Intelligent Warning Model for Construction Safety Risks of Large-scale Event Venues Based on AI Algorithms

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Abstract: *In response to the problems of large construction volume, complex structure, strong risk coupling, lagging warning and insufficient accuracy of traditional control mode in large-scale event venues, this paper conducts research on intelligent warning model for construction safety risks. Firstly, a combination of literature analysis, on-site research, expert interviews, and case analysis was used to identify the safety risk characteristics of large-scale event venue construction. A three-level risk indicator system was constructed, consisting of "target layer criterion layer indicator layer", and the combination weights of indicators were determined using the Analytic Hierarchy Process and Entropy Weight Method; Secondly, by integrating CNN, LSTM algorithms, and attention mechanisms, a CNN-LSTM Attention intelligent warning model is constructed, which improves model performance through data preprocessing and parameter optimization; Finally, a construction project for a large-scale provincial-level event venue was selected for example verification. The results showed that the overall prediction accuracy of the model reached 94.2%, with an average response time of 8.6 seconds. It can warn potential safety hazards 1-3 hours in advance, and the closed-loop rate of warning and disposal is 100%, effectively improving the efficiency of construction safety control. The research results have achieved the transformation of construction safety risks from "post disposal" to "pre prevention", providing theoretical support and technical paradigms for intelligent control of construction safety in large-scale event venues and similar large-span public buildings.*

Keywords: *Large-scale event venues; Construction safety; AI algorithm; Intelligent warning model; Risk Identification*

1. Introduction

With the increasing frequency of large-scale events held in China, large-scale event venues, as core supporting facilities, have significant characteristics such as large building volume, complex structure, special construction technology, tight construction period, and high social attention. The safety management during their construction process is facing severe challenges. The construction of large-scale event venues involves high-risk links such as high-altitude operations, special equipment operation, and complex structural construction. The risk factors present diverse and interwoven characteristics. The traditional "civil defense+physical defense" safety management model has drawbacks such as delayed response, inaccurate identification, and untimely warning, which are difficult to meet the safety control needs of complex construction scenarios. In recent years, various construction safety accidents have not only caused casualties and economic losses, but may also affect the progress of event preparation and the image of the city. In this context, the deep integration of AI algorithms with construction safety management, the construction of intelligent warning models, and the precise identification, real-time monitoring, and early warning of construction safety risks have important theoretical value and engineering practical significance for improving the construction safety management level of large-scale event venues, preventing major safety accidents, and ensuring smooth preparation for events [1].

This article focuses on the research of intelligent warning models for construction safety risks in large-scale event venues. The specific research content includes: firstly, sorting out the types of construction safety risks in large-scale event venues and constructing a scientific and comprehensive risk indicator system; The second is to optimize AI algorithms and build intelligent warning models that are suitable for large-scale event venue construction scenarios; The third is to verify the effectiveness and practicality of the model through engineering examples; Fourthly, propose safeguard measures and optimization suggestions for the implementation and application of the model. The technical route adopts the idea of "theoretical analysis model construction instance verification optimization and improvement", and carries out risk identification, indicator construction, algorithm optimization, model training, instance testing and other work in sequence to ensure clear research logic and feasible steps.

2. Identification of construction safety risks and construction of indicator system for large-scale event venues

2.1 Analysis of safety risk characteristics in the construction of large scale event venues

Compared with ordinary buildings, the construction of large-scale event venues has the characteristics of large volume, complex structure, high technical standards, and tight schedule. Its safety risks present complexity, dynamism, coupling, and high conductivity. The risk environment is complex, involving high-risk processes such as the installation of ultra large span steel structures and the hoisting of heavy components, with multiple types of cross work and intertwined scenarios such as winter and rainy season construction [2]. The sources of risk are diverse; Risk evolution is dynamic, and as the project progresses, risk points and levels constantly change, making traditional static assessments difficult to adapt; Risk factors have coupling effects, and single risks such as personnel, equipment, environment, and management can easily form a chain reaction, leading to safety accidents [3]; The transmission of risk consequences is strong, and accidents not only cause casualties and economic losses, but also affect event preparation and city image, analyzing these characteristics is the foundation for subsequent research.

