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Research Article

Potato disease identification using transfer learning approaches

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ABSTRACT

Potato crop is one of the prominent consumed foods by human beings. When potato crops are infected by diseases it affects farmers negatively and to run in a loss. Therefore, early detection of the potato crop disease can play a vital role in minimizing the loss of the farmers. Nowadays, artificial intelligence technologies, more specifically deep learning techniques, provide solutions to many crops disease-related problems. However, training deep learning models requires a high computational power and huge amount of data as they are data hungry models. Also, designing a custom CNN models a difficult task and there are some variations to be considered. To avoid these difficulties, we adopted two pretrained models of DenseNet121 and VGG19 through transfer learning approaches. The achieved accuracy for DenseNet121 and VGG19 models are 82.6% and 98.56% respectively. DenseNet121 model obtained the average precision, sensitivity, and F1-score of 88.19%, 82.53, and 82.04%, respectively. Whereas VGG19 yields 98.39% of precision, 98.39% of sensitivity, and 97.26% of F1-score in ternary 3-class classification (early blight vs healthy vs late blight).

1. INTRODUCTION

Agriculture is highly relying on several different factors such as water, pesticides, and fertilizers. With the rise of population around the world the food production demand is increasing parallelly [1]. As reported by Food and Agriculture Organization (FAO) by 2050 global food demands reaches %70 due to continuing global population growth [2]. Potato (Solanum tuberosum) counted as the fourth famous consumed food after wheat, rise, and maize[1]. The production of potato annually are 380 million tons and consumed as a nutrition by human around the world. Due to some biotic factors potato as many of the crops is suffering from several diseases which in turn causes loss in the crop yield. The most common potato diseases are early blight and late blight. The first one is caused by fungal pathogen. Whereas the latter is caused by an organism called Alternaria solani [3]. These kinds of diseases can be traditionally diagnosed by famers through visual perception. However, it highly depends on the farmer's knowledge and is not reliable enough. Therefore, the spectrometer has been produced to classify plant leaves as healthy and unhealthy. Also, in another method the DNA of leaves are extracted through the polymerase chain reaction (PCR) are used [4]. However, these techniques are time consuming and costs a lot. Thus, by benefiting from recent Artificial Intelligence (AI) technologies automated plant leaf disease detection can be achieved. Machine learning and deep learning techniques are as main branches of AI are being leveraged to automate the task of plant disease detection [5],[6],[7]. Deep learning is considered as a common practice in many areas such as computer vision, image classification, and pattern recognition [4]. Additionally, deep learning techniques and more specifically Convolutional Neural Network (CNN) has gained attention in plant disease detection. Due to its discriminative nature in classification tasks [8],[9], it has been leveraged in many detection tasks including plant leaf disease detection. Compared to other feature extractors like SIFT [10] CNN performs better than hand crafted feature extractors. Despite of its outperformance over other techniques in the literature, deep learning techniques poses many challenges such as requiring a large amount of data to be trained. To tackle this issue transfer learning techniques has been emerged [11]. So that the model is prevented from being overfitted and requires a large amount of data.

The rest of the paper is organized as follows. Section II provides a brief overview of some conducted works in the literature. Section III provides a detailed explanation about the proposed methodology. Section IV presents results and discussion, and the last section is conclusion.

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2. RELATED WORK

There are many conducted works on potato plant disease detection using deep learning techniques. For instance, Oishi et al. [12] proposed an explainable deep learning approach to detect potato disease through using portable cameras without utilizing any dataset. Rashid et al. [4] presented two level potato disease detection approach. In the first level, potato leaves from PlantVillage [13] dataset are detected and segmented through YOLOv5 deep architecture. Then in the second level a custom CNN model has been leveraged to classify between early blight and late blight potato leaves. In a different study Tarik et al. [14] proposed a custom deep learning architecture for potato leaf disease detection. The utilized dataset images used in this study was taken from Bangladesh. Arya et al. [15] conducted a comparative study for potato and mango disease detection through their leaves. In their study a custom CNN architecture and pretrained Alexnet[16] have been utilized. Again the experiments are conducted on PlantVillage dataset. Also, in the work of Iqbal and Talukder [17] traditional image processing and machine learning based approach have been used such as Haralick texture, Grey Level Co-occurrence Matrix (GLCM), k-Nearest Neighbors (KNN), and Decision Trees (DT). Lee et al. [18] presented a custom deep learning model with the inclusion of different image preprocessing techniques such as normalization, extracting Reion Of Interest (ROI), and color conversion. In this paper we have adopted two well-known deep convolutional neural network models which are already trained on ImageNet dataset [19]. DenseNet121[21], and VGG19 [20]. The underlying reasons behind tailoring transfer learning in our study are reducing requiring computational power and requiring a lot of data to train the model. In addition to this, designing a custom deep learning model is a difficult task and there are a lot of parameters to be considered.

