Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks

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***Abstract*—The automatic identification and diagnosis of tomato leaves diseases are highly desired in field of agriculture information. Recently Deep Convolutional Neural networks (CNN) has made tremendous advances in many fields, close to computer vision such as classification, object detection, segmentation, achieving better accuracy than human-level perception. In spite of its tremendous advances in computer vision tasks, CNN face many challenges, such as computational burden and energy, to be used in mobile phone and embedded systems. In this study, we propose an efficient smart mobile application model based on deep CNN to recognize tomato leaf diseases. To build such application, our model has been inspired from MobileNet CNN model and can recognize the 10 most common types of Tomato leaf disease. Trained on tomato leafs dataset, to build our application 7176 images of tomato leaves are used in the smart mobile system, to perform a Tomato disease diagnostics.**

***Index Terms*—Convolutional Neural networks, Tomato disease detection, Smart Mobile application, MobileNet.**

I. Introduction

Even if the tremendous effort deployed by the world to decreases the plant loss and food security, several references [1], [2], confirm that more than 20% of crop losses in global scenario is due to plant diseases. This issue has become serious in recent decade due to the impact of pollution and climate change. With recent development in various farming technologies, farmers opt for plant diseases databases or consult local pathologists through phones, instead of the classical procedure to send the plants to diagnostic laboratory in order to propose the appropriate treatment. Furthermore, there are many attempts to use ICT tools to improve efficiency of agricultural development, taking advantage of the wide use of mobile phones.

Regarding plant disease detection, there are many papers introduced this application using one of standard design architectures of CNN [3] such as SqueezeNet [4], ResNeXt (Aggregated Residual Transformations for Deep Neural Networks) [5], ResNet (Deep Residual Learning for Image Recognition) [6], NiN (Network In Network) [7], GoogLeNet [8], VGGNet [9], ZFNet [10], AlexNet [11], etc. Numerous techniques and applications have been made up to reduce crop loss because of diseases. But a few methods and applications have been proposed to identify plants diseases in general and Tomato diseases using Convolutional Neural Networks in particular. All related methods proposed below are developed and works on computer with powerful computation resources.

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[12] proposed a CNN method to identify Tomato disease based on wavelengths and RGB channels. The authors demonstrated that there is a relationship between specific wavelet color sensitivity of each disease. [13] introduced a Plant Species Recognition method that is different from the existing feature extraction based Deep Convolutional Neural Networks recognition approaches. [14] built an intelligent alerting system based on CNN for recognition for disease-pest of fruit-melon. [15] used CNNs to build a robust diagnostic system for all possible viral diseases for cucumber. [16] trained tow CNNs Models AlexNet and GoogleNet to identify 14 crop species and 26 diseases. A dataset of 7176 images of diseased and healthy plant leaves, have been used. It was the first attempt has paved the way for smartphone-assisted disease diagnosis, even if the both models used AlexNet and Google Net didn't work on Mobile phone.

All existing leaf plant diseases detection methods rely on the use of computer with power of calculation. One drawback of these methods is unable to be used in Mobile and embedded system with minimum resources of calculation. Although the number of researches made in this field, all smart systems have been built to detect plant diseases, based on the recent deep CNN, are mostly limited to the use on computer with a large storage capacity and resources computation. But with the development of Quantized CNN Models embed of smart application on mobile phone with limit resources become possible. Thus, in this work, we propose an embedded smart application to recognize tomato leaves diseases. Due to the impact of smartphones and mobile devices on human life, it has become necessary to made up an accurate, easy and inexpensive automated diagnostic system for plant diseases. Until now, there is no smart mobile application detecting Tomato diseases in particularly.

The remainder of this paper is organized as follows. In Section 2 , we present some related works. Section 3 introduces the adapted MobileNet architecture and learning algorithm of CNNs. The Dataset, experimentation and discussion of the developed CNN model to recognize the Tomato leaves diseases are given in Section 4. Conclusions and perspectives are presented in Section 5.

A. Advances in CNN Architectures: Embedded and mobile systems ConvNets

The application of deep convolutional networks in embedded and mobile systems is limited by algorithm's power consumption, bandwidth requirements, tight energy budgets, requirement of very low latency and limited processing resources [17], [18]. To solve these challenges, many algorithms are proposed: [17] introduced a fast CNN's based on Winograd's minimal filtering algorithms (Winograd's algorithm), which a generalization of minimal filtering algorithms of Toom and Cook. However [18] proposed a combination of ASP sensor with CNN backend Angle Sensitive Pixels (ASP) Vision. ASPs is a bio-inspired CMOS(complementarymetaloxide semiconductor) image sensors, that have Gabor wavelet impulse responses, and perform optical convolution for the CNN first layer. The idea is based on the hardcoding of first layer of CNNs to lead to significant energy savings.

