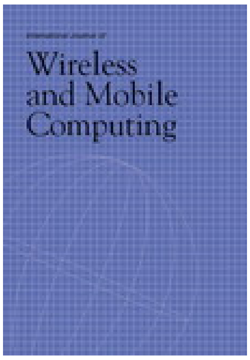

International Journal of Wireless and Mobile Computing

ISSN online: 1741-1092 - ISSN print: 1741-1084
https://www.inderscience.com/ijwmc

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DOI: 10.1504/IJWMC.2023.10061393

Article History:

Received:	09 May 2023
Last revised:	03 July 2023
Accepted:	24 July 2023
Published online:	07 February 2024

An abnormal identification method for operation and maintenance personnel of intelligent power distribution room based on monitoring video stream

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Abstract: With the rapid development of intelligent distribution rooms, the abnormal detection of safety helmet wearing by operators has gradually shifted from traditional manual monitoring to online recognition of monitoring videos. This paper proposes an abnormal identification method for operation and maintenance personnel of intelligent power distribution room based on monitoring video stream, which aims to solve the problem of insufficient robustness of the detection model due to the limited professional knowledge and practical experience of the design personnel involved in existing safety helmet wearing detection systems. Firstly, based on safety helmet wearing image data in existing distribution room scenes, a multi-operation-based data augmentation algorithm for safety helmet wearing in distribution rooms is designed to generate training data sources for safety helmet wearing in distribution room environments. Secondly, a distribution room operator safety helmet wearing detection model based on improved Yolov5 is constructed to achieve intelligent detection of unmanned distribution room monitoring images. Finally, simulation experimental results show that the proposed method realises intelligent detection of safety helmet wearing by operation and maintenance personnel in various complex environments of distribution rooms, with high robustness and detection rates.

Keywords: intelligent distribution room; safety helmet detection; image recognition; deep learning; Yolov5.

Reference to this paper should be made as follows: Huang, W., Wang, Z., Liu, J., Li, Y. and Han, L. (2024) 'An abnormal identification method for operation and maintenance personnel of intelligent power distribution room based on monitoring video stream', *Int. J. Wireless and Mobile Computing*, Vol. 26, No. 1, pp.83–91.

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1 Introduction

The power distribution network plays a crucial role in the socio-economic development as an important component of the power system. As a vital link to users in urban power distribution systems, distribution rooms are responsible for transmitting and distributing electricity, which is closely related to the stability of power supply and the reliability of user consumption. Therefore, the safety operation and management of distribution rooms have always been a critical part of power system operation and management. In order to cope with sudden dangers, operators and managers in distribution room management must wear safety helmets correctly before entering the workplace. However, the phenomenon of not wearing safety helmets correctly according to the requirements has repeatedly occurred, bringing huge hidden dangers to operational safety (Saxena, 2019).

With the continuous development of smart grids and digital image processing technology, many distribution rooms have added remote viewing capabilities for real-time visualisation monitoring of smoke and fire, personnel intrusion, etc., which greatly helps the safety and reliability of distribution room operations. Supervisors can directly check whether maintenance staff are wearing safety helmets correctly as required through remote monitoring videos (Zhang et al., 2022b). However, studies have shown that when a person simultaneously observes two monitoring screens, they will miss 45% of useful information in 10 minutes and 95% in 22 minutes and observing multiple monitoring screens will further distract their attention (Ahlström et al., 2021), leading to the omission of useful information. Therefore, relying solely on human resources to monitor abnormal safety helmet wearing of maintenance staff in distribution rooms is obviously not foolproof, as human concentration and attention will decline with monitoring time. Researching a method that can automatically detect abnormal safety helmet wearing of maintenance staff in distribution room monitoring videos is of great significance for ensuring the personal safety of maintenance staff and the stable operation of the power grid.

