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Deep Learning-Based Weed Detection and Removal Robot Using Raspberry Pi for Smart Agriculture

Vaibhav Prasad[1], Preet Sambare[2], Rohit Sharma[3], Mr. Vinayak Bembrekar[4]
[1, 2, 3, 4]*Department of Mechanical Engineering, Dr. D. Y. Patil College of Engineering, Akurdi, Pune, Maharashtra, India*

Abstract: Weed infestation in agricultural fields significantly reduces crop productivity by competing for essential resources such as nutrients, water, and sunlight. Traditional weed control methods, which includes manual weeding and chemical herbicide spraying, are becoming less effective due to increasing labour costs, environmental concerns, and inconsistent efficiency in large-scale farming operations. This research presents the design and development of an autonomous Deep Learning-Based Weed Detection and Removal Robot using Raspberry Pi for smart agriculture applications. The proposed system combines computer vision, deep learning, ultrasonic sensing, and a mechanical weed removal mechanism to enable precise and chemical-free weed management. The robot autonomously navigates through agricultural fields using a DC motor-driven chassis. An HC-SR04 ultrasonic sensor continuously monitors the path ahead, and whenever a plant or obstacle is detected within a predefined distance of 20 cm, the robot stops automatically. A Raspberry Pi Camera Module captures an image of the detected plant, which is then processed using a MobileNetV2-based Convolutional Neural Network (CNN) model deployed on Raspberry Pi. The trained model classifies the captured image into two categories: crop or weed. If the detected plant is identified as a crop, the robot resumes movement without any action. However, if the plant is classified as a weed, a motor-controlled cutter mechanism is activated to physically remove the weed without affecting nearby crops. A dataset containing 4,200 labelled crop and weed images was used for training and validation. The proposed deep learning model achieved a training accuracy of 98.3% and a validation accuracy of 96.7%, demonstrating reliable classification performance under varying field conditions. Experimental results indicate that the robot reduces weed removal time by approximately 73% compared to conventional manual methods while completely eliminating the use of chemical herbicides and manual labour. The system provides a low-cost, energy-efficient, and environmentally sustainable solution for precision farming and smart agricultural automation.
Keywords: Deep Learning, Weed Detection, Agricultural Robot, MobileNetV2, Raspberry Pi, Convolutional Neural Network, Precision Agriculture, Motor Controlled Cutter Mechanism, Image Classification, Smart Farming.

I. INTRODUCTION

Agriculture remains the backbone of India's rural economy, employing over 58% of the workforce and contributing significantly to national GDP. Despite technological advancements in irrigation, fertilization, and harvesting, weed management continues to be one of the most persistent challenges in crop production. According to the Indian Council of Agricultural Research (ICAR), unchecked weed infestation can cause yield losses ranging from 20% to 80% depending on the crop species and season [1]. Globally, weeds are responsible for losses exceeding USD 95 billion annually, making their control one of the highest-priority areas in agricultural research.

Traditional weed control relies heavily on two methods: manual hand-weeding and chemical herbicide application. While manual weeding is ecologically benign, it is labour - intensive, time-consuming, and prohibitively expensive in regions experiencing agricultural labour shortages. Herbicide-based approaches, although economically efficient in the short term, carry long-term environmental consequences including soil microbiome disruption, groundwater contamination, and the emergence of herbicide-resistant weed species [2]. These systemic limitations have generated strong research and commercial interest in intelligent, autonomous alternatives.

The convergence of embedded computing, computer vision, and deep learning has opened new frontiers for agricultural automation. Convolutional Neural Networks (CNNs) have demonstrated remarkable capacity for visual feature extraction and classification, achieving expert-level accuracy in diverse image recognition tasks [3]. Meanwhile, low-cost single-board computers such as the Raspberry Pi have matured sufficiently to support real-time inference at the edge, eliminating the need for cloud connectivity during field operations. These technological trends make it feasible to embed intelligent plant recognition into mobile agricultural robots.

This paper presents a complete system architecture, implementation, and empirical evaluation of an autonomous weed detection and removal robot.

