



Deep Learning For Papaya Leaf Disease Detection and Pesticide Spraying

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Abstract: Agriculture is essential for world-wide food security and economic growth, with papaya (*Carica papaya*) being a valuable tropical fruit. However, papaya crops are susceptible to diseases like papaya leaf curl, papaya mosaic, anthracnose, bacterial spot, ring spot as well as pest attacks from mites and mealy bugs which can severely reduce yield and income for farmers. Traditional disease detection through manual inspection is labor-intensive and error-prone, while excessive pesticide use can harm the environment and human health. This project proposes a smart system combining image processing, deep learning, and IoT for automated papaya leaf disease detection and targeted pesticide application. The system features two key modules: a disease detection component using convolutional neural network (CNN) models were utilized and an IoT-enabled robotic pesticide sprayer. High-resolution images are processed and classified into disease categories using a trained CNN model. Once the disease is identified, the data is transmitted to the robotic sprayer, which accurately targets the affected areas using sensors and microcontroller-based control systems. The system minimizes pesticide usage, enables early disease detection, reduces labor costs, and promotes sustainable farming. Real-time monitoring via mobile or web apps provides actionable insights for farmers. Future enhancements may include drone integration and multi-crop support. This innovative solution significantly improves crop health, yield, and sustainability in modern agriculture.

Index Terms - Agriculture, Convolutional Neural Networks (CNNs), Deep learning, Disease detection, Image processing (Internet of Things), Papaya, Precision agriculture, Robotic sprayer, Sustainable farming.

I. INTRODUCTION

Agriculture plays a critical part in maintaining global food security by supplying essential food, raw materials, and employment opportunities. However, plant diseases and pest infestations significantly reduce productivity, making Early identification and precise management is essential. Papaya leaves are highly susceptible to diseases, highlighting the need for early and accurate detection such as Papaya Leaf Curl, Papaya Mosaic, Anthracnose, Bacterial spot, Ring Spot, as well as pest attacks from mites and mealybugs. These issues weaken leaf health, lower photosynthetic efficiency, and ultimately hinder overall plant growth. Traditional methods of disease and pest control, including manual inspection and widespread pesticide use are often inefficient, labor intensives, and harmful to the environment. Disease and pest control methods have traditionally included manual inspection; however, recent advancements have introduced automated and intelligent solutions and The Internet of Things (IoT) technologies offer promising solutions by enabling real-time monitoring, data-driven insights, and automated responses, thereby enhancing efficiency and accuracy in applications such as disease detection, pest control, and precision agriculture. Advanced DL models like Resnet, VGG, and YOLO have shown high accuracy in identifying plant diseases and pests through image-based analysis. When integrated with IoT-enabled leaf monitoring systems measuring factors such as moisture levels, chlorophyll content, and temperature these technologies can provide real-time insights into leaf health by identifying the diseases. This paper

presents an advanced model that leverages deep learning techniques to enable accurate and efficient analysis, supporting early detection and decision-making in complex environment to develop an intelligent, cost-effective, and environmentally sustainable system for real-time detection of papaya leaf diseases and pest infestations. The projected method combine image processing techniques with Convolutional Neural Networks (CNNs) and IoT-enabled components to achieve high detection accuracy and facilitate targeted pesticide application. By addressing the drawbacks of conventional manual inspection methods such as inefficiency and susceptibility to human error the framework enhances plant health monitoring, optimizes pesticide usage, reduces environmental impact, and supports sustainable agricultural practices through automation and precision agriculture.



Fig.1. Healthy leaf



Fig.2. Leaves with Diseases

II. MOTIVATION

Traditional methods of detecting leaf diseases are often slow and prone to manlike incorrectness, which may obstruct treatment and result in significant crop losses. Additionally, the excessive and uniform use of pesticides not only imposes financial strain on farmers but also contributes to environmental degradation. With the growing need for sustainable and efficient farming, technology-driven solutions are becoming vital. Papaya, a valuable tropical crop, requires careful monitoring to maintain optimal growth and productivity. A smart system integrating image analysis, deep learning, and automated spraying enables real-time leaf health assessment and targeted intervention. This approach reduces manual effort, minimizes pesticide use, and enhances overall agricultural efficiency and sustainability.