In recent years, with the rapid development of deep learning and video surveillance systems, deep learning-based applications have achieved very good results in various fields (Dong et al., 2021; Yuan et al., 2021). Kou et al. (2023) first proposed using Histogram of Oriented Gradient (HOG) features to automatically recognise correct safety helmet wearing, providing a new idea for automatic detection of safety helmet wearing. Yang et al. (2022) extracted the feature vector of the safety helmet based on its relative position with the head or face, and used it as the input layer of the Back Propagation (BP) neural network to achieve automatic recognition of safety helmet wearing, but it was greatly influenced by the on-site background environment. Zhang et al. (2022a) used skin colour detection to locate the position of the face in the monitoring video image, then extracted images containing only the area above the face frame by frame, and finally completed the recognition of safety helmet wearing by combining support vector machines with Hu moment feature vectors. SubbaRao et al. (2021) used the deformable part model and proposed a composite feature vector of colour features, block-based Local Binary Pattern (LBP) features and HOG features, and finally used Support Vector Machine (SVM) for safety helmet wearing recognition. However, this method faced the drawback of an overly complex design process (SubbaRao et al., 2021). Hayat and Morgado-Dias (2022) proposed to prioritise using Convolutional Neural Network (CNN) to recognise maintenance personnel, then transform the colour space of maintenance personnel using hue, saturation and colour models, select the blocks that meet the safety helmet colour, and then perform colour and circle Hough Transforms (CHT) on these blocks to determine whether the safety helmet is worn correctly.

In summary, existing research on safety helmet recognition mostly uses traditional machine learning methods that require subjective feature design, and their performance is limited by the professional knowledge and practical experience of the designers, resulting in poor robustness. Therefore, this paper proposes an abnormal identification method for operation and maintenance personnel of intelligent power distribution room based on monitoring video stream. Firstly, a data augmentation algorithm based on multiple operations is proposed to generate training data sources for safety helmet wearing in distribution room environments. Then, an improved Yolov5-based model for detecting safety helmet wearing of maintenance personnel in distribution rooms is constructed to achieve intelligent detection of unattended distribution room monitoring images. Finally, experimental case studies are conducted to verify that the proposed method achieves intelligent detection of safety helmet wearing of maintenance personnel in various complex environments in distribution rooms, and the optimised Yolov5 algorithm not only improves the detection speed but also ensures detection accuracy.

2 Data augmentation algorithm for safety helmet wearing in distribution rooms based on multiple operations

Existing AI-based intelligent models rely heavily on historical data. However, there is currently no mature data source for safety helmet wearing in distribution rooms, and important places like distribution rooms in power grids cannot provide large amounts of data to avoid safety hazards (Wei et al., 2020). Therefore, this paper prioritises proposing a data augmentation algorithm for safety helmet wearing in distribution rooms based on multiple operations. This algorithm can generate data sources for whether maintenance personnel are wearing safety helmets correctly in distribution room environments, facilitating the training and performance testing and analysis of subsequent safety helmet detection models. The overall architecture of the algorithm is shown in Figure 1.

Owing to the various factors affecting the image features of the safety helmet to be detected, such as lighting, occlusion, distance from the camera and the colour of the helmet itself, the richness of the data source is the foundation for the high robustness and accuracy of the subsequent safety helmet detection model. The proposed algorithm expands a small amount of manually collected original data through multiple operations, including rotation, random cropping, scale scaling, Gaussian noise, brightness adjustment and flipping adjustment.

2.1 Annotation of original data

The original data cannot be directly used for training the safety helmet detection model. The data needs to be annotated by labelling corresponding labels on the region of interest (head). Figure 2 shows the annotation effect using the LabelMe annotation tool. After the annotation is completed, a json file is generated as shown in Figure 3, which is used for data augmentation and model training. This file records the image information and corresponding annotation information. Table 1 provides an explanation of the key units in the json file.

Figure 1 Overall architecture of data augmentation algorithm for safety helmet wearing in distribution rooms based on multiple operations (see online version for colours)

