ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2024, 9 (2): 184-197 doi: 10.28978/nesciences.1569560

Automatic Classification and Identification of Plant Disease Identification by Using a Convolutional Neural Network

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Abstract

The prompt detection of plant diseases mitigates adverse effects on plants. Convolutional neural networks (CNN) and intense learning are extensively utilized in computer vision and recognition of pattern tasks. Scientists presented several DL algorithms for the detection of plant illnesses. Deep learning (DL) models need many parameters, resulting in extended training durations and complicated implementation on compact devices. This research presents a unique DL model utilizing the inception tier and residual connections. Depthwise differentiated convolution is employed to decrease the variable count. The suggested model has undergone training and evaluation using three distinct plant disease databases. The level of accuracy achieved on the PlantVillage database is 97.2%, on the rice disease database is 98.4%, and on the cassava database is 96.3%. The suggested model attains superior accuracy relative to state-of-the-art DL methods while utilizing fewer variables.

Keywords:

Deep learning, Disease detection, convolutional neural network, Classification.

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Article history:

Received: 20/05/2024, Revised: 18/07/2024, Accepted: 22/08/2024, Available online: 30/09/2024

Introduction

Crop diseases induced mainly by bacteria and fungi adversely affect the yield and quality of agricultural produce (Fenu & Malloci, 2021). The prompt and early detection of disease signs is a significant difficulty in crop protection. The primary method for disease diagnosis on big farms in poor nations involves visual assessment by specialists and agronomists, which is time-consuming and expensive. The automated detection of illnesses using smart devices is a potential strategy for diagnosis and cost reduction. Deep learning (DL) (Sarker, 2021), especially Convolutional Neural Networks (CNNs) (Kattenborn, 2021), has recently garnered significant attention in agriculture for applications such as plant identification, fruit recognition, disease verification, weed identification, and pest identification. The rationale for the CNN-based model's appeal is its capacity to extract features from a data set (Ang, 2023). Numerous prominent DL designs have been created to diagnose plant illnesses (Swapna et al., 2020).

Application development and illness diagnosis with DL systems are attracting significant interest in the present context. The quantity of variables and computational expense in DL systems depends on the model's level and the number of filtering employed. DL systems often need a substantial amount of variables (Sarker, 2022). The computational expense of DL models is substantial. Challenges will arise in the implementation of devices with limited resources. Recently, researchers have employed DL architectures utilizing high-performance devices equipped with GPUs and processors (Lattuada et al., 2022). Using sophisticated gadgets equipped with GPUs is impractical in agriculture due to their exorbitant cost. There is a significant want for applications with reduced characteristics, lower power usage, and diminished computational requirements.

In light of the considerations above, the research has developed an innovative, lightweight DL system to detect plant illnesses. This study presents an innovative CNN architecture integrating Inception and ResNet with fewer variables to identify plant illnesses (Dawod & Dobre, 2022). The Inception design enhances feature extraction using numerous convolutions with varying filter sizes. The research has employed residual links to address the issue of vanishing gradients. The study employed deep separable convolution rather than expected, decreasing variable length and computational difficulty without compromising efficiency. The system has been developed on three distinct datasets, and its abilities have been assessed.

Related Works

DL models mainly include CNN, recurrent neural networks, deep belief networks, autoencoders, and generative adversarial networks (Ahmed et al., 2023). A CNN is a standard DL model applied to recognize material defects. The pixel information of a cracked image is convolved and pooled to realize feature extraction and obtain the abstract feature information in the image. Target detection can not only classify the objects of interest but also determine their relevant positions to detect the objects of interest accurately (Ma et al., 2021). At present, the target detection algorithm has two significant developments. The first stage is to generate candidate boxes, acquire features through CNN, and then use the classifier combined with the bounding box regression to complete the classification and positioning of the object of interest. The second stage predicts CNN boxes' location, size, and object category (Zand et al., 2022). With only one look at each

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image, you can know which objects of interest and their location are present in the image. The main feature of the YOLO series algorithm is to realize the end-to-end target detection and reduce the training and calculation of redundant candidate boxes through the non-maximum suppression, so the efficiency of the training and detection of the model is improved.

