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Design and Implementation of Corn Pest Detection System Based on YOLO Deep Learning Technology

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ABSTRACT: *In this paper, we carry out theoretical research on corn pest detection based on YOLO deep learning technology, realize the application development of corn pest identification based on lightweight model, design and implement a corn pest detection system based on YOLO (You Only Look Once) deep learning technology. The system uses deep learning technology to detect pests on corn leaves, and provides farmers with timely and accurate pest control information, thereby improving the yield and quality of corn. Through 4538 pictures, a target detection model for intelligent corn pest detection and recognition was trained. Based on this model, intelligent corn pest detection and recognition system with UI interface is developed, which can be used to detect 13 kinds of corn pest categories in the scene in real time, and it is more convenient to display the function. The system is developed based on python and PyQT5, supports image, video and camera target detection, and saves the detection results.*

The corn pest detection system based on YOLO deep learning technology provides efficient and accurate pest detection methods for agricultural production. The system can process a large number of image data in a short time, which can accurately identify the pests on corn plants, and give the location and category information of pests, realize real-time detection, and effectively improve the efficiency of corn pest monitoring. These systems not only improve the efficiency and quality of agricultural production, but also provide effective and rapid help for agricultural pest management. It is of positive significance to improve the increase of corn production and bring more convenience and benefits to agricultural production.

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I. INTRODUCTION

Corn is a relatively large proportion of many grains and grains. In production and life, the yield of corn and the quality of the yield will have an impact on people's lives and economy. Improving the quality and yield of corn is the focus of attention. From the current development trend of corn planting in our country, it can be seen that corn plays an important role [1]in ensuring my country's food security. According to the public data of the National Bureau of Statistics, my country's national corn planting in 2022 The area is about 43070 thousand hectares, and the output is about 277.2 million tons. It is the crop product with a wide sown area and high total output in my country, pest is one of the main factors [2] affecting crop yield. The distribution of corn planting in various regions of our country is not balanced. Most of them are concentrated in the northeast, north and southwest regions, forming an oblique and long corn planting belt, which develops from northeast to southwest, forming a region dominated by corn planting.

In recent years, the rapid development of cities and economy has reduced the cultivated area of corn, and the emission of various pollutants has also destroyed the growth environment of corn. The excessive use of natural resources has led to the inability to restore the ecosystem, and various diseases of corn have come. Corn pests are one of the important factors affecting corn yield, which brings huge economic losses to the world every year. Therefore, it is necessary to detect and treat corn diseases at the first time and solve them [3] before the disease expands. Traditional pest detection methods mainly rely on manual visual inspection, which is inefficient and vulnerable to human and environmental factors, making it difficult to ensure the accuracy and real-time detection.

With the continuous development of YOLO, the application of computer vision and image recognition technology in the agricultural field is more and more, which provides a new solution for corn pest detection. The design and implementation of corn pest detection system based on YOLO deep learning technology has important theoretical and practical significance. The system can quickly and accurately detect pests on corn leaves, improve the timeliness and effectiveness of pest control, reduce the impact of pests on corn yield, and ensure food security. The system can release labor, reduce the workload of farmers and improve the production efficiency [4] of corn. In addition, the implementation of the system can provide useful exploration and reference for the application of deep learning technology in the field of agriculture, and promote the development of agricultural informatization and intelligence. It is believed that the system will play an increasingly important role in agricultural production in the future, and make greater contributions to ensuring food security and promoting sustainable agricultural development.

Many internationally renowned universities and scientific research institutions have conducted in-depth research in this field. For example, Cornell University, University of California, Berkeley, etc. have done a lot of work on the improvement of pest detection algorithms and the construction of data sets.

Mohanty S P **Error! Reference source not found.**was the first people convolutional neural network applied to plant pests and diseases identification, for the use of mobile phones to diagnose plant pests and diseases provides a direction in 2016.

