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Research on Artificial Intelligence Detection Method of Lithium Battery Surface Defects for Production Line

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Abstract. Lithium batteries are widely used in new energy vehicles and electronic equipment. Aiming at the typical defects that are easy to occur in the production process of lithium batteries, this paper improves the performance and recognition accuracy of the algorithm by integrating void convolution and attention mechanism into the YOLOv5 basic framework. At the same time, whale algorithm is used to automatically optimize the algorithm parameters in the process of optimization. Finally, through simulation experiments. This method realizes the rapid and accurate identification of lithium battery defects in the rapid production process of automatic production line.

Keywords: lithium battery, defect detection, artificial intelligence, whale algorithm

1 Introduction

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As a key part of the lithium battery, the lug and plate of the lithium battery are prone to bubble, indentation, pinhole and other defects during the production and manufacturing process, which has a great impact on the safety of the lithium battery, and the quality inspection of the lithium battery is mainly focused on the above links. Traditional lithium battery detection mainly relies on manual detection, but manual detection has the following disadvantages:

1) The detection efficiency is low and does not adapt to the rhythm of modern automatic production;

2) The testing process is affected by the subjective factors of the testing personnel, and the standards cannot be unified, resulting in missed inspection and other situations;

3) The detection quality cannot guarantee the stability, and the detection results are greatly affected by the light and the visual fatigue of the detection personnel. In addition, due to the inevitable contact detection of manual detection, the risk of battery damage in the detection process itself is increased.

The detection and recognition technology based on artificial intelligence neural network has been widely used in many fields because of its characteristics of automatic recognition, autonomous learning, fast and stable. Therefore, in view of the common defects of lithium batteries, this paper proposes an efficient visual detection method for lithium batteries based on neural network algorithm. The work is as follows:

1) Based on YOLOv5 as the basic framework, it integrates void convolution and attention mechanism to improve the performance of the algorithm itself;

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2) When configuring the algorithm parameters, the whale algorithm is used for adaptive optimization to configure the most reasonable algorithm parameters;

3) The detection system is constructed, and the construction of hardware system and the realization of software system are introduced in detail.

The overall structure of this paper is composed of six chapters, of which the second chapter mainly studies and analyzes the relevant research results, providing a reference for the construction of this paper's ideas; The third chapter introduces the improvement and optimization process of the algorithm; The fourth chapter constructs the detection system, introduces the hardware simulation and software system; In the fifth chapter, the detection system is used to verify the detection ability of the algorithm in this paper for lithium battery defects; The sixth chapter is the conclusion, which makes a summary and prospect;

2 Related Work

The focus on the quality of lithium battery production and assembly is due to the recent rapid development of new energy and microelectronics technology, so the relevant research is less. Neel Kamal, using infrared thermal imaging method to identify and diagnose the surface defects of solar cells, is an exploration of non-contact detection method, which has reference significance for defect classification, but this method is difficult to accurately determine the type of defects [1]. Haibing Hu proposed a Sim - YOLOv5s algorithm for lithium battery shell defect detection. By embedding the attention mechanism in the backbone network, the recognition accuracy of the algorithm can reach 88.3% [2]. Harshad K. Dandage proposed a LSDD method for multi-scale image enhancement and classification. Using the enhanced data set of multi-scale patch samples generated from a small number of lithium-ion battery images, the recognition accuracy can reach 90.78% and the recall rate can reach 93.89% on the basis of only 26 source images [3]. Grazia Lo Sciuto, proposed a new method for defect classification of organic solar cells, and used a new feature extraction algorithm and EBNN with innovative pruning algorithm to identify and diagnose defects [4]. After extracting the defect image of lithium battery, Weisheng Mao used wavelet threshold to denoise the image, then normalized the histogram to enhance the image, and finally used Gaussian difference to monitor the defect. The experiment shows that the monitoring effect of metal leakage and scratches of lithium battery has been improved [5]. Zhaoming Ge proposed an improved feature detection algorithm of YOLOv5, which improved the detection accuracy of small targets by introducing attention module, and then improved the loss function to achieve the retention of favorable features and improve the convergence speed. Finally, the feasibility of the algorithm was verified by experiments [6]. Jianping Zhong preprocessed and segmented the collected battery defect image, extracted the morphological gray scale of the defect, fused the features using the back-propagation network, and finally used the whale algorithm to optimize the model parameters. The results show that the detection algorithm can improve the detection efficiency, and the false detection rate remains zero [7].

