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Research on agricultural disease detection technology based on artificial intelligence

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Abstract. Pests and disease are two major factors that reduce the yield of agricultural products per acre of arable land. A report from the Food and Agriculture Organization of the United Nations suggests that agricultural disease and pests cause a loss of more than 1/3 of agricultural production every year. However, farmers cannot check their crops all day without a break. Artificial Intelligence (AI) is developing rapidly this year, it performs well in image recognition. Thus, it is suitable to integrate AI in agriculture. This paper shows the outcome of the accuracy of the outcome when a model is trained using the ResNet-50 model and by some crop pathogens datasets downloaded from Kaggle and using a platform of mmpretrain. It also discusses the pros, cons, and areas for improvement when using AI to detect agricultural disease. This research aims to enhance crop yields and agricultural stability by helping integrate the model in agricultural production.

Keywords: Artificial Intelligence, image classification, crop diseases, resNet-50.

1. Introduction

Agriculture plays an important role in the economy of many countries. For example, according to the National Bureau of Statistics of China, the Added Value of China's Agriculture and Related Industries will take up 16.24% of GDP in 2022 [1]. Moreover, there is a much higher percentage in countries in Africa, in Sierra Leone the Agriculture accounts for more than half of the country's GDP[2]. Therefore, many countries will have big problems with no stable crop yield. From another perspective, the trend of the world's population has been increasing. More people means more food, and more food means more farmers and land to cultivate. However, in the end, land is limited.

Finding ways to make more crops grow on limited land is an urgent problem. Because too many unpredictable elements affect crop production, it is difficult to maintain a stable output of agricultural production. And one of the major factors is the diseases caused by microorganisms and pests. They can decrease productivity by 10% to 95% [3]. Using visually inspecting and evaluating the type of diseases entirely based on the farmer’s expertise has several challenges and limitations[4]. Higher crop yields can be attained without more land or farmers if this issue is resolved.

AI can be introduced to solve this problem. AI had a significant development in image detection in recent years, convolutional neural networks (CNN) can effectively extract image features to help classification. The author of this article used a ResNet50 model based on a convolutional neural network and used a dataset downloaded from Kaggle, a total of 200,000+ images. The training was done locally using the author's 3080 graphics card that he uses for gaming. Compared with human eyes, AI can

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identify diseases more accurately and efficiently if it is trained well. It also saves farmers' physical energy, allowing farmers to take measures according to the cause of disease of each crop.

2. Literature review

2.1. Convolutional Neural Network (CNN)

Traditional image recognition methods include image preprocessing, image segmentation, feature extraction, and classifier design, which are complex steps that rely on much prior knowledge. However, deep learning methods do not require manual design of feature parameters and can automatically learn image features from big data, thereby improving recognition efficiency and accuracy [5]. Convolutional Neural Network (CNN) is a deep learning model that performs best when processing data with a grid-like topology, such as images [6]. It consists of different layers with different functions. The convolutional layer iextracts local features from an image by applying filters across the input image through a sliding window. Pooling Layer reduces the size of the feature maps, decreases the computational load, and retains important features. Fully Connected Layer Combines local features into global features, it flattens the input and multiples it by a weight matrix to generate the output. And the Normalization Layer Accelerates the training process and improves model stability by batch normalization. The characteristic of its local connectivity and shared weights made it highly efficient, and it also has high durability. These huge advantages made CNNs the mainstream image detection or image classification model.

2.2. ResNet-50

The full name of ResNet is Residual networks, a type of CNN model. ResNet-50 is one of the variants of this architecture and is named for its 50 layers of residual networks.

It was designed to fix the gradient vanishing and gradient exploding problems by introducing the concept of residual blocks, which utilize skip connections to retain information from previous layers. The residual block can be represented as:

- $y = F(x, \{W_i\}) + x(1)$

Where x is the input, $F(x, \{W_i\})$ is the convolutional operation applied to the input, and $\{W_i\}$ are the weights of the convolutional layers. The addition of the input x helps in preserving the original information and gradients.[7]

In [8], ResNet has the highest performance among all the basic CNN architectures such as AlexNet, GoogLeNet, and Resnet. And according to [9], resnet-50 with SVM(Support Vector Machines) classifier got the best result.

