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RESEARCH ARTICLE

Deep Learning

Weedex : Deep learning enabled autonomous robot for detection and removal of paddy weeds

CS Silva*, TH Warnakulasooriya, EMUS Bandara, NDP Wanigasuriya and TTGMK Sewmini
Department of Instrumentation and Automation Technology, Faculty of Technology, University of Colombo, Homagama, SriLanka.

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Abstract: This research addresses the challenge of detecting and removing paddy weeds through the integration of computer vision, deep learning, and robotics. A dataset comprising the five weed species, *Fimbristylis miliacea*, *Panicum repens*, *Cyperus rotundus*, *Commelina diffusa*, and *Limnocharis flava,* was collected using a digital camera. The study focussed on developing a weed removal robot, named *Weedex*, with two core components: hardware design for mechanical weed removal and software model development for automated weed detection. Once weeds are detected by the software model, *Weedex* should be able to autonomously locate and mechanically remove the identified weed plants. To enhance model robustness and address class imbalance, data augmentation techniques such as random flips and color/brightness adjustments were applied. Object detection was performed using the algorithm YOLOv8-s, YOLOv8-x, and YOLOv8-seg. Deep feature extraction from detected objects utilized multiple pretrained architectures, including EfficientNet-B0, EfficientNet-B5, ResNet50, MobileNetV2, and a custom convolutional neural network. Model performance was evaluated using precision, recall, F1-score, and accuracy. Results demonstrate that EfficientNet-B5 consistently outperformed alternative feature extractors, while the combination of YOLOv8-seg with EfficientNet-B5 embeddings achieved the best performance (≈ 99% accuracy, F1 ≈ 0.99) on the test data. This improvement was attributed to pixel-level weed localization, reduced background interference in feature extraction, and robust similarity-based classification. This research provides a practical solution for automated weed management, potentially reducing herbicide use and labor requirements, and promoting sustainable and precision agriculture practices.

Keywords: Agricultural robotics, computer vision, deep learning, paddy weed detection and removal.

INTRODUCTION

Unwanted vegetation, commonly referred to as weeds, presents a significant obstacle in agriculture by competing intensely with cultivated crops for vital resources, including nutrients, sunlight, and water. This persistent competition often results in diminished crop yield and quality, thereby generating considerable economic losses for farmers worldwide. Conventional weed management practices, such as herbicide application and manual removal, have been widely adopted; however, these approaches are associated with limitations, including elevated production costs, human exposure to toxic chemicals, and adverse environmental impacts. Recent advances in robotics, coupled with computer vision and machine learning, offer promising opportunities to enhance weed management. The development of agricultural robots specifically designed for weed detection and eradication has emerged as a rapidly expanding area of research. Furthermore, integrating state-of-the-art machine learning algorithms and computer vision techniques into robotic systems enables effective solutions for automated weed identification and removal.

* Corresponding author (chathurika@iat.cmb.ac.lk; https://orcid.org/0000-0002-3914-5392)

The detection and identification of paddy weeds is very important since paddy provides millions of people with a key source of nutrition, ensuring their survival. Successfully controlling weeds during the vegetative stage can deliver a 95% weed-free yield (Yu & Jin, 2022). This research is expected to remove paddy weeds such as *Limnocharis flava* (Diya Gowa), *Commelina diffusa* (Gira Pala), *Cyperus rotundus* (Kaladuru), *Fimbristylis miliacea* (Kuda matta), and *Panicum repens* (Etora), shown in Figure 1. This research aims to develop a weed removal robot by focusing on hardware implementation and software-based weed detection. Computer vision, together with deep learning, will be used for object detection and feature extraction.

