Plant Pathology Disease Detection in Apple Leaves Using Deep Convolutional Neural Networks

Apple Leaves Disease Detection using EfficientNet and DenseNet

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Abstract— **Over the years, many events of plant diseases have inflected suffering on untold millions of people worldwide by causing an estimated annual yield loss of 14% globally. Plant pathology is the science of plant diseases that attempts to improve the chances for survival of plants under unfavorable environmental conditions and parasitic microorganisms that cause disease. Temperature, pH, humidity and moisture are environmental factors contributing to development of plant diseases. Misdiagnosis can lead to misuse of chemicals causing economic loss, environmental imbalance and pollution and emergence of resistant pathogen strains. Current disease diagnosis is time consuming, expensive and based on human scouting. Automatic disease segmentation and diagnosis from plant leaf images can be reasonably useful than the existing one. Automatic plant disease detection involves image acquisition, pre-processing and segmentation, followed by augmentation, feature extraction and classification using models. This project uses Deep Convolutional Neural Networks models namely EfficientNet and DenseNet to detect Apple plant diseases from images of apple plant leaves and accurately classify them into 4 classes. The categories include "healthy", "scab", "rust and "multiple diseases". In this project, the apple leaf disease dataset is improved using data augmentation and image annotation techniques, namely Canny Edge Detection, Blurring and Flipping. Based on augmented dataset, models using EfficientNetB7 and DenseNet are proposed providing accuracy of 99.8% and 99.75% respectively and overcoming known shortcomings of convolutional neural networks.**

Keywords— ***Machine Learning, Deep Convolutional Neural Networks, Data Augmentation, Canny Edge Detection, EfficientNet, DenseNet, Model Scaling, Feature Reuse.***

I. INTRODUCTION

Apples are grown all across the world and are one of the most efficiently and widely cultivated fruits contributing majorly to global yield. However, various diseases cause substantial loss to apple production. Therefore, accurate and timely detection of apple leaf diseases is crucial. In this paper, the dataset[19] is provided by Cornell Initiative for Digital Agriculture (CIDA) consisting of about 3600 training images categorised and classified into 4 classes, namely healthy, scab, rust and multiple diseases on the same leaf. While scab is a fungal plant disease characterised by crustaceous lesions on leaves and fruits, rust is another fungal ailment with tiny specks that range in many brown shades.

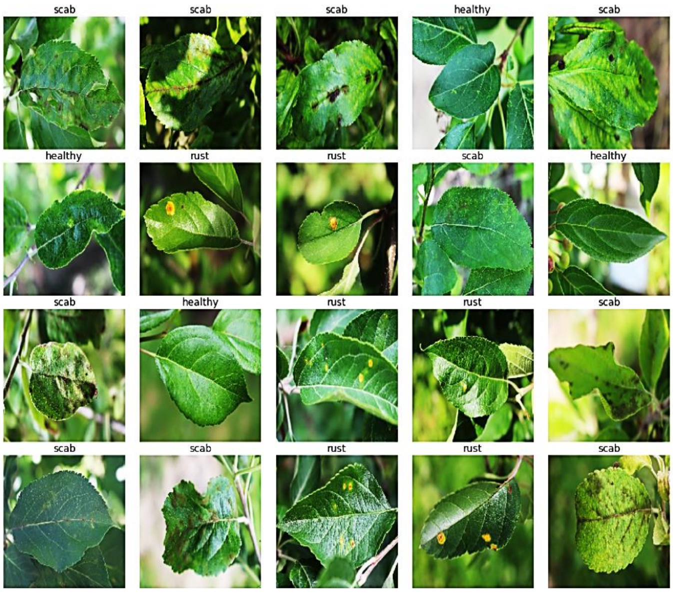


Fig.1 Images from training dataset with class label[19]

The conventional means involve human scouting – farmers and plant pathologists and use of pesticides for treatment thereafter. It is a challenging and time-consuming process, and most of the time leads to incorrect diagnosis with unbefitting application of the pesticides. Machine learning algorithms[10] have gained popularity in computer vision to improve the accuracy and rapidity of the automated plant pathology diagnosis outcomes. Machine Learning along with Computer Vision advances the computer capabilities for object detection, data sensing and understanding, classification and feature extraction. Computer Vision uses images and its pattern mappings for results while Machine Learning involves well-established approaches for predicting output namely[10], supervised, unsupervised and reinforcement learning, which include data acquisition, pre-processing, training the model and using either for predictions or classifications. The inputs are either a direct input of pixels or 3D points, or vectors representing features in terms of color and texture distributions, shape measures and/or edge measures.

The challenge to supervised learning is labelled training data requiring time and expertise and that to unsupervised learning is evolving patterns due to clustering. These approaches use

Support Vector Machines[12], K-Means Clustering[13], KNN, Naïve Bayes, Probabilistic Models and Neural Networks. These ML approaches heavily depend on data augmentation and pre-processing techniques for feature extraction[4]. However, because features selection is human based, these approaches still have quite low recognition rate and can ignore better features.

