APPLICATION OF IMAGE RECOGNITION TECHNOLOGY IN SURFACE DAMAGE DETECTION OF RED SEA BREAM

Xian Pan[1]*, Assoc. Prof. Dr. Rajamohan Parthasarathy[2], Youwu Liu[3]

Abstract

Image recognition is playing a more and more important role in all kinds of detection methods, and it is also a key link in artificial intelligence. It provides decision-making basis for computer or mechanical equipment to take correct action. In aquaculture and food processing industry, image recognition has the advantages of direct-viewing, real-time and adaptability, which provides powerful guarantee for the development of intelligent agriculture and food safety. This article mainly uses the image recognition, take Red Sea Bream as an example, carries on the damage detection to the fish surface, provides the reliable basis for the further processing. In this paper, YOLO v3 algorithm is used to improve the speed and accuracy of fish surface detection, thus providing a new idea for the development of intelligent aquaculture processing. Compared with the traditional way of food processing industry, the efficiency and accuracy of using image recognition to judge whether the surface of fish is damaged, whether the whole fish is intact and whether the whole fish meets the requirements are greatly improved. Finally, we need to solve the next problem, and the direction of development put forward their own ideas.

Keywords: Image Recognition, Food Processing Industry, Red Sea Bream, Surface Damage Detection, Fish

[1]*PhD Research Scholar, Faculty of Engineering, Built Environment and Information Technology SEGi University Kota Damansara, Malaysia Email: 554360134@qq.com

[2]PhD Research Supervisor, Faculty of Engineering, Built Environment and Information Technology SEGi University Kota Damansara, Malaysia Email: prajamohan@segi.edu.my

[3]PhD Research Scholar, Faculty of Engineering, Built Environment and Information Technology SEGi University Kota Damansara, Malaysia. Email: 271819256@qq.com

***Correspondence Author:** Xian Pan

*PhD Research Scholar, Faculty of Engineering, Built Environment and Information Technology SEGi University Kota Damansara, Malaysia Email: 554360134@qq.com

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I. INTRODUCTION

In the process of fish culture and fishing, fish are often damaged in different degrees due to the way of fishing, friction between fish and fish, and classification after fishing. Damage to the surface of the various fish to the final price of fish, appearance, whether or not meet food safety standards will have varying degrees of impact. In addition, in the deep processing of fish, due to the non-uniform force, the damage will often continue to expand, resulting in the fracture of the fish, leading to the fish's quality and shape can not meet the requirements for further processing. Eventually, a lot of fishery resources will be wasted. Therefore, it is necessary to detect fish surface damage accurately to ensure product quality and eliminate unqualified fish, so as to reduce production waste and improve enterprise profits. In recent years, with the different development of image recognition technology, the application of the scene is increasing. Image recognition is intuitive, real-time and adaptable, which provides a good solution for fish surface damage detection.

Through machine vision, pattern recognition, image processing and so on, Guo Zichun et al. studied the fast recognition method of color image of carp disease[1] The correctness and validity of diseased fish species recognition and spot segmentation were verified. A fish species recognition and spot segmentation system based on image recognition was developed. Tests show that the system has fast segmentation speed and high accuracy. This system shows the feasibility of image recognition technology in fish recognition. LI J Y. et al. propose a fish recognition system using computer vision and neural networks[2]. Firstly, the fish body is placed on the conveyor belt in various positions, and then the image is taken by the camera installed above and on the side of the conveyor belt. Li Qinzh et al. proposed an underwater detection system based on rotational invariance and length[3]. Install an underwater camera on one side of the tank, then force the fish to swim through the tank, take pictures of the fish, and finally extract information such as the length of the fish to detect the fish's state.

The image recognition technology of fish body damage detection based on computer vision is studied in this paper. Red Sea Bream is trained to improve the recognition accuracy and construct the practical application scene. In this process, we identify goals to be accomplished and future research directions. I hope our research can provide some useful references and new inspirations for the following similar studies.

