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Lightweight Real-time Detection Method for Dress Code of Anti-static Equipment

Qi Li, Jin Wei*

School of Electronic Information and Artificial Intelligence, Shaanxi University of Science & Technology, 710021, Xi'an, China
15029183151@163.com
**Corresponding author*

Abstract: *Detection of dress code for anti-static equipment is an important management link in clean workshops. To address the issue of difficulty in deploying multi-scale dress code detection methods for anti-static equipment in embedded systems, a lightweight real-time detection method for dress code of anti-static equipment is proposed. This article uses the MobileNetV3-small backbone network to extract features of anti-static equipment, making the model lightweight and easy to deploy. Adopting BiFPN structure to enhance the feature fusion ability of anti-static equipment at multiple scales, and using CIoU Loss and DIoU-NMS to accurately locate anti-static equipment targets, and improving the problem of missed detection of anti-static equipment when people are crowded, and improving the accuracy of dress code detection for anti-static equipment. The experimental results show that the algorithm improves accuracy by 2.1%, reduces parameter count by 43.8%, and reduces model size by 40.6% compared to YOLOv5s. The recognition speed on the Jeston Xavier NX system is 27FPS, and the recognition accuracy of wearing anti-static hats, anti-static clothing, and anti-static shoes is 98.1%, 96.2%, 95.8%, 94.2%, and 94.1%, respectively. It meets the requirements of real-time detection of anti-static equipment dress code.*

Keywords: *Detection of dress code for anti-static equipment, Lightweight, BiFPN, Jeston Xavier NX*

1. Introduction

In the clean workshop, employees are required to wear anti-static equipment (including anti-static clothing, anti-static shoes, and anti-static hats) to protect products from static electricity, which increases the product qualification rate [1]. Enterprises have strict requirements for the dress code of anti-static equipment. The "Q JFD003.201.108 Personal Wear and Protection Process Rules" stipulate that personnel should wear anti-static hats when entering the production workshop, ensuring that their hair is completely covered by the hat; Wear anti-static clothing, including both the top and pants, and the cuffs must not expose the arms or wrists; Wear anti-static shoes. An example of dress code requirements for clean workshop personnel is shown in Figure 1.

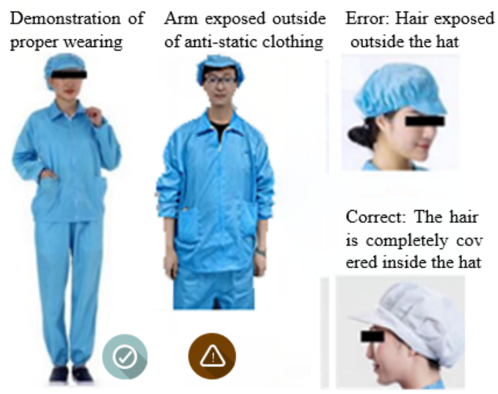

Figure 1 Example of Dress Code Requirements for Clean Workshop Personnel.

However, improper wearing or failure to wear anti-static equipment cannot effectively prevent the harm caused by static electricity to the product, which may lead to product damage and aging [2]. Enterprises are artificially supervised through video surveillance. Due to the large number of surveillance screens and the presence of human factors, it can lead to misjudgment, even negligence, and omission in supervision, and failure to promptly provide warnings for non-standard clothing [3]. Therefore, it is necessary to adopt an intelligent, real-time, and efficient method to detect the standardization of anti-static equipment attire and promptly correct any behavior of improper attire.

At present, a large amount of in-depth learning literature is focused on personal protective equipment, mostly focusing on whether to wear safety helmets, masks, safety vests, etc. [4,5,6,7], and there is no detailed research on the dress code with standardized requirements (such as anti-static clothing). In a small amount of research on dress code detection, He Lei et al. used the YOLOv5 algorithm to identify dress codes for long sleeved and short sleeved classification problems [8]. This method cannot distinguish whether the material of clothing meets the specified requirements. Mao Feng et al. proposed a method based on multi-scale attention networks (MAR-CNN) for detecting clothing irregularities in targets such as safety helmets and clothing, targeting multi-scale characteristics [9]. The above research has made some progress, but there are still problems such as low detection accuracy, large model parameters, and difficulty in deploying on embedded devices. Due to the limited space of the scene for detection of anti-static equipment dress code, the size, location, and individual differences of the target vary at multiple scales, resulting in differences in the performance of anti-static targets in the image, which affects the detection accuracy of the anti-static equipment dress code. Additionally, the monitoring and management of dress code for anti-static equipment has high requirements for real-time performance.

