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"Plant Health Monitoring and Disease Detection Using Python Image Processing Technique: An Innovative Approach"

Dr Jagadish N[1], Chandana K S[2], P Apoorva [2], Bhoomika G[2], Shravya A S[2]
[1]Associate Professor, Department of Electrical and Electronics Engineering, GSSSIETW, Mysuru
[2]UG Students, Department of Electrical and Electronics Engineering, GSSSIETW, Mysuru
KRS Road, Metagalli, Mysuru 570016, Karnataka, India .
Email: jagadisha.n@ggsss.edu.in, kschandanaks@gmail.com, apoorvap3265@gmail.com,bbhoomika056@gmail.com, shravyadisha@gmail.com.

***Abstract** (Size 10 & bold &Italic)*

Agriculture is the primary source of income forms any countries, and the health of crops directly impacts food security and economic stability of the country. Plant diseases caused by pathogens such as viruses, fungi , and bacteria contribute to nutritional losses which leads to financial losses across the globe .These diseases can spread quickly , affecting entire crops, so early detection is crucial to prevent wide spread damage .Regular monitoring and early diagnosis are crucial to maintaining the productivity and sustainability of the agricultural industry. In this project, an automated image processing system is proposed to assess plant health growing in different environments such as normal and plasma environment by analyzing features such as leaf size, color, plant volume, stem diameter etc.The system aims to detect diseases early by comparing the plant's features with a standard dataset. By identifying the type and stage of the disease, the system provides timely insights into the plant's condition. The automated technique not only reduces dependency on manual inspection but also enhances crop management by providing real-time data to farmers, allowing them to take appropriate actions to prevent crop losses.

Keywords — Plant Health Monitoring, Image Processing, Disease Detection, Machine Learning.

I. Introduction

Plants play a fundamental role in sustaining life on Earth, providing oxygen, food, and raw materials. They contribute to environmental stability by participating in biogeochemical cycles, maintaining atmospheric balance, and supporting biodiversity. However, plant health is constantly threatened by bacterial, fungal, and viral infections, which can lead to significant agricultural losses. These diseases impact various stages of crop production, sometimes reducing yields by up to 80–98%. Although plants have innate immunity, certain phytopathogens have adapted to overcome these defenses, so early detection and management are crucial for lessening losses [1].

Artificial intelligence (AI) and image processing technologies have transformed many sectors, including agriculture. AI image processing includes activities like pattern recognition, object detection, and classification, which can greatly enhance the accuracy of plant disease detection. Through the examination of leaf characteristics such as color changes, shape distortions, and lesion patterns, AI-driven systems facilitate quick disease identification, lessening dependence on human inspections. This method reduces labor needs and allows for timely interventions to avoid extensive crop damage [2].

The growing food demand worldwide, combined with climate change and population increase, requires new agricultural methods. Traditional disease detection is done through time-consuming manual inspections, which are not feasible for large-scale agriculture. Automated image-based plant health monitoring offers a promising solution, allowing continuous monitoring and real-time diagnosis.

This project revolves around the application of Python packages like OpenCV and TensorFlow for creating a smart system for the detection of plant diseases. By incorporating AI-powered image analysis, the research focuses on increasing the sustainability of agriculture and enhancing the productivity of crops [3].

II. LITERATURE SURVEY

A. "Plant Disease Detection Using Image Processing and Machine Learning (Pranesh Kulkarni, Atharva Karwande, 2015".

This study introduces a machine learning-based system for detecting plant diseases by analyzing leaf images. Using the Plant Village dataset, the system achieved 93% accuracy in identifying 20 diseases across five plant species. The methodology involves grayscale conversion, Gaussian filtering for image preprocessing, and feature extraction techniques focusing on leaf color and texture. A Random Forest classifier was employed, providing a computationally efficient and accurate solution. However, the study's reliance on statistical machine learning techniques limits its effectiveness in detecting complex diseases compared to deep learning-based models.

