IECAU-Net: A Wood Defects Image Segmentation Network Based on Improved Attention U-Net and Attention Mechanism

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Saw wood cracks are defects that affect the appearance and mechanical strength of sawn wood. Crack defects in the surface of sawn wood can be readily detected. Decisions regarding the presence and severity of such defects can affect the utilization rate of sawn timber. Due to the heavy workload, low efficiency, and low accuracy of manual inspection, traditional machine learning methods have strong specialization, complex methods, and high costs. By studying the semantic segmentation model of surface crack defects in sawn timber based on deep learning, the optimal model for segmentation and detection of surface cracks in sawn timber was established. The improved Attention U-Net model encoding stage was introduced into CBAM, and AdamW optimization was used instead of SGD and Adam to achieve better crack semantic segmentation results. The ECA module was introduced in the skip connection part, and the weighted fusion multi loss function was used instead of the original cross entropy loss function. The positions of the two modules were replaced to improve the accuracy of semantic segmentation of surface cracks in sawn timber. Through comparative experiments, the improved model also achieved higher scores in semantic segmentation indicators for surface cracks in sawn timber compared to other models.

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Keywords: Surface crack detection of sawn timber; Deep Learning; Semantic segmentation; U-Net

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INTRODUCTION

In the face of the imbalance between supply and demand, where there is a substantial demand for sawn timber yet a shortage of sawn timber resources, it is necessary to classify and use sawn timber in order to fully and efficiently utilize the limited sawn timber. The surface of sawn timber may have defects such as knots, decay, and cracks, which are also the key to grading sawn timber. Among these defects, surface cracks are serious imperfections. They impact the appearance quality and mechanical strength of sawn timber and are also a major criterion for grading. The accuracy of surface crack detection in sawn timber poses a challenge due to its susceptibility to interference from texture and other defects. By accurately detecting surface cracks in sawn timber, there is potential to better understand the properties of sawn timber and make rational use of it. At the same time, it provides a basis for subsequent processing to ensure the quality and appearance of sawn timber. According to the current research status of defects such as wood cracks, there are still problems in the detection of surface cracks in wood.

In traditional wood crack defect detection algorithms, an excessive dependence on equipment detection accuracy gives rise to high complexity and low efficiency in processing wood crack defect data. Although the focus of subsequent defect detection is shifting towards machine learning, the task of wood defect detection is still complex, requiring wood crack image segmentation, feature extraction, classifier classification and recognition, as well as a significant investment in labor costs. In the application of deep learning algorithms for detecting wood cracks and other defects, in contrast to traditional machine learning based detection methods, the steps of wood crack segmentation and feature extraction are reduced. Once the dataset is established, it can be input into the network for training, and the deep neural network automatically completes the feature extraction and other tasks, ultimately generating the recognition and segmentation of wood defect images. However, while object detection algorithms are more prevalently employed in detecting defects such as wood cracks, semantic segmentation algorithms for such defects are relatively scarce. Even with the use of semantic segmentation algorithms, there is still some distance to go in the subsequent classification of wood. Cracks cannot be separated due to similarity in background color, similarity in wood texture to cracks, and segmentation errors in both cracks and some joints.

This article addresses the issues raised above by using a deep learning model based on an improved U-Net to perform semantic segmentation of surface cracks in sawn timber. Then, a classification system for detecting and grading surface cracks in sawn timber is established to achieve the classification of surface cracks in sawn timber. For semantic segmentation of surface crack images in sawn timber, the U-Net deep learning model is mainly used. Based on this, the network framework is improved, and the main research focuses on adding Convolutional Block Attention Module (CBAM), Attention Gate (AG), and Efficient Channel Attention (ECA) modules to exchange the positions of each module, optimize the loss function, and adjust the parameters of the network model to obtain the best sawn timber surface crack semantic segmentation model. The goal is to apply the improved U-Net model for optimal surface cracking of sawn timber to sawn timber grading to improve the accuracy of detection.