Although its detection speed is fast, there are certain disadvantages, such as detection accuracy is not high, inaccurate positioning, etc., then multiple versions by optimizing the leading feature extraction network, using a variety of different scales of features for target detection, optimizing the feature aggregation network and add new data enhancement methods to improve the network model, make the model detection accuracy and detection speed is improved (Roy et al., 2022).

Image segmentation is an image detection segmentation of regions of interest by computer image processing. In recent years, image segmentation technology has developed rapidly, and many excellent algorithms have emerged, which can be divided into three categories: semantic segmentation, instance segmentation, and panoramic segmentation.

Singh et al. employed several pre-trained DL networks and optimized the model parameters for recognizing and categorizing plant illnesses (Singh et al., 2022). They attained a peak testing precision of 99.75% with DenseNet technology. Sethy et al. employed a deep feature-based approach and Support Vector Machine (SVM) classification to detect rice illnesses in the leaves (Sethy et al., 2020). Eleven deep CNN algorithms were used for feature extraction, while SVM was utilized for categorization. The ResNet50 algorithm's deep characteristics, combined with SVM, achieve an F1-score of 98.38%.

Ding et al. employed six distinct pre-trained DL structures to recognize ten different illnesses across four types of crops (Ding et al., 2023). Among the designs, VGG16 has the maximum performance precision of 90% on the test datasets. Shafik et al. employed knowledge transfer with Inception V3 to detect three illnesses and two pest infestations in cassava crops (Shafik et al., 2024). The collection comprises images including several leaves. The accuracy achieved with single-leaf photos surpasses that of photographs with many leaves. Doungous et al. employed cell phones to determine six distinct illnesses in the crop cassava (Doungous et al., 2022). The MobileNet DL framework has been used to train the network.

They used pictures and video clips of infected leaf images to assess efficiency. They attained an accuracy of 81.2% for images and 74.2% for video recordings. Joseph et al. demonstrated that DL with residual relationships surpasses traditional CNN in diagnosing several illnesses in cassava crops (Joseph et al., 2023).

Table 1. Type of image segmentation

classify	content
semantic segmentation	By the division of the pixels
Panoramic segmentation	All the pixels in the image are annotated with category information and instance information
instance segmentation	Combining object detection with semantic segmentation

Table 1 shows the types of image segmentation, in which the semantic segmentation is divided through the division of pixels. Panoramic segmentation segments all regions of interest by labeling category information and instance information to all pixels in the image. Example segmentation is a combination of object

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detection and semantic segmentation. The most common practical engineering algorithm is Mask R-CNN, and different strategies can be combined in different engineering applications to improve the effect of detection and segmentation.

Methodology

This work introduces an automated system for identifying leaf diseases in several crops, including apples, vegetables, grapevines, and corn. The pictures are initially split and subsequently sent to the CNN algorithms for deep extraction of features. The deep CNN characteristics are then categorized using an SVM algorithm. The database is randomly divided into a 70-30 training-testing ratio for the study. Figure 1 depicts the intricate architecture of the suggested system for leaf disease diagnosis and categorization.

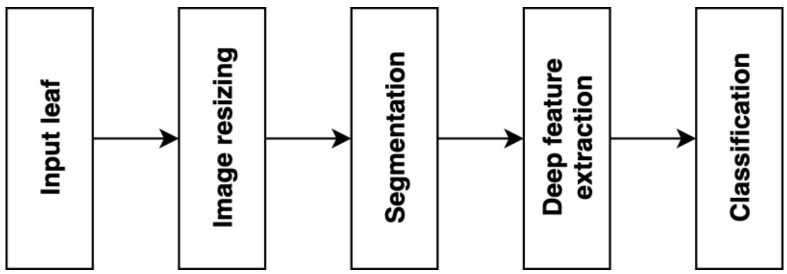

Figure 1. Workflow of the research

- Image Preprocessing and Segmentation

The dataset utilized in this research comprises photos of varying dimensions. The images are initially resized to 225x225 to diminish intricacy and expedite the training procedure. The study divided the leaf pictures. Segmentation is the procedure of partitioning a picture into many parts. The preprocessed photos are split by obscuring the background images and retaining only the leaf section.

