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Research on Multi-dimensional Data Analysis and Real-time Monitoring System of Grid Construction Safety Belt Based on Intelligent Algorithm

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Abstract This paper constructs a safety belt intelligent monitoring system for power grid construction scenarios, realizing real-time monitoring and early warning of safety belt status through hardware and software co-design. Relying on acousto-optic controller to realize real-time feedback of buckle status, mosaic enhancement and environmental noise simulation are used to improve data diversity. The YOLO network is improved by introducing cavity convolution and depth separable convolution to optimize the feature extraction efficiency, and combining with progressive attention area network to enhance the feature characterization ability of small targets. Experiments show that the accuracy, recall, and AP value of the improved YOLO-DCM-DSCM-PAAN algorithm are improved by 5.65%, 1.07%, and 3.88%, respectively, compared with the YOLO algorithm. After the introduction of the DCM module, the mIOU value and F1 score of YOLO-DCM reached 0.83 and 0.81, respectively. The ablation experiments show that Experiment 4 fuses the two modules, DSCM and PAAN, and improves the mIOU and F1 scores by 6.0% and 7.4%, respectively, on the basis of Experiment 1, which is a more obvious improvement. The detection accuracy of the proposed improved algorithm reaches 96.91%, which is 2.45% higher than the YOLOX algorithm. It proves that the improved algorithm in this paper can meet the demand of real-time monitoring of complex construction scenarios, and the study provides an innovative and intelligent solution for electric power operation safety.

Index Terms power grid construction, seat belt monitoring, YOLO network, progressive attention area network, target detection

I. Introduction

Grid infrastructure construction safety management is an important part of grid construction, in order to ensure the safety of the construction process, a series of control measures need to be taken to improve the level of safety management [1], [2]. Since on the power grid construction site, there are a lot of high place operations and overlapping cross operations, in order to prevent the possible fall of the operator at a certain height and position, the operator must fasten the construction safety belt when he ascends to the heights and high place operations [3]-[5]. According to the conditions of use, safety belts are categorized into boom work safety belts, area restriction safety belts, and fall suspension safety belts [6], [7]. However, the safety of safety belts cannot be predicted by anyone, and they need to be analyzed and monitored in real time frequently to ensure the safety of construction workers, and the emergence of intelligent algorithms makes it possible to achieve this goal [8]-[10].

In the context of intelligent algorithms, multidimensional data analysis belongs to the relatively more advanced data analysis concept, through the integration of multidimensional data analysis and power grid construction, it can optimize the power grid construction management to a certain extent [11]-[13]. In today's highly developed information technology, big data technology can promote multidimensional data analysis to become more accurate [14]. For electric power companies, construction safety belt analysis brings more development opportunities for the long-term development of the company, precisely because of the possibility of bias in the process of processing data, so depending on the conclusions of the data analysis, the electric power company in the initial stage of the construction of the construction of the company may occur the wrong decision [15]-[18]. The use of multidimensional data analysis, on the other hand, can realize the integration of data from multiple dimensions, thus significantly improving the quality of data and providing support for grid construction decision-making [19], [20].

In this paper, we firstly design the hardware layer acousto-optic controller, which realizes real-time acousto-optic warning of latch loosening through pressure sensor and wireless communication module. Mosaic data enhancement and weather simulation noise injection methods are proposed to extend the dataset diversity and model robustness.

The YOLO network is used as the basic framework, which is improved by utilizing null convolution and depth separable convolution. A progressive attention region network mechanism is proposed to further improve the detection accuracy of small targets. The effectiveness of the improved algorithm is verified through comparison and ablation experiments, and the mainstream algorithms are introduced to investigate the performance superiority of the improved algorithm.

II. Improved Yolo-based power grid construction seatbelt monitoring system design

II. A. Sound and light controller system design for electrical network construction seat belts

Power operation safety belt is used for maintenance, installation personnel in the work to protect their personal safety, but sometimes the operators lack of safety awareness, did not buckle the safety belt lock buckle, or the work surface is more complex, resulting in the lock buckle loose and cause fall accidents at height. In this paper, the design of the wireless barge sensing, electric power work safety belt firmly inserted, buckle loose real-time monitoring, when the hook is loose or broken will have the corresponding sound and light warning, located in the ground workers can also be based on real-time monitoring of the situation, to remind the staff to tighten the hooks and buckles.

