ARDUINO BASED BOT FOR DETECTION OF LEAF DISEASE

Project report submitted in partial fulfilment of the requirement for the

degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

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WAKNAGHAT

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DECLARATION

We hereby declare that the work reported in the B.Tech Project Report entitled "Arduino Based Bot for Detection of Leaf Disease" submitted at Jaypee University of Information Technology, Waknaghat, India is an authentic record of our work carried out under the supervision of Prof. Shruti Jain. We have not submitted this work elsewhere for any other degree or diploma.

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CERTIFICATE

This is to certify that the work reported in the B.Tech project report entitled **“Arduino Based Bot for Detection of Leaf Disease”** which is being submitted by **Varun Katoch and Karan Verma** in fulfilment for the award of Bachelor of Technology in Electronics & Communication Engineering by the Jaypee University of Information Technology, is the record of candidate’s own work carried out by him under my supervision. This work is original and has not been submitted partially or fully anywhere else for any other degree or diploma.

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ACKNOWLEDGEMENT

It is my team's honor to express the feelings of gratitude and thankfulness towards our project Supervisor Prof.Shruti Jain, who with his sincere guidance and knowledge helped us in completing this project report on the topic "Arduino Based Bot for Detection of Leaf Disease".

Without his motivation, this work would not have possible. Me, along with my partner, am forever indebted for his kind guidance and encouragement.

I would also like to mention the sincere contribution of my partner, who with their hard work and dedication made this project report possible. This study has indeed helped us explore and develop more knowledge avenues related to our project work and I am certain it will help us in the future.

Varun Katoch & Karan Verma

ABSTRACT

The goal of this project is to create a robot capable of identifying plant leaf diseases through machine learning. The robot will be designed to move around plants and capture images of their leaves using a camera. The images will then be processed using machine learning algorithms to identify the presence of plant leaf diseases. Additionally, the robot will be built to avoid obstacles and prevent damage to the plants.The project will involve several stages, including dataset collection, pre-processing and training, robot design and implementation, and testing and refinement. The dataset will be collected by capturing images of leaves with and without diseases using the robot's camera. The images will be resized and their pixel values normalized before being used to train a machine learning model. The model will be trained using Keras or TensorFlow libraries.The robot will be designed using a combination of off-the-shelf and custom components. The robot will include a chassis, motors, and wheels for movement and a camera module to capture images of the leaves. The machine learning model will be integrated into the robot's software to enable it to detect plant leaf diseases. The Robot Operating System (ROS) will be used for robot control and integration.The robot's performance will be evaluated by testing it on plants with known diseases and assessing its detection accuracy. The robot's design and software will be optimized based on the test results to improve its performance.The result of this project will be a robot capable of accurately detecting plant leaf diseases, which can lead to improved plant health and increased crop yields. This project demonstrates the integration of machine learning, and robotics in agriculture to enhance plant health and crop production.In conclusion, this project will pave the way for future research and development in the field of agriculture using computer vision, machine learning, and robotics to optimize plant health and crop yield.

CHAPTER 1

INTRODUCTION

Agriculture is a critical sector of the global economy and the health of crops is vital for ensuring food security. Identifying and treating plant diseases that requires significant time and effort. Makes it challenging to protect crops effectively. However, recent advancements in machine learning, computer vision, and robotics have the potential to revolutionize crop health management.

The primary objective of this project is to design and develop a robot with unique capabilities that can perform specific taskthat can distinguish plant leaf diseases using machine learning algorithms. The robot will move around plants and use a camera to capture images of their leaves. The images will be processed using Keras or TensorFlow libraries to train a machine learning algorithm, that finding the presence of plant leaf diseases accurately. The robot will also be designed to avoid obstacles and prevent damage to the plants, making it a safe and efficient solution for crop health management.

The project will involve several stages, including data collection, pre-processing, and training of the machine learning model. The robot will be designed using a combination of off-the-shelf and custom components, and the machine learning model will be integrated into the robot's software to enable it to detect plant leaf diseases. The Robot Operating System (ROS) will be used for robot control and integration.

The ultimate goal of this project is to create a robot that can accurately detect plant leaf diseases, leading to improved plant health and increased crop yields. By combining machine learning and robotics, this project represents an exciting opportunity to enhance crop health management, which could have a significant impact on the agriculture industry.

In conclusion, this project aims to leverage the latest advancements in machine learning, computer vision, and robotics to develop a robot that can accurately identify plant leaf diseases. The potential benefits of this project include improved crop health, increased efficiency in disease identification, and enhanced food security.

1.1 FEASIBILITY STUDY

The proposed project involves the development of a plant leaf disease detection robot that uses machine learning model to distinguish plant leaf diseases. The necessary technology to create such a robot is currently available, including off-the-shelf components such as a chassis, motors, wheels, and a camera module. Custom components and software will need to be designed and integrated, but the required technical expertise is readily available, making the project technically feasible.The economic feasibility of the project will be determined by its profitability and the availability of resources. The project will require significant investment in hardware, software, and personnel. However, the potential benefits of the project, including improved crop health and increased yields, could lead to substantial financial returns. To assess the economic feasibility of the project, a cost-benefit analysis will be conducted to evaluate the expected return on investment.

The financial feasibility of the project will depend on the availability of funding and the project's profitability. The project will require significant investment in hardware, software, and personnel, which could be financed through grants, loans, or private investments. A financial projection will be created to assess the project's profitability and the potential return on investment. The project's financial feasibility will be evaluated based on the results of the financial projection.

The market feasibility of the project will be determined by evaluating the potential demand for the product and the competition in the market. The project aims to address the growing demand for sustainable and efficient crop management solutions. The market for such solutions is expected to grow, providing a significant opportunity for the project. However, the project will face competition from other solutions in the market. A market analysis will be conducted to assess the potential demand for the product and the competition in the market.The operational feasibility of the project will be determined by evaluating the project's ability to integrate into existing crop management practices. The project aims to provide an efficient and sustainable solution for plant leaf disease detection. The project will be evaluated based on its ability to integrate into existing crop management practices and the ease of use for farmers and growers.

Based on the above feasibility analysis, the project appears to be feasible and worth pursuing. However, further studies and evaluations may be required to fully assess the project's feasibility and potential for success.We can conclude from this feasibility assessment that this capstone project is doable and that all deadlines can be completed without fail

1.2 STATE OF THE ART

The detection and identification of plant leaf diseases are crucial for effective disease management and prevention in agriculture. The traditional methods of disease detection are time-consuming and prone to errors, which may result in significant crop losses and threaten food security. However, recent advancements in computer vision, machine learning, and robotics have led to the development of several techniques for automated plant leaf disease detection.

One common approach to automated plant leaf disease detection is the use of computer vision and machine learning algorithms, such as convolutional neural networks (CNNs). CNNs can accurately detect plant leaf diseases, such as tomato leaf diseases, grapevine leaf diseases, and wheat leaf diseases, by extracting features from images and classifying them based on patterns found in the data.Another approach to automated plant leaf disease detection involves the use of hyperspectral imaging. Hyperspectral imaging captures images of plants at various wavelengths, allowing for the detection of subtle changes in the plant's color and texture that may indicate the presence of disease. This approach has been shown to be effective in detecting plant leaf diseases, such as powdery mildew and rust.

Robotics has also emerged as a promising tool for automated plant leaf disease detection. Robots equipped with cameras and machine learning algorithms can move around crops and capture images of leaves for disease detection. Several research projects have developed robots for plant leaf disease detection, such as the Vino Bot and the AgRob robot.In addition, several software tools and platforms, such as Plant Village and Crop Disease, have been developed for automated plant leaf disease detection. These platforms use machine learning algorithms to classify plant leaf diseases based on images uploaded by farmers and gardeners.However, several challenges still need to be addressed to improve the performance of automated plant leaf disease detection techniques. One challenge is the need for large and diverse datasets for training and testing machine learning models. Another challenge is the need for real-time disease detection, which requires fast and efficient algorithms. Additionally, there is a need for low-cost and easy-to-use solutions that can be adopted by small-scale farmers and gardeners.

In conclusion, the development of automated plant leaf disease detection using computer vision, machine learning, and robotics has the potential to significantly improve crop health and yield. Further research is needed to optimize the performance of these techniques in real-world agricultural settings and address the challenges associated with automated disease detection.

