Current Science
CS 5 (4), 3595-3606 (2025)
**Received** **18 April** 2025 | **Revised 15 May** 2025 | **Accepted 17 June**. 2025 | **Online Available 16 July** 2025
**https://doi.org/ 10.52845/CS/2025-5-4-22**

**Current Science**
Current Science

**OPEN ACCESS**
**ISSN(O) 2795-8639**

**Original Article**

# The Dense Convolutional Network for Rice Disease Recognition Based on Transfer Learning

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**Abstract:**
Crop diseases significantly impact agricultural productivity, making their timely detection and control critical. This study leverages artificial intelligence to detect and identify plant diseases from images, aiming to improve the targeting of disease management and reduce chemical usage, thus mitigating contamination and enhancing agricultural sustainability.

Focusing on rice as a case study, we propose a novel method to detect three common rice diseases using a Transfer Learning-based Dense Convolutional Network model. To address the challenges in intelligent disease detection, we enhance the dataset through channel transformation, symmetry, and rotation, which augment the model's ability to generalize across diverse rice disease conditions. By utilizing deep convolutional neural network, the model automatically learns discriminative features, bypassing the need for traditional, labor-intensive manual feature extraction.

The Transfer Learning approach allows us to transfer knowledge learned from the ImageNet dataset to the rice disease detection task, significantly improving performance and reducing training time. We apply digital image processing techniques and CNN to construct the system, and use a Softmax classifier to handle the multiclass disease classification problem.

Extensive experiments comparing different models demonstrate that the DenseNet based Transfer Learning model outperforms traditional methods in rice disease detection. Specifically, the model achieves 100% accuracy on both training and testing datasets for detecting diseased rice leaves. Furthermore, 10-fold cross-validation results in a mean accuracy of 99.81%, confirming the robustness and validity of the model. Our approach offers high diagnostic accuracy and shows potential for scaling to diagnose various plant diseases, with significant implications for advancing agricultural practices.

**Keywords: Disease Classification; Rice Diseases; Dense Convolutional Network; Transfer Learning**

## 1. Introduction

Agriculture belongs to the primary industry, cultivates plants and animals to produce food and industrial raw materials as well as supports the national economy's construction and development (Xie, et al., 2017)[1]. Rice cultivation is an important part of agricultural production. With the improvement of people's quality of life, rice is becoming more and more popular (Singh, et al., 2016)[2] and has become one of the staple foods for nearly half of the world's population (Blümmel, et al., 2020)[3]. However, rice diseases lead to low yield and poor quality of rice (Jain, 2024; Ofori, 2025; Zhang, et al., 2025)[4-6]. Therefore, efforts for efficient integrated rice disease management will not only increase the economic income of farmers, but also provide food security for people.

Traditional methods rely on farmers' observation and experience, which leads to inaccurate judgments due to lack of scientific basis (Islam, et al., 2020)[7]. With the popularity of mobile phones, rice farmers can easily access images of rice diseased leaves. Therefore, accurate identification of rice diseases through images can help farmers determine what diseases it is. The farmers can reduce the losses caused by the disease by making timely treatment based on the judgment results. Using computer and communication technology, an intelligent crop disease detection model is proposed, and an automatic identification system is established, which is of great significance to accurately judge the disease of rice plants.

With the popularization of electronic products, artificial intelligence methods will be the trend. Deep learning, a new field that has been rapidly developing for more than a decade, has received researchers' attention, because of its obvious advantages over shallow models related to both feature extraction and modeling (Schmidhuber, et al., 2015)[8]. Deep learning is adept at mining increasingly abstract feature representations from raw input data and has good generalization capabilities. It overcomes some of the problems that have been considered intractable in Artificial Intelligence in the past. Moreover, with the significant increase in the number of training dataset and in the processing power of chips, convolutional neural networks (CNN) have come into being. Researches on CNN began between the 1980s and 1990s, with time-delayed networks and LeNet-5 being the first CNN to emerge (LeCun, et al., 1989)[9]. After the twenty-first century, with the introduction of deep learning theory as well as the development of numerical computing devices, CNN has been developed rapidly. AlexNet, proposed by Hinton's team, introduces deep structure and dropout methods that change the field of image recognition (Krizhevsky, et al., 2012)[10]. Oxford Visual Geometry Group (VGG) deepens the network to about 20 layers, increasing the accuracy of image recognition dramatically (Simonyan, et al., 2014)[11]. Later, ResNet introduces Group convolution (He, et al., 2016)[12] and DenseNet introduces Dense connection (Huang, et al., 2016)[13], and good deep learning algorithms continue to emerge.

Crop disease detection and classification methods, mainly using digital image processing techniques (Barbedo, 2013; Barbedo and Arnal, 2017)[14,15], Principal Component Analysis (PCA), Support Vector Machines (SVM), K-Nearest Neighbor (KNN) and so on (Shah, et al., 2016; Ghosh, et al., 2022)[16,17]. In 2019, JA Pandian developed an augmented plant leaf disease dataset using basic image manipulation and deep learning–based augmentation techniques, including image flipping, cropping, rotation, color transformation, PCA color augmentation, noise injection, Generative Adversarial Networks , and Neural Style Transfer (Pandian, et al., 2019)[18].

