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Rice Disease Detection Using Deep Learning VGG-16 Model and Flask

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Abstract

As we all know 70 percent population of our country depends on agriculture. India is the second largest producer of rice and wheat.Agriculture is an impor-tant sector of Indian of Indian economy as it contributes about 17 percent of the total GDP and provide employment to over 60 percent population.Indian agriculture registered impressive growth over last few years, but due to various kinds of diseases this production rate was affected very much.In agriculture field disease management is the process of reducing disease in crops to enlarge quality and quantity of harvest yield.Creatures that cause contagious disease in crops include fungi, bacteria, viruses, virus-like-organisms, phytoplasmas, protojoa, etc. These organisms creates different types of diseases in plants like bacterial leaf blight, brown spot, hispa, leaf smut, black spot, powdery mildew, downy mildew, canker, rust, late blight, etc. In this research paper we are trying to create an web based application that identify some diseases from these which affects rice plant.We are implementing an Convolution Neural Network(CNN) based model named VGG-16 for classification of diseases in rice plant.As CNN is very highly accurate for prediction in image classification.

Keywords: Disease detection, Image processing, CNN, VGG-16, Deep learning.

Introduction

Plant disease detection is an important aspect of crop management, as it al-lows early identification and treatments of diseased plants. This can help to prevent the spread of the disease to other healthy plants, as well as minimize crop loss.There are variety of techniques that used for plant disease detection, including visual inspection, laboratory testing and the use of technology such as imaging and sensor system. One common method of plant disease detection is visual inspection, which involves looking for signs of disease on plant, such as discoloration, wilting or the presence of disease causing organisms. This method can be effective for identifying some diseases, but it can be time consuming and may not detect disease that don’t have visible symptoms. So visual inspection is a common method, but new technologies such as imaging and sensor system are showing promise as a way to detect disease at an early stage and with greater accuracy.

It is very difficult to invigilate plants developing in wet-lends like, rice plants, that is the idea of our study in this, as contrast to other plants species.In this study we discuss about detecting the disease of rice plant, which is used in al-most every country in the world, by using image processing and convolution neural network. There are some common diseases found in rice plants are, Bac-terial Leaf Blight, Brown Spot, Leaf Smut and Leaf Blast.These disease shows variation in accordance with to expanding section.Consequently this is challeng-ing to achieve the data essential for grouping of all diseases.In this study, four classification were made verifying to the data-set achieved. First three classes combines image of brown spot, neck blast and Leaf blast, and the fourth class concludes images of healthy rice plants.

A Convolution Neural Network is a part of neural network that is particularly well suited for image and video processing tasks. CNNs are based on the idea of ”convolution” operation, which involves taking a small matrix (known as filter or kernel) and sliding it over the input data, performing a dot product at each position to produce a new output feature map. One of the key features of CNNs is the use of multiple layers, each of which build on the output of the previous layer to extract increasingly complex feature from the input data.

In this study we use VGG-16 CNN based model for classification of diseases.

2.1 VGG-16 Model

VGG-16 is a convolution neural network model that was trained on the image net data-set. It was developed by Visual Geometry Group(VGG) at the univer-sity of Oxford and introduced in 2014. The 16 in VGG-16 refers to the numeral of weight layers in the model.VGG-16 is known for its deep architecture, with a total of 16 layers and for its use of small convolutional filter (3*3) that are stacked together to form a deep network. It is widely used for image classifica-tion and object detection tasks.

Figure 1 shows the architecture of VGG-16 Model.

VGG is although a relatively large-scale network with a total of 138 million parameters- it's massive even by today's recognized. Still the integrity of the vgg16 architecture is its main interest.The vgg architecture associates the most needy convolutional neural network features.

Figure 2 shows the architecture of Feature Extraction by VGG-16 Model.

