

LEAFLENS

Submitted in partial fulfilment of requirements for the award of Bachelor of
Technology degree in Biotechnology

Interdisciplinary Project

By

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DEPARTMENT OF BIOTECHNOLOGY

SCHOOL OF BIO AND CHEMICAL ENGINEERING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

CATEGORY-1 UNIVERSITY BY UGC

Accredited with grade “A++” by NAAC | 12B Status by UGC | Approved by AICTE

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DEPARTMENT OF BIOTECHNOLOGY

BONAFIDE CERTIFICATE

This is to certify that this project is the bonafide work of **KHALIDA UMAR (41230030)** and **B. PAVITHRA (41230039)** who carried out the Interdisciplinary Project entitled "**LEAFLENS**" under our supervision from **JANUARY 2024** to **APRIL 2024**.

Internal Guide

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Internal Examiner

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DECLARATION

We **KHALIDA UMAR (41230030)** and **B. PAVITHRA (41230039)** hereby declare that the Interdisciplinary Project Report entitled “**LEAFLENS**” done by us under the guidance of **Dr. V. RAMESH KUMAR, M.Phil., Ph.D.**, is submitted in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Biotechnology.

DATE: 06.05.2024

PLACE: CHENNAI



SIGNATURE OF THE CANDIDATE

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We are pleased to acknowledge our sincere thanks to The Board of Management of **Sathyabama Institute of Science and Technology** for their encouragement in doing this project and for completing it successfully. We are grateful to them.

We convey our thanks to **Dr. V. RAMESH KUMAR, M.Phil., Ph.D., Head of the Department**, Department of Biotechnology for providing us necessary support and details at the right time during the progressive reviews.

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We wish to express our thanks to **all Teaching and Non-teaching staff members** of the Department of Biotechnology who were helpful in many ways for the completion of the project.

ABSTRACT

Citrus canker (CC) is a severe hazard to the widely produced citrus fruit crop, caused by *Xanthomonas citri* subsp. *citri* (Xcc). It affects most citrus varieties, spreading rapidly through wind, rain splash, and warm weather. Symptoms include leaf loss, early fruit drop, dieback, and fruit blemishing.

The LeafLens project aims to tackle CC by creating a smartphone-based platform for early disease identification and management. It classifies CC into three stages: early, mid, and late, based on symptoms on fruit and leaves. The platform uses machine learning algorithms to classify illness stages and deliver real-time feedback on disease severity. This enables farmers to develop proactive disease management plans, promoting sustainable citrus production techniques.

Keywords : Citrus canker, *Xanthomonas citri* subsp. *citri* (Xcc), Disease stage classification, Early detection, Machine learning algorithms, Smartphone-based platform, Real-time feedback, Disease management strategies, Sustainable agriculture

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CHAPTER 1

INTRODUCTION

Citrus canker is a highly contagious bacterial disease that affects citrus plants like oranges, lemons, limes, and grapefruit. It is caused by the bacterium *Xanthomonas citri subspecies citri*. This disease causes distinctive lesions on the leaves, stems, and fruits of infected trees, resulting in defoliation, fruit drop, and, eventually, diminished fruit quality and output. This has had a huge influence on the global citrus sector. Infected plants can cause significant damage, resulting in economic losses for citrus growers and disruptions in worldwide citrus markets.

The top three manufacturers are India, China, and Brazil. Citrus fruits and juices are high in carbs, fibre, vitamin C, low fat, potassium, calcium, folate, thiamine, vitamin B6, niacin, vitamin A, magnesium, phosphorus, copper, flavonoids, riboflavin, limonoids, lignin, polysaccharides, fibre, carotenoids, and phenolic compounds. These compounds contribute to a variety of pharmacological effects, including anti-microbial, anti-oxidant, anti-cancer, cardiovascular, central nervous system, anti-inflammatory, anti-diabetic, reproductive, gastrointestinal, immune-logical, respiratory, obesity, and many more. Citrus production is constrained due to numerous diseases, insect pests, nutritional imbalances, improper cultural practices, and sudden climatic changes and numerous diseases, e.g., gummosis, citrus canker, citrus tristeza virus, citrus greening, and citrus tree decline, attack citrus plants, hampering their production, causing heavy economic losses, and socially impacting growers, consumers, and the industry.

Traditional disease detection systems rely significantly on trained agronomists conducting visual inspections, which can be subjective and time-consuming. To solve these issues, our project intends to create a preliminary disease diagnosis system based on modern technology and machine learning algorithms. The project aims to automate the detection of citrus canker symptoms on leaves, stems, and fruits through

the use of image processing techniques and machine learning models. The proposed approach will enable for the rapid and accurate detection of diseased citrus plants in the field, allowing growers to take urgent action to reduce the impact of citrus canker on their crops.