In 2007, Jingjing and Rongxiang used resampling, PCA based on resampled dataset, and first-order derivative spectroscopy to process the spectral dataset. This was based on first-order derivative spectroscopy for principal component analysis with a classification accuracy of 80% (Jingjing and Rongxiang, 2007)[18]. In 2012, Phadikar used Bayes and SVM classifiers to classify rice diseases with an identification rate of 79.5% and 68.1%, respectively (Phadikar, 2012)[19]. In 2017, Prajapati proposed K-means clustering for segmentation of foci based on mass-centered feeding and the use of support vector machines for multi-classification problems, obtaining an accuracy of 88.57% (Prajapati, et al., 2017)[20]. In 2019, Liang proposed an effective rice blast feature extraction and classification method using CNN. The evaluation results showed that the high-level features extracted by the CNN were more discriminative than LBPH and Haar-WT, with classification accuracies above 95% (Liang, et al., 2019)[21]. In 2020, Chen studied transfer learning of the deep convolutional neural networks for the identification of plant leaf diseases and considered using the pre-trained model learned from the typical massive datasets, and then transfered to the specific task trained by rice data (Chen, et al., 2020)[22]. At the same time, Patidar adopted the Residual Neural Network for detection, and the results showed that the Residual Neural Network detection speed was fast, and achieved an accuracy of about 95.83% on the dataset (Patidar, et al., 2020)[23]. Researches on the detection methods of plant diseases have made certain achievements. Cheng integrated the CBAM module into the YOLOv7 network to address practical challenges in rice disease identification, including complex backgrounds and irregular lesion shapes(Cheng, et al., 2024)[24].

In this paper, we continue our research based on existing methods to expand data using several image processing techniques for small samples of rice disease data and conduct comparative experiments to demonstrate the effectiveness of data enhancement. An artificial intelligence system model for crop disease detection is proposed by using Dense Convolutional Network to directly train and learn on plant images, automatically extract features, and Softmax regression algorithm for disease classification and identification. The rice disease model based on Dense Convolutional Network uses the model parameters borrowed from Transfer Learning to speed up the convergence of the model and improve the classification effectively, so that realizes the training of rice disease classification model based on small sample data applied by the deep convolutional network.

## 1. Results

### 2.1 Comparison of the results of the training process

Experiments are conducted using dense convolutional networks based on transfer learning for untreated rice disease data, method A enhanced data and method B enhanced data, respectively, as shown in Fig. 1. Both methods for data expansion result in faster and more stable convergence of the model.

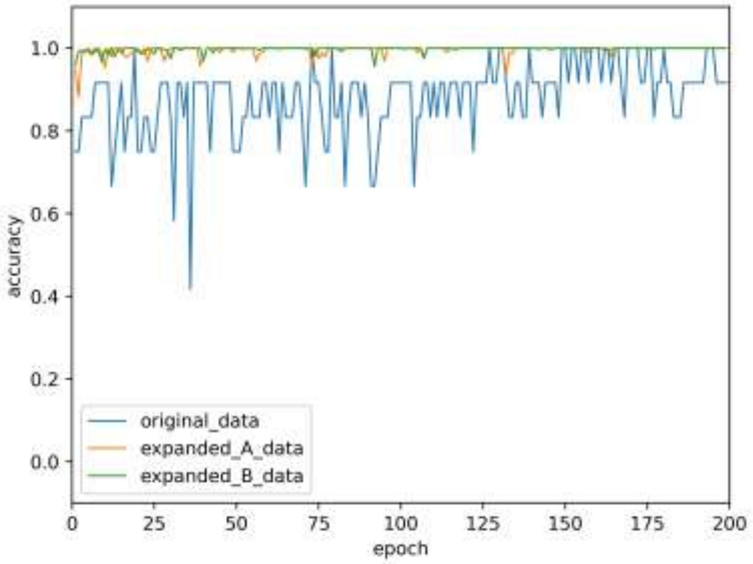
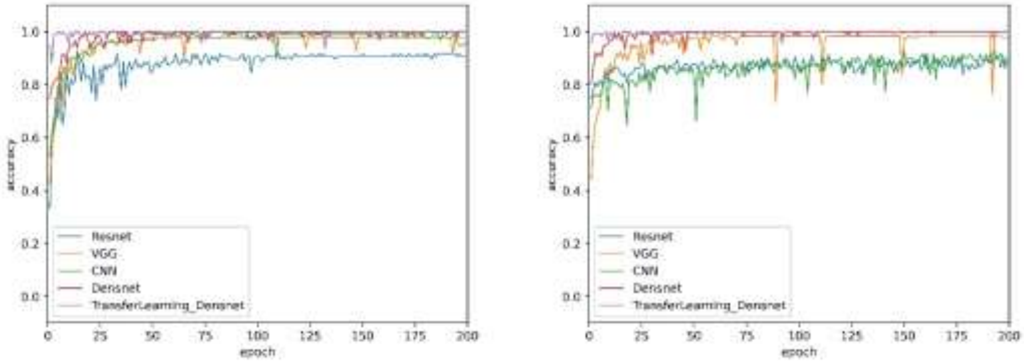


