Research Type (Original)

Agriculture Robot Using Image Processing

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Abstract

Background: Agriculture is a cornerstone of the economy, but traditional farming is labor-intensive and time-consuming. Advances in technology, such as Convolutional Neural Networks (CNNs) and robotics, can help address challenges like disease detection, weed control, and labor shortages. Tomatoes, a key crop, benefit from proper management using these innovations.

Objective: This project aims to design and develop an agriculture robot using IoT and Machine Learning to automate farming tasks, detect tomato plant diseases, and manage weeds more efficiently.

Methods: The robot is controlled by an ESP32 microcontroller connected via Wi-Fi for real-time monitoring. The system uses CNNs for disease detection in tomato plants, along with a custom-trained dataset using the TensorFlow framework. Mechanical arms perform tasks like seeding, watering, spraying fertilizers, and harvesting. A user interface for disease detection was designed for real time disease detection.

Results: The model achieved an accuracy of 95.0% for disease detection, 95.56% for fruit detection, and 95.14% for plant detection. These results highlight the effectiveness of the robot in managing tomato crops.

Conclusion: The agriculture robot provides a comprehensive solution to key farming challenges, enhancing efficiency through automation and improving crop health monitoring. The integration of IoT and ML offers a pathway toward sustainable and profitable agriculture, particularly in managing tomatoes. Further improvements and scaling could expand its application to other crops and farming tasks.

1. Introduction

Agriculture plays a crucial role in the economic stability of nations, yet traditional farming methods are often labor-intensive, time-consuming, and environmentally unsustainable. The advent of agricultural robots, integrated with modern and advanced technologies like Convolutional Neural Networks (CNNs), offers a transformative approach to modernize agricultural practices. These technologies address the inefficiencies and environmental concerns associated with manual labor and excessive chemical inputs [1].

Agricultural robots, or agribots, have been introduced to tackle various farming challenges, including disease detection, weed management, and soil condition monitoring. Tomatoes, a major crop, are particularly benefited by these advancements. Traditional methods of disease detection and weed control are laborious and require specialized skills. By utilizing computer vision and machine learning techniques, these tasks can be performed more efficiently, by saving time and reducing the need for skilled labor. The integration of Internet of Things (IoT) and Machine Learning (ML) into agriculture enhances productivity by automating repetitive tasks and improving the accuracy of crop management [2]. This is crucial in addressing several challenges faced by farmers, including labor shortages, climate change, and reduced soil fertility. Robotics in agriculture not only boosts efficiency but also offers potential environmental benefits by reducing the reliance on chemical inputs [3].

Conventional farming is hindered by challenges such as extreme weather, disease, and weeds. Additionally, the lack of advanced irrigation methods and accurate soil testing can lead to low productivity [4]. The shortage of labor further exacerbates these issues, highlighting the need for automated solutions. So, the aim of this project is to design and develop an agricultural robot prototype using IoT and ML technologies. The objectives include improving farm management through remote control and enhancing weed and disease management in tomato plants using image processing. Agricultural robots have the potential to revolutionize farming by increasing productivity, profitability, and environmental sustainability. They address pressing issues such as labor shortages and environmental pollution, making them a valuable asset in modern agriculture.

2. Literature Review

The agriculture robot came in existence since 1974 built by Eli Whitney which was able to isolate the cotton seed from the cotton fibre and it has the record of creating up to 50 pounds of cotton in one day [5]. The team of Amrita Sneha et.al. have developed a robot that can perform operations like humidity sensing, automatic ploughing and seed dispensing. The AVR AtMega Microcontroller is used for the monitoring and control. The robot tills the entire field and then proceeds to perform the ploughing operation while simultaneously performing the operation of dispensing the seeds on the tilled soil [6]. P. usha et. Al. discusses a robot system used for cultivating agricultural land without the use of manpower. The main aim is to reduce the work of the farm labourers and increase the productivity in any given span of time [7]. The authors in Tanveer et Al. elaborate the use of new technologies to increase the farm yield. The paper discusses use of latest electronic technology based on use of Microcontrollers and GSM [8]. In the report written by Dhavale et al. Arduino Uno Atmega 328p Microcontroller have been used for controlling the robot. Esp3266 wifi module is used for the communication. A soil moisture sensor is used for checking the water content in the soil [9]. The author Golakotta et al. expressed the concept of Internet of Things is used with the help of Wi-Fi module CC3000 operated on adafruit-IO free server with the help of android application. It is Equipped with self-contained wireless processor that simplifies internet connectivity [10]. Object oriented algorithms is proposed to detect the weed in the agricultural field [11]. A comprehensive and critical survey on image-based plant segmentation techniques is presented. In this context, "segmentation" refers to the process of classifying an image into plant and non-plant pixels [12]. Author proposed "Crop and weed detection based on texture and size features and automatic spraying of herbicides" they developed the image processing algorithm for yield finding and management of weed [13].

