IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received April 25, 2022, accepted May 7, 2022, date of publication May 17, 2022, date of current version May 25, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3175818

MobileNetV3 With CBAM for Bamboo Stick Counting

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This work was supported in part by the Huzhou Public Welfare Applied Research Project under Grant 2021GZ30, Grant 2021ZD2003, and Grant 2016GY11; in part by the Scientific Research Fund of Zhejiang Provincial Education Department under Grant Y201941626; in part by NSFC under Grant 62175037; in part by the Zhejiang Provincial Key Research and Development Program under Grant 2020C02020; and in part by the Postgraduate Research and Innovation Project of Huzhou University under Grant 2022KYCX48.

ABSTRACT This study aims to solve the problems of inaccurate weighing of bamboo sticks and inefficient manual counting. To overcome this problem, an improved MobileNetV3 model and a counting algorithm suitable for bamboo sticks—combined with a spatial-temporal attention mechanism—are proposed in this paper. Inspired by the idea of EfficientNet, scaling coefficients are used to scale the MobileNetV3 network structure as a whole in terms of width and height. The optimal model for bamboo-stick recognition is screened initially, and then the algorithm uses the convolutional block attention module (CBAM) attention mechanism to replace the squeeze-and-excitation (SE) attention mechanism in the MobileNetV3 network structure to allow the network to extract features in the two dimensions of channel and space. Since the number of bamboo sticks in a single image is extremely dense—generally around 1000–3000—it is difficult to effectively count them with existing algorithms. The proposed algorithm divides the image into multiple equally sized blocks and then uses the boundary processing algorithm to merge the cut bamboo stick images and count the number of sticks. Experimental results show that the proposed algorithm can effectively perform near real-time detection on a mobile terminal and its accuracy can reach approximately 97%, which is in line with actual production applications.

INDEX TERMS MobileNetV3, dense bamboo sticks, attention mechanism, border object merger.

I. INTRODUCTION

Bamboo has excellent characteristics, such as fast growth, easy regeneration, a low carbon footprint, environmental friendliness, and complete natural degradation. Therefore, its market prospects are very broad. Currently, there are two main ways to sell bamboo sticks, each with a drawback. The first is by weight; however, the bamboo's wetness affects its weight. The second is by number; however, manual counting is time-consuming and expensive. With the widespread application of image object detection and recognition technology [1] on mobile devices [2], [3], the problems of manual counting can be solved [4]. The main difficulties of bamboo stick recognition algorithms applied to mobile terminals are the following:

(1) Counting bamboo sticks requires high recognition accuracy, and misidentification will cause unnecessary business losses.

(2) Bamboo sticks are tiny objects; therefore, each image contains a host of bamboo sticks. It is a considerable challenge to detect such dense, small objects.

By improving the lightweight MobileNetV3 [5] network, propose an image recognition method based on image object detection for the counting of dense bamboo sticks. The main contributions of the proposed method are the following.

(1) Inspired by the EfficientNet [6] network, we designed network structures with different depths and widths and obtained the network structure most suitable for bamboo stick counting.

The associate editor coordinating the review of this manuscript and approving it for publication was Li He.

(2) An attention mechanism, the convolutional block attention module (CBAM) [7], is used to focus on the channel and spatial dimensions of the feature map to further improve the recognition accuracy.

(3) The number of bamboo sticks in each image is 1000–3000, which is a large number.

Because of the relatively limited computing power of mobile phones, we split an inputted dense bamboo image into multiple small images according to the same ratio of width and height for detection, and then merge the detection results of the small images. Algorithms are used to deal with the problem of secondary detection of boundaries and effectively optimize the network structure. The method advanced in this paper is not only innovative in terms of the algorithm—which improves the recognition accuracy of the original model—but also meets practical demands.

II. RELATED WORK

As a one-time consumable, bamboo sticks have a huge market demand. In response to this situation, Xu [8] proposed an automatic counting machine for bamboo sticks, which counts by detecting the pulse signals of the bamboo sticks passing by the photoelectric sensor on the conveyor belt. However, there is a problem that a lot of equipment needs to be purchased and the real-time counting effect is poor. In order to be able to use the recognition system in mobile devices, it is necessary to further reduce the number of parameter calculations and computational complexity, and improve the lightweight network model. Qin *et al.* [9] proposed a fast down-sampling MobileNet (FD-MobileNet). By performing 32 down-sampling, the improved model is half of the original MobileNet, which greatly reduces the computational cost and improves the real-time recognition effect. Chen and Su [10] adopted a depth multiplier combined with fractional maximum pooling or maximum pooling to improve the depth separable convolution of MobileNet, which reduces the amount of calculation and improves the accuracy. Sinha and El-Sharkawy [11] proposed three MobileNet architectures, using Drop activation to replace the Relu activation function, and introducing random erasure regularization technology to replace Dropout, which not only reduces the amount of calculation, but also improves the accuracy. Wang *et al.* [12] used dense blocks in the MobileNet network to reduce model parameters and computational complexity by setting a smaller growth rate.