Related Work

In the domain of wood surface defect image segmentation, traditional image segmentation approaches mainly encompass segmentation methods based on thresholding, region, edge detection, clustering, graph theory, and specific theories. Currently, the more prevalent methods are those of deep learning. Among them, semantic segmentation is aimed at partitioning an image into regions with semantic information, and each region is assigned a class label. In contrast to object detection, semantic segmentation not only pays attention to the location of the object but also focuses on the pixel-level boundary of the object. Typical algorithms for semantic segmentation include FCN (2017) (Fully Convolutional Network), U-Net (2017), Seg Net (2017), Mask R-CNN (2017), *etc*. Xie (2023) redesigned the residual layering module and convolution method of the Mask R-CNN model to optimize the detection and segmentation of wood defects such as cracks. However, the efficiency of detection and segmentation needs to be improved. Lin *et al*. (2023) proposed a data-driven semantic segmentation network based on U-Net for wood crack detection, which achieved more accurate segmentation results.

Attention Gate (AG)

The AG in the U-Net model was first proposed by Oktay *et al*. (2018). The AG attention module adapts and automatically learns to focus on target structures of different shapes and sizes in medical images. The model using AG implicitly learns to highlight salient features that are useful for specific tasks while suppressing irrelevant regions in the input image. Tong *et al*. (2021) extracted relevant information from coarse scales to determine gating to eliminate noise and irrelevant responses caused by skip connections. Before the connection operation, AG only performs the merging of related activations, filtering out neuron activations for forward and backward transmission. AG performs linear transformation without any spatial support, downsampling the gate signal to reduce the resolution of input feature mapping, thereby reducing the parameter and computational resource consumption of the network model. Wang *et al*. (2020a,b) used Attention Gate (AG) instead of direct addition operation in the process of connecting the encoder and decoder to extract low-level features of the image and reduce the loss of detail information. Ren *et al*. (2024) introduced an attention gating module at the skip connection to implicitly suppress irrelevant features in the input image, improve sensitivity to target objects, and enhance extraction ability in complex scenes. Xu (2023) added the AttentionGate structure to the network model, which improved the response speed of each layer of the network to the region of interest, especially in the ERT image reconstruction task, where the edge processing of the reconstructed image was improved, while effectively reducing the redundant background medium response caused by network deepening.

Convolutional Block Attention Module (CBAM)

CBAM mainly includes channel attention mechanism and spatial attention mechanism, which respectively capture the dependency relationship between channels and spatial pixel level relationship. The mixture of the two can adaptively extract channel and spatial features, which is a soft attention mechanism. Sheng *et al*. (2023) proposed introducing the CBAM attention mechanism in feature extraction networks, combining spatial attention module and channel attention module to filter information, focusing on the local effective information of feature images, and improving the detection ability of occluded or truncated targets. Yang *et al*. (2023) introduced the Convolutional Block Attention Module (CBAM) theory to optimize the YOLOX network in their study, further improving the performance of the network model. The experimental results showed that the introduction of CBAM improved the detection accuracy of YOLOX on the insulator dataset by about 3%, and the performance of the model was optimized to a certain extent. Jia *et al*. (2022) screened the optimal model for bamboo stick recognition and then adopted the Convolutional Block Attention Module (CBAM) attention mechanism to replace the Squeeze Excitation (SE) attention mechanism in the MobileNetV3 network structure, enabling the network to extract features in both channel and spatial dimensions, thereby improving recognition accuracy. Li *et al*. (2023) proposed a RepVGG-CBAM model with CBAM attention mechanism and applied the model to classify 10 types of surface defects on aluminum profiles. Experimental results have shown that adding CBAM attention mechanism after RepVGG stages 1 to 4 results in the strongest classification ability. Ge *et al*. (2024) introduced CBAM in the study of wood ring segmentation to solve the loss of downsampling information and thereby improve the performance of DAF Net++.

