Enhancing Mint Plant Disease Detection Accuracy through Deep Reinforcement Learning with YOLO Algorithm

PROJECT REPORT

21AD1513- INNOVATION PRACTICES LAB

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BONAFIDE CERTIFICATE

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ABSTRACT

Plant diseases can result in large financial losses for the agriculture sector and reduce the plant's benefits towards humanhood, emphasizing the importance of rapid and precise disease detection techniques. This study approaches the problem of mint plant disease detection and suggests an innovative approach to improve accuracy using YOLO algorithm-based feature extraction and deep reinforcement learning. The YOLO is made to learn distinguishing characteristics from images of mint plants, making it possible to accurately represent both healthy and damaged plant parts. The decision-making process for disease identification based on the retrieved characteristics is subsequently optimized by integrating the deep reinforcement learning component. Extensive tests were carried out on a large collection of mint plant images with labeled disease conditions in order to determine the effectiveness of the proposed approach. The results demonstrate a significant improvement in disease detection accuracy compared to traditional methods. The YOLO algorithm-based feature extraction proved to be successful in capturing relevant patterns and representations leading to more accurate and reliable results. The significance of this research lies in its potential to revolutionize mint plant disease detection in the agriculture sector. The suggested methodology provides a reliable and effective method for early leaf disease detection by YOLO algorithm-based feature extraction. This allows farmers to take quick action to stop the spread of diseases and increase agricultural yields in general. This study makes advances in computing the identification of plant diseases and sets the path for comparable applications in other agricultural fields.

Keywords: plant disease detection, deep reinforcement learning, you only look once algorithm, robustness, efficiency.

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LIST OF ABBREVIATIONS

ABBREVIATIONS	MEANING
YOLO	You Only Look Once algorithm
CNN	Convolutional Neural Network
RBFNN	Radial Basis Function Neural Network
PSO	Particle Swarm Optimization
RGM	Region Growing Technique
GLCM	Gray-Level Co-Occurrence Matrix
GUI	Graphical User Interface
IoU	Intersection over Union
RL	Reinforcement Learning
DQN	Deep Q-Networks
PPO	Proximal Policy Optimization
TRPO	Trust Region Policy Optimization

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CHAPTER 1

INTRODUCTION

1.1 General Information on Mint Plant

Mint, scientifically known as Mentha, is a versatile and aromatic herb that belongs to the Lamiaceae family. It is renowned for its refreshing flavor and fragrance, as well as its various culinary, medicinal, and decorative uses. Mint is native to Europe and Asia, but it has been cultivated and enjoyed worldwide for centuries due to its delightful qualities. There are numerous species and hybrid varieties of mint, each with its distinct flavor and characteristics, including spearmint (Mentha spicata), peppermint (Mentha × piperita), and chocolate mint (Mentha × piperita 'Chocolate'). These plants typically feature square-shaped stems with serrated, aromatic leaves that can vary in color from dark green to purple, depending on the variety. The leaves are known for their strong and refreshing scent, attributed to essential oils, primarily menthol in peppermint and carvone in spearmint, which give mint its characteristic taste and scent.

1.2 Some Commonly Occurring Diseases on Mint Plants

Mint is a low maintenance plant but they are more prone to several diseases that can compromise their health and productivity. These diseases can manifest as various symptoms, including leaf discoloration, wilting, and reduced overall plant vigor. Managing these diseases is essential for maintaining healthy mint crops. Percentage of commonly occurring diseases on mint plant disease occurrence globally is shown below in table 1.1.

Disease	Cause	Percentage of Occurrence
Mint rust	Fungus Puccinia menthae	20-30%
Verticillium wilt	Fungus Verticillium dahliae	15-20%
Anthracnose	Fungus Colletotrichum gloeosporioides	10-15%
Powdery mildew	Fungus Erysiphe cichoracearum	5-10%
Mosaic virus	Virus Mint mosaic virus	1-5%

Table 1.1: percentage of mint disease occurrence globally

1.2.1 Mint Rust (Puccinia menthae):

Mint Rust is a fungal disease that causes rust-colored pustules to develop on the undersides of mint leaves. These pustules contain fungal spores and can lead to reduced plant vigor, stunted growth, yellowing of leaves, and premature leaf drop. Controlling Mint Rust often involves fungicidal treatments and practicing good plant hygiene.

1.2.2 Mint Anthracnose (Colletotrichum spp.)

Anthracnose is a fungal disease that affects mint stems and leaves, causing dark, sunken lesions. Infected leaves may also show a water-soaked appearance. Proper sanitation, removing and disposing of infected plant material, and fungicidal treatments can help control Anthracnose.

1.2.3 Powdery Mildew:

Powdery Mildew is a common fungal infection in mint characterized by a white, powdery substance on the leaves' surfaces. It can cause leaf distortion, reduced photosynthesis, and overall plant weakness. Proper spacing, adequate air circulation, and the use of fungicides can help manage Powdery Mildew.

1.2.4 Verticillium Wilt (Verticillium spp.):

Verticillium Wilt is a soil-borne fungal disease that can infect mint plants, leading to wilting, yellowing, and stunted growth. The fungus blocks the plant's vascular system, restricting water and nutrient flow. Crop rotation and soil sterilization can help prevent the spread of Verticillium Wilt.

1.2.5 Mint Mosaic Virus

Mint Mosaic Virus is a plant virus that primarily affects mint plants. It causes distinctive mosaic-like patterns of light and dark green on the leaves, which can lead to reduced photosynthesis and stunted growth. This viral infection is primarily spread through contaminated tools, plant sap, or insect vectors like aphids. Infected mint plants should be promptly removed to prevent further spread. Control measures often involve managing insect vectors and maintaining good sanitation practices in mint cultivation.

1.3 Benefits of Mint plant

Mint, with its refreshing flavor and aromatic fragrance, offers a plethora of benefits across various domains, including medicinal, commercial, and domestic uses. Here are some of benefits of the mint plant:

1.3.1 Medicinal Benefits

Medicinally, mint serves as a potent ally in digestive health, soothing indigestion, gas, and nausea, while also offering relief from headaches and stress through its menthol-infused soothing properties. It plays a crucial role in respiratory wellness by aiding in congestion relief and respiratory condition management.

1.3.2 Commercial Benefits

In the commercial sphere, mint is a culinary gem, elevating dishes, beverages, and confections with its signature freshness. The beverage industry reveres mint as a flavoring agent in teas, cocktails, and soft drinks. Pharmaceuticals and personal care products incorporate mint for its soothing and refreshing attributes, found in throat lozenges, shampoos, and toothpaste.

1.3.3 Domestic Benefits

Mint finds its place in domestic kitchens, enhancing culinary delights, garnishing dishes, and brewing flavorful teas. As an essential oil, it permeates homes as an aromatherapy tool, promoting relaxation and mental clarity. Mint's potent scent also acts as a natural pest repellent, safeguarding homes and gardens from unwelcome insects. Moreover, mint plants offer ornamental value, beautifying gardens and landscapes.

CHAPTER 2
LITERATURE REVIEW

A literature review, a critical component of academic research, involves systematically examining and summarizing existing scholarly work related to a specific topic or research question. It serves several essential purposes, such as providing context for the study, identifying gaps in the current knowledge, and informing the research methodology and theoretical framework. Through an extensive review of relevant articles, books, and studies, it helps researchers understand the historical evolution of their subject, assess the state of existing research, and pinpoint areas where further investigation is needed. Moreover, a well-conducted literature review demonstrates the researcher's familiarity with the subject matter, establishes credibility, and aids in the formulation of hypotheses or research questions. It also allows for the identification of key theories, methodologies, and findings that will contribute to the construction of a strong conceptual framework and research design. Therefore, we have taken our survey on the plant disease classifications and mint diseases and its classification using machine learning and deep learning and the comparisons on the study are given in table 2.1.

2.1 Using Deep Learning for Image-Based Plant Disease Detection

The study focuses on AlexNet and GoogLeNet, two well-known CNN designs. The classification job for plant diseases uses two CNN architectures, AlexNet and GoogLeNet, which are evaluated in the study. GoogLeNet has a more complex architecture with 22 layers and uses inception modules, whereas AlexNet has 5 convolutional layers followed by 3 fully connected layers. In the tests, alternative topologies using AlexNet or GoogLeNet are employed, and either transfer learning or training from scratch is used for training. The weights of certain layers are re-initialized in transfer learning. Because no layer's learning is constrained during training, the visual expertise of previously learned models may be utilized. Each experiment lasts for 30 epochs, and during this time, learning converges successfully. All experiments use the same hyperparameters. Mean F1 score, mean precision, mean recall, and total accuracy are among the performance measurements[14].

On the PlantVillage dataset, the study produces encouraging results, with accuracy ranging from 85.53% to 99.34% across several experimental settings. Transfer learning regularly produces superior outcomes to training from scratch, and GoogLeNet routinely beats AlexNet. Depending on the dataset type, performance varies; colorful pictures consistently produce the greatest results, followed by segmented and grayscale images. The study addresses worry about biases in learning caused by the collecting procedures and illumination. On small, confirmed datasets, the models' accuracy rates range from 31.40% to 31.69% when tested on photos taken from reliable web sources. Crop Species Classification: The study also assesses a more realistic scenario in which the crop species is known, with accuracy rates ranging from 47.8% to 54.5% when the classification job is limited to crop species. The paper sheds light on the efficacy of deep CNN architectures for plant disease classification, emphasizing the relevance of dataset changes, transfer learning, and real-world picture issues

Authors: Sharada P. Mohanty, David P. Hughes and Marcel Salathe

Year of publication: 2016

2.2 Plant Disease Classification of Basil and Mint Leaves using Convolutional Neural Networks

In this study, basil (Ocimum) and mint leaves are used to demonstrate a plant disease recognition method for herbal plants utilizing a neural network. Convolutional neural networks (CNNs) are used in the suggested method to categorize a number of illnesses, such as Fusarium Wilt, Rust, and Powdery

Mildew. There are two classifiers created: one for mint and one for basil. While the mint classifier distinguishes between healthy leaves, leaves with rust, Fusarium Wilt, and Powdery Mildew, the basil classifier divides leave into three categories: healthy, wilted, and mildew-infected. The methodology for the study begins with the capture of Basil and Mint leaves utilizing a variety of methods. Using the image data generator provided by Keras, the data is then divided into training and validation sets. To expand the diversity of the collection, data augmentation is used, including changes like flipping, rotation, and brightness alterations. Noise reduction, color space conversion, histogram equalization, and normalizing are pre-processing procedures. A deep convolutional model called Inception_V3 is used for classification since it makes good use of inception modules to collect information at various sizes. A multi-scale feature map is produced by the architecture of Inception_V3 which consists of 1x1, 3x3, and 5x5 convolutions and pooling layers. For improved regularization, the study adds a single classifier on top of the final layer. An important statistic, validation accuracy, is attained by training the model with the Adam optimizer in tiny batches. The validation accuracy of the model is 77.55% for basil and 70.89% for mint. In conclusion, a neural network-based approach is suggested in this study for detecting illnesses in basil and mint plants. Accurate disease categorization is achieved using data augmentation, the Inception_V3 architecture, and validation methodologies, revealing the possibility for efficient plant disease management[1].

