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Microbial Colony Species Recognition Using an Enhanced YOLOv4 Algorithm with CBAM and k-means++ Optimization

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Abstract: The identification of microbial colonies based on their characteristics, such as size, shape, and color, is essential for recognizing different species, especially in the field of food hygiene. Traditional manual identification methods are labor-intensive and prone to error. This paper proposes an improved microbial colony recognition algorithm based on YOLOv4 to address these challenges. The method incorporates image preprocessing steps like median filtering and enhancement, followed by target labeling using the labelimg tool. The original YOLOv4 network structure is enhanced by introducing the Convolutional Block Attention Module (CBAM) to filter redundant information and using the k-means++ algorithm to optimize anchor boxes for improved object detection. The proposed model achieves a 9% increase in recognition accuracy over the unmodified YOLOv4 network in identifying *Escherichia coli* colonies. The results demonstrate the algorithm's high efficiency and accuracy compared to traditional manual methods, highlighting its potential for broad applications in microbial detection.

Keywords: Colony Recognition; YOLOv4; CBAM Attention Mechanism; K-means++ Clustering.

1. Introduction

Different microbial growth and reproduction of the colonies have different characteristics, these different characteristics are an important basis for identifying microbial species[1][1].Through the identification of the size, shape, color and other characteristics of microbial colonies, the types of microorganisms can be determined. As an important criterion for evaluating the quality of food hygiene, it is very important to identify Escherichia coli in microbial colonies[2].Manual identification is the main identification method of traditional detection, but manual identification usually has the disadvantages of high labor intensity, difficulty in counting some small colonies, and large error in statistical results. With the continuous development of computers and convolutional neural networks, the technology of using convolutional neural networks to identify targets in images is becoming more and more mature. The recognition rate has reached a relatively high level and is gradually replacing traditional manual recognition methods. Using convolutional neural network for colony recognition can reduce the labor intensity of inspectors and improve their work efficiency[3].

The current target detection algorithms are mainly one-stage target detection algorithm and two-stage target detection algorithm. The one-stage algorithm will directly predict the target based on the extracted features, while the two-stage algorithm will first generate candidate boxes for classification based on the extracted features. Therefore, the one-stage algorithm recognizes faster than the two-stage algorithm. One-stage typical algorithms include SSD, YOLO, two-stage typical algorithms include R-CNN, Fast R-CNN, etc. Yu Hui, Du Peipei et al.used CNN algorithm to classify spotted smooth colonies, round wavy colonies, oval colonies and irregular other colonies, and the average accuracy rate reached 87.5 % [4]. However, the classification of colonies only distinguishes the shape, and does not identify the types of colonies. Hu Jingjing, Tang Zhen and others used the morphological watershed algorithm to segment and identify the colony image, mainly for the identification of most of the round-like colonies [5]. This recognition method is only simply identified by the shape of the colony, and does not realize the identification of microbial colony species. Therefore, it is necessary to study the identification of microbial colony species.

In this paper, a microbial colony recognition algorithm based on YOLOv4 is proposed. This method first performs median filtering and image enhancement processing on the image, and then uses labelimg to mark the targets in the image. Then, by introducing the CBAM attention mechanism into the original YOLOv4 network structure and using the k-means++ clustering algorithm to optimize the target anchor box, the original YOLOv4 network structure is improved. The data sets are trained using the networks before and after improvement. The experiment compares and analyzes the results of the improved network structure and the network structure before the improvement to identify the E. coli colony. The improved network structure improves the recognition accuracy by 9 % compared with the network structure before the improvement, and more accurately identifies the target colony.

2. YOLOv4 Network Model

Compared with traditional feature recognition methods, the features learned by neural networks are more representative and can better distinguish between target objects and interfering objects.

YOLOv4 use CSPDarkNet53 network structure as the backbone network, PANet structure and spatial pyramid pooling (SPP) constitute the Neck part of YOLOv4, and YOLOv3 is the Head of YOLOv4 [6]. The network structure of YOLOv4 is shown in Figure 1:

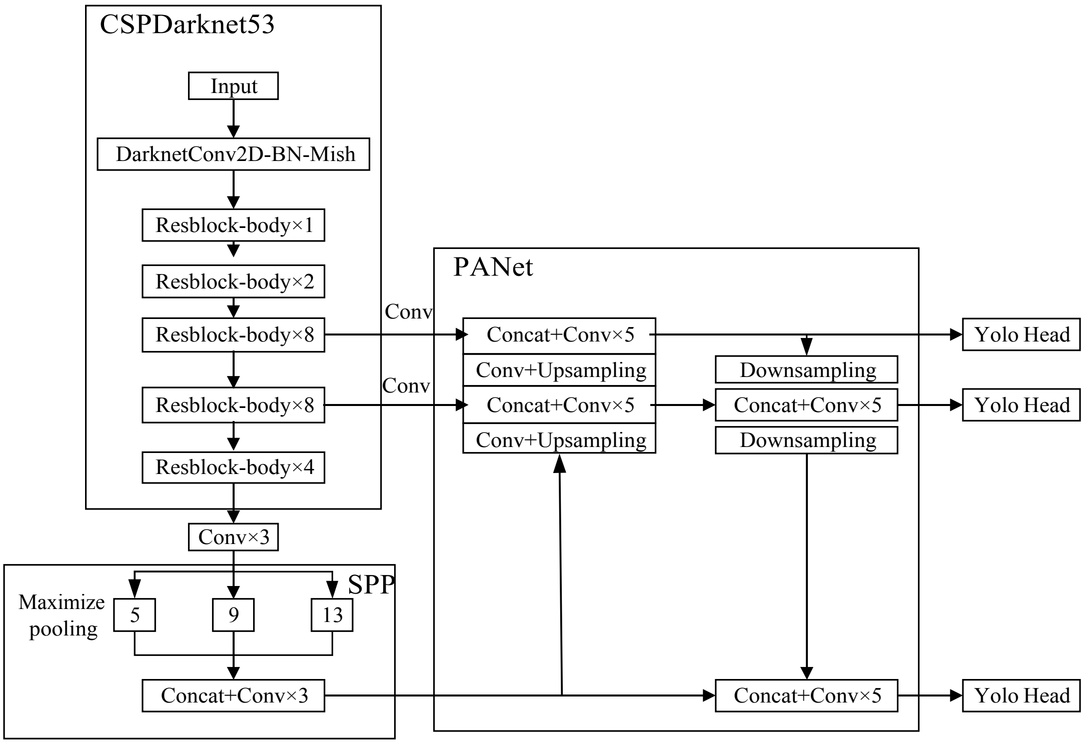

Figure 1. YOLOv4 network model

3. Dataset Producing

In this paper, a data set of E.coli colonies is made. There are 200 pictures in the data set. Each picture has multiple targets and more than 2000 targets. After the original image is denoised and enhanced, labelimg is used to label the escherichia coli on each image, and the.xml file is generated after labeling. The data set picture is shown in Figure 2 :

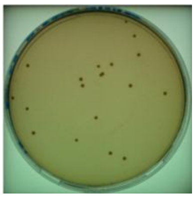

Figure 2. Dataset picture example

3.1 Limage Denoising

Common denoising methods include mean filtering, Gaussian filtering and median filtering. In this paper, median filtering is used for image denoising. Median filtering can effectively remove impulse noise and salt and pepper noise. While filtering noise, it can protect the signal at the edge from being blurred[7]. These advantages are not possessed by linear filtering methods. Median filtering is to replace the value of a point in a digital image or digital sequence with the median value of each point in a neighborhood of the point, so that the surrounding pixel value is close to the true value, thereby eliminating isolated noise points [6].The pretreatment method steps are as follows:

(1) Using a 3×3 moving window, the position of a pixel in the image coincides with the center of the template;

(2) The gray values of the center point and the eight pixels around the center point are arranged in the order from small to large (or from large to small) ;

(3) In the arranged gray sequence, select the gray value in the middle;

(4) Replace the center pixel with the intermediate gray value.

The median filtering diagram of 3×3 image is shown in Fig.3.

