# Automated Diagnosis and Cataloguing of Foliar Disease in Apple Trees using Ensemble of Deep Neural Networks

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**Abstract:**

*Trees are always under risk from a large variety of diseases causing microbes and bacteria, early detection and diagnosis of the disease reduces the disease rate. The main agenda of this paper is to propose an automated deep learning stationed ensemble of neural networks which helps us to identify the disease with utmost accuracy. The dataset used in this research is taken from the Plant Pathology FGVC7 Competition held on Kaggle. It contains of 3,642 high quality images of apple leaves with multiple foliar diseases captures under various lighting conditions, angles and noise. The Deep Learning model is trained to distinguish the type of disease among leaves of which are healthy, affected with apple rust, apple scab or leaves with multiple diseases. The ROC AUC score of the proposed method is 0.981 against the testing data on Plant Pathology FGVC7 Dataset.*

***Key Words*: Deep learning, Apple leaf diseases, real-time detection, convolutional neural networks, ensemble, deep convolutional neural network, multi-target learning, Kaggle.**

## 1. INTRODUCTION:

Apple is a deciduous tree widely known around the world for its fruits which is one of the most cultivated and consumed fruit in the world, due to its high nutritional and medicinal values. On an average more than 10,000,000 tonnes of apples are being produced every year. Despite its high production rate these trees are under risk from falling under plethora of diseases causing bacteria and pathogens .Only with proper care and control of insects, usage of fertilizers we can save the trees. Therefore initial detection and correct classification of disease help the farmer to take action in time. Current diagnosis and manual examining process is moderate and any misdiagnosis of the disease leads to false use of chemicals and fertilizers which in turn lead to evolution and development of new resistant bacteria making the situation worse. Deep learning models have the ability to classify the images and they have been proved to produce accurate results over the past years. The primitive intention of this paper is to propose an ensemble of deep convolutional neural networks and automisation of the task to predict the disease using a single leaf image. By proper image processing, data augmentation and finally feeding the image into state of art models. The ensemble model outperforms the state of art model to decrease the rate of error and thereby increasing the accuracy. Although some of the machine learning algorithms have the ability to perform image processing and feature extraction but they are not feasible as deep neural networks and they reduce the efficacy of disease diagnosis. Convolutional Neural Networks (CNNs) are perfect for image processing tasks. Convolutional layer is the building block of convolutional neural network which consists of several independent filters and each filter is independently convolved with images and performing dot products of previous convolutional layer input, similar to feedback of neurons in the brain for a specific stimulus.

## 2. PROBLEM SCENARIO:

### 2.1 Dataset:

The research data used is extracted from Kaggle PLANT PATHOLOGY 2020 FGVC7 competition. The dataset consists 3,642 images of Apple tree leaves categorised into healthy, rust, scab and multiple diseases. The model evaluation was done on the test dataset from Kaggle. The dataset class distribution is shown in Figure 1.