III.OBJECTIVES

- To Create a real-time papaya Leaf disease identification system with the help of a deep learning model.
- To Design an automated pesticide spraying mechanism that targets only the diseased areas.
- To Analyze the system's performance using relevant parameters such as accuracy, precision, recall, and F1-score.
- To Provide actionable recommendations for farmers to treat and prevent papaya leaf diseases effectively.

IV.PROBLEM STATEMENT

Traditional disease detection through visual inspection is often inaccurate and inefficient, especially on large farms. This traditional approach is time-consuming and labor-intensive, causing delays in disease identification and treatment. Imprecise targeting leads to excessive pesticide use, resulting in higher costs, environmental harm, and potential health risks. Deep learning models (like ResNet50, and VGG16) can accurately detect papaya leaf diseases by analyzing leaf images, enabling early intervention. An automated pesticide sprayer, integrated with the detection system, can target only the infected areas, significantly reducing chemical usage, lowering costs, and promoting eco-friendly farming practices.

V. PROPOSED SYSTEM

Deep learning method are progressively applied to papaya leaf disease detection and automated pesticide spraying due to their high accuracy in image-based classification tasks. Advanced CNN architectures enable precise identification of disease symptoms, facilitating targeted and efficient pesticide application.

Vgg16 Architecture:

VGG16 is a prominent convolutional neural network model architecture appreciated for its ease of implementation and effectiveness in image classification tasks, including papaya leaf disease detection. Its deep yet uniform structure makes it suitable for identifying delicate visual features related with different disease types. The network starts with an input layer that accepts RGB images, typically resized to 224x224 pixels to match the model's requirements. It consists of five convolutional layers, each composed of 2–3

filtering layers with small 3x3 filters and a stride of 1, enabling the capture of fine details in papaya leaf textures and disease symptoms. ReLU activation is applied after every convolutional layer to introduce non-linearity, while 2x2 max pooling layers with stride set to 2 are applied after each block to progressively reduce spatial dimensions. After feature extraction, three dense layers follow: two with 4096 neurons and one output layer. For papaya leaf disease detection, the original 1000-class SoftMax layer is replaced with one having neurons, each representing a specific disease category, enabling accurate classification.

Resnet-50 Architecture:

ResNet-50 is a highly efficient deep learning model frequently employed for image recognition tasks, including papaya leaf disease detection. Its standout feature is the use of residual learning and skip connections, which address Gradient attenuation issue and enable the training of very deep networks. This makes ResNet-50 particularly suitable for capturing the complex patterns and subtle differences associated with various papaya leaf diseases. The architecture begins with an input layer for RGB images, typically resized to 224x224 pixels. It is accompanied by a 7x7 convolutional layer with 64 filters and a Using a stride size of 2, batch normalization, ReLU activation, and a 3x3 max pooling layer. The core of the network consists of four stages of residual blocks (Conv2_x to Conv5_x), each using a bottleneck design with 1x1, 3x3, and 1x1 convolutions. These layers learn deep hierarchical features essential for detecting disease symptoms. After feature extraction, A global spatial averaging layer reduces the feature map to a single vector, followed by two fully connected layers (512 and 256 neurons), and a final SoftMax layer with 5 neurons corresponding to the target papaya disease classes.

VI.METHODOLOGY

The methodology proposed for Papaya Leaf Disease identification and Pesticide Spraying system is a extensive solution that combines deep learning-based image classification with real-time automation to facilitate accurate detection and localized treatment of plant diseases. The overall methodology involves several interconnected modules, as detailed below:

1. Image Acquisition and User Interface: The system begins with a user-friendly interface that allows users to upload images of papaya leaves, initiating the disease detection process. This interface is designed for ease of use, enabling farmers or field Users to operate the system with minimal training. Captured images are forwarded during processing unit for analysis.