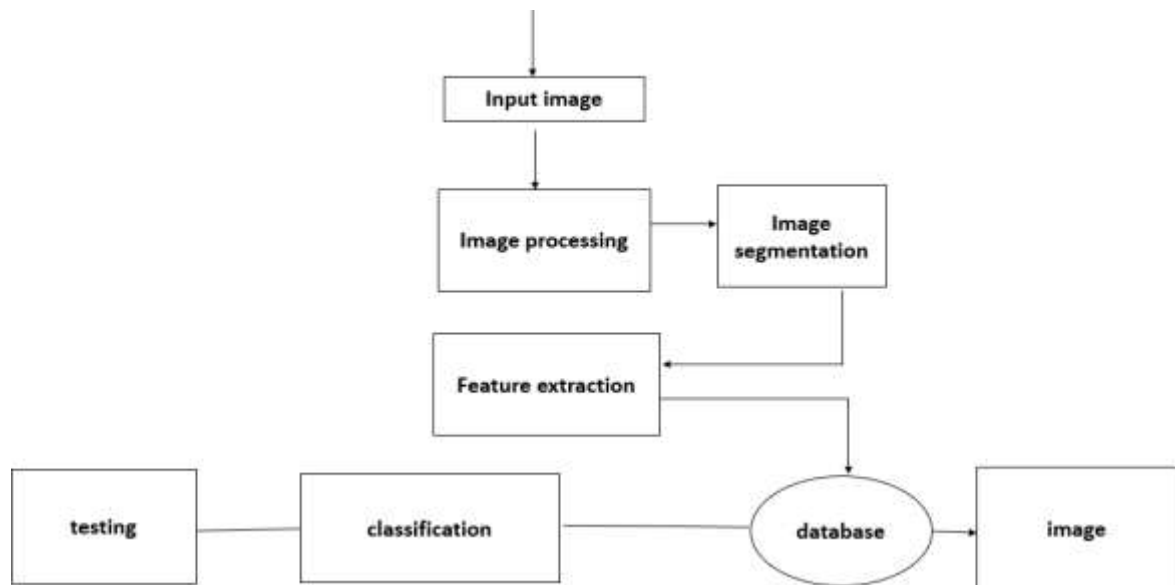


FIG 1.1 Block diagram of proposed system

The leafLens aims to automatically identify distinctive indications of citrus canker on citrus leaves, stems, and fruits by implementing advanced image processing techniques, such as feature extraction and pattern recognition, and standardising picture collecting protocols. The system will enable accurate and real-time categorization of healthy and sick citrus plants through the training of machine learning models on annotated datasets, giving citrus growers fast feedback. The final objective is to incorporate this disease detection technology into an approachable prototype that farmers and other agricultural experts can quickly embrace, enabling proactive disease control and promoting sustainable . Ultimately, this project intends to help improve citrus disease control procedures and promote sustainable citrus agriculture around the world.

1.1. DISEASE CYCLE AND EPIDEMIOLOGY

1.1.1. Infection

The bacteria penetrate the host by disrupting the leaf epidermis, inducing cell hyperplasia, and colonizing the apoplast. Under optimum conditions, the pathogen multiplies 3 to 4 log units per lesion; for further disease development, bacterial cells may emerge from stomata openings to provide inoculum within five days. For successful infection and lesion formation, free moisture for 20 min is required for the bacterial cells to ooze out from the lesion. As a result of water congestion, one to two bacterial cells are released from stomatal openings during inoculation. After the initiation of growth of the host, almost all infections take place on stems and leaves within the first six weeks, while the first 90 days after petals falling is the most crucial time period for fruit infection. Small and unnoticeable pustules are formed due to infections after this time period. It has been reported that fruits are more susceptible to disease than leaves; hence, observations have been made that lesions of different sizes can be found on the rind of the same fruit during the infection of the bacterium

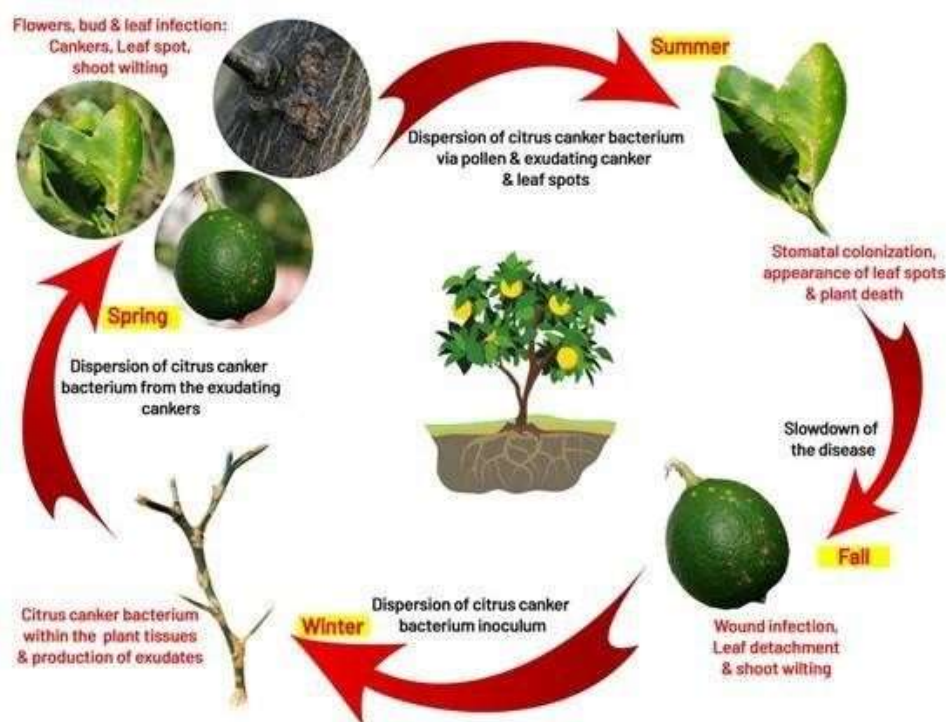


Fig 1.2. Dispersion of citrus canker bacterium in orchards.

(Source: Naqvi et al., Agronomy, 2022)

1.1.2. Survival

The main source of inoculation is cankerworm, leaves and twigs. The virus is transmitted from one season to the next mainly through infected branches and twigs, which are the first inoculum. In leaf and fruit diseases, organisms survive until fall; However, bacterial survival in infected leaves has been reported to be up to six months. It has been found that bacteria survived for more than 6 months on infected leaves, 52 days in sterile soil, and only 9 days in unsterilized soil. Bacteria have also been shown to survive in dry conditions at 30°C for 11 to 12 days. On citrus hosts, the bacteria survive epiphytically in low numbers and associate with non-citrus plants, grass hosts, and soil without causing symptoms. However, saprophytic soil organisms were not found in the absence of tissue or debris. The viability of pathogens in subtropical soils is limited. The vaccine dies within 24 to 72 hours on most inert surfaces such as fabric, metal, plastic, and wood in sunlight and shade. Due to the attack and competition of saprophytic bacteria, the number of bacteria decreases to an unknown level 1-2 months after the leaves or fruits fall to the ground.