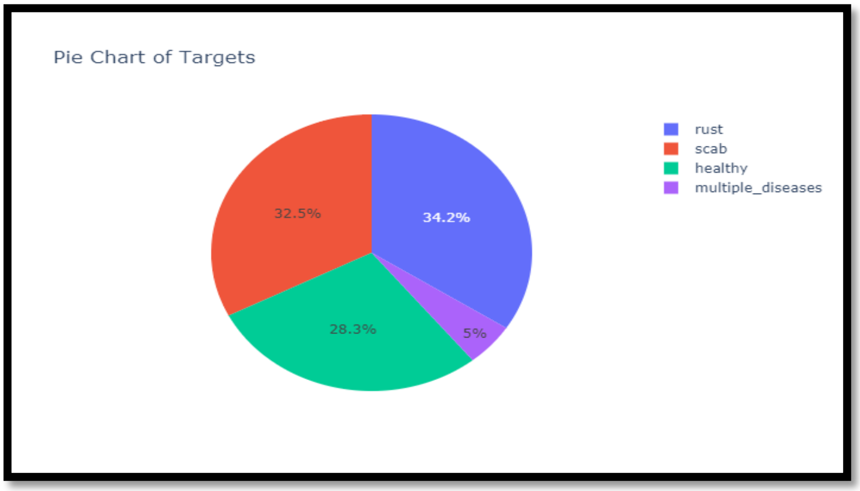


**Fig -1**: Classes distribution in Plant Pathology 2020 Dataset.

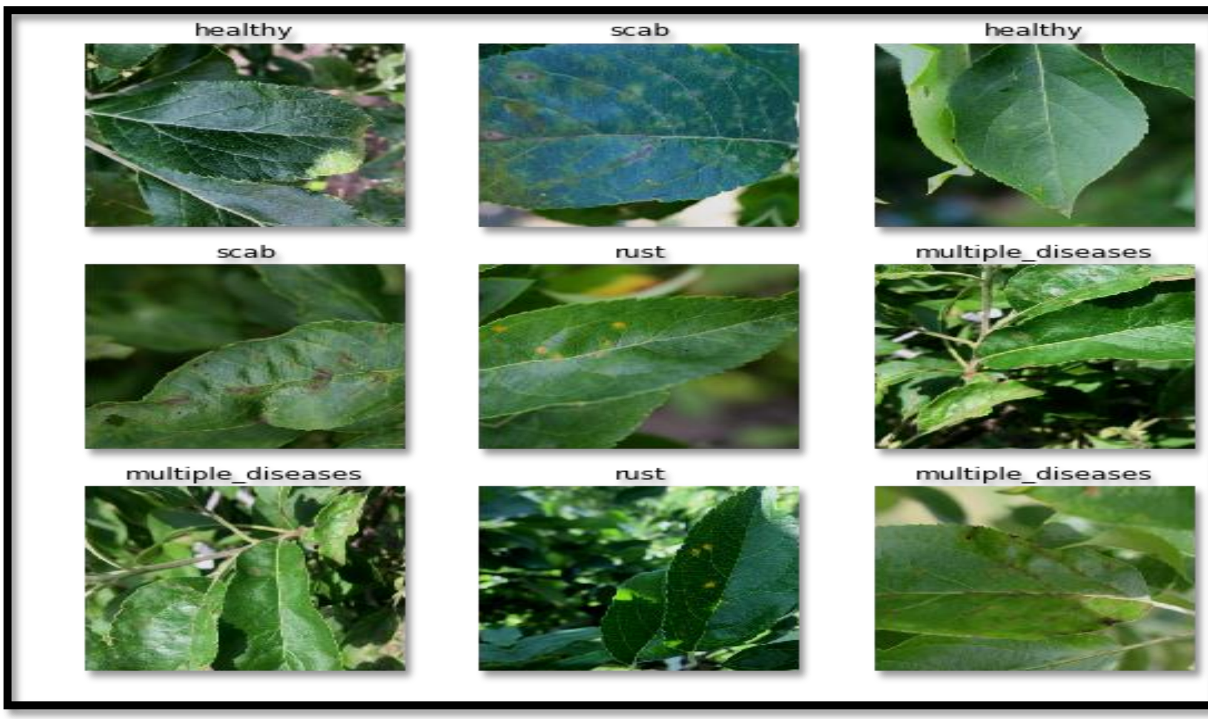


**Fig -2**: Sample Images of healthy and diseased leaves.

**2.2 Evaluation Metric:**

The evaluation metric used in this experiment is mean-column wise AUROC (Area Under Receiver Operating Characteristic Curve). The AUC - ROC Curve is used to measure model performance of classification problems, ROC is a probability curve and AUC is the degree of separability. It specifies the capability of model to distinguish among classes. Always the AUC score should be high, for better identification and classification. The following image shows the ROC curve of TPR(True Positive Rate) against FPR(False Positive Rate) with FPR on x-axis, TPR on y-axis.

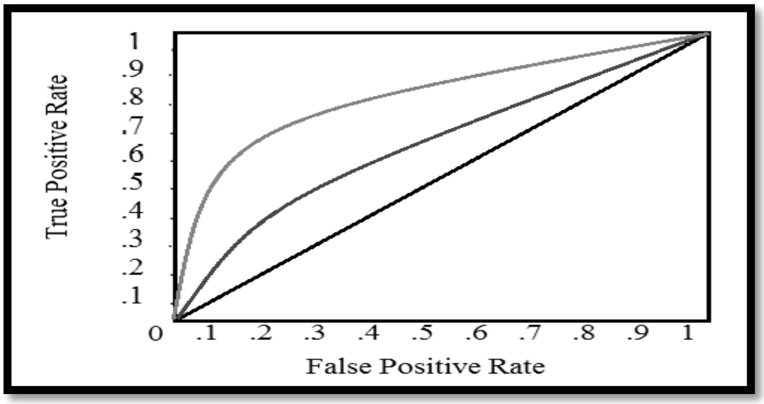


**Fig -3**: Receiver Operating Characteristic Curve.

Following terms are used in the AUC and ROC Curve:

1. TPR(True Positive Rate):

TPR = $\frac{TruePositive}{TruePositive+FalseNegative}$

2. Specificity:

Specificity = $\frac{TrueNegative}{TrueNegative+FalsePositive}$

3. False Positive Rate(FPR) :

FPR = $\frac{False\ Positive}{True\ Negative+False\ Positive}$

**3. METHOD:**

The Plant Pathology disease Identification problem can be termed as a Multi Label Image Classification problem

**3.1 Preprocessing:**

The training and validation of model was performed on preprocessed and augmented images of original images. To reduce the problem of overfitting, a high amount of data augmentations were done so that there is more variance of data.