This article uses the YOLOv5s network to detect the dress code of anti-static equipment, and the Jeston Xavier NX system as the deployment carrier to conduct real-time detection of the dress code of anti-static equipment. In response to the problem of a large number of parameters in the detection model for dress code of anti-static equipment, which is not conducive to the deployment of embedded devices, the MobileNetV3 small backbone network is used for feature extraction of anti-static equipment. Through deep separable convolution operations, the standard convolution is decomposed into deep convolution and point by point convolution to reduce the computational power of the model, making it lightweight and easy to deploy. Due to the limited space of the scene for the detection of anti-static equipment dress code, the anti-static equipment exhibits multi-scale characteristics, which affects detection accuracy. In this paper, the BiFPN structure is used to fuse different scale features of anti-static equipment to improve detection accuracy while ensuring the detection speed of the model. Finally, CIoU Loss and DIoU-NMS are used to accurately locate the target of anti-static equipment and improve the problem of missed detection of anti-static equipment when people are crowded, improve the accuracy of dress code testing for anti-static equipment.

2. Testing Method for Dress Code of Anti-static Equipment

The flowchart of the detection method for the dress code of anti-static equipment studied in this article is shown in Figure 2. This article considers the lightweight of the network model to meet the requirements of embedded deployment and improve the detection accuracy of anti-static equipment while ensuring detection speed. Firstly, MobileNetV3 small is used as the backbone network of YOLOv5s for feature extraction of anti-static equipment. Secondly, in the feature fusion layer, the tensor splicing operation responsible for feature information fusion is combined with the BiFPN structure to enhance the multi-scale feature fusion ability of anti-static equipment, Finally, the loss function was improved and the DIoU-NMS algorithm was used for prediction box screening to detect people, anti-static clothing, anti-static shoes, and anti-static hats. By locating the areas of anti-static clothing and anti-static hats, arm and hair exposed areas were detected, and the connectivity area between hair and arm exposed areas was determined based on dynamic thresholds to detect the dress standardization of anti-static equipment.

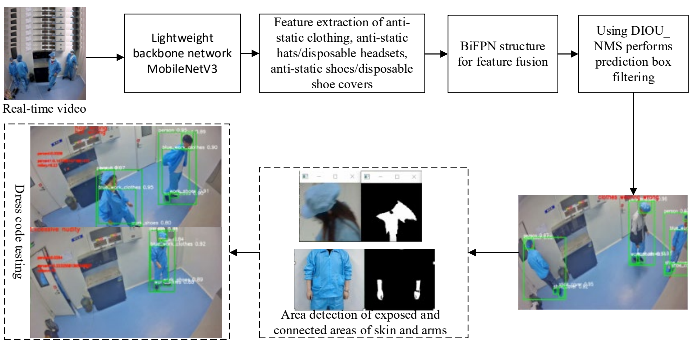

Figure 2 Flow chart of standardized testing methods for anti-static equipment attire.

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2.1. Lightweight Backbone Network

2.1.1. MobileNetV3

MobileNetV3 is a lightweight convolutional neural network architecture for mobile devices and embedded systems [10]. MobileNetV3 has made the following improvements and optimizations on the basis of the old version, enabling efficient inference and operation on the Jeston Xavier NX device.

(1) MobileNetV3 utilizes deep separable convolution technology to decompose standard convolution operations into deep convolution and point by point convolution, reducing the computational power required for the operation of the model for testing the dress code of antistatic equipment [11], and accelerating the inference speed of dress code for anti-static equipment.

(2) MobileNetV3 introduces an adaptive width inverse residual structure, allowing the network to dynamically adjust the number of channels based on different levels of feature maps, enabling the model to better adapt to different situations and positions of anti-static equipment wearing data and anti-static equipment feature extraction tasks.

(3) MobileNetV3 adopts the Hard Swish activation function, which maintains good performance while reducing computational complexity, making the inference speed of the anti-static equipment dress code detection model faster on the Jeston Xavier NX.

(4) MobileNetV3 also introduces the SE module, which adaptively adjusts the importance of channels by learning the relationships between internal channels in the feature map, enhances the model's attention to anti-static equipment features, and improves the performance and generalization ability of the detection model for the dress code of anti-static equipment.

2.1.2. Backbone Feature Extraction Network

YOLOv5, as a lightweight object detection network [12], can maintain a fast inference speed without sacrificing accuracy, and is suitable for the scene of anti-static equipment dress code detection. But on the Jeston Xavier NX system with limited resources, it is hoped that the model size will be smaller and the computational speed will be faster. Therefore, in order to achieve the deployment of the anti-static equipment dress code detection model on the Jeston Xavier NX system, this article uses MobileNetV3 small as the backbone network of YOLOv5s for feature extraction of anti-static equipment. Through deep separable convolution operation, the standard convolution is decomposed into deep convolution and point by point convolution, reducing the parameter and computational complexity of the anti-static equipment dress code detection model. The specific process of standard convolution decomposition is shown in Figure 3.

