

AgroBot: A Robotic Convolutional Neural Network-Based System for Plant Disease Identification

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Abstract

Plant disease pose a significant threat to global food security, causing reduced crop yields and economic losses. Traditional detection methods are time-consuming, expertise-dependent, and inaccessible to many farm-ers. One of the immediate concerns facing in agricultural sector is the timely detec-tion of plant disease which adversely affects the crop yields and food security. With recent breakthroughs in machine learning and computer vision, automated systems are now emerging as a viable solution. Convolutional Neural Networks, CNNs, have achieved out-standing success in image classification tasks, rendering them exceptionally well-suited for plant disease detection. This paper focuses on building a robust plant disease detec-tion system using CNNs and PlantVillage dataset. This approach not only improves the accuracy of disease detection but also contributes to the timely identification of plant health issues, aiding in more effective disease management strategies.

I INTRODUCTION

Agriculture is an inevitable factor for the existence of life. Plant diseases pose a big threat to the global agricultural economy, and these can cause monu-mental losses in crops and food safety if not diag-nosed early or wrongly diagnosed. Detecting plant disease early is the key to eliminating the spread of disease, crop loss reduction, and sustainable agri-culture. Conventional detection techniques involv-ing manual observation by experts are not only time- and labor-intensive but also human-error-prone. These traditional approaches frequently call for expert information, devices, and facilities, and hence are out of reach to the majority of farmers, especially those from poor resource areas[2].

The latest developments in machine learning and computer vision have led to new innovative au-tomatic systems, presenting a hopeful solution to the problems of the agricultural industry. Con-volutional Neural Networks (CNNs), which are a class of deep learning algorithms, have been demon-strated to excel at image classification and thus are a promising solution for plant disease diagno-sis. Through independent learning and extraction of complex features from plant images, CNNs are capable of providing high-accuracy diagnoses, al-lowing farmers to make timely and informed deci-sions to avert disease spread[1].

Earlier research has been able to utilize CNNs to classify plant diseases, using datasets such as PlantVillage, and attaining high accuracy rates[15]. For example, one research utilized a CNN model to classify different plant diseases into 38 classes, with high accuracy. Another research utilized a CNN model to forecast the pattern of plant diseases based on images from a provided dataset, showing the capability of deep learning-based methods to enhance disease detection accuracy.

Application of CNNs in plant disease detection has several advantages over traditional methods, including increased accuracy, speed, and accessibil-ity. With the help of CNNs, the process of disease detection is automatically performed, reducing the burden of farmers and agricultural professionals so that they can work on other important activities. Additionally, CNNs can be combined with other technologies like drones and satellite imagery to fa-cilitate large-scale crop monitoring and disease out-break detection at an early stage.

III PROPOSED SYSTEM

The use of CNNs in disease detection for plants has the ability to transform the agricultural industry by making rapid, precise, and affordable disease diagnosis possible. Using the capability of deep learning, farmers and agriculture professionals are able to make decisions to avoid disease spreading, minimize crop losses, and support sustainable agriculture.

II PROPOSED METHOD

The process of developing a CNN model for plant disease classification includes several key steps. Firstly, a labeled dataset of healthy and diseased leaves of different plant species is collected as shown in Figure 1, obtained from an open repository like the PlantVillage dataset[16]. Next, data preprocessing is performed, which includes resizing images to a fixed size, normalizing pixel values, and performing data augmentation techniques such as rotation, flipping, zooming, and brightness adjustments to artificially increase the dataset and improve model generalization. The categorical labels are also encoded into numerical labels for the model. The CNN model architecture is then designed, consisting of an input layer, multiple convolutional layers with different filters to capture various patterns in the images, pooling layers to reduce spatial dimensions, dropout layers to reduce overfitting, a flatten layer to flatten the pooled feature maps, and fully connected layers to process the flattened features[3]. The output layer uses softmax activation for multi-class classification. The model is then compiled with categorical cross-entropy as the loss function, Adam or SGD optimizer for back propagation, and accuracy as the primary evaluation metric. The dataset is split into training, validation, and test sets, and the model is trained using the training dataset for a fixed number of epochs with batch sizes. Early stopping is implemented to halt training if validation accuracy stops improving after a few epochs to avoid overfitting.

