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Analysis of Performance for Detection and Classification of Citrus Diseases on Citrus Fruits and Leaves using Transfer Learning Methods

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Abstract

Citrus is one of the nutritious fruits having antimutagenic and antioxidant properties. Prevention from disease is important for citrus fruit and leaf. The proposed work illustrates the implementation of image processing to determine the distinction between healthy and diseased citrus fruit and leaf. Different models are developed to identify disease like greening, scab, canker, melanose, black spot that could be found on the citrus fruit and leaves. Training is done using the dataset consisting of several images of diseased citrus fruit and leaves. In this analysis, transfer learning and data augmentation attempted to shape a model that focuses on the recognition of citrus diseases by processing acquired digital images of citrus leaves and fruit.The diseased leaf is classified more accurately (93.9%) by model whose base features were extracted from the Xception pre-trained model that beats the performance given by the VGG16 (92.7%). Similarly, in case of citrus fruit disease detection, model trained using Xception (91.4%) exceeds the performance provided by the model trained using VGG16 (83.6%).

Keywords

CNN, Pre-trained Model, ResNet, Transfer Learning, VGG, Xception

1. Introduction

Citrus fruit includes a set of vitamins, fibers, and minerals that signify balanced biological behaviors, such as flavonoids, carotenoids and limonoids. Various diseases could be found on the Citrus plant during its different stages of growth but identification of these disease at their early stages becomes hard in many regions of the country due to the short of the proper facilities. For the agricultural country like ours, Citrus diseases are largely accountable for the decline in productivity that in turn hampers the economy of whole country. Farmers need to identify disease correctly when it first occurs and treat the disease accordingly in a timely manner. These are some of the disease that a citrus fruit or leaf can have: Canker, Greening, Black spot, Scab, Melanose. Significant citric diseases may be detected and categorized by experts on the basis of their symptoms. However, this involves constant supervision and manual observation, which may be error-prone, expensive and tedious job too. An automated system for the detection of plant diseases can help farmers recognize the disease at an early stage and can try to cure the disease that has been detected in time.

Introducing about the method: the idea of reusing feature is most prevalent these days, this is used for the design of deep networks, like DenseNet [1] and ResNet [2]. The network becomes significantly deeper, more precise, and effective as a result of this idea. The underlying concept behind learning is to use labeled data or information from similar domains to assist a machine learning algorithm's performance[3]. The aim of this research is to use the concept of transfer learning to solve the problem of image classification with a limited number of training datasets.

The following are the two main contribution this paper makes in research field:

1. Different models are developed using various pre-trained model.
2. Performances of different models are analysed for detecting and classifying the diseases on citrus fruit and leaves.

2. Related Works

Soini et. al. [4] developed binary classification i. e. HLB positive or HLB negative, which allowed the initial model to be trained with less training images while generating better accuracy and faster results that was possible by categorizing tree images resulting the validation accuracy from 90.9% to 93.3%.

A tracking algorithm consisting of two steps was developed [5]: First, Kalman filtering was introduced to detect the new position of an object in video sequences. Secondly, the Hungarian algorithm was used to allocate the correct crop trajectory to each detected crop appearing in every image such that overall detection performance was brought up to 99.34

Authors[6] suggested approach to the integration of K-Means clustering, ANN and SVM strategies. K-Means for image Segmentation results in the task of mapping images of their respective disease groups on the basis of phenotypic characteristics such as texture, colour, arrangement of fruit holes.

[7] This study helped to distinguish diseased leaves using four key techniques: Preprocessing was done to normalize and change contrast, Segmentation was done to color transform into yCbCr and Bilevel thresholding, Feature was extracted by GLCM and thus classification was done using HMM.

W. Pan et al. [8] build densely connected neural networks resulting an intelligentdiagnosis system for classifying citrus disease with the accuracy exceeding 88%. Thissystem used the WeChat Applet on mobile device. Along with disease detection, usercan receive comments too

The paper 'Machine Learning and Fuzzy Logic' Disease Classification and Grading of Orange [9] implements multi-class SVM with k-means clustering for classifying disease with accuracy of 90% and Fuzzy Logic effectively measures the degree of disease severity of orange[10]. With a public dataset of 54,306 photographs of diseased as well healthy plant leaves obtained under controlled conditions, a deep convolution neural network was built to classify 14 crop species and also 26 diseases, resulting in an accuracy of 99.35 percent on a test set.

