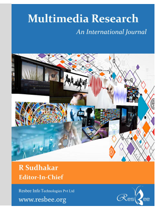
Vol.6 No.3 July 2023

Multimedia Research

Received 12 April, Revised 24 April, Accepted 15 May



An Improved Crop Disease Identification Based on the Convolutional Neural Network

AbdelouafiBoukhris
Computer Systems, Mathematics and Applications Engineering Laboratory, Faculty of Sciences, Agadir, Morocco
abdelouafi.boukhris@edu.uiz.ac.ma

Hiba Asri
LISI Laboratory, Department of Computer Sciences, Faculty of Sciences Semlalia, Marrakech, Morocco
hiba.asri@uca.ac.ma

AntariJilali
Laboratory of Computer Systems Engineering, Mathematics and Applications, Polydisciplinary Faculty of Taroudant, Ibn Zohr University, Morocco
j.antari@uiz.ac.ma

Abstract: The increase in population leads to an increase in the need for food production. A healthy, pest-free plant can providea considered amount of yield in time. However, many conditions affect crop production.Identifying crop disease accurately, fast, and intelligently, plays an important role in agriculture informatization development. Most existing methods are performed manually, which affects the identifyingresult. Careful monitoring and diagnosis of crops for a large area manually is a tedious process. To address these issues, we proposed an improved crop disease identification based on the convolutional neural network (CNN) architecture.The first operation is to resize crop images and to be normalizedthem.Here, we built a neural network toload data samples for training and dividedthe verification set and training set. Furthermore, to adjust the learning rate dynamically, we use Adam algorithms which combinedthe RMSprop algorithm and momentum algorithm to improve the training learning rate.Finally, we used PlantVillage dataset to carry out the validations, this dataset contains 38 different types of crops. The experimentalresult showed the test accuracy and validation accuracy are100% and 97.50% respectively. Compared with state-of-the-art methods, our proposed model has higher detection accuracy. The convolutional neural network proposed in this paper has a high accuracy and fast training speed. The proposed architecture is less time-consuming which can help to improve the development of smart agriculture.

Keywords: Convolution neural network, Layer, Momentum, RMSprop,Identification, Adam algorithms

Nomenclature

Acronym	Description
CNN	Convolutional Neural Network
NPDD	New Plant Diseases Dataset
DCNN	Deep Convolutional Neural Network
DBN	Deep Belief Networks
DBN	Dynamic Bayesian Network
SVM	Support Vector Machine
DLN	Deep Learning Networks
ANN	Artificial Neural Network
GLDD	Grape Leaf Disease Dataset
NPDD	New Plant Diseases Dataset
NAS	Network Architecture Search
MGPUs	Multi-Graphics Processing Units
ToLeD	Tomato Leaf Disease Detection

1. Introduction

Crop diseases reduce production greatly and negatively affectthe agriculture economybecause they spread and break out quickly. So, it is very important to use effective methods to identify crop diseases timely [7][16].

Ecological agriculture needs the development of intelligent methods non-destructive that can detect crop diseases early. Several methods have been proposed such as CNN architecture FL-EfficientNet[1] and the accuracy reached 99.72% based on the NPDD, image processing with a CNN using Vgg-19 [2] and the accuracy was 95.6% using the Plantvillage dataset. Another method based on the combination of CNN and an autoencoder called a V-Convolution encoder network[3], 14-layered DCNN for crop disease

https://doi.org/10.46253/j.mr.v6i3.a2

identification and classification [4], DCNN for the real-time detection of diseases in plant leaves YOLOv5 [5]reached an accuracy of 93%, improved AlexNet model is used to identify crop diseases and pests with the accuracy of 96.26%, DCNN was improved for a real-time detector for grape leaf diseases [8] and the accuracy was 81%, CNN based approach for tomato diseases detection and classification [9]with high accuracy from 76% to 100%. Light spectrum technology [10], identification of diseases based on thermal and stereo visible light images[12], image classification based on DBN [13], and thermal and stereo visible light images for detection of diseased tomato plants[12]. The technology of the light spectrum of crop leaves gives information about crop growing conditions, we can also use this technology for crop disease identification. Hyperspectral technology is used [10][19][21]to identify rice blast disease and the accuracy of this model reached 96%. [11] used hyperspectral imaging to identify the disease of angular leaf spots based on the level of chlorophyll and carotenoids extracted from cucumber leaves.[13] used an improved DBN based on a greedy learning strategy, this network is also used for image recognition.[12][14] proposed a detection system of tomato powdery mildew using machine learning methods.

