A Method for Recognizing and Counting Residual Bait of Penaeus Vannamei Based on Deep Learning

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ABSTRACT

This research has developed a neural network model based on deep learning, which consists of a recognition part and a counting part. The recognition part is realized by the Fully Convolutional Neural Network (FCN), and thecounting part is realized by the NAS-CNN model. Labelme (online labeling tool) was used to manually mark the two types of targets, the remnant bait and the white prawn, and a special data set for the identification of the white prawn was created. Experiments show that the FCN model has achieved excellent recognition results, with a training recognition accuracy rate of 99%, and a verification recognition accuracy rate of 96.13%. When counting the residual bait, the connected-component labeling (CCL) isused for the image with only sporadic residual bait. The accuracy rate reached 97.5%. The pictures with severe adhesion residual bait are counted using the NAS-CNN model training, and the verification accuracy rate can reach 88.52%.Experiments have proved that combined with the deep learning method, the white shrimp and the residual bait can be quickly and accurately identified and theresidual bait can be counted at the same time. This method provides a reference for exploring the scientific breeding methods of Penaeus vannamei, and can be extended to use in other aquaculture environments.

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CCS CONCEPTS

• **Semantics and reasoning**; • **Design and analysis of algorithms**; • **Machine learning**;

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KEYWORDS

Penaeus vannamei, Fully Convolutional Networks, Deep learning, Object counting

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1 INTRODUCTION

In recent years, global capture fisheries production has continued to decline, and the proportion of aquaculture production in total production has increased year by year. According to the statistics of the International Food and Agriculture Organization (FAO), the total output of the world aquaculture industry reached 80 million tons in 2016, and has maintained an annual growth rate of morethan 3 million tons in the past ten years [1]. The rapid development of theaquaculture industry will inevitably increase the demand for feed, which puts tremendous pressure on the supply of feed ingredients [2]. At the sametime, feed costs account for a large proportion of aquaculture. Depending on the breeding system and feeding intensity, feed costs need to account for 50% to 70% of production costs [3].In order to ease the pressure of feed production and reduce the cost of breeding, it has become very urgent to determine the amount of feed in the feeding process. At present, most farmers feed their feeds basedon their farming experience and farming scale. This crude use of feed will not onlylead to a large amount of waste of feed, but also residual bait and feces will also pollute the breeding environment [4]. The Penaeus vannamei studied inthis article is one of the main cultured species in aquaculture. The current culture mode also does not use standardized methods of feed, and it is mainly fed by farmers based on experience. This greatly increases the cost of feed, and at the sametime, the increased water pollution caused by the residual bait will also reduce the production of white shrimp. In view of the above problems, there is an urgent need for a