The robot integrates: (i) an ultrasonic proximity sensor (HC-SR04) for plant detection, (ii) a Raspberry Pi Camera Module for image acquisition, (iii) a MobileNetV2-based transfer learning classifier running on Raspberry Pi 4B for crop-versus-weed discrimination, and (iv) a motor-controlled cutter mechanism for targeted physical weed extraction. The system operates without human supervision and achieves high-accuracy classification under natural outdoor lighting conditions.

II. LITERATURE REVIEW / RELATED WORK

Recent advancements in artificial intelligence and agricultural automation have encouraged researchers to develop smart systems for weed detection and crop management. Deep learning, computer vision, and robotic technologies are increasingly being used to improve farming efficiency while reducing human effort and chemical usage.

Joshitha et al. [4] developed a Raspberry Pi based crop and weed classification system using machine learning techniques. Their work demonstrated that low-cost embedded systems can be effectively used for agricultural applications. However, the proposed system was mainly focused on classification and did not include an automated weed removal mechanism.

Fan et al. [5] proposed a deep learning based weed detection and target spraying robot for cotton fields. Their system achieved high weed detection accuracy and showed the potential of intelligent robotic solutions in agriculture. However, the system relied on spraying techniques, which still involve the use of chemicals for weed control.

Mohanty et al. [6] demonstrated the effectiveness of deep learning for plant image classification using large image datasets. Their study showed that convolutional neural networks can achieve high accuracy in agricultural image recognition tasks and inspired further research in crop and weed classification.

Kamilaris and Prenafeta-Boldú [7] presented a comprehensive survey of deep learning applications in agriculture. Their review highlighted the growing role of artificial intelligence in crop monitoring, disease detection, yield prediction, and weed management. The study also emphasized the importance of deploying efficient deep learning models on low-cost hardware platforms.

Olsen et al. [9] introduced the DeepWeeds dataset, which provides a large collection of weed images for training and evaluating deep learning models. The dataset has been widely used in weed detection research and has contributed significantly to the development of accurate weed classification systems.

Slaughter et al. [11] reviewed autonomous robotic weed control systems and discussed the future of precision agriculture. Their work highlighted the benefits of robotic weed management in reducing labor requirements and improving farming efficiency. However, many robotic systems discussed in the review were expensive and not easily accessible to small-scale farmers.

Based on the literature survey, it was observed that many existing systems focus either on weed detection or robotic navigation. Only a limited number of studies combine deep learning based weed classification with an affordable autonomous weed removal mechanism. Therefore, the present work aims to develop a low-cost Raspberry Pi based weed detection and removal robot that can identify weeds accurately and remove them without using chemical herbicides.

III. PROBLEM STATEMENT

After agricultural practice and research, weed management at the farm level continues to depend on either manual labour or broad-spectrum chemical herbicides. Manual weeding becomes economically unsustainable as agricultural wages rise, while chemical herbicides impose ecological costs through soil degradation, runoff pollution, and evolutionary selection pressure that produces herbicide-resistant weed biotypes. Existing automated solutions — primarily UAV-based aerial scouts and large-scale field robots — such required significant capital investment, trained operators, and infrastructure that is inaccessible to smallholder farmers.

Furthermore, few autonomous robotic platforms combine edge-deployed deep learning classification with a non-chemical, physically actuated weed removal mechanism. Many reported systems either rely on cloud connectivity (introducing latency and privacy concerns) or require high-performance GPUs that are economically prohibitive. There is a demonstrable need for a compact, affordable, and energy-efficient robotic platform that can: (a) autonomously navigate a crop field, (b) identify individual weeds with high accuracy using only onboard computation, and (c) physically extract weeds without disturbing adjacent crops or introducing any chemical inputs. This work directly addresses that need.

IV. RESEARCH OBJECTIVES

The objectives of this research are enumerated below:

1) Design and fabricate a low-cost autonomous agricultural robot capable of unassisted field traversal using a DC motor-driven chassis.
2) Implement an ultrasonic proximity detection system that halts the robot upon sensing a plant or obstacle within 20 cm.

