model, the choice of covariance function has a direct impact on the model fitting effect. Consequently, this study examines the suitability of different covariance functions for analyzing the fitting effect of the Gaussian regression model. Commonly used covariance functions include the neural network function (NN), the periodicity function (PER), the squared exponential function (SE), and the Matern function (Matern 32), etc. They are evaluated by the average relative error and fitting time. The fitting effect of Gaussian model under different covariance functions is shown in Fig. 6. In Fig. 6 (a), among the five different covariance functions, the NN has the smallest value of average relative error with an error value of 2.347. The average relative error values of LIN, PER, SE, and Mnter32 are 18.63, 15.21, 8.95, and 7.46, respectively, which are significantly higher than the research method. In Fig. 6 (b), the time consumption of LIN, PER, SE, Mnter32, and NN are 0.689, 2.53, 0.712, 0.694, and 0.527, respectively. Except for the periodicity function, the time consumption differences of other methods are relatively small. The covariance function has a significant impact on the fitting performance of the model, including its smoothness and generalization ability in the input space. A suitable covariance function can capture complex nonlinear relationships in data and achieve accurate prediction of new data. Therefore, considering the average relative error values and time consumption of different covariance functions, the neural network function has the best fitting effect, proving that the covariance function used in the study is reasonable.



(a) Average relative error (b) Time

Fig. 6. The fitting effect of different covariance functions.

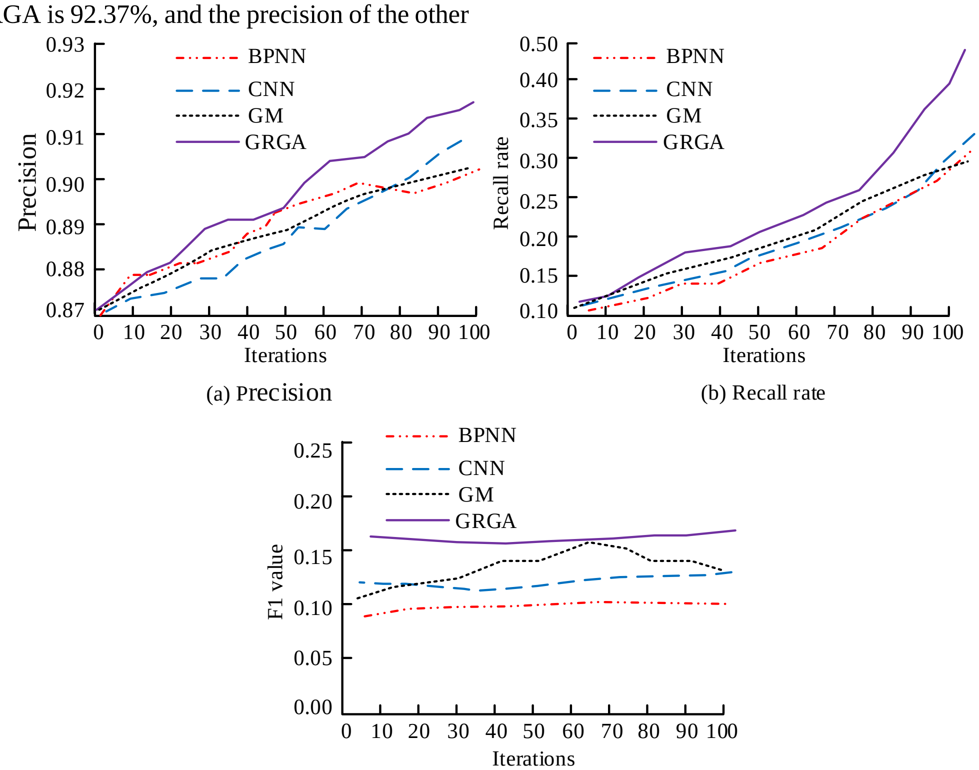
To better analyze the performance of the proposed method (GRGA), the study uses commonly used methods for comparison, including the Gray Prediction-based method (GM), Convolutional Neural Network-based method (CNN), and BP Neural Network-based method (BPNN). The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to evaluate the performance of the above methods. In the monitoring of foundation pit deformation, RMSE can measure the accuracy and reliability of monitoring data by calculating the difference between actual values and model measurements. MAE can effectively reflect the average error between the predicted and actual values of the model, which helps evaluate the accuracy and reliability of the model's predictions. The error values of the different methods in the process of deep foundation pit deformation are shown in Fig. 7. In Fig. 7 (a), the RMSE values of the GM, CNN, BPNN, and GRGA are 0.055, 0.079, 0.043, and 0.012, respectively. In Fig. 7 (b), the MAE values of the GM, CNN, BPNN, and GRGA are 0.078, 0.112, 0.059 and 0.015, respectively. Lower RMSE and MAE values mean that the deviation between the predicted values and the true values of the model is smaller, indicating that the model's predictions are more accurate. Overall, the RMSE and MAE of the proposed method are significantly lower than those of the comparative method, indicating better performance.



