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A STUDY ON DETECTION ALGORITHM OF SAFETY APPARATUS WEARING BY WORKERS AT HEIGHTS BASED ON DEEP LEARNING

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Abstract. *With the development of society, there are many workers engaged in high-altitude operation, and it is necessary to detect their safety apparatus wearing. However, the high-altitude environment is complex, workers need to move frequently, and there are many uncontrollable factors, which will lead to high-altitude accidents. Therefore, in the face of the problems of poor effect and insufficient real-time performance of safety protection equipment in the current construction field, this article proposes a light-load improved YOLOv5s network model to detect helmet wearing and safety belt wearing simultaneously. First, it performs data augmentation operation to augment the model's generality, then it replaces the YOLOv5s backbone network with the MobileNetV3 network to improving the calculation speed, and finally it applies the DIOU-NMS non-maximum suppression ratio method to reducing the missed detection of dense targets and improving the detection precision. The comparative experiment has proven that the improved YOLOv5s network model in this paper presents an outstanding detection effect, as it improves the detection precision and greatly reduces the calculation volume.*
Keywords: YOLOv5s, High-altitude operation, Helmet wearing, Safety belt wearing, Data augmentation

1. Introduction.

Construction, as one of the pillar industries of China, is strategically important in the national economic system [1]. However, the construction industry in China is blooming with many high-incidence accidents, high-altitude fall casualties in high-altitude operation accounted for 43.8% of all accidents in the construction industry, which highlights the workers' poor awareness of safety protection in high-altitude operation, and failure to wear helmets and safety belts properly is the main cause of casualties among those working at heights [2]. The protective apparatus for working at heights is good, but the environment at heights is complex, and workers at heights need to move frequently, involving too many uncontrollable factors, so it is of great significance to timely and precisely detect safety apparatus wearing by workers at heights [3]. However, some management personnel and high-altitude workers are not so aware enough of safety protection and do not wear helmets and safety belts properly, resulting in irreversible injury to their body health in the event of sudden dangers.

The traditional manual methods for safety apparatus detection, which wastes time and labour, are neither efficient nor complete in detecting, as it can neither find out hidden dangers in time nor protect the safety of workers at heights sufficiently [4]. Therefore, it is

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particularly important to adopt a more efficient and intelligent method to detect and protect the safety of construction workers at heights. Using a deep learning target detection algorithm, this paper proposes a method to detect the safety of high-altitude workers, and the method can not only improve the detection efficiency, but also save labour and material resources, as it detects whether high-altitude workers wear protective apparatus in real time [5]. Currently, most studies on safety equipment detection suffer from issues such as single detection target, slow detection speed, and poor detection performance of occluded targets. The algorithm proposed in this paper effectively addresses the problem of single detection target, enabling multiple targets to be detected simultaneously. Specifically, it can detect whether high-altitude workers wear both safety helmets and safety belts at the same time. Moreover, the real-time detection speed and detection performance of occluded targets have been significantly improved.

In order to reduce the overfitting phenomenon, the self-made data set was enhanced. In addition, the YOLOv5s network structure was improved, the backbone network was replaced by MobileNetV3 network to improve the computing speed, and the DIOU-NMS algorithm was used to remove redundant detection boxes.

The rest of this paper is organized as follows. Section 2 introduces the research status at home and abroad; Section 3 introduces the YOLOv5s network; Section 4 introduces the improvement of the algorithm in detail; Section 5 introduces the experimental process and results. Finally, Section 6 is the summary of this paper.

2. **Research Status.** At present, many Chinese and foreign scholars have conducted a series of studies on safety helmet detection. Among them, Chinese scholars Liu and Ye combined support vector machine (SVM) with skin color detection to detect helmets [6]. Li applied Vibe (Visual background extractor) algorithm to locating the human body, and then combined HOG and SVM algorithm to realize helmet wearing detection [7]. Shi et al. adopted the YOLOv3 algorithm to detect helmet wearing, using an image pyramid structure and a clustering method to improve the YOLOv3 network, and further train the network with multi-size pictures [8]. Moreover, foreign scholars have also carried out relevant researches, for example, Rubaiyat et al. in the United States conducted combined detection by using frequence-domain information from images and histogram of orientation gradient (HOG) algorithm, and then detected whether helmet is worn with ring Hough transform [9]. Doungmala and Klubsuwan in Thailand proposed a new detection technology Haar-like to improve the efficiency of helmet wearing detection in combination with these two helmet detection methods [10]. Hayat and Morgado-Dias in Portugal adopted an automatic detection system for helmet wearing at construction site based on the YOLO algorithm, which can perform effective real-time detection [11].