3) Develop a deep learning image classification pipeline using MobileNetV2 transfer learning to distinguish crop from weed with greater than 95% validation accuracy.
4) Deploy the trained model natively on Raspberry Pi 4B to achieve real-time inference without cloud dependency.
5) Design a motor-actuated cutter weed removal mechanism capable of precisely extracting weeds with minimal disturbance to neighbouring crops.
6) Integrate all subsystems — sensing, inference, actuation, and locomotion — into a unified Python-based control architecture.
7) Evaluate system performance against standard metrics including accuracy, precision, recall, F1 score, and inference latency.
8) Demonstrate a quantifiable reduction in weed removal time and effort compared to conventional manual methods.
9) Contribute a replicable, open-architecture hardware-software platform suitable for smallholder agricultural contexts in developing nations.

V. PROPOSED METHODOLOGY

The methodology is grounded in a closed-loop sense-classify-act paradigm. The robot continuously monitors its immediate environment, pauses upon detecting a candidate plant, classifies the plant using onboard deep learning inference, and then either resumes navigation (crop) or initiates physical removal (weed). This decision loop operates entirely at the edge, requiring no network connectivity during field deployment.

The workflow proceeds through five functional stages: (1) Autonomous locomotion via L298N-controlled DC motors; (2) Proximity-triggered halt via HC-SR04 ultrasonic sensor; (3) Image acquisition via Camera Module V2 at 1280×720 resolution; (4) MobileNetV2-based inference on Raspberry Pi returning a Crop / Weed label with confidence score; and (5) Conditional actuation — the cutter motor mechanism engages only on Weed classifications above a 0.85 confidence threshold. False positives below threshold are treated as indeterminate and logged for review.

VI. SYSTEM ARCHITECTURE

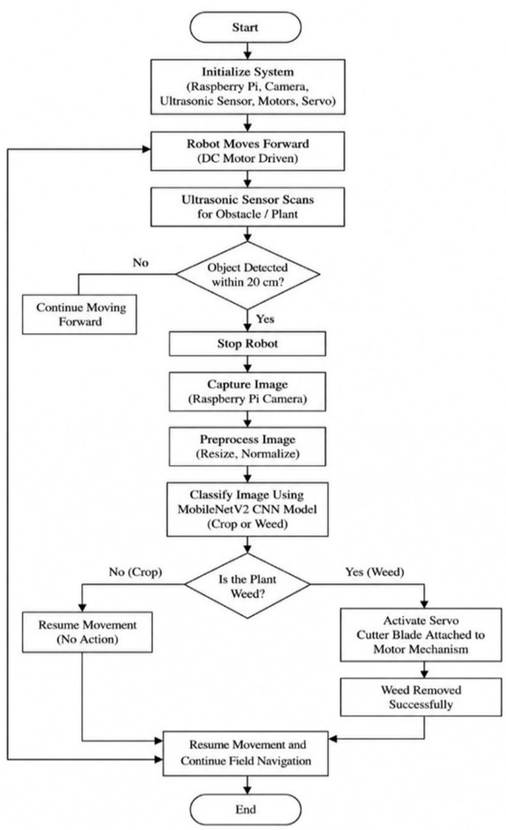

Figure 1: Detailed Workflow / Decision Flowchart

The system architecture is hierarchically structured across three tiers: (i) the perception layer comprising sensors and camera; (ii) the processing layer implemented on Raspberry Pi 4B; and (iii) the actuation layer consisting of the motor driver, DC motors, and cutter assembly. All inter-layer communication occurs via the Raspberry Pi's GPIO pins, CSI camera interface, and software I/O libraries, ensuring a tightly integrated, single-board architecture.

A. Perception Layer

The HC-SR04 ultrasonic sensor provides continuous distance measurements at 10 Hz. The camera module operates as a passive sensor, activated only upon proximity detection to conserve processing resources. The integrated approach minimizes false-positive captures caused by wind-induced plant movement at distances exceeding 20 cm.

B. Processing Layer

Raspberry Pi 4B (4 GB RAM variant) serves as the central processing unit. The TensorFlow Lite runtime executes the quantized MobileNetV2 model, achieving approximately 1.8-second inference per frame. A Python daemon manages the event loop, coordinating sensor polling, image capture, model inference, and GPIO-based actuator control through a state machine implemented in main_controller.py.