Small object detection has always been a problem in traditional image algorithms and convolutional neural network models. Traditional image detection algorithms have shortcomings such as poor model generalization and complex manual operation for small object detection. With the development of deep learning in recent years, the efficiency of small object detection has been significantly improved [13]. In order to solve the problem of small object detection and recognition, Li *et al.* [14] proposed to use a generative adversarial network to reduce the difference between small objects and large objects and improve the detection accuracy of small objects. Lin *et al.* [15] proposed that the feature pyramid network played a key role in small object detection. Singh and Davis [16] proposed the idea of image pyramid scale normalized SNIP, which adopted multi-size image input and selected the size of PriorBox to significantly improve the detection results of small objects. Liang *et al.* [17] proposed a dense convolutional network that horizontally connects pyramid and small object anchor points. Chen *et al.* [18] proposed a method to improve training based on data provided by feedback during training, which splices multiple small object images into a new image for training.

Some scholars have found that the attention mechanism also plays a key role in small object detection. Ran and Ren [19] used color information to guide visual attention to the most interesting areas in the image data and proposed an object detection method based on the visual attention mechanism. Jian *et al.* [20] used the SKBlock structure to expand the field of shallow feature maps and use a self-attention mechanism to improve its ability to recognize small objects. Zhang *et al.* [21] proposed to construct SEASAM attention module by utilizing the channel and spatial attention in MobileNetV3. Nie *et al.* [22] proposed a triple attention module. Jiang *et al.* [23] proposed a small object detection method combining feature fusion and spatial attention. Li *et al.* [24] proposed an adaptive attention mechanism. Wang *et al.* [25] proposed a feature stream pyramid network, which designed a feature stream based on the original FPN model and combined it with the CBAM attention module to significantly improve the accuracy of small object detection. Lim *et al.* [26] proposed a method of combining context and attention mechanisms.

III. PROPOSED METHOD

Aiming at dense bamboo stick detection, this paper proposes a bamboo stick detection method that improves the lightweight network model MobileNetV3. Sparse bamboo stick images are input into the model for training, and the model is optimized according to the experimental results. Finally, a model suitable for bamboo stick detection is developed. The dense bamboo stick image is divided into small pieces using an algorithm, and the small pieces are input into the model for detection. Finally, the detection results of the small image are merged into the original image size by the algorithm and the number of bamboo sticks is counted. The overall identification process is illustrated in Figure 1.

This study selects the lightweight network model MobileNetV3 as the basic network and uses a smaller scale scaling factor to change the channel and depth coefficients of the MobileNetV3 network. Through experimental comparison, it is finally determined that the empirical value of the Bneck channel scaling factor is 0.7, and the depth scaling factor is 1, which not only reduces the parameter operation, but also improving its accuracy. In addition, the squeeze-and-excitation (SE) module of the original MobileNetV3 network is replaced with a CBAM module, and the attention

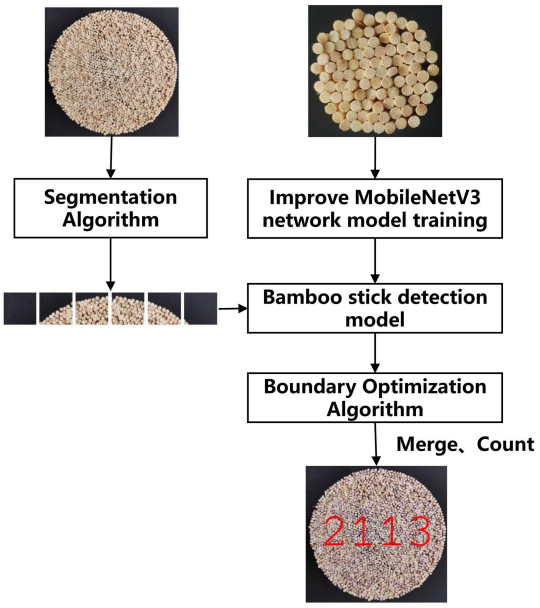


FIGURE 1. Flow chart.

