Citrus leaves disease diagnosis

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ABSTRACT

Agriculture is the most important sector in developing countries, so the main source of concern for farmers is plant diseases that lead to a lack of production and a waste of money and crops. In this paper, a system using computer-assisted convolutional neural networks (CNN) with camera is developed to characterize diseases of citrus trees. This proposed system can help farmers to increase and improve the quality of their agricultural productivity. In addition to reducing the spread of the disease through early detection. Citrus leaf dataset was created to train and test the model because citrus is one of the main crops in Iraq. The results of the experiment shown that the implemented CNN achieved high classification accuracy of (92%) with fewer parameters, making it flawless and promising outcomes.

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1. INTRODUCTION

Citrus is one of the most valuable commodities in Iraq. The directorate of agricultural statistics has conducted a study of the production of citrus trees in 2019. The survey, which is part of the central statistics Bureau's yearly plan and covers (5) primary varieties, includes oranges. Numerous diseases that harm citrus trees have expanded as a result of poor maintenance and a lack of pesticide application, which has led to low output and the death of significant numbers of citrus trees. When compared to other citrus trees, the average productivity of other citrus trees in Iraq is comparable to orange production amount, and the average productivity of the orange tree in Iraq was assessed to be only thirteen kilograms, which is a very low amount [1].

It is difficult to protect plants from disease. Therefore, precautions can be taken if trumpet diseases are detected appropriately and early. Identification of infected plants at a very early stage is crucial to replace expert advice in traditional methods of cultivation [2]. With images of plant leaves, this identification can be made automatically without a person present. To enhance accuracy, there are many techniques used in the classification and detection of infected plants, but it seems that the combination of increasing advances in computer vision and deep learning (DL) is leading to an enhancement of accuracy [3]. The advances of convolutional neural networks (CNNs) in recent years have greatly improved computer vision. The researchers were able to achieve excellent accuracy in image classification, object detection, and semantic segmentation due to these new networks [4]. The aim of the research is to use the leaves of citrus plants from a database that includes approximately 1,258 images of plants to contribute to detecting and identifying the infected plant from the healthy one in less time and cost, in addition to contributing to increasing citrus production and reducing manpower, effort, and cost. This algorithm can also be used in the future. With a drone equipped and a camera to overcome some of the difficulties that the farmer faces in the field. Figure 1 shows the main flowchart of the image classification with data augmenter.

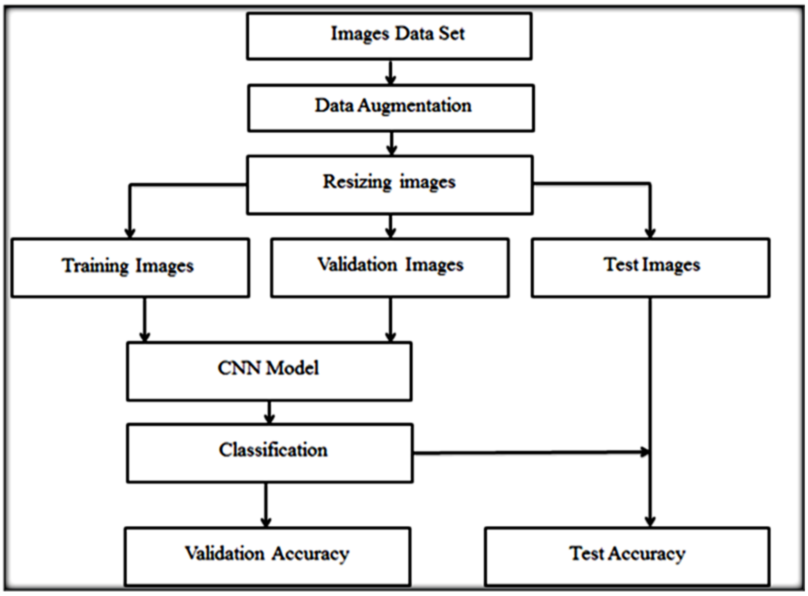


Figure 1. Classification using CNN

Bhatt *et al*. [5], clustered images into classes for effective image tagging using the features obtained from CNN trained on the ImageNet dataset. Classes were created for the photos. With the help of CNN features from the tea leaves category of photos, the support vector machine (SVM) classifier was trained, and it was able to achieve 93.75% classification accuracy when tea leaves were taken in an uncontrolled environment. Ferentinos [6] CNN models were created to identify plant diseases using images of healthy and diseased leaves. using a dataset of (87,848) photos of 25 different plant in 58 different (plant, disease) combination classes, including healthy plants. The best model architecture out of the ones that were trained identified the corresponding (plant, disease) pair with a success percentage of 99.53%. With a success percentage of 99.48%, visual geometry group (VGG) outperformed the other chosen models.