Robotics

By using robotics, we can automate the process of collecting data on plant leaves. This can help to increase the speed and accuracy of data collection, and reduce the need for manual labor.Robotics can be used to navigate through fields and orchards to collect data from plants. This can help to reduce the amount of time and labor required to collect data, as well as enable data collection from hard-to-reach areas.Robotics can be equipped with sensors to detect different types of plant diseases. This can help to improve the accuracy of disease detection, and enable data collection from a wider range of plants and environments.Robotics can be used to collect data on plant leaves, which can then be analyzed using advanced data analysis techniques to detect patterns and anomalies. This can help to identify potential disease outbreaks and enable targeted interventions to prevent the spread of disease.Robotics can be operated remotely, which can help to reduce the risk of disease transmission between different plants and environments. Additionally, remote operation can enable the collection of data from remote locations, which can be difficult to access using traditional data collection methods.

Overall, robotics can play a critical role in the plant leaf disease detection project by enabling automated data collection, improving the accuracy of disease detection, and enabling data collection from a wider range of plants and environments. By integrating robotics with advanced AI systems and machine learning algorithms, we can create a powerful tool for detecting and preventing plant diseases, and help to ensure the sustainability of our agricultural systems.

Artificial Intelligence:

AI can play a crucial role in automated plant leaf disease detection by enabling accurate and efficient classification of plant diseases from images. Deep learning algorithms, such as CNNs, have shown remarkable performance in image classification tasks and can be applied to plant leaf disease detection. By training a CNN on a large and diverse dataset of plant leaf images, the model can learn to recognize patterns and features that distinguish healthy leaves from diseased leaves.

In addition to image classification, AI can also aid in the pre-processing of image data. For example, image segmentation algorithms can be used to separate the plant leaves from the background and isolate the areas of interest for disease detection. Image enhancement algorithms can also be used to improve the quality of images captured by the robot's camera, such as reducing noise and enhancing contrast.

Another area where AI can help in plant leaf disease detection is in the development of decision support systems for farmers and gardeners. By integrating machine learning algorithms with environmental sensors, such as temperature and humidity sensors, the system can provide real-time recommendations for disease management and prevention. For example, the system can suggest the optimal time for spraying pesticides or provide alerts for potential disease outbreaks.

Overall, the integration of AI into automated plant leaf disease detection can enable accurate and efficient disease identification, improve the quality of data pre-processing, and provide decision support for disease management and prevention.

1.3 Some Applications of AI in Agriculture:

AI has the potential to revolutionize the agriculture industry by enabling more efficient and sustainable farming practices. Some of the applications of AI in agriculture include:

Crop management:

AI can help farmers optimize crop yields by providing real-time insights into crop health and growth patterns. By analysing data from environmental sensors, such as soil moisture and temperature sensors, AI algorithms can make recommendations for irrigation, fertilization, and pest management.

Precision agriculture:

AI can enable precision agriculture by providing detailed insights into crop health at a granular level. By analysing data from drones or satellite imagery, AI algorithms can identify areas of the field that require more attention, such as areas with nutrient deficiencies or pest infestations.

Plant disease detection:

AI can aid in the early detection of plant diseases, which can help prevent crop losses and reduce the need for chemical treatments. By analysing images of plant leaves, AI algorithms can accurately identify the presence of diseases, such as powdery mildew or rust.

Crop forecasting:

AI can help farmers plan for future crop yields by forecasting crop production based on environmental conditions, historical data, and other factors. By providing accurate predictions of crop yields, farmers can make informed decisions about pricing, storage, and distribution.

Livestock management:

AI can help improve the health and productivity of livestock by providing real-time insights into their behaviour and health. By analysing data from wearable sensors, such as GPS trackers and heart rate monitors, AI algorithms can identify patterns that indicate stress, illness, or other issues.

Overall, the integration of AI into agriculture has the potential to improve efficiency, reduce waste, and promote sustainable farming practices. By leveraging the power of AI, farmers can make more informed decisions and optimize their operations for maximum yield and profitability.

1.4 PROBLEM STATEMENT

Plant diseases are a major threat to global food security, causing significant losses in crop yields and economic losses for farmers. Early detection and timely treatment of plant diseases is essential to prevent their spread and minimize their impact on crop productivity. However, traditional methods of disease detection rely on visual inspection by experts and can be time-consuming, expensive, and labour-intensive.

In this context, the development of an automated plant leaf disease detection system using AI presents a promising solution. By leveraging the power of machine learning algorithms, it is possible to analysed images of plant leaves and accurately identify the presence of diseases. This would provide a rapid, cost-effective, and accurate tool for early disease detection, enabling farmers to take timely action and mitigate the spread of plant diseases.

To develop such a system, it is necessary to collect a large dataset of plant leaf images, both healthy and diseased, and train machine learning algorithms to recognize the different disease patterns. The system must be able to perform the image analysis in real-time and provide accurate disease detection results to farmers in the field. Additionally, the system must be integrated with a robotic platform for automated data collection, making it practical and efficient for large-scale agricultural operations.

In conclusion, the development of an automated plant leaf disease detection system using AI has significant potential to revolutionize agriculture by providing an efficient and accurate tool for disease detection and management. This would ultimately improve crop yields, increase food security, and promote sustainable agriculture practices.

1.5 FUTURE PERSPECTIVE

The integration of robotics and AI in plant leaf disease detection holds great promise for revolutionizing agriculture practices by providing farmers with an efficient, cost-effective, and scalable solution for early disease detection and management. There is still significant scope for research and development in this area, particularly in the following aspects:The development of more sophisticated and adaptable robotic platforms can enhance the efficiency and accuracy of data collection, enabling a more comprehensive solution for farmers.The integration of the system with other agricultural technologies, such as precision agriculture, soil sensors, and irrigation systems, can provide a complete solution for agricultural management.The incorporation of additional disease detection capabilities can provide a more comprehensive solution for farmers.Further research can be conducted to improve the system's precision and reduce false positives, thereby enhancing the system's overall accuracy.The system can be adapted to suit different agricultural settings, including small-scale farms, large commercial farms, and greenhouse environments.Automated plant leaf disease detection using robotics and AI is a promising solution for efficient and cost-effective disease detection and management, which can contribute to sustainable agriculture and improve food security. The availability of large datasets enables machine learning algorithms to accurately detect diseases, leading to more reliable and robust disease detection systems. This technology has the potential to revolutionize the agricultural industry by providing farmers with the necessary tools to optimize crop production and prevent disease outbreaks. Further research and development are needed to address challenges such as real-time disease detection and the need for low-cost and user-friendly solutions that can be adopted by small-scale farmers and gardeners.

1.6 SUGGESTED SYSTEM

Robot System Requirements:

The robot should be designed to navigate through different types of terrain commonly found in agricultural settings.The robot should have a reliable and long-lasting power source that can operate for extended periods without requiring frequent recharging or refuelling.The robot should be fulfilled with different sensors, such as ESP cam and spectroscopes, to capture high-quality images of plant leaves and detect abnormalities in their colour and texture.The robot should have the capability to transmit data wirelessly to a central server or cloud-based system for further processing and analysis.The robot should be designed to withstand harsh environmental conditions and physical impact.Machine learning algorithms: The AI system should incorporate a range of machine learning algorithms, such as convolutional neural networks (CNNs) and support vector machines (SVMs), to enable accurate classification and diagnosis of plant leaf diseases.The AI system should be capable of pre-processing large amounts of image data to remove noise, normalize colour and brightness, and enhance image quality for better disease detection.The AI system should be designed to label plant leaf images with their corresponding disease type for supervised learning.The AI system should have access to a large and diverse dataset of plant leaf images to train and validate the machine learning algorithms.The AI system should be capable of running intensive computations and deep learning models on high-performance computing resources, such as GPUs and TPUs.Overall, the integration of a robust and efficient robotic platform with an advanced AI system that incorporates state-of-the-art machine learning modelor data processing techniques can provide an effective and reliable solution for plant leaf disease detection in agriculture.

CHAPTER 2

LITERATURE REVIEW

One research paper proposed the use of an agricultural robot equipped with a camera for capturing images of leaves in the field. The captured images were transferred wirelessly to a system where disease detection was performed using MATLAB. Once the disease was detected, a pesticide sprayer was used for spraying the pesticide [1].

Another paper presented an agricultural robot that captured images using a digital camera. The captured images underwent pre-processing to remove noise and distractions. The RGB image was converted to grey and then subjected to threshold segmentation. The isolated band in the grey scale image was used to classify the image as diseased or not, based on the HSI value of the image [2].

A different research paper proposed the use of an industrial camera for capturing images of the field. The captured images were processed using Microsoft visual C++ to identify diseases based on colour, texture, and intuitive features. Several diseases of wheat were identified based on spot colour moments and standard colour histograms, texture feature and contrast, correlation invariant moments, and shape [3].