Through this, ResNet has performed great in image classification and object detection, and that is the reason I chose this model.

3. Methodology

3.1. Dataset

The dataset used in this paper is downloaded from Kaggle[10, 11]. There are more than 200,000 training images in total, the images will be scaled and cropped to 224*224 pixels during preprocessing. These images have five categories ---- Healthy, Bacteria, Fungi, Pest, and Virus. The purpose of this model is to classify images into these categories. A test dataset is also indispensable, so 2,000 images of each category were randomly separated as the test dataset. The ratio between the training and testing datasets is 20:1, whcih is not a commonly seen ratio. The ratio is set like this because 10,000 images are enough to cover all the conditions, so that more images can be used for training. Here are some examples in the training dataset shown of Figure 1.

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Figure 1. From left to right: Healthy, Bacteria, Fungi, Pest, and Virus.

3.2. Platform and preprocessing

For the training platform, the author chose to build a local mmpretrain environment. It is used because it provides many powerful pre-trained models, and its operation is relatively simple and can be figured out quickly. Before the training starts, there are many settings to be completed. The first is the depth of the most basic ResNet. Because the training data is relatively large, the ResNet50 model with fifty depth is used. The batch size is set to 32, which means that for approximately 20 0,000 images, each epoch will have a total of about 200,000/32=6,250 iterations. Because of the large number of iterations and the model is relatively large, the initial learning rate was adjusted from the default 0.1 to 0.01. Finally, I loaded a pre-trained weight downloaded from the mmpretrain official website[12] before the training data as the initialization of the model, which can greatly speed up the convergence of the model on the target data set.

3.3. Result

A total of 20 epochs were trained, their top-1 accuracy is shown in the Figure.2.

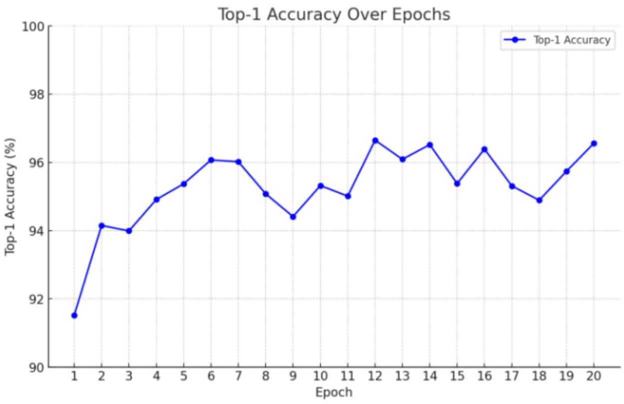

Figure 2. Top-1 Accuracy Over Epochs.

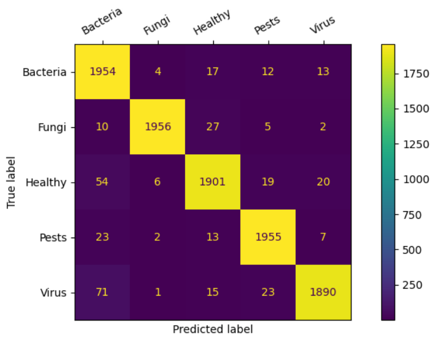

Figure 3. Confusion matrix of the 20th epoch.

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The model performs well on the test dataset, it has the highest accuracy of 96.65% on the 12th epoch and 96.56% on the 20th epoch. Since the accuracies of epochs near the 20th epoch are steadier than the 12th epoch, and the difference between the two percentages of accuracy is relatively negligible, the 20th epoch is considered as the best final result, and a confusion matrix of it is shown in Figure 3.

There are also tests for the images that are not included in the datasets downloaded from Kaggle. For example, this is an unknown plant with fungal disease, and the model can give the correct prediction, which is “Fungal”.