**3.1.1 Canny Edge Detection:**

It is a popular edge detection algorithm developed by John F.Canny in 1986. It includes the following steps.

1. **Noise Reduction** : The edge detection algorithm is sensitive to noise, hence noise elimination is done using Gaussian filters.
2. **Gradient Calculation**: This step identifies the intensity of edge and direction by calculating image gradient using edge detection parameters. After the smoothening of image is performed using Gaussian filter, it is now filtered with Sobel Kernel in horizontal and vertical directions in order to get the derivative in horizontal(Gx) and vertical(Gy).Where G stands for Edge Gradient.

   $$\boldsymbol{G = \sqrt{Gx^2 + Gy^2}}$$
3. **Non-Maximum Suppression** : After the gradient calculation is done, images are scanned in order to remove any undesirable pixels which may not include in the edge. Finally, as the image should have thin edges non-maximum suppression is applied to make the edges thin.
4. **Hysteresis Thresholding**: This step plays a vital role in edge detection, it is used for segregation of pixels into strong, weak and non-relevant. The pixels which have high intensity are categorized as strong pixels as they contribute to the final edge(High threshold), whereas the pixels which have lesser intensity than strong ones are identified as weak pixels. Finally the remaining pixels are not considered as they don't contribute to the edge (beneath low threshold).The pixels with intensity between these two thresholds are coined as weak. Finally, the edge tracking is done by hysteresis, using the threshold values. Hysteresis transforms the weak pixels into strong pixels if atleast one of the pixel around the processed one is a strong pixel.

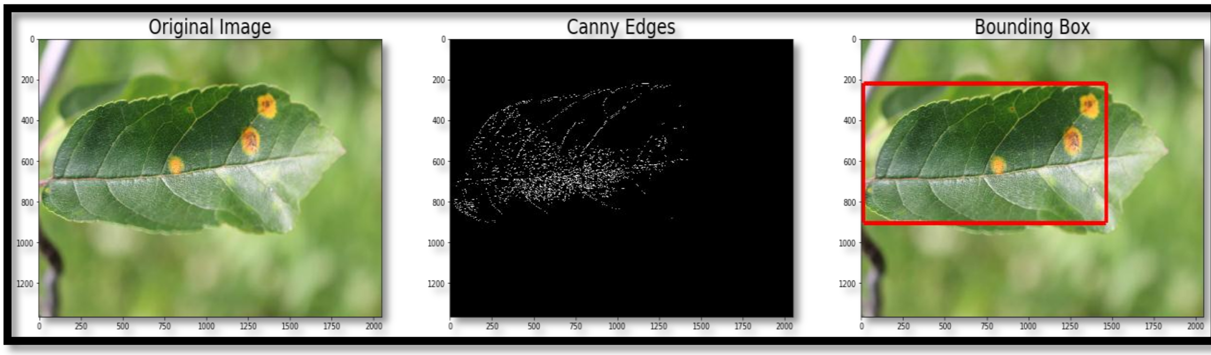


**Fig -4**: Result of Canny Edge Detection on Images.

### 3.1.2 Data Augmentation:

Data Augmentation is done on training and testing images(TTA) before feeding them into CNN. With the usage of tensorflow image library certain augmentations like Horizontal flip, vertical flip, rotation, sample wise normalization, random brightness and contrast, shearing are performed to images.


**Fig -5**: Sample Image Augmentation.

### 3.1.3 Network Architecture:

The neural networks are built using traditional Deep Convolutional Neural Network Architecture, it includes a feature extractor where extraction of preliminary features from input images takes place. Backpropagation of layers helps to tune themselves and eventually become coloured edge blobs.

**1. EfficientNet Model Architecture:**

The ability of the model to perform image feature extraction enhances accuracy, which in turn helps the model to learn and train from patterns observed in input image .One simple way to elevate the accuracy is to scale the images, so that model can learn from it. In general there are three scaling dimensions for a Convolutional Neural Network: depth, width and resolution. Depth of model describes the penetration of networks i.e, the number of layers in the network. Width specifies the width of the network i.e, no. of channels in a convolutional layer. Resolution means the image resolution that is passed to the model. One unique thing that differentiates EfficientNet from other models is its compound scaling feature. Uniform scaling of depth, width and resolution improves the model efficiency.