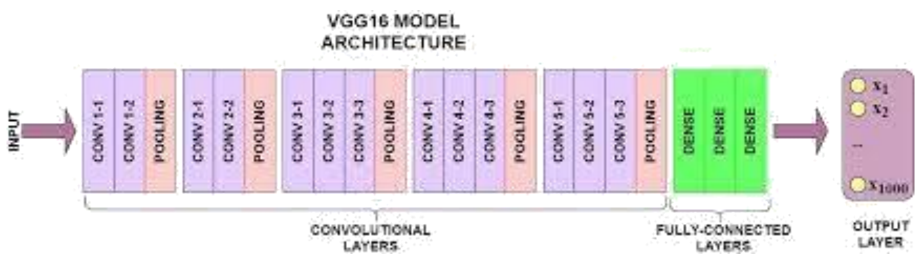

Figure 1: Architecture of VGG-16 Model

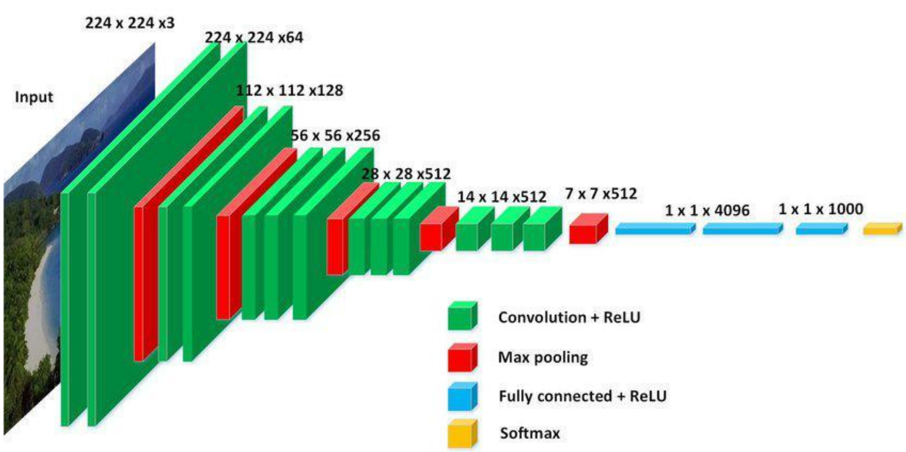

Figure 2: Architecture of Feature Extraction by VGG-16

A vgg network comprise of limited convolution filters. VGG-16 has three fully connected layers and thirteen convolution layers. Here is a rapid outline of the vgg architecture:-

Input- VGGNet takes a 224×224 image input.In the image-net clash, the model originator’s kept the input image size unvarying by cropping 224×224 section from the center of image.

Convolution Layers-the convolutional feature of vgg use the slightest desir-able approachable field of 3×3 . VGG also uses 1×1 convolution filter as the input straight transformation.

reLu Activation- next is the rectifier Linear unit (reLu) activation function element, Alexnet big modernization for lowering training time.

Hidden Layers- all the vgg network’s hidden layers are reLu instead of limited response normalization like alexnet.

Pooling Layers- A pooling layer chases several convolutional layers - this sup-port lower the dimensionality and the number of parameters of the feature maps constructed by each convolutional stride.

Fully Connected Layers- VGGNet combines 3 fully connected layers.The 1st two layers each have 4096 channels and the third layer has 1000 channels, one for each class.

Figure 3 shows the Configuration of VGG-16 Model.

2.2 Literature Review

2.2.1 Paper 1

In base paper[1] Irfan Okten et al. used image processing and Probabilistic Neural Network for recognition of rice leaves diseases on a small size data-set. And he get an accuracy of 76 percent.They use median filter for image pre-processing and after that they use otsu segmentation method for thresholding of image. And glcm method for feature extraction and at last PNN is used for classification.

Advantages:

1.Good generalization capabilities.

2.PNNs can be forceful, even when the training has some predilection.

Disadvantages

1. Gradual training.
2. Hard to comprehend the design of algorithm.

2.2.2 Paper 2

Ali Javed and Waleed Albattah et al.[2] used artificial intelligence based drone system using an improved efficient convolution neural network for plant disease detection.

