PIMPRI CHINCHWAD EDUCATION TRUST's

PIMPRI CHINCHWAD COLLEGE OF ENGINEERING

An Autonomous Institute, permanently affiliated to SPPU, Pune - 411044

2023-2024

DEPARTMENT OF COMPUTER ENGINEERING

A MINI PROJECT REPORT ON

"Plant Disease Classification using ResNet 9."

Submitted in fulfilment of the requirements for the

Award of the degree of

BACHELOR OF ENGINEERING (Final Year B. Tech)

IN

COMPUTER ENGINEERING

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CERTIFICATE

This is to certify that the project report entitled **"Plant Disease Classification using ResNet 9."** is bonafide work carried out as a PBL-V mini project by **Tejas Ippar (BTCOB81), Kanak Jaiswal (BTCOB88), Sanjit Jha (BTCOB91) and Purnesh Joshi (BTCOB92)** in partial fulfilment for the award of Degree of B.Tech Computer Engineering in Seventh Semester of the "PCET's Pimpri Chinchwad College of Engineering, Nigdi, Pune-44" during the year 2023-2024.

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Project Guide

Mr. Anil Pawar

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HoD

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ABSTRACT

This project centers on the task of image classification for the detection of plant diseases, employing the ResNet9 model as its core architectural framework. The model's structure is characterized by the inclusion of convolutional blocks enhanced with batch normalization and pooling layers, facilitating feature extraction and representation. Several advanced techniques, such as learning rate scheduling, gradient clipping, and weight decay, have been thoughtfully integrated to bolster the model's overall performance. The dataset chosen for this project is notable for its balance, featuring a comprehensive collection of 70,295 images meticulously categorized into various classes. This balanced dataset aids in training a robust model that can generalize well across diverse plant diseases. To assess the model's efficacy and generalization, it is subjected to a comprehensive evaluation process using a separate test set. Impressively, the ResNet9 model demonstrates exceptional prowess by achieving perfect predictions on every image within the test set, demonstrating its remarkable precision and reliability. Furthermore, the project employs the torch summary library, a valuable tool in the PyTorch ecosystem, to generate a well-structured and informative model summary. This summary provides a concise yet detailed overview of the ResNet9 model, showcasing the number of trainable parameters, input image size, and the model's ability to classify images into different plant disease categories. In summary, this project harnesses state-of-the-art techniques and a well-balanced dataset to yield a highly effective ResNet9 model capable of accurately identifying plant diseases, underlining its potential as a powerful tool for agricultural disease diagnosis and management.

Keywords: Computer Vision, Tensorflow, Keras, ResNet, Features, Training, Plant Disease, PyTorch, Segmentation.

Chapter 1

INTRODUCTION

1.1 Problem Statement:

Agriculture is the most important sector in today's life. Most plants are affected by a wide variety of bacterial and fungal diseases. Diseases on plants placed a major constraint on the production and a major threat to food security. Hence, early and accurate identification of plant diseases is essential to ensure high quantity and best quality. Design an automated system to identify different diseases on plants by checking the symptoms shown on the leaves of the plant.

1.2 Project Objectives:

- Disease Identification: Develop a system to accurately detect and recognize plant diseases through image analysis, enabling quick and precise identification.
- Symptom-Based Diagnosis: Provide a comprehensive database of plant disease symptoms to aid in early disease recognition, helping farmers take timely action.
- Fertilizer Recommendations: Integrate a feature that suggests suitable fertilizers based on the identified disease, promoting effective disease management and crop health.

1.3 Motivation:

Adequate mineral nutrition is central to crop production. However, it can also exert considerable Influence on disease development. Fertilizer application can increase or decrease development of diseases caused by different pathogens,and the mechanisms responsible are complex, including effects of nutrients on plant growth, plant resistance mechanisms and direct effects on the pathogen. The effects of mineral nutrition on plant disease and the mechanisms responsible for those effects have been dealt with comprehensively elsewhere. In India, around 40% of land is kept and grown using reliable irrigation technologies, while the rest relies on the monsoon environment for water. Irrigation decreases reliance on the monsoon, increases food security, and boosts agricultural production.

