Deep Learning Based Pest Identification on Mobile

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Abstract. Crops, vegetables, fruit trees, flowers and other cash crops, are often harmed by a variety of harmful organisms, plant pathogens, pests, weeds and pest rats, etc. Plant diseases and insect pests often occur, which are one of the main factors which causes the damage of leaves and crop failure. Therefore, in order to stop the pest, it is extremely important to identify the pests of plants and their characteristics correctly. In this paper, an effective and scalable image recognition algorithm is proposed for disease detection. Meanwhile, MobileNets is employed for developing our method on mobile devices. Finally, a dataset consists of three apple diseases is used to demonstrate the effectiveness of our method. In the experiments, transfer learning is used to train a deep convolutional neural network for identifying two types of pest damage, apple rusts and apple Alternaria leaf spot. Our results show that the MobileNets model offer a fast, affordable, and easy-to-deploy strategy for plant disease detection.

Keywords: Pest identification · Deep learning · Mobile

1 Introduction

Diseases and insect pests are one of the main causes of fruit loss, and timely prevention and treatment of diseases is of great significance [1]. However, due to the following problems, it is often difficult to obtain good control effects. (1) The level of cognition of pests and diseases is limited, and it is difficult to obtain expert guidance. (2) It is impossible to grasp the probability and development of surrounding pests and diseases on a larger scale, and it is powerless to make trend judgments. If we just rely on a few experts or insect researchers, through manual inspection and visual observation, the recognition efficiency is low and the recognition rate is extremely unstable. In this paper, we take apple leaf diseases as the research object and proposed a new method for plant diseases classification. Apples often suffer from different kinds of diseases, such as apple rusts and apple alternaria leaf spot. Apple Rusts – Rust usually appears as orange-yellow spots on the leaves, branches, and fruits of apple trees. There are three

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different forms of rust fungus, including cedar-apple rust, cedar-hawthorn rust and cedar-quince rust. Among these, cedar-apple rust is the most common rust that affects apple trees. Lesions usually occur in late spring or early summer with small, round, purple or black spots on the leaves at first. Then, the diameter of these spots gradually expanded to 1/8 to ¼ inch with a purple border, while some spots turned grayish brown. Most lesions may disappear at later stages. Some lesions may develop secondary swelling becoming irregular and darker, gaining a "frog eye" appearance. In recent years, many studies have focused on convolutional neural networks (CNNs), which have achieved significant results in the field of image classification. Thus, we propose a new apple plant disease classification method based on CNNs. Our method, based on MobileNetV1 [2], which using depthwise separable convolution as efficient building blocks.

The remainder of this paper is organized as follows: Sect. 2 provides the related work on plant disease classification. Section 3 introduces the architecture of MobileNet and the detail of the proposed method. Section 4 describes the experimental evaluation, the results, and how to deploy deep learning models. Section 5 summarizes the paper and the future extensions.

2 Related Work

In the last ten years, a number of work has been done on the classification of plant diseases based on machine learning techniques. These methods can be divided into two categories, including classification by traditional algorithms and classification by deep learning algorithms.

2.1 Classification by Traditional Algorithm

Traditional image classification algorithms include k-Nearest-Neighbor, support vector machines, and BP neural network etc. Moshou et al. [3] proposed a neural network algorithm based on leaf spectral information to monitor wheat yellow rust. Wang et al. [4] used BP neural network for early warning and monitoring of tomato late blight. Rumpf et al. [5] combined support vector machine (SVM) and leaf reflectivity to monitor beet pests and disease symptoms. Sannakki et al. [6] proposed an algorithm for automatic classification of pests and diseases on leaf images, which first analyzes the specific color information of infected plants by pattern recognition technology, separates the infected points, and then classifies them based on fuzzy theory. Xu et al. [7] realized the detection of wheat rust by image edge monitoring technology.