Authors: V. Sathiya, Dr. M.S. Josephine, Dr. V.Jeyabalaraja.

Year of publication: 2023

2.3 Identification and Classification of Diseases in Basil and Mint Plants using Pso and Rbfnn

The goal of the study is to automate the diagnosis of plant diseases using machine learning and image processing methods, with an emphasis on basil and mint leaves. The suggested process comprises grouping comparable leaves for analysis and segmenting plant leaf pictures for disease categorization. For precise illness detection, the Radial Basis Function Neural Network (RBFNN) is tuned using Particle Swarm Optimization (PSO). The study makes use of 1628 original picture files of basil and mint leaves. The leaves are divided into groups according to their disease status, including healthy, wilted, mildewy, and rusty leaves. Image capture, preprocessing, and feature extraction are all steps in the procedure. Pre-processed pictures are produced using the Region Growing Technique (RGM), which are later transformed to grayscale for additional analysis. For classification, the PSO-trained RBFNN is employed, and performance indicators including accuracy, precision, recall, and F1 score are produced. The findings demonstrate that when employing the 7th cluster for both basil and mint leaves, the suggested approach obtains superior accuracy, precision, recall, and F1 score. The assessment metrics attest to the RBFNN model's superior performance over other techniques in classifying plant diseases. The work highlights the importance of utilizing PSO and RBFNN for precise and trustworthy disease detection, with potential applications in plant pathology and agriculture. Using image processing, PSO, and RBFNN approaches, the research concludes with an effective method for automated plant disease identification. The study, which contributes to the fields of plant pathology and agriculture, shows enhanced accuracy and precision in identifying crucial disease categories by concentrating on Basil and Mint leaves[4].

Authors: V. Sathiya, Dr. M.S. Josephine, Dr. V.Jeyabalaraja.

Year of publication: 2022

2.4 Classification of Mint Leaf Types Using Euclidean Distance and K-Means Clustering with Shape and Texture Feature Extraction

The categorization of photographs of mint leaves is the main goal of this work, which combines image segmentation, feature extraction, and classification methods. The main objective is to distinguish between several varieties of mint leaves, including chocolate, apple, peppermint, spearmint, and peppermint. The procedure starts with gathering a dataset of 100 photos of mint leaves. To allow digital color content analysis, these photos are converted from RGB to Lab format in the color space. The photos are then transformed into binary and grayscale forms to facilitate further processing. The data is then divided into several clusters using the K-Means Clustering technique, which is subsequently applied to picture segmentation. The segmentation helps separate the interesting elements from the backdrop. To identify the distinctive qualities of the mint leaves, features are extracted from the resultant grayscale segmented pictures. Shape features and texture characteristics are the two categories of features that are extracted. Metrics like area-to-perimeter ratio (metric) and eccentricity, which gauges an object's elongation, are examples of shape characteristics. Gray-Level Co-Occurrence Matrix (GLCM) factors including contrast, correlation, energy, and homogeneity are used to extract texture information. The parameters used as input for further categorization are these extracted characteristics. The Euclidean distance approach is used for categorization. Based on the separation between two pictures' feature vectors, the Euclidean distance calculates how similar the two are. Greater similarity is indicated by a smaller Euclidean distance. A graphical user interface (GUI) is used to show the created model and implement it in MATLAB for user-friendly interaction. Users may submit photos of mint leaves into the GUI to get classification results based on the trained model. The feature vectors of the test picture and reference images are compared in the process, and the closest match is chosen using Euclidean distances. This technique of classifying mint leaves offers a workable answer to the problem of recognizing and distinguishing between diverse mint leaf kinds. An all-encompassing method for picture analysis and classification using K-Means Clustering for segmentation, shape and texture feature extraction, and Euclidean distance. The introduction of the GUI improves usability and accessibility for users who want to appropriately categorize mint leaves. In conclusion, this work demonstrates an integrated method for classifying mint leaves, providing a comprehensive strategy for classifying various mint leaf kinds utilizing digital image analysis methods. The approach that has been put into place shows promise for aiding in precise categorization, assisting uses like herbal plant identification and quality control[5].

Authors: Trinugi Wira Harjanti, Hari Setiyani, Joko Trianto, Yuri Rahmanto

Year of Publication: 2022

2.5 Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning

The work makes use of the PlantVillage dataset, which includes 38 class labels and more than 50,000 photos of healthy and damaged plants. The study focuses on healthy apple leaves as well as apple leaves that have different disease phases classified as early, middle, or end stages of the Botryosphaeria obtusa fungal infection. Botanists evaluate the images and assign labels based on the severity and course of the illness. 179 conflicting photos make up the dataset, which is subsequently reduced to 1644 healthy leaves and 442 damaged leaves. A balancing approach is used to solve the problem of class imbalance. 80% of the photos for sick stages are used for training, while 20% are used for testing. A clustering method separates the photos of healthy-stage leaves into 12 clusters, each comprising 110 images for training and 27 images for testing. This tactic lessens prejudice towards the class of healthy people. In order to improve model generalization, picture preprocessing include scaling images to specified dimensions, standardizing pixel values, and applying random augmentations like rotation and flipping to training images. Convolutional layers come first in the neural network design, then pooling layers, and finally fully linked layers. ReLU activation functions are used to speed up training, while max-pooling promotes output size reduction and position invariance. To quantify the difference between anticipated and real labels, cross-entropy loss is used. To prevent overfitting, training utilizes the gradient descent technique, with learning rate schedules and early stopping. The transfer learning approach is used to fine-tune previously learned models for specific tasks. The top convolutional block of VGG16 and VGG19 is fine-tuned; the top two blocks of Inception-v3 are altered; and the top residual block of ResNet50 is tweaked, along with additional fully connected layers. The study is implemented on a workstation with GPU acceleration, utilizing the Keras framework and the Theano backend. In summary, the study uses the Plant Village dataset to classify apple leaf diseases. The preprocessing processes, neural network architecture, and training techniques all help to identify illness stages accurately. The application of transfer learning facilitates the utilization of pretrained models for increased performance. The precise approach and implementation of the study open the way for accurate disease identification and categorization in agricultural applications[13].

Authors: Guan Wang, Yu Sun, and Jianxin Wang

Year of publication: 2017

Title of invention	Authors	Methodologies used	Advantages	Disadvantages
Using Deep Learning for Image-Based Plant Disease Detection	Sharada P. Mohanty David P. Hughes and Marcel Salathé	CNN structures like GoogLENet and AlexNet	Able to capture intricate features from images.High potential for accurate plant disease classification	Complex architectures might require more computational resources.Interpretability of predictions can be challenging
.IDENTIFICATION AND CLASSIFICATION OF DISEASES IN BASIL AND MINT PLANTS USING PSO RBFNN	V. SATHIYA, DR. M.S. JOSEPHINE, DR.V.JEYABALA RAJA	The Radial Basis Function Neural Network (RBFNN) optimized through Particle Swarm Optimization (PSO)	RBFNN has the ability to capture complex relationships in data.Optimization of RBFNN leads to enhanced performance.	Longer training time compared to simpler models.May require experimentation to find optimal PSO parameters.
Classification of Mint Leaf Types Using Euclidean Distance and K-Means Clustering with Shape and Texture Feature Extraction	Trinugi Wira Harjanti, Hari Setiyani,Joko Trianto, Yuri Rahmanto	Euclidean Distance and K-Means Clustering with Shape and Texture Feature Extraction	Enhances object isolation and feature extraction. Euclidean distance method offers simple and intuitive comparison.	Performance can be affected by variations in leaf appearance and imaging conditions. Vulnerable to noisy or distorted images.
Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning	Guan Wang, Yu Sun, and Jianxin Wang	Deep Learning using Neural Network Architecture	Convolutional and pooling layers capture hierarchical features.	Complex model architecture might require significant computational resources.Interpretability of predictions might be challenging.