Furthermore, many other scholars in different countries are studying safety belt detection. Among them, Chinese scholar Zheng improved the SSD algorithm by using deep neural network to identify safety belt wearing, where, it applies background modeling and human body detection algorithm to identifying the human body image and obtaining the human body detection result [12]. Feng et al. proposed a safety belt detection method for high-altitude operations based on Mask R-CNN, which combines safety belt detection with key point information of the human body to judge workers' violations, but the detection framework of this method is based on a two-stage method, of which the timeliness can hardly satisfy the requirement for practical application [13]. Cao et al. proposed to improve the detection precision of safety belt wearing by high-altitude workers with the latest YOLOX target detection model [14]. In other countries, Gómez-de-Gabriel et al. in Spain studied a sensor-based safety belt detection method, and they applied low energy consuming Bluetooth beacons to defining areas for safety belt wearing and detecting whether the safety belts are attached to the corresponding lifelines when workers enter these areas [15]. Chun et al. in the United States proposed a convolutional neural network (CNN) for safety belt detection, where the new network architecture of the NADS Net is mainly based on the backbone of a pyramid network featured in multiple detectors to improve the detection performance [16]. Kashevnik et al. in Russia proposed a safety belt detection model based on YOLO neural network over most of the traditional edge detection methods based on Hough, Canny and so on [17].

In all, Chinese and foreign scholars have made a lot of achievement in separate detection technology of safety helmet wearing and safety belt wearing, but there is still a lot of blank for exploration and improvement in simultaneous detection of helmet wearing and safety belt wearing by workers in high-altitude operations at the construction site. In view of poor real-time detection and slow operation speed, this paper made a research on the detection of safety apparatus wearing by construction workers at heights under the background of deep learning.

3. **YOLOv5 Algorithm.** As a one-stage target detection algorithm, YOLOv5 has a great advantage in detection speed. Improved over the YOLOv4, this algorithm is given both higher speed and higher precision. Generally, target detection algorithms can be divided into four modules, including the input terminal, the Backbone network, the Neck network and the Head output terminal [18]. The YOLOv5 algorithm consists of four versions, namely YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x. This article mainly introduces the YOLOv5s network, as shown in Figure 1, while in other versions the network is improved on the basis of this version.

