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RESEARCH ARTICLE

Wood Surface Defects Detection Based on the Improved YOLOv5-C3Ghost With SimAm Module

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ABSTRACT The detection of defects in wood is valuable for promoting the efficient exploitation of wood. So it is significant to further increase the accuracy of the detection of wood defects and enhance the real-time detection. In this paper, the YOLOv5 convolutional neural network is applied to wood defects detection, and the model is modified for both the YOLOv5n and YOLOv5m scales. The SimAM attention model was first incorporated into the network, and the learning rate decay strategy was replaced with CosLR, with Ghost convolution employed to minimize the model parameters. Finally, the modified network was tested for five types of wood defects, including live-knot, resin, dead-knot, knot-with-crack, and crack. It is demonstrated that the improvements resulted in a 1.5% increase in $mAP_{0.5:0.95}$ for YOLOv5n-C3Ghost and a 1.6% increase in $mAP_{0.5:0.95}$ for YOLOv5m-C3Ghost. In addition, there is a 51% and 63% difference in the number of model parameters, and a decrease in inference time and floating point operations respectively. The experiments indicate that our improved method not only enhances the accuracy of YOLOv5 in detecting wood defects, but also enables a reduction in the volume and computational cost of the model parameters.

INDEX TERMS Wood defects detection, convolutional neural networks, YOLOv5, SimAM.

I. INTRODUCTION

As the vast majority of carbon in terrestrial ecosystems, forests perform a distinctive and essential role in lowering the concentration of greenhouse gases in the atmosphere and mitigating global warming. With high toughness, low thermal conductivity, rich color and grain tones, aesthetics, accessibility, and biodegradability, wood is an environmentally friendly natural material [1]. In recent years, the function of forest resources has turned from timber usage to ecological conservation, and such a transition has inhibited wood supply [2]. However, the raw wood material is invariably subject to various defects such as knots, cracks, mold and decay due to natural, external or biological factors. Such defects impair the appearance of the wood as well as the quality of the wood product and considerably shorten its service life. Consequently, it is necessary to identify defects in wood during manufacture and to remove the defective parts in time to facilitate the efficiency of the wood. Distinctive faults in timber vary in appearance and they can be identified visually. However, manual visual inspection often requires a certain amount of experience and high labour costs. It also causes worker fatigue when there is a high volume of timber, which makes inspection inefficient [3]. Novel techniques are required to replace manual labour in order to achieve accurate and rapid identification of timber defects when processing timber, to optimize timber utilization and to reduce timber inspection costs.

Based on the above requirements, a large amount of research on visual wood defect detection has emerged. Traditional machine learning methods include Support vector machine (SVM), grayscale co-occurrence matrix, convex optimization, Back propagation (BP) neural network, etc [4]. Xiang et al. combined Local binary patterns (LBP) with wavelet transform to detect wood defects, and the accuracy of recognition results for cracks, live knots, and dead knots were over 90% [5]. Gu et al. used an improved support vector machine to classify four types of wood knot defects, and the average accuracy could reach over 96.5% [6]. Zhang et al. used principal component analysis (PCA) and crush sensing

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to process wood images, which not only improved the accuracy of detection but also improved the accuracy of detection [7]. Despite the good accuracy of traditional machine learning for defect classification, it suffers from the need for complex manual feature extraction and sophisticated classifier design, and the recognition accuracy still needs to be raised.

In recent years, Convolutional neural networks have made deep learning the mainstream of computer vision, with the advantages of automatic feature extraction and simple classifier [8], [9]. Yang et al. used a combination of deep learning feature extraction method and Extreme learning machine (ELM) classification method to fabricate a deep extreme learning machine model, and the average accuracy of identifying three defects reached 96.72% with a test time of 187 ms [10]. He et al. proposed a mix full convolutional neural network (Mix-FCN) to detect six defects, and the detection accuracy could reach 99.14% [11]. Gao et al. designed a BLNN network structure, and the classification accuracy of four wood knot defects could reach 99.20% [12]. Hu et al. employed progressive adversarial generative network to enhance the dataset, and followed by Mask R-CNN networks to identify three types of defects [13]. The above wood defects classification methods are highly accurate, but they can only classify single defects images and do not facilitate detection of wood with multiple target defects.