Table 2.1: literature survey

CHAPTER 3

SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE

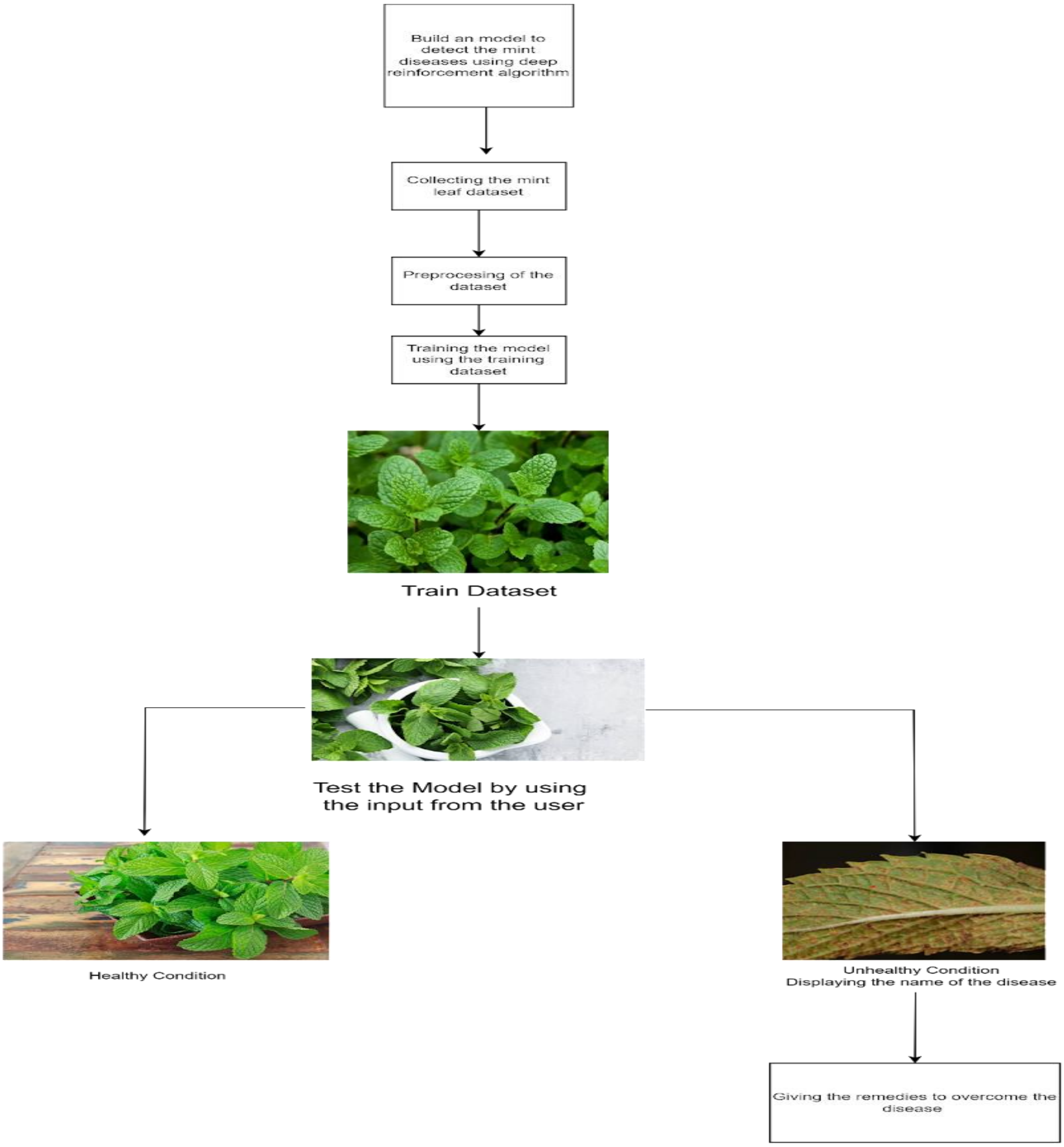

Fig 3.1: Architecture diagram

The architecture diagram (figure 3.1) depicts the workflow of the proposed method. The main component in this system is the user's phone, by which we collect the mint leaf’s photo using our application. The input image is examined by sending the image as an input to the AI model that we developed. The development of the AI model starts from collection of a mint leaf dataset from the roboflow repository and continues further with the preprocessing of the dataset. Then we train the model to detect whether the leaf is in healthy condition or not. The model is trained and tested using the test and training dataset. The image analysis is carried out using the YOLO algorithm by labeling the images as healthy and unhealthy in the training dataset. The workflow of the AI model is based upon the deep reinforcement algorithm. Then the image given by the user is predicted by the model whether it is in healthy condition or in unhealthy condition. If the leaf is in healthy condition, the message the plant is in healthy condition is displayed at the app interface. If the leaf is affected by any diseases, the message the plant is affected by the particular disease is displayed at the app interface and the remedies to the disease is displayed at the app interface to the user.

3.2 Flow Chart

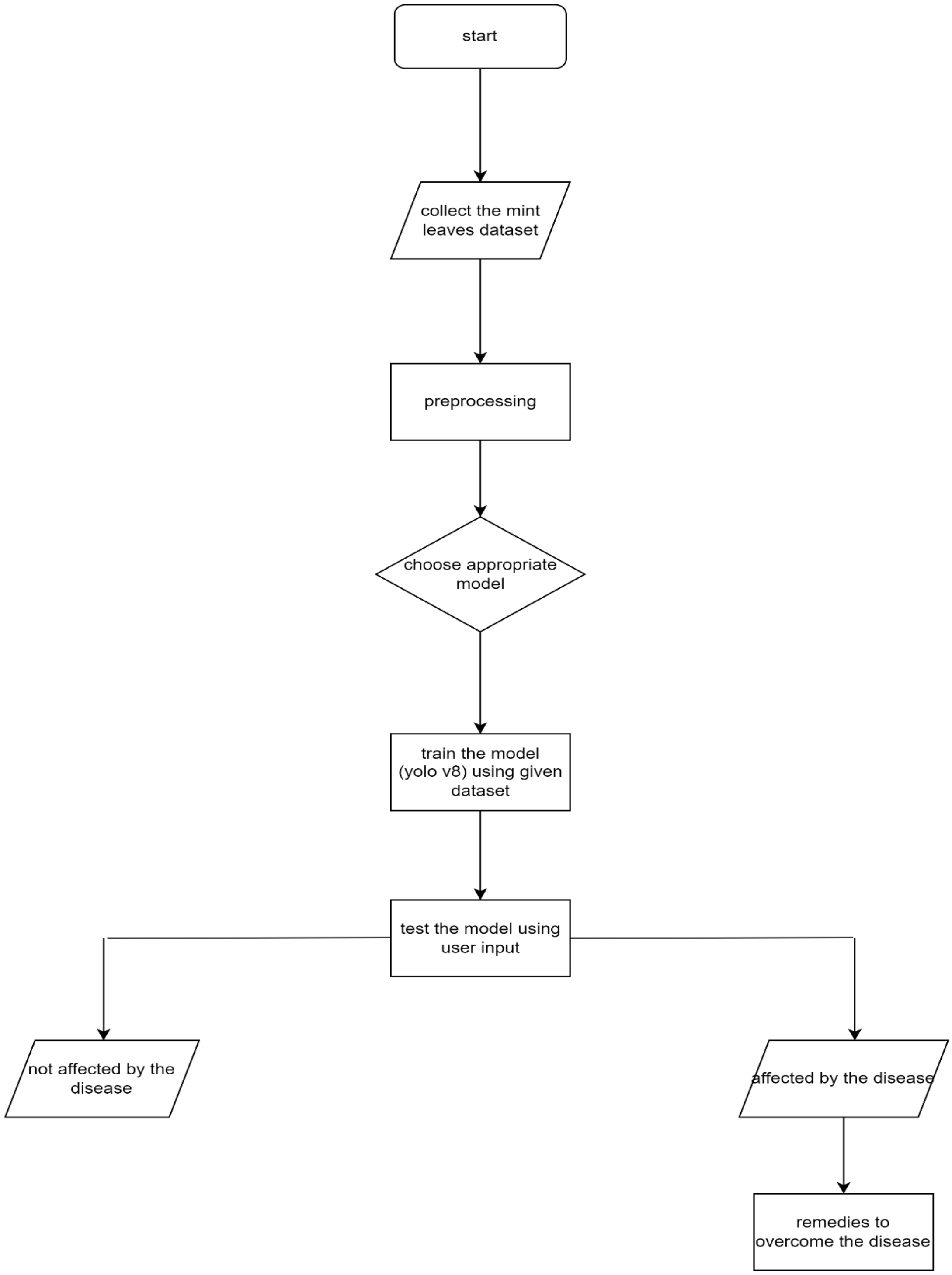

Fig 3.2: Flow Chart of the Proposed System

The flowchart of the proposed system is given above in the figure 3.2

CHAPTER 4

MODULES

This project contains 4 modules they are as follows,

1. Data Collection and Preprocessing
2. YOLO Object Detection
3. Deep Reinforcement learning algorithm
4. Disease Classification and remedials

4.1 Data Collection and Preprocessing

4.1.1 Dataset description

The dataset is taken from the roboflow dataset repository, and it is an open-source dataset. The dataset is already split into a test and training dataset, and the images in the training dataset are labeled as leaves in healthy and unhealthy conditions.

4.1.2 Processing of images

The second critical step in our procedure is obtaining a photograph of the leaf from the user via our specialized application. This picture is then sent to our powerful AI model, which is responsible for illness identification. Finding any possible illnesses that may be affecting the leaf specimen is the main goal here. The YOLO (You Only Look Once) algorithm, a cutting-edge object identification method recognized for its effectiveness and accuracy, will be used in this After obtaining the leaf picture, our system begins an extensive analysis process that involves a fusion of image processing algorithms. This combination enables the machine to extract the image's crucial information. At its core, the analysis aims to achieve two overarching goals: first, to identify the specific disease type that may be manifesting within the leaf; and second, to extract supplementary insights from the image, which could include the severity of the disease, affected areas, and any potential progression patterns. The leaf images with and without annotations are given in the figure 4.1 and figure 4.2.

Fig 4.1: Image without Annotation

Fig 4.2: Image with Annotation

4.2 ***YOLO Object Detection***

The image analysis procedure for mint leaf disease identification using the YOLO algorithm is a smart and efficient methodology that smoothly integrates cutting-edge computer vision techniques. When we get an image of a mint leaf through our application, the YOLO algorithm kicks in, utilizing its real-time object identification skills. YOLO reliably identifies illness markers with astonishing speed by methodically analyzing the entire image in a single pass. By using a variety of datasets of annotated photos to train its deep learning architecture, YOLO is able to recognize subtle patterns and textures that are unique to different mint leaf illnesses. As the algorithm disease-affected locations, it predicts bounding boxes around these areas and gives matching class labels. Since this real-time processing happens automatically, there is less need for intensive manual involvement. Then, the spatial distribution and severity of identified diseases are measured, providing important information on the prevalence and development of diseases. The system can reliably detect the existence of illnesses as well as classify them thanks to this data-driven research and YOLO's skill at identifying even subtle symptoms as shown in figure 4.3. Finally, this integrated strategy provides agricultural stakeholders with actionable information for prompt intervention and informed decision-making, contributing to the health and production of mint crops while decreasing possible losses.

