A

Project Report

on

Plant Disease Detection using Mask R-CNN

Submitted to

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SHRI SANT GAJANAN MAHARAJ COLLEGE OF ENGINEERING,
SHEGAON – 444 203 (M.S.)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that **Ms. Chanchal B. Junare, Ms. Revati M. Khandare, Ms. Sakshi P. Koche** and **Ms. Vaishnavi S. Ghanokar** students of final year Bachelor of Engineering in the academic year 2023-24 of Computer Science and Engineering Department of this institute have completed the project work entitled **"Plant Disease Detection using Mask R-CNN"** and submitted a satisfactory work in this report. Hence recommended for the partial fulfillment of degree of Bachelor of Engineering in Computer Science and Engineering.

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ABSTRACT

Plant diseases pose a significant threat to agricultural productivity and economic value, requiring efficient detection methods. Leveraging various morphological features and properties of plant leaves, our framework aims to accurately identify different types of plant diseases. Furthermore, we present Mask R-CNN, an all-encompassing system for segmenting individual objects within an image, crucial in various computer vision tasks. Mask R-CNN builds on the Faster R-CNN model by effectively identifying objects within images and producing detailed segmentation masks for each instance. We show the success of Mask R-CNN in addressing various complex problems, including instance segmentation, outperforming existing methods.

Keywords: - *Plant Disease Detection, Mask R-CNN, Instance Segmentation, Object Detection*

Contents

List of Abbreviations and Symbols

Abbreviation	**Stands for**
CNN	Convolutional Neural Network
RCNN	Region Based Convolution Neural Network
FCN	Fully Convolutional Network
SVN	Support Vector Machine
RPN	Region Proposal Network
ROI	Region of Interest
OpenCV	Open Source Computer Vision
IoU	Intersection over Union
COCO	Common Object in Context

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CHAPTER 1

<u>Introduction</u>

1. Introduction

Adi M. states the use of deep learning for AI detection and machine leariining models and it use in their research work" An Overview on Plant Disease Detection Algorithm Using Deep Learning". In recent years, deep learning technology in the study of plant disease recognition made more progress. Deep learning (DL) technology in the face of the user is transparent, the researchers of plant protection and statistics professional level is not high, can be automatically extracted image features and classification of plant disease spot, eliminating the traditional image recognition technology of feature extraction and classifier design a lot of work, can express original image characteristics, has the characteristics of the end-to end. These characteristics make deep learning technology in plant disease recognition-obtained-widespread attention, and it has become a hot research topic. [5]

This project introduces an innovative methodology of deep learning and transfer learning for automating the identification of plant diseases through the utilization of the deep learning model "Mask R-CNN". The primary objective is to address the significant challenge posed by plant diseases to agricultural productivity by leveraging advanced machine learning techniques. By integrating object detection and segmentation, the Mask R-CNN model facilitates precise pixel-level labeling across diverse objects, a capability particularly crucial in the agricultural domain.

We cover a broad spectrum of plant diseases and explore various machine learning classification techniques employed to detect these diseases across different types of plant leaves, through this paper. Mask R-CNN enhances the Faster R-CNN architecture by adding an additional branch specifically for predicting segmentation masks for each Region of Interest (ROI). This branch works alongside the existing classification and bounding box regression branches. The mask branch includes a streamlined Fully Convolutional Network (FCN) that is applied to each ROI, providing pixel-by-pixel predictions of segmentation masks. Implementation and training of Mask R-CNN are straightforward within the Faster R-CNN framework, allowing for versatile architectural designs. Furthermore, the additional computational load introduced by the mask branch is minimal, ensuring efficient performance and facilitating rapid experimentation.

1.1 Overview

The study underscores the critical importance of early disease detection in agriculture and emphasizes the transformative potential of deep learning and computer vision technologies in revolutionizing crop management practices. Through meticulous processes of dataset creation, annotation, and model training, the project demonstrates the effectiveness of Mask R-CNN in accurately identifying and pinpointing disease areas on plant leaves. The experimental results corroborate the efficacy of the proposed framework in enabling granular disease detection, offering actionable insights for farmers to efficiently manage their crops. This research not only highlights the significance of advanced technologies like Mask R-CNN in reshaping agricultural practices but also lays the groundwork for future advancements in plant disease detection and management.

Furthermore, the project emphasizes the need for continual exploration and refinement of such technologies to address evolving challenges in agriculture, paving the way for sustainable and resilient crop production systems. Through its comprehensive approach and rigorous methodology, this project contributes to the growing body of knowledge in the field of agricultural technology and underscores the importance of innovation in ensuring global food security and sustainability.

1.2 Background and Significance of the Problem

Agriculture stands as a cornerstone of human civilization, providing sustenance, economic stability, and livelihoods to billions worldwide. Yet, amidst its critical role, agriculture faces formidable challenges, among which plant diseases loom large. These maladies, caused by pathogens ranging from bacteria and fungi to viruses and pests, wreak havoc on crops, leading to diminished yields, economic losses, and threats to global food security.

Traditionally, identifying and managing plant diseases have relied on human observation, field surveys, and manual interventions. However, these methods suffer from inherent limitations, including subjectivity, inefficiency, and the inability to cope with the scale and speed of disease spread. Moreover, the dynamic nature of plant-pathogen interactions, exacerbated by factors such as climate change and globalization, underscores the urgency for more effective disease management strategies. In response to these challenges, the integration of advanced technologies such as machine learning and computer vision into agriculture has emerged as a promising avenue. These technologies offer the potential to revolutionize disease detection by enabling automated, accurate, and rapid identification of plant diseases directly from digital images of crop specimens.

Among the myriad machine learning approaches, the Mask R-CNN model stands out for its ability to perform instance segmentation, delineating individual objects within an image with pixel-level precision. By combining object detection and segmentation, Mask R-CNN offers a comprehensive solution for identifying and localizing plant diseases, facilitating targeted interventions and minimizing collateral damage.

The significance of developing automated plant disease detection systems extends far beyond the agricultural sector. It holds the promise of safeguarding food security, preserving natural resources, and promoting sustainable farming practices. By enabling early detection and intervention, these systems can mitigate the need for chemical pesticides, reduce environmental pollution, and enhance the resilience of agro ecosystems to climate variability. Moreover, automated disease detection aligns with broader trends towards digital transformation in agriculture, heralding a new era of precision farming and data-driven decision-making. Through the integration of sensor technologies, remote sensing, and machine learning algorithms, stakeholders can optimize resource allocation, improve crop management practices, and enhance the overall efficiency and productivity of agricultural systems.

In conclusion, the development of automated plant disease detection systems using advanced technologies like Mask R-CNN represents a critical step towards building resilient, sustainable, and future-ready agricultural systems. By harnessing the power of innovation, collaboration, and data-driven insights, we can confront the complex challenges posed by plant diseases and pave the way for a more food-secure and prosperous future for generations to come.

1.3 Aims of Research work study

The research work study on plant leaf disease detection using Mask R-CNN encompasses a set of core objectives aimed at propelling advancements in automated disease detection within agriculture. Primarily, the focus lies on crafting a sturdy and dependable automated system adept at precisely pinpointing various plant diseases from digital images of crop specimens. This involves the meticulous training of the Mask R-CNN model on diverse datasets to ensure its efficacy across a spectrum of crop varieties and disease presentations. Furthermore, the research aims to gauge the Mask R-CNN model's performance metrics encompassing detection accuracy, speed, and scalability, thereby furnishing valuable insights into its pragmatic applicability in agricultural milieus. Additionally, the study endeavors to probe the potential of incorporating sophisticated machine learning techniques, particularly instance segmentation, to refine the precision and effectiveness of plant disease detection. Harnessing the capabilities of Mask R-CNN for pixel-level segmentation of diseased regions, the research aims to attain more precise and nuanced disease identification, thereby facilitating targeted interventions and management protocols. Moreover, the research endeavors to evaluate the tangible applications of automated disease detection systems in agriculture, with a specific emphasis on enhancing crop management practices, diminishing reliance on chemical pesticides, and championing environmental sustainability.

Another crucial facet of the study involves collaborative engagement with agricultural experts, researchers, and stakeholders. Through active involvement with domain specialists and end-users, the study seeks to validate the practical utility and usability of the developed system in real-world agricultural scenarios. This collaborative ethos ensures that the research outcomes remain pertinent, pragmatic, and aligned with the exigencies and aspirations of the agricultural domain. Furthermore, the research aims to furnish insights and recommendations for future strides in automated plant disease detection technology. This includes identifying avenues for algorithmic enhancements, sensor innovations, and data collection methodologies to augment the efficacy and scalability of automated disease detection systems in agriculture.

1.4 Objectives and Scope of the work

In our pursuit to tackle the challenges presented by plant diseases and enhance agricultural productivity, we have outlined four interconnected objectives that will guide our research on plant leaf disease detection using the Mask R-CNN algorithm. These objectives lay the groundwork for our efforts, aiming to develop a comprehensive solution that harnesses advanced technology to accurately detect and localize plant diseases.

1.4.1 Objectives

1. To collect and annotate plant images for fine tuning the pre-trained Mask-RCNN model.
2. To use a machine learning model based on Mask R-CNN for precise detection of various plant diseases.
3. To integrate a user-friendly interface for easy interaction with the disease detection system, facilitating image upload and result interpretation.
4. To validate and evaluate the model's performance to ensure accuracy, sensitivity, and specificity in real-world scenarios and diverse datasets.