Efficient Channel Attention (ECA)

Zhang *et al*. (2023) introduced a lightweight attention mechanism called Efficient Channel Attention (ECA) to address the issue of background interference and increase the importance of insulator features. After adding ECA, the background noise is effectively suppressed, and more attention is paid to the insulator area, thereby improving the accurate detection ability of the model for insulator defects. Sheng *et al*. (2023) designed ECA Convblock in the backbone feature extraction network to prevent dimensionality reduction in model channel importance prediction, to enhance high-quality expression of target features, and to effectively improve defect detection accuracy. Li *et al*. (2022) made some modifications to the YOLOv5 model and introduced the ECA mechanism, assigning higher weights to important feature information and achieving good detection accuracy.

Wang *et al*. (2022) introduced a lightweight ECA attention mechanism in the feature pyramid model PANet, which enables weight analysis of the importance of different channel feature maps through cross channel interaction, enabling the network to extract more prominent features to distinguish categories. Wu and Gu (2023) proposed a gait classification model based on convolutional neural network (CNN) and efficient channel attention (ECA) module for gait detection applications based on surface electromyography (SEMG) signals. CNN was used to extract features from one-dimensional input surface electromyography signals to obtain feature vectors, which were then input into the ECA module for cross channel interaction. Wang *et al*. (2023) solved the problem of low target recognition accuracy and high model complexity in the field of 3D object detection. Referring to the VoxelNet model, the ECA mechanism was introduced to reduce the complexity of the model while maintaining good performance.

EXPERIMENTAL

Method Framework

To solve the problems of cracks being unable to be segmented due to similarity in background color, wood texture being similar to cracks, and segmentation errors occurring simultaneously with some joints, this paper proposes an improved Attention U-Net, namely IECA U-Net (Improved ECA-CBAM-AGU-Net). The architecture diagram of IECA U-Net is shown in Fig. 1.

Improved Attention Gate

In the face of CNN’s fall pose (FP) prediction problem for small targets with large deformation, locating is usually done first, followed by segmenting. Oktay *et al*. (2018) added the Attention Gate (AG) module to U-Net and proposed the Attention U-Net model, which directly achieves integrated localization and segmentation without the need to train multiple models and a large number of additional parameters, while suppressing irrelevant background region responses and eliminating the need to crop ROIs across networks. Compared to the prototype U-Net, there was significant improvement in performance. To adapt to the surface image of two-dimensional sawn timber, AG was improved by removing depth channels and Resampler. In the improved AG, the inputs x and g are convolved and added separately, and then the weight map is obtained through continuous ReLU, convolution, and sigmoid. Finally, the input x is multiplied, as shown in Fig. 2.