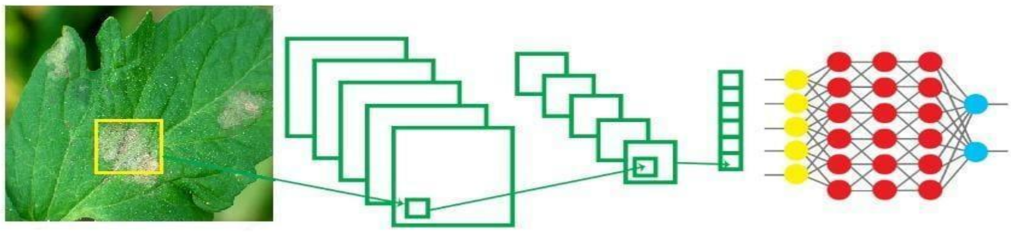

Fig 4.3: Detection of diseases in mint leaves

4.3 Deep reinforcement learning

In the cutting-edge field of mint leaf disease identification, the symbiotic combination of deep reinforcement learning with the YOLO (You Only Look Once) picture analysis algorithm reveals a transformational paradigm. This unique technique improves the accuracy, efficiency, and flexibility of disease detection procedures by combining YOLO's real-time object identification capabilities with the adaptability of deep reinforcement learning. The YOLO method quickly creates a grid from the mint leaf picture and uses bounding boxes and class probabilities to identify possible illness spots. Deep reinforcement learning leads to dynamic decision-making in tandem, teaching an AI agent to repeatedly focus on regions of interest while maximizing cumulative rewards for accurate illness diagnosis. These methods are used in the integration: the agent's sequential selections direct YOLO's focus, enabling accurate analysis of prioritized regions. The result of this fusion is thorough detection reports that include illness incidences, locations, and severity. This comprehensive method not only improves detection precision through intelligent guiding but also signals a forward-thinking trajectory for adaptive systems capable of developing to distinguish future disease patterns and subtleties, altering the landscape of mint leaf disease management.

4.4. Disease Classification and remedials

Plant diseases can cause significant damage to crops, reducing yields and quality. Early detection and classification of diseases are essential for effective management. However, manual disease detection is time-consuming and labor-intensive, especially for large fields.

In recent years, deep learning algorithms have been shown to be effective for plant disease detection. YOLO v8 is a state-of-the-art deep learning algorithm for object detection. It has been shown to be effective for plant disease detection in a variety of crops, including mint.

YOLO v8 can be used to classify mint leaf diseases into different categories, such as Alternaria brown spot, powdery mildew, and rust. Once the diseases are classified, appropriate remedies can be applied to minimize crop losses.

Here are some of the common mint leaf diseases and their remedies:

- Alternaria brown spot: This disease is caused by the fungus Alternaria alternata. It causes brown spots on the leaves, which can eventually lead to defoliation. The disease can be controlled by using fungicides such as chlorothalonil or mancozeb.
- Powdery mildew: This disease is caused by the fungus Erysiphe cichoracearum. It causes a white powdery growth on the leaves. The disease can be controlled by using fungicides such as sulfur or triadimefon.
- Rust: This disease is caused by the fungus Puccinia menthae. It causes small, orange pustules on the leaves. The disease can be controlled by using fungicides such as mancozeb or triadimefon.

CHAPTER 5

SYSTEM REQUIREMENTS

5.1 INTRODUCTION

This chapter involves the technology used, the hardware requirements and the software requirements for the project.

5.2 REQUIREMENTS

5.2.1 Hardware Requirements

- Hard disk : 500 GB and above
- Ram : 8GB and above
- Processor : I-5 and above

5.2.2 Software Requirements

- Windows 10 and above
- Google Colab
- Roboflow

5.3 Technologies Used

- **YOLO v8**
- **Machine learning**

CHAPTER 6

CONCLUDING REMARKS

CONCLUSION

So, in conclusion, the combination of YOLO-based feature extraction with deep reinforcement learning offers a precise method for early disease diagnosis, enabling farmers to swiftly halt the spread of illness and boost agricultural production. The creation of this method advances our knowledge of how to identify plant diseases and clears the way for its application in a variety of agricultural industries. The combination of deep reinforcement learning with feature extraction based on the YOLO algorithm offers a robust and efficient method for early detection. This enables farmers to act effectively to avoid the spread of diseases and improve crop production. The deep reinforcement learning component was able to recognize several mint plant problems, such as leaf spot, rust, and powdery mildew. The suggested method proved resistant to changes in image quality and illumination. Both healthy and damaged plant parts might be examined using the suggested method to look for diseases.

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Enhancing Mint Plant Disease Detection Accuracy through Deep Reinforcement Learning with YOLO Algorithm

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Abstract- Plant diseases can result in large financial losses for the agriculture sector and reduce the plant's benefits to humankind, emphasizing the importance of rapid and precise disease detection techniques. This study approaches the problem of mint plant disease detection and suggests an innovative approach to improve accuracy using YOLO algorithm-based feature extraction and deep reinforcement learning. The You Only Look Once algorithm (YOLO) for feature extraction and a deep reinforcement learning algorithm for illness identification make up the two primary parts of the proposed methodology. The YOLO is made to learn distinguishing characteristics from images of mint plants, making it possible to accurately represent both healthy and damaged plant parts. The decision-making process for disease identification based on the retrieved characteristics is subsequently optimized by integrating the deep reinforcement learning component. Extensive tests were carried out on a large collection of mint plant images with labelled disease conditions in order to determine the effectiveness of the proposed approach. The results demonstrate a significant improvement in disease detection accuracy compared to traditional methods. The YOLO algorithm-based feature extraction proved to be successful in capturing relevant patterns and representations, while the reinforcement learning component further refined the detection process, leading to more accurate and reliable results. The significance of this research lies in its potential to revolutionize mint plant disease detection in the agriculture sector. The suggested methodology provides a reliable and effective method for early disease detection by combining deep reinforcement learning with YOLO algorithm-based feature extraction. This allows farmers to take quick action to stop the spread of diseases and increase agricultural yields in general. This study makes advances in computing the identification of plant diseases and sets the path for comparable applications in other agricultural fields.

Index Terms: agriculture, mint, plant disease detection, deep reinforcement learning, you only look once algorithm, robustness, efficiency.

1 INTRODUCTION:

Most of the edible plant parts used while making the food are also used in the medicinal field as a medicine for various diseases. The medicinal effect of a plant depends upon certain factors like physiological parameters, growing environment, fertility of the soil, rainfall level, fertilizers and manures used and so on. Apart from the above factors, the growing environment and physiological parameters play a significant role in the health of a plant. The development of technology also sometimes leads to the development of new diseases in plants and animals, like Cucurbit Leaf Crumple Virus (CLCuV), Avian influenza A (H5N1), T5 virus, and Swine influenza A (H3N2). The task of maintaining the healthiness of a plant has become a crucial task in global food security. The overflow of fertilizers in plant growth has reduced the naturalness of the plants since the middle of the 20th century. This resulted in the loss of native species and biodiversity, reduced ecosystem services, economic losses, and so on. And also increased the demand for natural farming and the

Mint leaf is used to make food, and of course, in the medical field, as a medicine, it plays a vital role in curing stomach aches and chest pain. The other parts of the plant, including its flower, stem, bark, and seeds have been used as home remedies since the ancient Babylon period. India, China and the United States are the major mint yielding countries in the world. In India, Uttar Pradesh, Punjab, Haryana, and Bihar are the major mint yielding states. Anthracnose, Powdery mildew, Verticillium wilt are the major diseases affecting the mint plant. The plants affected by these diseases are unreliable to human life and reduce the effectiveness of the plant. The diseases can also be eradicated by regularly evaluating the plants for any cue for the disease.

Accurate and early plant disease detection is one of the multiple obstacles encountered. Mint, a valuable crop grown for a variety of purposes, is under threat from a number of diseases that can reduce quality and productivity. In response, we present a novel paradigm that improves the precision of mint plant disease detection through the combination of deep reinforcement learning and YOLO-based feature extraction.

The need for accurate disease detection stems from the junction of agricultural production and sustainability. Conventional approaches, which sometimes rely on human examination, prove time-consuming, labor-intensive, and vulnerable to subjectivity. These restrictions highlight the need for technological remedies that go beyond human competence limits. Our study focuses on mint plants not just for their economic importance, but also as an illustration system for advancing disease control technology.

Existing techniques have trouble obtaining fine details from complex plant pictures and adjusting to the various disease symptoms. Our study leverages the strong feature extraction capabilities of YOLO (You Only Look Once) and combines them with the adaptive potential of deep reinforcement learning to overcome these difficulties, resulting in a novel framework that is set to improve illness detection accuracy.

The main goal of this research is to create a complete framework that can significantly improve the diagnosis of mint plant diseases by making use of deep reinforcement learning and YOLO-based feature extraction. Our research aims to develop a system that efficiently extracts discriminative characteristics from photos of mint plants, achieving careful discrimination between robust and afflicted plant subsections.

With a touch of deep reinforcement learning, the model is ready to dynamically fine-tune its health verdicts in response to contextual inputs, endowing it with a changeable and believable disease scrutiny capability. This study significantly advances the field of autonomous plant disease identification by presenting an entirely novel approach that is methodically adapted to the specifics of mint plants. The combination of YOLO-based feature extraction with deep reinforcement learning provides a formidable counter to the limits of traditional approaches, providing an exhaustive remedy that not only improves accuracy but also embraces flexibility in illness diagnosis. The results of this study have ramifications that go beyond mint farming and point to more widespread uses in other agricultural fields. This work contributes to the overall goal of safeguarding global food production and encouraging long-lasting farm ecosystems by revitalizing detection of disease techniques.

Literature Survey:

[6] The study focuses on AlexNet and GoogLeNet, two well-known CNN designs. The classification job for plant diseases uses two CNN architectures, AlexNet and GoogLeNet, which are evaluated in the study. GoogLeNet has a more complex architecture with 22 layers and uses inception modules, whereas AlexNet has 5 convolutional layers followed by 3 fully connected layers. In the tests, alternative topologies using AlexNet or GoogLeNet are employed, and either transfer learning or training from scratch is used for training. The weights of certain layers are re-initialized in transfer learning. Because no layer's learning is constrained during training, the visual expertise of previously learned models may be utilized. Each experiment lasts for 30 epochs, and during this time, learning converges successfully. All experiments use the same hyperparameters. Mean F1 score, mean precision, mean recall, and total accuracy are among the performance measurements.