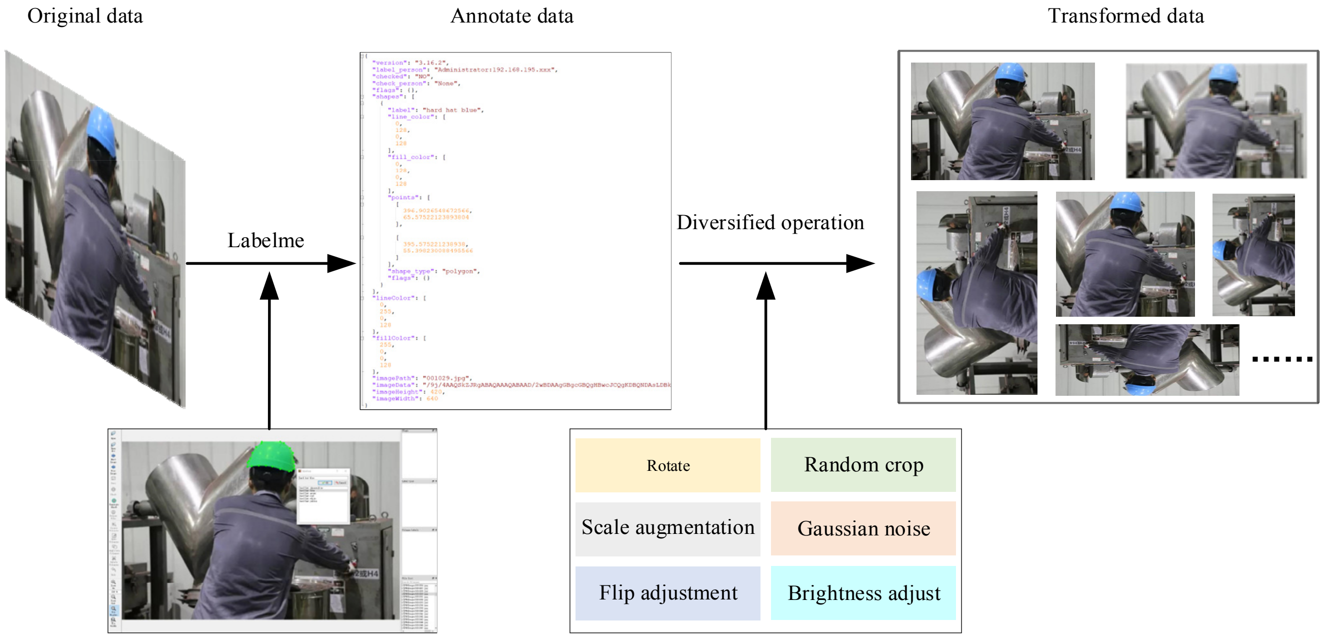


Figure 2 LabelMe annotation interface (see online version for colours)