Power work safety belt sound and light control system process shown in Figure 1. Sound and light warning device includes a power switch, DC power supply, pressure sensor, buzzer, wireless transmitter, hook start switch, indicator light, piezoelectric sensor is installed in the groove at the lock buckle, the wireless barge sound and light warning device is fixed in the lower part of the hook's fixed hook body, the power switch is set in the hook's electronic control device, when the power switch is activated, if the buckle is not buckled tightly or the work of the lock buckle when the buckle is loose, broken, the sensor will give the appropriate signal, then the buzzer will give the appropriate signal. The sensor will give the corresponding signal, then the buzzer and the indicator light will prompt the operator to remind them to take timely measures, in addition, the ground personnel will be based on the transmitted data, take timely emergency measures to protect the staff safety.

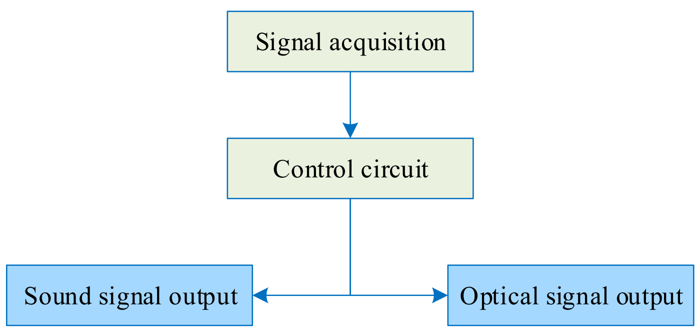


Figure 1: The process of the acousto-optic controller system

II. B. Seatbelt Wear Detection Data Enhancement

Deep learning target detection models need to be driven by a large amount of image data. Since the dataset is obtained by taking videos from multiple operational areas in the field and pumping the frames, there is no scene correlation between the operational areas in the dataset and the dataset is collected from each operational area with different weather conditions, shooting angles, and resolutions of the collected images. Therefore, it is necessary to do further data enhancement on the original image data before training the deep learning model. In this section, the dataset is subjected to two enhancement efforts: on the one hand, the mosaic data is used to enhance the diversity of the expanded images, and on the other hand, the raw image dataset is subjected to weather simulation using ambient noise simulation, thus enhancing the weather adaptability of the dataset.

II. B. 1) Mosaic data enhancement

In order to enhance the model generalization ability, this paper uses mosaic data enhancement scheme to increase the diversity of the dataset. Mosaic data enhancement first randomly extracts four images from the dataset, then crops and splices them at random positions, and finally synthesizes a new image. Since mosaic data enhancement crops the spliced images with a crosshair at a random position and then takes the corresponding parts for splicing. At the same time, the target frame corresponding to each original image is also limited by the crosshair crop, so it will not exceed the original image crop range. The advantage of mosaic dataset enhancement is that it enriches the background of the detected objects, and at the same time, the four images are merged into one for training by using the mosaic-enhanced dataset, which further reduces the consumption of computational resources during network training. The principle of mosaic dataset enhancement is shown in Fig. 2.