For crop disease identification, many traditional image recognitions are used which extract features by hand and then feed these features to the classifier to identify disease. Among these methods,SVMwasused for disease diagnosis.Using the PlantVillage dataset, [15][20]combine SVM and image segmentation to classify potato plants and obtained 95% of accuracy, this model was tested using more than 300 images.[19]use SVM to identify cucumber disease by extracting the color of the diseased cucumber.[17] used image processing and SVM for Apple leaf diseases classification, to select optimal values of parameters for SVM.The author alsoused a particle swarm optimization algorithm, and the accuracy of this model was 96.9%.However, traditional image recognition methods have some downsides like timeconsumption and exhaustion, because the feature extraction is done by hand. The only solution for a faster and more automatic result is to use DLN for disease identification.

DLN or ANN is a subset of machine learning constructed by three or more layers.DLN usesan amount of data to learn features thatsimulate the behavior of the human brain.DLN is trained using the amount of data for classification. There are many types of neural networks, among these networks, backpropagation (BP) was mostly used for shallow feature extraction rather than complex features and has three layers.[18][21]usedCNNfor rice ear blast disease detection and the accuracy of the model was 92%.[15][20] combined hyperspectral analysis and BP for the extraction of potato spatial distribution. [11][21] used BP for Rice leaf roll recognition and the accuracy of this method was more than 90%. It seems that using a network with more than three layers hadbetter classification performance. However, adding more layers can bring many problems like overfitting and more parameters to be determined. So, to overcome these problems a new network is used and named CNN[22], which wasconstructed with fewerparameters and studied by researchers. CNN extractsits features automatically from the amount of trained data and makes classification by output layer. Several advantages of CNN architectures like weight sharing, pool layer, and local connection help to reduce the number of parameters to be trained and reduce the complexity of the network. In addition, CNN is robust to the pan and doesn't need a manual operation for feature operation because the original images are directly input into the CNN network, So CNN architecture overcomes traditional methods problems where feature extraction is done by hand. CNN is the most used method for image recognition which can be used to classify crop diseases.

CNN is frequently used in recent years on crop disease classification and muchresearch has been done in this area. [23][21]usedAlexNet, a CNN algorithm for rice disease identification, and obtained an accuracy of 90%.For crop disease classification, [24] used CNN for feature extraction from satellite images obtained by UAV Remote Sensing, and the accuracy of the model is97.75%with three types of crop datasets.This model outperformed traditional methods like backpropagation and SVM. To detect the type of infection in tomato leaves, [25]combined CNN and attention mechanism and gain anaccuracy of 98% on the validation sets in the 5-fold cross-validation. The dataset used was PlantVillage with three types of diseases (leaf mold, late blight, and early blight). [27]combined a shallow CNN network and a classic machine-learning classification algorithm for plant diseaseidentification.Adam algorithm is an extension of stochastic gradient descent very used in deep learning applications to update the network weights based on training data. Adam was presented by Diederik P. Kingma, and Jimmy Ba (2015) [28], Adam combines the advantages of two extensions of stochastic gradient descent such as the Adaptive Gradient Algorithm and RMSprop. Many advantages of Adam algorithms likeComputationally efficient, little memory requirements, etc.

This paper proposesCNN architecture and image processingfor crop disease identification. We usedTensorFlow [26][27] to obtain good accuracy using the PlantVillage dataset.The proposed model is constructed basedon two steps. First, the PlantVillage dataset waspreprocessed to obtain accuracy.Secondly, we proposed an improved neural network with 6 layers trained based on the PlantVillage images. For training,we use the Adam optimizer algorithm that combines momentum and

RMSprop algorithms to tune the learning rate dynamically.The main contribution of our methodsis shown as follows:

- To improve the robustness of our network and accelerate the convergence ratethrough the PlantVillage dataset.
- To dynamically adjust the learning rate and to help the loss function to converge faster to the lower point through Adam algorithms.
- After each convolution,the model is adjusted according to the result of each convolution.

For the PlantVillage dataset the accuracy of our model the accuracy reached 100% for two kinds of diseases which demonstrate the effectiveness of our proposed method.

The organization of this paper is in this order: Section 2 presents the literature review, and Section 3portrays the methodology. The result is illustrated in section 4. Section 5 covers the discussion section 6provides the advantages and disadvantages, and Section 7 concludes the paper.

2. Literature Review

In 2022, Sun*et al.,* [1] have implemented Neural NAS technology for the detection the crop diseases. In this method, CNN architecture was called FL-EfficientNet for multi-category identification of plant disease images. This method contained three main steps. Initially, Neural Architecture Search technology helped to adjust the network according to a group of composite coefficients. In the second step, the features were extracted from the disease image and finally, using the Focal loss function the ability of the network model was improved. The experiment used NPDD and compares it results. The experimental results showed an accuracy of 99.72%, which is better than the above comparison network. FL-EfficientNet has the fastest convergence speed, and the training time of 15 epochs is 4.7 h.