3. METHODOLOGY

A. Dataset

The evaluation tests have been carried out over PlantVillage dataset [13], including different sets of plant leaf data such as apple, corn, grape, tomato, strawberry, and potato. The original number of potato dataset from the class of early blight, healthy, and late blight are 1000, 152, and 1000, respectively. Fig. 1 shows sample images from PlantVillage dataset.

1. (a) (b)

Fig .1. PlanVillage dataset samples: (a) early blight, (b) healthy, (c) late blight

B. Preprocessing

The images of the dataset are of 256x256 pixels. To be fit to the adopted pretrained models, the images have been resized to 224x224 pixels and fed to the models as input. To increase the number of images in each class and to be balanced we have applied some data augmentation techniques including rotation, horizontal flip, vertical flip, shear (0.01), zoom (0.01), width shift (0.01), and height shift (0.01) as shown in fig. 2 . The number of images yielded after augmentation in each class is 2000 images from which 1600, and 400 sample images are used for training and testing, respectively. To evaluate the proposed system, we have used 5-fold cross-validation; therefore 80% of the data are used for training and the remaining 20% are used for validating the model.

1. (a) (b)

Fig. 2. Data augmentation: (a) original, (b)horizontal flip, (c) vertical flip

C. Implementation Environment

The training is done on Nvidia GeForce Titan X (GTX) 1050 GPU, and machine having 8 GB of RAM and Intel Core i7+ processor. For high-performance GPU acceleration, cuDNN has been used, it accelerates many deep learning frameworks, including Caffe, and TensorFlow. Also, to set up GPU, Compute Unified Device Architecture (CUDA) toolkit version 6.0 and CUDA Deep Neural Network (cuDNN) version 7.5.0.56 have been used. Jupyter notebook is an open-source web application that runs the code of many languages. In this work, the python programming language version 3.6.8 has been used.

4. RESULTS AND DISCUSSION

The efficiency of the proposed methodology of the pretrained models has been evaluated through 5-fold cross-validation to classify potato plant leaves into early blight healthy and late blight. Fig. 2 illustrates the confusion matrix (CM) of all five folds of DeneNet121. The result of all five folds VGG19 is shown in fig. 3. Out of five equal portions of the utilized dataset, 4 parts are used for training and the left is for validation (i.e. 80% and 20% have been used for training and validation purposes, respectively). Table I shows the precision, recall, and f1-score for all five folds with their average of DenseNet121 architecture. It can be observed that from Table I the best fold in terms of precision, recall, and F1-score is fold 5 and the worse id fold 2. However, Table II represents the results for all five folds of VGG19 architecture. Surprisingly, the obtained results from all folds are the same except the fourth fold. It is noteworthy that VGG19 model outperformed DenseNet121 in respect of precision, recall, F1-score, and accuracy.

