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RESEARCH ARTICLE

# IRB-5-CA Net: A Lightweight, Deep Learning-Based Approach to Wheat Seed Identification

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**ABSTRACT** In this manuscript, a deep learning approach is used to research wheat seed variety identification and a fast and efficient wheat seed variety identification method (IRB-5-CA Net) is proposed based on the characteristics of wheat seeds and a self-constructed dataset, which provides ideas for wheat seed variety identification. Twenty-nine wheat varieties grown under natural light conditions were selected as the research objects, and a wheat seed dataset with the number of 4,385 seed photos was constructed by integrating sunny, cloudy, and rainy conditions with a blue hard paper as the background plate, and using a Nikon COOLPIX B700 digital camera for dataset collection. Based on the above self-constructed dataset, improving the MobileNetV2 model proposed a new lightweight method (IRB-5-CA Net) for wheat seed recognition. IRB-5-CA Net specific improvements are listed below: adding $5 \times 5$ convolution to the bottleneck without using the shortcut structure and adding the Coord Attention to the bottleneck with using the shortcut structure. After training IRB-5-CA Net on the self-built dataset, the average accuracy, average recall, and F1 values are 99.5%, 99.6%, and 99.6%. The model improves the average accuracy by 6.8%, 5.6%, 5.8%, and 8.3% compared to MobileNetV2, ResNet34, Efficientnetv2_s, and GoogLeNet. The IRB-5-CA Net was visualized using the pytorch_grad_cam method, in the output heat map, it can be seen that the model focuses more attention on wheat seeds, resulting in higher accuracy. Applying IRB-5-CA Net to other public datasets such as wheat seed disease, apple leaf disease, and AI Challenger 2018 crop disease detection, the average accuracy was 98.06%, 96.15%, and 94.02%. This study provides a theoretical basis for seed variety identification, disease identification, and other crop disease identification in wheat.

**INDEX TERMS** Coord attention, MobileNetV2, seed recognition, shortcut, wheat, visualization.

## I. INTRODUCTION

Wheat is one of the most important sources of food and nutrition for human beings, with more than one-third of the world's population using wheat as a staple food [1]. Wheat is rich in nutrients [2] such as starch, protein, fat, minerals, calcium, iron, thiamin, riboflavin, niacin, and vitamin A. Nutritional composition of wheat varies greatly from region to region as well as from variety to variety [3], and the merit of wheat varieties also has a critical impact on yield. Planting the appropriate seed in the appropriate area is a prerequisite for wheat yield as well as nutrient content. Considering the small size of wheat seeds and the small differences in characteristics between different varieties, it is difficult to differentiate varieties using physical methods. Deep learning methods, on the other hand, can analyze wheat seeds in real-time, anytime, anywhere, and can reduce distortions in natural light as well as under the microscope, and can automatically classify seed features with higher recognition accuracy.

Since the introduction of the convolutional neural network AlexNet [4] in 2012, many studies have applied deep learning techniques to agriculture. Hamid et al. [5] used the