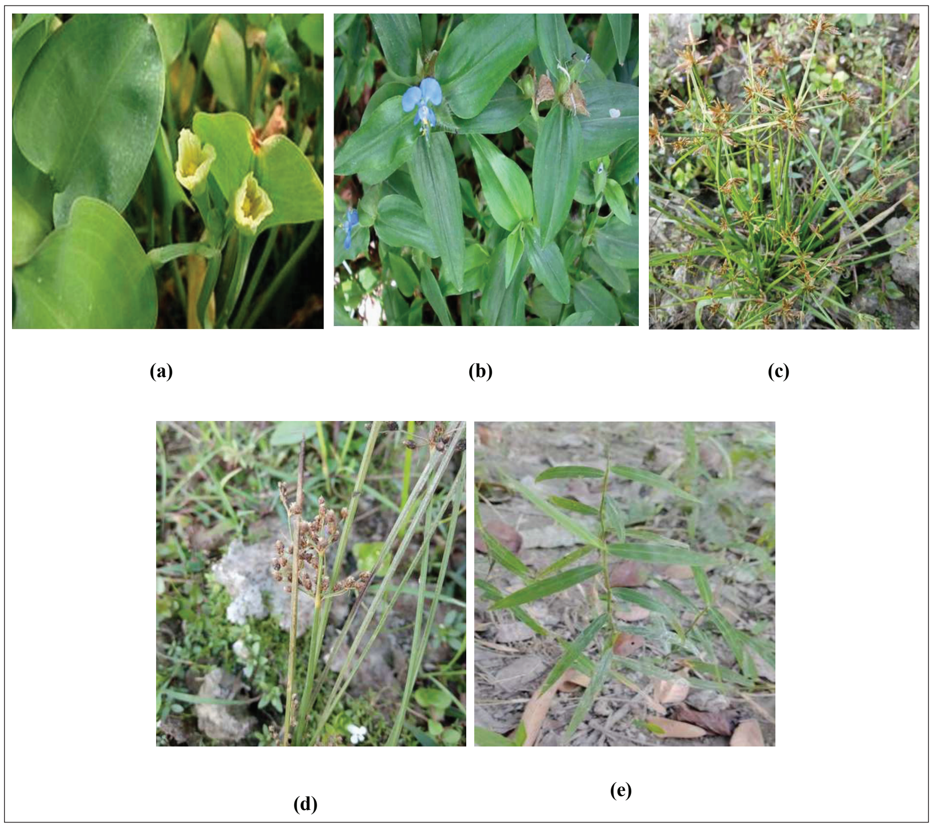

Figure 1: Paddy weeds, (a) *Limnocharis flava* (Diya Gowa), (b) *Commelina diffusa* (Gira Pala), (c) *Cyperus rotundus* (Kaladuru), (d)*Fimbristylis miliacea* (Kuda matta), and (e) *Panicum repens* (Etora)
Source: Ali et al., 2024 (figures b - e)

Literature review

The existing research on weed detection and removal using computer vision and deep learning highlights a rapidly evolving field of technological innovation in contemporary agriculture. In addition, progress in autonomous robotics, particularly the integration of artificial vision and image processing, has further enhanced the precision and efficiency of automated weed management. A weed-removal system based on artificial vision and movement planning by A*(A star) and rapidly exploring random tree (RRT) techniques was proposed by Guzmán et al., (2019). They provided the solution for finding weeds within a crop field using classifiers and the integration of a 3D-vision system that builds a point cloud featuring the plants to safeguard the weeds and the free space using Zed technology, along with search techniques such as A* and RRT to determine the trajectory that the weed-removal tool must follow. An automated weed removal system using a convolutional neural network was proposed by Rodenburg et al., (2010). The model classifies the input into two categories, namely plants and weeds. The centers of all classified weeds are calculated based on the original reference input image. Later, coordinates of the original image are assigned to the original coordinates in the field. Then the cutting machine moves to the appropriate coordinates and removes weeds, and the whole operation repeats. Sethia et al., (2020) proposed an automated computer vision-based weed removal bot. They proposed to develop a mobile model that can detect weeds in real-time with their position coordinates and scrape them off. Choudhari (2023) proposed an automatic weed detection and removal approach based on a four-wheeled robot. The system is deployed in the field where spinach was cultivated in a row-wise order. The vehicle can move in the real field to collect data. The main advantage of this system is that weeds are identified and can be selectively removed.