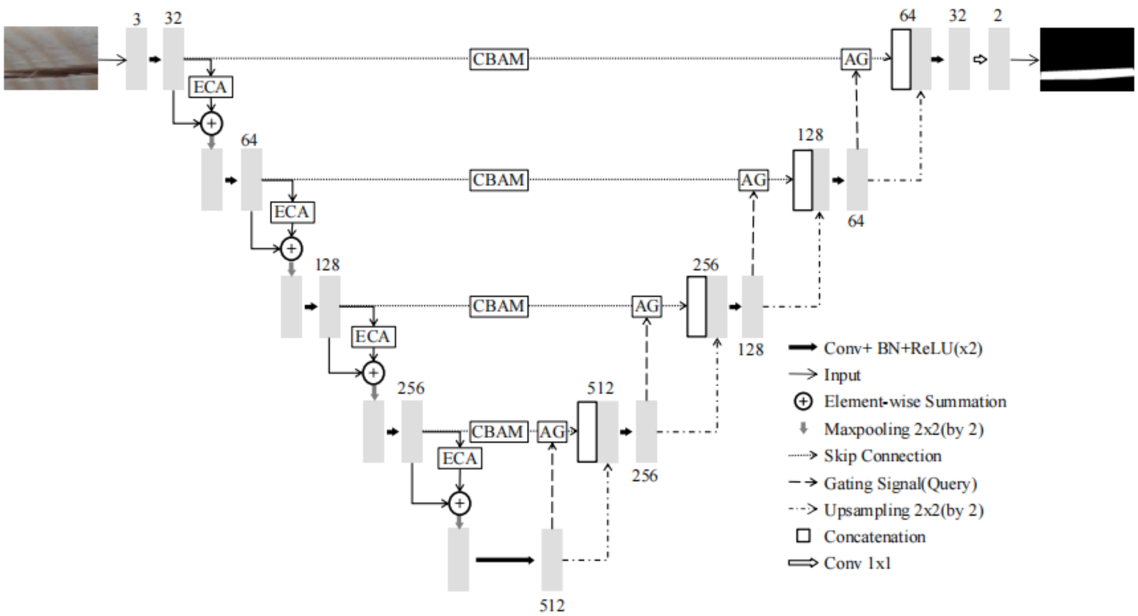

Fig. 1. Network framework for semantic segmentation of sawn timber surface crack image based on attention U-Net with CBAM

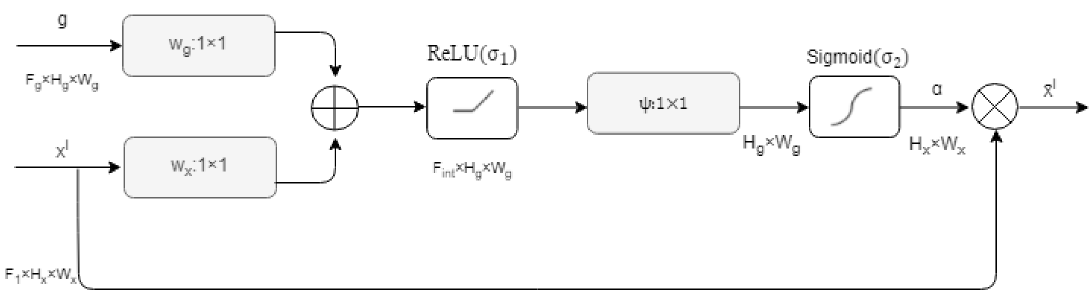

Fig. 2. AG Network Framework

In Fig. 2, the attention coefficient α ∈ (0,1) highlights the ROI and suppresses irrelevant background feature responses. The multiplication of alpha and feature maps is based on element-wise multiplication. The above figure uses additive attention to obtain gating coefficients, which performs better in experiments compared to multiplicative attention. σ 1 and σ 2 are ReLU and Sigmoid functions, respectively, and W1, W2, and ψ are all convolution operations. Among them, the Sigmoid function can make the training converge better.

Improved Convolutional Block Attention Module

On the basis of the original Attention U-Net, the Convolutional Block Attention Module (CBAM) proposed by Woo *et al.* (2018) was added during the downsampling process. CBAM is a lightweight and general-purpose module with few parameters. It is easy to use and can be well combined with the CNN of the original model. CBAM mainly includes channel attention mechanism and spatial attention mechanism, which respectively capture the dependency relationship between channels and spatial pixel level relationship. The mixture of the two can adaptively extract channel and spatial features, which is a soft attention mechanism. In the channel attention module, the input feature map is first compressed through max pooling and average pooling, and then the outputs of the two pooling features are used as inputs to the multilayer perceptron, which learns parameters. Finally, the Sigmoid function is used to obtain the importance of the features, and the importance probability of each channel is calculated to increase the weight of some channels. In the spatial attention module, the feature map output by the channel attention module is used as the input feature map of the spatial attention module. The image is compressed into a single channel along each channel through max pooling and average pooling at the channel scale. Then, parameters are learned through a 1x1 convolutional layer, and the importance of pixels is obtained through Sigmoid to generate spatial attention features, as shown in Eq. 1.

$$\begin{aligned} M_C(F) &= \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \\ M_S(F) &= \sigma\left(f^{7\times7}([AvgPool(F); MaxPool(F)])\right) \\ F' &= M_S(M_C(F)\otimes F)\otimes(M_C(F)\otimes F) \end{aligned} \tag{1}$$

where F' is the final refined output, $F \in R^{C\times H\times W}$ is the intermediate feature as input and $\otimes$ represents element multiplication, AvgPool, MaxPool, and MLP represent average pooling, maximum pooling, and multilayer sensing, respectively.

