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Smart Pesticide Spraying Robot for Fertigation Farm

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Abstract

The overuse of pesticides in farming contributes to environmental pollution, health risks, and higher operational costs. This study proposes and designs a Smart Pesticide Spraying Robot for fertigation farms using artificial intelligence to enable accurate and eco-friendly pesticide application. The system integrates an ESP32-CAM with Edge Impulse to implement an AI-driven object detection model capable of identifying polybags as spraying targets. Once a target is detected, the robot activates a spraying mechanism through a relay and navigates automatically using two DC motors controlled by an MDD3A driver. The performance of the robot was evaluated in both laboratory and fertigation farm environments using standard metrics, including F1 score, precision, and recall. Experimental results show that the model trained on a combined dataset of black and white polybags achieved the best performance, with 93.06% accuracy, 95% precision, and high F1 scores. Although the robot demonstrated successful autonomous spraying, some limitations, such as delayed response and occasional mis-spraying, were observed due to the ESP32-CAM's processing constraints. Overall, the findings indicate that the proposed low-cost, AI-powered robot is a promising solution for sustainable agriculture, with potential for further improvements in motion control, dataset expansion, and hardware performance.

1. Introduction

Robotic systems have been used extensively in warehouses and for industrial operations for many years. Research and efforts on autonomous tractors and automatic driverless cars began in the early 1960s in horticulture and agriculture. In order to create autonomous systems, researchers have integrated new sensor systems, positioning systems (GPS), geographical information systems (GIS), and communication technologies in recent decades. Typically, farmers spray chemicals on the farmyards to eradicate pests, fungi, or weeds. Crop yields are increased, and plant diseases are managed by this operation. Some of the problems include the use of chemical pesticides, which may endanger the environment if used excessively [1].

However, the operator is harmed when the pesticide is sprayed. Therefore, it is necessary to figure out how to regulate the quantity of chemicals sprayed as much as is necessary. Furthermore, it decreases human power, which is highly recommended because they can operate independently with a respectable level of accuracy. Robots are the ideal solution for this issue. With this method, robots can identify weeds on the ground and apply pesticides to them for an extended period of time with little assistance from humans. Therefore, automating this process reduces costs while ensuring human safety and environmental protection. Robots employ machine vision tools for a variety of purposes, including industrial robot assembly. The most important of these uses is image processing cameras designed for this purpose [2].

Moreover, in the greenhouses, autonomous pesticide robots are of interest to researchers because of the cost reduction of this operation. In addition, the application of robots in this field helps to keep the environment of the greenhouse clean without human operators. Using artificial intelligence in the wheeled mobile robot made it smart for following paths in pesticide spraying with minimum error. Also, some other types of robots are employed to spray chemicals on the trees or the farmyard. For example, a tree-climbing robot is presented to spread chemicals on leaves efficiently. Another type of robot which is utilized in spraying pesticides is the drone. They can fly over the crops and spray continually, but control the dose of chemicals based on the Geo-referenced map, which was not reported by this method [3].

1.1 Problem Statement

In traditional farming, the widespread use of pesticides is often necessary to control pests and protect crops, but the methods used for application are typically broad and imprecise. Farmers frequently apply pesticides across entire fields without distinguishing between affected and unaffected areas. This excessive and indiscriminate spraying leads to high chemical consumption, which not only increases costs but also causes unnecessary exposure of healthy crops, soil, and surrounding ecosystems to harmful chemicals. Over time, this degrades soil fertility, kills beneficial insects like pollinators, and disrupts the natural balance of agricultural environments. One of the most significant consequences of this overuse is chemical runoff, where rain or irrigation washes pesticides into nearby rivers, lakes, and groundwater sources. This runoff contaminates aquatic ecosystems, harms wildlife, and poses risks to human health by affecting water quality [4].