Sahidan *et al*. [7] provide flower and leaf recognition for identifying plants by CNN. Two datasets have been used for the training and testing. According to experimental findings, using only leaf images yields the highest accuracy for identifying plants, at 98%, compared to using only flower images or a combination of both, at 85% and 74%, respectively. Results for flowers were low and should be improved. Luaibi *et al.* [3] employed both models of AlexNet and ResNet. With data augmentation which increases the amount of training images in dimension lengthwise (DL) without requiring additional images, is suitable for small datasets. Two hundred photos of healthy and diseased citrus leaves are gathered to create a custom dataset. The results from the trained models with data augmentation are 95.83% for ResNet and 97.92% for AlexNet, respectively. The results are good and promising.

Liu *et al*. [8] they employed ResNet50, DenseNet201, InceptionV3 and MobileNetV2 models on a custom dataset containing six prevalent citrus diseases and compared the results in terms of speed, model size, and accuracy. Results demonstrate that their strategy maintains a high level of classification accuracy while reducing the model size and prediction time consumption. The accuracy of the 20 MB MobileNetV2 model was 87.28%. MobileNetV2, a compact network, has quick validation and comparable accuracy to other network models. The results of the proposed system are somewhat few and should be improved by adding more layers to obtain a higher accuracy. Kukreja and Dhiman [9] used CNN algorithm to identify/defects fruits. To identify and classify the image dataset, citrus photographs are gathered and divided into two categories: good and defective ones. On 150 photos, the CNN model was applied without any preprocessing or data augmentation, and it had a 67% accuracy rate. After that, the suggested model utilized 1,258 images together with data augmentation and pre-processing to improve CNN performance. The proposed model's precision is 89.1%. The results of the proposed system are also few and can be improved by increasing the resolution of the images and adding layers to obtain a more complex and better architecture and thus obtain a higher accuracy.

Gautam and Dahal [10] dataset which consists of pictures of infected citrus fruit and leaves, is used for training. Through the processing of collected digital images of citrus leaves and fruit, transfer learning and data augmentation tried to create a model that focuses on the identification of citrus diseases. In comparison to the VGG16's performance (92.7%), a model whose base features were taken from the Xception pre-trained model classified the diseased leaf more accurately (93.9%), the proposed system results are good. Rajbongshi *et al*. [11] combined transfer learning with the algorithms (CNN, DenseNet201, InceptionResNetV2, InceptionV3, ResNet50, ResNet152V2, and Xception) to improve accuracy. The steps involved in diseases detection are image acquisition, image segmentation, and features extraction. The dataset consists of 1,500 images of damaged and healthy leaves, uses several types of leaf diseases. The DenseNet201 outperforms by achieving the greatest accuracy of 98%, according to the total performance matrices. Their system acuuracy is good and promise for future works.

Khattak *et al*. [12] suggested CNN model aims to distinguish between fruit and leaf types that are healthy and those that have prevalent citrus diseases. On PlantVillage datasets, the CNN model was evaluated against a number of deep learning algorithms. The CNN model exceeds the competition in a number of measuring measures, and the testing findings show that it has a test accuracy of 94.55%. Sehree and Khidhir [13] employed five distinct neural network designs for transfer learning by training the fully connected layer(s) at the end of the deep learning layers: VGG16, ResNet50, MobileNet, Xception, and VGG19. With 100 epochs, an accuracy of 97.2% using ResNet50 produced, their model produces the best results in (296 x 296) pixels. Accuracy were (Xception 80%, MobileNet 95.3%, VGG19 94.5%, VGG16 95.3%, and ResNet50 97.2%). The results of the proposed system are good and promising and can be used in a practical way. The proposed system is to use an algorithm to distinguish the healthy plant from the infected plant with high accuracy and with less effort, and it was applied using a high-resolution camera inside the field to diagnose the infected plant in real time. As for the suitability of the work, the suitability of the work will be demonstrated by applying it to the field test, where factory images are taken, the images are processed, the algorithm is called, and the data is classified.

