Kalpa Publications in Computing
Volume 22, 2025, Pages 183–195
Proceedings of The Sixth International Conference on Civil and Building Engineering Informatics

An Improvement Safety Management Method for Welding Operations Based on Gaze Estimation and Object Detection

Ying Liang[1], Yi Tan[1]* and Dong Jia[2]
[1]Sino-Australia Joint Research Center in BIM and Smart Construction, Shenzhen University, Shenzhen, China.
[2]China Construction Fifth Engineering Division COPR.LTD, China

Abstract

In the field of construction engineering, particularly in steel structure construction, welding operations are of great importance. However, this activity carries significant safety risks, such as severe accidents like eye burns. Therefore, safety management and protective measures for these high-risk activities are especially crucial. Although computer vision-based object detection algorithms have already been applied in the construction sector, these algorithms generally lack the capability to process high-level semantic information. They can only detect objects but cannot understand the state of the objects. To address this issue, this paper proposes an improved welding safety inspection method based on gaze estimation and object detection. First, from a human-machine interaction perspective, the method combines gaze estimation and object detection to determine the worker's operational status. Second, conduct compliance checks on the personal protective equipment (PPE) used by welders. Experiments demonstrate the feasibility of this approach, enhancing its ability to respond to complex scenarios and contributing to improved safety levels in construction projects.

Keywords: Gaze estimation, Object detection, Safety management, Welding operations

1 Introduction

Welding is an indispensable process in construction engineering and is widely used in steel structure assembly, prefabricated component connections, and bridge engineering. It primarily serves to connect metals or other materials, ensuring structural integrity and stability. However, the hazardous environment of welding operations presents numerous safety challenges to the construction

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industry. According to data from the U.S. Bureau of Labor Statistics (BLS), welding accidents account for approximately 25% of fatal occupational accidents and include about one-third of non-fatal amputation incidents. Each year, more than 560,000 workers are injured in welding-related accidents. The U.S. Occupational Safety and Health Administration (OSHA) estimates that there are about 2,500 to 3,000 cases of severe arc flash burns annually, most of which occur on construction sites, particularly during welding on roofs and steel structures. Welding accidents are not only frequent but also extremely severe, highlighting the urgent need to strengthen safety measures and regulations in the construction industry.

Computer vision technology has already been capable of real-time safety detection on construction sites(Fang et al., 2020), including verifying whether workers are properly wearing basic safety equipment such as helmets and reflective vests. However, in certain high-risk construction scenarios, such as welding operations, relying solely on traditional object detection is insufficient to capture richer semantic information, which is necessary for conducting in-depth safety inspections. Gaze estimation technology, as a method that reveals an individual’s intent and focus of attention, provides a new dimension for understanding behavior in complex work environments. By analyzing the worker’s gaze points, this technology can infer whether their attention is focused on critical tasks, thus identifying potential safety hazards during specific activities.

Therefore, this study integrates object detection and gaze estimation technologies to bridge the "semantic gap" in scene understanding present in traditional object detection. The specific work includes the following: First, an analysis of the operational space limits for welding activities is conducted based on ergonomics. Next, object detection and gaze estimation are combined to assess the worker's operational status, determining whether the worker is engaged in welding or not. Finally, the compliance of the worker's PPE usage is further inspected.

2 Related Work

2.1 Construction Safety Management Based on Computer Vision

On construction sites, workers often fail to wear personal protective equipment (PPE) as required due to factors such as a lack of safety awareness and site constraints(Wong et al., 2020). Helmets and reflective vests are essential PPE that must be worn when entering a construction site, and their detection through object recognition has broad applicability. (Huang et al., 2021)used an improved Yolo v3 algorithm to detect whether workers were wearing helmets in compliance with safety standards.