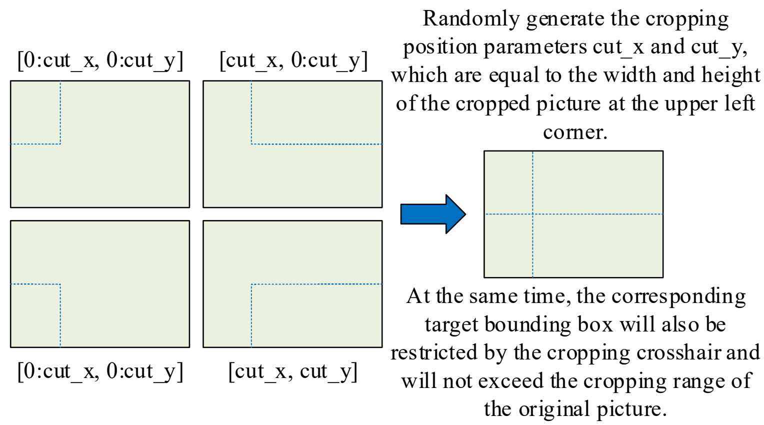


Figure 2: Principle of Mosaic data enhancement

II. B. 2) Environmental noise simulation

From the perspective of the actual scenario of the power grid construction work area, it is also necessary to consider the weather influencing factors such as cloudy, foggy and rainy days that may be encountered during the construction of the work area. The appearance of these environmental factors will lead to the reduction of model robustness. Therefore, this paper adopts the means to further enhance the dataset by subjecting the raw seatbelt wear detection data to random environmental noise simulation. Specifically, 30% of the collected raw image data is randomly selected for environmental noise simulation, thus allowing the detection model to have excellent results in practical use.

Adding noise to the original image is a common means of image enhancement, in this paper, we use OPENCV to add random noise, Gaussian noise and pretzel noise to the original data respectively to simulate weather scenes such as cloudy, foggy and rainy days, as follows:

(1) Gaussian noise: it is a kind of noise whose noise amplitude obeys the Gaussian distribution, which is manifested as the effect of different gray values, i.e., a variety of colors, on the image; adding Gaussian noise to the image can reach to make the original image more granular, and more effective features can be extracted in the feature extraction stage of the model.

(2) Salt and pepper simulation: It is the combination of salt noise (white) and Hu noise (black), which is manifested as black and white dark and bright spots. Adding salt and pepper noise to the image will make the original image appear similar to the effect of dust and rainy weather, and by controlling the ratio of black and white noise, we can make the image appear different effects.

(3) Random noise: random noise is the simplest kind of noise, add white noise randomly in the original image, that is, randomly change the gray value of the pixel to 255, by controlling the random noise can make the original image appear similar to the effect of foggy and cloudy days, play the role of data enhancement.

II. C.Improved Yolo-based Deep Learning Detection of Grid Construction Seat Belts

In recent years, with the rapid development of target detection in convolutional neural networks, more and more excellent models are used in the field of target detection. Due to the existence of complex background of power grid construction operations, weather and light changes, workers away from the camera resulting in small targets, dense personnel and occlusion. From the analysis of the data, it can be seen that small targets occupy the majority of the work site is a common phenomenon. This makes it extremely difficult to detect whether the operator is wearing a safety belt during construction. At present, there is no good method to detect whether the operator wears a safety belt, and the accuracy and real-time performance of small target detection cannot reach a good effect.

Therefore, in order to solve the above problems to reduce the risk of grid construction operations and improve the safety of operators, there is an urgent need to develop a method to automatically detect whether the operators are wearing seat belts during grid construction. Solving the problem of seat belt detection for small targets is the key to improve the accuracy and robustness of the algorithm. After sufficient research and experimental comparison, this paper introduces an automatic seat belt detection method based on convolutional neural network model. The method is based on the YOLO framework of target detection algorithm, which uses only one neural network to output the category and edge position information of the target object. However, the YOLO algorithm does not excel in small target detection performance due to the fact that the low-level high-resolution feature maps, which are mainly used by YOLO as small target detection, contain more weak features, which are not favorable for small target detection. Therefore, in order to enhance the feature information of these low-level feature maps to improve the detection of small targets, this paper introduces a null convolutional network (DCM) that improves the overall sensory field of the image and a depth-separable convolution (DSCM) that simplifies the network model to enhance the detection real-time, and proposes a progressive attention area network (PAAN) to improve the small target detection accuracy. In order to improve the inference speed of the detection network while maintaining the feature expression ability, and to improve the overall detection speed to enhance the real-time performance, the feature extraction and prediction network of YOLO is improved, by which it helps to improve the detection effect of the network model.