II.PROPOSED ALGORITHM

Among all kinds of surface damage methods, image recognition is the main method recently[4]. Compared with the traditional method, the damage location is better detected by image detection, which makes the damage in the image more intuitive and has higher accuracy and effectiveness.

A. Data

In this paper, because the size of fish surface damage is different, some of them are very different, so we use YOLO v3 algorithm to detect the damage of fish surface. About 800 pictures of fish injury were collected from Baidu and Bing in this experiment. Using the World Fish Base (FishBase), more than 1,000 images of Red Sea Bream were taken from different angles and placed. The common injury includes 3 kinds, respectively is the scratch, the incomplete, the pressure wound, the disease spot. Fig. 1. shows this.

Fig. 1. Image of fish body damage

B. Data enhancement

The quality and scale of data determine the upper limit of model learning. Because of the small number of data samples, the training effect will be affected[5]. Therefore, the use of mirror saturation contrast and flip operation to enhance the data can help increase the number of data, to prevent learning some unnecessary features, while avoiding the phenomenon of fitting.

Among them, vertical mirror image, horizontal mirror image and rotation operation are to transform the target position space and improve the learning ability of the model to the same target in different positions. In the same scene, because of using different images from different light sources as training materials, the model learning will get different feature information. After the target image is enhanced, the system can learn more feature information, so the saturated contrast enhancement data is added.

C. Data label production

During execution, YOLO v3 needs to form candidate boxes for the data preprocessing phase based on the actual boxes in the dataset[6]. Before starting the training, it is necessary to mark the pictures without injury and with fish injury, which will directly affect the final detection results. The action is to box out the target area in the diagram and record the class location and category information. In this paper, the labelImg information including 4 positions in the box is annotated by hand to form an XML file to save the annotation information of the corresponding image.

Fig. 2. LabelImg Image Manipulation Window

D. YOLOv3 detection model

The basic ideas of YOLO v3 are divided into three parts:

1) According to certain rules, a series of checkboxes are generated on the image. The target real box and candidate box are used for corresponding annotation. Where, the candidate boxes that coincide with the real box are defined as positive samples. A negative sample is defined if it deviates from the real position of the target and the position of the candidate box.
2) The convolution neural network is used to obtain the target features, and the candidate areas are identified and positioned simultaneously.
3) Finally, compare the test results with the labels of the real box to determine whether the results are accurate.

YOLOv3 uses DarkNet-53 networks instead of DarkNet-19 as the feature extraction network in YOLOv2(CHENG J Y,2022). The full convolution structure of DarkNet-53 networks is shown in the figure. It consists of convolutions of 3 * 3 and 1 * 1. At the same time, an activation layer and a batch normalization layer are set behind each convolution layer. In the whole network, there is no full connection layer and pooled layer. Instead of pooled layer, convolution layer with step size set to 2 is used for downsampling. At the same time, after 5 times of downsampling, the size of the feature image will become 1/32. DarkNet-53 of the original image, which also combines the structure of missing blocks. Fast link settings are set between convolution layers, which greatly reduces the difficulty of deep network training and makes the whole DarkNet-53 training faster.

	Type	Filters	Size	Output
	Convolutional	32	3×3	256×256
	Convolutional	64	3×3/2	128×128
1×	Convolutional	32	1×1	
	Convolutional	64	3×3	
	Residual			128×128
	Convolutional	128	3×3/2	64×64
2×	Convolutional	64	1×1	
	Convolutional	128	3×3	
	Residual			64×64
	Convolutional	256	3×3/2	32×32
8×	Convolutional	128	1×1	
	Convolutional	256	3×3	
	Residual			32×32
	Convolutional	512	3×3/2	16×16
8×	Convolutional	256	1×1	
	Convolutional	512	3×3	
	Residual			16×16
	Convolutional	1024	3×3/2	8×8
4×	Convolutional	512	1×1	
	Convolutional	1024	3×3	
	Residual			8×8