- Feature Extraction via CNNs

Due to their strong performance, CNNs are feed-forward neural networks extensively utilized in image identification and categorization domains. The suggested technique employs two fine-tuned transferable CNN models, AlexNet and VGG19, to derive profound characteristics from leaf pictures.

Transfer learning is a prevalent methodology for training new categorization networks by utilizing a network that has been pre-trained on a more extensive dataset. Visual Geometry Group (VGG) is among the highest-performing DL algorithms on the ImageNet dataset. The model is straightforward, effective, and inexpensive. It comprises 3x3 convolutional layers and 2x2 max-pooling tiers. The VGG19 design is illustrated in Figure 4. AlexNet was created to participate in the ImageNet Large Scale Visible Recognizing Competition (ILSVRC) in 2012, achieving a top-5 error rate of 15.3%. The model consists of 8 trainable tiers, comprising five convolutional layers and three fully connected tiers. AlexNet is portable and is extensively utilized for categorization jobs. A CNN processes the picture dataset, assigning filters and weights to each picture object to enable the algorithm to distinguish between distinct images.

CNN consists of several layers and is capable of processing extensive picture collections. The convolutional layer extracts deep characteristics from pictures with convolutional cores. The dot result among the kernel and the image is computed in this tier. The pooling tier succeeds the convolutional tier,

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which decreases dimensionality and computing difficulty. The Fully Connected tier is typically employed after the convolutional and pooling layers. This tier retains the profound traits obtained in the preceding layers.

- Classification

The deep characteristics are ultimately categorized utilizing an SVM classification employing a one-vs-all method. It uses a collection of autonomous binary classifiers formulated to address multi-class categorization challenges, yielding superior predicted accuracy compared to the individual classifications.

Faster Recurrent CNN (RCNN) Target Detection

Faster RCNN Target detection includes three basic steps: feature extraction, generation of candidate regions of interest, target classification, and location regression. The Faster RCNN model consists of two modules, RPN and Fast RCNN. First, the image to be trained or detected is input into the detection network. Second, a CNN extracts feature and forms a feature map. Then, the feature map is input into the RPN to generate possible defect proposal regions mapped onto the convolutional feature map. Next, the region of interest (ROI) pooling layer maps the candidate regions of different sizes to the convolutional feature map to extract the features of the same dimension. Finally, specific classification and exact boundary regression operations for the proposed regions will be used using the defect classification layer and bounding box regression layer.

Table 3. Faster RCNN Target detection steps

step	**feature extraction**	**Candidate regions of interest were generated**	**Target classification and location regression**
model formulation	Reverse propagation Network (RPN)	Fast RCNN	-
concrete content	Enter the images to be trained or detected into the detection network	Feature were extracted using convolutional neural networks to form feature maps	Enter the feature mapping into the RPN to generate possible defect proposal regions

Table 3 shows the steps of Faster RCNN target detection. RPN extracts the anchor box through a sliding window and inputs the low-dimensional short vectors into two parallel, fully connected network layers: the defect boundary box regression layer and the image defect classification layer. In the training set, various target pictures and non-target pictures are collected. The sample pictures must be small, and the corresponding target must be in the center of the photograph and occupy the whole picture. The CNN model, which that model has a high recognition rate. Select the appropriate size window and the appropriate fixed stride, and slide the test image from left to right and fall from the top. Each window area was discrimination-judged using an already trained CNN model. This window is the target area if there is no target and a non-target area. Figure 2 presents the Faster RCNN target defect detection framework by selecting a larger window and then repeating the operation of the third step.

