MINI-PROJECT

Assessment of state-of-the-art deep learning-based Cardamom Plant disease detection using U^2–net and EfficientNetV2

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Presentation Overview

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Problem Statement

- In India, there are 60.43% of the total land used in agriculture. The spread of various pests and disease still remains a challenge in quality farming.
- This has resulted in crop loss and economic loss which amounts to about 15-25% of food production in India.
- The approach of manual field crop disease detection has become ineffective due to time-consuming, labor-intensive and misleading factors which had direct impact towards the high error rate in disease classification.
- Therefore recognizing the plant diseases automatically in real-time using an alternative approach has become essential for farmers.

Abstract

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- Deep learning is chosen in various applications due to its profound discerning capability. In recent years, deep learning has extended its domain to plant pathology and has proven effective in different scenarios.
- This work focuses on two different plants, i.e., cardamom and grapes. Cardamom is a prominent spice, profoundly grown in evergreen forests of southern states such as Kerala, Karnataka, Tamil Nadu, and in certain northeastern states of India.
- Thus, the early detection of plant diseases in these plants can reduce the harvesting loss in dreadful cases. The work focuses on maladies of cardamom plants such as Colletotrichum Blight and Phyllosticta Leaf Spot and maladies of grape plants such as Black Rot, Esca, and Isariopsis Leaf Spot.
- The cardamom and grape dataset are fed into U2-Net for segmenting images and the obtained results are then compared with the classification outcomes such as Accuracy (%), F1-Score, Precision, recall of EfficientNetV2 with other state-of-art methods such as Convolutional Neural Network (CNN) and EfficientNet model.
- The proposed work with the state of art performance will aid in the faster detection of diseases found in these plants.

Base Paper Details

Base paper: Cardamom Plant Disease Detection Approach Using EfficientNetV2

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Base paper URL: https://ieeexplore.ieee.org/document/9663367

Introduction

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- Cardamom is widely used as a flavoring agent and is widely used in medicine, including allopathy and Ayurveda.
- The spread of various pests and disease continue to remain a significant challenge in the cardamom sector even after, rapid increase in modern technologies.
- Small cardamom is affected by a host of pathogenic bacteria, which seriously damages the crop and is often harmful and emerged frequently as a result of poor crop management.
- Agriculturists with less experience doing field study are often found to misjudge and use pesticides or insecticides indiscriminately during the screening process. This approach is often ambitious and ineffective.
- To address these challenges, image processing using an automatic plant leaf disease detection approach is essential.
- Real-time plant disease detection has some significant challenges, such as complex background and severity of the disease due to the images being captured in real-time scenarios from the farm field.
- Cardamom plant leaf images are captured in the farm field with complex backgrounds and the dataset is generated. The detection capability of the proposed approach is measured using the generated dataset.
- The grape plant leaf dataset was also used to assess the performance of the proposed approach.

Literature Survey

Title	Work	Methodology	Advantages	Limitation
Leaf image based cucumber disease recognition using sparse representation classification [2017]	Segmentation using K - means clustering, extracting feature from lesian information and classify using SR	K - means Clustering, spare representation (SR)	Classification in the SR space is able to effectively reduce the computation cost and improve the recognition accuracy.	Design of structured sparse model for large leaves image database.
Detection of plant leaf diseases using image segmentation and soft computing techniques [2017]	Extracting feature using color co-occurrence method, classification using MDC and SVM	Color co-occurrence method, MDC and SVM classifiers	Eliminates the needs for user input during segmentation, enhanced accuracy, friendly recovery measures.	Improvement in recognition rate is possible for the classification process

Literature Survey

Title	Work	Methodology	Advantages	Limitation
Enhanced visual attention-guided deep neural networks for image classification [2020]	Enhance the classification capability of the fully connected layers in a CNN by Huber loss function.	CNN, Huber loss function	Improvement in classification performance with negligible extra overhead	It doesn't enhance CNN's of different purpose such as Image Regression
Deep orange: Mask R-CNN based orange detection and segmentation [2019]	Deep Orange is a segmentation framework that augments Mask R-CNN by including HSV image	Mask R-CNN, Deep orange	Reduce false positive rate, improve mask segmentation performance.	Reducible color channels i.e., subset of RGB and HSV

Literature Survey

Title	Work	Methodology	Advantages	Limitation
A deep learning approach combining instance and semantic segmentation to identify diseases and pests of coffee leaves from in-field images [2021]	Semantic segmentation by U-Net and PSP-Net. Instance segmentation by Mask R-CNN. Classification by Res-Net.	Mask R-CNN, U-Net, PSP Net, Res- Net	Implement the entire framework in an embedded mobile platform	The lack of capacity to classify areas where two or more lesions overlap

Literature Survey

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Title	Work	Methodology	Advantages	Limitation
A deep learning approach for RGB image-based powdery mildew disease detection on strawberry leaves[2021]	Modifying the architectures of four CNNs and developing SqueezeNet-MOD1 and SqueezeNet-MOD2	AlexNet, SqueezeNet, GoogLeNet, ResNet-50, SqueezeNet and SqueezeNet modifications	The CNN approaches performed significantly better than the non-DL approaches.	The transferability to field conditions, challenges related to irregular lighting conditions, leaf orientation, and overlapping of leaves.
A comparative study of fine-tuning deep learning models for plant disease identification[2019]	Fine-tuning and evaluation of state-of-the-art deep convolutional neural network for image based plant disease classification	VGG net model, ResNet, Inception V4, DenseNet, Fine-tuning the models (Transfer Learning), Batch Normalization	Coherent increment in accuracy with rising number of epochs, with no manifestations of performance deterioration and overfitting.	Research needs to be done to improve on the computational time.

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Title	Work	Methodology	Advantages	Limitation
Research on deep learning in apple leaf disease recognition [2020]	Based on Densenet-121 deep convolution network, three methods were proposed to identify apple leaf disease	DenseNet, Cross entropy loss function, Focal loss function, Regression for classification.	The methods achieve better recognition results on the unbalanced data set, compared with the traditional single-label multi classification.	Limited to single plant disease identification.
Disease and pest infection detection in coconut tree through deep learning techniques[2021]	Image Segmentation, custom CNN, fine tuning pre-trained CNN.	K-means clustering segmentation, Keras pre-trained CNN models, Custom 2D CNN.	Improve the accuracy with limited dataset	Detect the severity level of the infections. Segmentation using deep learning.

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Title	Work	Methodology	Advantages	Limitation
Deep learning for classification and severity estimation of coffee leaf biotic stress[2020]	A multi-task system based on CNN. Use data augmentation techniques to make the system more robust and accurate.	Standard augmentation, Mixup. Several CNN architectures	Makes learning substantially faster since only a single model needs to be trained.	It is related to the low representativity of the dataset that covers only the main biotic stresses that affect coffee trees

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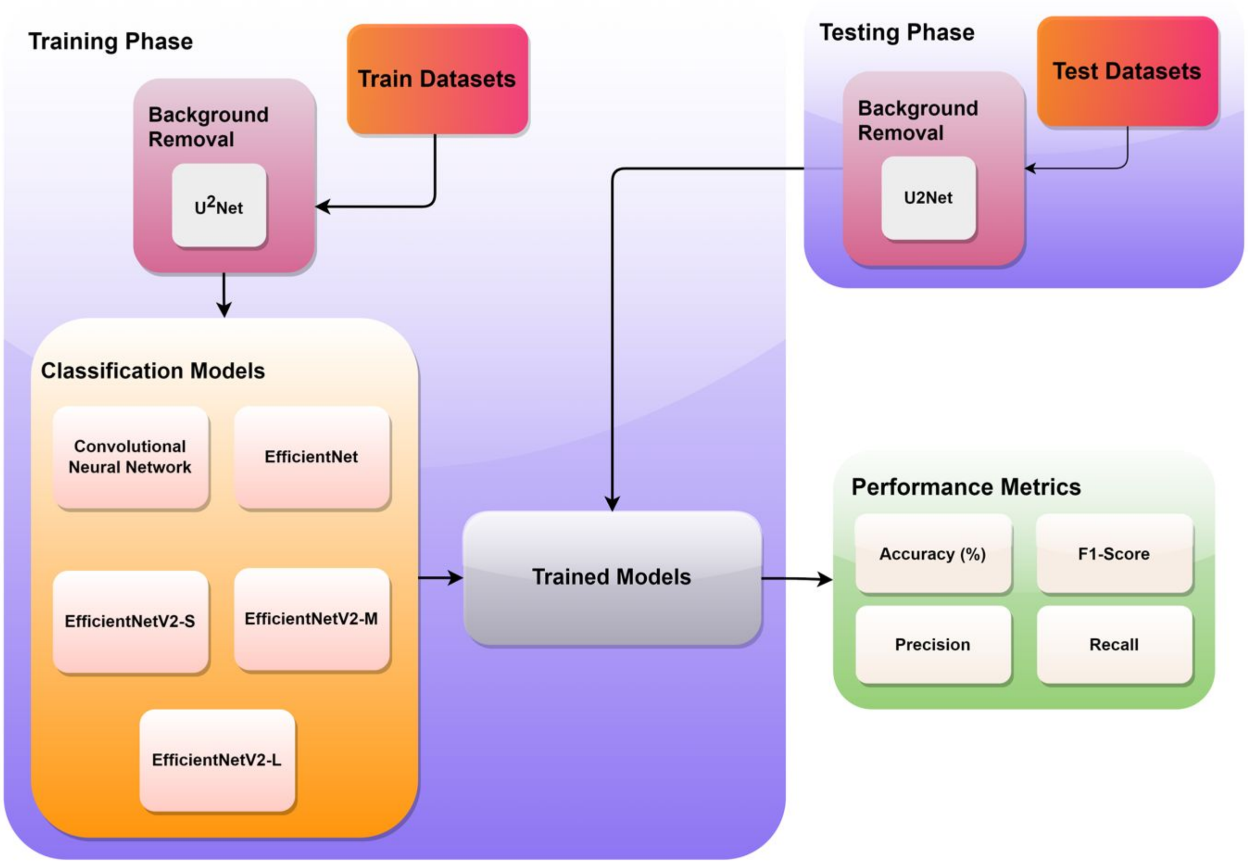
Project Workflow



Methodology

- **OVERVIEW:-**
  - a. There are 2 phase that is followed in this approach , the training and testing phase.
  - b. To reduce the background complexity, the datasets in two phases are passed to U^2-Net.
  - c. The classification models trained and used for finding performance metrics.

- First, in training phase the complex background of the images removed by extracting the multiscale features with U^2-Net.
- Second, the segmented images are then passed to various Deep-learning models such as Convolutional Neural Network, EfficientNet, EfficientNetV2-S, EfficientNetV2-M, EfficientNetV2-L and the resultant trained models are obtained.
- Then the testing images are again given to U^2-Net for background removal and is used to compute various performance metrics such as Accuracy, F1-Score, Precision and Recall.

Methodology

- **Background Removal**

  The background removal approach used in this study was U²-Net.

  It Consists of 3 Stages:-

  Stage 1:- ReSidual U-Block(RSU)

  a. Esticate Local Features

  b. Input Convolution Layer - Generation activation map

  c. Encoder-Decoder :- like that present in the U-Net

  Stage 2 :- Five Stage Decoder using dilated version of RSU.

  Stage 3 :- Saliency probability maps generation (attaching decoder with encoder stage)

  Employing Deep supersvison using the given loss function for reducing loss and manifest robust regularization

$$\text{Loss} = \sum_{n=1}^{N} w_{side}^{n} l_{side}^{n} + w_{fusion} l_{fusion}$$

Methodology

- **Classification Models**

Convolutional Neural Network :- It consists of feature map function, Relu activation, pooling layer ,fully connected layer and softmax loss

Hyperparameters:-

a. Hyperparameters that deal with Network Structure eg Kernel Size

b. Hyperparameters that deal with Training eg batch size, learning rate and dropout

Loss Function:-

$$\mathrm{L(M)} = -\frac{1}{n}\sum_{Y_i=1}^{n}\sum_{c=1}^{C}[\mathrm{Y}_{ic} log P(x_i = c) + (1 - \mathrm{Y}_{ic}) log(1 - P(\mathrm{Y}_i = c))]$$

EfficientNet :- It consist of CNN , Mobile inverted Bottleneck Convolution (MB-Conv)

EfficientNetV2 :- It consists of CNN, Fused MB-Conv(first 3 stages), MB-Conv(Subsequent stages)

The three different versions of EfficientNetV2 used in this work are **EfficientNetV2-S, EfficientNetV2-M and EfficientNetV2-L.**

Team members responsibility

Gokul R	Vishnu Nandakumar	Gowtam Rao G S
CNN Classifier	U^2-Net Segmentation	EfficientNet Classifier
EfficientNetV2 - L Classifier	EfficientNetV2 - M Classifier	EfficientNetV2 - S Classifier
Performance analysis and Report.		

Timeline Chart

- Work done for first review

  → Segmentation of images in the dataset using U^2-Net

  → Implementation of CNN and EfficientNetV2 - S classifier.

- Work done for second review

  → Implementation of EfficientNetV2 - M, EfficientNetV2 - L and EfficientNet classifiers.

DataSet

- **Cardamom Plant Dataset**

  Data Set URL: https://github.com/sunilchinnahalli/Cardamom-Dataset-2021

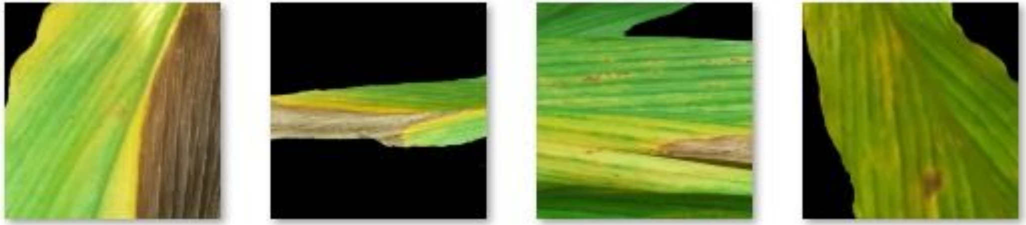
  The dataset contains 1744 images of Healthy Cardamom leaves along with two maladies of cardamom plants such as Colletotrichum Blight and Phyllosticta Leaf Spot of Cardamom

- **Grape Plant Dataset**

  Data Set URL: https://github.com/spMohanty/PlantVillageDataset

  The dataset contains 4062 images Healthy Grape leaves along with three maladies of grape plants such as Black Rot, Esca and Leaf Spot.

Cardamom DataSet

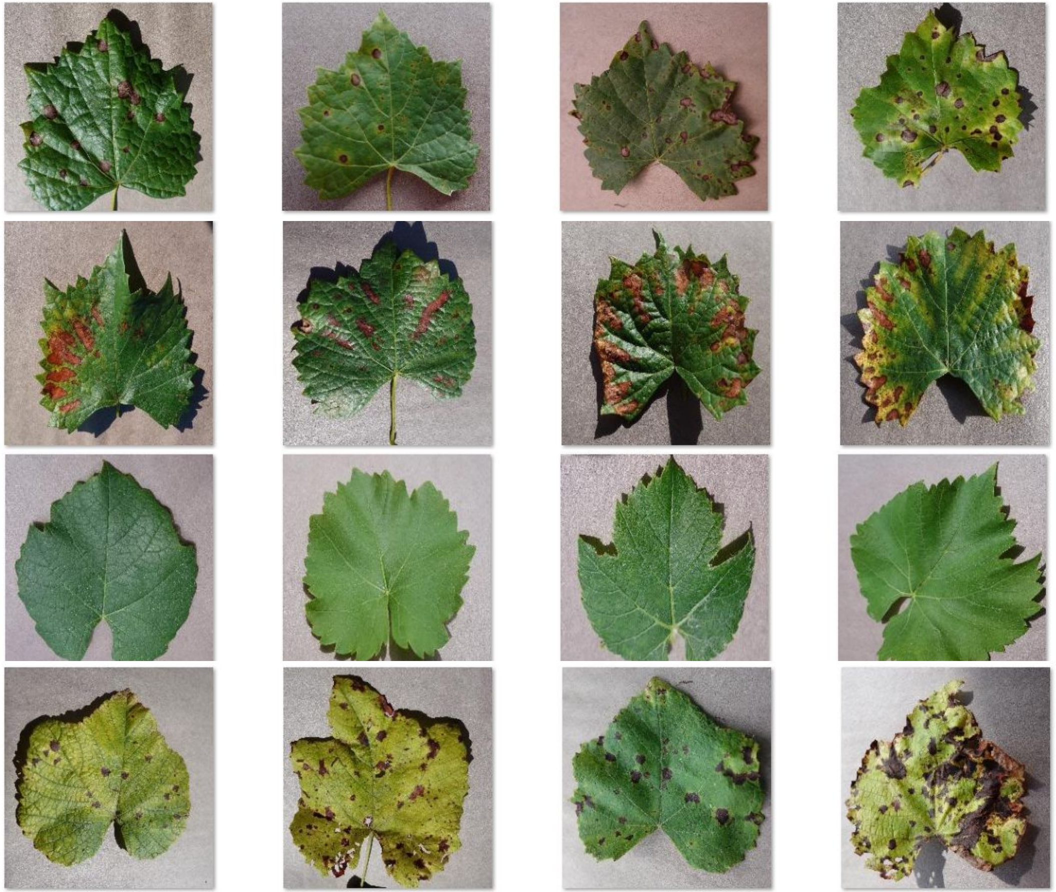


Colletotrichum Blight

Healthy cardamom leaves

Phyllosticta Leaf Spot

Grapes DataSet



BlackRot

Esca

Healthy

Leaf Blight

(Isariopsis_Leaf_Spot)

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Expected Outcome

Category	Performance Metrics	CNN	EfficientNet	EfficientNetV2-S	EfficientNetV2-M	EfficientNetV2-L
Cardamom plant dataset						
Colletotrichum Blight	Accuracy (%)	96.48	100	100	92.85	100
	F1-Score	0.98	0.98	1.00	0.95	0.98
	Precision	1.00	0.97	1.00	0.96	0.97
	Recall	0.96	1.00	1.00	0.93	1.00
Healthy	Accuracy (%)	98.76	98.76	98.76	97.53	98.76
	F1-Score	0.98	0.98	0.98	0.96	0.98
	Precision	0.98	.0.98	0.98	0.95	0.98
	Recall	0.98	0.99	0.99	0.98	0.99
Phyllosticta Leaf Spot	Accuracy (%)	98.48	96.96	96.96	96.96	96.96
	F1-Score	0.98	0.98	0.98	0.98	0.98
	Precision	0.98	1	0.98	0.98	1.00
	Recall	0.99	0.97	0.97	0.97	0.97
Grape plant dataset						
Black rot	Accuracy (%)	100	97.45	97.45	97.45	96.61
	F1-Score	0.97	0.96	0.95	0.95	0.93
	Precision	0.94	0.95	0.93	0.93	0.90
	Recall	1.00	0.97	0.97	0.97	0.97
ESCA	Accuracy (%)	98.55	97.82	92.75	95.65	95.65
	F1-Score	0.99	0.98	0.95	0.97	0.95
	Precision	1.00	0.99	0.95	0.99	0.95
	Recall	0.99	0.98	0.93	0.96	0.96
Healthy	Accuracy (%)	100	100	97.61	97.61	100
	F1-Score	0.99	1.00	0.99	0.98	1.00
	Precision	0.98	1	1.00	0.98	1.00
	Recall	1.00	1.00	0.98	0.98	1.00
Leaf Spot	Accuracy (%)	93.51	96.29	98.14	96.29	89.98
	F1-Score	0.97	0.97	0.98	0.97	0.94
	Precision	1.00	0.98	0.97	0.97	0.99
	Recall	0.94	0.96	0.98	0.96	0.90

