Rubber Leaf Disease Detection using Deep Neural Network with Transfer Learning

03CS7914 Project (Phase II)

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Shanu Joy.

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Abstract

India is a heavily agrarian country where majority of the population depends on agriculture. The goal of agricultural research is to improve food quality and productivity at reduced expenditure, with increased profit. Plant diseases result in significant production and financial losses as well as a decline in the quantity and quality of agricultural goods. Plant disease identification is now receiving more attention in the surveillance of vast fields of crops. Switching from one disease control strategy to another presents significant challenges for farmers. The classic method used in practice for identifying and detecting plant diseases is the expert's unaided eye observation. In order to prevent and control plant diseases, accurate forecasting and warning are essential. The recent rapid advancement of deep learning has made major contributions to the growth, regulation, maintenance, and improvement of agricultural productivity. In this study, new images are created using a typical data augmentation technique. The pre-trained MobileNet V2 with Squeeze and Excitation (SE) block is then fused to create a new network known as the SE-MobileNet V2, which is utilised to identify the various plant disease kinds.

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Chapter 1

Introduction

Over 70% of rural homes in India depend on agriculture, which also contributes to the country's economy. Agriculture industry contributes to more than 17 percent of the total Gross Domestic Product (GDP)[1]. As a result, the detection and identification of plant or tree diseases are crucial in the Indian agricultural sector. Because the leaves are the most sensitive component of the plant, early indicators of diseases in plants can be noticed there. The fungi, viruses and bacteria are the main reasons behind these plant diseases. Farmers and plant pathologists are involved in conventional disease control methods where the process is time-consuming, difficult and frequently leads to inaccurate diagnoses and inappropriate pesticide application.

The development of automated models enabling, accurate and timely identification of the diseases of plant leaves has advanced with the introduction of computer vision (CV), machine learning (ML) and artificial intelligence (AI) technologies. In this research era, several deep learning architectures have been put out by different authors. Deep learning is a method that effectively trains a large quantity of data, automatically learns the features of the input and gives the output based on the decision rules.

This project mainly focuses on the detection and classification of diseases affected on rubber leaves. Rubber tree which is also known as Hevea brasiliensis (H. brasiliensis) is an essential commodity used in manufacturing over 50,000 products worldwide [10]. This tree is originated from the Amazon basin and started to be commercially established outside of South America in the 19th century. Nowadays, rubber trees are mainly grown in tropical regions such as Africa, Asia, and Latin America. Natural rubber (cis-1,4-polyisoprene) is a latex polymer with high flexibility, resilience, efficient heat dispersion and impact resistance. Natural rubber is used to produce many kinds of rubber products such as medical gloves and heavy-duty tires for aircraft and trucks. India was the world's sixth largest producer of natural rubber in 2020 and the fourth largest in south Asia. Like any other crops, rubber tree also suffers from several kinds of diseases attacking the three major cross sections which are leaf, stem and root areas. These plants suffers from several diseases in different stages of its growth in nursery, immature and mature plantations. Common diseases affected on rubber tree includes leaf diseases, stem and root diseases. Some of the leaf diseases are,

1. Leaf spot/bird's eye spot
   Numerous small circular spots scattered on the leaf surface

2. Colletotrichum Leaf Spot (CLS)
   Small brown spots surrounded by yellow region.
3. Powdery mildew
   Fungus appears as white dusty colonies on leaf surface
4. Tip blight
   Brown lesions on young leaves
5. Abnormal Leaf Fall(ALF)
   On leaves dull grey, circular spots scattered on leaf surface
6. Algal spot
   Small translucent spots usually on the upper leaf surface
7. Corynespora Leaf fall(CLF)
   Spots with railway track symptoms which infect young and old leaves

Each of these diseases affects rubber leaves at different times and seasons. These diseases results in problems such as,

1. Reduction in rubber plant productivity
2. Reduce latex yield
3. Declination in rubber plantation area

The two diseases that affect rubber leaf during the month of May - July are Traditional Colletotrichum and New Colletotrichum (Circular spot). This project focuses on the detection and classification of these two diseases and healthy rubber leaves. **Colletotrichum Leaf Disease (CLD)** is considered as one of the major causes of declining yields of rubber in Asia. The fungus C.gloeosporioides (Penzing and Sacc.) was identified as the causative agent of CLD in rubber leaves.

- Traditional Colletotrichum
  It mainly infects tender and immature leaves, as initially seen by many brown conical or elevated spots. As the disease progresses, the infected leaves become visibly wrinkled and twisted, eventually falling off the petiole[11].

Figure 1.1: Traditional Colletotrichum

- New Colletotrichum (Circular spot)
  Appears as concentric rings that occur generally along the leaf margins, and occasionally in the middle of the mature leaf. These big lesions may combine to form recognizable larger patches of varying sizes. The central portions of this spot is light brown and papery[11].

Figure 1.2: New Colletotrichum (Circular spot)

In this work, a deep learning model is utilized with transfer learning approach for recognizing these diseases. Transfer learning is a method by which a pre-trained convolutional neural network can be repurposed for a new problem. Thereby the training time of the model can be reduced when compared to the model developed from scratch and gives an enhanced performance to the proposed model. Traditional data augmentation techniques are used together with deep learning algorithms to improve the accuracy of classification. It includes operations like clockwise rotation, anticlockwise rotation, flipping horizontally and vertically and blurring to increase the dataset size to almost double the original dataset size.

1.1 Proposed Project

This work proposes a deep learning model with transfer learning and traditional data augmentation approach for recognizing diseases in rubber leaf images.

