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**Full Paper**

# A Novel Machine Learning based Autonomous Farming Robot for Small-Scale Chili Plantations

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**Abstract**

The agricultural sector is a major economic force in Sri Lanka, which contributes to the national economy, food security, and employment. The traditional methods practiced by farmers mainly drove the growth of the agriculture sector over the last 2500 years. However, these traditional methods have often been ineffective against pest attacks in recent years causing significant losses to farmers and threatening food security. To counter these issues, officials and researchers have started formulating novel technology-based smart solutions. This study proposes a smart, autonomous mobile robot that can help detect pests and diseases in advance and assist in crop estimation of chili plants. The model is created as such for pest and plant disease detection in small-scale chili plantations with the hope of using it in other crop types for the same purpose in the future. Thus, the proposed approach together with the developed model can be used to enhance the growth of other plants as well. Identification of the type of garden and the detection of pests and plant diseases are achieved using machine learning techniques while the identification of nutrient deficiencies is achieved using image processing techniques. This proposed mobile robot incorporates sensory inputs, machine learning, robotics, and image processing. Furthermore, a mobile application acts as the interface between the user and the robot.

**Keywords:** Autonomous navigation, image processing, machine learning, pest detection, plant disease detection

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## Introduction

Pest and plant disease detection are some of the main issues that should be resolved in order to optimize the agricultural sector. Over the last few decades, many agriculture-related robots were designed to support the agriculture sector in Sri Lanka [1]. However, a critical drawback of the available solutions is that they are focused on either detecting a particular pest or a plant disease but not both [2]. The work presented in this work is not only capable of detecting both pests and plant diseases but also provides necessary instructions to the farmer as to what precautions should be taken to mitigate such issues. The range of pests and plant diseases detected by the proposed approach (i.e., model) can be further increased by updating the database with a new set of information.

Gaps at the administrative level [2] and farmers' lack of knowledge [3] have resulted in their inefficiency in carrying out mitigation strategies to eliminate the threat posed by pests and plant diseases. As a result, farmers often tend to apply excess fertilizers to plants, thus causing discoloration and plant damage instead of resolving these issues. At the same time, knowledge of treating plant diseases is less reliable especially in Sri Lanka since it is treated by inspection. Both farmers and the local community are directly affected by such agricultural issues. As a matter of fact, the attack of the Fall ArmyWorm (FAW) caterpillar has affected large scale maize cultivations in Sri Lanka [4]. Farmers have failed to save their crops even after spraying pesticides since the spread of the caterpillar was not controlled in the initial stage. Measures taken by responsible authorities have also failed in most instances. Moreover, as local farmers who engage in agricultural activities take agricultural loans, they face difficulty paying back these loans since the yield during respective seasons is not as expected. This issue has resulted in an escalation of prices of affected crops, thus making it difficult for part of the community to purchase them. Hence, it is apparent that this catastrophe could have been avoided if the caterpillar was detected at an earlier stage.

The study is carried out for small-scale chili plantations in the context of Sri Lanka. We have chosen chili plantations as an initial step to prepare our detection model for pest and plant disease detection such that the scope of our work could be extensible in the future by training and deploying the detection model for other crop types. Many companies in Sri Lanka focus on providing solutions for agricultural problems [1]. Vega Innovations focus on developing agrotechnology in greenhouse conditions [1]. SAASbot, a fully autonomous farming robot was developed in Sri Lanka to plant seeds and maintain plantations until the point of harvesting [4]. But we propose a robot that has features of autonomous navigation, detection of pests, plant diseases and nutrient deficiencies and identification of the garden type. Additionally, it is not dependent on external environmental conditions and hence can be deployed in open environments. Hayleys Agriculture Holdings have introduced an agriculture drone for aerial spraying in challenging environments. They focus on fine-tuning it to meet environmental conditions in Sri Lanka [6]. In addition, Sumathi Information Technologies have invested on using drone technology for remote monitoring of crops in order to assess the health of the crops [7]. But it is required to capture images of the entire plant from ground level for our work, which cannot be achieved using drones. Also, the deployment of drones is highly dependent on external environmental conditions. Compared to these solutions, the scope of our proposed solution is higher. Unlike aerial views taken by drones, the proposed robot is capable of scanning the entire plant from ground level using its camera mechanism. The use of cloud computing is challenging in the context of Sri Lanka [8]. Hence, we have used edge computing in our work in order to limit resources and simplify the infrastructure of the proposed solution.

Majority of people in Sri Lanka are more biased to traditional methods in order to get rid of pests and plant diseases. They use pest management practices traditionally known as "Kem" methods by using sticky traps and light traps [9]. Implementing these traditional strategies has not been successful for Sri Lankan farmers in the case of the attack of the Fall ArmyWorm caterpillar. On the other hand, modern solutions are based on the concept of establishing a physical interaction between the robot and the surrounding environment [10]. These modern techniques incorporate the use of ICT in the field of agriculture [11]. Semi-autonomous systems are used to automate certain agricultural activities such as harvesting along with human supervision [12]. Another method is the use of autonomous aircraft systems in agricultural activities so that difficult terrains can be traversed and 3D models can be created more conveniently [13]. Using such autonomous systems for agricultural activities such as chemical spraying requires less labour and reduces the exposure of humans to chemicals. Land-based autonomous systems are also used for pest detection in control environments [14]. These systems ensure that pests are detected at an early stage, thus validating proper pest control. Many deep learning based approaches are made use of in order to detect plant diseases. Different methodologies are currently used for plant disease detection with ANN methods [15,16]. The accuracy achieved in the classification of plant diseases by using the ANN model is 94.67% on average [17], thus prompting the use of such deep learning models to solve complex tasks. Furthermore, implementing such solutions does not necessitate user training or user's possession of prior knowledge on the subject.

Unmanned aerial systems are vulnerable to weather conditions [18]. They are capable of operating for a comparatively short period while incurring high costs, thus being inefficient for the task of pest detection. Moreover, they are not able to capture a ground view of the plant of interest. Though land-based autonomous systems are capable of capturing better images of the target plant, they are confined to a control environment. The use of semi-autonomous systems demands human supervision in order to regulate robot navigation in different types of terrains. At the same time, in order to ensure reliable plant disease detection, a more advanced image processing technique, that gives better accuracy, has to be used.

The proposed robotic design is incorporated with techniques related to machine learning and image processing. It can be used in gardens with potted plants and plant beds. The model can then be used to ensure the detection of pests such as caterpillars, snails and white thrips. Robotics is used to ensure proper autonomous navigation of the robot without toppling. A satisfactory amount of technical abstraction can be introduced into this method so that the end user does not need to possess prior experience. The scope of this work can be extended in a way that the robot serves its purpose in other crop cultivations as well. Compared to other past designs, the proposed robot design is a low cost solution that is not affected by different weather conditions. The rocker-bogie structure is capable of traversing a stretch of agriculture land fully autonomously.