Over the last few years, Deep Learning, a special class of Machine Learning algorithms having multiple layers for transforming data, has been predominately used in agriculture. Convolutional Neural Networks is an unsupervised deep learning model with capability to extract features automatically from training dataset, thereby avoiding complex pre-processing and ensuring high recognition accuracy. CNN models require very few neurons but large data for their training. Data augmentation and determining the best structures of the network model are difficult tasks. A basic CNN model is a neural network using just convolution and pooling layer. Deep CNN[7] is neural network with a lot of layers, called multi-layer perceptron. DNN models surpass CNN in simplicity, time and accuracy, whereas CNN requires a deeper architecture yet doesn't perform as well. However, CNN provides improved visual connection in evaluation process by taking images as input.

In this paper, more accurate DNN models namely EfficientNet and DenseNet are deployed, which will overcome the drawbacks of popular pre-trained CNN models - excess pooling layers, more parameters, more computation time, loss of feature maps and pattern information. EfficientNet[6] reduces parameters and ensures accuracy through model scaling and DenseNet deploys feature reuse. The paper also evaluates the possible model of relatively new Capsule Networks[5] for classification using simple reduced capsules on images. The proposed CapsNET model enhances the learning capacity of the DL models for apple plants, with few layers from CNNs.

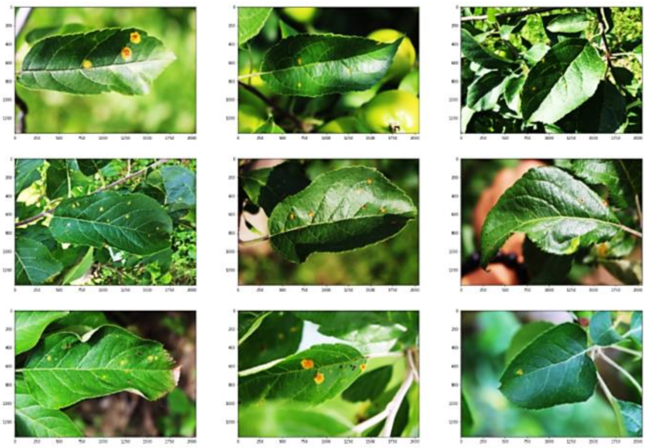


Fig.2 Plant leaves from Rust category[19]

The rest of the paper is organized as follows: In section II, we refer the previous works, present systems and their limitations. In section III, we briefly review the proposed system, novelty and its objectives. In section IV, we describe the evaluation methodology and experimental procedures used. In Section V, we present quantitative results and discuss our experiments. Finally, section VI concludes the paper.

II. PREVIOUS RELATED WORK AND PRESENT SYSTEMS

The conventional means of plant disease management implicate human scouting and mostly leads to incorrect diagnosis with excess use of the wrong pesticides causing great economic and environmental damage[2]. Lab setups are also required in this time consuming process. An automatic disease detection system using images of apple tree leaves can help in early detection and will help save the produce.

Traditional machine learning techniques like Support Vector Machines[12], Random Forests, K-Means Clustering[13] have gained traction and have shown considerable accuracy - SVM most commonly of all. In SVM model[4], enhanced hybrid method consisting of three pipeline procedures namely box filtering, Gaussian and Median filters is labored for image and spot enhancement, color differentiation, smoothing and noise removal. Each disease can have a different color, texture and scale, which is identified using SCP[4] and EM[4] algorithms highlighting the spots. SVM classifier then uses these extracted features.

In Grape disease detection[13], the two classes - Downy and Powdery Mildew demand color and texture features respectively. These features are segmented out using K-Means Clustering[13]. Texture features involve contrasts, uniformity, entropy, diagonal and difference variance. The nine colors and nine textures are then fed to Linear SVM for class classification.

In this model[12], only spot area is studied for color and texture using OTSU algorithm for lesion segmentation from a specific channel of L*a*b* color space. White pixels are compared with total pixels in the spot regions using Severity function and only the area of maximum disease, called Region of Interest, is trained on using Linear SVM.

However, these approaches are more suitable for uniform-background images and do not perform well with angle and shade on image factors, which reduces performance. They are heavily dependent on feature extraction through data preprocessing and augmentation techniques[12] to increase accuracy, reduce over-fitting and extract only the most important features.

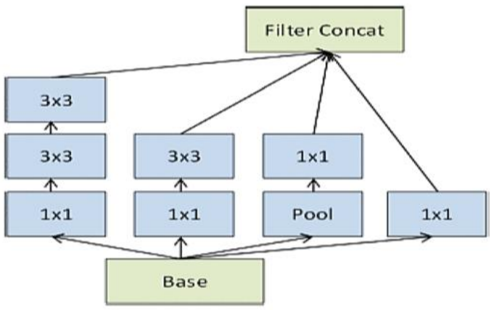


Fig.3 Inception Module in GoogLeNet

It is beneficial to use deep learning algorithms to avoid a tedious pre-processing task. CNN is the most popular model choice employed for classification of plant diseases. Improved CNN[2] involves SSD as object detector built on top of a hybrid model of VGG and GoogLeNet Inception models to extract and fuse disease spots. For Maize leaves[1], GoogLeNet and Cifar10 CNN improved models are used to classify nine types of disease classes by changing the parameter, modifying pooling combinations and adding ReLU functions. Over-fitting is prevented using rotation, mirroring, jittering, and conversion of all images to grayscale, followed by normalization for higher accuracy. Inception modules[1] with multiple parallel convolutional layers of varying sizes are deployed for feature capture, along with just three classifiers. However, only first classifier is trained thereby reducing the parameters. Cifar10 architecture adds a pooling layer and ReLU function between each pair of connected layers[1]. This addition has resulted in accuracy of 98.8%.