1.1.1 Problem Statement

Deep learning based model for the detection and classification of rubber leaf diseases.

1.1.2 Proposed Solution

Proposed solution is the automated detection of rubber leaf diseases with the help of a modified deep learning based model. Here a MobileNet V2 paired with Squeeze and Excitation block (SE) is selected and the pre-trained MobileNet V2 with SE block is fused to generate a new network, which is termed as the SE-MobileNet V2 that utilizes transfer learning for training the model and traditional data augmentation technique is used to synthesize new images.

Chapter 2

Report of Preparatory Work

Over the last few years, Computer Vision(CV) and deep learning have gained advancement in the development of models which can be used for the classification of leaves affected with different diseases.

2.1 Literature Survey Report

1. Krishnamoorthy N, Prasad LN, Kumar CP, Subedi B, Abraha HB, Sathishkumar VE.**Rice leaf diseases prediction using deep neural networks with transfer learning**[1]. Environmental Research. 2021 Jul 1;198:111275.

   In this study, a pre-trained InceptionResNetV2 deep convolutional neural network with a transfer learning strategy is employed to detect rice leaf illnesses. Leaf blast, bacterial blight, and brown spot are three of the most common diseases that damage rice plants. For this study, these three disease classes and a healthy class are taken into account. Every image pixel is rescaled during the pre-processing step. At the initial stage, all of the images were downsized to 224x224x3 pixels with values in the range of 0–1. The initial training image dataset is expanded using the image augmentation techniques like rotation, vertical and horizontal flipping of images, shearing, and random zooming. They used an ImageDataGenerator class provided by Keras to perform this task. For the feature extraction process, they used an InceptionResNetV2 model which was pre-trained via employing a transfer learning strategy. For categorizing the class labels of the rice leaf diseases, a new classifier was created utilizing a global average pooling, dropout (0.3), and four nodes with Softmax activation in the output layer. To make deep neural network training and validation easier, they employed the Keras 2.4.3 framework and the Tensorflow backend. The photos of rice leaves used in this experiment are taken from the Kaggle website. Leaf blast, brown spot, and bacterial blight are among the disease categories in this dataset, which also includes a healthy category. A total of 5200 images were produced. In each image, there is only one illness. For each class label, 1000 and 300 images are utilized in the training and test sets, respectively.

2. Picon A, Alvarez-Gila A, Seitz M, Ortiz-Barredo A, Echazarra J, Johannes A. **Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild** [2]. Computers and Electronics in Agriculture. 2019 Jun 1;161:280-90.

In this study, an adapted Deep Residual Neural Network for the detection of wheat leaf diseases is used. A three-stage learning procedure is used in this study's training workflow. In the first stage, they added photos of additional plant species classes to the Imagenet dataset, bringing the total number of classes to 1056. The model is then trained from scratch using a resnet50 architecture. The trained model is fine-tuned during the second stage. This fine-tuning is completed in the final training stage. During the training stage, the superpixel-based clustering algorithm preprocesses each image from the training dataset. As a result, each image is assigned a tile (or group of tiles in the case of superpixel-based segmentation), and each tile's label is determined from the manually segmented photos in the dataset. Random linear geometric distortions such as zoom, perspective, rotation, and displacement are applied to each rendered tile, and an artificial background is placed on a fraction of them to increase background diversity. The resulting image is utilized to train the convolutional neural network model, which is paired with the class memberships. The probabilistic estimates from the various tiles are combined in a final classifier that produces a final choice and associated confidence based on the average probability of the tiles. On wheat photos, this method is tested for Septoria (Septoria triciti), Tan Spot (Drechslera triciti-repentis), Rust (Puccinia striiformis and Puccinia re condita), and it was also put on a mobile smartphone app and validated in real field circumstances.

3. Singh UP, Chouhan SS, Jain S, Jain S. **Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease**[3]. IEEE Access. 2019 Mar 27;7:43721-9.

   In this study, they introduced a deep learning model called Multilayer Convolutional Neural Network (MCNN) for the categorization of mango leaves affected with the fungal disease called Anthracnose. The real-time Mango leaves dataset and the plantVillage dataset repository, which contains leaves from numerous plants, were used. This study used a total of 2200 images, of which 1070 were self-acquired images collected in real-time and the remaining 1130 were taken from the plantVillage dataset. These images were divided into four categories: diseased mango leave images, without disease images, diseased multiple plants leave images, and without diseased multiple plants leave images. All images are assigned to their relevant classes based on this category. 1760 images are used to train the CNN, with the remaining 440 images being used to test the model's performance. The images are initially preprocessed using histogram equalization, which balances the invariability of images acquired in real-world situations. The central square crop method is used to resize these images to a standard size image. After that, the proposed Multilayer Convolutional Neural Network-based ternary classification model is trained to recognize and classify mango leaves. Its major job is to determine whether the provided image is a mango leaf or not. The second task is to determine whether the mango leaf is not diseased (healthy), and the third task is to determine and classify whether the mango leaf is diseased or not. TensorFlow, an open-source software framework that uses the Python programming language, is used to implement the training and testing procedure.

4. Jiang P, Chen Y, Liu B, He D, Liang C. **Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks** [4]. IEEE Access 2019; 7:59069–59080.

