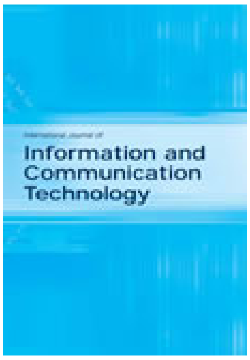

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IoT-based construction site safety management: real-time monitoring and early warning system construction

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Abstract: For the goal of ensuring the smooth progress of construction, it is urgent to design a real-time construction safety management method. First, the overall architecture of internet of things (IoT) real-time monitoring is constructed, which includes sensing layer, network layer, platform layer, and application layer; second, according to the accident causation theory, the construction risk monitoring index system is determined, and the key risk features are extracted. Subsequently, the improved ReliefF algorithm is used to select important construction risk features, and the hyperparameters of the support vector machine (SVM) are optimised by the particle swarm optimisation (PSO) algorithm, and important risk features are inputted into the PSO-SVM model to obtain final risk warning results. Application results of a construction project show that the data transmission delay of the system is less than 0.2 s, and the monitoring accuracy can reach 91.31%, showing excellent real-time and accuracy.

Keywords: construction site safety management; monitoring and early warning; internet of things; IoT; feature selection; support vector machine; SVM; particle swarm optimisation; PSO.

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1 Introduction

Under the background of continuous urbanisation, the construction industry is booming, and the number and scale of construction sites are increasing day by day. However, the construction site environment is complex, involving overhead work, machinery operation, electrical equipment use and many other links, safety accidents occur frequently, not only threatening the life safety of operators, but also causing huge economic losses and social impact (Lee and Lee, 2023). According to relevant statistics, the number of casualties caused by construction safety accidents each year should not be underestimated, and the traditional way of construction site safety management is not only inefficient, but also difficult to comprehensively cover all aspects of the construction site (Lee et al., 2009). The rise of internet of things (IoT) technology provides a new solution for construction site safety management. IoT technology through the sensor cloud computing and big data and other technical means, can realise the real-time monitoring and intelligent analysis of all data on the construction site, so as to timely discover potential safety hazards and take corresponding early warning measures (Chung et al., 2023). This IoT-based construction site safety management not only improves the efficiency and accuracy of safety management, but also reduces the incidence of safety accidents, providing a strong guarantee for the sustainable development of the construction industry (Zhou and Ding, 2017). Traditionally, construction site safety management is achieved through real-time monitoring and warning by building information modelling (BIM) (Naticchia et al., 2013). Hossain et al. (2023) investigated the use of BIM technology to achieve construction site monitoring visualisation and real-time warning functions; and to develop an application based on construction monitoring and warning. Wu et al. (2023) set up a three-level warning system according to the finite element model to effectively identify and prevent potential hazards on the construction site, thus guaranteeing construction safety. Kulinan et al. (2024) established a BIM 3D model for building fire prevention, which maps the parameters of the changes in the building structure and the surrounding environment during the construction process with the 3D model and realises real-time monitoring and warning for safety. Cheng et al. (2017) analysed the deficiencies of traditional construction monitoring and explored a new type of safety engineering monitoring management using BIM technology, but the accuracy of monitoring is not high.

Traditional safety monitoring methods are unscientific and inconvenient to manage, etc. IoT uses radio frequency (RFID) as the basis for remote information collection, and through the positioning system to link things with things. Kanan et al. (2018) utilised the advantages of IoT technology to develop a construction safety intelligent monitoring system to realise real-time collection of on-site information and timely assessment of the safety condition of deep foundation pit construction sites. Häikiö et al. (2020) used global positioning system (GPS) positioning technology to collect real-time information about data changes in the project structure and the surrounding environment, and established an IoT-based monitoring platform to realise intelligent monitoring of site conditions. Jayanthi et al. (2021) used IoT technology to collect and manage real-time data from all people and objects in the construction site, to realise the active warning function, and to improve the supervision and management efficiency of the construction site. Jiang et al. (2021) analysed the drawbacks of the current stage of China's construction site monitoring methods, through the study of monitoring and early warning specifications, with the help of IoT technology, developed a monitoring management information platform based on the web side, but there is a large time delay.