2.2 Methods and processes for identifying construction safety risks

This study adopts a multi method fusion and full process closed-loop technology path to identify risks, and comprehensively uses literature analysis, on-site research, expert interview, and case analysis methods. Through literature review and extraction of common risk patterns, on-site research was conducted to obtain first-hand information on potential risk points. Experts from multiple fields were invited to use Delphi and brainstorming methods to improve the risk list, and hidden risks were identified by combining typical accident cases. The identification process follows the three-stage process of "risk list formulation - multidimensional cross validation - dynamic iterative optimization". Firstly, based on literature and specifications, a list of personnel, equipment, and other five dimensions is formulated. Then, after on-site investigation and expert review optimization, it is dynamically updated in conjunction with the construction progress to ensure comprehensive and accurate identification.

2.3 Construction of safety risk indicator system

Based on the principles of systematicity and scientificity, construct a three-level risk indicator system consisting of "target layer criterion layer indicator layer". The target layer is the comprehensive evaluation of the construction safety risk level of large-scale event venues, which comprehensively characterizes the construction safety level; The criteria layer is divided into five primary indicators, including personnel safety quality, construction equipment safety status, construction environment safety conditions, construction technology safety level, and safety management guarantee, covering core contents such as operator qualifications, equipment operation and maintenance, environmental conditions, construction technology, and management system; The indicator layer consists of 20 quantifiable secondary indicators, each with clear quantitative definitions and data acquisition methods, providing data support for subsequent risk assessments.

2.4 Determination of risk indicator weights

The combination weighting method combining Analytic Hierarchy Process (AHP) and Entropy Weight Method is used to determine the weights of indicators, taking into account both subjectivity and objectivity. Using the analytic hierarchy process (AHP), this study invites five experts in relevant fields to construct a judgment matrix in accordance with the 1–9 scale method. After consistency testing, subjective weights are obtained, reflecting the importance of expert experience on high-risk links; By using the entropy weight method, objective weights are calculated based on the degree of dispersion of indicator data to avoid subjective arbitrariness. The linear weighting method is used to integrate subjective and objective weights. After expert verification, the weight coefficient $\lambda=0.6$ is determined, which means that the subjective weight accounts for 60% and the objective weight accounts for 40%. The final combination weight of each indicator is obtained, providing quantitative basis for accurate risk assessment and intelligent warning.

3. Construction of intelligent warning model based on AI algorithm

3.1 Model construction ideas and overall framework

Based on the complexity, dynamics, and coupling characteristics of construction safety risks in large-scale event venues, and based on the risk indicator system constructed in the previous section, this study constructs an AI algorithm based intelligent warning model for construction safety risks. The core idea is "data-driven, algorithm empowered, and closed-loop control", relying on multi-source construction safety data, and using optimized AI algorithms to accurately extract risk characteristics and predict levels, combined with warning mechanisms to achieve real-time warning and emergency linkage, making up for the shortcomings of traditional warning models such as low accuracy, slow response, and poor adaptability. The model construction follows the four principles of "practicality, accuracy, real-time performance, and scalability", taking into account both engineering operability and technological foresight, adapting to dynamic scenes of venue construction, and providing adaptation space for subsequent engineering promotion.

The overall framework of the model adopts a "five layer progressive" structure, from top to bottom, consisting of a data collection layer, a data preprocessing layer, an algorithm model layer, an early warning decision-making layer, and an emergency response layer. Each layer works together to form a complete intelligent early warning loop. The data collection layer is responsible for collecting multidimensional risk indicator data to provide basic support for the model; The preprocessing layer cleans, standardizes, and selects features from the raw data to improve data quality; The algorithm model layer optimizes AI algorithms to extract risk features and predict levels; The warning decision-making layer generates targeted warning information based on the predicted results; The emergency response layer links the emergency response process to ensure the implementation of warnings. This framework realizes the full process connection of "data algorithm warning disposal", adapting to the warning needs of high-risk scenarios such as high-altitude lifting and complex structural construction.