Moreover, manual pesticide application methods present their own set of problems. The process is labour-intensive, requiring farmers or workers to manually spray large areas, which is time-consuming and physically demanding. Inconsistent spraying patterns can result in under- or over-application, reducing the effectiveness of pest control efforts. Additionally, direct exposure to pesticides during manual spraying can lead to acute or long-term health issues for workers, especially in enclosed environments like greenhouses. As labour costs continue to rise, this method becomes increasingly inefficient and unsustainable for large-scale farming operations. The combination of environmental harm, economic inefficiency, and health risks underscores the need for innovative solutions in pest management. By addressing these challenges, agriculture can move towards more sustainable practices that protect both the environment and the well-being of farmers [5], [6].

2. Methodology

This section discusses the structure and method of this project. Research methodology is important because it will determine the working flow of the project by begin at collecting related data of hard ware and software, assembling the software coding and hardware of each components, construct the algorithm of every each components before it can assembled it as one product and finally troubleshooting the components of the static dosing system in order to ensure that all the system are error-free before it can implemented into real situation.

2.1 Overview of Smart Pesticide Sprayer Robot

Fig. 1 shows the overview of the Smart Pesticide Sprayer Robot. The OV2640 camera module is the robot's primary visual sensor. It takes pictures of the surroundings in front of the robot in real time. This tiny camera is integrated into the ESP32-CAM module. It can capture images of sufficient quality for object detection tasks despite its small size. An AI model trained with Edge Impulse uses the camera's images to recognize particular objects, especially polybags. To assist the robot in determining how to move or when to spray, the model detects whether the object is in the centre, to the left, or to the right of the camera's field of view.

The ESP32CAM board integrates with the OV2640 camera. It has sufficient power to operate simple AI models and manage outputs such as relays and motors. It manages everything, including reading the input image, executing the AI model, and, depending on what it finds, it can communicate with the motor driver and relay. The ESP32-CAM receives a direct deployment of the object detection model that was trained on Edge Impulse. The model doesn't need to send data to the cloud because it operates locally, on the edge. Because of this, the system can remain quick, responsive, and doesn’t need any internet connection. The ESP32-CAM code is written and uploaded using this Arduino. The Arduino sketch incorporates the AI model along with logic for robot movement and spraying actions. Throughout the project, it serves as the environment for development and debugging.

The output section, where the robot reacts by regulating its movement and turning on the spraying system after the ESP32-CAM has processed the image and the AI model has identified a legitimate target. Depending on where the object is detected, a DC motor either turns the robot in the proper direction or keeps it moving forward. The MDD3A motor driver, which regulates the motor's power and direction through the constrained fertigation paths, moves the load of the knapsack sprayer. A channel relay is activated when the target polybag is correctly positioned in the camera's field of view. This ensures that the water pump only activates to spray pesticide when it is truly required.

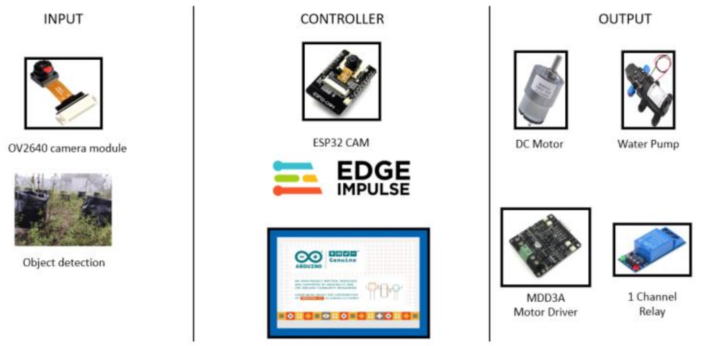


Fig. 1 *Overview of smart pesticide sprayer robot*

2.2 Robot Flowchart

Fig. 2 shows the robot's entire system flowchart. The operational sequence of a robot intended for automatic item detection and spraying is depicted in this flowchart. The robot is initialized at the start of the process, and then it moves forward continuously. The robot uses a camera system to identify items as it moves. The robot continues to advance if it detects no objects. The spray mechanism is activated for five seconds upon detection of an item. The robot moves again to carry out the detection procedure after spraying. Because of this loop, the robot can efficiently do repetitive activities, which makes it appropriate for use in automated agriculture.