**Figure 1 Comparative results of dense convolutional networks based on transfer learning applied to raw data and data enhancement**

In order to ensure the effectiveness of Transfer Learning-based Dense Convolutional Network for rice disease classification, the Transfer Learning-based Dense Convolutional Network pre-training model, traditional Dense Convolutional Network, traditional CNN, VGG and residual network methods are adopted to extract features from the experimental dataset and to perform classification identification by the same Softmax classifier, respectively. The training process of the rice disease dataset expanded by the two methods with different depth CNNs is shown in Figure 2. Figure **a** shows the comparison results of the data after different models acting on data enhancement (A). Figure **b** shows the comparison results of the data after different models acting on the data enhancement and cross-entropy was used (B).



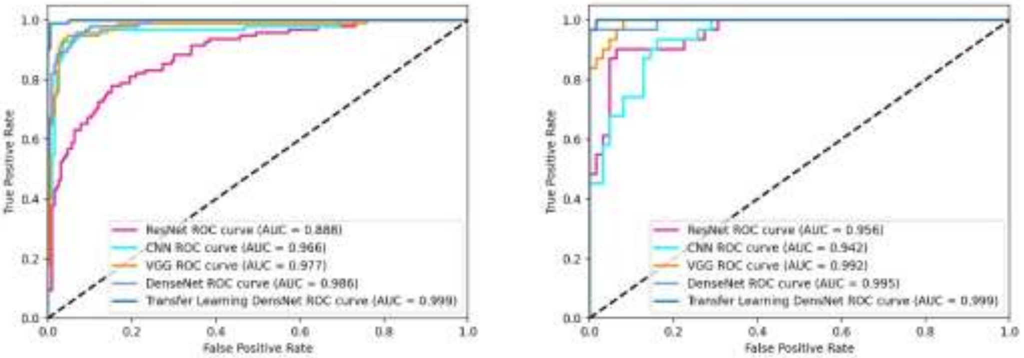
**(a)** **(b)**

**Figure 2** Training process accuracy curve

It can be seen from the Figure 2 that the training accuracy of the Dense Convolutional Network framework is significantly higher than that of other networks, while the Transfer Learning-based Dense Convolutional Network converges faster and more steadily than the ordinary Dense Convolutional Network. The Transfer Learning-based Dense Convolutional Network training process curve reaches an initial value of more than 90%, begins to flatten out after 25 epochs, fluctuates around 100% after 50 epochs, with more smooth convergence. Moreover, the effect of using cross-entropy is significantly more pronounced compared to not using cross-entropy.

This shows that this network, whose features are learned from the big dataset by the deep learning model with more than 200 times training, can solve the problem of rice disease identification well.

Receiver Operating Characteristic (ROC) curve shows in Figure 3. According to the ROC curve, the Area Under the Curve (AUC) of a Dense Convolutional Network based on transfer learning is closest to 1. The larger the AUC value is, the more likely it is that the current classification algorithm will rank positive samples ahead of negative samples, i.e., it will be able to classify better. Figure **a** shows the comparison results of the data after different models acting on data enhancement (A). Figure **b** shows the comparison results of the data after different models acting on the data enhancement (B) The curve is more stable when using cross-entropy.



**(a)** **(b)**

**Figure 3 AUC-ROC curve**

Overall, the deep network framework training process can achieve convergence owing to the expanded data volume, the support of computational clusters, and the transfer learning from large sample datasets. This proves that the deep network framework-based approach can effectively solve the problem of rice disease detection in few-shot datasets In addition, the cross-entropy used in the model can effectively improve the model compared to the model without it.

### 2.2 Cross-validation Results

The average accuracy of 20 times 10-fold cross-validation for data A and data B are 99.74% and 99.81%, respectively. This indicates that the model is highly robust and easy to generalize. The comparison with other methods is shown in Table 1.

**Table 1 Accuracy of different models**

| Method | Accuracy (data A) | Accuracy (data B) |
|---|---|---|
| Resnet | $88.05\% \pm 1.61\%$ | $86.87\% \pm 1.22\%$ |
| CNN | $94.47\% \pm 3.23\%$ | $85.54\% \pm 2.13\%$ |
| VGG | $93.41\% \pm 3.21\%$ | $97.51\% \pm 4.13\%$ |
| DenseNet | $99.43\% \pm 0.47\%$ | $99.53\% \pm 0.37\%$ |
| Transfer Learning DenseNet | $\mathbf{99.74\% \pm 0.26\%}$ | $\mathbf{99.81\% \pm 0.17\%}$ |

## 2. Discussions

The accuracy of crop disease detection is crucial for agricultural production, and effective detection methods provide the decision and methodological support for farmers to accurately decrease and reduce losses. To address this problem, this study effectively exploits the deep learning algorithm with excellent characteristics and gives a detailed model of Dense Convolutional Network for rice disease detection based on Transfer Learning. The model can distinguish the type of disease and predict the results with high accuracy to achieve the expected performance, which is suitable to be widely used in various fields. They use of entropy is significant for neural network models. The automatic identification system can be embedded in a mobile phone application, and the diseased rice leaves can be photographed through the mobile phone, and the trained recognition model can be imported into it. Through automatic feature extraction, the disease can be intelligently judged, and expert opinions can be given based on the disease. The method is simple to operate, can help farmers to deal with crop diseases in time, and solve or improve the diseases of novice farmers, such as misdiagnosis of diseases and misuse of pesticides.

