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Green Leaf Disease Detection

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Abstract: Because it feeds humanity, creates jobs, and directly supports national economic progress, agriculture is the backbone of the country. Identification of plant diseases is very crucial in agriculture. The increasing use of pesticides and sprays nowadays has led to a wide range of diseases affecting plants. Early disease detection would help farmers save more harvests if the infections could be stopped.

Plants can be saved if rotting spots are discovered early. Automatic plant disease detection not only saves time but also provides greater accuracy. Plant production is decreased by improper disease detection. Here, we use image processing techniques to identify a few common plant illnesses. First, we take the image of the plant anduse image processing to identify it. This project is being implemented using Python.

***Keywords**: Disease, Image processing, Accuracy, Detection, Python*

I. INTRODUCTION

Plant productivity is reduced when plant diseases are discovered. We use Python image processing techniques to find common plant ailments, concentrating on leaf diseases. We precisely identify and classify leaf diseases using Raspberry Pi and several image processing techniques. Through the use of image enhancement, segmentation, and classification, we can take better pictures. For the purpose of avoiding agricultural loss brought on by viral, fungal, and bacterial agents, precise leaf disease identification is essential. When processing images, Python software

II. LITERATURE REVIEW

1) Tete, T. N., & Kamlu, S. (2017, April). Detection of plant disease using threshold, k-mean cluster and ann algorithm. In *2017 2nd International Conference for Convergence in Technology (I2CT)* (pp. 523-526). IEEE. - Thresholding and k-means clustering algorithms are two separate segmentation approaches employed by Tete et al. In this research, their methodology K-figures display the original images for each of the inputs, followed by the segmented image's k-mean cluster and thresholding output. The number of cluster centers must be specified a priori when using the k-mean clustering algorithm. For the purpose of detecting plant illness, ANN algorithms are employed in this paper. The ANN algorithm has an accuracy rate of 85%. Compared to ANN, the SVM method is more accurate (91% correct).
2) Shaikh, D. A., Akshay, G. G., Prashant, A. C., & Parmeshwar, L. K. (2016). Intelligent autonomous farming robot with plant disease detection using image processing. *International Journal of Advanced Research in Computer and Communication Engineering*, *5*(4),1012-1016. IEEE - The methodology for a robot system to manage crops, identify crop illnesses, and monitor pesticide use. The camera-captured images in this system are processed using image processing techniques, and the results are then translated into binary codes and sent to the microcontroller unit via the RF module. In this study, the field is traversed by an agricultural robot. It takes a picture of the leaf and carries out disease detection procedures. Here, a robotic automobile is equipped with a camera that takes pictures, which are then wirelessly transmitted to the system by an RF module. In this system, MATLAB is used to process the collected images for disease identification. OpenCV is more effective than MATLAB.
3) Gavhale, K. R., & Gawande, U. (2014). An overview of the research on plant leaves disease detection using image processing techniques. *IOSR Journal of Computer Engineering (IOSR-JCE)*, *16*(1), 10-16. IEEE - K-means clustering and SVM are the two main image processing techniques employed in this study to identify leaf diseases. This method can help to a great extent with the precise diagnosis of leaf disease. It is believed that there are five phases involved in identifying leaf diseases: picture capture, image pre-processing, segmentation, feature extraction, and classification. We can use enough insecticides to successfully control the pests and boost crop output by calculating the amount of disease present in the leaf. By employing various segmentation and classification methods, this strategy can be expanded. All types of leaves are able to have diseases identified using this idea, and the user may also determine the proportion of leaves that are impacted by the disease, and the usercan rectify the problem very easily and with less cost.