3 Improvement and Optimization of Detection Algorithm

In the automatic production process, defect detection has a high requirement for timeliness, while defect recognition has no requirement for timeliness. In order to ensure the high timeliness of the detection core program, in the identification process, this paper uses the YOLOv5 [8] model as the basic framework. At the same time, in order to improve the problem of low detection accuracy of the YOLOv5 algorithm, this paper makes improvements from the aspects of void convolution and the introduction of attention mechanism. The detection process of the battery production line is shown in Fig. 1.

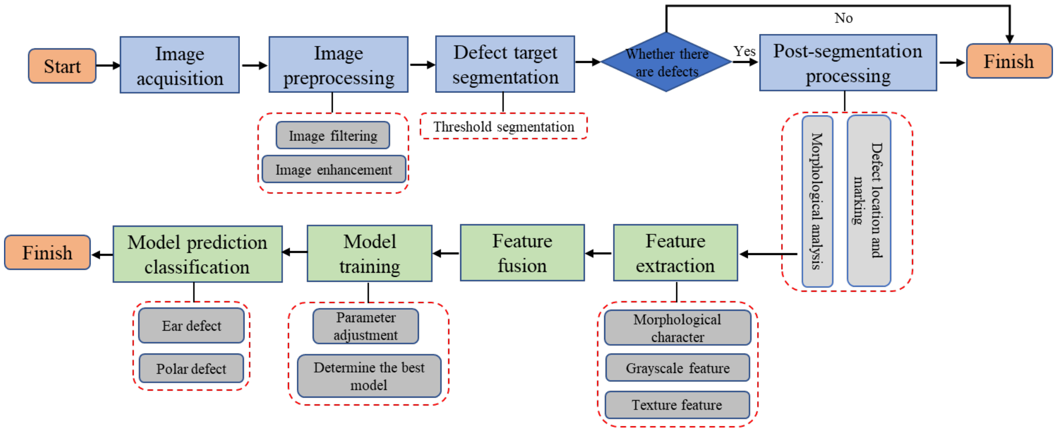


Fig. 1. Lithium battery defect identification process

3.1 Introduction of Void Convolution

In the image segmentation stage, the pooling layer compresses the feature image, and the convolution layer is used to extract the edge information and image features. The segmentation process will cause the image feature information to be unable to be completely extracted. In order to obtain reliable semantic information, the hole convolution is introduced into the YOVOv5 network structure, and the hole convolution is used to improve the characteristics of the output receptive field range without increasing the number of parameters. The size of feature map using void convolution is expressed as:

$$V_{out} = \frac{V_{in} + 2P - F}{S} - 1. \tag{1}$$

Where, V_{out} is the size of the output feature map, V_{in} is the size of the input feature map, F is the size of the convolution kernel, P is the number of cycles filled in the feature map, and S is the step size of the convolution. The structure after adding hole convolution is shown in Fig. 2:

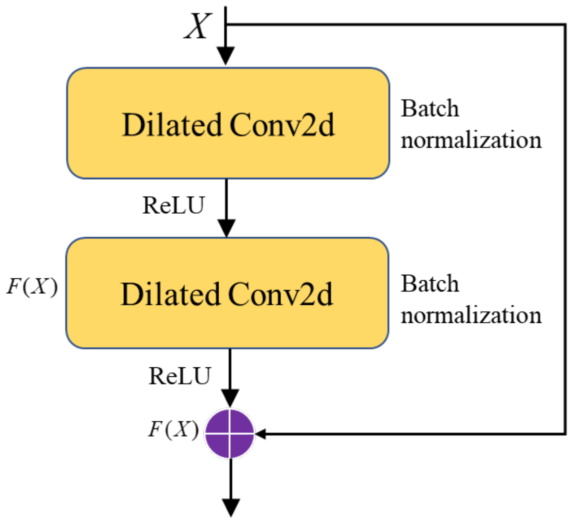


Fig. 2. Structure with void convolution

In the feature transfer layer, the distance between data is controlled by adjusting the expansion rate, and in the feature transfer layer, the distance between data is controlled by adjusting the expansion rate. Assuming that K is the convolution core of void convolution, and D is the void rate, then the equivalent convolution core $K^{'}$ is expressed as:

$$K^{'} = (D-1)\times(K-1)+K\ . \tag{2}$$

In this paper, cavity convolution is added in the fourth down-sampling to expand the receptive field to avoid losing small defects.

3.2 Introduction of Channel Attention Mechanism

The attention mechanism is based on SENet [9], and then uses adaptive selection to select the size of one-dimensional convolution kernel, and keeps the dimension unchanged during local cross-channel interaction, reducing network complexity and improving model performance. The working principle is shown in Fig. 3, name is ISENet, where H is the image height, W is the width, and C is the channel dimension.