In this study, the latest deep learning approach, which is based on an improved convolutional neural network is proposed to perform real-time detection of apple leaf diseases. The use of CNNs in a model proposed by this work provides a feasible real-time solution for early diagnosis and detection of apple leaf diseases automatically with high accuracy. This system helps to detect five types of apple leaf diseases, i.e., Alternaria leaf spot, Brown spot, Mosaic, Grey spot, and Rust, each having an effect on the qualitative and quantitative aspects of apple production. In this work, the CNN-based INAR-SSD model is trained using 75 percent of an apple leaf disease dataset (ALDD) consisting of 26,377 images of diseased apple leave, while, the remaining 25 percent is used for the testing purpose. Image annotation and data augmentation are the two steps that were employed on each image to increase the performance of the whole model. With this algorithm and knowledge that is provided by experts in the field of agriculture, the diseased areas of an image can be selected and labeled with the corresponding classes. All the disease images in the dataset have been annotated. Data augmentation operations include rotation transformations, horizontal and vertical flips, and intensity disturbance, which include disturbances of brightness, sharpness, and contrast. A Gaussian noise processing operation is also applied. This CNN-based model was implemented in the Caffe deep learning framework.

5. Srunitha K, Bharathi D. **Mango leaf unhealthy region detection and classification** [5]. InComputational Vision and Bio Inspired Computing 2018 (pp. 422-436). Springer, Cham.

This study provides a detection and classification implementation for mango leaf unhealthy regions. It identified areas that were susceptible to mango diseases such sooty mould, powdery mildew, and red rust. Multiclass SVM is employed in the proposed study for the classification and segmentation of illnesses using k-means. The suggested work is practical for all image sizes. Preprocessing is done before classification and segmentation. The pre-processing phase of an image includes of image acquisition, image enhancement, and segmentation, which segments the region of interest. Following segmentation, feature extraction and classification are carried out. Support vector machine (SVM) is utilised as a classifier, GLCM (grey level colour co-occurrence metrics) is used for feature extraction, and colour picture segmentation using k-means clustering is used for segmentation. It also used leaf vein segmentation technique that detects the vein pattern of the leaf.

6. Lu Y, Yi S, Zeng N, Liu Y, Zhang Y. **Identification of rice diseases using deep convolutional neural networks**[6]. Neurocomputing. 2017 Dec 6;267:378-384.

In this study, they presented a novel rice disease identification method based on deep convolutional neural networks. The rice leaves and stem images are pre-processed first, then the processed images are used to train CNNs. This CNN model improves the convergence speed while training the parameters in CNN, and obtains a higher recognition accuracy than the conventional model. The advantage of the proposed CNN is that here images are input directly into the model. First, sparse-auto encoding is used to learn the features from images. Second, they classified images from a reduced data set by applying convolution and pooling. The proposed CNN model applies the stochastic pooling method as it is simple enough to randomly select elements in a feature map according to their probability values, that is, the elements with large probability are easy to be chosen. Also, it strengthened the generalization ability of the CNN model. Third, the softmax regression learning algorithm is used to solve the multi-classification problem. Finally, they distinguished between 10 common different rice diseases. They created a Rice Diseases Images Database(RDID), which consists of a total of 500 rice disease images. Some images of rice diseases are captured from the Heilongjiang Academy of Land Reclamation Sciences, China. The 10 common rice diseases include rice blast(RB), rice false smut (RFS), rice brown spot (RBS), rice bakanae disease (RBD), rice sheath blight (RSHB), rice sheath rot (RSR), rice bacterial leaf blight (RBLB), rice bacterial sheath rot (RBSR), rice seeding blight (RSEB) and rice bacterial wilt (RBW).

2.2 System Study Report

Plant disease is a common threat to yield and quality of global production and bears responsibility for a significant portion of production cost. It is very difficult to monitor the plant diseases manually. Detecting disease on large number of plants is time consuming and not accurate. Consulting experts is of great cost. In such kind of conditions to improve the accuracy rate, image processing based plant disease detection methods may be used. In this era of research, a number of deep learning architectures have been proposed by various authors. Deep learning is an advancement of machine learning technique. Deep learning models accomplishes the task of developing automated models which empowers accurate and timely identification of plant leaf diseases.

Chapter 3

Project Design

Working of the proposed model is divided into 5 parts.

1. Dataset Collection
2. Image Pre-processing
3. Image Augmentation
4. Model Establishment
5. Plant Disease Detection and Classification