IoT can collect monitoring data through big data, cloud computing, and intelligence, which provides data support for safety management and early warning. Zhu and Wang (2022) used the historical construction data from IoT monitoring as the input of back propagation (BP) neural network, and the warning threshold was obtained after predictive analysis, but the prediction accuracy was not high. Liu and Tian (2019) extracted the key principal component features through principal component analysis and obtained the final warning results through a decision tree (DT) classifier to improve the prediction accuracy. Liu and Chen (2023) combined the convolutional neural network (CNN) with wavelet analysis method to give a wavelet energy spectrum and warning index using virtual impulse response function, and the results showed that this method can effectively predict the warning level of the construction site, so as to improve the safety and reliability of construction. Yang (2019) presented a new construction site warning indicator that can accurately identify the relevant risk situations and effectively predict the construction risk generation through support vector machines (SVMs).

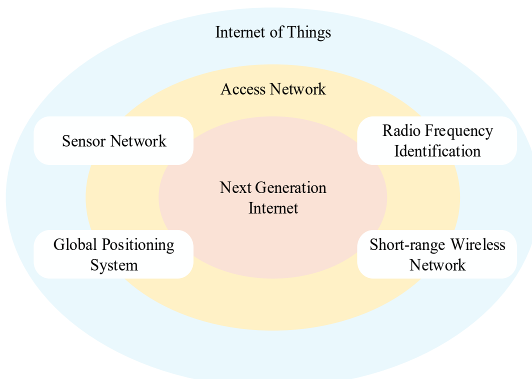
Based on the analysis of the above studies, it is clear that the some methods are unable to monitor and warn the safety risks of construction in a real-time and efficient manner. Moreover, existing construction site safety management methods mostly rely on manual inspections, which have time blind spots (such as nighttime operations) and subjective misjudgements, resulting in low monitoring efficiency. To cope with the above challenges, this paper proposes an IoT-based construction site monitoring and early warning system. First of all, based on IoT, the overall architecture of IoT real-time monitoring is constructed, which includes sensing layer, network layer, platform layer and application level. According to the accident causation theory, a key risk monitoring index system consisting of risk indicators for work at height, environment, equipment, protection, organisation and workers is identified, and the key risk features of construction are extracted from IoT data based on the indicators to form a key risk feature set for construction in IoT. Then the ReliefF algorithm is improved based on the idea of distance weighting (IReliefF), which is used to select important construction risk features, and to reduce the influence of abnormal samples through the contribution of distance-weighted neighbours when calculating feature weights. Finally, the important features are taken as the input of the particle swarm optimisation (PSO)-SVM model, the population is randomly initialised, and each particle representing the parameter vector is selected as the calculation parameter in the SVM, and the corresponding iterative training is performed on it. When the iteration meets the requirements, the obtained particle is the particle with the largest fitness function. This particle represents the optimal parameters trained by SVM to obtain an accurate construction risk prediction level. The experimental outcome indicates that the proposed system has a data transmission delay of 0.16 s and a prediction accuracy of 91.31%, which can realise accurate and real-time construction site monitoring and warning.

2 Relevant technologies

2.1 Introduction to the IoT

IoT is a network that connects physical objects to the Internet through information sensing devices, (e.g., RFID, sensors, GPS, cameras, etc.) according to an agreed protocol for information exchange and communication for intelligent identification, localisation, tracking, monitoring and management (Atzori et al., 2010). The conceptual model of IoT is shown in Figure 1, which is usually divided into sensing, network and application levels.

Figure 1 IoT conceptual model (see online version for colours)



1. The sensing level is the front-end of the IoT system, which owns one or more sensing devices and brings together the core technologies of the IoT system, and involves various types of sensors, electronic IDs, and wireless routers in the market. The sensing layer consists of three subordinate levels, i.e., data acquisition level, data processing level, and short-range data transmission level (Ray, 2018).
2. The role of the network transmission level is to transmit the data acquired by the sensing layer and carried out in the sensors over a short distance using a local area network (LAN) or a wide area network (WAN). At present, these communication network technologies are very developed, such as mobile communication networks, Internet, radio and television networks, satellite networks, etc.
3. The application level receives data from various sensors, decrypts and processes the data, and finally realises human-computer interaction. This level is mainly composed of various types of service platforms, which work together to serve the market through data sharing and transmission.

2.2 SVM algorithm

SVM is a powerful class of machine learning algorithms widely used for classification and regression tasks. The essence of SVM is the ability to find an optimal hyperplane that best separates data points from different classes while maximising the margin between these classes (Ding et al., 2017). Compared to machine learning algorithms such as BP and DT, SVM selects the best hyperplane by maximising the distance from the support vectors to the hyperplane, which allows the model to maintain good performance on unseen data.