For the problem of detecting the seat belt wearing of the operator far away from the camera, since the upper body of the operator only occupies a small part of the captured image, the resolution of the features will gradually decrease after repeated up-sampling operations, which ultimately leads to the fact that even though the highest layer feature map can express strong semantic information, the seat belt features are few or even disappeared at this point in time. The low-level high-resolution feature maps undergo only a few downsampling operations, at which time the feature maps still retain rich positional details but contain only weak semantic features. Existing multilevel feature fusion methods that fuse features at each level without discrimination introduce redundant background interference. Therefore, to accurately localize to the upper body region of a person and simultaneously identify whether a seatbelt is being worn or not, improving the predictive representational capabilities is necessary. The emergence of attentional region networks can effectively solve the above problem by learning the corresponding weights for the spatial location of the feature map and multiple channels in order to highlight the most favorable features for seatbelt detection and recognition, and enhance the predicted representational ability.

In this paper, inspired by the attention mechanism, we propose the Progressive Attention Network to apply spatial attention to encode the regional features at each level in a progressive manner to enhance the target region for prediction, especially for predictive features of small-scale seat belts. The proposed Progressive Attention Area Network (PAAN) aims to make the whole network structure focus not only on the overall information but also on the local information. Firstly, the image after feature fusion is input, and then the progressive attention area network is applied to judge a classification probability for the target in the image, and then output the target image with coordinate value and size size, where the coordinate value is represented as the center point of the subgraph, and the size size is represented as the size of the subgraph. On the basis of this, the next target gets the predicted features by applying the coordinate values and the size of the dimensions, and then the next target also applies the same method. The whole image is iterated using the above method to focus on the target information in the image. Different classification probabilities are predicted for targets of different scales in the whole image, and then these classifications are integrated to finally get the probability of recognizing the seatbelt category for the whole image. This method is to enhance the image prediction probability by applying a progressive approach to predict regionally for each target in each image. Here a continuous mask function $M(\cdot)$ is defined to allow the forward propagation to be done smoothly. This function $M(\cdot)$ is a variant of the two-dimensional boxcar function, which in turn yields Equation (1). Define X to be the feature map of the previous scale, and □ to denote element-by-element multiplication.

$$x^{att} = X \cdot M(t_x, t_y, t_l) \tag{1}$$

Let the top left point of the graph be t_l and the bottom right point be t_i. Then the PAAN output box $(t_{x(d)}, t_{y(d)})$ is shown in equation (2).

$$t_{x(d)} = t_x - t_l, t_{y(d)} = t_y - t_l \tag{2}$$

Then the continuous mask function $M(\cdot)$ is equation (3):

$$M(\cdot) = \left[h(x - t_{x(d)}) - h(x - t_{x(br)}) \right] \cdot \left[h(y - t_{y(d)}) - h(y - t_{y(br)}) \right] \tag{3}$$

where $h(\cdot)$ is a logistic function and a sigmoid function when $k = 1$, as shown in equation (4).

$$h(x) = \frac{1}{1 + exp^{-kx}} \tag{4}$$

When k is large enough, this logistic function can be thought of as a step function. In other words, if the point

(x, y) is inside the box, the value corresponding to M is approximated as 1 if it is inside the box, and 0 if it is inside the box otherwise.This property is the same as the two-dimensional boxcar function, and it can be used to approximate the cropping operation very well. Here we take $k = 10$.

III. Validation of the effectiveness of deep learning detection algorithm based on improved Yolo

III. A. Experimental setup

In this paper, the experimental environment is a 64-bit Windows 10 computer, the processor is Intel Core i7-8700 (3.2GHz), and the type of graphics card is NVIDIA RTX2080T.In order to accelerate the training process of the network, CUDA10.0 is used as the general-purpose computing architecture.

The dataset used in this experiment is the images of overhead maintenance personnel as well as ground supervisors at the power grid construction site provided by a city power supply company, and a total of 1,184 real-time images of different scenes intercepted under video surveillance are selected after data cleaning. For the prepared dataset, LabelImg software will be used to annotate according to the label, the xml file generated after annotation is saved under the corresponding path, and python code will be used to convert the xml format to txt format, and divide the training set and test set with the ratio of 8:2.

III. B. Validation of the effectiveness of the improved algorithm

III. B. 1) Comparative experiments

In order to validate the effect of PAAN module on the detection performance, this subsection conducts an experimental validation of the YOLO-DCM-DSCM-PAAN algorithm. In this experiment, the YOLO model is trained under the same conditions using the electric power operation seatbelt dataset to obtain the trained model. The experimental results of the trained YOLO model are compared with the YOLO-DCM-DSCM-PAAN network model proposed in this paper.