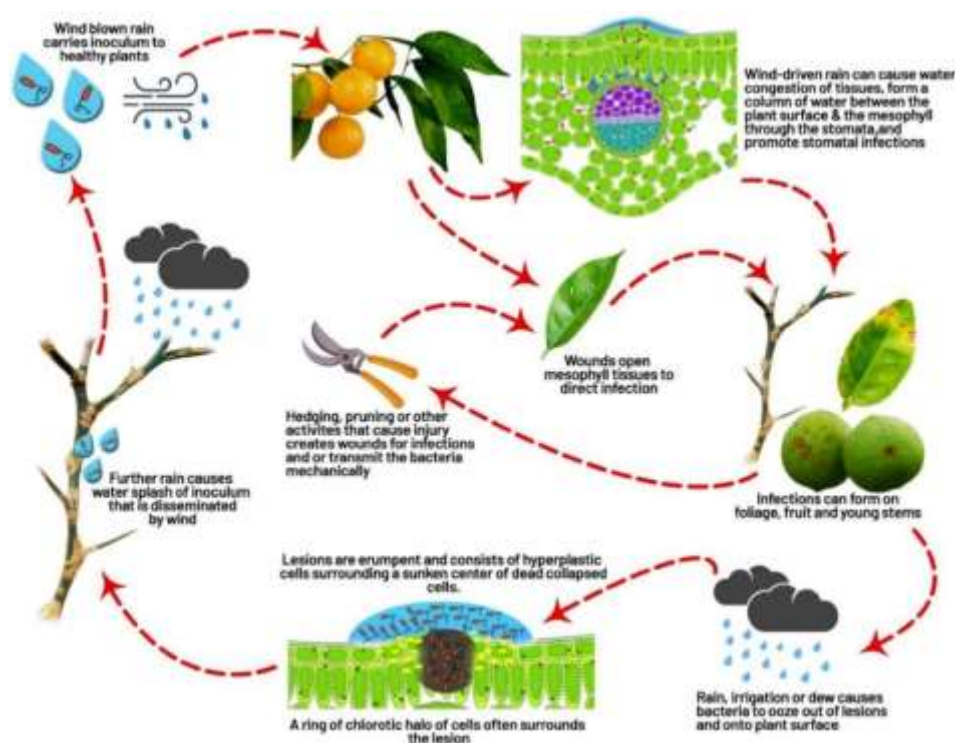


Fig 1.3. How canker bacterium initiates local infection into leaves, twigs, and fruits.

(Source: Naqvi et al., Agronomy, 2022)

1.1.3. *Transmission*

In natural conditions, hurricanes and rain are responsible for short-term transmission of the disease. However, long-term transmission between geographical areas is expected to occur primarily through infected plant material. During a major storm such as a typhoon, the disease can travel up to 10 to 15 kilometres. The spread of the disease was further investigated using models based on wind direction patterns and measurement data showing wind speeds of 8 m/s and precipitation of approximately 0.32 cm/h, similar to insects such as lemon yellow beetles when thunderstorms were possible. to enter. soil Injuries from pores or stings. The main reason for the spread of the disease is wind and rain.

CHAPTER 2

LITERATURE SURVEY

In 2018, Neha Chourasia developed a pioneering project titled "LEAF DISEASE DETECTION USING IMAGE PROCESSING," which focused on addressing the challenge of plant disease detection. One of the significant areas of research in computer vision, particularly over the last few decades, has been image retrieval. Content-Based Image Retrieval (CBIR) systems play a crucial role in automatically indexing, searching, retrieving, and browsing image databases. These systems rely on important properties such as color, shape, and texture features. The paper discusses a detailed classification of CBIR systems, including various techniques and their combinations to enhance performance. It also examines the impact of different matching techniques on the retrieval process.

Naureen Zainab's 2023 project introduces a novel deep learning-based approach for detecting and classifying the growth rate of citrus canker, a significant plant disease caused by *Xanthomonas citri*. By categorizing the disease into six distinct stages and employing DenseNet-121, the study achieves a high classification accuracy of 98.97%. This approach not only enables real-time identification of the disease but also offers insights into disease management and prevention by predicting the growth rate at different stages of infection.

Jaafar Abdulridha's 2019 project developed a remote sensing technique for detecting citrus canker, first in laboratory conditions and then in groves using an unmanned aerial vehicle (UAV). The study used a hyperspectral imaging system to detect citrus canker in different disease stages on Sugar Belle leaves and immature fruit, employing radial basis function (RBF) and K nearest neighbor (KNN) classification methods. In laboratory tests, RBF showed higher classification accuracy (94%, 96%, and 100%) than KNN (94%, 95%, and 96%). The water index (WI) and Modified Chlorophyll Absorption in Reflectance Index (ARI and TCARI 1) were found to be effective in detecting canker in different conditions. The UAV-based technique achieved 100% accuracy in identifying healthy and canker-infected trees.

Malik Abdul Rehman's 2020 project aimed to find effective chemicals and plant-based extracts to control citrus canker in Kinnow mandarin plants. The study, conducted at the Citrus Research Institute in Pakistan, tested nine treatments including control (no chemical), Neemsol, copper oxychloride, streptomycin sulphate, potassium acetyl benzoic acid, difenoconazole, and extracts of *Acacia nilotica*, *Datura alba*, and *Allium cepa*. These treatments were applied as foliar sprays four times a year. Copper oxychloride showed the highest disease control at 74%, followed by difenconazole at 56%. Among botanical extracts, *A. cepa*, *D. alba*, Neem Oil, and *A. nilotica* showed disease control rates of 74%, 64%, 59%, and 52%, respectively. The use of copper oxychloride, difenconazole, and extracts of *A. cepa* and *D. alba* are recommended for controlling citrus canker in Kinnow plantations..

Syed Atif Hasan Naqvi's 2022 project provides an in-depth analysis of citrus canker, a disease caused by *Xanthomonas citri* subsp. *citri* that poses a significant threat to the global citrus fruit crop. The project highlights the disease's impact on citrus production, particularly in Pakistan, where the average yield is lower than in other citrus-producing countries. The study identifies five distinct forms of citrus canker, with the Asiatic form being the most destructive. It explores the disease's epidemiology, pathogen biology, and management strategies, emphasizing the importance of quarantine measures and host resistance. The project also discusses recent advancements in the understanding of the pathogen's genome and its interaction with host plants, providing valuable insights for future research and disease management efforts.