In specific work scenarios, workers are required to wear particular personal protective equipment (PPE). For instance, when working at heights, workers must also wear safety harnesses.(Fang et al., 2019) used Faster R-CNN to detect the presence of workers and then took the pixel data from the identified bounding boxes as input for a CNN to recognize whether workers were wearing safety harnesses. (Li et al., 2022)combined object detection and pose estimation methods to recognize whether workers were wearing helmets and securing safety harnesses correctly. (Ding et al., 2018) integrated convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to automatically detect three unsafe behaviors when workers were climbing mobile scaffolding ladders. (Chen et al., 2023)implemented object detection of welding masks using YOLOv5S.

Simple object detection is no longer sufficient for managing safety on construction sites. In certain construction scenarios, it is necessary to determine the worker's operational context and then conduct safety inspections by combining scene information with regulatory requirements. (Khan et al., 2021)used Mask R-CNN and the spatial relationships between objects to infer that a worker was performing scaffold-moving tasks, thereby enabling relevant safety checks. (Fang et al., 2019)used

Mask R-CNN to detect and segment workers, steel structure supports, and concrete supports, using pixel overlap to examine the relationship between workers and supports to determine if the worker was on the support structures.

2.2 Related Work on Gaze Estimation

Gaze estimation, as an important method for inferring human behavior, has been widely applied across various fields. In driver assistance systems, it is used to detect the driver's attention state, reducing the risk of accidents caused by distraction or fatigue(X. et al., 2018). In market analysis, gaze estimation helps optimize product displays and advertisement layouts (Bermejo et al., 2020). In education and training, it monitors students' gaze behavior to assess engagement and learning outcomes (Tafasca et al., 2023). In psychology and behavioral research, gaze tracking is used to study social interactions and emotional states(L. et al., 2018). Additionally, augmented reality (AR) and virtual reality (VR) systems use gaze prediction to dynamically adjust content, enhancing immersion(Rahman et al., 2019). In public safety and privacy, gaze patterns assist in identifying abnormal behavior, bolstering security measures(Katsini et al., 2020). These applications demonstrate how gaze estimation advances intelligent interactions across different contexts, improving the efficiency of human interactions with devices and environments.

If gaze estimation is applied to the AEC (Architecture, Engineering, and Construction) industry, it could significantly enhance the intelligent management of construction sites. By analyzing workers' gaze directions, their work intentions—such as whether they are focused on the current task, materials, or equipment—can be inferred, ensuring accuracy and efficiency in their work. Additionally, predicting workers' operational status can help prevent potential safety hazards, thereby improving safety management on-site.

3 Method

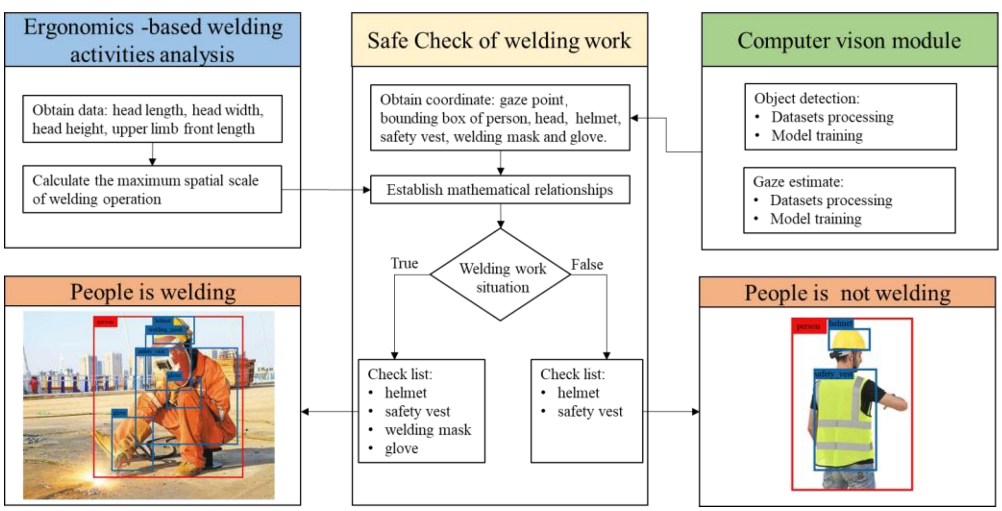


Figure 1: Method of this paper.

