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Deep Learning Model for Plant Leaf Disease Classification using Double Gan

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Abstract— Traditional plant disease diagnosis methods primarily rely on visual inspection, which can be limited in accuracy and scalability. To address these challenges, this study introduces a novel framework leveraging Double GAN, a generative adversarial network, to generate synthetic diseased leaf images. This approach helps overcome imbalanced datasets commonly encountered in plant disease datasets. The synthetic images, combined with real ones, are utilized to train a deep learning model, achieving an impressive accuracy of 99.80% in disease classification tasks. Furthermore, the framework integrates recommendations for preferred pesticides based on the identified disease, enabling targeted action and potentially reducing the reliance on broad-spectrum options. This innovative approach underscores the effectiveness of deep learning coupled with data augmentation techniques for accurate plant disease detection. It also provides valuable insights for promoting sustainable crop protection practices, highlighting the potential of advanced technologies in agricultural sustainability and productivity.

Keywords— Plant diseases, deep learning, Double Generative Adversarial Network (Double GAN), Data Augmentation, Image Classification, Sustainable Agriculture, Pesticide Recommendation.

I. INTRODUCTION

India, as an emerging economy, has traditionally heavily depended on agriculture as a primary income source for a significant portion of its population. However, the agricultural sector encounters various challenges, including substantial crop production losses in crop fields. Among these challenges, identifying plant leaf diseases emerges as a critical issue. Early detection of leaf diseases is crucial to prevent their spread to other plants, ensuring yield protection and averting financial losses for farmers. The consequences of plant leaf diseases can vary from minor disruptions to the complete devastation of entire plantations, significantly impacting the agricultural economy.In essence, effective management of plant leaf diseases is essential for sustaining agricultural productivity and ensuring the economic well-being of farmers in India.[1],[2],[3]. The integration of computer vision into precision agriculture presents an opportunity to significantly improve disease identification efficiency. Harnessing computer vision technologies can enhance the accuracy and precision of disease identification, providing a streamlined alternative to manual approaches.[4],[5].

Agriculture stands as a pivotal profession in developing nations such as India, playing a vital role in shaping the economy. Crop losses significantly impact a nation's financial stability. This can lead to famines and heightened unemployment rates within the agricultural sector. A key hurdle in combating plant illnesses and mitigating crop loss is the imperative for increased awareness among farmers.[6],[7],[8]. The Double GAN algorithm utilizes generative adversarial networks (GANs) to detect subtle patterns and anomalies associated with plant diseases. Deploying this algorithm in crop fields enables early disease detection, aiding farmers in proactive intervention to prevent disease spread and minimize crop losses. Moreover, the algorithm's adaptive nature allows it to learn and adjust to new disease strains, ensuring reliable performance across different environments and crop types. Besides disease detection, analyzing soil nutrient deficiencies is crucial. Tailoring fertilizer applications to address deficiencies in essential nutrients like nitrogen, phosphorus, potassium, zinc, and iron can enhance plant immunity, promote recovery from diseases, and optimize overall crop yields.

II. LITERATURE REVIEW:

The issue of uneven sample distribution was addressed in the PlantVillage database concerning leaf disease identification, utilizing methods such as flipping and translation to complement the dataset. Compared to regularization and other techniques, expanding the original dataset can significantly enhance model performance and mitigate overfitting risks.Furthermore, a rapid and reliable approach to quantify lesions using image recognition and an artificial neural network model was developed. These disease recognition methods have demonstrated promising results.This section delves into the literature surrounding the detection and classification of plant or crop diseases. Ashwin Kumar proposed an Optimal Mobile Network-based Convolutional Neural Network (OMNCNN) for the recognition and categorization of plant leaf diseases, incorporating phases such as pre-processing, segmentation, feature retrieval, and categorization. Bedi and Gole introduced a hybrid approach combining a Convolutional

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Auto Encoder (CAE) and Convolutional Neural Network (CNN) structure for autonomous plant disease diagnosis. Rahman et al. presented an advanced recognition and categorization approach based on deep learning (DL) models for effective disease identification tasks.