With the development of target detection frameworks, such as Faster R-CNN, SSD, and YOLO networks, computers can automatically locate the location of wood defects on pictures with multiple targets while making judgments about their categories. Urbonas used the Faster R-CNN network migration learning approach to locate and classify wood defects [14]. Ding et al. [15] and Yang et al. [16] detect wood defects by improving the SSD network and achieve good results. Wang et al. improved YOLOv3 by adding GridMask and GhostBlock to the network to increase the detection capability of wood defects [17]. However, the target detection network still has problems such as many parameters and complex models, which make the computer consume more computational resources and take longer time to perform training and detection.

The target detection network of YOLO series has been characterized by the one stage, which generates the location information and category information of the target directly using the features extracted by backbone [18]. YOLOv5 is the fifth generation of YOLO series, which has the advantages of small network model, fast inference and high detection accuracy, and has been applied to many fields [19], [20].

In this paper, the YOLOv5 convolutional neural network is refined by substituting Ghost convolution for conventional convolution, adding a cosine annealing learning rate decay strategy, and incorporating a SimAM attention mechanism model. The improved network provides higher accuracy on the one hand and reduces the number of parameters of the model on the other.

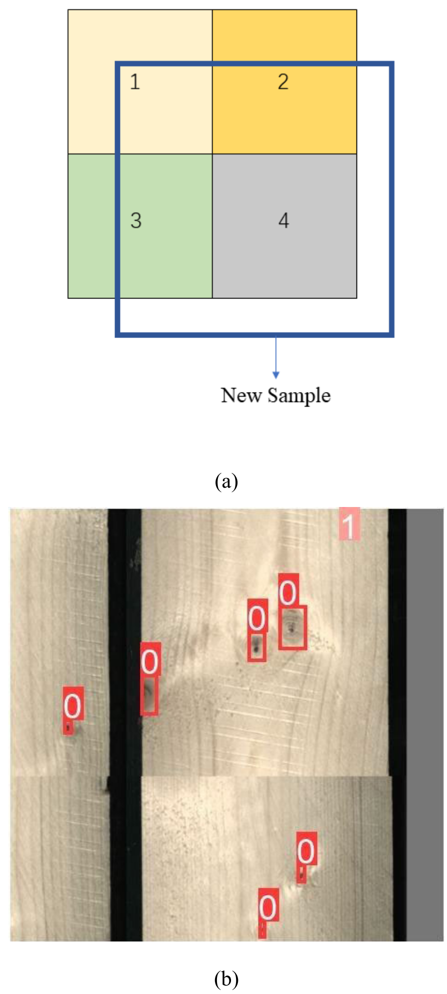


FIGURE 1. Principles and results of the mosiac operation. (a) Principles. (b) Results.

TABLE 1. Our wood defects dataset.

Dataset (640*640)	Number (Images)	Category	Number (Category)
Train	3057	Live knot	2847
		Resin	2624
Val	1086	Knot with crack	1835
Test	1086	Dead knot	2033
		Crack	1578

II. METHODOLOGY

A. ACQUISITION AND PRE-TREATMENT OF WOOD SAMPLES

The wood defects detection dataset in this paper was obtained from a public web dataset [21]. This dataset contains a total of 5429 images covering 10944 defects in 5 categories including live knot, resin, dead knots, knots with crack and crack. The size of the image is 640 × 640. Each image features several different wood defects, and Table 1 presents the number of

TABLE 2. Different parameters of YOLOv5n and YOLOv5m.