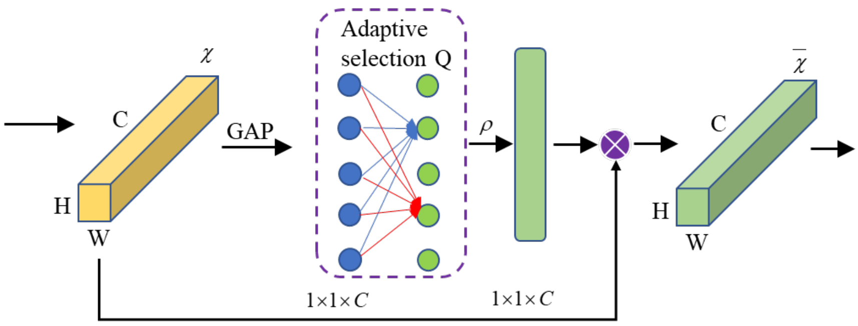


Fig. 3. ISENet structure diagram

After inputting the original image, use the global average pooling method for image processing, and then use the fast one-dimensional convolution of size M to generate the channel weight, calculate the corresponding probabilities of different channels, and then multiply them with the original input characteristics. The Q value is determined by the function adaptive method, C is the channel dimension, and the process is expressed as follows:

$$C = \phi(Q) = 2^{(\lambda * Q - b)}\ . \tag{3}$$

$$Q = \varphi(C) = \left| \frac{\log_2(C)}{\lambda} + \frac{b}{\lambda} \right|_{odd}\ . \tag{4}$$

Where, $|*|_{odd}$ represents the nearest odd number, $\lambda = 2$, $b = 1$, and channel attention can adaptively optimize the convolution kernel, enhance the useful semantic information in the feature map, eliminate redundant and invalid information, and improve the effective extraction of the surface defect features of lithium battery. Therefore, the structure schematic diagram of the improved YOLOv5 convolution neural network is shown in Fig. 4.