In the future, it will be possible to: i) use this algorithm to discriminate through fruit, not just leaves, and apply it using a robot with Bluetooth; ii) in addition to measuring soil moisture and displaying the results using a graphical user interface; an. iii) the proposed system can also be improved by classifying a number of diseases and not just distinguishing between healthy and diseased ones on the basis of plant leaves.

2. METHOD

1,258 photos of citrus leaves are split into our unique dataset as shown in Table 1. Two classes of leaves (healthy, infected) are classified, the models were trained. infected is (canker and black spot) infections. Figure 2 illustrates a dataset sample that was gathered from the internet and Mosul's orange orchards with a high-resolution camera.

Table1. Custom dataset division

Class	Training set (80%)	Validation set (20%)	Total (100%)
Healthy leaf	445	174	619
infected leaf	463	176	639
Total	908	350	1258

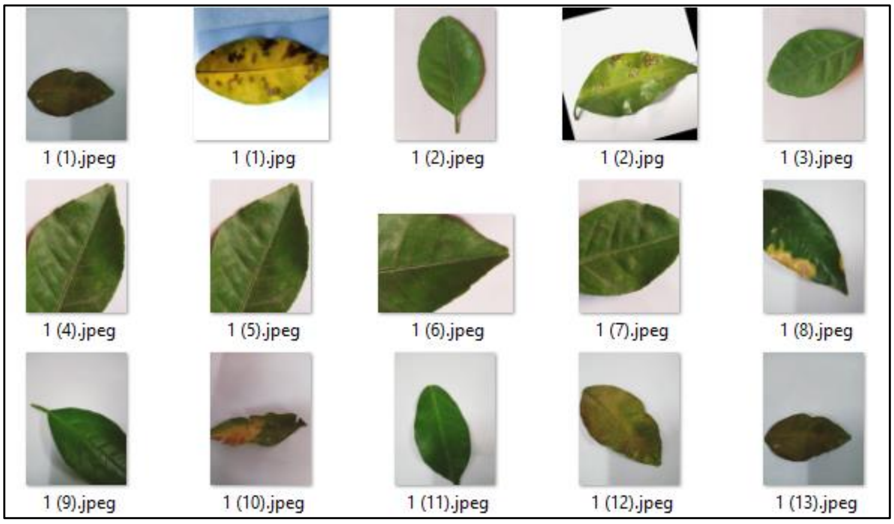


Figure 2. Samples of custom dataset

An open-source Python-based software library called TensorFlow was used. In addition to being developed in Python, Keras is a modular neural network library that can be used with TensorFlow. Both libraries are particularly fast as they can run on top of both the CPU and GPU [14], [15]. With the help of additional libraries such as Numpy and Pandas, Matplotlib is a Python library used for plotting graphs. It is a powerful Python tool for data visualization. It is used to draw two-dimensional matrix diagrams. Seaborn: It's uses Matplotlib, Pandas, and Numpy to plot graphs. It is a comprehensive suite of the Matplotlib library and is built on top of Matplotlib. Eliminates graphic overlap [16].

One DL architecture and image classification method is CNN. According to the technology utilized in their layering, they significantly lower the number of artificial neurons required in comparison to typical feedforward neural networks. CNN is a feed-forward, very effective detection technique. The network's topology is straightforward, and there are not many training parameters. A particularly powerful detecting method is CNN [3]. Convolution layers, pooling layers, activation function layers, and fully connected layers are the four different types of layers that make up CNN. Convolution layers create a feature map by employing the convolution process to extract an image's input. Different feature maps can also be applied multiple convolutional layers. This strategy is to assure complete extraction of various features [11], [17]-[19]. Convolutional processing offers three main benefits. The weight sharing method minimizes parameters number and consequently operations number in the same function map. The study of correlations between nearby pixels is made possible by local connectivity. invariance to the object's origin enables the target to be located regardless of the object's position in the image [3], [20].