C. Actuation Layer

Locomotion is provided by two 12V 200 RPM DC geared motors via the L298N dual H-bridge driver., sufficient to extract shallow-rooted weed specimens from prepared agricultural soil.

VII. HARDWARE COMPONENTS DESCRIPTION AND CIRCUIT DIAGRAM

Sr. No.	Hardware Component	Specification / Model	Purpose / Function
1	Raspberry Pi	Raspberry Pi 4 Model B (4GB RAM)	Main processing unit for control and image processing
2	Camera Module	Raspberry Pi Camera Module V2	Captures image of the detected plant
3	Ultrasonic Sensor	HC-SR04	Detects obstacle/plant within 20 cm
4	Motor Driver	L298N Motor Driver Module	Controls DC motors of the robot
5	DC Motors	6V-12V Geared DC Motors (2 Nos.)	Provides locomotion to the robot
6	Battery	12V, 7Ah Rechargeable Battery	Power supply for the entire system
7	Chassis	4-Wheel Robotic Chassis	Mechanical base for mounting components

Table I: Hardware Component Specifications

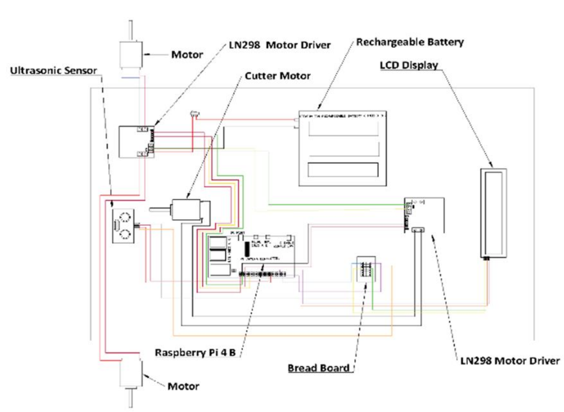

Figure 2: Circuit diagram

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VIII. SOFTWARE ARCHITECTURE

The software stack is implemented entirely in Python 3.9 and follows a modular pipeline architecture. Each functional module is encapsulated as a discrete class, enabling independent testing and future extensibility.

Layer	Library	Version / Type	Purpose / Description
Operating System	Operating System	Raspberry Pi OS (64-bit)	System operation and hardware management
Programming Environment	Python Language	Python 3.9	Primary programming language for development
Programming Environment	IDE / Code Editor	VS Code / PyCharm	Code writing, debugging and development
Core Libraries	OpenCV	OpenCV 4.7.0	Image acquisition, preprocessing and computer vision
Core Libraries	NumPy	NumPy 1.24.3	Numerical operations and array processing
Core Libraries	Pillow (PIL)	Pillow 10.0.0	Image handling and processing
Core Libraries	imutils	Imutils 0.5.4	Convenience functions for image processing
Core Libraries	Matplotlib	Matplotlib 3.7.1	Data visualization and plotting
Deep Learning Framework	TensorFlow	TensorFlow 2.12.0	Deep learning model development and training
Deep Learning Framework	TensorFlow Lite	TFLite 2.12.0	Model optimization and inference on Raspberry Pi
Deep Learning Framework	ImageDataGenerator	Keras Utility	Real-time data augmentation during training
Supporting Tools	scikit-learn	scikit-learn 1.2.2	Dataset handling and model evaluation
Supporting Tools	tqdm	tqdm 4.65.0	Progress bar for training loops
Supporting Tools	Pandas	Pandas 2.0.3	Data handling and analysis
Utilities	Serial Library	pyserial 3.5	Serial communication for sensors and actuators
Utilities	GPIO Library	RPi.GPIO 0.7.1	GPIO control for Raspberry Pi

Table II: Software Specifications

IX. DEEP LEARNING MODEL DESIGN

A. Model Selection — MobileNetV2 Transfer Learning

MobileNetV2 was selected as the base architecture due to its inverted residual structure with linear bottlenecks, which provides an excellent accuracy-to-computational-cost ratio on ARM processors [10]. Pre-trained on ImageNet (1.4 million images, 1000 classes), its convolutional feature extractor transfers effectively to botanical classification tasks. The top classification layers were replaced with a custom head: a Global Average Pooling layer followed by a 256-unit Dense layer with ReLU activation, a 0.4 Dropout layer for regularization, and a final 2-unit softmax output layer for binary Crop/Weed prediction.