In 2021, Kumar s,*et al.,* [2] have used a deep learning-based approach for image recognition to detect different types of plant diseases. They examined three main architectures of the neural network: Faster Region-based CNN, Region-based Fully CNN. and Single shot Multibook Detector (SSD). The input to the system is an image of a plant leaf, which is then processed by the CNN algorithm to detect the presence of any disease. The system can efficiently detect different types of diseases and deal with complex scenarios. The validation results show an accuracy of 94.6%, which demonstrates the feasibility of CNN and presents a path for AI-based deep learning solutions to this complex problem.

In 2022, Bharathi*et al.,* [3] haveexecuted a hybrid method by a combination of CNN and an autoencoder for detecting crop leaf diseases.Initially, using CNN with image processing methodologies such as image segmentation and filtering the disease in the crop was detected. The ML algorithms better recognize the plants, weed discrimination, etc. The plant leaf disease analysis was also done manually by using visual inspection. To overcome the time consumption, an automated procedure was used in crop monitoring on large farms, and it detects disease symptoms at an early stage.Which aids farmers in effective management methods. Using the Plant Village dataset, the model is trained to recognize crop infections based on leaf images and achieves an accuracy of 99.82%.

In 2022, Pandian *et al.,* [4] have ensembled 14-DCNN to detect plant leaf diseases using leaf images.The dataset used in the research consists of 147,500 images of 58 different healthy and diseased plant leaf classes and one no-leaf class. Data augmentation techniques were used to balance the individual class sizes of the dataset. The proposed DCNN model was trained in the (MGPUs) environment for 1000 epochs. The random search with the coarse-to-fine searching technique was used to select the most suitable hyperparameter values to improve the training performance of the proposed DCNN model. On the 8850 test images, the proposed DCNN model achieved 99.9655%.

In 2023, Khalid et al., [5] have applied a real-time plant health detection system using DCNN. It includes data collection, preprocessing, model choice, training, and evaluation. They created a dataset of images of money plant leaves andseparated them into healthy and unhealthy. They trained a YOLOv5 model to identify healthy and unhealthy leaves, achieving 93% accuracy on a test set.

In 2022, Wang *et al.* [6] have adopted deep learning for the detection of diseases in crops. Initially, samples were collected and preprocessed using nearest-neighbor interpolation.AlexNet model was used to improve the network structure and identify crop diseases and pests. The average recognition accuracy and recognition time are 96.26%.

In 2020, Xie*et al.* [8] have presented a real-time detector for grape leaf diseases based on DCNN. It involved the collection of grape-diseased leaves, expansion of grape leaf disease images through digital image processing technology to construct the GLDD, the introduction of the Inception-v1 module, Inception-ResNet-v2 module and SE-blocks to improve the feature extraction capability of the Faster R-CNN detection algorithm, and use of a double-RPN structure for locating the irregular and multiscale diseased spots. Through a deconvolution process, the high semantic information of Inception_5b is integrated with the high resolution of Inception_ResNet-v2. Thus, the detection model can predict diseased spots separately in each feature layer.It achieved a precision of 81.1% mAP on GLDD, and the detection speed reaches 15.01 FPS.

In 2020, Agarwal *et al*. [9] have devised ToLeD for detecting and classifying diseases in tomato plants. They used CNN model with 3 convolution and 3 max-pooling layers followed by 2 fully connected layers. The model was tested against pre-trained models like VGG16, InceptionV3, and MobileNet and showed better efficacy with a classification accuracy ranging from 76% to 100% for different classes and an average accuracy of 91.2% for the 9 diseases and 1 healthy class.

2.1 Review

Table 1 below illustrates the advantages, limitations, dataset used, and methodology of thestate-of-the-art.We considered eight papers that used different methodologies and datasets that helped to detect crop diseases at various levels.