Model	YOLOv5n		YOLOv5m	
	Channels (in, out)	n	Channels (in, out)	n
Conv K=6,S=2	3,16	1	3,48	1
Stage1	16,32	1	48,96	2
Stage 2	32,64	2	96,192	4
Stage 3	64,128	3	192,384	6
Stage 4	128,256	1	384,768	2

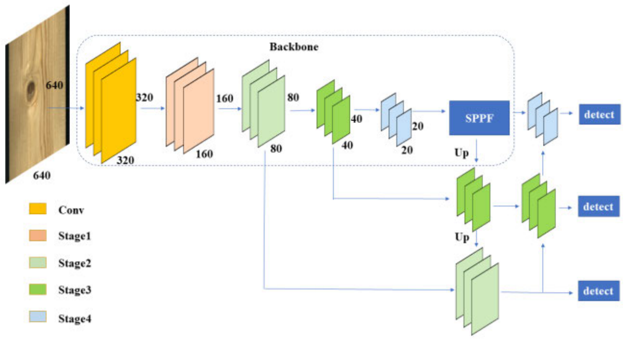
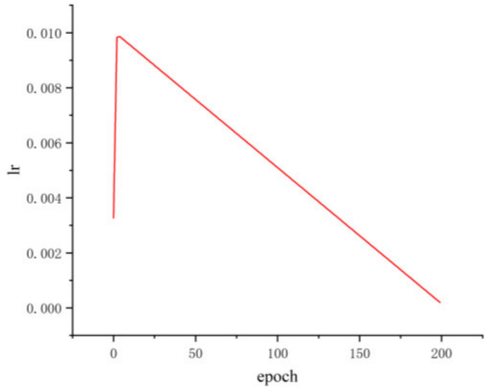


FIGURE 2. General framework of the original YOLOv5 algorithm. Original YOLOv5.

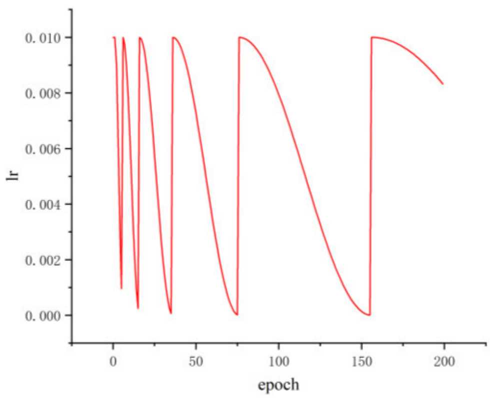
these five defects. The images in the dataset are divided into a training set, a validation set and a test set in a ratio of 6:2:2.

The Mosiac operation was implemented into the data preprocessing process. As shown in FIGURE 1 (a), the Mosiac operation is performed by randomly selecting 4 images from a batch, and then casually cropping, scaling and stitching these 4 images. The brightness and contrast of these 4 images are also stochastically altered when stitched together. Finally, the randomly misaligned portion of the intercept using the Mosiac template is taken as the input sample for the network. FIGURE 1(b) displays the results of the Mosiac operation, which increases the diversity of the input dataset, improves the richness of the samples and enhances the network's detection of small sample targets.

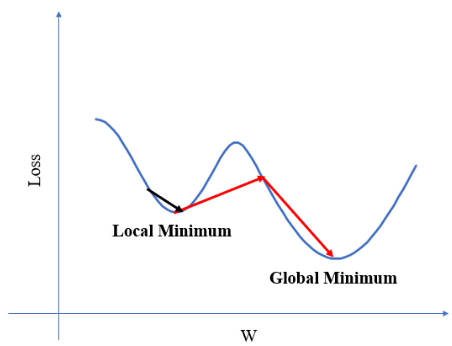
YOLOv5 is a first-order target detection model, proposed by Lenn Jocher in 2020. In FIGURE 2, the backbone network of YOLOv5 adopts DarkNet53 and SPPF. The neck network employs a combination of FPN and PANet. The detection heads of three sizes can predict targets at three scales, large and small on the feature mAP. The model of YOLOv5 is available in several different sizes by altering the depth parameter and the width parameter of the network. The larger the model size, the more complex the structure and the higher the accuracy, but at the same time the more resources the computation consumes. Therefore, considering the performance of the experimental apparatus, this paper chooses to experiment and refine on YOLOv5n and YOLOv5m. Table 2 illustrates the number of channels and modules of backboon for YOLOv5n and YOLOv5m. The width parameter of YOLOv5n is 0.25, the depth parameter is 0.33, and the number of parameters is 1.7 M. The width parameter of YOLOv5m is 0.75, the depth parameter is 0.67, and the number of parameters is 19 M.