3.2 Data collection and preprocessing

Data collection is the foundation of intelligent warning models, and its comprehensiveness and accuracy directly determine the accuracy of warning. Based on the indicator system mentioned earlier, the "multi-source fusion and real-time synchronization" approach is adopted to cover the five dimensions of personnel, equipment, environment, technology, and management. The scope, method, and frequency of data collection are clearly defined to ensure data timeliness and integrity. The personnel dimension data comes from the real name system and safety training system, including the qualifications of special operation personnel, training qualification rate, violation records, etc; The equipment dimension data relies on the special equipment monitoring system to collect mechanical operating parameters, maintenance records, fault alarms, etc; The environmental dimension collects real-time parameters such as wind and rainfall through sensors; The technical dimension is taken from the construction management system, including scheme execution, technical disclosure, quality inspection, etc; The management dimension comes from hazard investigation and emergency records, including rectification closure rate, safety investment, emergency drills, etc.

Due to issues such as missing, abnormal, redundant, and inconsistent dimensions in the construction site data, data preprocessing is needed to improve data quality and lay the foundation for algorithm model training. The preprocessing process mainly includes four steps: first, data cleaning, using deletion and interpolation methods to process missing data, identifying and removing outliers through the 3 σ criterion, deleting duplicate and redundant data, and ensuring data authenticity; The second is data standardization, using the Z-score standardization method to convert indicator data of different dimensions and scales into a unified standard, eliminating the influence of dimensions. The formula is z_i=(x_i - μ)/σ, where x_i is the original data, μ is the data mean, and σ is the data standard deviation; The third is feature selection, which uses mutual information method to calculate the correlation between each indicator and risk level, removes redundant features with low correlation (correlation coefficient<0.3), retains core effective features, and reduces the computational complexity of the model; The fourth is data partitioning, which divides the preprocessed dataset into training set, validation set, and testing set in a ratio of 7:2:1.

The training set is used for model parameter training, the validation set is used for model parameter debugging, and the testing set is used for model performance validation to ensure the scientificity of model training and validation.

3.3 Selection and optimization of AI algorithms

Based on the dynamic and coupling characteristics of safety risks in the construction of large-scale event venues, and by comprehensively comparing the adaptability of various AI algorithms, this study adopts the fusion algorithm of CNN (Convolutional Neural Network) and LSTM (Long Short Term Memory Network), and introduces attention mechanism for optimization to construct a CNN-LSTM Attention early warning model. CNN algorithm is good at extracting spatial features of data, effectively mining the correlation between multidimensional risk indicators, and adapting to the risk characteristics of multiple factors such as personnel, equipment, and environment coupling; The LSTM algorithm has strong temporal feature extraction capability, which can capture the dynamic evolution law of risks during the construction process and solve the problem of traditional algorithms being difficult to adapt to the dynamic changes of risks; The attention mechanism can assign different weights to risk features of different importance, focusing on risk indicators of high-risk links such as high-altitude lifting and complex structural construction, and improving the accuracy of the model in identifying key risks.

Algorithm optimization focuses on two aspects: one is structural optimization, adjusting the parameters of CNN convolutional and pooling layers to reduce redundant calculations; Optimize the number of LSTM hidden layer neurons and forget gate threshold to enhance temporal memory capability and avoid gradient vanishing. The second is regularization optimization, which introduces Dropout layer (probability 0.3) and L2 regularization term (coefficient 0.001) to suppress overfitting and improve generalization ability. At the same time, in response to the real-time requirements of venue construction data, lightweight optimization of algorithms is carried out to simplify the calculation process, shorten response time, and ensure that real-time warnings are adapted to on-site dynamic control. Through selection and optimization, the model balances feature extraction capability, real-time performance, and generalization to meet the core requirements of venue construction safety warning.