A model was developed by training and validating a network [11] and was implemented as an android application results a tool for helping decision making of professional in a phytosanitary sector.

3. Methodology

This methodology consists of four main modules:

- Image acquisition
- Image pre-processing
- Deep learning(feature extraction+classification)
- Performance evaluation.

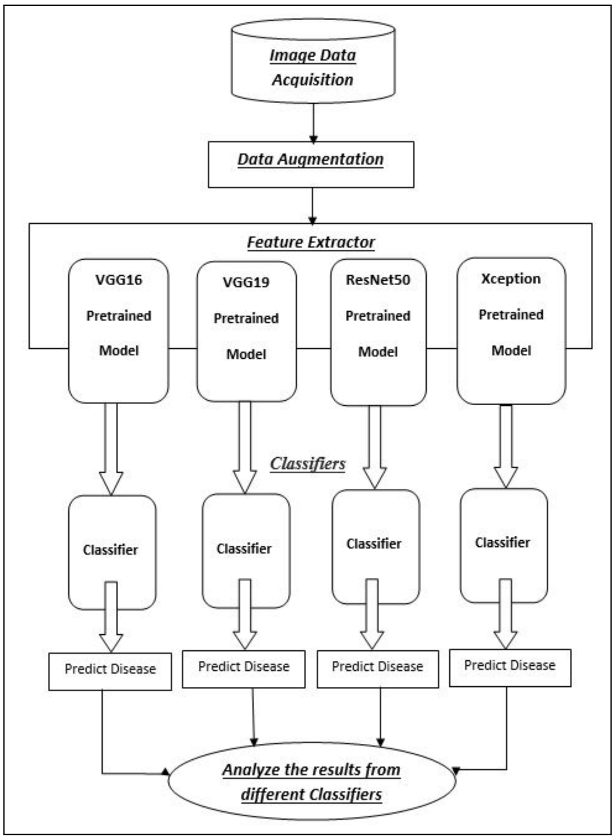

Figure 1: Classification procedure for defined Methodology

The Figure 1 illustrates the detailed methodolgy this research has gone through. Because of very small dataset available, Transfer Learning (Training the pretrained model with our own datasets) is implemented. There are different pretrained models available. Among those, four pre-trained model: VGG16, VGG19, Xception, ResNet50 have been used to extract the feature and top layers are then trained to classify the images belonging to different categories. Thus, for fruit and leaf disease detection, such four models are developed for each resulting eight models altogether. Moreover, the result from different classifiers is analyzed and compared so as to evaluate which pretrained model fit as the best among them.

3.1 Data set Collection

Deep learning models need tremendous data to learn properly. Collection of data images at a single platform was quite impossible for this research so dataset was built after the manual collection of images from different sources.The detail of data is given in Table 1 and Dataset is collected from different sources as mentioned in Table 2.

Categories	Leaf	Fruit
Healthy	90	840
Canker	250	290
Greening	1000	30
Blackspot	260	60
Melanose	40	—
Scab	—	60

Table 1: Figure showing Dataset Detail

Link	**Fruit & Leaves**	**Image size**
https://data.mendeley.com /datasets/3f83gxmv57/2.	150& 609	256X256
https://github.com/spMoh anty/PlantVillage-Dataset	0 & 1000	256X256
https://www.kaggle.com /moltean/fruits	639& 0	100X100
https://idtools.org/id/citr us/diseases/index.php	291& 31	100X150
Data collected during research	200& 0	256X256

Table 2: Figure showing dataset source detail

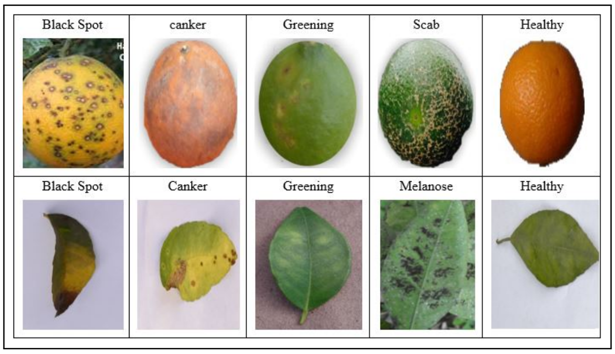

Figure 2: Sample of datasets (fruit and leaves)

3.2 Data Preprocessing

The size of the database was artificially expanded by the use of numerous transformation processes such as rotation, height shift and width shift, resulting in a larger database normally needed to improve deep network efficiency. This process is known as data augmentation. For the elimination of irregularities, different smoothing filters are used.