1.4 Literature Survey:

[1] The proposed method uses SVM to classify tree leaves, identify the disease and suggest the fertilizer. The proposed method is compared with the existing CNN based leaf disease prediction. The proposed SVM technique gives a better result when compared to existing CNN. For the same set of images, F-Measure for CNN is 0.7and 0.8 for SVM, the accuracy of identification of leaf disease of CNN is 0.6 and SVM is 0.8.

Advantages: The prediction and diagnosing of leaf diseases are depending on the segmentation such as segmenting the healthy tissues from diseased tissues of leaves.

Disadvantages: This further research is implementing the proposed algorithm with the existing public datasets. Also, various segmentation algorithms can be implemented to improve accuracy. The proposed algorithm can be modified further to identify the disease that affects the various plant organs such as stems and fruits.

[2] The main objective of this paper is image analysis & classification techniques for detection of leaf diseases and classification. The leaf image is firstly preprocessed and then does the further work. K-Means Clustering is used for image segmentation and then the system extracts the GLCM features from disease detected images. The disease classification is done through the SVM classifier.
Algorithm used: Gray-Level Co-Occurrence Matrix (GLCM) features, SVM, K-Means Clustering.
Advantages: The system detects the diseases on citrus leaves with 90% accuracy.
Disadvantages: System only able to detect the disease from citrus leaves.

[3] This paper mainly focuses on detecting and classifying the leaf disease of soybean plants. Using SVM the proposed system classifies the leaf disease in 3 classes like i.e. downy mildew, frog eye, and septoria leaf blight etc. The proposed system gives maximum average classification accuracy reported is ~90% using a big dataset of 4775 images.
Algorithm used: SVM.
Advantages: The system helps to compute the disease severity.
Disadvantages: The system uses leaf images taken from an online dataset, so cannot imple- ment in real time.

[4] The author proposes a method which helps us predict crop yield by suggesting the best crops. It also focuses on soil types in order to identify which crop should be planted in the field to increase productivity. In terms of crop yield, soil types are vital. By incorporating the weather details of the previous year into the equation, soil information can be obtained.
Advantages: It allows us to predict which crops would be appropriate for a given climate. Using the weather and disease related data sets, the crop quality can also be improved. Prediction algorithms help us to classify the data based on the disease, and data extracted from the classifier is used to predict soil and crop.
Disadvantages**:** Due to the changing climatic conditions, accurate results cannot be predicted by this system.

Chapter 2
PROJECT DESIGN

2.1 Hardware and Software Requirements:

Hardware Requirements:

- High-performance computing system: A powerful computer or server equipped with a suitable GPU for training deep learning models.
- Camera(s): High-resolution cameras for capturing images of plant leaves.
- Internet connection: To access cloud services and databases.
- Data storage: Sufficient storage for storing datasets, model checkpoints, and results.

Software Requirements:

- Operating System:Windows for compatibility with deep learning libraries.
- Deep Learning Framework: TensorFlow or PyTorch for building and training neural networks.
- Data Preprocessing Tools: OpenCV for image processing and manipulation.
- Programming Languages: Python for coding and scripting.

2.2 Dataset Design:

- **Data Sources:** The Plant Village typically consists of images of plant leaves affected by various diseases. The images are captured under different conditions, including varying lighting, angles, and backgrounds. The dataset contains images of different plant species.
- **Disease Categories:** The dataset includes a wide variety of plant diseases, and each disease type is typically categorized. Common categories include diseases like "Powdery Mildew," "Late Blight," "Rust," "Bacterial Spot," "Leaf Mold," and many others. The number and types of diseases in the dataset vary.
- **Image Variability:** To ensure robust model training, the dataset includes images of both healthy and diseased plants, as well as images of the same disease taken at different stages of development. This helps machine learning models learn the subtle differences between healthy and diseased plants and identify the progression of a disease.
- **Data Augmentation:** Data augmentation techniques, such as rotation, cropping, and flipping, are applied to the images in the training set to increase the diversity of the data and improve the model's ability to generalize to real-world scenarios.