(a) RMSE (b) MEA

Fig. 7. Comparison of errors between different models.

To further validate the performance of the research method, the study analyzes the recall, precision, and F1 score of the Gaussian regression model and the GRGA. F1 takes into account both accuracy and recall. In the monitoring of foundation pit deformation, it can effectively study the specific performance of the model in predicting foundation pit deformation. The results are shown in Fig. 8. In Fig. 8 (a), the precision of the GRGA is 92.37%, and the precision of the other three methods of BPNN, CNN, and GM are 90.52%, 90.03%, and 89.95%, respectively. In Fig. 8 (b), the recall of the GRGA is 47.52% and the other three methods are 34.20%, 32.01%, and 29.67%, respectively. In Fig. 8 (c), the F1 value of the GRGA is 0.17, and the F1 values of the remaining three methods are 0.10, 0.13, and 0.14, respectively. Therefore, it appears that the GRGA has a better performance.



(c) F1

Fig. 8. Comparison of recall, precision, and F1 for different methods.

To verify the performance of the GRGA, Freidman detection analysis is conducted. Benchmark methods GM and BPNN are introduced for comparison. The obtained P-values and χ^2 test results are shown in Table III. According to Table III, the research method has stability in the test results of different indicators. Although the P-values of the indicators for GM and BPNN are significant, the level of significance is low, and the model performance is significantly lower than that of the research method. Based on the comprehensive verification, the research method performs the best among various comparison methods, verifying its practicality and effectiveness in solving and analyzing the deformation of foundation pits.

TABLE III. FREIDMAN TEST RESULTS OF THE RESEARCH MODEL

Testing index	Research method		GM		BPNN	
Testing index	P	χ^2	P	χ^2	P	χ^2
Accuracy	0.001	6.257	0.01	4.901	0.02	5.554
Recall	0.001	10.329	0.01	6.782	0.01	3.712
F1	0.001	9.0264	0.05	5.998	0.01	6.072
RMSE	0.002	5.295	0.02	8.208	0.01	6.225
MAE	0.001	6.164	0.01	7.461	0.01	3.012

After comparing with commonly used methods, the study compares it with the benchmark method (GR) to verify the effectiveness of the improved strategy (GRGA). The results are shown in Table IV. According to Table IV, the F1 score, Precision, Recall, and AUC of the GRGA reach 0.85, 0.89, 0.92, and 0.93, respectively. In benchmark testing, the evaluation results of the GRGA's indicators are significantly better than its GR, demonstrating higher model performance.

Subsequently, to validate the effectiveness of the GRGA in data analysis, the sensitivity of several comparative methods is analyzed, and the results are shown in Fig. 9. In Fig. 9, the sensitivity and specificity values of BPNN are 0.786 and 0.791, while the sensitivity and specificity values of CNN are 0.823 and 0.837. The sensitivity and specificity of GM are 0.843 and 0.862. The sensitivity and specificity of GRGA are 0.888 and 0.959. From this perspective, this research method has better accuracy than its comparative methods, can achieve data convergence faster, and has a certain degree of stability in the calculation results.