CHAPTER 3

AIM AND SCOPE

3.1. AIM

The project aims to detect citrus canker disease early using machine learning and sensors, classify disease stages, and find natural ways to fight the bacteria, reducing the need for harmful pesticides.

3.2. SCOPE

- Purpose: Revolutionize citrus canker detection through real-time diagnostic results using image analysis.
- Innovation: Offers immediate and accurate citrus canker detection, aiding in prompt disease management.
- Technology: Utilizes image analysis for quick and reliable diagnosis, enhancing efficiency and precision.
- Impact: Addresses citrus canker issues promptly, preventing spread and minimizing crop damage.
- Model for Technology: Sets a precedent for leveraging technology to combat environmental challenges.
- Sustainability: Promotes sustainable economic growth by safeguarding citrus crops and farmers' livelihoods.

CHAPTER 4

MATERIALS AND EXPERIMENTAL METHODS

4.1. MATERIALS REQUIRED

The system requirements for a citrus canker preliminary disease detection system play a crucial role in ensuring the effective development, deployment, and performance of such a system. In this document, we will outline the system requirements for a plant disease detection system, considering both the hardware and software aspects.

4.1.1. HARDWARE REQUIREMENTS

- **Processor**

The system should have a capable processor to handle image processing tasks efficiently. A multi-core processor such as Intel Core i5 or higher is recommended.

- **Memory (RAM)**

Adequate RAM is essential for processing large image datasets. A minimum of 8 GB RAM is recommended, but higher capacity (16 GB or more) may be required for processing intensive tasks.

- **Storage**

Sufficient storage space is needed to store the dataset, trained models, and other system files. A minimum of 256 GB SSD storage is recommended for faster data access.

- **Graphics Processing Unit (GPU)**

While not mandatory, a dedicated GPU can significantly accelerate the training and inference process, especially for deep learning models. NVIDIA GeForce GTX 1060 or higher is recommended for GPU acceleration.

- **Camera:**

High-Resolution Camera: A high-resolution camera with at least 5 megapixels is required for capturing detailed images of plant leaves and symptoms. DSLR cameras or high-quality smartphone cameras can be used.

- **Internet Connectivity:**

Stable Internet Connection: An internet connection is required for accessing online resources, downloading updates, and potentially for cloud-based model training and deployment.

4.1.2. SOFTWARE REQUIREMENTS

Operating System

- **Linux (Ubuntu, CentOS) or Windows**

The system should support one of the widely used operating systems to run the required software tools and libraries seamlessly.

4.2. DEVELOPMENT ENVIRONMENT

- **Python**

The system should have Python installed, as most of the machine learning and computer vision libraries are available for Python.

- **Integrated Development Environment (IDE)**

Popular IDEs such as PyCharm, Visual Studio Code, or Jupyter Notebook can be used for code development and experimentation.

4.3. LIBRARIES AND FRAMEWORKS

- **TensorFlow or PyTorch**

These deep learning frameworks are essential for building and training convolutional neural networks (CNNs) for image classification tasks.

- **Open CV**

The OpenCV library provides essential functions for image preprocessing, feature extraction, and image manipulation.

- **NumPy and Pandas**

These libraries are useful for handling numerical data and performing data manipulation tasks.

- **Flask or Django**

A web framework like Flask or Django may be required for building a web-based interface for the plant disease detection system.

- **Dependencies**

Additional libraries and dependencies may be required based on specific algorithms, techniques, or external services integrated into the system.

the outlined hardware and software requirements, developers can ensure the smooth development, deployment, and operation of a plant disease detection system. These requirements provide a foundation for building a reliable and efficient system.

4.3. METHODS

Preliminary disease detection plays a crucial role in ensuring the health and productivity of citrus crops. Traditional methods of disease diagnosis often rely on visual inspection by agricultural experts, which can be time-consuming and subjective. In recent years, advancements in machine learning and computer vision techniques have enabled the development of automated systems for plant disease detection. In this document, we will explore various methods and algorithms used in the field of citrus disease detection, including image processing techniques, machine learning models, and deep learning architectures.

- **Image Processing Techniques**

Image processing techniques form the foundation of preliminary disease detection systems. These techniques involve manipulating and analyzing digital images to extract meaningful information about the presence of diseases in plants. Some

common image processing techniques used in plant disease detection includes:

- **Image Preprocessing:** Preprocessing techniques such as noise reduction, image enhancement, and color normalization are applied to improve the quality and consistency of input images.

Feature Extraction: Features such as color histograms, texture features, and shape descriptors are extracted from the preprocessed images to represent the visual characteristics of plant diseases.

- **Segmentation:**

Segmentation techniques are used to separate diseased regions from healthy plant tissues in the images, enabling focused analysis and diagnosis.

- **Morphological Operations:**

Morphological operations such as erosion, dilation, and filtering are applied to refine the segmented regions and remove noise.

- **Machine Learning Models:**

Machine learning models are commonly employed in plant disease detection systems to classify images based on extracted features. These models learn from labeled training data and can generalize to classify unseen images. Some popular machine learning algorithms used in plant disease detection include:

- **Support Vector Machines (SVM):**

SVM is a supervised learning algorithm that can classify images into different disease classes based on extracted features. It works by finding the optimal hyperplane that separates the classes with the maximum margin.

- **Random Forest:**

Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification accuracy. It is robust to overfitting and can handle high-dimensional feature spaces effectively.

- **k-Nearest Neighbors (k-NN):**

k-NN is a simple and intuitive classification algorithm that classifies images based on the majority vote of their nearest neighbors in the feature space. It is non-parametric

and does not require training a model explicitly.