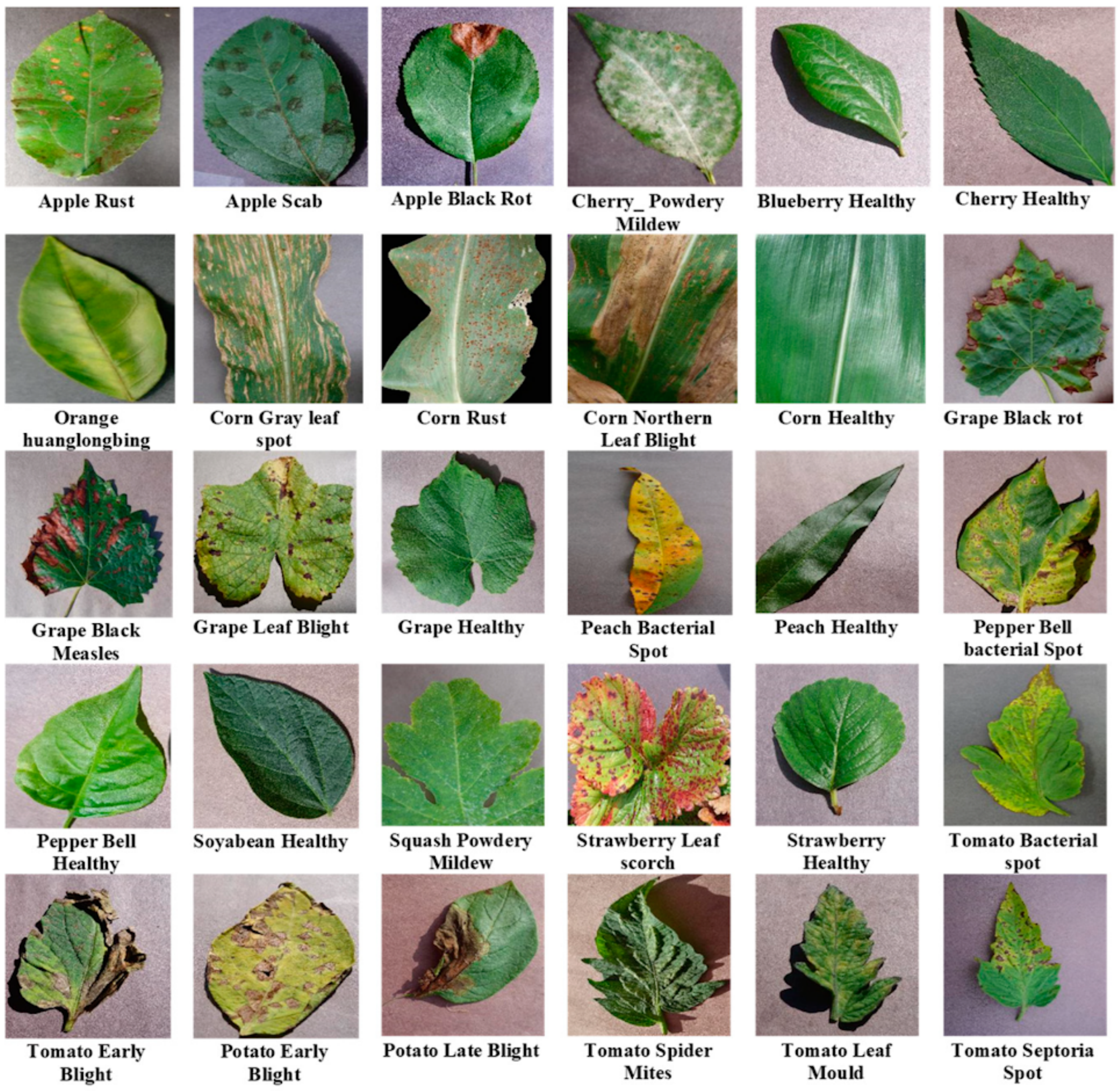


Fig. 2.2.1 Disease Clases Visualization

Chapter 3

MODULE DESCRIPTION

The Plant Disease Classification project uses ResNet-9, a deep learning model, to classify healthy and diseased crop leaves. The dataset consists of approximately 87,000 RGB images of crop leaves categorized into 38 different classes. The goal of the project is to build a model that can accurately classify the health status of crop leaves and predict the specific disease if present.