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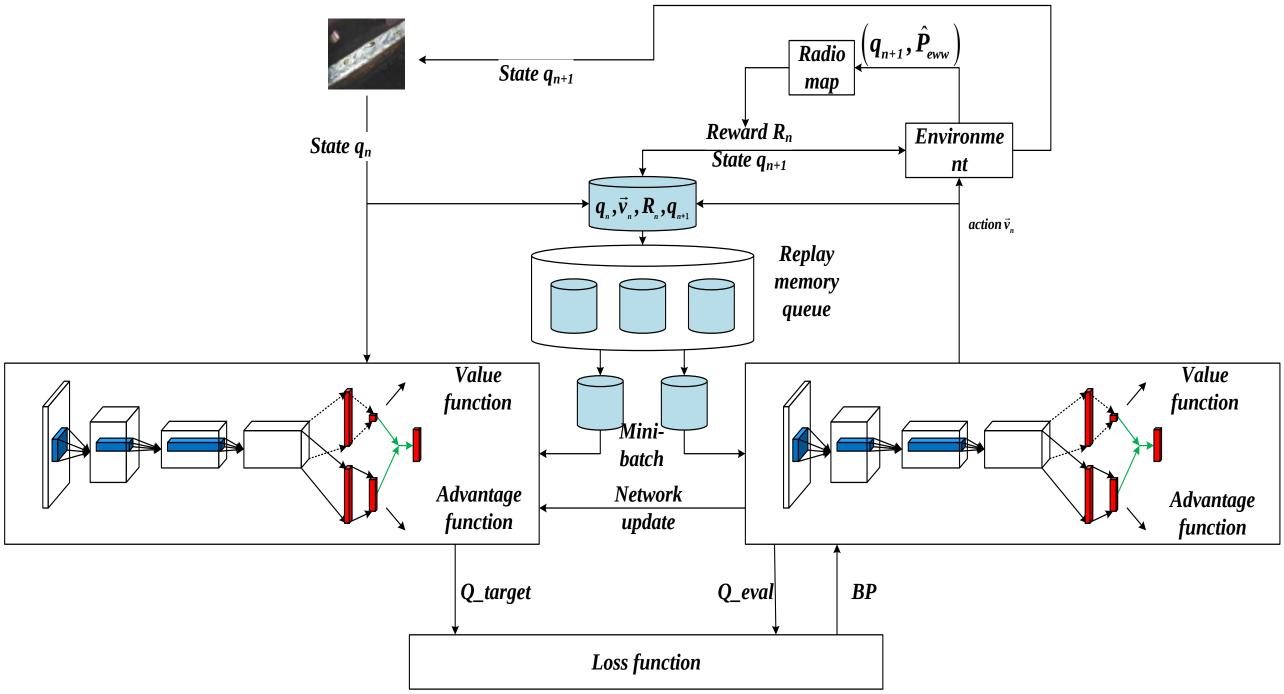

Figure 2. Faster RCNN Target defect detection framework

Disease Detection Method

CNN extracts the features by the convolution of the convolution kernel and input data, then processes the features by activation function and pooling. After training, the network's output can correctly identify the input data for classification.

Table 4. CNN fundamentals and structure

usage method	Convolution of the convolution kernel with the input data
processing method	Activation function and the pooling
purpose	So that the network output terminal can correctly identify the input data for classification

Table 4 presents the basic principle and structure of CNN, the input features after network backbone classification, such as not reached iterations, compared with the actual label through the loss function and optimization function to correct parameters, again into the convolution training process, when reaching iteration times in the field of computer vision, data enhancement is a very effective way to increase the amount of data. In this technique, similar instances are generated from the original instance, artificially increasing the size of the database. In this study, because there is no applicability to the ultrasonic nondestructive testing database, the experiment is challenging to obtain a large number of measured data; the most effective and feasible method is to enhance the data, namely the existing data flip, translation, or rotation, create more data, to make the neural network has better generalization effect, at the same time improve the recognition accuracy of the model.