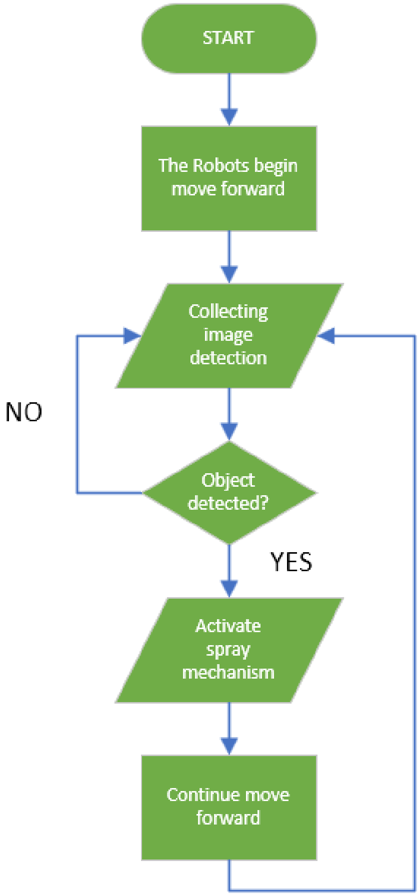


Fig. 2 *Flowchart of the robot system*

2.3 Schematic Diagram

Fig. 3 is a schematic diagram of the robot system, showing that the primary source is a 12V battery that supplies all the different components, especially the MDD3A motor driver. In addition to controlling the system and connecting to a 5V single-channel relay for switching functions. ESP32-CAM acts as a module signal to other components and also a camera for visual processing. A water pump functions as a sprayer and will receive a signal from the relay switch. This robot can move forward, backwards and turn because the Planetary DC motor, controlled by the MDD3A motor driver, generates enough power to reach the full potential of the DC motor. A manual switch is included to turn the system on and off, while the charging port allows the battery to be recharged. Proper wiring ensures stable connections for power, ground, and signal transmission, allowing the system to perform efficiently.

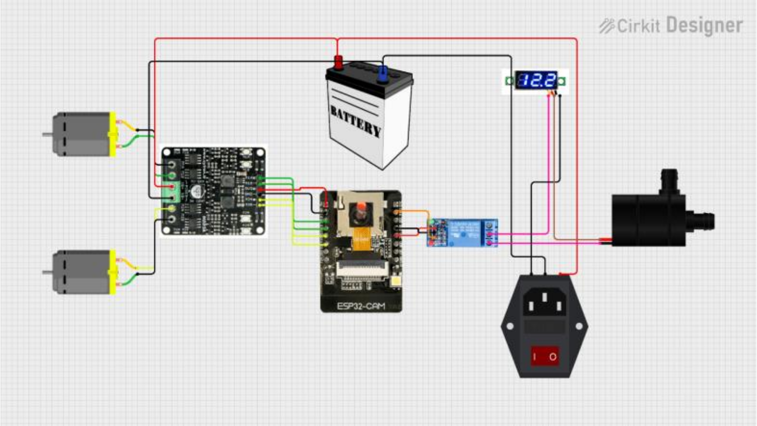


Fig. 3 *Schematic diagram*

2.4 Design of Smart Pesticide Sprayer Robot

Fig. 4 shows the real prototype pesticide robot. The pesticide-spraying robot's chassis is solid and supports its parts with a level platform base and a strong aluminium frame. The design's focal point is the blue compartment pesticide tank that holds about 16 litres and is firmly fixed to provide stability when being moved. A watertight electronic control box is also housed on the platform to safeguard the motor driver systems, relays, and ESP32-CAM module. For balanced and easy movement over a variety of terrains, the robot has two large, sturdy rear wheels and two smaller caster wheels up front. The structure ensures that the tank's weight is spread uniformly, and the robot's modest size makes it appropriate for usage in greenhouses and small-scale farming settings. The design enables the ESP32-CAM to be mounted at the front of the frame, even though the camera is not directly visible in the figure. The optimal camera position would be between 55 cm above the ground, based on the expected height of the tank and the frame. This would provide a clear, forward-facing, downward-tilted image that would be perfect for accurate pesticide spraying and real-time item recognition. This robot is a practical and effective solution for autonomous agricultural activities because of its suitable layout, long-lasting materials, and interoperability with IoT systems. Table 1 shows the specifications of the robot.