In [3], Multilayer Neural Network[3] involving AlexNet architecture is proposed where in each convolutional layer is followed by a ReLU function and pooling layer to enhance feature extraction and reduce the parameters. A flatten function is acting as hidden layer to convert images into a 1D array to ease out data handling. Feed forward network[11] deployed along with a hybrid meta-heuristic feature selection involving CNN with transfer learning and ANN with feature selection. Contrast enhancement is used to adjust pixel intensities and to capture maximum information, followed by normalization to speed up convergence during back propagation algorithm. Adam optimizer is used for optimization and cross entropy for loss estimation. ANN labored histogram equalization and adaptive grey wolf optimization for feature selection.

In [8], data augmentation was done followed by use of Channel-Spatial Attention (CSA) and Regional Proposal Network (RPN) to distinguish between effected and common regions. The accuracy is due to SoC and the Fast Translation algorithm[8]. The image is divided into pixels and based on colour information from the pixels, the quality of leaf life is identified and analysed. The processed data is matched with deep learning data sets to identify the type of disease and type of pesticide to be used. In "Mellowness Detection of Dragon Fruit Using Deep Learning Strategy"[9], Residual Network RESNET 152 was implemented to study all stages of fruit growth and separate ripe fruit from unripe and to set the right time for fruit. The training process is done with the images that are manually categorized as fruit with mellowness or ready for harvesting and not ready for harvesting, this was done with the help of experts.

GooLeNet[1] and AlexNet[11] architectures have less number of parameters and in order to increase accuracy, they are further improved by adding more pooling layers and/or an activation function between pairs of connected layers. This leads to loss of spatial distribution and rotational variance, which when not taken into consideration cause lower accuracy. Besides the strengths and limitations of the model choices, it can be inferred that similarity should be detected in images despite orientation and size variations of the disease spots and the algorithm should be computationally light to learn and run quickly. Classification will be more accurate if model works on segmented spots in the image as the region of interest, thereby necessitating the development of the proposed system.

III. PROPOSED SYSTEM

Popular CNN model architectures have more pooling layers appended to reduce parameters and increase accuracy. However, that leads to loss of features and spatial information. The novelty of this DNN system using EfficientNet and DenseNet attempts to overcome the shortcomings and consider rotational invariance and spatial information.

The proposed system will take into account RGB values of the images and individual channel distribution. After exploratory data analysis to draw insights, the system will augment the data using augmentation and annotation techniques[10] for better accuracy and less over-fitting, namely Canny Edge detection, Flipping, Rotations, Blurring and Brightness adjustment. EfficientNet-B7 and DenseNet – two DNN based ImageNet pre-trained models fit to this augmented dataset and their accuracy is evaluated over 40 epochs.

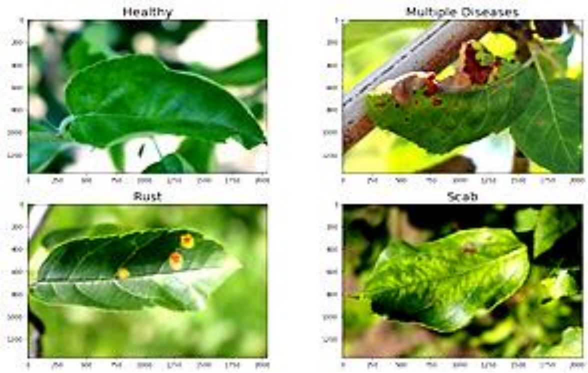


Fig.4 Plant leaf from each category[19]

EfficientNet[6] overcomes this drawback through compound scaling of layers (depth), channels (width) and resolution (image size) uniformly, thereby giving better computational performance even with a small dataset. When the image is larger, the network needs more layers to enlarge the reception field and more channels to capture better patterns in the larger image. EfficientNet-B7[6] is deployed as it uses the least number of parameters and gives the highest accuracy.

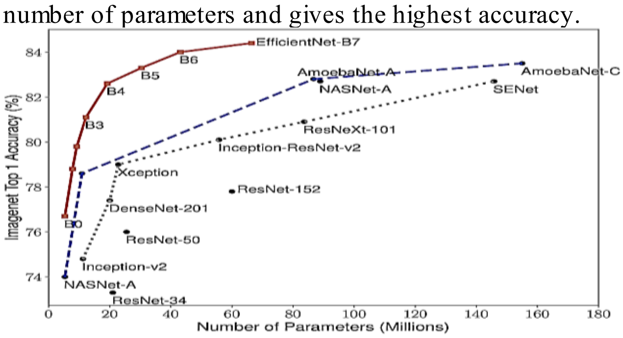


Fig.5 Comparison of EfficientNet's performance with other powerful transfer learning models [6]

As feature information passes through multiple layers namely pooling layer, besides loss, it can also "fade off" as it reaches the end of the network. To ensure maximum feature propagation, DenseNet[7] connects all layers for a collective knowledge transmission from all previous layers to the next. Concatenation and reuse of features allows a compact network with fewer number of channels and parameters.