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Advantages

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 Weight Layers	11 Weight Layers	13 Weight Layers	16 Weight Layers	16 Weight Layers	19 Weight Layers
Input (224*224 RGB image)					
Conv3-64	Conv3-64 **LRN**	Conv3-64 **Conv3-64**	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64
maxpool					
Conv3-128	Conv3-128	Conv3-128 **Conv3-128**	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128
maxpool					
Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256 **Conv1-256**	Conv3-256 Conv3-256 **Conv3-256**	Conv3-256 Conv3-256 Conv3-256 **Conv3-256**
maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 **Conv1-512**	Conv3-512 Conv3-512 **Conv3-512**	Conv3-512 Conv3-512 Conv3-512 **Conv3-512**
maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 **Conv1-512**	Conv3-512 Conv3-512 **Conv3-512**	Conv3-512 Conv3-512 Conv3-512 **Conv3-512**
Maxpool					
FC - 4096					
FC – 4096					
FC – 1000					
Soft-max					

Figure 3: VGG-16 Configuration

1.Straight-forward

2.Strong with complements to search space

Disadvantages

1.Costly testing of each illustration.

2.Consciousness to noisy or inappropriate inputs.

2.2.3 Paper 3

Yuan Rao and Fengyi Wang et al.[3] used improved swim transformer algorithm for cucumber plant disease detection.The proposed approach has the probable of negotiation with the usual competition of inadequate data-size and compli-cated environment in other comparable plant science assignments.
Advantages

1.Requisition less solemn statistical training.

2.Capability to implicitly detect complicated non linear.

Disadvantages

1.Higher calculation burden.

2.Inclination to over-fitting.

First thing for our study, the data-set for diseased and healthy leafs of the rice plants was collected from Kaggle web-page[13].The neuralNet was trained with the images of diseased and healthy rice leafs obtained from Kaggle web page.

In sequence to analyze the accuracy of the built network, the images of diseased and healthy rice plant gave to the network and the result was examined. An accuracy rate of 90 percent was achieved as a result of the testing.

3 Proposed Model

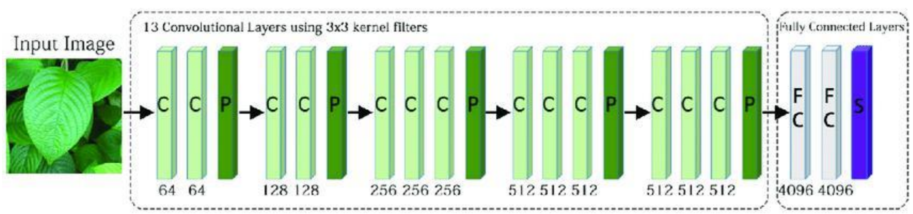

Figure 4: Process of Proposed Model

The present study comprise of four steps in order to find out the health state of the rice plants.

Figure 4 shows the Process of Proposed Model.

In the 1st step, taking rice images as input and Data Augmentation is carried out to increase the size of data-size taken.

In the second part, image pre-processing is carried out to process all the in-put images to prepare pictures data for model input.For instance, convolution neural network fully connected layers demanded that all the images be in ar-rays of the same size. Additionally, model pre-processing may shorten model training time and speed up model inference.

In third step, Neural Network model VGG-16 was applied for classification of leaves either it is healthy or diseased plant leaf.

In fourth step, we create a flask web app for making prediction using VGG-16 model.

In this study we make some modification in inbuilt vgg-16 model to increase its accuracy.

In this study we train our model for approx 4600 image data-set downloading from Kaggle. We have four classes in given data-set as neck blast, brown spot, leaf blast and healthy leaf's.In training phase we have 4000 images belonging to four classes and in validation phase we have 400 images which are also belongs to five classes. After compiling the model we have to train the model. After training we get 90 Percent Accuracy, which is far better then our base paper.