Fig. 3. DarkNet-53 Network Layer Characteristics

YOLOv3 further optimizes the accuracy of small target detection compared to YOLOv2[7]. By combining the fusion and sampling methods in feature pyramid networks with DarkNet-53, three different detection scales are combined. Then the multi-scale fusion method is used to detect the specific target. Through this way, can effectively improve the small target detection ability. Not only that, YOLO v3 combines deep and shallow features sampled from above to produce three different sizes of feature maps. Detection of small, medium and large targets, improving the overall accuracy of detection. YOLOv3 analyzes the target with three sizes of feature diagrams, and inherits the K-means clustering algorithm from YOLv3 to form three Anchor Boxes on each size of the feature diagram. If the size of the feature map is smaller, the value of the receptive field is larger, and the detection of large targets is more sensitive.

The following figure shows the network architecture of YOLO v3. Here, the Residual Block is the missing block unit, and a missing block unit includes a quick link and two DBL units. The DBL contains a convolution layer, a batch normalization layer, and a Leaky ReLU activation function. Concat represents a splice operation.

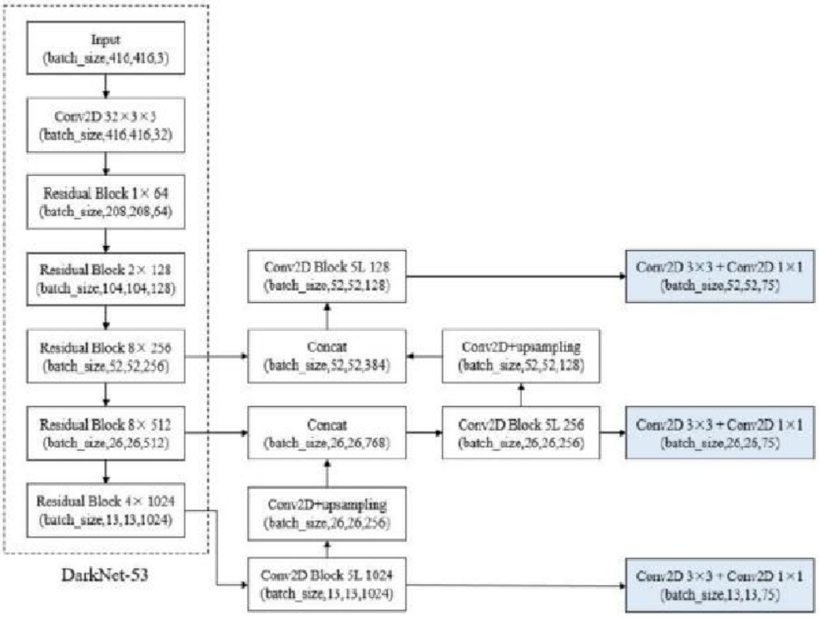

Fig. 4. YOLO V3 program diagram

In category prediction, in YOLO v3, the original Softmax classifier became a separate Logistic classifier. Softmax chooses the maximum probability value as the correct category, so that only one category is judged for the same target. At the same time, Logistic solves this problem well when there are multiple category tags for a target. It converts each category into two categories and uses the Signoid function to normalize the input values between [0,1].

The Sigmoid function formula is as follows[8]:

$$g(z) = \frac{1}{1+e^{-z}} \tag{1}$$

Among them, Z is the function of classification boundary. If the boundary function is linear, the formula is as follows[9]:

$$\theta_0 + \theta_1 x_1 + ,\ldots, + \theta_n x_n = \sum_{i=1}^{n} \theta_i x_i = \theta^T x \tag{2}$$

Substitution of this into the Sigmoid function yields the prediction function in the following formula[10,11]:

$$h_\theta(x) = g(\theta^T X) = \frac{1}{1+e^{-\theta^{T}X}} \tag{3}$$

III. EXPERIMENT AND RESULT

A. Experimental environment

In order to verify the effectiveness of the proposed YOLO v3 algorithm in fish surface damage detection, Red Sea Bream is used as an example to segment, mark and fill the color image.

