RESEARCH ON DEFECT IDENTIFICATION OF YU-LU-XIANG PEARS BASED ON IMPROVED LIGHTWEIGHT RESIDUAL NEURAL NETWORK MODEL
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基于改进轻量化卷积神经网络模型的玉露香梨缺陷识别研究

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ABSTRACT
The skin of Yu-Lu-Xiang pears is brittle and easily damaged during picking and sorting. In order to reduce the secondary damage caused by mechanical automatic sorting of Yu-Lu-Xiang pear after harvest, optimize the sorting process and improve the sorting accuracy. Based on the MobileV2Net model, a lightweight convolutional neural network model EC-MobileV2Net-Fast, which integrated transfer learning and attention mechanism, was proposed to identify skin damage defects of Yu-Lu-Xiang pears. According to the defects of Yu-Lu-Xiang pears with different damage degrees, a dataset containing four characteristics was created. The model accuracy rate, single defect identification accuracy rate, recall, specificity, parameter and so on were taken as evaluation indexes, and the interpretation ability of the model decision was analyzed by Grad-CAM thermal map. Preliminary evaluation results showed that the model produced the highest level of accuracy, underscoring the potential of deep learning algorithms to significantly enhance defect recognition and classification. It can improve sorting efficiency, reduce labor costs and strictly control after-sales quality.

摘要
玉露香梨的果皮极其脆弱，在采摘和分拣过程中容易损坏。为了减少玉露香梨收获后机械自动分拣造成的二次损害，优化分拣工艺，提高分拣精度。本文以 MobileV2Net 模型为基础，提出了一种融合迁移学习和注意力机制的轻量化卷积神经网络模型 EC-MobileV2Net-Fast 用以识别玉露香梨表皮损伤缺陷。根据玉露香梨不同损伤程度所表现的缺陷创建了含有 4 种特征的数据集。以模型准确率、单一缺陷识别精确率、灵敏度、特异度、参数量等作为评价指标，采用 Grad-CAM 热力图分析模型决策的解释能力。初步评估结果表明，模型产生了最高水平的准确性，强调了深度学习算法在显著增强玉露香梨缺陷识别分类方面的潜力。可以提高分选效率、降低劳动力成本和严格把控售后质量。

INTRODUCTION
Yu-Lu-Xiang Pears is a high-quality new variety of medium-ripe pear. This variety was crossbred from Korla pear as mother and Snow pear as father in Shanxi Academy of Agricultural Sciences Fruit Tree Research Institute (*Kai B., 2022*). Yu-Lu-Xiang pears had the fragrant taste of Korla pears, were juicy, crispy and sugary, which was popular with consumers as soon as it came on the market (*Haixia S. et al., 2023*). Because the skin of Yu-Lu-Xiang pears was thin and brittle, they were easily damaged during the picking process. If the damaged part was exposed to the air, in a short period of time, the quality of Yu-Lu-Xiang pears would decline sharply or even deteriorate. This affected the storage, processing and sales of Yu-Lu-Xiang pears. Therefore, it was key to grade the pears quickly and accurately after harvest to ensure the quality and price of the fruits.

With the rapid development of computer vision and artificial intelligence, deep learning technology became increasingly important in many fields (*Too E.C. et al., 2019*). By simulating human brain neural network, deep learning algorithm realized automatic extraction and analysis of image feature data (*Jiang P. et al., 2019*).

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The main deep learning network models included Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs). CNNs were the most important deep learning model in image recognition, which could achieve accurate classification through a large amount of data analysis and feature extraction. In the field of agriculture, this technology was mainly used in crop pest monitoring, field weed identification, and defect detection and classification of agricultural products (*Weijian H. et al., 2020*), especially in fruit and vegetable defect detection.

A network model was constructed by integrating CBAM attention mechanism based on the ResNet34 model for healthy and defective kiwifruit, which achieved a recognition accuracy of 99.5% (*Yunfei W., 2023*). An optimized CNNs topology model was developed by Wei P et al. for apple surface defect detection (*Wei P., 2023*). *Iosif A. et al., (2023),* used convolutional neural networks to evaluate apple quality, and the results showed that the deep learning model produced the highest accuracy and was able to accurately evaluate apple quality. Based on the ResNet model, by fine-tuning all layers of the model, a deep neural network model for external defect detection of tomatoes was proposed to achieve accurate extraction of external defect features of tomatoes (*da Costa et al., 2020*). *Yanhong* proposed a lightweight convolutional model for tomato disease damage, which not only improved the recognition accuracy of the disease but also shortened the detection time. The model, after being improved, had high stability (*Yanhong L. et al., 2022*). Zhang designed an identification and detection system for coated seeds, and the system achieved an identification accuracy of 96%, which thereby allowed for non-destructive testing of the coated seeds (*Xiwen Z. et al., 2022*). Based on the previous research results (*Bin W. et al., 2023*), the technical level of using machine learning methods to detect fruit defects needed to be improved.