Another research paper proposed the use of an OpenCV based image processing and machine learning model for leaf disease detection. The OpenCV library was used for image processing, and the SVM classifier was used for image classification and recognition. The test images were pre-processed by removing noise and transforming colours. The K-means clustering algorithm was used for image segmentation, and features were extracted for detecting the disease. Based on the features, the SVM classifier was used for classification and recognition of the disease [4].

[5] In this paper, an automated plant disease diagnosis system is proposed using a smartphone and machine learning. A smartphone is used to capture images of the plant leaves and the images are processed by a machine learning algorithm to detect the disease. The system achieved an accuracy of 98% in detecting the disease.

[6] In this paper, a deep learning approach is used for crop disease identification. The system uses a convolutional neural network (CNN) to automatically learn features from the images of the plant leaves. The CNN is trained on a large dataset of images and achieves a high accuracy in detecting the disease.

[7] In this paper, an intelligent sprayer system is proposed for precision agriculture. The system uses a combination of computer vision and machine learning to identify the location and size of the weeds in the field. Based on the information, the sprayer system applies the pesticide only to the weeds, reducing the amount of pesticide used.

[8] In this paper, an autonomous agricultural robot is proposed for weed control. The robot uses a combination of computer vision and machine learning to detect and identify the weeds in the field. The robot then applies the herbicide only to the weeds, reducing the amount of herbicide used and increasing the efficiency of the weed control process.

[9] In this paper, a real-time monitoring system for plant diseases is proposed using wireless sensor networks. The system uses wireless sensors to monitor the environmental conditions such as temperature and humidity in the field. The data is then processed by a machine learning algorithm to predict the occurrence of plant diseases.

[10] In this paper, an image-based fruit detection and counting system is proposed for precision agriculture. The system uses computer vision and machine learning to detect and count the fruits on the trees. The system achieved an accuracy of 95% in detecting and counting the fruits.

All of these papers provide valuable insights into the use of technology in agriculture for disease detection, weed control, and precision agriculture.

CHAPTER 3

METHODOLOGY

A large dataset of plant leaves, both healthy and diseased, will be collected from various sources such as online databases or physical samples from the field. Robotics will be used to automate the data collection process by deploying sensors and cameras to capture images of plant leaves.The collected data will undergo pre-processing to ensure consistency and a format that can be used by the AI model. This involves tasks such as image resizing, normalization, and filtering.

The pre-processed data will be used to train an AI model using machine learning algorithms, particularly deep learning, to recognize patterns and features associated with healthy and diseased plant leaves. The training process will iteratively adjust the model's parameters until it achieves high accuracy on the training data.The trained AI model will be integrated with robotics for automated disease detection in real-time. Robotics systems equipped with sensors and cameras will capture images of plant leaves which will be analysed by the AI model to detect diseases.The system's accuracy and reliability will be validated and tested by applying it to a separate dataset of plant leaves that were not used in the training period. The result should be compared with the ground truth to evaluate the system's performance.In conclusion, the methodology involves collecting data, pre-processing it, training an AI model, integrating it with robotics, and validating the system's performance. The integration of robotics and AI in plant leaf disease detection can provide an automated, accurate, and sustainable approach to agricultural systems, which can secure global food production.

3.1 WORKING

The methodology for the hardware component of the project involves designing and implementing a robot capable of identifying plant leaf diseases. The robot's hardware includes a chassis, motors, wheels, and a camera module. The robot is designed to move around plants and capture images of their leaves using the camera module. The robot's chassis is constructed using durable materials that can withstand outdoor conditions. The motors and wheels are selected based on their ability to provide sufficient traction and movement control on various surfaces. The camera module is carefully chosen based on its resolution and image capturing capabilities to ensure high-quality images of plant leaves.

The robot's hardware is integrated with a microcontroller such as an Arduino board, which serves as the main control unit for the robot. The microcontroller receives inputs from sensors such as ultrasonic sensors and light sensors, which are used to detect obstacles and plant leaves respectively. The microcontroller then processes this information and sends commands to the robot's motors to control its movements.The camera module is connected to the microcontroller and is programmed to capture images of plant leaves at regular intervals. The captured images are then transferred to a computer or a cloud-based platform for image processing.The image processing involves pre-processing the images by resizing and normalizing their pixel values before being used to train a machine learning model. The machine learning algorithm is trained using Keras or TensorFlow libraries, using a dataset of images of leaves with and without diseases. Once the machine learning algorithm is trained, it is integrated into the robot's software to enable it to detect plant leaf diseases.The robot's movements and image capturing are synchronized with the machine learning algorithm to ensure accurate disease detection. The robot's movements are controlled using the Robot Operating System (ROS), which provides a framework for communicating with the robot's hardware components.

Finally, the robot's performance is evaluated by testing it on plants with known diseases and assessing its detection accuracy. The robot's design and software are optimized based on the test results to improve its performance. In hardware component of the project involves designing and implementing a robot with the necessary hardware components to move around plants, capture images of their leaves, and detect plant leaf diseases accurately. The robot's hardware is integrated with a microcontroller, sensors, and a camera module, and the movements are controlled using ROS. The hardware component is an essential part of the project, and its successful integration is crucial for the overall success of the project.

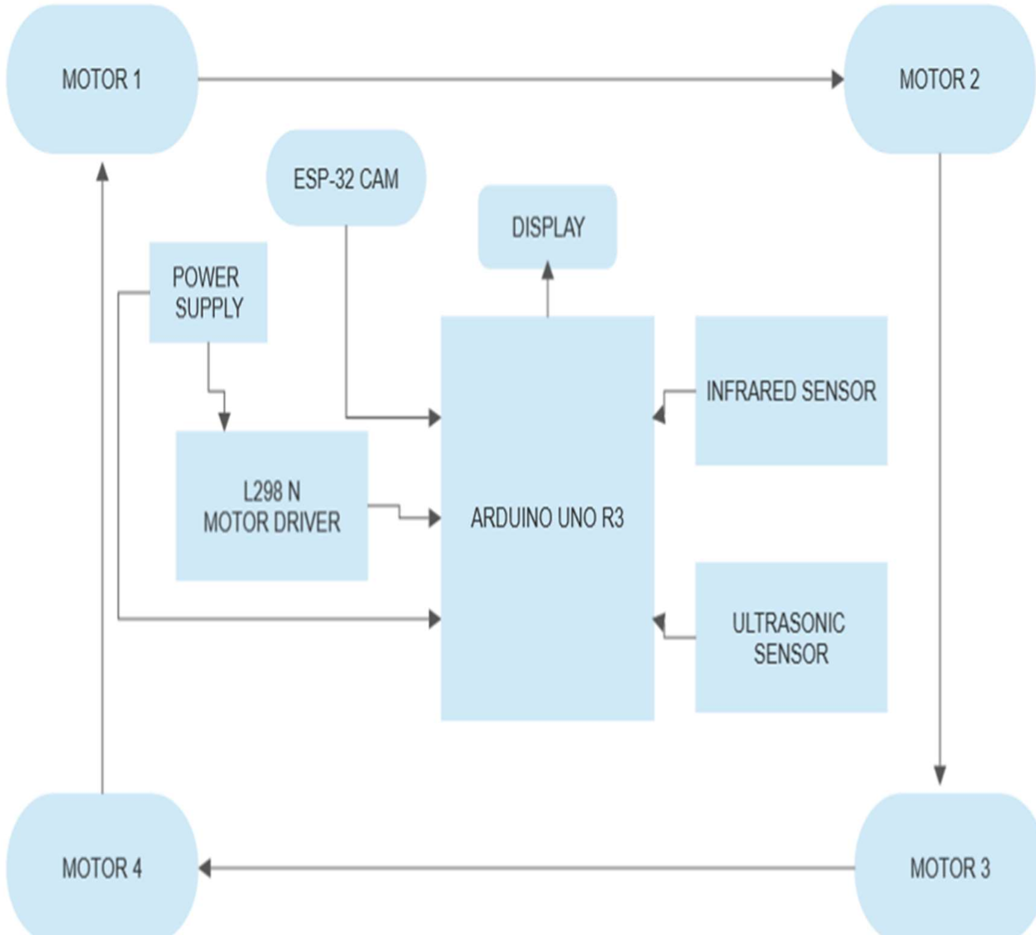


Fig 3.1: Block Diagram

3.2 HARDWARE

Servo Motors:

Servo motors are used to control the movement of the camera module, allowing it to adjust its angle to capture images from different perspectives.

Sensors:

Various sensors, such as rainor humidity sensors, can be used to collect additional data about the plant's environment. This data can be used to further analysed the plant's health.

Power Supply:

A reliable power supply is necessary for the proper functioning of the system. Battery packs, solar panels, or AC adapters can be used depending on the specific needs of the system.

