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DESIGN AND IMPLEMENTATION OF RC ROBOT FOR MULTIPURPOSE SPRAYING VIA APPLICATION

Dr. Vidhya D S. [1], Michelle Araujo e Viegas [2], Aadnan khan [3], Mohd Adnan Khan [3]

[1] Associate Professor, Don Bosco College of Engineering, Goa University, Goa, India
[2] Assistant Professor, Don Bosco College of Engineering, Goa University, Goa, India
[3] Student, Don Bosco College of Engineering, Goa University, Goa, India

ABSTRACT

The agriculture sector demands significant labor and resources, leading farmers to adopt automation. However, agricultural robots remain costly and complex, slowing adoption. Conventional pesticide spraying poses health risks and causes waste. To address this, a low-cost agricultural robot is developed to monitor crops and spray fertilizers and pesticides. The prototype includes a wheeled robot, spraying mechanism, wireless controller, and camera for crop health analysis. While its coverage is slightly lower than manual labor, it significantly reduces labor costs and resource wastage. With extended battery life, it ensures efficient operation. Future enhancements include full autonomy via rail- or line-following technology.

Keywords: Agriculture Sector, Automation, Health Risks, Pesticide Spraying, Full Autonomy

Corresponding Author
Dr. Vidhya D S.,
ds.vidhya@dbcegoa.ac.in

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1. INTRODUCTION

As the backbone of the Indian economy and the source of food security for its enormous population, agriculture is an essential part of the country's socio-economic structure. India has become one of the world's top producers of a variety of commodities, including tomatoes, thanks to its varied climate and lush agricultural area. However, the prevalence of leaf-related illnesses frequently risks the production of tomato crops in India, resulting in significant yield losses and financial consequences for farmers.

Solanum lycopersicum, the scientific name for tomatoes, is one of the most extensively grown and consumed vegetables in the nation. They are extremely vulnerable to a wide range of illnesses brought on by pathogens, including viruses, fungus, bacteria, and nematodes. The leaves, which are vital photosynthetic organs necessary for plant growth and fruit production, are where these illnesses mainly show themselves. These diseases have the potential to spread quickly if untreated, seriously harming tomato plants and risks agricultural productivity as a whole.

Indian farmers and agricultural researchers have been working hard in recent years to comprehend the many tomato plant illnesses. To mitigate the impact of these diseases, they have been investigating cutting-edge methods and integrated pest management strategies through study and field testing. Technological developments and information availability have also made it easier to share best practices and knowledge with farmers nationwide, enabling them to make knowledgeable decisions about disease prevention and management

The goal of this study is to contribute to the existing knowledge already available on tomato leaf diseases that are common in Indian agriculture.

We want to offer useful insights that can help farmers, researchers, and policymakers tackle the difficulties presented by tomato leaf diseases by examining the signs, causes, and management approaches of these conditions.

Our study aims to find sustainable solutions and efficient preventive methods that will help reducing crop losses and guarantee the long-term sustainability of tomato farming in India. In conclusion, researching tomato leaf agricultural diseases in India is crucial to resolving the difficulties that farmers have. By improving our knowledge of these diseases and creating practical management plans, we can safeguard tomato crops, increase agricultural productivity, and contribute to the overall growth and development of the agricultural sector in India.

2. BACKGROUND

[1] Remote control systems have been widely explored in agriculture for various applications. Research by Li et al. (2018) presented a remote-control system for agricultural machinery, enabling operators to control vehicles from a distance. The study highlighted the benefits of remote control, including increased safety and improved maneuverability, which can be adapted to an RC vehicle for crop management purposes. [2] Precision agriculture techniques have gained attention for optimizing fertilizer ap-plication in crop management. Studies by Shen et al. (2019) and Gao et al. (2020) discussed the use of precision agriculture technologies, such as variable-rate fertilization, to optimize nutrient distribution in agricultural fields. Incorporating a spraying arm into an RC vehicle provides a means to implement targeted fertilizer application based on specific crop requirements. [3] Robotics and automation have shown great potential in agriculture. Studies by Zhang et al. (2018) and Zhang et al. (2020) discussed the integration of robotic systems for various agricultural tasks. These systems encompassed autonomous navigation, precision spraying, and crop monitoring. These systems included crop monitoring, precision spraying, and autonomous navigation. Real-time data processing and decision-making algorithms are crucial for improving the capabilities of robotic systems in crop management, according to the literature [4]. In order to enable remote control of agricultural vehicles, wireless communication and control systems are essential. Research by Mota et al. (2019) focused on the development of wireless communication architectures for remote control and monitoring of agricultural machinery. They discussed the implementation of communication protocols, such as Zigbee and Wi-Fi, for reliable and efficient control signals transmission. [5] Several case studies have demonstrated the successful integration of remote-control systems, precision agriculture, and crop disease detection. For instance, research by Chen et al. (2020) presented a case study on remote control and autonomous navigation of an agricultural robot equipped with a spraying system. The study showcased the advantages of precise control and targeted spraying in crop management. [6] For agricultural robots to operate successfully, navigation and path planning are essential. Research by Ren et al. (2019) presented a review of navigation and path planning algorithms specifically designed for agricultural robots. For safe and effective field operations, the study emphasized the significance of terrain mapping, obstacle avoidance, and effective path planning algorithms.