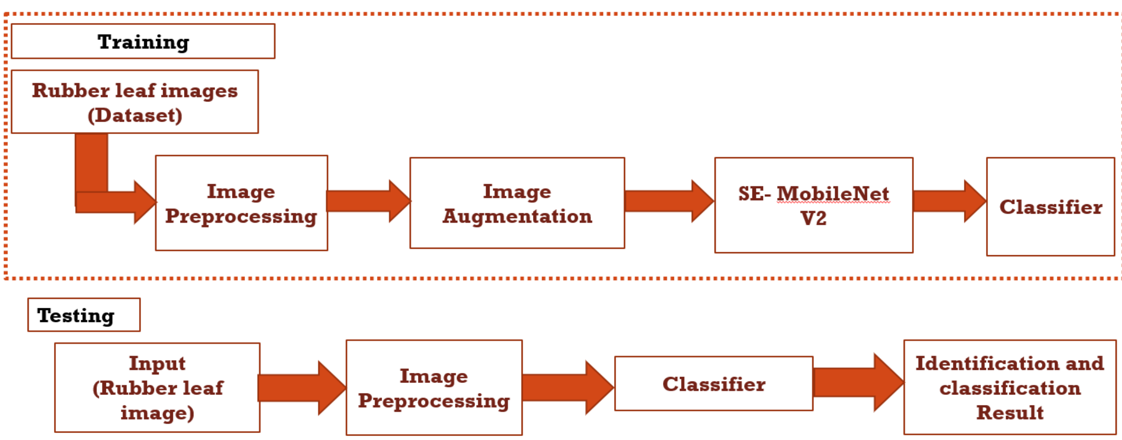

Figure 3.1: Block diagram of proposed model

3.1 Dataset

A self made rubber leaf dataset is generated for the implementation of model. This dataset contains a total of 474 rubber leaf images which includes Traditional Colletotrichum, New colletotrichum and healthy leaves. The rubber leaf images were collected from four rubber plantations using android phones (Realme x2, Oppo A31). For training purpose, this dataset is splitted as training set and validation set. 312 rubber leaf images collected from Rubber Research Institute of India (RRII) which includes 104 images of each class is used in the training dataset. Remaining 162 leaf images were captured from nearby rubber plantations (Malakkara, Kadammanitta and Chengannur). This 162 contains 54 images for each class. Of this 54, 44 is seperated for making validation dataset and 10 to make test set in each classes. Thus including all 3 classes, validation dataset contains 132 images and test dataset contains 30 images.

3.2 Image Pre-processing

This is a required task for preparing the raw input data and making it suitable for building and training deep learning model which also increases the accuracy and efficiency of a model. It helps to enhance the quality of data to promote the extraction of meaningful insights from the data.
Image clipping will be performed for images which are captured using mobile phone. It will perform cropping of the leaf image to get the interested image region.
Image Sharpening helps to emphasize details and enhance the edges of objects in an image. Sharpening filters makes transition between features more recognizable and obvious as compared to smooth and blurry pictures.
Unsharp filter, also called an unsharp mask filter, is used to sharpen an image contrary to what its name might imply. It is an extremely versatile tool that can improve the definition of fine detail and sharpen edges that are not clearly defined in the original image. The sharpening process works by first creating a slightly blurred version of the original image. Gaussian blur is used for blurring the image. By blurring, most of the high frequency components are suppressed, thereby generating unsharp image. Then subtract this unsharp image from the original image to generate a mask. As here using blurred or unsharp image to create a mask, this technique is called unsharp masking. Unsharp Mask m(x , y) can be represented as:

$$m(x, y) = f(x, y) - fb(x, y)$$

where, f(x,y) represents the original image and fb(x,y) represents blurred image. Then, this mask is added back to the original image resulting in enhanced high frequency components.

$$g(x, y) = f(x, y) + k \times m(x, y)$$

Here, k specifies weightage that is given to the mask being added. The above two equations can be combined into one as weighted average of original and blurred image.

$$\text{ie, } g(x, y) = (k + 1) \times f(x, y) - k \times fb(x, y)$$

3.3 Image Augmentation

Image augmentation is a technique of altering the existing data to create some more data for the model training process. It is the process of artificially expanding the available dataset for training deep learning model. Traditional image augmentation techniques are used. Applied operations are,

- Clockwise rotation

- Anticlockwise rotation
- Flipping horizontally and vertically
- Blurring

This is done to increase the dataset size to almost double the original dataset size. Thus new images are generated from available dataset. Image augmentation also helps to train the model with images having different orientations and shapes. Thus, trained model can predict class of an image even if it is not properly oriented.

3.4 Model Establishment

Here a MobileNet V2 paired with Squeeze and Excitation block (SE) is selected and the pre-trained MobileNet V2 with SE block is fused to generate a new network, which is termed as the SE-MobileNet V2 that utilizes transfer learning for training the model.

1. **MobileNet V2**

   Convolutional neural networks have become ubiquitous in computer vision ever since AlexNet popularized deep convolutional neural networks by winning the ImageNet Challenge: ILSVRC 2012. The general trend is to make deeper and more complicated networks in order to achieve higher accuracy . However, these advances which improves accuracy will not necessarily make networks more efficient with respect to size and speed. In many real world applications such as robotics, self-driving car and augmented reality, the recognition tasks need to be carried out in a timely fashion on a computationally limited platform. The problems with some of the existing architectures is that they may be very large in the order of 200-500 MB. So these are unsuitable for resource constrained devices due to their sheer size and resulting number of computations. So instead, MobileNet can be used. These networks are called "MobileNet" because it is a light weight deep neural networks best suited for image classification, mobile and embedded vision applications. There are other models as well but what makes MobileNet special is that it has very less computation power to run or apply transfer learning. Thus not only on mobile devices, it is also a perfect fit for computers without GPU or low computational efficiency with compromising significantly the accuracy of the results. It is also best suited for web browsers as web browsers have limitation over computation, graphic processing and storage. Some of the advantages are

   (a) Reduced network size - 17MB.
   (b) Reduced number of parameters
   (c) Small, low-latency convolutional neural network

   Thus MobileNet can be used either as a basic image classifier or as a feature extractor that is a part of large neural network. MobileNet differ from traditional CNN through the usage of depthwise seperable convolutions. Different versions of mobilenet are mobilenet V1, mobilenet V2, mobilenet V3. In MobileNetV2, there are two types of blocks. One is residual block with stride of 1. Another one is block with stride of 2 for downsizing. There are 3 layers for both

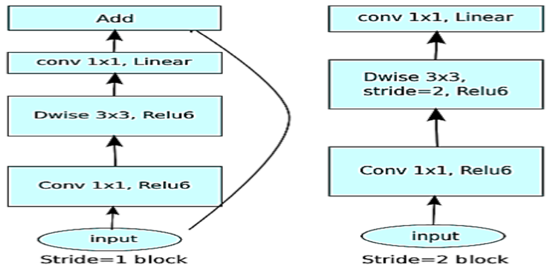

Figure 3.2: MobileNet V2 - blocks

types of blocks. This time, the first layer is 1×1 convolution with ReLU6. The second layer is the depthwise convolution. The third layer is another 1×1 convolution but without any non-linearity.