1.4.2 Scope of the work

The scope of our project encompasses the design, development, and evaluation of a machine learning-based solution for plant leaf disease detection using the Mask R-CNN algorithm. Key components of the project include:

1. Development of a Disease Detection Model: We will create a machine learning model based on the Mask R-CNN algorithm, trained on a dataset comprising digital images of diseased plant leaves.
2. Implementation of Instance Segmentation: The model will be capable of performing instance segmentation to accurately identify and outline individual diseased areas on plant leaves.
3. Integration of User Interface: A user-friendly interface will be developed to facilitate interaction with the disease detection system, allowing users to upload images and view results in a clear and intuitive manner.
4. Validation and Performance Evaluation: The developed model will undergo rigorous validation and performance evaluation to assess its accuracy and effectiveness in detecting plant diseases across different plant species and disease types.

Overall, our project aims to contribute to advancements in agricultural technology by developing a robust and user-friendly solution for plant leaf disease detection. Through the integration of advanced machine learning techniques, we aim to empower farmers and agricultural stakeholders with tools to mitigate the impact of plant diseases and ensure global food security.

CHAPTER 2

Literature Review

2. Literature Review

Deepak Kumar., [1] This paper focuses on detecting wheat mosaic virus using the Mask-RCNN model, which achieved high accuracy in segmenting wheat leaves and detecting the virus. Utilizing 15,536 wheat images from the Punjab region, each leaf and virus instance was annotated for training. The model achieved 88.19% accuracy in leaf segmentation and 97.16% accuracy in virus detection. This approach holds promise for reducing yield losses caused by the mosaic virus, with future plans to apply the model to remote sensing images for broader detection in larger areas.

Kaiming He., [2] In this paper, the author presents straightforward and efficient framework for instance segmentation, demonstrating strong performance not only in bounding box detection but also in its potential extension to pose estimation tasks. We anticipate that the straightforward nature and adaptability of this framework will streamline future investigations into various instance-level visual recognition tasks and beyond.

Pushpa Annabel., [3] This paper presents a novel approach to automate the identification of plant diseases using the Mask R-CNN deep learning model. Its main goal is to tackle the considerable impact of plant diseases on agricultural output by harnessing sophisticated machine learning methods. By combining object detection and segmentation, the Mask R-CNN model enables accurate labeling of individual pixels across various objects, a capability of particular significance in agriculture.

Lili Li., [4] This paper provides a comprehensive review of recent studies focused on plant leaf disease recognition using image processing, hyper-spectral imaging, and deep learning (DL) techniques. It highlights the importance of large datasets, data augmentation, transfer learning, and visualization techniques for improving DL model accuracy in disease recognition. However, it identifies several shortcomings in existing research, such as the lack of robustness in DL models across different datasets, the limited applicability of lab-based datasets like Plant Village, and challenges in utilizing hyper-spectral imaging for early disease detection due to issues in obtaining labeled datasets and defining invisible disease symptoms. The paper calls for the development of more robust DL models, the creation of larger and more representative datasets, and the resolution of challenges hindering the widespread use of hyper-spectral imaging in plant disease detection.

Adi M., [5] This paper addresses the growing concern among farmers regarding plant disease detection, highlighting the significance of techniques like Deep Learning, particularly in mobile applications equipped with deep learning models. The paper explores various architectures, including both pre-trained models like AlexNet, ResNet, and VGGNet, and user-defined models, emphasizing their effectiveness in disease detection. It provides an overview of how Deep Learning algorithms like CNN, GAN, and ANN are utilized in this context, along with evaluations of their performance metrics such as accuracy.

2.1 Introduction

An examination of various plant diseases and the diverse machine learning methods employed to classify diseases in different types of plant leaves.

Thus, to implement our idea of leaf disease detection using object detection and image segmentation of Mask RCNN, we integrated an application to have the instance level segmentation for disease detection.

2.2 Conclusion drawn from literature review

In summary, the literature reviewed provides comprehensive insights into the application of machine learning techniques, notably Mask R-CNN, in automating the detection and classification of plant diseases. By examining various plant diseases and exploring a range of machine learning classification methods across different types of plant leaves, researchers have demonstrated the efficacy of Mask R-CNN in enhancing the Faster R-CNN architecture. This enhancement, achieved through the addition of a mask prediction branch, enables pixel-level segmentation, thereby offering a more nuanced understanding of detected objects. Importantly, Mask R-CNN's streamlined implementation within the Faster R-CNN framework facilitates versatile architectural designs and efficient training processes, encouraging rapid experimentation and iterative model refinement.

The integration of Mask R-CNN into applications for leaf disease detection represents a significant advancement, allowing for precise instance-level segmentation and aiding in the timely identification and management of plant diseases. Despite these advancements, challenges such as data scarcity, model generalization, and computational resource constraints persist, highlighting the need for continued research and collaboration. Moving forward, addressing these challenges and further exploring the potential applications of Mask R-CNN in precision agriculture and crop management will be essential for realizing its full impact on agricultural sustainability and productivity.

2.3 Scope of this research work

The scope of this research work is multifaceted, encompassing several key aspects that extend beyond the mere application of Mask R-CNN in plant disease detection. Firstly, the research delves into the technological advancements within machine learning and computer vision, particularly focusing on the utilization of Mask R-CNN for pixel-level segmentation. By leveraging this advanced technology, the research aims to push the boundaries of automated plant disease detection, enabling more accurate and efficient identification of various diseases across different types of plant leaves. Moreover, the research involves interdisciplinary collaboration, bringing together experts from diverse fields such as agriculture, computer science, and machine learning. This collaboration allows for the integration of domain-specific knowledge with state-of-the-art technological innovations, facilitating the development of robust and effective solutions for addressing real-world agricultural challenges. Furthermore, the research emphasizes practical applications, aiming to integrate Mask R-CNN into applications for leaf disease detection that can be readily deployed in agricultural settings, benefiting farmers, agricultural practitioners, and stakeholders in the food supply chain.

Additionally, the research addresses scalability and generalization concerns, exploring strategies to improve model scalability and enhance generalization across diverse environmental conditions and plant species. Finally, the research considers the socioeconomic impact of automated plant disease detection using Mask R-CNN, aiming to enhance agricultural productivity, optimize resource allocation, and contribute to global food security and economic prosperity.

CHAPTER 3

Methodology

3. Methodology

The aim of this project is to introduce an innovative methodology for automating the detection of plant diseases using the deep learning model "Mask R-CNN." Its primary objective is to combat the significant challenges presented by plant diseases in agricultural settings through the application of advanced machine learning techniques. By combining object detection and segmentation, the Mask R-CNN model offers precise pixel-level labeling across diverse objects, a feature particularly essential in agricultural contexts. (see Figure 3.1).

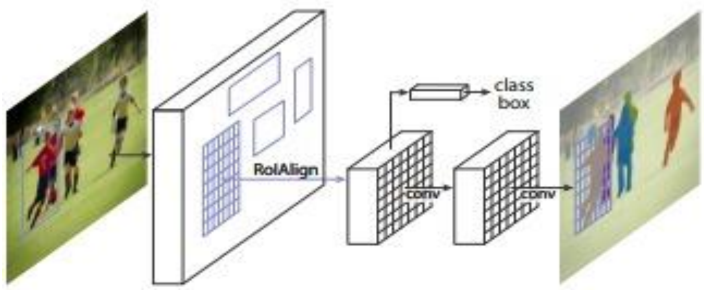

Fig 3.1: The Mask R-CNN framework for instance segmentation

The mask branch includes a streamlined Fully Convolutional Network (FCN) that is applied to each ROI, providing pixel-by-pixel predictions of segmentation masks.

3.1 Proposed Methodology of the System

The proposed methodology for used in plant disease detection system is differ from other models used for object detection as it is pre-trained model, it does have its own dataset and train this model by feeding more input data with data annotations to get the result. Here we are going to see first the working of Mask R-CNN model for object detection and segmentation and in next section working of Mask R-CNN for plant leaf disease detection.

3.1.1 Working of Mask R-CNN Model

Mask R-CNN, or Mask Region-Convolutional Neural Network, is a deep learning model specifically designed for image segmentation tasks, particularly in the context of object detection and instance segmentation.

1. Input and Feature Extraction:

The model takes an image as input, likely a preprocessed image of a leaf with a suspected disease.

Mask R-CNN utilizes a convolutional neural network (CNN) architecture. The CNN portion of the model extracts features from the image. These features are essentially patterns and shapes the model recognizes within the image.

2. Region Proposal Network (RPN):

An interesting aspect of Mask R-CNN is the Region Proposal Network (RPN). This sub-network within the model analyzes the extracted features to identify potential regions where objects (in this case, diseased areas of the leaf) might be located.

The RPN proposes rectangular shapes (bounding boxes) around these potential regions.

3. Feature Pooling and Classification:

Once the RPN generates bounding boxes, Mask R-CNN focuses on these specific regions. It extracts a more fine-grained set of features from these areas using a technique called ROI (Region of Interest) pooling.

These features are then fed into another sub-network that performs two tasks:

Classification: It classifies each proposed bounding box, determining if it actually contains a diseased region or not.

Box Refinement: It refines the bounding boxes generated by the RPN, making them more accurate in terms of size and position.