Fig. 4 *Prototype sprayer robot*

Table 1 *Robot Specification*

Component	Specification/Description
Chassis Frame	Aluminium Profile (20x20 mm)
Platform Base	Arclyc 2 pieces
Tank Capacity	Blue tank 16 litres total
Wheel Configuration	2 rugged rear wheels (140mm diameters), 2 small front wheels caster
Control Box	Waterproof electrical box (150mm x 110mm x 108mm)
Connectivity	Wifi (ESP32-CAM as an IP-based web camera
Camera Module	ESP32-CAM (mount height ~55cm from ground)
Motors	2 DC planetary motors
Power Supply	12V battery inside the tank
Spraying System	Connected via hose to the tank, get a signal from the relay
Navigation Type	Counter-based movement logic (Arduino Programmed)
Primary Function	Object detection via YOLOv8 and spraying automation
Dimension	40cm x 44cm x 50cm

3. Results and Discussion

This section discusses and analyses the process of how the robot is being set up. It also gives some explanation regarding the results from the algorithm being used. Testing and experimentation have been done based on the method to achieve the objective that needs to be applied to this project.

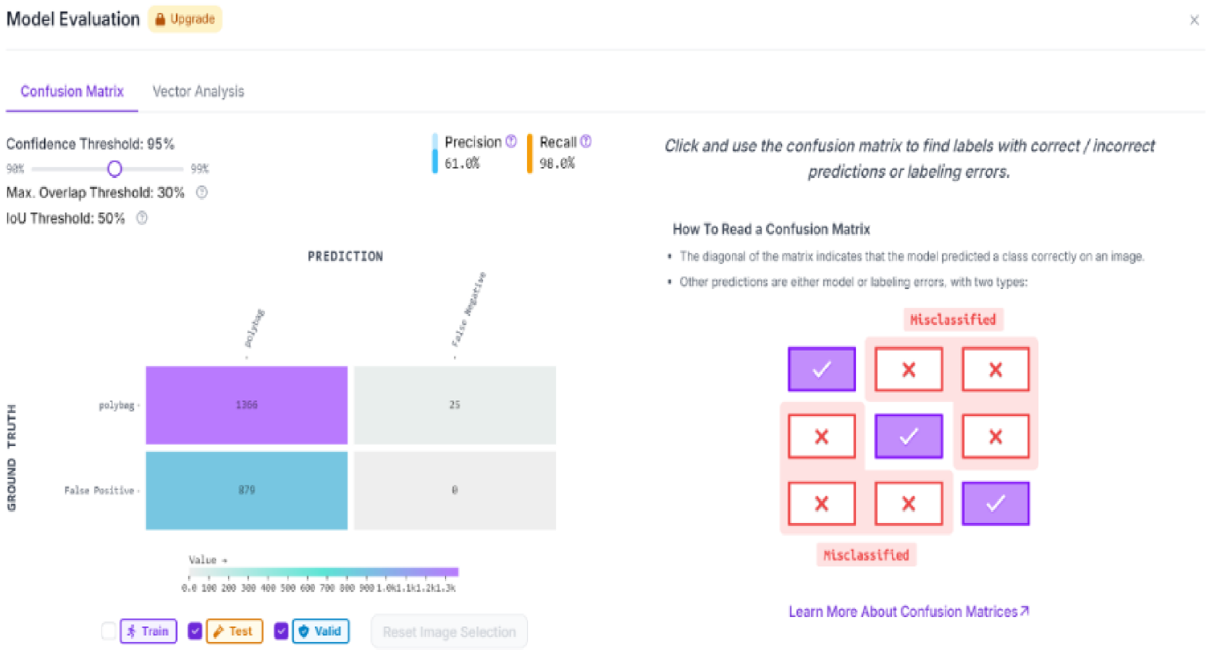
3.1 Dataset Collection

The dataset in Table 2 used for training the object detection model was prepared in several different versions to improve the accuracy and adaptability of the system. These versions were created to test how well the model could recognize different types of target objects. One version of the dataset included only black polybags, another contained only white polybags, and a third version combined both black and white polybags in the same dataset. By experimenting with these variations, it was possible to evaluate how well the model performed under different visual conditions and ensure that it could detect the polybags reliably in real-world scenarios, regardless of colour differences. This approach helped improve the model's robustness and overall detection performance in the fertigation environment.

Table 2 *Dataset version collected*

Version	Label	Image size (px)	Stretch applied
V1	Black polybag	160 × 160	Yes
V2	White polybag	160 × 160	Yes
V3	Black + White polybag	160 × 160	Yes