Table 1: *Comparison of state-of-the-art methods*

Authors	Methodology	Dataset	Advantages	Limitation
Sun*et al.*, [1]	CNNand Network Archit ecture FL-EfficientNet	NPDD	• FL-EfficientNet had the fastest convergence speed. • Reduced the weight of the samples in the training process. • Increased the weight of the hard classification samples for difficult classification samples. • Effectively solve the problem of unbalanced sample numbers through Focal loss. • Improved the average recognition rate of the network.	• The model was complex. • Overfitting • Higher training time
Kumar s,*et al.* [2]	Deep Learning	PlantVillage	• -Detect different types of plant diseases efficiently and deal with complex scenarios. • -It reduced economic losses by detecting diseases at an early stage. • -Improved the accuracy of disease detection.	• -It relied on the quality of the data. • -Can achieve maximum accuracy only if the data is good. • - Require a large amount of data to train the neural network, which were time-consuming and expensive.
Bharathi *et al.* [3]	CNN and V-Convolution encoder network	PlantVillage	• Accuracy increases with the increase in filter size. • Good Precision, Recall, and F1-score.	• Need 150 epochs to achieve good accuracy. • Training and testing accuracy decrease with the increase of epochs.
Pandian*e t al.* [4]	DCNN	Open datasets-PlantDisease 59	• The number of convolutional and pooling operations was lesser than the transfer learning techniques. • F1 scores are higher than the AlexNet, Inception-v3-Net, ResNet-50, and VGG16Net.	• More than 1000 epochs • More than 5 million training parameters. • Required more training time.
Khalidet al. [5]	DCNN	Kaggle	• Highest computational speed. • Low-resource demand	• Lowest average processing. • Inconsistency between feature maps of different scales.
Wang*et al.* [6]	Improved AlexNet model	YuluXiangli Experimental Field of Shanxi Agricultural University	• -Training time was a good recognition time. • -Overcome overfitting by detecting the characteristics of the fragrant pear leaf. • - Higher stability • - Lowest loss rate	• - Small datasets. •
Xie*et al.* [8]	DCNN	GLDD	• Solves the degradation problem of deep CNNs • Fast model • Detect small diseased spots. • The model predicted diseased spots separately in each feature layer. •	• Problem to extract features of multi-scale diseased spots. • Black rot and leaf blight were relatively difficult to detect.
Agarwal*e t al.* [9]	CNN	PlantVillage	• High accuracy • Less number of parameters. • 9 times faster than VGG and Inception.	• 1000 epochs to reach good accuracy. • Overfitting in a smaller number of classes.

2.2. Challenges

The existing method for the detection of crop diseases faces several challenges that need to be addressed through research. One such challenge is accuracyand quality in results [2][3][9]. To achieve higher quality then the process needs higherepochs. In [3][16] Farmer's experience of past dynastieshas an important role in these methods. This helps in the early detection of diseases. However, the manual method is laborious and needs a lot of time to identify diseases correctly.In many methods [1][2][4], the results were obtained easily but the process to obtain the result is complex. time-consuming and expensive. In [1][9] the results were obtained faster. However, adding more layers can bring many problems like overfitting and more parameters to be determined.

To enhance the accuracy and performance of identifying crop disease, an improved, accurate, and less time-consuming method, CNN should be developed.The most shortcoming of all the above-mentioned methods is that requires the use of expensive equipment such as spectrometers, which can limit their practical applications.

3. Methodology

The proposed method contains various processes such as Data processing, Disease identification, training, and testing to detect crop disease.

3.1 Data processing

To improve the quality of the dataset and the accuracy of the proposed model data processing was used.There aretwo steps in data processing they areImage cuttingand Image data normalization.Image cutting is used to resize images on the desired size of input nodes which reduces the usage ofimage pixels and enhances the trainability of neural networks. To accelerate the convergence rate and avoid overfitting and gradient disappearance, normalization processing was used. We also used data image enhancements to obtain the accuracy of our model by expanding the dataset. Figure 1 describes the steps of data processing.

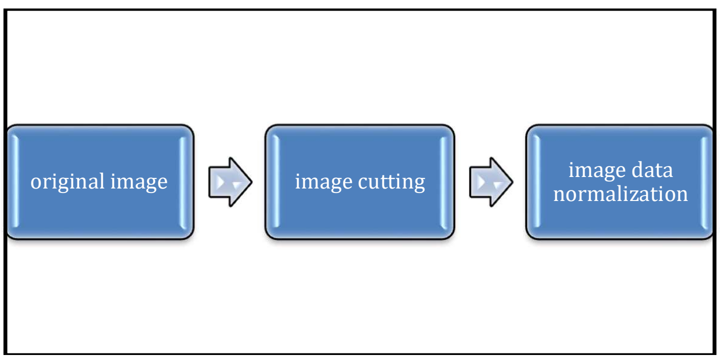


Fig.1. *Steps for Data Processing*

3.1.1Image cutting

The size of input images influences the number of neural network parameters (bias and parameter weight). The training time of the networks depends on these parameters, to speed up the learning and convergence, we must reduce the number of parameters by changing the dimensions of bias and weight. So, image cutting enhances the trainability of our network, makes training time less,and removed redundancy of features. Figure 2 illustrates an image cutting of a plant's leaves. Initially, the original images of the plant leaves were displayed, and the results after the image cutting was represented in the second image.