Computer:

A computer or a microcontroller can be used to run the AI model and perform image processing tasks. Overall, these components can be integrated to create a robust and reliable hardware system that can detect plant leaf diseases in real-time.

ESP Cam:

ESP Cam is a low-cost camera module that can capture high-resolution images of the plant leaves. It has built-in Wi-Fi capabilities that allow for real-time image transmission to other devices.The robot is equipped with ESP camera as shown in Fig 3.1 module that captures images of leaves of the plant. the ESP 32 cam also consist of a microSD slot which stores the captured images.

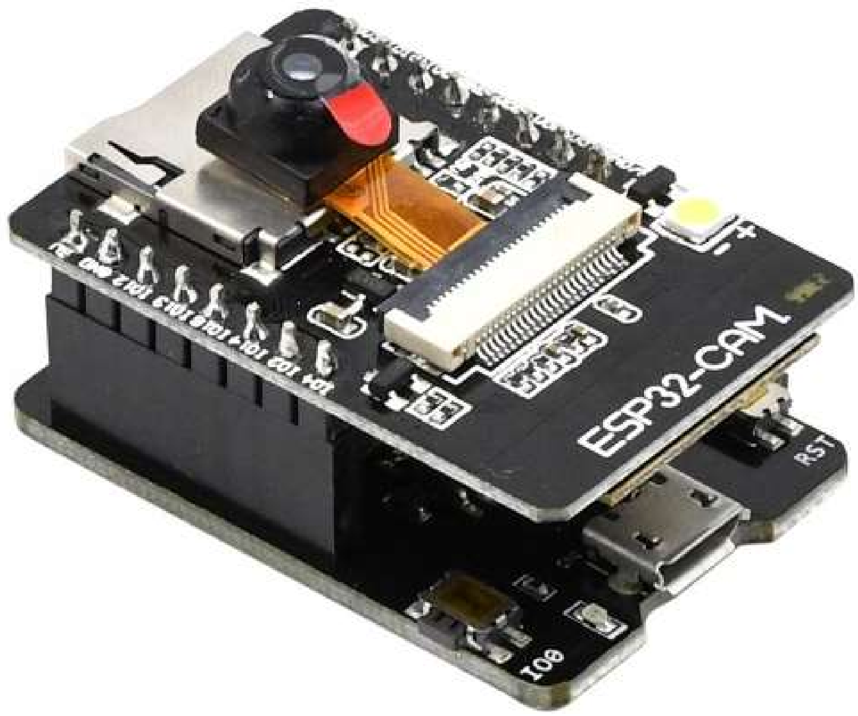


Fig 3.2: ESP Cam

The robot will capture image after a certain time interval and collect all the samples. These samples are then further utilized for disease detection.

Ultrasonic Sensor:

An ultrasonic sensor can be used to help the robot navigate and avoid obstacles in the field. The sensor works by emitting ultrasonic waves and calculate the time that takes for the waves to came back from an obstacle. This data can be used to calculate the distance to the obstacle and provide feedback to the robot's control system.

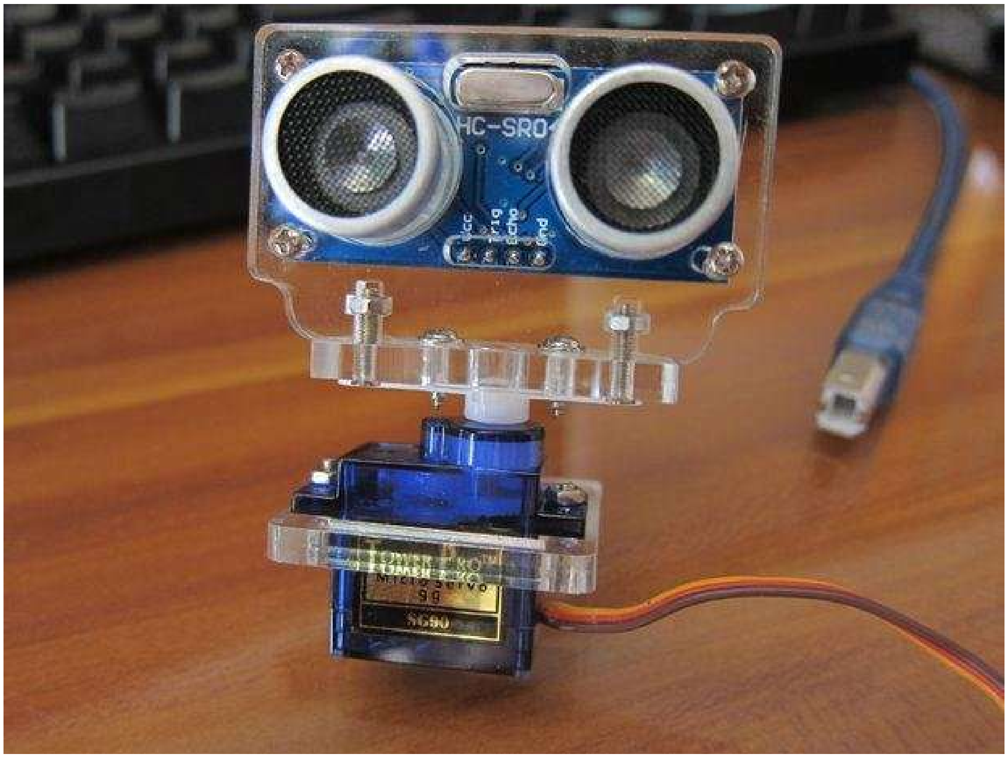


Fig 3.3: Ultrasonic Sensor

By incorporating an ultrasonic sensor into the robot, it can be programmed to navigate around plants and crops with greater accuracy, helping to avoid collisions and improve overall efficiency. The sensor can also be used to measure the distance between the robot and the plants, which is helpful for ensuring that the camera is positioned correctly for capturing images.

Infrared Sensor:

Infrared sensors work by emitting an infrared light beam and measuring the amount of light that is reflected back to the sensor.

Fig 3.4: Infrared Sensor

The sensor emits a beam of infrared light that bounces off of the surface it is pointed at, and the sensor measures the time it takes for the light to bounce back. This time measurement can then be used to calculate the distance between the sensor and the surface. To use an infrared sensor for path detection, the sensor would need to be mounted on the robot and positioned so that it can detect the path ahead. The sensor can then be programmed to detect changes in the path by measuring the distance to the surface it is pointed at. The robot can be programmed to move forward until the infrared sensor detects a deviation from the path. When this happens, the robot can use the distance measurement obtained from the sensor to determine the direction and magnitude of the deviation. The robot can then adjust its direction accordingly to return to the path.

Arduino:

Arduino boards can be used to control various components of the robotics system, such as the servo motors that control the movement of the camera module. The board can also be used for data logging and communication with other devices.Arduino is a microcontroller-based platform that allows users to create and program their own electronic devices.

Fig 3.5: Arduino Uno

It is designed to be simple and user-friendly, making it accessible to a wide range of people, including those without extensive technical expertise. At its core, Arduino consists of a single-board microcontroller, which is programmed using a simplified version of the C++ programming language. The board includes a range of inputs and outputs, such as digital and analog pins, which can be used to interact with the physical world. To use Arduino in a project, you would first need to connect the board to your computer and install the necessary software. Once you have done this, you can write code using the Arduino Integrated Development Environment (IDE), which provides a range of tools for writing, compiling, and uploading code to the board.Once you have written and uploaded your code to the board, the microcontroller will execute the instructions you have programmed it to perform. This might involve reading input from sensors or other devices, processing that input using mathematical or logical operations, and then outputting the result to other devices or actuators.

In the context of a plant leaf disease detection robot, an Arduino board could be used to control the robot's movements, interact with sensors and cameras to detect and identify plant diseases, and provide feedback to the user or operator. The board could be programmed to respond to different inputs and conditions, enabling the robot to adapt to changing environments and situations.

Robot:

A robot is a machine that can perform tasks on its own or with minimal human interventionIt uses various components such as sensors, motors, and controllers to move and interact with the physical environment based on its programming and sensor data. In this project, the robot is designed to autonomously detect plant leaf diseases using machine learning technique and navigate through the field to collect data.