B. "Disease Detection and Classification by Deep Learning (Saleem et al., 2019)".

This research employs convolutional neural networks (CNNs) to classify plant diseases with improved accuracy. The authors highlight the inefficiency of manual inspection methods and propose a cost-effective, AI-driven solution for large-scale agricultural monitoring. The system segments diseased areas and extracts critical features using deep learning frameworks such as OpenCV and TensorFlow. The study demonstrates the effectiveness of CNNs in recognizing crop diseases in bananas, tomatoes, and potatoes, with high classification accuracy. Future enhancements include integrating additional agricultural insights, such as pesticide recommendations and market trends.

C. "Plant Leaf Disease Detection, Classification, and Diagnosis Using Computer Vision and Artificial Intelligence: A Review (Bhargava et al., 2024)".

This review paper evaluates various image processing and AI techniques used for plant disease detection. The study emphasizes feature extraction methods, including colour, texture, and shape-based analyses,which enhance classification accuracy. Various segmentation techniques, such as thresholding, clustering, and region growing, are discussed for isolating diseased areas. While deep learning models offer improved accuracy, their dependence on extensive datasets and high computational power remains a challenge. The paper concludes that hybrid approaches combining AI and traditional techniques can yield more reliable results for precision agriculture .

D. "Plant Disease Detection and Classification Techniques: A Comparative Study (Demilie et al., 2024)".

This study focuses on the use of CNNs for automatic plant disease classification. The authors highlight CNN's ability to extract key features without manual intervention, significantly enhancing accuracy. Using the Plant Village dataset, the system was trained to recognize various plant diseases with high precision. The study also explores real-time applications, suggesting mobile-based implementations for farmers. However, the model's effectiveness depends on the availability of diverse, well-annotated datasets. Generalizability to new plant species and disease variations remains a challenge that requires further research.

E. "Plant Leaf Disease Classification and Detection System Using Machine Learning (Geetha et al., 2020)".

This research presents a plant disease detection system using k-nearest neighbours (KNN) for classifying tomato plant diseases. The study follows a four-stage process: image preprocessing, segmentation, feature extraction, and classification. By analyzing leaf texture, colour, and shape, the system effectively identifies diseased leaves. However, the reliance on KNN limits the model's scalability and efficiency compared to deep learning-based methods. The study suggests future improvements by incorporating deep learning techniques to enhance classification accuracy across multiple plant specie.

III. METHODOLOGY

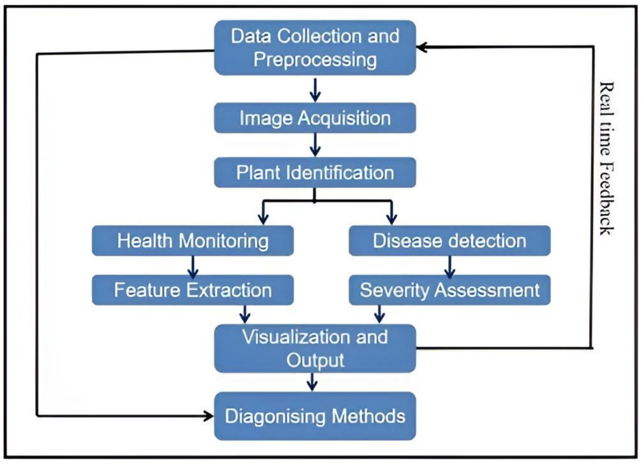

Fig 1: Methodology

The methodology used to develop an automated system for plant health monitoring and disease detection. This approach utilizes image processing techniques and machine learning models to analyze various plant features such as leaf size, color, and texture. The system aims to identify plant species, detect the presence of diseases, and assess the severity of the infection.

When the uploaded image is identified as a complete plant image detailing the segmentation process, feature extraction, and health assessment based on various physiological parameters.