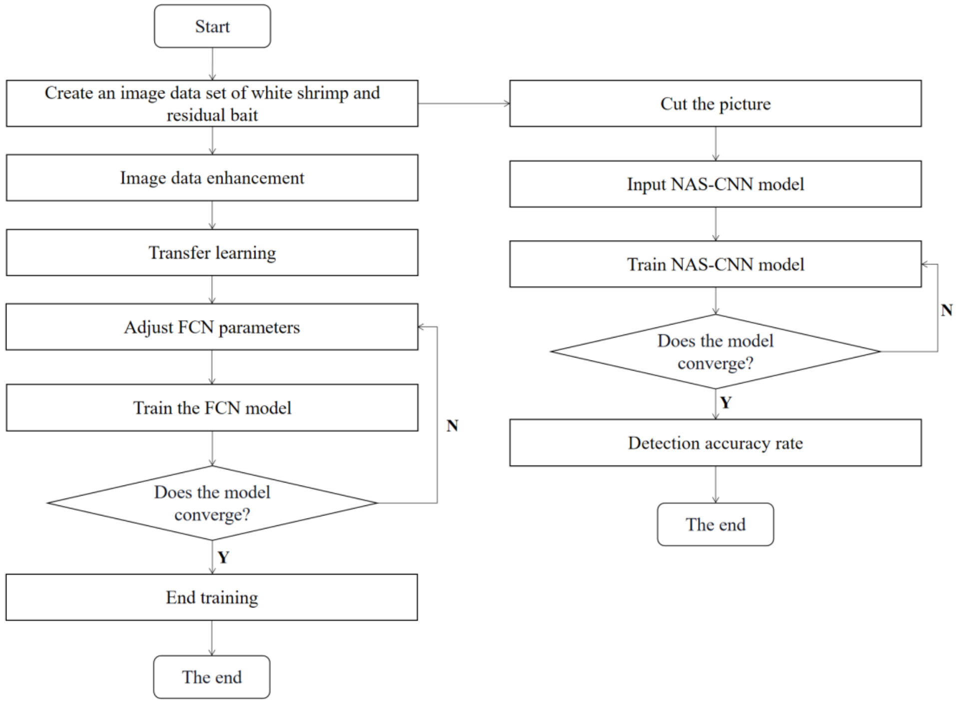

Figure 1: Schematic diagram of the main process of the remnant bait identification and counting system based on deep learning.

method to identify and count the remaining bait to further explore the scientific way of feeding the vannamei shrimp.

The work on counting the residual bait of Penaeus vannamei is still at the stage of using manual counting. Because the high temperature and humidity environment in the white shrimp breeding shed is not suitable for long-term manual operation, the counting of residual bait also needs to rely on machine learning to complete. However, due to the severe target adhesion, the different appearance of the residual bait and the change of the scale, it is still very challenging to count the residual bait in the image. This research has developed a novel target counting model, which uses FCN to identify residual bait and the NAS-CNN (Neural Architecture Search-Convolutional Neural Networks) network to find the best neural network structure and fits the relationship between the residual bait pixels and the number of residual bait in the image So as to realize the residual bait count. As far as we know, there are few studies on direct counting of residual bait in the field of P.vannamei farming.

The main purpose of this research is to (1) create a dedicated image data set for the identification of residual bait (2) use a full convolutional neural network (FCN) to accurately identify the residual bait at the pixel level, and (3) develop a NAS-based method Remnant bait counting neural network model to realize the count of remnant bait.

2 DATASET AND METHODS

In this paper, the FCN-8s model is usedto automatically identify white shrimp and residual bait in the image, and the NAS-CNN model is used to count the residual bait. The technical route is outlined in Fig. 1

2.1 Collection and processing of original pictures

The white shrimp and residual bait pictures collected in the experiment are from the two vannamei breeding bases in Xiangshan (N29°22', E121°54') and Fenghua (N29°65',E121°41'), Ningbo Among them, the Xiangshan breeding farm is shedbreeding, and the Fenghua breeding farm is open-air breeding. Before the images were collected, all Penaeus vannamei had been reared for more than 4 weeks to ensure that they were fully adapted to the current culture environment.