This study proposes an improved safety management method for welding work operations based on gaze estimation and object detection. The detailed methodology is illustrated in Figure 1.

1) First, coordinate information is obtained based on object detection and gaze estimation, including the gaze point and the bounding boxes for the person, head, helmet, safety vest, welding mask, and gloves.

2) Second, an analysis of the welding activity is conducted based on ergonomics. This involves calculating the worker's maximum operational workspace by acquiring data such as head length, head width, head height, and upper limb front length.

3) Finally, using the theoretical analysis and coordinate relationships mentioned above, mathematical relationships are established to determine whether the worker is engaged in welding. Additionally, checks are performed to ensure that the worker is correctly wearing the helmet, safety vest, welding mask, and gloves.

3.1 Ergonomics -based Welding Activities Analysis

Human body dimensions determine the geometric space occupied by the body and the range of human activities. They are the primary basis for analyzing the spatial range of welding activities. Based on the data from the "Human dimensions of Chinese adults " and the posture analysis of welding activities, the maximum range of welding space is calculated.

During welding operations, workers need to hold the welding torch to perform the task. Therefore, the maximum distance between the eyes and the welding point should be calculated by subtracting the head length from the extended upper limb length, then adding the length of the welding torch, as shown in Figure 2, with the specific calculation provided in Equation (1).

$$\text{spatial scale of welding operation}_{\max} = \text{upper limb front length} - \text{head length} + \text{welding torch length} \quad (1)$$

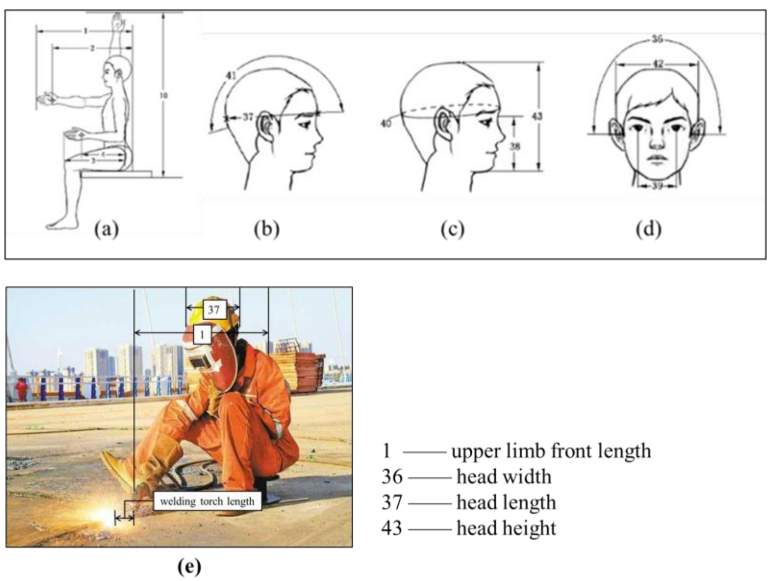


Figure 2: Ergonomics-Based Analysis of Welding Workspace Dimensions

Measurement Item	18-25 Years Old Male Body Dimensions Percentile			26-35 Years Old Male Body Dimensions Percentile			36-60 Years Old Male Body Dimensions Percentile		
	P5	P50	P95	P5	P50	P95	P5	P50	P95
Upper Limb Front Length	760	823	892	760	821	886	759	822	886
Head Length	175	187	200	175	187	200	176	188	200
Head Width	150	160	172	149	160	172	146	157	169
Head Height(h)	217	235	253	213	235	253	209	231	253
Welding Workspace Scale(d)	595	646	702	595	644	696	593	644	696
d/h	2.74	2.75	2.77	2.79	2.74	2.75	2.84	2.79	2.75