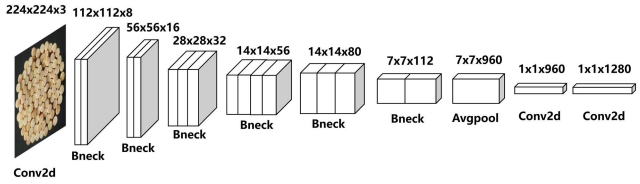


FIGURE 2. Improved MobileNetV3 network framework.

maps formed in the channel and space dimensions are superimposed, further improving the detection accuracy. The improved model is shown in Figure 2.

A. THE NETWORK STRUCTURE

Previous experimental experience has shown that for the improvement of convolutional neural networks, the focus is on the three dimensions of network depth, network width, and resolution. EfficientNet uses a series of fixed scale scaling factors to unify the dimensions of the network. Increasing the depth of the network can obtain richer features, but if the network depth is too deep, it will face the problem of gradient disappearance. Increasing the width of the network enables higher fine-grained features, but it increases the computational overhead and storage cost. This study adopts the idea of a series of fixed scale scaling coefficients to adjust the width and depth of the model. The channel value is obtained by multiplying the channel dimension by multiple factors, and an integer multiple of 8 with the smallest difference from the channel value is taken as the final channel value. The depth dimension is multiplied by a multiple and rounded up to obtain the depth value. After many comparison experiments, the channel values of the Bneck structure are finally determined to be 8, 16, 32, 56, 80, and 112, which are 0.7 times

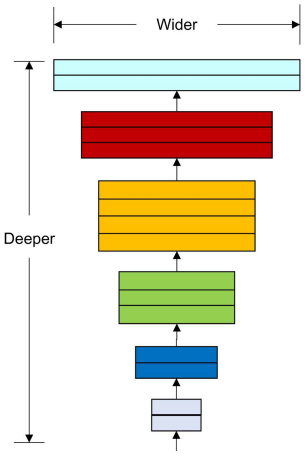


FIGURE 3. Improved Bneck compound scaling model.

that of the original Bneck structure, and the depth remains unchanged. The improved Bneck composite zoom model is illustrated in Figure 3.

B. CBAM ATTENTION MECHANISM

The Bneck structure of the MobileNetV3 network uses the squeeze and extraction modules to solve the loss problem caused by the different importance of different channels of the feature map during the convolution pooling process, however, the SE module focuses on the channel dimension of the feature map and ignores the spatial dimension of the target information. The CBAM module forms an attention map in the two dimensions of channel and space in turn, and performs element-wise multiplication operations on the attention map and the input feature map of the respective dimensions. The extracted target features are more comprehensive and have higher accuracy. Compared with the SE module, the channel attention mechanism module of CBAM [27] has more parallel global max pooling layers, and different pooling operations can extract richer high-level features [28], [29]. The Bneck structure in the bamboo stick recognition model performs dimension upgrade and deep convolution on the number of input channels and inputs the feature F obtained by the deep convolution into the channel attention module of CBAM to obtain the channel feature.

The feature F obtained by the deep convolution and the channel feature are multiplied bit by bit to obtain the feature F', which is input to the spatial attention module to obtain the spatial feature. The channel feature F' and the spatial feature are multiplied bit by bit to obtain the final feature F'', which is subjected to linear point-by-point convolution. Figure 4 shows the structural diagram after adding CBAM to the Bneck structure of MobileNetV3.

C. SEMANTIC GUIDANCE STRUCTURE

The counting process for dense bamboo sticks is illustrated in Figure 5. Before inputting the trained model, the dense bamboo stick data with labels needs to be processed. According

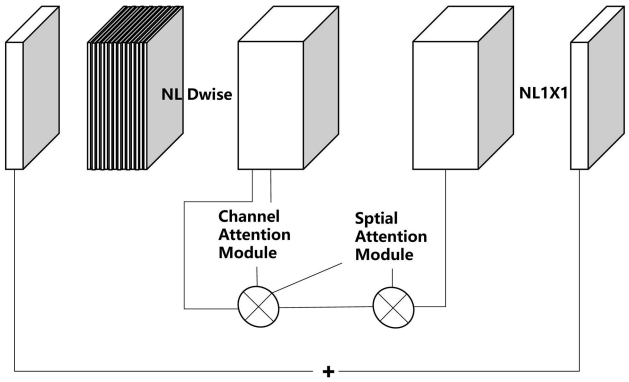


FIGURE 4. The structure diagram of MobileNetV3's Beck structure after adding CBAM.