The rest of this paper is arranged as follows: Section 2 provides a background of available literature and highlight their limitations, Section 3 provides the detailed methodology and materials used in terms of robot navigation, the image processing technique used to find nutrient deficiency, machine learning, structure of the movable camera incorporated, mobile application and the robot architecture, Section 4 presents the results and discussion and finally, Section 5 bears our conclusions.

**Background**

In this section we summarise the recent developments of different robotic structures used in modern agriculture. Mueller-Sim et al. [13] focused on the application of autonomous aircraft systems in agricultural activities in terms of weed management, chemical spraying, field mapping etc. These systems have the ability to traverse rough terrains and the ability to create accurate 3D models with the use of depth sensors. They are also able to interact with the environment physically for sample collection and chemical spraying. Along with these advantages comes an equal share of limitations in terms of its dependency on weather conditions, cost of technology and software for sensing and the processing time. Such aircraft systems are able to fly for a short period of time in order to save power. It is only able to capture an aerial view of the entire field.

Most of the agriculture robots are semi-autonomous in order to reduce damage to crops and to use less resources. Kashiwazaki et al. [12] proposed a method for harvesting and pest control using a greenhouse partner robot system with human supervision. A four-wheeled autonomous robot incorporated with tracker sensors was designed to run on a guidance line only within the greenhouse environment. Since the protocol for long distance interaction was not included in the system, the robot is not able to traverse in open fields.

Fully autonomous mobile robotics is a field that emerges from machine learning. Hajjaj and Sahari [11] focused on a study based on the application of ICT into the field of agriculture with the use of flexible and adaptive automated systems while incorporating robotic arms with grippers. The use of single robot systems was emphasized in terms of their navigation, control, image processing and terrain handling in an agricultural environment. Though the efficiency of the system is high, technological limitations such as the lack of supportive software and infrastructure exist. Birrell et al. [19] focused on harvesting iceberg lettuce using an autonomous robot. A custom end effector was used in this method in order to harvest lettuce with minimum damage. The vision and learning system used for detection consists of two CNNs, thus allowing the vision system to localize and classify the crop successfully. Though the method of detection and harvesting are successful, the robot is bulky and the production cost is high. Autonomous mobile platforms such as Robotanist are developed to assist agricultural activities in corn fields. It is incorporated with techniques such as GNSS, LiDAR and cameras [20]. A rover named TerraSentia is also an autonomous platform while being ultra-compact and lightweight [21]. Tiwari et al. [22] have proposed a new robotic system to detect and treat pests in the context of greenhouse crop cultivations. This method paves way to witness increased yields and to minimize the use of pesticides. On the other hand, it is constricted to closed environments only.

Durmus and Ustundag [23] designed an autonomous robot to process and monitor chemical spraying, disease diagnosis, soil analysis and other agricultural operations. Cloud based service was also developed in order to establish communication between the robot and farmers’ mobile devices and vehicles used for farming while an RF link is required to connect the robot to the cloud. As a matter of fact, this method demands a high budget and certain issues based on network security, reliability and availability arise when dealing with cloud systems. In the case of edge-computing [24], such issues do not arise since an end-to-end encryption can be established between the robot and the user. It is inefficient to use currently-used sensors such as GNSS, LiDAR, stereo cameras and thermal cameras for navigation in home gardens with a small land area [20].

Bhange and Hingoliwala [25] suggested a web based tool to detect fruit diseases, specifically pomegranates. It requires an image to be uploaded to the web, which might cause unnecessary delays when there is a network issue. Jhuria et al. [15] focused on detecting diseases on fruits using the concept of Artificial Neural Network (ANN). Three feature vectors were taken into consideration namely, color, texture and morphology. Khirade and Patil [16] focused on using ANN methods to classify plant diseases by inspecting the images of leaves. Dalai et al. [26,27] used Regional Convolution Neural Network (RCNN) based detection mechanism using Deep Learning for pest detection. Currently, there are limitations in the available techniques to identify pest attacks, plant diseases or nutrient deficiencies. To overcome this agricultural issue, we propose an alternative solution based on machine learning concepts, image processing techniques and edge computing. It involves the design of a mobile autonomous robot, which can easily be used by farmers to detect common pests and diseases that plants are prone to by using appropriate object detection algorithms and efficient image processing techniques.

In this paper, we propose an autonomous mobile robotic design based on edge-computing with the objective of designing a control unit and localization and positioning algorithms with the use of image processing techniques in the context of small-scale chili plantations to approach random potted plants. Supervised learning techniques are fed to the deep neural network with inputs such as the speed of robot wheels, image, orientation, sense of wheel rotation to autonomously navigate in between rows of plant beds. It is required to establish effective communication between the user and the proposed robot in a user-friendly manner. We propose a method that involves a mobile application so that an individual without prior knowledge can manipulate the proposed robot via the mobile application. After training the model as desired for chili plantations, the model can be trained further and deployed for pest and plant disease detection in other crop types in the future.

**Materials and Methods**

In this section we present the materials and methods used in our work. The robot locates itself before navigating through the garden. It then identifies if it is a garden with potted plants, beds or a negative. If it is a randomly potted plant, it determines its position in the garden after which it starts scanning and approaching the nearest plants according to the given algorithm. An overview of the methodology is shown in Figure 1. A movable camera tray is used to scan the entire plant in order to detect plant diseases and pests. Any such plant diseases and pests detected in the scan are temporarily stored along with the location of the plant, the corresponding plant disease, the necessary treatment etc... This process takes place repeatedly after scanning other plants as well. In the case of plant beds, the robot is trained to traverse along the side of the plant bed. It scans and records data related to each and every plant in the plant bed while moving forward. Afterwards, the end user is able to access stored data via a mobile application in a user-friendly manner.