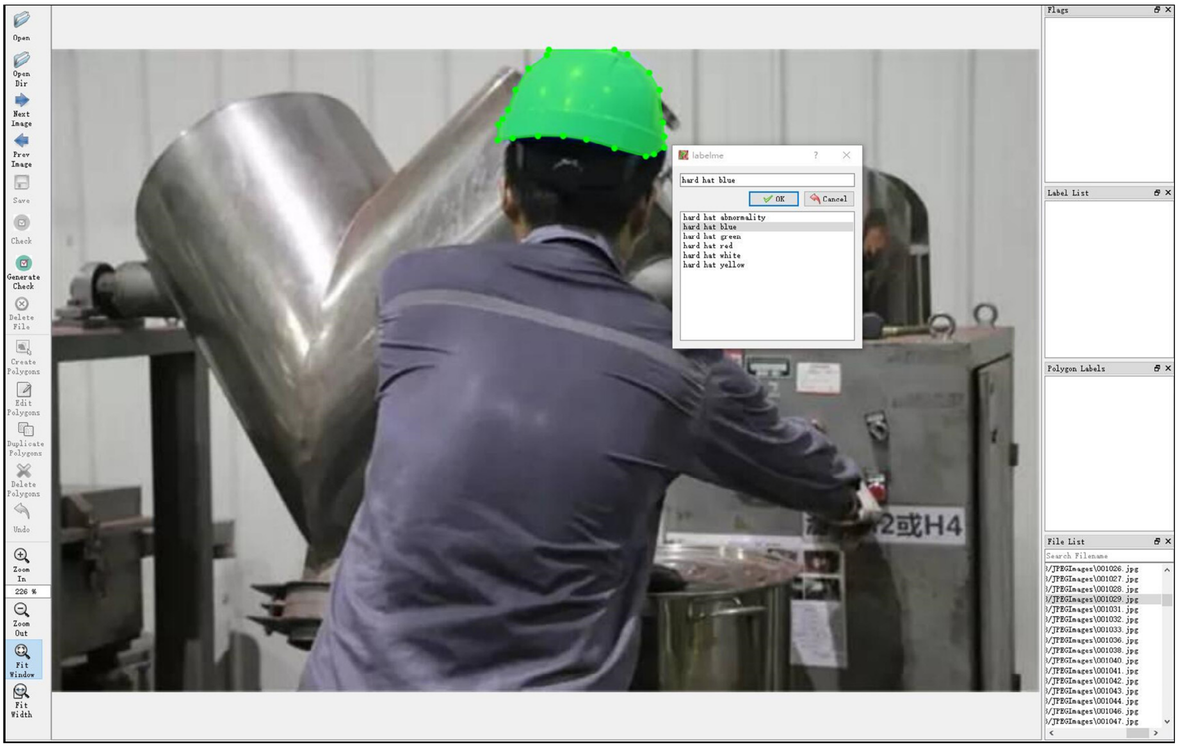


Figure 3 Internal information in the JSON file (see online version for colours)


```
{
  "version": "3.16.2",
  "label_person": "Administrator:192.168.195.xxx",
  "checked": "NO",
  "check_person": "None",
  "flags": {},
  "shapes": [
    {
      "label": "hard hat blue",
      "line_color": [
        0,
        128,
        0,
        128
      ],
      "fill_color": [
        0,
        128,
        0,
        128
      ],
      "points": [
        [
          396.90265486725666,
          65.57522123893804
        ],

        [
          395.57522123893938,
          55.39823008849556
        ]
      ],
      "shape_type": "polygon",
      "flags": {}
    }
  ],
  "lineColor": [
    0,
    255,
    0,
    128
  ],
  "fillColor": [
    255,
    0,
    0,
    128
  ],
  "imagePath": "001029.jpg",
  "imageData": "/9j/4AAQSkZJRgABAQAAAQABAAD/2wBDAAgGBgcGBQgHBwcJCQgKDBQNDAsLDBk
  "imageHeight": 420,
  "imageWidth": 640
}
```

Table 1 The description of image annotation information in JSON file

Element name	*Meaning*
label	Types of labels
line_colour	Line colour of the label area
fill_colour	Fill colour of the label area
points	Label point position
imagePath	Relative path to save image
imageData	Image data format
imageHeight	The height of the image
imageWidth	The width of the image

2.2 Data augmentation with diverse operations

Owing to the varying distances and angles of the operating personnel from the monitoring cameras, as well as the different lighting conditions at different locations and times in the actual distribution room, there are significant differences in image features. Good data augmentation can not only quickly increase sample size with limited data but also enrich the diversity of samples, avoiding overfitting. The following is a detailed introduction to the contents of the data augmentation operations in the safety helmet wearing data augmentation algorithm based on diverse operations in the distribution room.

1 *Rotation operation*: This operation mainly realises data augmentation by rotating the original image randomly clockwise and counter clockwise from 30 to 90°. Assuming the coordinates of the annotated object are $\left[\left(x_1, y_1\right),\left(x_2, y_2\right),\ldots,\left(x_i, y_i\right),\left(x_m, y_m\right)\right]$, $i = 1, 2, \ldots, m$, m is the total number of annotation points in the annotation area. The coordinates of the annotation area after rotation are denoted as $\left[\left(new\_x_1, new\_y_1\right),\ldots,\left(new\_x_m, new\_y_m\right)\right]$, X is the horizontal coordinate of the original image after rotation and Y is the vertical coordinate of the original image after rotation.

The calculation of the coordinates after rotating the annotation area 90° clockwise is as follows:

$$\begin{cases} new\_x_{UL} = Y - y_{BR} \\ new\_y_{UL} = x_{UL} \\ new\_x_{BR} = -Y - y_{UL} \\ new\_y_{BR} = x_{BR} \end{cases} \tag{1}$$

where $\left(x_{UL}, y_{BR}\right)$ and $\left(x_{BR}, y_{BR}\right)$ are the coordinates of the upper-left corner and lower-right corner of the annotation area respectively.

The calculation of the coordinates after rotating the annotation area 90° counterclockwise is as follows:

$$\begin{cases} new\_x_{UL} = y_{UL} \\ new\_y_{UL} = X - x_{BR} \\ new\_x_{BR} = y_{BR} \\ new\_y_{BR} = -X - x_{UL} \end{cases} \tag{2}$$

2 *Random cropping operation*: Considering that the safety helmet worn by operating personnel in the distribution room may be occluded by other objects, resulting in the safety helmet not appearing in a complete form. In such scenarios, the lack of training data can easily cause false positives and false negatives in detection models, leading to reduced model robustness. Therefore, it is necessary to augment such data sets through random cropping of the original general data. The calculation for updating the coordinates after cropping the annotation area is shown in formula (3):

$$\begin{aligned} &\left[x_{UL} - crop\_x\_\min, y_{UL} - crop\_y\_\min\right], \\ &\left[x_i - crop\_x\_\min, y_i - crop\_y\_\min\right], \\ &\left[x_{BR} - crop\_x\_\min, y_{BR} - crop\_y\_\min\right] \end{aligned} \tag{3}$$

where $(crop\_x\_\min, crop\_y\_\min)$ is the starting coordinate of the cropping area.