4. Mask Prediction:

This is where Mask R-CNN goes beyond standard object detection. In addition to classifying and refining bounding boxes, the model also predicts a segmentation mask for each bounding box classified as containing a disease.

This mask is a binary image with the same dimensions as the original image. Pixels within the bounding box corresponding to the predicted disease are assigned a value of 1, while the background pixels are assigned a value of 0.

Essentially, the mask provides a more precise delineation of the diseased region within the leaf.

5. Output:

The final output of Mask R-CNN for the plant disease diagnosis system consists of two parts:

Segmentation masks for each bounding box, indicating the exact pixels within the leaf that the model predicts as diseased. By combining object detection with pixel-level segmentation, Mask R-CNN offers a robust approach for identifying and precisely locating diseased areas in plant leaves based on image analysis.

3.1.2 Plant Disease Identification Using Mask R-CNN

The plant disease, characterized by various symptoms such as discoloration and deformities, poses a significant threat to crop health. Once the pathogen infects a plant, it can rapidly spread throughout the entire crop. Therefore, there is a pressing need for accurate detection and localization of each diseased area on the plant leaves. In this study, we suggest using the Mask-RCNN object detection model to identify and pinpoint each diseased area on plant leaves. The proposed framework for plant disease detection is illustrated in Figure 3.1.1.

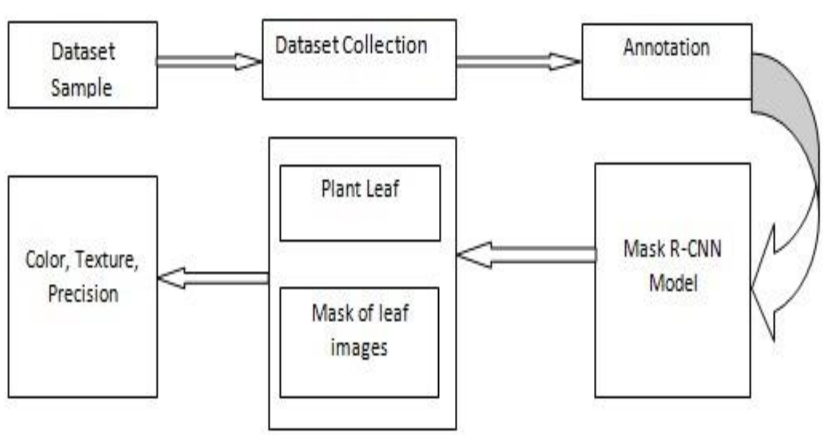

Fig 3.1.1: Proposed Structure for plant disease detection

Dataset Sample

In this project we used pictures of plant leaves. To do this, we have collected images of plant leaves from online download. These images were split into 125 for training and 50 for testing. We had to follow two main steps to create a dataset for detecting infected areas in different environments:

Image Collection: We took pictures of plant leaves from different angles and scenes, both from the internet. Since these images came in various sizes, We needed to make them all the same size to work with a specific tool called Mask RCNN. We used a script to resize the images and filled in any empty parts with zeros.

Image Processing: We used a annotator tool to mark the damaged areas on the plant leaf images. Then, we divided the marked images into two sets: one for training and one for testing. They organized these images into folders named "train" for training samples and "val" for test samples. Each image in these folders had a corresponding .json file with annotation information, detailing where the scratches were.

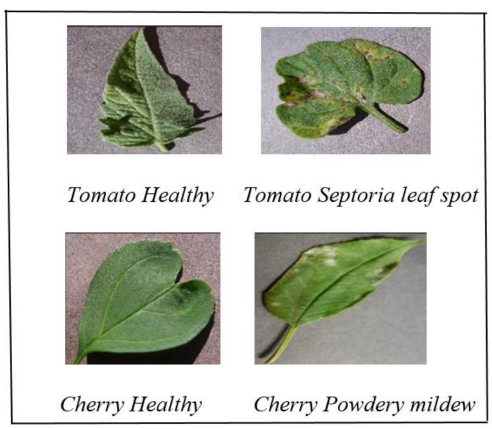

Fig 3.1.2: Image dataset collection

Image notation

Image annotation is a pivotal step in enabling the detection of plant diseases using the Mask-RCNN model. Accurate annotation is essential for the model to effectively identify and delineate diseased areas on the plant leaves. To accomplish this, we employed the VIA, an open-source annotation tool. The annotation process consisted of several stages: initially, labeling the healthy plant leaf images; followed by segmenting the plant leaf images; and finally, By annotating the regions affected by various diseases on each plant leaf, the plant leaf images were carefully marked using the annotation tool. This allowed for the subsequent training of the Mask-RCNN model for accurate disease detection, as illustrated in Figure 3.1.3.

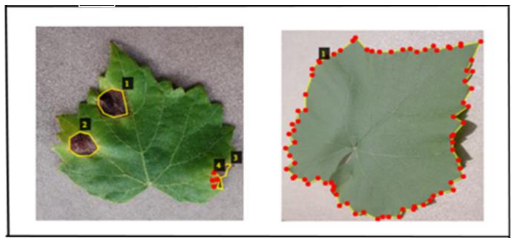

Fig 3.1.3: Diseased Image and Healthy Image Annotation

Mask RCNN

In the system, the Mask-RCNN model for detecting plant diseases on each leaf. By utilizing the Mask-RCNN model, we were able to easily identify and accurately pinpoint plant diseases on leaves. The architecture of the Mask-RCNN model utilized in this study is illustrated in Figure 5. With the assistance of the Mask-RCNN model, identifying and pinpointing the locations of plant diseases on leaves became straightforward.

In the Mask-RCNN model, the Region Proposal Network (RPN) generates various anchor boxes to identify potential regions of interest for object detection. These boxes are then assessed to see if any objects are present within them. During this process, the RPN calculates two types of losses: mask loss and boundary box losses, refining the detection accuracy. It also produces binary masks for each image, improving object delineation. The anchor boxes help delineate regions for feature alignment, achieved through Region of Interest (ROI) alignment.

Following alignment, fully connected layers are utilized for bounding box regression and object classification. These layers fine-tune the bounding box coordinates and assign class labels to detected objects. Finally, each object's detection is represented by a mask, generated through various convolutional layers. This approach ensures precise object identification and delineation.

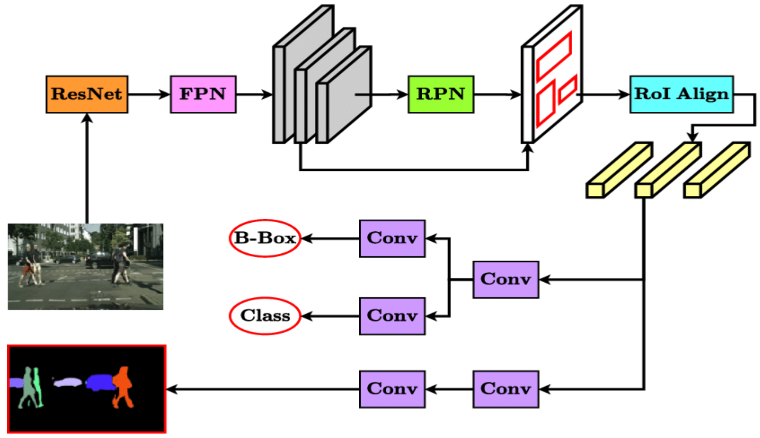

Fig 3.1.4: Structure of Mask R-CNN Model

Experimental Result

Following the segmentation of individual plant leaves, the subsequent task of the Mask-RCNN model involves pinpointing the precise locations of infected areas on each leaf. Consequently, the model not only segments the leaves but also accurately identifies and delineates disease spots on individual leaf images. Therefore, the Mask-RCNN model proves to be highly effective in detecting disease areas on plant leaves at a granular level.

3.2 UML Modeling of the System

Our approach involves the utilization of Unified Modeling Language (UML) diagrams as a powerful tool for representing various perspectives and aspects of software systems. Specifically, we employ UML diagrams to provide a comprehensive view of system architecture, design patterns, and interactions among system components. Moreover, we complement the use of UML diagrams with other graphical representations to offer a multi-faceted depiction of the software landscape.

3.2.1 Use Case Diagram

The Use Case Diagram for the plant disease detection system employing Mask R-CNN showcases the various actors and their interactions with the system. In this context, the primary actors typically include the users and the system itself.

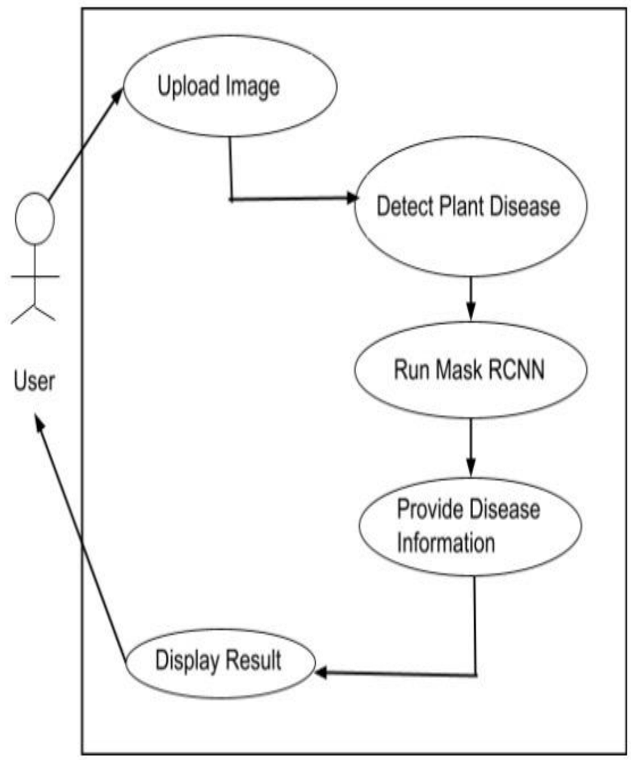

Fig 3.2: Usecase Diagram

- **Actor:**

User: This is the sole actor depicted in the diagram. They represent anyone who interacts with the system to diagnose plant diseases. This could include farmers, gardeners, agricultural researchers, or anyone concerned about the health of their plants.