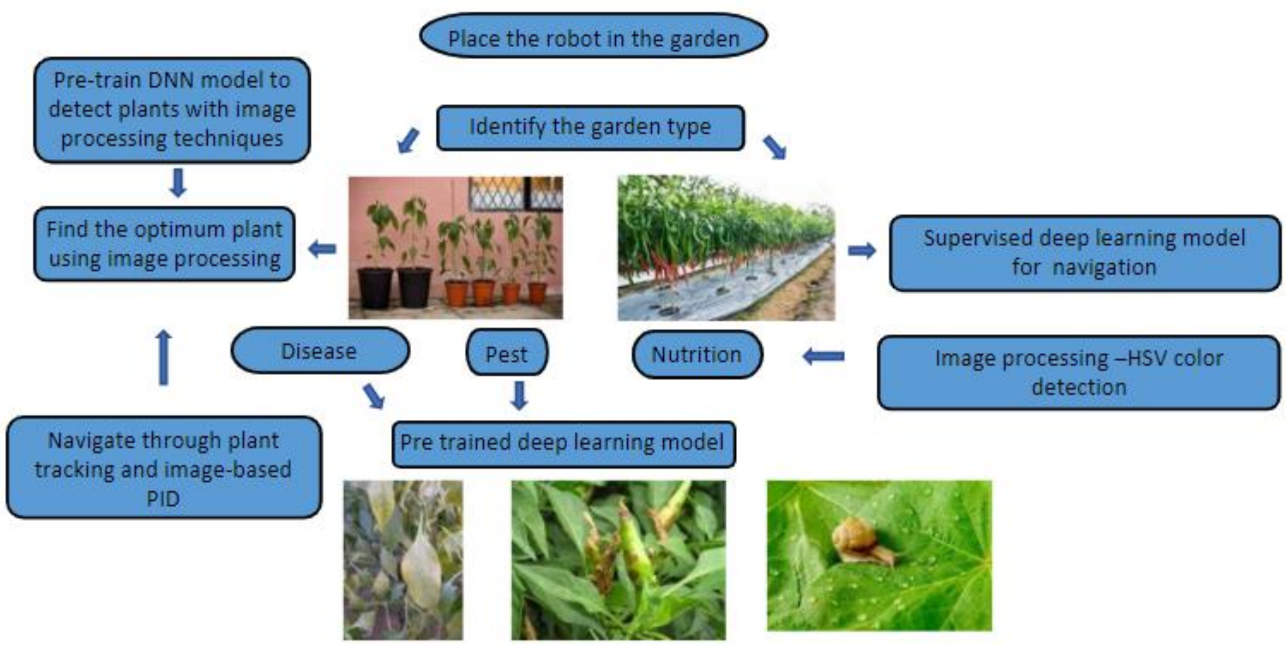



**Figure 1.** Overview of the methodology

The concepts of image processing, machine learning, deep neural networks and edge technology are used in our work to give solutions to certain agricultural issues. It is incorporated with the feature of autonomous navigation, thus requiring less human supervision and providing responses with less delay. Since sensor arrays are not incorporated in the system, the initial cost, estimated around 50,000 LKR rupees, is comparatively less. The key features thus mentioned are linked with robot navigation, plant detection, path following and identifying plant diseases and pests. These are discussed in the following subsections in detail.

***Navigation***

The state-of-the-art method involves the use of Simultaneous Localization And Mapping (SLAM) in robot navigation. The general procedure is to allow the robot to roam around the agricultural field in order to achieve simultaneous positioning and map drawing. Implementing this technique results in the additional consumption of power for robot navigation in order to draw the map. The robot has to navigate each and every time the placement of potted plants changes to get the map drawn, thus consuming unnecessary power. We propose a different navigation technique for the proposed robot to eliminate the need to draw a map to optimize resources. An overview of the proposed navigation process is shown in Figure 2.

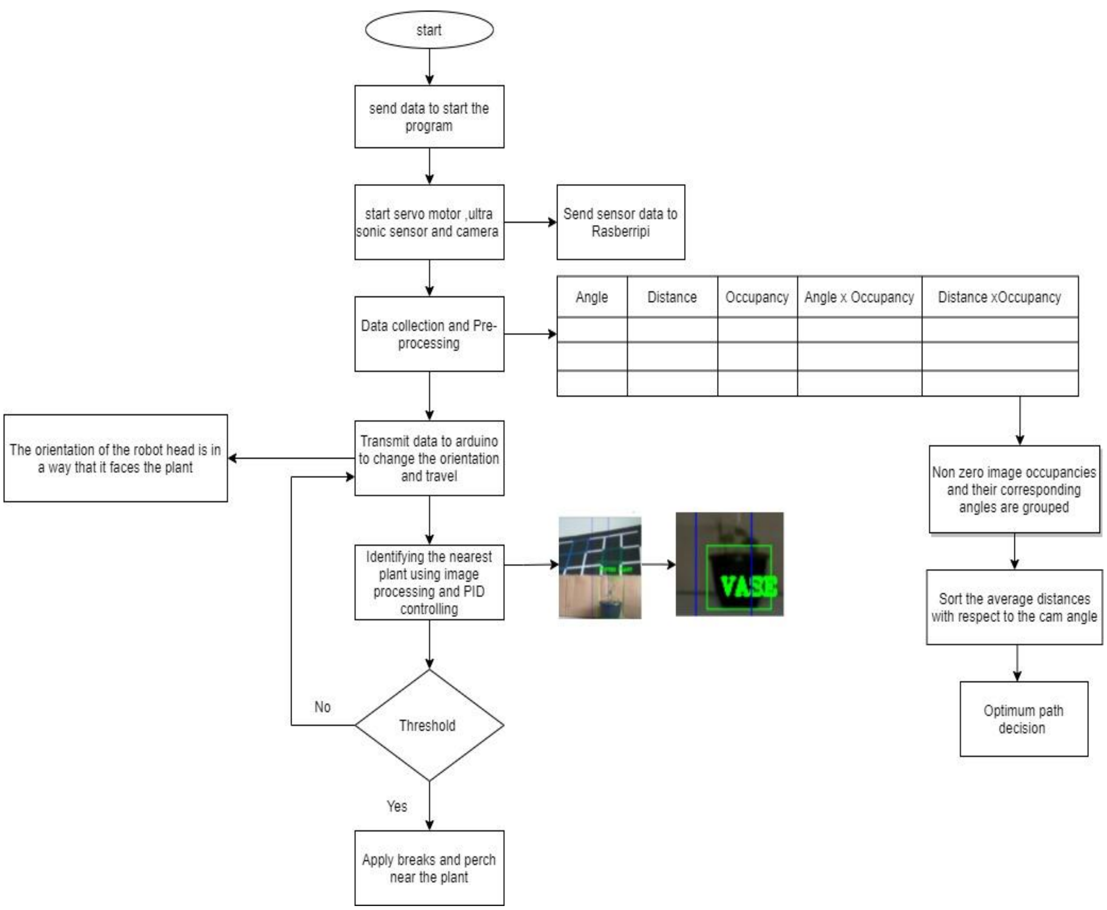



**Figure 2.** Overview of the navigation process

A dataset is prepared on potted plants, plant beds and negative images, which are images other than those of potted plants and plant beds. In order to demonstrate the performance of the model, Google images of potted plants, plant beds and negative images are taken. The TensorFlow machine learning library can be used to train the classification problem. There are many models such as VGG16 [28], ResNet [29] and Inception [30] to solve the image classification problem, out of which the Inception v3 model is used in our work. The proposed robot takes random images of the surroundings and feeds them to the model. After classifying the image to be a garden with potted plants or plant beds, the robot carries out relevant subsequent procedures. In the case of negative images, the robot halts its subsequent procedures.