- **Deep Learning Architectures:**

Deep learning architectures, particularly convolutional neural networks (CNNs), have shown remarkable performance in various image recognition tasks, including plant disease detection. CNNs can automatically learn hierarchical features from raw pixel data, eliminating the need for handcrafted feature extraction. Some commonly used CNN architectures in plant disease detection include:

AlexNet: AlexNet is a pioneering CNN architecture that achieved significant performance improvements in image classification tasks. It consists of multiple convolutional and pooling layers followed by fully connected layers.

VGG (Visual Geometry Group) Net: VGG Net is characterized by its simplicity and uniform architecture, consisting of multiple convolutional layers with small filter sizes and max-pooling layers.

- **ResNet (Residual Network):**

ResNet introduced the concept of residual connections, which allow the network to learn residual mappings instead of directly learning the desired mappings. This enables training of very deep networks with improved performance.

- **Transfer Learning:**

Transfer learning is a technique where a pre-trained model, trained on a large dataset such as ImageNet, is fine-tuned on a smaller dataset of plant disease images. This approach leverages the knowledge learned by the pre-trained model and adapts it to the specific task of plant disease detection. Transfer learning can significantly reduce the amount of labeled data required for training and improve the performance of the model.

4.4. ALGORITHM

Preliminary disease detection is a critical task in agriculture, as it enables early identification and management of diseases, thereby ensuring crop health and productivity. In recent years, advancements in machine learning, computer vision, and image processing techniques have revolutionized the field of plant disease detection. Various algorithms have been developed and applied to analyze digital images of citrus and accurately classify diseased and healthy plant tissues. In this document, we will explore some of the key algorithms used in plant disease detection, including traditional machine learning algorithms, deep learning architectures, and ensemble methods.

- **Support Vector Machines (SVM):**

Support Vector Machines (SVM) is a supervised learning algorithm used for classification and regression tasks. In the context of plant disease detection, SVM is often employed to classify images of plants into different disease categories based on extracted features. SVM works by finding the optimal hyperplane that separates the classes in the feature space with the maximum margin. By defining a decision boundary between diseased and healthy plant tissues, SVM can effectively discriminate between different types of diseases.

- **Convolutional Neural Networks (CNNs):**

Convolutional Neural Networks (CNNs) have emerged as powerful tools for image recognition and classification tasks, including plant disease detection. CNNs are a type of deep learning architecture inspired by the visual cortex of the human brain. They consist of multiple layers of convolutional and pooling operations followed by fully connected layers. CNNs can automatically learn hierarchical features from raw pixel data, enabling them to capture complex patterns and variations in plant images.

- **Random Forest:**

Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification accuracy. In the context of plant disease detection, Random Forest can be used to classify images based on handcrafted features extracted from the images. Each decision tree in the ensemble is trained on a subset of the data, and the final prediction is made by aggregating the predictions of individual

trees. Random Forest is known for its robustness to overfitting and ability to handle high-dimensional feature spaces effectively.

- **k-Nearest Neighbors (k-NN):**

k-Nearest Neighbors (k-NN) is a simple and intuitive classification algorithm used in plant disease detection. k-NN works by finding the k nearest neighbors of a given sample in the feature space and assigning the majority class label among them to the sample. In the context of image classification, k-NN can be applied to classify images based on the similarity of their feature representations. k-NN is non-parametric and does not require training a model explicitly, making it suitable for small-scale plant disease detection applications.

- **Ensemble Methods:**

Ensemble methods combine multiple base learners to improve the overall performance of a predictive model. In the context of plant disease detection, ensemble methods such as AdaBoost, Gradient Boosting, and Bagging are commonly used. These methods train multiple weak learners on different subsets of the data and combine their predictions to make a final decision. By leveraging the diversity of individual learners, ensemble methods can achieve higher classification accuracy compared to single models.



Fig 4.1 Methodology for Plant Disease Detection

(Source: Agronomy)

- **Data Collection:**

The first step in developing a preliminary citrus canker disease detection system is to collect a diverse and representative dataset of plant images. This dataset should include images of various citrus plants, growth stages, and environmental conditions. Additionally, the dataset should cover a wide range of disease types and severities to ensure the robustness and generalization of the detection model. Data collection can be conducted through field surveys, online repositories, or collaboration with agricultural experts and research institutions.

- **Data Preprocessing:**

Once the dataset is collected, preprocessing steps are applied to prepare the images for analysis. This includes resizing the images to a uniform size, normalization to adjust for variations in lighting and contrast, and augmentation techniques to increase the diversity of the dataset. Preprocessing may also involve manual annotation of images to label diseased and healthy plant tissues for supervised learning algorithms.

- **Feature Extraction:**

Feature extraction is a crucial step in plant disease detection, where relevant information is extracted from the images to represent them in a suitable format for analysis. Traditional feature extraction methods may include handcrafted features such as color histograms, texture descriptors, and shape-based features. Alternatively, deep learning approaches can automatically learn hierarchical features from raw pixel data using convolutional neural networks (CNNs).

- **Model Training:**

Once the features are extracted, they are used to train a machine learning model for disease detection. This involves splitting the dataset into training and validation sets, selecting an appropriate algorithm or architecture, and optimizing the model parameters using techniques such as cross-validation and grid search. For deep learning models, training typically involves feeding the extracted features into a CNN architecture and fine-tuning the network weights using gradient-based optimization algorithms like stochastic gradient descent (SGD) or Adam.

- **Model Evaluation:**

After training, the performance of the detection model is evaluated using the validation set. Evaluation metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's ability to correctly classify diseased and healthy plant tissues. Additionally, techniques such as confusion matrix analysis and receiver operating characteristic (ROC) curve analysis may be used to further evaluate the model's performance and identify areas for improvement.

- **Model Deployment:**

Once the model is trained and evaluated, it can be deployed for real-world plant disease detection applications. This may involve integrating the model into a mobile or web-based application, deploying it on edge devices for offline use, or incorporating it into existing agricultural machinery and systems. Continuous monitoring and maintenance of the deployed model are essential to ensure its reliability and effectiveness in detecting plant diseases in agricultural settings.