Feature maps size is then reduced by the pooling layer. This procedure improves the input's resistance to noise and distortion [11], [17]. The pooling layer is increasingly employed to reduce measurements of the network parameters and function mappings. Because they factor in nearby pixels in their computations, pooling layers are consequently invariant to encoding. Max pooling layers and average pooling layers are the two main types of pooling layers. The majority of implementations employ max-pooling because it can increase generalization, speed up convergence, and select superior invariant features [3], [20]. CNN depend on 3rd layer (the activation function) [11], [17]. Convergence of the neural network heavily depends on selecting the suitable activation function. Rectified linear unit (ReLU) is the most effective activation function utilized in hidden layers of neural network. By thresholding values at 0, as in (x)=max (0, x), it operates [21]. Conventionally, the ReLU activation layer is applied after each convolutional layer [3]. CNN that uses the ReLU function trains much more quickly than CNN that uses the Tanh or sigmoid functions [22]. ReLU is shown in Figure 3.

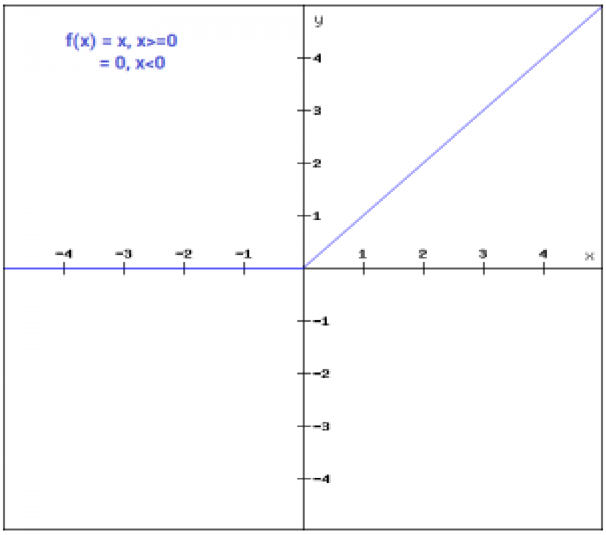


Figure 3. ReLU activation function [23]

Final layer that is fully connected layer (FC), to get the result, add up the weights of the previous layers of features [7], [24]. At this point, the input picture is identified using the FC layer by comparing the features to the training set [3]. The CNN architecture is depicted in Figure 4. Compared to other classification techniques, the CNN requires less preprocessing of the input images for the feature extraction stage [18]. The CNN architecture cleared in Table 2.

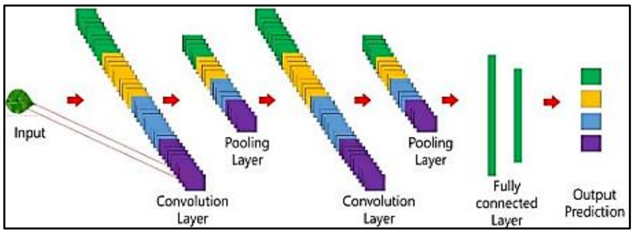


Figure 4. Main structure of CNN [24]

Table 2. Structure of the implemented CNN architecture

Layer	Size
Convolution	32, 3, 3
Pooling	2, 2
Convolution	64, 3, 3,
Pooling	2, 2
Convolution	96, 3, 3
Pooling	2, 2
Convolution	128, 3, 3
Pooling	2, 2
Convolution	256, 3, 3
Pooling	2, 2
Dense	512
Dense	128
Dense	1

2.1. The built-in algorithm

Step 1. Convolution layer utilized for feature extraction from the input image (224x224) pixels. Number of filter equal 32, (3x3) filter size with It utilizes the ReLU activation function. This performs considerably more quickly than any sigmoid function.

Step 2. After each convolution layer, max pooling must be applied to reduce matrix size (2x2) used. Second convolution layer (64) to extract more features with same filter and same activation function. Then same max pooling used for same purpose in step 1. Dropout of (0.3) added here to avoid overfitting. Third convolution layer (96) added with max pooling and dropout to maximize performance and get more features in training. Fourth convolution layer (128) with max pooling and dropout used.

Step 3. Obtain one-dimension matrix which links with classification layer, flattening layer used. Convolution layer (256) added with max pooling to maximize performance and extract more features.