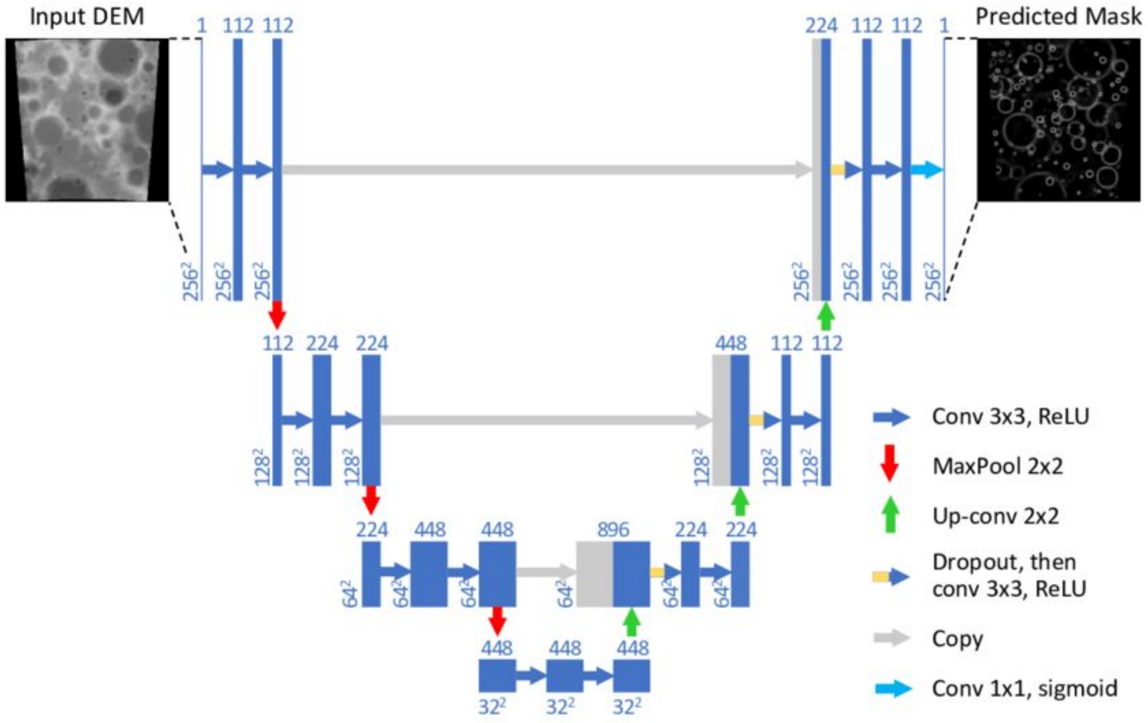
Hardware And Software Requirements

- Hardware Requirements
  - GPU Based environment

- Language Used:-
  - Python

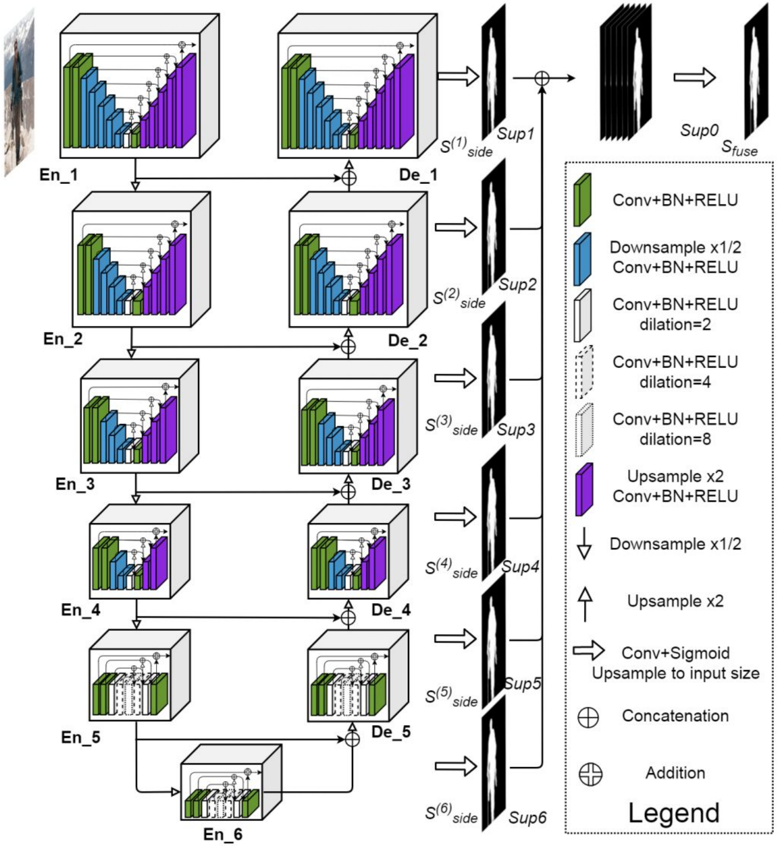
- Libraries Used:-
  - Matlab
  - Numpy
  - Tensorflow
  - Keras
  - Scipy
  - MatplotLib
  - Pandas.

U-Net Architecture Visualised



- Semantic segmentation is to label each pixel of image with corresponding class of what is being represented.
- The encoder path captures the context of the image producing feature maps.
- Decoder path used to enable precise localization using transposed convolutions.
- Preserving the mapping of spatial information from each layer, image is concatenated with the corresponding image from the contracting path.

U²-Net Architecture

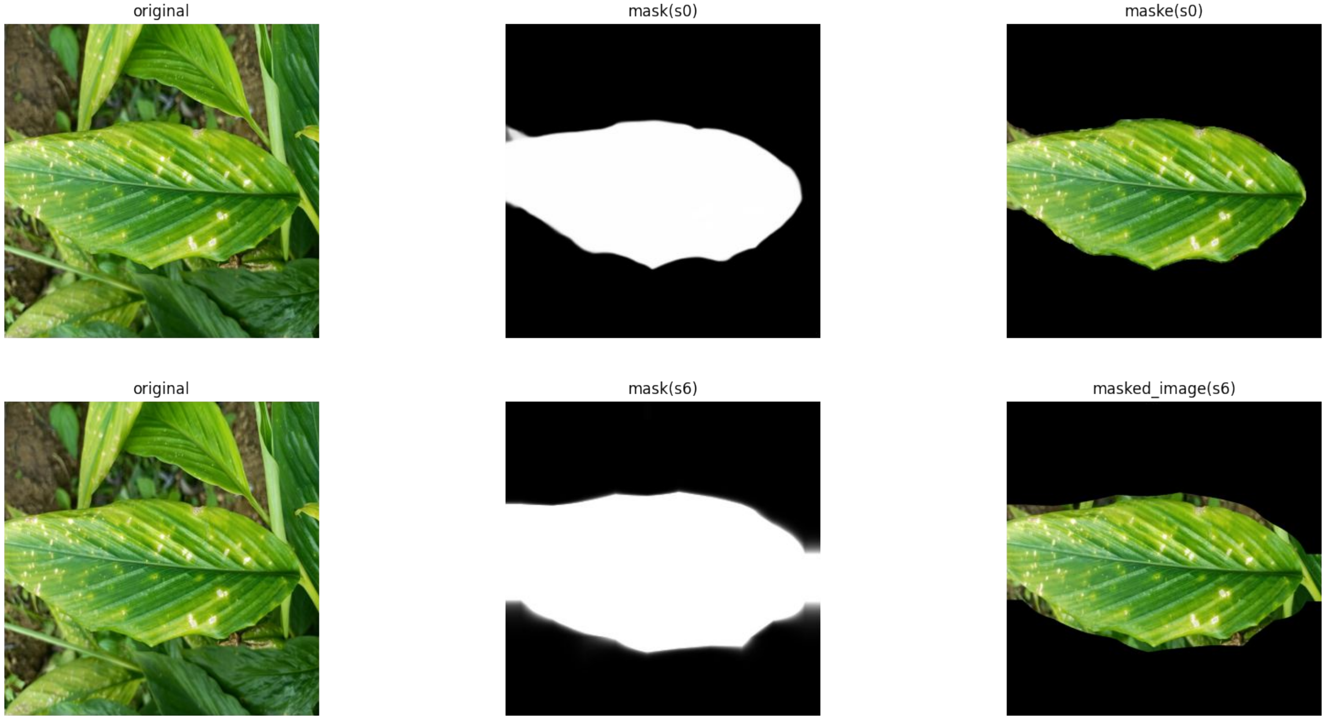


- U²-Net is a two-level nested U-structure that is designed for SOD without using any pre-trained backbones from image classification. It can be trained from scratch to achieve competitive performance
- The residual connections within each UNet block enables focus on local details while the overall residual U-Net architecture enables fusing these local details with global (multi scale) contextual information
- RSU mainly consists of three components:
  - An input convolution layer,
  - U-Net like symmetric encoder-decoder structure with height of L (takes the intermediate feature map F1(x) as input and learns to extract and encode the multi-scale contextual information U(F1(x))
  - A residual connection which fuses local features and the multi-scale features by the summation: F1(x) +U(F1(x)).

U^2-Net

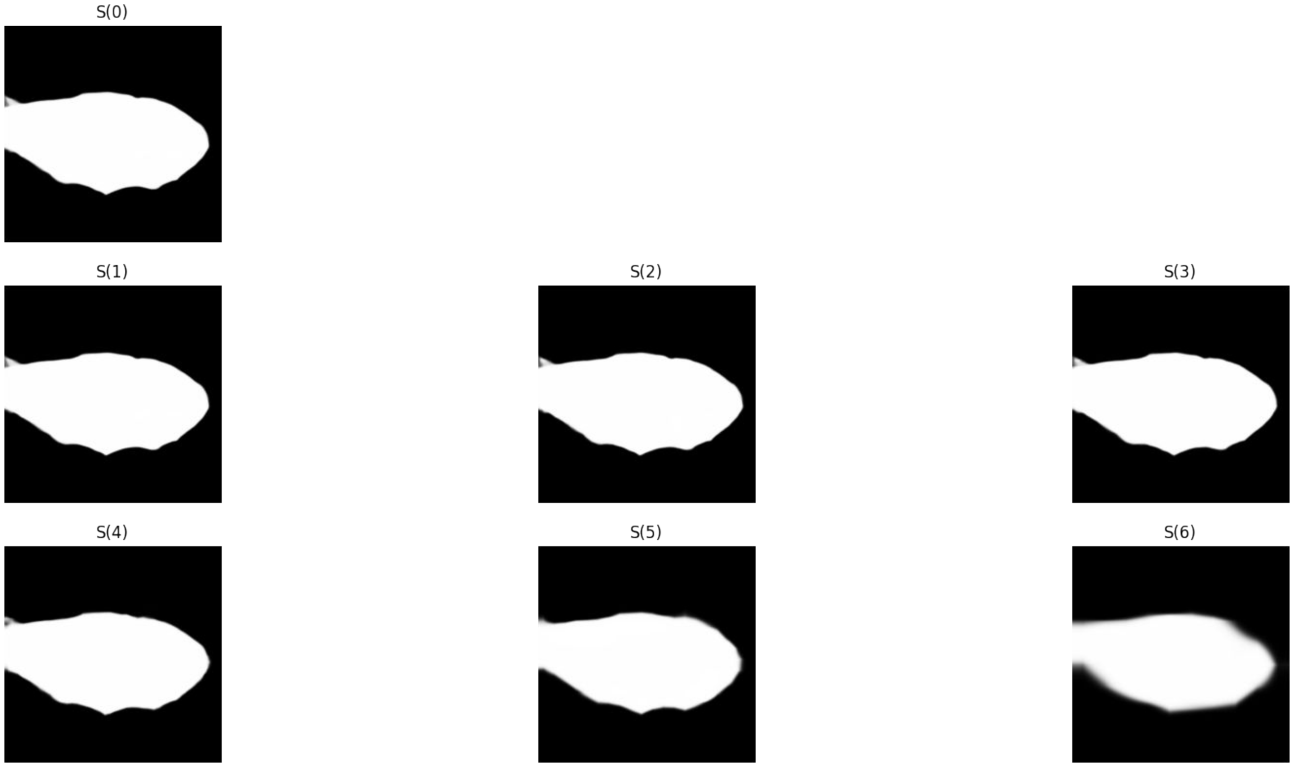
- In encoder stages, **En_1, En_2, En_3, and En_4**, residual U-blocks RSU-7, RSU-6, RSU-5, and RSU-4 are used respectively, “7”, “6”, “5”, and “4” denote the heights (L) of RSU blocks.
- The resolution of feature maps in **En_5 and En_6** is relatively low, further downsampling of these feature maps leads to loss of useful context. Hence, in both **En_5 and En_6** stages, RSU-4F are used, where “F” means that the RSU is a dilated version, in this stage the pooling and upsampling operations are replaced with dilated convolutions (Dilated Conv → is basically a convolution with a wider kernel created by regularly inserting spaces between the kernel elements, it helps to expand the area of the image covered without pooling), so that RSU-4F have the same resolution as its input feature maps.
- U^2-Net first generates six side output saliency probability maps **S (6) side, S (5) side, S (4) side, S (3) side, S (2) side, S (1)** side from stages **En_6, De_5, De_4, De_3, De_2 and De_1** by a 3×3 convolution layer and a sigmoid function(applies upsampling to input image size before sigmoid), after that fused together to form **S_fuse.**

Output of U²-Net



- The output of s6 is somewhat blurred, because we didn’t concat any spatial information from the previous layers(encoders).

Output of saliency map from U2 net



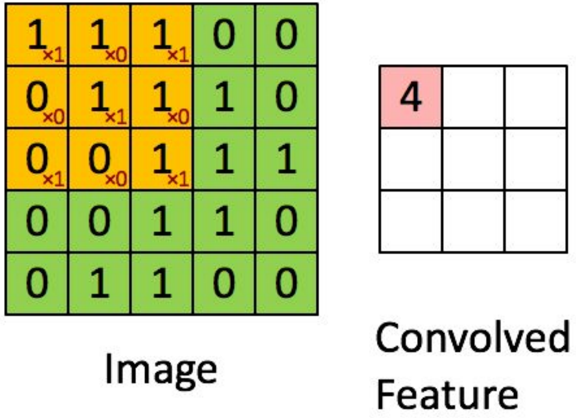
Saliency map provides pixel unique quality

Convolution Layer - CNN

- In convolution layer network, we search patterns in the image. In the first few layer, it can detect corners and lines, and pass these patterns through the neural network to recognize complex features.

- Types of layers in cnn: convolutional, pooling and activation layers.

- In convolutional layer, to recognize patterns we apply some filters/kernel. When training an image, these weights will change based on loss.



Convolution Layer - CNN

- Pooling layer is mainly used for reducing spatial dimensions, So that we have less parameters to train to avoid overfitting.

- Activation layer is used for squashes the value in the range.

- RELU: Rectified Linear Unit → returns x if the x is positive else 0.

- The first layers basically just encode direction and color. These direction and color filters then get combined into basic grid and spot textures. These textures gradually get combined into increasingly complex patterns.

- Feature map contains most information about the patterns in the images.