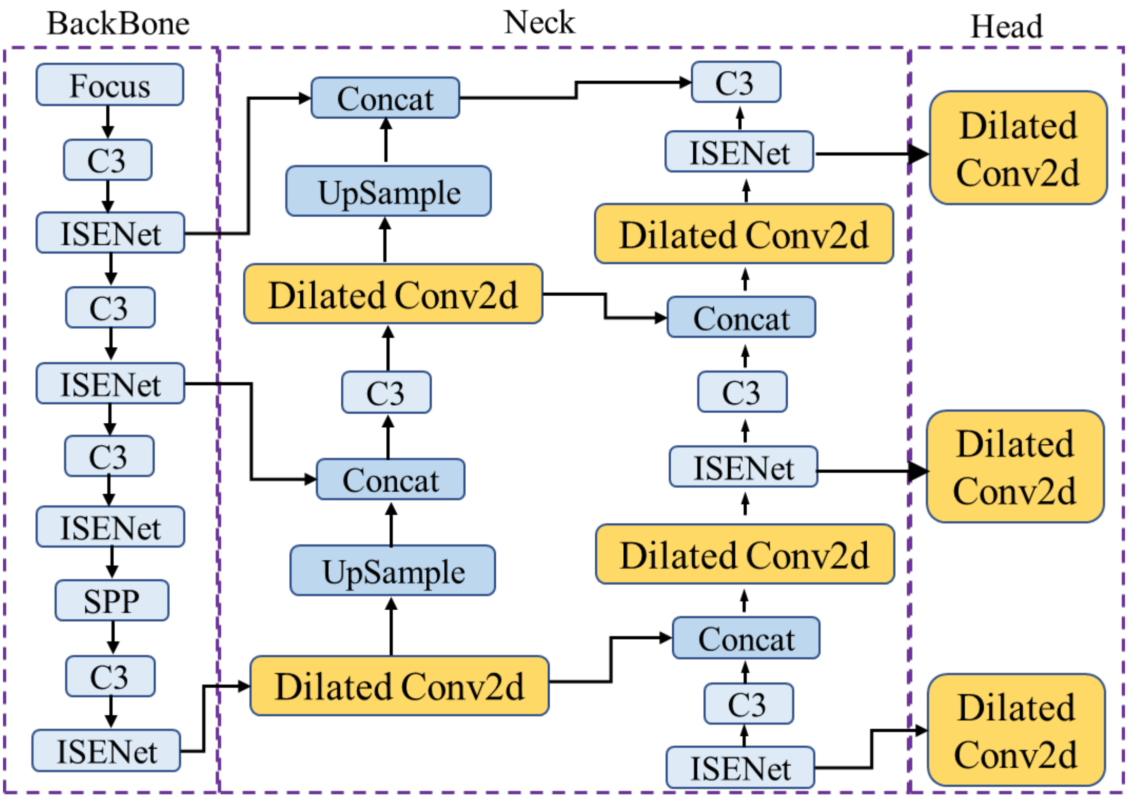


Fig. 4. Improved YOLOv5 structure

3.3 Model Parameter Selection Optimization

The initial weight and initial threshold are particularly important for the speed of model recognition, but they are difficult to obtain accurately. Improper selection of initial parameters will cause the model to fall into local optimization, network oscillation and slow convergence. Therefore, this paper uses whale optimization algorithm to find the optimal solution of parameters [10]. The algorithm process is as follows:

1) The mathematical model is expressed as:

$$D = \left| X(t) - CX_{rand}(t) \right| . \tag{5}$$

$$X(t+1) = X_{rand}(t) - AD . \tag{6}$$

Where, t is the number of iterations, X is the whale position vector, X_{rand} is the randomly selected whale position vector, A and C are coefficient vectors, and the formula is expressed as:

$$A = 2ar_1 - a . \tag{7}$$

$$C = 2r_2 . \tag{8}$$

$$a = 2 - \frac{2t}{T_{\max}} . \quad \textbf{(9)}$$

Where, r_1 and r_2 are random vectors within the range of interval $[0,1]$, a is the convergence factor, and $T_{\max}$ is the maximum number of iterations. In the whale algorithm, the whale position is updated through continuous iteration. The fluctuation range of A in the model will decrease with the decrease of the convergence factor a. Therefore, the search mechanism can be controlled by adjusting the value of a.

2) Obtain the optimal parameter solution of the model, which is realized by simulating the process of fish hunting by whale algorithm. When the model determines that the current solution is the optimal solution, the position vector of the current optimal solution is continuously updated. The mathematical process is as follows:

$$D = \left| X(t) - CX_{best}(t) \right| . \quad \textbf{(10)}$$

$$X(t+1) = X_{best}(t) - AD . \quad \textbf{(11)}$$

X_{best} represents the current optimal position vector of the whale, the position vector of the current solution X, and the target optimal solution vector X', then the whale algorithm approaches the target optimal solution by adjusting the vector A and vector C.

3) Get the optimal solution

After rounding up the optimal solution of the target, the algorithm obtains the optimal solution through spiral contraction. The mathematical process is as follows:

$$D' = \left| X^*(t) - X(t) \right| . \quad \textbf{(12)}$$

$$X(t+1) = X^*(t) + D' e^{bl} \cos(2\pi l) . \quad \textbf{(13)}$$

Where, b is the spiral contraction constant, l is the random number within the range of interval $[-1,1]$, and D' is the distance between the current position of the whale and the position of the prey. Initialize the whale algorithm, set the population size as $N = 500$, the maximum number of iterations as $T_{\max} = 300$, and the convergence factor as $a = 1.2$. Take the initial weight and threshold as the initial position vector of each whale. After iteration and mean square deviation calculation, the value of X_{best} can be obtained [11].

4 Establishment of Intelligent Detection System for Lithium Battery Defect Automatic Assembly Line

In order to meet the rapid and real-time detection of lithium batteries, it is necessary to build a complete detection production line to realize automatic detection. Therefore, considering the upstream and downstream links of production, the lithium battery defect detection production line is composed of four parts: the feeding system, the handling system, the visual detection system, and the loading and unloading transmission system. The overall design effect of the production line is shown in Fig. 5.

What needs to be mainly described is the software design of the intelligent detection system, which uses Tkinter software to realize the computer software interface design. Tkinter module is the interface of Python's standard Tk GUI toolkit. As a Python specific GUI interface, Tkinter is a Python built-in and editable GUI interface.

The visual inspection module uses a computer and a camera to complete the defect detection of the battery. The hardware includes a computer, a DALSA linear array camera, an OSE linear array light source and a detection roller, and the DALSA linear array camera obtains images. The development platform of the algorithm is

Windows10, and the CPU model is Intel (R) Core (TM) i7 - 10500 CPU @ 2 9 GHz, GPU is Nvidia GeForce GTX1080.