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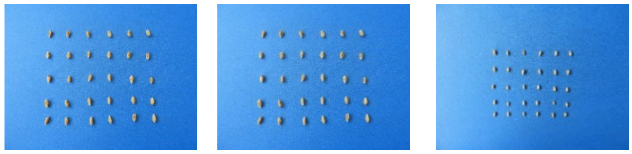
MobileNetv2 to classify 14 different classes of seeds, with a final test set accuracy of 95%. Laabassi et al. [6]used InceptionV3 [7], MobileNet, Xception [8], ResNet50 [9], and DensNet20 [10] to classify a dataset of 31,606 wheat seeds consisting of four wheat categories and finally found that MobileNet had a higher test accuracy of 95.49%. Javanmardi et al. [11] used a deep convolutional neural network as a general-purpose feature extractor to classify maize seeds with a final accuracy of 98.1%. Lu et al. [12] achieved an accuracy of 96.28% after disease identification of maize seeds by adding a 7 × 7 deep convolution block to the ShuffleNetV2 network model used to enhance the effective receptive field of the network. Mengyan et al. [13] identified maize seed varieties by adding SE attention to the VGG16, and the final accuracy reached 98.86%. Changji et al. [14] added CBAM attention and cross-layer non-local module in ResNet50 to classify crop diseases, and the final recognition accuracy reached 88.61%. Huanxin et al. [15] introduced Efficient channel attention (ECA) and Attentional Feature Fusion (AFF) in the MobileNetV2 for disease recognition on crop leaves, and the final identification accuracy reached 98.4%. Moyazzoma et al. [16] used MobileNetV2 to classify crop diseases, and a final validation accuracy of 90.38%. Gulzar [17] proposed TL-MobileNetV2 by introducing different layers into MobileNetV2 architecture in place of the original classification layer, and the accuracy obtained after the recognition of images of 40 different types of fruits using the model was 99%. Elfatimi et al. [18] used the MobileNetV2 to classify bean leaf varieties, with an average classification accuracy higher than 97% on the training set. Ma et al. [19] used parallel connections instead of cascade connections to improve the CBAM attention, and after adding it into MobileNetV2 for the identification of maize seed varieties, the final accuracy reached 98.21%. Jaithavil et al. [20] used Transfer Learning to train three network models VGG16, InceptionV3, and MobileNetV2 on more than 1200 paddy seed datasets with overall recognition rates of 80.00%, 83.33%, and 83.33% respectively. Zhou et al. [21] added attention modules such as SELayer [22], EcaLayer [23], CBAM [24], and CoordAtt to YoloV5s and after experiments, it was found that YoloV5s with the addition of the CoordAtt attention had the best performance. Zhao et al. [25] introduced the CoordAtt attention mechanism to YOLOv5s as well as replacing the backbone module in the network with the convolutional blocks in the RepVGG [26] block structure to detect the flowering period of yellow chrysanthemums, and the final average accuracy reached 93.9%.

Given the above experimental methods, this paper aims to improve the MobileNetV2, to propose a lightweight fast, and efficient method for wheat seed variety identification, and to provide a theoretical basis for other crop variety identification.

## II. DATASET ESTABLISHMENT AND SEGMENTATION

The wheat seed image datasets in this study were all collected at the China Wheat Industry Technology System Tianshui Integrated Experiment Station (35°44′ N, 106°08′ E, average altitude 1413m, average annual rainfall 570mm, annual sunshine hours 2012h). Photographs were taken at multiple angles and scales under natural outdoor light using a Nikon COOLPIX B700 digital camera in automatic mode with a maximum ISO 1600 limit and a minimum shutter speed of 1/30 s. The images were in JPG format and were collected between 15 July 2021 and 20 July 2021, with three sunny days, one cloudy day, and one day of light rain during the period. All seeds had a moisture content between 7.5% and 10% at the time of photography. Raw images of some of the seed periods are shown in Fig. 1. The filming period included a variety of different weather conditions and natural light conditions, increasing the diversity of the images taken. The 29 wheat varieties selected were all mainstream winter wheat varieties within Gansu Province, such as Ji Mai 19, Lan Tian 15, and Zhou Mai 19. About 30 plants of each variety were selected separately. Where 30 wheat seeds of the same variety were placed on a blue background plate for photography because the single wheat seeds are very small. The original image seed picture was about 4 MB, and each variety shot's specific information is shown in Table 1. The data for the training and validation sets were selected according to the ratio of 8:2.



(a).jimai19 (b).lantian15 (c).zhoumai19

**FIGURE 1.** Images of wheat seed stage dataset.

In order to increase data diversity and reduce overfitting, the images need to be preprocessed before performing the experiments. For the training set, the input 1600 × 1200 pixel images are firstly randomly cropped to different aspect ratios, then the resulting cropped images are scaled to 224 × 224 pixels, followed by random horizontal flipping, and finally normalized. For the validation set, the input 1600 × 1200 pixel image is first randomly cropped to 224 × 224 pixels and finally normalized.

## III. EXPERIMENTAL METHODS

### A. MOBILENETV2 NETWORK

MobileNetV2 network [27] was proposed by the Google team in 2018. The network consists of stride=1 block and stride=2 block stacked on top of each other, when stride=1, the block is an Inverted Residual Block. The reason why the Inverted Residual Block is first Dimensionality Boost and then Dimensionality Reduction is that MobileNetV2 replaces the Residual Block with Depthwise Separable Convolution, which reduces the number of parameters, but the ability to extract the features. If the channel compression is performed, the feature extraction ability will be further reduced, so the Dimensionality Boost is used to extract the features. The two Blocks are shown in Figure 2, Figure 3.