The flowchart for prospective system is as revealed below in Figure 5.

3.1 Data Set

VGG-16, specific convolution's neural network is used for plant disease detec-tion.The rice leaves images necessary for training of network were collected from the Kaggle web-page.A total of 4500 images of rice were collected,4000 im-ages used for training the model and 400 images used for validation of trained model.In this data-set there are four classes as healthy, leaf blast, brown spot, neck blast.

3.2 Image Pre-processing in CNN

Image pre-processing is advancement of image data that compress deformation and enhance some image features which are essential for further processing. In this study we modify our pre-processing step as it takes input image of size 224 with batch size 64.And dividing the data-set in train data generator and test data generator with data augmentation (process of increasing data-set size by re-scaling, zooming and flipping.

Data acquisition pre-processing process is shown in Figure 6.

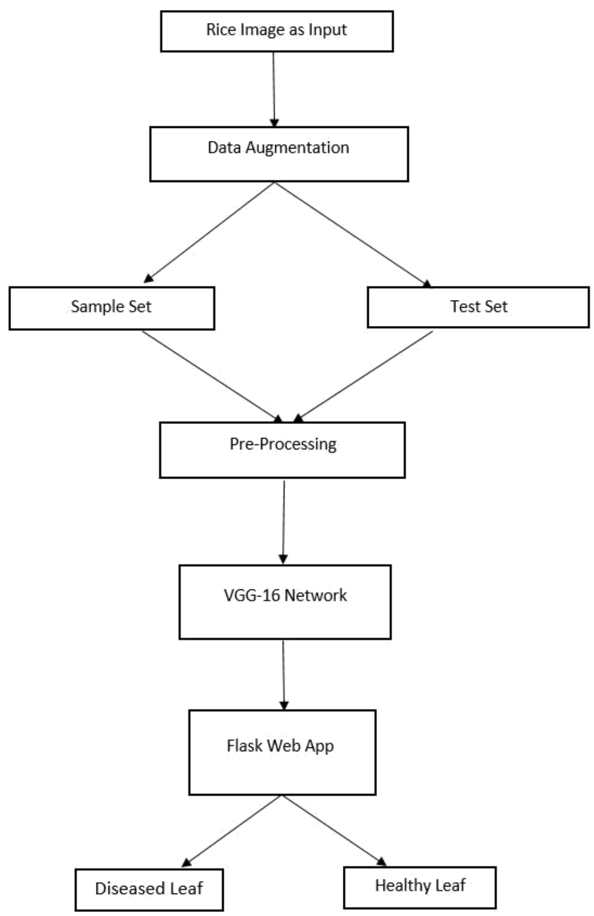

Figure 5: Flowchart For Proposed System

Algorithm:

- scan the picture files (saved on drive)
- Decrypt the JPG content to RGB grids of pixels with channels
- Covert these into floating-point tensors for input to neural networks
- Formulate the pixel values (between 0, 255) to the [224,224,3] interval (as neural network this length gets efficacious)