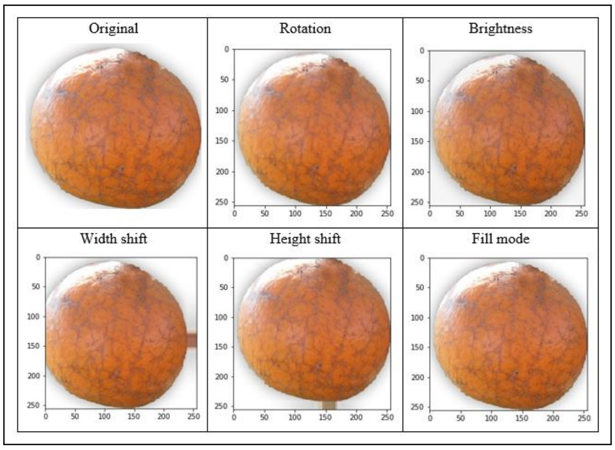

Figure 3: Example showing the data augmentation of an image

3.3 Feature Extraction

Deep learning technology was revolutionized after the advent of massive databases such as ImageNet also hardware-accelerated computers such as the graphical processing unit, and the world began to see major deep learning algorithms such as AlexNet, Inception, VGGNet, Residual Networks (ResNet), GoogLeNet and Xception. In 2012, AlexNet made an impressive advance in the revolutionary deep learning model to be trained on the ImageNet database by categorizing 1000 different objects [12]. Afterward, numerous study groups along with VGG from Oxford University and GoogLeNet from Google both suggested separate deeper neural models than AlexNet in 2014[3]. To classify the disease, a transfer learning system with fine tuning is used. As a fixed feature extraction mechanism, a pre-trained model is used since the dataset is small.

3.4 Fine tuning

The top-most layers were omitted in this section. Also, two new dense layers and a classification layer with a softmax feature were used to replace the deleted layers. These new implemented layers were learned using the characteristics obtained from the layers of the pre-trained deep learning models. Without changing their weights, the transferred layers were frozen to obtain image patterns. This scenario is applied for all four pre-trained models in an application, i.e. As shown in Figure 4, VGG16, VGG19, ResNet50, Xception, where the dataset used for training was 80% , validation 10% and tests 10%.

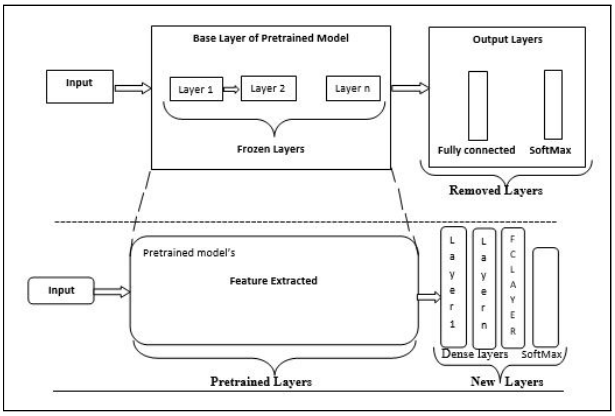

Figure 4: Fine tuning overview

To sum up, the model extracts the features from the pre-trained model and along with these new layers are added to generate new categories from the output layers.

3.5 Implementation Details

Tensorflow and Keras were used to create the networks that would be learned and tested. Tensorflow is a numerical computation software library that's also open-source. Keras is a neural network high-level API that operates on top of Tensorflow. In each of the pre-trained models, two or three dense layers were added. Each layer used the rectified liner unit as an activation feature. In addition to fully connected layers, a SoftMax classifier was used to calculate the probability of each image sample belonging to a certain class such as Black spot, canker, greening, Melanose, and healthy fruit. Categorical cross-entropy was used as the objective function. And, as an optimizer, Adam was used to train the algorithm, with a batch size of 32 as the learning law. In addition, one fully connected layer with units was added during the transfer learning process.
In case of VGG16, VGG19, and resNet50 models, the images were resized to 224*224 pixels and 299*299 for the Xception model due to a restriction in the possible input sizes for the pretrained networks in Keras.