## 3. Conclusion

To solve the problem of crop disease detection, this study does the following work for small sample rice disease data.

1) Process the data. Firstly, reduce the data noise and remove the background in the image except for the rice leaves to avoid the interference of the background to the study. Then expand the data volume, use symmetric transformation, swap the RGB channels of the images and rotation to enrich the diversity of the data, which can alleviate the overfitting phenomenon of the model.

2) Dense convolutional network based on transfer learning and cross-entropy. A deep convolutional network with dense blocks is constructed to train learning knowledge using large sample data sets, and the trained model is transferred and applied to achieve fast convergence of small sample data sets.

3) Application of dense convolutional networks based on transfer learning for rice disease detection. The deep learning knowledge in computer field is effectively applied to rice disease detection to achieve automatic feature extraction and accurate disease identification.

## 4. Materials and Methods

### 5.1 Samples

### 5.1.1 Introduction to the Sample Data

This study uses data provided by the UC Irvine Machine Learning Repository. After consulting experts in the agricultural field to identify and validate the names of diseases, the dataset is created manually by sorting infected leaves into different disease categories. The dataset contains three diseases: bacterial leaf blight, leaf smut and brown spot, each with 40 images. Each image contains a diseased rice leaf, and examples of some of the diseased leaves in the dataset are shown in Figure 4.

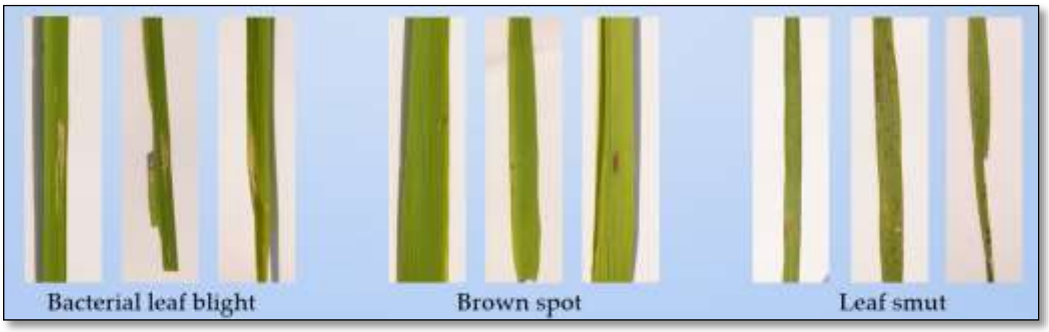


**Figure 4 Examples of an image of a diseased leaf**

### 5.1.2 Processing of Sample Data

Due to the small amount of rice data, the sample size needs to be expanded to allow for repeated training of deep learning algorithms, where errors propagate backwards, and parameters are adjusted in order to obtain models with a high degree of accuracy. This study adopts two types of methods to enhance data.

A. Enhance data through symmetric transformation and channel transformation. An example of image processing is shown in Figure 5. The image symmetric transformation formula is

$$\begin{cases} P_a\,[i,j,c] \;=\; P[i,W-j,c] \\ 1 \le i \le H \\ 1 \le j \le W \\ 1 \le c \le 3 \end{cases} . \tag{1}$$

The formula for the exchange of channel R and channel G is

$$\begin{cases} P_b\,[i,j,1] = P[i,j,2] \\ P_b\,[i,j,2] = P[i,j,1] \\ P_b\,[i,j,3] = P[i,j,3]. \\ 1 \le i \le H \\ 1 \le j \le W \end{cases} \tag{2}$$

The formula for the exchange of channel R and channel B is

$$\begin{cases} P_c\,[i,j,1] = P[i,j,3] \\ P_c\,[i,j,2] = P[i,j,2] \\ P_c\,[i,j,3] \;=\; P[i,j,1]. \\ 1 \le i \le H \\ 1 \le j \le W \end{cases} \tag{3}$$

The formula for the exchange of channel G and channel B is

$$\begin{cases} P_d\,[i,j,1] = P[i,j,1] \\ P_d\,[i,j,2] \;=\; P[i,j,3] \\ P_d\,[i,j,3] \;=\; P[i,j,2], \\ 1 \le i \le H \\ 1 \le j \le W \end{cases} \tag{4}$$

where $i, j$ and $c$ are all integers, $P$ represents the tensor of the original image, $Pa$ represents the matrix of the symmetrically transformed image, $Pb$ represents the matrix of the image converted from channel R to channel G, $Pc$ represents the matrix of the image converted from channel R to channel G, $Pd$ represents the matrix of the image converted from channel R to channel G, $H$ represents the height of the picture, $W$ represents the width of the picture.

