

**An Industrial Oriented Mini Project Report  
on**

**LEAF DISEASE DETECTION**

**Submitted in partial fulfillment of the requirements for the  
award of the degree of**

**BACHELOR OF TECHNOLOGY**

**in**

**COMPUTER SCIENCE AND ENGINEERING**

**by**

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**BVRIT HYDERABAD College of Engineering for Women**

**(NBA Accredited – EEE, ECE, CSE and IT)**

**(Approved by AICTE, New Delhi and Affiliated to JNTUH, Hyderabad)**

**Bachupally, Hyderabad – 500090**

**2021 - 2022**

## **DECLARATION**

We hereby declare that the work presented in this project entitled **“LEAF DISEASE DETECTION”** which is being submitted by us in partial fulfillment for the award of the degree of **Bachelor of Technology** in the department of **Computer Science and Engineering** at **BVRIT HYDERABAD College of Engineering for Women** affiliated to **Jawaharlal Nehru Technological University Hyderabad** Kukatpally, Hyderabad – 500085 is the result of original work carried out by us under the guidance of **Dr. Nara Sreekanth**, Associate Professor, Department of CSE.

This work has not been submitted for any Degree / Diploma of this or any other institute/university to the best of our knowledge and belief.

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### **Certificate**

This is to certify that an Industrial Oriented Mini Project Work report, entitled **“LEAF DISEASE DETECTION”** is a bonafide work carried out by Ms. A. MARY PRANAVI (18WH1A0563), Ms. H. SHILPA RANI (18WH1A0577) in the partial fulfillment for the award of B.Tech. degree in **Computer Science and Engineering, BVRIT HYDERABAD College of Engineering for Women, Bachupally, Hyderabad**, affiliated to **Jawaharlal Nehru Technological University Hyderabad**, Hyderabad under my guidance and supervision.

The results embodied in the project work have not been submitted to any other University or Institute for the award of any degree or diploma.

Guide

**Dr. Nara Sreekanth**

**Associate Professor,CSE**

Head of the Department

**Dr.K.Srinivasa Reddy**

**Professor and HoD,CSE**

External Examiner

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## **ABSTRACT**

Agricultural productivity is something on which economy highly depends. This is the one of the reasons that disease detection in plants plays an important role in agriculture field, as having disease in plants are quite natural. If proper care is not taken in this area then it causes serious effects on plants and due to which respective product quality, quantity or productivity is affected. Detection of plant disease through some automatic technique is beneficial as it reduces a large work of monitoring in big farms of crops, and at very early stage itself it detects the symptoms of diseases i.e. when they appear on plant leaves. This project presents a real time method based on deep convolutional neural network for corn leaf disease recognition. In comparison with other deep-learning models, the implemented model achieved better performance in terms of accuracy and it required less training time. The accuracy results in disease detection demonstrated that the deep CNN model is potential and could have a significant impact on disease detection efficiency, as well as potential in disease detection in real-time farming methods.

### **LIST OF FIGURES**

S.No	Description	Page. No
1	Architecture	11
2	Flow Diagram	12
3	Sample Output	18

## **LIST OF CONTENTS**

S.No	Topic	Page No.
1	Introduction	8
2	Literature survey	9
3	Design	11
4	Implementation	13
5	Results	18
6	Conclusion & Future scope	21
7	References	22

## **1.INTRODUCTION**

### **1.1 Problem statement:**

During their growing stages, plants are susceptible to a variety of illnesses. One of the most difficult challenges in agriculture is early diagnosis of plant diseases. If illnesses are not detected early on, they can have a negative impact on the overall output, resulting in lower revenues for farmers.

**1.2 Objective:** Plant illnesses are consistently observed with the naked eye, prompting people to make complex decisions about which fertilisers to use. It necessitates in-depth knowledge of disease kinds as well as a great deal of expertise to ensure accurate disease identification. To solve this problem, we devised a Deep Learning-based method for identifying plant diseases.

**1.3 Proposed system:** To anticipate the disease that has affected the leaf, the proposed method applies a Deep Convolutional Neural Network. The system requires users to upload a leaf image and determine which illness has affected the leaf.

For this system, We gathered a big dataset that are affected by diseases and pests in real-world circumstances. It is divided into four classes: three for diseased, and one for healthy plants. We can see that there are 7316 Train images and 1829 validation images each of them divided again into 4 Classes.