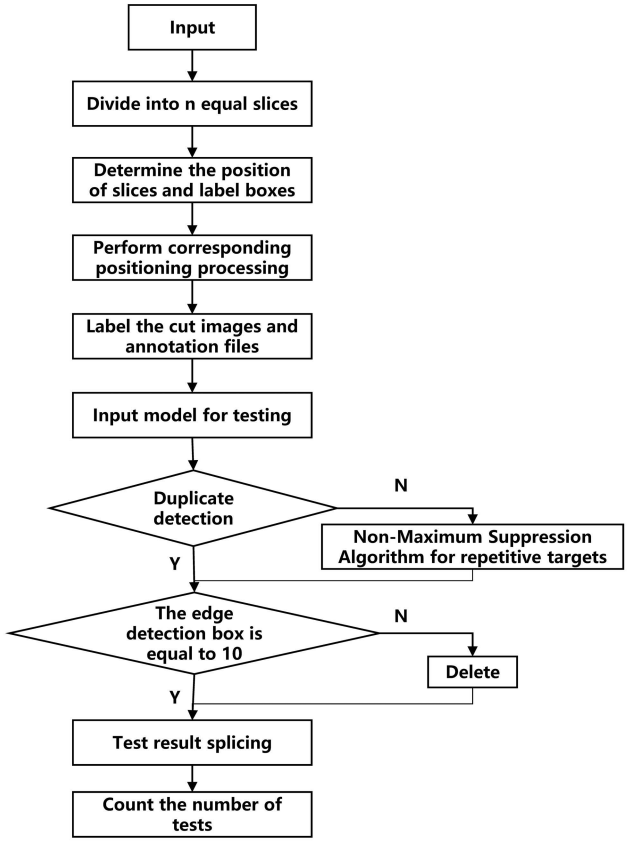


FIGURE 5. Dense bamboo stick identification process.

to the width and height of the image to be sliced, the required slice size for partition into N equal parts is calculated.

formula (1) is used to calculate the slice width W_1 and height H_1, where W is the width and height of the original image, N is the number of divisions. The height is the same.

$$W_1 = \frac{W}{N} \tag{1}$$

Sliding the slice from left to right and from top to bottom to cut the image. During the slicing process, the 9 kinds of situations that appear in the label box and the slice (the label box is in the upper left corner, lower left corner, upper right corner, lower right corner, right top, right bottom, right-left, right and center of the slice) are analyzed. Figure 6 shows the position of the label box at the upper left corner of the slice.

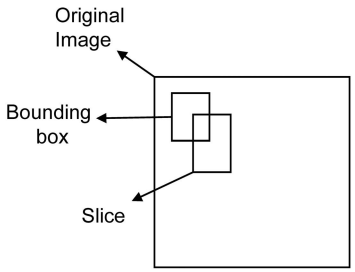


FIGURE 6. The positional relationship between the label box and the slice.

Determine whether the upper left corner and lower right corner of the object point are in the slice area. For example, if the upper left corner and lower right corner of the object point are in the slice area at the same time, it is judged as the center position, the other positions are the same. Then recalculate the x_{min}, y_{min}, x_{max} and y_{max} of the label box on the cut image. If the object point is at the center of the new image after cutting, the new image x_{min} is the original image x_{min} minus the slice x_{min}, the new image x_{max} is the new image x_{min} plus the original Figure x_{max} minus x_{min}, the other points are the same. Discard the box with too small cutting. When performing the last slice of each row and column, the width and height of the original image are used to subtract the slice size, the overflow part is adjusted. The non-maximum suppression algorithm is used to deal with the repeated calculation of the object in the repeatedly cut region.

The cut image and its corresponding label file are input into the model for detection. For the problem that a bamboo stick is repeatedly detected at the edge of the cut image, analyze the x_{min}, y_{min}, x_{max} and y_{max} sizes of the edge detection frame of the cut image. Compared with the size of the normal image detection frame, it is concluded that the edge detection frame with $(x_{max} - x_{min}) < 10$ or $(y_{max} - y_{min}) < 10$ needs to be eliminated in the detection process.

We set the number of rows and columns according to the number of divisions, paste the detection results from left to right and top to bottom according to the image labels, process the overlapping images through an algorithm, and finally get the original size image, and calculate all bounding boxes. Count and display to the center of the screen, the counting result of the dense bamboo stick image is shown in Figure 7.

IV. TRAINING

A. THE NETWORK STRUCTURE

The experimental data in this paper comes from the bamboo sticks provided by farmers who sell bamboo in Anji. We randomly grab less than 100 bamboo sticks and bundle them together. The heights of 5cm, 10cm, 15cm, and 20cm were taken from the front and left and right inclination to take

FIGURE 7. Bamboo stick count result.