3 *Scale scaling operation*: This operation is mainly used to address the issue of discrepancies in the size and proportions of safety helmets due to different shooting angles of monitoring cameras in the distribution room. To enrich such data, a corresponding scaling factor σ is applied to one side of the original image while fixing the other side.

4 *Gaussian noise operation*: Convolutional neural networks are sensitive to high-frequency features in input images and increase the learning weight for these features, thereby reducing the weight for low-frequency features. For example, high-frequency features have no positive feedback on the training and recognition of the model, and there is a high probability that the detection model will experience overfitting. To solve the overfitting caused by high frequency, random black-and-white pixel Gaussian noise is added to the image to distort the image information and improve the robustness of the model. The noise model is shown in formula (4):

$$p_{\text{Gaussian}}(z) = \frac{1}{\lambda\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\lambda^2}} \tag{4}$$

where z represents the grayscale value of the model, μ represents the mean of z and λ represents the variance of z. The strength of introducing noise to the original image can be adjusted by changing the two parameters μ and λ.

5 *Brightness adjustment operation*: Owing the different lighting conditions at different times and locations in the distribution room monitoring, the clarity of images of operating personnel at work varies and the proportion of shadow areas is different, resulting in different image features. The brightness adjustment operation simulates different lighting conditions by interfering with the brightness of the image, thereby enriching the sample data with different illuminance. The specific adjustment expression is as follows:

$$new\_gray_{image} = gray_{image} * \theta \tag{5}$$

where new_gray_{image} is the grayscale value of the image after quantisation adjustment; $gray_{image}$ is the original grayscale value of the image; θ is an adjustment coefficient between 0 and 1 that represents the degree of brightness adjustment. When $\theta = 1$, the brightness of the image remains unchanged; when $\theta < 1$, the image will become darker.

6 *Flip adjustment operation*: The image flip adjustment operation is relatively simple, mainly including two methods: horizontal flip and vertical flip. The new image is obtained by adjusting the width or height of the original image. The algorithm uses flip() function in OpenCV to achieve it.

3 Detection model for safety helmet wearing of distribution room workers based on improved Yolov5

Convolutional neural network is a type of neural network with deep learning capabilities that does not require manual feature design for specific recognition tasks (Chen et al., 2023). It extracts features from images at different levels through convolutional layers, pooling layers, etc. In this paper, we construct a detection model for safety helmet wearing of distribution room workers based on the improved Yolov5 model. The model adopts local receptive fields, weight sharing and spatial sampling techniques and has good robustness for translation, rotation and scaling. Even if the shape and posture of the operator's head change in the monitoring video, it can still be recognised well.

Yolov5 is divided into Yolov5s, Yolov5m, and Yolov5l according to the depth and width of feature maps. In this paper, we use Yolov5s as the basic model and replace the original feature pyramid network with Adaptive Attention Module (AAM) and feature enhancement module (AF-FPN). The optimised Yolov5 structure consists of four parts: Input, Backbone, Neck and Output.