Our CNN Architecture

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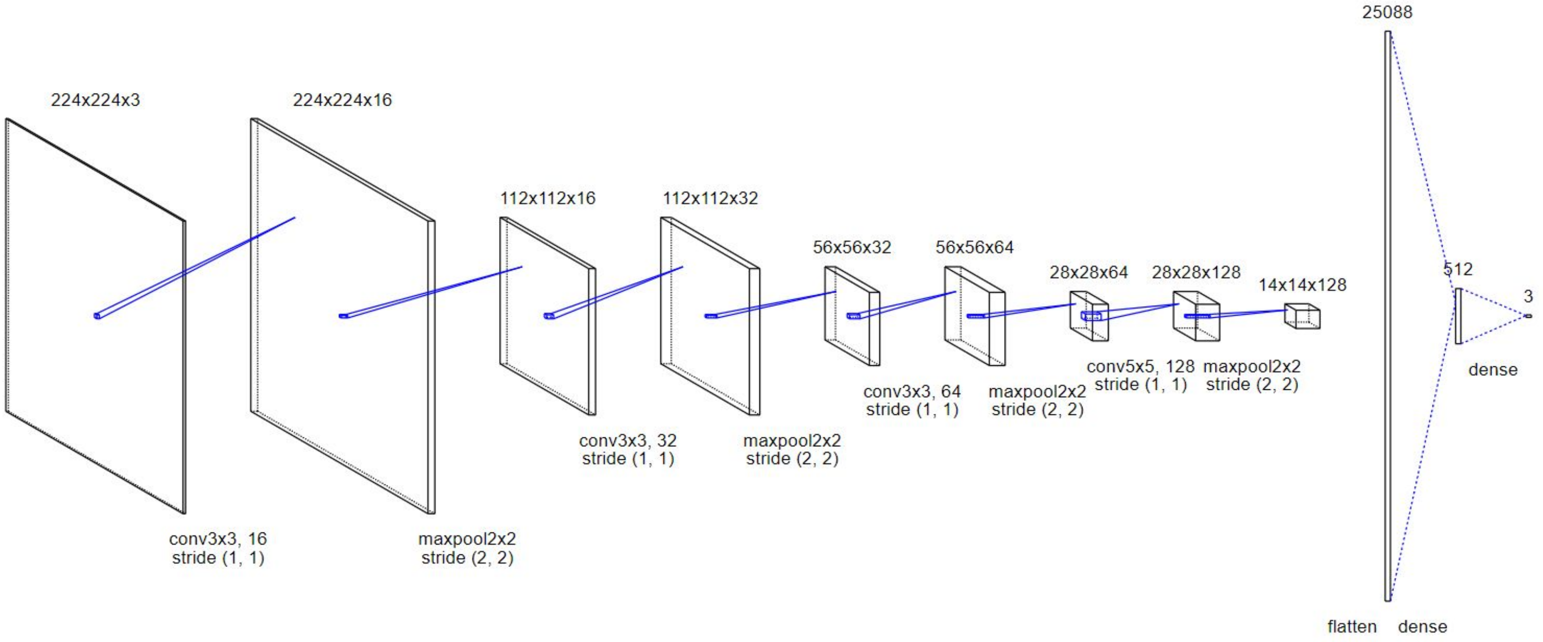
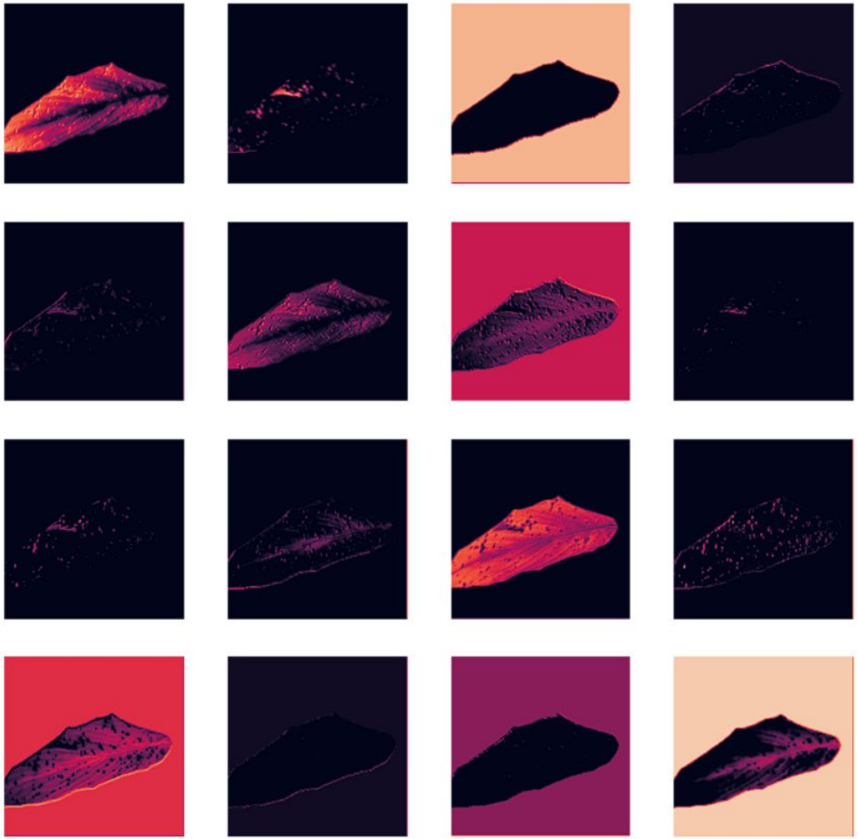


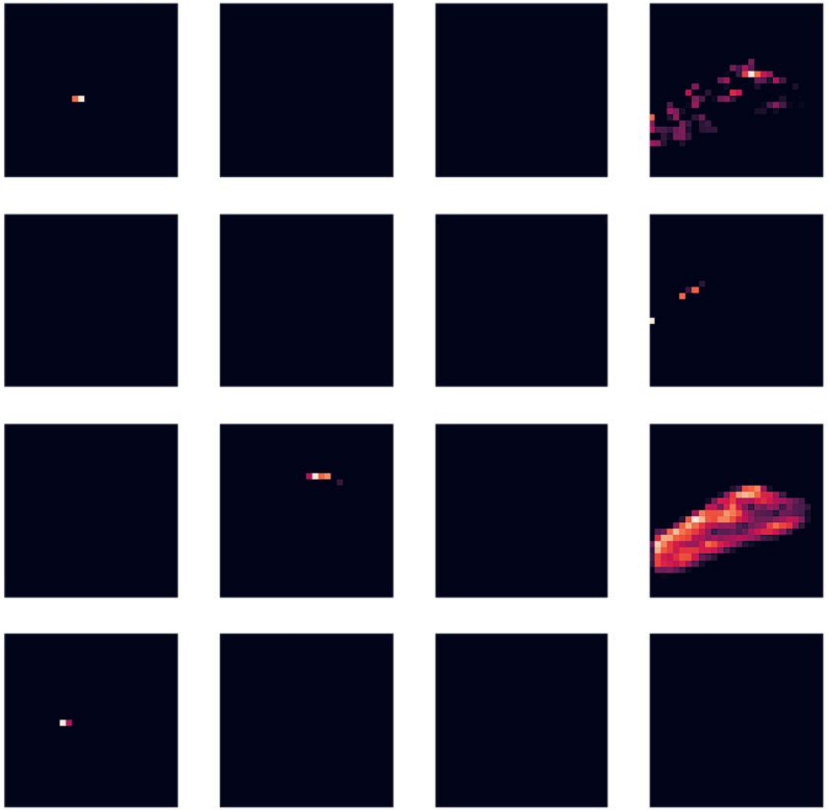
Visualizing detection of filters



Output of convolution filters in the first layer
- **Detection of line and edges**

Visualizing detection of filters

(1, 28, 28, 128)



Features detection in last convolutional
Layer - this layer detecting more
Complex features, which helps for classification

EfficientNet - Rethinking model scaling for CNN

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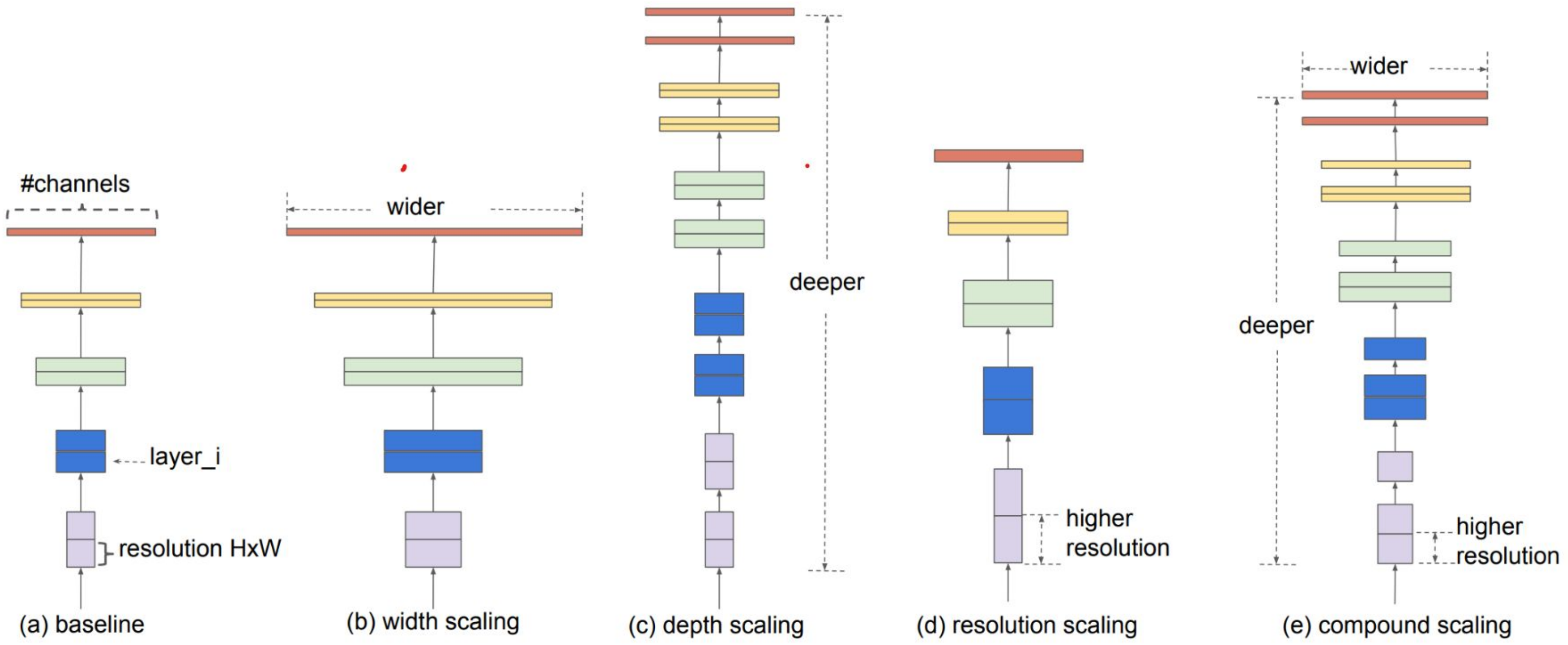
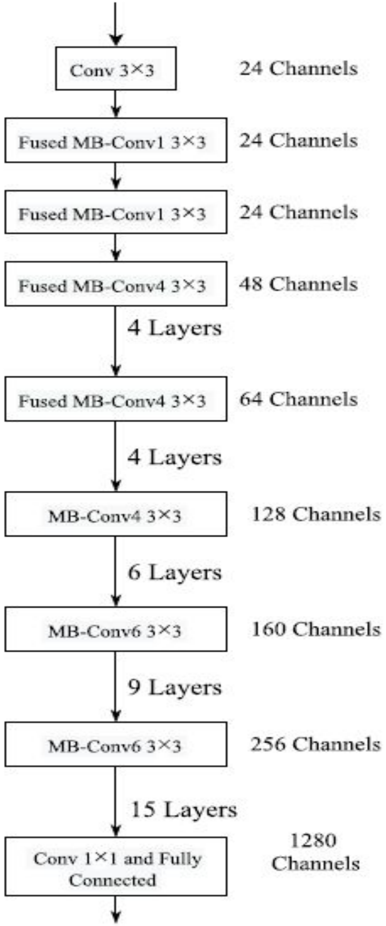
- Perform **Compound Scaling** - that is, scale all three dimensions while maintaining a balance between all dimensions of the network.
  a) Width scaling is adding more features maps to each layers,
  b) Depth scaling is increasing more layers to the neural network,
  c) Resolution scaling is increasing the resolution of the input images

- The concept of compound scaling is advantageous because if the input image is larger (higher resolution), the network will require more layers (depth) and channels (width) to capture greater fine-grained patterns on the larger image.
- A neural architecture search to find a baseline architecture that maximizes an objective function that includes both the model accuracy and FLOPS.

EfficientNet Model Scaling



Efficient Net - V2 S



Understanding & Improving Training Efficiency of EfficientNet

- Large image size results in significant memory usage. The total memory on GPU/TPU is fixed, smaller batch size is used, which drastically slows down the training.
- Depthwise Convolutions are Slow in Early Layers but Effective in Later Stages (a single convolutional filter for each input channel)
- EfficientNetV1 architecture equally scales up all the stages using a simple compound scaling rule. However, these stages are not equally contributed to the training speed and parameter efficiency.

Efficient Net - V2 S

- The MBConv layer above is nothing but an inverted bottleneck block with squeeze and excitation connection added to it
- Fused-MBConv replaces the depthwise conv3×3 and expansion conv1×1 in MBConv with single regular conv3×3.Fused-MBConv can improve training speed with a small overhead on parameters and FLOPs.
- But if all blocks use Fused-MBConv (stage 1–7), then it significantly increases parameters and FLOPs while also slowing down the training.

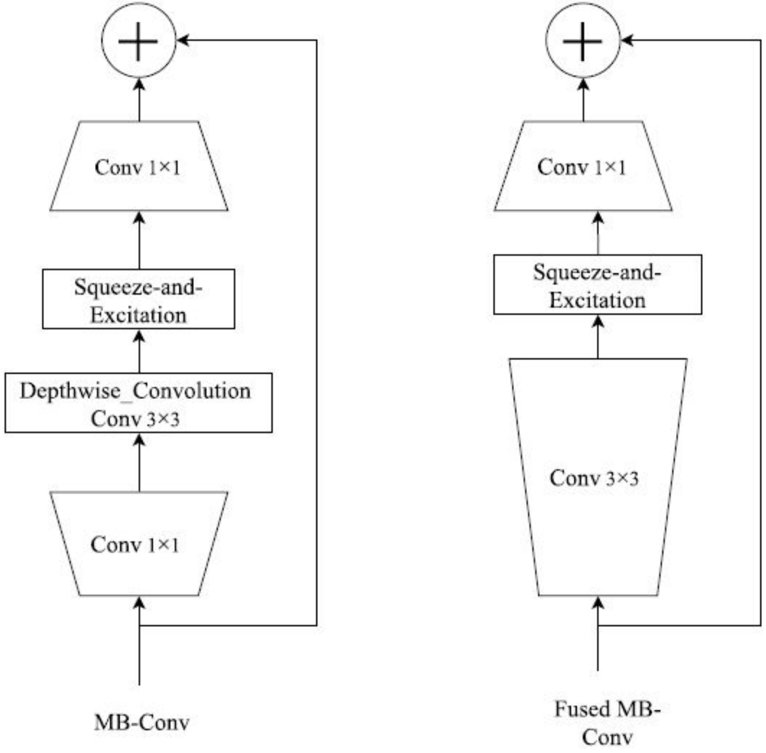
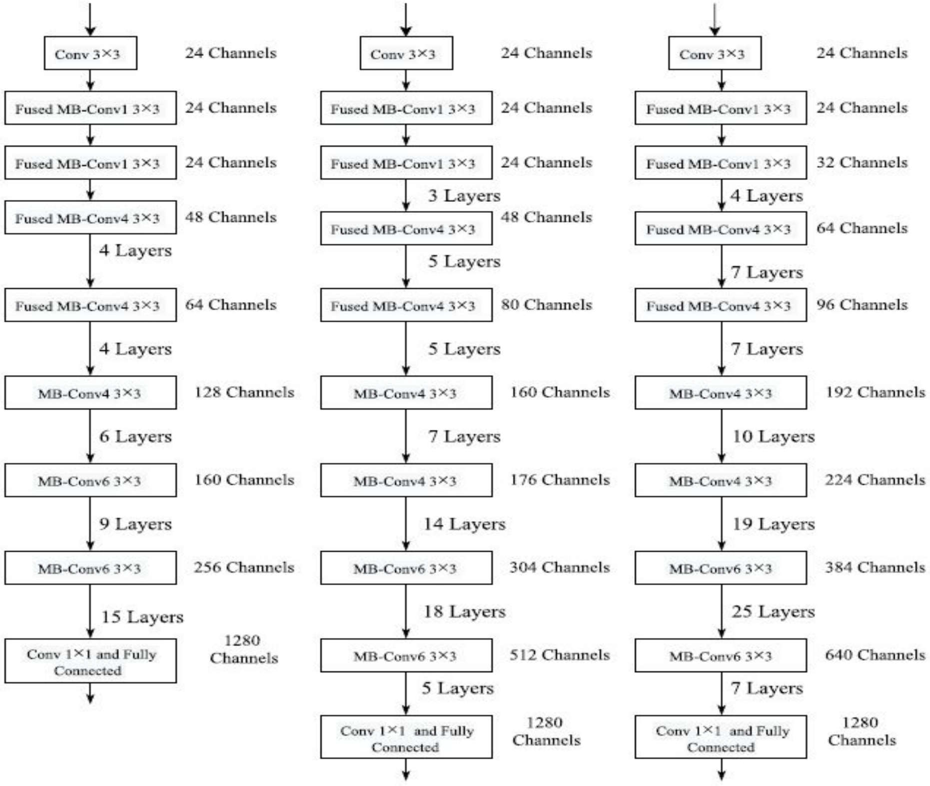


FIGURE 6. Structure of MB-Conv and fused MB-Conv [6].

EfficientNet-V2 Models(V2M,V2L)



a) V2-S b) V2-M c) V2-L

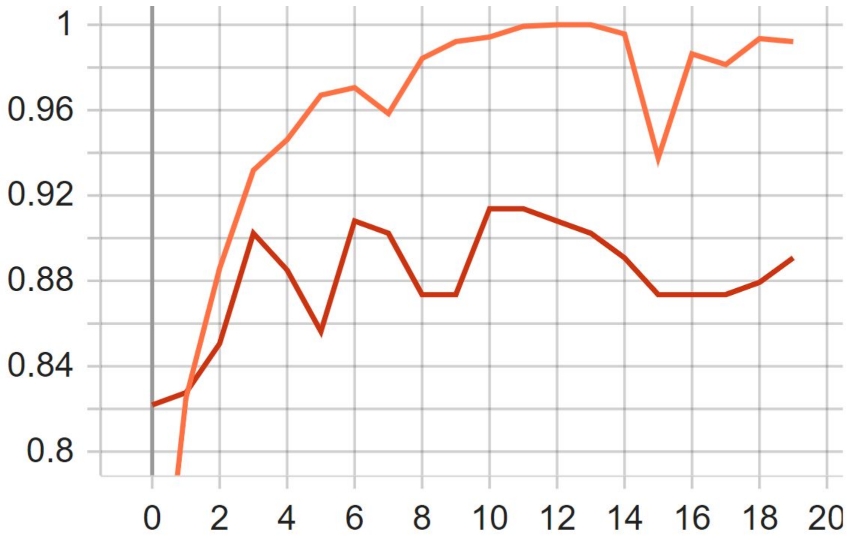
K-Fold Cross Validation

K-Fold CV is where a given data set is split into a ***K*** number of sections/folds where each fold is used as a testing set at some point. The general procedure is as follows:

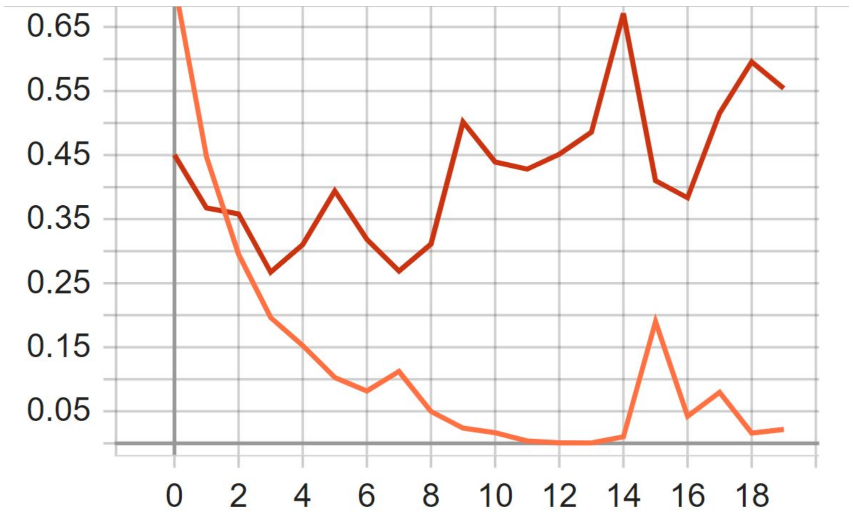
1. Shuffle the dataset randomly.
2. Split the dataset into k groups
3. For each unique group:
    1. Take the group as a hold out or test data set
    2. Take the remaining groups as a training data set
    3. Fit a model on the training set and evaluate it on the test set
    4. Retain the evaluation score and discard the model
4. Summarize the skill of the model using the sample of model evaluation scores