X. DATASET COLLECTION AND PREPROCESSING

A. Dataset Composition

For this project, we collected images from different sources to prepare the dataset. The images were taken from the PlantVillage and Weed-AI datasets, photographs captured during field testing of our prototype, and some additional images generated using Roboflow for data augmentation.

The final dataset contains a total of **4,200 images**. Out of these, **2,100 images are crop images** and **2,100 images are weed images**. Since both classes have an equal number of images, the dataset is balanced and suitable for training the deep learning model.

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Parameter	Value
Total Dataset Size	4,200 Images
Crop Images	2,100
Weed Images	2,100
Number of Classes	2 (Crop and Weed)

Table III: Dataset Summary

B. Preprocessing Pipeline
Before training the model, all images were preprocessed so that they could be used efficiently by MobileNetV2.
First, all images were resized to **224 × 224 pixels**, which is the required input size for the model. After that, the pixel values were divided by 255 so that all values lie between **0 and 1**. This helps the model train faster and gives better results.
To improve the performance of the model and make it work well in different conditions, data augmentation was also used. The following operations were applied randomly during training:

- Horizontal and vertical flipping of images.
- Random rotation between −25° and +25°.
- Small shifts in image width and height (up to 15%).
- Zooming in and out of images.
- Brightness changes to represent different lighting conditions.
- Small shear transformations to create slight variations in image shape.

XI. IMAGE CLASSIFICATION WORKFLOW
The image classification process starts when the robot detects a plant. The camera captures an image and sends it to the Raspberry Pi for processing. The image is resized and prepared before being given to the MobileNetV2 model.The model analyzes the image and predicts whether the plant is a crop or a weed. It also provides a confidence score for the prediction. If the confidence score is above 0.85, the robot follows the prediction and takes the required action.
If the detected plant is a crop, the robot continues moving forward. If the detected plant is a weed, the weed removal mechanism is activated. When the confidence score is below 0.85, the robot does not take any action and moves to the next plant. This helps avoid mistakes and improves the safety of the system.

XII. MECHANICAL WEED REMOVAL MECHANISM

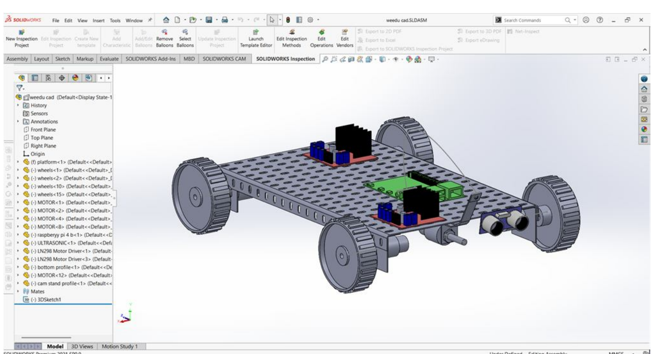

Figure 3: Detailed CAD Model

The weed removal is done using a cutter blade placed on a motor at 300 RPM which is used to remove weeds from the soil.

When the deep learning model detects a weed, the cutter motor starts rotating a high-speed blade. The blade cuts the weed stem right at or just below the soil surface to kill it effectively. Once the cut is done, the motor stops the blade and the robot moves forward again. The complete mechanism is mounted horizontally on the structure of the model. This helps in removing weeds accurately without disturbing nearby crops.

The motor is controlled by the Raspberry Pi through its GPIO pins using Python programming. The entire weed removal process takes around **2 to 3 seconds**, after which the robot continues its normal operation.

This mechanism is simple, low-cost, and easy to use. It removes weeds without using any chemicals, making the system environmentally friendly and suitable for smart farming applications.