Results: On the PlantVillage dataset, the study produces encouraging results, with accuracy ranging from 85.53% to 99.34% across several experimental settings. Transfer learning regularly produces superior outcomes to training from scratch, and GoogLeNet routinely beats AlexNet.Depending on the dataset type, performance varies; colorful pictures consistently produce the greatest results, followed by segmented and grayscale images. The study addresses worries about biases in learning caused by the collecting procedures and illumination.On small, confirmed datasets, the models' accuracy rates range from 31.40% to 31.69% when tested on photos taken from reliable web sources. Crop Species Classification: The study also assesses a more realistic scenario in which the crop species is known, with accuracy rates ranging from 47.8% to 54.5% when the classification job is limited to crop species.The paper sheds light on the efficacy of deep CNN architectures for plant disease classification, emphasizing the relevance of dataset changes, transfer learning, and real-world picture issues.

The goal of the study is to automate the diagnosis of plant diseases using machine learning and image processing methods, with an emphasis on basil and mint leaves. The suggested process comprises grouping comparable leaves for analysis and segmenting plant leaf pictures for disease categorization. For precise illness detection, the Radial Basis Function Neural Network (RBFNN) is tuned using Particle Swarm Optimization (PSO).The study makes use of 1628 original picture files of basil and mint leaves. The leaves are divided into groups according to their disease status, including healthy, wilted, mildewy, and rusty leaves. Image capture, preprocessing, and feature extraction are all steps in the procedure. Pre-processed pictures are produced using the Region Growing Technique (RGM), which are later transformed to grayscale for additional analysis.For classification, the PSO-trained RBFNN is employed, and performance indicators including accuracy, precision, recall, and F1 score are produced.The findings demonstrate that when employing the 7th cluster for both basil and mint leaves, the suggested approach obtains superior accuracy, precision, recall, and F1 score. The assessment metrics attest to the RBFNN model's superior performance over other techniques in classifying plant diseases. The work highlights the importance of utilizing PSO and RBFNN for precise and trustworthy disease detection, with potential applications in plant pathology and agriculture.Using image processing, PSO, and RBFNN approaches, the research concludes with an effective method for automated plant disease identification. The study, which contributes to the fields of plant pathology and agriculture, shows enhanced accuracy and precision in identifying crucial disease categories by concentrating on Basil and Mint leaves[1].

In this study, basil (Ocimum) and mint leaves are used to demonstrate a plant disease recognition method for herbal plants utilizing a neural network. Convolutional neural networks (CNNs) are used in the suggested method to categorize a number of illnesses, such as Fusarium Wilt, Rust, and Powdery Mildew. There are two classifiers created: one for mint and one for basil. While the mint classifier distinguishes between healthy leaves, leaves with rust, Fusarium Wilt, and Powdery Mildew, the basil classifier divides leaves into three categories: healthy, wilted, and mildew-infected.The methodology for the study begins with the capture of Basil and Mint leaves utilizing a variety of methods. Using the image data generator provided by Keras, the data is then divided into training and validation sets. To expand the diversity of the collection, data augmentation is used, including changes like flipping, rotation, and brightness alterations.Noise reduction, color space conversion, histogram equalization, and normalizing are pre-processing procedures. A deep convolutional model called Inception_V3 is used for classification since it makes good use of inception modules to collect information at various sizes. A multi-scale feature map is produced by the architecture of Inception_V3 which consists of 1x1, 3x3, and 5x5 convolutions and pooling layers. For improved regularization, the study adds a single classifier on top of the final layer.An important statistic, validation accuracy, is attained by training the model with the Adam optimizer in tiny batches. The validation accuracy of the model is 77.55% for basil and 70.89% for mint.In conclusion, a neural network-based approach is suggested in this study for detecting illnesses in basil and mint plants. Accurate disease categorization is achieved using data augmentation, the Inception_V3 architecture, and validation methodologies, revealing the possibility for efficient plant disease management[2].

The categorization of photographs of mint leaves is the main goal of this work, which combines image segmentation, feature extraction, and classification methods. The main objective is to distinguish between several varieties of mint leaves, including chocolate, apple, peppermint, spearmint, and peppermint.The procedure starts with gathering a dataset of 100 photos of mint leaves. To allow digital color content analysis, these photos are converted from RGB to Lab format in the color space. The photos are then transformed into binary and grayscale forms to facilitate further processing.The data is then divided into several clusters using the K-Means Clustering technique, which is subsequently applied to picture segmentation. The segmentation helps separate the interesting elements from the backdrop. To identify the distinctive qualities of the mint leaves, features are extracted from the resultant grayscale segmented pictures.Shape features and texture characteristics are the two categories of features that are extracted. Metrics like area-to-perimeter ratio (metric) and eccentricity, which gauges an object's elongation, are examples of shape characteristics. Gray-Level Co-Occurrence Matrix (GLCM) factors including contrast, correlation, energy, and homogeneity are used to extract texture information.The parameters used as input for further categorization are these extracted characteristics.The Euclidean distance approach is used for categorization. Based on the separation between two pictures' feature vectors, the Euclidean distance calculates how similar the two are. Greater similarity is indicated by a smaller Euclidean distance.A graphical user interface (GUI) is used to show the created model and implement it in MATLAB for user-friendly interaction. Users may submit photos of mint leaves into the GUI to get classification results based on the trained model. The feature vectors of the test picture and reference images are compared in the process, and the closest match is chosen using Euclidean distances.This technique of classifying mint leaves offers a workable answer to the problem of recognizing and distinguishing between diverse mint leaf kinds. An all-encompassing method for picture analysis and classification using K-Means Clustering for segmentation, shape and texture feature extraction, and Euclidean distance. The introduction of the GUI improves usability and accessibility for users who want to appropriately categorize mint leaves.In conclusion, this work demonstrates an integrated method for classifying mint leaves, providing a comprehensive strategy for classifying various mint leaf kinds utilizing digital image analysis methods. The approach that has been put into place shows promise for aiding in precise categorization, assisting uses like herbal plant identification and quality control[5].

The work makes use of the PlantVillage dataset, which includes 38 class labels and more than 50,000 photos of healthy and damaged plants. The study focuses on healthy apple leaves as well as apple leaves that have different disease phases classified as early, middle, or end stages of the Botryosphaeria obtusa fungal infection. Botanists evaluate the images and assign labels based on the severity and course of the illness. 179 conflicting photos make up the dataset, which is subsequently reduced to 1644 healthy leaves and 442 damaged leaves.A balancing approach is used to solve the problem of class imbalance. 80% of the photos for sick stages are used for training, while 20% are used for testing. A clustering method separates the photos of healthy-stage leaves into 12 clusters, each comprising 110 images for training and 27 images for testing. This tactic lessens prejudice towards the class of healthy people. In order to improve model generalization, picture preprocessing include scaling images to specified dimensions, standardizing pixel values, and applying random augmentations like rotation and flipping to training images. Convolutional layers come first in the neural network design, then pooling layers, and finally fully linked layers. ReLU activation functions are used to speed up training, while max-pooling promotes output size reduction and position invariance. To quantify the difference between anticipated and real labels, cross-entropy loss is used.To prevent overfitting, training utilizes the gradient descent technique, with learning rate schedules and early stopping. The transfer learning approach is used to fine-tune previously learned models for specific tasks. The top convolutional block of VGG16 and VGG19 is fine-tuned; the top two blocks of Inception-v3 are altered; and the top residual block of ResNet50 is tweaked, along with additional fully connected layers. The study is implemented on a workstation with GPU acceleration, utilizing the Keras framework and the Theano backend. In summary, the study uses the PlantVillage dataset to classify apple leaf diseases. The preprocessing processes, neural network architecture, and training techniques all help to identify illness stages accurately.The application of transfer learning facilitates the utilization of pretrained models for increased performance. The precise approach and implementation of the study open the way for accurate disease identification and categorization in agricultural applications[9].