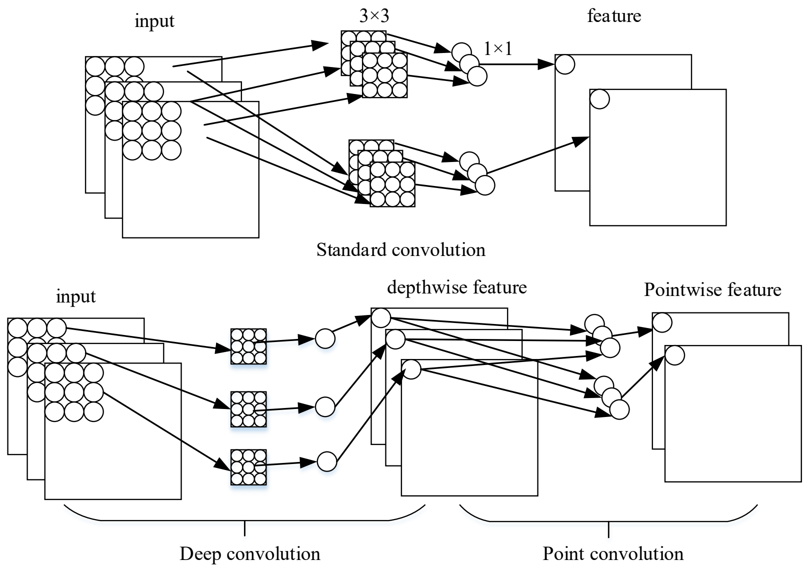

Figure 3 Decomposition process diagram of standard convolution.

The calculation process of deep separable convolution is shown in equation (1):

$$G_{h,w,m} = \sum\nolimits_{i,j} K_{i,j,m} F_{h+i-1,w+j-1,m} \tag{1}$$

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In the formula, G represents the output feature map; K is the convolutional kernel; F is the input feature map; i, j represents the pixel position of the feature map; h, w represents the size of the output feature map; M is the number of channels.

The calculation amount of deep convolution, point by point convolution, and standard convolution is shown in equation (2):

$$\frac{k\times k\times C+C\times N}{k\times k\times C\times N}=\frac{1}{N}+\frac{1}{k^2} \tag{2}$$

In the formula, k represents the size of the convolution kernel for deep convolution; C represents the number of input feature maps; N is the number of convolution kernels for pointwise convolution [13]. From equation (2), it can be seen that after deep separable convolution operation, the computational workload is significantly reduced, ensuring the minimum reduction in detection accuracy of anti-static equipment while greatly reducing the number of model parameters. The structure of the improved backbone network is shown in Table 1. In the table, “-1” represents the input from the previous layer, “1” represents only one MobileNet operation, and the values of the arguments represent the number of input channels, the number of output channels, the number of channels after 1×1 convolution dimensionality enhancement, the size of the convolutional kernel, step size, whether SE is used, and whether HS is used, respectively.

Table 1 Improved YOLOv5s backbone extraction network structure.

From	Number	Params	Module	Arguments
-1	1	464	Conv_bn_HSwish	[3,16, 2]
-1	1	612	MobileNet_Block	[16,16,16,3,2,1,0]
-1	1	3864	MobileNet_Block	[16,24,72,3,2,0,0]
-1	1	5416	MobileNet_Block	[24,24,88,3,1,0,0]
-1	1	13736	MobileNet_Block	[24,40,96,5,2,1,1]
-1	1	55340	MobileNet_Block	[40,40,240,5,1,1,1]
-1	1	55340	MobileNet_Block	[40,40,240,5,1,1,1]
-1	1	21486	MobileNet_Block	[40,48,120,5,1,1,1]
-1	1	28644	MobileNet_Block	[48,48,144,5,1,1,1]
-1	1	91848	MobileNet_Block	[48,96,288,5,2,1,1]
-1	1	294096	MobileNet_Block	[96,96,576,5,1,1,1]
-1	1	294096	MobileNet_Block	[96,96,576,5,1,1,1]
-1	1	50176	Conv	[96,512,1,1]

After calculation, the total number of model parameters after replacing the backbone network with MobileNetV3 small is 3888418, and the model size is 7.9MB. The original backbone network model of YOLOv5s has a total of 7273971 parameters, with a model size of 13.82MB. From this, it can be seen that the parameter quantity of the lightweight improved model has been reduced by 46.5%, and the model size has been reduced by 42.6%, meeting the requirements of deploying detection algorithms for anti-static equipment dress code on embedded devices.