TABLE IV. RESEARCH METHOD BENCHMARK TESTING

Performance Metric	GR	GRGA
F1 score	0.79	0.85
Precision	0.81	0.89
Recall	0.85	0.92
AUC	0.82	0.93

B. *Analysis of the Practical Application Effect of Deep Foundation Pit Deformation Modeling*

Four different profile monitoring points (ABCD) are set up in the horizontal direction to monitor the deformation changes in both vertical and horizontal directions. The monitoring period lasts for one year, and data collection is completed in six stages, with an interval of two months between each stage. Then, the obtained deformation monitoring data of the foundation pit are analyzed. To address the outliers and heterogeneity of the initial intention during data collection, some outliers are removed. Removing outliers that contain important information may result in the model being unable to capture the true distribution of the data. Therefore, replace outliers with the mean. The substitution method can preserve the integrity of the dataset and avoid information loss. The specific deformation data of four monitoring points are fitted, and the visualization results between their deformation warning values and actual deformation are shown in Fig. 10. In Fig. 10 (a), the difference between the warning results obtained by fitting using the research method and the actual results is small. The results obtained from the fifth monitoring are basically consistent with the actual results. In Fig. 10 (b), (c), and (d), the difference between the actual values obtained and the fitted values is relatively large, but the overall error range is within an acceptable range.

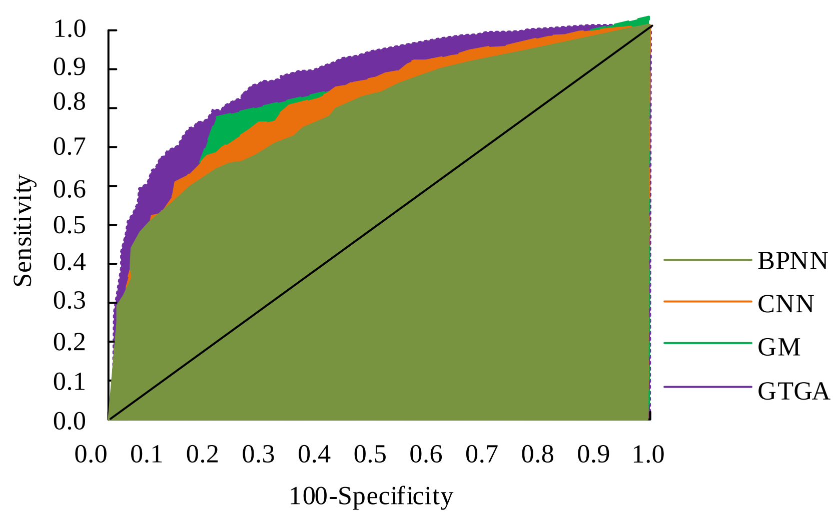


Fig. 9. Sensitivity and specificity analysis.