The report by Cheng et al. provides an overview of agricultural robots used for crop management. It discusses various types of Agribots, including autonomous vehicles, robotic arms, and drones, and their applications in tasks such as seeding, spraying, and harvesting. The review also highlights the challenges and future prospects of Agribot's technology [14]. Other author (Parihar et al. 2016) paper presents a comprehensive review of robotics in agriculture and forestry. It covers different types of Agribots, their applications in field operations, and the benefits they offer in terms of labor reduction, increased efficiency, and improved crop yield. The review also discusses the challenges faced in implementing Agribot technology and possible solutions [15]. The article published by Hannan et al. on agricultural robotics and their potential in addressing challenges in the agriculture sector. It discusses the use of robotics in tasks such as planting, weeding, and harvesting, along with the integration of advanced technologies like computer vision and machine learning. The review also highlights the economic and environmental benefits of Agribots [16]. The prototype of disease detection and seeding robots was introduced earlier with minimal functionalities that was designed on the basis of field operations [17].

So, the model of the agribot is more functionable than the above reviewed projects and journals. Along with mechanical tasks, it could be designed to detect the abnormality in the plants. With advance sensing with accurate information on soil condition, crop health and environmental factors, it is designed to make intelligent decisions and optimize agricultural practices. The deep learning algorithm with CNN has been used which is more than 90% efficient to provide the best result.

3. Methodology

The system block diagram (see Fig. 1) consists of an ESP32 as a microcontroller which acts as the main part of the system, because controlling of all sorts of components take place using the microcontroller. Here, in case of the vehicle, it is manual, which is controlled by using esp32 Bluetooth module, which is integrated in the esp32 board along with Wi-Fi module. So, by using the Bluetooth module and the signals generated by the modules, the portion of the vehicle is mobile by the help of the gear DC motors. Along with that, the Wi-Fi module in the board acts as a connectivity between the devices and the server of the esp32, from where the mechanical part such as moving of moisture sensor to the soil and DHT22 sensor towards the surroundings take place by the help of the servo motors driving at certain angle. When esp32 reads the data from the moisture sensor and if the moisture of the soil seems low, then the mini-DC water pump sprayed the water in the field. An ultrasonic sensor is used to detect the water level. Since, the position of the ultrasonic is pre-set in the mechanical model, it is programmed as, when the water level is found to be 2cm, then the dc motor stops irrigating the field. In the designed model, the ultrasonic was set at 5cm above, so if the distance is found to be 3cm from water surface, the irrigation stops.