Cardamom Convolution Graph

Categorical_Accuracy



Loss



Cardamom Convolution Graph

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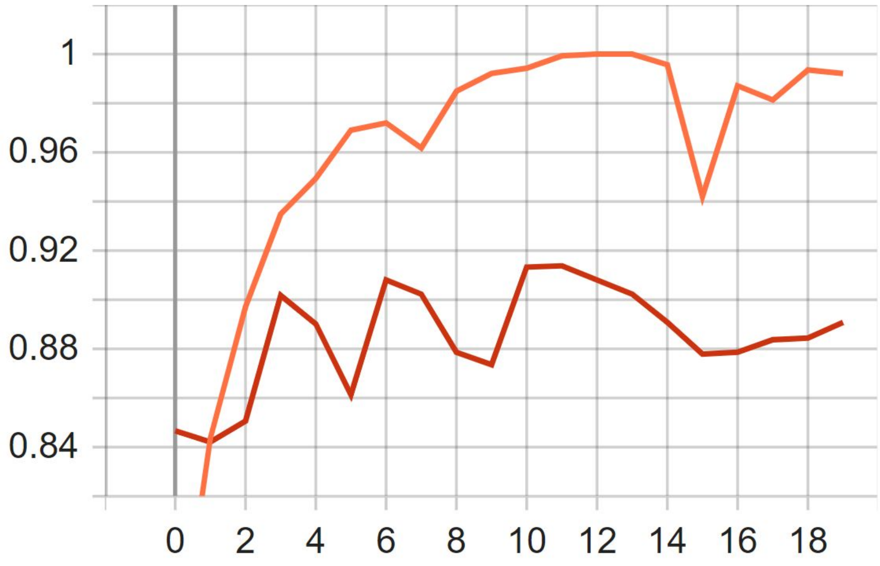
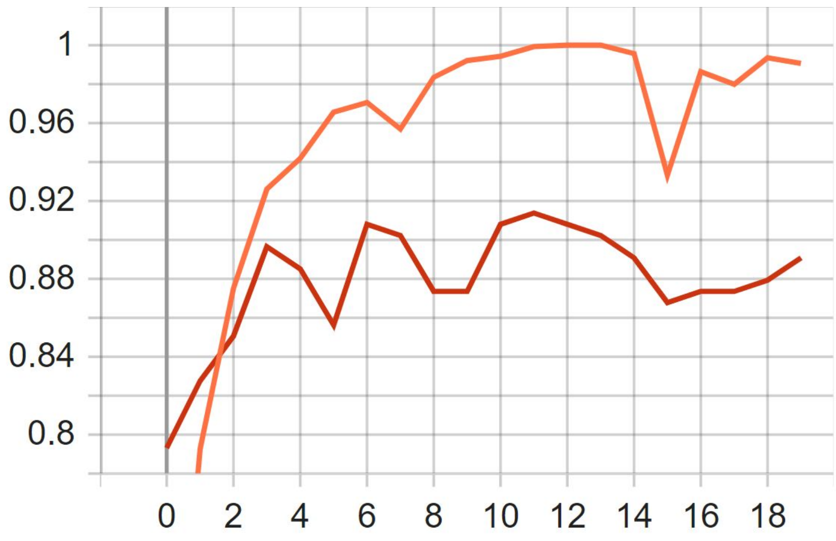
Precision