[19] introduced Quantized-CNN for Mobile Devices is a framework of convolutional neural network (CNN), that achieves $3.03\times$ speed-up against the Caffe implementation.

II. Adaptation of MobileNet

The based CNN's Model can work on mobile phone with acceptable speed and obtain a high classification accuracy. The principle contribution of this work is : (1) The CNN model of MobileNet is first adapted and applied to the question of diagnostic of Tomato leaves diseases. The built application can identify and recognize the 10 most common types of Tomato leaves diseases. (2) The test and the use of the application show that MobileNet CNN model, in addition to the high recognition ratio, works speedily on popular mobile phone using its own camera. Below we described the CNN MobileNets Model.

1) MobileNets: A team of Google researchers [20] introduced an efficient models named MobileNets for mobile and embedded vision applications. The MobileNet model consists on depthwise separable convolutions, which reduces between 8 to 9 times less computation than standard convolutions, and then smaller and faster MobileNets using width multiplier and resolution.

A. Brief description of adapted model

MobileNets is based on the both concepts depthwise separable filters and factorization thing reduces the amount of computation in the first layers. To reduce the computation, the convolution is factorized into a depthwise that applies each filter to each channel and then pointwise which uses a 1×1 convolution to combine the depthwise.In addition to the both operations, MobileNets use ReLU activation function for both layers. Here we compare the cost of computation between the use of standard convolution and depthwise technique. The fact that MobileNet uses 3×3 depthwise separable convolutions, reduces the computation 9 times less. Let consider that W is the size of input image with M the input channels, F ($D_k \times D_k$) is size of the kernel convolution (generally are 3×3 or 1×1), N is the number expected output channels, s is the stride of convolution (that is set to 1 or 2), P is usually the used padding, then we get the tensor (image after convolution), $D_K \times D_K \times M \times D_F \times D_F$ instead of the Standard convolution $DK \times DK \times M \times N \times DF \times DF$ convolution), $D_K \times D_K \times N \times M \times D_F \times D_F$.

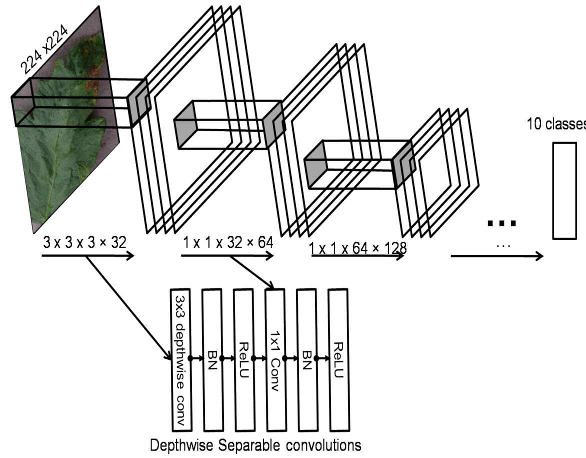


Fig. 1. The structure of deep convolutional neural networks

Architecture of deep convolutional neural networks model Inspired by successful model in mobile and embedded systems that is MobileNet CNN architecture.

The figure 1 illustrates the details of CNNs-based architecture and its parameters. The model accepts an input color image of size 224×224. it consists on a series of Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm(BN) and ReLU. One layer correspond to 3×3 Depthwise Conv, BN, 1×1 Convolution, BN and ReLU activation function. To get classification of diseases, the model is ended by average Pooling of pooling layers, full connected and the Softmax function with 10 classes.

III. Dataset and experimentation

To build our application we have used a dataset of images on plant health, a 7176 images of tomato leaves are used to train the model, then made up a smart mobile system able to perform a Tomato disease diagnostics.

The figure 2 below shows Tomato leaves with the most common kinds of diseases and Table 1 presents images number of each class.

We have tested our application on some test images example, and we have got the results on below table (II). Our results of recognition of the excepted diseases are got with significant gaps compared to others diseases. for example, we get Fungi leaf mold passalora Fulvia-fulva disease with 0.99% compared to others diseases as shown in the table(II). The reason behind the larger gap, maybe due to the big difference of appearance between diseases.

Figures 3 and 4 show the average loss and accuracy curves of that CNN model.