2.2. BiFPN Feature Fusion Network

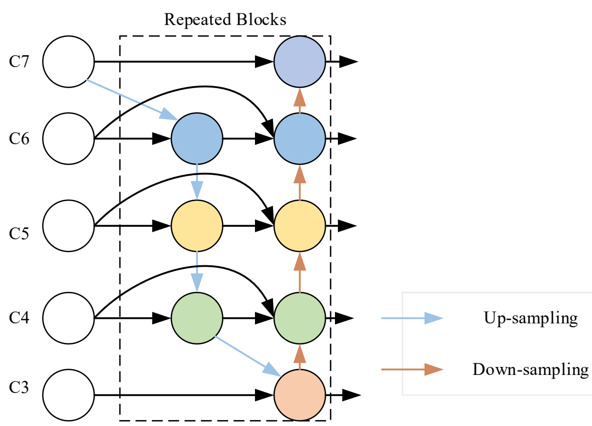

Figure 4 BiFPN Structure Diagram.

The core idea of the Bi-directional feature pyramid network (BiFPN) [14] is to fuse feature layers from different scales through "top-down" and "bottom-up" bidirectional channels, in order to reduce feature information loss caused by excessive down-sampling levels in the model. Its structure is shown in Figure 4, where C3 to C7 represent five different scale feature layers from the feature extraction network. BiFPN introduces learnable weights that are applied layer by layer to each feature layer, enabling the network to autonomously learn and adjust these weights, thereby determining the importance of each input feature in the fusion process.

Due to the limited space of the scene for detection of anti-static equipment dress code, the size, location, and individual differences of the target vary at multiple scales, resulting in different appearance features, textures, and details of anti-static targets in the image, which affects the detection accuracy of the anti-static equipment dress code. Therefore, this article adopts the BiFPN structure for multi-scale feature fusion, and combines BiFPN in the tensor stitching operation responsible for feature information fusion in Neck. The combined stitching operation is recorded as “BiFPN_Concat”. Due to the high requirements for the detection of anti-static equipment dress code, such as the location information of anti-static clothing, anti-static hats, and anti-static shoes, as well as the characteristics of the wearing parts of the human body, BiFPN integrates feature layers from different scales of target size, position, and individual differences through "top-down" and "bottom-up" bidirectional channels. The high-resolution shallow feature map better preserves the location information and detailed information of the anti-static clothing. The combined feature fusion network can set learning weight parameters, allowing the network to learn the position and detail feature information of anti-static clothing in different scale feature layers, achieving effective fusion of multi-scale feature information while ensuring the detection speed of the model, and improving the detection accuracy of anti-static equipment. The overall network structure of Yolov5s after improvement is shown in Figure 5.