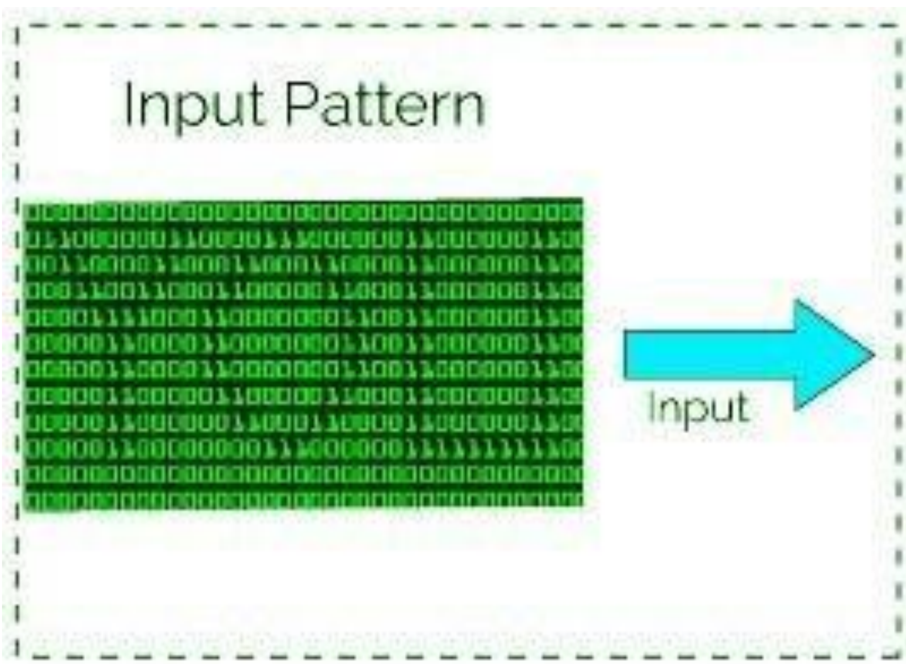

Figure 6: Data Acquisition Pre-Processing

3.3 Computations in VGG-16

The method involved in determining the output size from each convolution layer is written as -

[(N-f)/S]+1

Where, N = input size (224), f = Kernel size (3), S = Strides The model summary is as shown in Figure 7:

As we can see there are 14 million plus parameters in VGG-16 for training, out of which we only use 1 lac plus parameters for our model training with given data-set.And remaining parameters are still available for training.

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 244, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 244, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 244, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 4)	100356

Total Params : 14,815,044
Trainable Params : 100,356
Non-trainable Params : 14,714,688

Figure 7: Model Summary

4 Discussion and Result

Flask is a mini Web Framework dictated in Python.It is categorize as a mini framework because it doesn't needs appropriate tools or libraries. It has no database consideration layer from validation or any other elements where pre-ceding third party libraries supply common functions.Flask is used for develop-ing web applications using python.

The graphical user interface of Plant Disease Detection is as shown in Figure 8. Advantages

1.There is a built in development server and a fast debugger provided.

2.Scalable

3.Easy to negotiate

4.Lightweight

5.Not a lot of tools

6.Flexible

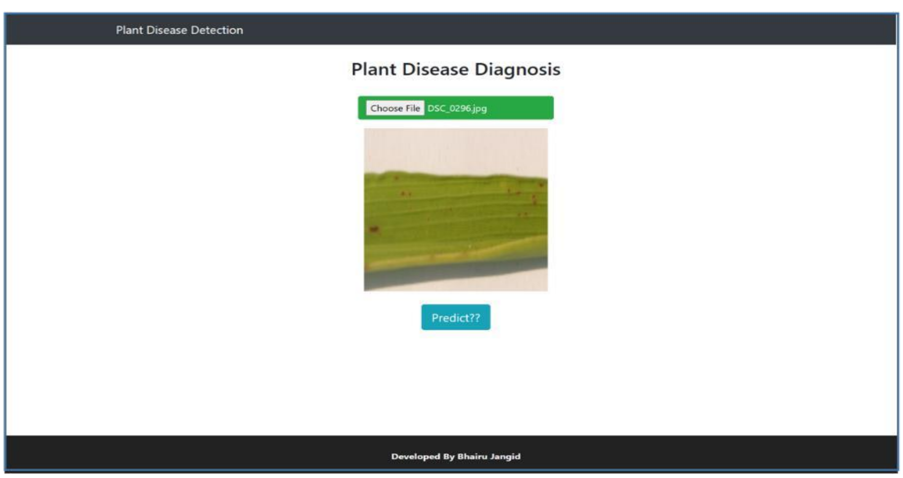

Figure 8: The intrusion of Plant Disease Detection Graphical User Interface

In this interference firstly, we load an image from disk (system) and after load-ing we have to click on Predict?? button to running the model and predicting about diseases present on rice leaf.