The project used the models in 2 phases:

- Training phase
- Testing phase

In the training phase, the models are set up and trained on the training dataset. Then in the testing phase, the models are tested on testing dataset.



## **2. THEORETICAL ANALYSIS OF THE PROPOSED PROJECT**

### **2.1 Literature Survey**

- The authors of [1] developed a maize leaf feature enhancement framework effectively increase maize features in a pervasive environment. They created the DMS-Robust Deep learning model, a Novel Neural Network based on the backbone CNN architecture. The end result states that DMS-Robust Data augmentation was built for the goal of recognition and classification, and that it offers the greatest level of recognition accuracy.
- The authors of [2] have focused on determining and evaluating maize leaf diseases. They implemented upgraded Googlenet and Cifar10 deep learning models for leaf disease identification, that have since been proposed. These two models are used to train and test nine different types of maize leaf images obtained by optimizing the parameters, modifying pooling combinations, adding dropout procedures, and reducing the number of classifiers. To enable agricultural producers to make timely and sensible decisions based on crop disease data. The trained model can be used in a range of ways using mobile devices.
- The authors of [3] have worked on the identification and classification of maize leaf disease images. They suggested a method of fine-tuning model parameters based on transfer learning EfficientNet in this research, which will increase the accuracy and speed of network recognition for a limited sample of maize disease dataset. To gain richer image data, they performed data cleansing and data augmentation on the dataset. This experimental method could be implemented in mobile devices as a useful tool for diagnosing and treating maize diseases, minimising

disease-related losses.

- In [4], the authors worked on a categorization system for maize leaf disease images. The 200 photos in this experiment are divided into four categories: healthy, cercospora, common rust, and northern leaf blight. Convolutional neural networks (CNN) are a type of neural network that can be used to (CNN). AlexNet, virtual geometry group (VGG) 16, VGG19, GoogleNet, and the Feature extraction obtained features automatically were all examined. Machine learning approaches for classification include k-Nearest neighbour, decision tree, and support vector machine. They also employed AlexNet and support vector machines, which have high accuracy, sensitivity, and specificity, respectively, for the best classifiers.
- In [5], The author worked on increasing the effectiveness and speed of disease detection in real-time maize spraying operations, and he proposed an upgraded ResNet50 maize disease identification model. The maize disease recognition model developed in this paper has a greater recognition accuracy than existing models. Maize mosaic disease, grey leaf disease, rust, leaf blight disease, and maize health are among the five maize illnesses recognised. Dropout strategy and ReLU incentive function are employed between the network layers to avoid overfitting in the training phase. This model provides a high degree of generality and robustness.
- The author [6] has developed a real-time approach for the detection of corn leaf disease using a deep convolutional neural network. On a system with GPU, modifying the hyper-parameters and optimizing the pooling combinations enhances deep neural network performance. The Intel Mo-

vidius Neural Compute Stick, which contains dedicated CNN hardware blocks, was used to deploy this pre-trained deep CNN model onto the Raspberry Pi 3. The accuracy of this model is 88.46 percent. This model can also run on standalone smart devices like as the Raspberry Pi, smartphones, and drones.