**2. ResNet Model Architecture:**

As stated above with the increase of deeper neural networks model performance and accuracy improves, but it has been noticed that after substantial depth model performance starts to degrade this is infact the bottleneck of VGG model. One of the major problems that ResNet solves is vanishing gradient. The problem of the vanishing gradient arises when the network is too deep. Loss calculation which is done with the help of gradients decreases and gradually shrinks to zero, as a result the corresponding weights never gets updated and finally the learning of the model comes to halt. To overcome this ResNet allows flow of gradients directly, skipping the intermediate connections as a result model accuracy increases.

**3. DenseNet Model Architecture:**

The architecture of DenseNet is similar to the ResNet. Traditional Neural Networks work in a way such that output of the Layer($L_i$) is input to the next Layer($L_i$ +1). DenseNet architecture uses a Residual Connection i.e, for a layer the input is obtained by the summation of the outputs from the previous connected layers as a result more information and features flow in the network which makes the model easy to train.

**4. Ensembling:**

The advantage of using deep neural networks is their flexibility to scale in accordance with the training data, but as said due to its flexibility they tend to produce high variance which in turn results in producing different predictions at different criterias. So, inorder to reduce the variance of model, increased accuracy and efficacy the straightforward method is to use ensemble of multiple models which reduces variance and increases the accuracy of predictions.

The final model is obtained from the stacking ensemble of these models. Firstly the preprocessed input images are fed into the four models at resolutions(768 * 768) : EfficientNet-B7, EfficientNet-B6(Mingxing Tan and Quoc V. Le 1,2019),DenseNet201(Gao Huang,Zhuang Liu,Laurens,Kiian) with test-time augmentation (horizontal and vertical flip,rotate,zoom).The flowchart of the ensemble model is as shown in the Figure 7.