A. Isolating Green Areas - This preprocessing step isolates the green portions of the plant using HSV color space. The green color range is defined with specific lower and upper bounds, ensuring that only green parts of the plant are segmented for further analysis. This helps focus on healthy foliage while ignoring non-green areas.

```
Load the image and convert it to HSV
color space image=cv2.imread(image_path)
hsv=cv2.cvtColor(image,cv2.COLOR_BGR2 HSV)
 # Define the range for green color and create a mask
lower_bound = np.array([40, 50, 50])
upper_bound = np.array([80,255,255])
mask = cv2.inRange(hsv,lower_bound,upper_b ound)
 # Apply the mask to extract green parts
result=cv2.bitwise_and(image,image, mask=mask)
```

B. Calculating Plant Health Metrics -The leaf size is calculated by finding contours on the binary plant mask and summing their areas. The area is then converted from pixels to square centimeters using a pixel-to-cm conversion factor derived from a reference object in the image.

```
 #Calculate leaf size based on contour
Area contours,_= cv2.findContours(plant_mask,
 cv2.RETR_EXTER NAL,
 cv2.CHAIN_APPROX_SIMPLE)
leaf_area=sum(cv2.contour Area (contour) for
 contour in contours) leaf_size_cm2 = leaf_area *
 (pixel_to_cm**2)
```

C. Plant Volume Estimation- The plant's volume is estimated using its pixel area, the plant's measured height, and a density factor. This factor adjusts for differences in plant structure and density, making the volume estimation more precise.

```
 #Estimate plant volume using mask area and
height
plant_area = np.sum(plant_mask > 0)
plant_volume_cm3 = plant_area
*height_in_cm
*(pixel_to_cm**2)*density_factor
```

D. **Color Intensity Statistics**-Color intensity statistics such as average intensity and variance are computed for red, green, and blue channels. These metrics help detect signs of diseases, discoloration, and nutrient deficiencies in the plant.

```
# Calculate average intensity and variance
 for RGB channels
masked_image=cv2.bitwise_and(image,imag
 e,mask=mask) channels =
 cv2.split(masked_image
stats=[(np.mean(channel[mask>0]),
 np.var(channel[mask>0])) for channel
 in channels]
```

E. Green Proportion Calculation - The green proportion indicates the percentage of healthy foliage by comparing the green area to the total plant area. A higher proportion typically indicates a healthier plant, while a lower value suggests potential disease or damage.

```
 #Calculate green proportion in the segmented
mask
green_mask=(hsv[:,:,0]>35)&(hsv[:,:,0]<85)&(h
sv[:,: ,1]>60) green_area =
np.sum(green_mask &(mask > 0))
green_proportion=(green_area/total_area)*100
```

IV. RESULTS

In this section , the results obtained from the implemented methodology are presented, showcasing the performance metrics, visual outputs, and key findings :

This section presents the results of health monitoring for complete plant images -

In this study, we are cultivating Toordal and Sunflower plants in two distinct environments: a normal ambient environment and a plasma-treated environment with a specified discharge voltage. The plasma environment is hypothesized to influence plant growth and physiological characteristics through enhanced nutrient absorption and stress tolerance. We are systematically observing key features of the plants, including leaf size, plant volume, color intensities, and green coverage, to evaluate their growth and health.

A. Feature extraction of complete plant image of Toordal growing plasma environment of 10KV for 6 minutes :

Fig 2: Original toordal complete plant image

Fig 3: Preprocessed toordal plant image

	Feature	Value
0	leaf_size (cm²)	1853.345000
1	plant_volume (cm³)	12789.000000
2	blue_mean (intensity)	80.311338
3	green_mean (intensity)	130.545633
4	red_mean (intensity)	92.341536
5	blue_var (intensity)	2962.660947
6	green_var (intensity)	7178.646072
7	red_var (intensity)	3779.923443
8	green_proportion (%)	75.229494

Fig 4: Results obtained by testing complete plant image of toordal grown in plasma environment of 10kv for 6 minutes

Interpretation of each numerical value obtained from the Toordal plant grown in a plasma environment:

I. Leaf Size (1853.345 cm²) : This indicates a relatively large leaf area for the Toordal plant, suggesting a healthy growth rate and good photosynthetic potential under plasma environmental conditions. Larger leaf areas are typically associated with vigorous growth.

II. Plant Volume (12789.0 cm³): A high plant volume reflects substantial biomass, suggesting that the Toordal plant has developed robust structural growth and might benefit from the plasma environment enhancing its overall vigor.

III. Blue Mean (80.31 intensity): The moderate blue intensity suggests that the plant reflects an average amount of blue light, possibly indicating healthy structural characteristics and a balanced surface composition.