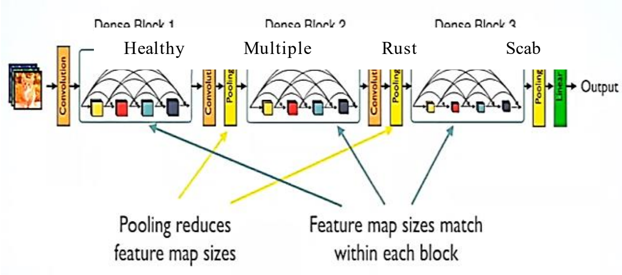


Fig.6 DenseNet

Another novel system Capsule network (CapsNET) is proposed to overcome these shortcomings by avoiding loss of information through exclusion of pooling layer. CapsNet thus transfers information through capsules[5] which are groups of neurons representing probability of a class by performing computations on input using encoders and condense the results into vectors. The decoders give the probability distribution into the different classes and reconstruct the image.

The following objectives are to be met through our proposed system.

i. To develop an automated classifier for identification of the given classes.[19]
ii. To accurately classify unlabeled testing dataset.[19]
iii. To identify leaves with multiple diseases.[18]
iv. To deal with rare classes and novel symptoms, if any.
v. To address factors like angle of image, shade on the leaf and age of the leaf.[1]
vi. To correctly segment spots[12] using Canny Edge Detection algorithm[10].

IV. METHODOLOGY

A. DATA ACQUISITION

The Apple leaves dataset[19] has about 3600 real life images of apple foliar diseases with variable angles, illumination and surfaces. The dataset as part of the Fine-Grained Visual Categorization (FGVC) workshop is financially supported by Cornell Initiative for Digital Agriculture (CIDA)[19] and is classified into training and test dataset, labelled and unlabeled respectively. The training data has about 3600 images classified as healthy, rust, scab and multiple on a single leaf. 516 images are labelled Healthy making up 28.3% of the total. Scab and Rust have 592 and 622 images respectively and there are 91 images labelled under Multiple, 5% of the total.

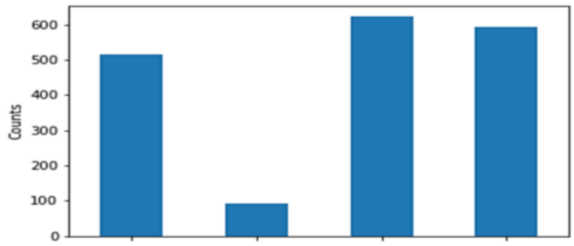


Fig.7 Number of images in each class[19]

B. DATA PREPOCESSING

Before training and fitting the model, all the unlabelled entries from the training set are removed. The incorrect labels are corrected. This pre-processed data is augmented using annotation and augmentation techniques and then split into training and validation dataset.

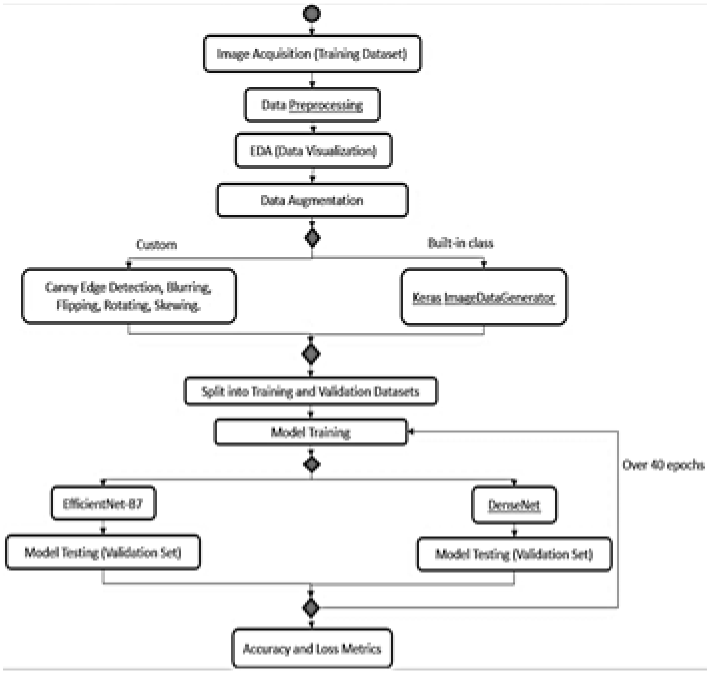


Fig.8 Activity Flow Diagram for Proposed System

C. EXPLORATORY DATA ANALYSIS

The RGB values of the images are analysed by computing the mean values of each channel in the entire training dataset and channel distribution is studied. The blue channel has the most uniform distribution but also shows variation across the images. The greener parts of the image have very low blue values and diseases regions have high blue values suggesting blue channel to be the key to detecting the disease in the unhealthy leaves.