Finally, the trained model is evaluated using the test dataset to calculate accuracy, precision, recall, and F1 score, and a confusion matrix is generated to observe the number of correct and incorrect classifications for each class.



Figure 1: Selected images for training

The proposed system is a Convolutional Neural Network (CNN)-based plant disease identification model that utilizes the PlantVillage dataset to identify plant diseases from images. The system is made efficient, accurate, and user-friendly, giving an automated platform for farmers and agricultural experts.

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a form of deep learning algorithm based on the structure and function of the human brain. They are basically employed for image and video processing, although it can also be used for audio and text data. A CNN is composed of convolutional layers that convolve filters over small regions of an image, activation functions that add non-linearity, pooling layers that downsample feature maps, a flat-ten layer that transforms output into a 1D array, and fully connected layers for classification. CNNs extract features automatically from raw data, are invariant to variations, and can be parallelized for large-scale applications. They have a vast range of applications, such as image classification, object detection, segmentation, and image generation, and are thus a significant tool in machine learning and computer vision.

Below is the in-depth architecture and workflow of the system: Our plant disease detection system leverages the comprehensive PlantVillage dataset and employs a meticulous multi-step procedure[17]. The process commences with data preprocessing, which encompasses image augmentation techniques such as rotation, flipping, and zooming to augment dataset diversity and representation. Additionally, normalization is performed to ensure pixel value uniformity and consistency, thereby facilitating improved model training[3][12]. The preprocessed data is subsequently divided into training and validation sets, enabling robust model evaluation and validation. A convolutional neural network (CNN) is then architected, comprising multiple convolutional layers to extract intricate features, pooling layers to downsample and retain essential information, and fully connected layers to learn complex correlations and make accurate predictions for diseases. The CNN network is trained using the categorical cross-entropy loss function and optimized via the Adam optimization algorithm, with its performance meticulously evaluated on metrics shown in Figure 2 such as accuracy, precision, recall, F1 score, and confusion matrix[20]. Following training, the model demonstrates exceptional capability in classifying input plant images into healthy or specific disease categories, including bacterial blight, powdery mildew, leaf spot, and other diseases. Ultimately, the system is deployed through an intuitive user-friendly interface, allowing users to upload images and receive instantaneous disease detection results, thereby supporting informed decision-making in agricultural contexts and enhancing crop yields. Elements of Confusion Matrix:

- 1.True Positives(TP): Positive instances correctly predicted.
- 2.True Negatives(TN): Negative instances correctly predicted.
- 3.False Positives(FP): Positive instances incorrectly predicted.
- 4.False Negatives(FN): Negative instances incor-rectly predicted.