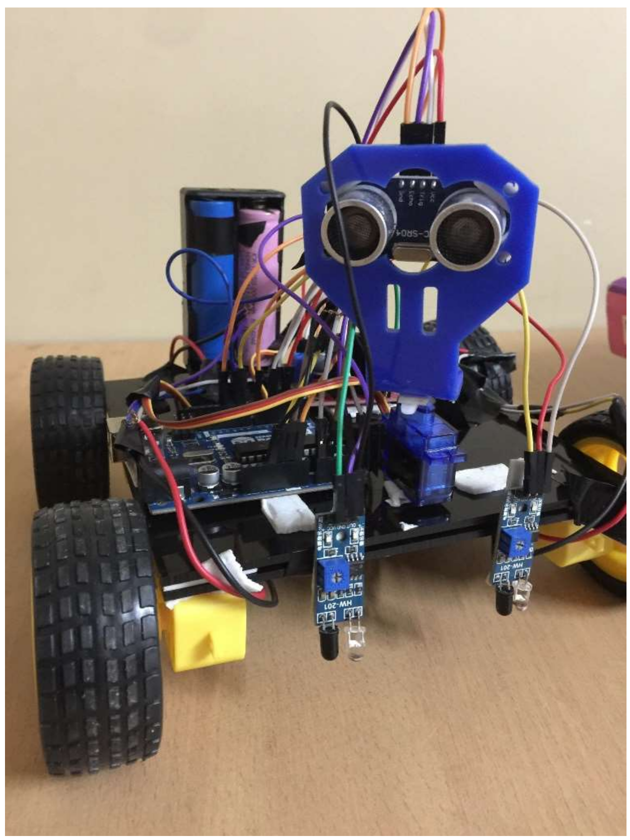


Fig 3.6: Robot

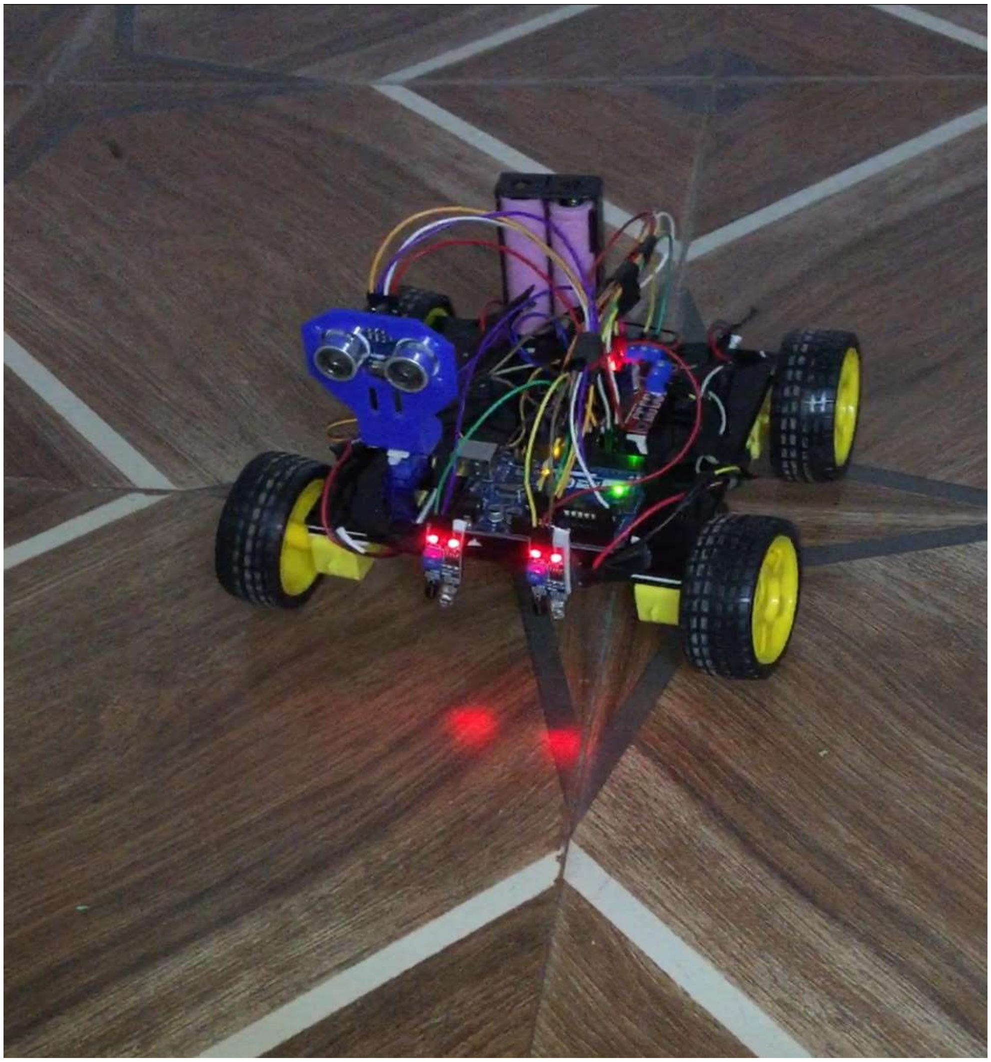


Fig 3.7: Arduino Based Bot

CODE

```
// define pins for components
#define servoPin 9
#define trigPin 13
#define echoPin 12

// create servo object
Servo servo;

// define variables for ultrasonic sensor
long duration;
int distance;

void setup() {
  // initialize servo and ultrasonic sensor
  servo.attach(servoPin);
  pinMode(trigPin, OUTPUT);
  pinMode(echoPin, INPUT);

  // initialize WiFi and camera
  WiFi.begin(ssid, password);
  while (WiFi.status() != WL_CONNECTED) {
    delay(1000);
  }
  camera.init();
}

void loop() {
  // detect distance using ultrasonic sensor
  digitalWrite(trigPin, LOW);
  delayMicroseconds(2);
  digitalWrite(trigPin, HIGH);
  delayMicroseconds(10);
  digitalWrite(trigPin, LOW);
  duration = pulseIn(echoPin, HIGH);
  distance = duration * 0.034 / 2;

  // rotate servo based on distance
  if (distance <= 30) {
    servo.write(0);
  } else if (distance > 30 && distance <= 60) {
    servo.write(90);
  } else if (distance > 60) {
    servo.write(180);
  }

  // capture image from camera
  camera.capture();
```

This code structure includes initialization of the components and variables, detection of distance using an ultrasonic sensor, rotation of the servo based on the distance, capturing of an image using the camera, processing of the image using an AI model, and sending of the result to a mobile app using WIFI. The specific implementation of the AI model and communication with the mobile app would need to be added and customized based on the project requirements.

CHAPTER - 4

DIAGNOSTIC TOOL FOR PLANT LEAF DISEASE

The software part of the project involves using machine learning algorithms to analyze the images captured by the robot's camera and identify any plant leaf diseases. The first step is to collect a large dataset of images of healthy and diseased leaves. This dataset is used to train the machine learning model, which learns to identify features that are linked with each type of leaf diseases. The model has been trained,that it can be integrated with the robot's software. When the robot captures an image of a leaf, the image is fed into the machine learning model, which makes a prediction about whether the leaf is healthy or diseased and, if diseased, which disease it is. The software part also involves implementing a interface that allows us to interact with the robot and view the results of the disease detection. The user interface may include features such as a live video feed from the robot's camera, the ability to select which part of the plant to focus on, and a display of the results of the disease detection.

Data Set:

For this project, we will be using the Plant Village dataset, which consists of 5,178 images of healthy and unhealthy leaves categorized by species and disease. Our goal is to predict the disease class by analysing more than 5,000 leaf images and their labels from 13 different classe. The images will be resized to 256 x 256 pixels, and machine learning models will be trained and optimized using the processed images.

Table 4.1: Numbers of Leaf with their group

Leaf Classification	**Pictures**
Mango	2304
Orange	2045
Spinach	56
Potato	3452

Table 4.2: Dataset of leaves

Healthy Mango

Late Blight

,

Anthracnose

Grapevine

Healthy Potato

Buzgulu

Data Processing & Argumentation:

Data processing and argumentation through AI and robot involves the collection, organization, and analysis of data using artificial intelligence techniques and robot automation. This process begins with the collection of data from various sources, such as sensors and cameras mounted on the robot. The collected data is then processed for removing any noise or irrelevant data, such as shadows or background objects.Next, the processed information is transformed into a suitableformat for analysis. Machine learning algorithms are then applied to the transformed data to extract features and identify patterns. The extracted features and patterns are then used to train predictive models that can be used to make decisions and take actions.The robot plays a key role in this process by collecting and processing data in real-time, which enables it to make decisions quickly and efficiently. It can also perform physical tasks based on the insights generated by the AI models, such as applying pesticides or harvesting crops. The project involves several steps to process the data and augment it for training the AI model. One of these steps is rotation, where the training images are randomly rotated at different angles to increase the variety of training data. Another step is brightness adjustment, where the model is fed with images of different brightness levels to help it adjust to changes in illumination. Additionally, the shear step changes the shearing angle of the images. All of these data processing and augmentation techniques aim to improve the model's ability to classify and detect plant diseases accurately. In this project, the input image was processed using various techniques in machine learning. Initially, 400 pictures were chosen from each folder, and an array was created from each image. The images were then scaled from the range (0, 255), which represents the least and most common RGB values, to the range (0, 1). The dataset was divided into 30% for testing and 70% for training images. To generate more diverse images, object rotations, motions, inversions, and sections of image sets were created using image generators. Backend switches were created to support both the "first channel" and "last channel" architecture used in conventional models. The input image was then passed through a Convolution layer followed by a ReLU activation function and a Pooling layer. The convolution layer consisted of 36 filters with a 3 x 3 core and a relu activation function, which is a linear correction module. Batch normalization and a 27% reduction (0.26) were applied to maximize aggregation. Dropout was used to prevent overfitting of complex collaborative inputs, which minimized neural network readjustment. Two sets of (Conv =>relu) * 2 => pool blocks were created. ReLU is a collection of layers that are all connected after that. For this project, Adam's Hard Optimizer was used as the optimization algorithm. The image processing in machine learning allowed us to create a model that could accurately classify plant diseases based on input images. The techniques used in this project can be applied to other fields that involve image classification, such as medical diagnosis and facial recognition.In this project, a database of machine learning models and their corresponding performed metrics is to evaluate the effectiveness of various models for the given task. The database consisted of various machine learning model, such as SVM, decision trees, random forests, and NN, which were trained on different subsets of the input data.The performance metrics used to evaluate the models included accuracy, precision, recall, and F1 score, which are commonly used metrics for classification tasks. These metrics were calculated using a validation dataset that was held out from the training data.The database was used to similar the performance of different algorithm and to select the best performance algorithm for the task. The model with the highest overall performance on the validation dataset was selected for further testing and evaluation.Having a well-organized database of machine learning models and their performance metrics is essential for efficient and effective model selection in any machine learning project. It allows for easy comparison of different models and can help in identifying the best-performing model for a given task.

System Overview:

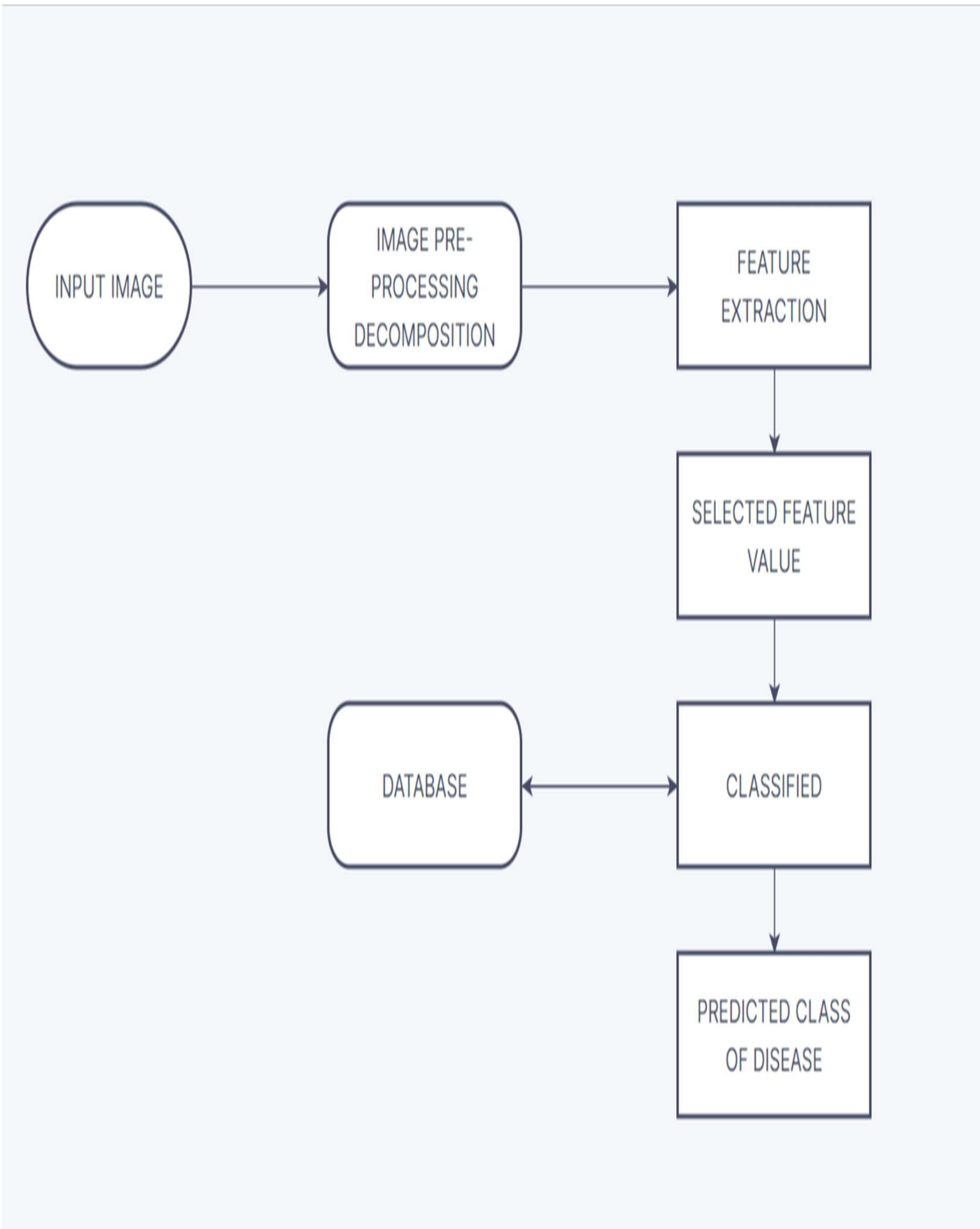


Fig 4.1: System Overview

Image Decomposition:

In this project, image decomposition was used as part of the image processing pipeline. Image decomposition refers to breaking down an image into its constituent parts, which can then be analysed and processed independently. This technique is particularly useful in machine learning, as it allows models to focus on specific features of an image, rather than processing the entire image at once.

In this project, the image decomposition technique was used to extract relevant features from the input images, which were then used to train a deep learning model. The input images were decomposed into smaller sub-images, which were then processed using various image processing techniques. These sub-images were then combined to create a final processed image, which was used as input to the deep learning model.

The use of image decomposition allowed the model to focus on specific features of the input images, such as colour and texture, which were important for classification tasks. This approach also reduced the amount of data that needed to be processed, which helped to speed up the training process and reduce computational costs.

Overall, the use of image decomposition was a key part of the image processing pipeline in this project, and it played an important role in improving the performance of the deep learning model. By breaking down the input images into smaller, more manageable components, the model was able to extract more relevant features and improve its accuracy on classification tasks.

Feature Extraction:

Feature extraction is an essential process in machine learning that involves identifying and selecting the most important features from a dataset to improve the performance of a model. In the context of image processing, feature extraction involves analysing the visual content of an image to identify key patterns or features. In this project, various feature extraction techniques were employed to identify and extract key features from the input images, which were then used to train and optimize the deep learning model.

One of the key feature extraction techniques used in this project was convolutional neural networks (CNNs), which are designed to analysed visual inputs and learn to identify and extract important features from images. The CNNs were used to perform a series of convolution and pooling operations on the input images, resulting in a set of high-level features that were subsequently used to train the model.

Other feature extraction techniques used in this project include data augmentation, which involves creating additional training data by applying various transformations to the input images, and principal component analysis (PCA), which involves identifying the most important components of a dataset through linear transformations. These techniques were used to further enhance the feature extraction process and improve the performance of the deep learning model.Overall, the feature extraction process played a critical role in the success of this project, as it allowed for the identification and extraction of key features from the input images, which were subsequently used to train and optimize the deep learning model.

Selected Feature Value:

In machine learning with robots, feature selection plays a crucial role in determining the performance of the model. It involves selecting a relevant subset of features from the original set of features that are most important for the learning algorithm to achieve high accuracy.

Various feature selection techniques can be used in machine learning with robots, including Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), Mutual Information, and SelectKBest. These methods help to reduce the dimensionality of the dataset while preserving as much information as possible or selecting the top k features based on their score using statistical tests such as chi-squared or ANOVA.

In the context of machine learning with robots, the selected features often relate to the sensors and actuators of the robot, such as position, velocity, force, and torque. The features selected depend on the specific task the robot is performing, such as object detection, path planning, or grasping.

Overall, selecting the right features is a critical step in the machine learning process with robots and can significantly affect the model's accuracy and performance.