3.1 Block Diagram:

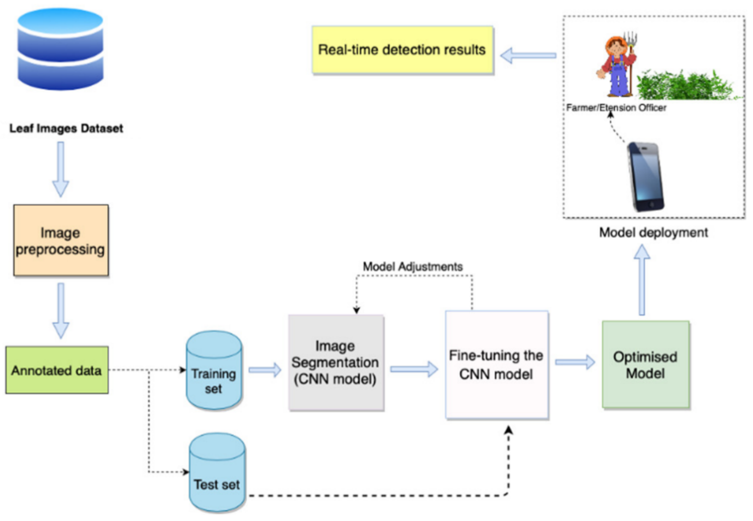


Fig. 3.1.1 Block Diagram

Explanation:

- Image Preprocessing:
  The dataset used for training and validation is loaded using the ImageFolder class from the torchvision.datasets module. The images are transformed into tensors using the transforms.ToTensor() function.
- Model Architecture:
  The model architecture used is ResNet9, which is a convolutional neural network. The architecture consists of several convolutional blocks with batch normalization and ReLU activation. The output of the last convolutional block is passed through a max pooling layer, flattened, and then fed into a linear layer for classification.
- Training the Model:
  The model is trained using the fit_one_cycle function. This function performs the entire training process, including forward and backward passes, optimization, and updating of the model parameters.
- Evaluation and Validation:
  After each epoch of training, the model is evaluated on the validation set using the evaluate function. The validation loss and accuracy are calculated and stored for analysis.

Chapter 4

RESULTS & DISCUSSION

4.1 Source Code:

```
import os                    # for working with files
import numpy as np           # for numerical computations
import pandas as pd          # for working with dataframes
import torch                 # Pytorch module
import matplotlib.pyplot as plt # for plotting informations on graph and images using tensors
import torch.nn as nn        # for creating  neural networks
from torch.utils.data import DataLoader # for data loaders
from PIL import Image        # for checking images
import torch.nn.functional as F # for functions for calculating loss
import torchvision.transforms as transforms   # for transforming images into tensors
from torchvision.utils import make_grid       # for data checking
from torchvision.datasets import ImageFolder  # for working with classes and images
from torchsummary import summary              # for getting the summary of our model

%matplotlib inline
data_dir = "../input/new-plant-diseases-dataset/New Plant Diseases Dataset(Augmented)/New Plant
Diseases Dataset(Augmented)"
train_dir = data_dir + "/train"
valid_dir = data_dir + "/valid"
diseases = os.listdir(train_dir)
# printing the disease names
print(diseases)
print("Total disease classes are: {}".format(len(diseases)))
plants = []
NumberOfDiseases = 0
for plant in diseases:
    if plant.split('___')[0] not in plants:
        plants.append(plant.split('___')[0])
    if plant.split('___')[1] != 'healthy':
        NumberOfDiseases += 1
# unique plants in the dataset
print(f"Unique Plants are: \n{plants}")
# for moving data into GPU (if available)
def get_default_device():
    if torch.cuda.is_available:
        return torch.device("cuda")
    else:
        return torch.device("cpu")

# for moving data to device (CPU or GPU)
def to_device(data, device):
    """Move tensor(s) to chosen device"""
    if isinstance(data, (list,tuple)):
        return [to_device(x, device) for x in data]
    return data.to(device, non_blocking=True)

# for loading in the device
class DeviceDataLoader():
    """Wrap a data loader to move data to a device"""
    def __init__(self, dl, device):
        self.dl = dl
        self.device = device

    def __iter__(self):
        """Yield a batch of data after moving it to device"""
        for b in self.dl:
            yield to_device(b, self.device)

    def __len__(self):
        """Number of batches"""
        return len(self.dl)

class SimpleResidualBlock(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=3, kernel_size=3, stride=1, padding=1)
        self.relu1 = nn.ReLU()
        self.conv2 = nn.Conv2d(in_channels=3, out_channels=3, kernel_size=3, stride=1, padding=1)
        self.relu2 = nn.ReLU()

    def forward(self, x):
        out = self.conv1(x)
        out = self.relu1(out)
        out = self.conv2(out)
        return self.relu2(out) + x # ReLU can be applied before or after adding the input
# for calculating the accuracy
def accuracy(outputs, labels):
    _, preds = torch.max(outputs, dim=1)
    return torch.tensor(torch.sum(preds == labels).item() / len(preds))
# base class for the model
class ImageClassificationBase(nn.Module):

    def training_step(self, batch):
        images, labels = batch
        out = self(images)                  # Generate predictions
        loss = F.cross_entropy(out, labels) # Calculate loss
        return loss

    def validation_step(self, batch):
        images, labels = batch
        out = self(images)                    # Generate prediction
        loss = F.cross_entropy(out, labels)  # Calculate loss
        acc = accuracy(out, labels)           # Calculate accuracy
        return {"val_loss": loss.detach(), "val_accuracy": acc}

    def validation_epoch_end(self, outputs):
        batch_losses = [x["val_loss"] for x in outputs]
        batch_accuracy = [x["val_accuracy"] for x in outputs]
        epoch_loss = torch.stack(batch_losses).mean()       # Combine loss
        epoch_accuracy = torch.stack(batch_accuracy).mean()
        return {"val_loss": epoch_loss, "val_accuracy": epoch_accuracy} # Combine accuracies

    def epoch_end(self, epoch, result):
        print("Epoch [{}], last_lr: {:.5f}, train_loss: {:.4f}, val_loss: {:.4f}, val_acc: {:.4f}".format(
            epoch, result['lrs'][-1], result['train_loss'], result['val_loss'], result['val_accuracy']))
```