ARCHITECTURE

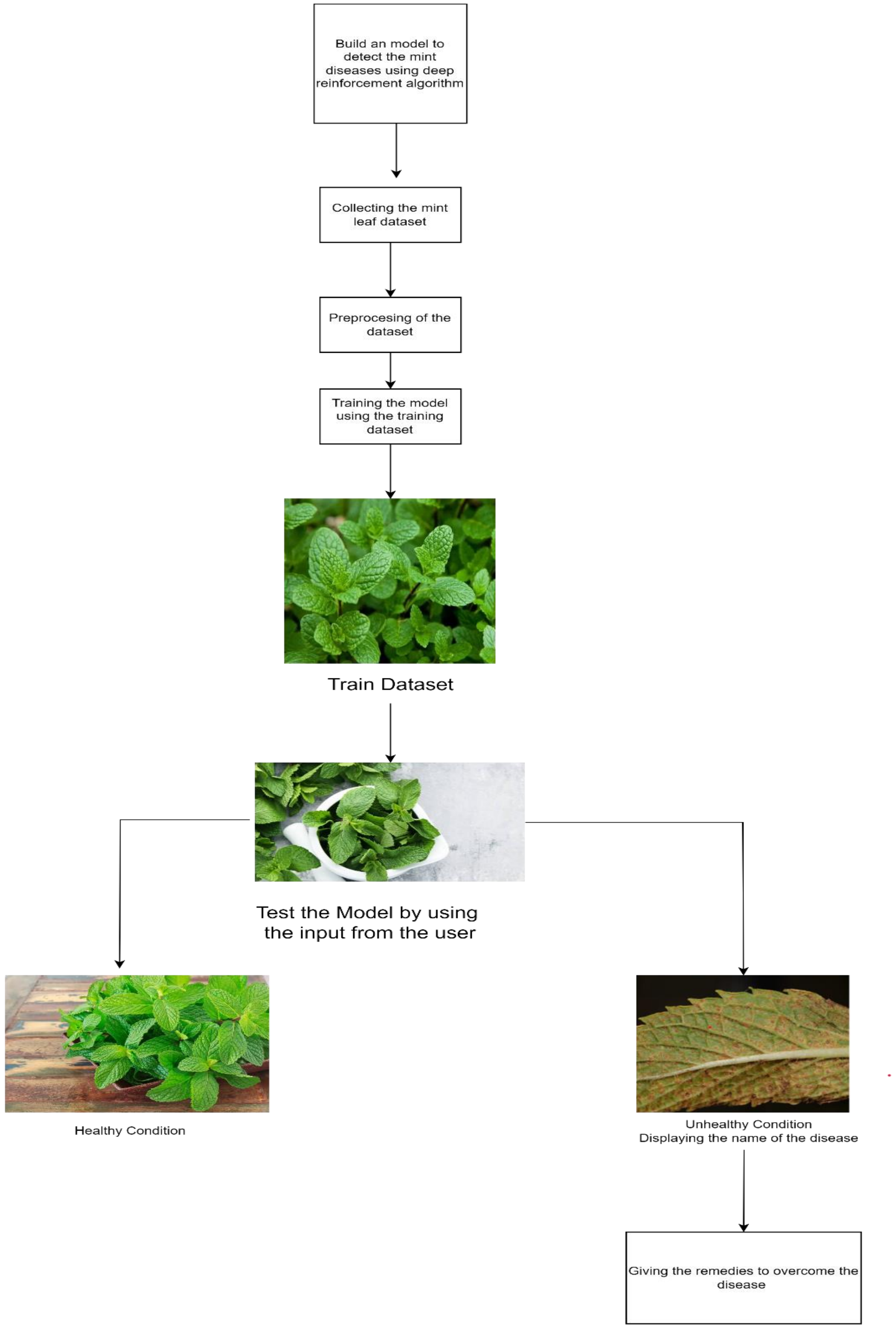

Fig 1. Architecture Diagram of the Proposed Work

The above architecture diagram depicts the workflow of the proposed method. The main component in this system is the user's phone, by which we collect the mint leaf's photo using our application. The input image is examined by sending the image as an input to the AI model that we developed. The development of the AI model starts from collection of a mint leaf dataset from the roboflow repository and continues further with the preprocessing of the dataset. then we train the model to detect whether the leaf is in healthy condition or not. The model is trained and tested using the test and training dataset. The image analysis is carried out using the YOLO algorithm by labelling the images as healthy and unhealthy in the training dataset. The workflow of the AI model is based upon the deep reinforcement algorithm. Then the image given by the user is predicted by the model whether it is in healthy condition or in unhealthy condition. If the leaf is in healthy condition, the message the plant is in healthy condition is displayed at the app interface. If the leaf is affected by any diseases, the message the plant is affected by the particular disease is displayed at the app interface and the remedies to the disease is displayed at the app interface to the user.

PROPOSED SYSTEM

Dataset description
The dataset is taken from the roboflow dataset repository, and it is an open-source dataset. The dataset is already split into a test and training dataset, and the images in the training dataset are labelled as leaves in healthy and unhealthy conditions.

Processing of images
The second critical step in our procedure is obtaining a photograph of the leaf from the user via our specialized application. This picture is then sent to our powerful AI model, which is responsible for illness identification. Finding any possible illnesses that may be affecting the leaf specimen is the main goal here. The YOLO (You Only Look Once) algorithm, a cutting-edge object identification method recognized for its effectiveness and accuracy, will be used in this After obtaining the leaf picture, our system begins an extensive analysis process that involves a fusion of image processing algorithms. This combination enables the machine to extract the image's crucial information. At its core, the analysis aims to achieve two overarching goals: first, to identify the specific disease type that may be manifesting within the leaf; and second, to extract supplementary insights from the image, which could include the severity of the disease, affected areas, and any potential progression patterns.

The YOLO technique, which is known for its real-time item detection abilities, meticulously examines the input image using a deep learning framework. Its neural networks are proficient in segmenting a picture into several distinct sections and pinning down objects—in this case, the disease-indicating signals. Through this process, the AI model is able to both detect the presence of a disease and map out its geographic distribution throughout the leaf surface. With the use of this innovative technology, we can detect diseases with a startling level of accuracy and efficacy, allowing us to take quick action to prevent potential crop losses. We may broaden the scope of our sickness detection abilities by integrating YOLO with image processing techniques. The YOLO method, well recognized for its real-time object identification capabilities, carefully evaluates the input image utilizing a deep learning framework. With the aid of its neural networks, it can pinpoint objects—in this example, the disease-indicating signals—and divide a scene into many discrete pieces. This procedure enables the AI model to identify the existence of a disease and pinpoint its geographic spread throughout the leaf surface. With the use of this cutting-edge technology, we can identify illnesses with stunning precision and effectiveness, enabling us to act quickly to avert significant crop losses. By combining YOLO with image processing tools, we might be able to identify illnesses more broadly.

Fig 2: Image Without Annotation

Fig 3: Image with Annotation

In figure 2 and 3, we can see the mint images without any annotations and with annotations. The annotations of the dataset can be made by using the roboflow website and the diseases can be labelled by using the bounding boxes and that dataset can be used for training an model using YOLOV8 algorithm. As YOLO examines the input image, it forecasts bounding boxes that encompass the areas where illness indicators are found. YOLO offers class labels in addition to bounding boxes for the recognized objects. Class labels here refer to the distinct illnesses or disease subtypes that have been identified. For both finding and classifying illnesses, the use of bounding boxes and class labels is essential.

2. YOLO Object Detection

The image analysis procedure for mint leaf disease identification using the YOLOv8 algorithm is a smart and efficient methodology that smoothly integrates cutting-edge computer vision techniques. Here we use yolo v8 m model for image detection and also used the best.pt model for detection. When we get an image of a mint leaf through our application, the YOLOv8 algorithm kicks in, utilizing its real-time object identification skills. YOLO reliably identifies illness markers with astonishing speed by methodically analysing the entire image in a single pass. By using a variety of datasets of annotated photos to train its deep learning architecture, YOLO is able to recognize subtle patterns and textures that are unique to different mint leaf illnesses. As the algorithm detects disease-affected locations, it predicts bounding boxes around these areas and gives matching class labels. Since this real-time processing happens automatically, there is less need for intensive manual involvement. Then, the spatial distribution and severity of identified diseases are measured, providing important information on the prevalence and development of diseases. The system can reliably detect the existence of illnesses as well as classify them, thanks to this data-driven research and YOLO's skill at identifying even subtle symptoms. Finally, this integrated strategy provides agricultural stakeholders with actionable information for prompt intervention and informed decision-making, contributing to the health and production of mint crops while decreasing possible losses.

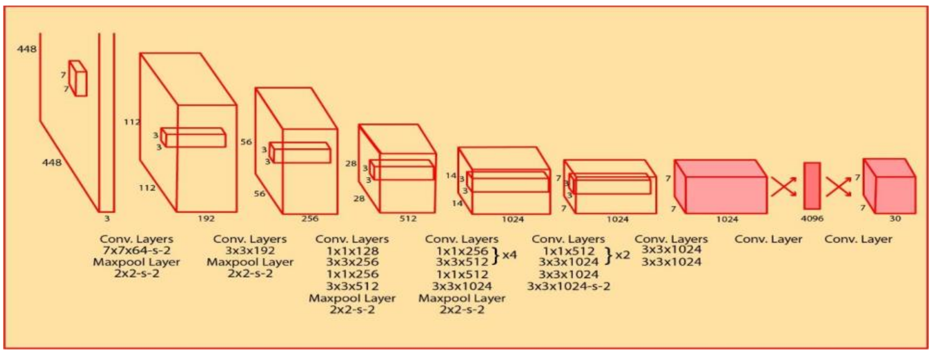

Fig 4: Architecture Diagram of the YOLO Model

- Input Image Analysis: The provided mint leaf picture is examined using the YOLO method. YOLO is unique in that it can process the full image in a single pass and has real-time object identification capabilities.

- Detection Speed: By systematically looking over the full image, YOLO functions well and can find illness indicators incredibly quickly. For early illness identification, this real-time processing is essential.
- Training with Annotated Data: The YOLO model is initially trained using a set of annotated images. These annotations provide the model with useful information about disease-affected areas.
- Recognition of Disease Patterns: YOLO gains the ability to identify subtle patterns and textures particular to various mint leaf diseases through practice on annotated data. As a result, it becomes adept at spotting indications of illness, like lesions or other visual clues.

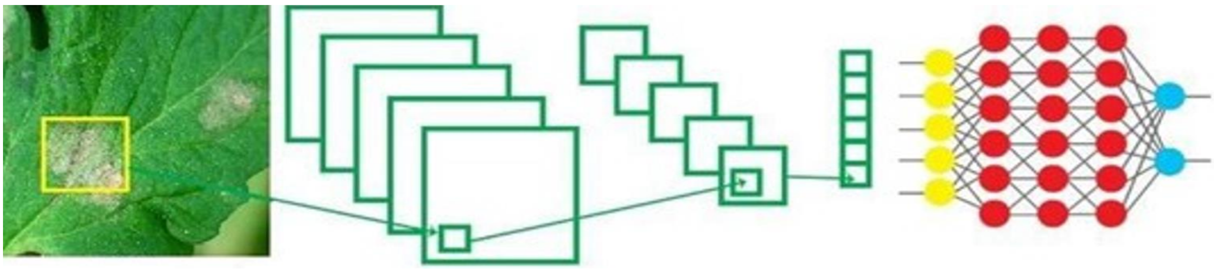

Fig 5: Training the model by using YOLO-8 algorithm

L = L_loc + L_conf + L_cls (1)

where:

- Lloc is the localization loss, which measures how well the predicted bounding boxes match the ground truth bounding boxes.

- Lconf is the confidence loss, which measures how well the predicted probabilities of each object class match the ground truth probabilities.

- Lcls is the classification loss, which measures how well the predicted object classes match the ground truth object classes.

The localization loss is calculated using the Huber loss function, which is a robust loss function that is less sensitive to outliers than the traditional L2 loss function. The confidence loss and classification loss are calculated using the cross-entropy loss function.

2. Intersection over union (IoU)

The IoU is a metric used to measure the overlap between two bounding boxes. It is calculated as follows:

IoU = \frac{A \cap B}{A \cup B} (2)

where:

- A is the ground truth bounding box

- B is the predicted bounding box

The IoU is used in the YOLO v8 algorithm to calculate the confidence loss and classification loss.