Therefore, the theory of damage defect characteristics of other similar fruits was used for reference, and it was combined with the defect characteristics of Yu-Lu-Xiang pears (*Shengqiao X. et al., 2022*). This paper developed a lightweight CNNs model, which fused the transfer learning (*Zhongpei W. et al., 2021*) and channel attention mechanism (*Jiapeng Q. et al, 2023*) based on the MobileV2Net model for identifying the defects of Yu-Lu-Xiang pears. The transfer learning enhanced the weight of the feature extraction layer and sped up the convergence of the model. Additionally, ECA channel attention mechanism enhanced the ability of the model to recognize and acquire subtle targets. The LeakyReLU activation function was employed to replace the ReLU6 activation function, addressing the issue where neuron parameters cannot be updated and resulted in death due to excessively small activation values. The results showed that the improved network model could effectively classify the skin damage of Yu-Lu-Xiang pears.

MATERIALS AND METHODS

Materials

The samples of Yu-Lu-Xiang pears were harvested from the Yu-Lu-Xiang pear base located in Beiguang Village, Taigu District, Jinzhong City, Shanxi Province in September 2023. The defects on the surface of samples include cracks, bumper injury and brown rot spots caused by diseases, etc. An image capturing obscura was made to ensure that the process of image acquiring was not interfered with by the external environment. The size of the obscura was 430mm × 430mm × 430mm, and the bottom plate used a white frosted board. The light source, an adjustable white ring LED tube with a color temperature of 5500K and a power of 8W, was installed at the top of inside the camera obscura, with a height of 40cm. The shooting equipment used a Panasonic G85 camera with 16 million pixels, which was placed on the top of outside of the camera obscura, and acquired the sample images through the reserved camera holes on the camera obscura. The image acquisition device is shown in Figure 1.

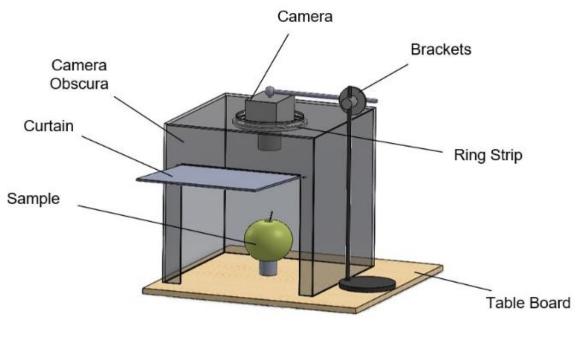


Fig. 1 - Image acquisition device

According to the grading standard of Korla pear (****Korla Pear, 2020*), Fresh pear (****Fresh Pear, 2008*) and the damage degree of samples, the Yu-Lu-Xiang pears were categorized into four types: Full, Crack, Damage, and Rot, as illustrated in Figure 2. The photos were taken according to the angles between shooting direction and the surfaces of the samples at 45° and 135°, respectively. A total of 520 original images with a resolution of 3424×3424 pixels were collected, of which 130 were Full, 128 were Crack, 128 were Damage, and 134 were Rot.

Fig. 2 - Examples of partial fruit samples

Image Preprocessing

Due to the large space occupied by the original images, the training speed of the model would have been slow if these data had been directly input into the training model. In this paper, the resolution of all original images was uniformly resized to 224×224×3 pixels through normalization processing to adapt to the input of model and improve the convergence speed of model. To improve the generalization ability of the CNNs and prevent overfitting in the training process, data enhancement techniques were used based on the original data including brightness adjustment, sharpness enhancement, noise addition, mirroring, rotation, and vertical flipping, this resulted in a total of 5200 sample images. Subsequently, the images were selected and divided into train and test sets in a 7:3 ratio by a self-designed random function for sample partitioning, with 3640 images in the train sets and 1560 images belonging to the test sets.