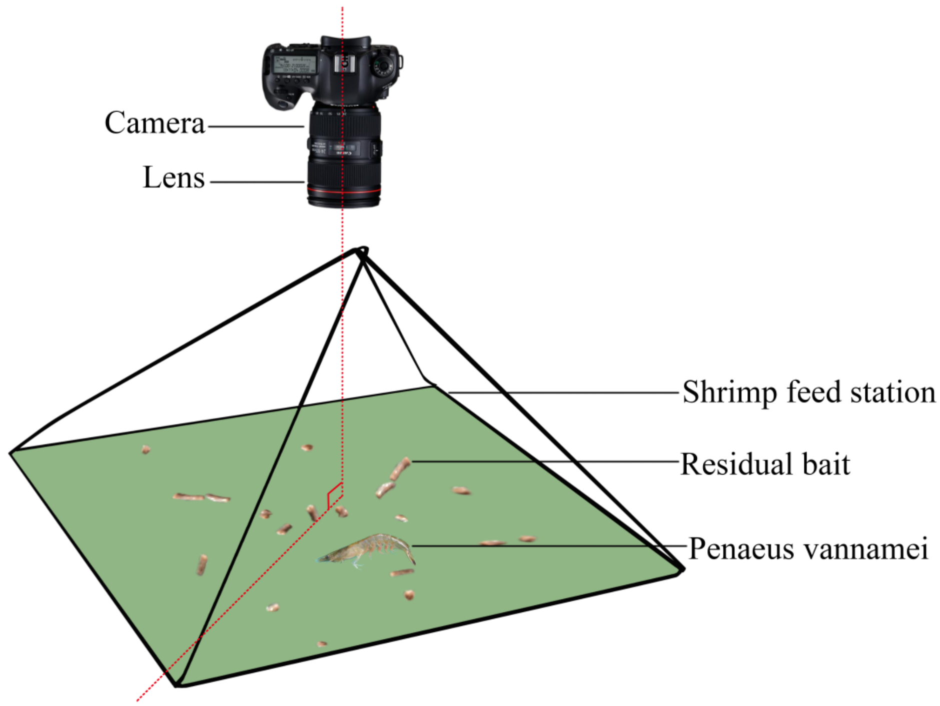

Figure 2: Schematic diagram of image acquisiti-on mode.

The image acquisition time is September 20, 2019, the water temperature is 20-25°C, the weather is clear, and the light intensity is high. Before taking pictures, the staff will spread the feed on the feed table. After the feed platform sinks into the pool water, wait for the white shrimp to fully feed, then lift the feed platform out of the water, and use a digital camera (Nikon D7000) to photograph the feed platform, as shown in Fig. 2. The two white shrimp breeding bases each collected 25 pictures, a total of 50 pictures, and storedthem in Png format. The pixel size of the photo taken by the digital camera is 4496 pixels×3000pixels. Because the image size is too large, it is not conducive to the subsequent FCN model processing. The script program is used to crop each original image into 100 small images to filter out some meaningless images. Number the image and save it.

2.2 Picture annotation

After Picture annotation removes meaningless pictures, use Labelme software to mark the images. Labelme is an image labeling software with a graphical interface, the programming is Python, and the graphical interface uses pyQt. Using the function of constructing polygons, it can mark the two targets of remnant bait and white shrimp, and fill these two types of marks with two different colors (Fig. 3). The annotated annotated image and the original image will be saved separately, and ensure that the two can correspond to each other.

2.3 FCN date set construction

The amount of sample data is a key factor in deep learning. Image data sets often need to be expanded. This expansion can not only improve the classification effect, but also improve the generalization ability of the model. When only a few samples of training data are available, data augmentation is a common method of FCN [5]. After referring to the enhancement methods used in the relevant literature, this study uses keras'built-in ImageDataGenerator to achieve image augmentation: brightness enhancement, contrast enhancement, rotation angle and flipped image processing are performed on the original residual bait image.

An example of the expanded image is shown in Fig. 4. The original image data set has a total of 3081 available images, and after expansion, there are a total of 12,324 images.After completing the data set expansion, the image is divided into training set and test set according to the ratio of 3:1.

2.4 FCN model

The FCN model can effectively generate a spatial score map for each pixel. The input of the image can be of any size, and the outpu recognition map will also be an image of the corresponding size [6]. This is due to the rewind Layering can restore the image to any size. This experiment is based on the FCN model of Vgg-16 structure design. The FCN network model structure we tried to use is shown in Fig. 5