XIII. MATHEMATICAL / PERFORMANCE ANALYSIS

The performance of the proposed model was evaluated using different classification metrics. These metrics help us understand how accurately the model can identify crops and weeds.

The following terms are used in the confusion matrix:

- True Positive (TP): Weed is correctly identified as weed.
- True Negative (TN): Crop is correctly identified as crop.
- False Positive (FP): Crop is wrongly identified as weed.
- False Negative (FN): Weed is wrongly identified as crop.

The performance of the model is measured using the following formulas:

Accuracy

Accuracy = (TP + TN) / (TP + TN + FP + FN) ...(1)

Accuracy shows the overall correctness of the model.

Precision

Precision = TP / (TP + FP) ...(2)

Precision indicates how many plants predicted as weeds are actually weeds.

Recall

Recall = TP / (TP + FN) ...(3)

Recall measures how many actual weeds are correctly detected by the model.

F1 Score

F1 Score = 2 × (Precision × Recall) / (Precision + Recall) ...(4)

F1 Score provides a balance between precision and recall.

Specificity

Specificity = TN / (TN + FP) ...(5)

Specificity measures how accurately the model identifies crop plants.

These metrics were used to evaluate the performance of the proposed weed detection system and to compare its results with conventional methods.

XIV. EXPERIMENTAL SETUP

The proposed robot was tested in two different environments to check its performance.

In the first phase, the robot was tested indoors in a controlled setup. A small soil bed was prepared and both crop and weed plants were placed in it. Proper lighting was provided so that the camera could capture clear images.

In the second phase, the robot was tested outdoors in a small field under natural sunlight. The tests were carried out at different times of the day, such as morning, afternoon, and evening, to observe the performance of the system under different lighting conditions.

The robot was tested several times in both environments. During each test, it detected plants, captured images, classified them as crop or weed, and removed weeds whenever required. The results obtained from these experiments were used to evaluate the accuracy and efficiency of the proposed system.

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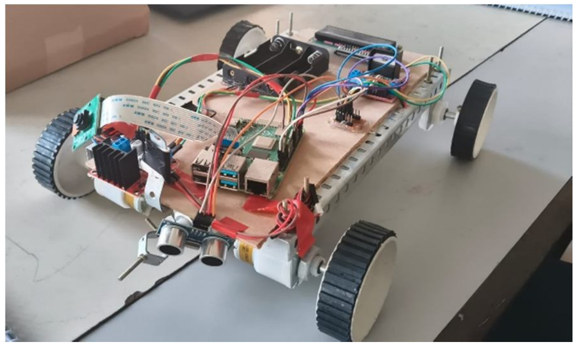

Figure 4: Prototype Image

The deep learning model was trained separately using TensorFlow and then deployed on the Raspberry Pi. After training, the model was integrated with the robot so that it could perform image classification in real time during field operation.

XV. RESULTS AND DISCUSSION

A. Model Training Performance

The MobileNetV2 model showed good performance during training and testing. The model achieved a training accuracy of **98.3%** and a validation accuracy of **96.7%**. These results show that the model can successfully identify crops and weeds with high accuracy.

The trained model was deployed on the Raspberry Pi and tested with real images captured by the robot. The system was able to classify plants correctly in most cases and performed well in both indoor and outdoor conditions.

Figure 5: Testing Results Images

B. False Positive Analysis

During testing, a few crop plants were incorrectly identified as weeds. The false positive rate was found to be **3.5%** in indoor testing and **4.8%** in outdoor testing.

The outdoor environment contains changes in sunlight, shadows, and different backgrounds, which can sometimes affect image classification. Even with these challenges, the model was able to give reliable results and maintain good overall performance.

C. Comparative Analysis with Conventional Methods

The proposed robot performs weed detection and removal automatically without using chemical herbicides. Compared to manual weeding, the system reduces human effort and saves time.

The robot can identify weeds accurately and remove them without affecting nearby crops. Due to its low cost, easy operation, and eco-friendly approach, the system can be useful for small and medium-scale farms, especially in countries like India.