MobileV2Net Model Infrastructure

The MobileNet series network (*Jiaqi Q., 2022*) is a lightweight convolutional neural network that was proposed in 2017 (*Md Taimur Ahad et al, 2023*). The MobileV1Net was the primary network in this series, which adopts primarily the innovative convolutional mode of depthwise separable convolution in its structure to reduce the number of parameters and computational requirements of the model and significantly enhance its operational efficiency and real-time performance on mobile devices, and introduces the width factor α for flexible adjustment of the model size to reach a balance between accuracy and efficiency. Subsequently, the MobileV2Net occurred on the foundation of MobileV1Net, which had been continuously evolving. The MobileV2Net borrowed the inverse residual structure from the ResNet network, which avoided the gradient vanishing problem and improved the modeling effect (*Yang Z., 2021*).

As shown in Figure 3, the network architectures of MobileV1Net, MobileV2Net, and ResNet were illustrated. Compared to MobileV1Net, MobileV2Net introduced an additional step in its network structure, namely, the input features were beforehand subjected to a 1×1 convolution to increase the depth of feature maps through channel expansion. Compared with the ResNet, the MobileV2Net followed a data processing sequence with the opposite pattern of "expansion-convolution-compression". Furthermore, MobileV2Net employed depthwise separable (DW) convolutions for feature separation, whereas ResNet utilized standard convolutions for this purpose.

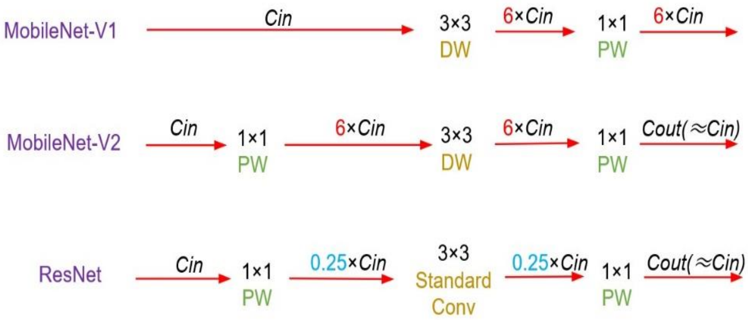


Fig. 3 - Network Comparison Structure

The inverse residual structure (Shortcut) controlled the residual connections through manipulating the stride size. When the stride was set to 1, the network adopted the inverted residual connection, as illustrated in Figure 3(a). Accordingly, when the stride was 2, the network utilized the direct connection between layers, as depicted in Figure 3(b). This structure not only enhanced the model's recognition accuracy but also maintained a relatively low computational complexity and parameter count. Therefore, the MobileV2Net was adopted widely in mobile devices and embedded systems.

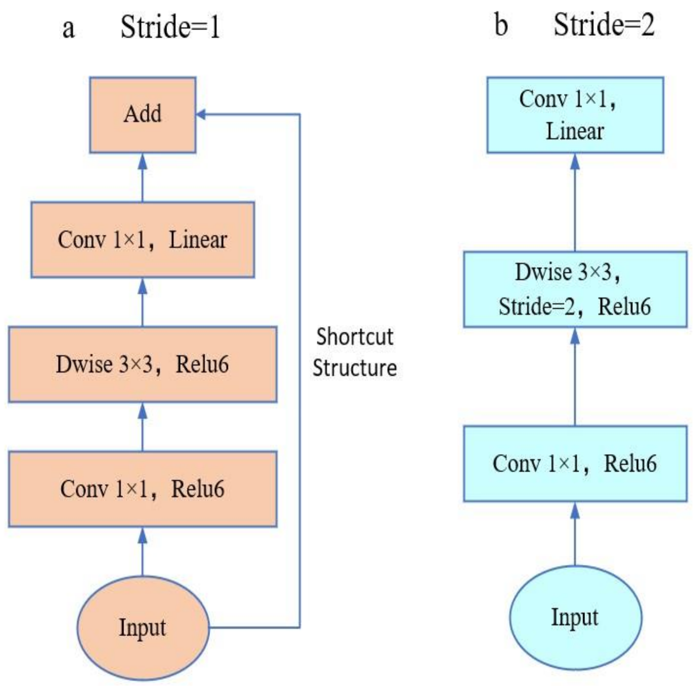


Fig. 4 - a: Stride =1 residual module; b: Stride=2 Directly connected modules

EC-MobileV2Net-Fast model

Figure 5 illustrated the constructed EC-MobileV2Net-Fast model. Initially, the pre-training network was gained by transfer learning on the ImageNet dataset, and established the target task as skin damage classification for Yu-Lu-Xiang pears.