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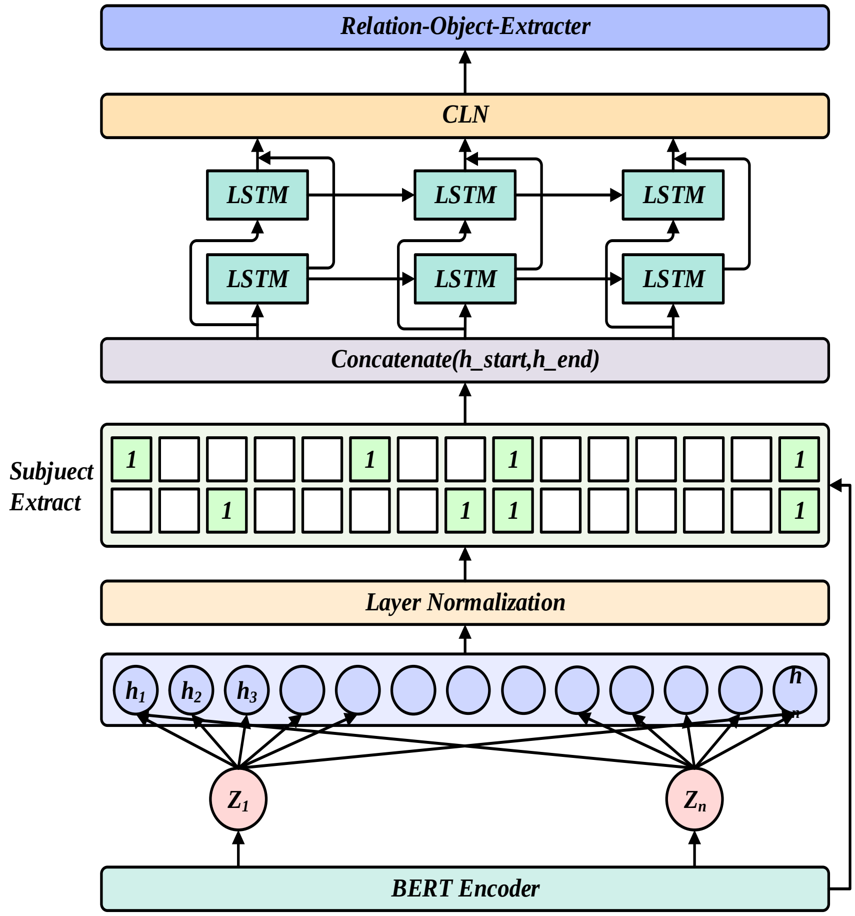

Figure 3. Long Short Term Memory (LSTM) time-series data processing process

Figure 3 offers an in-depth portrayal of the intricate temporal data processing carried out by the LSTM network. Central to this visualization is the LSTM architecture, which meticulously captures temporal dependencies in sequential data. Raw temporal data undergoes preprocessing for normalization, scaling, and missing value handling, from financial market indices to sensor readings. Preprocessed data is then segmented into fixed-size timesteps, essential for LSTM's sequence-to-sequence operation. These timesteps flow into LSTM's memory cells, each equipped with gating mechanisms that regulate information flow. As data traverses LSTM layers, the network learns to extract and encode temporal patterns. This learning is facilitated by the BPTT algorithm, minimizing prediction errors. Finally, the LSTM generates an output, which could be a prediction, categorical label, or any desired outcome. This output is visually represented, offering insights into how LSTM processed the temporal data. Characteristic detection is shown in Figure 4.