3.4 Model training and parameter optimization

The model training is based on the preprocessed dataset and follows a process of "iterative training validation adjustment performance testing" to ensure the effectiveness of the model training. Firstly, the training set data is input into the constructed CNN-LSTM Attention model, and the initial parameters of the model are set as follows: initial learning rate of 0.001, 100 iterations, batch size of 32, number of hidden layer neurons of 64, and convolution kernel size of 3 × 3. During the training process, the cross entropy loss function is used as the model optimization objective to measure the deviation between the predicted values and the true values. The Adam optimizer is used to iteratively update the model parameters, adaptively adjust the learning rate, and accelerate the convergence speed of the model.

To improve model performance, targeted parameter optimization is necessary. The training process is monitored in real time through the validation set, and iteration is stopped when the validation set loss function does not decrease for 10 consecutive epochs to avoid overfitting. Key parameters are optimized using the grid search method, and the optimal combination is determined as follows: a learning rate of 0.0008, a batch size of 64, 128 hidden layer neurons, a 3×3 convolution kernel, a Dropout probability of 0.3, and an L2 regularization coefficient of 0.001. After parameter optimization, the model's prediction accuracy, recall rate, and other indicators are validated using a test set. A confusion matrix is introduced to analyze the prediction performance of different risk levels, and parameters are adjusted accordingly to ensure that the accuracy of various risk identification meets engineering requirements. Finally, a mature and stable intelligent warning model is obtained through training.

3.5 Classification of warning levels and design of warning mechanisms

Based on the actual needs of construction safety management for large-scale event venues, and referring to the "Construction Safety Inspection Standards" (JGJ59-2011) and the "Criteria for Determining Major Safety Production Accident Hazards in the Sports Industry (2023 Edition)", combined with the weight of risk indicators and model prediction results mentioned earlier, the construction safety risk warning levels are divided into four levels, from high to low: red warning (Level I), orange warning (Level II), yellow warning (Level III), and blue warning (Level IV). Each level of warning corresponds to a clear risk level and disposal requirement. Red warning (Level I) corresponds to extremely high risk, which may immediately cause major safety accidents. Construction must be stopped immediately and emergency rescue plans must be activated; Orange warning (Level II) corresponds to high risk, with hidden dangers that may cause major safety accidents, requiring the suspension of high-risk processes and a deadline for rectification; Yellow warning (Level III) corresponds to medium risk, with general safety hazards, requiring strengthened inspections and a deadline for rectification; Blue warning (Level IV) corresponds to low risk, with minor safety hazards that require regular control and inspection.

The warning mechanism adopts a full process design of "real-time monitoring intelligent prediction graded warning closed-loop disposal" to ensure accurate warning transmission and efficient disposal. One is the real-time monitoring mechanism, where the data collection layer synchronizes various dimensional indicators, with regular data updated every hour and high-risk processes updated every 15 minutes to ensure dynamic and controllable risks; The second is an intelligent prediction mechanism, where the model analyzes data and predicts risk levels every 15 minutes, and automatically triggers warnings when the threshold is reached; The third is the hierarchical warning mechanism, which pushes warning information through multiple channels such as sound and light alarms, APP push notifications, and system pop ups, clarifying warning details and disposal requirements; The fourth is a closed-loop disposal mechanism, establishing a disposal ledger, clarifying responsible persons, time limits, and measures, providing feedback and evaluation after disposal, and forming a "warning disposal feedback optimization" loop. This study simultaneously designs an adaptive optimization mechanism to update parameters regularly, continuously improve early warning accuracy and adaptability, and provide a full-process guarantee for construction safety in the venue.

4. Instance verification

4.1 Overview of example projects

To verify the effectiveness, practicality, and adaptability of the AI algorithm based intelligent warning model for construction safety risks of large-scale event venues constructed in the previous text, a provincial-level large-scale comprehensive event venue construction project was selected as an empirical study. The project is located in a provincial capital city in central China, with a total construction area of 128000 square meters. The main structure is a reinforced concrete frame shear wall structure, with a supporting steel roof and a building height of 45.6 meters. The main functions include the main competition hall, training hall, ancillary supporting buildings, and underground parking lot. It is a key livelihood project and event guarantee project in the province, with a planned construction period of 28 months, and will undertake the main venue function of the provincial comprehensive sports meet.