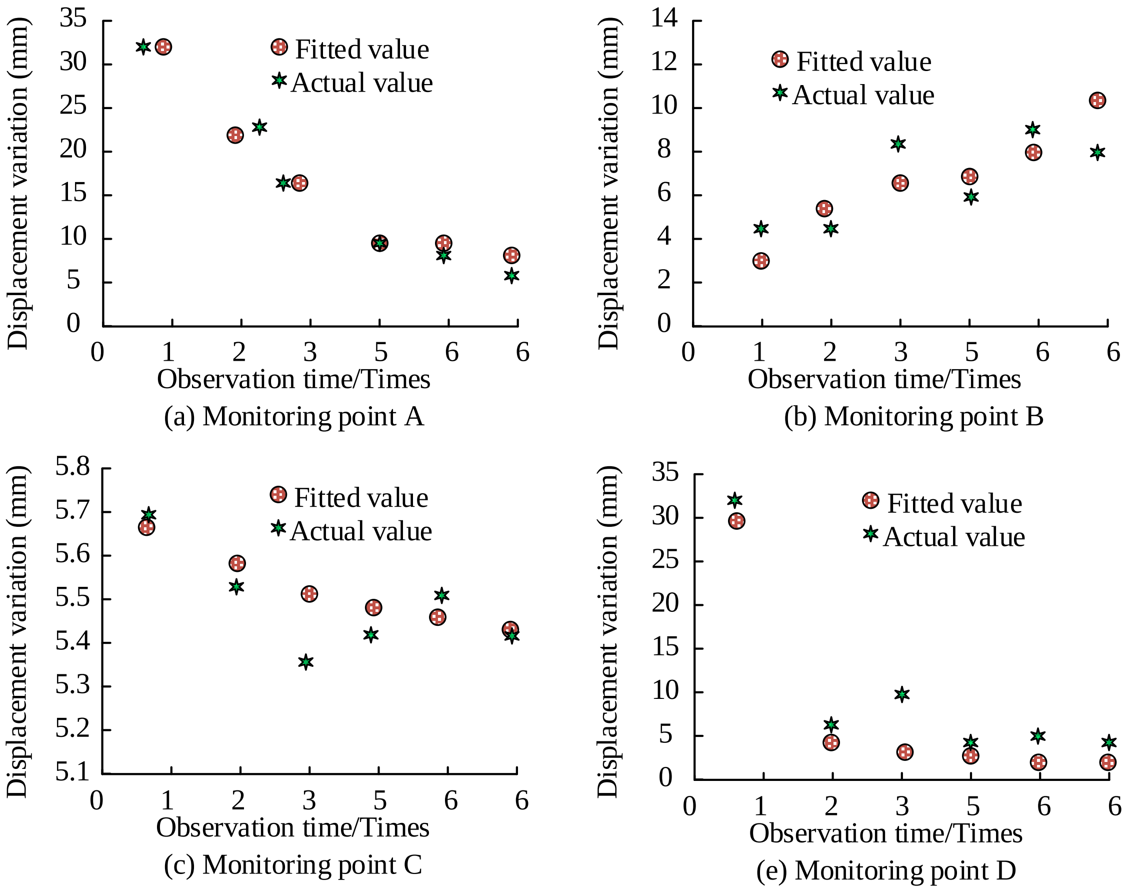


Fig. 10. Visualization results of deformation warning values and actual deformation.

Taking the four monitoring points set up for the study as the base point, the cumulative pit deformations in the vertical and vertical directions are analyzed, and the cumulative pit deformations in the vertical and horizontal directions are obtained as shown in Fig. 11. In Fig. 11 (a), in the vertical direction, the cumulative deformation in the four cross-sections varies significantly, and the average deformation in the four cross-sections reaches 1.32 mm, 1.21 mm, -3.47 mm, and -6.51 mm, respectively. Fig. 11 (b) shows the cumulative deformation in the horizontal direction. All the four monitoring locations show significant displacement changes between the second and the fourth monitoring, which may be related to the changes of construction and climatic conditions and other changes.