- **Continuous Improvement:**

Plant disease detection is an ongoing process, and continuous improvement of the detection system is necessary to adapt to changing environmental conditions, emerging disease threats, and evolving agricultural practices. This involves collecting new data, retraining the model with updated information, and incorporating feedback from end-users and domain experts to enhance the system's performance and usability over time.

4.6. WORKING PRINCIPLE

- **Data Collection**

The first step in developing a preliminary plant disease detection system is to collect a diverse and representative dataset of plant images. This dataset should include images of various citrus plant species, growth stages, and environmental conditions. Additionally, the dataset should cover a wide range of disease types and severities to ensure robustness and generalization of the detection model. Data collection can be conducted through field surveys, online repositories, or collaboration with agricultural experts and research institutions.

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4.7. SOURCE CODE

To train the model

```
import os

import numpy as np

from PIL import Image

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense


# Image parameters

img_width, img_height = 150, 150

input_shape = (img_width, img_height, 3) # 3 channels for RGB images


# List of directories and corresponding labels

directories = [

    ('/content/D Dataset/stage 1', 0),

    ('/content/D Dataset/stage 2', 1),

    ('/content/D Dataset/Stage 3', 2),

]


# Collect image paths and corresponding labels

images = []

labels = []

for directory, label in directories:

    for root, _, filenames in os.walk(directory):
```

```

for filename in filenames:

    if filename.endswith(('.png', '.jpg', '.jpeg')): # Check if the file is an image

        path = os.path.join(root, filename)

        img = Image.open(path)

        img = img.resize((img_width, img_height))

        img = np.array(img) / 255.0 # Normalize pixel values to range [0, 1]

        images.append(img)

        labels.append(label)


# Check the content of directories

for directory, _ in directories:

    print("Content of directory:", directory)

    print(os.listdir(directory))


# Check the number of images and labels

print("Number of images:", len(images))

print("Number of labels:", len(labels))


# Convert lists of images and labels to NumPy arrays

images = np.array(images)

labels = np.array(labels)


# Check the shapes of images and labels

print("Shape of images:", images.shape)

```

```

print("Shape of labels:", labels.shape)

# Model architecture
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(4, activation='softmax') # Output layer with softmax activation for multi-
class classification
])

# Compile the model

model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'], run_eagerly=True)

# Train the model

try:
    history = model.fit(images, labels, epochs=10)
except ValueError as e:
    print("Error during training:", e)

```

```
# Save the model with a different name  
model.save('Data_trained_disease_model.h5')
```

4.8. PREDICT PLANT CODE

```
import numpy as np  
  
import TensorFlow as tf  
  
from PIL import Image  
  
import matplotlib.pyplot as plt  
  
  
# Load the trained model from the .h5 file  
model = tf.keras.models.load_model('Data_trained_disease_model.h5')  
  
  
# Define a function to preprocess images  
def preprocess_image(image_path):  
    image = Image.open(image_path)  
    image = image.resize((150, 150))  
    image = np.array(image) / 255.0  
    return image  
  
  
# Define the path to the test image  
test_image_path = '/content/Canker (100) (1).jpg'  
  
  
# Make predictions on the test image
```

```
processed_image = preprocess_image(test_image_path)

prediction = model.predict(np.expand_dims(processed_image, axis=0))
```

```
# Define class labels
```

```
classes = ['Early Stage', 'Mid-Stage', 'Last Stage']
```

```
# Define content for each class
```

```
class_content = {
```

```
    'Early Stage': """"EARLY STAGE:
```

- Sanitation: Trimming of the infected parts to stop the spread.
- Pesticides application: Apply every 7-14 days of interval.

Chemical treatment suggestions:

1. Copper oxychloride (synthetic chemical): 3g/L water.
2. Diphenaconazole (synthetic chemical): 0.5ml /L water.
3. Allium cepa extract (botanical chemical): 10ml /L water.

Important considerations during chemical treatment:

- Weather conditions: Ensure no rain for at least 24 hours for chemical adherence to the plant surfaces.
- Plant growth stages: Pay special attention when periods of rapid growth or when fruit is setting.
- Local regulations and recommendations: Consult local agricultural authorities for tailored advice and adhere to guidelines.
- Product label: Always follow the product label for concentration, frequency and safety precautions.

```
""",
```

'Mid-Stage': ""MID-STAGE:

- MID STAGE:

- Avoid over-irrigation: Be careful with the splashing of water. Drip or micro irrigation sprinkler is recommended.
- Pesticides application: Apply every 7days of interval.

Chemical treatment suggestions:

1. Copper oxychloride (synthetic chemical): 3g/L water.
2. Diphenaconazole (synthetic chemical): 0.5ml /L water.
3. Allium cepa extract (botanical chemical): 10ml /L water.

Important considerations during chemical treatment:

- Weather conditions: Ensure no rain for at least 24 hours for chemical adherence to the plant surfaces.

Product label: Always follow the product label for concentration, frequency and safety precautions.

""

}

```
# Print predicted class probabilities and class label
```

```
predicted_class_index = np.argmax(prediction)
```

```
predicted_class_label = classes[predicted_class_index]
```

```
print("Predicted class probabilities:", prediction)
```

```
print("Predicted class:", predicted_class_label)
```

```
# Print content based on predicted class
```

```

if predicted_class_label in class_content:
    print(class_content[predicted_class_label])
else:
    print("No content available for predicted class:", predicted_class_label)

```

Convert the probabilities into a bar chart

```
plt.bar(classes, prediction[0][:len(classes)])
```

```
plt.xlabel('Class')
```

```
plt.ylabel('Probability')
```

```
plt.title('Predicted Class Probabilities')
```

```
plt.show()
```

```
"""
```

```
'Last Stage': """LAST STAGE:
```

- LATE STAGE:
- Tree removal: To prevent the spread to nearby healthy trees
- Pesticides application: Apply every 5-7 days of interval.

Chemical treatment suggestions:

1. Copper oxychloride (synthetic chemical): 3g/L water.
2. Diphenaconazole (synthetic chemical): 0.5ml /L water.
3. Allium cepa extract (botanical chemical): 10ml /L water.