3.6 Model Evaluation

In order to assess the efficacy of classification algorithms, various statistical efficiency metrics are used. Classification report was generated and measurements like Accuracy, Recall, F1- score, Precision were evaluated.

3.7 Reduce Overfitting Problem

Overfitting can occur as network depth increases, resulting in a weak classification impact. Furthermore, since deep learning works well on massive datasets, a lack of training samples may be a major factor. Therefore, in this thesis different methods have been applied to minimize the problem of overfitting:

- Dataset is enlarged by different augmentation technique.
- Regularization techniques L2 is used.
- Early stopping is done with the patience value 10. Due to this, in any epoch if the model goes to overfit, it is stopped

4. Results and Discussion

The pre-trained models based on CNN are used. While specifying high learning rates increases the likelihood of losing previous knowledge, limited learning rates are allocated. A small learning rate would ensure that the CNN weights do not distort too quickly and too much so small learning rates are assigned i.e 0.001. The dataset with data augmentation is used in the process of training the model. This is a standard technique for transfer learning and is always a successful solution when there is a small amount of data available for training. Therefore, to predict specified classes using the pre-trained model as a base, the final classification layer was constructed on top. It is then possible to produce a summary of a model describing the number of trainable and non-trainable model parameters.
The model is trained assigning 100 epochs and with each "epoch", the training and validation error and accuracy is printed for each. As training progresses, the validation accuracy can improve with each epoch, and finally achieve a steady value when the model does not gain any more valuable knowledge from the training results.
In this section, the findings of the research are described along with their pictorial explanations in Figure 5 to Figure 12.

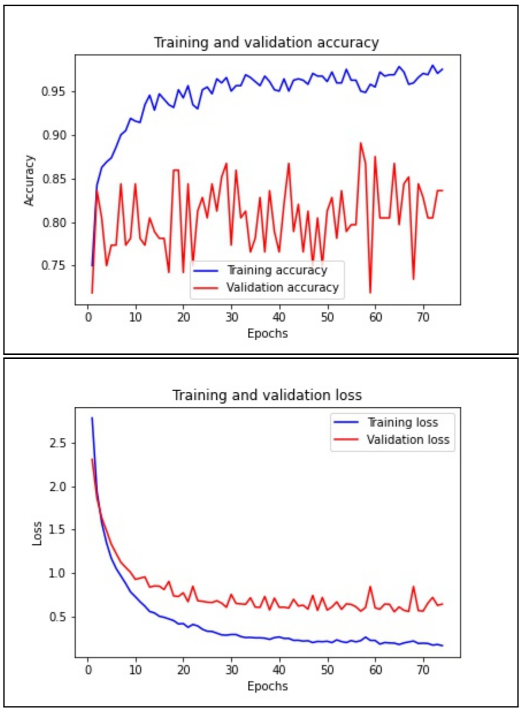

Figure 5: Training and Validation Accuracy and loss curve using VGG16 model for fruit disease classification

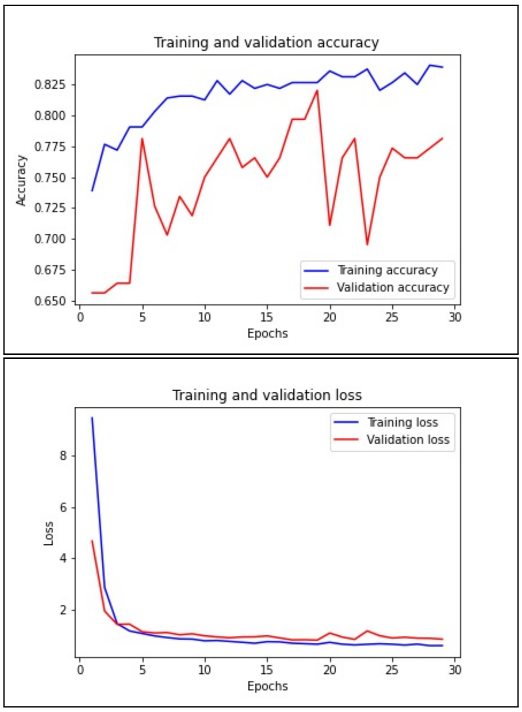

Figure 7: Training and Validation Accuracy and loss curve using Resnet50 model for fruit disease classification