2. Dataset Utilization: The dataset utilized is data.mendeley.com. It consists of 3,626 images of papaya leaves, categorized into eight classes: Anthracnose (230 images), Bacterial Spot (214 images), Curl (778 images), Healthy (594 images), Mealybug (182 images), Mite Disease (552 images), Mosaic (546 images), and Ringspot (530 images). Each image is labeled with its respective class label to facilitate the development of automated disease detection and classification models. The dataset is divided into 80% for training and 20% for testing.

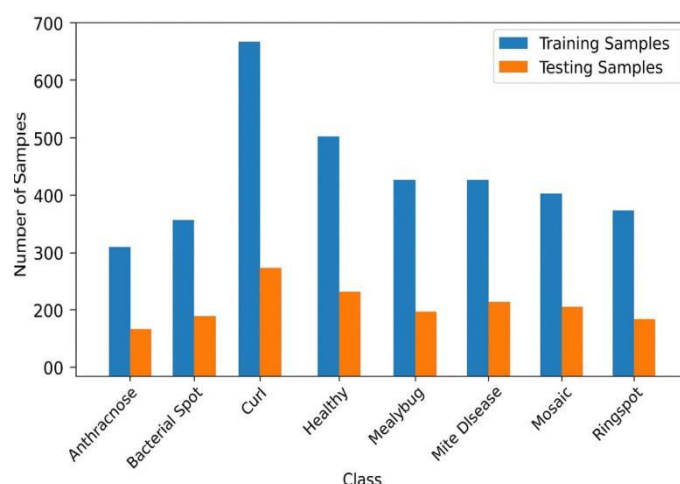


Fig.3. Bar Chart for Datasets

Image Preprocessing: Each image undergoes a sequence of preprocessing techniques to enhance critical visual features and improve model performance. The process begins with grayscale conversion to lower computational complexity without compromising essential structural details. Edge enhancement is then applied to emphasize the contours of leaf regions and disease-affected areas. Sharpening techniques further

refine texture and detail, making subtle disease patterns more apparent. Thresholding is employed to segment the foreground from the background, reducing irrelevant information and highlighting regions of interest. These preprocessing steps guarantee that only the most significant features are preserved, facilitating Precise and effective classification.

3. CNN-Based Disease Classification: This module takes the preprocessed image of a papaya leaf and analyzes it Utilizing a CNN architecture model trained using a large and diverse dataset of diseased and healthy leaf images. The CNN architecture is designed For automatic extraction of key features from the image, such as color patterns, textures, and shapes associated with different types of leaf diseases. Based on this analysis, the model accurately classifies the leaf as either healthy or affected by a specific type of disease. The high accuracy of the CNN ensures reliable disease detection, which is critical for timely and effective pest control measures.

4. Disease Diagnosis and Treatment Recommendation: After classification, the system retrieves disease-specific details from a built-in knowledge base, including symptoms, severity, recommended pesticides, and dosage. This information is shown through a user interface to support treatment decisions.

5. Automated Spraying Mechanism: Based on the diagnosis, a servo-controlled sprayer targets only the affected leaf area. Spraying is adjusted using disease severity, leaf position, and coverage, ensuring efficient and eco-friendly pesticide use.