If the classified image happens to be a random potted plant, the following procedure is carried out. A raspberry pi camera, which acts as the component to take the perspectives of the robot, feeds the captured image into the EfficientNet-Lite network [31], which is deployed to the raspberry pi single-board computer [32], in order to detect a plant or a pot in the image captured. In the meantime, the distance to the plant from the robot is estimated through occupancy by checking if the plant is within the given threshold. Along with that, raw data is collected from the ultrasonic sensor to draw a map approximately. The COCO dataset [33], which comprises the potted plant and vase categories out of a total of 91 object categories, is used to train the pre-trained network.

Data pre-processing is carried out using camera view data, ultrasonic data and camera data. The presence of a plant is reflected by the value of occupancy. Image occupancy is combined with distance and angle data to give non-zero and zero values. The set of zeros and non-zeros are grouped after which the length of all non-zero groups is determined and the average of the group with the highest frequency of non-zero values is computed. Finally, the average of all the groups with non-zero values to draw the approximate map. The same process takes place as the robot approaches a different plant.

***Image Processing***

The distance to the plant can be determined using image processing. The distance between the camera and the potted plant can be determined by considering the center point of the bounding box drawn by the neural network that bounds the potted plant and that of the potted plant. The camera is calibrated prior to determining the distance. The plant is placed at known distances in order to determine the distance. The area of the bounding box that bounds the detected potted plant is also recorded. Finally, using interpolation technique, a continuous line can be drawn using splines after which the equation of the line can be determined using MS-Excel as illustrated in Figure 3. The distance to a particular plant can be found as such.

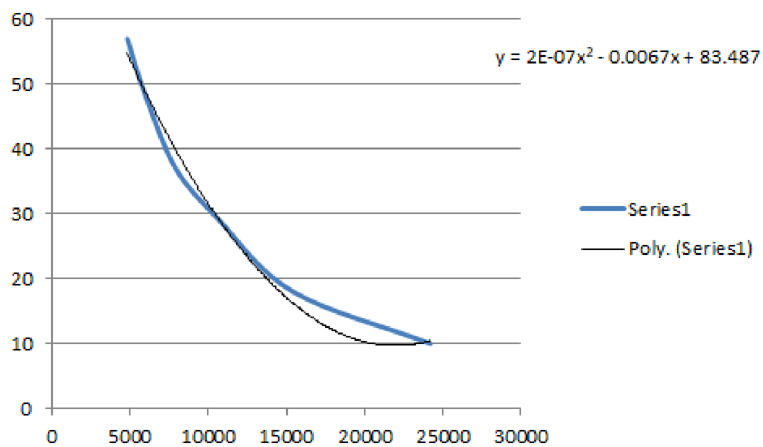



**Figure 3.** Interpolation of Manual distance vs contour area

In order to reduce the probability that the robot bypasses a plant, the following technique can be used. Angles falling in the range of 0 to 180 degrees with respect to the robot can be divided into 12 regions. A priority list is eventually created. The intention behind creating such a priority list is to minimize the probability that a plant is bypassed. The robot makes use of the priority list to approach the nearest plant. It approaches the plant with the highest priority. When the plant is behind the robot, it will not be captured in the next scan. Referring to Figure 4, if theta is less than beta, the robot approaches the plant whose distance is the least and occupancy is the highest. Otherwise, the robot approaches plants according to the priority list.

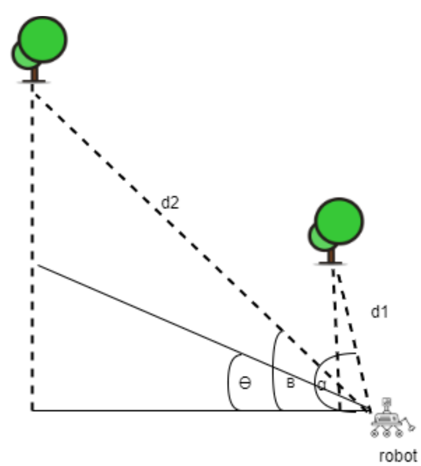
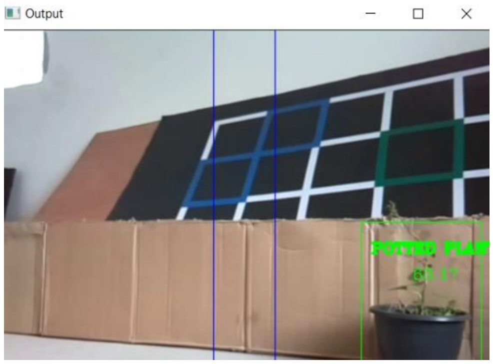
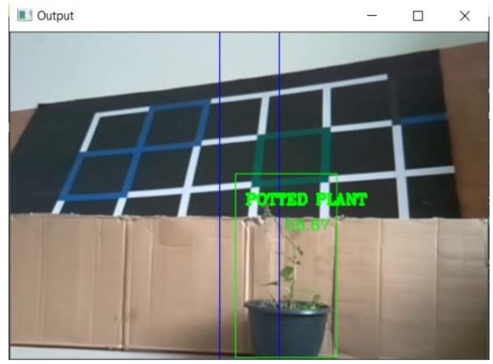



**Figure 4.** Geometric interpretation of the area in order to choose the first plant for scanning

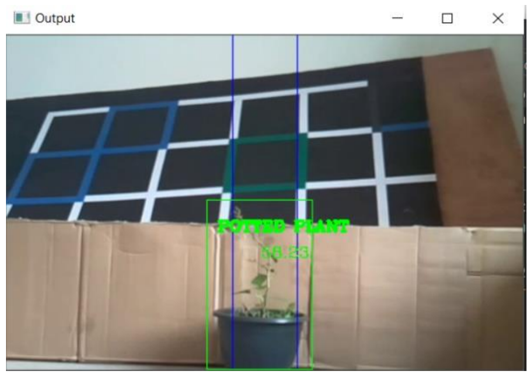
The robot moves in the direction of the desired plant and manoeuvres itself in such a way the detected plant is in the center of the frame as shown in Figure 5. When the plant is within the frame, an x value is calculated. The x coordinate denotes the extent to which the center of the plant is deviated from the center of the frame. This x value is fed into the code bunch of the PID function. The relevant rpm values of the left and right channels of motors are fed into the microcontroller unit.




(a)




(b)




(c)

**Figure 5.** (a), (b), (c) Plant tracking using PID controlling

The rpm and time are used to calculate the robot's distance. The rotated angle of the robot and the position of the plant are stored in a particular storage location. After scanning the approached plant, the robot moves to the next plant and scans it entirely. When the third plant is approached, the data of the first plant is discarded. Data regarding the remaining plants are used to calculate distances to the currently approached plant using trigonometry.