Kelsee B et al. **Error! Reference source not found.**proposed the use of migration learning in training deep convolutional neural networks in 2017, and detected and identified five diseases of cassava, with the lowest green mite recognition accuracy reaching 95%. Jiang P et al. **Error! Reference source not found.**2019 in SSD **Error! Reference source not found.**algorithm based on VGGNet **Error! Reference source not found.**the experimental results show that the proposed real-time detection method achieves an average accuracy of 78.80% and a detection speed of 23.13 FPS(Frames-per-Second), which is similar to the original SSD. **Error! Reference source not found.**(Single Shot Multibox Detector) algorithm improves mAP (Mean Average Precision) by 2.98%. These research teams not only focus on algorithm performance improvement, but also focus on applying technology to actual agricultural production to provide farmers with practical pest control tools.

In addition to academia, some agricultural technology companies have also actively explored the research and application of deep learning in corn pest detection. For example, Bayer, Monsanto and other companies have launched intelligent pest monitoring systems based on deep learning, which are widely used in agricultural production. These systems effectively improve the yield and quality of corn by monitoring the occurrence of pests in real time and providing timely control suggestions for farmers. Although some achievements have been made in corn pest detection based on deep learning abroad, there are still some challenges and problems. For example, how to deal with pest detection in complex background and improve the generalization ability of the model are the key problems to be solved. In addition, how to better integrate deep learning technology with other agricultural information technologies to achieve more intelligent and efficient pest control is also the focus of future research.

Through this research, we can promote the application of deep learning technology in the field of corn pest control, improve the production efficiency and quality of corn, and provide strong support for the sustainable development of agriculture. Access to information to understand corn diseases and pests mainly include corn ear worm, corn borer (or straw) worm, root cutter (black cutter, striped cutter) and other [14]. Collect pictures or videos of corn pests, including pest images of various types, growth stages and forms, and sort out high-quality image samples for training and testing by integrating existing literature data and network search data, and manually screening and cleaning. And use the LabelMe labeling tool to label the target border (Bounding Box) and category in each picture. Choosing the right deep learning model is a key step in the research. This may involve the research and analysis of the structural characteristics and training process of the one-stage and two-stage target detection models. After the deep learning framework is built, the model is trained and tested using the self-built corn pest data set. The feature extraction network of the initial model may not be fully applicable to the corn pest identification task. Therefore, the research may include replacing or optimizing the feature extraction network of the original model, such as using ResNet50 instead of VGG16, to improve the feature extraction capability [15] of the model.

The research goal of the design and implementation of corn pest detection system based on YOLO deep learning technology is to solve the problems in actual production, improve the efficiency of agricultural production and the quality of agricultural products, and promote the sustainable development [16] of agriculture. Improve the accuracy and efficiency of pest identification: Through deep learning technology, the system can automatically learn and extract the characteristics of pests, so as to achieve accurate identification of pests. This can not only reduce the error rate of manual recognition, but also improve the speed and efficiency of recognition. At the same time, real-time performance is guaranteed to meet the needs of actual production. Reduce manual intervention and cost: reduce the number of manual labeling and intervention, reduce labor costs, improve the level of automation, so that the system has more practical application value.

Real-time monitoring and early warning of pests: The corn pest recognition and detection system based on deep learning can obtain the image data of corn field in real time, and judge the existence and distribution of pests through model analysis. When the number of pests is found to exceed the preset threshold, the system can automatically issue early [17] warning information to remind agricultural producers to take timely control measures. This helps agricultural producers respond to pest threats in a timely manner and reduces the impact of pests on corn yield and quality.

II. EXPERIMENTAL ENVIRONMENT

Convolutional Neural Network (CNN): Convolutional neural network as shown in Fig.1. (Convolutional Neural Networks, referred to as CNN) is the deep feedforward neural network. With the characteristics of local connection [18] and weight sharing. It is one of the representative algorithms of deep learning (deep learning) and is good at dealing with image, especially image recognition and other related machine learning problems, for example, image classification, target detection, image segmentation and other visual tasks have a significant improvement effect, which is one of the most widely used models.