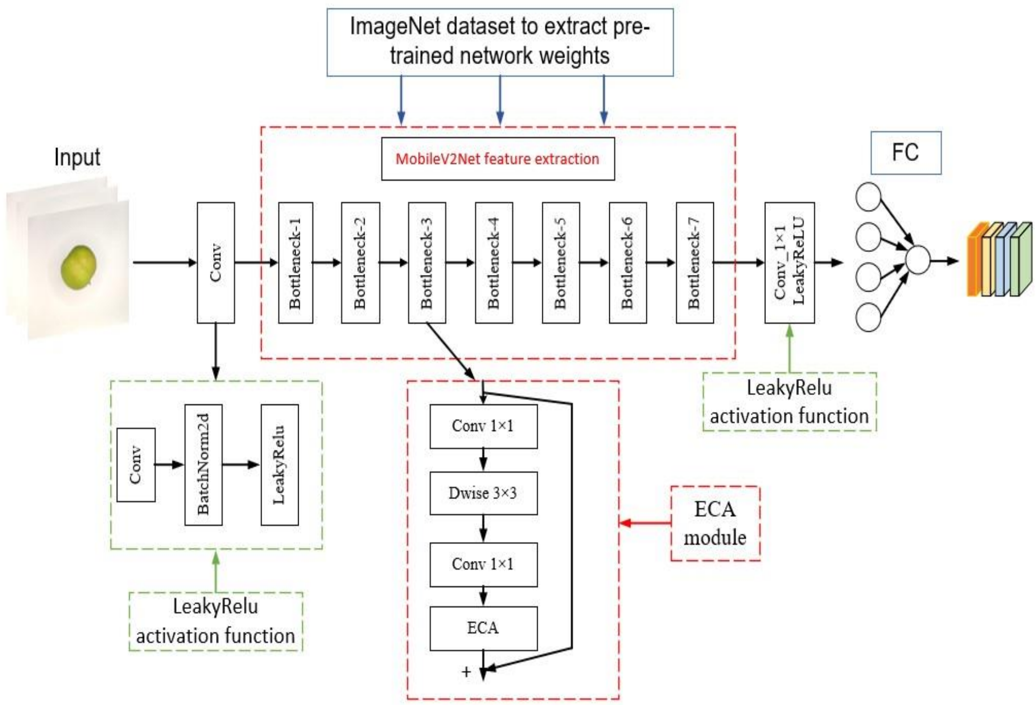


Fig. 5 - EC-MobileV2Net-Fast model

At the same time, the ECA channel attention mechanism was introduced to improve the model's capability of identifying and extracting subtle features. Furthermore, the Relu6 activation function was employed in the new network to substitute the LeakyRelu activation function, which took the problem of neuronal activity when the input was negative into account. Through these measures, the expression ability of the new model was enhanced, the negative input could generate non-zero output, avoided the neuronal death problem, and improved the classification efficiency.

RESULTS

Model Results

In this study, Windows10 was used as the operating system, with an Intel Core i5-13400H CPU, an NVIDIA GTX 4060 Ti GPU, 16GB of RAM, and a model running environment of Pytorch 1.7.1+cu110. To compare the effectiveness of the improved EC-MobileV2Net-Fast network model in this experiment and evaluate the classification performance for Yu-Lu-Xiang pears, eight classification network models were adopted: Vgg16, ResNet34, ResNet50, MobileV2Net, GoogleNet, DenseNet121, ShuffleNet and AlexNet. These networks were trained with 100 epochs, a learning rate (LR) of 0.0001, and a batch size of 16. To mitigate overfitting during training, the SGD optimizer and L2 regularization settings were employed. For specificity analysis, when all hyperparameters were kept constant, the Accuracy, the Recall, the Specificity, the Model size, the number of network parameters (Params), and the training time were selected as evaluation metrics, as summarized in Table 1.