We demonstrate, as shown in Table IV, that our adapted model based on MobileNets model might achieve a encouraged results on tomato diseases, which achieves using

(a) Bacterial Spot Xanthomonas campestris

(b) Early Blight Alternaria solani

(c) Late Blight Phytophthora infestans

(d)Leaf Mold Passalora fulva

(e) Septoria Leaf Spot Septoria lycopersici

(f) Two Spotted Spider Mite Tetranychus urticae

(g)Target Spot Corynespora cassiicola

(h)Mosaic Virus

(k) Yellow Leaf Curl Virus

(l) Tomato leaf healthy

Fig. 2. Tomato leaves with diseases

Class(disease type)	Number of images
Bacterial Spot Xanthomonas campestris	793
Early Blight Alternaria solani	406
Late Blight Phytophthora infestans	727
Leaf Mold Passalora fulva	361
Septoria Leaf Spot Septoria lycopersici	735
Two Spotted Spider Mite Tetranychus urticae	721
Target Spot Corynespora cassiicola	548
Mosaic Virus	140
Yellow Leaf Curl Virus	2101
Tomato leaves healthy	644
Total	7176

TABLE I
IMAGES NUMBER OF EACH CLASS

Stochastic gradient descent optimizer a 88.4% accuracy on classification.

The application works on real time using a standard phone with its own camera, even if until now, automatic plant diseases recognition on mobile devices has not used.

There are many ways to increase the overall accuracy of a CNN Model. Our adapted CNN Model have tested with many

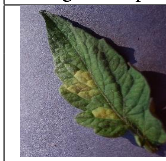
Image example	Obtained result	Expected results
	- leaf mold passalora fulva 0.99999 - septoria leaf spot septoria lycopersici 5.87832e-06 - mosaic virus 2.34571e-06 - late blight phytophthora infestans 1.02782e-06 - early blight alternaria solani 2.06558e-07	- leaf mold passalora fulva

TABLE II
TOMATO SAMPLE TEST IMAGE WITH PREDICTED AND EXPECTED RESULTS

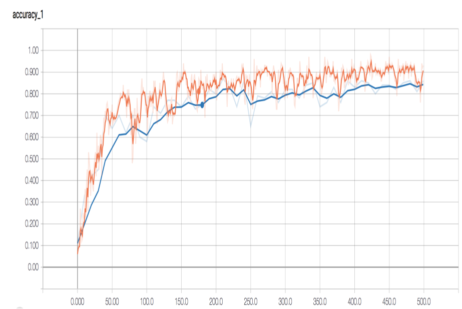


Fig. 3. Average accuracy curve

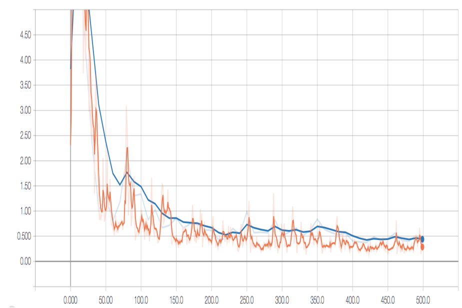


Fig. 4. Average loss curve

optimization algorithms such as Stocastic gradient descent, adadelta optimizer, adagrad, adagradDA, Momentum, Adam, Ftrl, proximaladagrad and RMSprop optimizers. Some of those results figure out in table III.

Optimization method	Final test accuracy
Stocastic gredient descent	88.4%
Adagrad	88.3%
SGD with Momentum	87.6%
Adam	88.5%
Proximal Gradient Descent	89.2%
Proximal Adagrad	88.8%
RMSProp	85.9%

TABLE III
TOMATO DISEASES RECOGNITION PERFORMANCE WITH RESPECT OF OPTIMIZATION ALGORITHM

In addition our adapted model have tested too with many training steps and with changing many configuration parameters. For example, we have adjusted learning rate, that while its value is decreased, the training will take longer, but improve the overall accuracy as shown in table 4.

learning rate	0.01	0.005	0.001
Accuracy	86.7%	88.9%	90.3%

TABLE IV
TOMATO DISEASES RECOGNITION PERFORMANCE IN FUNCTION OF VALUES OF LEARNING RATE

IV. CONCLUSION

Our contribution and results while being a new using of mobile device on farms to recognize the plants diseases based on deep convolutional neural networks, compared to the previously published, is still preliminary, and deriving from a rather straightforward adaptation of MobileNets goolge Model. Deep convolution neural networks have achieved great performance breakthroughs in machine learning fields, but there still exist some research challenges. The proposed CNN based model can effectively classify 10 common tomato leaves diseases through image recognition. We can extend the model for fault diagnosis. To improve tomato diseases identification accuracy, we still need to provide thousands of high-quality tomato diseases images samples. We believe that the simple use of deep convolutional neural networks in computer vision and its applications, specially smart mobile plant diseases recognition is going to decrease the lack of food because of diseases, so increase production and save life of so many hungry people in the world.

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