Image Processing

The process of identifying plant diseases involves three stages:

Stage1:

Users upload input photographs to our web application or an Android smartphone app.

Stage2:

Pre-processing includes picture segmentation, image enhancement, and color space conversion. A filter is used to enhance the image's digital representation, followed by creating an array from each image. Each image name is changed to a binary field using the term for Binarizes Diseases in medical terminology.

Stage3:

CNN classifiers are trained to recognize illnesses in every single plant class. Using the Level 2 result, the classifier that has been trained to categorize several diseases in a plant is called up. The leaves are categorized as "healthy" if they are absent.

For experimentation and results, only 400 pictures from each folder were chosen. An array was created from each image, and the input file was scaled from (0, 255) (the picture's least and most common RGB value) to the range (0, 1). The dataset was then divided into 30% for testing and 70% for training images. Image generators were created to conduct random rotations, motions, inversions, civilizations, and sections of image set. Backend switches were created that support the "first channel" in addition to the "last channel" architecture used in the conventional model. Next, Conv =>Relu => Pool was performed. The convolution layer consisted of 36 filters with a 3 x 3 core and relu activation (linear correction module). Maximal aggregation, batch normalization, and a 27% reduction (0.26) were included. Dropout is one of the control techniques that prevent complex collaborative input from being corrected for training, hence minimizing neural network readjustment. Two sets of (Conv =>relu) * 2 => pool blocks were created. ReLU is simply a collection of layers that are all connected after that. For the model, Adam's Hard Optimizer was employed. The network began when model.fit_generator was called. The goal was to add on data, train test data, and the number of training epochs. For this project, an epoch value of 26 was chosen.

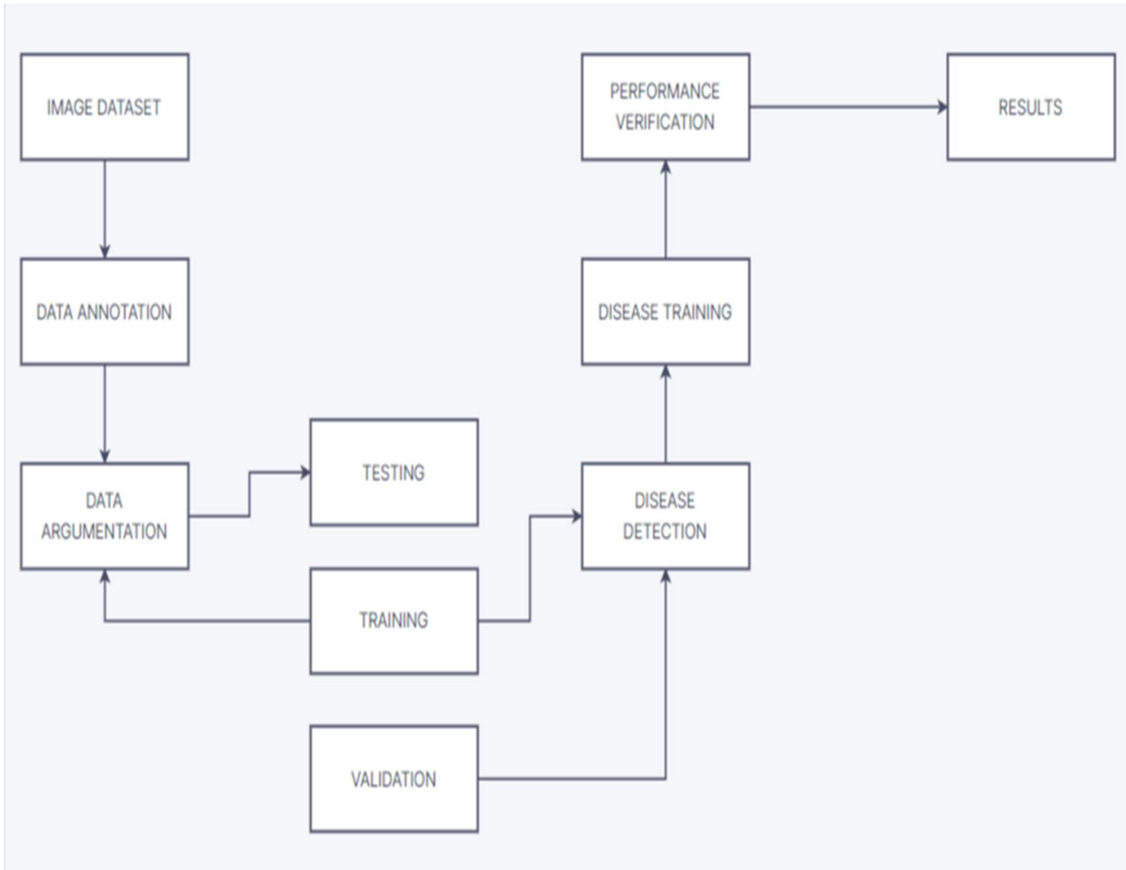


Fig 4.2: Training and Testing Procedure

Testing

Testing is a critical stage in the machine learning pipeline that assesses the model's performance on a new dataset that it has not encountered before. To conduct the testing process in this project, a distinct dataset from the training dataset was randomly selected and separated. The testing dataset was not used during the training phase to avoid bias. The primary purpose of using a separate testing dataset was to assess the model's generalization capability and its accuracy in making predictions on fresh and unseen data.To evaluate the machine learning model's accuracy, the testing dataset was fed into the trained model to get predictions. Then, these predictions were compared to the ground truth labels to calculate the model's accuracy. Machine learning evaluation metrics such as precision, recall, F1 score, and confusion matrix were also employed to evaluate the model's performance.

Once the model's performance was assessed, necessary modifications or adjustments could be made to improve its accuracy and generalization performance. In conclusion, the testing phase is an essential step in this project's machine learning process because it assures the model's ability to make accurate predictions on new, unseen data, which is crucial for its real-world applications.

Training:

In this project, the training of machine learning models comprised various crucial steps. The first step was to collect and pre-process a dataset to make it suitable for training. The pre-processing steps included cleaning the data, normalization, and selecting relevant features. After the pre-processing, the dataset was split into training and validation sets. The training set was used to train the model, while the validation set was utilized to assess the performance of the model during training and prevent overfitting.The next step was to choose the most appropriate machine learning algorithm for the task at hand. The selection of the algorithm depended on the type of problem, such as classification or regression, and the dataset's characteristics. After selecting the algorithm, the model was trained using an iterative process. During each iteration, the model was provided with training data, and the algorithm adjusted the model's parameters to minimize the error between the predicted and actual outputs.The training process continued until the model's performance on the validation set reached a satisfactory level. The performance was measured using different metrics such as accuracy, precision, recall, and F1 score, depending on the type of problem. Finally, the trained model was tested on a separate test set to evaluate its generalization performance. The test set was independent of the training and validation sets and was used to simulate the model's performance in real-world scenarios.In summary, the training of machine learning models in this project involved several steps, including data pre-processing, algorithm selection, iterative training, and performance evaluation. These steps ensured that the models were accurate, reliable, and able to generalize to new data.

Validation

Validation is a critical step in machine learning projects to ensure that the model has learned from the data and can generalize well to new data. In this project, cross-validation techniques are utilized for the validation of the machine learning model. Cross-validation is a method where the data is divided into several folds, and the model is trained on each fold while being tested on the remaining folds. This technique helps to assess the model's performance on different subsets of data and ensures that the model is not overfitting to a specific subset of data.K-fold cross-validation is a popular cross-validation technique used in this project, which involves dividing the data into K equal-sized folds. The model is then trained on K-1 folds and validated on the remaining fold. This process is repeated K times, with each fold being used once as the validation set. Another cross-validation technique utilized in this project is stratified k-fold cross-validation, which ensures that each fold contains an equal distribution of target classes. This technique is useful in dealing with imbalanced datasets, where one class has significantly fewer samples than the others.Various performance metrics such as accuracy, precision, recall, F1 score, and ROC AUC are used during the validation process to evaluate the model's performance. These metrics help to identify any issues with the model and guide further improvements. Overall, validation is a crucial step in machine learning projects, and cross-validation techniques ensure that the model is robust and can generalize well to new data.