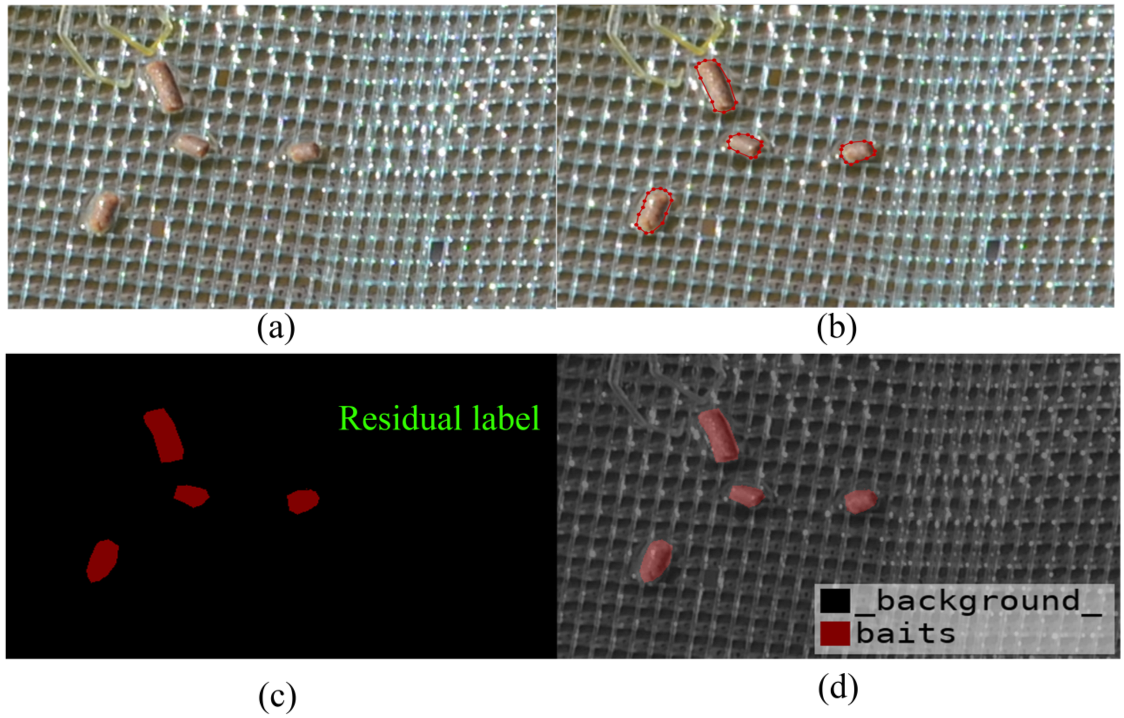

Figure 3: Make the label image, (a) the original image (b) construct the polygonal circle and select the residual bait pixel area (c) the label image (d) the visualization mask image.

2.5 Counting module

Due to the fact that the adhesion of individual bait images is too serious and the target of the bait is too small, it is difficult to use the CCL algorithm for counting processing. In order to deal with this problem, a window with a size of 32 pixels×32 pixels is used to randomly sample the image (Fig. 6), and the sampled image is input to NAS-CNN. The size of the remnant bait image after cutting is 32 pixels×32 pixels. Let the number of remnants of the original image (320 pixels×320 pixels) be A, the number of remnants on the small image is a, and the error is s, then the entire original image The number of remaining bait is:

$$A = \sum_{I=0}^{99} a_i \pm s \tag{1}$$

Due to the lack of depth information, the overlapping residual bait is regarded as Figure 6. Schematic diagram of random sampling of remnant bait image with 32 pixels×32 pixels window.one layer, and the number of residual bait ina single image is not more than 5, which reduces the difficulty of manual counting of training sample data and reduces the types of neural network fitting. By manually counting 6,460 cut images, there are 980 images of no residual bait, 999 images of 1 residual bait, 1046 images of 2 residual bait, 1101 images of 3 residual bait, and 1121 images of 4 residual bait. 1212 pieces of 5 residualbaits are used as the input data of the training set.

Call the NASNET-A model at https://tfhub.dev/google/imagenet/nasnet_mobile/classification/4, and add a three-layer Dense layer at the end of the original model to output the prediction results. The weight of the original model is obtained by training the ILSVRC-2012-CLS data set for image classification, referring to the transfer learning method, directly loading the initial weight of the model to train the residual baitcount dataset. See Table 1 for model parameters.