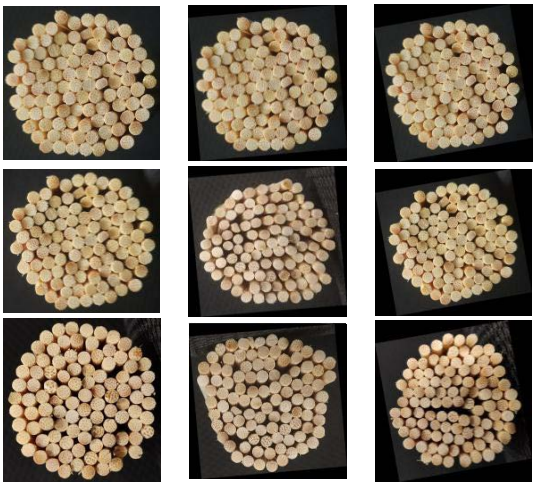


FIGURE 8. Sparse bamboo stick image sample.

pictures, screen clear and effective experimental data, and then use labelimg software to label them. The sparse bamboo stick samples collected were 600. Basic image processing techniques such as cropping and flipping process some data to obtain 700 samples to form a sparse bamboo stick sample set, and then randomly divide the image data into a training set and a validation set according to a ratio of 5:1. The sparse bamboo stick sample set is shown in Figure 8 shown.

In the model testing process, the dense bamboo stick images taken from the front of each bundle of bamboo sticks with a diameter of about 15cm were used. Since the diameter of each bamboo stick varies, the range of each bundle of bamboo sticks is about 1000-3000. Figure 9 shows sample data of dense bamboo stick images.

B. HYPERPARAMETER SETTING

The method in this study is based on the MobileNetV3 network in the open-source TensorFlow Object Detection API Model 2.0, the experimental environment is Linux, the

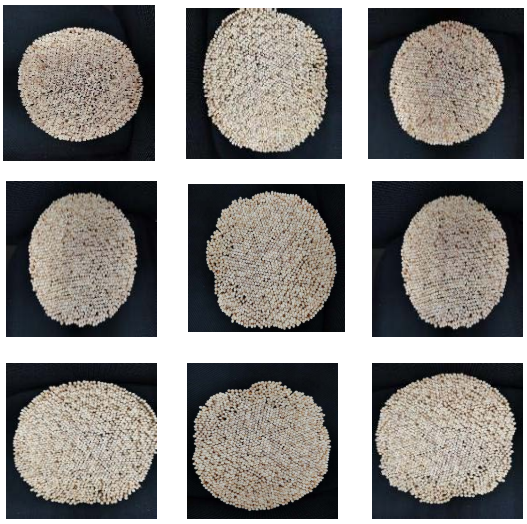


FIGURE 9. Dense bamboo stick image sample.

TITAN RTX GPU is used for training. When training based on the improved MobileNetV3 bamboo stick recognition system, some parameters are set as follows: Batch_size is 64, the learning rate of 2000 steps before training is 0.001, the learning rate afterward is 0.004, the IOU threshold is 0.5.

C. EXPERIMENTS AND RESULTS

The MobileNetV3 model is directly trained with dense bamboo stick images. After multiple down-samplings, the images are aggregated into a point on a deep feature map, which makes the model indistinguishable, and the experimental effect is extremely poor. The average precision (AP) only reaches 1%, and training cannot be performed. Therefore, we propose the use of sparse and clear bamboo stick images to train the original MobileNetV3 model, which obtains a suitable bamboo-stick detection model. Then, a cutting of dense bamboo stick images experiment was conducted to select the optimal number of cut copies. Finally, the optimal bamboo-stick detection model was obtained by optimizing the original model.

The rotated sparse bamboo-stick images were unified into a single image with a size of 320 $\times$ 320 pixels, and the data volume was further expanded through random clipping and horizontal flipping during model training to improve the model's generalization ability. Herein, we compare the recall rate, average accuracy, and detection quantity of each dense bamboo-stick image by cutting the dense bamboo skewers into 25 and 36 equal parts after boundary optimization. The experimental results show that the recall rate of 36 slices is improved by 10.24% compared with 25 slices, and the average accuracy increased by 8.59%. In addition, considering the subsequent merge boundary and error between the detection and actual numbers, it is determined that the dense bamboo-stick image is divided into 36 equal parts, as shown in Table 1.