SVM has the advantages of strong generalisation ability, jumping out of local optimal solutions, and clear structure (Tan et al., 2019). Starting with a set of training samples, the input variable x is constructed. Using the mapping function $F(x)$, which corresponds to the high-dimensional feature space insight, the parameters w and b are adjusted to capture the characteristics of the data samples using the fitting process $f(x) = wF(x) + b$. To accommodate the nonlinearity, a kernel function is introduced to assess the impact of the nonlinear regression fit. The model parameters are shown in equation (1) and the constraints are shown in equation (2) to equation (4), respectively.

$$\text{Minimise}: \frac{1}{2}W^2 + C\sum_{1}^{n}\left(\xi_i + \xi_i^*\right) \tag{1}$$

$$y_i - [wF(x) + b] \leqslant \varepsilon + \xi_i \tag{2}$$

$$[wF(x) + b] - y_i \leqslant \varepsilon + \xi_i^* \tag{3}$$

$$\xi_i \xi_i^* \geqslant 0 \tag{4}$$

where W is a vector of weights, b is a model parameter, C is a penalty factor, and ξ is a slack variable.

By satisfying the Karush-Kuhn-Tucker (KKT) condition and using the Lagrange multiplier method, the relevant parameters of the function can be obtained, and the final prediction is as follows.

$$f\left(x, \alpha_i, \alpha_i^*\right) = \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right) K\left(x_1, x_i\right) + b \tag{5}$$

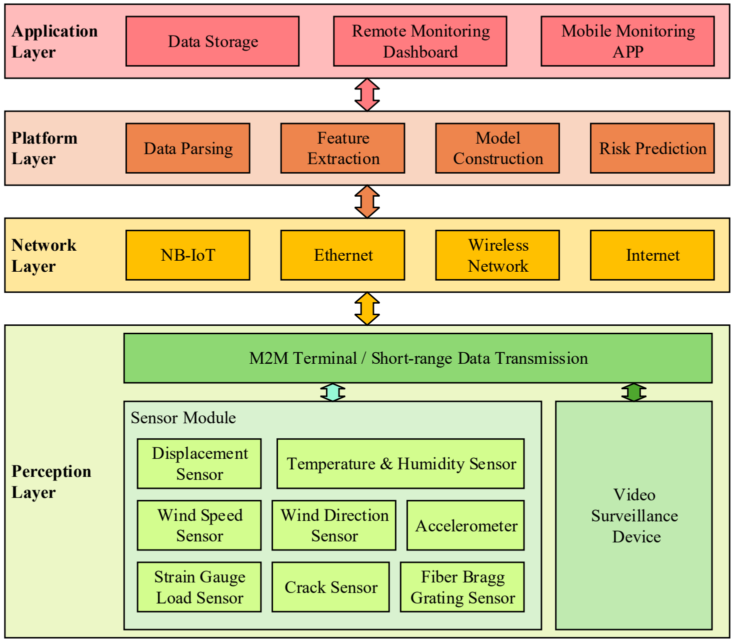
where α_i and α_i^* are the Lagrange multipliers and $K(x_1, x_i)$ is the nuclear function.

3 Overall design of IoT-based real-time monitoring for construction site safety management

3.1 Overall architecture of IoT-based real-time construction site monitoring system

To avoid construction site safety accidents, there is an urgent need to study the real-time monitoring technology of key risks in construction. Firstly, the overall architecture of real-time construction site monitoring technology based on IoT is constructed, and secondly, according to the theory of accident causation, the key risk monitoring index system is determined, and based on the indexes, the key risk features of construction are extracted from the IoT, and the key risk feature set of construction is composed of the IoT, which will provide the data support for the establishment of the subsequent early warning model.

Figure 2 The overall architecture of IoT-based remote monitoring system (see online version for colours)



Since the key risks of construction mainly exist in the construction site, in order to facilitate the monitoring of the key risks of construction, it is possible to collect the key risk data received by different sensors in the process of construction, and construct the overall architecture of IoT-based remote monitoring technology, as shown in Figure 2. The overall architecture consists of a sensing level, a network level, a platform level and an application level, and the monitoring process is as follows.

1 Multiple sensors in the sensor layer module are installed at the construction site to collect a series of construction risk data such as horizontal displacement, temperature, humidity, wind direction, wind speed, cracks, acceleration, and strain at the construction site.

2 Utilise M2M terminals to provide a short-distance data transmission channel between the sensor module and the network layer. At the same time, the construction site is divided into zones, and cameras and other video monitoring equipment are installed in each zone to collect real-time video images of the construction site.