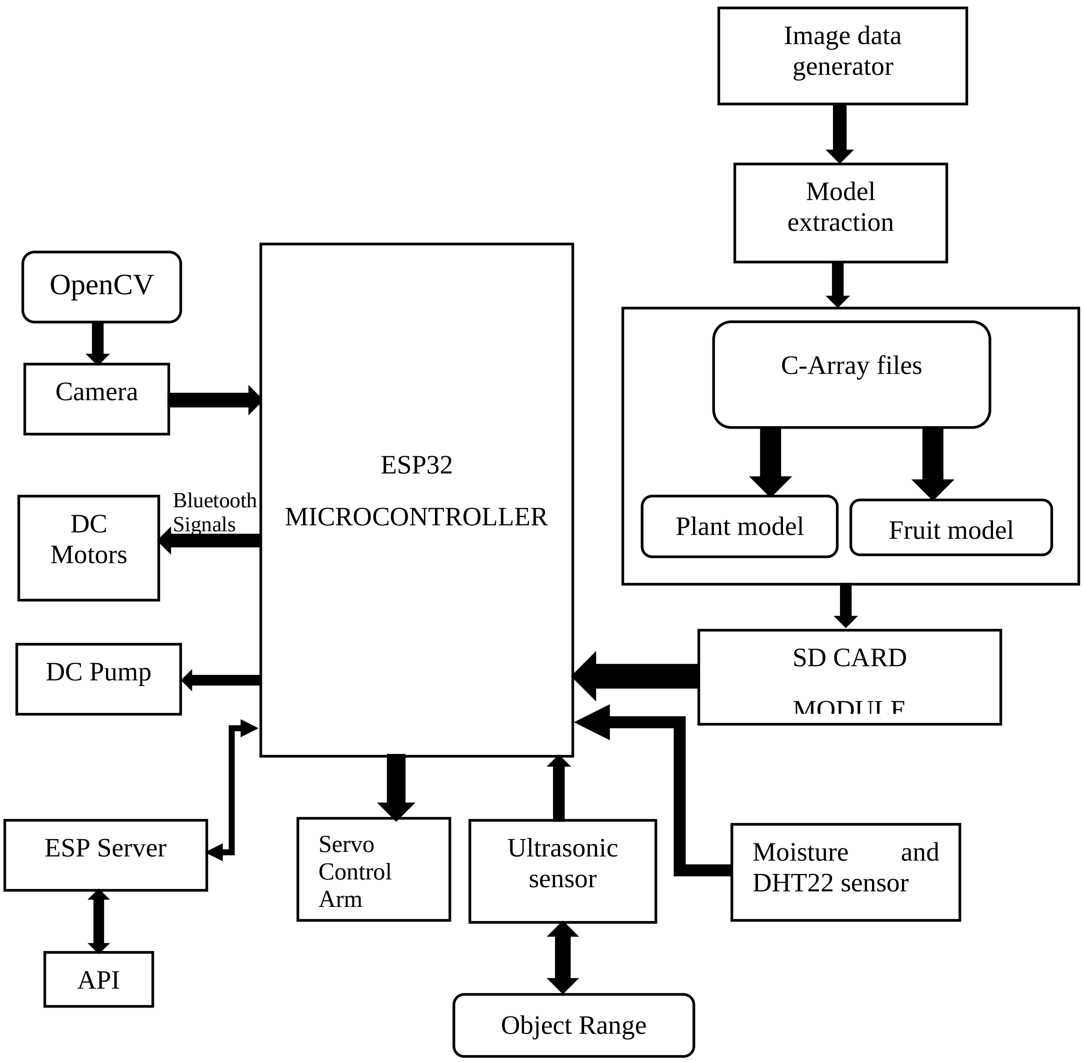


Fig. 1*: System Block Diagram*

Mathematically,

Original sensor position = 5cm above the ground

Required Level of the water = 2 cm

So, the water level can be determined as: original sensor position – level of water

i.e. (5-2) cm = 3cm (irrigation stops).

Here, the robotic arm is drive by the OpenCV mechanism. For this purpose, a memory module is installed with the micro-SD card, which get connected to the esp32 using connectors as a jumper wires. The SD card is loaded with the C array files of the trained model. Now, by using the camera and the OpenCV library to detect the real time objects i.e. fruit and plant, the detected objects are examined by matching them with the model's images. Further that, the arm responds if it detects the fruits. For the weeds to get selected, if the tomato plant matches the model's file, it is considered as not a weed and vice versa. Image Data Generator is used for getting the input of the original data and further, it transforms the transformation of this data on a random basis and gives the output resultant containing only the data that is newly transformed. After picking up the fruit and the weed, using the gripper controlled by servos, the elbow position of the servo gets rotate in -90 degree from its original position, where the basket is pre-set for the accumulation of the weeds and fruits. An ultrasonic sensor is used to detect the range of those objects, so that the servo moves to that range.