- **Use Cases:**

Upload Image:

This primary use case allows the user to initiate the diagnosis process. The user interacts with the system by uploading an image of the diseased plant. The system should accept various image formats and provide clear instructions on image requirements (e.g., lighting, resolution) for optimal diagnosis.

Provide Disease Information:

Following the image upload, this use case represents the core functionality of the system. Here, the system analyzes the uploaded image. This might involve image processing techniques and potentially a disease classification model to identify the most likely disease affecting the plant. Upon successful identification, the system presents the user with information about the diagnosed disease. This information could include:

- Disease name and description
- Symptoms typically associated with the disease
- Potential causes of the disease
- Recommended treatment options

Additional Considerations:

The diagram doesn't explicitly depict error handling scenarios. Ideally, the system should provide informative messages if the image upload fails or if the disease cannot be confidently diagnosed. Additionally, the use case "Provide Disease Information" could be expanded to encompass the possibility of suggesting preventative measures or best practices to avoid future plant diseases.

Overall, the use case diagram effectively captures the core functionalities of the plant disease diagnosis system, highlighting the user's role in uploading an image and the system's responsibility in analyzing the image and providing relevant disease information.

3.2.2 Activity Diagram

An activity diagram can be employed to illustrate the sequential flow of steps involved in the detection process.

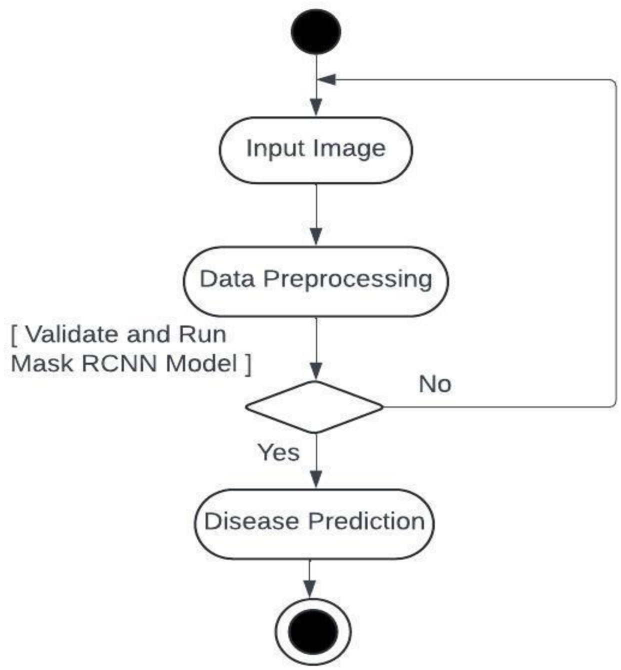

Fig 3.3: Activity Diagram

This activity diagram depicts the workflow of a plant disease detection system using Mask R-CNN. Here's a detailed description of each step:

- **Start:**

This marks the beginning of the disease detection process.

- **Input Image:**

The user interacts with the system by uploading an image of a leaf with suspected disease. This image could be captured using a mobile app camera or uploaded from a local storage location.

- **Preprocess Image:**

This step is where the uploaded image undergoes transformations to ensure compatibility with the Mask R-CNN model. Common preprocessing techniques include:

Resizing: The image might be resized to a standard dimension as required by the model for analysis.

Color Format Conversion: The image's color format might be converted to a specific format the model is trained on, such as RGB.

Normalization: The pixel values in the image might be normalized to a specific range (e.g., 0 to 1) for improved model performance.

Background Removal: Irrelevant background information surrounding the leaf might be removed to focus on the region of interest.

Once acquired, the data is split into two primary sets:

Training Set: This set makes up the majority of the data (usually 70-80%). It's used to train the Mask R-CNN model to identify disease patterns.

Test Set: This set represents a smaller portion of the data (usually 20-30%). It's used to evaluate the model's performance on unseen data after training.

- **Run Mask R-CNN Model:**

The system loads a pre-trained Mask R-CNN model. This model is a deep learning architecture specifically designed for object detection and instance segmentation. In this context, it's used to detect diseased areas within the leaf.

Predict Using Mask R-CNN: The preprocessed image (or the original image if no preprocessing is done) is fed into the loaded Mask R-CNN model. The model then analyzes the image to identify regions with potential diseases.

- **Disease Identification:**

Based on the analysis, Mask R-CNN generates outputs that include disease identification:

Bounding Boxes- These highlight potential disease regions within the image.

Segmentation Masks- These provide a more precise delineation of the diseased areas.

Predicted Disease Labels- This is the core aspect of disease identification. The model assigns labels or classifications to the detected regions, indicating the most likely diseases present in the leaf.

- **Stop:**

This signifies the completion of the user interaction cycle. The user has received the disease detection results.

3.2.3 Flowchart

The flowchart for plant disease detection typically involves several key steps. Visualization of the process of plant disease detection is done through a comprehensive flowchart.

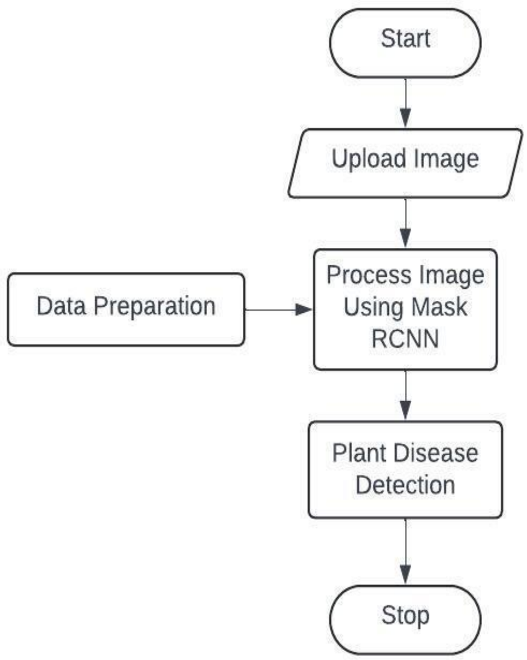

Fig 3.4: Flowchart Diagram

Above flowchart diagram depicts a flowchart illustrating a plant disease detection system using Mask R-CNN. Here's a breakdown of each step:

- **Start:**

This is the starting point of the flowchart.

- **Upload Image:**

In this step, the user uploads an image of a leaf suspected of having a disease. The system likely accepts images through a user interface, which could be a mobile app or a web platform.

- **Process Image Using Mask R-CNN:**

This is the core step of the system. The preprocessed image (or the original image if preprocessing is not applied) is fed into the Mask R-CNN model for analysis. Mask R-CNN is a deep learning model specifically designed for object detection and instance segmentation. In this context, it's used to detect diseased regions within the leaf image.

- **Disease Detection:**

After analyzing the image, Mask R-CNN generates two main outputs:

Bounding Boxes: The model identifies and outlines rectangular regions in the image, it predicts contain disease. These bounding boxes highlight the areas of interest for further analysis.

Segmentation Masks (Optional): Some Mask R-CNN implementations can generate segmentation masks in addition to bounding boxes. A segmentation mask is a binary image with the same dimensions as the original image. Pixels within the bounding box corresponding to the predicted disease are assigned a value of 1, while the background pixels are assigned a value of 0. This provides a more precise delineation of the diseased area compared to bounding boxes.

- **Review Results:**

A human expert can review the results generated by Mask R-CNN, particularly if the model's confidence level in the disease prediction is low. The expert can:

Confirm the disease diagnosis suggested by the model. Suggest alternative diagnoses based on their knowledge and experience. Recommend further tests for conclusive identification of the disease.

- **Stop:**

This is the ending point of the flowchart, signifying the completion of the plant disease detection process. The user receives the results, which may include the original image with bounding boxes around detected diseases, and potentially disease labels or confidence scores.

3.2.4 DFD Level Diagram

The Data Flow Diagrams of the system illustrates the workflow and data interactions involved in plant disease detection.