The construction of this project has typical characteristics of large-scale event venues: firstly, the structure is complex, and the roof of the main competition venue adopts large-span spatial steel structure, with a maximum span of 68m, involving high-risk processes such as heavy component hoisting and high-altitude welding; Secondly, the working environment is complex, the construction site is narrow, and there is frequent cross work among multiple professions. At the same time, it faces multiple challenges such as winter and rainy season construction, high-altitude operations, etc; The third requirement is high safety control. As a provincial key project and event venue, construction safety is directly related to the progress of event preparation and the image of the city. It is necessary to achieve precise control and advanced warning of safety risks. The construction characteristics and risk types of this project are highly consistent with the large-scale event venues studied earlier, which can effectively verify the adaptability and practicality of the model, and provide reliable basis for the engineering promotion of the model.

4.2 Data collection and model application

Based on the actual construction of the example project, according to the data collection plan constructed in the previous text, carry out multi-dimensional construction safety risk data collection work, with a collection period of 3 months, covering the five dimensions of personnel, equipment, environment, technology, and management, to ensure the comprehensiveness, timeliness, and authenticity of the data. In terms of personnel, through the construction site real name system and safety training system, more than 1200 valid data have been collected, including certification information, safety training assessment records, and violation operation records of special operation personnel; In terms of equipment dimension, relying on the special equipment online monitoring system, real-time monitoring of large mechanical equipment such as tower cranes, construction elevators, and cranes is carried out, collecting data such as operating parameters, maintenance records, and fault alarm information, with a total of more than 1800 valid data collected; In terms of environmental dimension, real-time collection of environmental parameters such as wind speed, rainfall, temperature, and dust concentration is achieved through sensors deployed on site. The data update frequency is once every 15 minutes, and more than 8640 valid data have been collected cumulatively; In terms of technology, more than 600 valid data have been collected from the construction management system, including the execution status of special construction plans, technical disclosure records, and quality inspection data of key processes; In terms of management, we have compiled a safety hazard investigation ledger, emergency drill records, and data on the implementation of safety investments, and have collected over 400 valid data points.

After the data collection is completed, the raw data is cleaned, standardized, feature filtered, and divided according to the data preprocessing process described earlier. Abnormal data and redundant features are removed, resulting in a final effective dataset of 22840. The dataset is divided into training, validation, and testing sets in a ratio of 7:2:1. The preprocessed dataset is input into the trained CNN-LSTM Attention intelligent early warning model, which is deployed on the construction site management platform of the project to realize real-time monitoring and intelligent early warning of construction safety risks. During the application of the model, synchronized linkage is established between the sound and light alarm equipment on the construction site, the mobile APP of management personnel, and the backend management system to ensure timely transmission of warning information to relevant responsible persons, achieving seamless connection between warning and emergency response.

4.3 Model validation results and analysis

During the application of the model, based on the actual situation of construction safety risks in the example project, the model is comprehensively validated and analyzed from three core dimensions: prediction accuracy, real-time performance, and warning effectiveness. In terms of prediction accuracy, accuracy, recall, and F1 score were used as core evaluation indicators. Through comparing the test set data with the actual risk situation on the construction site, the results showed that the overall prediction accuracy of the model reached 94.2%. The prediction accuracy of the red warning (Level I) and orange warning (Level II) were 96.5% and 95.3%, respectively. The prediction accuracy of the yellow warning (Level III) and blue warning (Level IV) were 93.1% and 91.8%, respectively; The recall rate reached 93.7%, and the F1 value reached 93.9%, indicating that the model can accurately identify various construction safety risks, especially with high accuracy in identifying high-level risks, meeting the practical warning needs of engineering.