IV. Green Mean (130.55 intensity): The higher green intensity indicates a significant chlorophyll presence, which is a strong indicator of plant health. For Toordal, this suggests optimal growth and nutrient absorption efficiency in the plasma environment.

V. Red Mean (92.34 intensity): The red intensity reflects a balanced pigmentation, indicating that the plant is not undersevere stress, as stressed plants often show either higher or lower red reflectance due to changes in pigmentation.

VI. Blue Variance (2962.66 intensity): The moderate variance in blue intensity may indicate slight heterogeneity in the plant's structure or surface characteristics, which could be due to the natural arrangement of leaves and stems.

VII. Green Variance (7178.64 intensity): The higher variance in green intensity suggests some uneven distribution of chlorophyll, which may result from overlapping leaves or differences in leaf maturity.

VIII. Red Variance (3779.92 intensity): The red variance indicates variability in pigmentation across the plant, which could reflect different levels of stress or variations in light absorption by various parts of the plant.

IX. Green Proportion (75.23%): The high percentage of green coverage indicates that the majority of the plant's visible area is healthy, photosynthetically active foliage. For Toordal, this is an excellent sign of overall plant health in the plasma environment, with minimal visible stress or disease.

The numerical results show that the Toordal plant is thriving in the plasma environment, with a high leaf size, significant green proportion, and a balanced distribution of color intensity. However, the variances in green and red intensities suggest some non-uniformity in leaf health or maturity, which might be an area to investigate further. Overall, the results highlight the positive impact of the plasma environment on the plant's growth and health.

B. This section will address the process of analyzing uploaded images identified as leaf samples. The uploaded image is identified as a leaf and passed through a trained Convolutional neural network (CNN) to classify it into one of 38 predefined classes.

These classes in clude various plant types such as apple, blueberry, and cherry, with images of both healthy and diseased leaves. The CNN is trained on approximately 75,000 images, ensuring robust performance.Below is the structured workflow :

I. Dataset and Model Initialization: The validation dataset is loaded to infer class names, which represent the healthy and diseased states of different plants. This helps in understanding the mapping between the model's outputs and the disease classes.

```
validation_set=tf.keras.utils.image_dataset_from_dire
ctory( 'valid', labels="inferred",
label_mode="categorical", image_size=(128, 128),
batch_size=32)
class_name= validation_set.class_names
print(class_name)#Prints the list of 38 classes the
model can predict
```

II. Loading the Trained Model: The trained CNN model is loaded form a king predictions. This line loads the pre- trained model, which is trained on 75,000 images, and is capable of recognizing 38 different plant diseases.

```
cnn=tf.keras.models.load_model('trained_plant_disea
se_mode l.keras')
```

III. Visualizing the Input Image: Before making predictions, the uploaded leaf image is displayed to verify its contents.This snippet reads the image using OpenCV and displays it using Matplotlib to visually confirm the test image.

```
Import cv2
import matplotlib.py
plot as plt
image_path='path_to_test_image.jpg'
  #Replace with the actual path to your image
img = cv2.imread(image_path)# Load the image
img=cv2.cvtColor(img,
cv2.COLOR_BGR2RGB)#Convert BGR to RGB
for correct
color display plt.imshow(img) plt.title('TestImage')
plt.xticks([])
plt.yticks([]) plt.show()
```

IV. Preprocessing the Test Image: The test image is resized and converted to a format compatible with the model's input requirements.The image is resized to 128x128 pixels, and the single image is converted into a batch format because the model expects a batch of images as input.

```
From tensorflow.keras.preprocessing.image
import load_img, img_to_array
image=load_img(image_path,target_size=(128,
128))
   #Resize the image input_arr =
img_to_array(image)
   # Convert the image to an array
input_arr=np.array([input_arr])
   #Batch the image(for model compatibility)
```

V. Making Predictions:The preprocessed image is passed through the CNN model to get predictions.

```
predictions = cnn.predict(input_arr)
result_index=np.argmax(predictions)#Get the
index of the class with the highest probability
model_prediction = class_name[result_index]
   # Map the index to the disease name
print(f"Predicted Disease: {model_prediction}")
```