3 After receiving and parsing the data, the platform layer extracts the key risk features of construction based on the key risk monitoring indicators of construction, constructs the construction risk monitoring and early warning model by using IReliefF and PSO improved SVM, predicts the results of the key risks of construction, and transmits the prediction results to the application layer.

4 While storing the data, the application level realises real-time monitoring of key construction risks by viewing construction site video images, risk data and key risk prediction results in real time through the mobile monitoring app.

3.2 Selection of technical indicators and feature extraction for monitoring key risks on construction sites

Construction site key risk monitoring technical indicators are based on the theory of accident causation in ergonomics (Mitropoulos et al., 2005), through the analysis of three elements in the construction process, namely, people, machinery and the environment, to determine the causes of the key risks of the construction, which is used as the main indicators for monitoring the key risks of the construction. Referring to the existing research, the construction key risk monitoring indicators are divided into six categories of indicators: construction workers' work at height risk, construction environment risk, machinery and equipment risk, safety protection risk, management organisation risk, and workers' health conditions risk.

After determining the key risk monitoring indicators, the construction key risk characteristics are extracted from the IoT data based on the indicators. For example, to determine whether there are environmental risks in construction, relevant data are collected from sensors such as temperature and humidity sensors, wind direction sensors, and wind speed sensors in the heterogeneous IoT sensing layer, and then transmitted to the platform layer via IoT to parse the data and extract features. The key risk characterisation parameters for real-time IoT sensor data are extracted from three main aspects: real-time sensed data traffic, IoT protocol connections, and the difference between IoT uplink traffic and downlink traffic.

1 The expressions for extracting the critical risk features δ_1, δ_1 of the sensed data from the real-time sensed data traffic are as follows.

$$\delta_1 = \sum_{i=1}^{n} \beta \times k \times m \tag{6}$$

where β is the data variable to be sent and its range is set in the sensor device, k is the IoT channel bandwidth, and m is the number of channels.

2 Extracting key risk characteristics of sensing data from IoT protocol connections. Since IoT can make different TCPs connect to several different sensors at the same time, the number of special messages formed when TCP establishes and disconnects is used as the key risk feature δ_2 of sensing data, and its expression is as follows.

$$\delta_2 = \frac{W + H + G}{3} \times (W \times H \times G) \tag{7}$$

where W is the number of termination messages, H is the number of reset messages, and G is the number of synchronisation sequence number messages.

3 Extract sensing data from the difference between IoT uplink traffic and downlink traffic as key risk features δ_3 and δ_4. When various types of data traffic are aggregated, there will be a small difference between IoT uplink traffic and downlink traffic. Therefore, the ratio of the difference between the IoT uplink and downlink traffic to the entire heterogeneous IoT traffic can be taken as the key risk feature δ_3, and the time-domain feature v of the sensed data can be expressed by using the information entropy and information gain of this data (Buscemi et al., 2016), as shown below.

$$\delta_3 = \sum_{o=1}^{o} \left(Q^2 + 1\right) / Q \tag{8}$$

$$\delta_4 = \sum_{o=1}^{o} \lg \frac{C_o}{C} (C - C_o) \times \frac{1}{2} \tag{9}$$

where Q is the total amount of sensed real-time data, C_o is the relevant risk data collected by one sensor O, and C is the relevant risk data collected by all sensors.

The full risk characterisation dataset extracted in the above way is the key risk characterisation set δ_2, i.e., $\delta_z = [\delta_1, \delta_2, \delta_3, \delta_4]$, for building construction in IoT.

4 Construction site risk early warning model based on ReliefF and SVM

4.1 Construction risk feature selection based on optimised ReliefF algorithm

After extracting the construction key risk feature set δ_z, the IReliefF algorithm and the improved SVM model of PSO are used to construct the construction risk warning model, and the overall process is shown in Figure 3. δ_z is pre-processed by IReliefF feature selection to obtain the optimal set of critical risk features, which is used to downscale δ_z to improve the prediction speed. The optimal key risk feature set is divided into training set and prediction set by cross-validation method, and the kernel function and penalty parameters are selected, while PSO solves the model parameters to obtain the optimal key risk prediction model of SVM.

ReliefF algorithm is a filter-based (filter) feature selection method (Aggarwal et al., 2023), but the key of ReliefF algorithm lies in the distance calculation, and the traditional Euclidean distance calculation method has high complexity. For this reason, IReliefF algorithm will feature samples in accordance with the length of the distance from the centre of the way to mention 10% as the sample core circle, in the process of calculating the weights of each time, randomly selected from the core circle of the sample as the centre of the weight calculation, and at the same time, in order to solve the problem of different features corresponding to the number of different samples, the use of the new distance calculation method instead of the calculation of the Euclidean distance method.