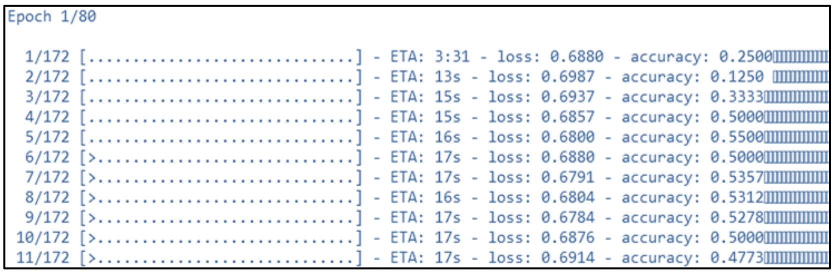
Step 4. This layer is full connection and added for prediction. Sigmoid activation function used to decide that citrus leaf is health or infected.

2.2. Training

CNN trained on 80 epochs with 172 steps per epoch on our custom dataset which contain about (1,258) images. Training parameters were: (dropout=0.3, optimizer=Adam, Batch size=4, Image size=224x224). A sample of training process shown in Figure 5, with laptop specifications and software requirements shown in Table 3.

Table 3. Hardware and software requirements

Hardware components	Configuration
Processor	Core-i7 8th generation
Processor speed	1.8 GHz
RAM size	8G
Operating system	windows 10 of 64 bits
GPU	Internal UHD Graphics 620 4G
Hard disk type	SSD
Software components	Version
Python Idle	3.9.7
Keras	2.9.0
Tensorflow	2.9.1
Matplotlib	3.5.2
Seaborn	0.11.2
NumPy	1.22.4



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Epoch 1/80

  1/172 [..............................] - ETA: 3:31 - loss: 0.6880 - accuracy: 0.2500
  2/172 [..............................] - ETA: 13s - loss: 0.6987 - accuracy: 0.1250
  3/172 [..............................] - ETA: 15s - loss: 0.6937 - accuracy: 0.3333
  4/172 [..............................] - ETA: 15s - loss: 0.6857 - accuracy: 0.5000
  5/172 [..............................] - ETA: 16s - loss: 0.6800 - accuracy: 0.5500
  6/172 [>.............................] - ETA: 17s - loss: 0.6880 - accuracy: 0.5000
  7/172 [>.............................] - ETA: 17s - loss: 0.6791 - accuracy: 0.5357
  8/172 [>.............................] - ETA: 16s - loss: 0.6804 - accuracy: 0.5312
  9/172 [>.............................] - ETA: 17s - loss: 0.6784 - accuracy: 0.5278
 10/172 [>.............................] - ETA: 17s - loss: 0.6876 - accuracy: 0.5000
 11/172 [>.............................] - ETA: 17s - loss: 0.6914 - accuracy: 0.4773
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Figure 5. Sample of training

3. RESULTS AND DISCUSSION

CNN trained on 1,258 images divided to 80% training set and 20% validation set. After training the implemented CNN, a file with extension (.h5) produced with about 62 MB size, which represent the CNN weights. Training and validation results accuracy were 97% and 97%, respectively, as shown in Figure 6. While training and validation losses were 0.00001 and 0.00065, respectively, as shown in Figure 7. The percentage of the training set's correctly defined data samples is known as the training accuracy. The percentage of correctly clarified data samples from some of the other samples is what is meant by the validation accuracy [25].

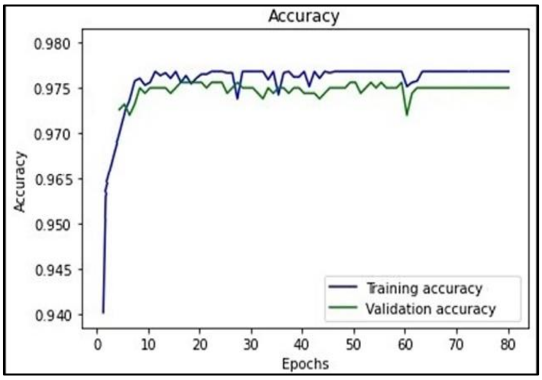

Figure 6. Training and validation accuracies

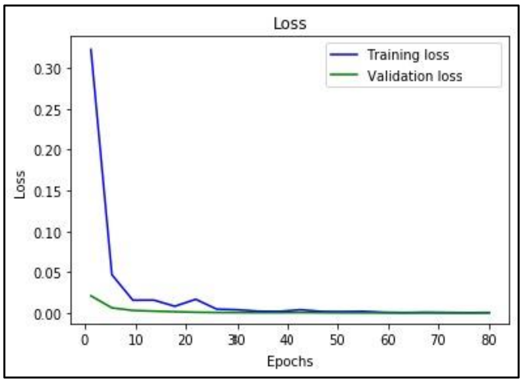

Figure 7. Training and validation losses

The accuracy of the model, which was tested on some images of healthy and sick leaves, was 92%, which is excellent and indicates promising outcomes for the work to come in which we will apply the model to real-time video from high-resolution cameras. The outcomes of the experiment demonstrate that the best accuracy can only be achieved when using leaf photos. The simulated result of proposed model is represented by confusion matrix given in Figure 8 which shows the better classification result.