3.1. Algorithm and Flowchart

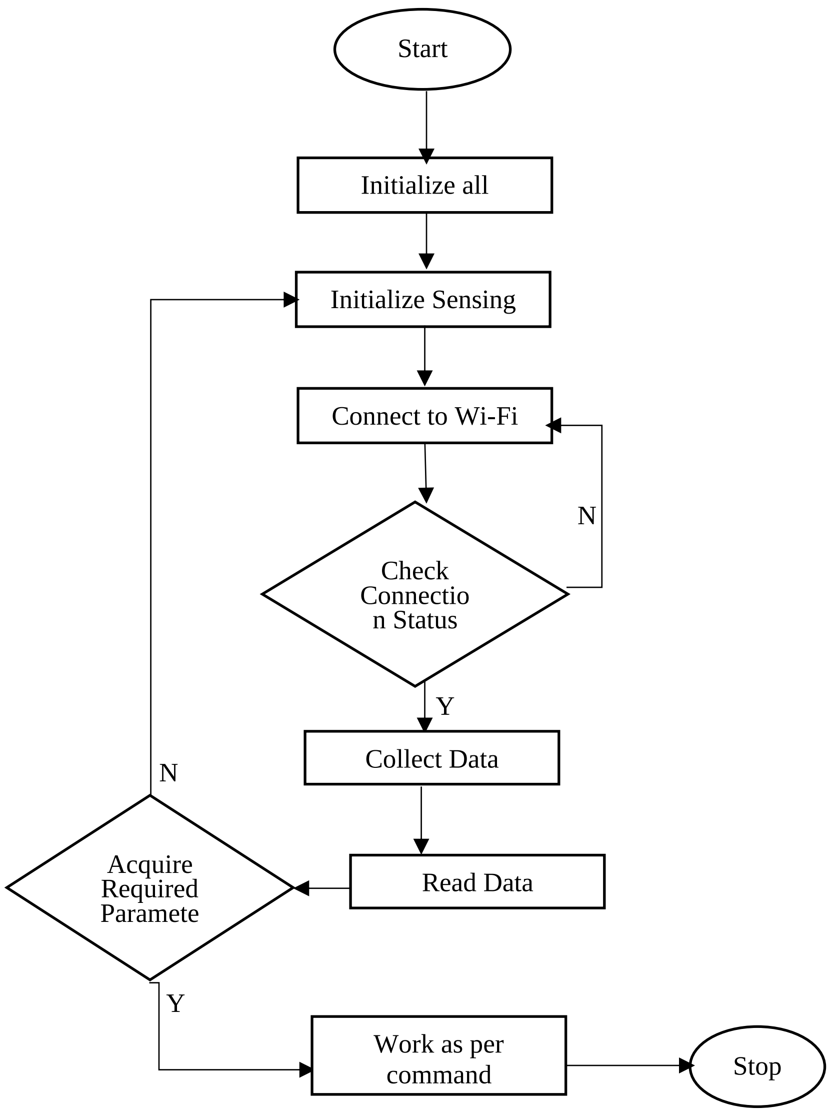


Fig. 2: *Flowchart of Machinery part*

3.2. Image processing

In this model, the image processing is done to detect the weeds among the crops and disease in leaves of a plant. Manual work for detecting the crop and weed takes a long time and more effort. So, by using the approaches like image processing, it can be easily handled in short period of time. The CNN model can be used to train the dataset of the weed and crop. The provided input image gets categorized and classified once the training is completed [11]. The convolution layer is used to extract the features from the image. The Rectified Linear Unit (ReLU) activation function is used to convolutional layer. It helps to break up the linearity even further, compensating any linearity that may be imposed on an image during convolution process by introducing non-linearity. The ReLU aids in avoiding the exponential growth of the computation required to run the neural networks [18]. CNNs are trained to recognize and extract the best features from images that are relevant to the problem.

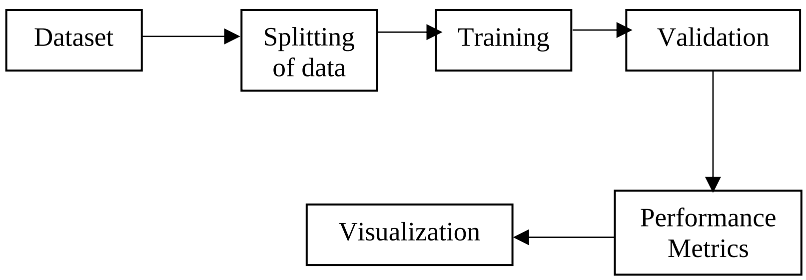


Fig. 3*: Model Performance*

Firstly, the dataset is collected which is then split into two parts which can be 72% for training and 28% for the validation and testing. After that, the model is trained by using transfer learning technique or from scratch. The performance metrics are used for the classification of the images, such as particular plant disease or weeds. Finally, the visualization techniques are used to detect or classify the images. Since, the tomato has been prioritized, the tomato's images are used to compare, which is trained from the dataset. Then, the bot operates on it based on instructions provided. The figure below (see Fig. 4) represents the step-by-step process for the detection of disease and plants.