4) Elfatimi, E., Eryigit, R., & Elfatimi, L. (2022). Beans leaf diseases classification using mobilenet models. *IEEE Access*, *10*, 9471-9482. IEEE - This study employed TensorFlow and a MobileNet model to identify and classify bean leaf disease using a public dataset of images of leaves. In addition to examining the ideal network architecture, hyperparameters, and optimization strategies, it tackled the categorization of bean leaf disease. The optimal configuration for classifying bean leaf diseases was determined by comparing various architectures separately in the study. In controlled environments, Elfatimi et al. used the MobileNetV2 architecture to achieve faster training times, more accuracy, and simpler retraining. On a single dataset with two sick classes and one healthy class, they evaluated and constructed MobileNet topologies, testing the approach on 1296 images of bean leaves. With an average accuracy of over 97% on the training dataset and over 92% on the test data, the findings demonstrated the robustness of the model and classification performance of the MobileNet model for bean leaf diseases.
5) Lv, M., Zhou, G., He, M., Chen, A., Zhang, W., & Hu, Y. (2020). Maize leaf disease identification based on feature enhancement and DMS-robust alexnet. *IEEE Access* - In this paper, Lv et al. put out a technique for identifying novel-based maize leaf diseases. In this strategy, a framework for improving the properties of the maize leaf is first designed, with the ability to do so in a complicated environment. Then, DMS-Robust Alexnet, a unique neural network based on the backbone Alexnet architecture, is created. Dilated convolution and multi-scale convolution are used in the DMS-Robust Alexnet to enhance the power of feature extraction. Batch normalization is used to strengthen the model's robustness while preventing network overfitting. The Adabound optimizer and the PRelu activation function are used to increase convergence and accuracy. It has been demonstrated in trials that the maize leaf disease feature augmentation method is helpful in enhancing the capability of DMS-Robust Alexnet identification. The proposed method demonstrates strong robustness for maize disease images collected inthe natural environment, providing a reference for the intelligent diagnosis of other plant leaf diseases.
6) Wu, Y., Feng, X., & Chen, G. (2022). Plant Leaf Diseases Fine-Grained Categorization Using Convolutional Neural Networks. *IEEE* - Wu et al. propose in this study a method for attention network-based fine-grained disease categorization to address the problem. The "Classification Model" makes use of attention mechanisms to increase identification capacity. The "Classification Model" now needs to pay more attention to discriminating between areas to discover differences rather than paying more attention to global features since the "Reconstruction-Generation Model" was introduced during training. Adversarial loss was employed to separate the produced image from the original image in order to conceal it. The model's complexity cannot be raised because the "reconstruction-generation model" and the "discrimination model" are only employed during training and do not function throughout the inference stage. Unlike the standard classification network, the method of generalization ability enhancement further enhances identification accuracy. And the method needs less memory but can achieve low-performance terminal real-time identification of peach and tomato leaf diseases. And it can be applied in other crop disease identification fields with similar application scenarios.
7) Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J., & Zhang, Z. (2021). Plant disease detection using generated leaves based on doubleGAN. IEEE - In order to balance such datasets, Zhao et al. employed DoubleGAN (Double Generative Adversarial Network) to create images of ill plant leaves. DoubleGAN was suggested as a method to get high-resolution pictures of diseased leaves with fewer samples. There are two stages in DoubleGAN. Stage 1 inputs included both healthy and unhealthy leaves. To create the pretrained model, the WGAN (Wasserstein Generative Adversarial Network) was first fed photos of healthy leaves as inputs. The pretrained model was then used to generate 64*64 pixel images of unhealthy leaves using the input of unhealthy leaves. Stage 2 involved expanding the unbalanced dataset by obtaining equivalent 256*256 pixel pictures using a Super Resolution Generative Adversarial Network (SRGAN) comparison with photos produced by DCGAN. The accuracy of plant species and disease recognition reached 99.80% and 99.53%, respectively.

III. METHODOLOGY

A. Data Collection

A dataset of photos of sick plant leaves was gathered for the CNN and Raspberry PI leaf disease detection systems. The training dataset was created by labelling the photos according to the type of sickness or healthy state. To guarantee a representative dataset, various sources, including field trips, internet repositories, and private collections, were utilized.

B. Data Preprocessing

Preprocessing was done on the labels and leaf pictures collected. By eliminating duplicates, mistakes, and pointless data, the data had to be cleaned. Incomplete values were filled in. Techniques for transforming data were used, including scaling, normalization, and standardization. To choose the most pertinent features, feature extraction was used. Data integration gatheredinformation from various sources to produce an extensive dataset. Data reduction methods like PCA and SVD decrease dimensionality.

C. Model Design

To identify leaf illness, a convolutional neural network (CNN) was created. Convolutional layers, max pooling layers, and fully linked layers were all incorporated into the model. To expand the size of the training dataset and avoid overfitting, data augmentation was used. Layers for random flips, rotations, zooming, rescaling, convolution, max pooling, dropout, flattening, and fully linked layers with ReLU and softmax activation functions were all included in the model design.

D. Model Training

The collection of photos of sick plant leaves was used to train the CNN model. During training, the model was fed batches of photos and labels while having its weights and biases adjusted to reduce error and increase accuracy. The CNN model was created and trained using the Keras API. Techniques for data augmentation were used to improve generalization. Tuning was done on hyperparameters such as learning rate, batch size, and epochs. Validation data assisted in performance monitoring and overfitting avoidance. For later use, model weights and architecture were stored.

E. Model Evaluation

A separate test dataset was used to assess the trained CNN model. Accuracy, precision, recall, and F1 score were all tested as performance indicators. Evaluation revealed the model's advantages and disadvantages, opening the door to prospective improvements using strategies like regularization or hyperparameter tweaks.

F. Model Deployment

For practical purposes, the trained model was put to use. The model might be hosted on a web server, deployed as a container, embedded in an application, or deployed to edge devices like Raspberry Pi, among other options. The model size, inference speed requirements, and resource availability were some of the considerations when deciding on a deployment strategy.