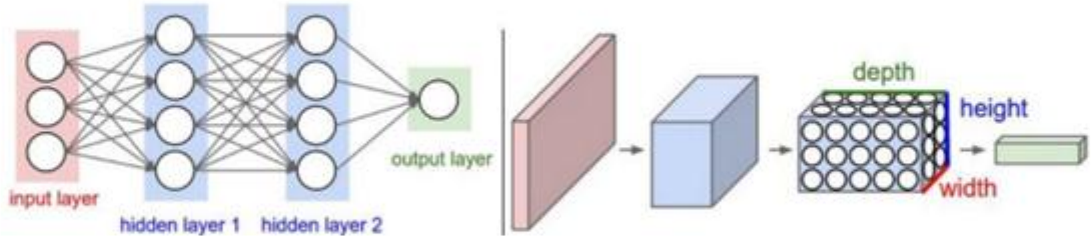

Fig. 1 Neural network and convolutional neural network

The convolutional neural network extracts image [19] features through the convolutional layer, reduces the feature dimension through the pooling layer, and finally classifies or regressors through the fully connected layer, so as to achieve efficient processing and understanding of the image. The training process is divided into two stages:Forward propagation phase: select training samples (x,y) and input x into the network. Randomly [20] initialize the weights (usually choose decimals), the information from the input layer through a layer of feature extraction and transformation, and finally to the output layer, get the output result.

Backpropagation phase: The output result is compared with the ideal result to calculate the global error (I. e. Loss). The resulting errors are transferred back to the neurons of different layers, and the weights and bias are adjusted according to the "iterative method" to find the globally optimal results.

Improvements to YOLO v8:YOLO v8 is a SOTA (State of the arts) model [21] that builds on the success of previous YOLO releases and introduces new features and improvements to further boost performance and flexibility. Specific innovations include a new backbone network, a new Anchor-Free detection head, and a new loss function that can run on a variety of hardware platforms from CPU (Central Processing Unit) to GPU (Graphic Process Unit).

Model Structure Design of YOLO v8:YOLO v8 is [22] the leading-edge target detection technology. The YOLO v8 model improves C3 module (CSP Bottleneck with 3 convolutions) into C2f module (CSP Bottleneck with 2 convolutions). The C2f module structure is shown in the following Fig.2.The CBS(Convolutions Bn SiLU) module in the figure consists of a fundamental convolution (Conv), a batch normalization (BN), and an activation function (SiLU). The C2f module adopts multi-branch and tributary design, which provides richer gradient information for the model, strengthens the feature extraction ability of the model, and improves the learning efficiency [23] of the network. network structure of YOLO v8 is Fig. 3. shown.