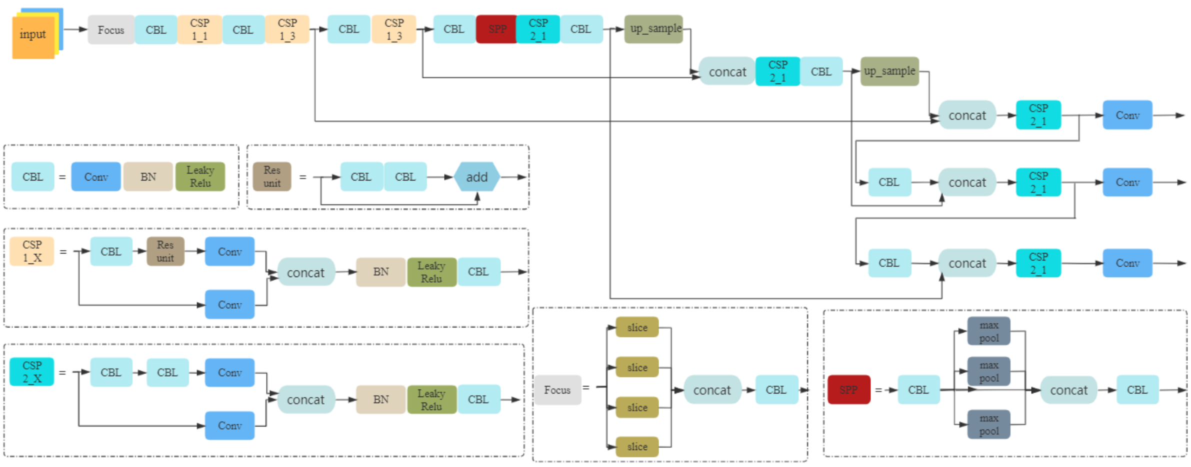


FIGURE 1. YOLOv5s network structure

The input terminal is to pass the image into the algorithm, and it will often carry out some pretreatment operations on the image, scaling the image size to make it consistent with the network input size [19]. In the process of model training, the input of YOLOv5 adopts the same Mosaic data augmentation method as YOLOv4, which can greatly improve the training speed of the model and the precision of the network. In addition, an adaptive anchor frame calculation and adaptive image scaling method is proposed; the Backbone network is usually a classifier network with excellent performance, which is used to extract some general feature representations; the Neck network uses feature pyramid network (FPN) for feature fusion, and path aggregation network (PAN) is added to improve the capability of multi-scale feature detection; the Head output is to mainly output the target detection result, the anchor box mechanism of the output layer is the same as that of YOLOv4, where GIOU_Loss is used as the loss function of the bounding box, and non-maximum value suppression (NMS) is used in postprocessing to filter various boxes to improve the detection precision and multi-target detection capacity of the algorithm [20].

4. Research Method.

4.1. Improvement of the Backbone network. The Backbone network in the YOLOv5s network model is replaced with the MobileNetV3 backbone network, where data features are extracted, and the network structure is shown in Figure 2. As a light-load neural network, MobileNetV3 is superior in few parameters, fast speed, and small memory usage. Compared with previous versions, the neural network architecture search (NAS) and h-swish activation function are added and the SE channel attention mechanism is introduced to improve the performance and speed effectively [21].

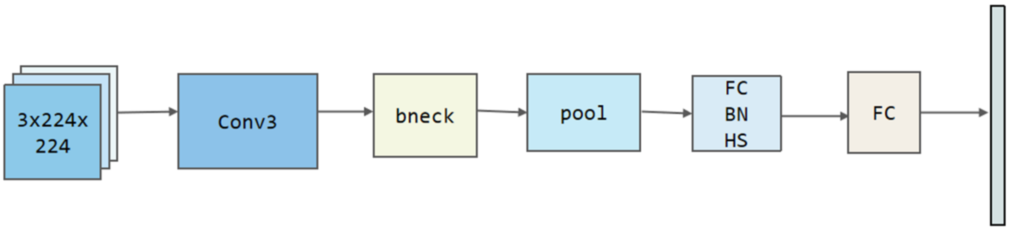


FIGURE 2. MobileNetV3 network architecture

Here, the special bneck structure used in MobileNetV3 is shown in Figure 3, and we can see that the bneck structure consists of two parts, the backbone part and the short-cut part. In the backbone part for the input feature layer, a 1×1 convolution is used to perform dimension-up operation, the number of channels is expanded, a 3×3 depth-separable convolution is used for feature extraction, global average pooling is performed on the feature layer obtained, and after two full connections, the result is multiplied with the feature layer obtained previously, and finally a 1×1 convolution is used for dimension-down operation. The short-cut part is to connect the input to the output when the step length is equal to 1 and the input and output feature maps have the same shape. In general, a large number of 1×1 convolution and 3×3 convolution, instead of 5×5 convolution, are used in the MobileNetV3 network structure to simplify the network calculation, improve the calculation speed and reduce the demand for computing power [22].