G. Connecting to a Robotic Car

The use of a Raspberry Pi with GPIO pins allowed the leaf disease detection system to be connected to a robotic vehicle. The motor controller and other parts of the car were in communication with the Raspberry Pi. Depending on the status of the plants it identified, signals from the leaf disease detection system guided the car's journey. Wireless protocols like Wi-Fi or Bluetooth were used for communication between the system and the Raspberry Pi. PyBluez or Bluepy libraries, for example, made the Bluetooth connection possible. Based on input signals, the movement of the car was controlled by Python libraries like RPi.GPIO.

H. Website Development

The outcomes of the leaf disease detection system are presented on a mobile-friendly website. The website had a straightforward user experience and presented the results clearly. Utilized were web development technologies including HTML, CSS and JavaScript. Remote access was possible because the website was hosted on a web server.

I. Integration and Deployment

In order to ensure connection with the mobile phone and online interface, integration included linking the trained model with the Raspberry Pi and robotic automobile. On the Raspberry Pi, the required programs and libraries were installed. The system was set up in the field, allowing for disease diagnosis and crop monitoring. Users used the website interface to access the system. Receive notifications when illnesses are found. Utilizing the leaf disease detection system effectively through integration and deployment increased crop output while using fewer chemicals.

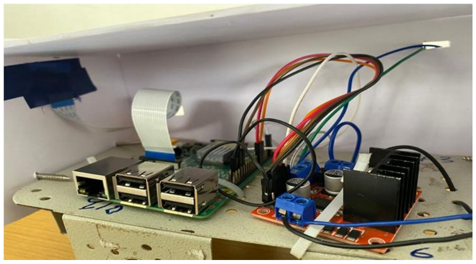

Fig.1 Circuit

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IV. RESULT

This technique is an effective instrument for keeping track of plant health and spotting problems. It has the ability to completely transform the agricultural sector by allowing farmers to identify plant illnesses early and take the necessary precautions to avoidcrop losses. The system integrates cutting-edge technology, including robots, computer vision, and machine learning, to produce an effective and precise plant disease detection solution. Additionally, the system has potential for future growth and enhancement, including increased precision, cloud computing integration, real-time monitoring, remote sensing, and expansion to additional plant species. In conclusion, the CNN and Raspberry Pi-based leaf disease detection system that is linked to a robot car and an online display represents a substantial leap in plant health monitoring and has a lot of room for growth in the future. We examined eight leaf diseases as part of this experiment on disease identification using image processing techniques. We practiced and tested photographs of the affected area, then displayed the results on a mobile device. After training all the photos, each sick leaf taken from the dataset was examined. The name of the leaf illness is presented following training and testing.

A. Hardware Results

1) The robotic car is able to move in different directions based on the user's input through the web interface.
2) The motor driver is able to control the speed and direction of the motors in the robotic car.
3) The camera module is able to capture images of the leaves and send them to the Raspberry Pi board for processing.
4) The Raspberry Pi board is able to process the images and send the results to the web server for display.

B. Software Results

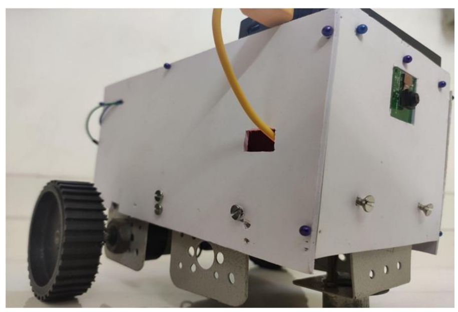

Fig.2 Hardware Model

- The CNN model is able to accurately classify the leaf images as healthy or diseased with a high level of accuracy.
- The OpenCV image processing library is able to preprocess the images before they are fed to the CNN model for classification.
- The Flask web framework is able to create a web server that serves the web application and displays the results of the leaf disease detection system.
- The HTML/CSS/JavaScript web interface is able to provide a visually appealing and user-friendly interface.