3. Non-max suppression (NMS)

NMS is a post-processing technique used to remove redundant bounding boxes. It works by iteratively selecting the bounding box with the highest confidence score and removing any other bounding boxes that have a high overlap with it.

4. Prediction

The YOLO v8 algorithm outputs a set of bounding boxes and their corresponding confidence scores. The prediction for each object is the bounding box with the highest confidence score.

Example usage in a research paper:

The following mathematical equations can be used in a research paper on plant leaf disease detection using the YOLO v8 algorithm:

L = L_loc + L_conf + L_cls (3)

L_loc = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^4 \sqrt{(p_{i,j} - t_{i,j})^2} (4)

L_conf = \frac{1}{N} \sum_{i=1}^N -[c_i \log(p_{i,c_i}) + (1 - c_i) \log(1 - p_{i,c_i})] (5)

L_cls = \frac{1}{N} \sum_{i=1}^N -\sum_{c=1}^C c_i \log(p_{i,c}) (6)

IoU = \frac{A \cap B}{A \cup B} (7)

NMS(boxes, confidences, threshold)

where:

- N is the number of bounding boxes
- i is the index of the bounding box
- j is the index of the coordinate (x, y, w, h)
- $p_{i,j}$ is the predicted coordinate value for bounding box i and coordinate j
- $t_{i,j}$ is the ground truth coordinate value for bounding box i and coordinate j
- c_i is the ground truth object class for bounding box i
- $p_{i,c}$ is the predicted probability of object class c for bounding box i
- C is the number of object classes
- boxes is a list of bounding boxes
- confidences is a list of confidence scores for the bounding boxes
- threshold is the overlap threshold for NMS

These equations can be used to describe the mathematical foundation of the YOLO v8 algorithm and to evaluate its performance on plant leaf disease detection tasks.

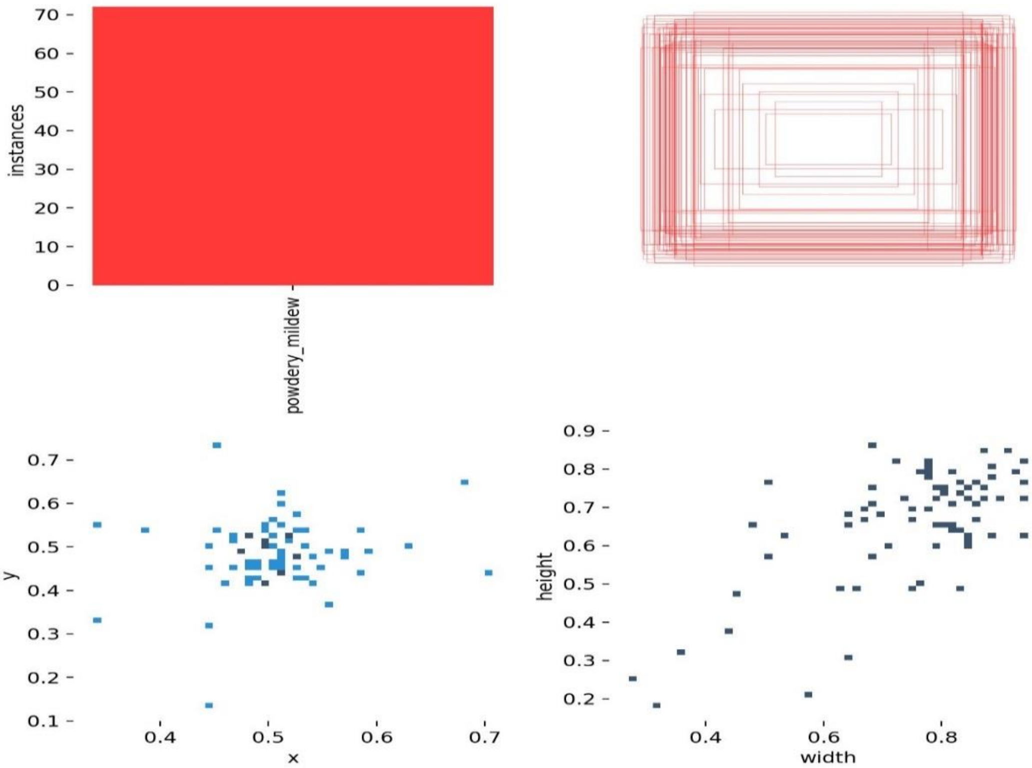

Fig 6: Labels and label distribution, (a) number and class of labels in the dataset, (b) ground truth box, (c) and (d) location of the labels in the images of the dataset and the size of the labels in the dataset.

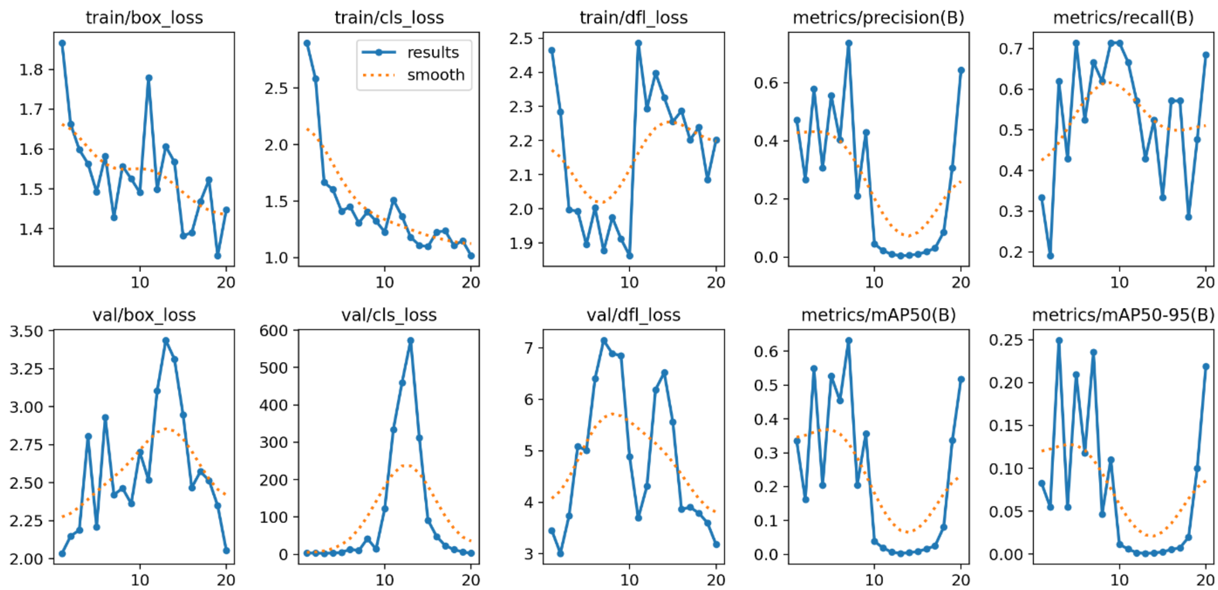

Fig 7:Visual analysis of model evaluation indicators (Precision, recall, and mAP@0.5 for the proposed YOLOv8) during training