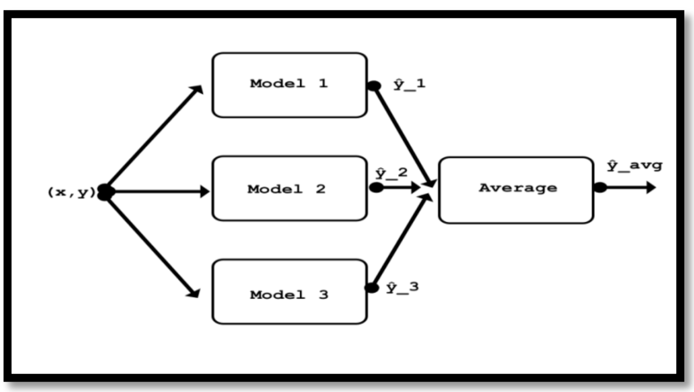


**Fig -6**: Working of ensembled model.

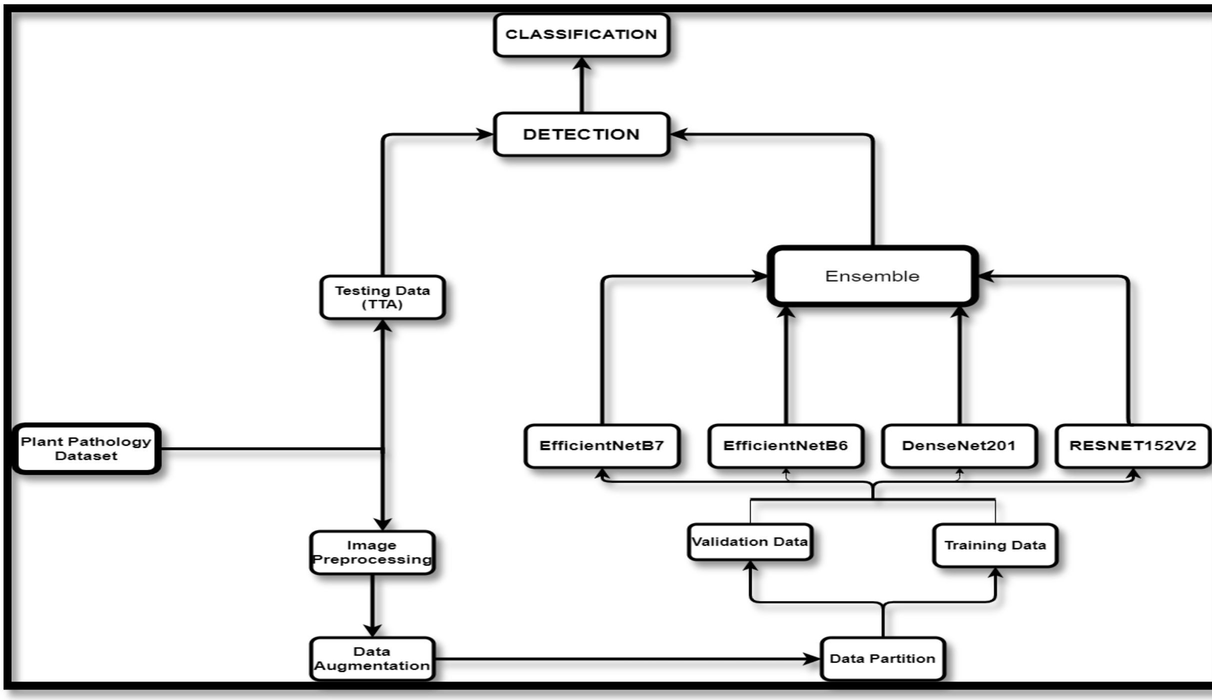


**Fig -7**: Flow chart of Ensembled Model to identify the type of Foliar Diseases.

## 4. TRAINING PROCESS:

The training of all four models is initialized with weights from Imagenet-pretrained. The model is trained for 40 epochs with preprocessed augmented training data and learning rate scheduler. The Learning rate scheduler of the model in shown in the Figure 8.

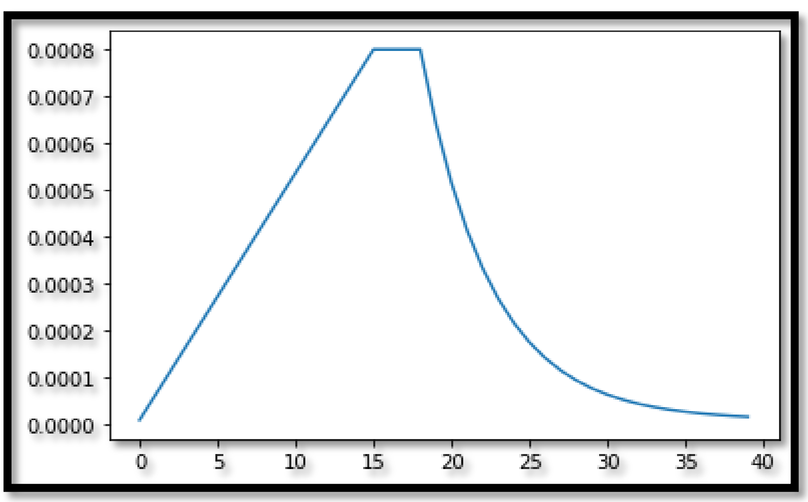


**Fig -8**: Learning Rate of the individual models.

## 5. SYSTEM CONFIGURATION:

The experiment was performed on a Kaggle Kernel with an Intel R Xeon(R) CPU E5-2650 v3 @ 2.30 GHz accelerated by TPU v3-8. The TPU v3-8 has 4 dual-core TPU chips with 128gb RAM. The models were implemented in Tensorflow Library.

**6. RESULTS:**

The results of experiment were provided in the following table. The testing of the model is done in two parts. Firstly, the local testing data and the testing data provided by the Kaggle. With the usage of ensembled model on local dataset better accuracy is achieved, hence it was used on Kaggle test dataset containing 1,821 testing images.

**Table -1**: Experimental results and metrics trailed, using **TTA**.

| Model | Accuracy |
|---|---|
| EfficientNet-B7 | 0.974 |
| EfficentNet-B6 | 0.965 |
| DenseNet201 | 0.969 |
| InceptionResNet15V2 | 0.975 |
| Stacked Ensemble | 0.981 |

**7. CONCLUSION:**

Prior detection and identification of diseases in trees helps to eradicate the misuse of chemical fertilizers and improved production. This paper proposes the usage of Deep Ensembled Neural Networks and automation of foliar diseases identification in Apple trees by single picture of the Apple tree leaves. The main advantage of Ensembled Neural Networks is its increased generalization and variance reduction. The proposed model is ensemble of 4 CNN architectures (EfficientNet-B7, EfficientNet-B6, DenseNet201, InceptionResNet15V2). The experimental results shows that the suggested method achieves higher accuracy rate of 98.1%.

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