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Transfer Learning for Plants' Disease Classification with Siamese Networks in low data regime

RAOUHI El Mehdi[1] , LACHGAR Mohamed[1], KARTIT Ali[1] and HRIMECH Hamid[2]

LTI Laboratory, ENSA, University Chouaib Doukkali, El Jadida, Morocco

[1] LTI laboratory, ENSA, Chouaib Doukkali University, El Jadida 1166, Morocco.

[2]University Hassan 1st, ENSA of Berrechid, LAMSAD, B.P 218, Morocco.

E-mail: mu.aatila@gmail.com , m.lachgar@gmail.com, alikartit@gmail.com, hamid.hrimech@uhp.ac.ma

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ABSTRACT

Timely disease detection in plants remains a challenging task for farmers. They do not have many options other than consulting fellow farmers. Expertise in plant diseases is necessary for an individual to be able to identify the diseased leaves. For this, Deep Convolutional Neuronal Networks based approaches are readily available to find solutions for various problems related to plant disease detection. Actually advanced deep CNN-based models successfully performed good accuracy. However, due to a smaller number of image samples available in the datasets, there exist problems of over-fitting obstructing the performance of deep learning approaches. In this work, we used a Siamese convolutional neural network (SCNN) model with different Transfer Learning (TL) models to classify plants diseases. In our approach, we extend the insufficient and various volume data by species using data augmentation techniques. Experiments are performed on a publicly available dataset open access series of imaging studies (Plant Village), by using the proposed approach, an excellent test accuracy of 96.77% is achieved for the classification of plants disease using variant training sample size especially those on low data regime. We proceed to compare Transfer Learning with Siamese Network with their state-of-the-art most CNN architectures and discovered that the proposed model using Siamese Network outperformed the state-of-the-art models in terms of performance, efficiency, and accuracy.

Keywords: ***Deep Learning, Convolutional Neuronal Networks, Transfer Learning, Siamese Networks***

I. INTRODUCTION

The agricultural sector is a major provider of jobs. the dependence of a large population on production for the subsidy of basic needs to meet their needs is a matter of survival. moreover, the ability to detect plant diseases which risks disrupting production or even harming it leads farmers to turn to new techniques to improve the quality of their products at a lower cost than expert consultation or laboratory analysis. There are various methods for plant disease detection based on artificial neural network (ANN) [1], Siamese Network [2], convolutional neural network (CNN) [3], and its combination. Convolutional Neural Network used on plant disease detection deal with computational cost that increase accordingly to data volume for training [4], otherwise the majority of farmers use low-end mobile devices with natural background and lighting conditions, to challenge the transfer learning model we focus on images in natural environmental conditions with non-trivial background noise. Against this background, we use the Plant village dataset which is a dataset of 20,639 images across 13 plant species and 27 classes (17-10, disease-healthy) and use the Siamese Network to test their impact on the performance accuracy [5-11].

The following sections of the paper is presented as follows. Firstly, in section 2, we present the most recent related works. Then in section 3, we provide the theoretical overview of the Convolutional Neuronal Architecture used in our experiments and describe which should be used in which situation to make a better choice for an easy and quicker convergence and best performance. Next, in section 4, an analysis and a comparison of the performance of five CNN pre trained models, mainly AlexNet, GVV, GoogleNet, ResNet and Siamese Networks are done on the application of plants disease detection. We use a dataset of 20,639 images of diseased and healthy plant leaves collected under controlled conditions to see how overall accuracies vary accordingly on different transfer learning architecture in the network. Based on our results from that analysis, we make the prediction by giving input images using the pre trained models with different CNN architectures and conclude that the models using Siamese Network are best suited for variant size of dataset accordingly to specific disease in low data regime.

II. RELATED WORKS

This section present the related work carried out in this perspective. First, the most studies found in the literature use transfer learning in their experiments [12]. A large number of studies carried out on the Plant village dataset which has the images collected using a regularized process with reprocessed background generating high precision results which remains very limited when the image quality to be used in the real conditions. This observation confirms this advantage with the results obtained in the work of the authors of [13]. Also this constraint generates the need to create a complete database.