3.3. Object Detection flowchart

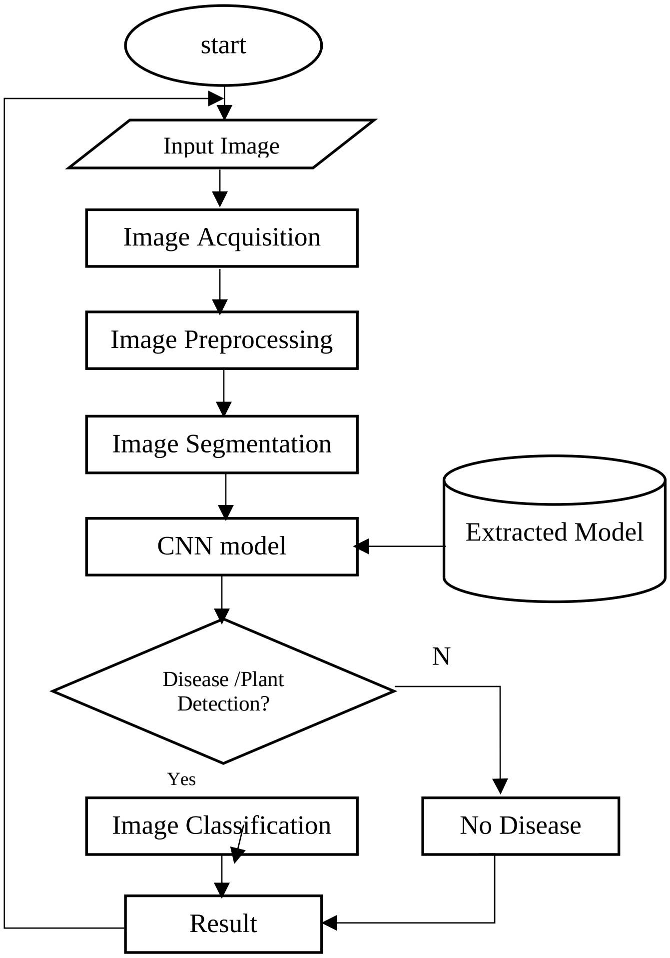


Fig. 4*: Object Detection Flowchart*

3.4. Arm Design

The working mechanism of an arm can be seen in the figure below (see Fig. 5). An arm will be use for the picking of tomatoes and to pull the weeds around the tomatoes. For this purpose, fingers on the arm will be design, made up of plastic. To enable the grip settings, the servo motor will be used on the joint of the fingers. There could be a certain splash or shakes while picking the tomato directly, which can badly affect the plant, so to avoid it, the combinational handle of fingers will be attached to servo, which act like an elbow. After take grip on fruit of plant, the servo will make the hand rotate in certain angle, due to which the tomato gets rid of the stem easily. Also, for the weed the same process can be done. Now, to accumulate the picked tomatoes, a basket can be set by design a handle in the bot, so that it will be easy for the hand to setup the rotation in the predetermined angle and leave the tomato from the grip.

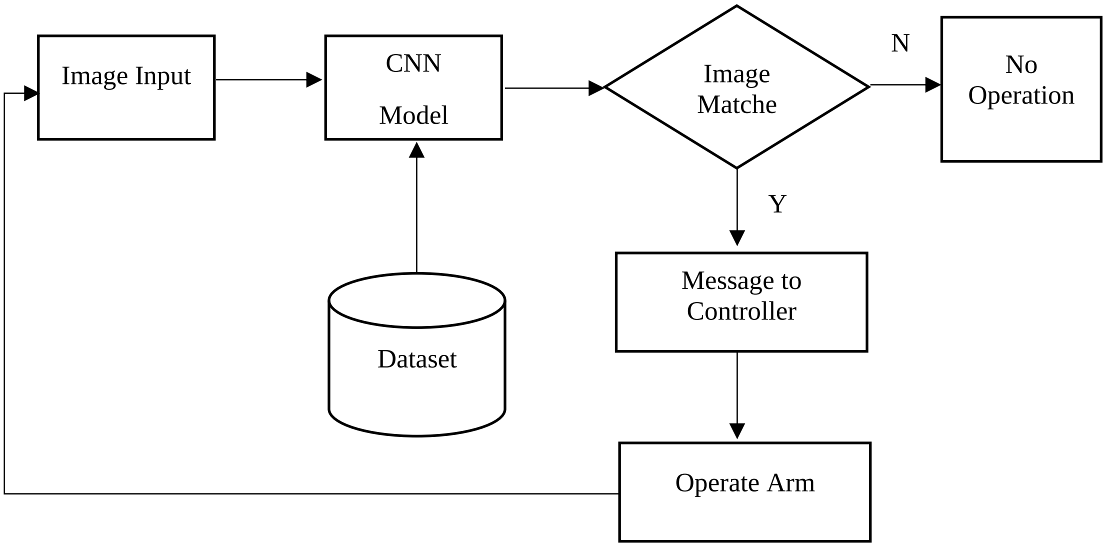
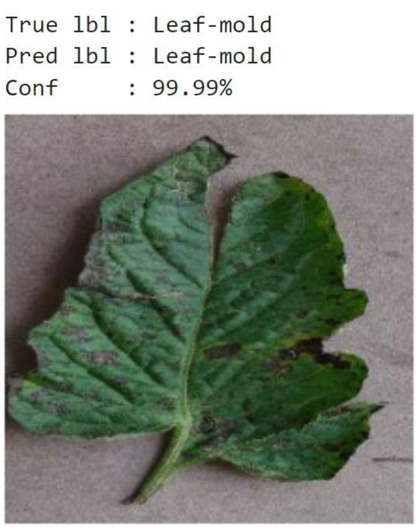