Measurement Item	18-25 Years Old Female Body Dimensions Percentile			26-35 Years Old Female Body Dimensions Percentile			36-60 Years Old Female Body Dimensions Percentile		
	P5	P50	P95	P5	P50	P95	P5	P50	P95
Upper Limb Front Length	678	749	815	688	750	813	696	757	822
Head Length	166	177	188	166	177	188	167	179	190
Head Width	144	154	164	142	152	163	141	150	161
Head Height(d)	209	228	246	209	228	246	206	227	246
Welding Workspace Scale(h)	522	582	637	532	583	635	539	588	642
d/h	2.50	2.55	2.59	2.55	2.56	2.58	2.62	2.59	2.61

Table 1: Human Dimensions of Chinese Adults Data Table

The "Human Dimensions of Chinese Adults" provides data categorized into seven percentiles: the 1st, 5th, 10th, 50th, 90th, 95th, and 99th percentiles. Typically, the 5th, 50th, and 95th percentiles are used to represent body dimensions for individuals with short, average, and tall statures, respectively.According to the "Regulations on Safety Technical Training and Assessment for Special Operation Personnel", special operation personnel must be at least 18 years old and not exceed the statutory retirement age (60 years for men and 50 years for women).The "Big Data Analysis Report on Labor Employment in the Construction Industry (2021)" shows that:By gender, male workers dominate the construction industry, accounting for 89%, while females make up 11%.By age distribution, 38.78% of construction workers are over 50 years old, 26.94% are aged 40-49, 22.98% are aged 30-39, 7.41% are aged 25-29, and 3.89% are under 24. Based on this data, the relevant body dimensions were selected, as shown in Table 1. The maximum value of the d/h ratio, i.e., 2.84, was chosen for further analysis.

3.2 Identification of Welding Activities

Through observing welding activities, it was found that the welder's gaze is typically focused on the welding point during the operation. Therefore, the results from both the gaze estimation model and the object detection model—namely, the gaze point and the welding area—are used to determine whether the worker is engaged in welding, as shown in Figure 3(a). When the coordinate relationships between the gaze point and the welding area simultaneously satisfy Equations (2) and 3), that is, when the x and y coordinates of the gaze point are within the bounding box of the welding area, it can be concluded that the welder's gaze is focused on the welding point. During welding operations, it is inevitable that supervisors may also be watching the welding point, as depicted in Figure 3(b). Based on the ergonomics analysis of the welding workspace, when the coordinate relationships of the head, eye, and gaze point simultaneously satisfy Equations (4) to (6), that is, when the head height in the image is calculated using Equation (4), the worker's working distance is calculated using Equation (5), and then the ratio range between the Welding Workspace Scale and head height, as analyzed in Table 1, is used to determine whether the worker is welding.

Figure 3: Identification of welding activities

$$\text{welding\_area\_x}_{\min} < \text{x} < \text{welding\_area\_x}_{\max} \tag{2}$$
$$\text{welding\_area\_y}_{\min} < \text{y} < \text{welding\_area\_y}_{\max} \tag{3}$$
$$\text{head height} = \text{head\_y}_{\max} - \text{head\_y}_{\min} \tag{4}$$
$$\text{working distance} = \sqrt{(gaze_x - eye_x)^2 + \left(gaze_y - eye_y\right)^2} \tag{5}$$
$$\text{working distance / head\_height} \leq 2.84 \tag{6}$$

3.3 Identification of PPE

Once it has been determined that the worker is engaged in welding, a specific safety check is required to ensure compliance with PPE requirements. This involves verifying whether the worker is wearing the appropriate PPE, including a helmet, safety vest, welding mask, and gloves as required.

(1) Identification of Helmet

The analysis for identifying workers who are wearing helmets correctly is as follows: The typical height of a safety helmet is about 14 cm. Based on Table 1, the head height of Chinese adults is approximately twice the height of the helmet. If the widths of the bounding boxes for the head and the helmet are the same, the Intersection over Union (IOU) is used to determine whether the worker is wearing a helmet.

When the IOU is greater than or equal to 0.5, the worker is considered to be wearing a helmet. If the IOU is less than 0.5, the worker is not wearing a helmet. See Figure 4 for details.