Computer vision algorithms quickly evaluate visual data, allowing for efficient and accurate weed detection, which, when fed into machine learning models, continuously improves accuracy and adapts to different weed species and environmental factors. This integration not only streamlines weed management operations but also reduces labor costs, providing farmers with valuable time and contributing to sustainable agriculture (Monteiro & Santos, 2022).

A convolutional neural network is an artificial intelligence technique capable of training millions of images and predicting thousands of different classes from these images. This results in the widespread application of convolutional neural networks (CNN) in most state-of-the-art models for recognition and detection tasks (Zhou & Shao, 2022). Weed detection in paddy fields using an improved RetinaNet network was proposed by Peng *et al.* (Peng, Zhou, & Shao, 2022). This paper proposed a model named WeedDet based on RetinaNet. Det-ResNet reduced the loss of detailed information and improved the feature extraction ability of detailed textures by modifying the initial convolution structure of ResNet. (Let-ResNet and ResNet need a reference.) A unique model for weed and paddy detection using regional convolutional neural networks was proposed by Vaidhehi & Malathy, (2022). The detection of paddy weeds was considered with the aid of an automatic weed predictor model.

The YOLO algorithm's increased popularity can be attributed to its better performance. The abbreviation YOLO stands for 'You Only Look Once'. YOLO employs object detection as a regression problem that provides real-time object detection using neural networks. The original YOLO was written by Joseph Redmon in a custom framework called Darknet (Varghese & Sambathe, 2024) and later several YOLO versions were released: YOLO, YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, YOLOv7, YOLOv8. Notably, machine learning, particularly the YOLO algorithm and its versions YOLOv7 and YOLOv8, has emerged as a powerful tool for real-time weed detection. The YOLOv8 architecture comes in multiple scales—such as YOLOv8-small (YOLOv8-s), YOLOv8-large (YOLOv8-l), and YOLOv8-extra-large (YOLOv8-x) and YOLOv8-segmentation (YOLOv8-seg) that balance trade-offs between speed, efficiency, and accuracy. Narayana & Ramana (2023) have used publicly available datasets called the early crop weed dataset and 4weed dataset and obtained 99.8% precision in real-time detection of weeds using YOLO7. The development of a weed detection system based on YOLOv5 architecture using machine learning and neural network algorithms was done by Urmashev, et al., (2021) and achieved an accuracy of 83.3 %, 87.5 %, and 80 % from K-Nearest Neighbors, Random Forest, and Decision Tree classifiers, respectively.

Literature has reported several studies on weed detection in paddy fields. Weed detection in paddy fields using an improved WeedDet based on the RetinaNet network was proposed by Peng, Li, Zhou, & Shao (2022). The modelling of an automatic weed predictor model to aid farmers in handling the weed coverage and scattering of weeds in the paddy field was proposed Vaidhehi & Malathy (2022). They proposed an automatic weed predictor to support paddy weed coverage and scattering of seeds. Jin et al. (2021) proposed a CenterNet model and achieved a precision of 95.6% and a recall of 95.0%. A color index-based segmentation was applied to extract weeds from the background utilizing image processing techniques. Literature related to the autonomous detection and identification of weeds in Sri Lankan paddy fields is very limited. Edirisinghe *et al.* (2022) have used image processing and statistical methods to identify the weed types using multispectral UAV images. However, this study used UAV-based image processing rather than field-deployed robotic systems.

Several studies such as Guzmán *et al.* (Guzmán, Acevedo, & Guevara, 2019) and Sethiya *et al.* (Sethia, Guragol, & Sandhya, 2020), propose detection and localization systems, but few have demonstrated field-tested integration with mechanical or robotic weed removal tools. There is still a gap in translating detection into effective removal. Many studies rely on limited or public datasets. This raises concerns about model generalization to diverse weed species, particularly under imbalanced data conditions. Earlier approaches (e.g., simple classifiers, color-index segmentation, or ResNet-based WeedDet) struggle with fine-grained weed–crop differentiation. Therefore, there is a requirement for an advance feature extraction and segmentation method. While mobile robots and CNN-based detectors have been proposed, many remain at the prototype or lab-testing stage. Therefore, there is a requirement to introducing scalable, low-cost, and farmer-adoptable solutions suitable for large-scale deployment in paddy cultivation. The key contribution of this study lies in the development of an autonomous weed removal robot that integrates hardware-based mechanical extraction with deep learning–driven weed detection. A novel dataset of five major paddy weed species will be collected, and advanced computer vision models, including YOLOv8 variants and multiple pretrained feature extractors, will be employed to achieve detection and classification.