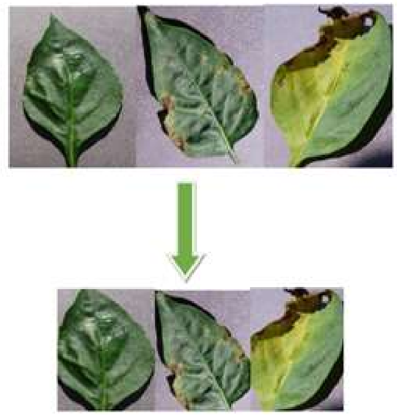


Fig.2.*Image cutting*

3.1.2 Image data normalization

To map the feature of images into one limited domain, image data normalization was used. After this step,the negative influence is avoided from anomaly data, which can accelerate the convergence rate and all data have a similar distribution. In this proposed architecture, the normalization of disease image data is [-1,1], In equation 1, μ is the average value. The average value of this equation is 0 ($\mu=0$) and σ represents the standard deviation.The value of the standard deviation is 1 (σ=1).

$$x = \frac{(X - \mu)}{\sigma^3}. \tag{1}$$

The numerical range of the features may vary strongly which leads to slow convergence of the network. For example, if we want to predict the price of a plot of land from several inputs like surface, age, etc. The numerical ranges of the surface are from 100 to 1000 m², while the age range is from 0 to 60. Slow convergence would occur if we inputted these data intothe proposed deep learning model. Figure 3 shows the effect of normalization, as illustrated the steepest gradient is searched with a large oscillation.

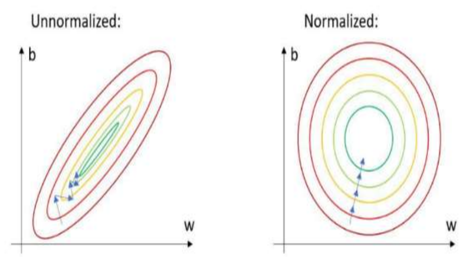


Fig.3.*Normalized data allows faster convergence*

The learning ratefor the large surface required a large range and provide results in slow convergence.

4. Plant disease identification based on CNN

4.1 Overview of theNetwork

This method is based on CNN which we use max pooling, ReLU, batch normalization used in each convolution layer, and dropout.Figure 4 represents the architecture of the proposed network.

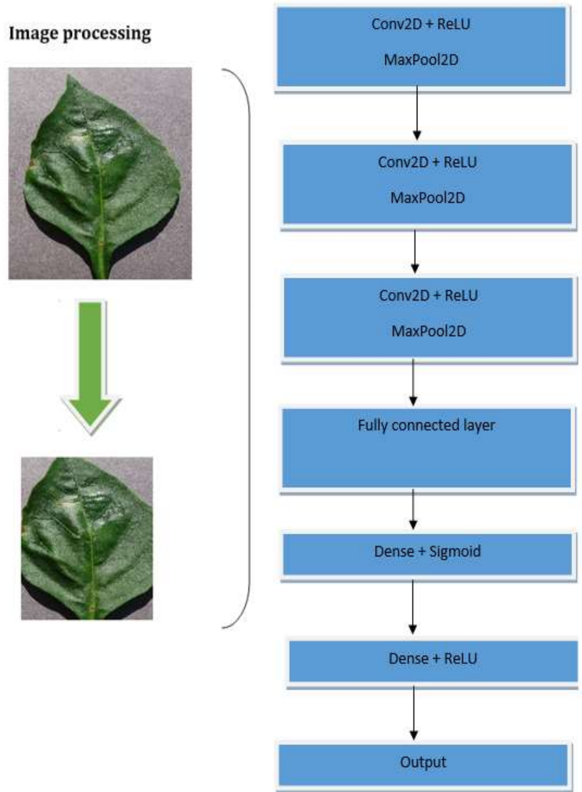


Fig.4. *Overview of the proposed method (CNN)*

Each step includes convolution operation and local normalization. Then we applied the featureReLU (the activation function), max pooling, and dropout. The proposed method used some parameters that are shown in Table 2. The first layer uses 16 convolution kernels (16*3*3*3) with the size of 3x3 for feature extraction and used the same type of padding. A non-linear activation function ReLU was used in the network to approximate better.

After convolution,Batch normalization is applied to increase the convergence of the network. For the second layer,the same processing method was used. The activation function used in this method is ReLU, the expression of this function is:

$$f(x) = \max(0, x) . \tag{2}$$

Table 2: *Parameters setting in the proposed CNN.*

Parameter	Information
Activation function	ReLU
Optimizer	Adam
Convolution type	Arithmetic
Convolution stride	1
Pooling type	Max Pooling
Pooling stride	2
Pooling size	2x2
Inputshape	64*64*3
Filters	32
Kernelsize	3*3
Loss	binary_crossentropy
Activation function for the output layer	Sigmoid
Padding	Same

The feature map is pooled after each ReLU operation. The pooled output size is 64*64*16. To prevent overfitting of our model, the dropout is used with ascale of 0.5.The same method was used in all convolution layers. At the end of the convolution operation, we use the SoftMax function after the pooling operation. The equation of SoftMax is expressed as:

$$y_k = \frac{\exp \ a_k}{\sum_{i=1}^{n} \exp \ (ai)} . \tag{3}$$

There isa totalof 7,15,958 parameters out of which 7,14,486 parameters need to be trained.