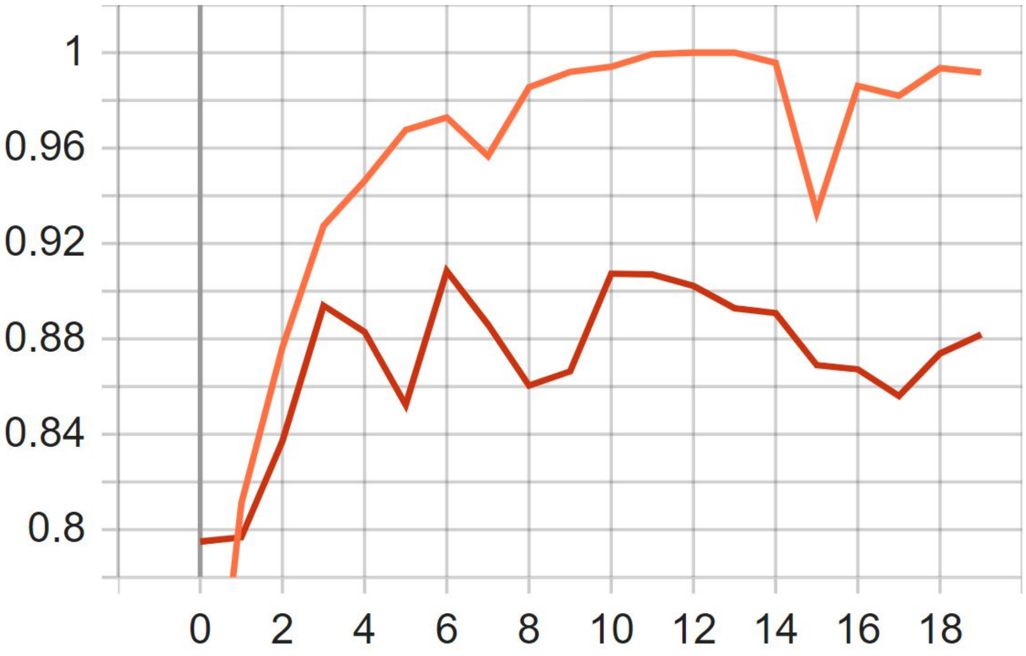


Recall



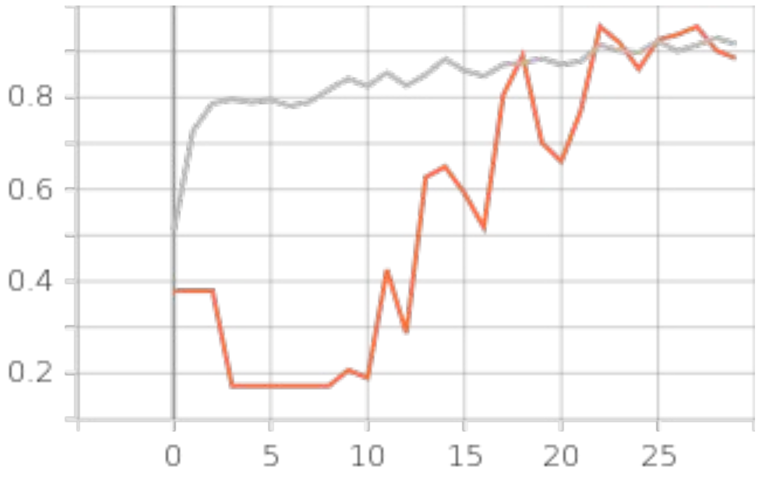
Cardamom Convolution Graph

F1_Score

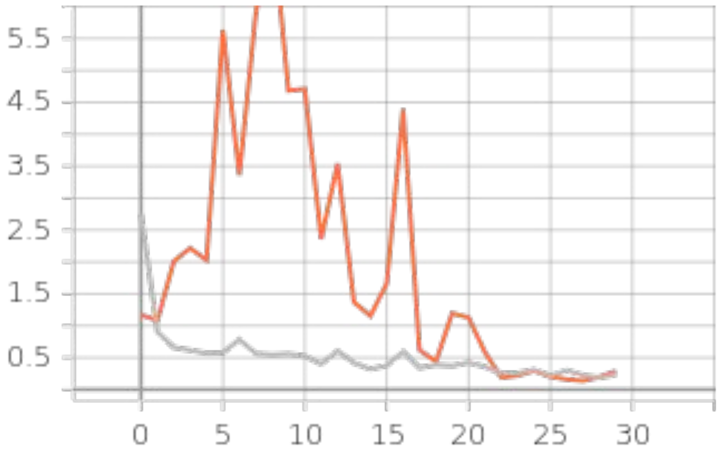


Cardamom EfficientNet Graph

Categorical_Accuracy

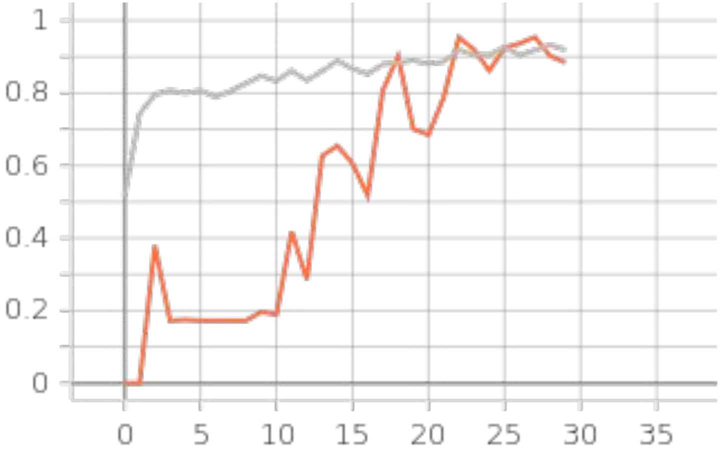


Loss

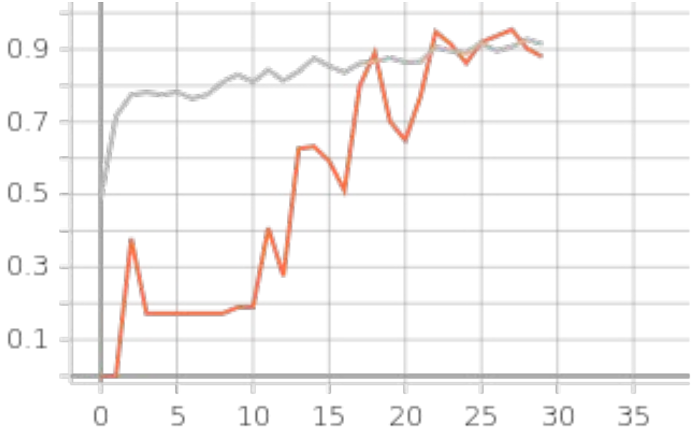


Cardamom EfficientNet Graph

Precision

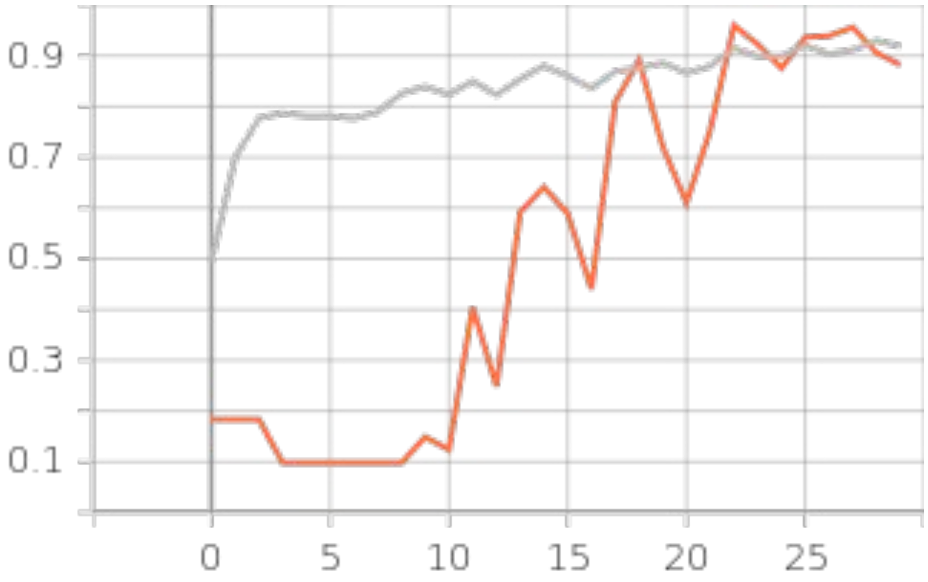


Recall



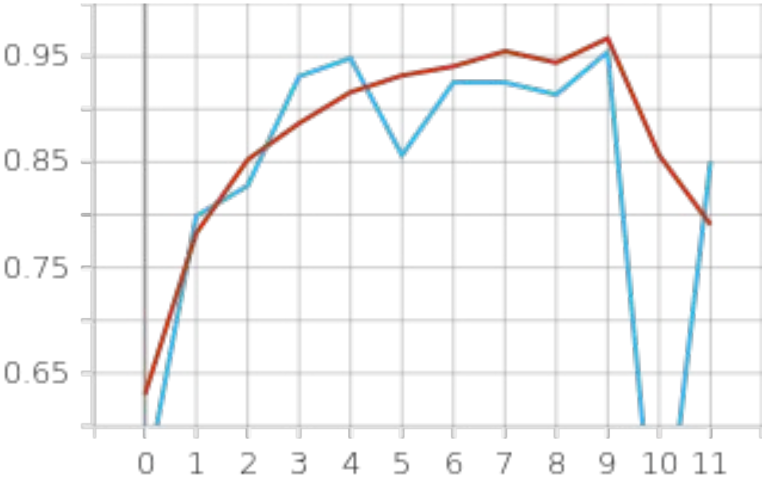
Cardamom EfficientNet Graph

F1_Score

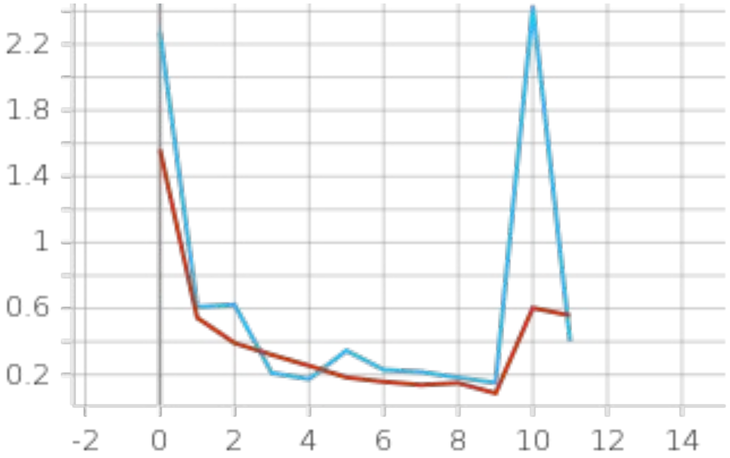


Cardamom EfficientNetV2-S Graph

Categorical_Accuracy

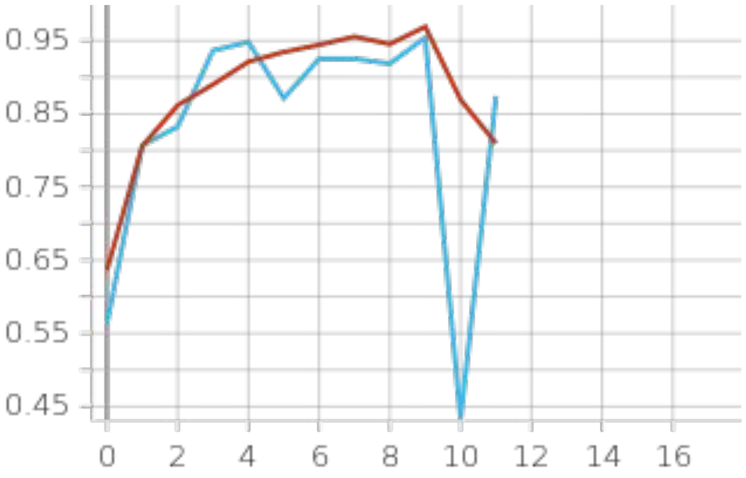


Loss

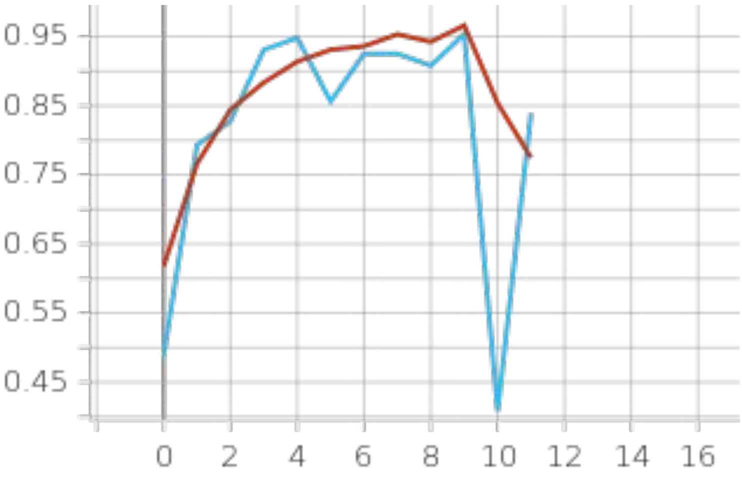


Cardamom EfficientNetV2-S Graph

Precision

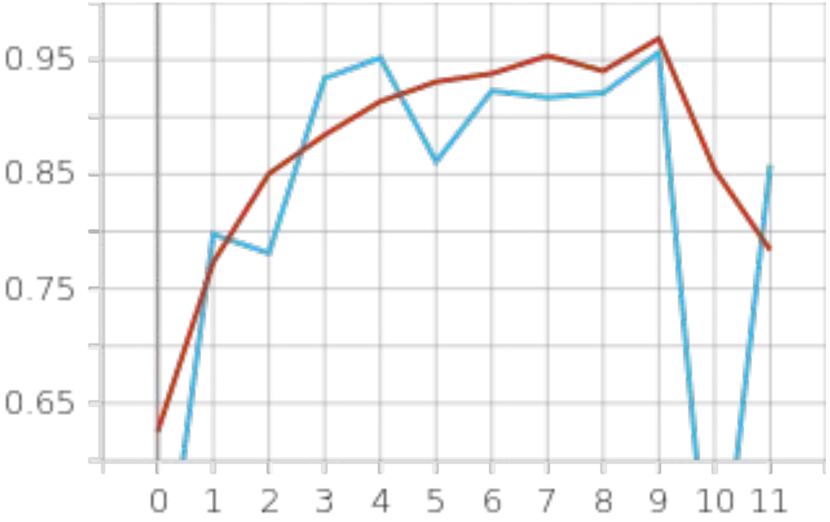


Recall



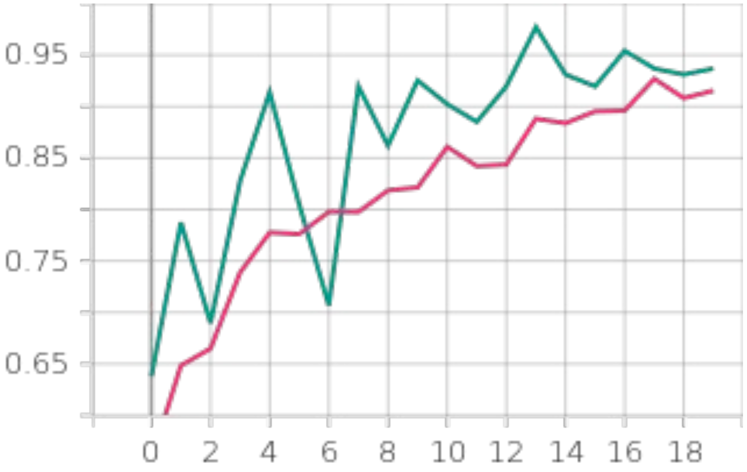
Cardamom EfficientNetV2-S Graph

F1_Score

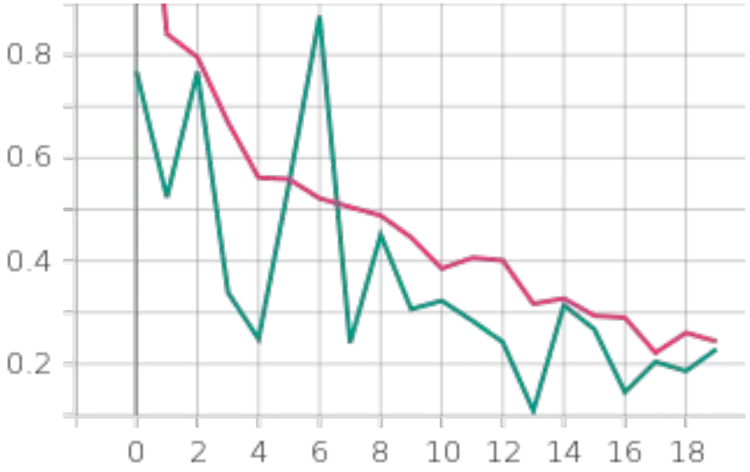


Cardamom EfficientNetV2-M Graph

Categorical_Accuracy

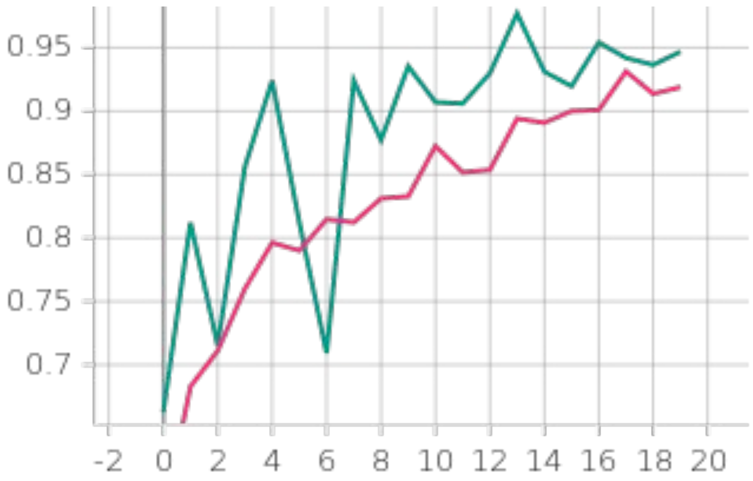


Loss

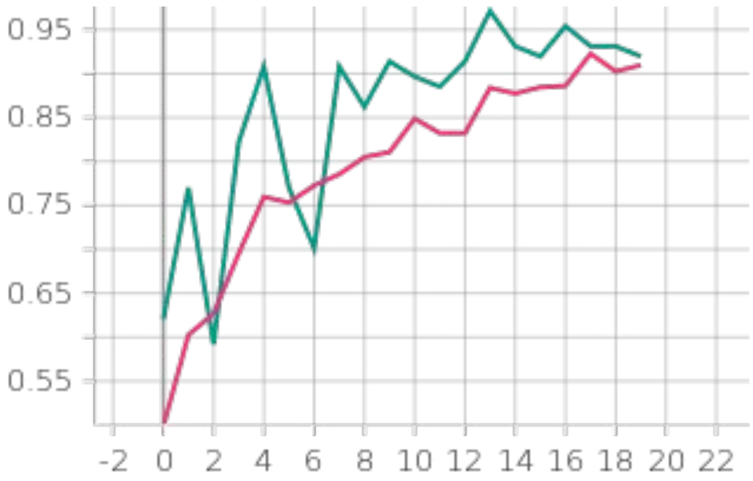


Cardamom EfficientNetV2-M Graph

Precision

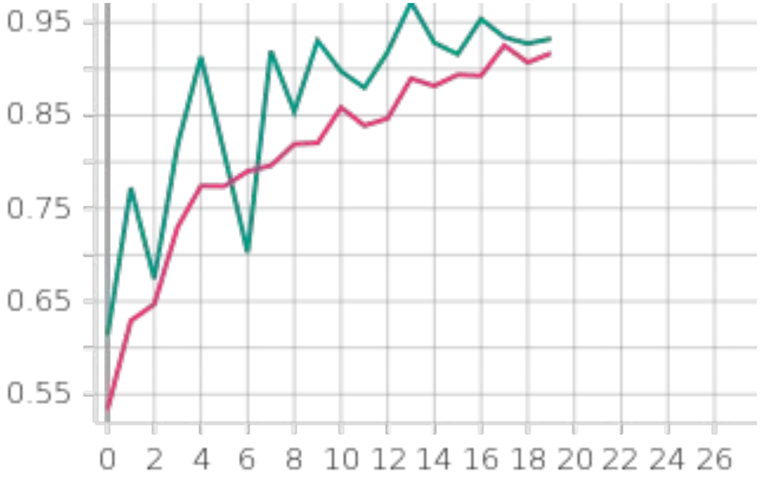


Recall



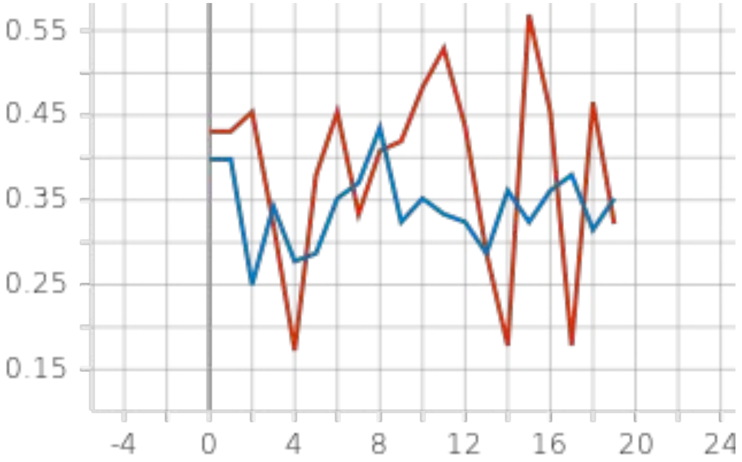
Cardamom EfficientNetV2-M Graph

F1_Score

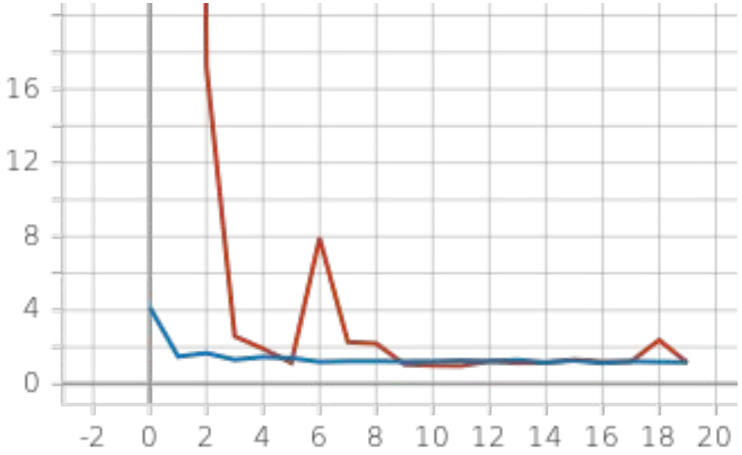


Cardamom EfficientNetV2-L Graph

Categorical_Accuracy

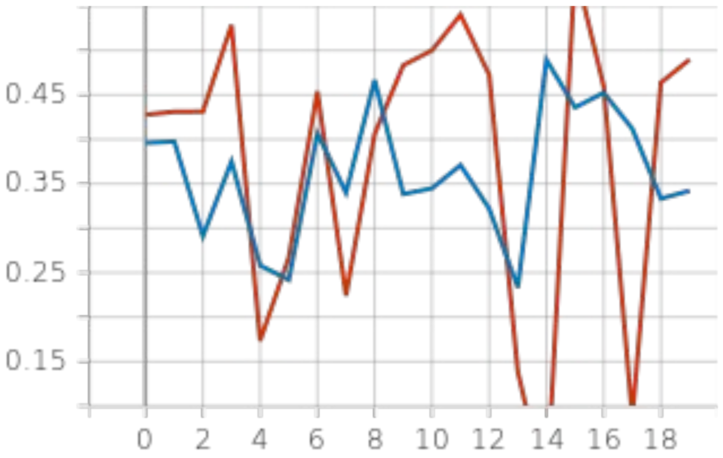


Loss

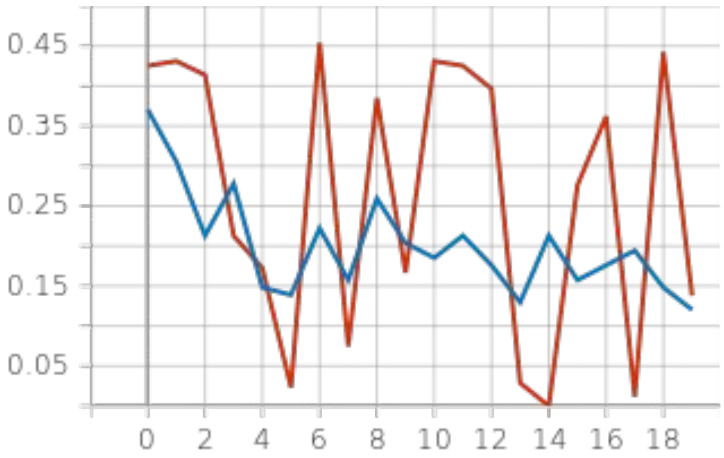


Cardamom EfficientNetV2-L Graph

Precision

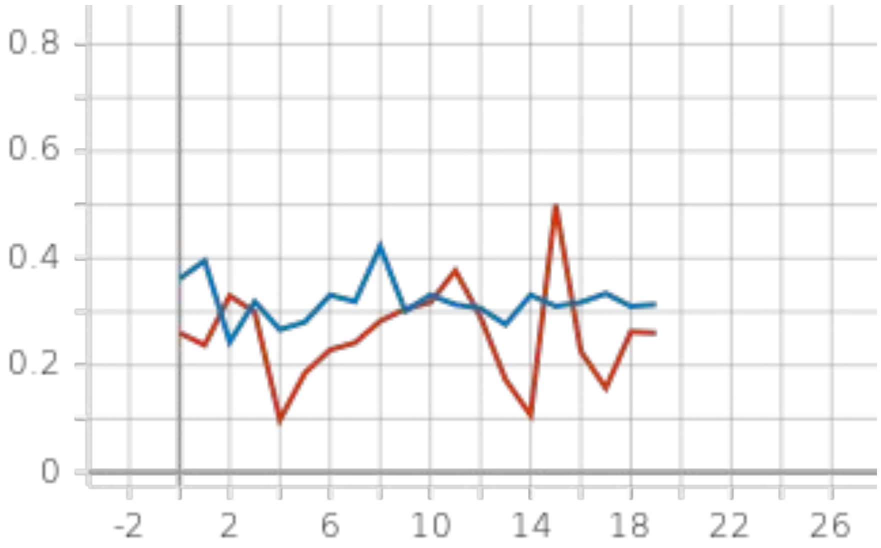


Recall



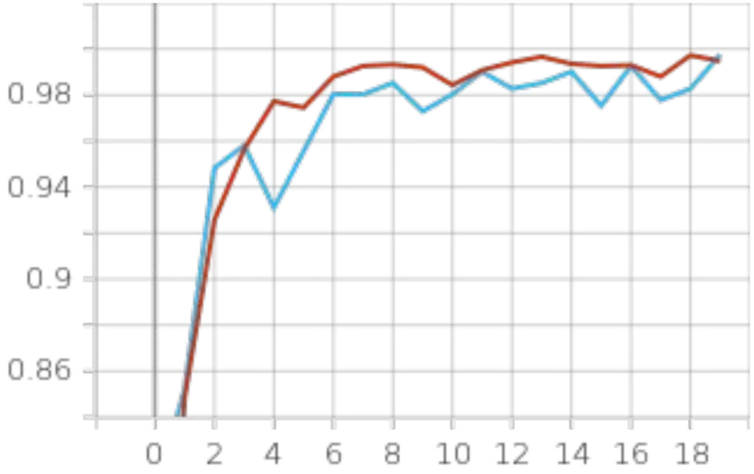
Cardamom EfficientNetV2-L Graph

F1_Score

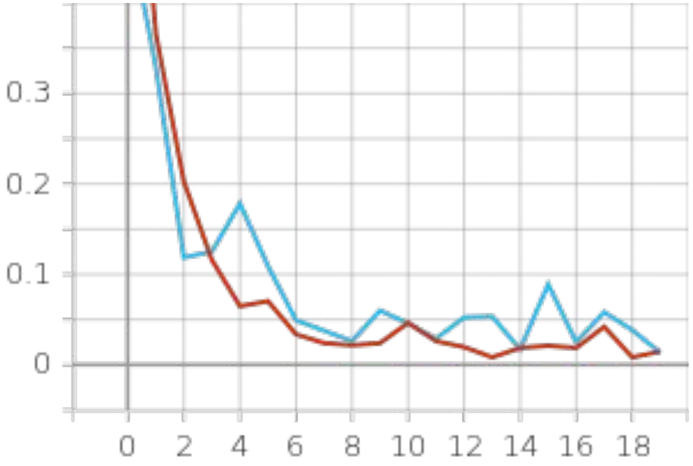


Grape Convolution Graph

Categorical_Accuracy

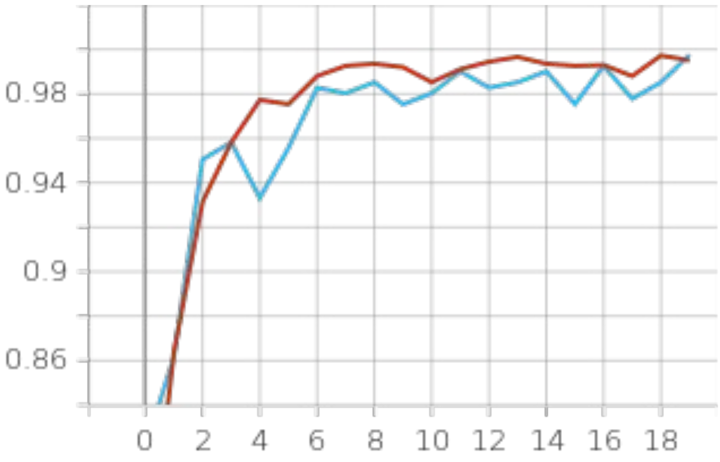


Loss

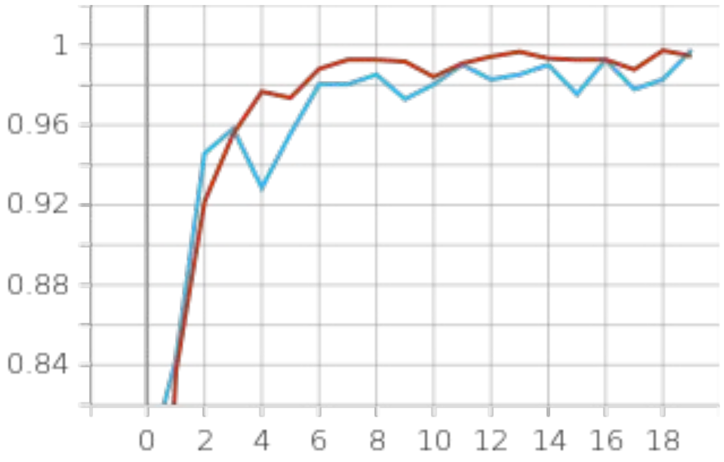


Grape Convolution Graph

Precision



Recall



Grape Convolution Graph

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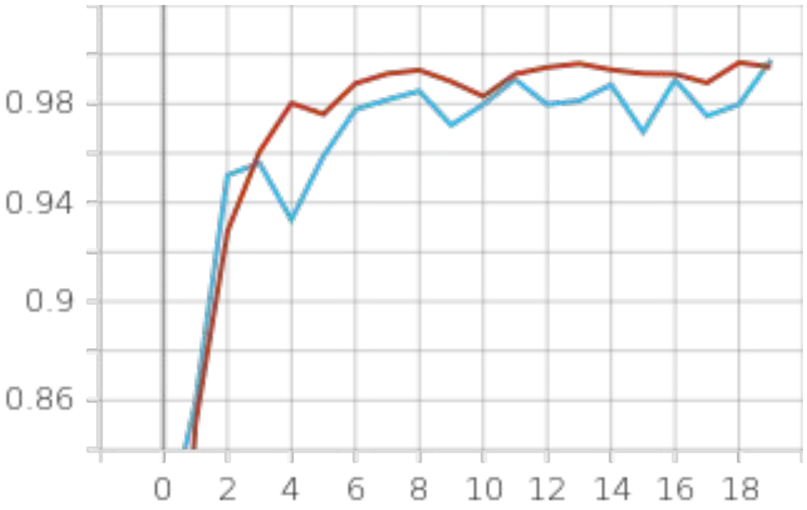
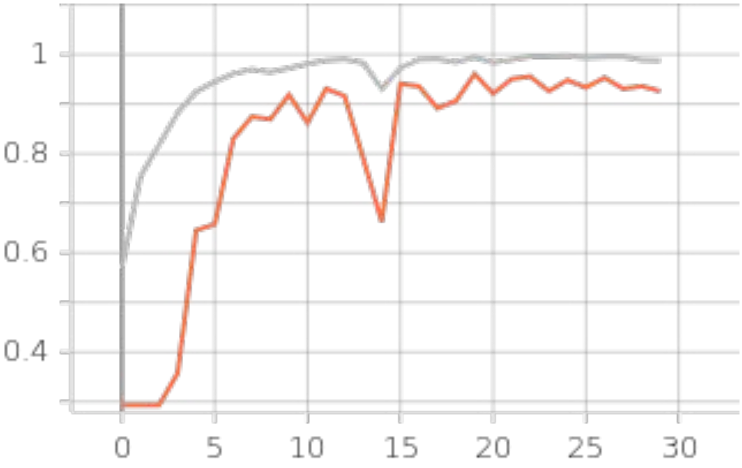
F1_Score