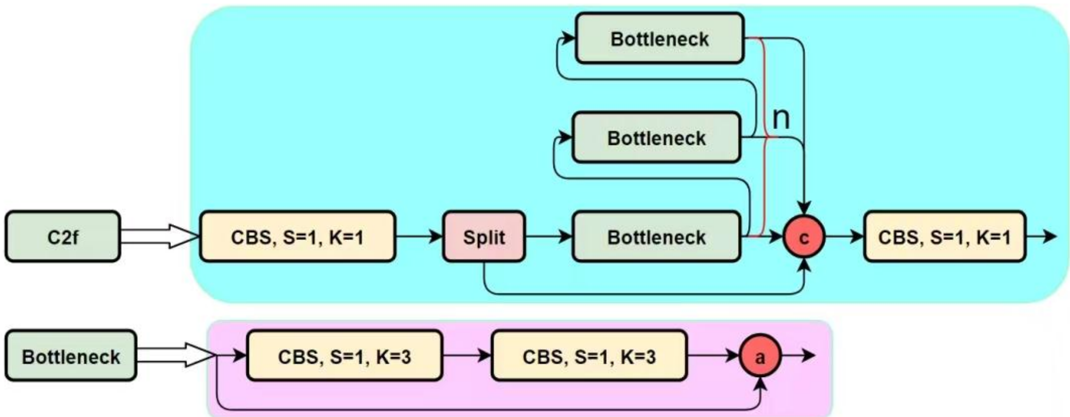

Fig.2 C2f Module Structure Diagram

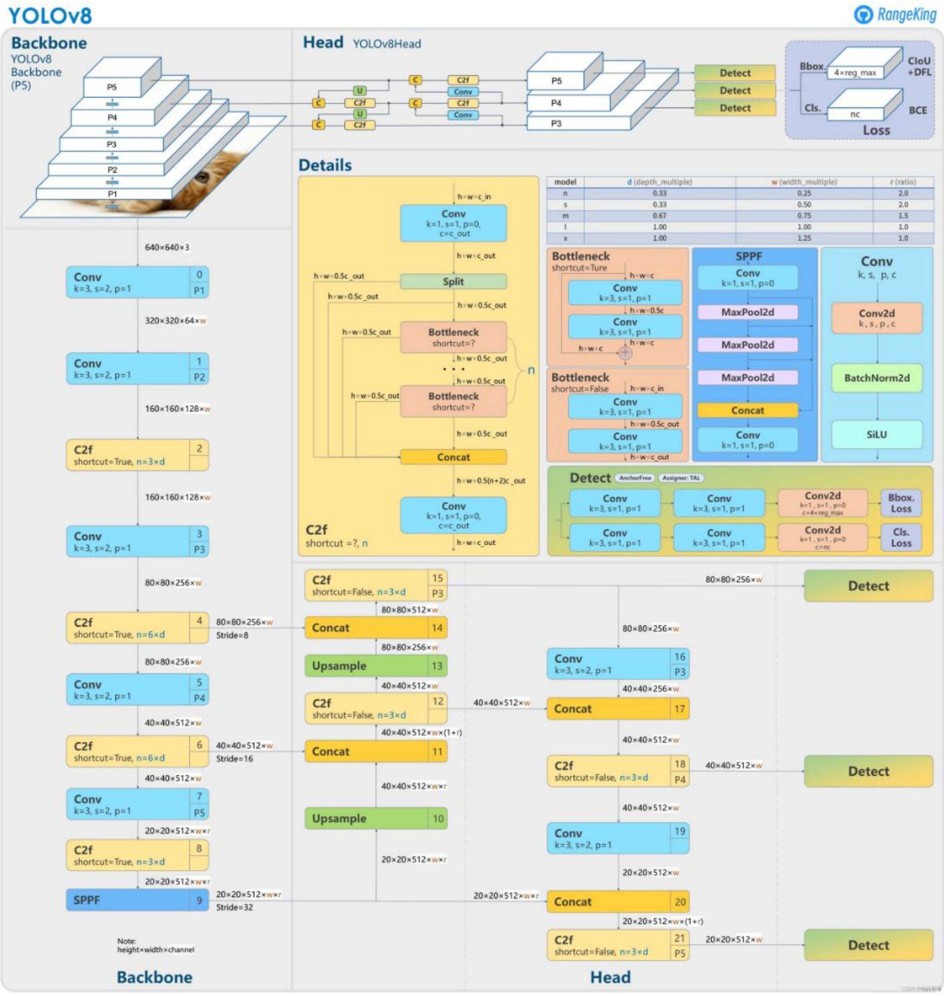

Fig. 3 Main Network Structure of YOLO v8

The Loss calculation process consists of two parts: positive and negative sample allocation strategy and Loss calculation. Most modern target detectors work on positive and negative sample allocation strategies, typically sim-OTA like YOLOX. (Optimal Transport Assignment), TOOD (Task-aligned One-stage Object Detection) TaskAligned Assigner and RTMGet(Real-Time Multi-scale Target Detection) DynamicSoftLabelAssigner, most of these Assigner are dynamic allocation strategies. **Error! Reference source not found.**YOLO v5 still uses a static allocation strategy. Considering the superiority **Error! Reference source not found.**of the dynamic allocation strategy, the TaskAlignedAssigner is directly referenced in the YOLO v8 algorithm. TaskAlignedAssigner matching strategy is simply summarized as: select positive samples based on scores weighted by the scores of classifications and regression.