4.2 Trained Process

TheCNN model hasthree convolution layers and three training processingsteps. The first step consists of loading the data sample and dividingthe dataset into verification and training sets. The second step is image enhancements, set learning rate, and training of themodel.In the last stepof the training,The CNN model accuracy is obtained through saved loss and accuracy data and evaluation. The CNN model training flow chart is represented in Figure 5.

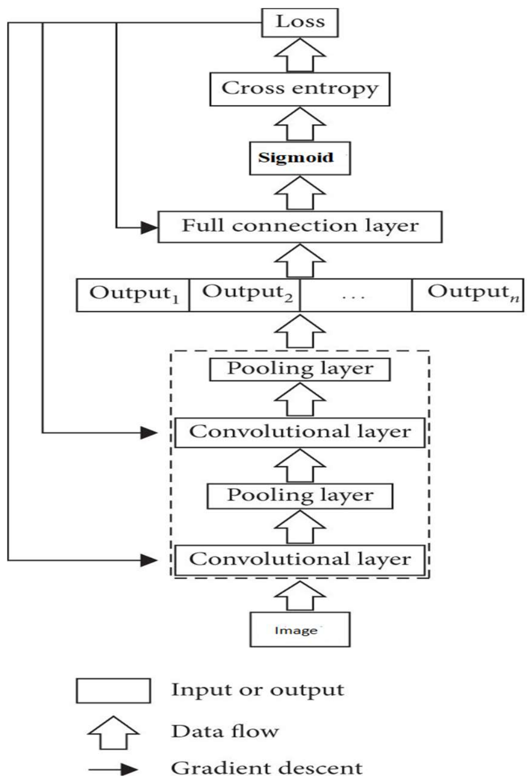


Fig.5.*Flow chart for CNN model training*

4.3 Implementation

- Initially, the dataset is divided into verification and training sets.
- The model is then trained using supervised learning.
- The forward propagation initializes the weight of the network, the input data are passed forward to the convolution layer and fully connected layer to obtain the output.
- Then in the backpropagation, the model calculates the error between the target value and the output value based on theresult of the model and updates the weight of the network based on the algorithm of gradient descent.
- The loss function is the difference between the real value and the predicted value of the model.When the predicted value is closest to the real value, there is a minimum value of the loss function based on the gradient descent algorithm.
- The activation function was used inReLU and for feature extraction.We adopt convolution and pooling operations.
- To minimize the loss function, adjust the learning rate, and speed up the convergence.Here,the proposed model uses the Adam optimizer combined withthe RMSprop algorithm and the momentum algorithm. So, it reduces the time for training and improves the accuracy.
- The proposed model also usescategorical_crossentropy as a loss function of multi-classification.

4.4 PlantVillage dataset

In this paper, the PlantVillage dataset is used for the training and verification of the proposedmethod. This dataset contains several crop disease images and healthy crop imagesfor research in crop disease and diagnosis. There are 14 plant categories such as peach, apple, orange,etc., with a total of 54,306 crop leaf images. Some of the plant images are shown in Figure 6.

Fig.6.*Images from the PlantVillage dataset*

4.5Platform Requirement

The proposed method is run using Python 3.8 and TensorFlow. The hardware used isWindows 10 64bit, core i7, 12 Go memory, and graphic card NVIDIA GEFORCE GTX.

5. Results Analysis and Discussion

We used the PlantVillage dataset for training and verification ofthe experiment.The experiment was conducted ona personal computer with core i7 7th generation. There are45 iterations carried out on the full PlantVillage dataset. The loss and accuracy of our model are shown in Figure 7. With the increase of iterations, the accuracy increases also and tends to be stable after 40 iterations. After all the iterations are completed the accuracy of our model is 100% after 45 epochs. The loss rate of training and testing decreases with the increase of iteration and reachesasmall value.

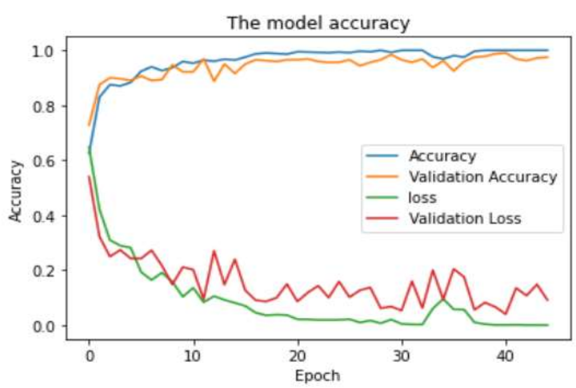


Fig.7.*Graph of accuracy and loss*

We can see that the loss tends to the minimum value after 45 epochs and the value of training loss is 1.8221e-04, the accuracy is 100%, and validation accuracy is 97.50%. Figure 8 represents the accuracy of the training and validation of the model.