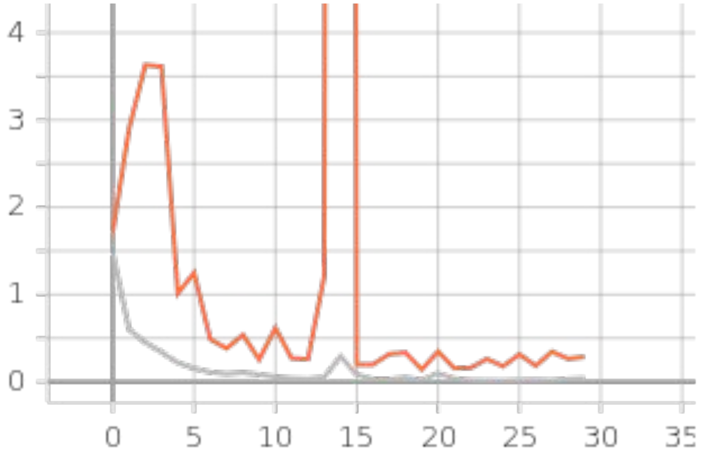


Grape EfficientNet Graph

Categorical_Accuracy

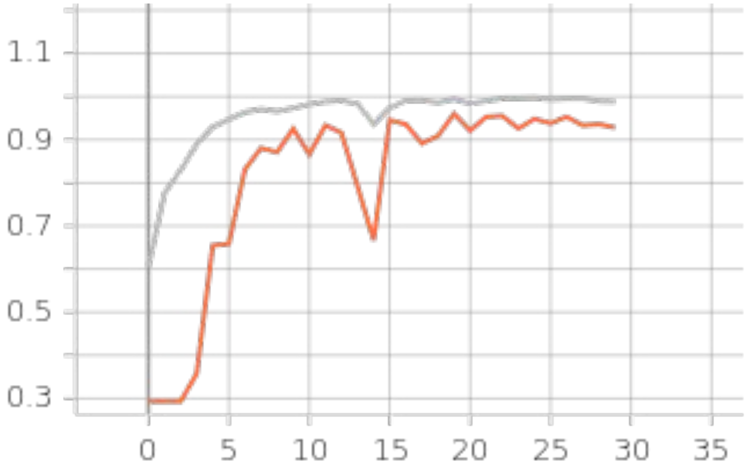


Loss

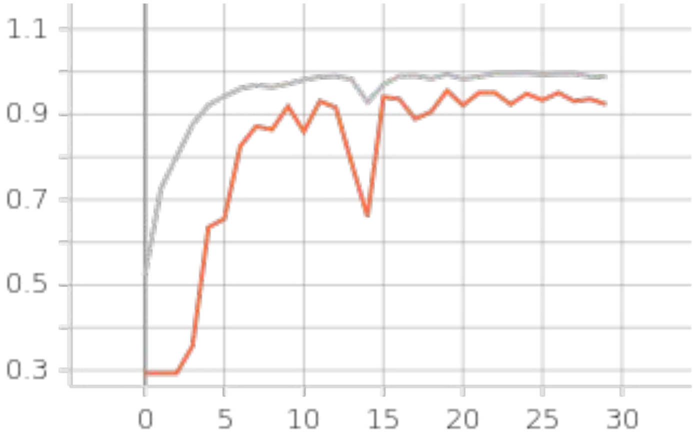


Grape EfficientNet Graph

Precision

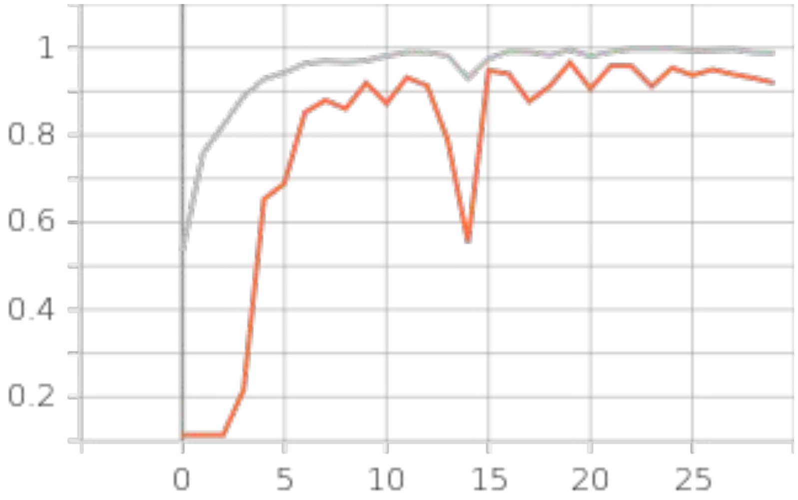


Recall



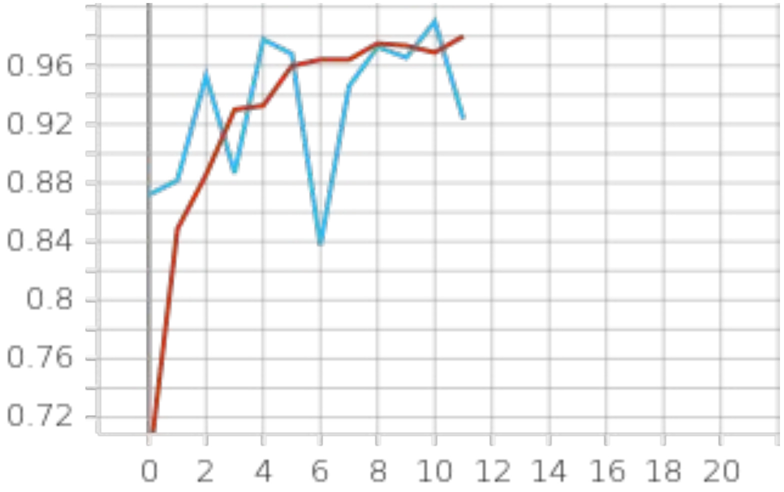
Grape EfficientNet Graph

F1_Score

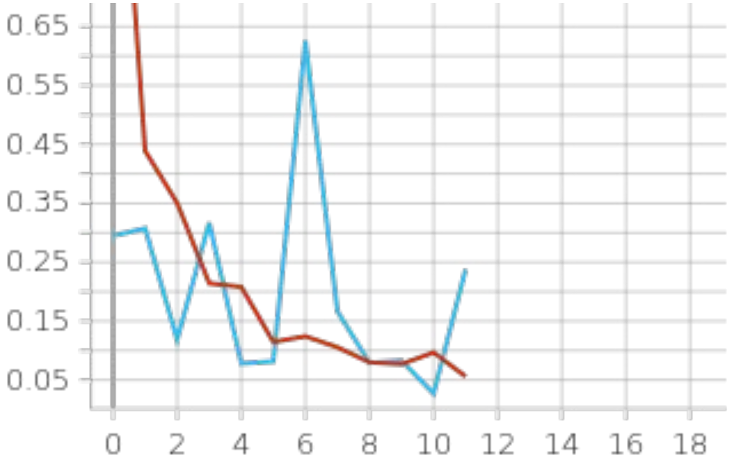


Grape EfficientNetV2-S Graph

Categorical_Accuracy

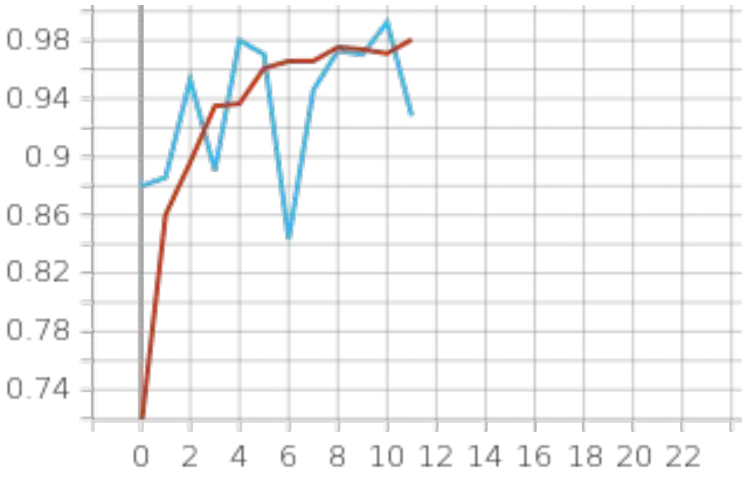


Loss

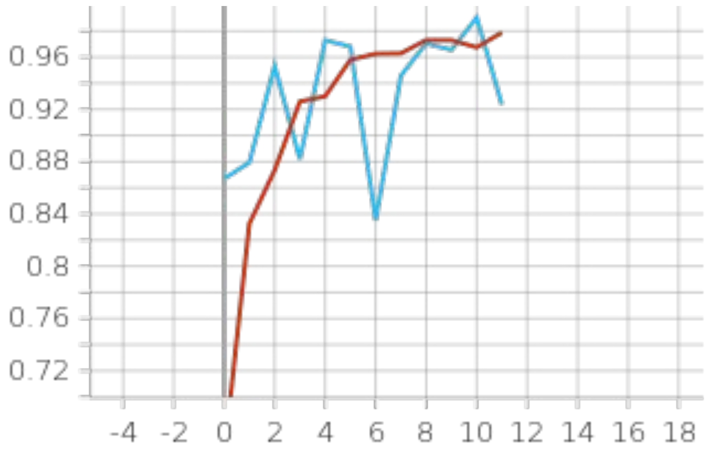


Grape EfficientNetV2-S Graph

Precision



Recall



Grape EfficientNetV2-S Graph

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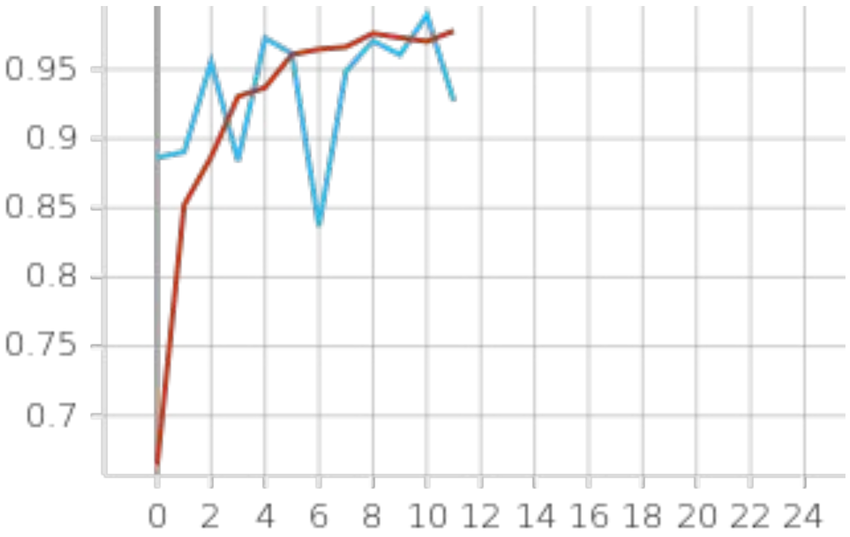
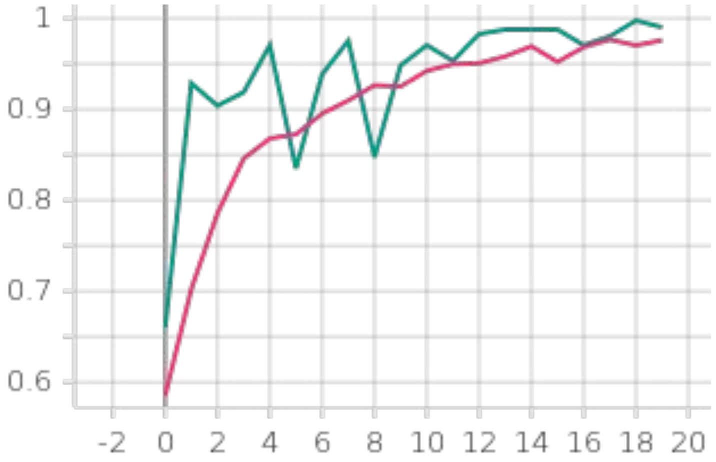
F1_Score