The software system interface includes the material feeding control function, defect detection function, system verification function and user help function. The material feeding control function can control the travel speed of the automatic production line. The system checks whether the detection system can operate normally, subject to the results of the test pictures. Defect detection is the main function interface of the system. The functional structure of the software system is shown in Fig. 6.

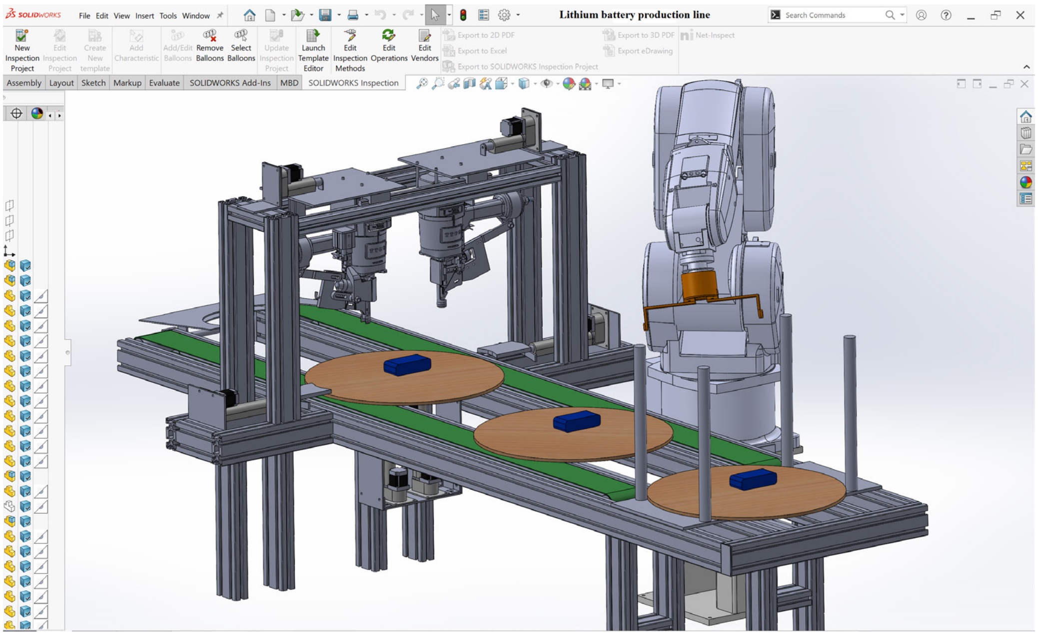


Fig. 5. Rendering of lithium battery production line

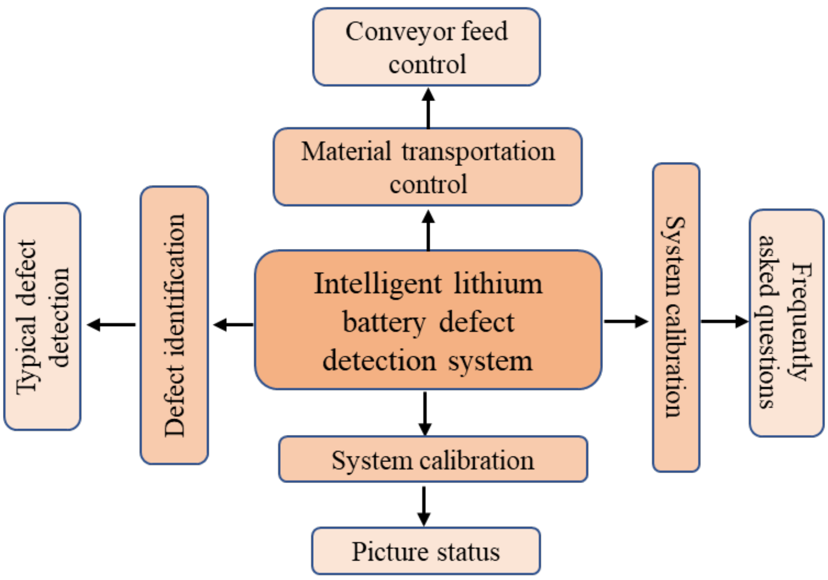
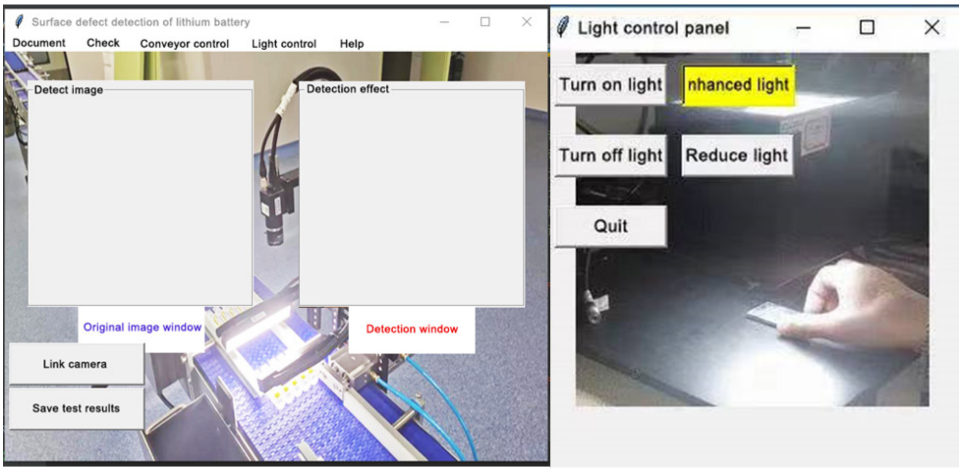


