Research on Safety Behavior Identification and Real-Time Intervention Mechanism of Construction Site Based on Artificial Intelligence

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Abstract: This paper focuses on the difficult problem of safety management in the construction site, aiming at realizing accurate identification and real-time intervention of safety behaviors with the help of artificial intelligence (AI) technology. By setting up an experimental environment, equipment was deployed at the construction site to collect 8000 image data covering a variety of safe and unsafe behaviors, and the CNN-LSTM hybrid model was trained. After testing, the model performs well in behavior recognition such as helmet wearing, equipment operation and seat belt wearing, with the accuracy of 96%, 94% and 95% respectively. The average processing time of a single image is 0.04 seconds, and the average response time of the system is 0.18 seconds. The research shows that the AI-based system is highly effective and real-time in identifying and real-time intervening safety behaviors in the construction site, which provides an innovative and feasible scheme for improving the safety management level of the construction site, but the accuracy of identification in complex environment still needs to be improved.

1. Introduction

Under the background of the rapid development of today's construction industry, the safety of the construction site has always been the top priority. With the acceleration of urbanization, all kinds of large and complex construction projects are constantly emerging, and the activities of personnel and equipment on the construction site are more frequent, and the security risks are also increasing [1]. According to incomplete statistics, the number of economic losses and casualties caused by safety accidents on the construction site is shocking every year, and a large proportion of accidents are attributed to unsafe behaviors of personnel [2]. Therefore, it is of great significance to effectively identify the safety behavior of the construction site and intervene in time to ensure construction safety and reduce accidents.

In recent years, AI technology has made a breakthrough, and its successful application in many fields has brought new opportunities to solve the safety management problems in construction sites [3]. With its powerful data analysis and pattern recognition capabilities, AI can extract valuable information from the complex environment of the construction site and realize accurate identification of personnel safety behaviors [4]. Through real-time monitoring and analysis, potential safety risks can be found in time and intervention measures can be taken to nip accidents in the bud.

Internationally, some developed countries have taken the lead in the research and practice of AI in construction site safety management. By using advanced sensor technology and computer vision algorithm, they realized intelligent monitoring and behavior analysis on the construction site [5]. In China, although the related research started a little late, with the increasing emphasis on construction safety, the application of AI in this field has gradually increased [6]. However, the current research still has shortcomings in terms of technology integration and the effectiveness of real-time intervention mechanism.

It is urgent to carry out in-depth research on safety behavior identification and real-time intervention mechanism in construction site based on AI. This is not only helpful to improve the

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scientific and intelligent level of safety management on the construction site, but also an inevitable requirement to ensure the sustainable development of the construction industry and safeguard the safety of life and property of construction workers. This study expects to provide innovative and practical solutions for the safety management of the construction site through systematic exploration.

2. Theoretical basis of AI in safety behavior identification of construction site

AI contains a variety of technologies, which lays a theoretical foundation for the identification of safety behaviors on the construction site. As the core of AI, machine learning enables computers to learn and recognize patterns based on data [7]. In the safety behavior identification of construction site, a large number of marked safety and unsafe behavior data can be used to train the machine learning model, so that the model can learn the characteristics of different behavior patterns, thus realizing the classification and identification of new behavior data. As a branch of machine learning, deep learning is based on deep neural network, which has powerful automatic feature extraction ability [8]. Convolutional neural network (CNN) has an outstanding performance in the field of image recognition. Image data are often collected by cameras in construction sites. CNN can extract and analyze the characteristics of people's actions and postures in images, and accurately judge whether people's behaviors are safe or not. Although natural language processing technology is mainly used in the text field, it also plays an auxiliary role in the safety management of the construction site [9]. For example, the text data such as construction logs and safety reports are analyzed, and potential safety problems and behavior patterns are mined to provide more dimensional information for safety behavior identification.

3. Design of AI-based safety behavior identification and real-time intervention system in construction site

This system aims to use AI technology to realize accurate identification and real-time intervention of construction site safety behavior, and effectively improve the level of construction safety management. The system mainly consists of data acquisition and preprocessing module, safety behavior identification module, real-time intervention module and data storage and management module.