- **DFD Level-0**

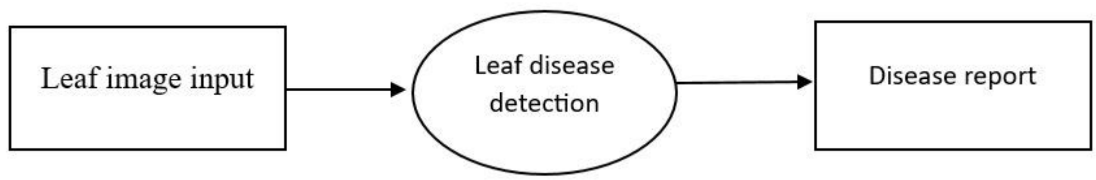

Fig 3.5.1: DFD Level-0 diagram

As shown in Figure 3.5.1, the DFD level-0 diagram begins with the input of a leaf image, which serves as the primary data source. This image is then processed by our leaf disease detection model, utilizing various algorithms and techniques to analyze the image and identify any potential diseases present on the leaf. The model's output provides a comprehensive diagnosis of the leaf's health status, detailing any detected diseases or abnormalities. This information is then communicated to the user, either through a graphical interface displaying the results or via a textual report. Through this process, the data flow diagram illustrates the sequential journey of data from input to output, showcasing the systematic approach of our leaf disease detection system in providing accurate and timely results to users.

The main data source for the data flow diagram is an image of a leaf, which is input first. After that, our leaf disease detection model processes this image, applying several of different approaches and algorithms to examine it and determine whether any potential illnesses are visible on the leaf. The output of the model offers a thorough diagnostic of the leaf's condition, including information on any illnesses or anomalies that were found. The data flow diagram demonstrates the methodical approach of our leaf disease detection system in delivering precise and prompt findings to users by showing the sequential path of data from input to output through this procedure.

- **DFD Level-1**

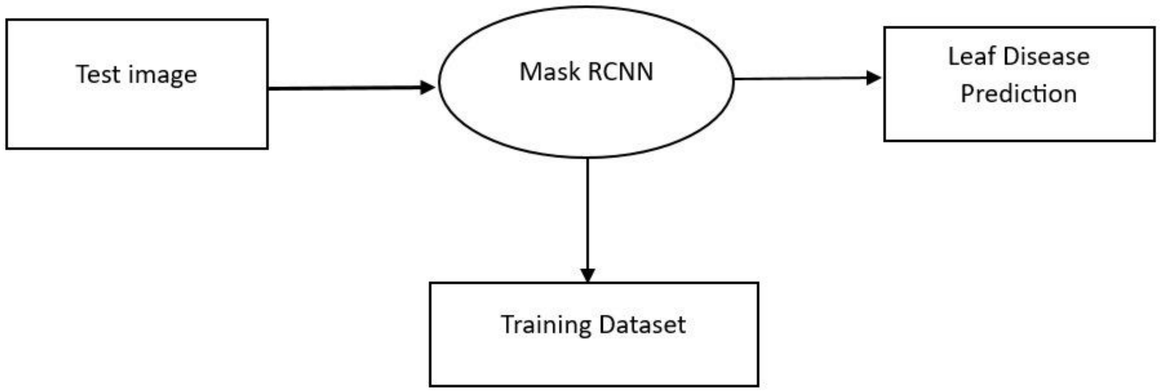

Fig 3.5.2: DFD Level-1 diagram

DFD level-1 diagram of Plant Disease Detection depicts the training phase of our leaf disease detection system using the Mask R-CNN algorithm. Test images, representing various leaf samples with different diseases, serve as the input data for the training process. These images undergo a series of preprocessing steps, including resizing, normalization, and augmentation, to ensure optimal training conditions.

The Mask R-CNN model then utilizes its deep learning architecture to learn and extract meaningful features from the input images, enabling it to accurately detect and classify leaf diseases. Throughout the training process, the model continuously refines its parameters through back propagation, adjusting its internal representations to minimize prediction errors and improve performance. Once the training is complete, the trained model is capable of efficiently analyzing new leaf images and providing accurate predictions regarding the presence and type of diseases present, as depicted in subsequent stages of the data flow diagram.

- **DFD Level-2**

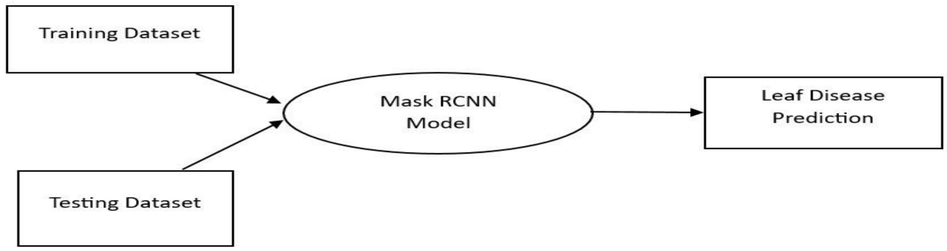

Fig 3.5.3: DFD level-2 diagram

DFD level-2 diagram illustrates the transition from training to testing in our leaf disease detection system using the Mask R-CNN model. The training dataset, consisting of labeled leaf images representing various diseases, serves as the primary input for training the model. Through an iterative process, the Mask R-CNN algorithm learns to recognize patterns and features associated with different leaf diseases, refining its parameters to optimize predictive accuracy. Once the training is complete and the model has been sufficiently trained on the training dataset, it transitions to the testing phase. Here, the same trained model is evaluated using a separate testing dataset, which contains unseen leaf images. The model applies its learned knowledge to the testing dataset, accurately predicting the presence and type of diseases present on the leaves. DFD2 demonstrates the effectiveness of our trained Mask R-CNN model in accurately detecting leaf diseases in real-world scenarios, highlighting its practical utility and reliability.

CHAPTER 4

<u>Implementation</u>

4. Implementation

4.1 Technology Stack used for Implementation

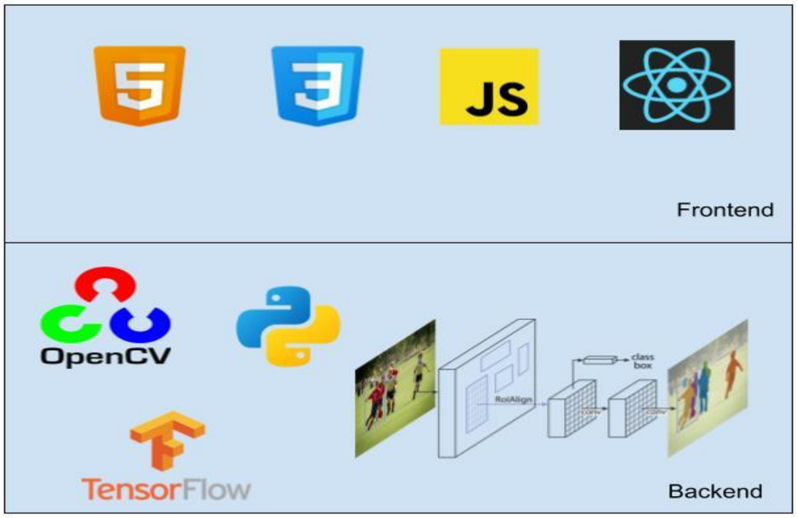

Fig 4.1: Technologies used for Implementation

- **Python**

Python 3.6.8: Python serves as the primary programming language for developing the backend logic and machine learning algorithms. It provides a rich ecosystem of libraries and tools for data processing, model training, and web development. In the context of plant disease detection, Python is used to orchestrate various tasks, including data preprocessing, model training, and serving predictions to the frontend.

- **Tensorflow**

TensorFlow: TensorFlow, an open-source machine learning framework developed by Google, is instrumental in plant disease detection. It enables the creation and training of deep learning models, such as convolutional neural networks (CNNs), which are well-suited for image classification tasks. In the project, TensorFlow is utilized to implement and train the Mask R-CNN model. This model is capable of accurately segmenting and identifying plant diseases from leaf images by leveraging its convolutional layers and region-based segmentation techniques.

- **OpenCV**

OpenCV (Open Source Computer Vision Library): OpenCV is a powerful open-source library for computer vision and image processing tasks. It provides a wide range of functionalities, including image manipulation, feature extraction, and object detection. In the context of plant disease detection, OpenCV is used for various preprocessing tasks on input images. This may include tasks such as resizing images to a standard size, enhancing image quality, and extracting relevant features. Additionally, OpenCV may be employed for tasks like edge detection and color space conversion, which are essential for identifying diseased areas on plant leaves.

- **Flask Framework**

Flask Framework: Flask is a lightweight and flexible web framework for Python, designed for building web applications and APIs. In the project, Flask serves as the backend framework for developing the web application responsible for serving predictions from the trained Mask R-CNN model. Flask enables the creation of RESTful APIs that receive input images, process them using the trained model, and return the results to the frontend. It handles the communication between the frontend and backend, allowing users to upload images and visualize the results of plant disease detection in real-time.

- **React.js**

React.js: React.js is a JavaScript library for building user interfaces, particularly single-page applications. In the project, React.js powers the frontend interface of the web application, providing an interactive and responsive user experience. Through React.js components, users can upload images, visualize the results of plant disease detection, and interact with the application seamlessly. React.js facilitates the creation of a dynamic and user-friendly interface that enhances the overall usability of the plant disease detection system.

Overall, this detailed tech stack leverages the strengths of Python, TensorFlow, OpenCV, Flask, and React.js to develop a comprehensive solution for plant disease detection. Each component plays a crucial role in different aspects of the project, from preprocessing input images to serving predictions to end-users. Together, they enable the creation of a robust and user-friendly application that empowers farmers and agricultural practitioners with valuable insights for managing crop health effectively.