Fig. 6. System function design

The defect detection function interface is shown in Fig. 7(a). The main function of the battery defect detection system is to process the image obtained from the industrial camera, and the detection target is whether there are defects in the lithium battery lug, and to identify the type of defects. The two image windows in the center are used to display the detection image when calibrating the system, the “File” in the upper menu bar is used to select the detection image required for calibration, the “Detection” is used to start calibration and detection, the “Conveyor Control” is used to open the control panel and control the conveyor directly in the main interface, and the “Help” is used to display the system’s environment configuration and some precautions during use Solutions to common problems.

The light source control function is connected with the PC through the serial port program, and the control panel is used to control the switch and brightness of the light source. At the same time, in order to enhance the experience, when you click the “enhanced lighting” button, the button will appear yellow flashing, indicating the enhanced lighting; When you click the “Reduce light” button, the button will flash in black, indicating that the light is reduced, as shown in Fig. 7(b).



(a) Main interface (b) Light source interface

Fig. 7. System interface

5 Experimental Process and Result Analysis

5.1 Experimental Results and Analysis of Algorithm Performance Analysis

Common defects of lithium batteries include dents, scratches, pinholes, etc. The schematic diagram of each defect is shown in Fig. 8.

The 520 lithium battery images with defects are collected, and the number of images is relatively small in terms of model training requirements. Therefore, image enhancement processing, image random scale transformation, random flip, contrast adjustment and other processing can effectively avoid over-fitting during model training. After data enhancement, the data set has a total of 2080 defective images, which contain one or more defects, In this paper, the lithium battery surface defect images are randomly divided into training sets and test sets according to the ratio of 8:2. The parameters of the model operation system have been described in the previous chapter. In order to verify the improvement of the improved algorithm performance, the change of the loss function of the improved YOLOV5 model and the original YOLOV5 model are compared. The comparison diagram is shown in Fig. 9.