Next in [14], the authors mentioned that in view of the non-production of varieties of symptoms by the bias of controlled inoculations, this generates certain visual manifestations of diseases occurring in the field. found under more realistic conditions. Additionally, the visual aspects of a plant disease can vary as symptoms progress and as environmental factors progress. To summarize, the effects of using small data sets on the robustness of deep learning tools for classifying plant diseases is well apparent in the simulation results. This is an important parameter that influence the result accuracy obtained by the contribution of this study.

After that, in [15], the authors studying an image database, containing 13 plant species with very distinct characteristics in terms of number of samples and diseases, this was used to challenge the Convolutional Neuronal Network under a variety of conditions. Deep learning networks formed with different size of datasets and nature allow a better understanding of the strengths and weaknesses of this type of network.

Finally, the authors in [16], present a method called transfer learning which resume to use a deep neural network trained on a big dataset and get a solution to deal with image classification problems in many domains particularly plant disease detection. An important constraint in the classification is the image quality, the latter when collected in real conditions are different from those recovered in a controlled environment. [18].

Our contribution consists to evaluate the performance of Transfer Learning pre trained models using Siamese Network in low data regime.

III. ARCHITECTURAL INNOVATIONS IN CNN

The architectures of Convolutional Neural Networks have not stopped evolving since 1989 [10]. The optimization of criteria and parameters, regularization, classification and structural reformulation present continuous evolutions. Moreover, a good number of these improvements are focused on the restructuring of the processing units and the design of new blocks.

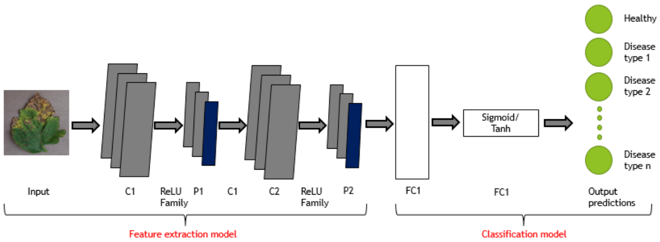

Figure 1. Example of CNN architecture used in plant disease detection

A. AlexNet

The AlexNet architecture was one of the first deep networks to significantly improve the accuracy of ImageNet classification compared to traditional methods. It is composed of 5 convolutional layers followed by 3 fully connected layers. AlexNet, proposed by [19] because the derivative of sigmoid becomes very small in the saturating region and therefore the updates to the weights almost vanish. It's important to use ReLU function to gain on calculation cost and avoid the vanish gradient problem.

ReLU function is mathematically defined as:

$$f(x) = \max(0, x) \tag{1}$$

B. VGG

The use of CNN in image recognition tasks has boosted research in architectural design. To this end, [23] proposed a simple design principle for convolutional architecture named VGG, was modular in the layering model. VGG is constructed in 16 or 19 layers of depth relative to AlexNet to simulate the relationship of depth with the representational capability of the network [20].

1) VGG16. VGG16 was published in 2014 and is one of the simplest (among the other CNN architectures used in ImageNet competition). Its Key Characteristics are:

- Contains total 16 layers in which weights and bias parameters are learnt.
- Contains 13 convolutional layers piled one after the other and 3 dense layers.
- Slow to train and produces the model with very large size.

2) VGG19. VGG19 is alike model architecture VGG16 with 3 additional convolutional layers, it consists of a total of 16 Convolution layers and 3 dense layers. Following is the architecture of VGG19 model. In VGG networks, the use of 3 x 3 convolutions with stride 1 gives an effective receptive filed equivalent to 7 * 7. This means there are fewer parameters to train.

C. GoogLeNet

The GoogleNet architecture comes with a new concept of building block in convolutional neural networks, integrating the principle of multi-scale convolutional transformations. In this architecture, the conventional layers are now split into small blocks called micro neural network as proposed in the Network in Network (NIN) architecture [20].

Also known as GoogleNet consists of total 22 layers and was the winning model of 2014 image net challenge.

- The key idea of inception module is to design good local network topology
- The inception modules also consist of 1 x 1 convolution blocks
- The overall network's dimensions are not increased progressively.
- Consist of two auxiliary classification outputs which are used to inject gradients at lower layers.