## **2.2 Software requirements:**

- Windows 10
- Google Colab

## **2.3 Hardware Requirements:**

- Intel core i3 processor
- RAM 4GB
- Hard Disk Drive 1 TB

### 3. DESIGN

#### Architecture:

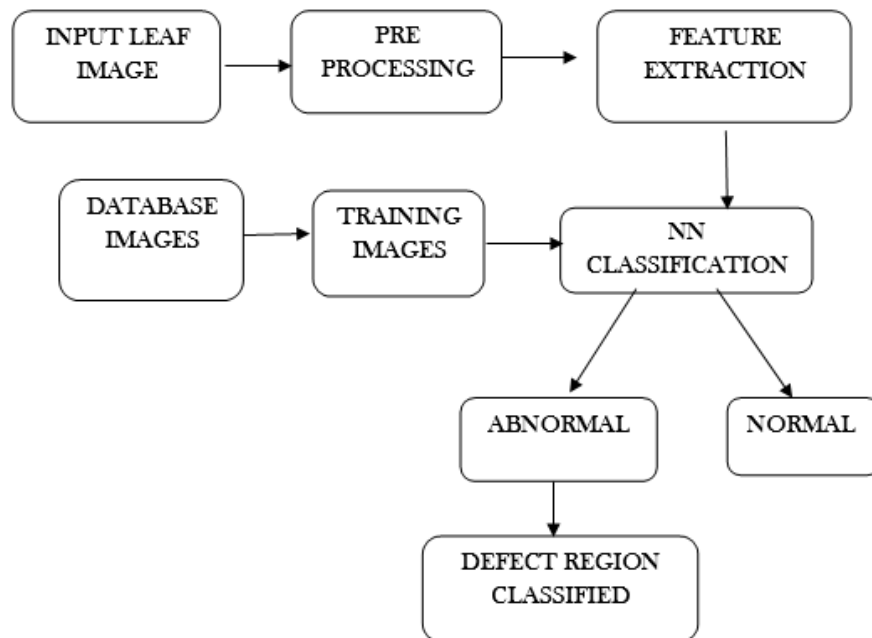


Figure 1. Architecture

### Flow Diagram:

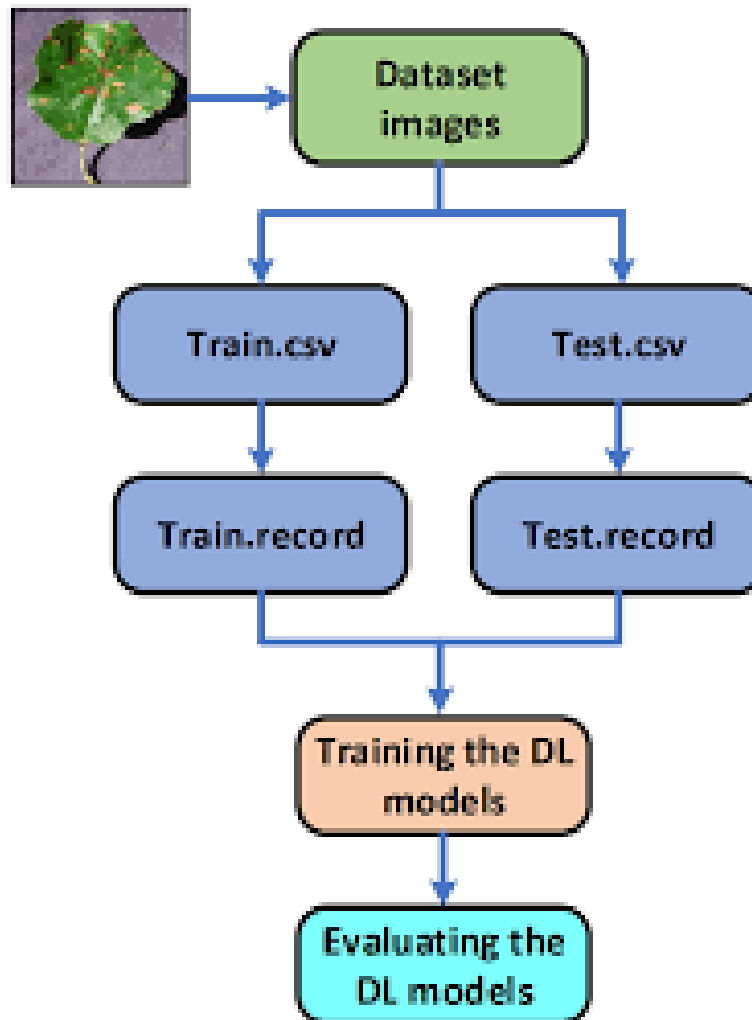


Figure 2. Flow Diagram

## **4. IMPLEMENTATION**

### **4.1 Methodology**

The proposed methodology includes the three important stages namely:

- 1)Data Acquisition
- 2)Pre-processing
- 3)Classification

- Data Acquisition

The acquired dataset consists of around 9145 images belonging to 4 different classes. The dataset includes images of all major kinds of leaf diseases that could affect the maize crop. Each of the downloaded images belongs to the RGB color space by default and were stored in the uncompressed JPG format.

- Pre-processing

The acquired dataset consisted of images with minimal noise and hence noise removal was not a necessary preprocessing step. The images in the dataset were resized to  $60 \times 60$  resolution in order to speed up the training process and make the model training computationally feasible. The process of standardizing either the input or target variables tends to speed up the training process. This is done through improvement of the numerical condition of the optimization problem. It is also made sure that the several default values involved in initialization and termination are appropriate.