First, the feature vector W is initialised, and then, based on the Pareto principle, the distance from each sample to the centre of the class is calculated according to the new distance calculation method, and the closest 10% of the samples are selected as the core circle of the samples. Randomly select a sample x as the new class centre within the sample core of each class, and take its k nearest neighbours again. Next, take k nearest neighbour samples from all other samples that are different from sample x. Finally, the i, j^{th} feature weight vector is calculated according to the weight update formula.

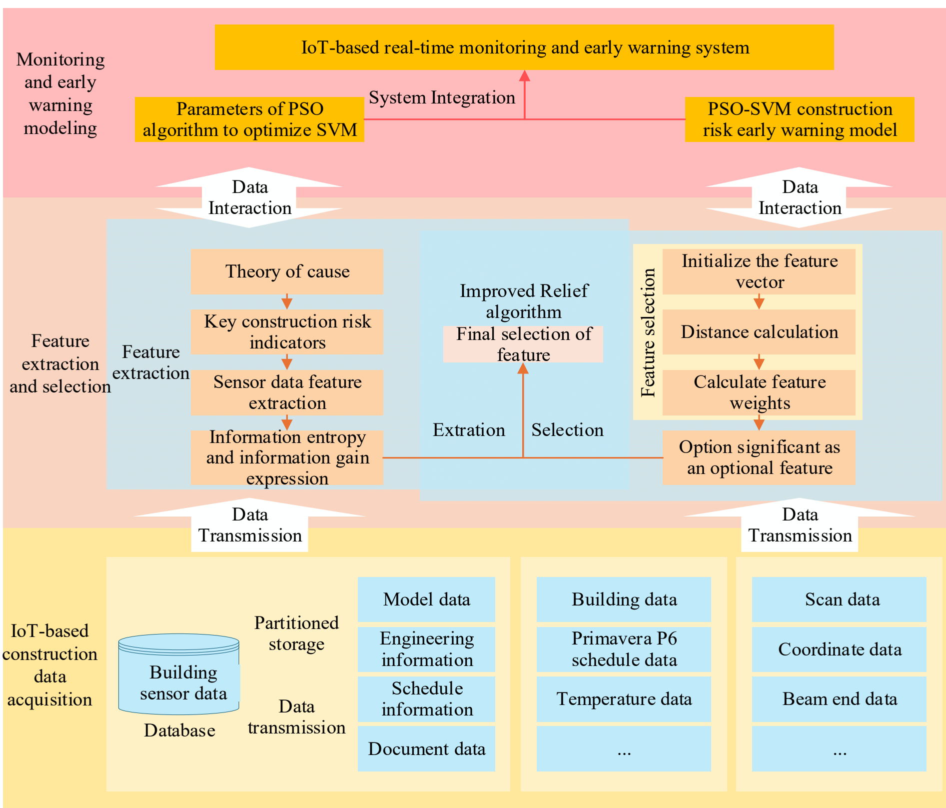
$$\begin{aligned} W^{i,j} &= W^{i,j-1} + \sum_{c \neq c(x)} \frac{\frac{1}{l-1} \sum_{j=l}^{k} L_{dist}\left(x, M_j^c(x)\right)}{m * k * l} \\ &= -\sum_{j=1}^{k} \frac{L_{dist}\left(x, H_j(x)\right)}{m * k * l} \end{aligned} \tag{10}$$

where l is the number of feature categories, m is the number of features and L_{dist} is the distance approach proposed in this paper as shown in equation (11).

$$\begin{aligned} L_{dist} &= \frac{1}{N}\sum_{N=1}^{N}\frac{1}{K}\sum_{i=1}^{k}\left[\left|u_c - x_i\right|\left|-\lambda_s\right.\right]^2 + \frac{1}{N(N-1)} \\ &= \sum_{u_i=1}^{k}\sum_{u_j=l}^{k}\left[2\lambda_d - \left\|u_i - u_j\right\|\right]^2 \end{aligned} \tag{11}$$

where u_c is the centre of a sample in the same category as sample x, u_j is the centre of a sample in a different category than sample x, λ_s and λ_d are centres of mass.