Important considerations during chemical treatment:

- Weather conditions: Ensure no rain for at least 24 hours for chemical adherence to the plant surfaces.

- Plant growth stages: Pay special attention when periods of rapid growth or when fruit is setting.
- Local regulations and recommendations: Consult local agricultural authorities for tailored advice and adhere to guidelines.

4.9. FUTURE PROSPECTS

The future prospects of preliminary citrus canker disease detection systems are promising, with ongoing advancements in technology, research, and innovation driving the evolution of these systems. Here are some key areas where future developments and opportunities are expected:

- Plant growth stages: Pay special attention when periods of rapid growth or when fruit is setting.
- Local regulations and recommendations: Consult local agricultural authorities for tailored advice and adhere to guidelines.
- Product label: Always follow the product label for concentration, frequency and safety precautions.

- **Advancements in Imaging Technology:**

As imaging technology continues to improve, preliminary plant disease detection systems will benefit from higher resolution cameras, multispectral and hyperspectral imaging sensors, and drone-based remote sensing platforms. These advancements will enable more accurate and detailed imaging of plant tissues, facilitating early detection and diagnosis of diseases.

- **Integration of IoT and Sensor Networks:**

The Internet of Things (IoT) and sensor networks offer opportunities to enhance preliminary plant disease detection by enabling real-time monitoring of environmental conditions, soil moisture levels, and plant health indicators. Integrating sensor data with image analysis algorithms can provide comprehensive insights into crop health and disease dynamics, allowing for proactive management strategies.

- **Artificial Intelligence and Machine Learning:**

Continued advancements in artificial intelligence (AI) and machine learning (ML) algorithms will enable more sophisticated and adaptive disease detection models. Deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can automatically learn complex patterns and features from large-scale datasets, improving the accuracy and robustness of disease classification.

- **Cloud Computing and Edge Computing:**

Cloud computing and edge computing technologies offer scalable and efficient solutions for processing and analyzing large volumes of image and sensor data in real-time. Cloud-based platforms provide centralized data storage, analysis, and collaboration capabilities, while edge computing enables on-device processing and decision-making, reducing latency and bandwidth requirements.

- **Remote Monitoring and Mobile Applications:**

Mobile applications and web-based platforms allow farmers and agricultural stakeholders to remotely access and monitor plant disease detection systems from anywhere, using smartphones, tablets, or computers. These applications provide real-time alerts, recommendations, and decision support tools, empowering users to take timely actions to mitigate disease risks.

- **Interdisciplinary Research and Collaboration:**

Collaborative research efforts between agronomists, plant pathologists, computer scientists, and engineers will drive interdisciplinary innovations in plant disease detection. By combining expertise from diverse fields, researchers can develop holistic solutions that address the complex challenges associated with crop health and disease management.

- **Bioinformatics and Genomic Analysis:**

Advances in bioinformatics and genomic analysis enable researchers to study plant-pathogen interactions at the molecular level, identifying genetic markers associated with disease resistance or susceptibility. Integrating genomic data with phenotypic and

environmental information can enhance our understanding of disease dynamics and facilitate the breeding of disease-resistant crop varieties.

- **Sustainable Agriculture and Precision Farming:**

Plant disease detection systems play a crucial role in supporting sustainable agriculture practices and precision farming techniques. By enabling targeted interventions and resource optimization, these systems help minimize pesticide use, reduce environmental impact, and enhance crop yields and quality.

CHAPTER 5

RESULTS AND DISCUSSION

5.1. RESULT

Through an in-depth analysis of existing literature on detection systems, our study has pinpointed important areas to enhance the management of citrus plant health. We have effectively created a sophisticated detection system that greatly improves accuracy by identifying plant problems early on. This system provides an easy-to-use platform designed to meet the demands of farmers as well as industrial users. Our system's main achievement is the combination of image processing and machine learning techniques, which have been optimised across a wide range of datasets. This accomplishment represents a significant advancement in the culture of citrus plants by encouraging sustainable growth and efficient disease management. Our findings highlight the significance of utilising cutting-edge technologies to strengthen agricultural sector stakeholders, enable preventative actions, and enhance citrus plant health outcomes.

5.2. DISCUSSIONS

5.2.1. MERITS

- **Enhanced precision**

By combining image processing and machine learning technology, problems affecting citrus plants can be identified early on and with more precision.

- **Early Detection**

Proactive interventions are made possible by early-stage detection capabilities, which lower the likelihood of plant diseases spreading widely and improve plant health outcomes.

- **User-Friendly Platform**

By creating an interface that is easy to use, a system may be used by a variety of users, such as farmers and professionals in the sector, which encourages acceptance and utilization.

- **Sustainable Agriculture**

The system promotes sustainable agricultural practices and the growth of citrus trees by enabling prompt interventions and disease management.

5.2.2. DEMERITS

- **Technology Complexity**

Combining machine learning with image processing technologies can make a system more complicated, needing specialised knowledge to maintain and implement.

- **Data Requirements**

To effectively use these technologies, a variety of detailed datasets are required, which can be difficult to obtain and manage, especially for distinct regional or seasonal fluctuations.

- **Cost Implications**

The development and implementation of cutting-edge technologies may entail high upfront expenses, which may restrict their availability to smaller-scale farmers or areas with less developed economies.

5.2.3. SOLUTION FOR DEMERITS

- **Simplified User Interface**

To combat the complexity of technology, provide an intuitive user interface that lowers the requirement for specialised technical knowledge and makes interaction easier.

- **Data Collaboration and Sharing**

To ensure the system's adaptability and efficacy in a variety of scenarios, cultivate partnerships with agricultural stakeholders to promote data sharing and cooperative efforts in dataset collection and management.

- **Cost-Effective Solutions**

To cut infrastructure expenses, investigate open-source software solutions and take advantage of cloud computing resources. To encourage widespread use, take into account scalable price mechanisms or incentives for small-scale producers.

- **Continuous Improvement**

Put in place a feedback loop system that enables ongoing modification and enhancement in response to changing agricultural requirements and user experiences.