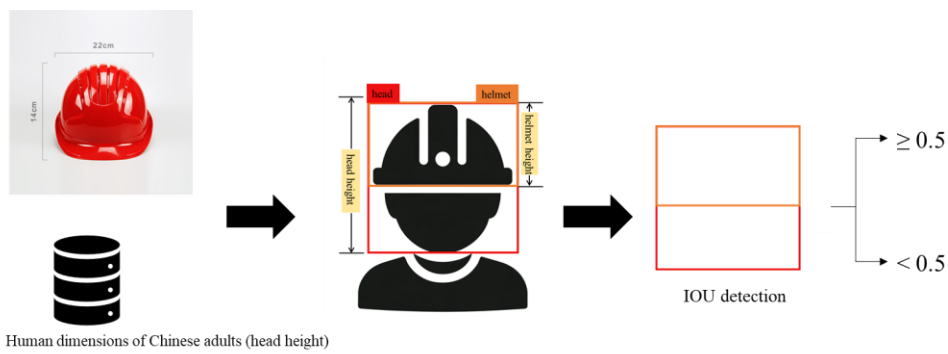


Figure 4: Identification of helmet

(2) Identification of Safety Vest

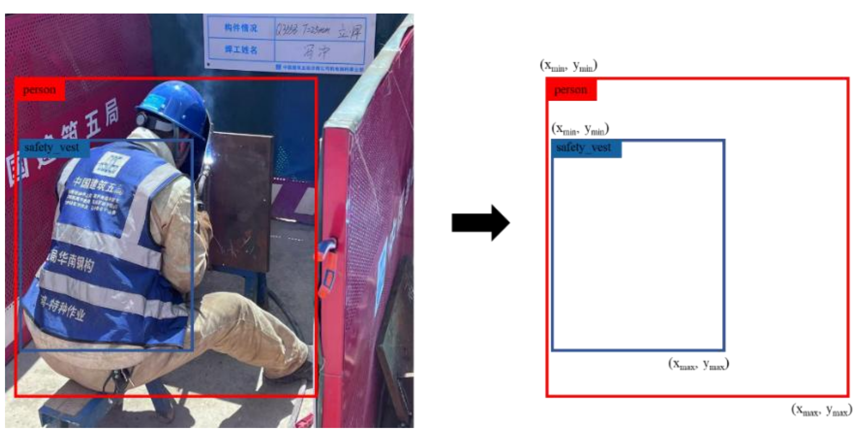


Figure 5: Identification of safety vest

The analysis for identifying workers correctly wearing a reflective vest is as follows: The bounding box for the safety vest is enclosed within the bounding box for the person. The spatial relationship between these bounding boxes can be expressed by Equations (3.1) and (3.2). See Figure 5 for details.

$$\text{person\_x}_{\text{min}} < \text{safety\_vest\_x}_{\text{min}}, \text{person\_y}_{\text{min}} < \text{safety\_vest\_y}_{\text{min}} \quad (7)$$

$$\text{safety\_vest\_x}_{\text{max}} < \text{person\_x}_{max}, \text{safety\_vest\_y}_{\text{max}} < \text{person\_y}_{max} \quad (8)$$