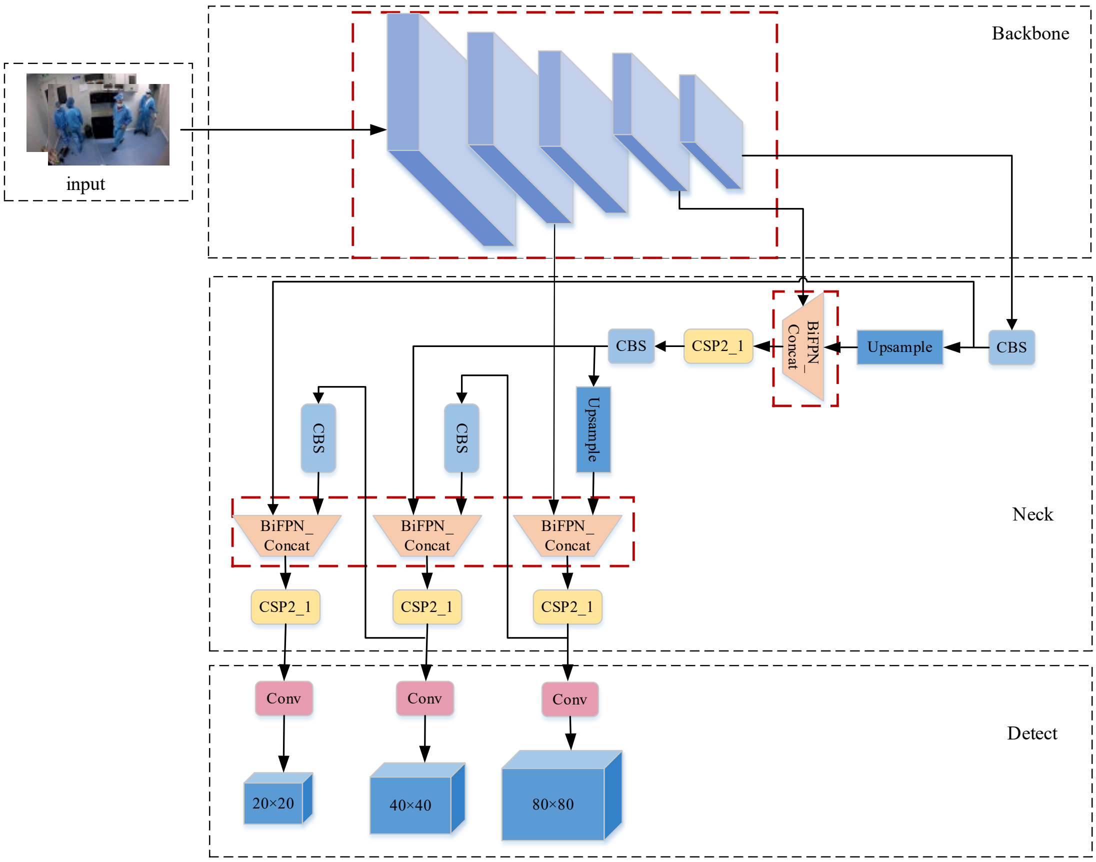

Figure 5 Improved network structure diagram.

2.3. Improvement of Loss Function

The BiFPN structure performs bidirectional weighted fusion of multi-scale features of anti-static equipment, obtaining rich spatial and semantic information. The CIoU Loss is used to calculate the loss of bounding box regression [15], which can make the target positioning of anti-static equipment more accurate, thereby ensuring high accuracy of the anti-static equipment dress code detection model while maintaining fast speed. CIoU Loss considers the overlapping area, center point distance, and aspect ratio of the target border, reflecting the difference between the predicted box and the actual box. The formula is defined as equation (3).

$$L_{\mathrm{CIoU}} = 1 - \mathrm{IoU} + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha \times v \tag{3}$$

In the equation: α is a factor used to balance the loss caused by the aspect ratio and intersection ratio; v is a parameter that measures the consistency of aspect ratio.

Due to limited space for inspection of dress code for anti-static equipment and dense crowds during commuting, there are people close to each other, resulting in missed detection of anti-static equipment targets. This article uses DIoU-NMS to replace NMS to improve the problem of missed detection of anti-static clothing targets in crowded situations [16]. The calculation of DIoU-NMS is shown in formulas (4) to (5).

$$S_i = \begin{cases} S_i, \mathrm{IoU} - R_{\mathrm{DIoU}}(M, B_i) < \varepsilon \\ 0, \mathrm{IoU} - R_{\mathrm{DIoU}}(M, B_i) \geq \varepsilon \end{cases} \tag{4}$$

$$R_{\mathrm{DIoU}} = \frac{\rho^2(b, b^{gt})}{c^2} \tag{5}$$

In the formula, M represents the candidate box with a high confidence score; B_i is used to determine whether the prediction box needs to be removed.

2.4. Implementation of Anti-static Equipment Dress Code Detection

This article uses the network constructed above to detect whether anti-static hats, anti-static clothing, and anti-static shoes are worn, locate them in the area of anti-static clothing and anti-static hats, and detect skin exposed outside anti-static clothing and hair exposed outside anti-static hats through semantic and color features, then calculate the area of the exposed connection area between hair and arms, and adjust the dynamic threshold through feedback mechanism to determine whether hair and arms are exposed, and detect if the anti-static cap and anti-static clothing are properly dressed in order to achieve detection of anti-static equipment dress code. Finally, the model was ported to the Jeston Xavier NX system, and a visual monitoring interface was established to real-time detect the standardization of anti-static equipment attire, and to promptly correct any improper attire behavior.

3. Experiment and Result Analysis Conclusions

3.1. Data Set

The data in this study is sourced from the wind shower room in a clean workshop of a company in Xi'an, China Aviation Corporation. The data collection uses a network camera, fixed on the ceiling of the wind shower room, with an angle of 37° upwards. It records videos of employees commuting and non daily staff entering and exiting simultaneously. The videos include wearing anti-static helmets, non-standard wearing of anti-static helmets, and not wearing anti-static helmets. The video includes personnel who wear anti-static hats, wear anti-static hats irregularly, and do not wear anti-static hats, wear anti-static clothing in a complete and standardized manner, only wear the upper body and only the off duty body, wear non-standard and non anti-static clothing, wear anti-static shoes, and do not wear anti-static shoes. Select employee peak commuting videos as test data, and other videos as training data. Perform frame capture processing on the videos, convert them into images, and clean the data to remove a large amount of duplicate and aimless data. Use LabelImg software to annotate the dataset. The targets of anti-static clothing compliance testing include people, heads, anti-static clothing, anti-static hats, disposable headsets, anti-static shoes, and disposable shoe covers. Expand the data samples by flipping, mosaic, cropping, and other operations on the labeled anti-static equipment dress code data to enrich the data and improve the generalization ability of the model. Produce a dataset of 32000 pieces of anti-static equipment dress code, with a ratio of 7:2:1 for training, testing, and validation sets, and a data image resolution of 1280×720.