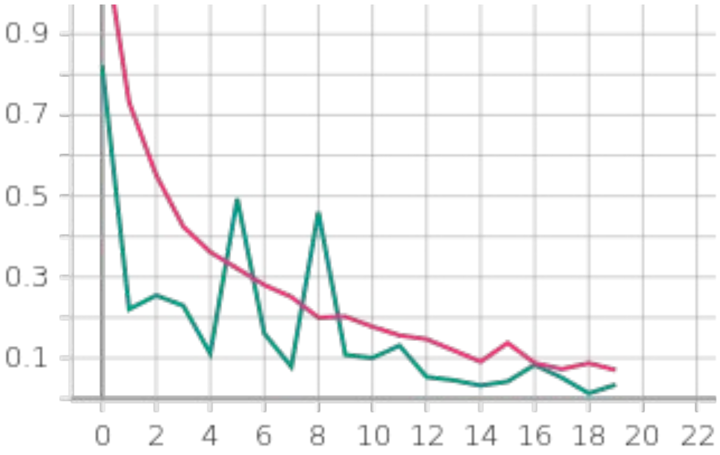


Grape EfficientNetV2-M Graph

Categorical_Accuracy

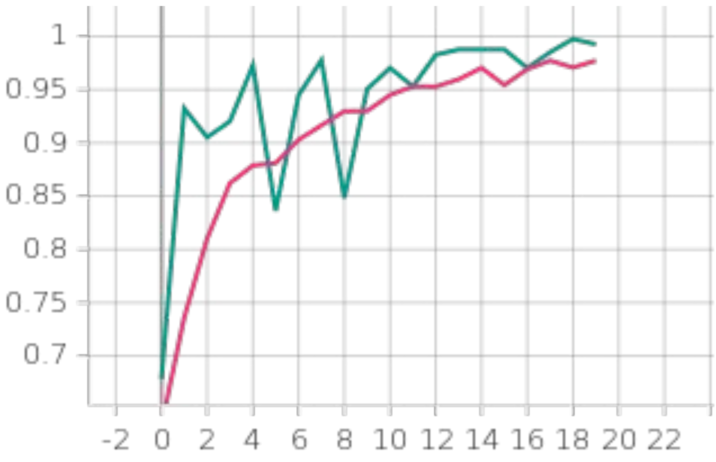


Loss

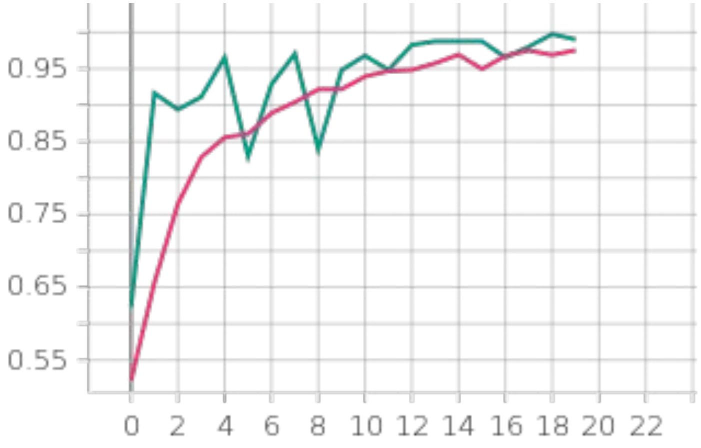


Grape EfficientNetV2-M Graph

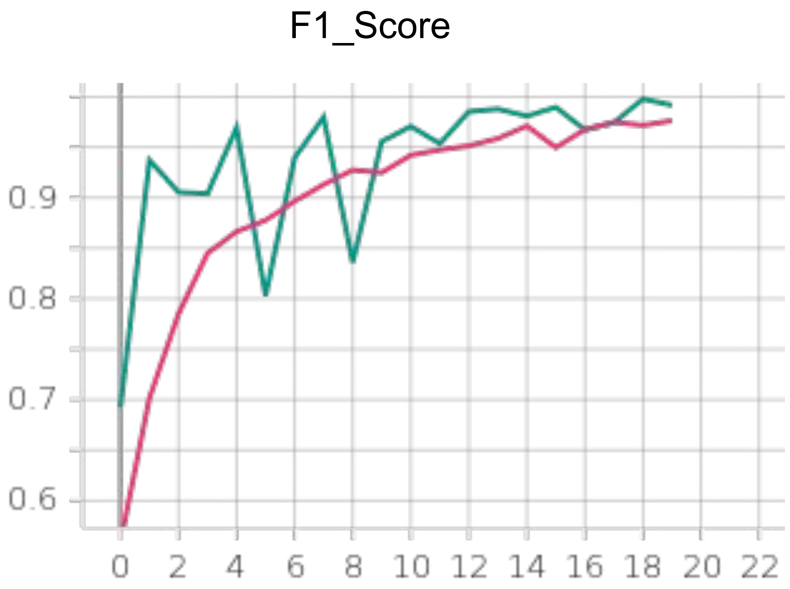
Precision



Recall

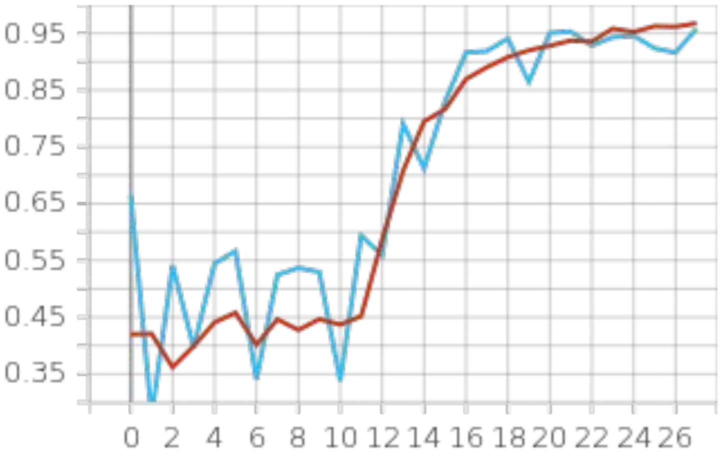


Grape EfficientNetV2-M Graph

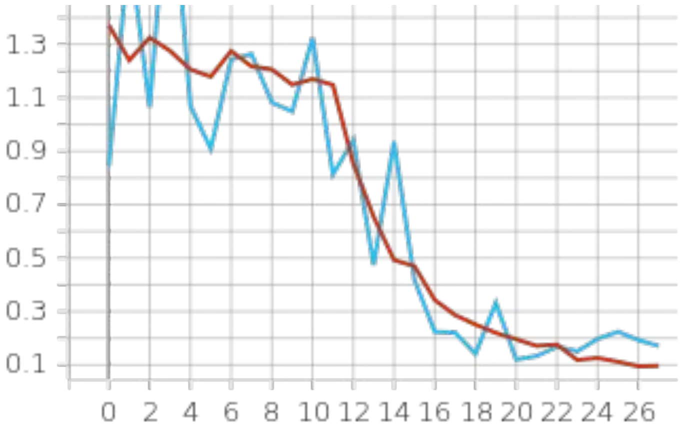


Grape EfficientNetV2-L Graph

Categorical_Accuracy

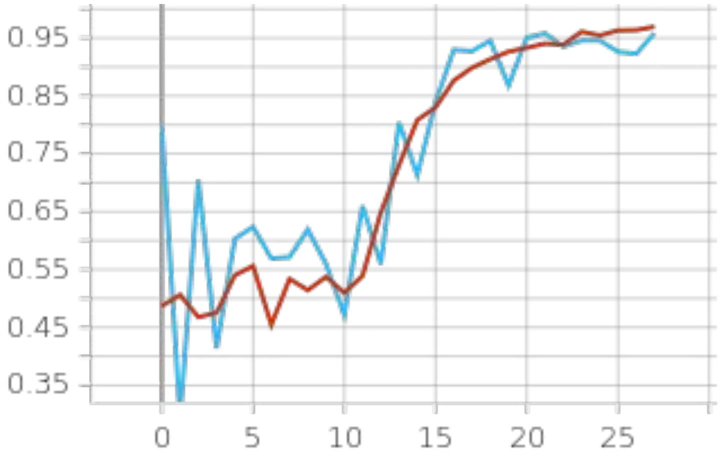


Loss

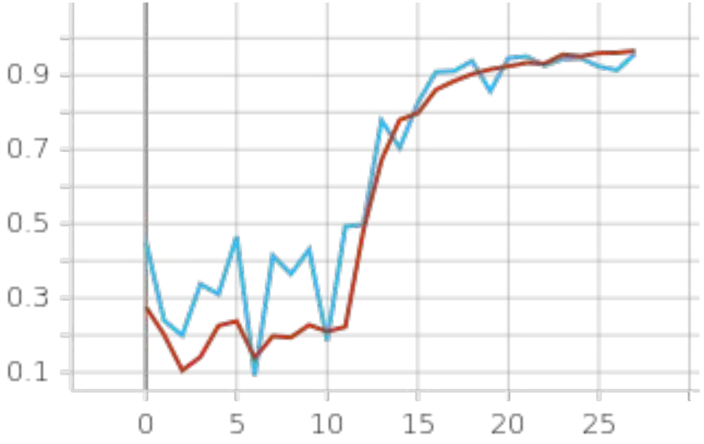


Grape EfficientNetV2-L Graph

Precision

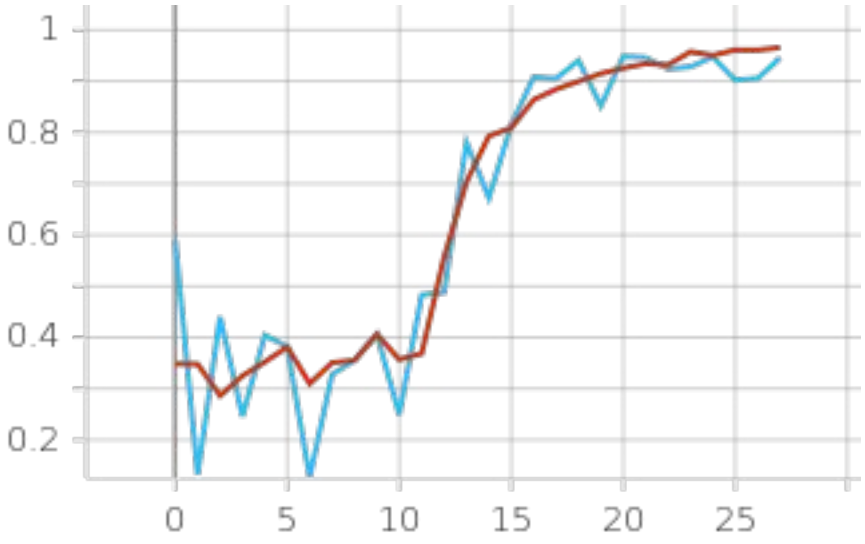


Recall



Grape EfficientNetV2-L Graph

F1_Score



Output for Cardamom with External Dataset

Category	Performance Metrics	CNN	EfficientNet	EfficientNet V2-S	EfficientNet V2-M	EfficientNet V2-L
Blight	Accuracy	93.33	100	100	100	26.66
	F1-Score	0.93	1.0	1.0	1.0	0.26
	Precision	0.93	1.0	1.0	1.0	0.26
	Recall	0.93	1.0	1.0	1.0	0.26
Healthy	Accuracy	96.20	98.7	93.6	96.02	91.13
	F1-Score	0.96	0.98	0.93	0.96	0.91
	Precision	0.96	0.98	0.93	0.96	0.91
	Recall	0.96	0.98	0.93	0.96	0.91
PLS	Accuracy	89.55	89.55	94.02	97.01	35.82
	F1-Score	0.89	0.89	0.94	0.97	0.35
	Precision	0.89	0.89	0.94	0.97	0.35
	Recall	0.89	0.89	0.94	0.97	0.35

Output for Grape with External Dataset

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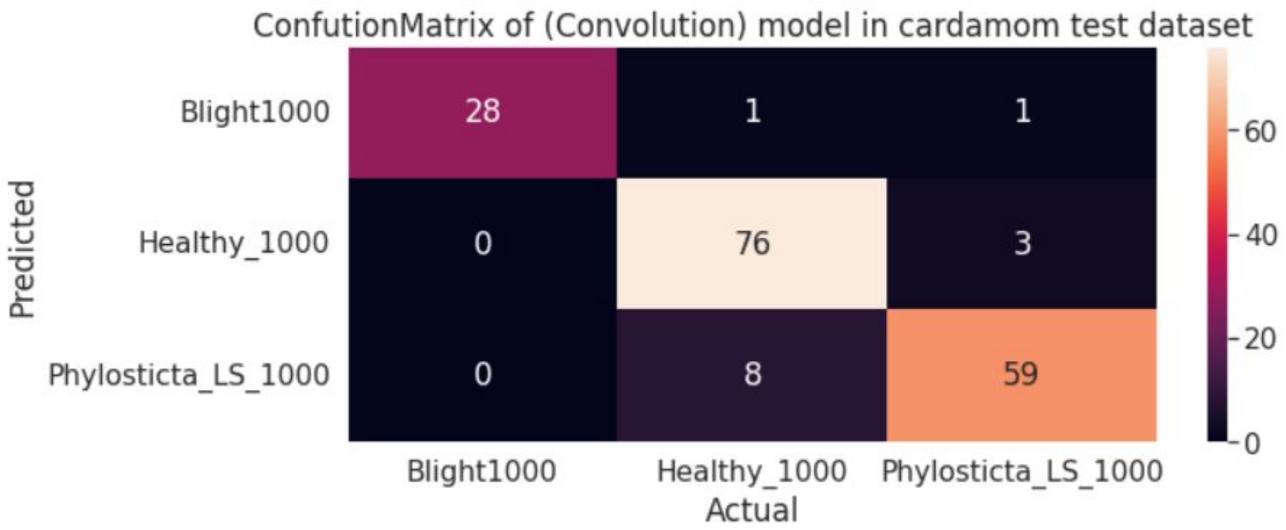
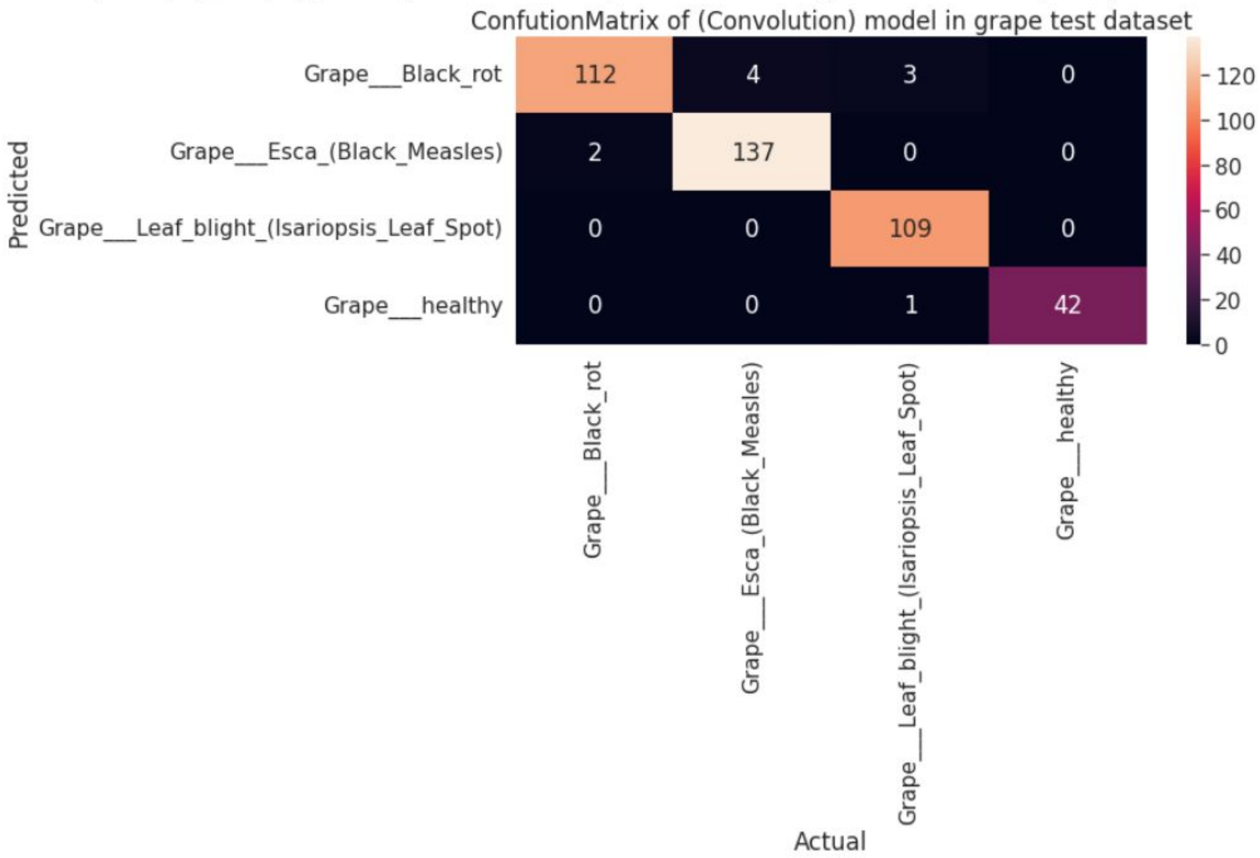
Category	Performance Metric	CNN	EfficientNet	EfficientNet V2-S	EfficientNet V2-M	EfficientNet V2-L
Black Rot	Accuracy (%)	99.15	89.07	93.27	100	94.95
	F1-Score	0.99	0.89	0.93	1.0	0.94
	Precision	0.99	0.89	0.93	1.0	0.94
	Recall	0.99	0.89	0.93	1.0	0.94
ESCA	Accuracy (%)	97.12	97.84	100	99.28	97.84
	F1-Score	0.97	0.97	1.0	0.99	0.97
	Precision	0.97	0.97	1.0	0.99	0.97
	Recall	0.97	0.97	1.0	0.99	0.97
Healthy	Accuracy (%)	97.67	100	95.34	100	100
	F1-Score	0.97	1.0	0.95	1.0	1.0
	Precision	0.97	1.0	0.95	1.0	1.0
	Recall	0.97	1.0	0.95	1.0	1.0
LeafSpot	Accuracy (%)	99.08	98.16	100	97.24	100
	F1-Score	0.99	0.98	1.0	0.97	1.0
	Precision	0.99	0.98	1.0	0.97	1.0
	Recall	0.99	0.98	1.0	0.97	1.0