Table 1: NAS-CNN model structure and parameters

Layer	Output Shape	Param
keras_layer (KerasLayer)	(None, 1001)	5327773
dense (Dense)	(None, 240)	240480
dense_1 (Dense)	(None, 120)	28920
dense_1 (Dense)	(None, 6)	726

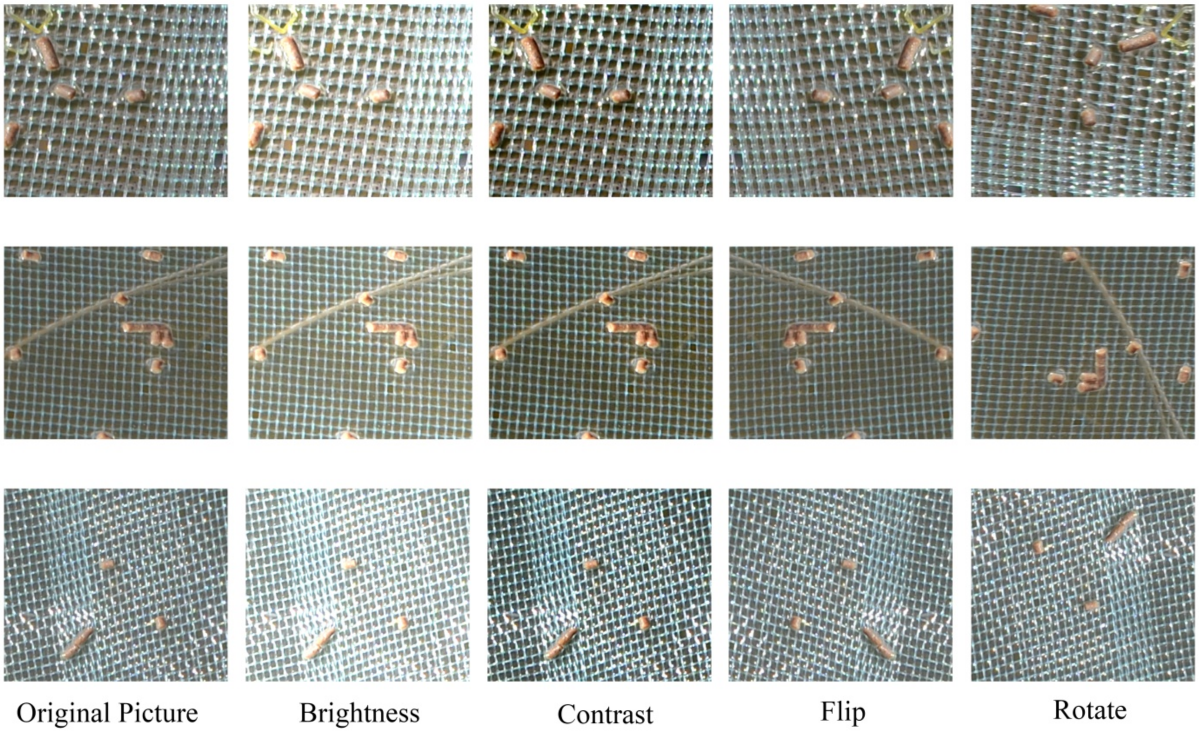

Figure 4: Schematic diagram of data set expansion method.