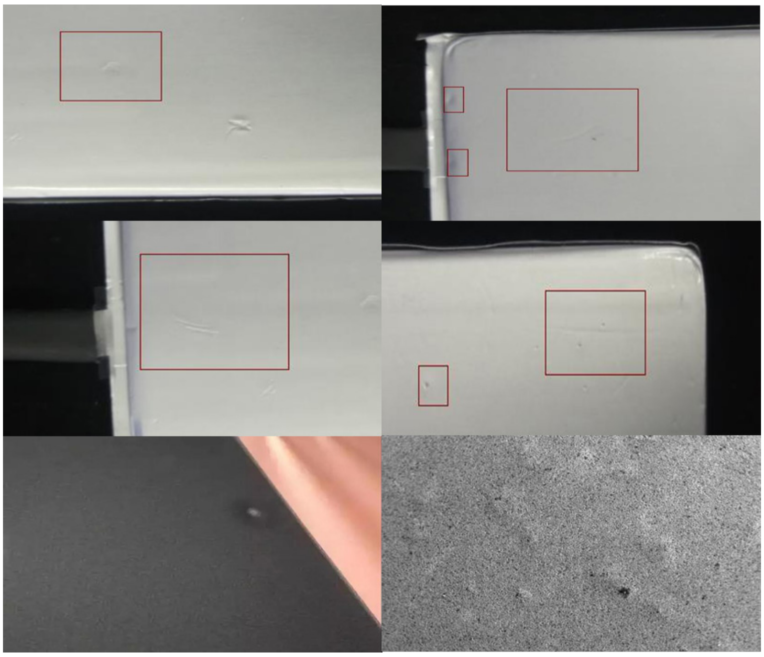


Fig. 8. Typical defect pictures

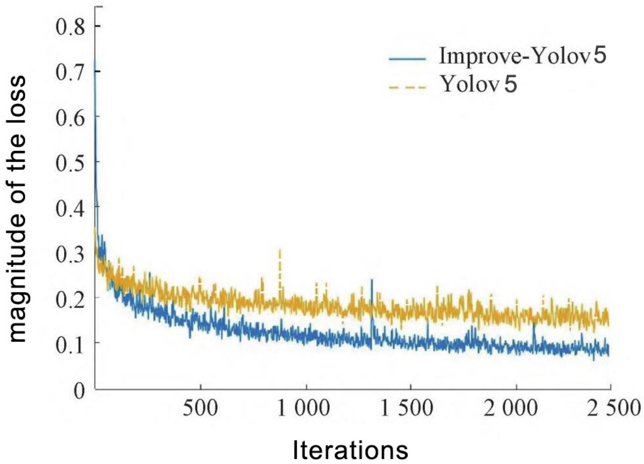


Fig. 9. Comparison of training results

The final loss function value of the improved YOLOv5 model is significantly lower than that of the original model. After 1700 iterations, the loss tends to be stable, and the loss value is stable at about 0.08, with good convergence and no fitting phenomenon

In order to quantitatively evaluate the performance of the improved network in this paper, the average accuracy (mAP) and frames per second (FPS) commonly used in target detection are used to evaluate the effect of detecting surface defects of lithium batteries. In order to quantitatively compare the detection and recognition effects of the improved YOLOv5 with other models, the model in this paper is compared with SSD, YOLOv4 and the original YOLOv5. Fig. 10 shows the average accuracy value results of the four models for detecting four types of defects, and Fig. 11 shows the comparison of various indicators of the detection results of the surface defects of lithium batteries by the improved models in this paper.