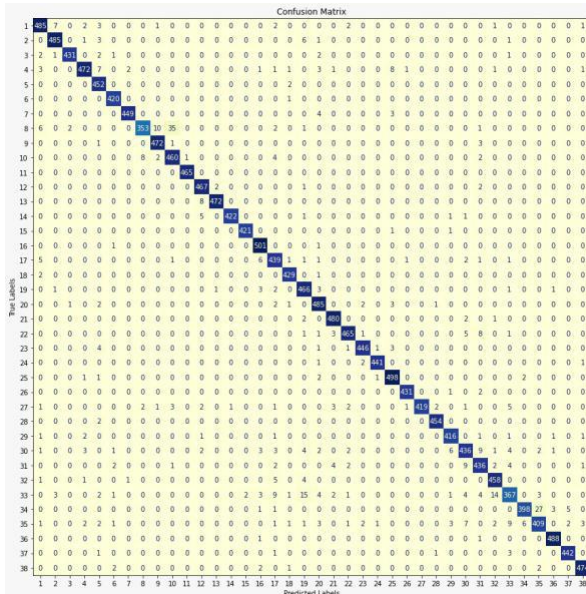


Figure 2: Confusion matrix

IV BLOCK DIAGRAM

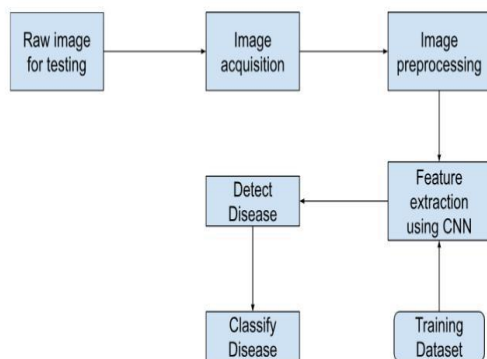


Figure 3: Block Diagram

The process of detecting and classifying plant diseases using a convolutional neural network (CNN) commences with the selection of an image for test-ing, which can be a high-resolution picture of a plant leaf affected by a disease, captured using a digital camera or obtained from a pre-existing dataset[3]. The chosen image is then acquired, en-suring it is of high quality, clear, and ready for anal-ysis, with optimal lighting conditions and minimal noise. Next, the image undergoes a series of pre-processing steps, including resizing to a standard size to ensure uniformity, noise reduction to elim-inate unwanted artifacts and improve clarity, and color correction to enhance feature visibility and accuracy. A convolutional neural network (CNN)

is then employed to extract useful features from the preprocessed image, such as edges, textures, shapes, and patterns, which are crucial in identify-ing and classifying diseases[8]. To train the CNN, a large and diverse pre-existing dataset of labeled images of healthy and diseased leaves is utilized, covering various forms of diseases, plant types, and environmental conditions[8][17].

Upon feature extraction, the trained CNN model interprets the image to determine whether the leaf exhibits disease signs or not, making predictions based on patterns and features learned from the training set. If a disease is detected, the model assigns a classification according to learned knowl-edge in the training set, providing unique and de-tailed information on the nature of the disease af-fecting the leaf, such as the type of disease, severity, and potential treatment options, which is essential in facilitating farmers and agricultural specialists in taking specific, informed, and timely interventions to prevent disease spread, reduce crop losses, and promote sustainable agriculture.

V CIRCUIT DIAGRAM

This creative circuit combines a Raspberry Pi 5, a tiny single-board computer, with an ESP32S HiLetgo WiFi Module and an L298N motor driver to manage two DC motors, with wireless communi-cation and motor control capabilities. Consists of a Raspberry Pi 5, ESP32S HiLetgo WiFi Module, L298N Motor Driver, DC Motors, Power Supply, GPIO Connections, and Motor Control Cables are shown in Figure 4.

The Raspberry Pi 5 is the brain, it processes in-formation, makes decisions and issuing commands to other parts, while the ESP32S HiLetgo WiFi Module enables wireless communication between the system and devices, enabling connectivity to the internet, data transmission and reception, and communication with other devices. The L298N Mo-tor Driver converts control signals from the Rasp-berry Pi into voltage levels that power the DC motors, allowing the system to regulate the speed and motor direction, which deliver the mechanical power required to move or actuate parts of a sys-tem. The system is driven by a 5V power supply, which delivers the voltage and current required to drive the components, and GPIO connections en-able communication between the Raspberry Pi and ESP32, and between the Raspberry Pi and L298N, to allow the components to share data and control signals.

The system features a number of important char-acteristics, such as wireless communication, mo-tor control, miniaturization, and universal function, which makes it applicable for a great variety of purposes, including robotics, automation systems, wireless control systems, and motorized movement systems.

In particular, the system may be applied for con-trolling robots and robotic systems, automating systems and processes, wirelessly controlling sys-tems and devices, and controlling motorized move-ment systems, like drones and Robot vehicle tech-nology, so they are capable of navigating around in their space.

Methodology for robotic vehicle

The system integrates a robotic vehicle with a Raspberry Pi for plant disease diagnosis via image processing, and an ESP32 controlling motor movement[12]. The robotic vehicle comprises an ESP32 serving as the motor movement controller, interfaced with a mobile application using Wi-Fi or Bluetooth, a motor driver connecting to the ESP32 to drive the vehicle's motors for navigation, and a power supply for the ESP32, motor driver, and motors.