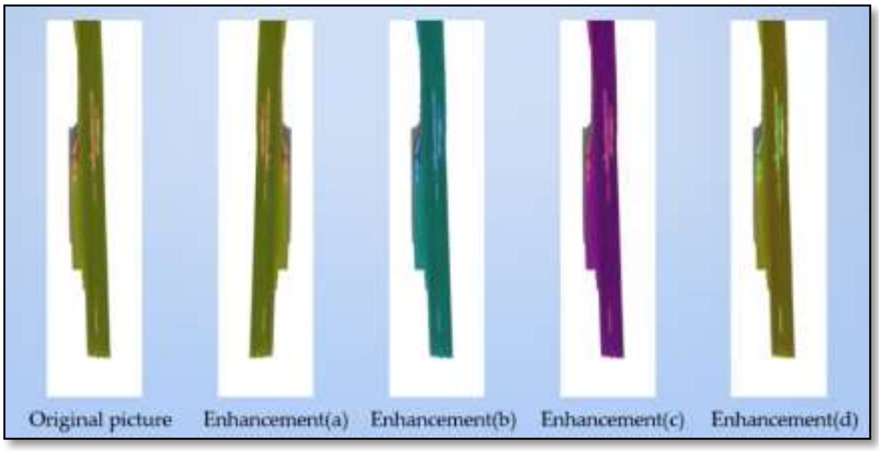


**Figure 5 Image enhancement example (A)**

B. Enhance data through image rotation. Taking the center of the image as the center of rotation, rotate the image by 10 degrees, 20 degrees, 30 degrees, 40 degrees... One picture is expanded to 36 pictures. An example of image processing is shown in Figure 6.

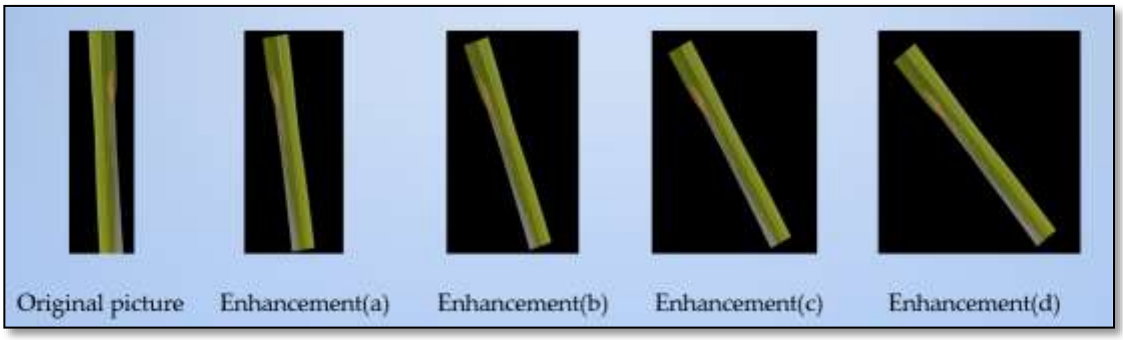


**Figure 6. Image enhancement example (B)**

After expanding the data, pictures of rice leaves with bacterial leaf blight, brown spot and leaf smut are labeled as 0, 1, and 2, respectively. The distribution of sample categories in the dataset is shown in Table 2.

**Table 2 Distribution of sample categories**

| Label | Test results | Sample size | Expanded sample size (A) | Expanded sample size (B) |
|---|---|---|---|---|
| 0 | Bacterial leaf blight | 40 | 320 | 1440 |
| 1 | Brown spot | 40 | 320 | 1440 |
| 2 | Leaf smut | 40 | 320 | 1440 |

Images of the three diseases are placed together and in disorder, and then the dataset is divided. On the one hand, a 10 cross-validation method is used to ensure the reliability of the study. Repeat 10 times in the same way, with different test data and training data for each time. On the other hand, the dataset is divided into 10 parts, and 9 of them are done for training and 1 for validation in turn, and the mean of the 10 results is used as an estimate of the accuracy of the algorithm.

### 5.2 Methods

A dense convolutional network-based rice disease model is used to extract the characteristics of different rice diseases by training from input data to classify them. This study compares the image classification of Google’s public ImageNet dataset with the Dense Convolutional Network, although the dataset and the classification goal are different, the overall idea is similar. Image Net dataset is an image database with a large sample size and varieties. Many studies often use thousands of data in the process of training classification models. However, when obtaining the data of rice diseases, it is found that there is fewer diseased rice. When the amount of data is not sufficient to support the model training, neural networks, which have a generality of image extracted features, are utilized to obtain the optimal parameter structure for training and learning based on the Image Net dataset.

To address the problem of small sample rice disease classification, this study uses Transfer Learning and Dense Convolutional Networks to transfer existing knowledge to the classification process of small sample dataset. The overall framework of the small sample rice disease classification model is shown in Figure 7.