Figure 3 Construction site monitoring and early warning system (see online version for colours)



4.2 *Early warning of construction site safety risks based on PSO-SVM algorithm*

The SVM model needs to be set up with corresponding parameters, two of which are quite important for the final calculation, one is the penalty factor C, which is used to control the degree of penalisation on the samples, and the other is the kernel function σ, which represents the radial basis function width. These two parameters can have a direct impact on the performance of SVM (Cervantes et al., 2020). Firstly, the population is randomly initialised, and then the particles representing the parameter vectors are selected as the computational parameters in the SVM, and the corresponding iterative training is done, and finally the parameter values obtained in each iteration are recorded, and when the iteration meets the requirements, the particles obtained are the optimal parameters trained by the SVM, so as to increase the accuracy of the early warning.

1 Initialise the parameters of the particle swarm. Set d_1 and d_2 as the acceleration factors, and set the inertia weight w and the maximum number of evolution iterations M. The position of the i^{th} particle in the m^{th} iteration is denoted as $p_i^m = (C_i^m, \sigma_i^m)$, and the rate of evolution of the i^{th} particle in the m^{th} iteration is denoted as v_i^m. The orientation of any s particles is denoted as $p_1^0, p_2^0, ..., p_s^0$, so as to form the initial particle group p^0; the random initial velocity of particles is denoted as $v_1^0, v_2^0, ..., v_s^0$, where the position of each particle is denoted as $p_i^m = (p_{i1}^m, p_{i2}^m, ..., p_{in}^m)$, and the optimal solution for each particle is denoted as p_{id}^m.

2 Calculation of population fitness. The feature vector after feature selection is trained on the SVM, and then the trained output value $\hat{y}_i$ is obtained, and the corresponding curvature mode difference is y_i. Its fitness function is defined, as shown in equation (12). In the m^{th} iteration, the maximum fitness function is denoted as $g''_{\max}$, as shown in equation (13).

$$g_i^m\left(p_{id}^m\right) = \sum_{i=1}^{N}\left(y_i\left(p_{id}^m\right) - \hat{y}_i\right)^2 \tag{12}$$

$$g''_{\max} = \max_{i \in l} g_i^m\left(p_{id}^m\right) \tag{13}$$

3 Judge whether the iteration can be terminated. Compare the maximum value $g_{\max}^m$ of the fitness function calculated for the $m - 1^{th}$ time with the maximum fitness value $g_{\max}^{m-1}$ of the m-1st time, and judge, if $g_{\max}^m = g_{\max}^{m-1}$, the calculation is terminated. Otherwise, proceed to step (4).

4 The velocity and position of the particles are updated as shown in equation (14) and equation (15), respectively. Through the iterative operation of the particle swarm, the global optimal positions $p_{\max}(C_{\max}, \sigma_{\max})$ and $(C_{\max}, \sigma_{\max})$ of the particles can be obtained as the SVM parameters optimised by the PSO, and the output results are assigned to the SVM to complete the classification and prediction of the samples.

$$v_i^{m+1} = \omega \cdot v_i^m + d_1 \cdot \eta_1 \cdot \left[p_{id}^m - p_i^m\right] + d_2 \cdot \eta_2 \cdot \left[p_{id}^m - p_i^m\right] \tag{14}$$

$$p_i^{m+1} = p_i^m + v_i^{m+1} \tag{15}$$

where η_1 and η_2 represent random functions with values from 0 to 1.

5 Set the optimal construction risk feature samples as d-dimensional vectors, the number of samples is N, the category to which they belong is $\{x_i, y_i\}$, x_i is the i^{th} risk feature vector, y_i is the class marker, and R_d is the d-dimensional feature space. Set T

as the training data set in the feature space, then the classification hyperplane of the feature space is $\omega \cdot X + b = 0$. After normalising the data, the constraints on the linearly separable key risk feature samples are as follows.

$$y_i\left[(\omega \cdot x_i)+b\right] \geqslant 0 \tag{16}$$

The minimum categorisation surface is obtained when the above constraints are met and the weights are $1/2(\|w\|^2)$ at the same time. The Lagrange multiplier method is used to transform the optimal classification surface into the dual problem $\varepsilon(\alpha)$, as shown below, where i is the Lagrange multiplier, and α_j, x_j, and y_j are the mapping results of i, x_i, and y_i, respectively. Subject to the inequality constraints, there is a unique solution to equation (17). Based on the above equation, the optimal classification function for construction key risk features is shown in equation (18), where b^* is the optimal classification threshold.