MATERIALS AND METHODS

The methodology of this research primarily focuses on the development of a weed removal robot, referred to as *Weedex,* as shown in Figure 2. The development process is structured into two major components: (i) hardware design and implementation for weed removal, and (ii) software model development for accurate weed detection.

Design and development of the weed removal prototype called 'Weedex'

Leveraging SolidWorks software, a three-dimensional model of the *Weedex* was created, which allowed for visualization to refine the design before development. Using the simulation capabilities of SolidWorks, the interaction of the *Weedex* components with each other was pre-experimented.

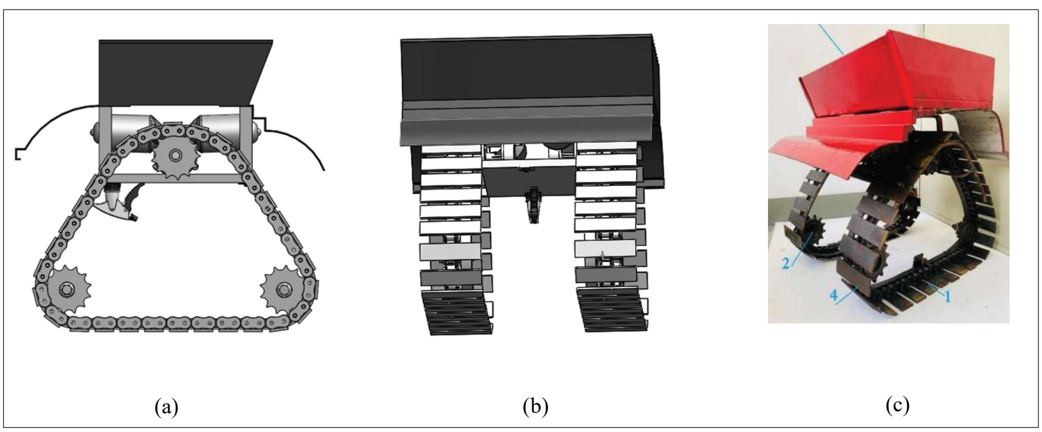

Figure 2: Weedex, (a) side view of the design (b) front view of the design (c) final Prototype

Overall, dimensions of the *Weedex* were taken according to field conditions because paddy is cultivated by the transplant method. The distance between two transplanted rows is 12 inches (30.48 cm). Considering that the width of the *Weedex* is taken as 15 inches (38.1cm) the *Weedex* can travel between the rows by observing the paddy row. The height of the prototype is taken as 10 inches (25.4cm spacing is required) since, the paddy has competition from the weeds for 4 to 6 weeks, and the maximum height of the paddy that can be grown is not more than 8 inches within that time period.

The *Weedex* assembly incorporates fundamental hardware components, including two chains, two DC motors, chassis, and body, all constructed from durable metals. The body is crafted from lightweight metal to ensure optimal functionality. The *Weedex* is made from iron components and has two sides that use tracks to move. The utilization of tracks as the primary mechanism for travel is a deliberate choice driven by the uneven ground settings typically encountered in agricultural fields. The strategic width of 15 inches between the two tracks is considered a choice, aligning with the standard length between two rows of transplanted paddy field. This dimension ensures that as the *Weedex* traverses between the transplanted rows, the track length adeptly accommodates this distance. Tracks welded with flat irons are used to ensure that the *Weedex* comes in contact with the ground. These tracks direct both sides of the prototype. The tracks are supported by a track guard attached to the curved chassis. The chassis serves as the central structure where all hardware components are seamlessly integrated. This includes mounting the chains and sprocket wheels, crucial elements for the functionality of *Weedex*. The *Weedex* is powered by motors running on a 12V DC power supply as the primary power source.