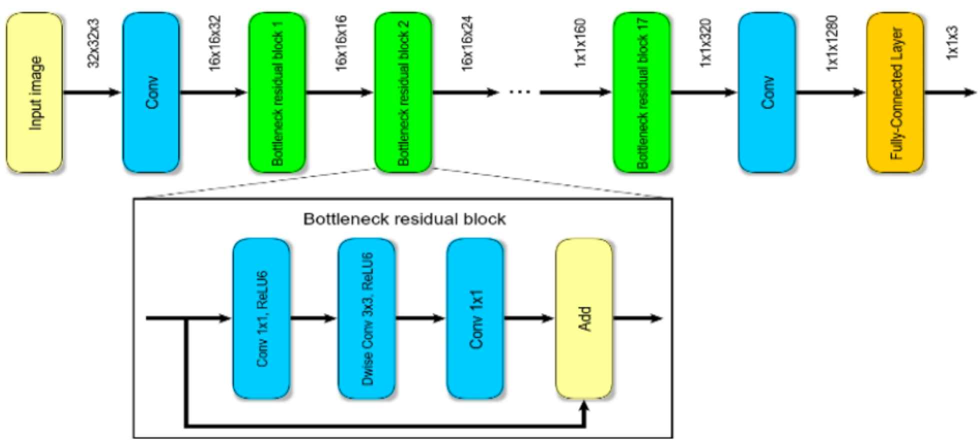

Figure 3.3: MobileNet V2

Input	Operator	t	c
$224^2 \times 3$	conv2d	-	32
$112^2 \times 32$	bottleneck	1	16
$112^2 \times 16$	bottleneck	6	24
$56^2 \times 24$	bottleneck	6	32
$28^2 \times 32$	bottleneck	6	64
$14^2 \times 64$	bottleneck	6	96
$14^2 \times 96$	bottleneck	6	160
$7^2 \times 160$	bottleneck	6	320
$7^2 \times 320$	conv2d 1x1	-	1280
$7^2 \times 1280$	avgpool 7x7	-	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k

Figure 3.4: MobileNet V2 - Architecture Summary

2. **Squeeze and Excitation (SE) network**

Convolution filters are responsible for constructing the feature map (channels), where each channels represents each particular feature, eg., edges, texture etc. These feature maps have different magnitudes of importance. A feature map containing edge information might be more important and crucial for learning than another feature map which is used for learning background texture transitions. CNN networks weights each of its channels equally when creating the output feature map. SE network changes this by adding a channel-wise attention mechanism that weights each channel adaptively. SE network was first introduced by Hu et al. [7] in 2017, and it won the ImageNet challenge competition with outstanding performance. The core component of the SE network is the SE block, which consist of three components:
Squeeze module
Excitation module
Scale module
The squeeze module is implemented using a global average pooling layer. Global Average Pool (GAP) operation reduces the whole feature map to singular value by taking the average of all pixels in that feature map. Excitation block assigns weights to each compressed channels using fully connected layers and sigmoid activation function. At first, module learns weights by using fully connected layer. Then by using ReLU (output the input directly if it is positive, otherwise zero) and sigmoid activation function (0,1), weights are normalized. Then by using scaling module, reweighting is assigned to the input feature map by performing scaling operation. If a channel is multiplied with value near to zero, it will reduces the pixel values of that feature map. If channel is multiplied with value near to one, not much change in

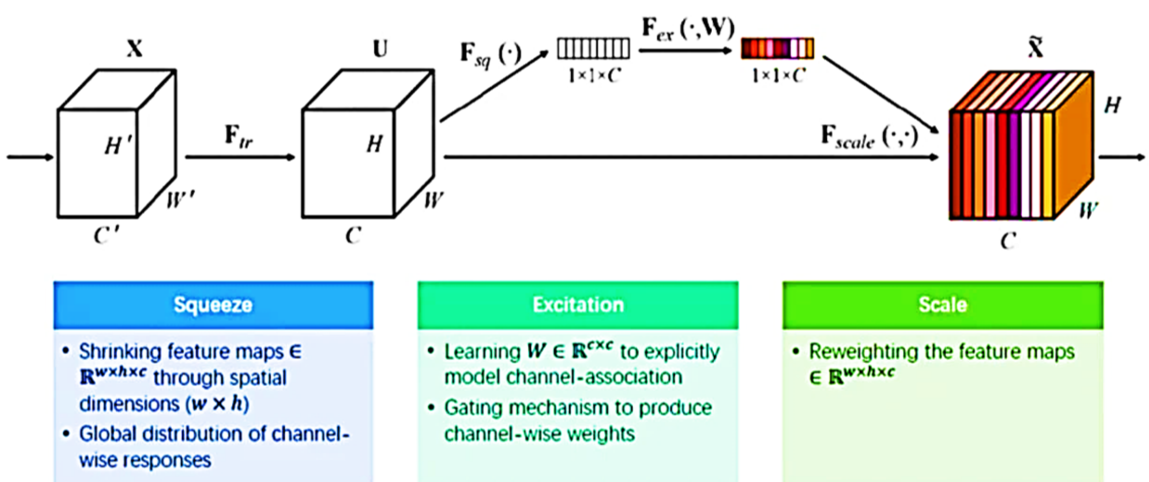

Figure 3.5: Squeeze and Excitation (SE) block

the pixel values. It reduces non-relevant channel information and the relevant channel are not much affected. Thus feature map only contain relevant information, which represents the representation power of entire network. This essential features are passed on to the classification part.