The model evaluation can show the performance of the object detection model by using a confusion matrix, as shown in Fig. 5. This feature provides a visual summary of the performance of the model in distinguishing the target class ‘polybag’. Confidence threshold was set at 95% as mentioned before, which gives a reason the model only considers predictions with a confidence level above this value. Maximum overlap threshold and IoU (Intersection over Union) threshold were set at 30% and 50% which help to define how detected objects must overlap with a labelled ground truth to be considered a correct prediction.



Confidence Threshold: 95%

Max. Overlap Threshold: 30%

IoU Threshold: 50%

Precision 61.0%

Recall 98.0%

	polybag	False Negative
polybag	1366	25
False Positive	879	0

Click and use the confusion matrix to find labels with correct / incorrect predictions or labeling errors.

How To Read a Confusion Matrix

- The diagonal of the matrix indicates that the model predicted a class correctly on an image.
- Other predictions are either model or labeling errors, with two types:

Fig. 5 *Model evaluation*

3.2 Edge Impulse Training Experiment

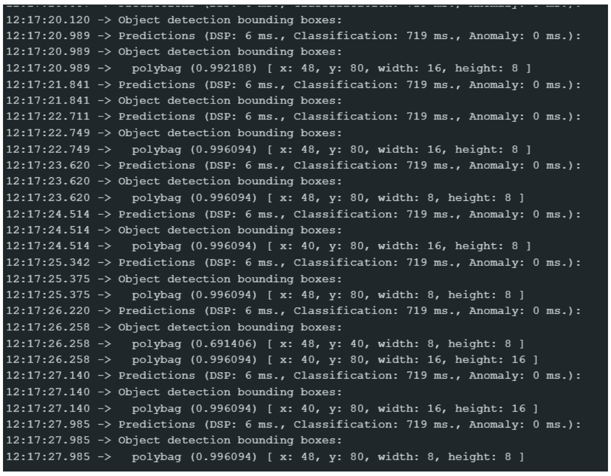
Edge Impulse platform design for developing and deploying embedded machine learning models. It was utilized to build a custom object detection model to identify polybags used in fertigation. That object was identified as the spraying target, so the robot will perform autonomously. This experiment's dataset has been transferred from Roboflow and contains assumptions in terms of prediction during detection, performance accuracy, and also early testing on ESP32CAM. As this platform has its own feature to annotate the image from the dataset, this project has decided to use the Roboflow dataset cause the format in COCO is available on Edge Impulse. It is because this format has divided the dataset into test and train. By that, Edge Impulse easily read that folder, and automatically, the dataset is separated into those two parts. This experiment is continued with creating an Impulse design to take raw data from the dataset, uses signal processing to extract features and then uses a learning block to classify new data. Table 3 shows the model comparison after the training process