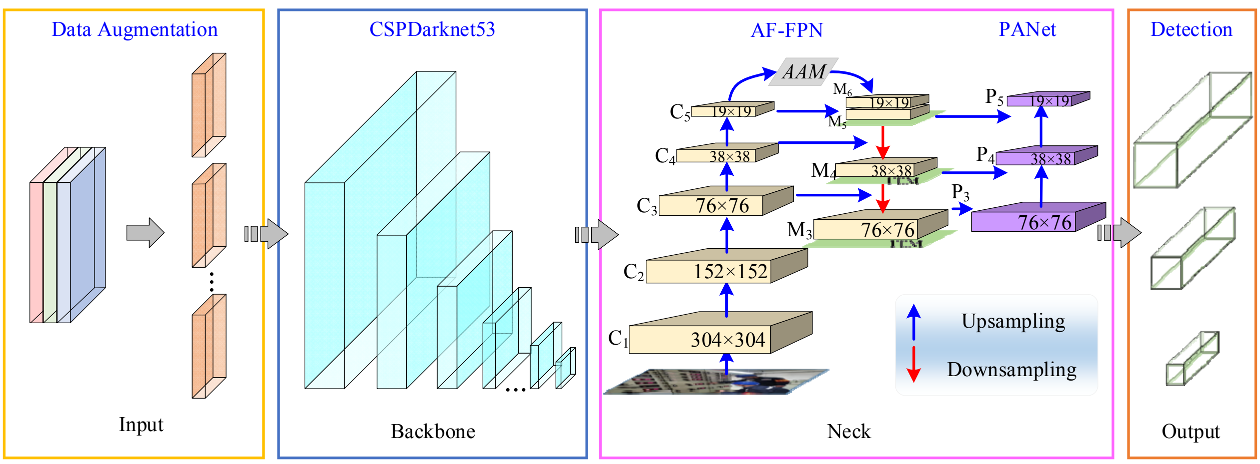
1 At the input end, a data augmentation method based on Mosaic is designed. This method randomly calls four images, stacks them with random sizes and distributions, enriches the data, increases many small targets and improves the recognition ability of small objects. Four images can be calculated simultaneously, which is equivalent to increasing the mini-batch size and reducing GPU memory consumption. Yolov5 can first set anchor sizes through clustering, and then calculate different anchor values in each training set during the training process. Adaptive image size scaling mode is used for prediction, which reduces black borders and improves prediction speed.

2 The Backbone not only uses the CSPDarknet53 structure but also uses the Focus structure as a reference. This module is used to extract some common feature representations.

3 The Neck network is usually located in the middle of the Backbone network and the Output network, and it can further improve the diversity and robustness of features. AF-FPN adds adaptive attention modules and feature enhancement modules on the basis of traditional feature pyramid networks. The former reduces feature channels and reduces the loss of context information in high-level feature maps; the latter enhances the representation of the feature pyramid and speeds up inference, while achieving state-of-the-art performance.

4 Output is used to output the detection results of safety helmet wearing of distribution room workers. In traditional YOLOv5, GIOU_Loss is used as the bounding box loss function. In GIOU_Loss, a way of measuring the intersection scale is added to solve the problem that two boxes cannot reflect the distance between them. At this time, the function loss is not differentiable, and GIOU_Loss cannot calculate the case where the two boxes have no intersection. Therefore, non-maximum suppression is used for selecting predicted boxes in the inference process. This paper changes the ordinary NMS method in yolov5 algorithm to Diou_nms, making the results obtained by NMS more reasonable and effective.

Figure 4 Overall architecture of the detection model for safety helmet wearing of distribution room workers based on the improved YOLOv5 (see online version for colours)



4 Experiments

To validate the effectiveness and engineering applicability of the proposed method, a case study analysis and model comparison experiment were conducted based on real monitoring data from a provincial-level power company in China. All experiments were performed on a workstation with Windows 10 Enterprise, a Quadro P8000 graphics card with 48 GB memory manufactured by NVIDIA, an Intel(R) Xeon(R) Gold 5118 CPU @ 2.30 GHz processor and 64GB RAM. The deep learning framework used was PyTorch, launched by Facebook. The model was initialised with pre-trained parameters on the COCO data set and fine-tuned network parameters, with specific initial parameters shown in Table 2. Since the optimal model requires continuous parameter tuning and repeated training of data, the above parameters were not set when obtaining the final model.

Table 2 Initial parameters for model training

Parameter name	*Parameter value*
Learning rate	0.002
epoch	100
batch size	32
weight_decay	0.0006
lr_step	50
lr_factor	0.1
NMS	0.5
maximum iterations	80000

4.1 Verification of experiment data set expansion

Owing to the requirements of China's Power Data Security Law, the data set of original safety helmet-wearing data obtained by distribution room maintenance personnel is limited. In order to obtain a rich source of data for training the safety helmet detection model, this paper first implemented the data augmentation algorithm based on multivariate operations proposed in Section 2. Since each image has multiple targets, the annotated data far exceeds the amount of image data.

The distribution of the expanded data set through multivariate operations is shown in Table 3. The total number of annotated targets in the entire data set is 19,578. Among them, there are 2413 targets without safety helmets, 5054 targets with blue safety helmets, 786 targets with green safety helmets, 3877 targets with red safety helmets, 2336 targets with white safety helmets and 5112 targets with yellow safety helmets.