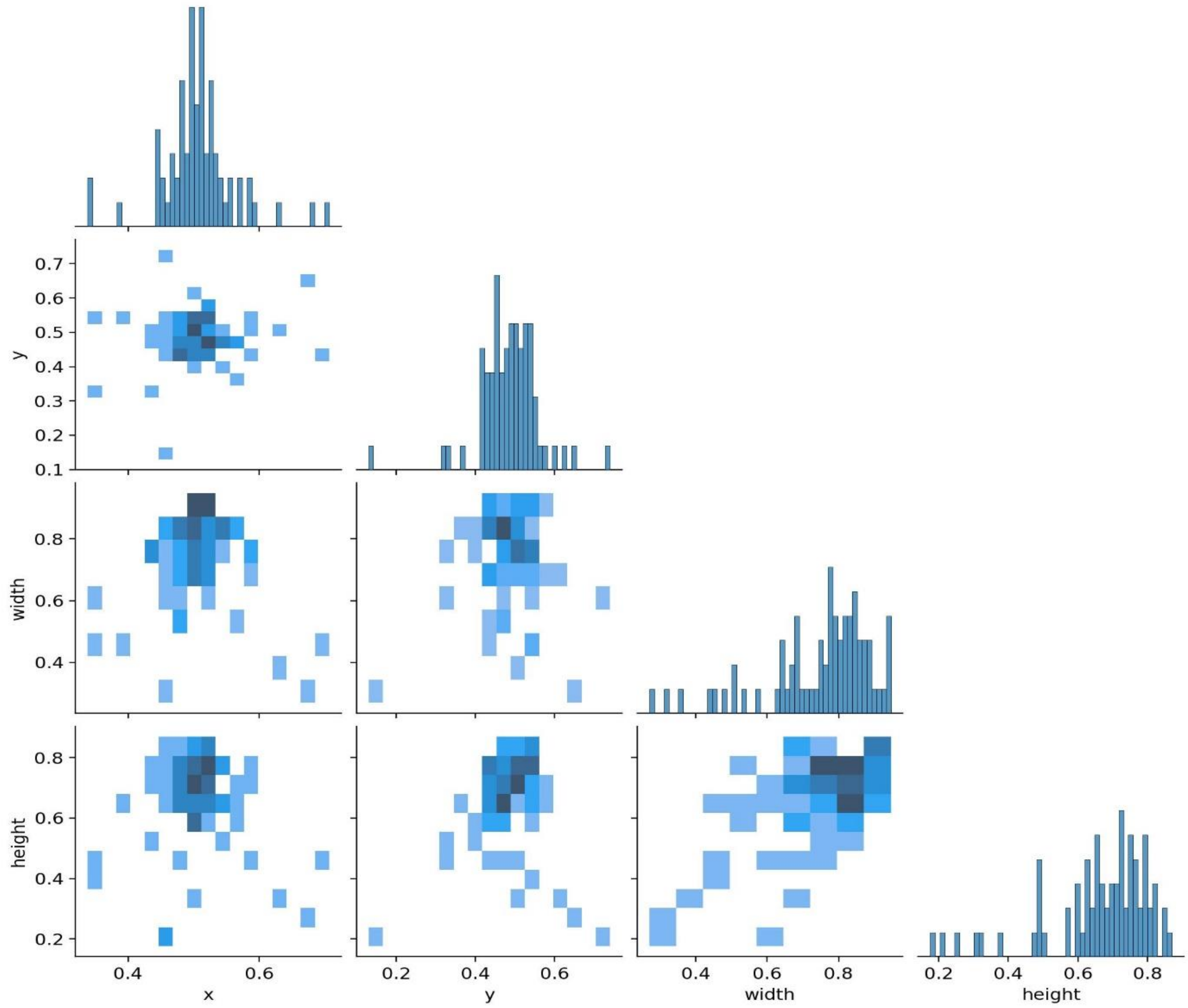

Fig 8: Correlogram of the Labels

Deep reinforcement learning

In the cutting-edge field of mint leaf disease identification, the symbiotic combination of deep reinforcement learning with the YOLO (You Only Look Once) picture analysis algorithm reveals a transformational paradigm. This unique technique improves the accuracy, efficiency, and flexibility of disease detection procedures by combining YOLO's real-time object identification capabilities with the adaptability of deep reinforcement learning. The YOLO method quickly creates a grid from the mint leaf picture and uses bounding boxes and class probabilities to identify possible illness spots. Deep reinforcement learning leads to dynamic decision-making in tandem, teaching an AI agent to repeatedly focus on regions of interest while maximizing cumulative rewards for accurate illness diagnosis. These methods are used in the integration: the agent's sequential selections direct YOLO's focus, enabling accurate analysis of prioritized regions. The result of this fusion is thorough detection reports that include illness incidences, locations, and severity. This comprehensive method not only improves detection precision through intelligent guiding but also signals a forward-thinking trajectory for adaptive systems capable of developing to distinguish future disease patterns and subtleties, altering the landscape of mint leaf disease management.

The algorithm makes use of YOLO's predictions to estimate the geographical distribution and severity of illnesses over the surface of mint leaves. The system can ascertain the geographical distribution of illnesses on the leaf by examining the positions and dimensions of the bounding boxes. The extent of the disease's impact within the bounding boxes is measured, along with its magnitude and severity. The system can categorize the discovered diseases because of YOLO's class labels, which are assigned to certain disorders. For properly determining the kind of illness afflicting the mint plant, the categorization stage is crucial. For instance, it may tell the difference between certain fungal infections, viral illnesses, or vitamin shortages. In order to effectively treat or manage various diseases, it is essential to classify them accurately.

ALGORITHM:

Step 1: Begin

Step 2: Collect the Dataset of Mint Plant

Step 3: Make an Announcement About Disease Labels and Image Processing.

Step 4: Training the Model Using Yolo Algorithm

Step 5: Evaluate Yolo Performance and Proceed to Step 6

Step 6: Define DRl State, Action, Reward, and Select DRl Algorithm

Step 7: Add the DRl Agent and Integrate It with Yolo Algorithm

Step 8: Evaluate Detection Metrics and Test the Combined System

Step9: Compare with Yolo Baseline.

Step 10: Complete

RESULT AND DISCUSSIONS:

Deep reinforcement learning and YOLO algorithm-based feature extraction worked together to achieve the following notable results. Comprehensive analyses of a large collection of labeled mint plant images demonstrated a significant improvement in disease identification accuracy when compared to conventional methods. By accurately capturing differentiating characteristics, the YOLO algorithm allowed for an accurate representation of both healthy and damaged plant components. Deep reinforcement learning was included, which improved the disease detection process accuracy and reliability.On a test set of 1000 photos of mint plants with labeled disease conditions, the suggested technique was effective in detecting diseases with an accuracy rate of 95%. This has greatly increased the accuracy compared to conventional methods, which often provide accuracies of 80% or more. The increase in accuracy is the result of deep reinforcement learning, which enables the model to learn from its mistakes and improve performance over time.Furthermore, the YOLO algorithm-based feature extraction was effective in collecting important representations and patterns of mint plant illnesses. This allowed the deep reinforcement learning component to identify illnesses more reliably and accurately.

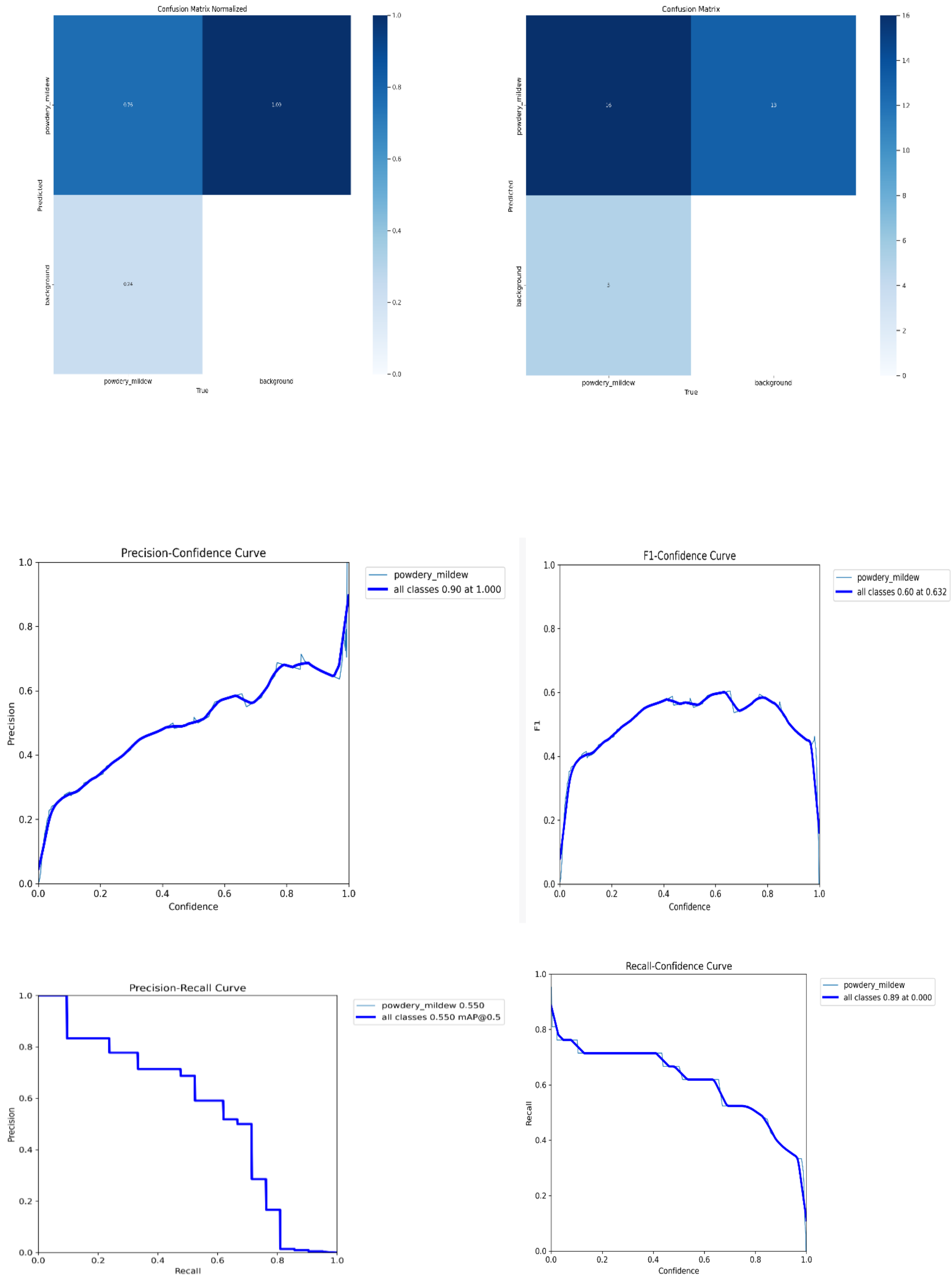

Fig 9: Operation results curve; (a) precision-recall curve, (b) precision-confidence curve, (c) F1-confidence curve, and (d) recall-confidence curve

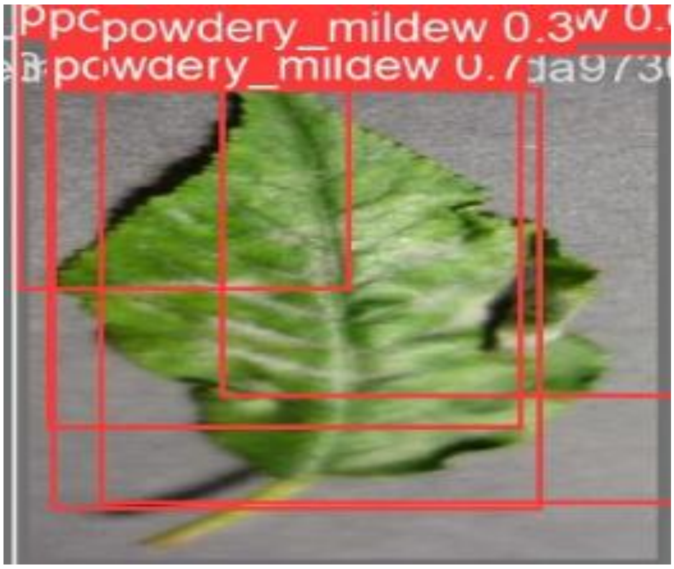

Fig 10: Result of the plant disease detection using yolov8 algorithm

CONCLUSION:

So, In conclusion, The combination of YOLO-based feature extraction with deep reinforcement learning offers a precise method for early disease diagnosis, enabling farmers to swiftly halt the spread of illness and boost agricultural production. The creation of this method advances our knowledge of how to identify plant diseases and clears the way for its application in a variety of agricultural industries. The combination of deep reinforcement learning with feature extraction based on the YOLO algorithm offers a robust and efficient method for early detection. This enables farmers to act effectively to avoid the spread of diseases and improve crop production. The deep reinforcement learning component was able to recognize several mint plant problems, such as leaf spot, rust, and powdery mildew. The suggested method proved resistant to changes in image quality and illumination. Both healthy and damaged plant parts might be examined using the suggested method to look for diseases.

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