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3.2. Experimental Environment and Parameter Settings

The model algorithm in this article is based on the Python framework and Python language. During the model training and testing phase, the experimental environment parameters are shown in Table 2. The network model parameters during the experimental process of this article: the Batch_size is 16, the weight attenuation coefficient is 0.0001, the number of training iterations is 300, and the initial learning rate value is 0.001. When testing the real-time detection results of anti-static equipment dress code, the speed and accuracy of anti-static equipment dress code detection are tested on the Jeston Xavier NX system.

Table 2 Experimental Environment Parameters.

Title	Params
GPU	Nvidia GeForce GTX 2080Ti (16 GB)
CPU	Intel Core i7-10700F, CPU 2.90 Hz,RAM 32GB
operating system	Ubuntu 18.04
Deep learning framework	Pytorch1.7.1+ CUDA 1.10.0
Programming Language	Python 3.6

3.3. Evaluating Indicator

In order to verify the performance of the detection model for dress code of anti-static equipment, the detection evaluation indicators used in this article include detection accuracy (P), recall rate (R), and mean AP (mAP), as shown in equations (6) ~ (8).

$$P = \frac{TP}{TP + FP} \tag{6}$$

$$R = \frac{TP}{TP + FN} \tag{7}$$

$$mAP = \frac{1}{c}\sum_{i=1}^{C} AP_i \tag{8}$$

3.4. Experimental Results

In order to verify the effectiveness of the anti-static equipment dress code detection model, this article used a self-made anti-static equipment dress code dataset in the experimental environment described in Table 2 to train and test the improved model and YOLOv5s, SSD [17], Faster R-CNN [18] models. The comparison of experimental results is shown in Table 3.

Table 3 Comparison of anti-static clothing target recognition results using different algorithms.

Algorithm	P/%	R/%	mAP/%	Number of parameters /10^6	Model size /MB
Faster R-CNN	76.5	87.9	89.8	26.2	108
SSD	72.7	79.8	78.5	13.7	90.1
Yolov5s	87.7	93.2	89.6	7.3	13.82
Ours	89.1	93.2	91.7	4.1	8.2

From Table 3, it can be seen that the proposed network outperforms other models in terms of model size and detection accuracy, with a 40.6% reduction in size compared to the YOLOv5s model. This enables the deployment of detection model of anti-static equipment dress code on the Jeston Xavier NX.

In order to verify the impact of various improvement points in the detection model for dress code of anti-static equipment, an ablation experiment was designed, and the experimental results are shown in Table 4. In the Table 4, "√" indicates the addition of this improvement, "×" Indicates that this improvement has not been added.

According to Table 4, experiment 1 shows that the detection accuracy of the unmodified YOLOv5s network on the anti-static equipment dress code dataset reached 89.6%, with a parameter quantity of 7.3×10^6, with a model size of 13.82MB; Experiment 2 used the MobileNetV3 small backbone extraction network, and after deep separable convolution, the detection model of anti-static equipment dress code was reduced by 1.2 percentage points in average accuracy, 46.5% in parameter quantity, and 42.6% in

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model size; On the basis of experiment 2, experiment 3 adopted the BiFPN structure to enhance the feature fusion ability of the network at multiple scales, which improved the average accuracy by 1.4 percentage points, increased the number of parameters by 5.1%, and increased the model size by 3.7% compared to experiment 2; On the basis of experiment 3, experiment 4 used CIoU Loss to calculate the border loss, making the target positioning of anti-static equipment more accurate, which increased the average accuracy by 1.6 percentage points compared to experiment 3. The model size and parameter quantity remained unchanged; On the basis of experiment 4, experiment 5 used DIoU-NMS to improve the problem of missed detection of anti-static equipment targets when people were crowded. Compared with experiment 4, the average accuracy increased by 0.3 percentage points, and the model size and parameter quantity remained unchanged; Compared to experiment 1, the average accuracy increased by 2.1 percentage points, the number of parameters decreased by 43.8%, and the model size decreased by 40.6%; In summary, the improved YOLOv5s algorithm model in this article significantly reduces the number and size of parameters, achieving lightweight network structure while improving detection performance, and meeting the requirements for deployment of the detection model of dress code for anti-static equipment on Jeston Xavier NX.

Table 4 Comparison results of adding different improvement points.