3. METHODOLOGY

Figure 1 below flow chart illustrates how the receiver receives the input from the IR remote and motor driver is used to operate the motor [6]. Image processing is used to process the camera's input into the Raspberry Pi, which is then used to receive the herbicide is sprayed by application using the data from the camera and Wi-Fi module.

Figure 1

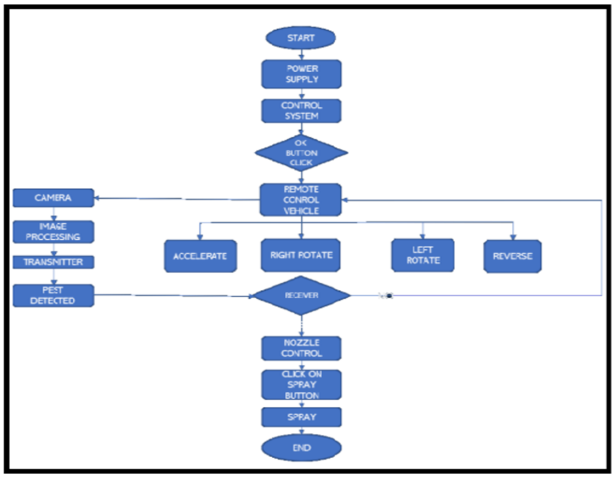

Figure 1 Flowchart

a) IR Remote Controller

The IR controller works as an input device that allows users to control the system remotely. Users can send specific commands or signals to the system by pressing buttons on the remote control.

b) Arduino Nano

The Arduino Nano board is responsible for receiving the infrared remote control signals. It works like a microcontroller, which means it can read these signals and interpret them as commands [7]. The Arduino Nano processes the received signals and determines the appropriate actions based on the received command. Figure 2 shows block diagram of RC robot system

c) Motor Driver

The motor controller is a piece of hardware connected to the Arduino Uno. It provides the necessary control signals to control the motors connected to the system. When the Arduino Uno receives commands from the infrared remote control, it sends the corresponding signals to the motor driver to control the speed, direction and other parameters of the connected motors

Figure 2

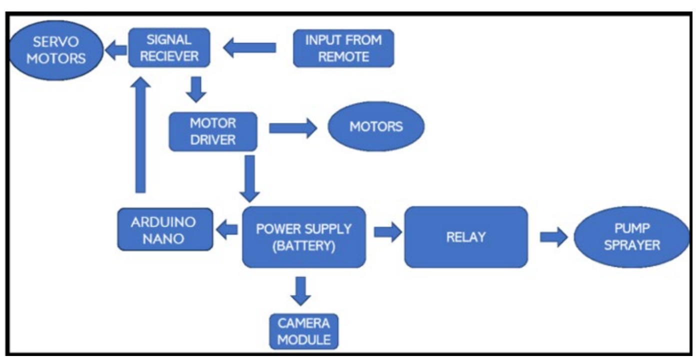

Figure 2 Block Diagram

d) Camera

The system includes a camera that records images or videos. The camera is probably connected to a computer or an Arduino Uno board.

e) Wi-Fi module

The camera and computer can communicate wirelessly thanks to the system's WiFi module. The WiFi module enables the transmission of data from the camera

to the computer without physical cables. It creates a network connection between the camera and the computer, allowing data to be transferred wirelessly.

f) Pesticide Application

The system includes a mechanism to spray the pesticide based on the information received from the camera. A camera records images or videos, and image processing algorithms running on a computer analyze those images to identify certain objects or conditions [8]. Once the desired targets or conditions are identified, the computer application can send commands to activate the pesticide spraying mechanism. The WiFi module transmits these commands from the computer to the insecticide spraying mechanism and starts the spraying process.

g) Image Processing

Images captured by the camera are processed on a computer using image processing techniques. Image processing involves analyzing, processing and extracting information from images to produce desired results. This may include tasks such as object detection, image recognition or image enhancement. The specific image processing algorithms and techniques used depend on the application requirements [9].

h) Image Processing Steps

In the below figure 3 it shows the CNN model generated and the classification of leaf disease based on the dataset provided to the model.