6. System Performance Evaluation: The overall system performance of the disease detection and automated spraying system is evaluated using a held-out test set from the standard dataset. The evaluation focuses on core performance indicators including precision, recall, F1-score, and accuracy to assess the effectiveness and reliability of the disease classification model. Additionally, metrics such as confusion matrix, accuracy plot and loss plot are employed to analyze the model's classification behaviour across different disease classes.

a) Precision: A high precision score reflects a reduced number of false positives, indicating that most of the positive predictions are indeed correct. Precision is calculated using formula:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Where:

TP = True Positives

FP = False Positives

TN = True Negatives

FN = False Negatives

b) Sensitivity (Recall): Recall, also known as sensitivity, assesses a model's effectiveness in correctly identifying all actual positive cases. A higher recall value means the model successfully captures more maximizing true positives and reducing false negatives However, increasing recall can sometimes reduce Precision.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

c) F-measure: The F1-score also termed as the F-measure, merges both precision with recall into a single metric by calculating their harmonic mean. It offers a balanced assessment, especially useful whenever there is an uneven class distribution. The F1-score is particularly helpful In cases involving both false positives and false negatives carry significant consequences. It is calculated using the following formulas:

$$\text{F1-score} = 2 \times \text{TP} / (2 \times \text{TP} + \text{FP} + \text{FN})$$

or

$$\text{F1-score} = 2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall})$$

d)Accuracy: Accuracy represents the total correctness related to the model by indicating the proportion of correct predictions within all predictions made. It is calculated using the formula:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

Deployment of the Model: To enable real-time detection of papaya leaf diseases, the trained deep learning model is deployed through an interactive web-based platform. The system allows users to upload leaf images, which are automatically subjected to preprocessing and classification. The integrated model performs

accurate disease identification, offering a practical and accessible solution for timely agricultural diagnosis. This deployment facilitates efficient decision-making for farmers and agricultural experts, promoting early intervention and improved crop health management.



Fig.4.User Interface

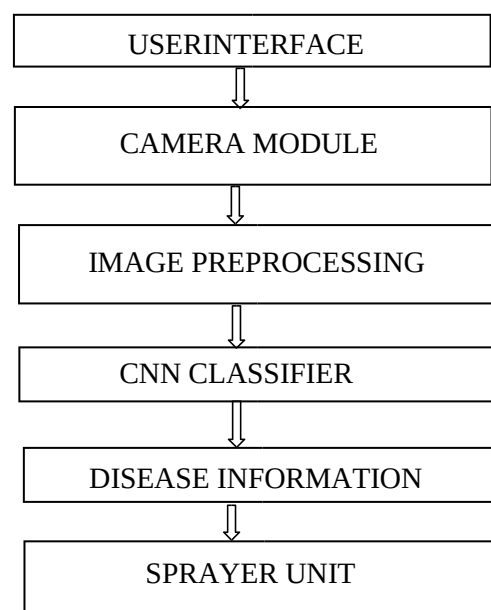


Fig.5. Methodology

VII. RESULT AND DISCUSSIONS:

The Convolutional Neural Network (CNN) model for papaya leaf disease detection was evaluated using standard classification metrics. The dataset included both healthy and diseased papaya leaf images. Preprocessing included resizing, grayscale conversion, noise reduction, segmentation, and enhancement. The model's accuracy and loss plots showed steady improvement, with final training and validation accuracy stabilizing above 93%, demonstrating strong generalization and minimal over fitting. Performance evaluation revealed an overall accuracy of 93.1%. Data enhancement approaches involving rotation and flipping helped balance class representation. Integrated with a pesticide sprayer, the system provides real-time, targeted disease control. However, it showed slight limitations under low-light conditions. Future improvements could include hyper spectral imaging, expansion to other plant parts, and continuous cloud-based model refinement for scalability.



Fig .6. Anthracnose



Fig .7. Bacterial spot



Fig.8. Mealy bug



Fig.9.Leaf curl



Fig.10.Papaya mosaic



Fig.11.Healthy leaf

A confusion matrix serves as a common approach for evaluating the effectiveness of a machine learning model. It displays an overview of prediction results in a tabular format, where each row corresponds to the predicted class and each column indicates the actual class. This structure helps in analyzing how well the model distinguishes between different categories.