2.2 Classification by Deep Learning Algorithm

Deep learning-based image classification methods include LeNet, AlexNet, MobileNet and ResNet etc. Sladojevic et al. [8] uses deep convolutional neural network to successfully identify 13 pests and diseases from healthy leaves of five crops with an average accuracy of 96.3%. Fujita et al. [9] proposed a four-layer convolutional neural network method to identify cucumber leaf diseases and pests, after four fold cross-validation, recognition accuracy reaches 82.3%. Amara et al. [1] combined LeNet deep learning model with image feature extraction technology to monitor the pests and diseases of two kinds of banana leaves. Picon et al. [10] combined image segmentation and deep convolutional neural network to monitor three common wheat diseases.

3 The Proposed Deep Learning Model for Pest Identification

Convolutional neural network (CNN) is a representative algorithms of target recognition, and there have been AlexNet, VGG, GoogleNet, VGGNet, Resnet and so on. In order to pursue higher accuracy, more deeper network with more parameters and more complex computing structure are constructed. However, once the network incubated in these laboratories is deployed in production practice, it will encounter various unexpected difficulties. For example, computing is inefficient, especially on mobile devices with limited computing resources, such as mobile phones/pads. Suppose we take a picture, and then ask an AI-powered APP to help us identify what's on the picture, and it thinks for more than ten seconds, which is unacceptable efficiency.

In order to combine the power of CNN with specific production practice, and make it more practical and usable, the existing methods can be roughly divided into two categories, including compressed pre-trained networks and directly trained small networks. MobileNet model belongs to the second approach.

The MobileNet is built on depthwise separable convolutions, except the first layer is a full convolutional layer. As shown in Fig. 1, the depthwise separable convolution consist of depthwise layers and pointwise layers, which followed by batchnorm and ReLU. MobileNet has 28 layers. The model introduces two simple global hyperparameters to balance the delay and accuracy effectively. These two superparameters, width multiplier and resolution multiplier, allow model builders to obtain a good balance between model size and accuracy according to the constraints of the problem.

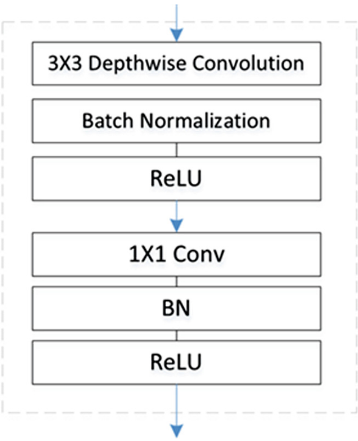

Fig. 1. The structure of Depthwise Separable convolutions.

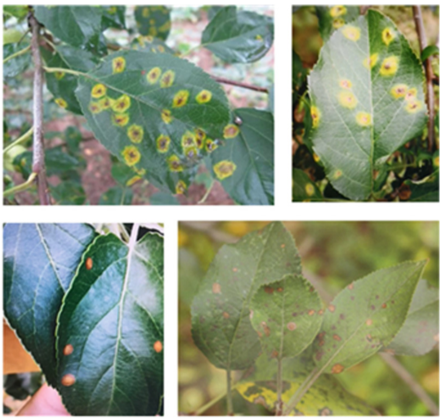

Fig. 2. Example of two apple diseases

4 Experiments and Discussion

4.1 Experiment Setup

For MobileNet model training and testing, a database containing 1582 photographs of leaves of healthy and infected plants was constructed, which contains three classes of apple leaf diseases (including classes: healthy leaf, alternaria leaf blotch leaf, and rust leaf). These images were collected by the agriculture experts who are visiting and surveying kinds of orchards in Shaanxi Province (see Fig. 2). Table 1 shows the number of original pictures and enhanced images corresponding to different diseases.

To increase the amount of data for training and increase noise data, an image generator was created. With this image generator, we can expand the dataset by randomly rotating, translating, flipping, trimming, and cutting the images. A larger dataset allow us to get better results.

The MobileNets training is done in Tensorflow with the help of asynchronous gradient descent having 10000 training steps. The training parameters of the network were set as Table 2.

Table 1. Dataset of apple leaf diseases.