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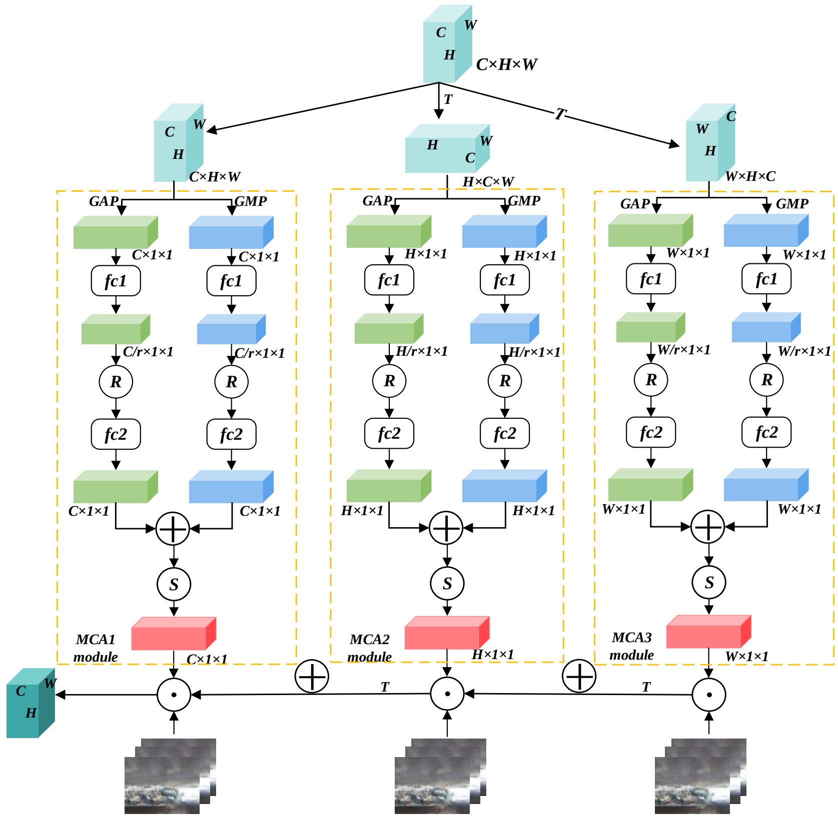

Figure 4. Characteristic detection

Figure 5 showcases the process of predicting image feature segmentation. It divides an image into distinct regions, each with homogenous features. Starting with an image from various sources, it undergoes preprocessing to enhance quality and remove noise. Then, meaningful features are extracted using edge detection and color segmentation techniques. These features guide the segmentation process, which groups pixels with similar characteristics into contiguous segments. The resulting segmented image is presented, along with any predictions or labels. Depending on the specific application, these segmented regions can be leveraged for various tasks, including object detection, scene comprehension, or content-based image retrieval. The figure concludes with a visual representation of the segmented image, clearly depicting the distinct regions and their corresponding features. By harnessing the principles outlined in Figure 4, image feature segmentation prediction enables computers to parse and interpret visual information in a meaningful and beneficial manner for various applications.

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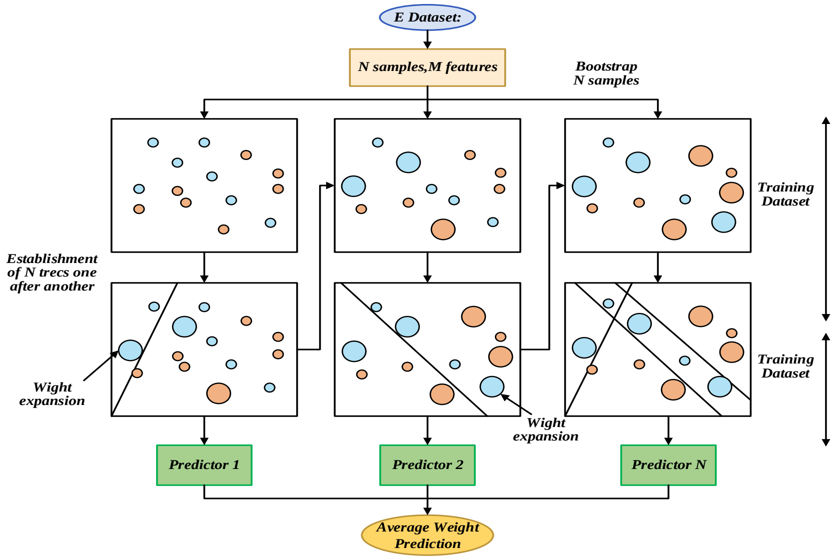