Num	MobileNetV3-small	BiFPN	CIoU Loss	DIoU-NMS	mAP/%	Number of parameters /10^6	Model size /MB
1	×	×	×	×	89.6	7.3	13.82
2	√	×	×	×	88.4	3.9	7.9
3	√	√	×	×	89.8	4.1	8.2
4	√	√	√	×	91.4	4.1	8.2
5	√	√	√	√	91.7	4.1	8.2

3.5. Real Time Detection Results of Dress Code for Anti-static Equipment

In order to achieve real-time detection of dress code for anti-static equipment, this article designs a visual monitoring interface and deploys the model on the Jeston Xavier NX system. After real-time testing and verification, the system can achieve real-time detection of five types of non-standard behaviors: not wearing anti-static hats, not wearing anti-static clothes, not wearing anti-static shoes, wearing anti-static clothes irregularly, and wearing anti-static hats irregularly. If any non-standard behaviors are detected, a voice alarm will be issued, remind staff to promptly correct non-standard behaviors. The visual monitoring interface is shown in Figure 6.

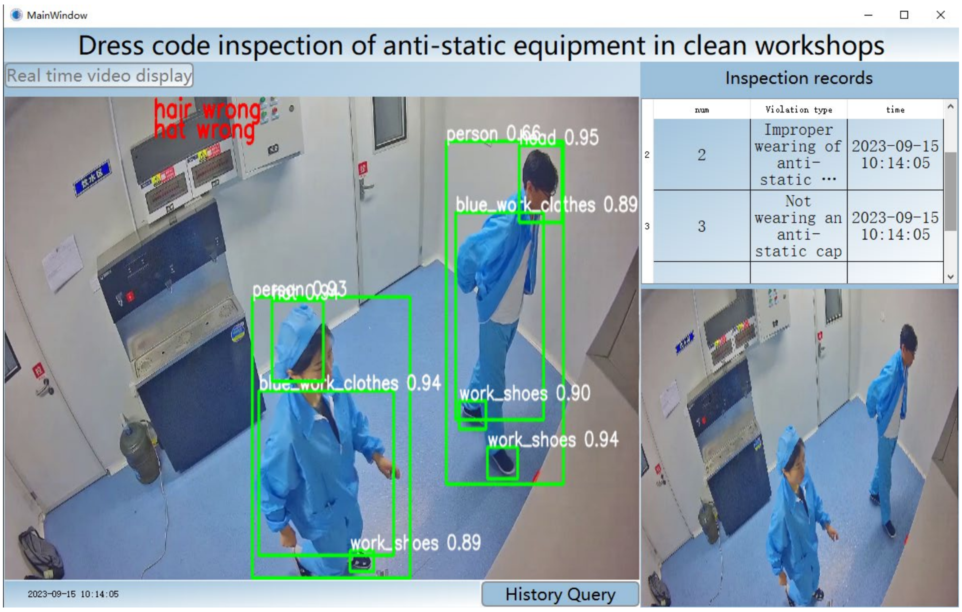

Figure 6 Visual Inspection Interface.

Compared with the original yolov5 model for performance testing, it ran at a speed of 27 FPS on the Jeston Xavier NX, nearly doubling the speed and achieving real-time detection results. The test results are shown in Table 5.

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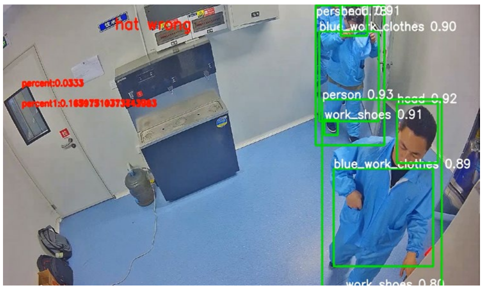
Table 5 Comparison of running results on Jeston Xavier NX.

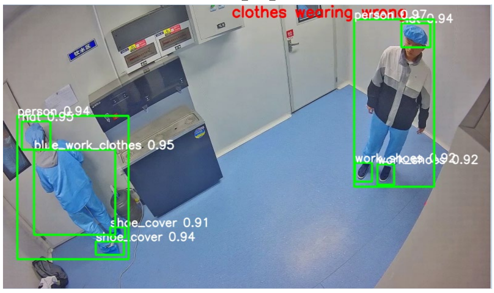
Algorithm	P/%	R/%	mAP/%	FPS
Yolov5s	87.7	92.1	89.6	14
Ours	89.1	93.2	91.7	27

Real time testing of dress code was conducted on the Jeston Xavier NX system, and the results of the anti-static equipment dress code testing are shown in Figure 7.