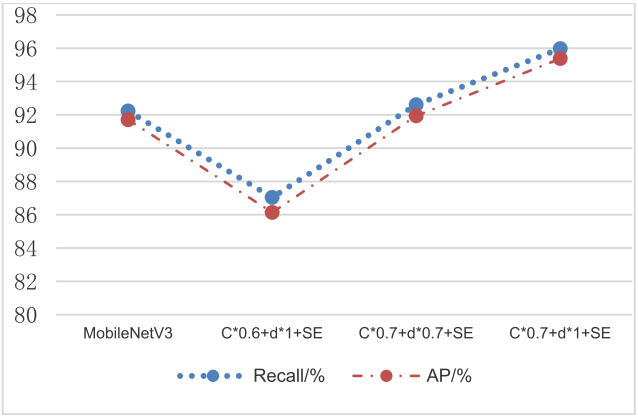
This approach combines the idea of calculating a series of scaling coefficients with EfficientNet, and concludes that a

TABLE 1. Comparison of detection results of dense bamboo stick segmentation.

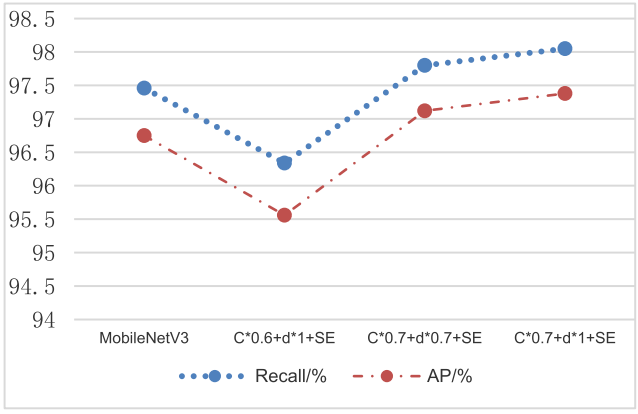
Model	Recall/%	Ap/%	Actual Number	Detected Number
MobileNetV3 (25)	78.90	78.71	1840	1513
	74.76	74.65	1760	1368
	89.50	89.31	1700	1597
	76.38	76.12	1800	1448
	92.33	91.62	1248	1262
	84.76	84.46	1752	1569
	75.54	75.23	1765	1376
	85.93	89.66	1755	1609
	89.95	96.70	2045	1907
MobileNetV3 (36)	**92.23**	**91.71**	**1840**	**1782**
	93.06	**92.79**	**1760**	**1725**
	92.79	**92.04**	**1700**	**1692**
	91.44	**90.12**	**1800**	**1806**
	92.21	**91.54**	**1248**	**1287**
	91.96	**91.06**	**1752**	**1759**
	93.66	**93.09**	**1765**	**1742**
	94.87	**94.03**	**1755**	**1847**
	98	**97.38**	**2045**	**2115**

series of scaling coefficients of the Bneck structure in the MobileNetV3 model are as follows: width coefficient 0.6 combined with depth coefficient 1, width coefficient 0.7 combined with depth coefficient 1, width coefficient 0.7 combined with depth coefficient 0.7. The idea of dichotomy is then adopted to select coefficients from the two aspects of width and depth, and the recall rate and average precision of the worst and best dense bamboo stick images collected are compared. The experimental results are shown in Figure 10, in which c is the width of the model and d its depth. When the Bneck structure scaling factor selects a width factor of 0.7 combined with a depth factor of 1, in the case of poor image quality (a), compared with the original MobileNetV3 model, the recall rate is increased by 3.75%, and the accuracy is increased by 3.67%. In the case of good image quality and good original model recognition accuracy (b), the recall rate and average accuracy are improved by approximately 0.5%; this is enough to prove the effectiveness of the Bneck scale scaling factor in bamboo-stick detection and recognition proposed in this paper.

In this paper, the CBAM spatial-temporal attention module is integrated into the Bneck structure of the MobileNetV3 model, and feature extraction is carried out in channel and space dimensions. By comparing the original MobileNetV3 model (designated model 1), MobileNetV3 with a scaling factor of 0.7 combined with a depth factor of 1(2), MobileNetV3 combined with CBAM model (3), MobileNetV2 model (4), and ResNet101 model (5). This paper proposes comparisons of the MobileNetV3 model combining the CBAM and a width scaling factor of 0.7 combined with a depth factor of 1 (6). The experimental results shown in Figure 11 show that the MobileNetV3 model combined with CBAM and scaling



(a) Analysis of detection results in case of poor image quality



（b）Analysis of detection results when the image quality is good

FIGURE 10. Comparative analysis of different scale scaling factors with original MobileNetV3.