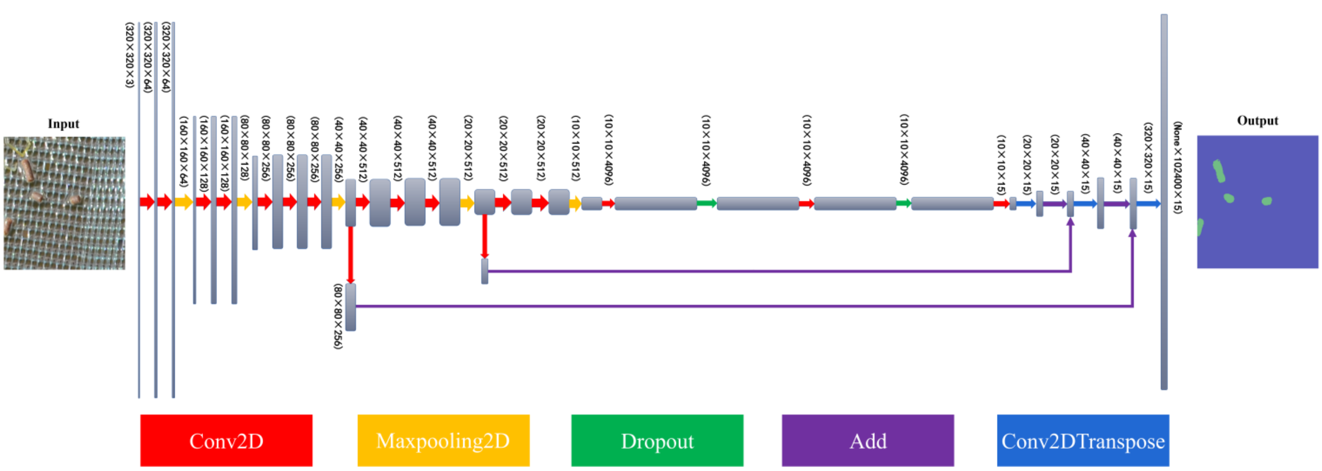

Figure 5: FCN structure diagram.

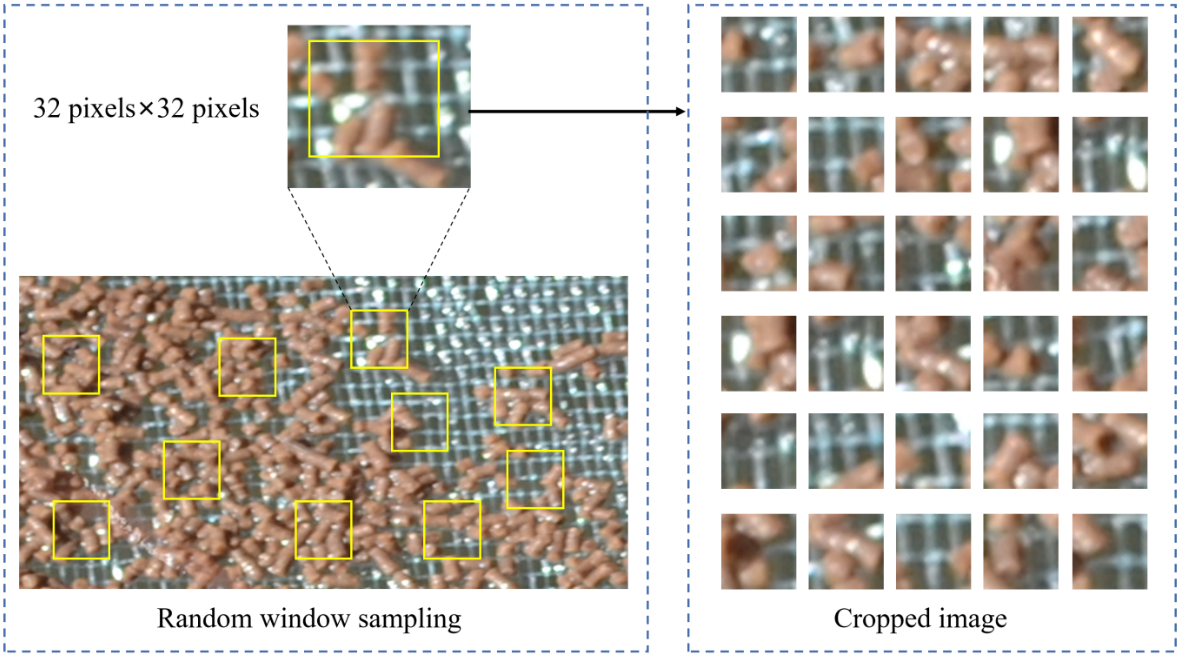

Figure 6: Schematic diagram of random sampling of remnant bait image with 32 pixels×32 pixels window.

3 RESULTS AND DISCUSSION

The training and testing environment of the network model is based on the Windows 10 operating system, the Python version is 3.6.5, and the model code is implemented based on Kreas-TensorFlow. The hardware environment of the system experiment is Intel i5 processor, 8GB memory, NVIDIA RTX 2060.