**TABLE 1. Wheat image dataset.**

| Classes | Wheat varieties | Number |
|---|---|---|
| 1 | jimai19 | 155 |
| 2 | jimai20 | 155 |
| 3 | jimai21 | 150 |
| 4 | jimai22 | 155 |
| 5 | jimai44 | 155 |
| 6 | jimai47 | 150 |
| 7 | lantian15 | 150 |
| 8 | lantian19 | 150 |
| 9 | lantian26 | 150 |
| 10 | lantian33 | 150 |
| 11 | lantian34 | 150 |
| 12 | lantian35 | 150 |
| 13 | lantian36 | 150 |
| 14 | lantian37 | 150 |
| 15 | lantian39 | 150 |
| 16 | lantian40 | 150 |
| 17 | lantian42 | 150 |
| 18 | lantian43 | 155 |
| 19 | lantian45 | 150 |
| 20 | lantian48 | 150 |
| 21 | lantian53 | 145 |
| 22 | lantian54 | 155 |
| 23 | lantian55 | 150 |
| 24 | lantian56 | 150 |
| 25 | zhoumai19 | 155 |
| 26 | zhoumai20 | 150 |
| 27 | zhoumai21 | 160 |
| 28 | zhoumai22 | 145 |
| 29 | zhoumai23 | 150 |

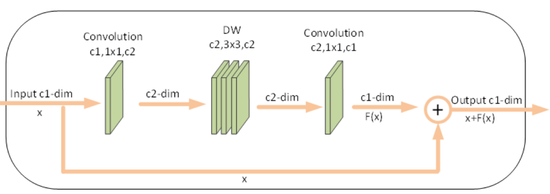



**FIGURE 2. Stride = 1 block.**

## B. THE COORDATT ATTENTION

The CoordAttention [28] was proposed by embedding location information into the Channel attention. This attention decomposes the channel attention mechanism into two 1-dimensional feature encoding processes, one of which encodes feature information and the other encodes channel information. The structure of this attention is shown in Figure 4.

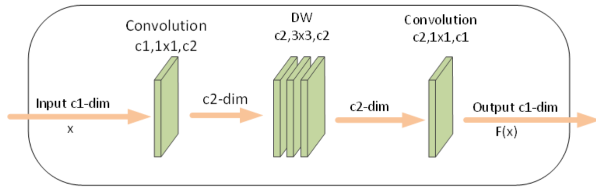



**FIGURE 3. Stride = 2 block.**

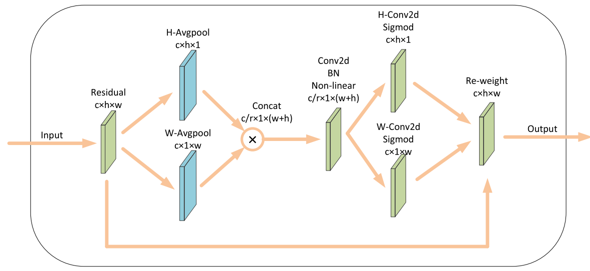



**FIGURE 4. CoordAttention.**

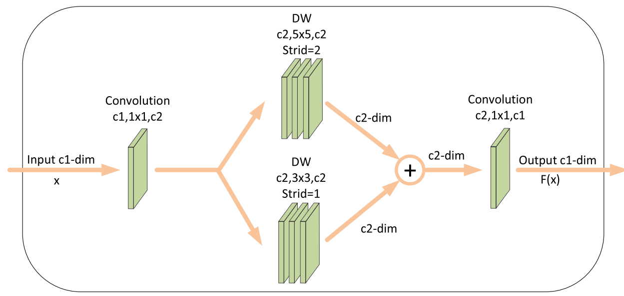



**FIGURE 5. IRB5 module structure.**

## C. IRB-5-CA NET

The MobileNetV2 has a low number of parameters and is suitable to be deployed on mobile for subsequent experiments, so it was chosen for improvement. Considering that when the wheat seed data was taken, 30 seeds of the same variety were evenly placed on the blue background, although Stride=2 block was dimensionality boost, when only $3 \times 3$ convolution was used for the identification, its receptive field was small and less information about the wheat seeds identification, so convolution kernel of $5 \times 5$ and DW convolution of 2 steps was added to Stride=2 block. The improved module is named STRB5(Stride=2 block5), the structure of this module is shown in Figure 5.