The data acquisition and preprocessing module is responsible for collecting all kinds of data on the construction site, including video image data collected by cameras, environment and equipment status data obtained by sensors, etc. For video image data, image enhancement should be carried out first, with the purpose of improving image quality and enhancing the recognition of key features. The histogram equalization method makes the gray histogram of the image evenly distributed by redistributing the gray value of the image, thus improving the contrast of the image. Its principle formula is:

$$s_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n} \quad k = 0,1,\cdots,L-1 \quad (1)$$

Where r_k is the k-th gray value of the original image, s_k is the transformed gray value, n_j is the number of pixels with the gray value r_j, n is the total number of pixels of the image, and L is the total number of gray levels of the image.

After obtaining the image data, we use the target detection algorithm - You Only Look Once (YOLO) to locate the people and key equipment in the image. Compared with other algorithms, YOLO algorithm has certain advantages in detection speed and accuracy, and it is more suitable for scenes with high real-time requirements on the construction site. After that, the feature of the detected target is extracted, which provides a data basis for subsequent behavior recognition.

The safety behavior identification module identifies safety behaviors based on the deep learning model. CNN is used to analyze the depth of the extracted image features. A multi-layer CNN model is constructed, including convolution layer, pooling layer and full connection layer. The convolution layer extracts the local features in the image through the convolution kernel, and its convolution operation can be expressed by the following formula:

$$\mathrm{feature}_{i,j} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \mathrm{input}_{i+m,j+n} \times \mathrm{kernel}_{m,n} + b \quad (2)$$

Where $\mathrm{feature}_{i,j}$ is the element value of the feature map at (i, j) position after convolution, input is the input image, kernel is the convolution kernel, M and N are the number of rows and columns of the convolution kernel respectively, and b is the offset. Pooling layer is used to reduce data dimension and computation.

In the training process, a large number of labeled image data of safe and unsafe behaviors are used to optimize the model. Futhermore, long-term and short-term memory network (LSTM) is introduced. Considering the time series characteristics of behaviors, LSTM can deal with the long-term dependence in time series data, better capture the changing characteristics of behaviors in time dimension, and improve the accuracy of behavior recognition. By combining the advantages of CNN and LSTM, a CNN-LSTM hybrid model is constructed to identify safety behaviors. The back propagation algorithm is used to adjust the parameters of the model to minimize the loss function, so that the model can accurately distinguish different types of safety behaviors.

Real-time intervention module: when the safety behavior identification module judges that there is unsafe behavior, the real-time intervention module is started immediately. According to the types and severity of unsafe behaviors, the module makes corresponding intervention strategies. For the slight behavior of not wearing the helmet correctly, the system automatically sends out a voice reminder through live broadcast; For serious illegal operation of equipment, in addition to voice reminder, related equipment can also be remotely controlled to suspend operation. Futhermore, the system sends the unsafe behavior information to the mobile terminal of the site safety management personnel in real time, so that they can arrive at the site in time for processing. Intervention records will be synchronously stored in the data storage and management module for subsequent safety analysis and summary.

The data storage and management module is responsible for storing all kinds of data generated during the operation of the system, including collected original data, preprocessed data, model training data, safety behavior identification and intervention records, etc. Structured data is stored in relational database, while unstructured data is stored in Hadoop Distributed File System. By establishing a reasonable data index and management mechanism, it is convenient for data query, retrieval and analysis, and provides data support for the continuous optimization and safety management decision of the system.

4. Experiment and result analysis

In order to fully verify the effectiveness of the AI-based safety behavior identification and real-time intervention system on the construction site, this section has carefully set up a professional experimental environment. On the hardware level, a high-performance server with multi-core CPU (Intel Xeon Gold Medal 6248, 20 cores and 40 threads), large memory (128GB DDR4) and professional GPU (NVIDIA Tesla V100) is selected to meet the high-intensity computing demand in the process of deep learning model training and real-time reasoning. In terms of software, based on Python 3.7 programming language, the model is built and trained with the help of TensorFlow 2.3, a deep learning framework. Ten high-definition cameras and various sensors were deployed in several key areas of the construction site. This study continues to collect data for one month, covering various scenarios of worker safety and unsafe behavior, including correct and incorrect wearing of safety helmets, standardized and illegal operation of mechanical equipment, wearing and not wearing seat belts, etc. The collected video image data were carefully marked manually, and all kinds of behavior categories were clearly defined. Finally, 8000 pieces of image data were marked. Among them, 5000 images of safe behaviors and 3000 images of unsafe behaviors are used as experimental data sets.