4.2 Model detection comparison and visualisation

To evaluate the performance of the model and the accuracy of detecting safety helmet wearing by distribution room operators, this paper uses Mean Average Precision (mAP), Giga Floating-point Operations Per Second (GFLOPs), Params and Frame Per Second (FPS) as evaluation indicators for model performance (Liao, 2023). Among them, mAP is the mean of the average accuracy of all categories. GFLOPs refers to the number of floating-point operations per second, which represents the complexity of the network model and affects the detection speed of the model. Params refers to the number of parameters in the network model, which directly affects the graphics memory occupied during the operation of the network model. FPS refers to the number of images that the network model can detect per second and is used to evaluate the detection rate of the model.

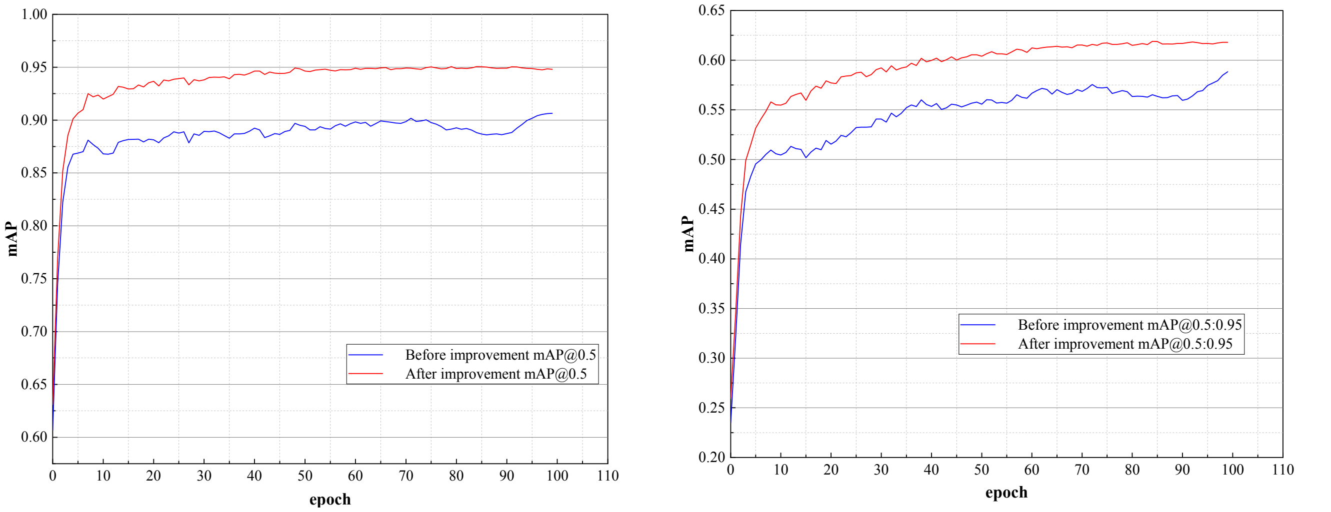
Table 3 Data set allocation table

Target class	*Annotate the number of targets.*	*Number of targets in the training set.*	*Number of targets in the test set.*
Hard hat abnormality	2413	1810	603
Hard hat blue	5054	3791	1263
Hard hat green	786	590	196
Hard hat red	3877	2908	969
Hard hat white	2336	1752	584
Hard hat yellow	5112	3834	1278

To verify the performance of the improved Yolov5 model for detecting safety helmet wearing by distribution room operators, training and testing were conducted on the constructed safety helmet data set. The changes in mAP values before and after model improvement are shown in Figure 5. Figure 5(a) shows the mAP@0.5 training comparison curve, and Figure 5(b) shows the mAP@0.5:0.95 training comparison curve, where the horizontal axis is the training cycle and the vertical axis is the mAP value.