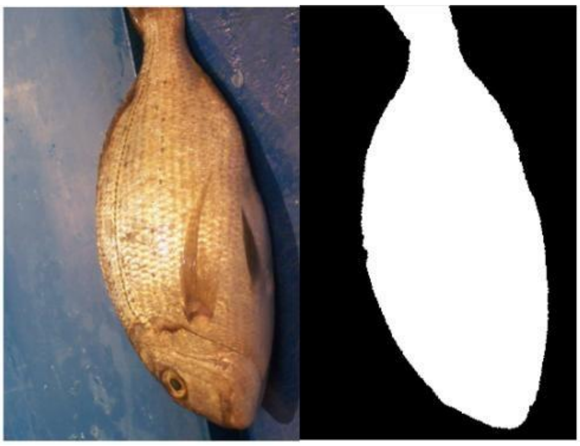

Fig. 5. Original Image and segmentation effect image

This experiment is mainly implemented on Paddlex platform, which can integrate many powerful functions such as numerical calculation, analysis, high-dimensional matrix calculation, high-dimensional scientific data visualization etc[12]. It provides a suitable programming environment for image processing[13]. The specific parameters of desktop computer used in this paper are Windows

10,64 bit system. The CPU is I7-9700K bit with 8GB of memory[14].

B. Parameter settings

In model training, set the model to YOLOv3, Backbone to DarkNET53, pre-training model to COCO, input size 608px, height 608px, GPU, Epoch 100, learning rate 0.000101417, Batch size 1. The ratios of training set, verification set and test set are 70%, 20% and 10% respectively

C. Model evaluation

As shown in the following figure, the sum loss value of all subnet loss functions of the system is 3.07, which meets the requirements of the system. The RCNN subnet classification loss function value Los _ cls is about 0.0115. From the curve of bbox _ map, the best value of bbox _ map is 100.0. Therefore, it can be seen that the YOLO v3 algorithm can meet the system requirements, the results are also more ideal.