The main objective of this architecture comes down to an optimization for the increase of the performance and the reduction of the computation cost.

D. Residual Network (ResNet)

All the previous architecture used Deep Neural Networks in which they piled up many convolution layers until the introduction of ResNET with residual learning that revolutione the Convolutional Neuronal Architecture and get an efficient approch for the training of the networks. It was learnt that deeper networks are performing better [20]. However, it turned out that this is not really true. Following are the problems with deeper networks:

- Present a difficulty to optimize the Network
- Exploding Gradients (If the derivatives are large then the gradient will increase exponentially as we propagate down the model until they eventually explode)
- Accuracy first saturates and then degrades

Authors of ResNet came up with the genius idea of skip a concept that lead the deeper layers be able to learn something as equal as shallower layers. These connections are enabled by skip connections. So the role of these connections is to perform identity function over the activation of shallower layer, which in-turn produces the same activation. This output is then added with the activation of the next layer. To enable these connections or essentially enable this addition operation, one need to ensure the same dimensions of convolutions throughout the network, that's why resnets have same 3 by 3 convolutions throughout.

E. Siamese Network

This architecture contains a twin networks joined by a similarity layer. The two Convolutional Neural Networks are not different networks but are two copies of the same network [21], hence the name Siamese networks.

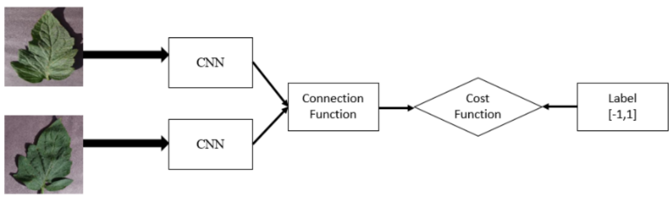

Figure 2. The structure of the Siamese Convolutional Neural Network

As shown in Figure 2, a SNN consists of two similar subnets, called twin networks, associated at their outputs. The Twin Networks not only have a similar architecture, additionally they share weights, execute in parallel and are responsible for generating vector representations for the inputs.

IV. CASE STUDY

Plant diseases affect crop production, causing significant losses to farmers and threatening food security. Using deep learning, we are trying to create a model capable of detecting diseases in the plant and using evaluation metrics, such as accuracy functions. The aim was to compare the transfer learning model using or not Siamese network particularly in low data regime.

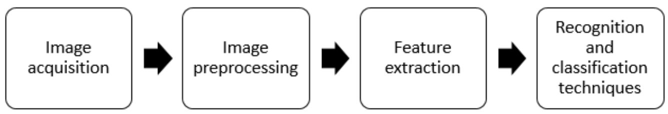

Figure 3. General steps applied to plant disease identification

As shown in Figure 3, the identification process begins with an image acquisition step to proceed to capture images of healthy and diseased plants under different shooting conditions. Then a thorough analysis is needed to process and edit the image and prepare it for the next step, such as image enhancement, segmentation and filtering. In particular, image segmentation methods, such as thresholding, are frequently used to detect outlines and boundaries of images used in the dataset.

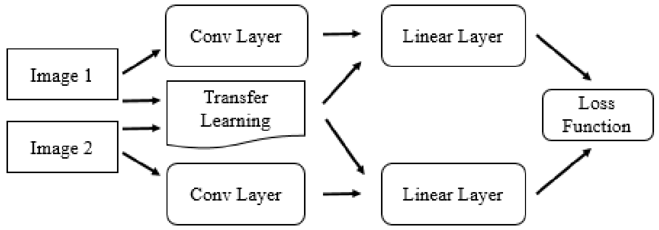

Figure 4. Transfer Learning model using siamese network

The choice to use the learning transfer technique is motivated mainly by the possibility or contribution to use the knowledge (characteristics, weight, etc.) of the model previously trained for a new model, and moreover to solve and contribute to classification problems on low volume datasets for new learning tasks unlike traditional learning techniques based on well identified tasks, different datasets and separate training models. Does not retain knowledge transferable from one model to another. Otherwise, the principal advantage of using transfer learning combined with Siamese Network for the classification is that the learning process does not start from scratch, instead the model starts from models that have been learned during a process of solving a problem. different problem similar in nature to the one being solved.