3.1 Reference results of FCN model

The model loss function image is shown in Fig. 7. The trained FCN model is used to identify residual bait, and the final recognition accuracy reaches 96.13%. Fig. 8 shows the recognition result of the sample image. The results show that the recognition and classification results are basically consistent with human recognition intuition. Under two different light intensity conditions, the algorithm has achieved better recognition results and has strong robustness. Therefore, FCN can be used as a practical method to identify residual bait.

3.2 Reference results of NAS-CNN model

In order to verify the error range of the remnant bait detection and counting, this study selected 5 remnant bait images of 320 pixels×320 pixels to test the correct rate of the counting system. The system counting result is compared and analyzed with the measured data. The measured data of the residual bait in the image is obtained

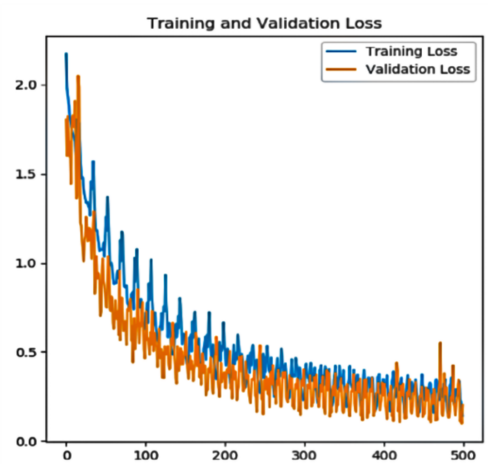

Figure 7: Loss function graph of training set and prediction set.

by manual counting. Due to the overlap and incompleteness of the residual bait images, the subjectivity of manual counting is