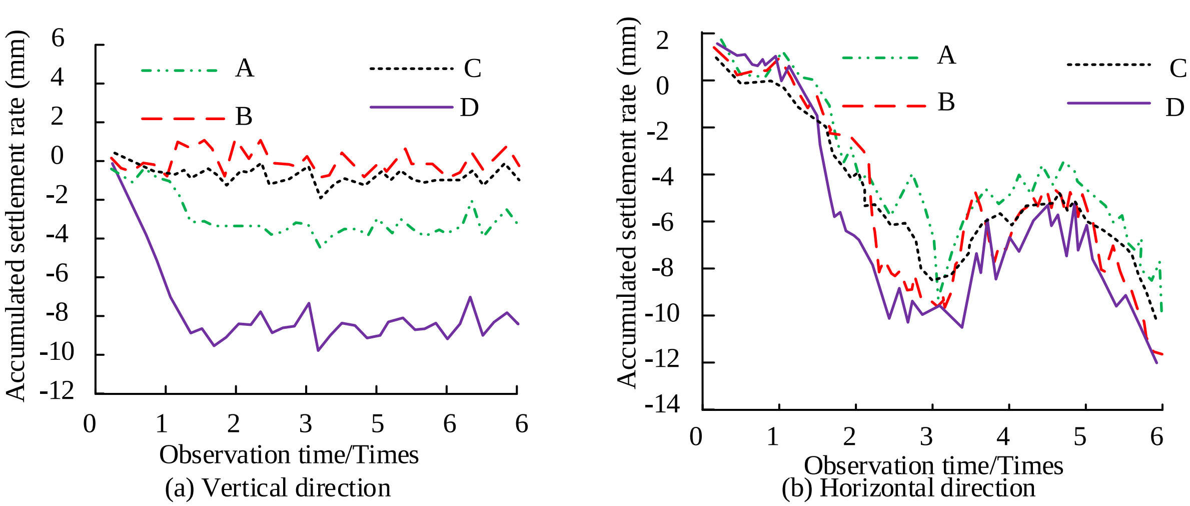


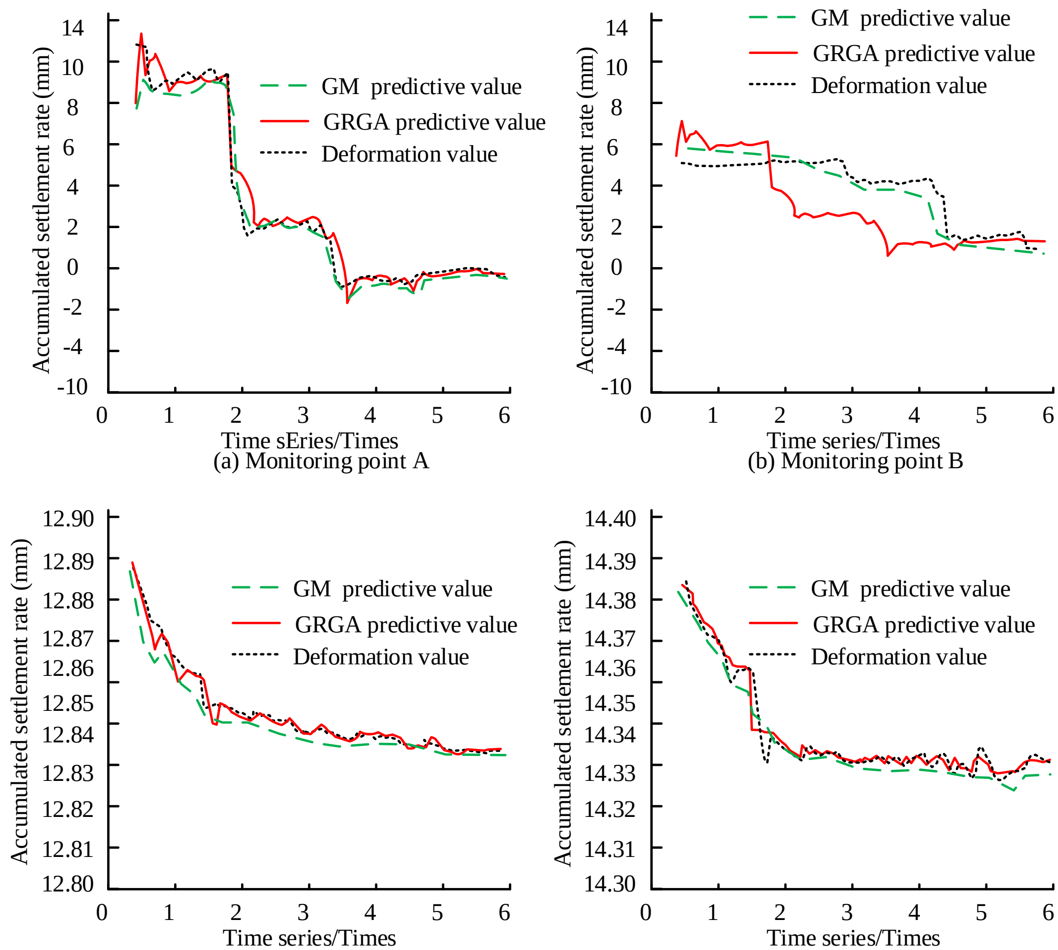
Fig. 11. Accumulated settlement in vertical and horizontal directions.

The most prominent manifestations during the deformation process of deep foundation pits are surface settlement, deformation of foundation pit enclosure, and uplift of foundation pits. The study statistically analyzes the actual and predicted values of the three types of pit deformations under different monitoring times of the pit monitoring project, and the obtained statistics are shown in Table V. This research method can provide ideal warnings for different types of deep excavation deformations.

In the same monitoring location, the proposed early warning analysis of the deformation trend of the deep foundation pit is carried out using the GM method and the research method. The obtained early warning results are shown in Fig. 12. Fig. 12 (a), (b), (c), and (d) represent the deformation warning results for four different monitoring locations, respectively. In general, the proposed method demonstrates superior performance in tracking the specific deformation trend. While some of the specific points align closely with the actual values, there are also instances where the proposed trend significantly deviates from the observed data. From this point of view, the performance of the GRGA can better track the specific trend of deep foundation pit deformation. Especially for the detail changes, there is a better presentation effect, which can better facilitate the subsequent audit monitoring management.