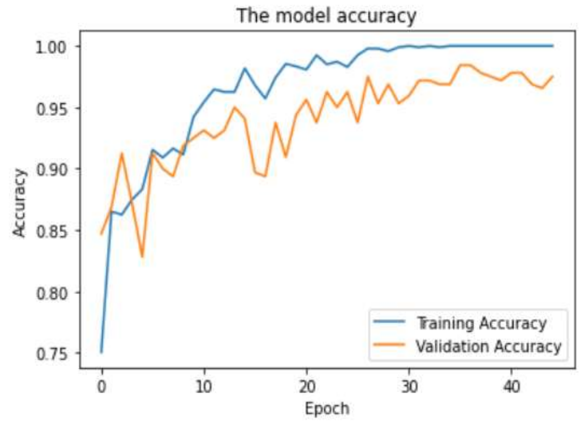


Fig.8.*Graph of accuracy rate*

Figure 9 represents the loss rate of the validation and training data.

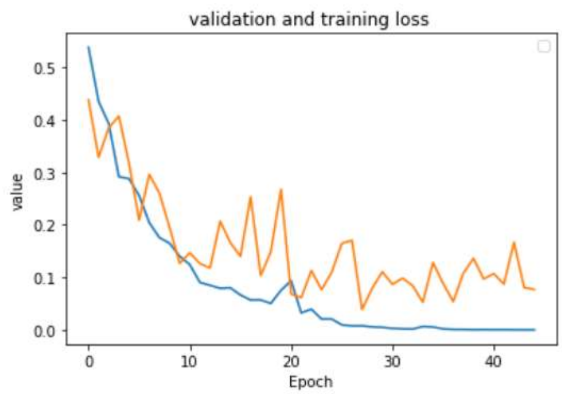


Fig9.*Graph of loss rate*

6. Advantages And Disadvantages

Advantages

- The PlantVillage dataset was preprocessed to obtain accuracy, improved the robustness of the network, and accelerate the convergence rate.
- The Adam optimizer algorithm and RMSprop algorithms tuned the learning rate dynamically to obtain learning efficiency and lead to faster convergence of loss function.
- The convolution of the feature map is adjusted based on the result of each convolution.
- CNN extracts its features automatically from the amount of trained data and makes classification by output layer.
- CNN architectures are weight sharing, pool layer, and local connection help to reduce the number of parameters to be trained and reduce the complexity of the network.
- CNN is robust to the pan and doesn't need a manual operation for feature operation.
- The proposed method reducedthe time required for training and improves the accuracythan other existing methods.

Disadvantage

- The numerical range of the features may vary strongly which leads to slow convergence of the network.

7. Conclusion

From the proposed method,After 45 epochs of training in the PlantVillage dataset, the CNN network achieved anaccuracy of 100% which is higher than the other existingmethod. The experimental result also shows that the validation accuracy is 97.50%. The CNN proposed in this paper has a high accuracy and fast training speed.

Furthermore, It is necessary to conduct additional research on other datasets with more data to test the model and improve the accuracy of the model for new data.

8. Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensuredthat they have not conducted any studies with human participants or animals.

References

[1] Sun, X., Li, G., Qu, P., Xie, X., Pan, X. and Zhang, W., "Research on plant disease identification based on CNN", Cognitive Robotics, Vol. 2, pp.155-163, 2022.

[2] Kumar, S., "Plant disease detection using CNN", Turkish Journal of Computer and Mathematics Education (TURCOMAT), Vol. 12, no. 12, pp.2106-2112, 2021.

[3] Bharathi, I. and Sonai, V., "Image-Based Crop Leaf Disease Identification Using Convolution Encoder Networks", In Machine Learning and Data Mining-Annual Volume 2022.

[4] Pandian, J.A., Kumar, V.D., Geman, O., Hnatiuc, M., Arif, M. and Kanchanadevi, K., "Plant disease detection using deep convolutional neural network", Applied Sciences, Vol. 12, no. 14, p.6982, 2022.

[5] Khalid, M., Sarfraz, M.S., Iqbal, U., Aftab, M.U., Niedbała, G. and Rauf, H.T., "Real-Time Plant Health Detection Using Deep Convolutional Neural Networks", *Agriculture*, Vol. 13, no. 2, p.510, 2023.

[6] Wang, B., "Identification of crop diseases and insect pests based on deep learning", Scientific Programming, pp.1-10, 2022.

[7] Shoaib, M., Shah, B., Ei-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T., Hussain, T. and Ali, F., "An advanced deep learning models-based plant disease detection: A review of recent research", *Frontiers in Plant Science*, Vol. *14*, p.875, 2023.