$$t = s^{\alpha} \times u^{\beta} (2.3)$$

Loss calculation includes two branches: classification branch and regression branch, without the previous objectness branch. The classification branch still uses BCE Loss, but the regression branch needs to be bound to the integral form notation proposed in the Distribution Focal Loss, so the Distribution Focal Loss is used, and the CIoU Loss is also used. YOLO v8's detection, segmentation, and pose models are pre-trained on the COCO dataset, while the classification model is pre-trained on the ImageNet dataset. On first use, the model is automatically downloaded YOLO v8 provides a total of 5 different sizes of target detection model and segmentation model selection from the latest Ultralytics release. (Table 1below and

Table(**2). Segmentation Model YOLO v8**respectively), which is convenient for developers to balance performance and accuracy.

Table(1). Target Detection Model YOLO

Cast	Dimensions	mAP val 50-90	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	Parameters (M)	FLOPs (B)
YOLOv8n	640	37.3	80.4	0.99	3.2	8.7
YOLOv8s	640	44.9	128.4	1.20	11.2	28.6
YOLOv8m	640	50.2	234.7	1.83	25.9	78.9
YOLOv8l	640	52.9	375.2	2.39	43.7	165.2
YOLOv8x	640	53.9	479.1	3.53	68.2	257.8

Table(2). Segmentation Model YOLO v8

Cast	Dimensions	mAP b0x 50-90	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	Parameters (M)	FLOPs (B)
YOLO v8n-seg	640	36.7	96.1	1.21	3.4	12.6
YOLO v8s-seg	640	44.6	155.7	1.47	11.8	42.6
YOLO v8m-seg	640	49.9	317.0	2.18	27.3	110.2
YOLO v8l-seg	640	52.3	572.4	2.79	46.0	220.5
YOLO v8x-seg	640	53.4	712.1	4.02	71.8	344.1

Data collection is the basis for building a deep learning model, for corn pest detection and recognition system, in order to achieve the desired effect first need to collect a large number of corn pest image data, in order to more suitable for the actual farmland may encounter a variety of situations. In addition, in order to increase the diversity of the data set, data enhancement techniques such as rotation, scaling and translation can also be used. The high-quality image samples for training and testing are sorted out, including 4538 pictures, of which the training set contains 3857 pictures and the validation set contains 681 pictures. Some images in the data set are shown in theFig.4, including the detection and identification of 13 common corn pests, such as Table.3.