Additionally, the control system integrates electronic components, featuring a Raspberry Pi 3B+ board as the core processing hub, a camera serves for the acquisition of images of paddy fields, a relay module for precise control, and two DC Pulse Width Modulation (PWM) motor controller drivers dedicated to the motors offering precise control over DC motors using PWM. This combination of mechanical components and electronic control systems forms the integral structure of the prototype.

Once the weeds are detected by the software model, *Weedex* integrates the detection outputs with its mechanical system to precisely localize each weed within the field. The robot then autonomously maneuvers its actuators to grasp and remove the identified weed plants, ensuring targeted weed management while minimizing damage to surrounding crops. Weedex has not been field tested in this study.

Image Acquisition

The images were collected from the paddy rows of the subplots in the Regional Rice Research and Development Center (RRRDC), Bombuwala. For dataset preparation, 246 images of *Limnocharis flava*,were collected from a Canon EOS 80 Dcamera equipped with an 18-135 mm lens. Other images of four distinct weed types such as 257 images of *Fimbristylis miliacea*, 234 images of *Panicum repens*, 213 images of *Cyperus rotundus*, and 267 images of *Commelina diffusa* were collected from the publiclya vailable dataset (Alietal., 2024). The five paddy weed species used in this research, were evenly and proportionally distributed across the training (70%), validation (15%), and test (15%) subsets such that, each of the five weed species maintained approximately the same class proportion in all three datasets, thereby preventing class imbalance and bias during model training and evaluation. This method guarantees that the model is exposed to a representative distribution of all weed species in every phase of the learning process. In this study, a one-time random split was employed rather than k-fold cross-validation due to computational constraints and dataset characteristics. Further, this approach minimizes the risk of over-fitting and provides a reliable estimate of the model's generalization capability.

Preprocessing of images

To enhance model generalization and address class imbalance, data augmentation techniques were applied, including random, horizontal, and vertical flips, as well as color and brightness adjustments. These transformations increased the diversity of the training set, thereby reducing the risk of overfitting. In the image preprocessing stage, all images were uniformly re-sized to 456 × 456 pixels to ensure consistency in input dimensions. Subsequently, pixel values were normalized using the standard ImageNet mean and standard deviation, facilitating stable convergence during training and enabling effective transfer learning from pretrained models.

Object detection

For object detection, the YOLOv8 model was implemented. This research has used YOLOv8-s, YOLOv8-x and YOLOv8-seg. The difference between YOLOv8-s and YOLOv8-x primarily lies in their model size, number of parameters, and the trade-offs between speed and accuracy. YOLOv8-s (small) is a lightweight model with fewer layers and parameters, optimized for speed and efficiency. YOLOv8-x (extra-large) is the most complex and parameter-heavy version of the YOLOv8 family. It provides higher detection accuracy, robustness, and better performance on complex datasets, but this comes at the cost of significantly greater computational requirements, longer training times, and slower inference speed. YOLOv8-seg represents a functional extension of the architecture designed for instance segmentation rather than just object detection. While standard YOLOv8 models output bounding boxes and class labels to identify objects within an image, YOLOv8-seg additionally provides pixel-level segmentation masks, enabling more precise delineation of object boundaries. The models generated bounding boxes around each detected object, enabling precise extraction of weed instances for further analysis and downstream processing.

Feature extraction and classification

For feature extraction, deep features were obtained from detected objects using multiple pretrained models, including EfficientNet-B0, EfficientNet-B5, ResNet50, MobileNetV2, and a custom CNN. A customized CNN model, inspired by the VGG16 architecture, was developed by incorporating five additional convolutional layers and one dense layer. The dense layer employed ReLU activation, followed by a final output layer with sigmoid activation for classification.