To focus the attention of the model more on wheat seeds and improve the identification accuracy of the model, CoordAttention is added to the model. The introduction of residual mapping will be more sensitive to the output results of the model, and the adjustment of the weights will be more useful and better, so the CoordAttention is added to the inverted residual module (Stride=1 block) to increase the accuracy of the model for the identification of wheat varieties. The inverted residual module after adding the CoordAtt attention is named IRBCA (Inverted Residual Block CoordAtt), and the structure of this module is shown in Figure 6.

The IRB-5-CA Net network structure is shown in Table 2

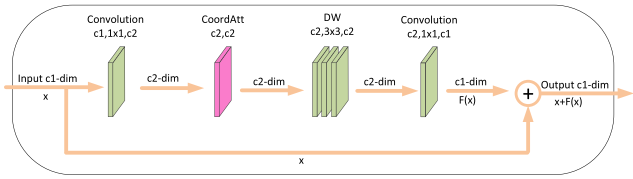



**FIGURE 6.** IRBCA module structure.

**TABLE 2.** IRB-5-CA net network structure.

| Feature map | Convolution blocks | t | c | n | s |
|---|---|---|---|---|---|
| 2242×3 | Conv2d | null | 32 | 1 | 2 |
| 1122×32 | IRBCA | 1 | 16 | 1 | 1 |
| 1122×16 | STRB5 | 6 | 24 | 2 | 2 |
| 562×24 | STRB5 | 6 | 32 | 3 | 2 |
| 282×32 | STRB5 | 6 | 64 | 4 | 2 |
| 142×64 | IRBCA | 6 | 96 | 3 | 1 |
| 142×96 | STRB5 | 6 | 160 | 3 | 2 |
| 72×160 | IRBCA | 6 | 320 | 1 | 1 |
| 72×320 | conv2d 1×1 | null | 1280 | 1 | 1 |
| 72×1280 | Avgpool 7×7 | null | null | 1 | null |
| 1×1×1280 | Conv2d 1×1 | null | k | null | |

Note: where t is the expansion factor, c is the number of channels of the feature matrix, n is the number of repetitions of the convolution block and s is the step size.

As shown in Table 2, the IRB-5-CA Net is primarily made up of IRBCA and STRB5 modules stacked on top of each other. Use the IRBCA module to replace the original bottleneck if the shortcut is used, and the STRB5 module to replace the original bottleneck if the shortcut is not used. The t, c, n, and s in the model, as well as the input feature maps and the number of feature channels, remained the same as in the original model and did not change.

### D. EXPERIMENTAL ENVIRONMENT AND PARAMETERS

This experiment was deployed in the supercomputing platform of Zhongke Shuguang, and the Pytorch was used to construct the improved model. The training is done using a Linux 64-bit operating system, its processor configuration is HaiGuang 7185, memory is 128G and computational network is 200GB. Optimiser is used SGD optimizer and momentum parameter is set to 0.9 and other parameters are default. The learning rate is 0.001 and the batch size is set to 8.

## IV. EXPERIMENTAL RESULTS AND ANALYSIS

### A. ABLATION EXPERIMENTS

To investigate whether the added modules are beneficial for the variety identification of wheat, after deploying the model to the supercomputing platform and using the wheat seed dataset for training, the results after loading the model weights obtained on the training set to the model for identification of the validation set are shown in Table 3.

As shown in Table 3, based on the original MobileNetV2 model, the model obtained by replacing stride=2 block with STRB5 is named Model 1, the model obtained by replacing stride=1 block with IRBCA is named Model 2, and the model obtained by replacing both of the above is named Model 3 (IRB-5- CA Net). The average accuracy by model 1 on the validation set is 95.7%, which is the lowest among the three models, and the number of floating point operations and the number of parameters used is higher; model 2 has an increase of 1.1% in accuracy compared to model 1, and the number of floating point operations and the number of parameters is the lowest; model 3 achieves the highest average accuracy of 99.5%, and the recall and the F1 value are both higher, and the number of floating point operations and the number of parameters used are the highest among the three models. The results from Model 1, Model 2, and Model 3 show that the above-mentioned improvements in the model give better results in the identification of wheat varieties.