- Classification

Convolutional neural networks (CNN) can be used for the creation of a computational model that works on the unstructured image inputs and converts them to corresponding classification

output labels. They belong to the category of multi-layer neural networks which can be trained to learn the required features for classification purposes. They require less pre-processing in comparison to traditional.

## 4.2 Code

```
# -*- coding: utf-8 -*-  
"""LDD.ipynb
```

*Automatically generated by Colaboratory.*

*Original file is located at  
<https://colab.research.google.com/drive/1dq02pkdWoBUCBI6TXib3lhAK9Czi5Erl>  
"""*

```
import os  
import numpy as np  
import glob  
import matplotlib.pyplot as plt  
import keras  
from keras.models import Sequential  
from keras.layers import Conv2D  
from keras.layers import MaxPooling2D  
from keras.layers import Flatten  
from keras.layers import Dense  
from keras.layers import Dropout  
from tensorflow.keras.optimizers import Adam  
from keras.layers import Activation, AveragePooling2D, BatchNormalization
```

```

from keras.preprocessing.image import
    ImageDataGenerator

from google.colab import drive
drive.mount('/content/drive')

!unzip "/content/drive/MyDrive/ML_Project/
_____LeafDisease.zip"

base_dir = os.path.join(os.getcwd(), 'LeafDisease')
base_dir0= os.path.join(base_dir, 'New_Plant_Diseases
Dataset(Augmented)')
base_dir1= os.path.join(base_dir0, 'New_Plant_Diseases
Dataset(Augmented)')
train_dir = os.path.join(base_dir1, 'train')
validation_dir = os.path.join(base_dir1, 'valid')

def get_files(directory):
    if not os.path.exists(directory):
        return 0
    count=0
    for current_path,dirs,files in os.walk(directory):
        for dr in dirs:
            count+= len(glob.glob(os.path.join(current_path,
                dr+"/*")))
        return count

train_samples =get_files(train_dir)
num_classes=len(glob.glob(train_dir+"/*"))
validation_samples=get_files(validation_dir)

```



```

print( num_classes , " Classes " )
print( train_samples , " Train_images " )
print( validation_samples , " validation_images " )

train_datagen=ImageDataGenerator( rescale =1./255 ,
                                   shear_range=0.2 ,
                                   zoom_range=0.2 ,
                                   validation_split=0.2 ,
                                   #validation split 20%.
                                   horizontal_flip=True)
test_datagen=ImageDataGenerator( rescale =1./255)

img_width ,img_height  =256,256
input_shape=(img_width ,img_height ,3)
batch_size  =32

train_generator  =train_datagen.flow_from_directory
( train_dir ,target_size=(img_width ,img_height) ,
  batch_size=batch_size )
test_generator=test_datagen.flow_from_directory
( validation_dir ,shuffle=True ,target_size=
  (img_width ,img_height) ,batch_size=batch_size )

train_generator.class_indices

model = Sequential()
model.add(Conv2D(32, (5, 5),input_shape=
input_shape , activation='relu '))
model.add(MaxPooling2D( pool_size=(3, 3)))
model.add(Conv2D(32, (3, 3),activation='relu '))

```

```

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(128, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
model.summary()

model_layers =[layer.name for layer in model.layers]
print('layer_name_:',model_layers)

validation_generator=train_datagen.flow_from_directory(
    train_dir, # same directory as training data
    target_size=(img_height, img_width),
    batch_size=batch_size)

from tensorflow import keras

opt=keras.optimizers.Adam(lr=0.001)
model.compile(optimizer=opt,
loss='categorical_crossentropy',metrics=['accuracy'])
train=model.fit_generator(train_generator,
                           epochs=15,
                           steps_per_epoch=
                               train_generator.samples//batch_size,
                           validation_data=validation_generator,
                           validation_steps=
                               validation_generator.samples