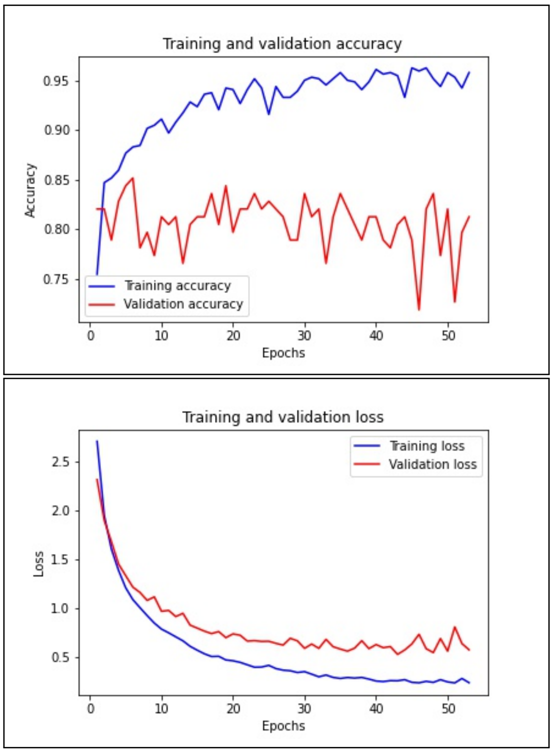

Figure 6: Training and Validation Accuracy and loss curve using VGG19 model for fruit disease classification

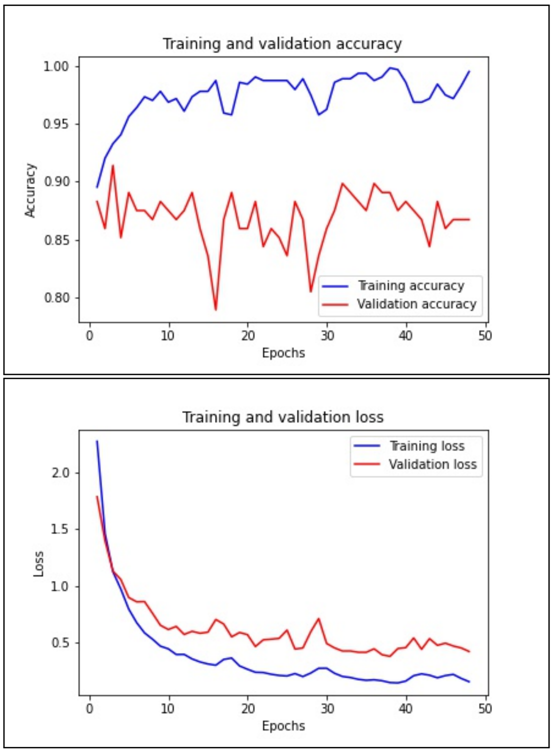

Figure 8: Training and Validation Accuracy and loss curve using Xception model for fruit disease classification

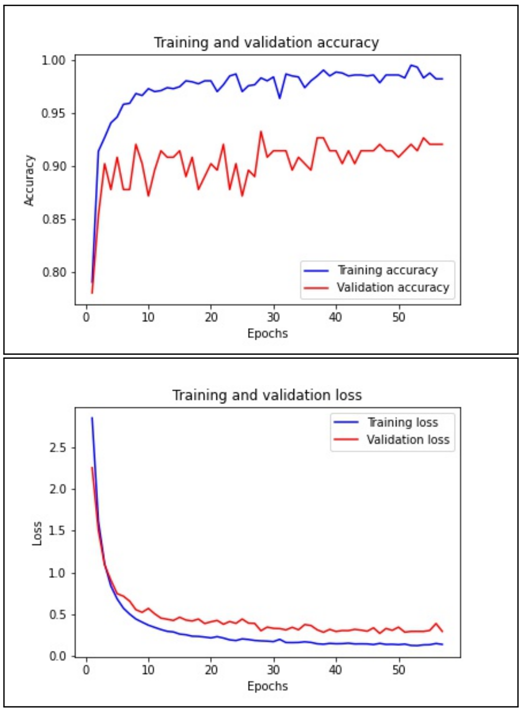

Figure 9: Training and Validation Accuracy and loss curve using VGG16 model for Leaf disease classification