**TABLE 3.** Validation set ablation experiment results.

| Models | Influencing factors | | Average accuracy rate | FLOPs | Params | Average recall | F1 |
|---|---|---|---|---|---|---|---|
| | STRB5 | IRBCA | | | | | |
| 1 | ✓ | Null | 95.7% | 4.69×108 | 3.03×106 | 95.6% | 95.9% |
| 2 | Null | ✓ | 96.08% | 3.39×108 | 2.70×106 | 96.8% | 96.7% |
| 3 | ✓ | ✓ | 99.5% | 4.83×108 | 3.47×106 | 99.5% | 99.6% |

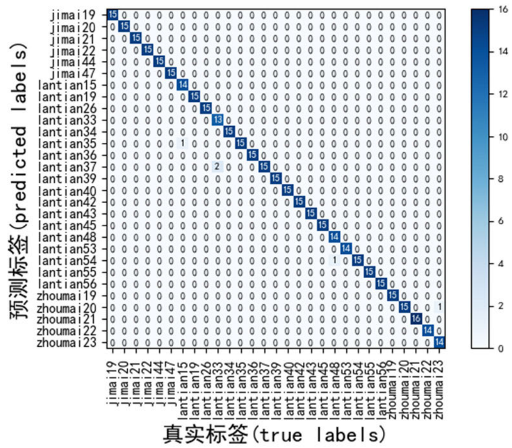



**FIGURE 7.** Confusion matrix.

### B. EXPLORING MODEL PERFORMANCE

To explore the actual performance of the model, identification of the validation set using IRB-5-CA Net and the results are shown in Figure 7 and Table 4.

As shown in Figure 7, most of the varieties of wheat seed photographs were correctly identified, only 1, 2, 1, and 1 pictures were incorrectly identified in Blue Sky 15, Blue Sky 37, Blue Sky 54, and Zhou Mai 20, respectively, and there were no incorrectly identified photographs in other varieties of wheat, with a high overall rate of correct identification.

As shown in Table 4, except for lantian33 and lantian37, the identification accuracies of all wheat varieties, recall, and F1 values reached more than 90%, indicating that the improved model is more effective in the identification of

**TABLE 4. Results of wheat identification by variety.**

| Wheat varieties | Accuracy (%) | Recall (%) | F1 (%) |
|---|---|---|---|
| jimai19 | 100 | 100 | 100 |
| jimai20 | 100 | 100 | 100 |
| jimai21 | 100 | 100 | 100 |
| jimai22 | 100 | 100 | 100 |
| jimai44 | 100 | 100 | 100 |
| jimai47 | 100 | 100 | 100 |
| lantian15 | 100 | 93.3 | 96.5 |
| lantian19 | 100 | 100 | 100 |
| lantian26 | 100 | 100 | 100 |
| lantian33 | 100 | 86.6 | 92.8 |
| lantian34 | 100 | 100 | 100 |
| lantian35 | 93.7 | 100 | 96.7 |
| lantian36 | 100 | 100 | 100 |
| lantian37 | 88.2 | 100 | 93.7 |
| lantian39 | 100 | 100 | 100 |
| lantian40 | 100 | 100 | 100 |
| lantian42 | 100 | 100 | 100 |
| lantian43 | 100 | 100 | 100 |
| lantian45 | 100 | 100 | 100 |
| lantian48 | 100 | 93.3 | 96.5 |
| lantian53 | 100 | 100 | 100 |
| lantian54 | 93.7 | 100 | 96.7 |
| lantian55 | 100 | 100 | 100 |
| lantian56 | 100 | 100 | 100 |
| zhoumai19 | 100 | 100 | 100 |
| zhoumai20 | 93.7 | 100 | 96.7 |
| zhoumai21 | 100 | 100 | 100 |
| zhoumai22 | 100 | 100 | 100 |
| zhoumai23 | 100 | 93.3 | 96.5 |

wheat varieties. To further explore the performance of IRB-5-CA Net, the feature learning process of IRB-5-CA Net, as well as MobileNetV2 on the training set, is visualized based on the pytorch_grad_cam visualization method (the model involves a large number of layers, so only the modules with c=16, c=24, c=32, c=64 and c=96 are visualized), and the results are shown in Figure 8.

As shown in Figure 8, after visualizing Block1 and Block2, the positions identified by the two models do not differ much, and they are all concentrated on wheat seeds; after visualizing Block3, IRB-5-CA Net identifies more all the seed data, while the MobileNetv2 identifies only a small part of the seed data; and after visualization of Block4 and Block5, IRB-5-CA Net identifies more locations focused on rows 2-5 seeds and less on row 1 seeds, while the MobileNetv2 identifies some of the more useless background panels, resulting in low recognition accuracy.