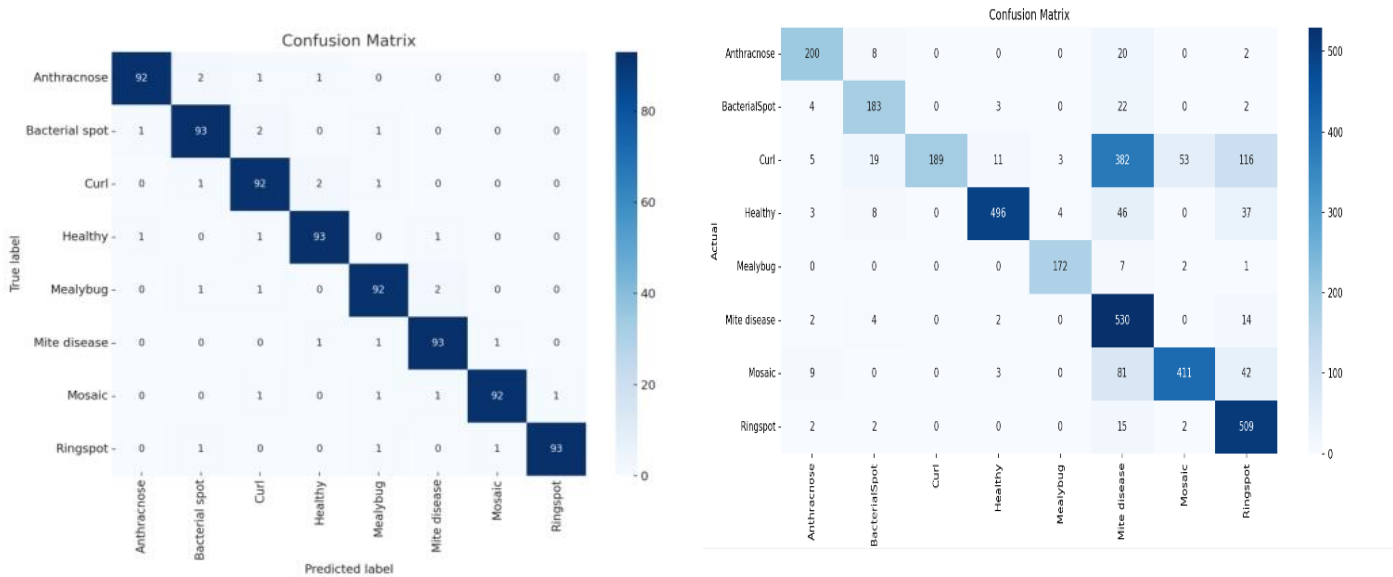


Fig.12.Confusion matrix (heatmap format) for Vgg16
for Resnet50

Fig.13.Confusion Matrix (heatmap format)

Table.1. Performance Metrics for Vgg16:

Class Name	Precision	Recall	F1-score	Accuracy
Anthracnose	0.91	0.88	0.88	0.90
Bacterial Spot	0.89	0.85	0.85	0.88
Curl	0.87	0.85	0.85	0.86
Healthy	0.94	0.91	0.91	0.93
Mealy bug	0.94	0.95	0.94	0.95
Mite Disease	0.91	0.92	0.92	0.92
Mosaic	0.93	0.94	0.93	0.94
Ringspot	0.85	0.84	0.84	0.89