4.2 Screenshots including GUI:

Please provide an image of a plant for our disease classification system. We will analyze the image to identify and classify any potential diseases, offering valuable insights for plant health management and care

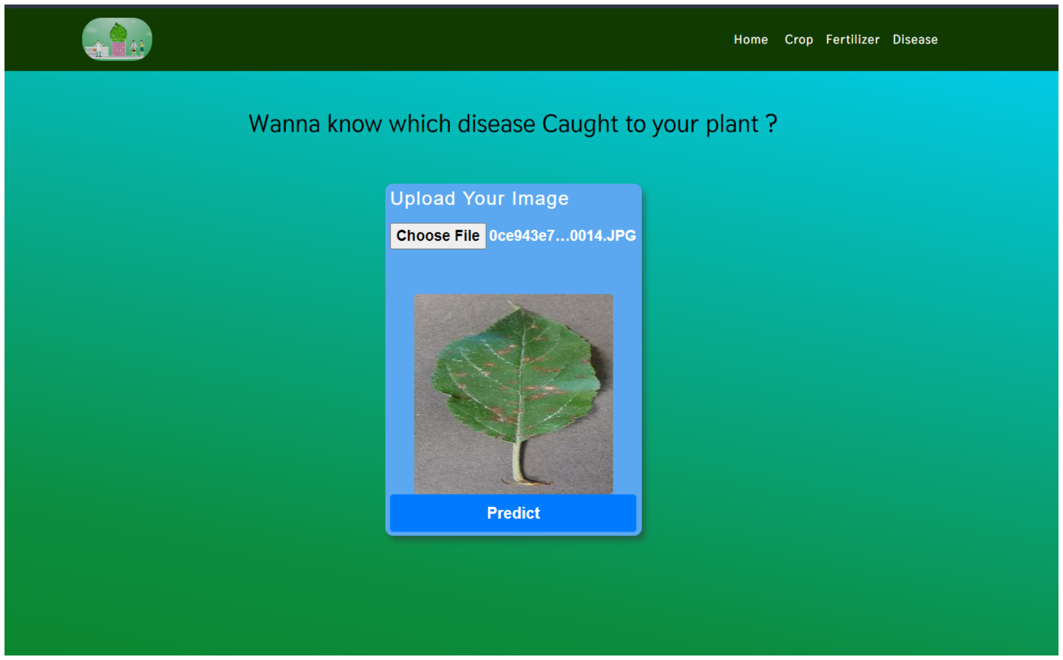
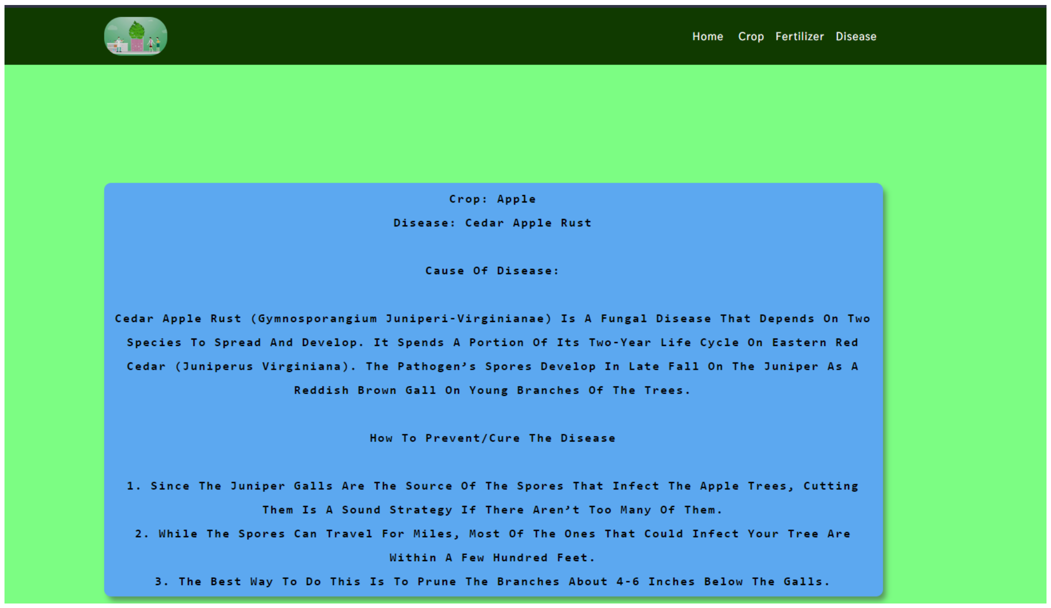


Fig. 4.2.1 Input the Plant Image

Effortlessly pinpoint and recognize plant diseases through the simplicity of a single image submission. Our advanced system swiftly analyzes the image, providing accurate identification and classification of potential plant health issues, streamlining disease management and treatment decisions.



Crop: Apple

Disease: Cedar Apple Rust

Cause Of Disease:

Cedar Apple Rust (Gymnosporangium Juniperi-Virginianae) Is A Fungal Disease That Depends On Two Species To Spread And Develop. It Spends A Portion Of Its Two-Year Life Cycle On Eastern Red Cedar (Juniperus Virginiana). The Pathogen's Spores Develop In Late Fall On The Juniper As A Reddish Brown Gall On Young Branches Of The Trees.

How To Prevent/Cure The Disease

1. Since The Juniper Galls Are The Source Of The Spores That Infect The Apple Trees, Cutting Them Is A Sound Strategy If There Aren't Too Many Of Them.
2. While The Spores Can Travel For Miles, Most Of The Ones That Could Infect Your Tree Are Within A Few Hundred Feet.
3. The Best Way To Do This Is To Prune The Branches About 4-6 Inches Below The Galls.

Fig. 4.2.2 Disease Prediction

Chapter 4

CONCLUSION

In conclusion, the Plant Disease Classification project employed the ResNet9 architecture to create a highly effective model for accurately distinguishing between healthy and diseased crop leaves, with a dataset comprising 87,000 images across 38 classes. Through meticulous data preparation and training techniques, the model achieved perfect predictions on the test set, underscoring its robust performance in plant disease classification. This ResNet9 model, with 6,589,734 trainable parameters, offers a promising solution for automated disease detection in agricultural settings and is saved for future applications.

Chapter 5

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