(a) Linear decay strategy



(b) CosLR



(c) CosLR principle

FIGURE 3. Linear decay strategy and CosLR.

B. IMPROVED YOLOv5 NETWORK

1) COSLR

FIGURE 3(a) displays the learning rate decay strategy adopted by the original YOLOv5, which combines linear learning rate decay and preheating. In this experiment, cosine annealed learning rate (CosLR) learning rate decay was availed. In FIGURE 3(b), cosine annealing is carried out

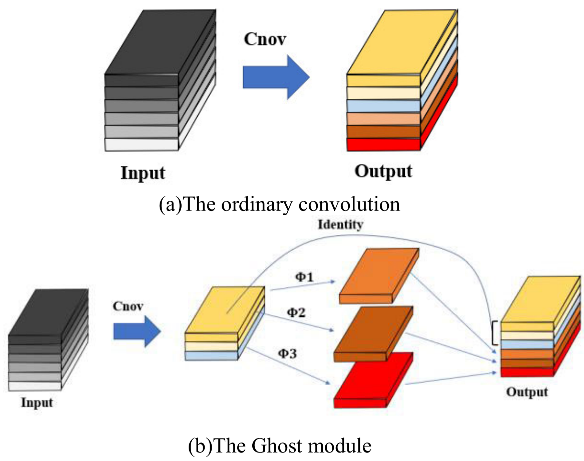


FIGURE 4. The ordinary convolution and the ghost module.

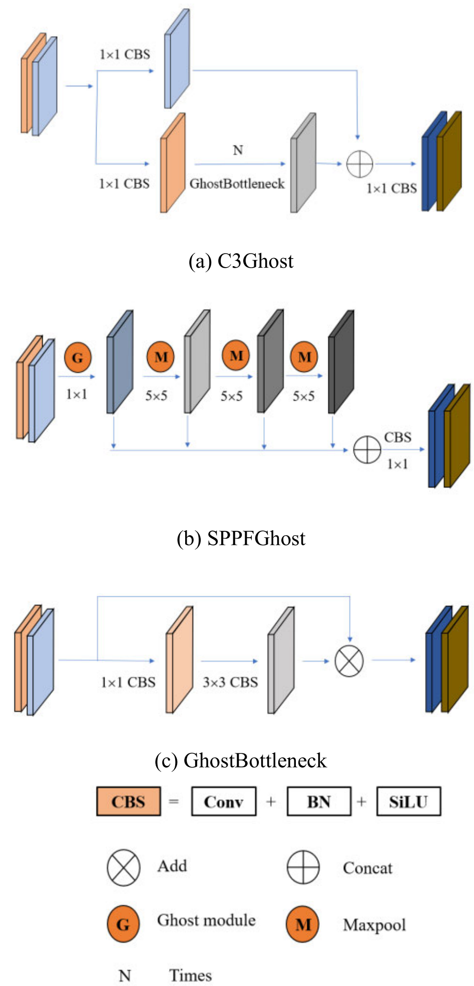


FIGURE 5. Some module structure of the improved YOLOv5.

by learning rate decay using a quarter-cycle of the cosine function. It is difficult to find the optimal solution when the learning rate decays to a small level if the network falls into a local minimum when solving the loss function. Therefore, a sudden increase in the learning rate when falling into a local minimum can cause the loss to jump out of the local minimum and thus continue the search for the global optimal solution. In this experiment, the growth frequency of cosine annealing is varied. The initial period is 5 epochs with a growth rate of 2. The epochs with the highest learning rate are 5, 15, 35, 75 and 155.