After 800 iterations of training of the YOLO-DCM-DSCM-PAAN algorithm, the variation of the loss function values of the training set with the growth of Epoch is shown in Fig. 3. As can be seen from the figure, due to the use of the algorithm to control the learning rate of the model training, the first 250 epochs of the model training phase of the train loss and val loss are both rapidly decreased, the train loss reaches 0.075, val loss reaches 0.081. Then from 250 epochs onwards the learning rate is reduced, the train loss and val loss and gradually reduce at the same time, until 600 epochs start, the loss value tends to level off, the network has reached a better convergence effect, the final value of train loss stabilized at about 0.062, to complete the overall training process.

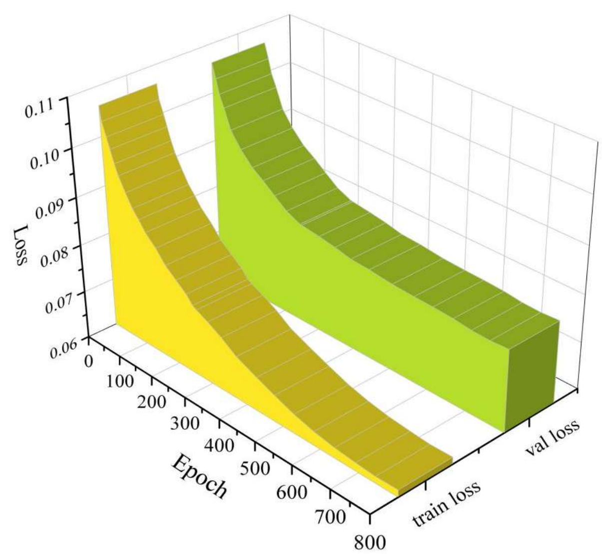
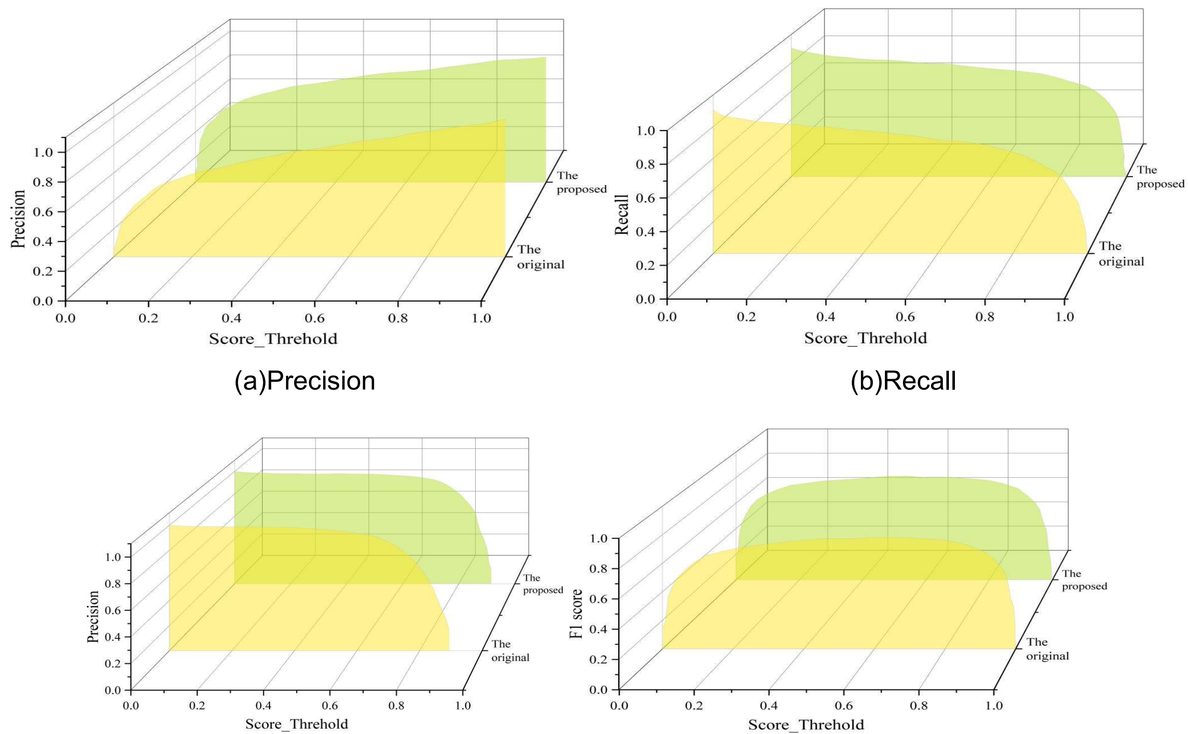