Fig. 5*: Flowchart of Arm Technology*

5. Result

From the designed model, the output regarding the prediction of the diseases among the leaves of tomato, prediction of plants and fruits have been done. It can be seen that (see Fig. 6) the prediction of the disease in leaves of the plant is good with significant prediction percentage. The robot model has been designed along with arms (see Fig. 12).

The obtained sample of the predictions are shown as:



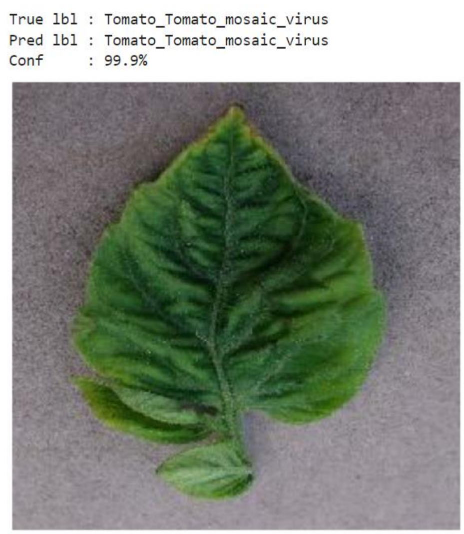


Fig. 6: *Result of prediction using trained model*

The API was designed to detect the tomato diseases on real time using the mobile camera. The result obtained can be shown as:

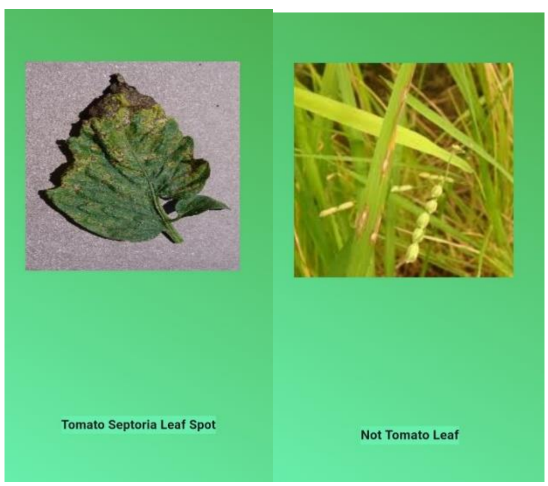


Fig. 7: *Result of disease detection*

Fig. 8*: Disease detection UI*

5. Discussion

A comprehensive dataset of tomato images, including both healthy and diseased plants, was accumulated. The machine learning model, developed and trained using the TensorFlow framework, achieved a 95.0% accuracy (see Fig. 9) in detecting tomato plant diseases. The user interface for disease detection was designed using Flutter (see Fig. 8), with the system also reaching 95.56% accuracy in fruit detection (see Fig. 10) and 95.14% accuracy in plant identification (see Fig. 11). This high level of accuracy enables early disease detection, which can significantly reduce crop loss.

In addition to the smart detection capabilities, the robot handles various mechanical functions. It is designed for seeding, watering, spraying fertilizers, ploughing, and harvesting. These operations are managed by an ESP32 microcontroller, which also allows for real-time monitoring and control via IoT integration. By automating these essential tasks, the robot addresses common challenges in agriculture, such as labor shortages and time-consuming manual processes.