Improved Efficient Channel Attention

This section continues to optimize and improve the Attention U-Net by adding the Efficient Channel Attention (ECA) module (2023) to the skip connections of the Attention U-Net network (referred to as CBAM-ECA-AG). The ECA module is a channel attention module that supports plug and play, which can enhance the channel features of the input feature map, achieve local channel interaction without dimensionality reduction, and significantly reduce the complexity of the model. Figure 3 shows the network framework of the ECA module.

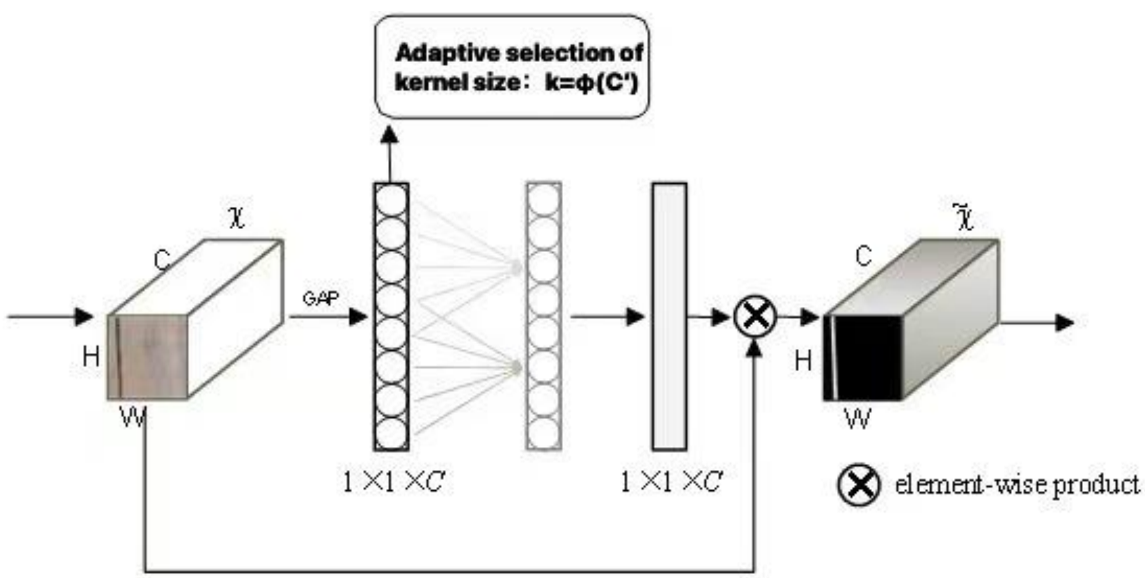

Fig. 3. E C A Module Network Framework

In the figure, "GAP" represents global aver/*-age pooling and "⊗" represents matrix dot multiplication, which involves multiplying the elements at the corresponding positions in the matrix. Firstly, input a feature map with dimensions of H×W×C. Then, the global average pooling is used to finely compress the spatial features of the input feature map to obtain a 1 × 1 × C feature map. Then the original input feature map H×W×C channel is multiplied by channel to obtain a feature map with channel attention.