III. PROPOSED METHODOLOGY

Innovating a comprehensive system for detecting various diseases across various places is complex by visualizing agricultural fields manually for the symptoms of affecting leaves consumes much time too and analyzing the fertilizers is hard to implement to overcome these issues a new deep learning method is proposed for detecting, categorizing and fertilizer recommendation for the affected leaf. It consist of 4 steps,

That are, (i) Pre-processing (ii) Segmentation (iii) Feature Extraction (iv) Classificationthese techniques are briefly explained below.

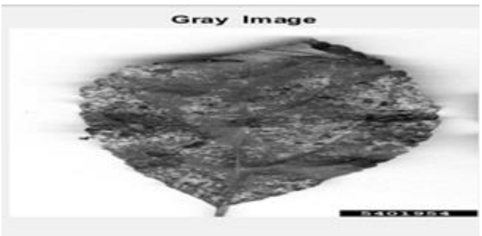
Step 1: Pre-Processing

Preprocessing in image processing encompasses a range of techniques designed to ready images for analysis or subsequent processing. It encompasses diverse operations aimed at boosting image quality, diminishing noise, and extracting pertinent information. Typical preprocessing steps comprise resizing, denoising, normalization, cropping, rotation, color space conversion, and histogram equalization. These methodologies contribute to enhancing the efficiency of subsequent image processing tasks such as segmentation, feature extraction, and object recognition. The preprocessing process is typically divided into three phases: (i) converting the image to grayscale, (ii) enhancing contrast, and (iii) converting the image from RGB format.

```
% Step 1 - Preprocessing
%ImageResize ReI = imresize(I,[256 256]);
%figure;imshow(ReI);
 title ('Resized Test Image');
```

1. Gray Scale Conversion:

Converting an image to grayscale involves transforming a color image into a black-and-white version, where each pixel denotes only its brightness value. This conversion is achieved by averaging the color channels or applying specific coefficients to compute luminance. Grayscale images are less complex and demand less memory, rendering them valuable for tasks such as image analysis and computer vision.

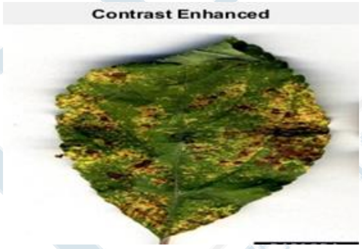


% Gray Conversion

```
GrI = rgb2gray(ReI);
figure; imshow(GrI);
title ('Gray Image');
```

2. Contrast enhancement:

In image processing, contrast enhancement involves employing methods to heighten the visual contrast between distinct regions of an image by amplifying the intensity disparity among them. The objective is to intensify dark areas while brightening lighter areas, ultimately augmenting overall contrast and highlighting finer details within the image.Top of Form



% Noise Removal and Filtering

```
NrI = imadjust(ReI,stretchlim(ReI));
figure, imshow(NrI);title('Contrast Enhanced');
```

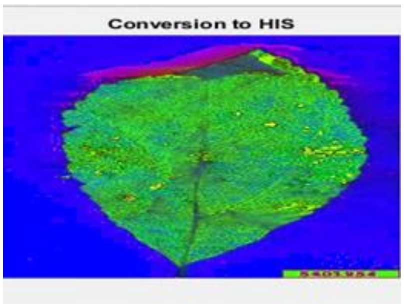
3. Converting an image from RGB:

Converting an image from RGB (Red, Green, Blue) color space to HIS (Hue, Intensity, Saturation) color space involves transforming the pixel values to represent these three components. Here's a brief explanation of the transformation:

Hue (H): Represents the dominant wavelength of color. It is typically measured in degrees ranging from 0 to 360, with 0 and 360 both representing red, 120 representing green, and 240 representing blue.

Intensity(I): It represents the brightness or luminance of color and is determined as the mean of the three RGB components, usually normalized within the range of [0, 1].

Saturation (S): Represents the purity or vividness of the color. It measures the distance of the color from a neutral gray of equal intensity. Saturation valvalues range from 0 (neutral gray) to 1 (fully saturated color).