Table 1

Comparison of test results

Model	Accuracy	Recall	Specificity	Params	Model size /MB	Training time/s
Vgg16	98.13%	0.981	0.994	134285380	512	6145
ResNet34	98.30%	0.982	0.994	21286724	81.3	2866
ResNet50	98.33%	0.983	0.994	23516228	90	3238
MobileV2Net	90.70%	0.907	0.968	2228996	8.74	2625
GoogleNet	98.00%	0.980	0.993	5977652	39.4	3730
DenseNet121	93.71%	0.937	0.979	6957956	27.1	3745
ShuffleNet	97.94%	0.979	0.993	1257704	4.96	2612
AlexNet	95.96%	0.959	0.986	14589636	55.6	1917
EC-MobileV2Net-Fast	99.67%	0.996	0.998	3504903	8.75	2630

As shown in Table 1, compared to other classification networks, the improved EC-MobileV2Net-Fast network exhibited advantages in terms of accuracy, model size, and training time. Overall, EC-MobileV2Net-Fast significantly reduced the computing and storage costs associated with network models, thereby further enhancing the practicality and efficiency of the network.

Table 2 showed the precision comparison of the model in identifying single defect samples of fruit. By comparing the precision of single samples, the performance of the model in terms of feature extraction and classification boundary demarcation for each type of fruit could be judged.

Table 2

The precision of identification of six types of models

Model	Single defect sample recognition precision			
	Full	Crack	Damage	Rot
Vgg16	0.990	0.966	0.981	0.987
ResNet34	0.975	0.989	0.997	0.971
ResNet50	0.977	0.981	0.995	0.980
MobileV2Net	0.960	0.830	0.955	0.888
GoogleNet	0.982	0.959	0.995	0.985
DenseNet121	0.965	0.896	0.962	0.926
ShuffleNet	0.982	0.966	0.981	0.987
AlexNet	0.977	0.932	0.997	0.935
EC-MobileV2Net-Fast	0.995	0.997	0.995	1.0

As was evident from Table 2, the improved EC-MobileV2Net-Fast model achieved an identification precision exceeding 0.995 for all four types of Yu-Lu-Xiang pear fruits. Notably, the most significant gains in precision were observed from the "crack" and "rot" defects, with values of 0.997 and 1.0 respectively. This outcome may have stemmed from the fact that the edge of the "crack" damage exhibited color characteristics similar to those of "rot" damage in the image information following air erosion.

The traditional network model struggled to capture the relevant fine details when processing such intricate information, thus failing to achieve accurate classification. In contrast, the improved model incorporated a channel attention mechanism, which enabled the network to focus on subtle features at the edges and enhanced its defect extraction capability.

During the model training process, real-time monitoring of the training dynamics was instrumental in gaining insights into the model's learning progress. Figure 6 presented a comprehensive dynamic evaluation of the model's performance by depicting the evolution of Loss and Accuracy for both the train and test sets across four distinct figures, namely (a), (b), (c), and (d). This visualization offered an intuitive understanding of how the model's performance evolved.