A deep neural network is trained to navigate between plant beds if the classified image is a plant bed. Collected and stored data is then used to train the deep neural network by making use of the supervised learning approach in order to ensure the autonomous nature of the robot. The gyroscope data, motor speed, ultrasonic sensor data and image data are gathered by running the robot through remote control via Bluetooth or wifi. The gathered data is stored in the storage of raspberry pi and are used to train the model in the PC. The trained model is then deployed to the raspberry pi. After the evaluation of the model, the robot is allowed to traverse the field for a test run. Afterwards, all decisions are taken by the deep neural network, which is deployed to the raspberry pi.

Also, the plant succumbs to nutrient deficiency depending on the composition of soil. In most applications, sensors are fixed to each plant in the garden in order to assess the health of the plant. This approach happens to be ineffective and incurs high cost. Alternatively, nutrient deficiency in plants can be identified by focusing on the color variation in plant leaves. We focus on identifying four categories of nutrient deficiencies according to this color variation [34].

- **Magnesium deficiency** - marked interveinal chlorosis (appears almost white), develops on the older leaves and then the middle-aged leaves, desired nutrition level is in the range 0.3 -1.2%.
- **Iron deficiency** - Deficiency occurs in the youngest expanding leaves at the tips of the branches, Most often observed in crops growing in alkaline soils [pH>7.0]
- **Potassium deficiency** - leaf bronzing, older leaves turn tan and brown at the margins, plants under K stress are smaller than normal and produce fewer and smaller leaves with thinner walls, deficiency is observed in lower leaves first and advances to middle leaves, desired nutrient level 3.0-5.0%
- **Nitrogen deficiency** - reduced growth, smaller leaves and fruits than normal, general yellowing of leaves and reduction of green color of fruit, deficiency observed in older leaves first, desired nutrient level- 3.0-5.0%

Sample images are gathered from the field. An image processing technique named Hue Saturation Value (HSV) [35] filter is used to find the upper and lower bounds of the hue and saturation values for each color of the nutrient deficiency. The HSV filter is created accordingly. Then the relevant color is extracted from the image. A machine learning approach is used to find if the region captured is a stem or a youngest expanding leaf. The images are then labelled and fed to the pre-trained model for training making use of the concept of transfer learning. Both programs are executed simultaneously. Thus, the robot is able to identify the nutrient deficiency if the color variation is in the youngest expanding leaves or stem as can be seen in Figure 6.

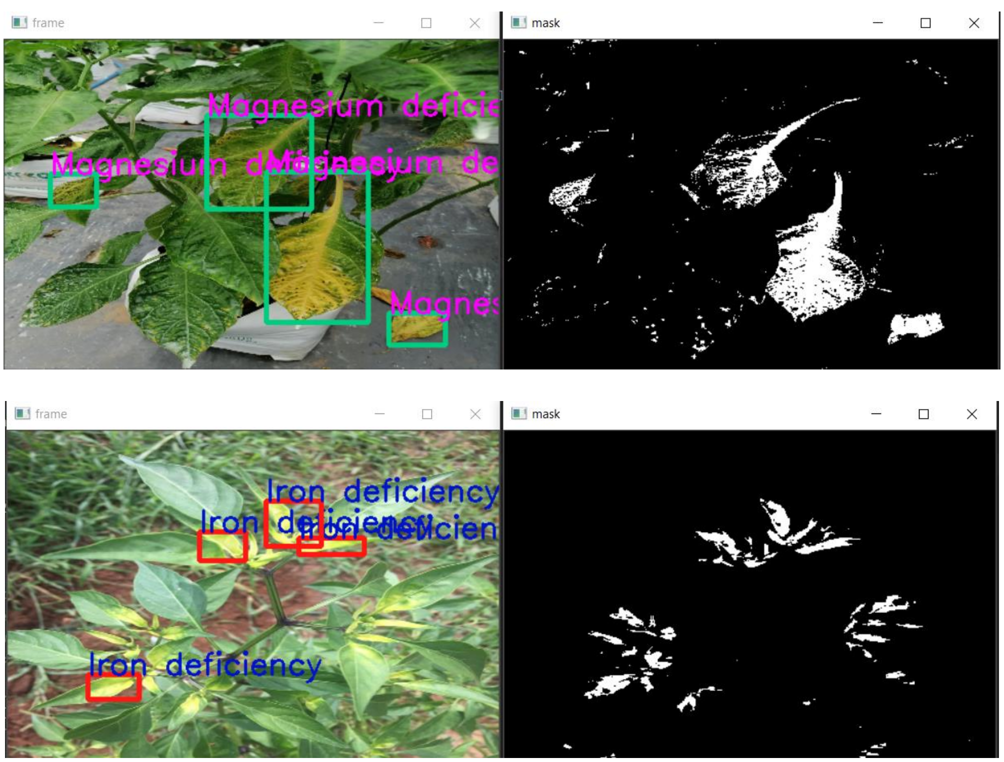



**Figure 6.** Identifying nutrient deficiencies using HSV filter

***Machine Learning***

We have used transfer learning methods in our training process since the traditional machine learning models require training from scratch which is computationally expensive and requires large amount of data to obtain good performance. Hence, transfer learning methods are computationally efficient and better results can be achieved using small data set as it has been pre-trained using COCO dataset [33].

In this scenario we have chosen EfficientNet-Lite from all the models of TensorFlow version 2 detection zoo model for the pest and diseases detection. Many experts have conducted researches about the precision and speed of this transfer learning zoo models [36]. Considering all these factors, we chose EfficientNet-Lite model as the optimum model which has better accuracy and detecting speed for the detection of pest and plant diseases. Additionally, EfficientNet-Lite is the optimum model that is compatible with the processing power of Raspberry pi as the edge device [37]. According to Figure 7 and 8, EfficientNet-Lite has the lowest model size and latency displaying an accuracy level above 74% compared to other models, thus being the most optimum resource.

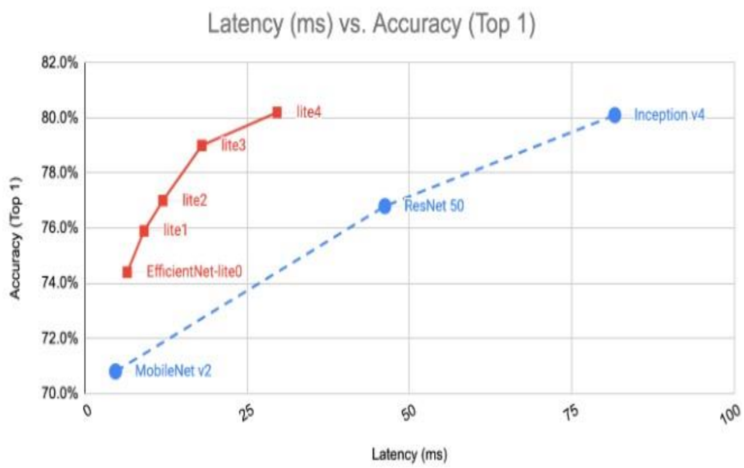



**Figure 7.** Latency vs Accuracy (Reproduced with permission. [38])


**Figure 8.** Model size vs Accuracy (Reproduced with permission. [38])

Images of caterpillars, snails, white thrips, curly leaves, bacterial spots, wilted leaves, chili plants are captured using the raspberry pi camera from agricultural lands and labelled. The images of chili plants are used to label ripe and unripe chilies. The EfficientNet-Lite model is trained and deployed to the raspberry pi. The model is then capable of detecting pests, plant diseases and estimating crops. The EfficientNet-Lite model is chosen for this purpose in order to manage resources and to get an optimum fps.