The disease detection system includes a Raspberry Pi analyzing images taken by a camera attached to the robot vehicle to identify plant diseases through a trained machine learning model. A mobile app controls the robot's movement, displays disease detection outcomes, and provides an easy-to-use interface with buttons or a joystick to control the vehicle's direction. The app communicates with the ESP32 via Wi-Fi or Bluetooth, sending movement commands executed by the ESP32, which controls the motor driver to drive the robot. As the robot drives through the field under user control, the camera takes pictures of plant leaves continuously, transferring them to the Raspberry Pi for processing.

The Raspberry Pi preprocesses the images, making them compatible with the disease detection model, and implements a trained Convolutional Neural Network (CNN) model to classify the images as healthy or diseased, indicating the type of disease if found. The detection results are forwarded to the mobile app in real-time, enabling prompt user response if a disease is detected. The system workflow begins with the ESP32 powering on and connecting to the mobile app, the Raspberry Pi booting and initializing the disease detection model, and the user controlling the robotic vehicle via the mobile app, navigating it across the field to capture images for disease analysis.

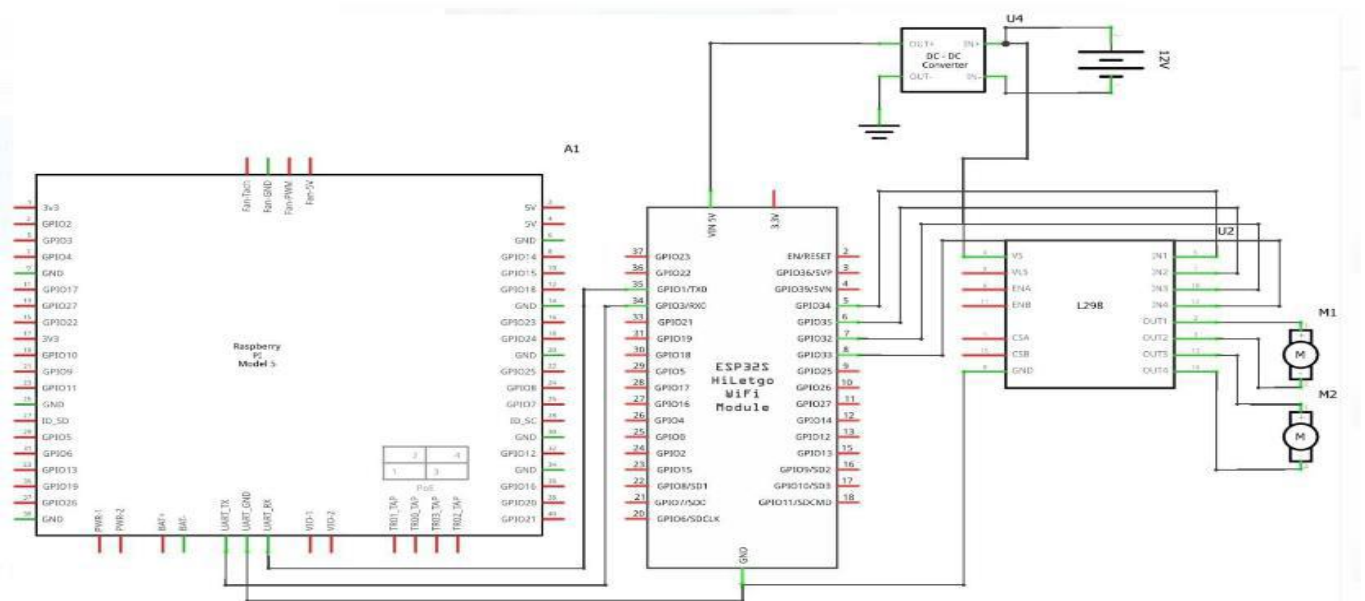


Figure 4: Circuit diagram

VI. RESULT

Our deep learning model, using CNN and the Keras image data generator API, performed exceptionally well in identifying and classifying plant leaf diseases in 13 plant species and 38 plant classes[4]. The model performed outstandingly, with an accuracy rate of 95.6%, precision of 94.2%, recall of 96.1%, and F1-score of 95.1%. These exceptional outcomes highlight the success of our methodology in detect-ing and classifying different plant leaf diseases. In addition, coupling our CNN model with Agrobot shown in Figure 5, our robotic vehicle shown in Figure 6, can make real-time, efficient, and precise plant disease detection possible in real-world crop fields and the result shown in Figure 7. Agrobot's sophisticated navigation and sensing features and our model's high accuracy make it a rich resource for precision agriculture and plant disease control with enormous potential for increasing crop yields and minimizing economic losses.