(3) Identification of Weld Mask

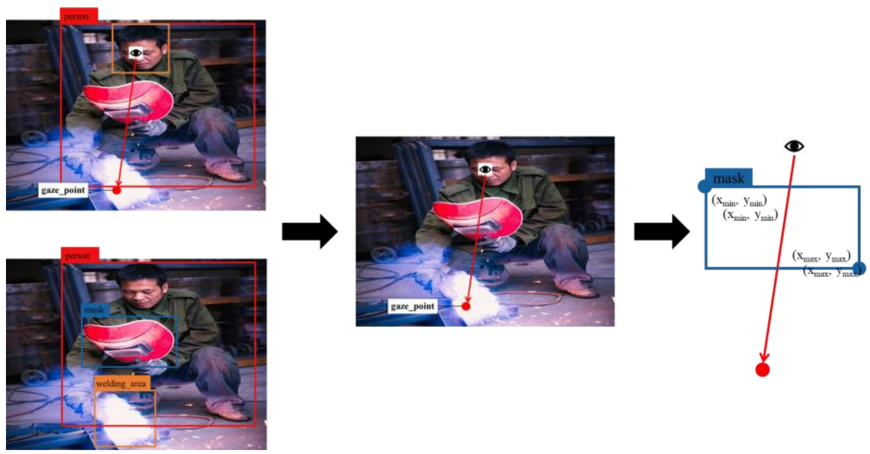


Figure 6: Identification of weld mask

The analysis for identifying workers correctly wearing a welding mask is as follows: When a welder is using a welding mask, the gaze arrow will intersect with the bounding box of the mask at two points. The spatial relationship can be represented by Equation (9) to Equation (13). If the straight line L intersects with any one of the sides L1, L2, L3, or L4 of the mask's surrounding frame, it is considered that the worker is wearing a welding mask. See Figure 6 for details.

$$L: (y - gaze_y)(gaze_x - eye\_x) = (gaze\_y - eye\_y)(x - eye\_x) \quad (9)$$

$$L1: y = x_{min}\ (x_{min} < x < x_{max}) \quad (10)$$

$$L2: y = x_{max}\ (x_{min} < x < x_{max}) \quad (11)$$

$$L3: x = y_{min}\ (y_{min} < x < y_{max}) \quad (12)$$

$$L4: x = y_{min}\ (y_{min} < x < y_{max}) \quad (13)$$

(4) Identification of Glove

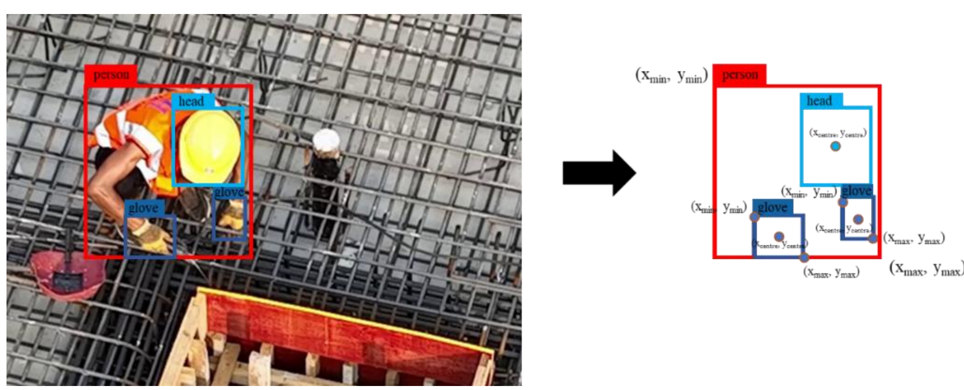


Figure 7: Identification of glove

The analysis for identifying workers correctly wearing gloves is as follows: The bounding box for the gloves is enclosed within the bounding box for the person. The spatial relationship between these bounding boxes can be expressed by Equations (14) and (15). See Figure 7 for details.

$$\mathrm{person\_x_{min}} < \mathrm{glove\_x_{min}}, \mathrm{person\_y_{min}} < \mathrm{glove\_y_{min}} \tag{14}$$

$$\mathrm{glove\_x_{max}} < \mathrm{person\_x}_{max}, \mathrm{glove\_y_{max}} < \mathrm{person\_y}_{max} \tag{15}$$

4 Experiment

4.1 Data Collection and Model Training

This study utilizes Object-aware Gaze Target Detection (Tonini et al., 2023) for gaze estimation and YOLOv8 for object detection.

Gaze Estimation Dataset: The dataset was collected through web scraping and augmented, resulting in a total of 2304 images. 80% of the images were selected as the training set, while 20% were used as the test set. The results of the model training are shown in Table 2, where P represents precision, R represents recall, and mAP50 represents the mean Average Precision when the IOU (Intersection over Union) is 0.5.

Object Detection Dataset: This dataset was collected through both web scraping and videos taken on construction sites of welding workers performing operations, resulting in a total of 3208 images. 80% of the images were used for training, and 20% for testing. The results of the model training are presented in Table 3, where AUC represents the confidence level of the predicted gaze heatmap relative to the actual gaze points, Distance refers to the distance error between the predicted and actual gaze points, Avg. denotes the average distance error, and Min. distance represents the minimum distance error.