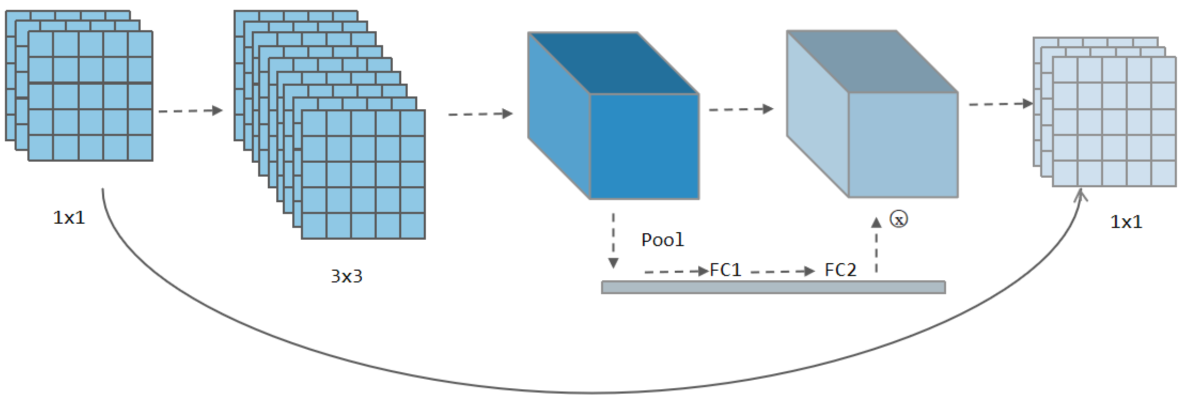


FIGURE 3. Bneck network structure

4.2. **Improvement of NMS ratio.** In the classic NMS algorithm, IOU is the only factor to be considered, and the calculation formula is shown as Formula (1). However, in practical application scenarios, when the distance between two objects is very close, the IOU value will be very large, and after NMS processing, only one detection box remains, which often leads to missed detection [23]. In order to better improve the precision and recall rate of detection, this paper adopts the DIOU-NMS algorithm, which pays attention to both the IOU value and the distance between the center points of the two boxes. If the IOU between the two boxes is large, and the center distance between the two is also large, the two boxes may be deemed as the boxes of the two objects and will not be filtered out. The calculation of DIOU-NMS is shown as Formula (2).

$$\mathrm{IOU} = \frac{A \cap B}{A \cup B} \tag{1}$$

$$S_i = \begin{cases} S_i, & \mathrm{IOU} - R_{\mathrm{DIOU}}(M, B_i) < \varepsilon \\ 0, & \mathrm{IOU} - R_{\mathrm{DIOU}}(M, B_i) \geq \varepsilon \end{cases} \tag{2}$$

where M is the one with the highest value of all predicted boxes, B_i is used to judge whether to remove the predicted box, S_i is the classification fraction, ε is the NMS threshold set, and R_{DIOU} is the distance between the center points of two boxes. The specific calculation is shown as Formula (3).

$$R_{\mathrm{DIOU}} = \frac{\rho^2\left(b, b^{gt}\right)}{c^2} \tag{3}$$

where $\rho^2(.)$ is the Euclidean distance, b is the center point of the predicted boundary box, b^{gt} is the center point of the real boundary box, and c is the shortest diagonal length of the smallest enclosing box of the two boxes. The difference between DIOU-NMS and NMS is that when there are two boxes with far center points, the DIOU-NMS algorithm will think that they are located on different objects and will not perform the deletion operation, and thus it can reduce missed detection in dense cases [24].

4.3. **Data augmentation.** The neural network often involves with a lot of parameters counted in million units, and it needs a lot of data for training to bring these parameters into normal operation. However in practical projects, it is hard to find sufficient data for training, so it needs data augmentation means to augment sample data [25]. In this paper, the images in the data set are augmented by random cutting, random inversion, random contrast augmentation, random shear and Mixup to increase the number of training samples, and meanwhile appropriate noise data are added to improve the model generality [26].

5. Experiments.

5.1. **Data set construction.** In the field of target detection, the data set required for experiments has always been one of the most important bases, but the current open source data set cannot satisfy the needs in experiment. This paper discusses a project for the simultaneous detection of helmet wearing and safety belt wearing by workers in high-altitude operation; therefore, a helmet and safety belt data set is customized by data collection, data screening and data processing. Data for experiment in this paper are collected by web crawler, video cropping and field shooting, etc. [27]. The data set includes images of helmet and safety belt wearing by workers working at heights in the construction site under different lighting conditions, different resolutions and different angles of view. In addition, the images collected are processed by data screening and data labeling, images are manually labeled by labelImg to generate the corresponding xml label files, which are then converted into the txt format required by the network model.

In this paper, a total of 2,000 images related to helmets and safety belts are collected and sorted out, and the detection targets of the data set are divided into four categories: helmet, no_helmet, belt and no_belt. The images in the data set are randomly assigned to the training set and the verification set in a ratio of 8 : 2. The final training set consisted of 1,600 images and the verification set of 400 images.

5.2. **Experimental environment and parameters.** This paper chooses the Linux system and the ubuntu18.04 operating system for experimental development, the GPU is Tesla v100, the computing architecture is CUDA 10.1, the deep learning framework is PyTorch1.8, and the programming language is Python3.7. The image resolution is 640×640, the training batch is set to 16, the number of training rounds is 200, and the initial learning rate is set to 0.001.

5.3. **Evaluation indicators.** In target detection algorithms, performance indicators which are commonly used include precision, recall, average precision (AP), mean average precision (mAP), parameters and float operation per second (FLOPs), etc, for which, TP refers to the positive targets correctly classified in the algorithm; FP refers to the wrong positive targets classified; FN refers to the wrong negative targets classified [28].