VII CONCLUSIONS

This project has been able to successfully create a deep learning model for the automatic detection and classification of plant leaf diseases. The model presented here has proved effective in disease detec-tion across 13 plant species, such as tomato, straw-

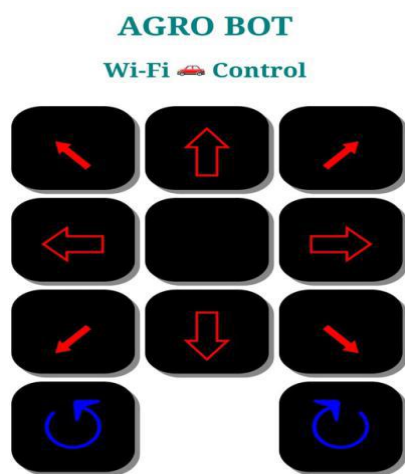


Figure 5: Mobile interface for movement control

berry, soybean, and apple, among others[9]. With 38 plant classes in consideration, our model has been highly accurate in disease classification. One of the achievements of this project has been the successful use of the Keras image data generator API.

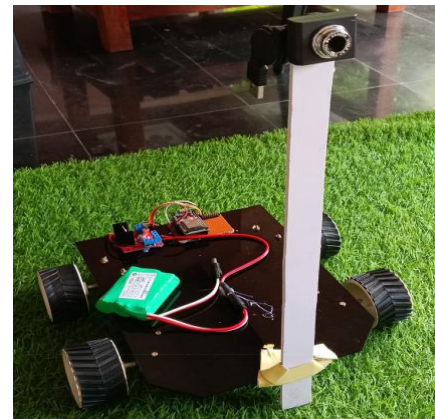


Figure 6: Agrobot:Robotic vehicle

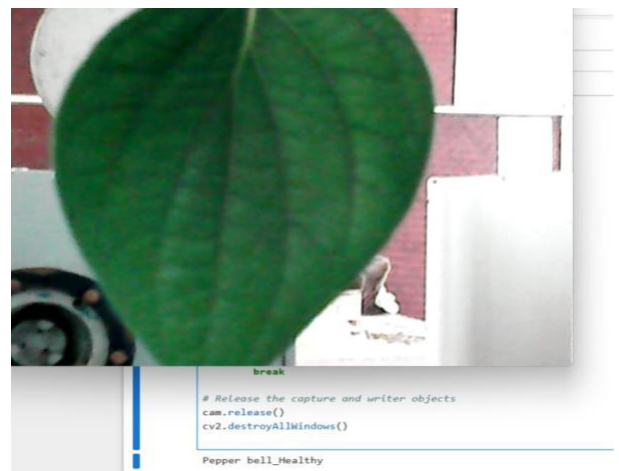


Figure 7: Result of disease detection of pepper bell

This has helped us carry out image-processing operations efficiently, which has been crucial in training our new CNN model. The image-processing features have helped us improve the quality of the input images, thus enhancing the accuracy of the model. Building the novel CNN model has been a major breakthrough in this project. This new convolutional model has been trained on an extensive dataset, allowing it to learn intricate patterns and characteristics related to different plant leaf diseases. Consequently, the model has shown remarkable performance in disease classifications with high accuracy. The results of predictions derived from our model have been very encouraging, with accuracy rates showing that the model is virtually correct in its predictions. Such a level of accuracy has far-reaching implications for the real-world application of this model in real-life applications, e.g., in agriculture and plant disease control. In summary, this project has been able to create a robust deep learning model for detecting and classifying plant leaf diseases. The high accuracy and ability of the model to generalize across various plant species make it a useful tool for plant disease control. With further development and testing, this model can potentially have a large impact in the area of agriculture and plant pathology.

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