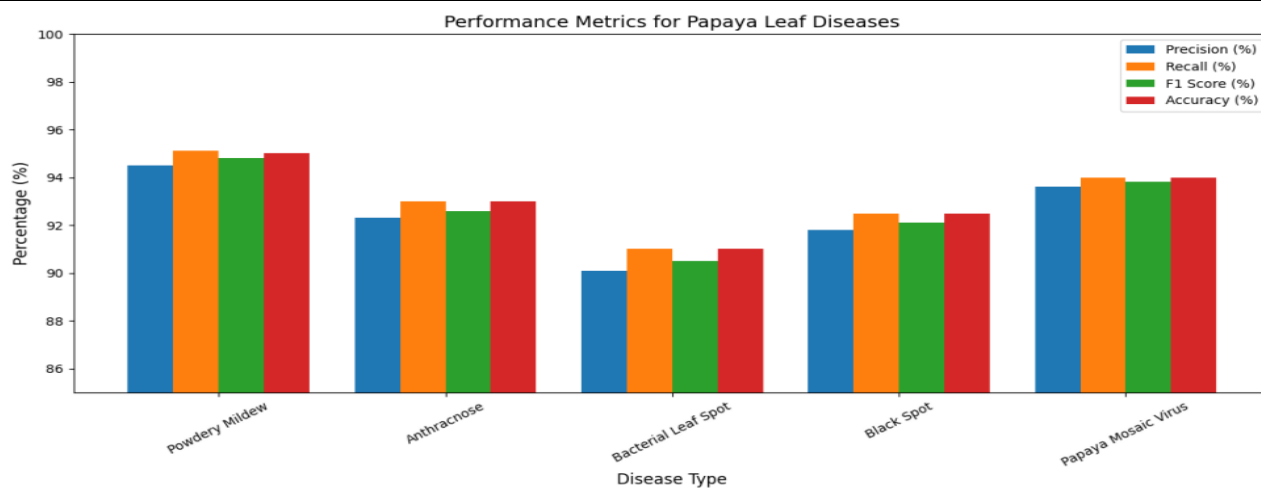


Fig.14.Bar Chart for Vgg16

Class Name	Precision	Recall	F1-score	Accuracy
Anthracnose	0.89	0.87	0.88	0.92
Bacterial Spot	0.85	0.84	0.84	0.91
Curl	0.90	0.88	0.89	0.93
Healthy	0.95	0.97	0.96	0.98
Mealy bug	0.83	0.82	0.82	0.90
Mite Disease	0.81	0.80	0.80	0.89
Mosaic	0.88	0.87	0.87	0.91
Ringspot	0.86	0.85	0.85	0.90