When using one-dimensional convolution, adaptive selection of one-dimensional convolution kernel size is used to determine the coverage of local cross channel interactions, as shown in Eq. 2,

$$\mathrm{k} = \Psi(C) = \left| \frac{\log_2(C)}{\gamma} + \frac{b}{\gamma} \right|_{odd} \tag{2}$$

where k is the size of the convolution kernel, C is the number of channels, which are used to adjust the ratio between the number of channels C and the size of the convolution kernel, where 2 and 1 are taken respectively.

Optimization of Loss Function

In semantic segmentation tasks, there may also be foreground regions (in this case, surface cracks on sawn timber) that are much smaller than background regions. Using a cross entropy loss function may result in poor network performance, so it is necessary to optimize the loss function. This paper uses a multi loss function fusion method, introducing Dice loss and IoU loss, and linearly combining them with cross loss. The enhanced fusion method is used to assign different weights to each loss function, and the weights of the loss functions are adjusted according to the different characteristics of the training data to obtain the best results. Among them, Dice loss is determined by the Dice coefficient of semantic segmentation evaluation index, and the specific formula is:

$$\mathrm{Dice}Loss = 1 - Dice \quad coefficient \tag{3}$$

The IoU loss is determined by the IoU intersection to union ratio, and the specific formula is,

$$IoULoss = 1 - IoU \quad \mathrm{IoU}Loss = -\ln(IoU) \tag{4}$$

The loss function is expressed as:

$$\mathrm{Loss} = \alpha BCELoss + \beta DiceLoss + \gamma IoULoss \tag{5}$$

where α, β, and γ are used to adjust the parameters of the loss function weight.

RESULTS AND DISCUSSION

Implementation Details

The proposed model was built upon the PyTorch library. All experiments and the model training were done on a 16 GB NVIDIA RTX4060Ti GPU. The training process employed the Adam optimizer with an initial learning rate of 5e−4, a batch size of 8, and 100 iterations.

Evaluation Index

In order to better compare the performance of various models, five evaluation indexes were used Prc (Percision.Prc), Rec (REcall, Rec), F1(F1 Score), IoUc (Intersection over Union, IoUc) and Miou (Mean Intersection over Union, MIouc).

Comparative Analysis of Experimental Results

This model specifically added the Efficient Channel Attention (ECA) module to the skip connections of the Attention U-Net network (referred to as CBAM-ECA-AG). The ECA module is a channel attention module that supports plug and play, which can enhance the channel features of the input feature map, achieve local channel interaction without dimensionality reduction, and significantly reduce the complexity of the model. By conducting ablation experiments, replacing the CBAM module and ECA module, optimizing the loss function and other experimental parameters, a model framework was determined that can segment surface cracks of sawn timber with high segmentation accuracy. Finally, comparative experiments were conducted with other semantic segmentation models (FCN, Seg Net, and DeepLabV3+) to evaluate the performance of the improved Attention U-Net compared to other semantic models

In order for the model to achieve better segmentation results on the mask image, the authors will continue to explore the impact of changes in the weight of the loss function. Table 1 compares the semantic segmentation evaluation performance of ECA-CBAM-AGU-Net models with different fusion weights of the loss function.

Table 1. Influence of Different Fusion Weights Of ECA-CBAM-AG U-Net Model Loss Function on Semantic Segmentation Index of Sawn Timber Surface Crack

Model U-Net+ECA+AG+skipCBAM (lr5e-4,wd5e-5,ep100)	Prc	Rec	F1c	IoUc	MIoU
0.2ce+0.5dice+0.3iou	82.41	63.84	73.06	57.56	78.09
0.3ce+0.5dice+0.2iou	86.93	61.08	71.74	55.94	77.27
0.1ce+0.5dice+0.4iou	87.84	58.94	70.54	54.49	76.52
0.4ce+0.2dice+0.4iou	88.91	62.05	73.09	57.60	78.13
0.4ce+0.1dice+0.5iou	90.09	58.37	70.85	54.85	76.72
0.3ce+0.5dice+0.2iou	**90.37**	55.96	69.61	52.80	75.68
0.3ce+0.6dice+0.1iou	84.86	63.63	72.73	61.38	77.88
0.4ce+0.3dice+0.3iou	88.96	65.48	75.43	60.55	79.65
0.25ce+0.5dice+0.25iou	82.04	**70.92**	**76.07**	**61.39**	**80.04**