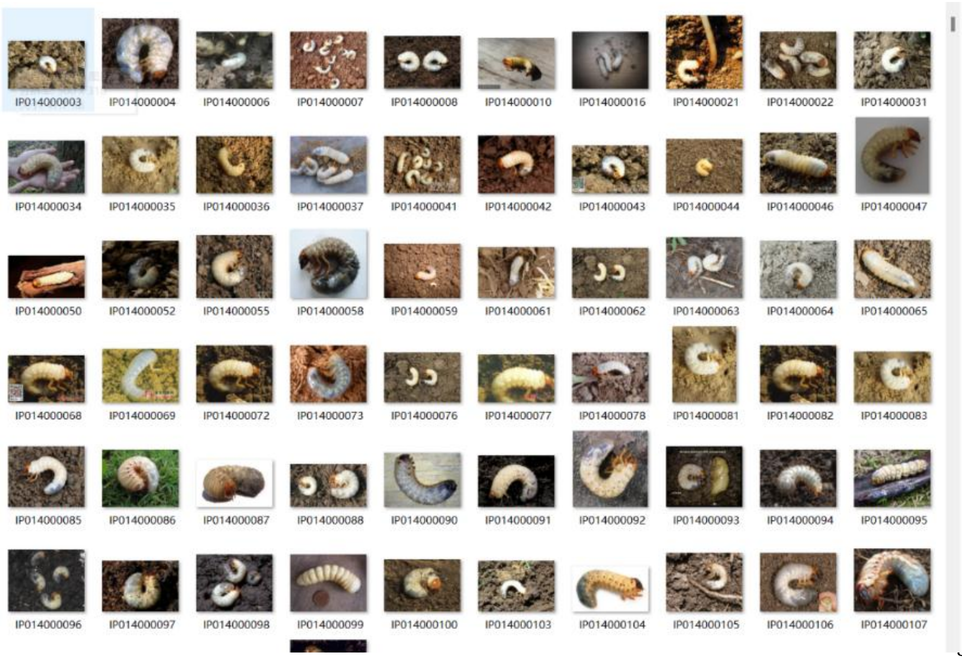

Fig. 4 pictures of some corn pests

Table(3). Pest species and names.

Serial	Name	Serial	Name
1	larvae	2	Mohidna chirp
3	wire bug	4	Jade spot borer
5	black noctuid	6	large noctuid
7	Yellow floor tiger	8	Red Spider
9	corn borer	10	Noctuid moth
11	Aphids	12	White Star
13	Peach little		

Maize pest image markeruse the LabelMe labeling tool to label the target border (Bounding Box) and category in each picture as shown in Fig.5. Data annotation is a key step in deep learning model training, which involves classifying and labeling the collected image data. For the detection and recognition system of corn diseases and insect pests, it is necessary to accurately label **Error! Reference source not found.**and the diseases and insect pests in the image, including the type, location and degree of the diseases and insect pests. The accuracy of labeling directly affects the recognition effect of the model, so the labeling process needs to be careful and rigorous.

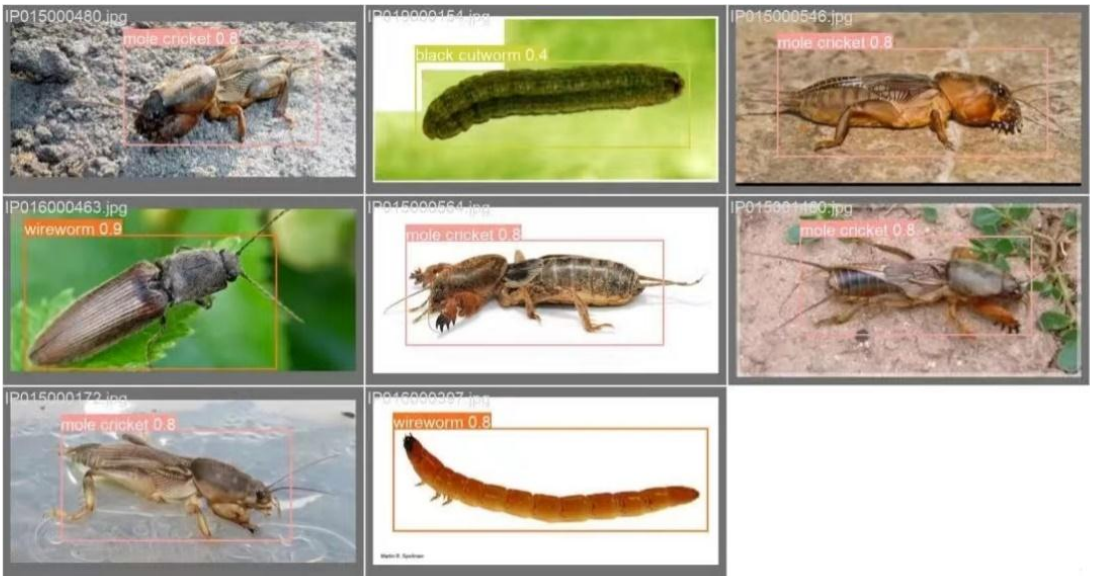

Fig. 5 Some Corn Pest Labeling Pictures

In training, there are mainly 3 aspects of loss: positioning loss (box_loss), classification loss (cls_loss) and dynamic feature loss (dfl_loss),and the results as Fig.6shown in.