4.2 Snapshots of the Implementation

In this project, we have developed a website application for disease detection on plant leaves using pre-trained Mask R-CNN model. Here in this application user have to take input image of plant leaf. When the image has been uploaded, after processing Mask R-CNN model the mask is created on the plant leaf on diseased area. It will show the disease present and probability of the disease. The snapshots of the implementation as given as below,

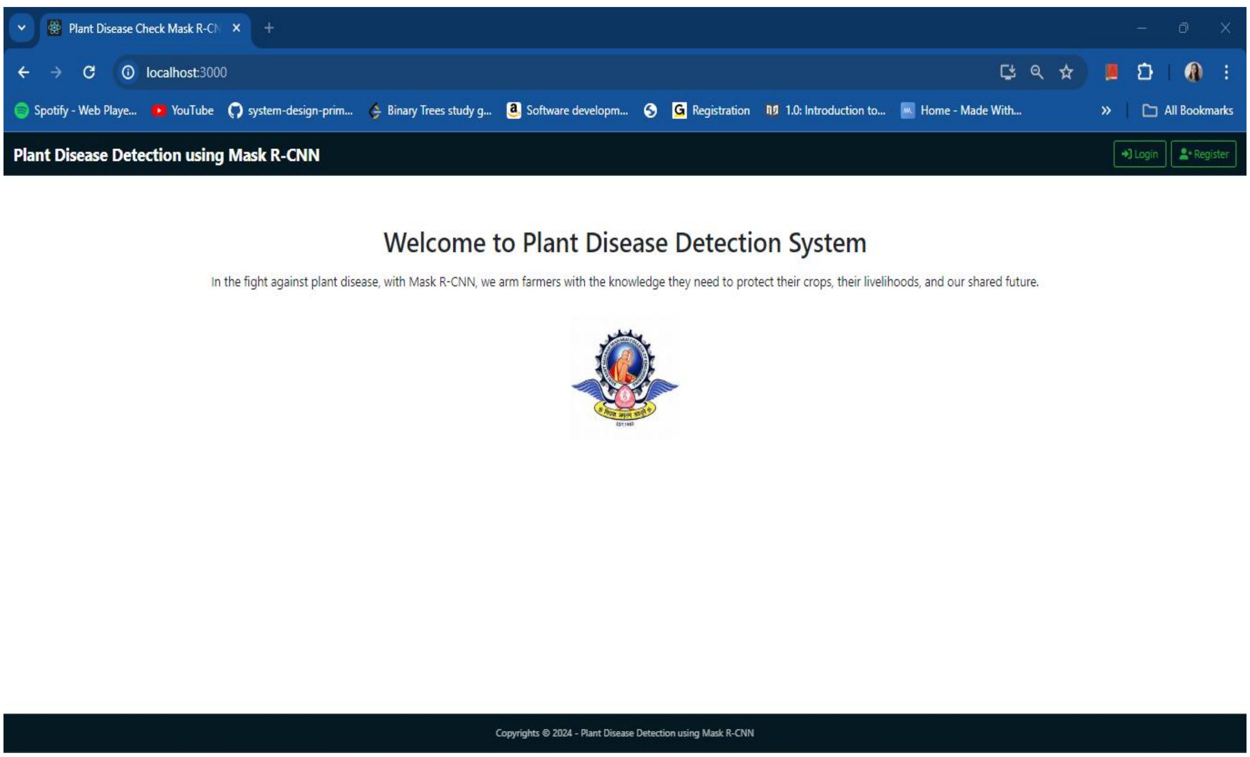

Fig 4.2.1: Landing Page of Application

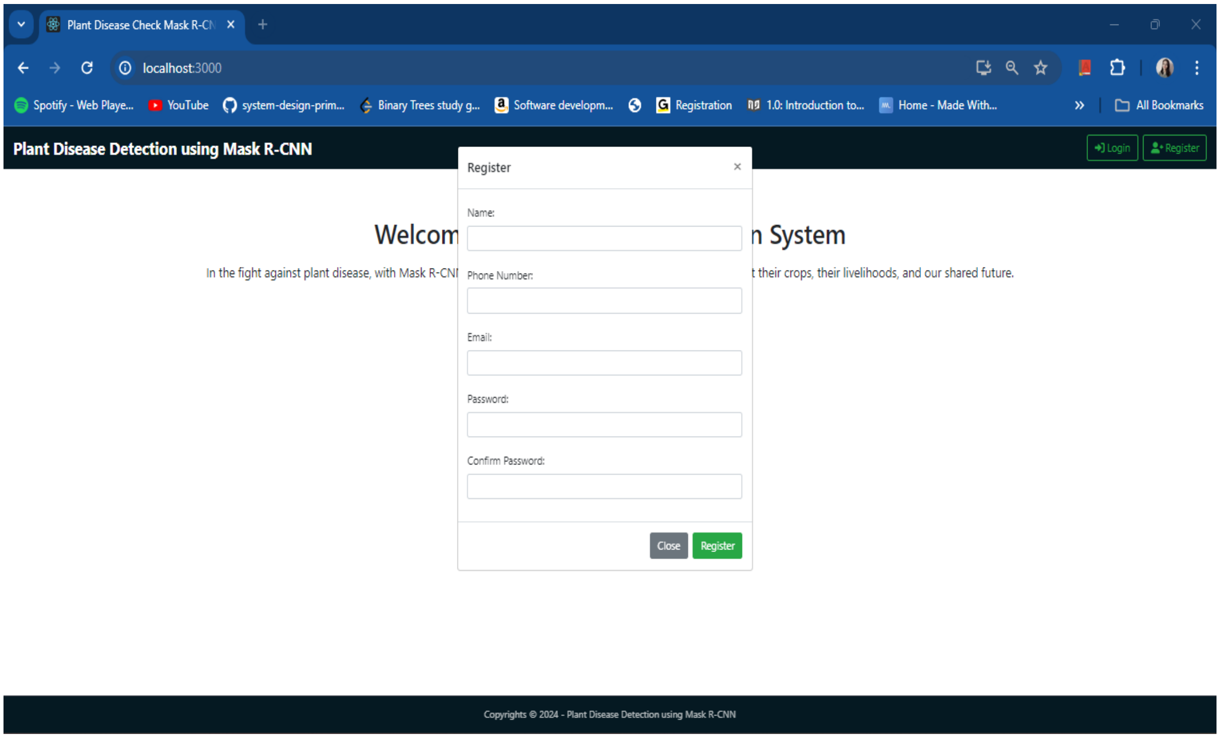

Fig 4.2.2: Registration Page

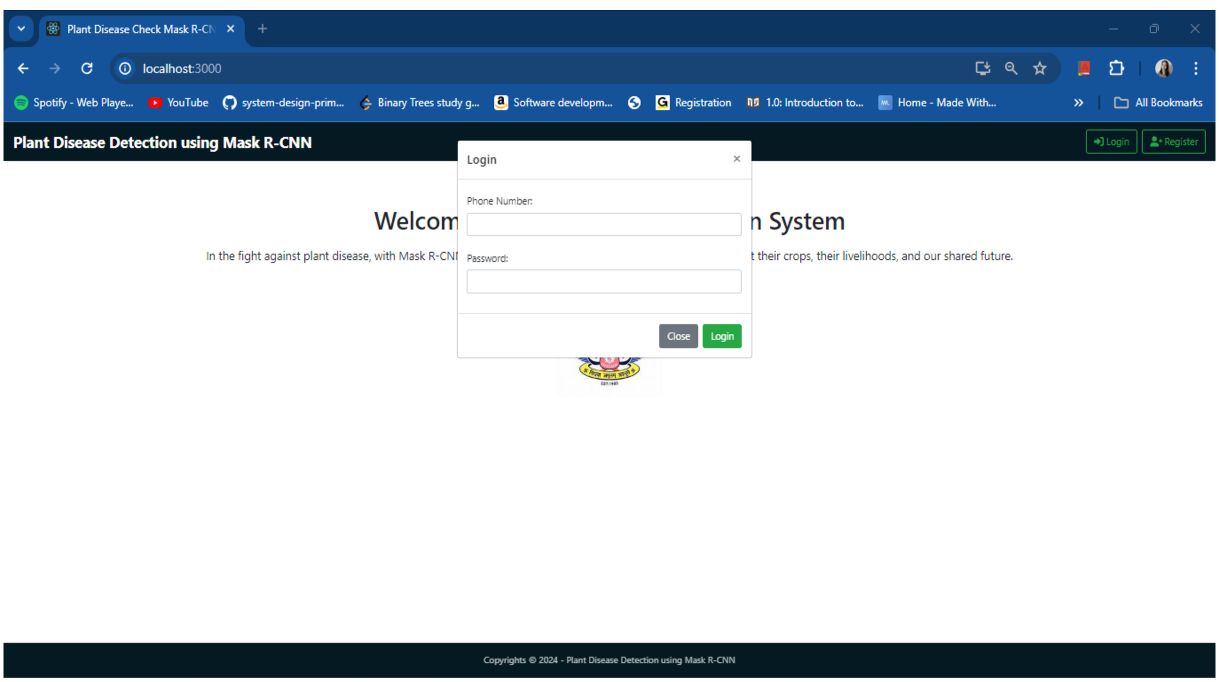

Fig 4.2.3: Login Page

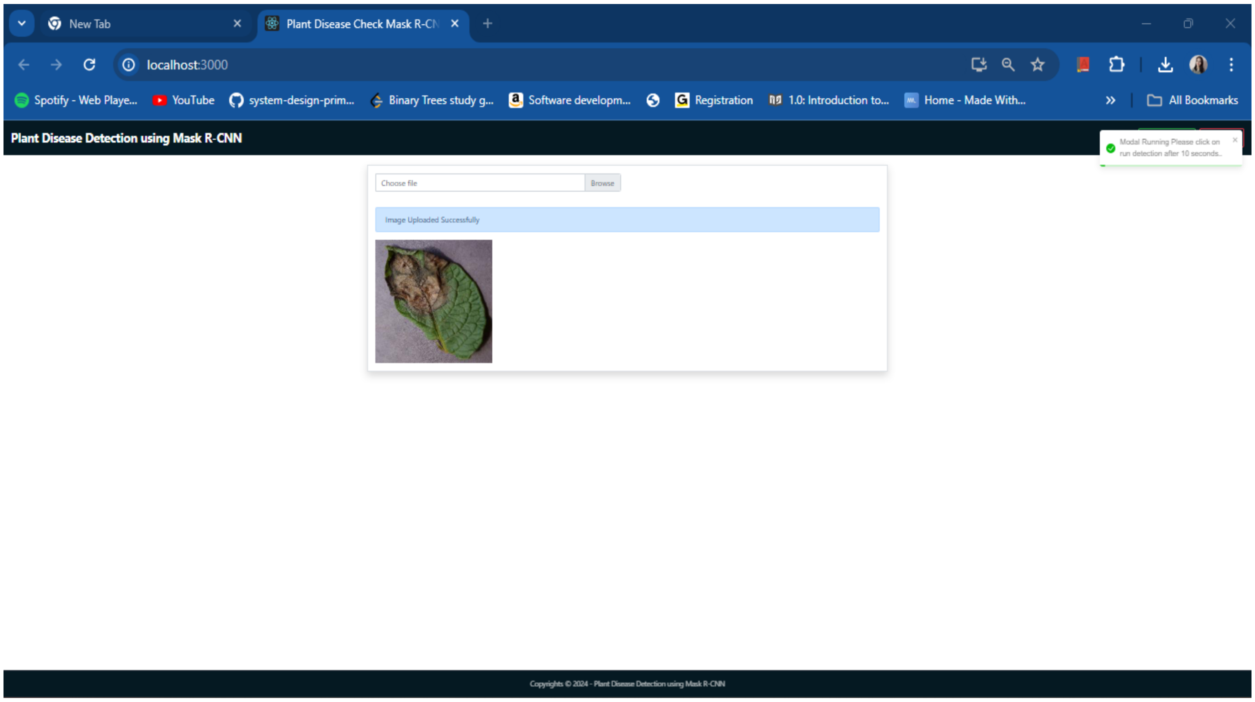

Fig 4.2.4: Input Image

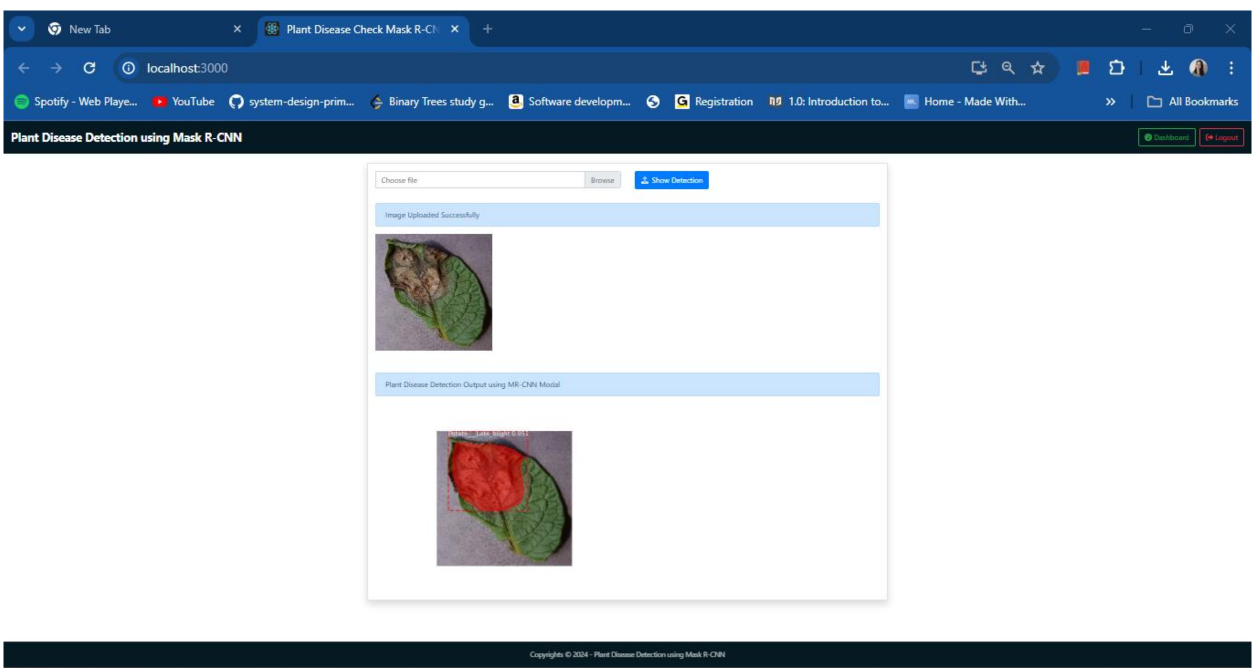

Fig 4.2.5: Disease Detection by creating mask on leaf image

CHAPTER 5

Computer Simulation

5. Computer Simulation

Creating a computer simulation for plant disease detection using Mask R-CNN (Mask Region-based Convolution Neural Network) involves several steps. Below is a detailed guide on how to approach this:

Understanding Mask R-CNN:

Familiarize yourself with the Mask R-CNN architecture, which is an extension of Faster R-CNN. Mask R-CNN is capable of object detection and instance segmentation, making it suitable for detecting and delineating diseased regions in plant images. Learn about the key components of Mask R-CNN, including the backbone network (e.g., ResNet), Region Proposal Network (RPN), Region of Interest (RoI) Align, and Mask Head.

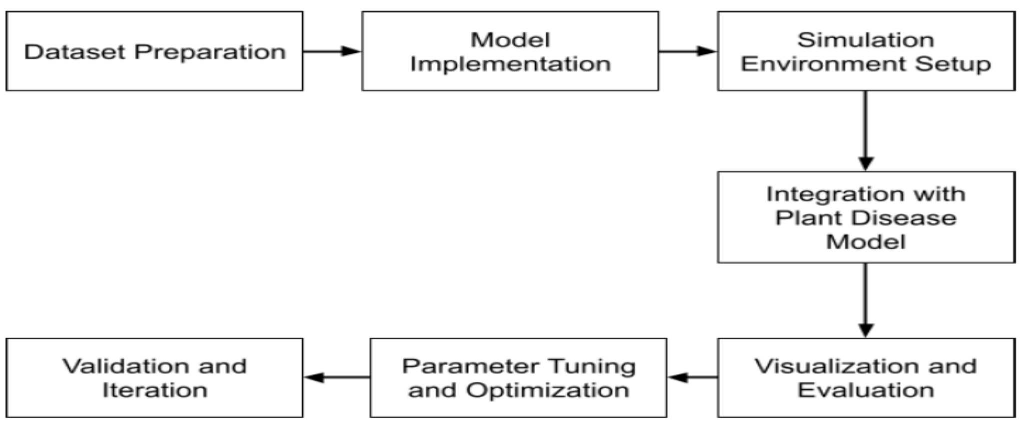

Fig 5.1: Understanding Mask R-CNN

- **Dataset Preparation:**

Gather a dataset of plant images containing instances of both healthy plants and plants affected by various diseases. Include annotations for bounding boxes and pixel-level masks outlining the diseased regions.