Following the feature extraction, a feature database was constructed using the training images from each weed class. The extracted embeddings were normalized and systematically stored, forming a structured reference database to support similarity-based classification during inference. For object classification, the detected regions were classified by comparing their extracted feature embeddings against the reference feature database using cosine similarity. Each region was then assigned to the class label corresponding to the highest similarity score, ensuring accurate categorization of the weed species.

Specifically, the YOLOv8s-seg model is employed for detecting and segmenting weed regions within input images. Following detection, EfficientNet-B5, pretrained on ImageNet, is utilized as a feature extractor rather than a classifier. Its classification layer is removed and replaced with a custom embedding network composed of dense, ReLU, dropout, linear, batch normalization, and normalization layers to generate discriminative feature vectors for each detected weed region. A feature database is then constructed by computing and storing these feature vectors from all training images, organized by class. During inference, a test image is processed through the pipeline: YOLOv8 detects weeds, each detected region is cropped and passed through EfficientNet-B5 to extract features, and these features are compared with the database using similarity metrics. The weed is subsequently assigned to the class label with the highest similarity score. Optionally, the system can also visualize results by drawing bounding boxes and confidence-based labels on the detected regions, providing an end-to-end solution for automated weed identification and classification.

Evaluation

The performance of the proposed weed detection and classification model was evaluated using metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the model by calculating the proportion of correctly classified instances among the total number of samples. Precision represents the ability of the model to correctly identify weed instances among all predicted weed samples, while recall indicates the capability of the model to detect actual weed instances present in the dataset. The F1-score, which is the harmonic mean of precision and recall, provides a balanced measure of the model's classification performance, particularly in cases of class imbalance. These evaluation metrics provide a comprehensive assessment of the effectiveness and reliability of the proposed approach for accurate paddy weed classification. To ensure a more reliable performance assessment, predictions labeled as "Unknown" were optionally filtered out. In addition, a comparative analysis of YOLOv8 variants along with the feature extraction models—EfficientNet-B0/B5, ResNet50, MobileNetV2, and the custom CNN—was conducted to determine the most effective architecture for accurate weed classification.

RESULTS AND DISCUSSION

The classification performance was evaluated across five weed classes: Class 0 – *Fimbristylis miliacea*, Class 1 – *Panicum repens*, Class 2 – *Cyperus rotundus*, Class 3 – *Commelina diffusa*, and Class 4 – *Limnocharis flava*.

As shown in Table 1, EfficientNet-B5 consistently achieved the highest precision and recall across nearly all classes, demonstrating its robustness even for smaller or less distinct categories such as Class 1 and Class 3. EfficientNet-B0 also performed well, though slightly lower than B5. In contrast, ResNet50 showed weaknesses in Class 1, while MobileNetV2 underperformed in Class 2, achieving only 0.61 precision. The Custom CNN recorded comparatively low scores across several classes, reflecting the limitations of its simpler architecture. Overall, EfficientNet-B5 proved to be the most reliable feature extractor, maintaining strong and consistent performance across all weed types.

As shown in Table 2, the EfficientNet-B5 model demonstrated robust performance across all weed classes, highlighting its ability to effectively balance both precision and recall. In contrast, the other models showed noticeable class imbalances, where high recall for certain classes was offset by poor precision in others, resulting in an increase in false positives or missed detections. This indicates that while alternative models may excel in capturing certain weed types, their inconsistency across classes makes them less reliable compared to the stability of EfficientNet-B5.

As shown in Figure 3, YOLOv8-x has improved detection when compared with YOLOv8-s for the same test image of *Commelina diffusa.*

Table 3 shows the results of YOLOv8-seg with the EfficientNet-B5 classifier.