3. **SE-MobileNet V2**

   Existing MobileNet V2 is modified by pairing with SE block. Pre-trained MobileNet V2 with SE block is fused to generate a new network, which is termed the SE-MobileNet V2, which can be utilized to identify the plant disease types. This modification is done to enhance the capability of learning the tiny disease spot features for plant disease images. The SE block is fused in between the feature extraction and classification part.

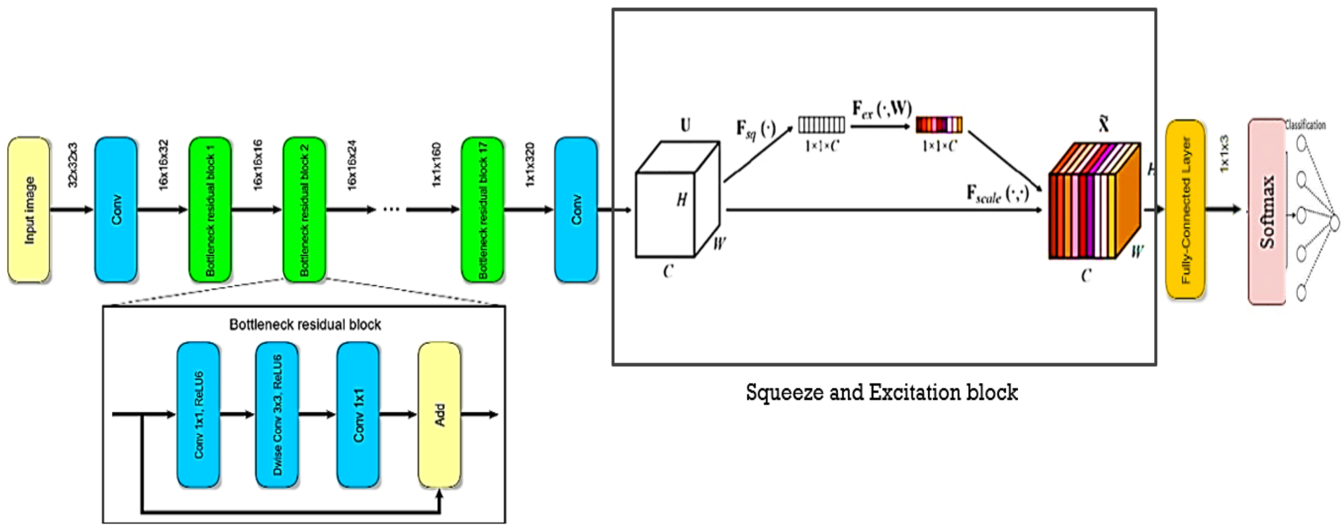

Figure 3.6: SE- MobileNet V2

3.5 Plant disease detection and classification

Augmented images will be given as input to SE-MobileNet V2. After performing feature extraction and channel attention mechanism, a classifier would be generated which can be used for the detection and classification of plant diseases.

This classifier is then used for performing testing of the model. For tesing, first input image will get pre-processed and then pre-processed image is passed on to the classifier. Classifier first detects whether it is healthy or diseased. If it is healthy, healthy class will get displayed. Otherwise classifier performs a classification to determine that particular image is belonging to which disease class and then displays that particular class.

3.6 Hardware & Software Requirements

Operating System	: 64-bit Operating System
Supporting software and libraries	: Python, Tensorflow, Keras
Processor	: Intel Core i5 7th Gen 2.50GHz
RAM	: 8GB
Graphics Card	: AMD RADEON Graphics card
Supporting Environment	: Google Colab

Chapter 4

Implementation

The proposed model is implemented in Tensorflow framework using Google Colab platform. Implementation stage consist of 3 steps, pre-processing using unsharp filter, augmentation and classification step. These operations are implemented in openCV framework. A self made dataset is used for training purpose.

4.1 Image Pre-processing using Unsharp filter

Before training, dataset is pre-processed using image sharpening technique. Unsharp filter is the sharpening filter used. First, a blurred image is generated from original image. For blurring, 7 x 7 gaussian kernel is used.

Figure 4.1: Input image

Figure 4.2: Blurred Image

This blurred image is called unsharp image. This is then subtracted from the original image to generate a mask. This mask is then added back to the original image to obtain sharpened image. This is represented using equation,
$g(x, y) = (k + 1) \times f(x, y) - k \times fb(x, y)$.
fb(x,y) is the blurred image. Value of k = 2.

Figure 4.3: Sharp Image

4.2 Image Augmentation

Pre-processed images are augmented using traditional augmentation techniques. Collected training images are 312 with 104 images in each classes. Augmentation is performed on this 104 image to make it 300 i.e., 196 images are augmented for each class. Thus total of 900 images are generated from 312 images to make training dataset. Collected images in validation dataset is 132 with 44 images in each class. This 132 images are augmented to 375 in order to generate 125 images for each classes.