% Conversion to HIS

```
I_HIS = rgb2hsi(NrI);
figure,imshow(I_HIS);
title('Conversion to HIS);
```

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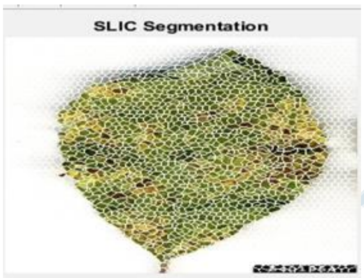
Step 2: Segmentation

SLIC (Simple Linear Iterative Clustering) segmentation is a method used to divide an image into compact and uniform regions called superpixels. It works by initializing cluster centers across the image, assigning pixels to the nearest cluster based on color and spatial proximity, and iteratively refining the clusters until convergence. SLIC is efficient, producing uniform superpixels suitable for various computer vision tasks.

For best outcomes, it may be necessary to choose parameters and apply post-processing techniques during the detection and classification of crop diseases. Utilizing DL, ML, and computer vision techniques is crucial in the agricultural sector [1]. The objective is to create algorithms and methods using leaf or plant feature images for automatic detection and classification of plant diseases, aiding farmers in disease management. After thoroughly examining various recent ML and DL-based approaches,




```
% SLIC
[Ni, l, Am, C] = slic
(NrI, 3000, 10, 1, 'median');
figure;
imshow(drawregionboundaries(l, NrI, [255 255 255]));
title('SLIC Segmentation');
```

Step 3: Feature Extraction

Feature extraction, a core concept in image processing, computer vision, and machine learning, involves identifying and capturing pertinent information or patterns from raw data like images, creating a more concise and meaningful representation. In the HIS (Hue, Intensity, Saturation) color space, the hue component segregates color information independently of brightness (intensity) and colorfulness (saturation). By extracting the hue image, we isolate this hue information from the original image, emphasizing the color characteristics of the scene.

(i) **Hue image**:

The "Hue image" refers to an image representation where each pixel's value represents the hue component of its corresponding pixel in the original image

The literature on plant disease detection and classification has highlighted several challenges, aiding researchers in exploring factors that can significantly affect real-time systems for plant identification and diagnosis. Various factors and issues can impact disease identification and classification, driving further investigation and innovation in this field.

Hue represents the dominant wavelength of color, essentially indicating the color tone or "pure" color of the pixel, irrespective of its brightness or saturation.

(ii) Saturation Image:

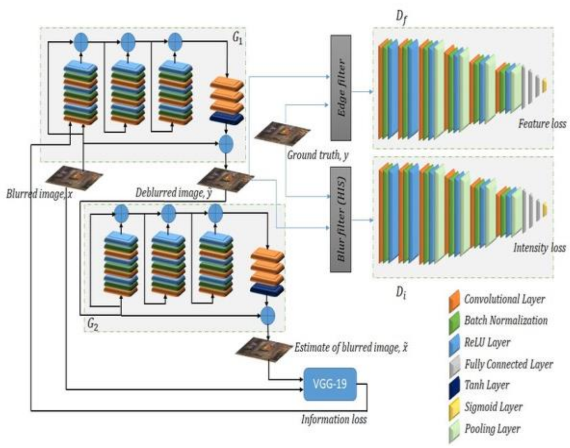
The "saturation image" is an image representation where each pixel's value represents the saturation component of its corresponding pixel in the original image. Saturation measures the intensity or purity of a color, indicating how vivid or intense the color appears, independent of its brightness or hue.

(iii) Intensity Image:

The "intensity image" is a representation of an image where each pixel's value represents the intensity component of its corresponding pixel in the original image. Intensity refers to the brightness or luminance of a pixel, independent of its information.

```
% Extract out the H, S, and V images individually
hImage = I_HIS(:,:,1);
sImage = I_HIS(:,:,2);
iImage = I_HIS(:,:,3);
figure;
subplot(1,3,1); imshow(hImage); title('Hue Image');
subplot(1,3,2); imshow(sImage); title('Saturation Image');
subplot(1,3,3); imshow(iImage); title('Intensity Image');
set(gcf, 'units','normalized','outerposition',[0 0 0.9 0.9]);
addpath(genpath('seg'));
NrI = imresize(I, [256 256]);
```

STEP 4: CLASSIFICATION



Network Architecture of DoubleGAN Algorithm

The Concept Behind Doublegan:

The training process involved separate training of the WGAN in stage I and the SRGAN in stage II. Once the training was finished, random noise served as input, and the generated network segments from stages I and II were extracted individually and subsequently linked in sequence.