This combination of advanced mechanical systems and machine learning-driven detection provides a holistic solution for modern farming, increasing efficiency and reducing the need for manual intervention. Future improvements could involve expanding the system's capabilities to work with other crops and adapting it to different environmental conditions.

5.1. Training and Validation Graphs

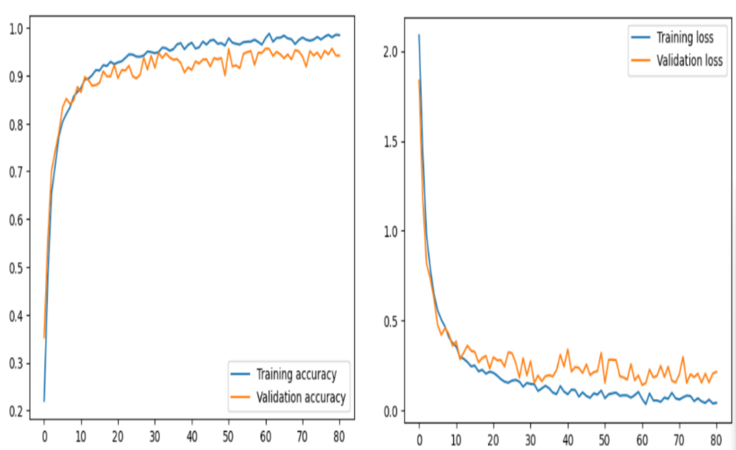


Fig. 9*: Disease Detection*

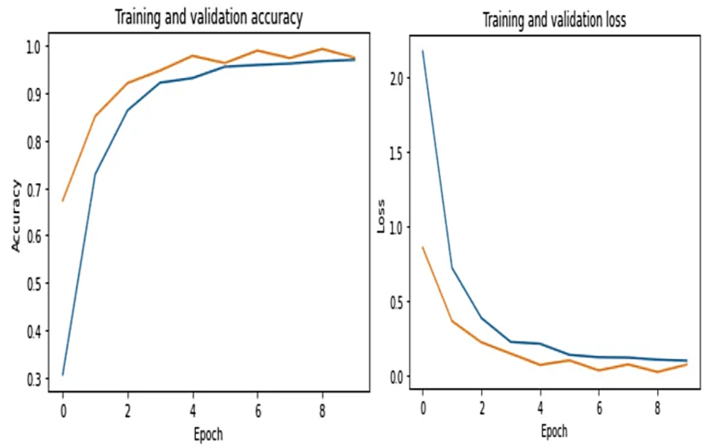


Fig. 10*: Fruit Detection*

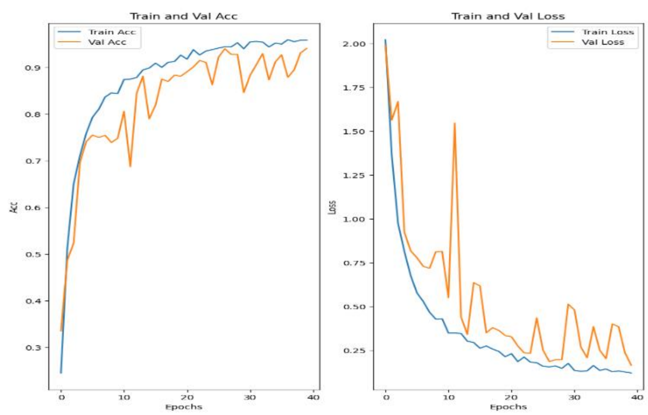


Fig. 11*: plant detection*

6. Conclusion

In conclusion, the development of the Agricultural Robot using Image Processing represents a significant advancement in the field of agriculture. Through the integration of robotics and sophisticated image processing techniques, the project provided an autonomous solution for tasks such as plant disease detection, tomato fruit detection, weed detection along with the help of an arm to pick the fruit, DC water pump to irrigate the farm.

The agribot detected the diseases gaining the F1 score of 95.0%, alongside the plant and fruit were detected with an accuracy of 95.56% and 95.14% respectively.

The robot's hardware, including its chassis board, cameras, microcontroller, and additional sensors, was carefully selected and integrated to ensure optimal performance in diverse agricultural environments. As technology continues to advance, this project serves as a foundation for future innovations in precision agriculture.

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