Table 1: Results related to YOLOv8-s and classifiers

	EfficientNetNet-B0			EfficientNetNet-B5			ResNet50			MobileNetV2			CustomCNN		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Class 0	0.90	1.00	0.95	0.96	1.00	0.98	0.960.	0.90	0.92	0.72	0.78	0.75	0.79	0.56	0.65
Class 1	0.76	0.86	0.81	0.91	0.95	0.95	0.54	0.95	0.69	0.75	0.82	0.78	0.71	0.68	0.70
Class 2	0.96	0.88	0.92	1.00	0.88	0.94	0.81	0.88	0.85	0.61	0.88	0.72	0.44	0.72	0.55
Class 3	0.79	1.00	0.88	0.92	1.00	0.96	0.67	0.98	0.79	0.74	0.98	0.84	0.65	0.95	0.77
Class 4	0.99	0.88	0.93	1.00	0.98	0.99	1.00	0.74	0.85	1.00	0.80	0.89	0.95	0.76	0.84
Accuracy			0.91			0.98			0.83			0.84			0.77
Macro avg	0.88	0.92	0.90	0.97	0.96	0.96	0.80	0.89	0.82	0.76	0.85	0.80	0.71	0.73	0.70
Weighted avg	0.92	0.91	0.91	0.98	0.98	0.98	0.88	0.83	0.83	0.87	0.84	0.84	0.82	0.77	0.78

Table 2: Results related to YOLOv8-x and classifiers

	EfficientNet-B0			EfficientNet-B5			ResNet50			MobileNetV2		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Class 0	1.00	0.93	0.96	1.00	1.00	1.00	0.92	0.91	91	0.77	0.89	0.83
Class 1	0.89	0.77	0.83	0.95	0.95	0.95	0.48	0.96	0.62	0.86	0.82	0.84
Class 2	0.96	0.96	0.96	1.00	1.00	1.00	0.89	1.00	0.92	0.88	0.88	0.88
Class 3	0.73	1.00	0.85	0.89	1.00	0.94	1.00	0.75	0.85	0.70	1.00	0.82
Class 4	0.99	0.90	0.95	1.00	0.96	0.98	0.75	0.75	0.86	0.99	0.83	0.90
Accuracy			0.92			0.97			0.84			0.87
Macro avg	0.92	0.91	0.91	0.97	0.98	0.97	0.90	0.90	0.83	0.84	0.88	0.85
Weighted avg	0.93	0.92	0.92	0.98	0.97	0.97	0.84	0.84	0.85	0.90	0.87	0.87

(a) (b)

Figure 3: Comparison between (a) YOLOv8-s and (b) YOLOv8-x in weed detection

Table 3: Results related to YOLOv8-seg with EfficientNetNet-B5 classifier

	EfficientNetNet-B5		
	Precision	Recall	F1-score
Class 0	1.00	0.98	0.99
Class 1	1.00	0.98	0.99
Class 2	0.98	1.00	0.99
Class 3	0.98	1.00	0.99
Class 4	1.00	0.99	0.99
Accuracy			0.99
Macro avg	0.99	0.99	0.99
Weighted avg	1.00	0.99	1.00

YOLOv8-seg is used for weed detection because segmentation provides pixel-level masks, which improve localization and reduces misclassification for small and irregularly shaped weeds. Compared to standard YOLOv8 models (s and x), segmentation ensures that only the object area is analyzed during feature extraction, resulting in higher detection precision and recall.

Table 4 shows a summary of the performance of different YOLO variants (YOLOv8-S, YOLOv8-X, and YOLOv8-seg) integrated with various feature extractors for weed detection and classification. Within the YOLOv8-S model, EfficientNet-B0 served as a reliable baseline, while EfficientNet-B5 emerged as the strongest performer, outperforming other baseline extractors. ResNet50 underperformed due to sensitivity to class imbalance, whereas MobileNetV2 provided a

Table 4: Summary of the performance of YOLOv8-s vs YOLOv8-x vs YOLOv8-seg

YOLO Model	Feature extractor	Precision (avg)	Recall (avg)	F1-score (avg)	Accuracy
YOLOv8-s	EfficientNet-B0	0.88	0.92	0.90	91%
	EfficientNet-B5	0.97	0.96	0.96	98%
	ResNet50	0.80	0.89	0.82	83%
	MobileNetV2	0.76	0.85	0.80	84%
	Custom CNN	0.71	0.73	0.70	77%
YOLOv8-x	EfficientNet-B5	0.97	0.98	0.97	97%
	EfficientNet-B0	0.92	0.91	0.91	92%
	ResNet50	0.81	0.90	0.83	84%
	MobileNetV2	0.84	0.88	0.85	87%
YOLOv8-seg	EfficientNet-B5 + Custom embedding	0.99	0.99	0.99	99%

lightweight option with moderate success. The custom CNN achieved the lowest accuracy, highlighting the limitations of its simplified architecture.