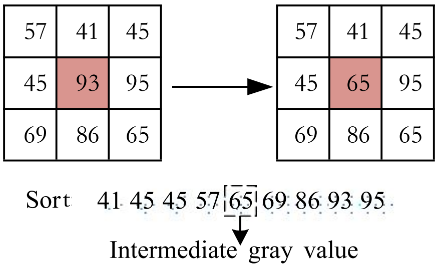

Figure 3. 3 × 3 median filtering principle

The colony images before and after denoising are shown in Figure 4(a) and(b):

(a) Colony original image (b) Colony median filter image

Figure 4. Colony denoising image

3.2 Image Enhancement

In order to improve the recognition effect, the image is enhanced by brightness enhancement, chromaticity enhancement, contrast enhancement, sharpness enhancement, gray world algorithm enhancement and automatic white balance algorithm enhancement. After six different image enhancement, to compare their enhancement effect to select the effect of good method, because people 's subjective evaluation will be affected by the environment, hobbies, mood and other factors, only by human eye observation to determine the enhancement effect is not objective. Therefore, the more authoritative objective evaluation criteria peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) are used to determine the quality of the enhancement effect. The greater the peak signal-to-noise ratio and structural similarity, the better the enhancement effect. The peak signal-to-noise ratio and structural similarity values of the six enhancement methods are shown in Table 1. By comparison, it can be seen that the image enhancement effect of sharpness enhancement is the best among the six enhancement methods.

Table 1. Image enhancement effect

Image Enhancement Method	Peak Signal to Noise Ratio	Structural Similarity
Color	25.56057	0.9984229179242176
Sharpness	41.85502	0.9943014620918109
Contrast	23.489574	0.9650536591151397
Brightness	12.518632	0.9073687562210877
Gray world	21.04358	0.9670889212885163
Automatic white balance	13.551775	0.9627287156141693

The effect of the colony image before and after image enhancement is shown in Figure 5. It can be seen that the difference between the colony target and the background is more obvious after the sharpness enhancement of the image, which is conducive to better detection of the target colony. Therefore, the sharpness enhancement method is selected to enhance the images in the data set.

(a)original colony (b) colony after sharpness enhancement

Figure 5. Comparison of image enhancement effect

4. Attention Mechanism

The attention mechanism is to find the key information we need more among the numerous input information, reduce or even filter out irrelevant information, so as to solve the problem of information redundancy, and improve the efficiency of calculation and the accuracy of the results [9]. Common attention mechanisms are SENet, ECANet, SANet, CBAM. This paper adopts CBAM attention mechanism.

CBAM attention mechanism consists of channel attention mechanism and spatial attention mechanism. The input feature map first passes through the channel attention mechanism, and the input feature map and the channel weight are multiplied to obtain a new feature map. The new feature map then passes through the spatial attention mechanism, and the new feature map of the input spatial attention mechanism is multiplied by the normalized spatial weight to obtain the final weighted feature map. The CBAM attention mechanism structure is shown in Figure 6 :

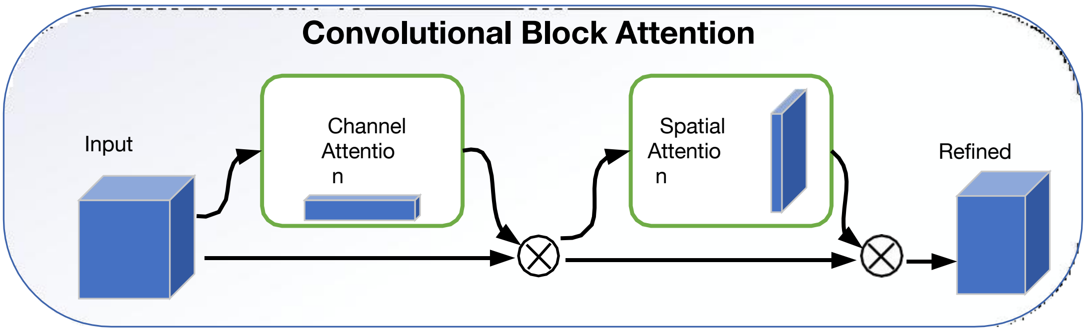

Figure 6. CBAM attention mechanism structure diagram

The YOLOv4 model structure after adding CBAM attention mechanism is shown in Figure 7 :