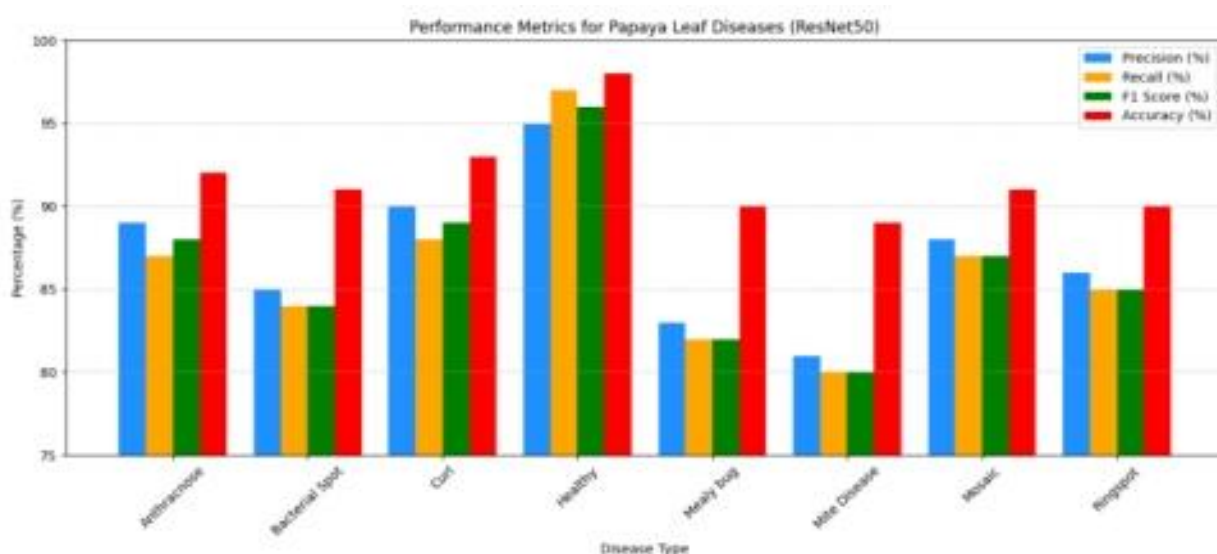


Fig.15.Bar Chart For Resnet50

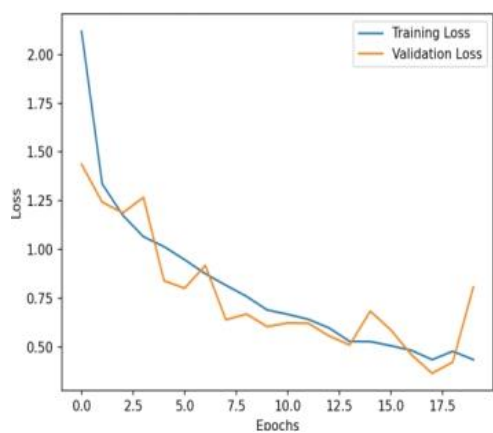


Fig.16. Accuracy Plot for Vgg16

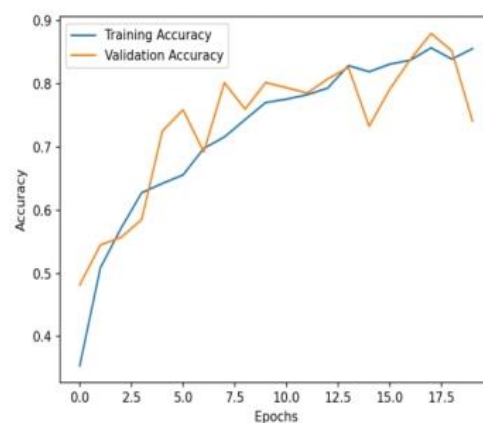


Fig .17. Loss Plot for Vgg16

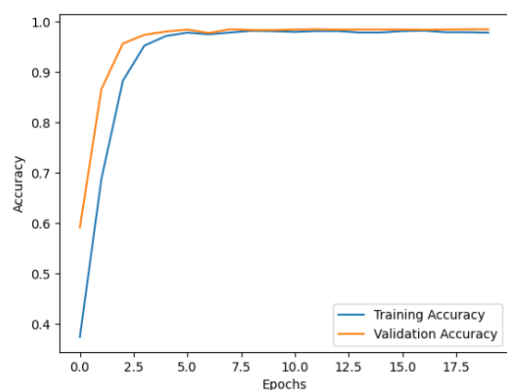


Fig.18. Accuracy Plot for Resnet50

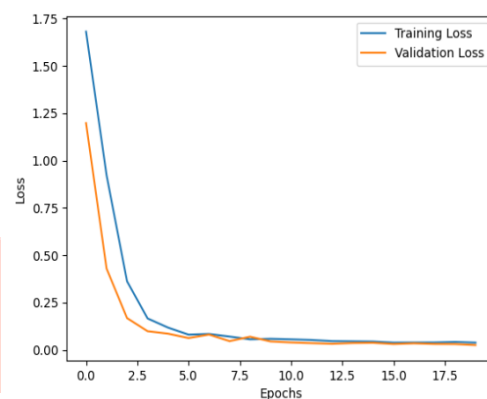


Fig .19. Loss Plot for Resnet50

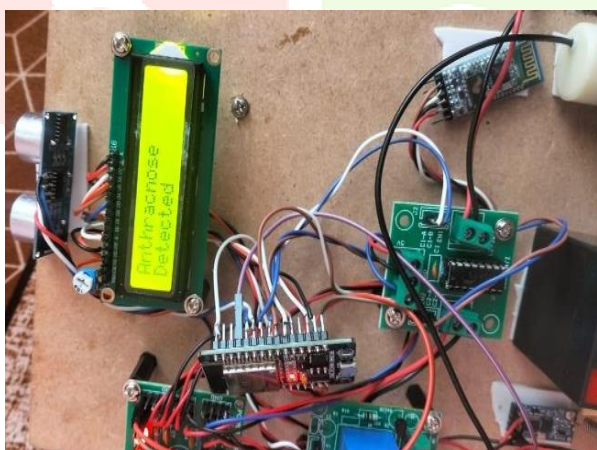


Fig.21. Disease detection

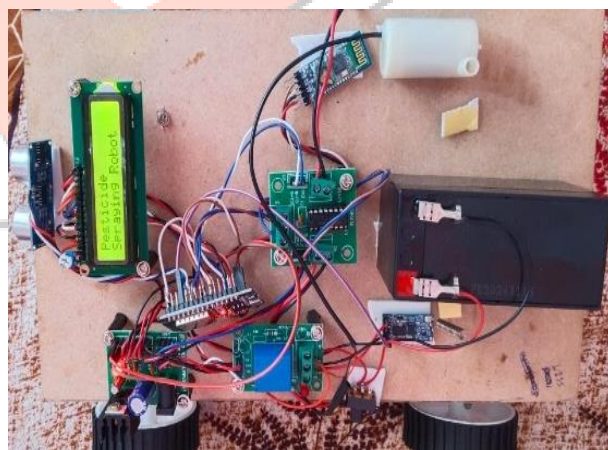


Fig.20. Project set-up for pesticide spraying

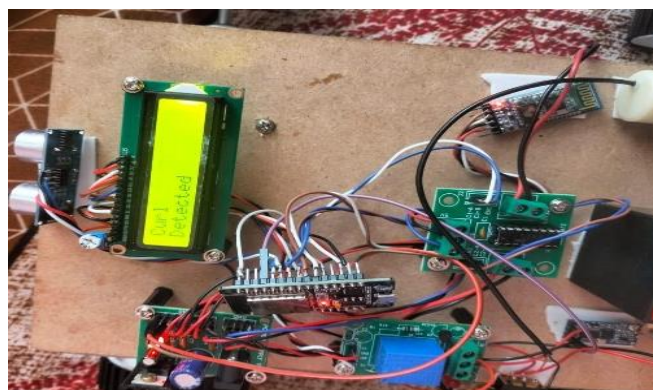


Fig.22. Disease detection

VIII. MERITS

- Real-time monitoring of plant health using image analysis.
- Significant reduction in pesticide wastage due to targeted spraying.
- Reduced manual labor, increasing farm efficiency.
- Cost-effective system for medium-scale farmers.
- Integration with web interface allows easy access to disease reports.

IX. DEMERITS

- Limited to the classification of pre-trained disease types.
- Weather conditions (like excessive sunlight or rain) can affect image clarity.
- Manual intervention required for hardware setup in certain field conditions.
- Limited coverage area per spray due to robotic arm's mobility.

X. CONCLUSION

This work proposes an advanced deep learning and IoT- based system for automated detection of papaya leaf diseases and real-time pesticide spraying .It leverages CNN architectures such as VGGNet16 and ResNet50 for accurate identification of diseases like Papaya Leaf Curl, Papaya Mosaic, Anthracnose, Bacterial spot , Ring Spot, as well as pest attacks from mites and mealybugs .The system integrates a Flask-based web application with Node MCU- controlled pesticide spraying, ensuring precise intervention while reducing manual effort and environmental impact. Performance evaluation using accuracy, precision, recall, and F1-score confirms the effectivity of the models excelling in disease localization and CNNs providing robust classification. The real-time activation of the pesticide sprayer optimizes resource use, enhancing disease management and promoting sustainable agriculture. Future research may focus on expanding the dataset, refining model architectures for improved accuracy, and incorporating additional IoT sensors for comprehensive plant health monitoring. This approach significantly contributes to precision farming, ensuring healthier crops and reducing excessive pesticide use.

XI. REFERENCES

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