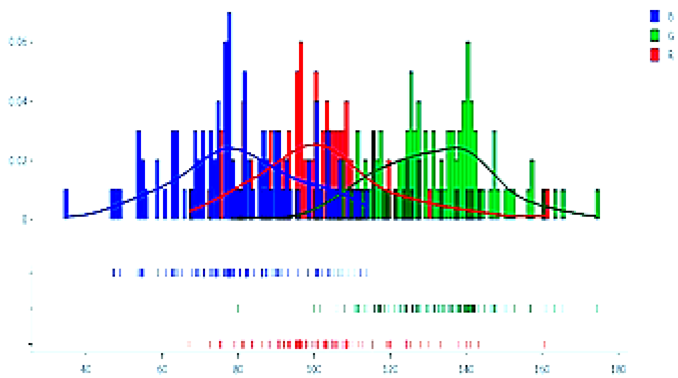


Fig.9 Channels distribution in the training images

Analysis of the number of images of apple plant leaves for different classes[19] reveals that 34.2% of total images in the training data have Rust, 32.5% have Scab, 28.3% are Healthy and just 5% in Multiple class.

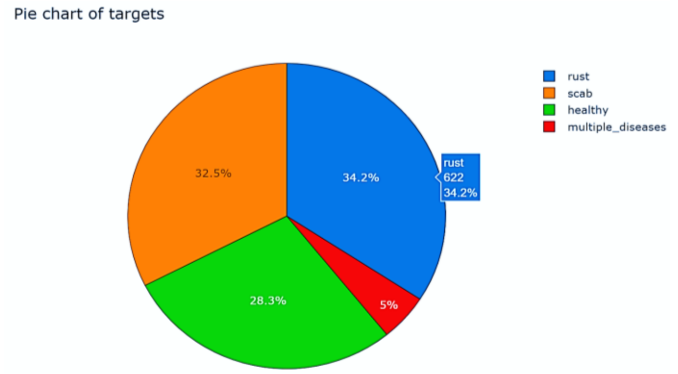


Fig.10 Number of images from different classes[19]

D. DATA AUGMENTATION

To avoid over-fitting of the model, data augmentation is done either through separate algorithms[10] or through Keras ImageDataGeneration Class[18] which will perform flip, rotation, brightness variation, blurring and skew operations at once on each image and will generate required number of augmented images for each original. These techniques generated an augmented dataset of about 10000 images.

The algorithms used are:

i. Canny Edge Detection algorithm to detect the edges of the disease spot using Gaussian filter. Sobel Kernel is used to find the angles using intensity gradient, perpendicular to the edge and thereafter detecting edges using threshold values.

ii. Flipping algorithm is applied on image channels involving index-switching. The row and column orders are inter changed in vertical and horizontal flipping respectively.

$$Image = A_{ijk} \tag{1}$$

$$Horizontal\ flip - A_{ijk} \rightarrow A_{i(n+1-j)k} \tag{2}$$

$$Vertical\ flip - A_{ijk} \rightarrow A_{(m+1-i)jk} \tag{3}$$

iii. Blurring involves slight noise inclusion using Gaussian distribution without making the spots completely invisible.

iv. Rotation and skewing by small angles is done either through custom functions or Keras ImageDataGenerator. ImageDataGenerator accepts input images batch and applies a series of arbitrary transformations to each image such as resizing, brightness adjustment, rotation, etc. However, it is not an additive operation, that is, after transformation on original images, returns only the newly transformed augmented data.

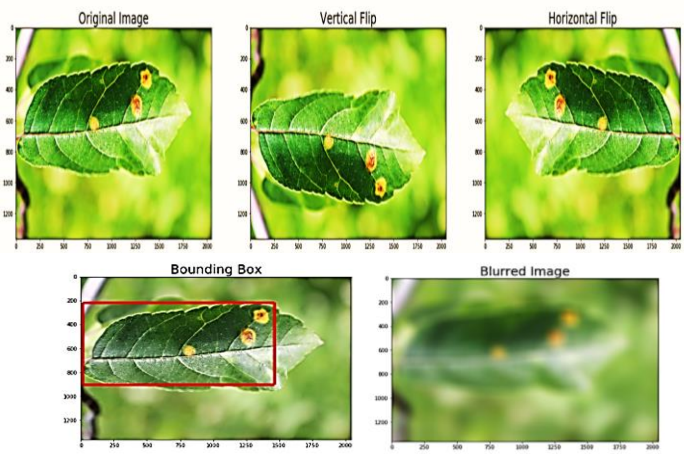


Fig.11 Data augmentation techniques output on a single image

E. MODEL BUILDING AND TRAINING

Common Layers of Architecture

Convolutional Layer algorithm[2] involves a 2D kernel moving along the length and depth of the image and calculating the dot product with a smaller sub matrix at every step, including a final double summation. This algorithm when performs on augmented data, provides higher accuracy.

$$Conv(f,h) = \sum_j \sum_k h_{jk} \cdot f_{(m-j)(n-k)} \tag{4}$$

Pooling Layer algorithm[2], similar to convolutional layer, instead of computing dot products of sub matrix and kernel, only computes the maximum value in a window and helps in dimension lessening of feature maps without a kernel.

$$MaxPool(f,h)mn = \max(m+j-1,\ n+k-1, \forall\, 1 \leq m \leq l, 1 \leq n \leq l) \tag{5}$$

Rectified Linear Unit is an activation function introducing non-linearity in the neural network and increasing capacity of the model. For a negative value of x, it returns 0 and x otherwise.