Class	P ↑	R ↑	mAP50 ↑
all	0.928	0.876	0.907
head	0.97	0.94	0.978
weld_mask	0.919	0.897	0.94
helmet	0.981	0.934	0.972
welding_area	0.827	0.722	0.736
person	0.968	0.977	0.987
safety_vest	0.963	0.972	0.989
glove	0.84	0.578	0.673
extinguisher	0.956	0.988	0.726

Table 2: Results of object detection

AUC ↑	Distance↓	
	Avg.	Min.
0.866	0.298	0.253

Tabel 3: Results of gaze estimate

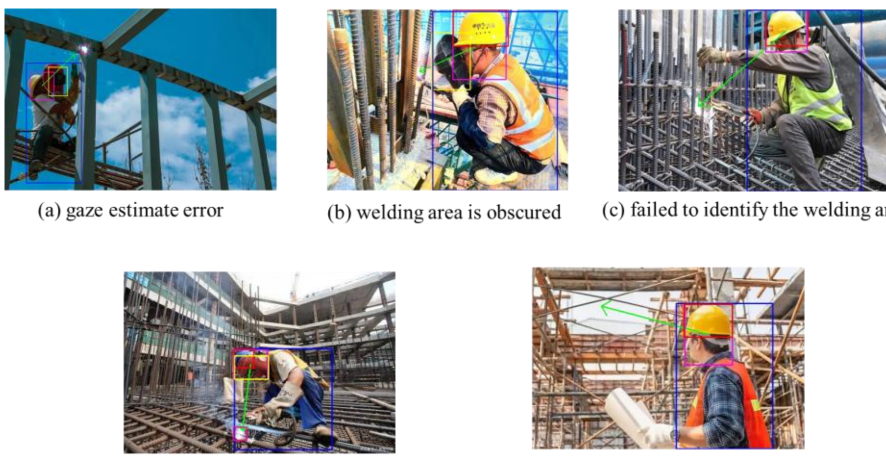
4.2 Control Experiment

Two sets of image datasets were used for the experiment. Group A consists of 20 images taken from actual welding operations on-site. Group B consists of 20 images from on-site scenes where no welding operations were being performed. The experimental results are shown in Table 4, where T represents "True" and F represents "False." The first T or F indicates the ground truth, and the second represents the prediction made by the proposed method. Detailed error samples can be seen in Figure

Group	Sample	Is welding	Safety check			
			With helmet	With safety vest	With weld mask	With glove
	001.jpg	T/T	T/T	T/T	F/F	T/F
	002.jpg	T/T	T/T	T/T	F/F	T/T
	003.jpg	T/T	T/T	F/F	T/T	T/F
	004.jpg	T/F	F/F	F/F	T/-	T/-
	005.jpg	T/T	T/T	F/F	T/F	T/T
	006.jpg	T/T	T/T	T/F	T/T	T/T
	007.jpg	T/F	T/T	T/F	T/-	T/-
	008.jpg	T/T	T/T	T/T	F/F	T/T
	009.jpg	T/F	T/T	T/T	F/-	T/-
	0010.jpg	T/T	T/T	T/T	T/T	T/F
	0011.jpg	T/T	T/T	F/F	T/T	F/F
	0012.jpg	T/T	T/T	T/F	F/F	T/T
	0013.jpg	T/T	T/T	F/F	T/T	T/F
	0014.jpg	T/T	T/F	T/F	T/T	T/F
	0015.jpg	T/F	T/T	F/F	T/-	T/-
	0016.jpg	T/T	T/T	T/F	T/T	T/F
	0017.jpg	T/T	T/T	F/F	T/T	T/F
	0018.jpg	T/T	T/T	T/F	T/T	T/F
	0019.jpg	T/F	T/T	T/F	T/-	T/-
Group A	0020.jpg	T/T	T/T	F/F	T/T	T/F
Precision		75%	95%	65%	93%	40%
	0021.jpg	F/F	T/T	T/F	-/-	-/-
	0022.jpg	F/F	T/T	F/F	-/-	-/-
	0023.jpg	F/F	T/T	F/F	-/-	-/-
	0024.jpg	F/F	T/T	F/F	-/-	-/-
	0025.jpg	F/F	T/T	T/F	-/-	-/-
	0026.jpg	F/F	T/T	T/T	-/-	-/-
	0027.jpg	F/F	T/T	T/F	-/-	-/-
	0028.jpg	F/F	T/F	F/F	-/-	-/-
Group B	0029.jpg	F/F	T/T	T/F	-/-	-/-