***4 DOF Movable Camera***

Since there is a need to scan the entire plant, the camera should be incorporated with the ability to rotate. The 4 DOF movable camera tray is made using CNC operating principles. Once the robot parks closer to the plant, the camera platform receives a signal to rotate the camera in the direction of the plant and then to move translationally along the z axis. The camera platform has the ability to move in the x-y plane. Actuators are connected to the camera platform in order to allow translational movements along x, y and z axes. A servo motor is connected to the camera platform in order to allow the rotation of the camera around the z axis. All the signals are given by the raspberry pi to the microcontroller unit to initiate rotation. The microcontroller passes signals to the motor driver, after which rotation is initiated such that the camera pole moves to the desired x, y coordinates. The target x, y coordinates of the camera pole are hardcoded and depend on the position of the robot with respect to the plant. Hence, after the robot stops at a plant, the position of the robot with respect to the plant is analyzed, whether it is on the left or right side. Then, the camera pole moves towards the plant to the respective x, y coordinate. The design of the camera platform designed using SolidWorks is shown in Figure 9. It is designed in a way that the entire plant is scanned such that relevant images can be captured and fed into respective models.

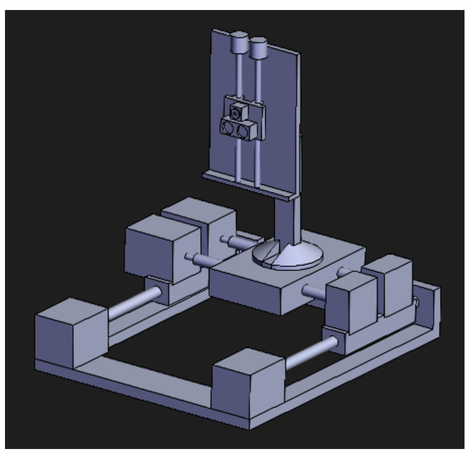


**Figure 9.** Structure of the camera platform

***Mobile Application***

Data is collected from the environment while the robot traverses the field. A mobile application is required to communicate gathered data to the user in a user-friendly manner so that the user is not required to have prior knowledge about the subject.

***Robot Architecture***

It is required that the surface of the garden is recognized in order to ensure proper navigation of the robot while overcoming obstacles such as stones, heaps of sand and mud puddles. We used the rocker bogie mechanism [39] in our robot architecture in order to enable robot movement without toppling. This architecture incorporates six wheels out of which the front wheels rotate about a hinge, thus introducing stability to the structure. The 3D model of the rocker bogie structure of the proposed robot that is designed using SolidWorks are shown in Figure 10.

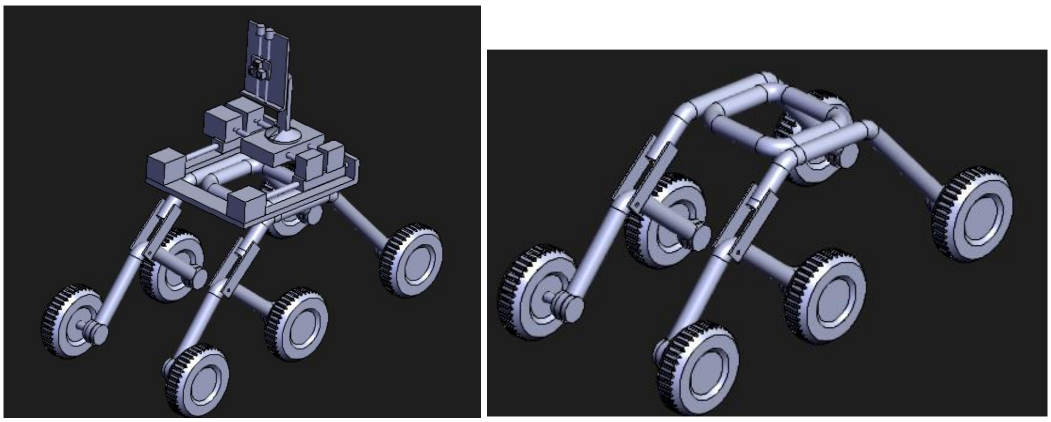


**Figure 10.** Rocker bogie structure

The results obtained with respect to each subsection mentioned above are explained in Results and Discussion Section.

The materials used in our work are as follows:

***Raspberry Pi***

The Raspberry Pi is a low cost, credit-card sized computer that has low power consumption. It can support the connection of many peripherals. It is equipped with Broadcom BCM277, Quad core Cortex-A72 (ARM v8) 64-bit SoC @1.5GHz and a 2GB LPDDR4-3200 SD RAM. It has a Linux Based operating System (Raspbian Buster). The decision-making process of this project is handled by this microcontroller unit. It also handles the image processing and machine learning process of this project as well.

***ESP32:***

ESP 32 is a Dual-Core 32-bit LX6 Microprocessor with clock frequency up to 240MHz. It has 520 KB of SRAM, 448 KB of ROM and 16 KB of RTC SRAM along with 34 Programmable GPIOs. The higher GPIO pins are utilized to control motors and the 4 DOF camera tray. High resolution of motor PWM allows smooth controlling of motors. It enables serial connectivity that includes 4 x SPI, 2 x I2C, 2 x I2S, 3 x UART, thus being able to communicate with Master Raspberry pi.

***IMU:***

IMU is an integrated 6-axis motion-tracking device that is incorporated with a 3-axis gyroscope, 3-axis accelerometer along with a dedicated I2C sensor bus. It is used to measure the angle of rotation. Magnetometer

HMC5883L is used to measure the value of the Earth's magnetic field along the 3 axes.

***Pi camera module:***

Pi camera module is a 5MP O5647 Camera Module. It has a CSI (Camera Serial Interface) interface and a still picture resolution of 2592 x 1944. It is used to capture necessary images that are to be fed to the model.

The system hardware overview is shown in Figure 11.