EfficientNet-B7 Model[6]

Common modelling practice is to increase depth or width of CNN arbitrarily or use large input images during training as well as testing. However, this often requires excess tuning and provides less efficiency. Arbitrary scaling helps initially but saturates quickly along with many parameters.

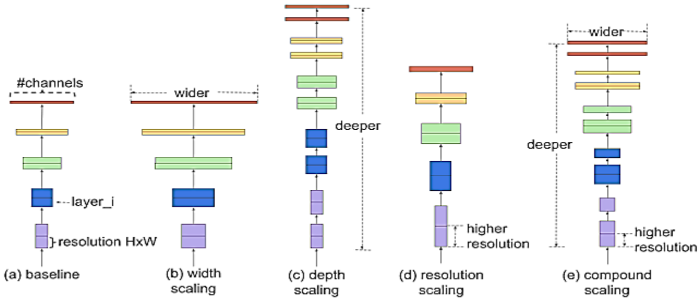


Fig.12 Compound Scaling in EfficientNet

EfficientNet[6] uniformly scales the depth, width and resolution, that is, number of layers, number of channels and image size respectively and gives better performance by keeping the architecture organized with less parameters. Scaling of each dimension is based on a fixed, computed set of scaling coefficients. Optimal set of coefficients for each dimension is computed by performing a grid search which will find the relation between different sizes of the network measurements under a fixed constraint, for instance 2x more FLOPS.

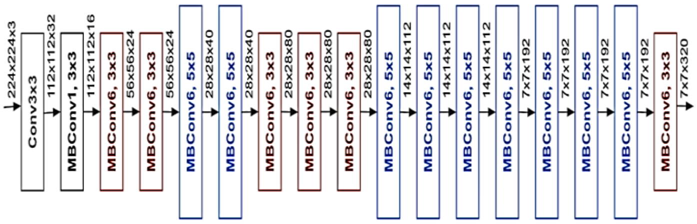


Fig.13 Basic EfficientNet Architecture[6]

The model architecture employs the Mobile Inverted Convolution (MBConv), also called Inverted Residual Block, that uses an inverted structure involving sum and product based operations, skipping connections in the narrow regions and squeezing the network to equal the initial number of channels. MBConv[6] follows narrow to wide to narrow architectural approach, an inverted form of the traditional Convolutional network – first widening with a 1x1 Convolution, followed by 3x3 Depth-wise Convolution which significantly reduces the parameters and then a 1x1 Convolution to reduce channel numbers. EfficientNet-B7 model performs model dimensions scaling with very high accuracy per parameter, reducing parameters and forming a more compact shallow architecture.

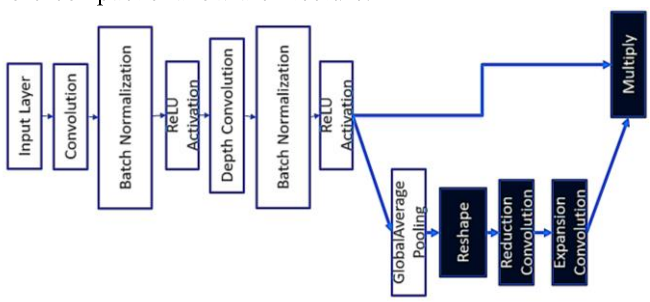


Fig.14 A block of layers in EfficientNet Architecture in the proposed system

DenseNet Model[7]

As information from the input passes through multiple layers, it may "wash off" by the time it reaches the end of the network. To overcome this and warrant maximum information propagation in the network, all the layers are directly connected to each other, all with same feature-map sizes. DenseNet employs features reuse and concatenation wherein each layer receives information and input from all preceding layers and transfers the combined knowledge through its feature map to all the subsequent layers. Therefore, while traditional CNNs have N number of connections for N layers – one between each pair, the proposed DenseNet has N (N+1) / 2 connections[7].

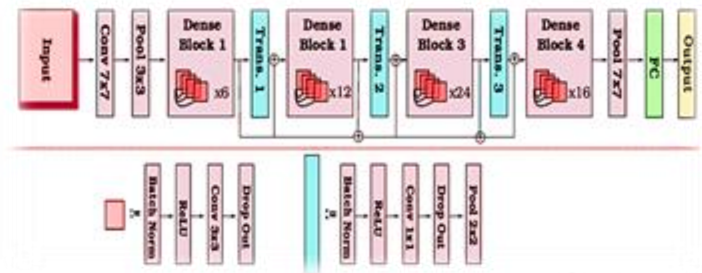


Fig.15 Basic DenseNet Architecture[7]

Each layer has access to gradients from the original input to loss functions at each preceding layer, facilitating a deeper network structure requiring fewer parameters as it avoids re-reading of feature maps. By using composite function[7] which consists of convolution, pooling, batch-normalization and activation layers, the output of previous layer is transformed as input to the next. These variable number of composite function layers are also called Filters and/or Transition Layers acting between pairs of DenseBlocks[7] (groups of layers dividing DenseNet) to reduce feature map sizes and augment number of channels. 1x1 and 3x3 Convolution layers along with Batch Normalization, Activation and Drop Out layers form a DenseBlock and receive transformed inputs from outer transition layers. The proposed system deploys DenseNet121 with 121 number of total layer and 7,041,604 total parameters including trainable and non-trainable parameters.