In Table 1, the semantic segmentation evaluation index scores of the ECA-CBAM AGU-Net model vary with different weights of α, β, and γ using multiple loss functions. When α=0.3, β=0.5, and γ=0.2, Prc achieved 90.37%, which is the highest score in Prc. When α=0.25, β=0.5, and γ=0.25, the model achieves 70.92%, 76.07%, 61.39%, and 80.04% in Rec, F1c, IoUc, and mIoU, respectively. From the perspective of semantic segmentation indicators, this weight is the optimal weight.

The model developed in this work was compared with other semantic segmentation models (FCN, Seg Net, and DeepLabV3+) through experiments. Among them, FCN, DeepLabV3+, Seg Net uses Adam optimizer and cross loss function. The remaining learning rates lr, weight decay wd, and iteration times ep are consistent with ECA-CBAM AGU Net.

Table 2. Comparison of Different Segmentation Models of Sawn Timber Surface Cracks

Model	Prc	Rec	F1c	IoUc	MIoU
FCN (adamlr5e-4wd5e-5-ep100)	83.01	62.36	71.22	55.30	76.92
DeepLabV3+ (adamlr5e-4wd5e-5-ep100)	84.52	63.44	72.47	56.84	77.71
SegNet (adamlr5e-4wd5e-5-ep100)	**89.55**	61.98	73.26	57.80	78.24
U-Net+ECA+AG+skipCBAM (lr5e-4,wd5e-5,ep100,0.4ce+0.3dice+0.3iou)	88.96	65.48	75.43	60.55	79.65
U-Net+ECA+AG+skipCBAM (lr5e-4,wd5e-5,ep100,0.25ce+0.5dice+0.25iou)	82.03	**70.92**	**76.07**	**61.39**	**80.04**

As shown in Table 2, Seg-Net achieved the highest score of 89.55% in Prc for various semantic segmentation evaluation indicators, but the model was lower than the ECA-CBAM AGU-Net (0.4ce+0.3dice+0.3iou) model in Rec, F1c, F1c, IoUc, and MIoU, and the difference in Prc between the two was not significant. From the perspective of evaluation indicators, ECA-CBAM AG U-Net (0.25ce+0.5dice+0.25iou) still has the highest scores in Rec, F1c, IoUc, and MIoU indicators, but Prc is indeed the lowest.