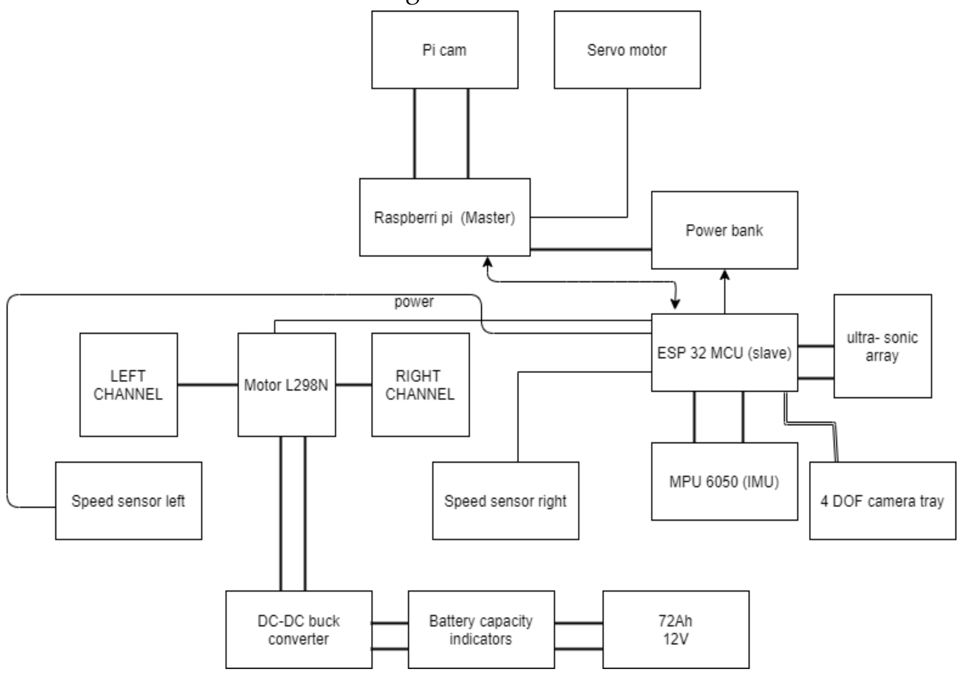



**Figure 11.** System hardware overview

***Anaconda Navigator***

Anaconda navigator is a free open source software desktop graphical user interface (GUI). It is used to launch applications such as Spyder, PyCharm Python IDE and Jupyter notebook after installing necessary libraries and preparing the suitable environment. The packages that are used for image classification and object detection are numpy, matplotlib, tensorflow, keras.lxml, pandas, Open CV. Data analysis, manipulation, preprocessing and visualization can be done more conveniently using this software tool.

***PyCharm Python IDE***

PyCharm Python IDE is an integrated development environment used for computer programming using python programming language. In this project, it is used to develop algorithms for navigation, image classification, object detection and decision-making.

***Arduino IDE***

Arduino IDE is used to program the Atmel and ESP32 microcontroller units. The Arduino IDE is created with a combination of C++ and Java languages. Motors and the 4 DOF camera are controlled according to signals transmitted by the Raspberry Pi and ESP32 microcontroller units.

***TensorFlow Machine Learning Library***

TensorFlow Machine Learning Library is an optimized machine learning library to easily imply calculations using many matrices. It is used for image classification and object detection tasks using transfer learning methods by importing the EfficientNet-Lite pre-trained model. 85 images were used for training while 13 images were used for testing purposes. The weights of the final layer of the pre-trained model are adjusted according to the number of classification.

## Results and Discussion Section

Agricultural robotics is a field that many researchers base their study on. Funds for research activities on this subject are escalating over the years. In this paper, the design of an autonomous agriculture robot with the capability of identifying pests and plant diseases is proposed. The EfficientNet-Lite model is chosen over other available models in order to ensure optimum resource usage. The Inception model is chosen to solve the image classification problem to enable the robot to identify the type of garden.

At the initial stage, the EfficientNet-Lite model identifies the type of garden, whether it is a garden with random potted plants, plant beds or if it is a negative as shown in Figure 12. Depending on the occupancy values, the detected random potted plant is approached according to the proposed algorithm. If the garden is identified to be a garden with random potted plants, the model tries to identify a plant or a pot in the image captured. Figure 13 shows the result of the model in identifying potted plants and vase in a garden with random potted plants.

We have used 85 images of pests, plant diseases and crops for training and 13 images for validation purposes. Pests and plant diseases are detected by the EfficientNet-Lite model as shown in Figure 14 and 15. The pests and plant diseases are detected with an fps (frames per second) of 5 fps and are surrounded by bounding boxes along with the class name and corresponding accuracies. Plant diseases such as bacterial spots, curly leaves and wilted leaves are detected in the same way as shown in Figure 15. Crop estimation is achieved by identifying ripe and unripe chilies in the images captured as shown in Figure 16.


**Figure 12.** Results of taking random images to identify the garden type (i.e. garden with potted plants or plant beds)