2) GHOST MODULE

The Ghost module featured in GhostNet by Han et al. reduces the number of parameters of the model [22]. It is showed in FIGURE 4 The Ghost module starts with a 1x1 convolution kernel to downscale the input feature maps to 1/2 the number of channels, and then convolves it with a group equal to the number of channels. Finally, the feature maps of the two convolutions are concatenated to obtain the feature maps with the number of channels equal to the initial input. As shown in FIGURE 5.5, the C3 module and SPPF module of Yolov5 are replaced with C3Ghost and SPPFGhost modules in this experiment.

3) SimAM ATTENTION MODEL

In FIGURE 6, Channel attention and Spatial attention focus on 1-dimensional and 2-dimensional relations, while SimAM attention can focus on 3-dimensional attention relations [23]. SimAM attention does not require additional training parameters and uses the energy function E to calculate the relationship between the target pixel point and the surrounding pixels. Equation 1 is the energy function, where t is the target neuron and λ is a constant, while μ and σ^2 are the mean and variance of the target neuron removed within this channel. In Equation 2, the energy function is converted to pixel weights using the sigmoid function, and a range of value restrictions is taken.

$$E = \frac{4(\sigma^2 + \lambda)}{(t-\mu)^2 + 2 + 2\lambda} \tag{1}$$

$$\tilde{X} = sigmoid(\frac{1}{E}) \odot X \tag{2}$$

III. DISCUSSION

For the evaluation of network models in this paper, the metrics are mean accuracy ($mAP_{0.5:0.95}$), parameters (Params), time and floating point (FLOPs). The $mAP_{0.5:0.95}$ is the average accuracy computed for all defect classes at an IOU threshold of 0.5 : 0.95. Params is the number of weighted parameters of the network. Time is the average inference time of the model. FLOPs is the number of floating point operations consumed by the model in operation. The following is the solution process for $mAP_{0.5:0.95}$.

$$P = \frac{TP}{TP + FP} \tag{3}$$

$$R = \frac{TP}{TP + FN} \tag{4}$$

TABLE 3. Evaluation metrics of improved YOLOv5n.

Methods	SimAM	CosLR	Ghost	$mAP_{0.5:0.95}$ (%)	Params (M)	Time (ms)	FLOPs (G)
YOLOv5n				41.8	1.68	1.3	4.1
+SimAM	√			43	1.68	1.6	4.1
+CosLR		√		42.7	1.68	1.3	4.1
+SimAM+CosLR	√	√		**43.7**	1.68	1.6	4.1
Authors	√	√	√	43.3	**0.82**	**1.4**	**2.4**

TABLE 4. Evaluation metrics of improved YOLOv5m.

Methods	SimAM	CosLR	Ghost	$mAP_{0.5:0.95}$ (%)	Params (M)	Time (ms)	FLOPs (G)
YOLOv5m				43.6	19.90	5	47.9
+SimAM	√			44.5	19.90	5.4	47.9
+CosLR		√		45.2	19.90	4,9	47.9
+SimAM+CosLR	√	√		**45.9**	19.90	5.3	47.9
Authors	√	√	√	45.2	**7.46**	**4.8**	**19.4**

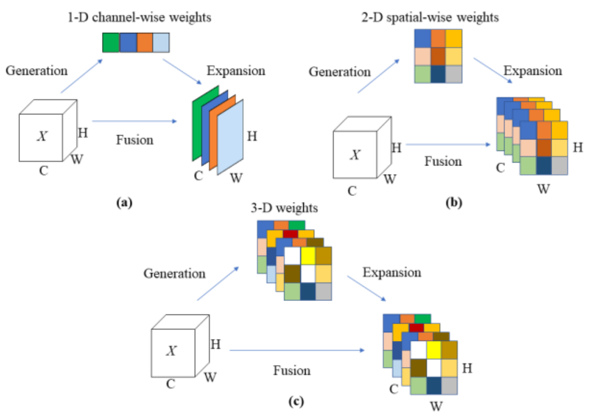


FIGURE 6. Comparisons of different attention module. (a) Channel-wise attention. (b) Spatial-wise attention. (c) SimAM.