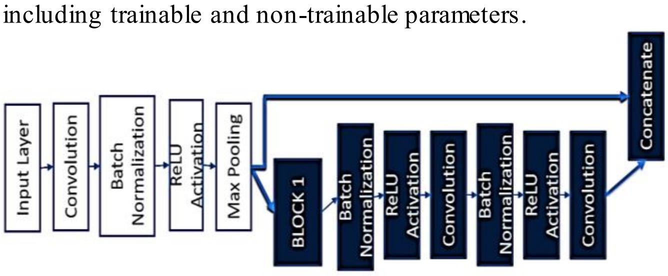


Fig.16 Outer Transition Layers and DenseBlock 1 with its internal layers, depicting concatenation operation with original input signal in proposed DenseNet system.

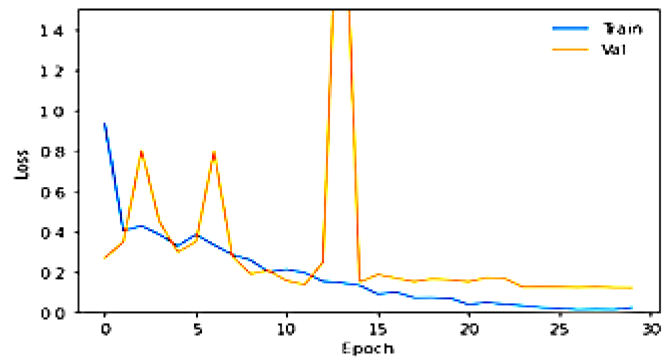
F. MODEL TESTING

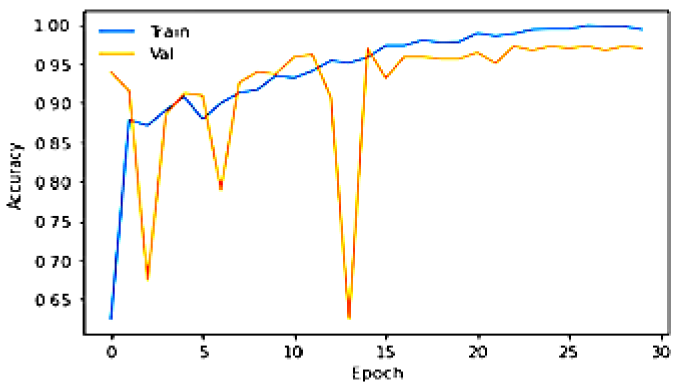
The EfficientNetB7 and DenseNet121 models are trained and have high accuracy with augmented training dataset. The same models are then fit to the validation and test datasets[19] for testing and improvements. The testing data[19] has about 1800 unlabelled images that are to be classified into the four classes.

Fig.17 Test dataset without labels, to be classified using models

V. EXPERIMENTAL RESULTS

DenseNet: The training metrics settle and resolve quite quickly after just 2 or 3 epochs whereas the validation metrics fluctuate and show greater volatility. They settle only after 13-14 epochs which is expected since validation data is new and unseen, thereby, making it difficult to make predictions on than the training data. The validation metrics vacillate in an inconsistent fashion until the 7th epoch and starts to generalize properly.





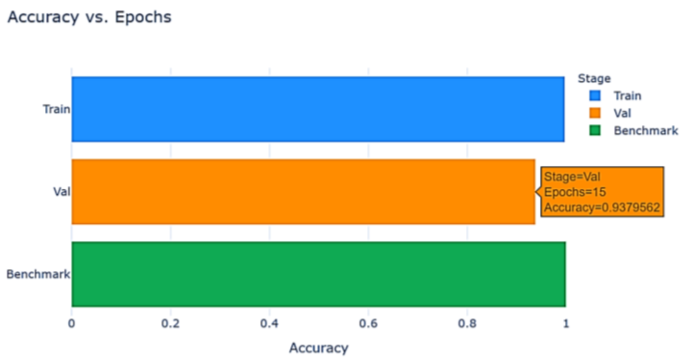


Fig.18 Loss and Accuracy after each Epoch in DenseNet Model

EfficientNet – B7: The losses fall and accuracies surge quite consistently. The training metrics settle down very fast right after 1 or 2 epochs whereas the validation metrics don't show high volatility and fluctuations as compared to DenseNet. Both the training and validation metrics steadily rise towards 1.