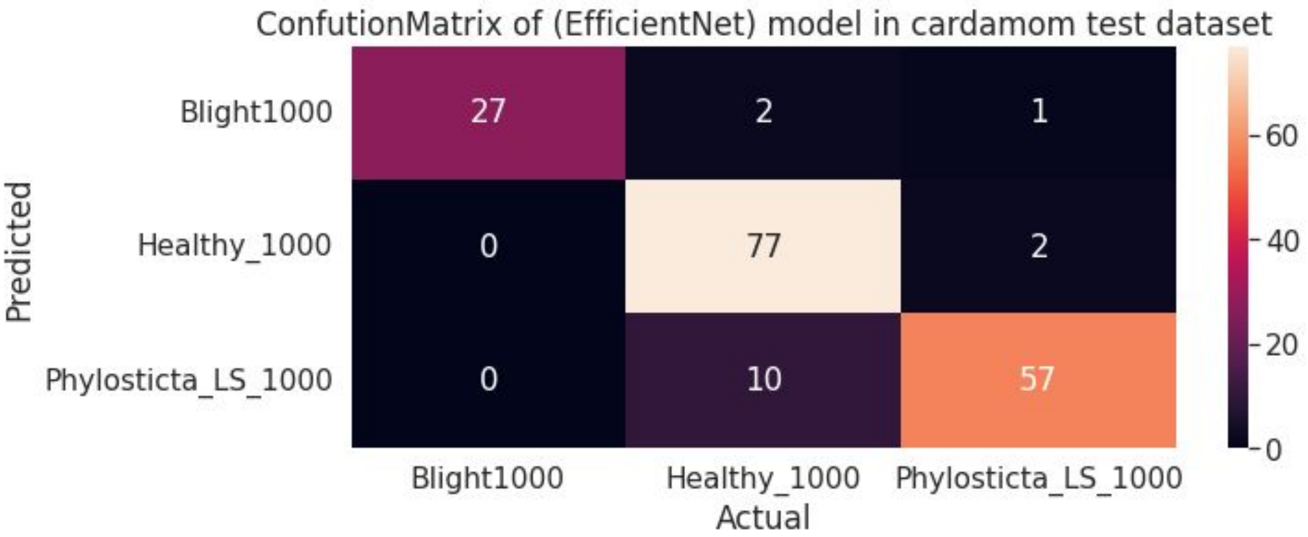
Confusion matrix of Convolution Model



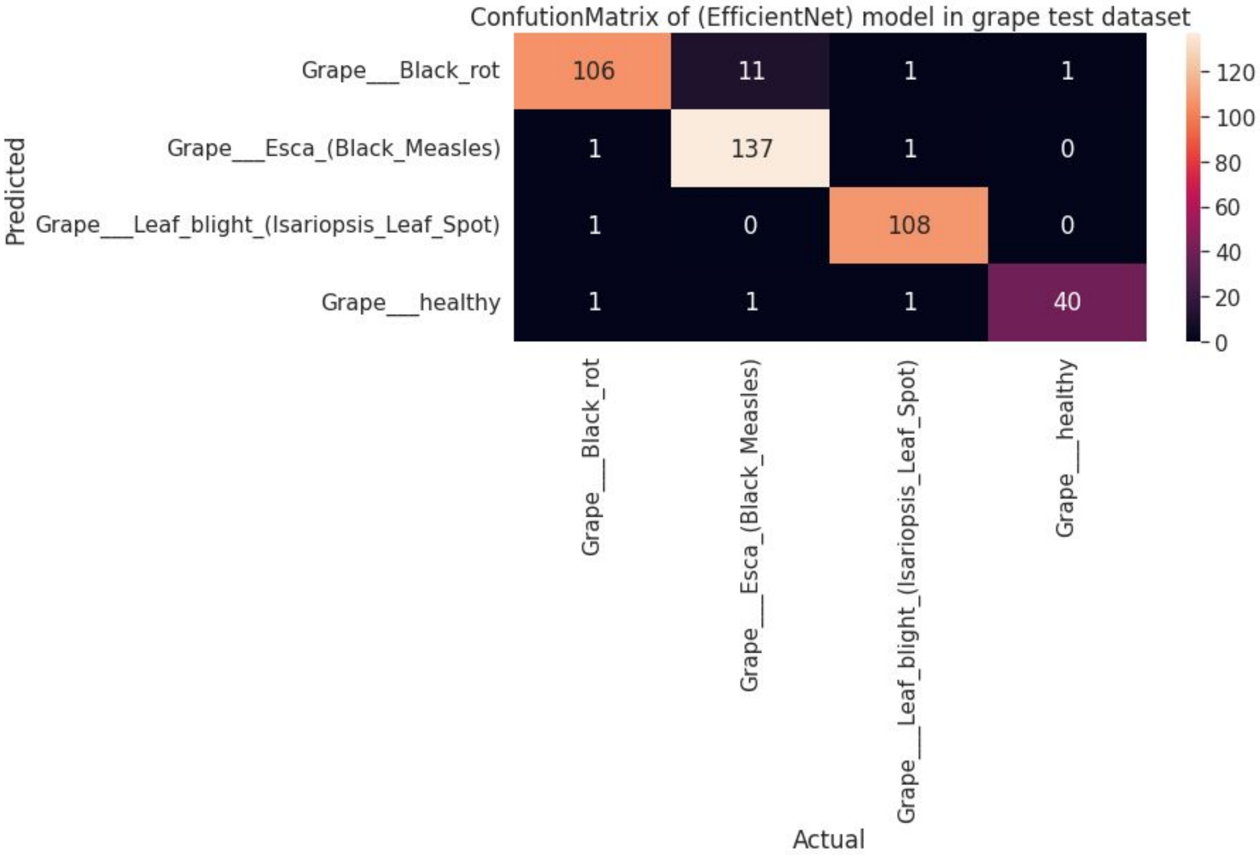
Confusion matrix of Convolution Model



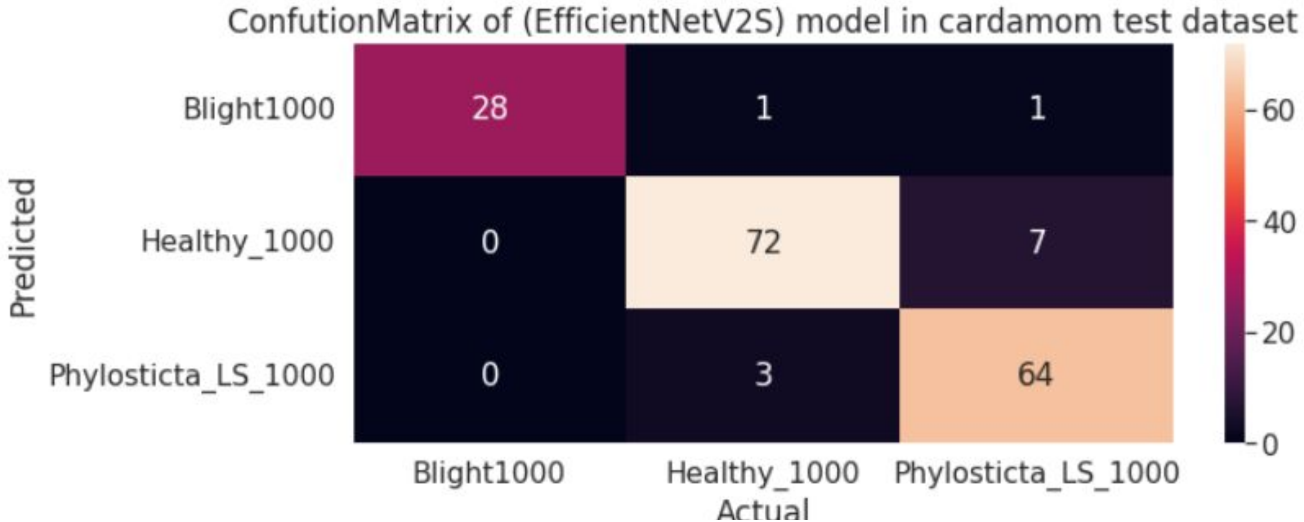
Confusion matrix of EfficientNet Model



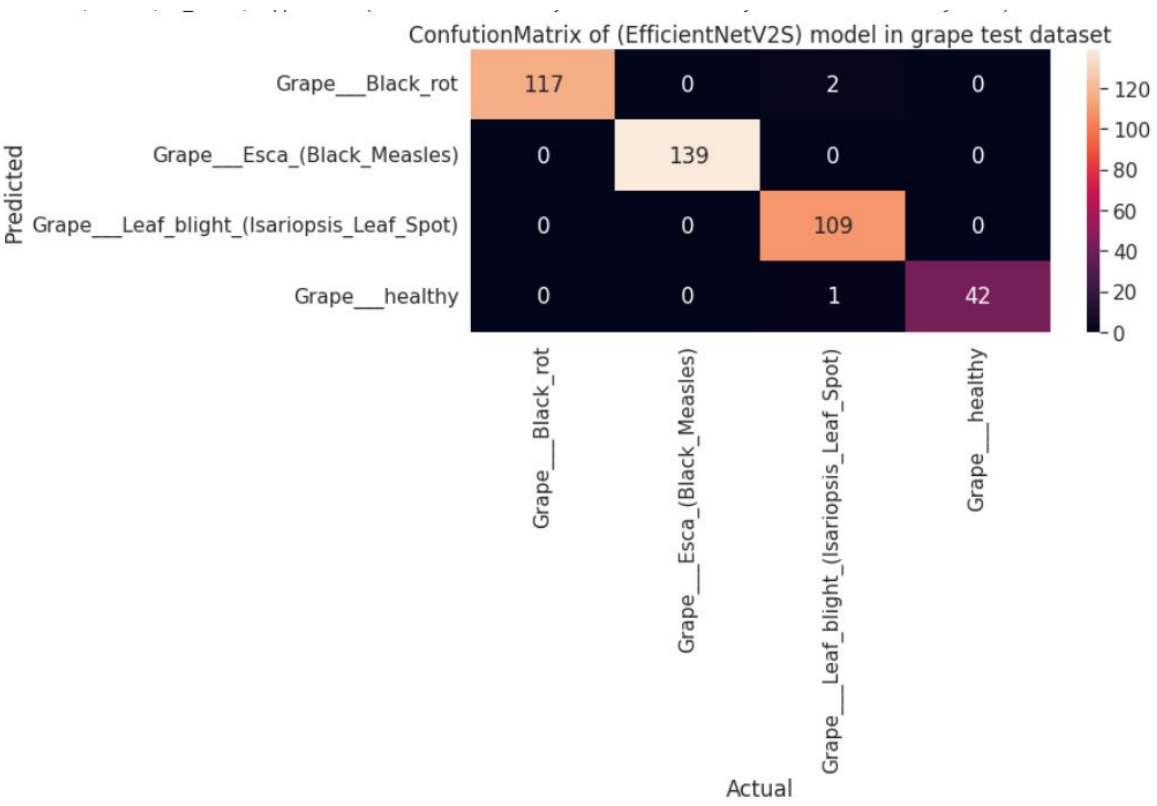
Confusion matrix of EfficientNet Model



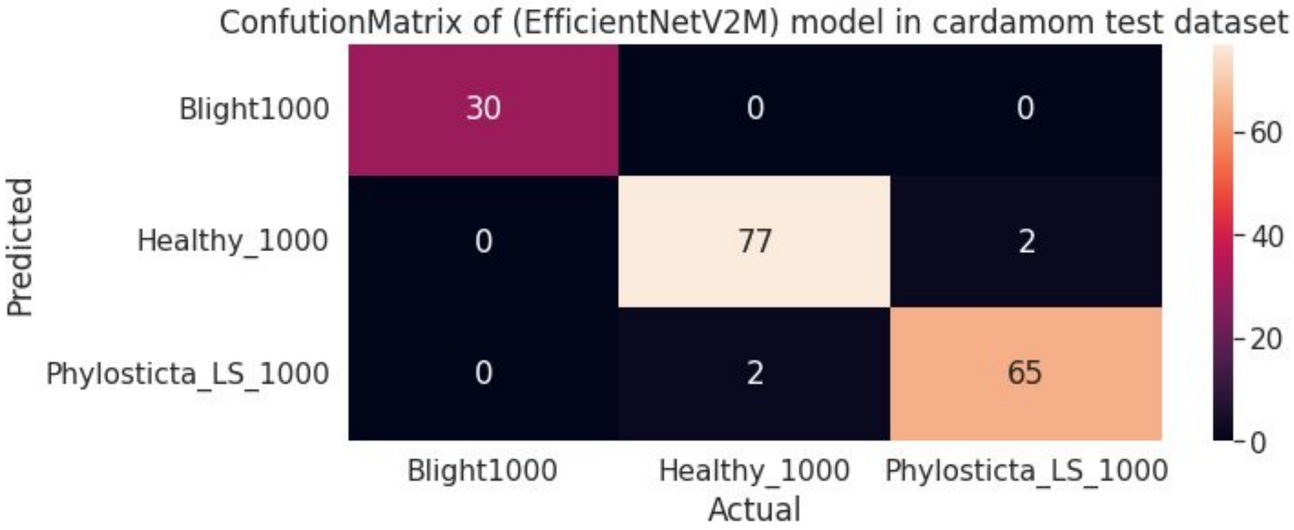
Confusion matrix of EfficientNetV2-S Model



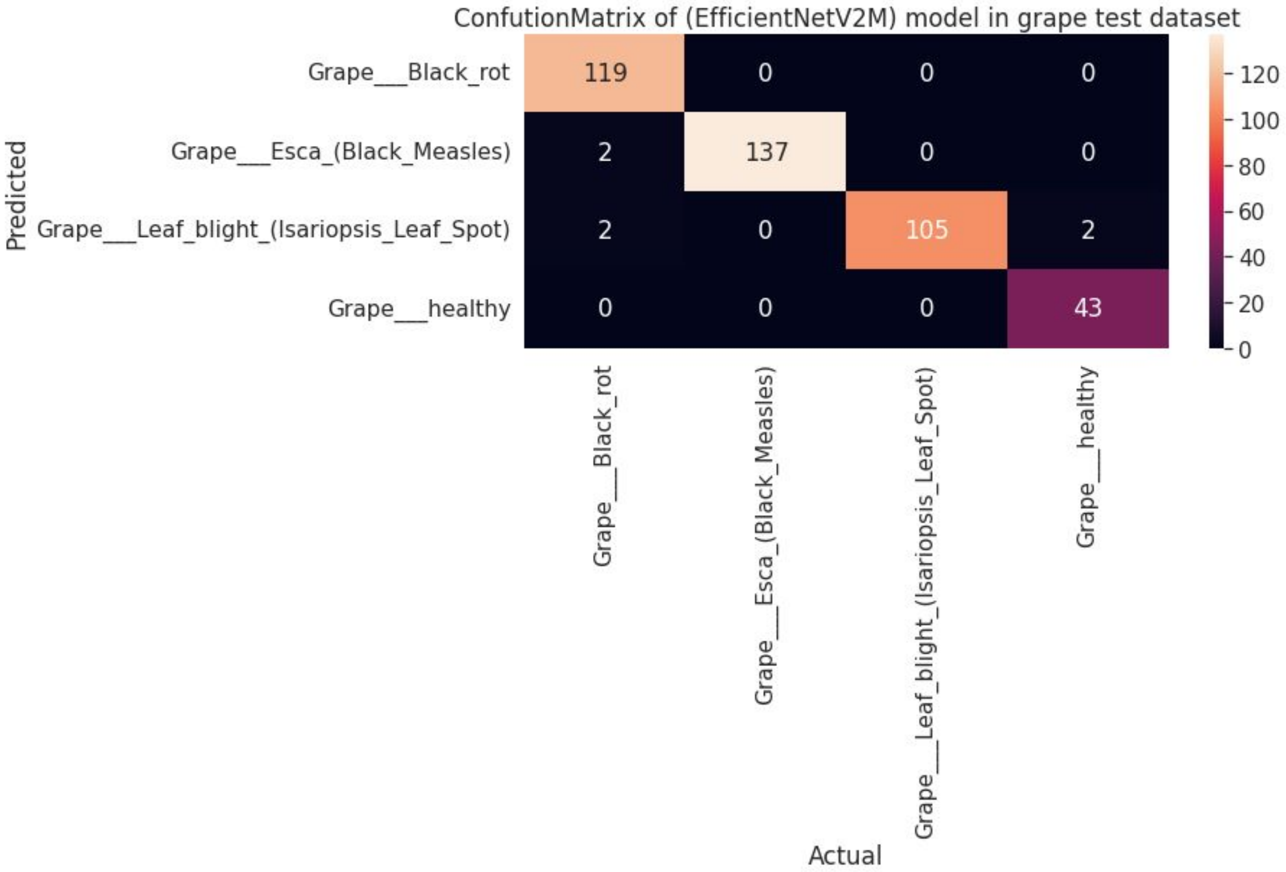
Confusion matrix of EfficientNetV2_S Model



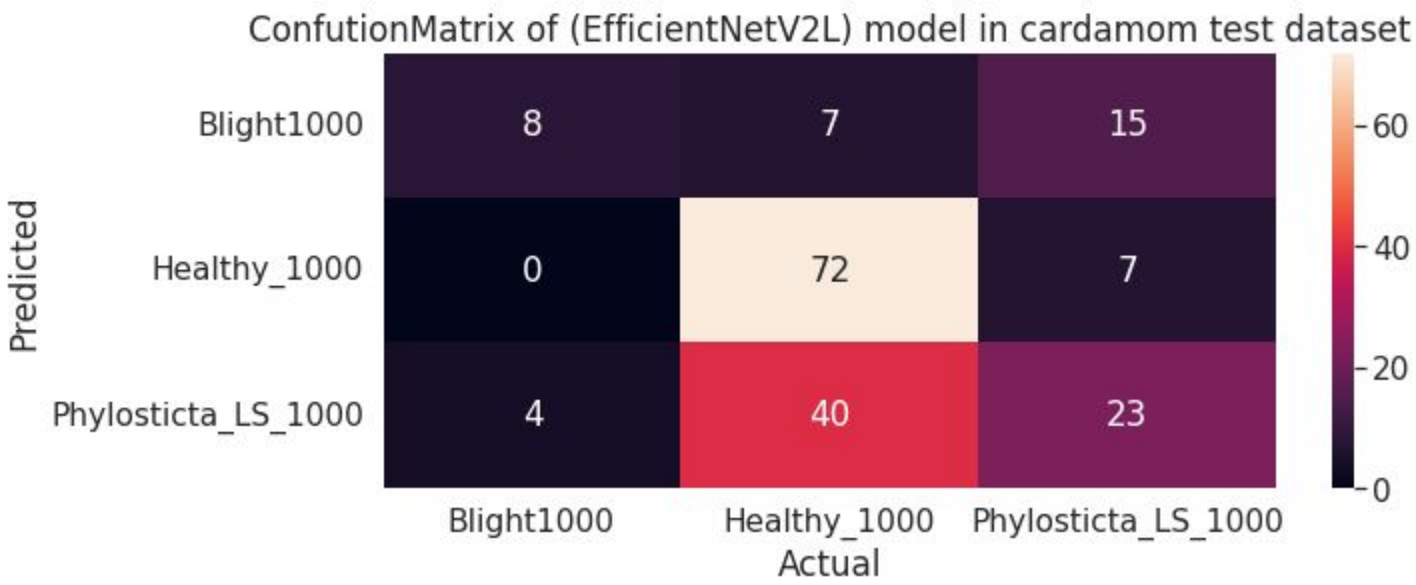
Confusion matrix of EfficientNetV2_M Model



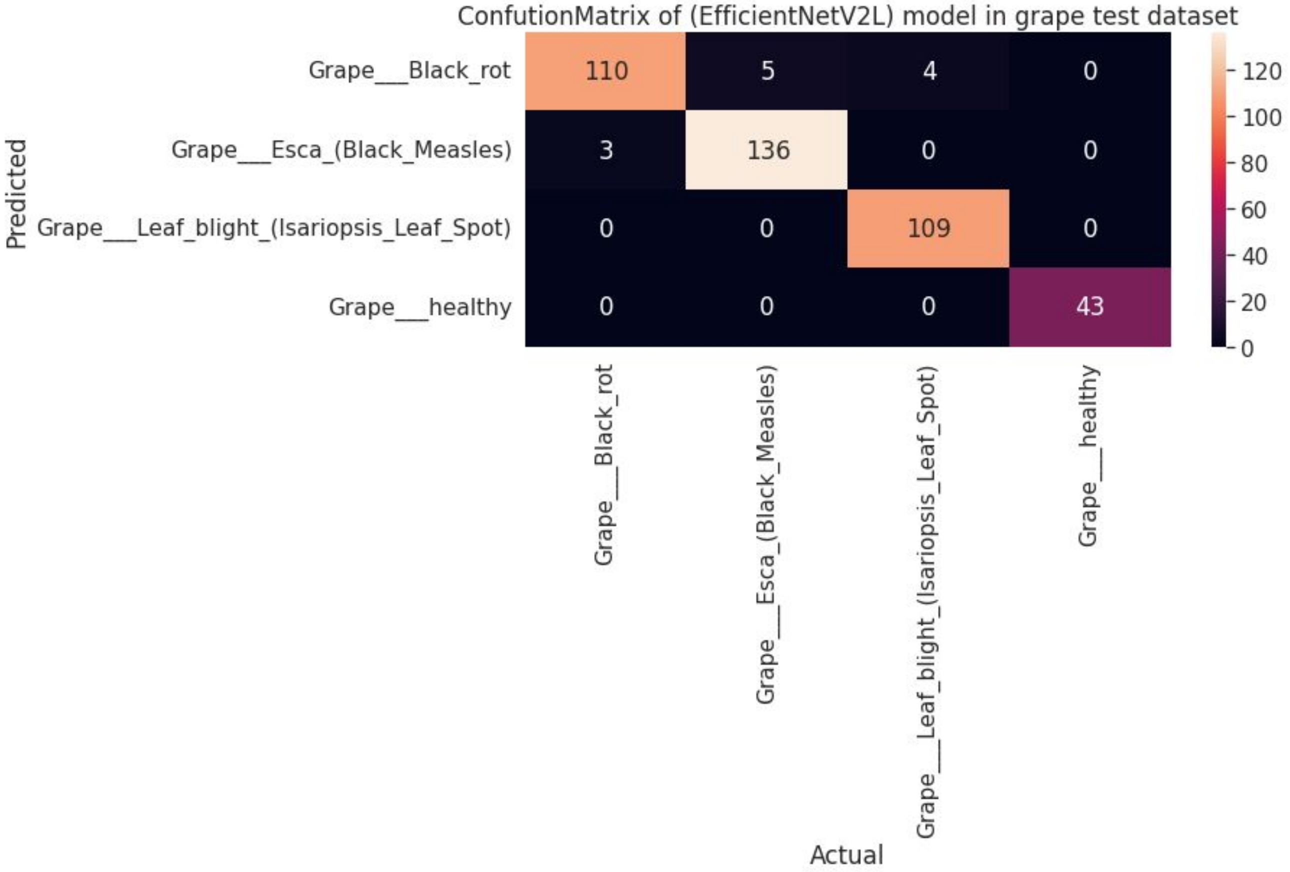
Confusion matrix of EfficientNetV2_M Model



Confusion matrix of EfficientNetV2_L Model



Confusion matrix of EfficientNetV2_L Model



Testing on Whole Dataset

Sl. No	Plant Name	Performace Metrics	CNN	EfficientNet	EfficientNet V2-S	EfficientNet V2-M	EfficientNet V2-L
		Accuracy(%)	92.6134	91.47	93.18	97.72	58.52
		F1-Score	0.933	0.92	0.938	0.981	0.5063
1	Cardamom	Precision	0.943	0.938	0.945	0.981	0.594
		Recall	0.923	908	0.933	0.981	0.507
		Accuracy(%)	97.56	95.36	99.26	98.53	97.07
2	Grape	F1-Score	0.977	0.953	0.991	0.983	0.975
		Precision	0.979	0.96	0.993	0.98	0.975
		Recall	0.975	0.949	0.989	0.987	0.976

5 - fold Accuracy for cardamom

model_name	5_Fold	5_Fold_accuracy
cnn	[0.9169054627418518, 0.9283667802810669, 0.9312320947647095, 0.8939828276634216, 0.9281609058380127]	0.919729614
efficientnet	[0.8968481421470642, 0.9111747741699219, 0.9197707772254944, 0.9197707772254944, 0.916666865348816]	0.912846231
efficientnet_v2l	[0.9512894153594971, 0.8997134566307068, 0.9197707772254944, 0.9169054627418518,0.9219197779893875]	0.9219

5 - fold Accuracy for grape

model_name	5_Fold	5_Fold_accuracy
cnn	[0.9754601120948792, 0.9693251252174377, 0.9864864945411682, 0.974201500415802, 0.974201500415802]	0.975934947
efficientnet	[0.9656441807746887, 0.9619631767272949, 0.9705159664154053, 0.9643734693527222, 0.9815725088119507]	0.96881386
efficientnet_v2l	[0.9645695949145614,0.9811151254457133,0.97156123541321531,0.9763232654123645,0.976321254123665]	0.972361

Conclusion

- The cardamom plant leaf dataset obtained included various unnecessary factors such as the background noise and various environmental factors such as angle of the capture, lighting, etc.
- U^2-Net architecture is utilized to remove the unnecessary and complex background, with which results are obtained without degrading the original image quality.
- CNN, EfficientNet, EfficientNetV2 were the models trained and tested, avoiding the use of pre-trained weights for EfficientNet and EfficientNetv2. EfficientNetV2-S and EfficientNetV2-L models were noted to have prevailed over other models.
- Upon external testing EfficientNetV2-S achieved 99.26% detection accuracy respectively.

Reference

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