Figure 3

Figure 3 Image Processing Flowchart

i) Datasets

Figure 4 shows healthy leaf and other different leaves. A healthy tomato leaf is typically green in color and has a smooth texture. It is free from any signs of disease or pest damage. The leaf should be pliable and not wilted or discolored. Healthy leaves are important for photosynthesis and overall plant vigor. Proper care, including regular watering, balanced nutrition, and adequate sunlight, can help maintain the health of tomato leaves [10].

Figure 4

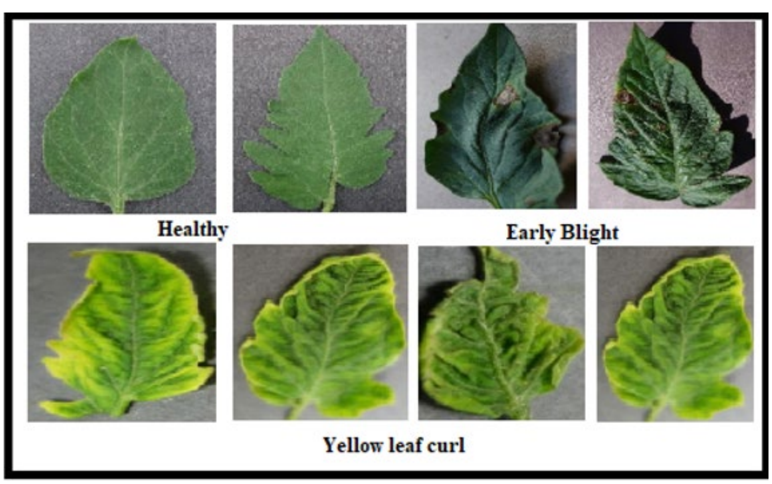

Figure 4 Healthy Leaf Sample

A frequent fungus that infects tomato plants is called early blight. Early blight is characterized by dark, spherical lesions on the plant's lower leaves that have concentric rings. As the disease progresses, the lesions may enlarge and cause the leaves to turn yellow and eventually die. Fungicides and proper plant care, such as pruning infected leaves and providing adequate spacing between plants, can help manage early blight.

Tomato yellow leaf curl virus is one of several viruses that cause the viral disease known as yellow leaf curl, which affects tomato plants [11]. Symptoms of yellow leaf curl include upward curling of leaves, yellowing of the leaves, and stunted growth. Infected plants may also produce fewer fruits or have fruits with poor quality. There is no cure for yellow leaf curl once a plant is infected, so prevention is key. Measures such as using virus-free seedlings, controlling whiteflies (which transmit the virus), and removing infected plants can help prevent the spread of yellow leaf curl.

j) Dataset Preparation

To train the tomato leaf disease detection model, a dataset comprising photos of healthy leaves, leaves with early blight, and leaves with yellow leaf curl disease is required. The sources, picture labeling, and dataset organization are all covered in this section’s description of the dataset collection procedure. It also emphasizes how crucial a diverse and representative dataset is for building a strong model.

Figure 5

Figure 5 Datasets

Data Augmentation and Preprocessing Techniques for enhancing images are used to expand the dataset and enhance model generalization [12]. The data augmentation methods used to increase the model's ability to manage variations in leaf images are explained in this section. In order to standardize the input data, image preprocessing techniques like rescaling and normalization are also used.

Figure 6

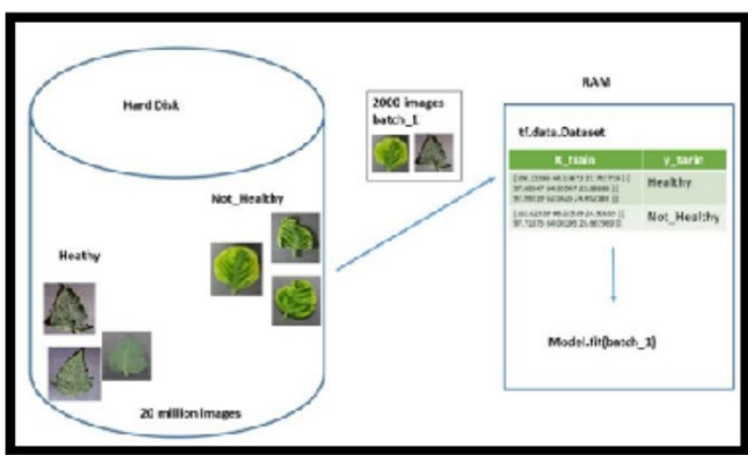

Figure 6 Processing

k) Model Architecture

The deep learning model for tomato leaf disease detection is constructed using the Tensor Flow-Keras framework. Convolutional layers for feature extraction, max-pooling layers for down sampling, and fully linked layers for classification make up the model's architecture, which is described in this section. The architecture is built using the VGG16 as a starting point and then modified to address the particular issue.