Figure 4. A tomato leaf with Septoria leaf spot, which is a fungal disease.

Figure 5. Test for the image shown in Figure 4.

Finally, to test the versatility of the model, this paper used this model to predict the plants in my home. The figure is a photo of the leaves of my own Epiphyllum that I took with my mobile phone. One is healthy, and the other has an unknown problem. The prediction of healthy one gives the correct answer, and the bad one gives the prediction of “Fungal”, so that antifungal pesticide is suitable for this Epiphyllum.

Figure 6. Leaf of Epiphyllum.

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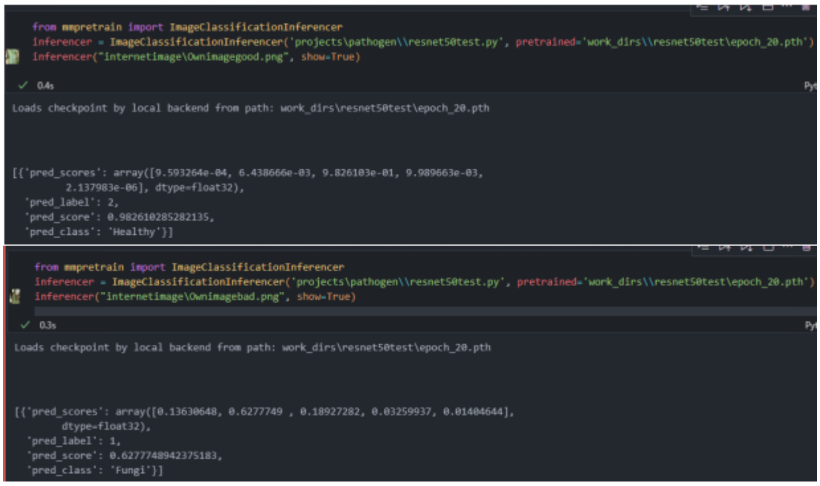

Fugure 7. Predictions for Epiphyllum.

4. Discussion

This model performed very well based on the top-1 accuracy results on the test dataset. It can handle most situations and greatly reduce the damage caused by crop diseases, but it also has some problems. The input image must be a single leaf. If there are too many backgrounds or a lot of interference other than leaves, the accuracy will drop a lot, which means that this model still lacks durability. I think this problem can be solved by adjusting the images in the training dataset. Before training, make some changes to the brightness of the image or randomly put some interference items on the training image, the trained model often has higher versatility.

Farms can not install cameras to monitor every plant, so the better way is to use more in conjunction with the image detection model. So, an Internet of Things technology can be used. Farmers should use a camera to cover a large area of crops, use the image detection model to identify each plant, and then use the image classification model I trained to classify diseases. If a disease is detected, farmers will be prompted and then take the corresponding pesticides to intervene.

96.56% is a high accuracy, but it is not enough. This means there was a mistake in 29 samples. Higher accuracy not only reduces unnecessary use of pesticides but also allows farmers to intervene more quickly when diseases strike. If it is to be put into use, the accuracy rate must be at least higher than 99.9%, and it needs to take much work to achieve this accuracy.

5. Conclusion

Although this model has shown a high accuracy rate, more is needed; some models have a higher accuracy than this model. For example, a MobileNet model has achieved an average accuracy of 98.7%[13], but there is still much room for improvement. Therefore, in future research, more models must be tested to determine the most suitable model.

To increase food production on limited land, AI is used to recognize crop diseases. This essay shows ResNet-50 model is trained to identify agricultural disease. It was trained on a platform mmpretrain and has an accuracy of 96.56%. To make the model more versatile and more durable, some shortcomings of this model and suggestions for improvement are put forward. These models can help humans by chaining in the Internet of Things. In the future, more efficient and accurate models will be invented, and they should all be tested to see if they can diagnose crop diseases well. If the model is to apply to more regions, the types of training data sets must be richer. More and better training datasets are essential to train a good model.

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