Figure 5. Schematic diagram of image feature segmentation prediction

Environmental Configuration and Structure

The CNN used in this study was implemented based on the Keras framework in version Tensorflow2.0, with CPU model I7-8750H, GPU model 1050TI, and memory 16G. Three network structures were adopted, namely LeNet-5, VGG 16, and ResNet. LeNet5 The structure is the most simple, containing two convolution layers, two pooling layers, and three fully connecting layers; VGG 16 has a complex structure with 13 convolution layers, five pooling layers, and three fully connecting layers; the residual network ResNet contains residual structure with the most complicated structure with five residual modules and two fully connecting layers, including two residual modules containing four convolution layers and one pooling layer, and the other three residual modules contain five convolution layers and one pooling layer respectively. One-dimensional and two-dimensional convolution use precisely the same network structure. Table 5 shows the parameter comparison of the different network structures.

Table 5: Parameter comparison of different network structures

Model name	LeNet-5	VGG16	ResNet
number of plies	5	16	25
Convolutional layer number	2	13	23
Convolutional kernel size	5	31	3
Pool layer number	2	5	5
Pool choice	Max Pooling	Max Pooling	Max Pooling
Cylinization kernel size	2	2	2
Number of fully connected layers	3	3	2

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Results and Discussion

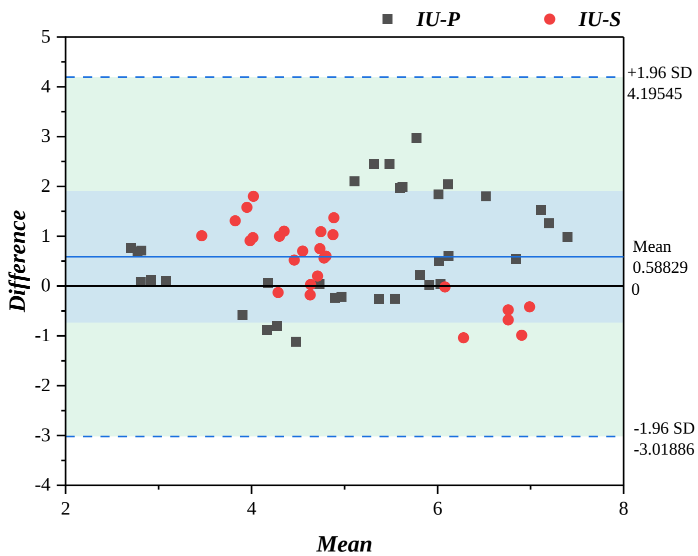

Figure 6: Characteristic distribution analysis

This study presents a nondestructive testing method based on a deep neural network. The galvanized hot-and-rolled high-strength steel plate was applied to automotive parts for real-time measurement of process signals. Figure 6 elegantly presents the findings of the feature distribution analysis, offering a captivating glimpse into the intricate tapestry of segmented image regions. The intricate patterns and clusters revealed within these distributions emphasize the subtle similarities and vast diversities among the segmented features and offer profound insights into their spatial organization within the image. By meticulously examining these distributions, researchers can gain a deep comprehension of the image's intricate structure and rich content, ultimately facilitating more precise and effective predictions across various computer vision tasks. As can be seen from Figure 7, the present method achieves excellent performance.