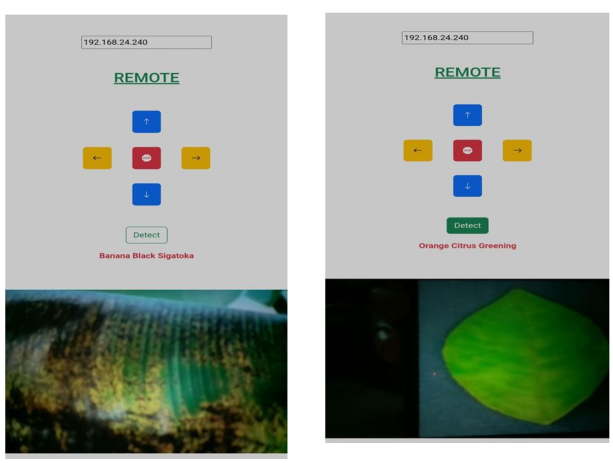

Fig.3 Results

V. CONCLUSION

This study clarifies the numerous theories and approaches used by researchers to categorize diseases and handle difficult situations. Utilizing image processing techniques is primarily intended to lessen the effect of plant diseases on agricultural output. Furthermore, it is critical to comprehend the relationship between disease symptoms and how they affect yield. Plant diseases may be quickly and precisely identified via image processing, which also allows for the automatic detection of dead leaves. For non-experts, our methodology provides a workable solution that yields prompt and accurate results. The Raspberry Pi is used by the proposed system, called GREEN LEAF DISEASE DETECTION to identify and stop the spread of plant illnesses. With computerized disease symptom identification, agricultural productivity could be greatly increased.

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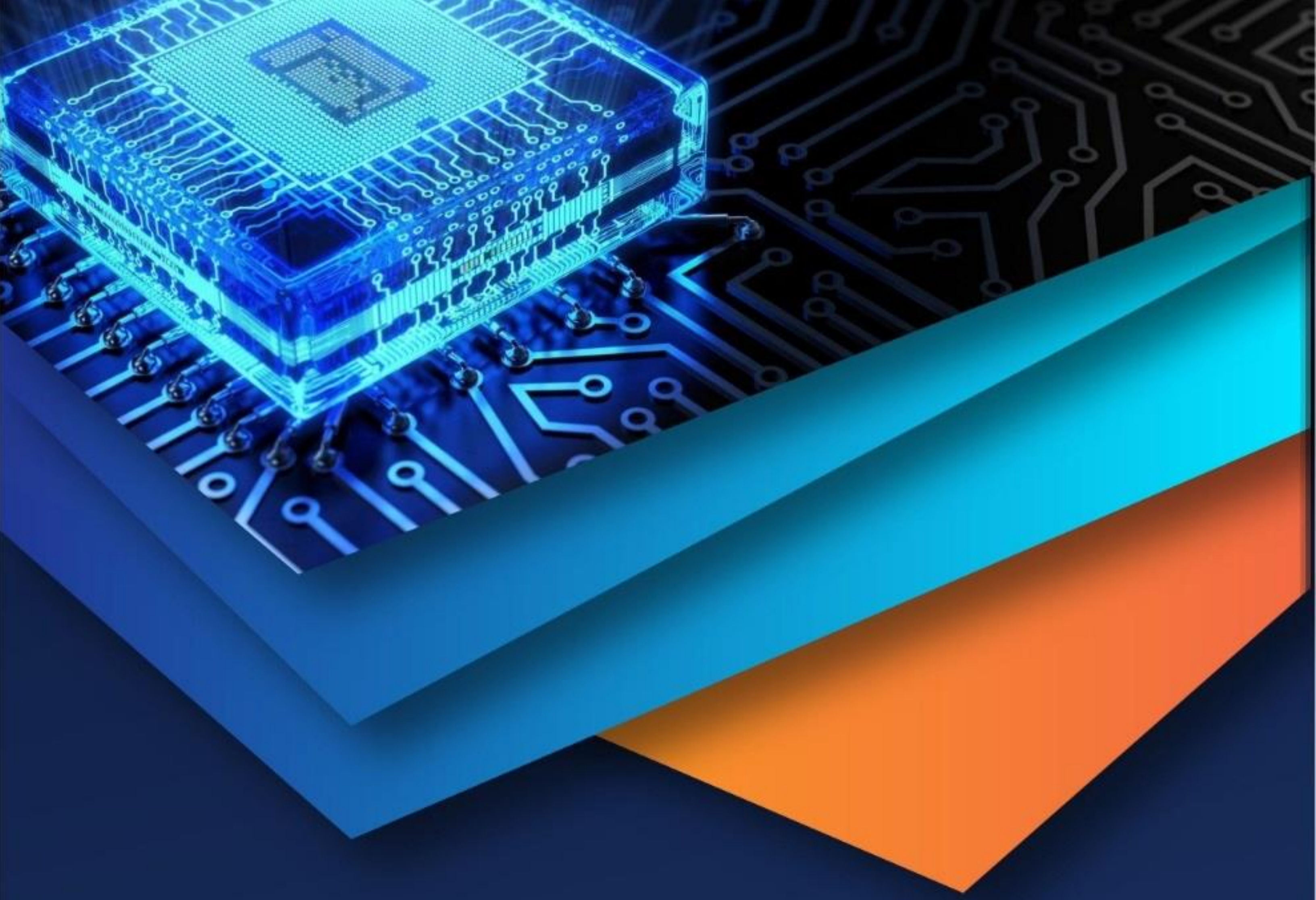

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