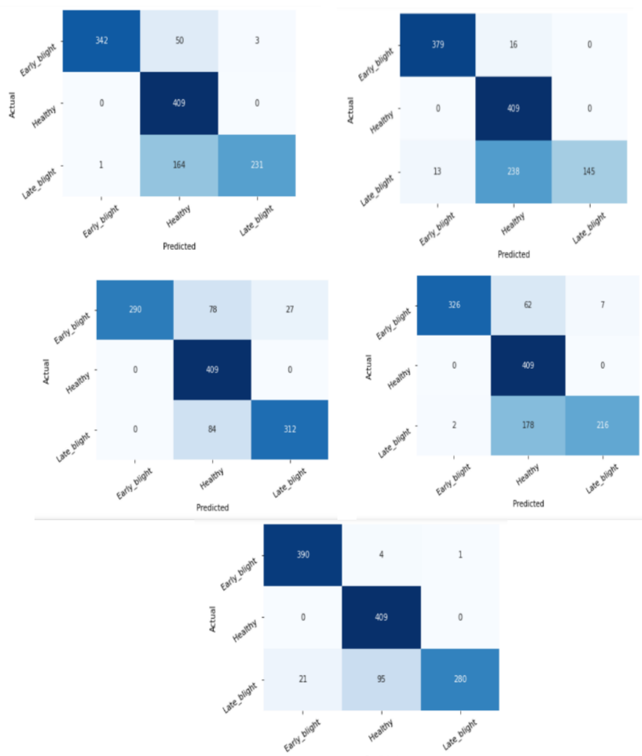

Fig. 3. Confusion Matrices for all 5-folds DenseNet121 architecture

TABLE I. PERFORMANCE EVALUATION DENSENET121 MODEL.

Folds	Precision(%)	Recall	F1-score(%)	accuracy
Fold-1	88.33	81.66	81.66	81.83
Fold-2	86.33	77.66	75.66	77.75
Fold-3	88	84	84.33	84.25
Fold-4	86.33	79.33	79	72.25
Fold-5	92	90	89.66	89.91
Average	88.19	82.53	82.04	82.6

TABLE II. PERFORMANCE EVALUATION VGG19 MODEL

Folds	**Precision(%)**	**Recall**	**F1-score(%)**	**accuracy**
Fold-1	98.66	98.66	98.66	98.58
Fold-2	98.66	98.66	98.66	98.66
Fold-3	98.66	98.66	98.66	98.58
Fold-4	98.33	98.33	98.33	98.25
Fold-5	98.66	99	98.66	98.75
Average	98.59	98.66	98.59	98.56

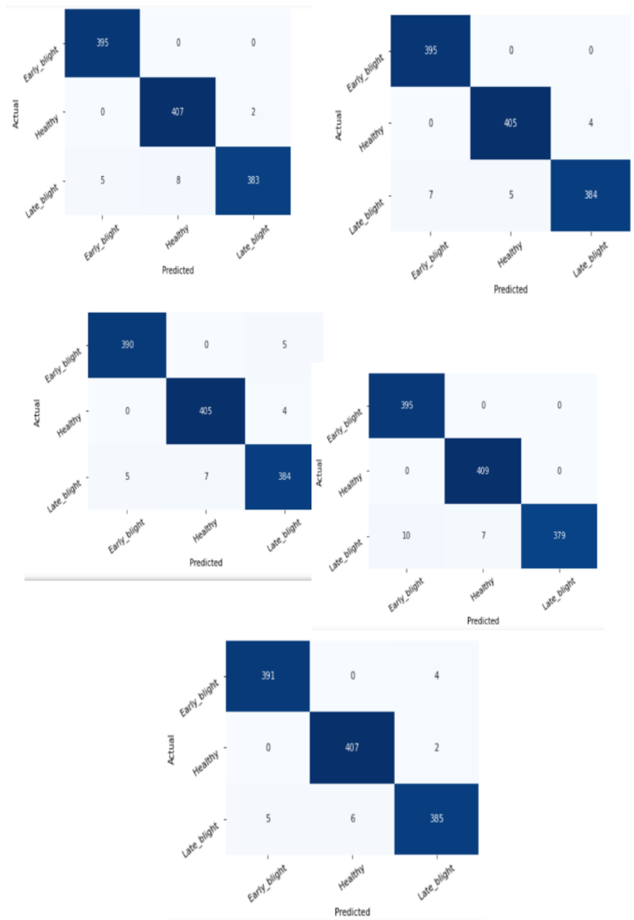

Fig .3. Confusion Matrices for all 5-folds VGG19 architecture

5. CONCLUSION

In this study, we presented for identifying potato disease identification from their leaves. To avoid computational cost and requiring lots of data to train the model, we have exploited transfer learning approaches. To evaluate both utilized models CM, F1-score, precision, recall, and accuracy have been considered as a metric. The proposed VGG19 model results outperform DeneNet121 in the literature of potato plant disease identification. According to the evaluated results VGG19 model can potato crop leaf diseases with an accuracy of 98.56% while the DenseNet121 achieves just 82.6% for that task.

Conflicts Of Interest

The authors declare no conflicts of interest.

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