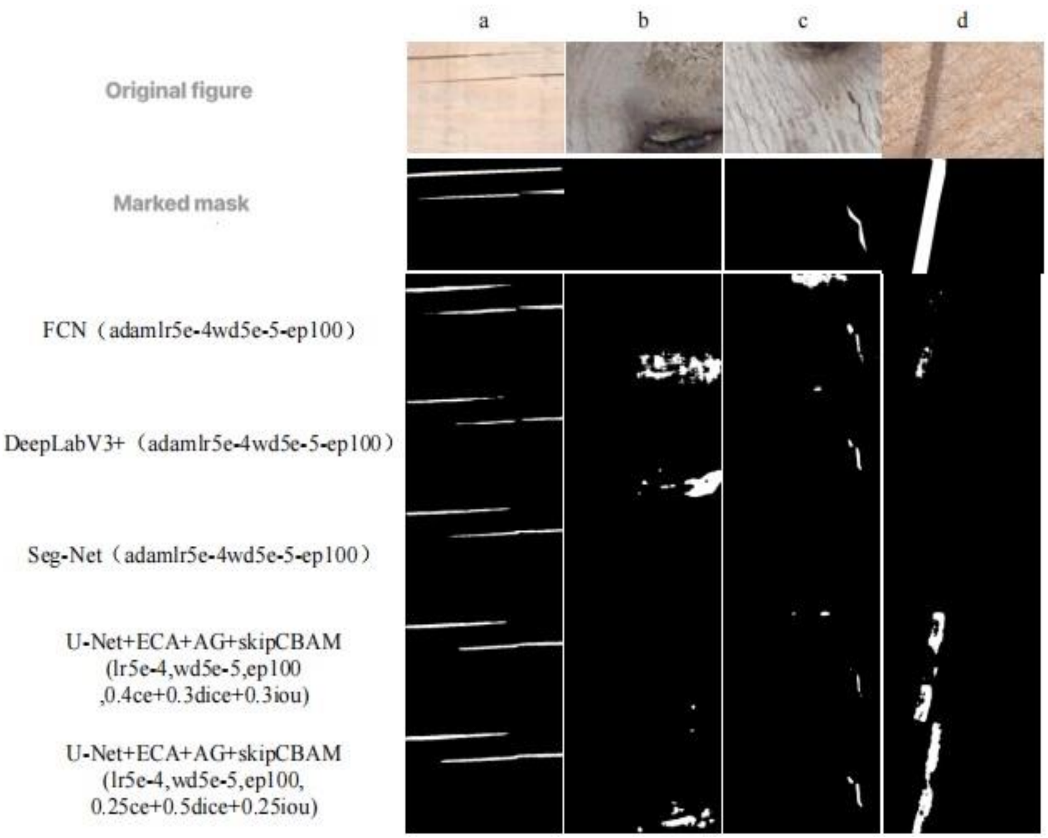

Fig. 4. Comparison of segmentation effects of different models on surface cracks of sawn timber

Although other models have poorer semantic segmentation metrics than the authors' model in the self-made surface crack pattern dataset, it does not mean that this model performs poorly on other datasets. It may perform better than our model on other datasets, which largely depends on the quality of the dataset, the number of samples, and the accuracy of data labeling.

Figure 4 compares the segmentation effects of different models on surface cracks in sawn timber.

In the figure, FCN is susceptible to the influence of background knots, which severely respond as cracks. DeepLabV3+expands the response area of nodes and does not segment cracks that are similar to the background. Seg Net only segments obvious cracks, and when there are knots, knots, and cracks that exist simultaneously and are similar to the background cracks, no cracks are segmented. Taking all factors into consideration, priority should be given to using loss functions with fusion weights of α=0.4, β=0.3, and γ=0.3. Although the multi loss function fusion of this weight did not reach the best level on Prc, it is only second to 0.25ce+0.5dice+0.25iou in Rec, F1c, IoUc, and MIoU indicators, and Prc has increased by 6.92 percentage points compared to the latter. At the same time, in terms of segmentation performance, it can also segment cracks with similar backgrounds. Based on the comprehensive semantic segmentation evaluation index data and mask prediction segmentation performance, the ECA-CBAM AG U-Net (0.4ce+0.3dice+0.3iou) model is the best.

CONCLUSIONS

1. An improved Attention U-Net model was applied in a study of semantic segmentation of surface cracks in sawn timber. Using integrating experimental and comparative research, the Attention U-Net model was optimized and improved to obtain the optimal semantic segmentation model for surface cracks in sawn timber. Introducing CBAM in the encoding stage of the Attention U-Net model and using AdamW optimization instead of SGD and Adam achieved good crack semantic segmentation results, which can segment most obvious cracks.
2. On the basis of the above, the ECA module was introduced to the skip connection part of the model, and multiple loss functions with different weights were fused instead of the original binary cross entropy loss function. The ECA module and CBAM module positions were replaced, and the optimizer parameters were adjusted (including weight attenuation of 5e-5 during training and learning rate adjusted to 5e-4). The number of iterations was increased to 100, and the ablation experiment was carried out. Compared with the previously improved model, the semantic segmentation index of surface cracks in sawn timber was significantly improved, laying a foundation for further work.

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