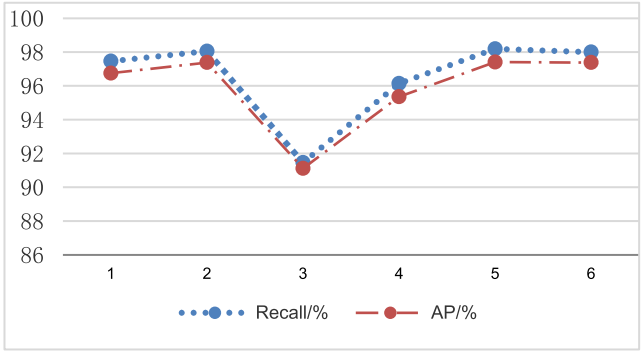


FIGURE 11. Comparative analysis of different models.

TABLE 2. The time it takes for different models to detect an image.

Model	Time/s
1	0.905
4	1.616
5	1.314
6	**1.329**

coefficients has a higher recall rate and average precision than other models, and the number of bamboo sticks detected is closer to the actual number.

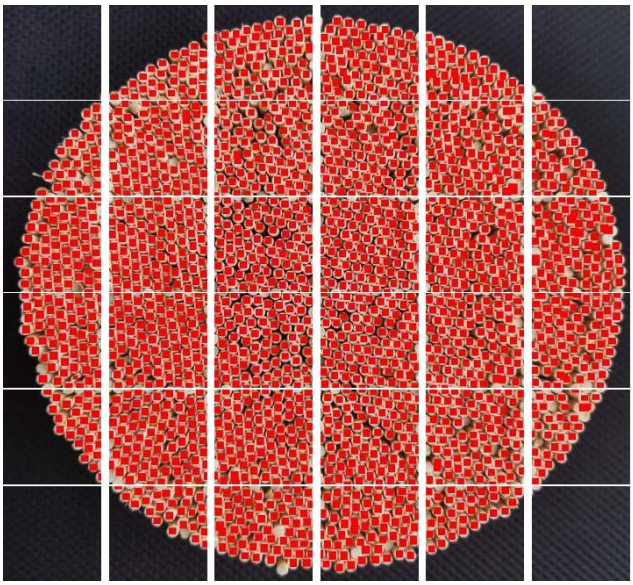


FIGURE 12. Segmentation detection result.

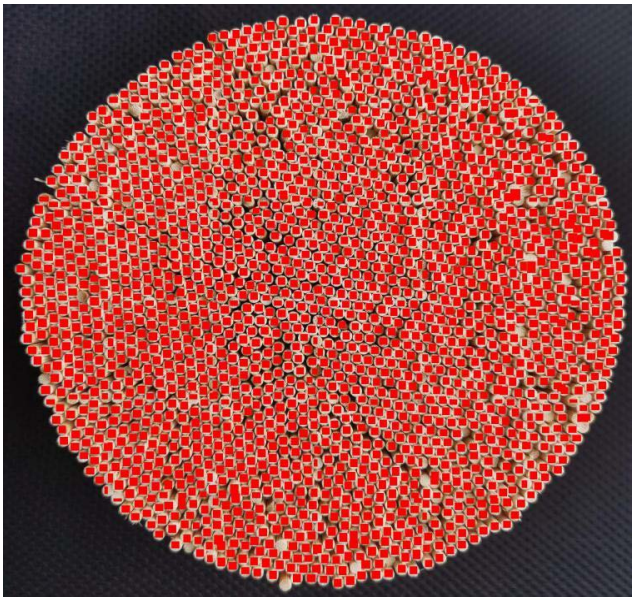


FIGURE 13. Intensive image detection results.

Table 2 shows the time it takes for the original MobileNetV3 model (1), the MobileNetV2 model (4), the ResNet101 model (5), and the model proposed in this paper (6) to detect an image. The detection speed of the model proposed in this paper reaches 1.329/s.

Comparing the results of counting dense bamboo-stick images obtained using models 1–6, this paper proposes that the Bneck structure scale coefficients are selected as a width coefficient of 0.7 and depth coefficient of 1. Combined with the CBAM and compared with the original MobileNetV3 model, the results are improved by 4.52% under the conditions of shooting light interference and arbitrary binding

TABLE 3. Test results of different models.