A. Loading the data

We used the Plant Village dataset, an open dataset of 20 639 composed of diseased and healthy plant leaves images gathered on laboratory conditions. Plant Village Dataset taken both in the laboratory and in real conditions from the crop fields. The plant images cover 13 species of crops including: pepper, potato and tomato. It contains images 27 classes (17-10, disease-healthy).

TABLE I. CLASS DISTRIBUTION OF DISEASES

Classes	Number of images
Pepper__bell___Bacterial_spot	997
Pepper__bell___healthy	1478
Potato___Early_blight	1000
Potato___healthy	152
Potato___Late_blight	1000
Tomato__Target_Spot	1404
Tomato__Tomato_mosaic_virus	373
Tomato__Tomato_YellowLeaf__Curl_Virus	3209
Tomato_Bacterial_spot	2127
Tomato_Early_blight	1000
Tomato_healthy	1591
Tomato_Late_blight	1909
Tomato_Leaf_Mold	952
Tomato_Septoria_leaf_spot	1771
Tomato_Spider_mites_Two_spotted_spider_mite	1.676
Total:	**20639**

B. Data Preprocessing

Firstly, we proceed to preprocessing the data by scaling the data points. Secondly, we achieved a split on the data using 80% of the images for training and 20% for testing. Finally, we created an image generator object. This image enhancement approaches were applied for the upgrade of the distribution of pixels over an extensive range of intensities, linear contrast stretching was applied on the images. During the image acquisition process, some undesirable noise information was added to the image due to nonlinear light intensity conceded as noise.

C. Experimentation Results

After training and validating the model, we obtain our results. Training accuracy is usually the accuracy when the model is applied on the training data. When the model is applied on test data from different classes, it is known as validation accuracy. For data augmentation techniques we used brightness, random scaling, rotation, and mirror flipping [22]. The figure bellow shows a graph, which contains training and validation accuracy of our model by activation functions.

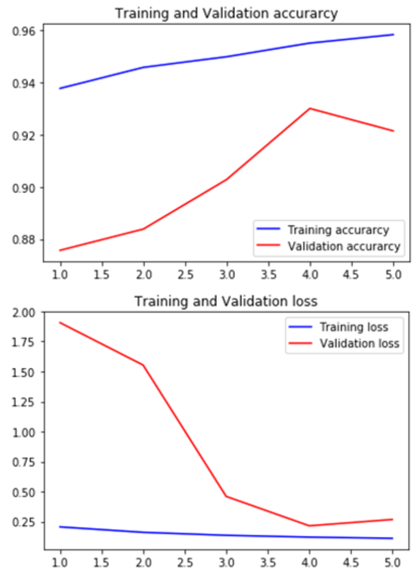

Figure 5. Training and Validation Accuracy Vs Loss graph: VGG16

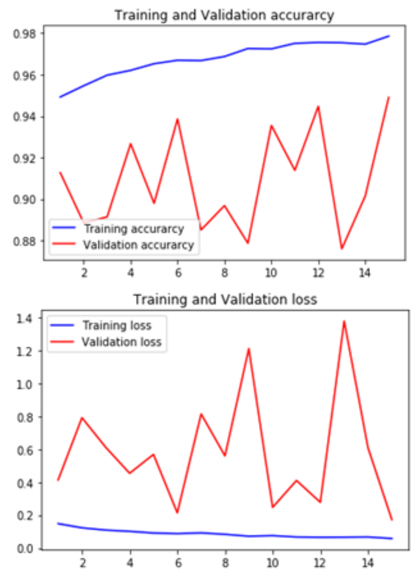

Figure 6. Training and Validation Accuracy Vs Loss graph: VGG19

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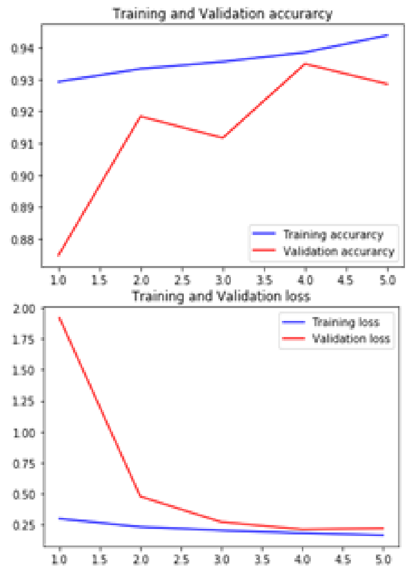