$$\begin{cases} \varepsilon(\alpha) = \min \sum_{i=1}^{N} \alpha_i y_i - \frac{1}{2} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \left(x_i \cdot x_j\right) \\ \sum_{i=1}^{N} \frac{1}{2} y_i \alpha_i = 0 \\ \alpha_i > 0 \end{cases} \tag{17}$$

$$f(x) = sign\left\{ \sum_{i=1}^{N} \alpha_i y_i \left(x_i, x_j\right) \cdot X + b^* \right\} \tag{18}$$

5 Experimental results and analyses

To verify the ability of this paper's system ours to remotely monitor the key risks of building construction, it is applied to a building construction project. The project is undertaken by a construction engineering company, the project content for the construction of commercial housing, the project planning area of 479,306 m^2, a total construction area of 253,765 m^2. The sensors used in the monitoring process include temperature sensors, humidity sensors, and pressure sensors, and the penalty factor of SVM is 1, and the approximation threshold is 0.8. The daily time-course curves of the beam-end displacements and temperatures at the three monitoring points of the construction building are shown in Figure 4. The trend of the displacement response of the beam end of the building is mainly due to the temperature change, and there is an obvious negative correlation between the total trend of the beam end displacement and the total trend of the temperature fluctuation, and there is a certain offset at the extreme value of the two, and it can be seen that there is a certain time lag in the response of the beam end displacement of the building.

From the results of the above analysis, it can be seen that the building beam end displacement and temperature have extremely similar trends and patterns of change, compared with the figure can be known that the two show a negative correlation between the relationships. In order to further determine the correlation between the two and the degree of correlation, using the observation of the distribution of the building beam end displacement and temperature, as shown in Figure 5. The correlation coefficient of the building beam end displacement and temperature in the range of 0.930~0.991, are greater than 0.80, and the slope is less than 0, which shows that the expansion joints of the building are in a normal state of work, full of its deformation coordination ability, and will not produce construction accidents.

Figure 4 The daily time-course curves of the beam-end displacements and temperatures (see online version for colours)

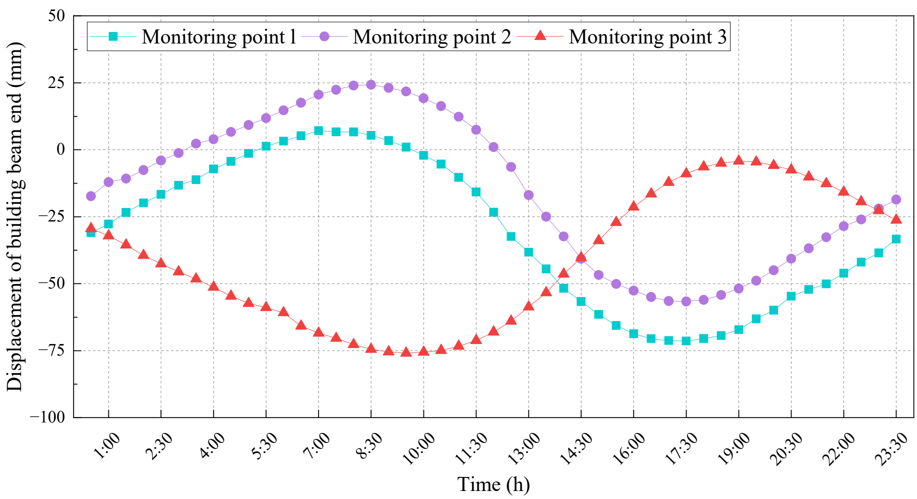
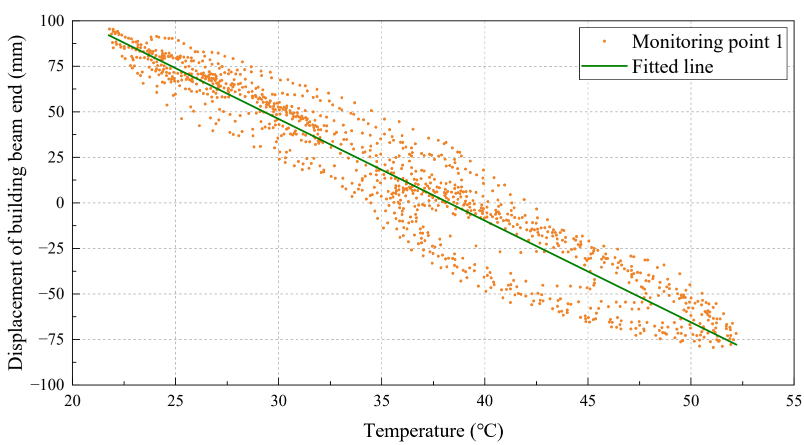