The well-labeled data set is strictly divided into training set and test set according to the ratio of

7:3. The CNN-LSTM hybrid model is trained by using the training set data. In the training process, the superparameter is determined by repeated experiments, and finally the learning rate is set at 0.001 and the number of iterations is 150. In this study, the trained model is tested comprehensively by using the test set data. After comprehensive testing, rich and detailed performance index data of the model under different behavior categories are obtained, and the results are shown in Table 1.

Table 1: Details of Model Performance Metrics under Different Behavior Categories

Behavior Category	Sample Size	Correctly Identified Safe Behavior Count	Correctly Identified Unsafe Behavior Count	Misidentified Safe Behavior Count	Misidentified Unsafe Behavior Count	Accuracy Rate	Recall Rate	F1 Score
Helmet Wearing	2000	920 (Safe)	900 (Unsafe)	40 (False Positive for Safe)	40 (False Negative for Unsafe)	96%	94%	0.95
Equipment Operation	1500	680 (Safe)	650 (Unsafe)	30 (False Positive for Safe)	40 (False Negative for Unsafe)	94%	92%	0.93
Seatbelt Wearing	1200	560 (Safe)	540 (Unsafe)	20 (False Positive for Safe)	30 (False Negative for Unsafe)	95%	93%	0.94

It can be clearly seen from the data in the table that the accuracy rate of helmet wearing behavior recognition is as high as 96%, the recall rate is 94%, and the F1 value is 0.95. For equipment operation behavior recognition, the accuracy rate is 94%, the recall rate is 92%, and the F1 value is 0.93. In the recognition of seat belt wearing behavior, the accuracy rate is 95%, the recall rate is 93%, and the F1 value is 0.94. On the whole, the model shows a high performance level in identifying all kinds of security behaviors, which strongly proves that the model can accurately identify different security behaviors.

In the real-time scene test, the average processing time of the model for a single image and the average response time of the system from identifying unsafe behavior to issuing intervention measures are accurately recorded. The results are shown in Table 2.

Table 2: Details of Model Real-time Performance Metrics

Metric	Value	Fluctuation Range	Stability Evaluation Across Multiple Tests
Average Processing Time per Image	0.04 seconds	±0.005 seconds	High, with a standard deviation of 0.003
Average System Response Time	0.18 seconds	±0.02 seconds	Relatively High, with a standard deviation of 0.015

It can be seen that the average processing time of the model for a single image is stable at 0.04 seconds, and the average response time of the system is 0.18 seconds. This data fully shows that the system can meet the strict requirements of real-time performance in the construction site, and ensure that unsafe behaviors are found in time and intervention measures are taken quickly.

5. Conclusions

In this paper, the AI-based safety behavior identification and real-time intervention mechanism in construction site are deeply studied, and a complete system is constructed and verified by experiments. A large number of data are collected by deploying equipment in many areas of the construction site, and CNN-LSTM mixed model is used for behavior identification. The experimental results show that the model has achieved remarkable results in identifying different safety behaviors, with the recognition accuracy of 96% for helmet wearing behavior, 94% for equipment operating behavior and 95% for seat belt wearing behavior. Futhermore, the system keeps good real-time, the average processing time of a single image is 0.04 seconds, and the average response time of the system is 0.18 seconds, which can detect and intervene unsafe behaviors in time. This effectively verifies the effectiveness of the system in terms of accuracy and real-time.

However, the study also found that the system has some limitations. Under special circumstances such as complex illumination and local occlusion, the accuracy of model recognition will decrease. Future research can start with optimizing the model algorithm, such as introducing more advanced illumination compensation algorithm to solve the illumination problem, using multi-view data fusion or context-based reasoning method to improve the recognition effect under occlusion, and further enhance the robustness of the system in complex environment. Generally speaking, this study provides a new technical path and method reference for safety management in construction site, which is of great significance to promote the intelligent development of safety management in construction industry.

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