For the YOLOv8-x model, overall performance showed incremental improvements compared to YOLOv8-s. In particular, EfficientNet-B5 remained the most effective and stable, followed by EfficientNet-B0, which showed slight gains compared to its baseline. ResNet50 and MobileNetV2 continued to reflect their earlier performance patterns, with modest improvements.

In summary, the YOLOv8-seg model combined EfficientNet-B5 with custom embedding in the proposed research achieved the best overall results indicating 99% for precision, recall, F1-score and accuracy. Similar models for weed detection and classification were reviewed and those results were compared with the outputs of the proposed research. Narayana et al. propose a YOLOv7-based object detection approach for creating a weed detection system. Experimental results revealed that the YOLOv7 model achieved the F-score, precision, and recall values for the bounding boxes as 97.6%, 99.8%, and 95.5% respectively on the early crop weed dataset and 78.53, 79.83, 86.34, and 74.24 on the 4weed dataset (Narayana & Ramana, 2023). Deng et al. propose a method for weed target detection based on YOLOX. In performance comparisons of different models, including YOLOv3, YOLOv4-tiny, YOLOv5-S, SSD and several models of the YOLOX series, namely, YOLOX-S, YOLOX-M, YOLOX-nano, and YOLOX-tiny, the results show that the YOLOX-tiny model performs best. The F1-score and recall values from the YOLOX-tiny model are 95%, and 98.3%, respectively (Deng et al. 2023). Wang *et al.* created a dataset of weeds called "Weed25". YOLOv3, YOLOv5, and Faster R-CNN were employed to train weed identification models using the Weed25 dataset and obtained average accuracies of 91.8%, 92.4%, and 92.15% respectively (Wang et al., 2022).

Kumar et al. (2023) utilized five (05) convolutional neural networks (CNNs)-based architectures, namely MobileNets, MobileNetV2, and EfficientNets (B0–B2), with the DeepWeeds dataset. Results showed that EfficientNets outperformed MobileNets on all three datasets achieving accuracy value of 96.40%.

The experimental results demonstrate that the proposed approach outperforms the selected baseline classifiers in the literature. The improved performance of the proposed approach can be attributed to its ability to effectively extract and learn discriminative features from paddy field images.

CONCLUSION

This study presents a comprehensive approach for the automated detection and removal of paddy weeds using computer vision, deep learning, and robotics. A dataset containing five distinct weed species was collected and augmented to enhance model generalization and address class imbalance. The weed removal robot, *Weedex*, was developed with a dual focus on hardware implementation and software-based weed detection. Object detection was achieved using YOLOv8 variants (YOLOv8-s, YOLOv8-x, and YOLOv8-seg) in combination with feature extraction through multiple pretrained models, including EfficientNet-B5/B0, ResNet50, MobileNetV2, and a custom CNN, enabled accurate localization and classification of weed plants. Among the configurations tested, EfficientNet-B5 consistently outperformed other feature extractors, while the integration of YOLOv8-seg with EfficientNet-B5 embeddings achieved the best performance.

The outcomes of this study contribute to the field of agricultural image analysis by providing a practical and effective framework for improving weed detection under real-world conditions. Future research should focus on optimizing the weeder's design to reduce its overall weight, thereby enhancing operational efficiency in field applications. Additionally, the integration of path-tracking mechanisms aligned with transplanted paddy rows represents a crucial direction for development. Strengthening the training dataset with a larger collection of original field images would further enhance the robustness and accuracy of the detection model, ensuring more reliable weed identification in paddy cultivation.

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