Augment the dataset by applying transformations such as rotation, scaling, and flipping to increase diversity and robustness.

- **Model Implementation:**

Utilize an existing implementation of Mask R-CNN, such as the one provided in the popular deep learning frameworks like TensorFlow or PyTorch. Fine-tune the pre-trained Mask R-CNN model on your dataset of plant images. Retrain the model's backbone layers and adjust hyperparameters to adapt it to the characteristics of plant disease detection.

- **Simulation Environment Setup:**

Set up a simulation environment using a programming language like Python. Use libraries such as OpenCV or PIL for image processing and visualization. Develop scripts to simulate the acquisition of plant images under various conditions, including different lighting, camera angles, and backgrounds.

- **Integration with Plant Disease Model:**

Integrate the trained Mask R-CNN model into the simulation environment. This involves loading the model weights and configuring the inference pipeline.

Implement logic to feed simulated plant images to the Mask R-CNN model and process the output predictions.

- **Visualization and Evaluation:**

Visualize the results of the simulation by overlaying bounding boxes and segmentation masks on the input plant images. This helps in understanding the model's performance in detecting and segmenting diseased regions. Evaluate the simulation results quantitatively by computing metrics such as precision, recall, and intersection over union (IoU) between predicted and ground truth masks.

- **Parameter Tuning and Optimization:**

Fine-tune simulation parameters such as image resolution, noise levels, and disease severity to mimic real-world scenarios accurately. Optimize computational resources and simulation speed to ensure efficient execution and scalability.