XVI. ADVANTAGES

The proposed weed detection and removal robot offers several benefits for modern farming. It can automatically identify weeds and remove them without requiring continuous human effort, which helps farmers save both time and labour. Since the system does not use chemical herbicides, it is safer for crops, soil, and the surrounding environment. The MobileNetV2 model provides good accuracy in distinguishing between crops and weeds, allowing the robot to make reliable decisions in the field. The use of Raspberry Pi and simple mechanical components keeps the overall system affordable and suitable for small and medium-scale farmers. The cutter mechanism removes weeds along with their roots, which helps reduce weed regrowth. Overall, the system provides an efficient, low-cost, and eco-friendly solution for weed management.

XVII. APPLICATIONS

The proposed system can be used in different agricultural applications where weed control is required. It is suitable for crops such as wheat, rice, maize, and various vegetable crops. The robot can help farmers reduce the time and effort spent on manual weeding while improving field maintenance. Since the system does not rely on chemical herbicides, it can also be used in organic farming practices. Apart from farming applications, the project can be used for educational and research purposes in the fields of robotics, artificial intelligence, embedded systems, and smart agriculture. The system can also serve as a base model for future agricultural automation projects.

XVIII. LIMITATIONS

Although the proposed system gives good results, it still has some limitations. The current model can only classify plants into two categories, namely crop and weed, and cannot identify different weed species individually. The weed removal mechanism works best for small and shallow-rooted weeds and may not completely remove large or deep-rooted weeds. The robot also requires sufficient space between crop rows for smooth movement and operation. In addition, the processing time required for image capture and classification can slightly reduce the working speed of the robot in fields with a high weed population. Battery backup is another limitation, as the robot can operate only for a limited duration before recharging is required.

XIX. FUTURE SCOPE

The proposed system can be improved further in several ways. In future work, the deep learning model can be trained to identify multiple weed species instead of only classifying plants as crop or weed. GPS integration can be added to record weed locations and help farmers monitor weed distribution across the field. More advanced object detection models can also be used to improve detection speed and accuracy.

Further improvements can include increasing battery life through larger batteries or solar-assisted charging systems. The weed removal mechanism can be redesigned to handle a wider variety of weed types and field conditions. Multiple robots can also be deployed together to cover larger agricultural areas in less time. These improvements can make the system more practical and effective for real-world farming applications.

XX. CONCLUSION

The proposed weed detection and removal robot successfully combines deep learning and robotics for smart farming applications. The system uses a MobileNetV2 model to identify crops and weeds and a cutter mechanism to remove weeds automatically. Experimental results showed that the model achieved a validation accuracy of 96.7%, demonstrating its ability to classify plants reliably under different conditions. The robot helps reduce manual labor, saves time, and eliminates the need for chemical herbicides. The use of low-cost hardware such as Raspberry Pi makes the system affordable and suitable for small and medium-scale farms. Overall, the project demonstrates that artificial intelligence can be effectively applied in agriculture to improve productivity and support sustainable farming practices. With further improvements in detection capability, navigation, and battery performance, the system has strong potential for future agricultural applications.

REFERENCES

[1] Y. Gharde, P. K. Singh, R. P. Dubey, and P. K. Gupta, "Assessment of Yield and Economic Losses in Agriculture Due to Weeds in India," Crop Protection, vol. 107, pp. 12–18, May 2018. DOI: 10.1016/j.cropro.2018.01.007

[2] K. Jabran, G. Mahajan, V. Sardana, and B. S. Chauhan, "Allelopathy for Weed Control in Agricultural Systems," Crop Protection, vol. 72, pp. 57–65, Jun. 2015. DOI: 10.1016/j.cropro.2015.03.004 (covers herbicide-resistance, ecological harm, and need for alternatives)

[3] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advances in Neural Information Processing Systems (NeurIPS), vol. 25, pp. 1097–1105, 2012.