5.3. ANALYSIS

Early detection systems for citrus canker have traditionally relied on visual inspection by trained professionals or farmers to identify symptoms such as leaf lesions, fruit blemishing, and tree dieback. These manual inspection methods, while effective to a certain extent, were labor-intensive, subjective, and prone to human error. The accuracy of disease diagnosis often varied depending on the experience and expertise of the individual conducting the inspection.

On the other hand, the "LeafLens" project is focused on developing a user-friendly platform using machine learning and image processing technologies for early detection and management of citrus canker (CC) caused by *Xanthomonas citri* subsp. *citri* (Xcc). Citrus canker is a destructive disease affecting citrus crops globally, characterized by symptoms like leaf loss, fruit drop, and blemishing. LeafLens aims to enable early detection by analyzing uploaded images of citrus leaves and fruit to identify characteristic CC symptoms such as lesions and discoloration. The project also seeks to categorize CC into early, mid, and late stages based on symptom severity to guide targeted management strategies. Key features include a simple

mobile interface for users to upload images and receive real-time assessments of disease severity using machine learning algorithms. By facilitating timely intervention and optimizing resource use, LeafLens aims to enhance disease management practices, ultimately contributing to improved citrus crop health and sustainability. Challenges include ensuring diverse and high-quality datasets for model training and scalability for widespread adoption across different regions. The project represents a promising technological solution to combat citrus canker and support sustainable citrus cultivation practices worldwide.

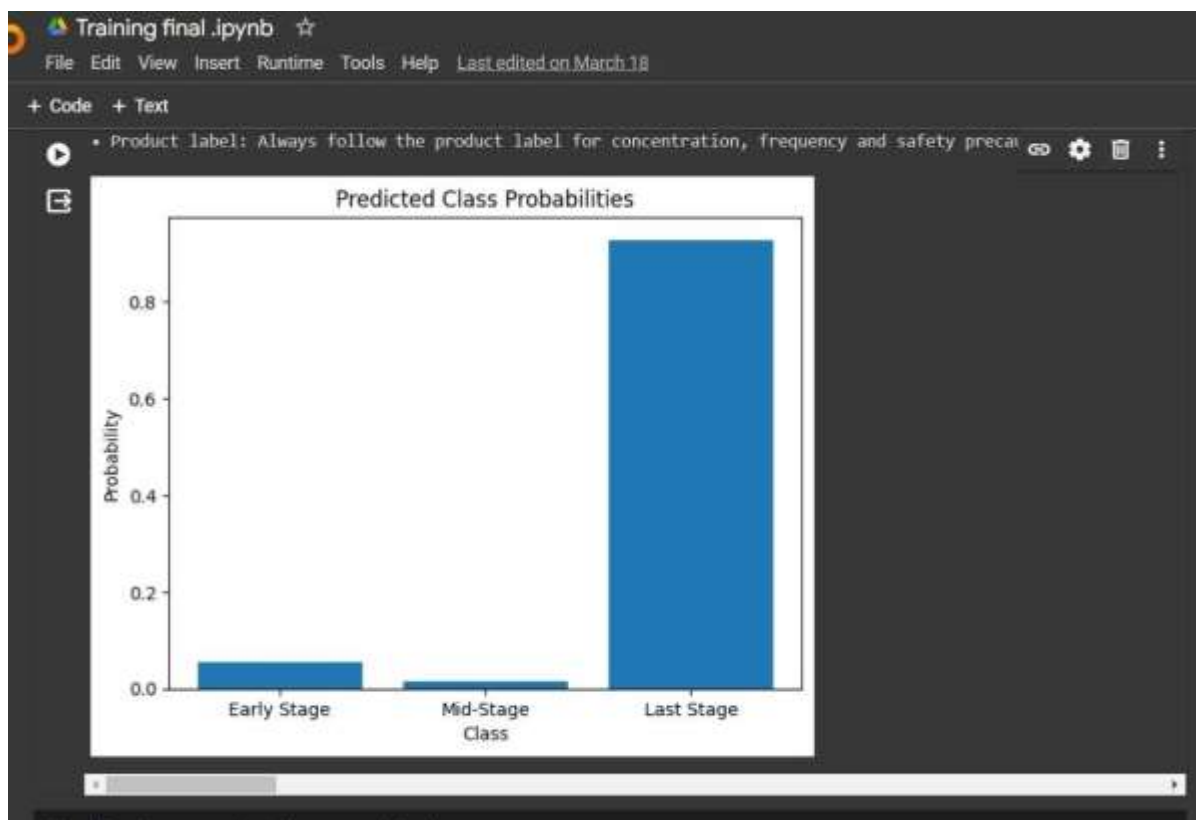


FIG 5.1 ACCURACY ANALYSIS CHART

CHAPTER 6

SUMMARY AND CONCLUSION

6.1. SUMMARY

The development of leaflens, a citrus canker early detection technology, demonstrates the application of engineering knowledge to automate the detection of citrus canker symptoms on leaves, stems, and fruits using machine learning and modern sensor technologies.

The project enhances disease detection accuracy, promotes proactive disease control practices, reduces the need for harmful pesticides, and fosters collaboration between agricultural experts and technology developers.

It also emphasizes effective communication of complex engineering concepts to the agricultural community and society, and ensures efficient management of resources and project timelines for successful implementation in citrus agriculture.

6.2. CONCLUSION

The development of leaflens represents a significant leap in non-invasive citrus canker detection technology, showcasing how agricultural disease control is being transformed by technology. This innovation offers a non-intrusive method that can detect the disease early, enhancing the efficiency and scalability of disease management strategies. However, there is a need to enhance the accessibility and adaptability of such technologies to diverse agricultural environments, ensuring their widespread adoption.

Leaflens and similar technologies hold immense promise for proactive disease control and sustainable agricultural practices. By leveraging machine learning, artificial intelligence, and data analytics, we can further refine early detection capabilities and foster a more resilient citrus production ecosystem. Embracing these advancements and fostering interdisciplinary collaboration will be pivotal in advancing citrus canker detection and promoting sustainable agricultural practices globally.

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