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First Stage of GAN

The first stage of GAN was used to generate a clear, lowresolution 64*64 image. Unlike in the traditional GAN, the loss of the discriminator was the Wasserstein distance between the generated data and the real data, which is defined as:

$$W(P_{data}, P_G) = \max_{D\in 1-Lipschitz} \{E_{x\sim P_{data}}[D(x)] - E_{x\sim P_G}[D(x)]\} \quad (1)$$

In equation (1), x represents the real image from the data distribution $Pdata$; D represents the discriminator network, G represents the generator network, and E represents the expected value. Unlike traditional GANs that use JS divergence, where the overlap between $Pdata$ and PG can be ignored or non-overlapping parts, resulting in a constant value (log 2) and gradient disappearance issues, the Wasserstein distance addresses this by accurately reflecting the distance between $Pdata$ and PG even when there is no overlap. This stabilizes training, preventing model collapse due to gradient disappearance, making it advantageous for training GANs effectively.

The Second Stage of the GAN:

In the second stage, the input images generated in the first stage are processed through the SRGAN to super-resolution reconstruct low-resolution input images, resulting in clear, high-resolution plant leaf images. The GAN framework aims to minimize perceptual losses by modeling based on Mean Squared Error (MSE), which compensates for the lack of detail. The loss function is structured as:

$$l^{SR} = l_X^{SR} + a l_G^{SR} \quad (2)$$

Equation (2) defines $lXSR$ as the content loss, $lGSR$ as the adversarial loss, and a as the adversarial loss weight, set to 10-3 in this experiment. The content loss, employing MSE loss, ensures consistent content alignment between the generated image and the original image. This loss is calculated as pixel-level loss between the super-resolution image and the real image.

$$l_{MSE}^{SR} = \frac{1}{r^2WH}\sum_{x=1}^{rW}\sum_{y=1}^{rH}(I_{x,y}^{HR} - G(I^{LR})_{x,y})^2 \quad (3)$$

Equation (3) introduces r as the down-sampling factor, while W and H represent the width and height of the image, respectively. To address the absence of high-frequency details in images generated by MSE, a ReLU layer from the pre-trained VGG16 model was utilized. Subsequently, both the generated and matched real images were fed into the trained VGG model, extracting characteristic pixels from the middle layer of both images and computing the Euclidean distance between them. The formula is expressed as follows:

$$l_{YGG}^{SR} = \frac{1}{W_{i,j}H_{i,j}}\sum_{x=1}^{W_{i,j}}\sum_{y=1}^{H_{i,j}}((\emptyset_{i,j}(I^{HR}))_{x,y} - (\emptyset_{i,j}G(I^{LR}))_{x,y})^2 \quad (4)$$

Equation (4) introduces Wi, j and Hi, j as the height and width of the extracted feature surface, respectively. The adversarial loss was employed to ensure that the generated image belonged to the natural image domain, effectively preventing the discriminator from distinguishing between images originating from either the generated or real image sources. This concept is illustrated as follows:

$$l_G^{SR} = \sum_n^N = -\log D\,(G(I^{LR})) \quad (5)$$

Equation (5) describes $D(G(ILR))$ as the probability estimation of the discriminator D for the super-resolution image $G(ILR)$. This arrangement is designed to optimize gradient performance.

```
% % ANN Clasification
fprintf('Loading Data...\n')
load('CNN_Data.mat');
fprintf('Data Loaded Successfully...\n')
inputs = X_cent_1'; %512 features
load('CNN_Label.mat')
test_x = cnn_net(Ni);
train_cnn = mean(X_cent_1,2);
test__cnn  = mean(test_x,2);
cnn_data = ismember(train_cnn, test__cnn);
cnn_mem  = find(cnn_data(:,1)>0);
fprintf('* * * * Affected Disease * * * * \n')
if (cnn_mem >= 0) && (cnn_mem <= 5)
% % Mosaic disease
disp('1. Mosaic')
helpdlg({'  Disease Name: Mosaic'.
'Fertilizer: MICRONUTRIENT NUTRITION'});
fprintf(S,'%s','1');
elseif (cnn_mem >= 16) && (cnn_mem <= 20)
% % Marssonina Leaf disease
disp('2. Marssonina Leaf')
helpdlg({'  Disease Name: Marssonina Leaf  '...);
'Fertilizer: PHOTOSYNTHETIC NUTRITION'});
fprintf(S,'%s','2');
elseif (cnn_mem >= 21) && (cnn_mem <= 25)
% % Anthracnose disease
disp('3. Anthracnose Disease')
helpdlg({'  Disease Name: Anthracnose Disease  '...
'Fertilizer: Nitrogen Fertilizer'});
fprintf(S,'%s','3')
elseif (cnn_mem >= 26) && (cnn_mem <= 30)
% % Bacterial Leaf Spot Disease
disp('4. Bacterial Leaf Spot Disease') helpdlg({'  Disease
Name: Bacterial Leaf Spot Disease '...
'Fertilizer:  Sulfur Sprays, Neem Oil'});
fprintf(S,'%s','4');
elseif (cnn_mem >= 31) && (cnn_mem <=          35)
% % Downy Mildew disease
disp('5. Downy Mildew');
helpdlg({'  Disease Name: Downy Mildew  '...
'Fertilizer: Copper Spray'});
fprintf(S,'%s','1');
elseif (cnn_mem >= 46) && (cnn_mem <= 50)
disp('6. Rust Disease ')
helpdlg({'  Disease Name: Rust Disease   '...
```

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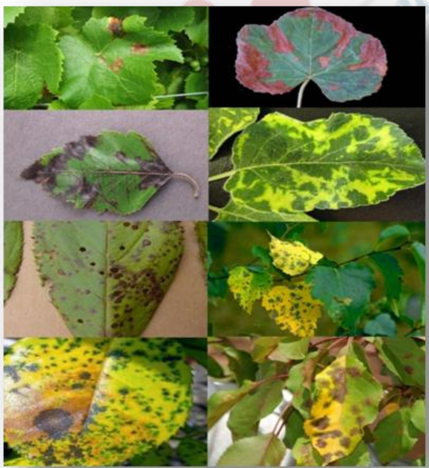
```
'Fertilizer: Scotts Turf Builder Lawn Food'});
fprintf(S,'%s','2');
elseif (cnn_mem >= 61) && (cnn_mem <= 65)
% % Cercospora Leaf Spot Disease
disp('7. Cercospora Leaf Spot Disease')
helpdlg({'  Disease Name: Cercospora Leaf Spot   Disease
'... 'Fertilizer: Cultural Controls - ammonium nitrate,
ammonium sulfate, or quick-release urea formulation '});
fprintf(S,'%s','3');
elseif (cnn_mem >= 76) && (cnn_mem <= 82)
disp('16. Normal')
helpdlg('  Normal  ');
else
disp('No')
end
```

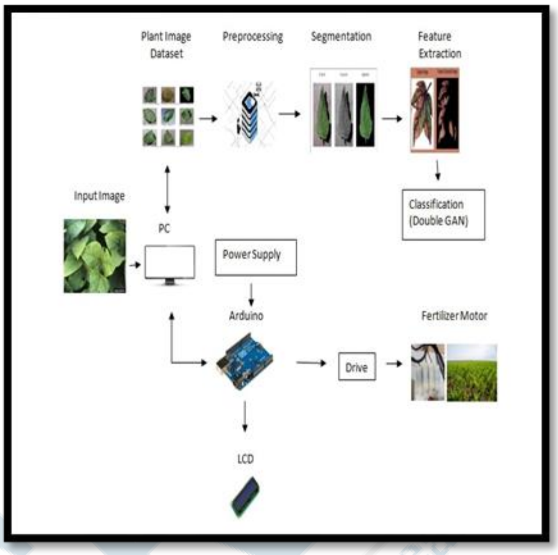
Proposed Block Diagram:

The proposed block diagram presents a sophisticated system designed to address the pressing need for efficient plant disease detection and treatment in agriculture. At its core, the system leverages advanced technologies such as image processing, microcontroller-based control, and mechanical actuation to provide a holistic solution for farmers and agricultural practitioners. Starting with the initial input of plant leaf images from a dataset, the system embarks on a journey of analysis and action. The preprocessing steps carried out on a personal computer (PC) play a crucial role in enhancing the quality of the input images, preparing them for subsequent stages of analysis. These preprocessing steps may include operations such as noise reduction, contrast enhancement, and image normalization, all aimed at optimizing the data for accurate segmentation and feature extraction.

After the preprocessing stage, segmentation follows, which involves dividing an image into meaningful regions. This segmentation allows the system to concentrate its analysis on relevant parts of plant leaves, ultimately enhancing the accuracy and efficiency of disease detection.



Sample Results for Detecting the leaf disease using DoubleGAN



Feature extraction, a pivotal component of the system, relies on the capabilities of an Arduino board interfaced with a power supply and an LCD display. The Arduino board serves as the computational heart of the system, executing algorithms to extract discriminative features from the segmented leaf images. These features may include texture patterns, color distributions, or morphological characteristics indicative of specific diseases or health conditions in plants. The integration of an LCD display into the system provides real-time feedback to the user, enhancing the transparency and usability of the automated process. Through the display, farmers can monitor the progress of the disease detection and treatment stages, gaining insights into the health status of their crops. The display also serves as a user interface, facilitating interaction with the system and enabling adjustments or interventions as needed. The subsequent stage of the system involves the deployment of mechanical actuators, specifically four motors, for targeted treatment of diseased plant leaves. These motors, controlled by the Arduino board, enable precise and localized application of fertilizers or other therapeutic agents to the affected areas, minimizing waste and maximizing efficacy. By automating the treatment process, the system streamlines agricultural operations, freeing up valuable time and resources for farmers to allocate elsewhere. The pump display stage, which briefly illuminates to indicate the activation of the pump for fertilizer application, serves as a visual confirmation for the user. However, recognizing the potential need for extended display time to accommodate varying user preferences and operational requirements, the system offers flexibility in adjusting the duration of the display. This adaptability enhances the user experience and ensures that the system aligns with the diverse needs of its users across different agricultural contexts.

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IV. RESULT & DISCUSSION

During the data collection phase, gather a substantial dataset comprising images of both healthy and diseased plant leaves, ensuring diversity across plant species and diseases. Standardize the images through preprocessing, which may involve resizing, normalization, and augmentation to enhance dataset variability. Subsequently, train the Double GAN model using the preprocessed dataset. This model comprises two neural networks, a generator, and a discriminator, trained concurrently in a competitive framework. In detection phase once the Double GAN model is trained, deploy it in crop fields or greenhouse environments where plant health monitoring is required. Capture images of plant leaves using cameras or drones. Image analysis process the images captured in the field through the trained Double GAN model. The model will analyze the images and identify any subtle patterns or anomalies indicative of plant diseases. At the result Interpretation that based on the analysis, the Double GAN algorithm will provide a diagnosis for each plant leaf image, indicating whether it is healthy or diseased.

Accuracy: Evaluate the accuracy of disease detection achieved by the Double GAN algorithm compared to traditional methods. Discuss any improvements or limitations observed.

Early Detection: Highlight the advantage of early disease detection enabled by the Double GAN algorithm. Discuss how early detection can help farmers take proactive measures to prevent the spread of diseases and minimize crop losses.

Cost-effectiveness: Consider the cost-effectiveness of implementing Double GAN technology for disease detection in crop fields. Compare the cost of implementation to potential benefits such as increased crop yield and reduced pesticide usage.