The results show that IRB-5-CA Net is more suitable for the identification of wheat varieties and better model performance.

### C. MODEL COMPARISON

The results after training IRB-5-CA Net, MobileNetV2, ResNet34, Efficientnetv2_s, and GoogleNet on the training set with the same parameters respectively are shown in Table 5.

As shown in Table 5, the number of IRB-5-CA Net floating point operations and the number of parameters are larger than the MobileNetV2 and smaller than the other three types of models. In terms of accuracy, IRB-5-CA Net has the highest among the five classes of models at 99.5%, which is an improvement of 6.8%, 5.6%, 5.8%, and 8.3% compared to MobileNetV2, ResNet34, EfficientNetv2_s, and GoogLeNet. Comparative experimental results show that IRB-5-CA Net has a greater advantage over similar models for wheat seed variety recognition, using a smaller number of parameters and floating point operations to a higher identification accuracy.

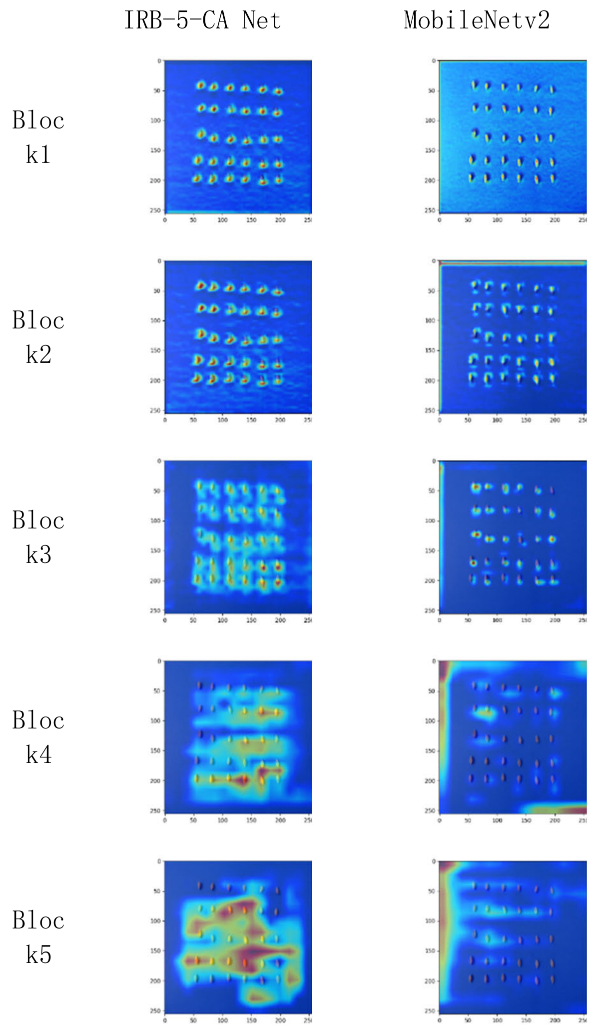



**FIGURE 8. Model visualisation results.**

**TABLE 5. Experimental results.**

| Models | Average accuracy (%) | FLOPs | Params(MB) |
|---|---|---|---|
| IRB-5-CA Net | 99.5 | 4.83×108 | 18.01 |
| MobileNetV2 | 92.7 | 3.26×108 | 13.37 |
| ResNet34 | 93.9 | 3.67×109 | 83.15 |
| EfficientNetv2_s | 93.7 | 2.89×109 | 81.86 |
| GoogLeNet | 91.2 | 1.58×109 | 51.03 |

### D. EFFECTIVENESS OF THE PROPOSED MODEL ON OTHER DATASETS

In order to verify whether the model has better results on other datasets, the IRB-5-CA Net was used as a model for wheat

**TABLE 6.** Experimental results.

| Data set | Average accuracy | Average precision | Recall | F1 |
|---|---|---|---|---|
| Wheat seed diseases | 98.06% | 98.31% | 98.05% | 98.5% |
| Apple leaf diseases | 96.15% | 96.16% | 96.12% | 96.4% |
| AI Challenger 2018 | 94.02% | 95.02% | 94.25% | 94.06% |