Figure 7. Training and Validation Accuracy Vs Loss graph: ResNet

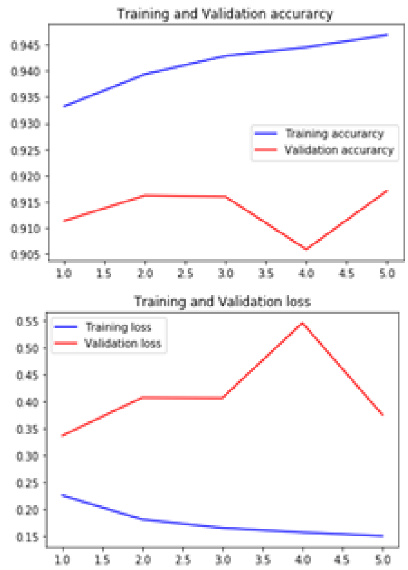

Figure 8. Training and Validation Accuracy Vs Loss graph: InceptionV3

TABLE II. CALCULATING MODEL ACCURACY FOR 5 EPOCHS

CNN Model	Model Accuracy (TL)	Model Accuracy (TL+SNN)
ResNet-50	92.85%	93.77%
VGG16	91.70%	92.92%
VGG19	92.14%	93.52%
Inception_ModelV3	94.90%	**96.77%**

As shown by the curve accuracy in Fig. 8 the model achieves a remarkable performance using the Siamese network, in addition, the curve of the loss function follows the same performance and shows that the use of this networks optimize considerably the convergence of the model.

Table 2 shows the accuracies obtained on the test set from different classifiers trained on the extracted image embeddings from the transfer learning and the twin network of Siamese network. The results obtained shows that the performance of the model using Siamese network are better than those with only transfer learning.

V. DISCUSSION OF RESULTS

With the aim of measuring the effectiveness and performance of the method of learning approaches using classification / identification metrics in the low data regime. We compared the original Siamese Network and the network based on Transfer Learning using the different CNN architectures (ResNet-50, VGG16, VGG19, Google Net.). First using feature extraction, we found that there is severe overfitting although the accuracy improves a lot over a shallow network compared to the data augmentation technique. The validation precision reaches 93% for the VGG16 and VG19 architectures and the over-adjustment can be quite slight, on the other hand the loss is high, in this case this implies that the performances remain subject to optimization. In addition, for Inception V3, the validation precision reaches 96.77% while the validation loss undergoes a slight increase. However, the latter exhibit high performance of those of VGG16 and VGG19 with higher precision and lower loss value.

The graphs obtained from simulations carried out on the small data set show that the models achieve higher precision than the base model using transfer learning techniques and faster even in CPU mode. This shows that when high precision is required and time is pressed, models using the Transfer Learning approach on a Siamese network are a better option than shallow models. When using data augmentation and strong abandonment on a very deep model, the model achieves very high accuracy. In another way, depth offers the possibility of achieving high precision, data increase and stall control significantly. This shows that a very small dataset can use the power of depth.

Experimentation clearly shows that the use of a dataset with a limited number of images for training directly impacts the performance of plant disease classification beyond the technical constraints previously discussed in the literature.

VI. CONCLUSION

Experiments have shown the lack of efficacy of models learnt by transfer learning on low data regime [16], thereby, showing the significance of real-world datasets. In this project, we addressed the problem of classification of diseased/healthy leaves in real-world images using Siamese network in low data regime. We deduce that the integration of images from the

Siamese network gives more efficient results than those extracted from the transfer learning approach, an excellent test accuracy of 96.77% is achieved for the transfer learning of plants disease using Siamese network in low data regime.

Perspective work can be oriented in improving the dataset used with the integration of new data processing techniques and activation functions associated with new CNN architecture to be simulated.

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