TABLE V. ERROR ANALYSIS OF PIT DEFORMATION PREDICTION (MM)

Excavation deformation type	Time	Actual value	Predictive value
Surface subsidence	2	10.651	10.656
	4	10.659	10.661
	6	10.667	10.662
	8	10.684	10.681
	10	10.703	10.695
	12	11.214	11.219
Deformation of enclosure structure	2	8.562	8.641
	4	8.647	8.648
	6	8.718	8.802
	8	8.866	8.871
	10	9.510	9.504
	12	9.964	9.935
Pit uplift	2	14.112	14.135
	4	14.347	14.356
	6	14.548	14.537
	8	14.791	14.776
	10	15.602	15.598
	12	15.964	15.985



(a) Monitoring point A (b) Monitoring point B

(c) Monitoring point C (d) Monitoring point D

Fig. 12. Fitting the deformation trend of deep foundation pits.

To further validate the effectiveness of the research method, it was compared with methods proposed by other scholars on different datasets, including "AI Earth-China's Surface Deformation" mentioned above and "Safety Management Data for Deep Excavation Construction". The latter comes from the data statistics of a construction project on the Zhejiang Provincial Data Knowledge Registration Platform, which includes 25,251 pieces of data. Comparison methods include the PSO-GM-BP model proposed by Cui D et al. [11], the PDRL model proposed by Pan Y et al. [13], GM and BPNN. The precision prediction results of the obtained deformation are shown in Table VI. The research method outperforms its comparative methods in terms of monetization in various indicator tests. In dataset A, the precision, recall, and F1 of the research method are 93.75%, 94.33%, and 89.06%, respectively. The precision, recall, and F1 of the GM are 79.52%, 79.52% and 80.75%. The precision, recall, and F1 of the BPNN are 82.03%, 83.79% and 85.94%. In dataset B, the research method precision, Recall and F1 are 83.47%, 80.56%, and 83.77%, respectively. From this perspective, the study has better performance and can accurately analyze the specific deformation size of the foundation pit.

To further validate the application effect of the research model in different engineering projects, an experimental verification was conducted on a foundation pit project under sandy soil conditions in a certain location. Select sample data from a monitoring point in both horizontal and vertical directions for analysis. Collect monitoring data from point H3 in the horizontal direction and L5 in the vertical direction of the foundation pit for analysis. Using the monitoring data from 2018 as an example for analysis. A total of 246 sets of data were obtained, and 5 sets of sample data were randomly selected for displacement change prediction analysis. From Table VII, it can be seen that in this engineering project, the prediction errors of both horizontal and vertical displacements are within a reasonable error range, with the maximum error occurring in sample 4 of the horizontal displacement monitoring point, which is 0.9mm. In most cases, the predicted value is smaller than the actual value. Overall, this method has good accuracy and applicability, and can adapt to different geotechnical conditions.

TABLE VI. COMPARISON OF PRECISION, RECALL AND F1 OF RESEARCH METHOD

Datasets	AI Earth-China's Surface Deformation			Safety Management Data for Deep Excavation Construction		
Methods	Precision	Recall	F1	Precision	Recall	F1
PSO-GM-BP	76.45%	84.27%	83.04%	78.25%	81.06%	79.45%
PDRL	83.02%	82.12%	85.34%	80.05%	79.86%	81.33%
Research method	93.76%	94.33%	89.06%	83.47%	80.56%	83.77%
GM	79.52%	82.31%	80.75%	77.25%	75.96%	76.31%
BPNN	82.03%	83.79%	85.94%	79.56%	80.26%	76.59%

TABLE VII. PREDICTION AND ANALYSIS OF DISPLACEMENT CHANGES UNDER SANDY SOIL CONDITIONS

H3				L5			
Sample Number	Actual displacement (mm)	Predicted displacement (mm)	Error (mm)	Sample Number	Actual displacement (mm)	Predicted displacement (mm)	Error (mm)
1	24.1	23.6	0.5	6	5.2	5.6	0.4
2	25.6	25.4	0.2	7	5.9	5.4	0.5
3	27.9	27.5	0.2	8	6.3	6.0	0.3
4	28.5	27.6	0.9	9	7.4	6.9	0.5
5	28.6	28.2	0.4	10	7.8	7.5	0.3