4.1 Result

When we train our inbuilt vgg-16 model with some modification then the ac-curacy of trained model on 50 epochs is as shown in Figure 9. Figure 9 shows the training and validation accuracy of trained model with training loss and validation loss.

In trained model the training and validation accuracy is increased epoch per epoch as well as the training and validation loss is decreased epoch per epoch.

```
128/128 [==============================] - 240s 2s/step - loss: 0.1613 - accuracy: 0.8774 - val_loss: 0.3394 - val_accuracy: 0.7143
Epoch 40/50
128/128 [==============================] - 242s 2s/step - loss: 0.1528 - accuracy: 0.8882 - val_loss: 0.2363 - val_accuracy: 0.7906
Epoch 41/50
128/128 [==============================] - 242s 2s/step - loss: 0.1522 - accuracy: 0.8852 - val_loss: 0.2544 - val_accuracy: 0.7512
Epoch 42/50
128/128 [==============================] - 243s 2s/step - loss: 0.1502 - accuracy: 0.8874 - val_loss: 0.2459 - val_accuracy: 0.7931
Epoch 43/50
128/128 [==============================] - 245s 2s/step - loss: 0.1472 - accuracy: 0.8877 - val_loss: 0.2327 - val_accuracy: 0.7709
Epoch 44/50
128/128 [==============================] - 243s 2s/step - loss: 0.1451 - accuracy: 0.8955 - val_loss: 0.2843 - val_accuracy: 0.7463
Epoch 45/50
128/128 [==============================] - 243s 2s/step - loss: 0.1405 - accuracy: 0.9004 - val_loss: 0.2151 - val_accuracy: 0.8103
Epoch 46/50
128/128 [==============================] - 243s 2s/step - loss: 0.1427 - accuracy: 0.9012 - val_loss: 0.2566 - val_accuracy: 0.7808
Epoch 47/50
128/128 [==============================] - 244s 2s/step - loss: 0.1465 - accuracy: 0.8955 - val_loss: 0.2295 - val_accuracy: 0.7956
Epoch 48/50
128/128 [==============================] - 246s 2s/step - loss: 0.1433 - accuracy: 0.8906 - val_loss: 0.2262 - val_accuracy: 0.8153
Epoch 49/50
128/128 [==============================] - 243s 2s/step - loss: 0.1428 - accuracy: 0.8938 - val_loss: 0.2923 - val_accuracy: 0.7685
Epoch 50/50
128/128 [==============================] - 244s 2s/step - loss: 0.1488 - accuracy: 0.8828 - val_loss: 0.2600 - val_accuracy: 0.7808
```

Figure 9: Accuracy Result of Trained Network

4.2 Google Colaboratory

Google Colab is a excellent platform for Deep Learning admirer, and it can also be used to test basic machine learning models, achieve experience and establish an intuition about deep learning condition such as hyperparameter tuning, pre-processing data, model-complexity , over-fitting and more.

We train our model on Google Colab, because Google Colab provide us the facility of GPU and TPU as the run-time environment.As we know we can’t train our model on our system CPU because it takes a day or sometime even weeks to train and for management of time we can’t do this.And on google colab we will able to train our model within 2 hours.

4.3 Training and Validation Curve

The training and validation curve is representing training accuracy, training loss and validation accuracy, validation loss. As we can see that the training and validation accuracy is increased and the training and validation loss is decreased.

The training and validation accuracy and loss is shown in Figure 10.

5 Conclusion

Inside the outlook of our study, the disease of rice plants was exposed using VGG-16 model, which is one of the Convolution Neural Network. For the iden-tification of diseases, leaves pictures of 4500 rice plants were collected and VGG-16 was trained with these pictures.Here a new method of using deep learning method was examined in order to spontaneous classify and discover plant dis-ease from leaves pictures. An accuracy rate of 90 percent was achieved when the rice plants pictures that it had never watched were provide to the VGG-16. A GUI has been improved to accomplish all these actions. When the detection of disease in the rice plant is collated with other neural network models, it has been noticed that the training duration is much smaller.