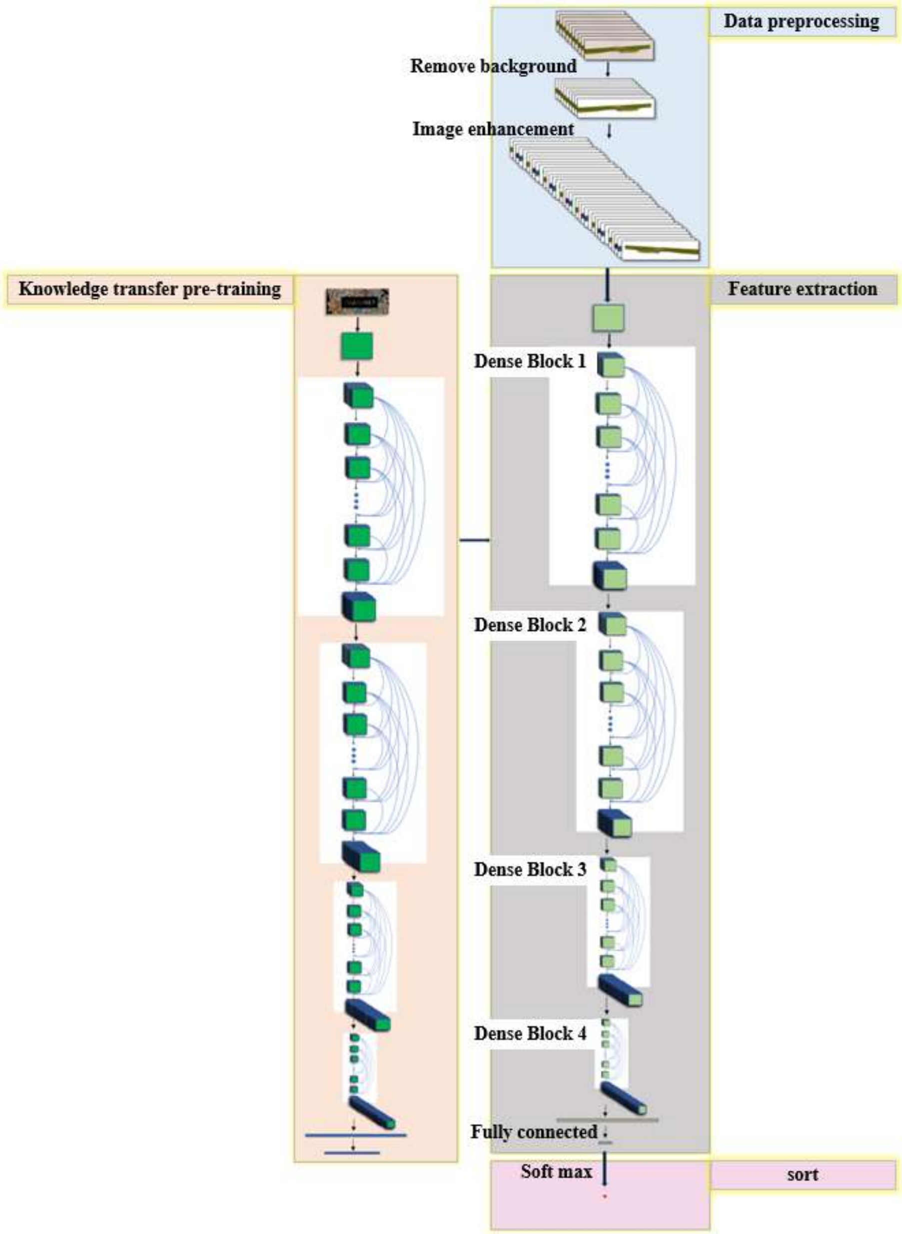


**Figure 7. Overall framework of the small sample rice disease classification model**

### 5.2.1 Rice Disease Classification Model

A dense convolutional network with a depth of 121 contains 4 dense blocks and 3 transition layers, and 4 dense blocks contain 6, 12, 24, and 16 dense layers, respectively. Each transition and dense layer perform batch standardization, ReLU function activation, convolution, and pooling operations. The Dense Convolutional Network increases the depth of the feature map through dense layers to ensure that more features are extracted. The increased depth brings more computational effort, and the transition layer reduces the computational difficulty by decreasing the feature map size. The input size is 3*224*224 for the three-channel image data, and the output size is 1*3 for the vector after a series of convolution, pooling, and Batch Normalization operations. The Softmax algorithm is used to obtain the category to which the rice disease images belonged.

According to the above test model, the parameters involved are tuned, and the parameter settings for the rice disease detection model are shown in Table 3. In order to fully prove the validity of the results, this study adopts the 10-fold cross-validation method. By changing the random seeds, different results of random division of the data set were derived, and each random seed was cross-validated once by 10-fold. Twenty times 10-fold cross-validation was performed in this study.

**Table 3 Parameter settings of the rice disease detection model**

| Model parameter | Parameter name | Parameter value |
|---|---|---|
| epoch | Training set overall training times | 200 |
| batch_size | Size of each batch of training samples | 32 |
| k | Cross-validation fold | 10 |
| lr | Learning rate | 0.0001 |
| image_H | Image height | 224 |
| image_W | Image width | 224 |
| classes | Number of classes | 3 |
| seed | Random seeds | 42 |

### 5.2.2 Dense Convolutional Network pre-training

The purpose of the Dense Convolutional Network pre-training task is to transfer the model's ability to extract features. The Image Net dataset is applied to continuously iteratively update the pre-trained network structure and network parameter weights through forward propagation and backward propagation to reach the optimal parameter structure. Although the ImageNet dataset is not very similar to the rice images, they both have similar edge features, texture features and geometric features. The similarity between the rice image dataset used in this study and the training data of the pre-trained model is very low, which is consistent with the feature of Transfer Learning approach. Therefore, the feature transferring in the transfer learning approach is used to remove the last layer of the pre-training network, extract its previous weights, and feed it into the Dense Convolutional Network of rice disease data for classification training. The Dense Convolutional Network with Transfer network parameters and structure is used to extract rice image features, and the extracted features are classified by the training classifier to solve the rice disease classification problem.