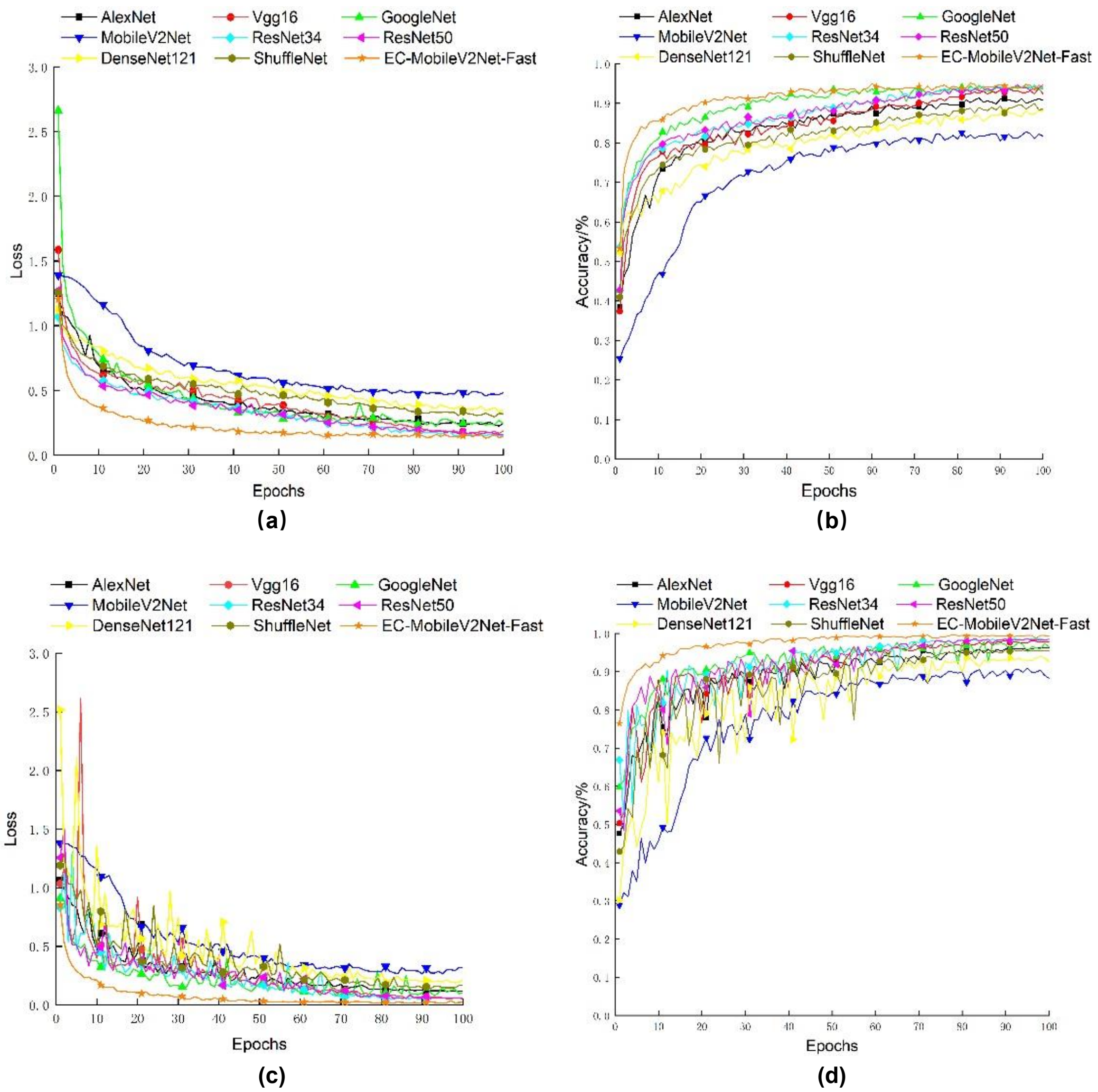


Fig. 6 (a) Train Loss Curve; (b) Train Accuracy Curve; (c) Test Loss Curve; (d) Test Accuracy Curve

Figures 6(a) and 6(b) illustrated the trend in the difference between the predicted and actual values of the model during the iterative process, while Figures 6(c) and 6(d) demonstrated the model's classification capabilities. The loss curve revealed that the improved network exhibited a lower loss rate and faster convergence compared to other networks. Typically, the loss rate curve and the accuracy curve exhibited a complementary trend; as the loss rate declined rapidly, the accuracy rate increased correspondingly, indicating that the network swiftly learned the characteristics of the input data and effectively mapped them to the correct output. After 50 iterations, the network had grasped the essential features of the input data and accurately mapped them to the desired output. In comparison with other models, the EC-MobileV2Net-Fast model demonstrated a marked improvement, with a substantially reduced loss rate and a peak accuracy rate achieved.

Ablation Comparison Test

To further explore the effectiveness of the network model, seven sets of ablation experiments were designed. The results of the ablation experiments were shown in Table 3, where "√" indicated that this item was adopted, and "×" indicated that this item was not adopted.