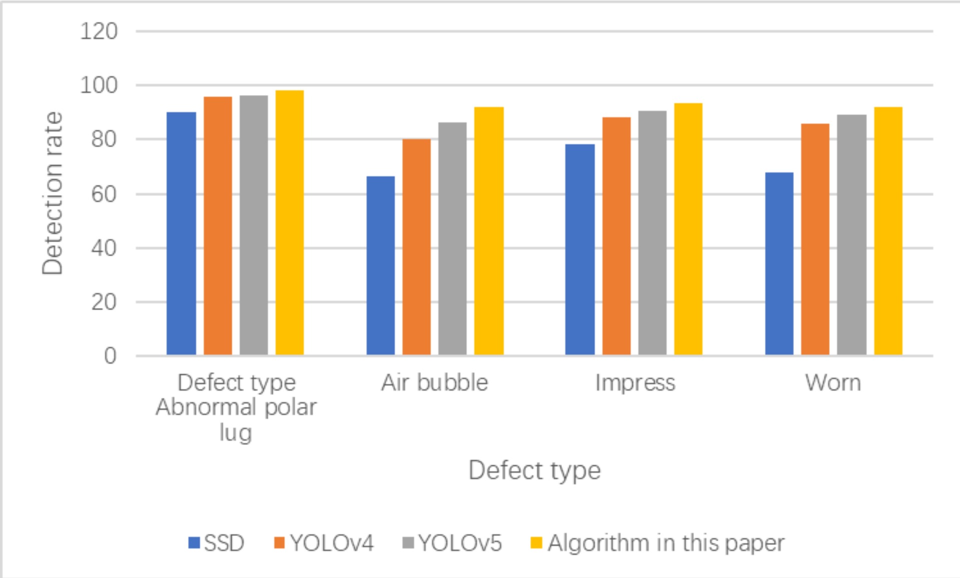


Fig. 10. Comparison chart of detection rate

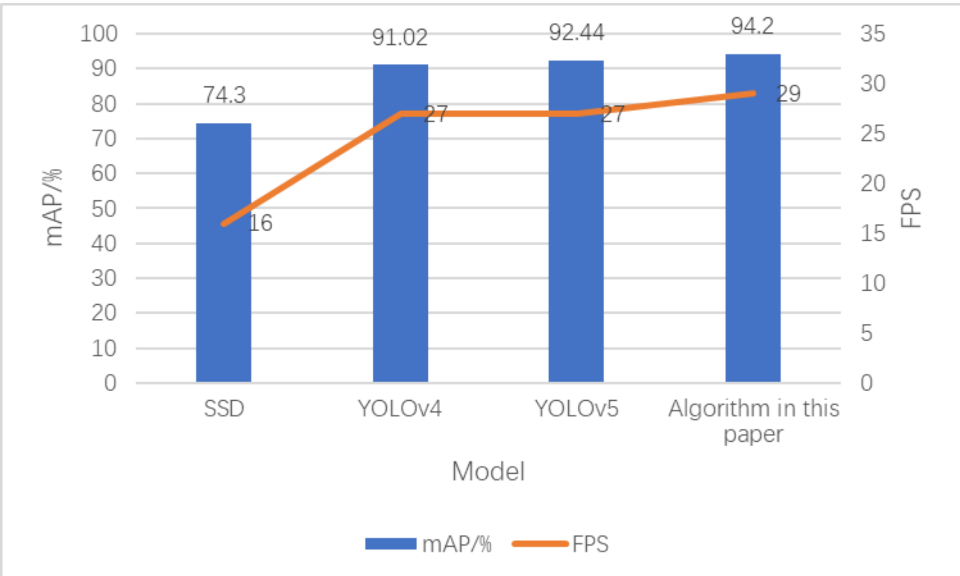


Fig. 11. Comparison of model performance indicators

Compared with the original network, the average accuracy of YOLOv5, which introduced the hole convolution and ISENet module, increased by 1.76%, and the FPS increased by 2f/s, which verified that the hole convolution and ISENet mechanism can improve the accuracy and speed of the lithium battery surface defects, and at the same time showed that replacing the traditional convolution has significantly improved the accuracy of the detection of lithium battery defects, effectively solving the problem of high sample noise and single background which is not conducive to feature extraction. The improved YOLOv5 model in this paper does not add too many parameters and inserts a lightweight attention channel mechanism into the neck network, so the detection speed is not significantly improved compared with the original version, while the mAP is 19.9%, 3.18% and 1.76% higher than SSD, YOLOv4 and the original YOLOv5 network respectively. It can be seen that the comprehensive performance of the method in this paper is the best, which can meet the requirements of recognition accuracy and speed in industrial production at the same time.

Through the pre-work detection and verification of the model, and at the same time, adjust the light source to the appropriate brightness, load the test image under the original image window, click the detection, and the detection effect is as shown in Fig. 11. No error is reported, which proves that the system operates normally. After self-inspection, connect the data acquisition platform, start the camera, turn on the light source, start the conveyor belt, adjust the speed of the conveyor belt to 0.1m/s, put the battery on the acquisition platform, and start video detection. When the conveyor belt brings the battery into the camera's field of view, the detection results are shown in Fig. 12. When the conveyor belt transfers the lithium battery to the camera's acquisition range, the system starts to detect and mark the detected defects directly on the video screen.

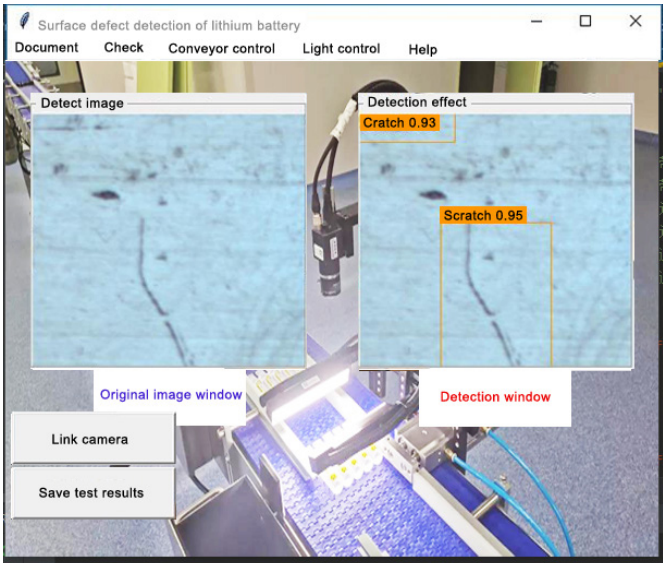


Fig. 12. Detection result

6 Conclusion

Aiming at the current situation of lithium battery defect detection in the lithium battery production line, this paper designs an intelligent detection algorithm suitable for the production line process, and completes the construction of the production line detection system. The performance of the algorithm is improved by incorporating the void convolution and attention mechanism into the basic framework, and then the Whale algorithm is used to configure parameters for the model. Finally, the effectiveness of the algorithm and the improvement of the new capability are verified in the experiment process, which can meet the requirements of efficient and high-speed detection in the production. The future research direction will focus on comprehensive battery defect detection and further improve the main performance.

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