To further validate the generalization performance of the model, the deformation data of the foundation pit engineering project during the construction process of a certain subway line 8 is used to verify the model. The depth of the foundation pit is 18.7-24.3m. Construction began in June 2018, and the project covered an area of 5681 m2. At the same time, four different monitoring points (named 1, 2, 3, and 4) are set up to collect real-time deformation data of the foundation pit and dynamically update the collected deformation data set. The deformation data monitored every four months are selected for analysis, as shown in Table VIII. Table VIII shows that the deformation data of the foundation pit predicted and analyzed by the research method are basically consistent with the measured data, and the existing errors are also within a reasonable range. Based on this data analysis, it can further prove the feasibility of the research model in different data environments, that is, the model has a certain degree of generalization performance.

TABLE VIII. PREDICTION AND ANALYSIS OF FOUNDATION PIT DEFORMATION (MM)

Time	1	2	3	4
2018.10	2.4	1.7	5.4	10.1
2019.02	2.5	3.6	9.2	13.8
2019.06	2.9	5.2	11.3	15.4
2019.10	3.1	6.8	12.7	19.6

In the application of deformation models for foundation pits, the first step is to collect relevant monitoring data during the construction process, such as surface settlement, horizontal displacement, excavation depth, etc. These data are the foundation for building and validating predictive models. Then preprocess the data to ensure its accuracy and consistency. Then train the model and continuously adjust its parameters to improve its prediction accuracy. Finally, the trained prediction model will be integrated into the construction project for real-time monitoring and early warning of foundation pit deformation. The integration of deformation prediction models for foundation pits into practical engineering projects is of great significance. This can not only improve construction safety and optimize construction decisions, but also promote intelligent construction and drive industry technological progress.

V. Conclusion

Excavation monitoring is a very important component of civil engineering safety, as well as an important guarantee and technical support for the smooth progress of subsequent projects. The traditional pit deformation monitoring method has many shortcomings in the early warning management process. Accordingly, the study constructed a deep pit deformation early warning model based on Gaussian regression model, and then used genetic algorithm to optimize the model. The experimental results showed that the accuracy of the proposed method was 92.37%, the recall rate was 47.52%, and the F1 value was 0.17, significantly higher than its comparison method. Freidman showed that the research method has better stability. In comparison with the benchmark method, the research method has yielded considerable optimization outcomes, thereby substantiating the assertion that the proposed enhancement strategy is efficacious. The research method measured significant differences in the longitudinal cumulative deformation of four sections. The average deformation of the four sections was 1.32mm, 1.21mm, -3.47mm, and -6.51mm, respectively. In the real-time updated dataset collected from a certain engineering project, the data measured by the research method was basically consistent with the actual measured data, and the errors that exist were also within a reasonable range. The results demonstrate that the proposed method is more effective in the early warning management of deep foundation pit deformation. It produces a more accurate fit between the actual deformation and the early warning results, with an acceptable level of error.

The comparison results of different datasets are different, which is the result of multiple factors working together. Firstly, the data sources of different datasets are different, that is, there are differences in data collection methods and standards, which affects the data results. Then, different data processing methods may lead to errors and biases, resulting in differences in comparison results. In addition, there are differences in sample sizes among different datasets, which directly affects the comparison results. Finally, in the process of data analysis, the comparison results may also be influenced by subjective factors such as human judgment, which can affect the comparison results. During the comparison process, it is advisable to choose datasets with similar sources, consistent collection methods, and high-quality annotations for comparison. At the same time, preprocessing and standardization of the data should be carried out before comparison to reduce the impact of data differences on the comparison results.

However, there are also corresponding difficulties in practical analysis under deterministic conditions, such as deviations between theoretical models and actual conditions, limitations in calculation methods, etc. Meanwhile, the scalability of the model in different types of projects has not been validated. Therefore, future research based on the perspective of artificial intelligence can optimize the model and further improve its application performance in construction engineering. It can also timely and effectively monitor changes in engineering data caused by changes in the surrounding environment, providing effective support for construction safety and quality. Based on future engineering construction, the monitoring performance of this model in foundation pit deformation has been optimized, thereby expanding its application in different construction projects. This can effectively meet the design requirements of various other engineering construction projects, such as subway, large shopping malls, residential community construction, etc.

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