Table 3

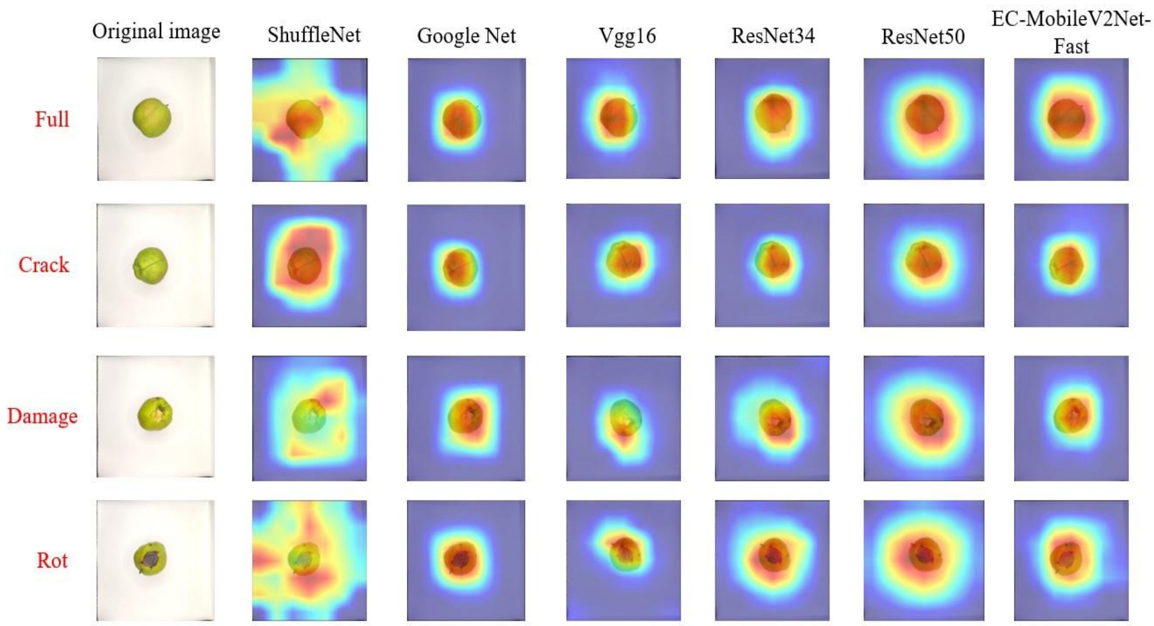
Comparison of ablation experiments

Model	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7
ECA module	√	×	×	√	√	×	√
Transfer learning	×	√	×	√	×	√	√
LeakyReLu	×	×	√	×	√	√	√
Accuracy	95.64%	91.85%	89.80%	99.40%	88.10%	90.83%	99.67%
Single picture inference time	15.5 ms	15.7 ms	14.8 ms	15.2 ms	15.3 ms	14.8 ms	14.4 ms

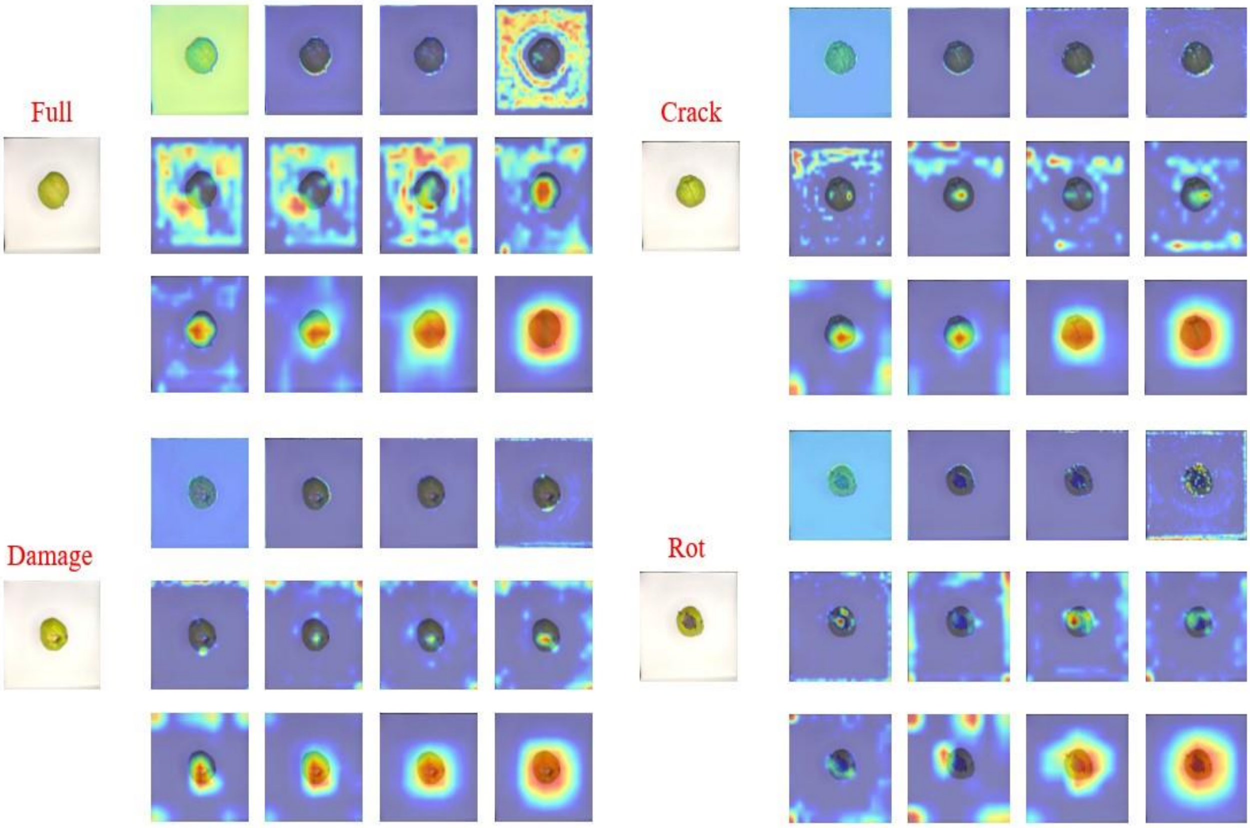
As evident from the table, the integration of the ECA module notably enhanced the model's feature extraction capability, thereby laid a robust foundation for high-precision recognition. The utilization of LeakyReLU, with its distinctive activation characteristics, expedited the model's inference process. Furthermore, the incorporation of transfer learning fortified the synergistic effects of the ECA and LeakyReLU modules, ultimately enabling the improved model to achieve optimal performance.