4.1 EXPERIMENTATION AND RESULT

The project begins by selecting only 400 images from each folder, which are then converted into arrays. The input file is scaled from 0 to 255, which is the range of the least and most common RGB values, to the range of 0 to 1. The dataset is then split into 70% training images and 30% testing images. Image generators are created to conduct random rotations, motions, inversions, civilizations, and sections of the image set. Backend switches that support both the "first channel" and the "last channel" architecture are created. The Conv =>Relu => Pool method is then performed, with a convolution layer consisting of 36 filters with a 3 x 3 core and relu activation. Maximal aggregation, batch normalization, and a 27% reduction are added to the model. Dropout is used as a control technique to prevent complex collaborative input from being corrected during training, minimizing neural network readjustment. Two sets of (Conv =>relu) * 2 => pool blocks are then created, and ReLU is used as a collection of layers that are all connected. The model employs Adam's Hard Optimizer, and the network begins at the point where model.fit_generator is called. The goal is to add data, train test data, and select the number of training epochs, with an epoch value of 26 chosen for this project.

4.5 RESULTS

4.5.1 Result of Mango Leaves:

Fig 4.3: This image belongs Mango_Bacterial_Spot with a 92.63percent confidence

Fig 4.4: This image belongs Mango_ Healthy with a 92.63percent confidence

4.5.2 Result of Potato Leaves:

Fig4.5: This image belongs Potato_ Early_Blight with a 97.63percent confidence

Fig4.6: This image belongs Potato_ Late_Blight with a 97.63percent confidence

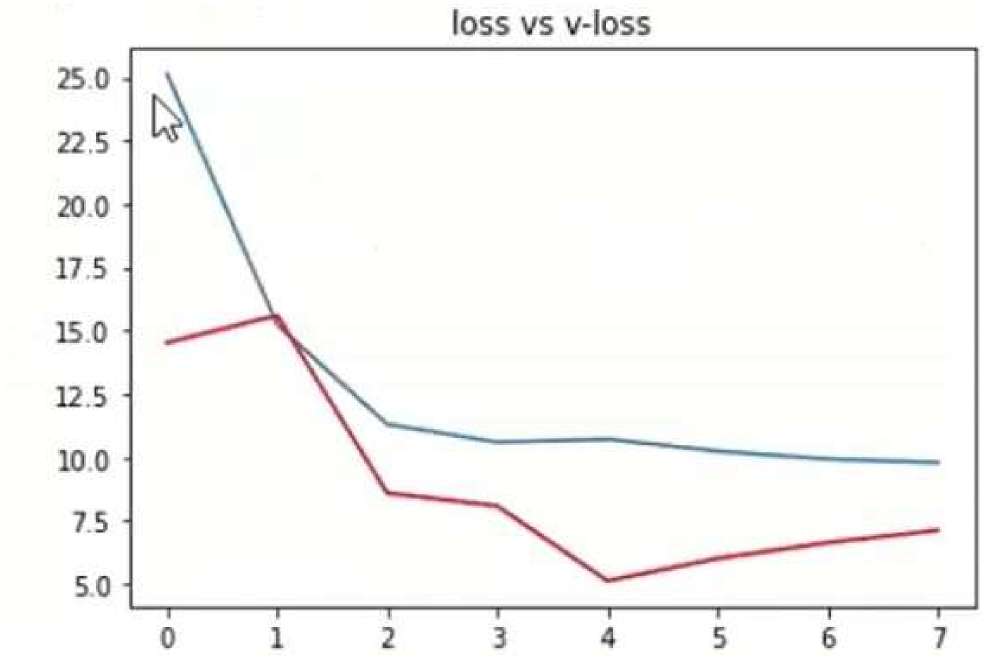


Fig 4.7: Loss of Training and Validation

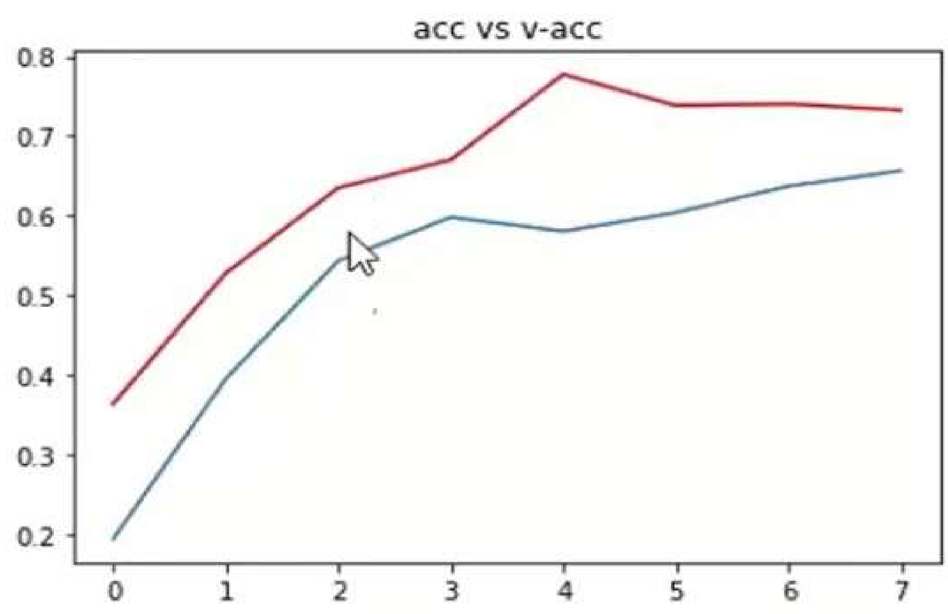


Fig4.8: Accuracy of Training and Validation

CHAPTER 5

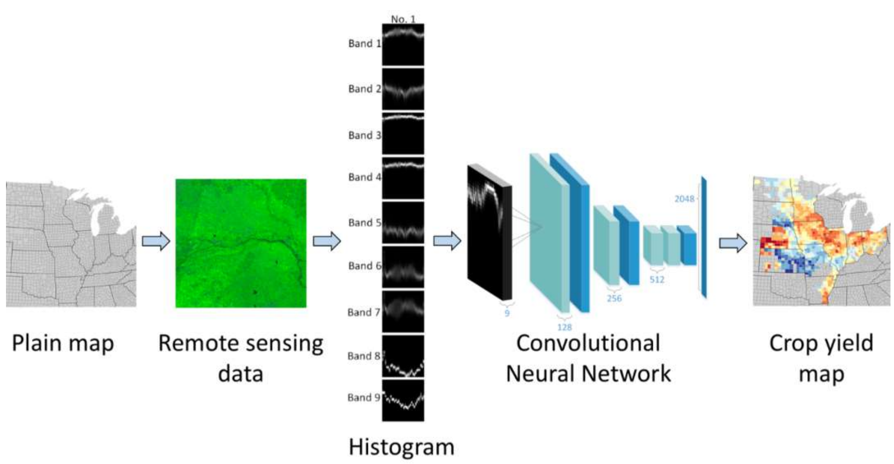
CONCLUSION AND FUTURE WORK

Conclusion:

In conclusion, the proposed plant disease identification system using CNN is effective in detecting plant diseases accurately. The results obtained from the experiments show that the model is efficient in diagnosing diseases in plant leaves. The image processing techniques, including segmentation, colour space conversion, and image enhancement, helped in pre-processing the images, thus improving the performance of the model. The accuracy obtained for the classification of diseases in plant leaves is promising and suggests that the proposed model can be used for real-world applications.

Future Work:

The proposed system can be further improved in several ways. One potential area for improvement is the dataset used for training the model. A more extensive and diverse dataset can be used to train the model and enhance its performance. Another possible improvement could be the integration of other image processing techniques to further enhance the accuracy of the system. Additionally, the proposed system can be extended to identify other plant parts, such as stems and fruits, to identify diseases accurately. Overall, the proposed system has great potential for improving crop management and reducing losses due to plant diseases.



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PAPER PUBLICATION

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Plat Leaf Disease Detection using Internet of Thing and Machine Learning

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Abstract : Crop diseases are a noteworthy risk to nutrition security; however their quick distinguishing proof stays troublesome in numerous parts of the world because of the non attendance of the important foundation. In this research article authors have designed a model for the detection of plant disease using Internet of things (IoT) and machine learning models. The main goal is to guarantee farmers' early detection of plant diseases, which will reduce the need for pesticides. A more stable and wealthy society is made possible by eliminating the problem of plant diseases. Farmers click the image of leaf and sensors with Arduino sends the real time data to cloud where think speak will visualize the data which was tested and validated using machine learning model is implemented by existing online database. Emergence of accurate techniques in the field of leaf- based image classification has shown impressive results. Support vector machine results in 94.65% accuracy.

Keywords : Plant leaf detection, Arduino, Internet of things, Classification

I. INTRODUCTION

The economy of our nation is heavily reliant on agriculture. Crop damage may result in unforeseen losses that have an influence on the farming sectors' output, which will then have a direct impact on the economy [1]. Therefore, caring for the plants is essential to upholding the high standards of agriculture and ensuring effective output and profit. It is not

PLAGIARISM REPORT

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