CASE 1: Disease Detection in Apple Plant Leaf Affected by Mosaic Disease

In Case 1, we utilized Double GAN technology for the detection of mosaic disease in apple plant leaves. Mosaic disease is a common viral infection characterized by distorted leaf patterns and reduced yield in apple crops. The goal of this study was to leverage the power of generative adversarial networks (GANs) within the Double GAN framework to accurately detect subtle patterns and anomalies indicative of mosaic disease in apple plant leaves.In the Data Collection and Preprocessing, we collected a comprehensive dataset comprising images of healthy apple plant leaves and leaves affected by mosaic disease. These images were preprocessed to standardize dimensions, normalize colors, and augment dataset diversity.

Plant Sample	Disease affected	Fertilizer Recommended
	Mosaic	Micronutrient nutrition

The Double GAN model was trained on the preprocessed dataset. This model consists of two neural networks, a generator and a discriminator, trained simultaneously in a competitive setting to generate realistic images of both healthy and diseased apple plant leaves. Based on the analysis, the Double GAN algorithm provided a diagnosis for each apple plant leaf image, indicating whether it was healthy or affected by mosaic disease. Case 1, demonstrated the efficacy of using Double GAN technology for early detection of mosaic disease in apple plant leaves, with practical implications for precision agriculture and disease management strategies. Additionally, the recommendation of the "Micronutrient Nutrition" fertilizer for the affected plant leaf.

CASE 2: Disease Detection in Aspen Plant Leaf Affected by Marssonina Disease

The application of Double GAN technology for the early detection and management of Marssonina leaf disease in aspen plants. Marssonina leaf disease poses a significant threat to aspen forests, leading to defoliation and reduced tree health. Therefore, there is a need for advanced technologies that can accurately identify and diagnose Marssonina leaf disease in its early stages. In this case study, Double GAN technology is employed to analyze images of aspen leaves and detect subtle patterns indicative of Marssonina leaf disease. In data collection and preprocessing, the first step in the case study involves the collection of a comprehensive dataset comprising images of healthy aspen plant leaves and leaves affected by Marssonina leaf disease. These images are collected from aspen forests and undergo preprocessing to standardize dimensions, normalize colors, and augment dataset diversity.

Plant Sample	Disease affected	Fertilizer Recommended
	Marsssonina leaf	Photosynetic nutrition

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Preprocessing techniques such as resizing, color normalization, and data augmentation ensure that the dataset is suitable for training the Double GAN model and enhances its ability to generalize across different lighting conditions, angles, and variations in leaf appearance. In detection phase, after training, the Double GAN model is deployed in aspen forests to capture images of plant leaves using cameras or drones. These images are then processed through the trained model to analyze and identify subtle patterns indicative of Marssonina leaf disease.

CASE 3: Disease Detection in Cineraria Plant Leaf Affected by Downy mildew Disease

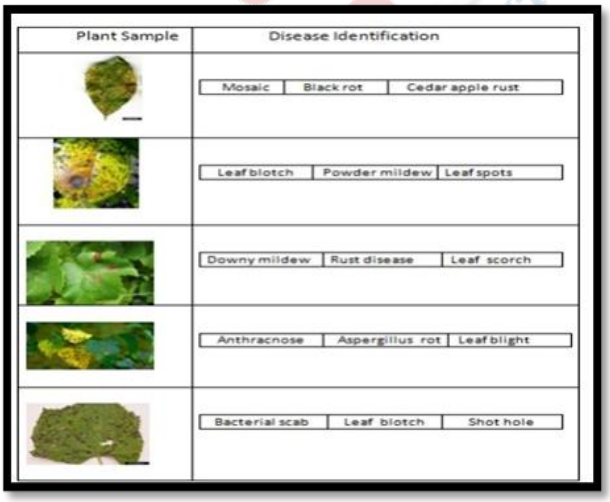
The application of Double GAN technology for the early detection and management of downy mildew in cineraria plants. Downy mildew is a common fungal disease that poses a significant threat to cineraria plants, leading to leaf discoloration, wilting, and reduced plant vigor. Traditional methods of disease detection often rely on visual inspection, which may not be sensitive enough to detect early signs of infection. In this case study, Double GAN technology is employed to analyze images of cineraria leaves and detect subtle patterns indicative of downy mildew.