VI. Displaying the Predicted Disease: The image is displayed again, with the predicted disease name included in the title. This snippet shows the test image with the predicted disease name prominently displayed, ensuring a user-friendly output.

```
plt.imshow(img)
plt.title(f"DiseaseName:{model_prediction}")
plt.xticks([]) plt.yticks([]) plt.show()
```

This section will address the process of analyzing uploaded image1 identified as leaf samples. The uploaded Blueberry leaf image as shown in fig 4.10 was resized to 128x128 pixels and converted into a format suitable for the model. The class_name[result_index]was identified as Blueberry healthy, indicating that the leaf was healthy. The uploaded image was displayed ,along with the prediction as shown in fig4.11.The output confirmed the image was of a healthy Blueberry leaf, as expected.

Fig 5: Uploaded leaf image of blueberry

Fig 6: Detection of leaf as healthy blueberry

The model successfully classified the input as Blueberry healthy with high confidence, demonstrating its ability to differentiate between diseased and healthy plant leaves. This result aligns with the expected condition of the leaf.

V. CONCLUSION

The current research entailed a systematic experimental study targeting two primary phases: monitoring plant growth and disease identification. For monitoring growth, ToorDal and Sunflower plants were grown in two conditions: normal and plasma-treated (for different durations and voltage levels). Image processing was used to identify features such as leaf size, plant volume, and green proportion, allowing us to monitor growth differences. In the second stage, we trained a Convolutional Neural Network (CNN) on a dataset of 75,000 images representing 38 classes of plants, healthy and diseased leaves. We then used the model to classify uploaded leaf images into particular disease categories or as healthy.

The findings of the research showed significant differences in plant characteristics between plasma and normal environments. For instance, in Sunflower plants treated at 15 kV plasma for 9 minutes, leaf sizes and green proportions were greater compared to those treated for 6 minutes, suggesting an increase in photosynthetic efficiency with optimized plasma treatment. In disease detection, the system accurately identified a Blueberry leaf that is healthy, an Apple leaf infected by Scab disease, and a Corn leaf infected by Cercospora Leaf Spot.

These results reflect the efficacy of plasma treatment for improving plant health and the ability of CNN-based models for accurate disease detection, opening doors to new-age agricultural practices.

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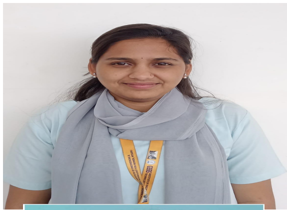
Biographies and Photographs

	Guide: Dr. Jagadisha N is an Associate Professor in the EEE Department at GSSSIETW since December 2020. He holds a Ph.D. in High Voltage Engineering (2020), an M.Tech in Energy Systems Management (2012), and a B.E. in Electrical & Electronics Engineering (2008). He has prior experience as an Assistant Professor at GSSSIETW (2012-2020), a Senior Quality Audit Engineer at Ramboll IMI Soft (2009-2010), and a Design Engineer at SunLux Technologies (2008-2009). His research focuses on plasma techniques for pollutant removal, with interests in Energy Systems & Management and EV Technologies. Email Id: jagadisha.n@gsss.edu.in Phone number: 8553541360
 	Name : P Apoorva USN: 4GW21EE027 Phone no : 9483219790 Email ID: apoorvap3265@gmail.com Department : Electricals and Electronics Engineering Institution: GSSS Institute of Engineering and Technology for Women, Mysuru Name : Chandana K S USN: 4GW21EE007 Phone no : 7411463625 Email ID: kschandanaks@gmail.com Department : Electricals and Electronics Engineering Institution : GSSS Institute of Engineering and Technology for Women, Mysuru
	Name : Chandana K S USN: 4GW21EE039 Phone no : 9019849280 Email ID: shravyadisha@gmail.com Department : Electricals and Electronics Engineering Institution : GSSS Institute of Engineering and Technology for Women, Mysuru
	Name : Bhoomika G USN: 4GW22EE400 Phone no : 8904667353 Email ID: bhoomika056@gmail.com Department : Electricals and Electronics Engineering Institution : GSSS Institute of Engineering and Technology for Women, Mysuru