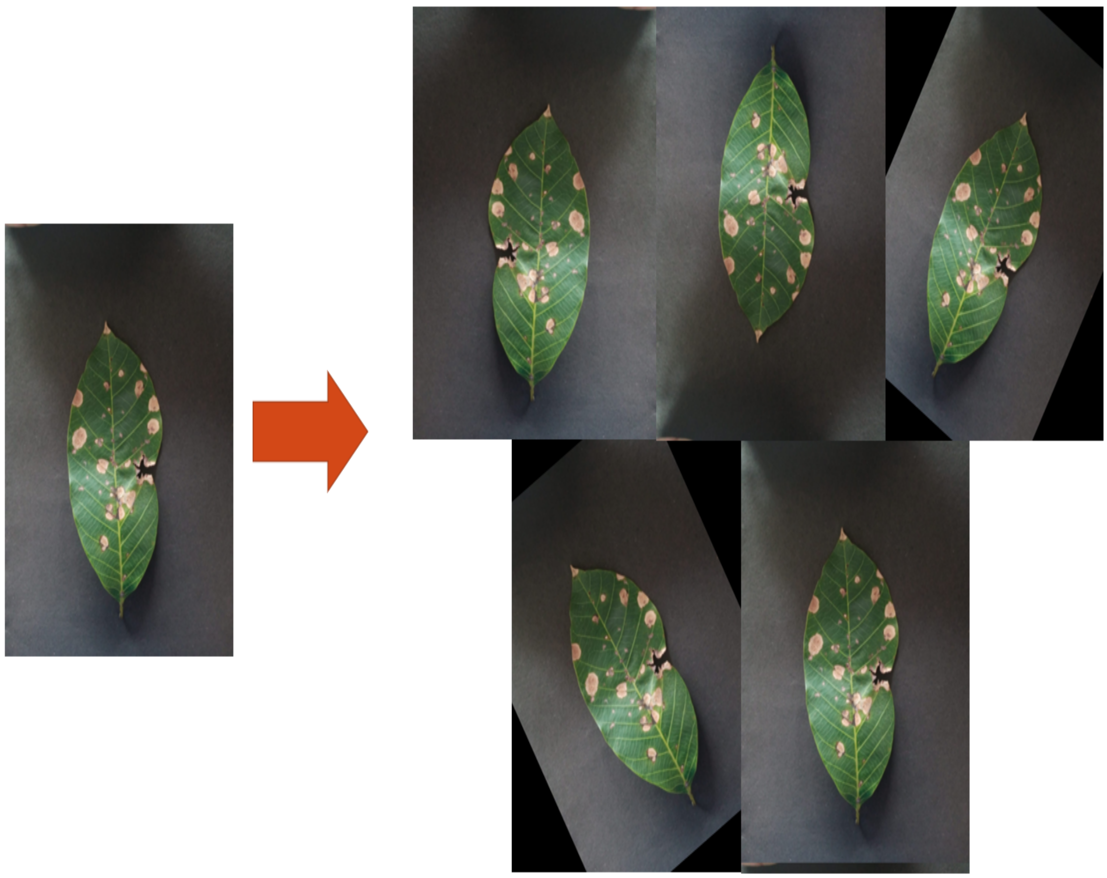

Figure 4.4: Augmentation performed on Circular spot leaf

4.3 Classification using SE-MobileNet V2

Training of SE-MobileNet V2 model is performed to generate a classifier. Input to SE-MobileNet V2 model is training and validation dataset. Model is trained with a training dataset having 900 images containing 300 images in each of the 3 classes with a batch size of 96 and image size of 224 x 224. In order to evaluate model performance, validation dataset is used which contains a total of 375 where 125 images belonging to each of the 3 classes. Adam optimizer is used for updating the learning rate of network. This network is trained in 100 epochs.

Chapter 5

Results & Conclusions

5.1 Performance Analysis of Model

Model is tested with a total of 30 images i.e, 10 images in each of the 3 classes. Performance accuracy of the model is calculated using confusion matrix. A confusion matrix visualizes and summarizes the performance of a classification algorithm. Various elements associated with confusion matrix are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). By using these parameters, precision, recall, f1-score and accuracy of the model is calculated.

```
Found 30 images belonging to 3 classes.
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:23
WARNING:tensorflow:5 out of the last 12 calls to <function Mode
Confusion Matrix
[[ 9  0  1]
 [ 2  8  0]
 [ 0  0 10]]
Classification Report
              precision    recall  f1-score   support

    Circular       0.82      0.90      0.86        10
     Healthy       1.00      0.80      0.89        10
 Traditional       0.91      1.00      0.95        10

    accuracy                           0.90        30
   macro avg       0.91      0.90      0.90        30
weighted avg       0.91      0.90      0.90        30
```

Figure 5.1: Performance analysis

Some of the results are shown below.