ImageNet dataset with sufficient number of samples is used in the Dense Convolutional Network pre-training process. The extensive knowledge learned by the Dense Convolutional Network pre-training model on the ImageNet dataset is fully utilized to optimize the identification problem of the rice disease image classification. Compared to randomly initializing the weighting parameters of all layers of the network, feature transferring helps the network to converge quickly by using the training dataset to train the network from the beginning.

### 5.2.3 Training of the Transfer Dense Convolutional Network for Rice Disease Data

After initializing the network using the ImageNet dataset, the training set of the rice data is imported for re-training the model. The training set is a randomly selected 90% of the rice data after processing in disorder, and the remaining 10% is used as a test set. By continuously inputting rice disease data, the model continues to learn on the original basis and automatically extracts the characteristics of rice diseases to obtain more appropriate weight parameters for rice disease classification.

The loss function uses the Cross Entropy Error Function (CELF) which is very useful in doing classification training. The Cross Entropy formula is expressed as:

$$\mathrm{loss}(W) = -\frac{1}{N}\sum_{n=1}^{N}\sum_{c=1}^{C}\boldsymbol{y}_c^{(n)}\log\hat{\boldsymbol{y}}_c^{(n)} = -\frac{1}{N}\sum_{n=1}^{N}\left(\boldsymbol{y}^{(n)}\right)^T\log\hat{\boldsymbol{y}}^{(n)}, \qquad (5)$$

where $N$ is the total number of samples; $C$ is the total number of categories; $X^n$denotes the nth sample; $\boldsymbol{y}^{(n)}$ denotes the true probability distribution; and $\hat{\boldsymbol{y}}^{(n)}$ denotes the posterior probability at each category.

In machine learning to train the network, when the input data and labels have been determined, then the true probability distribution is also determined, so the information entropy is a constant. Relative entropy is also called Kullback-Leibler divergence (KL divergence). The value of KL divergence indicates the difference between the true probability distribution and the predicted probability distribution, and a smaller value indicates a better prediction, therefore, KL divergence needs to be minimized, and cross entropy is equal to KL divergence plus information entropy, and the formula is easier to compute compared to KL divergence, so the cross-entropy loss function is used to compute the loss.

The optimization method uses Adaptive Moment Estimation (Adam). Adam is an adaptive learning rate optimization method. Adam dynamically adjusts the learning rate by using the first-order moment estimation and second-order moment estimation of the gradient. Adam algorithm is obtained by combining Momentum and RMSprop with bias correction. Adam is simple to implement, computationally efficient and requires little memory, and the update of parameters is unaffected by the scale-transformation of the gradient, the hyperparameters are well interpreted, and usually require no or very little fine-tuning, and can automatically adjust the learning rate. It is suitable for unstable objective functions and for problems where the gradient is sparse or where there is a lot of noise in the gradient.

### 5.2.4 Softmax Classifiers

The classifier takes the output of the preceding fully connected layers and does a linear regression to calculate the score for each of the three categories, with the highest scoring category output as the result. This study uses Softmax regression algorithm, also known as polynomial or multi-category Logistic regression algorithm. Softmax regression algorithm is to analyze the relationship between the probability of the dependent variable taking a certain value and the independent variable, essentially a model that can solve multi-category problems and the output is the probability that the sample belongs to each category, choosing the best probability from these probabilities corresponding to the of the category as the predicted category for that sample.

In this paper, the bacterial leaf blight, leaf smut and brown spot of rice are classified and identified as examples. For a three-category problem, the category label $y \in \{0,1,2\}$ can have three values. Given a sample $x$, a Softmax regression predicts the conditional probability of belonging to category $c$ as follows:

$$\mathrm{P}(y = c|\boldsymbol{X}) = softmax(\boldsymbol{W}_T^3\,\boldsymbol{X}) = \frac{exp\left(\boldsymbol{w}_c^T\boldsymbol{x}\right)}{\sum_{c=1}^{3} exp\left(\boldsymbol{w}_c^T\boldsymbol{x}\right)}, \qquad (6)$$

where $\mathbf{W}_c$ is the weight vector of class $c$. The decision function of the Softmax regression can be expressed as:

$$\hat{y} = \underset{c=0}{\overset{2}{\arg\max}}\; p(y = c|\boldsymbol{X}) = \underset{c=0}{\overset{2}{\arg max}}\; \boldsymbol{W}_T^C\,\boldsymbol{X}. \qquad (7)$$

For this study, the dataset is extracted through the Dense Convolutional Network of transfer learning, and then it is transformed into feature data, which is classified into “normalized” probabilities by a 1024 to 3-dimensional fully connected layer with a Softmax function at the final output layer, and the category with the highest probability is taken as the test result.