```

```

// batch_size , verbose=1)

acc = train.history['accuracy']
val_acc = train.history['val_accuracy']
loss = train.history['loss']
val_loss = train.history['val_loss']
epochs = range(1, len(acc) + 1)
#Train and validation accuracy
plt.plot(epochs, acc, 'b', label='Training_accuracy')
plt.plot(epochs, val_acc, 'r',
         label='Validation_accuracy')
plt.title('Training_and_Validation_accuracy')
plt.legend()

plt.figure()
#Train and validation loss
plt.plot(epochs, loss, 'b', label='Training_loss')
plt.plot(epochs, val_loss, 'r', label='Validation_loss')
plt.title('Training_and_Validation_loss')
plt.legend()
plt.show()

from keras.models import load_model
model.save('CornLDD.h5')
model.save('drive/MyDrive/ML_Project/LDD.model')

from keras.models import load_model
model.save_weights('leaf_weights.h5')

classes = train_generator.class_indices

```

```

classes

from keras.models import load_model
classifier = load_model
                ('drive/MyDrive/ML_Project/LDD.model')

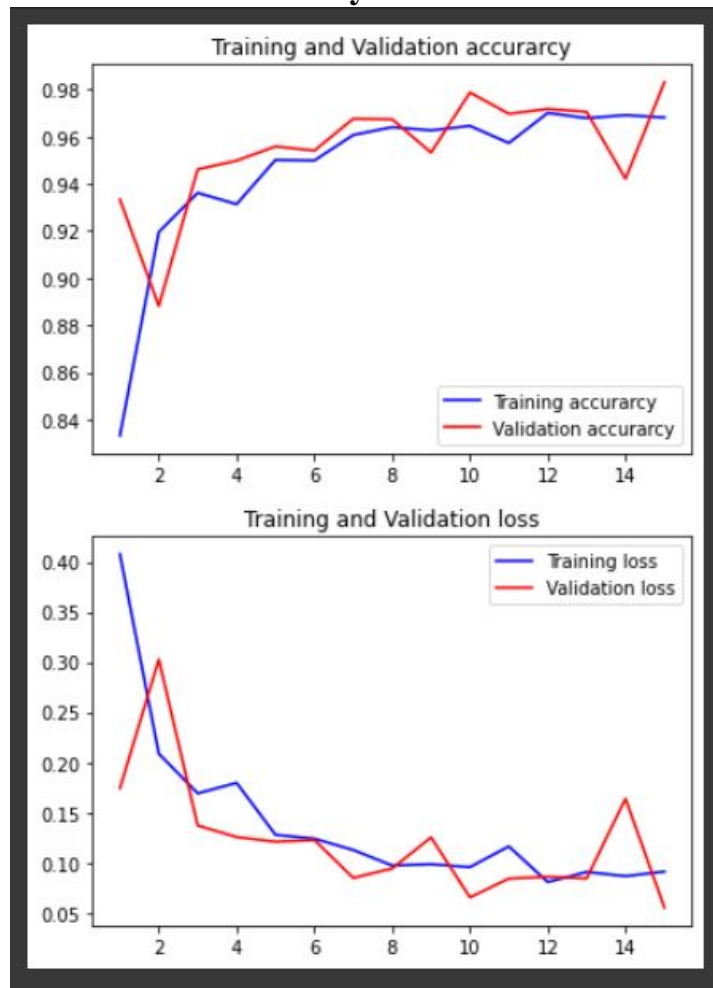
from google.colab import files
uploaded = files.upload()

from tensorflow.keras.preprocessing import image
path = "CornCommonRust1.JPG"
test_image = image.load_img(path)
from matplotlib.pyplot import imshow
plt.imshow(test_image)
test_img = image.load_img(path, target_size=(256,256))
test_img = image.img_to_array(test_img)
test_img = np.expand_dims(test_img, axis=0)
result = classifier.predict(test_img)
a = result.argmax()
s = train_generator.class_indices
name = [ ]
for i in s:
    name.append(i)
for i in range(len(s)):
    if (i==a):
        p=name[i]
p

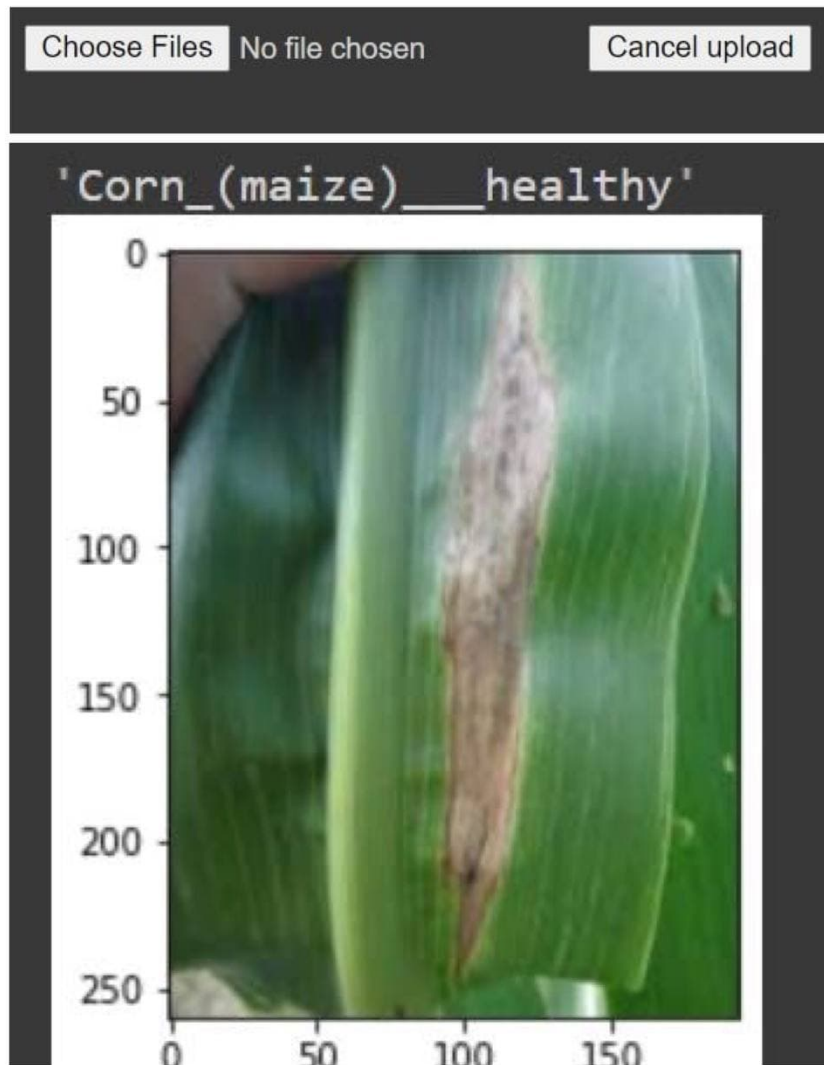
```