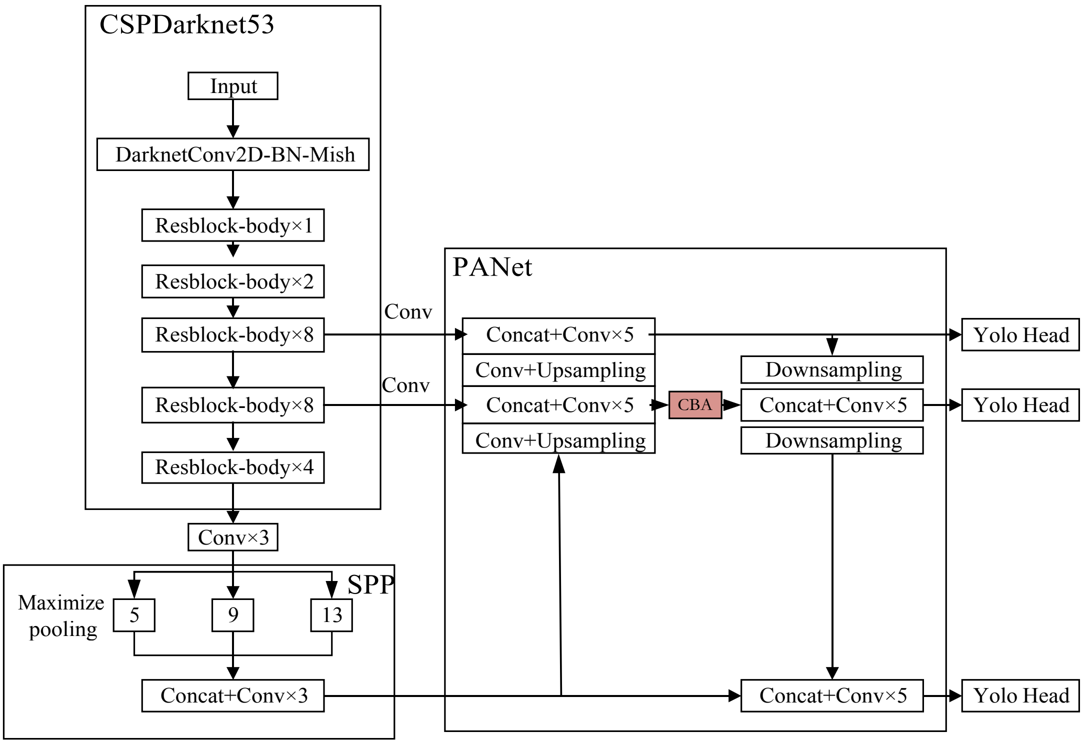

Figure 7. YOLOv4 model after adding CBAM attention mechanism

5. K-means++Clustering Algorithm

The k-means++clustering algorithm is an improvement based on the k-means clustering algorithm. The two algorithms determine the initial clustering center in different ways. The initial clustering center of the k-means clustering algorithm is randomly determined. The k-means++clustering algorithm first randomly selects a clustering center, and then calculates the distance between all points and this clustering center. The greater the distance, the greater the possibility of becoming the next clustering center. Repeat this step until k clustering centers are selected.

The specific steps are :

(1) Randomly select the first cluster center.

(2) Calculate the distance from each sample point to the existing cluster center to get the shortest distance D (x).

(3) According to the obtained distance, the probability of each sample becoming the next cluster center is calculated in formula (1).

(4) Select the next cluster center according to the probability.

(5) Repeat steps 2 to 4 until K cluster centers are extracted.

6. Analysis of Experimental Results

The recognition results of Escherichia coli are shown in Figure 8(a)(b). Figure 8(a) is the recognition result obtained by using the original YOLOv4 network training data set, and Figure 8(b)is the recognition result obtained by using the improved YOLOv4 network training data set. The red box marks the colony of Escherichia coli, Eco is the abbreviation of Escherichia coli, and the decimal number written after Eco represents the probability that the target is considered to be Escherichia coli. The identification accuracy in Figure 8(a)is mostly concentrated at 0.6 and 0.7, and it is obvious that some colonies are not identified. The recognition accuracy in figure 8(b)is mostly about 0.8, which is significantly improved compared with that before improvement, and it can be seen that the unrecognized colonies are also effectively reduced by comparison.

(a) Test results before improvement (b) Test results before improvement

Figure 8. Colony detection results

7. Conclusion

This paper presents a microbial colony recognition algorithm based on YOLOv4, which realizes the recognition of microbial colony species. Firstly, the image in the data set is denoised and enhanced to reduce the image noise and enhance the image features to improve the accuracy of image recognition. Then, the CBAM attention mechanism is introduced into the original YOLOv4 network structure to reduce the redundancy of invalid information, and the k-means++clustering algorithm is used to optimize the target anchor frame. Compared with the recognition results before improvement, the improved recognition results have been significantly improved. Compared with the artificial recognition results, the improved recognition results have high efficiency and small error. In a word, this method can effectively reduce the work intensity of inspectors without reducing the recognition accuracy, and has a very broad application prospect.

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