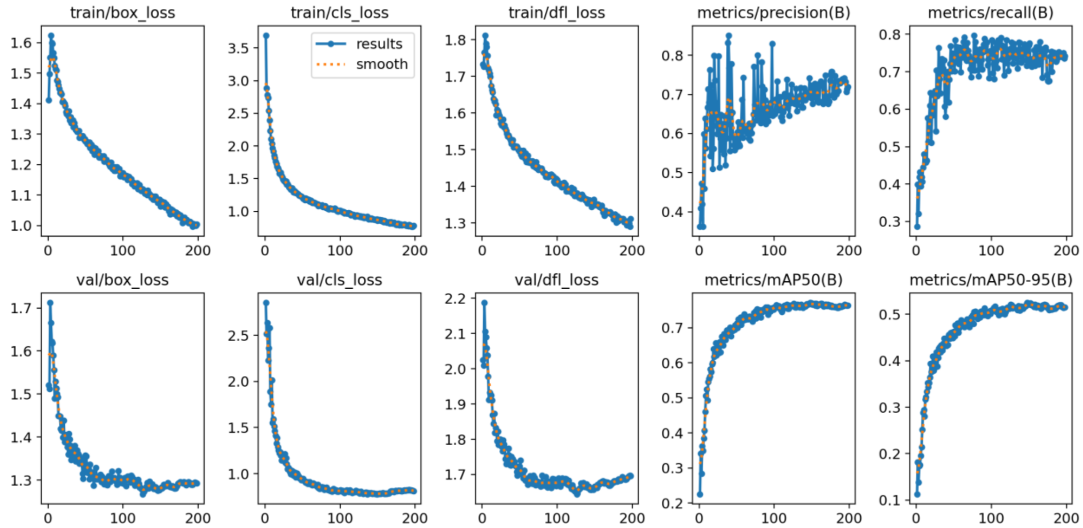

Fig. 6 Training Results

Execute the code for picture detection, will detect the pest species directly marked in the picture, the results as Fig.7shown in.

Fig. 7 Results Labeling Training Model

III. RESULTS AND DISCUSSION

After opening the corn pest detection system, click the picture icon to select the picture to be detected, or click the folder icon to select the folder where the picture to be detected is located. The specific operation demonstration is as follows: After clicking the target drop-down box, the result information of the specified target can be selected for display. Click the Save button to save the test results in the save data directory. It should be noted that the target position on the right side displays the target position with the highest confidence by default. The test results are displayed in the lower left table. The detection result is as Fig.9shown below.