Group B	0030.jpg	F/F	T/T	T/T	-/-	-/-
	0031.jpg	F/F	T/F	T/T	-/-	-/-
	0032.jpg	F/F	T/T	T/T	-/-	-/-
	0033.jpg	F/F	T/T	T/F	-/-	-/-
	0034.jpg	F/F	T/T	T/T	-/-	-/-
	0035.jpg	F/F	T/T	T/F	-/-	-/-
	0036.jpg	F/F	T/T	T/T	-/-	-/-
	0037.jpg	F/F	T/T	T/T	-/-	-/-
	0038.jpg	F/F	T/T	T/T	-/-	-/-
	0039.jpg	F/F	T/T	T/F	-/-	-/-
	0040.jpg	F/F	T/T	T/F	-/-	-/-
Precision		100%	90%	70%	-	-

Table 4: Results of the control experiment



(a) gaze estimate error (b) welding area is obscured (c) failed to identify the welding area

(d) failed to identify people with helmet (e) failed to identify safety vest

Figure 8: Sample images of misclassified cases

5 Disscussion

Through the comparison experiment, it was found that the accuracy of determining welding activities was 75%. (1) The errors were mainly due to the following reasons: 1) As shown in Figure 8(a), the gaze estimation dataset lacked sufficient angles for upward and downward operations. 2) As shown in Figures 8(b) and 8(c), occlusion in the welding area made it difficult for object detection to effectively identify the target. Regarding object detection, the accuracy for helmet recognition was 95% in Group A and 90% in Group B. As shown in Figure 8(d), the primary cause of errors in some specific angles was that the Intersection over Union (IoU) between the head and helmet was less than 0.5. For the safety vest, the accuracy was 65% in Group A and 75% in Group B, significantly lower than the results from YOLOv8 model training. As shown in Figure 8(e), this was mainly because some workers in the experimental group wore orange reflective vests, and the training dataset lacked samples of this color. The accuracy for recognizing the weld mask was 93%, while the accuracy for detecting gloves was only 40%, which was due to poor model training, necessitating further expansion of the dataset.

In summary, the method proposed in this study shows certain potential for practical applications. However, limitations in the dataset and insufficient optimization of the mathematical model have led to some errors. Future improvements should focus on: 1) expanding and diversifying the dataset, particularly by adding samples for different working angles to enhance the precision of recognition of welding activities, and increasing types of PPE to address missed detection of PPE; and 2) further optimizing the mathematical relationship formulas to improve the identification of PPE wearing. These improvements will help enhance the method's effectiveness in real-world construction scenarios, thereby strengthening safety management on construction sites.

6 Conclusion

This study proposes a safety management method for welding operations based on gaze estimation and object detection. By combining these two technologies, it aims to address the limitations of traditional object detection methods in understanding scenes in high-risk construction tasks. Experimental validation shows that the method is feasible in identifying welding operations and checking whether workers are wearing personal protective equipment (PPE) as required. The existing errors are attributed to limitations in the dataset and the need for optimization of the mathematical model. Future improvements should focus on enriching the dataset by increasing the diversity of working angles and PPE samples, as well as further optimizing the mathematical relationships to enhance system accuracy and robustness. These improvements will help improve the method's effectiveness in real construction scenarios, thereby strengthening safety management on construction sites.

ACKNOWLEDGMENTS

This study was supported by the National Natural Science Foundation of China [Grant Nos. 52308319].

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