Precision: usually it is the ratio of the target number of real positive samples to the number of all positive samples in the forecast samples, namely

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

Recall: to calculate the ratio between the target number of real positive samples to the number of forecast samples in the forecast samples, namely

$$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

Average precision (AP): to calculate the average precision of the forecast samples, namely:

$$\mathrm{AP} = \int \mathrm{PdR}$$

In the formula above, P is the precision rate, R is the recall rate, and the AP value of the target can be calculated from the integral of curve P-R in interval $[0, 1]$. Mean average precision (mAP): it usually evaluates the overall forecast effect of all target categories in the entire network model. The larger the mAP values is, the better the network model performs, and n is the number of targets, that is

$$\mathrm{mAP} = \frac{1}{n} \sum_{i=1}^{n} \mathrm{AP}_i$$

Parameters: the number of all parameters included in the calculation process of the network model, that is, the spatial complexity of the algorithm.

Float operation per second (FLOPs): usually it is also called the volume of calculation to measure the complexity of the entire network model.

5.4. **Experimental analysis.** In this paper, an improved YOLOv5 model is adopted for safety detection in the construction field, and a customized helmet and safety belt data set is used to verify the detection effect of the improved model [29]. Figure 4 shows the loss function curves of the training set, including the boundary box loss function curve, the target detection loss function curve and the classification loss function curve. Figure 5

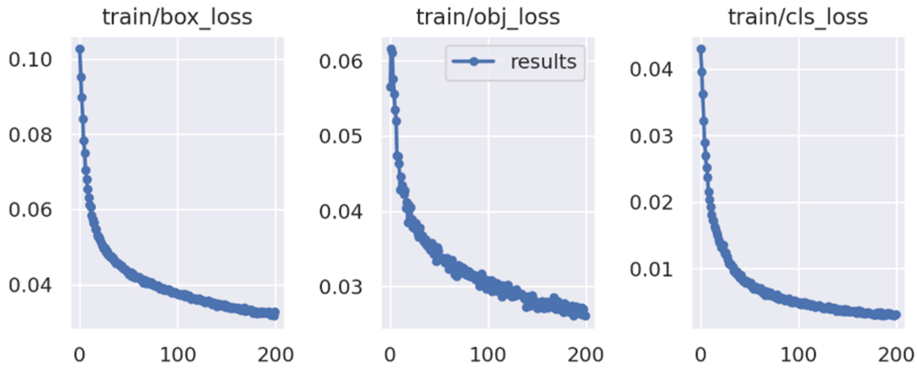


FIGURE 4. Training set loss function curve

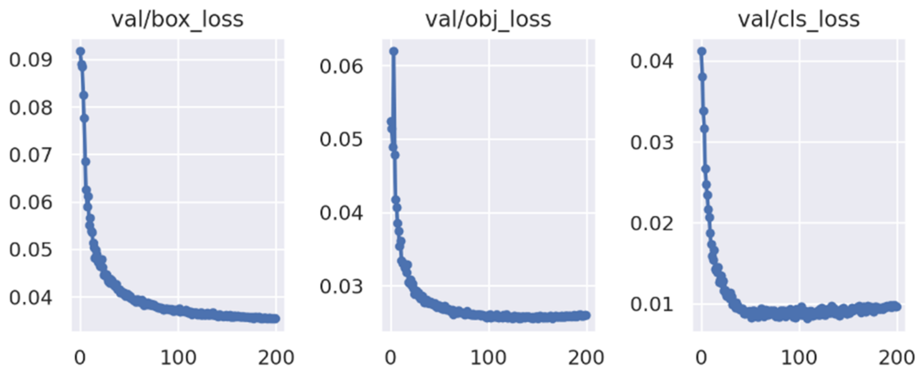


FIGURE 5. Verification set loss function curve

TABLE 1. Comparison of different algorithms on this data set

Algorithm	P/%	mAP/%	Parameters/M	FLOPs/G
Faster R-CNN	88.7	82.4	183.2	95.4
SSD	89.2	83.6	24.4	142.6
YOLOv5	92.6	87.2	7.2	15.3
This paper	93.1	87.9	4.1	4.2

shows the loss curve of the verifying set, indicating that with the increase of the number of rounds, the loss value gradually decreases, all the loss values below 0.036, and the curves are gradually stabilized after 200 rounds of training, indicating that the curves converge well.