l) Training Process

Using the provided dataset and a batch-wise training method, the model is trained. The training parameters, including batch size and epoch count, are described in this section. It describes how to load and enhance photos using the Image Data Generator class. Accuracy and loss metrics are provided as the model training process progresses.

m) Model Evaluation

A distinct validation dataset is used for evaluation in order to assess the trained model's performance. Among the evaluation metrics mentioned in this section are accuracy, precision, recall, and F1 score. By examining the confusion matrix, the model's ability to differentiate between each category of tomato leaf disease is evaluated. The evaluation results demonstrate the model's effectiveness in identifying and classifying diseases.

n) Real Time Disease Detection

A real-time system for the detection of tomato leaf disease uses the trained model [13]. This section describes how to use Open CV to grab a live video stream from a system-connected camera module. In order to execute real-time inference and deliver prompt feedback on the presence of illnesses in the photographed tomato leaf images.

4. RESULTS AND DISCUSSION

The remote-controlled car was built which consists of a motor driver, battery, two planetary motors, XT60 connector, belt and pulley, robot wheels, shaft and shaft coupler. Aluminum rods were used in the construction of the arm, and two servo motors were positioned to allow for two-axis rotation.

Figure 7

Figure 7 RC with Arm Implementation

The arm was placed on the robot and the servo motors are connected to the receiver of the remote controller.

Figure 8

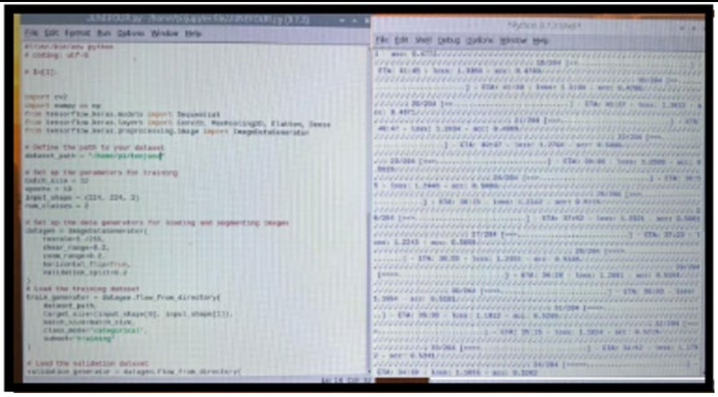

Figure 8 Classification Model

S

The dataset is separated into training and validation datasets, and the convolution neural network model was ready for uploading to the Raspberry Pi. The convolution neural network model is uploaded to the Raspberry Pi after the necessary libraries have been downloaded.

Figure 9

Figure 9 Leaf Detection Using Image Processing

Figure 10

Figure 11 Image Processing for Leaf Detection

Based on the dataset provided the leaf is classified using the CNN model. Blynk IOT app was used for controlling the spraying of the pesticide.

Figure 11

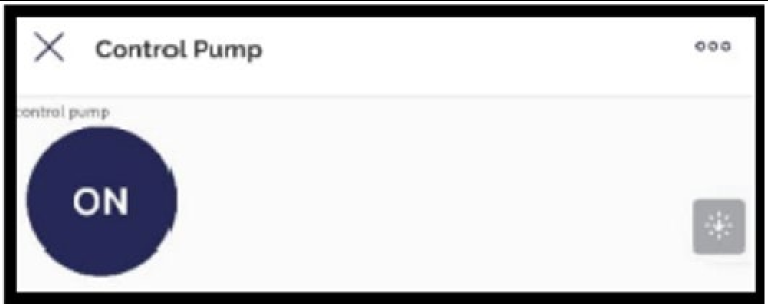

Figure 11 Blynk Interface for Spraying

5. CONCLUSION AND FUTURE SCOPE

The development of a low-cost agricultural robot for crop monitoring and pesticide spraying presents a promising solution to the challenges faced by farmers. By integrating automation, this prototype significantly reduces labor costs, minimizes health risks associated with pesticide exposure, and optimizes resource utilization. While its coverage is slightly lower compared to manual labor, the robot's efficiency and cost-effectiveness make it a viable alternative, especially for small and medium-scale farms. The inclusion of a wireless controller and a camera-based crop health analysis system further enhances its functionality, enabling farmers to make data-driven decisions. With extended battery life, the system ensures prolonged operation, increasing its practicality in real-world applications.

CONFLICT OF INTERESTS

None.

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None.

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