Feature Visualization Result

Among the aforementioned comparison models, the top five models with the highest accuracy were chosen for a thermal map comparison with the enhanced EC-MobileV2Net-Fast model. Randomly selected from the test set were four types of original images of Yu-Lu-Xiang pear fruits. The thermal maps of the final layer for all models were generated using Grad-CAM technology (*Selvaraju R et al, 2019*), as depicted in Figure 7(a). The layer-by-layer heat maps of the four damaged fruits based on the improved model EC-MobileV2Net-Fast are shown in Figure 7(b), the enhanced model demonstrated a superior capability in precisely pinpointing the defect locations and accurately highlighting the regions of interest (ROIs) for specific defect categories, This observation aligned with the manual sorting process, where similar regions of specific features were recognized for classification purposes.



(a)



(b)

Fig. 7 – (a) Heat Map Comparison; (b) Improved model layer-by-layer heat map

CONCLUSIONS

In this study, an enhanced lightweight CNNs model, EC-MobileV2Net-Fast, was proposed specifically for recognizing various degrees of damage and defects on the surface of Yu-Lu-Xiang pears. By incorporating a channel attention mechanism, the focus on critical subtle feature areas was significantly augmented, which enabled the model to extract and identify these subtle yet vital features with greater precision. Consequently, the overall classification accuracy of the model was improved. Fused transfer learning into the model, using the feature extraction capability of the pre-trained model to make the model adapt to new tasks quickly with a small amount of data, accelerated the training process and improved the generalization ability of the model. By optimizing the activation function, the problem of neuron deactivation when the input was negative was effectively solved, and the stable performance of the model in complex environment was ensured.

Compared to the traditional classical models, including VGG16, ResNet34, ResNet50, MobileV2Net, GoogleNet, DenseNet121, ShuffleNet, and AlexNet, EC-MobileV2Net-Fast demonstrated remarkable enhancements on accuracy, the specific increases being of 1.54%, 1.37%, 1.34%, 8.97%, 1.67%, 5.96%, 1.73% and 3.71%, respectively. Moreover, the EC-MobileV2Net-Fast model also excelled in other key metrics of model, such as the recall and precision of single fruit recognition. Therefore, the model improvement strategies proposed in this study had substantially enhanced its classification capabilities, showcasing its superiority and robustness in recognizing surface damage defects of Yu-Lu-Xiang pears.

Therefore, this study provided a systematic classification method for the sorting of Yu-Lu-Xiang pears after harvesting, realized the non-destructive testing for Yu-Lu-Xiang pears defects, and provided theoretical and technical support for deepening the theoretical research of Yu-Lu-Xiang pears and automating the classification after transplantation to mobile devices.

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