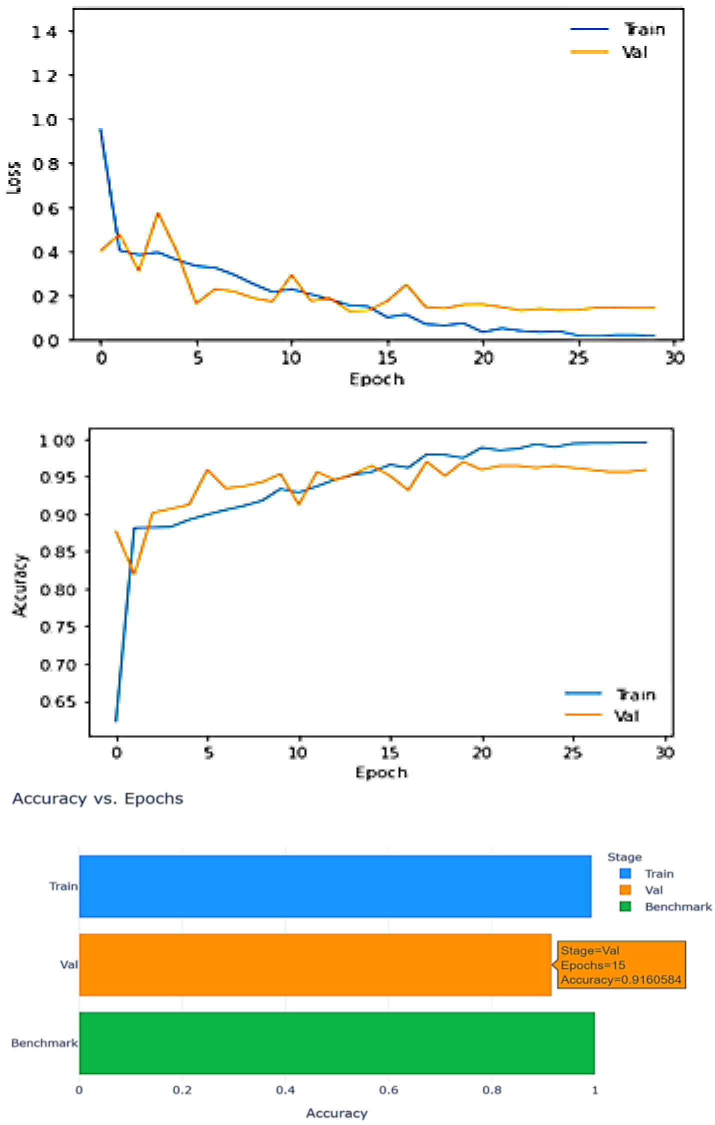


Fig.19 Loss and Accuracy after each Epoch in EfficientNet Model

At epoch 40, the EfficientNet-B7 model has shown a categorical accuracy of 0.9981 and loss of 0.0070. The validation loss is 0.1380. On the other hand, at epoch 40, DenseNet has shown a categorical accuracy of 0.9975.

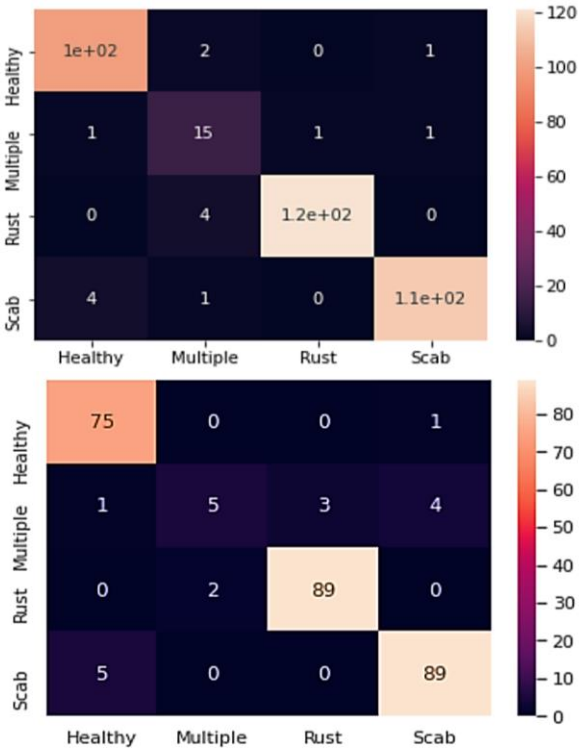


Fig.20 Confusion Matrix on validation dataset for accuracy and sensitivity of the proposed EfficientNet and DenseNet respectively.

The confusion matrix is providing a holistic view of the performance of the classification models and the errors made. The classifiers have performed decently for the validation dataset considering the relatively larger values of true positive and true negatives. It has concluded an accuracy of 0.94 for the proposed model.

VI. CONCLUSION

The need of the hour is to have an automated plant disease detection system using the infected leaf images. While traditional machine learning approaches are appeasing[10], they don't work well with non-uniform backgrounds and can't automatically extract features as accurately and need extensive pipeline of methods for data pre-processing before model training. Deep CNN models[7] have the capability to extract and fuse features without elaborate filtering techniques. However, for high accuracy, data augmentation is required to prevent over-fitting. Image annotation and augmentation methods[10] such as edge detection, flipping, convolution, blurring, etc can be used to build models with better training set. ImageDataGenerator Class provides a swift method to generate a newly augmented dataset many times the size of and from the original, post random transformations. While AlexNet[11], VGG, GooLeNet[1] and other popular CNN models also show high accuracy, they are very heavy models with high number of parameters and pooling layers, which in turn causes loss of spatial and rotational information. DNN models like EfficientNet[6] and DenseNet[7] are proposed and can be used to classify leaf diseases from leaf images even with small training data. Their ability of uniform model scaling[6] and feature reuse through concatenation[7] respectively delivers a reduction in number of parameters and an accuracy of 99.8% and 99.75% respectively over 40 epochs. Stacking, ensembling and strong validation techniques can lead to further more accurate and robust models.

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