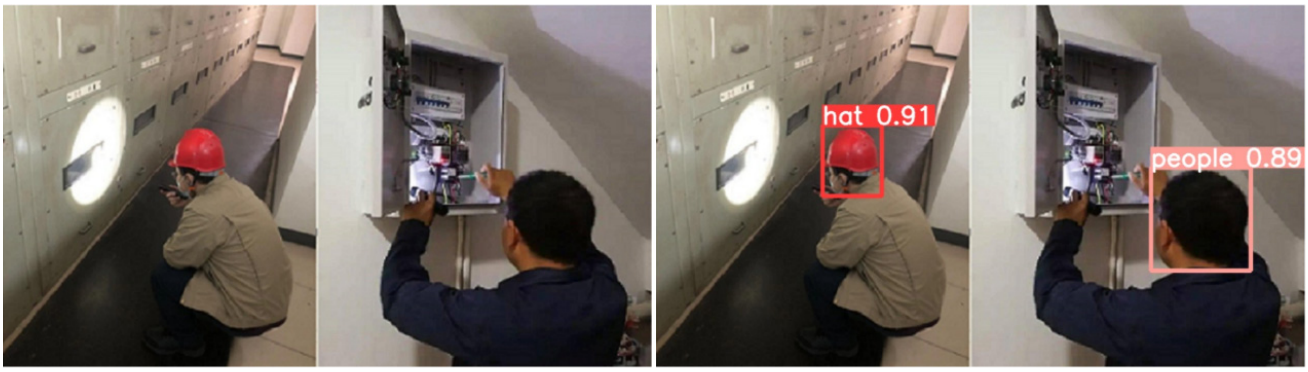
According to Figure 5, the mAP@0.5 value before model improvement was 90.65%, and the mAP@0.5:0.95 value was 58.83%. After model improvement, the mAP@0.5 value reached 95.06% and the mAP@0.5:0.95 reached 61.89%, representing an improvement of 4.41% and 3.06%, respectively. Therefore, the improved model in this paper can effectively improve the detection accuracy of safety helmet wearing and has strong adaptability to distribution room environments. Figure 6 provides specific detection examples of the proposed model, which can accurately detect whether a safety helmet is worn or not.

Figure 5 Comparison of mAP training curves (a) (a) mAP@0.5 training curve (b) (b) mAP@0.5:0.95 training curve (see online version for colours)



(a) (b)

Figure 6 Detection examples of the safety helmet wearing detection model for distribution room operators (see online version for colours)



To further verify the effectiveness and superiority of the proposed method, comparative experiments were conducted on the constructed safety helmet data set between the improved algorithm in this paper and Faster-RCNN, Yolov5x, SSD and Yolov5s (Otgonbold et al., 2022). Table 4 shows the experimental results of each indicator for the comparative experiment.

Table 4 Comparison of different algorithms on the safety helmet data set

Model	*mAP/%*	*GFLOPs*	*Params/10^6*	*FPS/ms·frame^{-1}*
Faster-RCNN	80.55	416.7	118.7	154
Yolov5x	91.08	239.2	92.1	36
SSD	82.13	252.9	22.3	88
Yolov5s	90.61	15.4	7.6	21
Ours	95.06	23.0	7.9	25

By analysing Table 4, we can draw a conclusion that on the constructed safety helmet data set for distribution rooms, our model's mAP value was improved by 14.51%, 3.98%, 12.93% and 4.45% compared to Faster-RCNN, Yolov5x, SSD and Yolov5s algorithms, respectively, indicating better detection performance. The computational complexity of the model is ranked as Faster-RCNN > Yolov5x > SSD > Ours > Yolov5s. The ranking based on the number of images the network model can detect per second is Yolov5s > Ours > Yolov5x > SSD > Faster-RCNN, demonstrating that the proposed algorithm meets real-time detection requirements. Overall, the proposed method has lower parameter quantity and computational complexity than most classic models. Compared with traditional Yolov5s, the detection time per frame image increased by 4 ms and the parameter quantity of the model increased after improvement, but this led to a significant improvement in the final mean average precision of the model. Therefore, considering multiple aspects, our method demonstrates clear advantages overall.

5 Conclusion and future work

This paper focuses on the detection of safety helmet wearing by distribution room operators in complex scenes of intelligent distribution rooms. To address the problem of insufficient robustness of detection models caused by the limitations of designer's professional knowledge and practical experience in existing safety helmet detection systems, an abnormal identification method for operation and maintenance personnel of intelligent power distribution room based on monitoring video stream was proposed. Firstly, a concatenated form of mixed pooling combined with spatial pyramid was used to enhance the ability to extract and express detailed information while reducing computational complexity. Secondly, the detection accuracy of safety helmets at far distances was optimised by adding shallow feature maps. Finally, comparative experiments were conducted between the proposed method and other mainstream models, which demonstrated that our model has good accuracy and engineering usability.

In future research, we will focus on reducing the parameter quantity and computational complexity of the model without compromising its accuracy, further improving the overall performance of the detection model for safety helmet wearing by distribution room operators.

Acknowledgements

The research was supported by the Science and Technology Project of State Grid Jilin Electric Power Co., Ltd. (grant numbers: 2022–18).

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