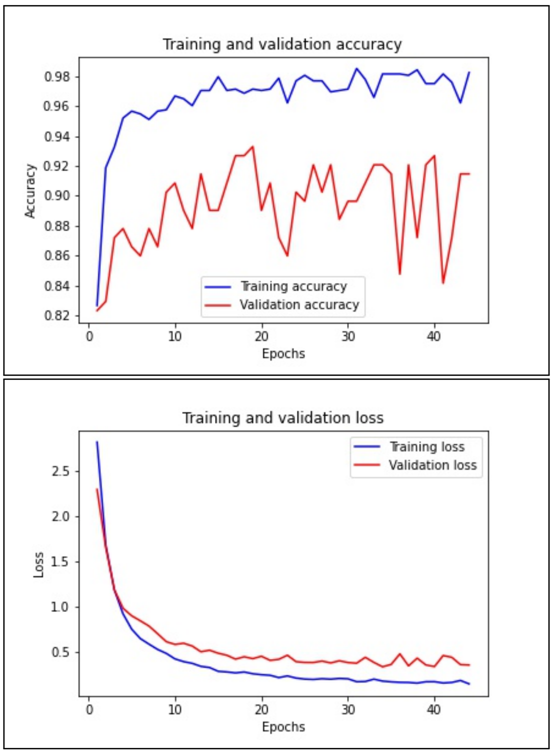

Figure 10: Training and Validation Accuracy and loss curve using VGG19 model for Leaf disease classification

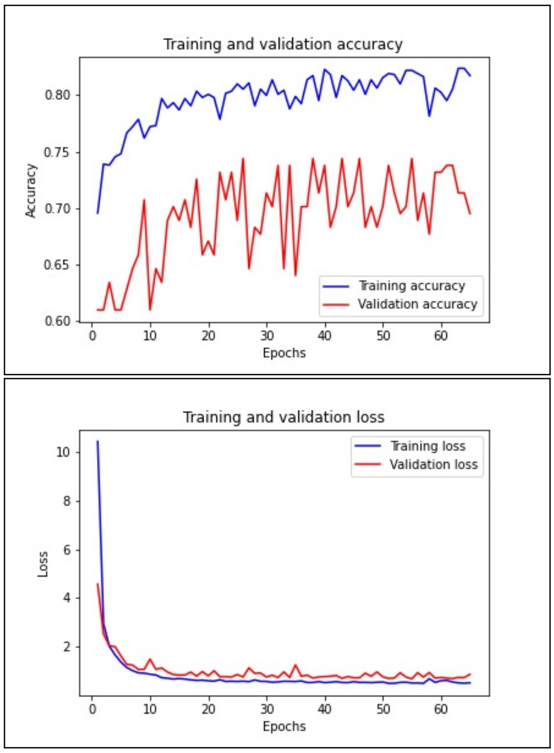

Figure 11: Training and Validation Accuracy and loss curve using Resnet50 model for Leaf disease classification

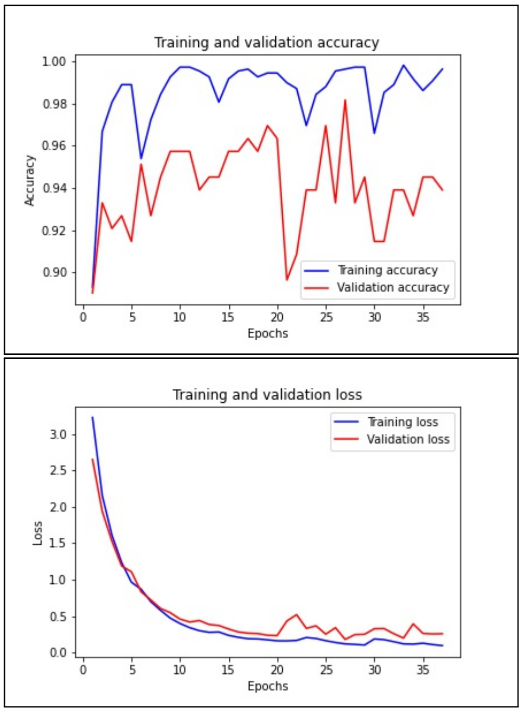

Figure 12: Training and Validation Accuracy and loss curve using Xception model for Leaf disease classification

5. Analysis

Finally, we can measure the overall accuracy calculated on the test set as a final metric as show in Figure 13 illustrating both in case of Fruit as well as Leaf, model developed by Xception gives more accuracy as compared to other methods.