## 5. RESULTS

### Accuracy and Loss



Training and Validation accuracy and loss)



**Output in Colab notebook**

Browse... 0d2e2971-f1c9-4278-b35c-91dd8a22a64d\_\_RS\_Early.B 7581.JPG



**Result: Corn\_(maize)\_\_\_healthy**

**Output in GUI**

## **6. CONCLUSION & FUTURE SCOPE**

Our Model (Deep Learning algorithm), detects the disease very accurately for the crop. By our method, farmers can protect their crops from diseases and increase the quantity of production. This helps a disease-free environment and helps in increasing the productivity of the crop. Finally, we would suggest that the farmers can follow this method to avoid these diseases which can spread in the leaf of the crop. Deep learning technique is used as it can improve the image processing of every image and make it clear with efficient leaf segmentation. This image processing technique can help for better images which can help in the feature extraction. Our application will be helpful for farmers in every possible way and can yield a better quantity and quality of their crops. This is not only helpful for disease detection but also suggests better pesticides suited for the crop.



## 7. REFERENCES AND DATASET

- 1 Lv, Mingjie Zhou, Guoxiong He, Mingfang Chen, Aibin Zhang, Wenzhuo Hu, Yahui. (2020). Maize Leaf Disease Identification Based on Feature Enhancement and DMS-Robust Alexnet. IEEE Access. PP. 1-1.
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- 5 Wang, Guowei, Haiye Yu, and Yuanyuan Sui. "Research on Maize Disease Recognition Method Based on Improved ResNet50." Mobile Information Systems 2021 (2021).
- 6 Mishra, Sumita, Rishabh Sachan, and Diksha Rajpal. "Deep convolutional neural network based detection system for real-time corn plant disease recognition." Procedia Computer Science 167 (2020): 2003-2010.
- 7 Data set: (<https://www.kaggle.com/vipooooool/new-plant-diseases-dataset>)