Model	Recall/%	Ap/%	Actual Number	Detected Number
MobileNetV3	92.23	91.71	1840	1782
C*0.6+d*1+SE	87.04	86.14	1840	1767
C*0.7+d*0.7+SE	92.61	91.94	1840	1823
C*0.7+d*1+SE	95.98	95.38	1840	1912
C*1+D*1+CBAM	97.11	96.29	1840	1974
MobileNetV2	86.66	86.52	1840	1639
ResNet101	88.81	88.39	1840	1717
C*0.7+d*1+CBAM	**94.05**	**93.46**	**1840**	**1879**
MobileNetV3	93.06	92.79	1760	1725
C*0.6+d*1+SE	85.28	84.74	1760	1624
C*0.7+d*0.7+SE	92.89	92.61	1760	1718
C*0.7+d*1+SE	94.36	94.04	1760	1765
C*1+D*1+CBAM	94.87	94.55	1760	1783
MobileNetV2	86.97	86.87	1760	1566
ResNet101	91.99	91.74	1760	1663
C*0.7+d*1+CBAM	**95.26**	**94.94**	**1760**	**1760**
MobileNetV3	94.87	94.03	1755	1847
C*0.6+d*1+SE	95.81	95.04	1755	1860
C*0.7+d*0.7+SE	96.25	95.59	1755	1885
C*0.7+d*1+SE	97.3	96.53	1755	1881
C*1+D*1+CBAM	97.24	96.44	1755	1885
MobileNetV2	87.7	87.31	1755	1628
ResNet101	93.05	92.49	1755	1757
C*0.7+d*1+CBAM	**97.57**	**96.73**	**1755**	**1863**
MobileNetV3	91.44	90.12	1800	1806
C*0.6+d*1+SE	90.3	89.12	1800	1797
C*0.7+d*0.7+SE	92.74	91.79	1800	1823
C*0.7+d*1+SE	93.33	92.39	1800	1841
C*1+D*1+CBAM	94.36	93.28	1800	1858
MobileNetV2	87.53	86.98	1800	1664
ResNet101	92.25	91.51	1800	1782
C*0.7+d*1+CBAM	**93.93**	**92.86**	**1800**	**1828**
MobileNetV3	92.79	92.04	1700	1692
C*0.6+d*1+SE	83.95	83.29	1700	1541
C*0.7+d*0.7+SE	94.43	93.89	1700	1706
C*0.7+d*1+SE	94.43	93.8	1700	1744
C*1+D*1+CBAM	98.3	97.57	1700	1837
MobileNetV2	87.52	87.37	1700	1523
ResNet101	82.02	81.55	1700	1466
C*0.7+d*1+CBAM	**97.31**	**96.57**	**1700**	**1712**
MobileNetV3	97.46	96.75	2045	2088
C*0.6+d*1+SE	96.34	95.56	2045	2206
C*0.7+d*0.7+SE	97.8	97.12	2045	2098
C*0.7+d*1+SE	98.05	97.38	2045	2088
C*1+D*1+CBAM	98.19	97.41	2045	2118
MobileNetV2	91.46	91.12	2045	1927
ResNet101	96.14	95.36	2045	2087
C*0.7+d*1+CBAM	**98**	**97.38**	**2045**	**2115**

shape. The difference between the detected and actual quantities is within 1%. When the dense pictures were clear and the bundles relatively neat, test results reached 97.38% accuracy. The experimental results are shown in Table 3, c represents the width of the model, and d represents the depth of the model. The results of segmentation detection in this paper are shown in Figure 12. The results of dense bamboo sticks are shown in Figure 13.

V. CONCLUSION

In this paper, a lightweight network model is constructed for the implementation of dense bamboo-stick counting on mobile terminals. The divide-and-conquer concept is adopted to solve the problem that it is difficult to directly extract effective features from dense bamboo-stick images. Experimental verification shows that it is very clear that the number of model detections is close to the actual number. Herein, we propose a Bneck scaling factor suitable for the bamboo-stick detection task that not only reduces the amount of the model's parameter calculations but also further improves the accuracy of bamboo-stick detection. The proposed algorithm integrates a spatial-temporal attention mechanism to replace the original model channel attention mechanism, extracts more effective features, and further reduces the counting error of dense bamboo sticks, providing new ideas for future research directions.

Compared with existing bamboo-stick counting methods, the proposed method greatly improves the real-time efficiency of dense bamboo-stick counting, and it has the advantages of low cost, simple maintenance, and convenient operation compared with large-scale, photoelectric-sensor-based counting equipment. It provides a new technology for promoting the automation of and building intelligence into the bamboo industry. In future work, it will be necessary to further optimize the errors that are difficult to eliminate in the cutting edge detection of dense bamboo-stick images, and further improve the accuracy of dense bamboo-stick recognition. In planned follow-up work, we will collect more samples in actual production and apply the research results to actual bamboo stick production.

ACKNOWLEDGMENT

(Liangquan Jia and Yawen Wang are co-first authors.)

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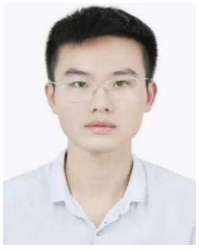

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