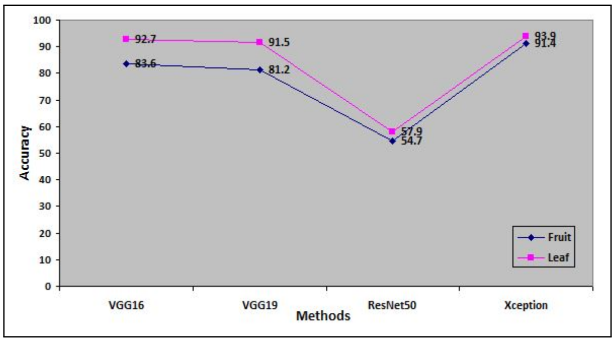

Figure 13: Accuracy Analysis on test set

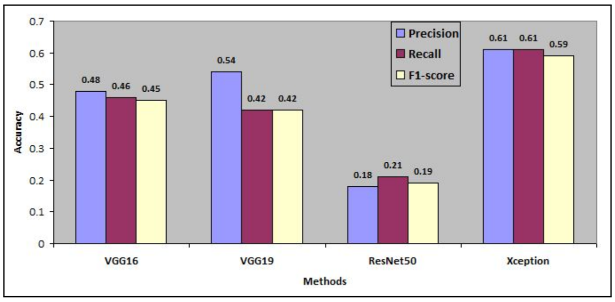

Figure 14: Comparison of Performance from different model (fruit disease)

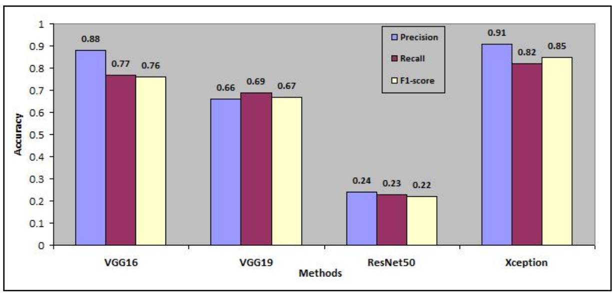

Figure 15: Comparison of Performance from different model (leaf disease)

The Figure 14 shows model trained from Xception has most precise value for classification of citrus Fruit disease with f1-score value 0.59 whereas model trained from resnet50 shows very low results with value 0.19. Also, Figure 15 also indicates that the Xception model has the most reliable value for citrus leaf disease classification with f1 score 0.85, while the Resnet50-trained model results in just f1 score 0.22.

Among those models Xception Performed better for both the cases: leaf disease detection as well fruit disease detection. Xception perform well as it is an efficient architecture that rely on depth wise separable convolution and there is a shortcut connection between convolution blocks. Here, resnet50 performance is very poor. This is due to the model's complexity, which varies depending on network sizes and parameters that must be optimized. Also because of very less data, as the number of epochs goes higher, overfitting grows rapidly. The learning rate need to be decreased after a certain epoch for having the better performance.

6. Conclusion and Future Enhancements

This research focuses on identifying the healthy or unhealthy citrus fruit. Transfer learning and data augmentation attempted to shape a model that focuses on the recognition of citrus diseases by processing acquired digital images of citrus leaves and fruit. Altogether eight models: Four for each citrus fruit and citrus leaves are developed using VGG16, VGG19, ResNet50 and Xception. After analysis, it is found citrus leaf disease is classified more accurately with f1 score 0.85 by model whose base features were extracted from the Xception model. Similarly, in case of citrus fruit disease detection model trained using Xception results in f1 score 0.59. Overall, the results showed that transferring an Xception model that had been pre-trained on an imagenet dataset could be a good way to construct a deep neural network model for disease classification of citrus fruit and leaves.

As future work, We can develop a software for GUI to implement the developed model. Next, to improve the performance, We can increase the dataset and further optimize our method. Also, Not only detecting of occured disease, additional feature could be added to this system i.e. providing suggestions of the remedial for corresponding disease from the expert system.

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