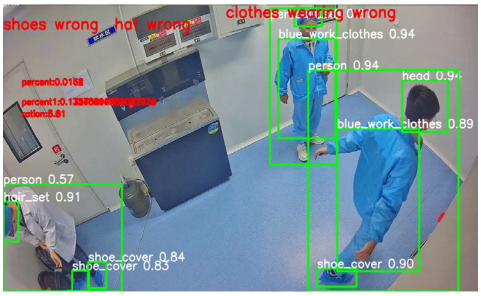
(a) Improper attire of multiple individuals' anti-static equipment.



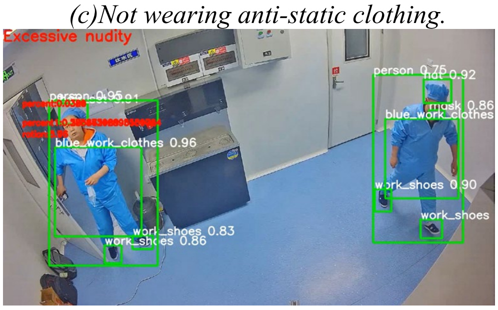
(b) Not wearing an anti-static cap.



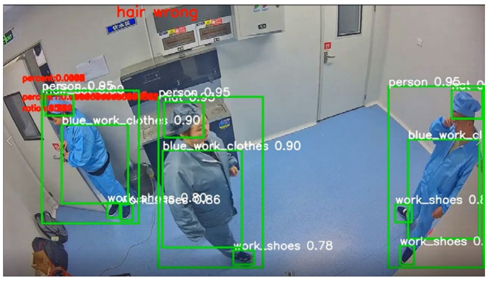
(c)Not wearing anti-static clothing.



(d) Not wearing anti-static shoes.



(e) Improper wearing of anti-static clothing.



f) Improper wearing of anti-static hats.

Figure 7: Test results of dress code for anti-static equipment.

In Figure 7, figure (a) shows the detection results of multiple individuals wearing non-standard anti-static equipment, and figure (b) shows the detection results of not wearing anti-static hats, and figure (c) shows the detection results of not wearing anti-static clothes, figure (d) shows the detection results of not wearing anti-static shoes, and figure (e) shows the detection results of improper wearing of anti-static clothing, and figure (f) shows the detection results of non-standard wearing of anti-static hats. From Figure 7, it can be seen that the scene space for the detection of dress code for anti-static equipment is limited. The changes in target size, position, and individual differences at multiple scales result in the accurate detection of anti-static equipment and types of clothing irregularities in the presence of different image target sizes and occlusion by multiple individuals. This algorithm proves the generalization ability of the model. Capturing the real-time detection video results and obtaining 300 samples for result statistics, the accuracy of identifying five types of non-standard behaviors in the air shower workshop, including not wearing anti-static hats, not wearing anti-static clothing, not wearing anti-static shoes, wearing anti-static clothing irregularly, and wearing anti-static hats irregularly, was 98.1%, 96.2%, 95.8%, 94.2%, and 94.1%, respectively. The detection results of non-standard attire of anti-static equipment are shown in Table 6.

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Table 6 Detection results of five types of dress code violations.

Types of dress code violations	Recognition accuracy /%
Not wearing an anti-static cap	98.1
Not wearing anti-static clothing	96.2
Not wearing anti-static shoes	95.8
Improper wearing of anti-static clothing	94.2
Improper wearing of anti-static hats	94.1

4. Conclusion

To address the issue of difficulty in deploying multi-scale dress code detection methods for anti-static equipment in embedded systems, a lightweight real-time detection method for anti-static equipment dress code is proposed. This article uses the Mobilenetv3 small backbone network to extract features of anti-static equipment, making the model lightweight and easy to deploy. Adopting the BiFPN structure, enhancing the feature fusion ability of anti-static equipment at multiple scales, using CIoU Loss and DIoU-NMS to accurately locate anti-static equipment targets, improving the problem of missed detection of anti-static equipment when people are crowded, and improving the accuracy of dress code detection for anti-static equipment, and finally achieving detection for dress code of anti-static equipment through bare connected area detection. The experimental results show that the parameter quantity and model size of detection for dress code of anti-static equipment in this article have been significantly reduced, achieving lightweight network structure while improving detection performance. Real time detection of anti-static equipment attire standardization has been achieved on Jeston Xavier NX, with a speed of 27 FPS and an average recognition accuracy of 95.7%. The accuracy rates for identifying five types of non-standard behaviors: not wearing an anti-static hat, not wearing anti-static clothing, not wearing anti-static shoes, wearing anti-static clothing irregularly, and wearing anti-static hats irregularly are 98.1%, 96.2%, 95.8%, 94.2%, and 94.1%, respectively. The visualization results test verified the generalization ability of the model, meeting the needs of anti-static equipment monitoring and management.

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