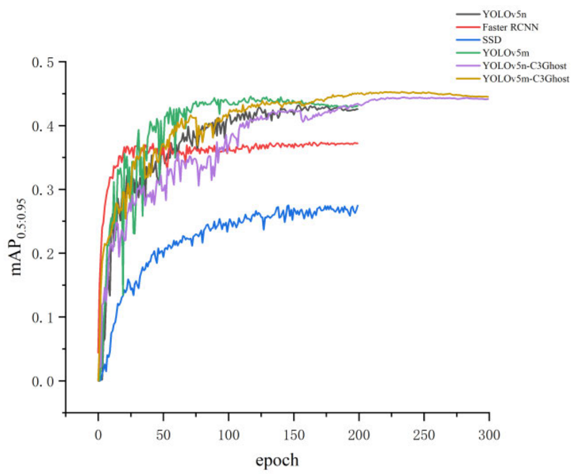


FIGURE 7. $mAP_{0.5:0.95}$ of all networks at training time.

$$AP_i = \int_1^0 P(\mathrm{R})d(\mathrm{R}) \tag{5}$$

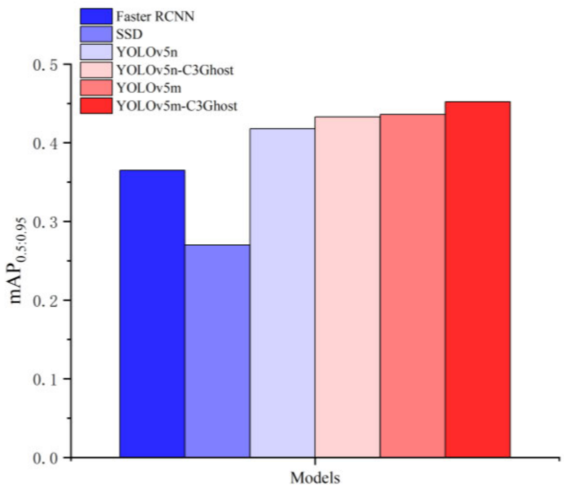
$$mAP_j = \frac{1}{N}\sum\nolimits_{i=1}^{N} AP_i \tag{6}$$

$$mAP_{0.5:0.95} = \frac{1}{10}\sum mAP_j(j = 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95) \tag{7}$$

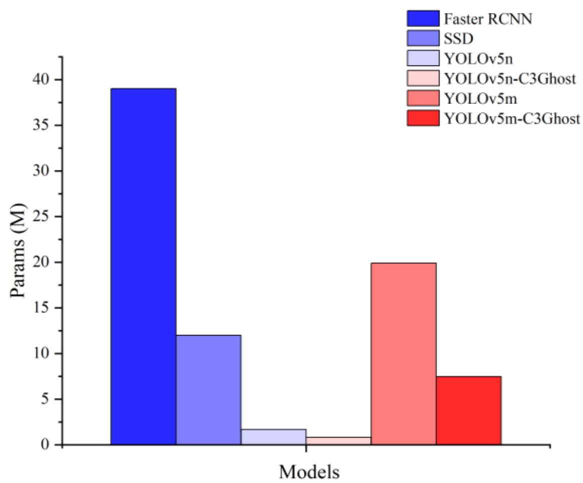
where, TP is the amount of correctly predicted samples for a category, FP is the amount of false detections, and FN is the amount of true samples that were not detected. P is the rate of Precision. R is the rate of Recall. AP is average precision. mAP_j is the mean average precision of the one defect. N is the kinds of wood defects.