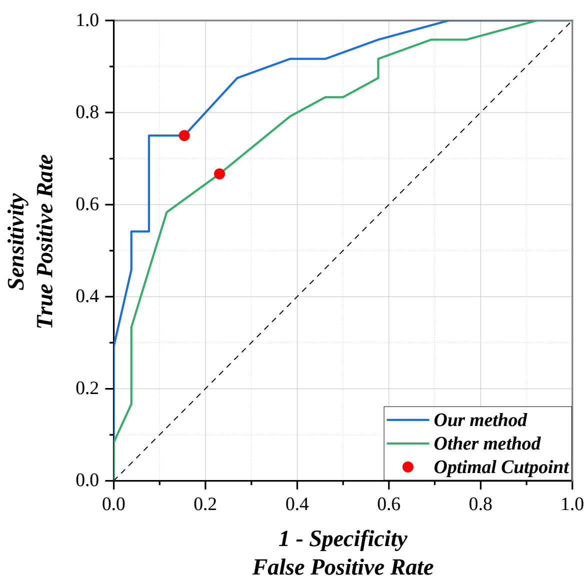

Figure 7: ROC curve

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CNN is used to identify defects in ultrasonic detection echo signals, and the goal is to find a network structure that does not depend on feature extraction technology and should have robustness and high recognition accuracy.

Table 6: Analysis of the experimental results

Condition	Conclusion
A proper network structure is important	The VGG 16 network performs better than the LeNet5 and ResNet
Was trained using the same CNN structure	Two-dimensional images have higher recognition accuracy than 1-dimensional data
When the data volume is low	Using data enhancement can improve the recognition accuracy

Table 6 presents the analysis of the experimental results of the study and found that:

1. A suitable network structure is fundamental. In the experimental comparison, the VGG 16 network performs better than LeNet5 and ResNet. LeNet5 The model is relatively simple and needs to fit the data better. At the same time, ResNet has a residual structure and is higher than VGG 16 in complexity, leading to easier overfitting during training.

2. When training with the same CNN structure, the two-dimensional images have a higher recognition accuracy than the one-dimensional data. When trained with the same CNN structure, the number of parameters for the 2-D convolution is tenfold more than the 1-D convolution, which can better fit the function.

3. When the amount of data is small, data enhancement can improve the identification accuracy. Since there is no publicly available dataset of ultrasonic defect detection echo signals, obtaining them on a large scale is challenging, and data augmentation can partially solve this problem.

4. Different optimization means are conducive to improving the identification accuracy. You can change the activation function to Leaky ReLU in the network and add it

Batch Normalization Layer, etc., to reduce overfitting and improve the network's generalization ability. Analysis experiments show that as long as the appropriate CNN model is selected, very high accuracy can be obtained without feature extraction precisely because of the unique structure and excellent performance of CNN.

Table 7. Result analysis

Dataset	**Accuracy (%)**	**Recall (%)**	**Precision (%)**	**F score (%)**
Rice	94.21	93.54	98.34	98.12
Plant Village	98.23	97.67	97.96	96.87
Cassava	89.52	96.89	98.52	97.47

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The research has computed the confusion matrix to assess the model's efficacy. Table 7 presents the performance metrics of the built model across three plant databases. The Rice crop database yields superior testing precision compared to the PlantVillage and Cassava datasets. The mean forecast results exceed 96% on the rice and PlantVillage datasets.

Conclusion

DL is a contemporary and sophisticated method of picture-recognizing patterns, which has proven highly successful in diagnosing plant diseases. This research presents a unique CNN model utilizing inception and residual connections to classify plant illnesses successfully. The research has included depthwise separable convolutions within the inception design, resulting in a 70% reduction in computational cost by decreasing the number of variables. Training the network needs significantly less time than conventional CNN. The experimental findings indicate that the suggested model attains superior performance reliability. The research utilized three distinct plant databases to assess the model's resilience. The testing accuracies of the proposed approach are 96, 98, and 96% for the Plantvillage, Rice, and Cassava datasets, correspondingly. The author achieved accuracy rates of 89.5 and 89.7% utilizing a simple CNN and a deep residual neural network on an imbalanced database. The author attained an accuracy percentage of 81.2% on the balancing database. The suggested model achieves an accuracy rating of 78.3% on the imbalanced cassava database. The rice database attained an accuracy score of 97.8%, but the suggested model earned a superior accuracy of 98.2% on the identical dataset. In the future, the research will evaluate the efficacy of the proposed approach across many agricultural domains, including identifying weeds and recognizing pests. Future studies will identify plant diseases using various datasets encompassing diverse photos and geographical locations. Applying clustering-based unstructured techniques in illness detection is a significant feature.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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