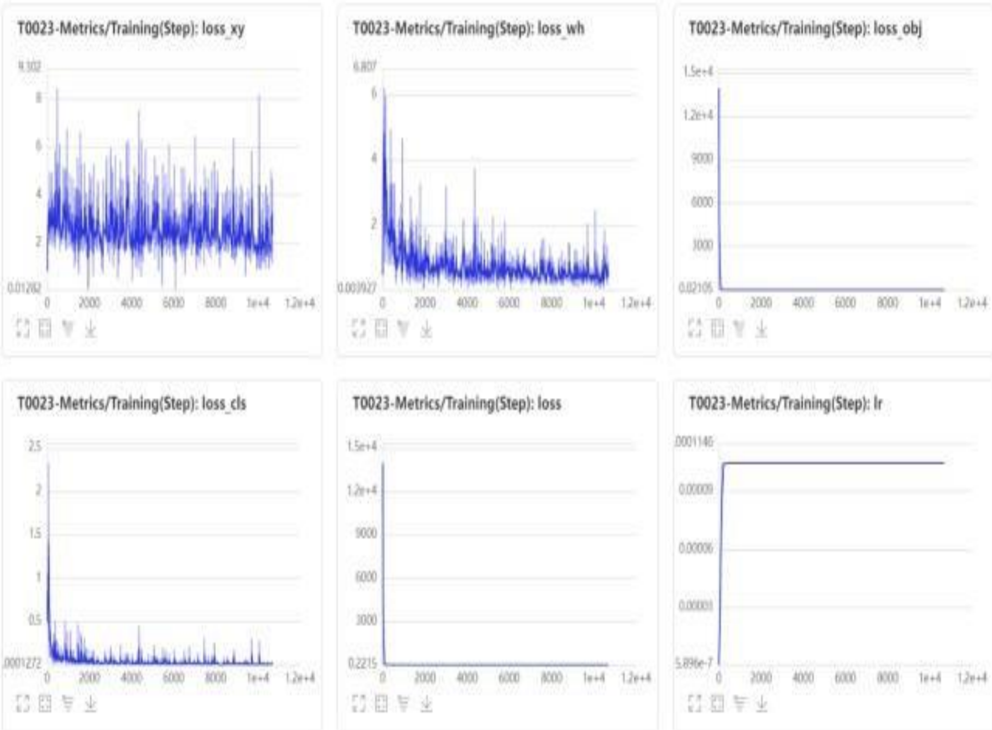

Fig. 6. Parametric curves during training

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2022-12-19 02:09:08 [INFO]   [TRAIN] Epoch=100/100, Step=105/107,
loss_xy=1.667395, loss_wh=0.103010, loss_obj=0.043413,
loss_cls=0.011379, loss=1.825198, lr=0.000104, time_each_step=0.32s,
eta=0:0:0
2022-12-19 02:09:08 [INFO]   [TRAIN] Epoch=100/100, Step=107/107,
loss_xy=1.080004, loss_wh=0.417529, loss_obj=0.349364,
loss_cls=0.005290, loss=1.852186, lr=0.000104, time_each_step=0.32s,
eta=0:0:0
2022-12-19 02:09:08 [INFO]   [TRAIN] Epoch 100 finished,
loss_xy=2.1525126, loss_wh=0.46616417, loss_obj=0.4435323,
loss_cls=0.011511343, loss=3.0737202 .
2022-12-19 02:09:08 [INFO]   Start to evaluate(total_samples=30,
total_steps=30)...
2022-12-19 02:09:11 [INFO]   Accumulating evaluatation results...
2022-12-19 02:09:11 [INFO]   [EVAL] Finished, Epoch=100,
bbox_map=100.000000 .
2022-12-19 02:09:11 [INFO]   Current evaluated best model on eval_dataset
is epoch_60, bbox_map=100.0
```

Fig. 7. Training log

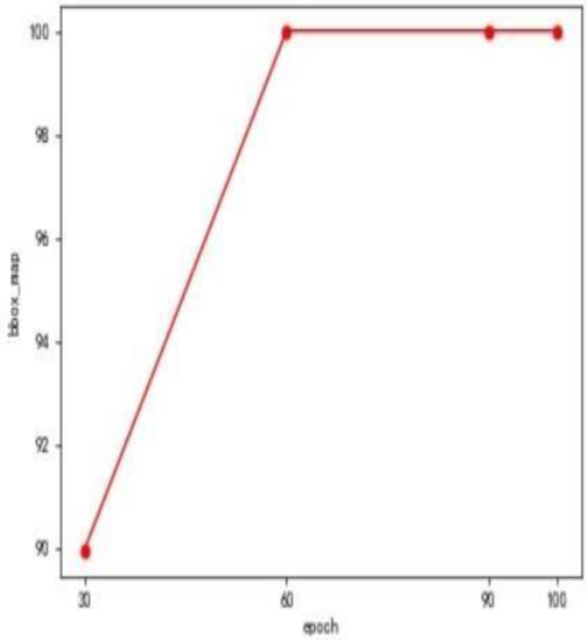

Fig. 8. Save model bbox _ map curves by turn

IV. CONCLUTION

Damage detection is a common recognition technology to judge whether an object satisfies the requirement of process. Essentially, the recognition technology is the pattern recognition problem. Based on the analysis and research of image recognition technology, this paper applies this technology to fish skin damage detection, combining theory with practice. At the same time, the following conclusions are drawn:

1) From the image, image recognition, image recognition process and the algorithm of image recognition system, YOLOv3 algorithm is used to form the system, and the YOLOv3 algorithm can meet the task requirements.
2) Example of a damage detection system incorporating surface characteristics of Red Sea Bream fish.
3) The data of the system is enhanced by mirror saturation contrast and flip operation, which helps to obtain the image of the whole fish body completely, improve the quality of image information, and thus improve the detection and recognition ability of the surface damage of the fish body.
4) This system is used for nondestructive testing on the surface of Red Sea Bream and has certain application value. It can be extended to the surface testing of other fish and has a good development prospect.

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