### Funding Declaration

This work is supported by Natural Science Foundation of Jilin Province (grant number 20200201157JC) and Science and Technology Project of Jilin Provincial Department of Education (grant number JJKH20191295KJ). This work is also supported by the Fundamental Research Funds for the Central Universities, JLU.

## Author Contribution declaration

**Ming Liu**: Writing - review & editing, Methodology, Investigation, Conceptualization. **Shengze Yu**: Writing - review & editing, Writing - original draft, Formal analysis. **Xinxin Shi**: Writing - review & editing, Methodology. **Qi Wang**: Data Curation, Vaildation. **Xin Yu**: Project administration, Methodology, Conceptualization.

## References

1. Xie J, Yu J, Chen B, et al. Chapter one-Facility cultivation systems “Facility Agriculture”: A Chinese model for the planet [J]. Advances in Agronomy, 2017: 1-42.
2. Singh V, Jat M L, Ganie Z A, et al. Herbicide options for effective weed management in dry direct-seeded rice under scented rice-wheat rotation of western Indo-Gangetic Plains[J]. Crop Protection, 2016, 81: 168-176.
3. Blümmel M, Duncan A J, Lenné J M. Recent advances in dual purpose rice and wheat research: a synthesis[J]. Field Crops Research, 2020, 253: 107823.
4. Ofori A D, Zheng T, Titriku J K, et al. The Role of Genetic Resistance in Rice Disease Management[J]. International Journal of Molecular Sciences, 2025, 26(3): 956.
5. Jain S, Kumar R, Agrawal K. Original Research Article Performance analysis of various deep learning models for detecting rice diseases[J]. Journal of Autonomous Intelligence, 2024, 7(3).
6. Zhang C, Li S, Yang F, et al. Does the adoption of direct-seeded rice affect pesticide use? Evidence from China[J]. Journal of Integrative Agriculture, 2025.
7. Islam A H M S, Schreinemachers P, Kumar S. Farmers’ knowledge, perceptions and management of chili pepper anthracnose disease in Bangladesh[J]. Crop Protection, 2020, 133: 105139.
8. Schmidhuber J. Deep learning in neural networks: An overview[J]. Neural networks, 2015, 61: 85-117.
9. LeCun Y, Boser B, Denker J S, et al. Backpropagation applied to handwritten zip code recognition[J]. Neural computation, 1989, 1(4): 541-551.
10. Krizhevsky A, Sutskever I, Hinton G E. ImageNet classification with deep convolutional neural networks[J]. Communications of the ACM, 2017, 60(6): 84-90.
11. Simonyan K. Very deep convolutional networks for large-scale image recognition [J]. arXiv preprint arXiv: 1409.15 56, 2014.
12. He K, Zhang X, Ren S, et al. Deep residual learning for image recognition [C]// Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 770-778.
13. Huang G, Liu Z, Van Der Maaten L, et al. Densely connected convolutional networks [C] //Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 4700-4708.
14. Arnal Barbedo J G. Digital image processing techniques for detecting, quantifying and classifying plant diseases[J]. SpringerPlus, 20 13, 2(1): 660.
15. Arnal Barbedo J G. A new automatic method for disease symptom segmentation in digital photographs of plant leaves[J]. European journal of plant pathology, 2017, 147(2): 349-364.
16. Shah J P, Prajapati H B, Dabhi V K. A survey on detection and classification of rice plant diseases[C]//2016 IEEE International Conference on Current Trends in Advanced Computing. IEEE, 2016: 1-8.
17. Ghosh S, Singh A, Jhanjhi N Z, et al. SVM and KNN Based CNN Architectures for Plant Classification[J]. Computers, Materials & Continua, 2022, 71(3).
18. Pandian J A, Geetharamani G, Annette B. Data augmentation on plant leaf disease image dataset using image manipulation and deep learning techniques[C]//2019 IEEE 9th international conference on advanced computing (IACC). IEEE, 2019: 199-204.
19. Phadikar S, Sil J, Das A K. Classification of rice leaf diseases based on morphological changes[J]. International Journal of Information and Electronics Engineering, 2012, 2(3): 460-463.

20. Prajapati H B, Shah J P, Dabhi V K. Detection and classification of rice plant diseases [J]. Intelligent Decision Technologies, 2017, 11(3): 357-373.
21. Liang W, Zhang H, Zhang G, et al. Rice blast disease recognition using a deep convolutional neural network[J]. Scientific reports, 2019, 9(1): 1-10.
22. Chen J, Zhang D, et al. Using deep transfer learning for image-based plant disease identification[J]. Computers and Electronics in Agriculture, 2020, 173: 105393.
23. Patidar S, Pandey A, Shirish B A, et al. Rice plant disease detection and classification using deep residual learning[C]//Machine Learning, Image Processing, Network Security and Data Sciences: Second International Conference, MIND 2020, Springer Singapore, 2020: 278-293.
24. Cheng D, Zhao Z, Feng J. Rice diseases identification method based on Improved YOLOv7-Tiny[J]. Agriculture, 2024, 14(5): 709.