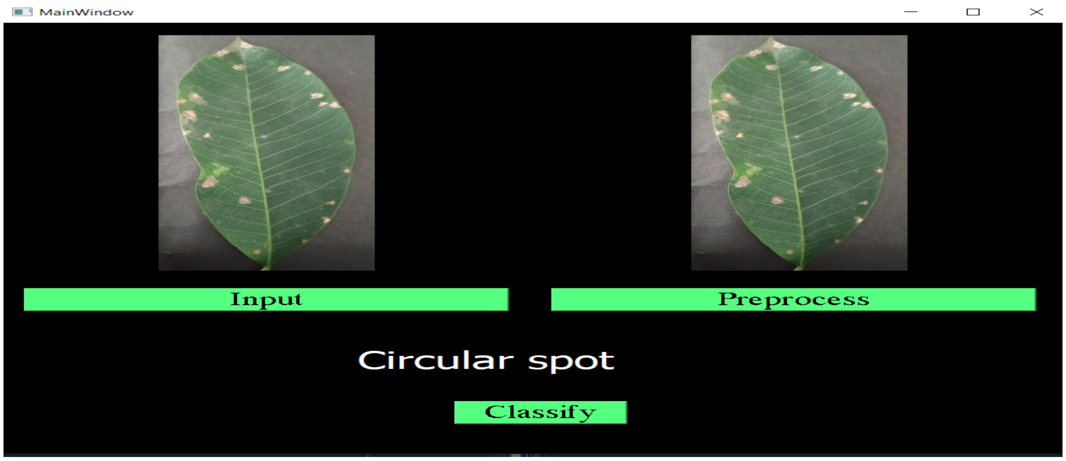

Figure 5.2: Test-1

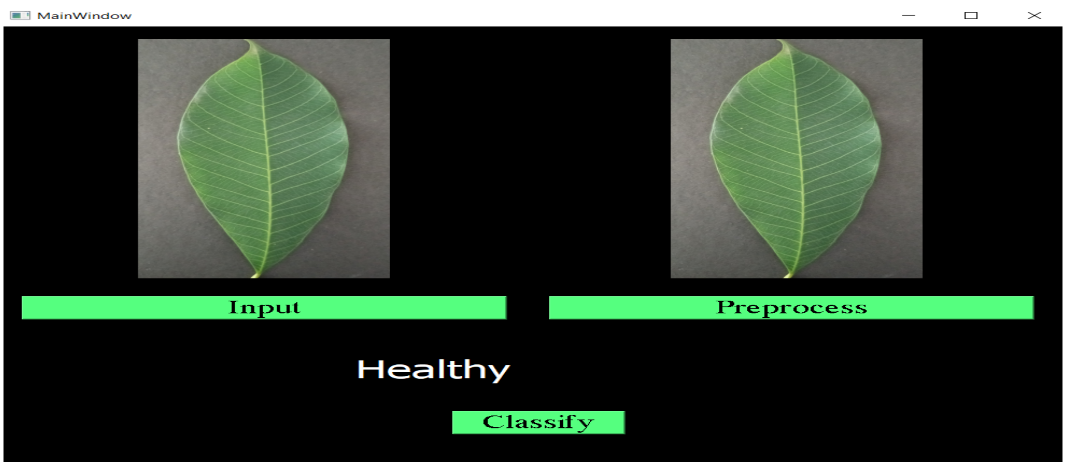

Figure 5.3: Test-2

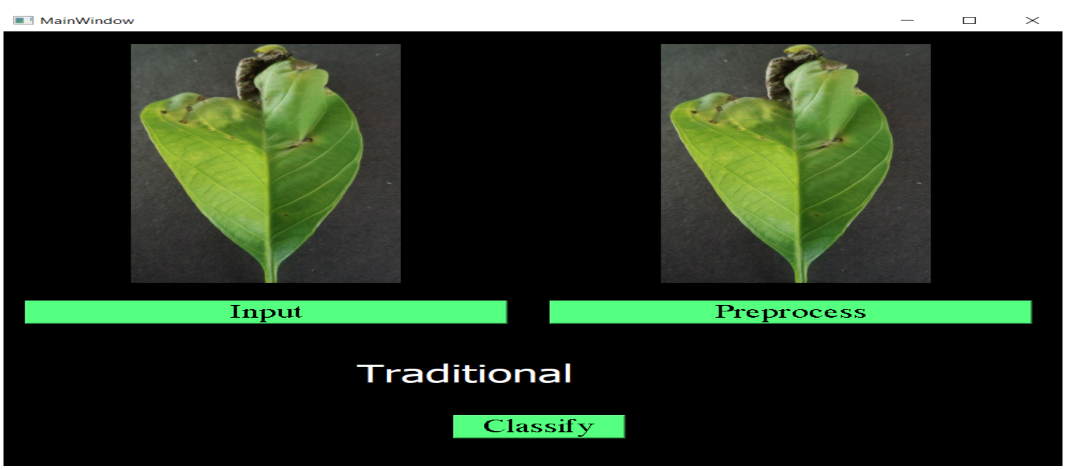

Figure 5.4: Test-3

5.2 Conclusion

A deep learning based model for the identification and classification of diseases affecting rubber leaves is being developed as part of this project. There are very few literary works based on diseases of the rubber leaves. This study aims to create a modified deep learning model with transfer learning and conventional data augmentation approach for identifying various diseases in rubber leaf images. A self-made dataset of rubber leaves was first gathered. Following that, the images underwent conventional augmentation and preprocessing. The pre-processing method used is called sharpening. Data augmentation techniques include blurring, flipping horizontally and vertically, rotating in a clockwise and anticlockwise direction, and rotating data. Classification is performed using a modified MobileNet V2 model, i.e., SE-MobileNet V2. By using SE-MobileNet V2 model, Traditional Colletotrichum, New Colletotrichum (Circular spot) and healthy rubber leaves were classified. This model achieved 90 % accuracy on test dataset.

5.3 Future Scope

This project is mainly focused on the detection and classification of rubber leaf diseases. In future, it can be modified by adding an extra CNN classifier which make it to work on other leaves datasets also. By adding extra CNN model, rubber leaves can be differentiated from other leaves. In future, this model can be improved for detecting stem diseases characteristics of rubber tree.

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