Plant Sample	Disease affect	Fertilizer Recommended
	Downy Mildew	Copper Spray

In data collection and preprocessing, the first step in the case study involves the collection of a

comprehensive dataset comprising images of healthy cineraria plant leaves and leaves affected by downy.

Images of Different Plants Dataset:



Plant Sample	Disease Identification		
	Mosaic	Black rot	Cedar apple rust
	Leaf blotch	Powder mildew	Leaf spots
	Downy mildew	Rust disease	Leaf scorch
	Anthracnose	Aspergillus rot	Leaf blight
	Bacterial scab	Leaf blotch	Shot hole

Mechanism:

Pre-Treatment Plant Dataset Vs Post- Treatment Plant Dataset:

The pre-treatment dataset consists of images or data points of plants affected by various leaf diseases. Giving proper fertilizer or treatment, the post-treatment dataset consists of images or data points representing the same plants after they have healed or improved in health. The dataset reflects plants that have shown,

Unaffected vs Affected leaf

Pre LED stage Vs Post LED stage:

Prior to treatement, the LED display remains inactive and does not convey any information. In the post-treatment stage, the LED display is activated to indicate the status of the pump stage, displaying details on which pump is to be opened or closed. Information on the activation status of the pump stage (open/close) is display in the LED screen.

Pre-processing stage of Motor Vs post-processing stage of Motor:

In the pre-processing stage the motor is inactive, indicating that the system is idle and not currently spraying fertilizer. When the process is activated it triggered by some condition (e.g., detection of disease-affected plants, a timer, manual activation), the motor starts its process. The motor begins operating to drive the pump. Based on the specific requirements (such as the type of plants, area to cover, severity of the disease, etc.), valves controlling the flow of fertilizer are opened. Fertilizer is sprayed onto the plants via the pump and the opened valves. The spraying continues for a specific time period.After the process Completed the predefined time period for spraying fertilizer is complete, the motor and pump stop operating.

Based on your setup requirements, consider incorporating sensors to detect diseases, timers to regulate spraying duration, and control systems to manage motor, pump, and valves operations. It is essential to implement safety measures to ensure accurate fertilizer application and to safeguard plants and the environment from harm.

V. CONCLUSION:

Our project integrates MATLAB preprocessing techniques, including DoubleGAN segmentation, with an Arduino-based automated fertilizer application system to revolutionize plant disease management in agriculture. Initially, MATLAB preprocesses input leaf images, enhancing quality and consistency through noise reduction and contrast enhancement. This preparatory step optimizes subsequent analyses, ensuring accurate disease detection and treatment. Segmentation, facilitated by the advanced DoubleGAN algorithm, precisely delineates diseased regions within plant leaves. By isolating affected areas, DoubleGAN enhances discrimination between healthy and diseased tissues, facilitating targeted intervention. This segmentation accuracy forms the basis for effective treatment strategies, crucial for optimizing crop health and productivity. The Arduino-based control system serves as the project's core, coordinating automated fertilizer application to identified diseased areas. Interfaced with relay motors, the Arduino board orchestrates fertilizer dispensation based on segmented leaf regions. This real-time control mechanism ensures precise and timely treatment delivery, minimizing resource wastage while maximizing treatment efficacy. In practical terms, our system provides substantial benefits for agricultural practitioners. By accurately detecting and treating diseased leaves, it mitigates crop losses and enhances overall yield potential. This is especially impactful in large-scale agricultural operations, where even marginal improvements in crop health translate to substantial productivity gains. Additionally, the user-friendly interface empowers farmers to manage plant diseases effectively, simplifying complex agricultural tasks and enabling informed decision-making regarding crop health management. Moreover, by leveraging cutting-edge technologies such as MATLAB and Arduino, our project contributes to the digital transformation of agriculture. Through computational algorithms and real-time control systems, we enhance agricultural efficiency, sustainability, and resilience. Ultimately, our project represents a pivotal advancement in sustainable agricultural development, offering a transformative solution for addressing plant diseases and optimizing crop yields in modern farming contexts.

VI. ACKNOWLEDGEMENT

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