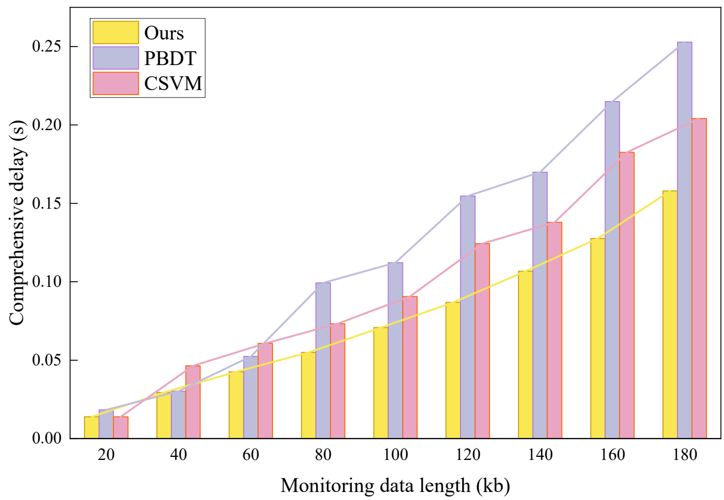
Figure 5 The distribution of the building beam end displacement and temperature (see online version for colours)



For the goal of verifying the transmission capability of this paper's method for the collected monitoring data, PBDT (Liu and Tian, 2019) and CSVM (Yang, 2019) are selected as the comparison method, and Eclipse IoT-Testware open-source test tool is used to conduct comprehensive delay test, and the test results are shown in Figure 6. As the length of transmitted monitoring data increases, the combined latency of the three methods also increases. When the length of transmitted monitoring data increases to

180 kb, the combined latency of IoT is 0.16, which is lower than that of PBDT and CSVM, indicating that ours is more time-efficient in monitoring the key risks of building construction.

Figure 6 Comprehensive delay of various system (see online version for colours)



The accuracy, mean square error (MSE), mean absolute error (MAE), and running time comparisons of PBDT, CSVM, and Ours methods are shown in Table 1. PBDT was the worst performer across all metrics, with prediction accuracy and run time of 80.56% and 207 s, respectively. This is because although PBDT uses PCA to remove feature redundancy, the DT keeps splitting nodes until all training samples are 'perfectly classified', resulting in an overly complex tree structure that captures noise rather than regularities. The construction safety risk warning accuracy obtained by ours method using PSO optimised SVM is 91.31% and the running time is 35 s, while comparatively, the prediction accuracy of CSVM using traditional SVM for construction risk warning decreases to 87.39%, and the running time extends to 138 s, it is obvious that Ours has higher accuracy compared to CSVM. In addition the MSE and MAE of ours are smaller than CSVM, indicating that ours has better generalisation ability as well as robustness.

Table 1 Comparison of prediction performance of different methods

Method	*Accuracy/%*	*MSE*	*MAE*	*Running time/s*
PBDT	80.56	0.181	2.439	207
CSVM	87.39	0.085	1.851	138
Ours	91.31	0.013	1.032	35

6 Conclusions

As a high-risk field, the building construction industry is characterised by frequent safety accidents, which seriously threaten the safety of people's lives and property. In order to avoid construction safety accidents and realise real-time construction site safety management. This paper proposes an IoT-based construction site monitoring and warning system. Firstly, based on IoT, we build the overall architecture of IoT real-time monitoring, which includes sensing layer, network layer, platform layer and application layer, and determine the construction risk monitoring index system according to the accident causation theory. Construction site risk characteristics are extracted from three aspects: real-time sensed data traffic, IoT protocol connections, and the difference between IoT uplink traffic and downlink traffic. The IReliefF algorithm is then used to select important construction risk features and reduce the impact of anomalous samples by weighting the contribution of neighbours by distance when calculating feature weights. Finally, the important features are taken as input to the PSO-SVM model, the population is randomly initialised, and the particles representing the parameter vector are selected as the calculation parameters in the SVM, and corresponding iterative training is performed on them. Finally, the parameter values obtained in each iteration are recorded. The obtained particles represent the optimal parameters trained by SVM to obtain accurate prediction results. The application simulation results in a building construction project show that the proposed system has low data transmission delay and high prediction accuracy, which provides a practical technical reference for the construction industry to create a safer construction environment.

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Declarations

All authors declare that they have no conflicts of interest.

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