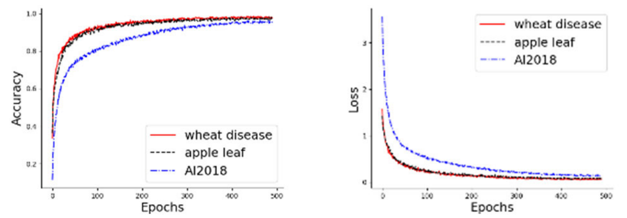



**FIGURE 9.** Experimental results.

seed diseases (this dataset contains 6 different types of wheat imperfections classified according to the national standard: diseased grain, insect-eaten grain, moldy grain, germinated grain, broken grain and normal grain, downloaded from https://aistudio.baidu.com/aistudio/datasetdetail/136684), apple leaf diseases (this dataset contains 5 common apple leaf diseases: leaf blight, rust, grey spot, spotted leaf spot, brown spot, Downloaded from https://aistudio.baidu.com/aistudio/datasetdetail/11591), AI Challenger 2018 Crop Disease Detection (contains healthy samples of 10 crop varieties of apples, cherries, grapes, oranges, peaches, strawberries, tomatoes, peppers, maize, and potatoes, and 27 disease samples, of which 24 were analyzed in terms of the extent of the disease, and the remaining 3 have similar extent of morbidity, the download address is https://aistudio.baidu.com/aistudio/datasetdetail/76075). The accuracy, as well as loss curves on the training set after training the same number of rounds on the public dataset, are shown in Figure 9, and the results after loading the model weights on the training set to the validation set are shown in Table 6.

As shown in Table 6, IRB-5-CA Net has a better identification result on other agricultural datasets such as wheat seed disease, apple leaf disease, and AI Challenger 2018 crop disease detection dataset. The model identification accuracy is only 94.02% on the AI Challenger 2018 dataset, which is considered to be probably because the dataset had three disease samples with similar degrees of incidence, which has an impact on the identification accuracy.

## V. CONCLUSION

Wheat seeds of different varieties show less variability and are difficult to distinguish with the eye alone. The detection cost is high and timeliness cannot be guaranteed using chemical detection methods. Compared with chemical detection methods, the use of deep learning methods for wheat seed variety identification is simple, faster, timeliness is guaranteed, the use of low cost, and there are not many requirements for the identification of the environment, you can be in any location for fast, accurate and efficient variety identification.

In this paper, IRB-5-CA Net is proposed by improving the lightweight model MobileNetV2. The specific improvements are as follows: by analyzing the self-constructed seed dataset and the characteristics of different varieties of wheat seeds, a $5 \times 5$ convolution kernel is added to the inverted residual module without using a shortcut to increase the model's receptive field, so that the model can learn more information; and attention is added to the inverted residual module using shortcut to make the model pay less attention to the blue background plate and focus more on the wheat seed, thus improving the identification accuracy.

The experimental results show that the accuracy, recall, and F1 values by IRB-5-CA Net identification of each variety of wheat are high, more than 90% except for lantian33 and lantian37, and the average accuracy to 99.5%. After visualizing IRB-5-CA Net, the model focuses more on the seeds and less on the blue background panel. IRB-5-CA Net compares with MobileNetV2, ResNet34, Efficientnetv2_s, and GoogLeNet, and the average accuracy is improved by 6.8%, 5.6%, respectively, 5.8%, and 8.3%. Applying the improved model to other public datasets such as the wheat seed disease dataset, apple leaf disease dataset, and AI Challenger 2018 crop disease detection also had better recognition results.

In summary, IRB-5-CA Net is suitable for the identification of leaf diseases on wheat seeds and other agricultural products with good results, and the model has only 18.01MB of parameters, which is mobile-friendly and convenient for subsequent use in real life.

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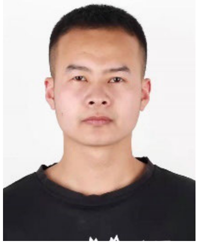

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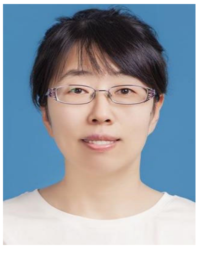

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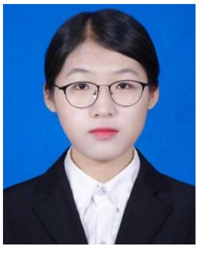

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