Figure 3: Changes in training loss

In order to verify the superiority of the improved model, we compare the trained model with the original YOLO model, respectively, on the dataset and compare the final accuracy and recall, and the comparison results are shown in Fig. 4(a~d).

As can be seen from the figure, the accuracy of the improved YOLO-DCM-DSCM-PAAN algorithm is 85.31%, which is 5.65% higher compared to the accuracy of the pre-improved YOLO algorithm of 79.66%. The recall rate of the improved algorithm is 77.35%, which is an improvement of 1.07% compared to the recall rate of 76.28% before the improvement. Also, the AP value of the improved algorithm for detecting seat belts reaches 85.11%, which is an improvement of 3.88% compared to the original precision of 81.23%. The increase in accuracy and recall means that the improved YOLO-DCM-DSCM-PAAN model can locate the target more precisely, remove the interference of redundant frames, and gain more powerful information extraction capability after adding the PAAN module.



(a)Precision (b)Recall

(c)AP (d)F1 score

Figure 4: Comparison of algorithm detection results

III. B. 2) Ablation experiments

The effects of different backbone networks on the experimental results of the target detection part were further compared, and the training effects of different backbone networks are shown in Table 1, where the DCM module denotes a way in which the convolution kernel can be arbitrarily shifted to replace the traditional convolution. As can be seen from Table 1, the YOLO network still achieves better average intersection and merger ratios mIOU (0.80) and F1 scores (0.79) when the number of layers is lower than that of the ResNet network, which demonstrates that the network structure has a stronger feature description capability than simple cross-layer connections. After the DCM module is introduced into the backbone network, the mIOU value and F1 score are improved to different degrees, and the mIOU value and F1 score of YOLO-DCM reach 0.83 and 0.81, respectively, which indicates that the addition of the DCM module can learn more accurate regional features for complex human structure targets, resulting in improved detection accuracy.

Table 1: Training Effects of Different backbone Networks

Backbone network	Detection index			
	mIOU	F1 score	Optimal round(epoch)	Detection speed(FPS)
ResNet	0.71	0.70	151	21
ResNet-DCM	0.74	0.72	168	17
YOLO	0.80	0.79	155	14
YOLO-DCM	0.83	0.81	159	11

In this paper, four sets of ablation experiments are designed. Among them, Experiment 1 is the YOLO-DCM model, Experiment 2 adds the DSCM module on the basis of Experiment 1, Experiment 3 adds the PAAN module on the basis of Experiment 1, and Experiment 4 fuses Experiment 2 and Experiment 3. The corresponding experimental results of these four groups of experiments are shown in Table 2.

From Table 2, it can be seen that after adding DSCM module to Experiment 2, the mIOU and F1 scores are improved by 2.4% and 4.9%, respectively, compared with Experiment 1, which indicates the effectiveness of feature fusion, and the amount of computation is decreased. After adding the PAAN module in Experiment 3, the mIOU and F1 scores were improved by 3.6% and 4.9% respectively over Experiment 1, indicating the effectiveness of adding the PAAN module. Finally, the fusion of both DSCM and PAAN modules by Experiment 4 improved the mIOU and F1 scores by 6.0% and 7.4%, respectively, on the basis of Experiment 1, which is a more obvious improvement.