[4] K. L. Joshitha, S. Nishanthini, B. J. Harshini, and T. Sadhana, "Raspberry Pi Based Crop and Weed Classification Using Machine Learning Algorithm," IOP Conference Series: Earth and Environmental Science, vol. 980, article 012029, 2022. DOI: 10.1088/1755-1315/980/1/012029

[5] X. Fan, X. Chai, J. Zhou, and T. Sun, "Deep Learning Based Weed Detection and Target Spraying Robot System at Seedling Stage of Cotton Field," Computers and Electronics in Agriculture, vol. 214, article 108350, Nov. 2023. DOI: 10.1016/j.compag.2023.108350

[6] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," Frontiers in Plant Science, vol. 7, article 1419, Sep. 2016. DOI: 10.3389/fpls.2016.01419

[7] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep Learning in Agriculture: A Survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018. DOI: 10.1016/j.compag.2018.02.016

[8] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, Jun. 2016, pp. 770–778. DOI: 10.1109/CVPR.2016.90

[9] A. Olsen, D. A. Konovalov, B. Philippa, P. Ridd, J. C. Wood, J. Johns, W. Banks, B. Girgenti, O. Kenny, J. Whinney, B. Calvert, M. Rahimi Azghadi, and Q. N. White, "DeepWeeds: A Multiclass Weed Species Image Dataset for Deep Learning," Scientific Reports, vol. 9, article 2058, Feb. 2019. DOI: 10.1038/s41598-018-38343-3

[10] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Salt Lake City, UT, USA, Jun. 2018, pp. 4510–4520. DOI: 10.1109/CVPR.2018.00474

[11] D. C. Slaughter, D. K. Giles, and D. Downey, "Autonomous Robotic Weed Control Systems: A Review," Computers and Electronics in Agriculture, vol. 61, no. 1, pp. 63–78, Apr. 2008. DOI: 10.1016/j.compag.2007.05.008

[12] I. Sa, Z. Chen, M. Popovic, R. Khanna, F. Liebisch, J. Nieto, and R. Siegwart, "weedNet: Dense Semantic Weed Classification Using Multispectral Images and MAV for Smart Farming," IEEE Robotics and Automation Letters, vol. 3, no. 1, pp. 588–595, Jan. 2018. DOI: 10.1109/LRA.2017.2774979

[13] F. Dang, D. Chen, Y. Lu, and Z. Li, "YOLOWeeds: A Novel Benchmark of YOLO Object Detectors for Multi-Class Weed Detection in Cotton Production Systems," Computers and Electronics in Agriculture, vol. 205, article 107655, Feb. 2023. DOI: 10.1016/j.compag.2023.107655

[14] T. Duckett, S. Pearson, S. Blackmore, and B. Grieve, "Agricultural Robotics: The Future of Robotic Agriculture," UK-RAS Network White Paper, Sheffield, UK, 2018. [Online]. Available: https://arxiv.org/abs/1806.06762

[15] G. Olsen, G. Goswami, and M. Haugen, "A System for Weeds and Crops Identification — Reaching over 10 FPS on Raspberry Pi with the Usage of MobileNets, DenseNet and Custom Modifications," Sensors, vol. 19, no. 18, article 4051, Sep. 2019. DOI: 10.3390/s19184051

[16] N. Bah, A. Hafiane, and R. Canals, "Deep Learning with Unsupervised Data Augmentation for Weed Detection in Line Crops," IEEE Access, vol. 8, pp. 69448–69468, 2020. DOI: 10.1109/ACCESS.2020.2986399

[17] R. Gerhards and S. Christensen, "Real-Time Weed Detection, Decision Making and Patch Spraying in Maize, Sugarbeet, Winter Wheat and Winter Barley," Weed Research, vol. 43, no. 6, pp. 385–393, Dec. 2003. DOI: 10.1046/j.1365-3180.2003.00349.x

[18] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, no. 7553, pp. 436–444, May 2015. DOI: 10.1038/nature14539

[19] A. Howard, M. Sandler, B. Chen, W. Wang, L.-C. Chen, M. Tan, G. Chu, V. Vasudevan, Y. Zhu, R. Pang, H. Adam, and Q. Le, "Searching for MobileNetV3," in Proc. IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, South Korea, Oct. 2019, pp. 1314–1324. DOI: 10.1109/ICCV.2019.00140

[20] E.-C. Oerke, "Crop Losses to Pests," Journal of Agricultural Science, vol. 144, no. 1, pp. 31–43, Feb. 2006. DOI: 10.1017/S0021859605005708