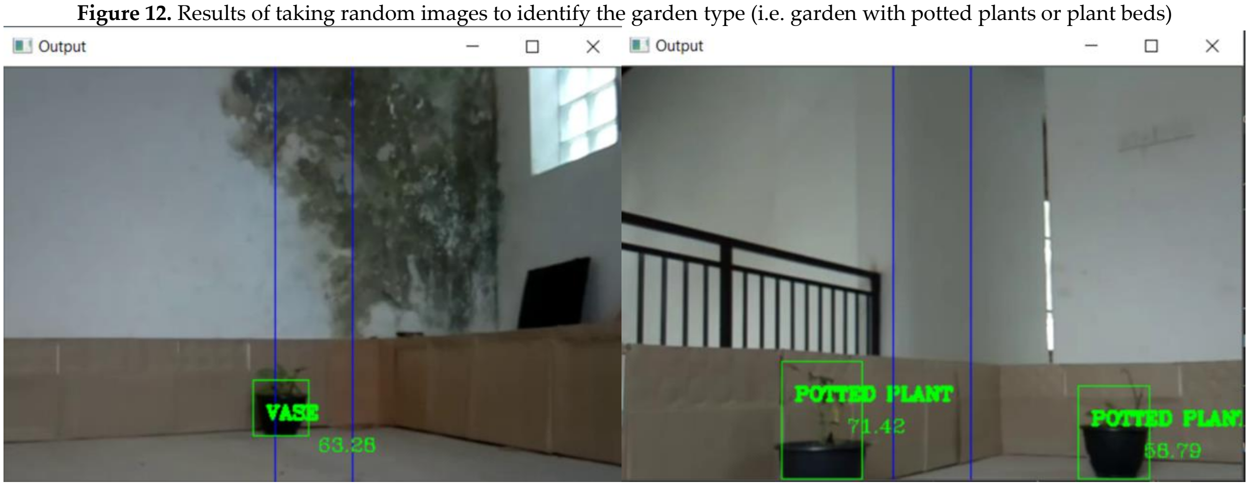



**Figure 13.** Identification of potted plants and vase by using EfficientNet-Lite model in random potted planted garden


**Figure 14.** Snail detection using EfficientNet-Lite model

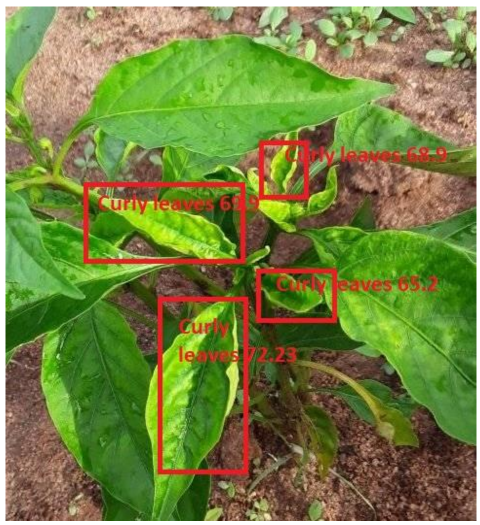



**Figure 15.** Detection of curly leaves using EfficientNet-Lite model

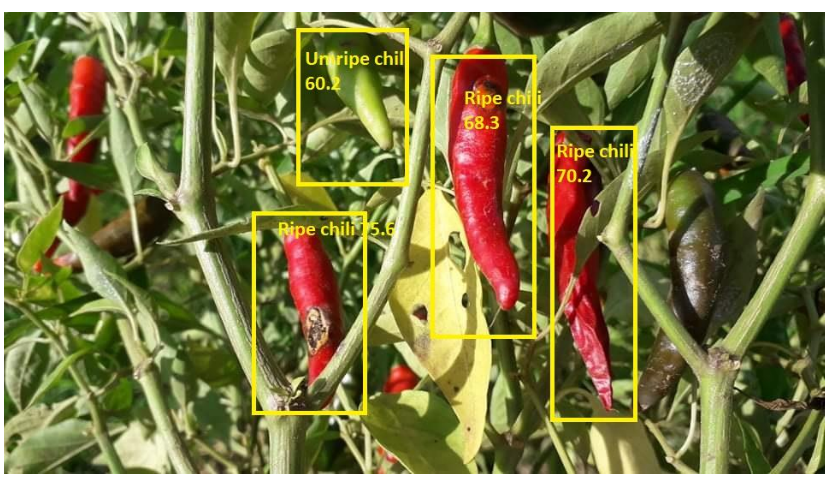



**Figure 16.** Crop estimation using EfficientNet-Lite model

In the training process, we used 100 epochs in order to train the dataset 100 times and set the batch size to 4. Validation loss of the model was achieved at about 37%, thus satisfying the lower loss value. The whole model was trained by setting up the parameter train_whole_model to True in order to fine-tune the whole model instead of just training the head layer to improve the accuracy of the model. During the training process, it is required to look at the value of validation accuracy at the end of each epoch to avoid overfitting. Then, after obtaining the desired AP value, that model is exported to the desired location by converting the model to TensorFlow Lite format. The default post-training quantization technique is full integer quantization [40]. Hence, quantization helps shrinking the model size by 4 times at the expense of some accuracy drop. This allows the TensorFlow Lite model to be smaller and to run faster on Raspberry Pi CPU.

As per the results shown in Table 1, AP and AR are averaged over multiple Intersection over Union (IoU) values. Specifically, the model has used 10 IoU thresholds of .50:.05:.95. The AP is averaged over all categories. Traditionally, this is called "mean average precision" (mAP) and there is no distinction between AP and mAP (and likewise AR and mAR). Our model has 69.63% AP for snails and 49.09% for curly leaves. Also, the AP values at several IoU values at 50 and 75 as 97.98% and 68.08% respectively. In COCO, there are more small objects than large objects. Approximately 41% of objects are small (area < $32^2$), 34% are medium ($32^2$ < area < $96^2$), and 24% are large (area > $96^2$). Area is measured as the number of pixels in the segmentation mask. After the training process, 66.16% AP is achieved for larger objects, 58.71% for medium objects and -1.0 for smaller objects. AR is the maximum recall given for a fixed number of detections per image. Accordingly, 76.66% Average recall is achieved for larger objects, 65.75% AR for medium objects and -1.0 AR for smaller objects is achieved using our model. AR results are such that we achieved 31.21% AR for one detection per image, 67.49% AR for 10 detection per image and 67.64% AR for 100 detection per image.

**Table 1.** Evaluation data of EfficientNet-Lite model

| **Description** | **Values** |
|---|---|
| Average precision (AP) | -1.0 |
| Average precision at IoU = .50:.05:.95 (AP) | 0.5936852 |
| Average precision at IoU = .50 (AP50) | 0.9798000 |
| Average precision at IoU = .75 (AP75) | 0.6808724 |
| Average precision for curly leaves | 0.4909968 |
| Average precision for snail | 0.6963736 |
| Average precision for large objects: area > $96^2$ (APl) | 0.6616505 |
| Average precision for medium objects: $32^2$ < area < $96^2$ (APm) | 0.5871219 |
| Average recall (AR) | -1.0 |
| | 0.7666666 |

| | |
|---|---|
| Average recall for large objects: area > $96^2$ (ARl) | 0.6575758 |
| Average precision for medium objects: $32^2$ < area < $96^2$ (APm) | |
| Average recall given 1 detection per image (ARmax1) | 0.3121212 |
| Average recall given 10 detections per image (ARmax10) | 0.6749417 |
| Average recall given 100 detections per image (ARmax100) | 0.6764568 |

Thus, the average precision generated by the model in the detection of pest and plant diseases are at satisfactory levels. According to Table 1, the model has a precision of 0.696 when rounded to 3 decimal places. This indicates the proportion of correct positive identifications of the model. Hence, our model is correct 69.6% of the time in the detection of snails. At the same time, our model has an average recall of 0.676 when rounded to 3 decimal places, thus being 67.6% for 100 detections per image. This indicates the proportion of actual positives that the model can identify correctly.

## Conclusion

Agriculture-specific navigation and a special image processing technique are used to meet the challenges of agriculture lands to assist farmers by notifying them before a crisis takes place. Though this robot is designed to assess the health of chili plants in terms of pest attack and plant diseases, it can further be extended to assess the health of other plants as well. Large sensor arrays can be incorporated in the mechanical structure in order to mitigate the overall cost of the design. The robotic structure can be modified by incorporating necessary components to the design in order to monitor the soil content, water percentage, temperature and lighting conditions along with a robotic arm with grippers to enable crop harvesting, thus allowing it to be used in large-scale farming in the future. Thus, a novel approach is proposed to solve prevailing agricultural issues in small-scale farming to support and to ensure the implementation of practical agricultural robots.

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