Table 2: Ablation Experiment Results

Experimental plan	Relevant indicators				
	mIOU	F1 score	Parameter quantity(MB)	Computational power (GFLOPs)	Detection speed(FPS)
Experiment 1	0.83	0.81	166	0.268	11
Experiment 2	0.85	0.85	170	0.279	10
Experiment 3	0.86	0.85	172	0.281	9
Experiment 4	0.88	0.87	177	0.293	7

III. C. Comparative validation of performance levels

In order to verify the effectiveness of the algorithm's loss function, this experiment uses DIoU, SIoU, GIoU, and WoUv1 and WoUv2 five kinds of loss functions for comparison, the other parts of the detection model are kept unchanged, and the test is conducted under the same dataset, and the experimental results are shown in Table 3. It can be seen that the loss function in this paper has the most obvious effect on the network performance improvement, compared with other loss functions it has the most improved mAP value, and with the second best performance of WoUv2 than the improvement of 1.06%.

Table 3: Experimental Results of the loss function

Loss function	Model parameter quantity/ten thousand	Precision rate/%	Recall rate/%	mAP@0.5/%	FPS
DIoU	440	96.25	90.12	95.28	60
SIoU	440	94.17	92.13	95.71	55
GIoU	440	95.28	91.54	94.39	58
WoUv1	440	94.35	90.88	94.62	54
WoUv2	440	96.96	91.75	95.77	56
The proposed	440	97.13	92.15	96.83	50

In order to better verify the superiority of the improved algorithm in this paper, some mainstream target detection algorithms such as YOLOv5s, YOLOv4, YOLOX, RetinaNet network and SSD model are selected to compare with the improved algorithm in this paper, and the experimental results are shown in Table 4.

According to the experimental results can be obtained, no matter from the average precision mean value and detection speed, this paper improves the algorithm parameter size advantage is obvious, the detection accuracy is higher, and has a better recognition effect. Among them, although the detection speed of YOLOX algorithm has certain advantages compared with several other detection algorithms, the detection accuracy is lower, only 94.46%. The improved algorithm proposed in this paper has a higher detection accuracy of 96.91%, which is 2.45% higher than the YOLOX algorithm, with an obvious advantage in detection accuracy and a more outstanding comprehensive performance, which verifies the superiority of the improved algorithm in this paper.

Table 4: Compares the experimental results

Algorithm	Precision rate/%	Recall rate/%	mAP@0.5/%	FPS
SSD	90.26	89.41	89.88	26
YOLOv5s	94.83	86.45	93.72	53
YOLOv4	91.59	90.25	89.71	44
YOLOX	95.22	91.25	94.46	79
RetinaNet	89.77	86.28	86.11	28
The proposed	97.28	92.23	96.91	49

IV. Conclusion

In this paper, we build a power grid construction seatbelt monitoring system, design a deep learning detection algorithm based on improved Yolo, and explore its effectiveness through experiments.

The accuracy, recall, and AP values of the improved YOLO-DCM-DSCM-PAAN algorithm are 85.31%, 77.35%, and 85.11%, respectively, which are improved by 5.65%, 1.07%, and 3.88%, respectively, compared with the pre-improved YOLO algorithm. It means that the improved YOLO-DCM-DSCM-PAAN model can locate the target more accurately, remove the interference of redundant frames, and gain more powerful information extraction ability after adding the PAAN module.

The YOLO network still achieves better average intersection ratio mIOU (0.80) and F1 score (0.79) when the number of layers is lower than that of the ResNet network, and after the DCM module is introduced to both the backbone networks, the mIOU value and F1 score of YOLO-DCM reaches 0.83 and 0.81, respectively.The ablation experiments show that Experiment 4 on both DSCM and PAAN modules are fusion, which improves the mIOU and F1 scores by 6.0% and 7.4% respectively on the basis of Experiment 1, and the improvement effect is more obvious.

The loss function mAP value in this paper is improved by 1.06% compared with WoUv2, which is the second best performer, and the proposed improved algorithm has a high detection accuracy of 96.91%, which is 2.45% higher than that of YOLOX algorithm, while maintaining a good detection speed. The proposed algorithm has obvious advantages in detection accuracy, and the comprehensive performance is more outstanding, which verifies the superiority of the improved algorithm in this paper.

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