- **Validation and Iteration:**

Validate the simulated results against real-world data to ensure the fidelity and reliability of the simulation. Iterate on the simulation design, model architecture, and dataset augmentation strategies based on feedback and performance evaluation.

CHAPTER 6

Experimental Investigation

6. Experimental Investigation

The project "Plant Disease Detection using Mask R-CNN" blends cutting-edge technology with agricultural science to combat crop diseases effectively. This experimental investigation aims to validate the efficacy of the proposed method in accurately identifying and segmenting diseased regions on plant leaves, thereby aiding in early detection and prevention strategies.

The experimental setup involves several key components:

Dataset Preparation: A diverse dataset comprising images of healthy and diseased plant leaves is curated. These images encompass various plant species and a range of common diseases affecting them. Care is taken to ensure an adequate representation of different disease severities and environmental conditions.

Model Training: The Mask R-CNN (Region-based Convolutional Neural Network) architecture is employed for disease detection and segmentation. Initially, the model is trained on the prepared dataset using transfer learning techniques. Pre-trained weights from a general object detection dataset, such as COCO (Common Objects in Context), may be utilized to expedite convergence and enhance performance.

Hyperparameter Tuning: Several hyperparameters, including learning rate, batch size, and network depth, are fine-tuned to optimize the model's performance on the specific task of plant disease detection. Techniques like grid search or random search may be employed to efficiently explore the hyperparameter space.

Validation and Evaluation: The trained model is rigorously evaluated using metrics such as precision, recall, F1-score, and Intersection over Union (IoU). A separate validation set, distinct from the training data, is utilized to assess the model's generalization capability and robustness to unseen samples.

Benchmarking: The performance of the proposed method is compared against existing approaches for plant disease detection, including traditional methods based on handcrafted features and other deep learning architectures. Benchmarking enables a comprehensive assessment of the proposed method's superiority in terms of accuracy, speed, and scalability.

Real-world Testing: To validate the practical applicability of the proposed solution, field experiments may be conducted in collaboration with agricultural experts or farmers. Real-world testing allows for the identification of potential challenges and the refinement of the model to better suit practical deployment scenarios.

Analysis of Results: The results obtained from the experimental investigation are thoroughly analyzed to gain insights into the strengths and limitations of the proposed method. Factors influencing performance, such as dataset quality, model architecture, and training strategies, are carefully scrutinized to inform future research directions and improvements.

Documentation and Dissemination: The findings of the experimental investigation are documented in a comprehensive report, detailing the methodology, results, and conclusions. Additionally, the results may be disseminated through academic publications, conference presentations, or online platforms to contribute to the broader research community and facilitate knowledge sharing.

In summary, the experimental investigation in the project "Plant Disease Detection using Mask R-CNN" encompasses dataset preparation, model training, hyperparameter tuning, validation, benchmarking, real-world testing, result analysis, and dissemination. By combining advanced computer vision techniques with domain-specific knowledge in agriculture, the project aims to revolutionize the way plant diseases are detected and managed, ultimately enhancing crop yield and food security.

CHAPTER 7

Result and Discussion

7. Result and Discussion

We extended the training duration to 100 iterations, during which the learning rate decreases over 70 iterations. Additionally, we adjusted the threshold to 0.9, meaning that detections with confidence below 90% are disregarded.

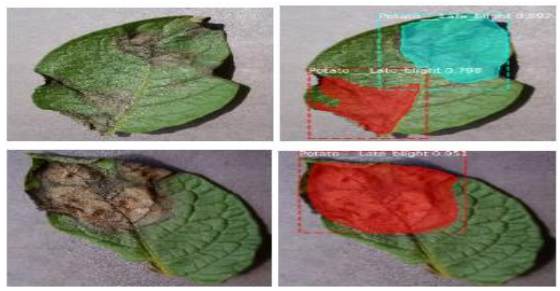

Fig 7.1: Results of Mask R-CNN Model

Following the segmentation of individual plant leaves, the subsequent task of the Mask-RCNN model involves pinpointing the precise locations of infected areas on each leaf. Consequently, the model not only segments the leaves but also accurately identifies and delineates disease spots on individual leaf images. Therefore, the Mask-RCNN model proves to be highly effective in detecting disease areas on plant leaves at a granular level.

The results obtained from the Mask R-CNN model demonstrate its effectiveness in both segmenting individual plant leaves and accurately identifying disease spots on each leaf. This granular level of detection showcases the model's capability to not only detect plant diseases but also precisely locate infected areas within leaf images. Overall, these findings affirm the efficacy of the Mask R-CNN model in plant disease detection tasks, highlighting its potential to aid farmers in managing crop health more efficiently and effectively.

CHAPTER 8

Conclusion, Contribution, Scope for future work

8. Conclusion, Contribution, Scope for future work

8.1 Conclusion

This project introduces an innovative methodology for automating the identification of plant diseases through the utilization of the Mask R-CNN model. The primary objective is to address the significant challenge posed by plant diseases to agricultural productivity by leveraging advanced machine learning techniques. By integrating object detection and segmentation, the Mask R-CNN model facilitates precise pixel-level labeling across diverse objects, a capability particularly crucial in the agricultural domain.

The study underscores the critical importance of early disease detection in agriculture and emphasizes the transformative potential of deep learning and computer vision technologies in revolutionizing crop management practices. Through meticulous processes of dataset creation, annotation, and model training, the project demonstrates the effectiveness of Mask R-CNN in accurately identifying and pinpointing disease areas on plant leaves. The experimental results corroborate the efficacy of the proposed framework in enabling granular disease detection, offering actionable insights for farmers to efficiently manage their crops. This research not only highlights the significance of advanced technologies like Mask R-CNN in reshaping agricultural practices but also lays the groundwork for future advancements in plant disease detection and management.

8.2 Contribution

The project "Plant Disease Detection Using Mask R-CNN" has made significant contributions to the field of agriculture and crop management. By developing a sophisticated machine learning-based platform, the project has empowered farmers and agricultural practitioners to effectively monitor and manage plant health in their fields. The core contribution of the platform lies in its ability to accurately detect and identify plant diseases from leaf images, thereby enabling proactive measures to mitigate crop diseases and ensure optimal yield.

One of the key contributions of the platform is its utilization of advanced machine learning techniques, particularly Mask R-CNN, to achieve precise and granular detection of plant diseases. By leveraging Mask R-CNN's capabilities for instance segmentation and object detection, the platform can accurately pinpoint the locations of diseased areas on individual plant leaves. This high level of accuracy and granularity provides farmers with valuable insights into the health status of their crops, enabling them to take timely and targeted interventions to protect their yields.

Moreover, the platform's integration of user-friendly interfaces and web-based applications has further amplified its utility and accessibility. By providing farmers with intuitive tools for uploading leaf images and visualizing detection results, the platform streamlines the process of disease monitoring and management. Additionally, features such as detailed disease reports and recommendations for treatment further enhance the platform's effectiveness in supporting informed decision-making by farmers.

In addition to its contributions to crop health monitoring, it's important to highlight that the project serves as a proactive solution for addressing plant disease outbreaks and minimizing crop losses. Unlike traditional methods of disease detection that rely on manual inspection and subjective assessment, this platform offers an automated and data-driven approach that can identify diseases in their early stages, allowing for prompt intervention and control measures.

Overall, the project "Plant Disease Detection Using Mask R-CNN" has significantly advanced the field of agriculture by providing farmers with a powerful tool for proactive disease management. Through its innovative approach and user-centric design, the platform empowers farmers to safeguard their crops and optimize agricultural productivity, ultimately contributing to food security and sustainable agriculture.

8.3 Scope for future work

The future work in plant disease detection using Mask R-CNN encompasses several key areas for exploration and advancement. This includes expanding datasets to cover a wider range of plant diseases and conditions, optimizing model architectures and training methodologies, and developing real-time implementation frameworks for on-the-spot diagnosis in agricultural fields. Additionally, integrating Mask R-CNN with precision agriculture technologies, exploring robotics and automation applications, and leveraging crowd sourced monitoring systems are promising avenues for further research. Interdisciplinary collaboration will be crucial for developing comprehensive solutions that address the challenges of plant disease detection and management, ultimately advancing sustainable crop production practices.

Furthermore, the project emphasizes the need for continual exploration and refinement of such technologies to address evolving challenges in agriculture, paving the way for sustainable and resilient crop production systems. Through its comprehensive approach and rigorous methodology, this project contributes to the growing body of knowledge in the field of agricultural technology and underscores the importance of innovation in ensuring global food security and sustainability.

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SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

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1	Alakananda Mitra, Saraju P. Mohanty, Elias Kougianos. "Chapter 5 A Smart Agriculture Framework toAutomatically Track theSpread ofPlant Diseases Using Mask Region-Based Convolutional Neural Network", Springer Science and Business Media LLC, 2022 Publication	3%
2	Submitted to Texas State University- San Marcos Student Paper	3%
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4	Minh Dang, Hanxiang Wang, Yanfen Li, Tri-Hai Nguyen, Lilia Tightiz, Nguyen Xuan-Mung, Tan N. Nguyen. "Computer Vision for Plant Disease Recognition: A Comprehensive Review", The Botanical Review, 2024 Publication	1%

Dissemination of Work

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