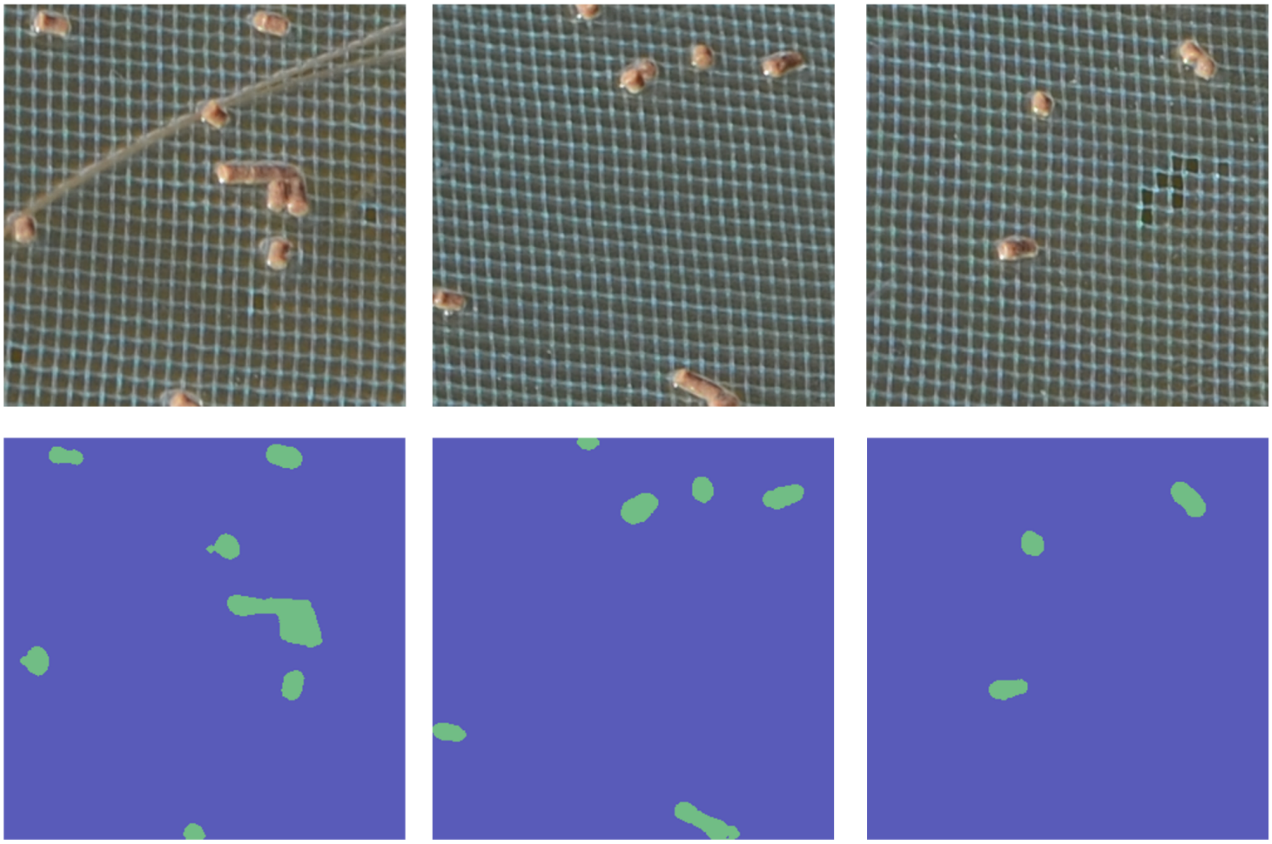

Figure 8: Remnant bait recognition effect display diagram.

increased. In order to ensure the correctness of the counting and the rigor of theexperiment, this research has formulated a unified principle of counting the residual bait. The overlapping part that cannot be accurately counted is regarded as a layer, and the five team members separately conduct the residual bait in each image count. For each residualbait image, the average of 5 count results is used as the residual bait measured data of the image to reduce the subjective error of manual counting.

Compare and analyze the counting results of the NAS-CNN counting module with the measured data, and the results are shown in Table 2

Table 2: NAS-CNN model counting results test

Picture ID	NAS-CNN	Artificial
DSC_5856_2	154	152
DSC_5856_11	225	235
DSC_5856_25	140	146
DSC_5856_48	300	375
DSC_5856_52	146	135

4 CONCLUSIONS

(1) Constructed an FCN model suitable for identification of remnant bait of Penaeus vannamei, realizing accurate recognition ofremnant bait in complex environment. The overall recognition accuracy rate of the model is 96.13%.

(2) CCL and NAS-CNN methods are used to count the residual bait with different adhesion degrees. The results of the residual bait counting test show that the accuracy of the CCL method for the sporadic residual bait counting accuracy rate is 91.4%, and the normalized root mean square error is small, 1.06%. The NAS model has an accuracy rate of 88.52% for the

verification set of severely adhered residual bait, which is in line with actual production applications.

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REFERENCES

[1] FAO, 2018. Fishery and Aquaculture Statistics 2016. Food and Agriculture Organization of the United Nations, Rome, Italy.
[2] Gatlin, D.M., Barrows, F.T., Brown, P., Dabrowski, K., Gaylord, T.G., Hardy, R.W., Herman, E., Hu, G., Krogdahl, Å., Nelson, R., Overturf, K., Rust, M., Sealey, W., Skonberg, D., J Souza, E., Stone, D., Wilson, R., Wurtele, E., 2007. Expanding the utilization of sustainable plant products in aquafeeds: a review. Aquac. Res. 38, 551–579.
[3] Md.moazzem Hossain.,Md.LokmanAlf.,Saleha Khan.,Md.Mahfuzul Haque.,Md.Shahjahan.,2020.Use of Asian watergrass as feed of grass carp .Aquaculture Reports.Volume 18,100434
[4] Zhou, C., Zhang, B., Lin, K., Xu, D., Chen, C., Yang, X., Sun, C., 2017. Near-infrared imaging to quantify the feeding behavior of fish in aquaculture. Comput. Electron. Agric. 135, 233–241. https://doi.org/10.1016/j.compag.2017.02.013.
[5] François Chollet.,Deep Learning with Python.,2018,pp110-111
[6] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classifification with deep convolutional neural networks. Adv Neural Inf Process Syst 2012;25(2):11, 6–14.