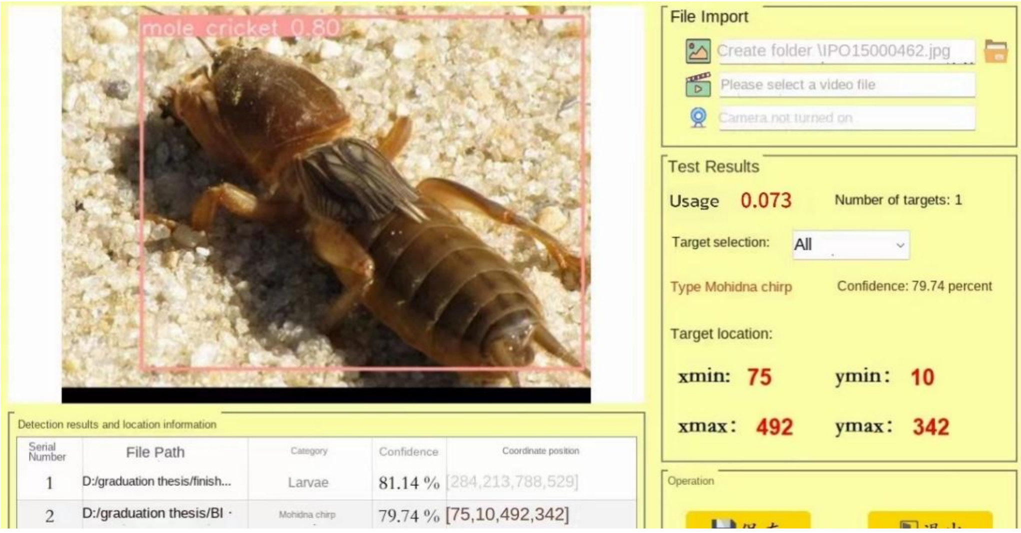

Fig. 9 Detection Results

In addition to picture detection and video detection, real-time detection can also be carried out through the camera. The camera can detect pest activities in real time, help managers understand the number and distribution of pests, and take effective measures. At the same time, it is convenient to understand the ecological habits of pests and other information, which provides a better scientific basis for prevention strategies. The specific detection results are shown in Fig.9. After the camera is turned on, the pest species, location and number of targets can be automatically identified, the confidence level can reach 79.87, and the confidence level difference of multiple detection results is about 5%, with high accuracy.

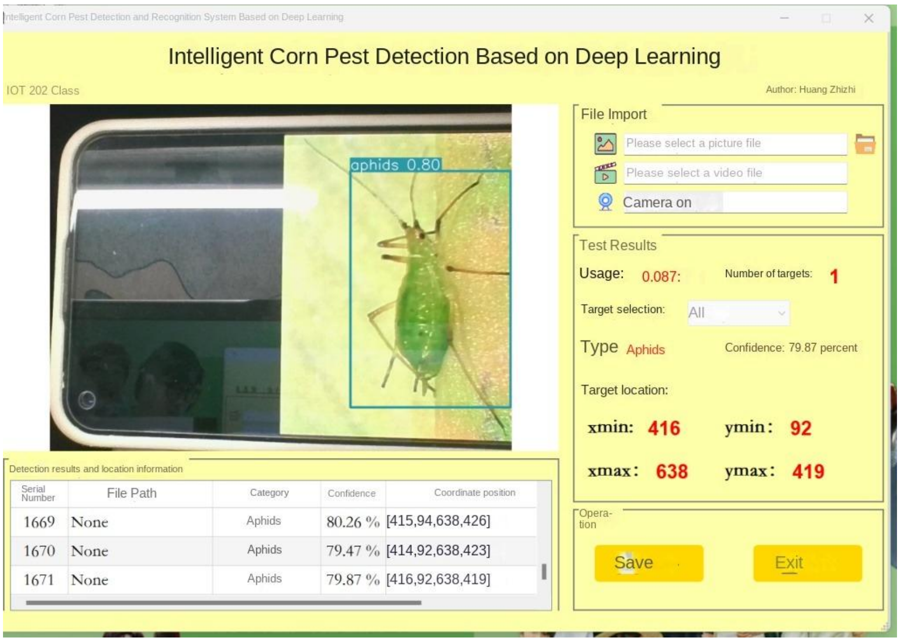

Fig. 9Camera Detection Results

IV. CONCLUSION

The theme of this paper is the design and implementation of corn pest detection system based on YOLO deep learning technology. Through YOLO v8 target detection technology, 13 kinds of corn pests can be detected through pictures, videos and cameras. In agriculture, corn pest detection can monitor target objects, find out the location of pests, timely understand the number and distribution of diseases and insect pests, and then formulate corresponding prevention and control plans, take targeted prevention and control measures, improve the prevention and control effect, reduce the economic losses caused by diseases and insect pests, and reduce the loss of energy, reduce the use of pesticides. It has a significant impact on crop production. Of course, because of factors such as hardware, technology and time, there are still many improvements in this article, which need continuous improvement as the direction of later work.

1. In farmland, because pests and other pests are fast in the process of flight, because the camera cannot capture them quickly, it will lead to the picture information of pests or harmful birds or the picture information intercepted is fuzzy, thus affecting the accuracy of the model. Later will be the acquisition of the picture to achieve further optimization.

2.In farmland, there are many uncertain factors, such as when the sunlight is dazzling, the picture taken will be too bright, and at night, the picture taken will be too dark. These factors will lead to the collected data. Poor, will eventually affect the accuracy of detection and recognition.

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