[8] Xie, X., Ma, Y., Liu, B., He, J., Li, S. and Wang, H., "A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks", *Frontiers in plant science*, Vol. *11*, p.751, 2020.

[9] Agarwal, M., Singh, A., Arjaria, S., Sinha, A. and Gupta, S., "ToLeD: Tomato leaf disease detection using convolution neural network", *Procedia Computer Science*, Vol. *167*, pp.293-301, 2020.

[10] Yang, Y. and He, Y., "Early prediction of antioxidant enzyme value of rice blast based on hyper-spectral image", *Transactions of the Chinese Society of Agricultural Engineering*, Vol. *29*, no.20, pp.135-141, 2013.

[11] Zhao, Y.R., Li, X., Yu, K.Q., Cheng, F. and He, Y., "Hyperspectral imaging for determining pigment contents in cucumber leaves in response to angular leaf spot disease", *Scientific reports*, Vol. *6,* no.1, pp.1-9, 2016.

[12] Raza, S.E.A., Prince, G., Clarkson, J.P. and Rajpoot, N.M., "Automatic detection of diseased tomato plants using thermal and stereo visible light images", *PloS one*, Vol. *10,* no. 4, p.e0123262, 2015.

[13] Zhong, P., Gong, Z., Li, S. and Schönlieb, C.B., "Learning to diversify deep belief networks for hyperspectral image classification", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. *55*(6), pp.3516-3530, 2017.

[14] Raza, S.E.A., Prince, G., Clarkson, J.P. and Rajpoot, N.M., "Automatic detection of diseased tomato plants using thermal and stereo visible light images", *PloS one*, Vol. *10,* no.4, p.e0123262, 2015.

[15] Islam, M., Dinh, A., Wahid, K. and Bhowmik, P., "Detection of potato diseases using image segmentation and multiclass support vector machine", In *2017 IEEE 30th canadian conference on electrical and computer engineering (CCECE),* pp. 1-4. IEEE, 2017, April.

[16] Wang, T., Xu, H., Hai, Y., Cui, Y. and Chen, Z., "An improved crop disease identification method based on lightweight convolutional neural network", *Journal of Electrical and Computer Engineering*, pp.1-16, 2022.

[17] Sun, S., "Classification of Apple Leaf Diseases Based on Image Processing and Support Vector Machine [D]", Xi'an University of science and technology, Xian, China, pp.25-50, 2017.

[18] Huang, S.P., Sun, C., Qi, L., Ma, X. and Wang, W., "Detection method of rice ear blast based on deep convolution neural network", Journal of agricultural engineering, Vol. 20, pp.169-176, 2017.

[19] Y. Tian, C. Zhang, and C. Li. 2004. "Application of support vector machine in plant lesion shape recognition," Journal of agricultural engineering, vol. 20, no. 3, pp. 134–136.

[20] Y. Zhou. 2018. "Extraction of Potato Spatial Distribution Based on BP Neural Network [D]", Chinese Academy of Agricultural Sciences, Beijing, China.

[21]R. Zhao, C. Qi, and L. Duan. 2018. "Rice leaf roll recognition based on BP neural network," Journal of southern agriculture, vol. 49, no. 10.

[22]LeCun, Y., Bottou, L., Bengio, Y. and Haffner, P., "Gradient-based learning applied to document recognition", *Proceedings of the IEEE*, Vol. 86, no.11, pp.2278-2324, 1998.

[23] Krizhevsky, A., Sutskever, I. and Hinton, G.E., "Imagenet classification with deep convolutional neural networks", Communications of the ACM, Vol. 60, no. 6, pp.84-90, 2017.

[24] Ren, Y., Zhang, X., Ma, Y., Yang, Q., Wang, C., Liu, H. and Qi, Q., "Full convolutional neural network based on multi-scale feature fusion for the class imbalance remote sensing image classification", Remote Sensing, Vol. 12, no. 21, pp.3547, 2020.

[25] Karthik, R., Hariharan, M., Anand, S., Mathikshara, P., Johnson, A. and Menaka, R., "Attention embedded residual CNN for disease detection in tomato leaves", Applied Soft Computing, 86, p.105933, 2020.

[26] Girija, S.S., "Tensorflow: Large-scale machine learning on heterogeneous distributed systems", *Software available from tensorflow. org*, Vol. *39,* no.9, 2016.

[27] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M. and Kudlur, M., "Tensorflow: a system for large-scale machine learning", In Osdi, Vol. 16, No. 2016, pp. 265-283, 2016, November.

[28] Diederik P, Kingma, Jimmy Ba," Adam: A Method for Stochastic Optimization", 3rd International Conference for Learning Representations, San Diego, 2015.