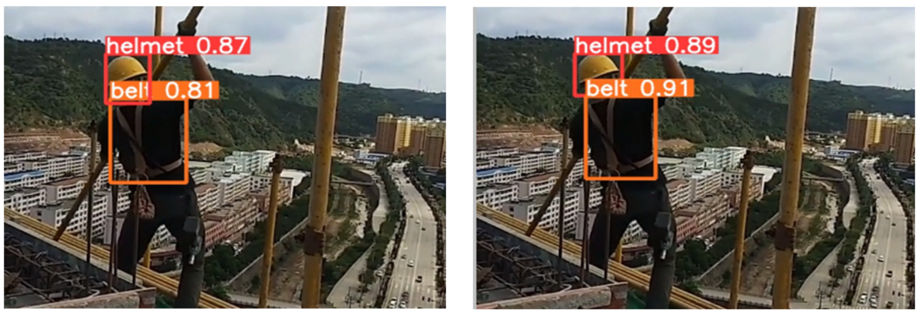
In order to better prove the superiority of the algorithm in this paper, the improved algorithm in this paper is compared with several mainstream algorithms, including Faster R-CNN, SSD and YOLOv5, as shown in Table 1, where P and mAP are the evaluation indicators [30]. Faster R-CNN is a typical two-stage detection algorithm, which extracts candidate frames with region proposal network (RPN) in a high detection precision. SSD and YOLOv5 are single-stage detection algorithms, in which the SSD algorithm applies multi-frame prediction or usually detects with CNN directly in practice, while the YOLO algorithm is fast in detection.

Table 1 shows that the improved YOLOv5 algorithm proposed in this paper can greatly improve the efficiency of simultaneous detection of helmet wearing and safety belt wearing for construction workers. The experimental result proves that compared with the original YOLOv5 algorithm, the mAP has not changed much, but the network calculation load has been greatly reduced by 11.1 percentage points to approximately a quarter of the original. Compared with the SSD algorithm, the mAP is increased by 4.3 percentage points, the number of model parameters is reduced by 20.3 percentage points, and the calculation load is significantly reduced. Compared with the Faster R-CNN algorithm, the precision of the improved algorithm has increased by 4.4 percentage points, and the model parameters are much fewer than the Faster R-CNN. Therefore, both the detection precision and the average precision of the improved YOLOv5 algorithm in this paper are increased, both the number of network parameters and the load of calculation are significantly reduced, the network calculation speed can be better improved and the memory space can be saved, and the requirement for real-time monitor can be satisfied.

In order to evaluate the detection effect more intuitively, a same picture is placed in the YOLOv5 model and the improved model of this paper for detection, and the detection effects are compared as shown in Figure 6, where the left is the detection effect of the YOLOv5 model and the right is of the improved algorithm.

Figure 6 shows the detection effects in various scenarios, where Figure 6(a) shows the effects of missed detection, indicating that missed detection is obviously improved

(a) Missed detection



(b) Dark scenario

(c) Dense targets

FIGURE 6. Comparative detection

by the improved algorithm as helmet and safety belt can be detected simultaneously while only safety belt is detected before; Figure 6(b) shows the detection effects in a dark scenario, indicating that the detection effect of the improved algorithm is also significantly improved in weak light; Figure 6(c) shows the detection effects on dense targets. Any way, the improved algorithm is advanced in missed detection, detection on dense targets and detection in dark scenarios.

6. **Conclusions.** To simultaneously detect protective apparatus wearing of helmet and safety belt by workers at heights in the construction field and make it easier to deploy on terminal devices, this paper proposes a light-load network structure: first, it performs data augmentation operation to augment the model's generality, then it replaces the YOLOv5s backbone network with the MobileNetV3 network to reduce the network calculation complexity and improve the calculation speed, and finally it applies the DIOU-NMS to reducing missed detection on dense objects and improving the detection precision. The comparative experiment has proven that the algorithm in this paper can reduce the load of computation and the number of parameters, and is significantly superior to satisfy the requirement for real-time detection. It can be extensively applied in the field of high-altitude operation to improving detection efficiency and protecting workers' personal safety. In the future, the authors will constantly expand the data set, put complex backgrounds into research and explore light load realization so as to make it better deployed on terminal devices.

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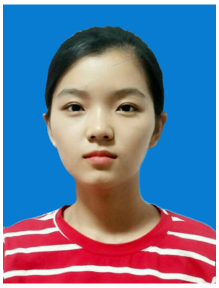

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