Apple leaf diseases	Number of original images	Number of processed images
Apple-healthy	126	791
Apple rusts	273	1935
Apple alternaria leaf spot	383	2106
Total	782	4832

Table 2. Hyper-parameters

Parameter	Learning Rate	label_smoothing	moving_average_decay	batch_size	num_clones	learning_rate_decay_factor	num_epochs_per_decay
Value	0.18	0.1	0.9999	96	4	0.98	0.625

4.2 Experimental Results and Discussion

After training the neural network model (Fig. 3), the following four steps will be done in our software (Fig. 4): load the trained model, accept incoming data and preprocess it, predict using our loaded model, and handling the prediction output.

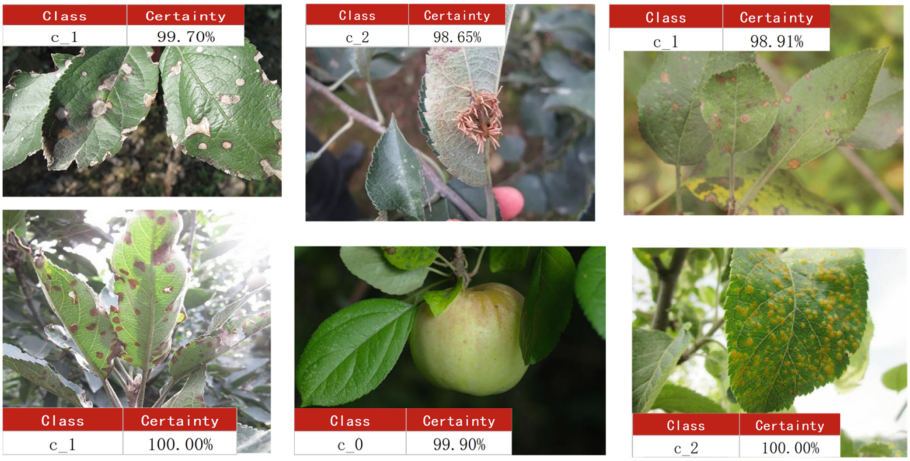

Fig. 3. Representative examples of classifications of testing images.

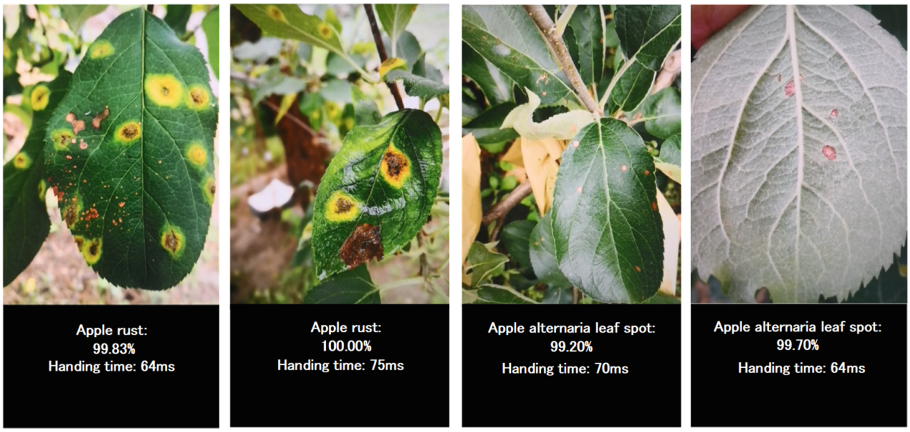

Fig. 4. Representative examples of mobile interface

5 Conclusions

Due to the threat of various diseases, the apple constant and quality received serious damage. In this work, a mobile pest identification system based on deep learning was proposed. The proposed models are named MobileNets, which is a lightweight neural network model based on depthwise separable convolutions. Then the MobileNets are applied to a wide variety of fruit trees image datasets, and deployed on the mobile phone. Using our proposed method, farmers can enter photos of diseased leaves, and get feedback of the type of the disease in less than 1 s.

In the future, we will test more apple trees diseases with our model, and combine with disease prediction to provide guidance for the protection and treatment of plant diseases.

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