In this study, the improved model was able to detect leaves between healthy and diseased.

In future studies, i'll try to implement it as an android application with ex-tending it to more types of diseases on very large size data-set. An application which can able to run on any android or IOS device without an error to helps farmers with less effort.

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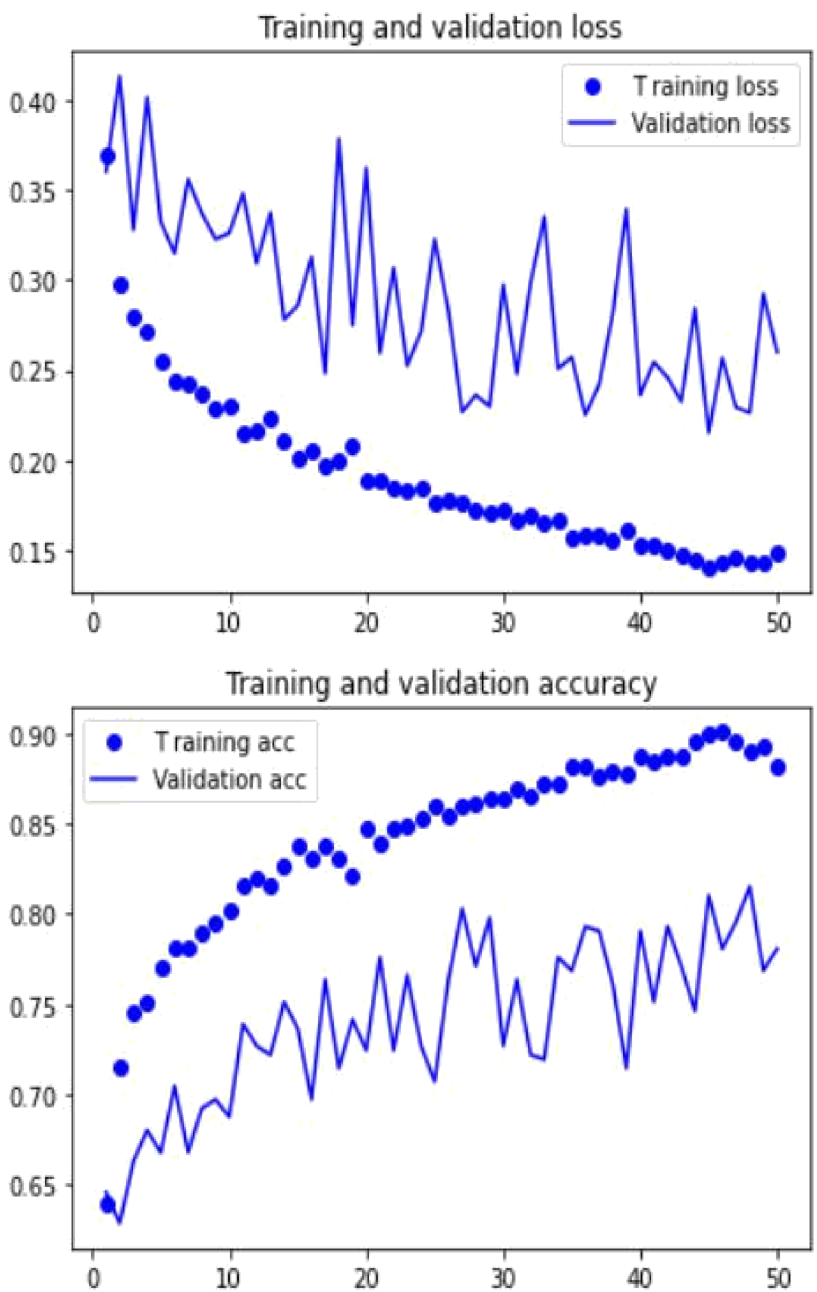

Figure 10: Training and Validation Curve

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