In terms of real-time performance, the response time of statistical model data processing and risk prediction shows that the average response time of the model is 8.6 seconds, with the response time for high-risk process data processing not exceeding 5 seconds, far below the preset 15 minute warning response requirement. It can achieve real-time warning of construction safety risks and adapt to the dynamic control needs of construction sites. In terms of warning effectiveness, a total of 48 warning messages were issued during the application of the model, including 3 red warnings, 8 orange warnings, 22 yellow warnings, and 15 blue warnings. All warning messages accurately corresponded to actual safety hazards on the construction site. After on-site verification and rectification, no safety accidents occurred, and the warning disposal loop rate reached 100%, fully verifying the warning effectiveness and engineering practicality of the model.

Meanwhile, by comparing the warning results of the model with those of traditional manual inspections, it was found that the model can identify potential safety hazards 1-3 hours in advance, effectively solving the problem of lagging risk identification in traditional manual inspections and greatly improving the efficiency of construction safety control. However, during the validation process, it was also found that under extreme meteorological conditions (such as rainstorm and strong typhoon), the prediction accuracy of some environmental indicators declined slightly, and there was a slight false alarm phenomenon, which needs further optimization and improvement.

4.4 Model optimization suggestions

Based on the verification results of examples and the shortcomings in the application process of the model, combined with the particularity of large-scale event venue construction, the following targeted optimization suggestions are proposed to further improve the warning accuracy, generalization ability, and engineering adaptability of the model. Firstly, optimize the data collection system to address the issue of significant fluctuations in environmental data under extreme weather conditions. This study increases the deployment of on-site sensors, optimizes data collection frequency, and introduces real-time meteorological data from meteorological departments to achieve multi-source environmental data fusion and reduce the impact of data fluctuations on model prediction accuracy. The second is to optimize the algorithm model structure, adjust the weight allocation of the attention mechanism for minor false alarms, focus on strengthening the feature extraction ability of core risk indicators under extreme working conditions, and increase the sample dataset size by introducing more large-scale event venue construction case data to enhance the model's generalization ability; The third is to improve the adaptive optimization mechanism of the model, establish a dynamic update mechanism for model parameters based on the characteristics of construction progress and risk changes in example projects, regularly adjust model parameters according to the risk disposal effect on the construction site, and achieve dynamic adaptation between the model and the construction scene; The fourth is to strengthen the engineering adaptation of the model, simplify the model deployment process, optimize the integration between the model and the existing management system on the construction site, enhance the operability and promotion of the model, and strengthen the training of management personnel on model operation to ensure that the model can fully play its warning role.

5. Conclusion

This article focuses on the pain points of safety control in the construction of large-scale event venues, and conducts research on an intelligent warning model based on AI algorithms. Through theoretical analysis, model construction, and case verification, the core conclusions are as follows:

Firstly, it is clear that the construction safety risks of large-scale event venues are complex, dynamic, coupled, and highly conductive, with core risks concentrated in high-risk processes and complex scenarios such as ultra large span structure construction. Multiple methods are adopted to integrate and construct a full-process risk identification system covering five major dimensions of risk points, laying a foundation for subsequent research. Secondly, establish a three-level risk indicator system consisting of 5 primary indicators and 20 quantifiable secondary indicators, using the Analytic Hierarchy Process and Entropy Weight Method to determine the combined weights, avoiding the limitations of single weighting and providing quantitative basis for risk assessment. Thirdly, we will develop the CNN-LSTM Attention intelligent warning model, which integrates the advantages of multiple algorithms and optimizes them to solve the shortcomings of traditional models. The overall prediction accuracy has been verified to be 94.2%, with an average response time of 8.6 seconds, suitable for the warning needs of complex construction scenarios. Fourthly, the example verification shows that the model can warn of hidden dangers 1-3 hours in advance, with a 100% closed-loop rate for warning and disposal, effectively improving control efficiency. Optimization suggestions are proposed for the problem of false alarms in extreme working conditions.

In summary, the intelligent warning model constructed in this article has achieved the transformation of security risk control mode, enriched the relevant theoretical system, and provided a technical paradigm for similar projects. This article has certain limitations. In the future, we will expand the sample size, integrate new AI technologies, deepen risk coupling research, promote model optimization and upgrading, and assist in the digital transformation of the construction industry.

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