Table 3 *Model comparison*

Model version	Object Type	Accuracy	Precision	Recall	F1 Score	Key Strength
V1	Black polybags	81.25%	0.87	0.87	0.87	Balance but needs improvement
V2	White polybags	93.75%	0.90	0.96	0.93	High recall and overall accuracy
V3	Black & White polybags	93.06%	0.95	0.89	0.92	Best for multi-class precision

3.3 Model Deployment and Evaluation on a Robot with ESP32-CAM

Model deployment integrated with ESP32CAM on the robot. The main objective was to evaluate the robot's ability to detect polybags and respond accurately through movement and spraying action. After experimenting on the Edge Impulse platform, the real environment shows inconsistent accuracy. As a result, the robot sometimes failed to react based on the detection, even though the lighting was enough to see the polybag. In some other cases, the bounding boxes were detected, but the confidence level can be considered too low to trigger any action. As Fig. 6 shows, object detection on the serial monitor.



```
12:17:20.120 -> Object detection bounding boxes:
12:17:20.989 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:20.989 -> Object detection bounding boxes:
12:17:20.989 ->   polybag (0.992188) [ x: 48, y: 80, width: 16, height: 8 ]
12:17:21.841 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:21.841 -> Object detection bounding boxes:
12:17:22.711 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:22.749 -> Object detection bounding boxes:
12:17:22.749 ->   polybag (0.996094) [ x: 48, y: 80, width: 16, height: 8 ]
12:17:23.620 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:23.620 -> Object detection bounding boxes:
12:17:23.620 ->   polybag (0.996094) [ x: 48, y: 80, width: 8, height: 8 ]
12:17:24.514 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:24.514 -> Object detection bounding boxes:
12:17:24.514 ->   polybag (0.996094) [ x: 40, y: 80, width: 16, height: 8 ]
12:17:25.342 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:25.375 -> Object detection bounding boxes:
12:17:25.375 ->   polybag (0.996094) [ x: 48, y: 80, width: 8, height: 8 ]
12:17:26.220 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:26.258 -> Object detection bounding boxes:
12:17:26.258 ->   polybag (0.691406) [ x: 48, y: 40, width: 8, height: 8 ]
12:17:26.258 ->   polybag (0.996094) [ x: 40, y: 80, width: 16, height: 16 ]
12:17:27.140 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:27.140 -> Object detection bounding boxes:
12:17:27.140 ->   polybag (0.996094) [ x: 40, y: 80, width: 16, height: 16 ]
12:17:27.985 -> Predictions (DSP: 6 ms., Classification: 719 ms., Anomaly: 0 ms.):
12:17:27.985 -> Object detection bounding boxes:
12:17:27.985 ->   polybag (0.996094) [ x: 48, y: 80, width: 8, height: 8 ]
```

Fig. 6 *Serial monitor real-time on ESP32CAM*

4. Conclusion

This project can conclude the combination of automation, embedded vision, and artificial intelligence to create a smart pesticide-spraying robot for fertigation systems. The robot can identify polybag targets in real time by using the ESP32-CAM module and Edge Impulse's object detection model. In response, it can navigate in the direction of the object and initiate a spray mechanism. This method seeks to minimise the overuse of pesticides while guaranteeing accurate and effective application only when required.

By using Edge Impulse to implement machine learning, the system was able to be trained with a custom dataset, improving detection performance under various circumstances. The model's deployment to a real-time embedded platform further demonstrates how affordable hardware can be used in precision agriculture applications. Although the detection capability operated with reliability, the robot's actuation and movement system presented a number of difficulties. Problems like inconsistent spraying, delayed response, and incorrect direction were noted, suggesting that the coordination between hardware control and vision processing needs to be improved. These drawbacks provide important information for future enhancements, such as improving motor driver components, streamlining the inference loop, and perhaps decoupling the control logic from the camera module.

Lastly, this project establishes a solid framework for creating intelligent agricultural robots. It lays the groundwork for future advancements toward a more reliable, self-sufficient, and precise smart spraying solution while highlighting the potential of integrating AI and embedded systems to promote sustainable farming practices.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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