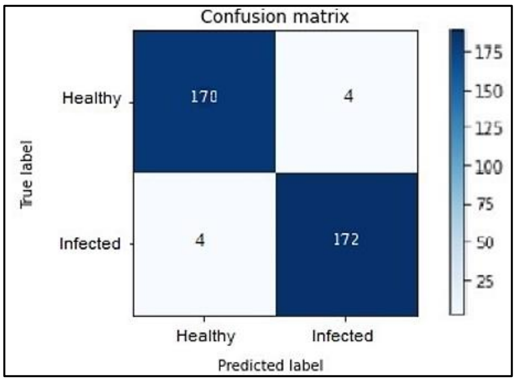

Figure 8. Confusion matrix

A test was carried out inside an agricultural orchard containing 13 orange trees. The possibility of detecting the infected tree was carried out by relying on the leaves of the tree, and the results were close to the truth. As in the following diagram, the healthy plant is represented by (1) and the diseased plant by (0). Can Be seen in Figure 9.

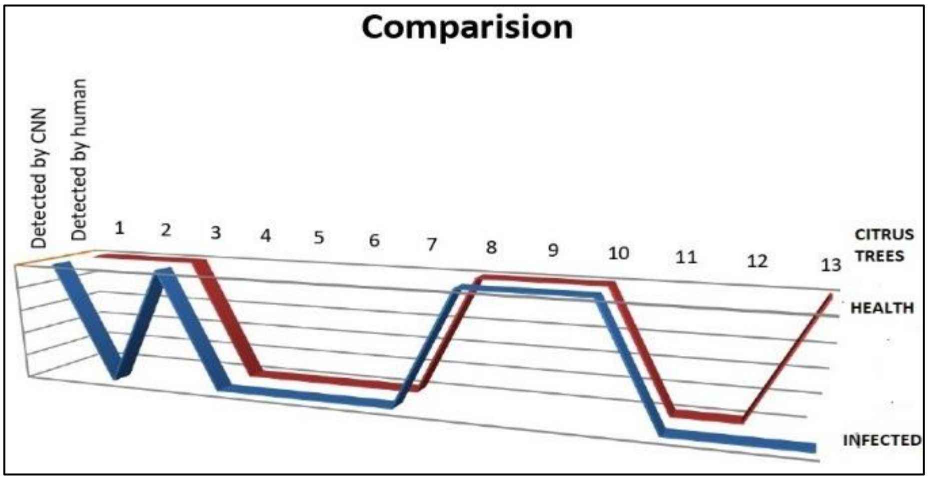

Figure 9. Test results inside an agricultural orchard

4. CONCLUSION

In this paper, CNN was utilised to examine a collection of photos made up of both healthy citrus leaves and (2) different forms of illnesses. Using just photos of leaves, this article assesses CNN's performance in terms of identifying plants. The outcomes of the study demonstrate that the best accuracy can be achieved when using leaf photos. The results of this study show that using a CNN to extract illness evidence from a picture is a reliable method for accurately automating the detection of citrus disease. A 2x2 confusion matrix has been produced following the conclusion of training and evaluating the picture data. The highest accuracy is 92% found for the CNN model. The findings lead us to the conclusion that increasing the amount of data used to train DL models will lead in more proficient models, and that image variations produced by augmentation techniques will improve the ability of the suitable models to apply what they have learned to new images. With a training duration of 40 minutes, CNN is the structure with the simplest learning curve.

For further research, many diseases and pests of citrus can be examined and classified. A variety of DL models can be used, including CNN convolutional long-short term memory (C-LSTM), CNN, and hybrid models like bi-directional-LSTM (BI-LSTM) and recurrent neural network (RNN). In addition, the precision agriculture framework can be designed and implemented on the basis of the internet of things.

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