The timber-deficient dataset was trained on Faster RCNN, SSD, YOLOv5n and YOLOv5m respectively. As shown in FIGURE 7, where the $mAP_{0.5:0.95}$ of Faster RCNN, SSD and YOLOv5n was smoothed out. The improved YOLOv5n-C3Ghost and YOLOv5m-C3Ghost did not converge until 225 calendar hours due to training with cosine annealing. In contrast, YOLOv5m and YOLOv5m-C3Ghost was already overfitted at 200 epochs. Once all the networks had converged, the model was used to test the data in the test set. On the test set, the $mAP_{0.5:0.95}$ values of YOLOv5n-C3Ghost and YOLOv5m-C3Ghost were much higher than those of the Faster RCNN and SSD in FIGURE 8. In addition, YOLOv5n-C3Ghost has the least number of parameters, and the number of parameters of YOLOv5m-C3Ghost were much lower than those of the Faster RCNN and SSD.

In Tables 3 and 4, the $mAP_{0.5:0.95}$ of YOLOv5m and YOLOv5n improved after the learning rate was attenuated



(a) $mAP_{0.5:0.95}$



(b) Parameters

FIGURE 8. The metrics of all networks on the test set.

using cosine annealing. Specifically, the $mAP_{0.5:0.95}$ improved by 0.9% for YOLOv5n and 1.6% for YOLOv5m. This suggests that a learning rate decay strategy involving the use of cosine annealing assists the network in finding the optimal point. The addition of SimAM to Backbone enhanced the feature extraction capability of the network, resulting in improved final detection results. $mAP_{0.5:0.95}$ improved by 1.2% for YOLOv5n and by 0.9% for YOLOv5m. At the point when both SimAM and CosLR were added to the network, $mAP_{0.5:0.95}$ improved by 1.9% for YOLOv5n and 2.3% for YOLOv5m. Finally, following the introduction of Ghost convolution, the number of model parameters for the improved YOLOv5m-C3Ghost was 37% of that for the original YOLOv5m, while the number of model parameters for the improved YOLOv5n-C3Ghost was 50% of that for the original YOLOv5n. In addition, the average inference time per graph was reduced by 0.1 ms and 0.2 ms, respectively, and the floating-point operations were reduced by 41% and 59%. However, the $mAP_{0.5:0.95}$ was reduced by 0.4% for YOLOv5n-C3Ghost and by 0.5% for YOLOv5m-C3Ghost.

IV. CONCLUSION

In this paper, two different scales of wood defect detection models, YOLOv5n and YOLOv5m, are modified and the following conclusions are obtained.

1) The YOLOv5 networks before and after the improvement outperform the traditional Faster RCNN, SSD network in terms of performance. The $mAP_{0.5:0.95}$ of the improved YOLOv5n-C3Ghost is 43.3%, and the $mAP_{0.5:0.95}$ of the improved YOLOv5m-C3Ghost is 45.2%.
2) The recognition accuracy of YOLOv5n-C3Ghost and YOLOv5m-C3Ghost for wood defect samples increases with the incorporation of the SimAM attention mechanism.
3) By adopting the CosLR learning rate decay strategy, the YOLOv5n-C3Ghost and YOLOv5m-C3Ghost break through the local minima in solving the loss function and can find better weights.
4) Used the C3Ghost and SPPFGhost modules. The improved YOLOv5n-C3Ghost has 0.82 M parameters, and the improved YOLOv5m-C3Ghost has 7.46 M parameters. The average inference time of the improved YOLOv5n-C3Ghost is 1.4 ms, and that of the improved YOLOv5m-C3Ghost is 4.8 ms. The FLOPs of the improved YOLOv5n-C3Ghost is 2.4 G, and that of improved YOLOv5m-C3Ghost is 19.4 G.

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