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Research Article

UAV-based intelligent weed detection using YOLO11 and PSPNet for precision agriculture

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Abstract

Weeds significantly threaten rice yield and quality, necessitating precise herbicide spraying to control their growth and enhance agricultural productivity. However, conventional methods address object detection and segmentation separately, limiting their efficiency in identifying areas infested with weeds. This study introduces YOLO11-PSPNet, a combination of YOLO11-s and the Pyramid Scene Parsing Network (PSPNet), for weed detection and semantic segmentation using Unmanned Aerial Vehicle (UAV) images. A dataset was developed that comprised real-time images of rice paddy fields captured via UAV, which included weed varieties such as *Echinochloa* (barnyard grass), *Cyperus difformis* (small flower umbrella sedge), and *Echinochloa colona* (jungle rice). YOLO11-s detects weed-infested regions by generating bounding boxes, whereas PSPNet performs pixel-wise segmentation to ensure accurate weed localisation. Then, the proposed RAdam optimiser with a Sharpness-Aware Minimization (SAM) function was introduced to train the model YOLO11-PSPNet, which improved the training stability of the proposed model. The proposed YOLO11-PSPNet model was trained and tested on a UAV-based dataset, achieving a mAP50 of 99.56% with an inference time of 6.2ms. These results validate the efficiency of the model in precise weed detection, leading to improved crop health and higher yields. This study highlights the potential of YOLO11-PSPNet in precision agriculture for optimizing weed management using advanced deep-learning techniques.

Keywords: convergence speed; data annotation; EVO II Pro drone; pyramid pooling module; region-specific segmentation; tillering stage; weed species

Introduction

Rice is one of the most important food crops in the world, thriving comfortably in hot and humid tropical climates. However, weeds in paddy fields are the primary reason for the reduction in rice production

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and quality. Over 30,000 plant species are classified as weeds, with 250 posing significant threats (Xuan *et al.*, 2025), often reducing crop yields by as much as 34%. Weeds compete with rice for sunlight, nutrients, and water, which hinders crop growth (Mao *et al.*, 2024; Chen *et al.*, 2025a). The aggravated growth of weeds can be due to soil disturbance and changes in light, temperature, moisture, and pH in crop fields (Ameena *et al.*, 2024). In the past, various methods, including manual weeding, mechanical and machine weeding, and traditional spraying, have been used to control weeds. Hand weeding is also a control solution for weeds, but it requires a large number of workers. To overcome these challenges, remote sensing methods have been used to enhance weed management by monitoring and capturing images of the Earth's surface without direct contact.

To improve rice production, Unmanned Aerial Vehicles (UAVs) must be used in the fertiliser or herbicide spraying process, which addresses the labour shortage in rural areas (Rosle *et al.*, 2021; Meesaragandla *et al.*, 2024). UAVs, commonly referred to as drones, are extensively used in precision agriculture to detect potential problems and capture high-resolution images for examination and research (Yu *et al.*, 2022). The advancement of Deep Learning (DL), computer vision, and Machine Learning (ML) algorithms has led to rapid weed detection in paddy fields (Sharma *et al.*, 2024). To reduce herbicide usage, Site-Specific Weed Management (SSWM) using Variable Rate Technology (VRT) is employed to apply herbicides. These methods primarily focus on weed sensing and mapping technologies (Genze *et al.*, 2022).

Weed detection in paddy fields is challenging due to visual and environmental complexities. Rice and weed species often share similar colour tones and leaf textures, resulting in high inter-class similarity. In this situation, DL effectively detects weeds (Murad *et al.*, 2023). Dense canopy structure leads to overlapping vegetation, causing partial occlusion of weed pixels. UAV-based imaging additionally introduces scale variation, illumination changes, water reflection, soil background noise, and shadow interference under field variability (Moazzam *et al*, 2023). The YOLOv10n network enhances weed detection and fertiliser spraying capabilities (Li *et al.*, 2024). DL technology has become a significant image-processing approach. DL models, such as Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), have yielded remarkable results in weed detection, pest identification, and maturity grading (Zhang *et al.*, 2024b). Although recent advances in DL and UAV-based imaging have enabled object detection or segmentation tasks for weed detection, existing methods often address these tasks separately, limiting their precision and practical applicability for targeted weed localization. This study aims to bridge this gap by developing an integrated weed detection and segmentation YOLO11-PSPNet (You Only Look Once-Pyramid Scene Parsing Network) framework that leverages UAV imagery to enable precise, site-specific weed management in rice fields, reducing chemical usage and promoting sustainable agriculture. The main contributions of this study are as follows:

- We developed a real-world rice paddy field dataset created during the tillering stage to control weeds at an early stage. In our study, the primary weed species observed and annotated in the dataset included *Echinochloa* (barnyard grass), *Cyperus difformis* (small-flowered umbrella sedge), and *Echinochloa colona* (jungle rice), as these are among the most widespread and problematic weed types in rice fields in our study region.
- This study proposes a YOLO11-PSPNet framework that performs weed detection and segmentation simultaneously for spraying applications, whereas existing models perform only one of these functions. This study utilised a YOLO11-s object detection model to detect weed-infested regions and generate bounding boxes, enabling the immediate identification of weeds without scanning the entire field. This study utilised region-specific semantic segmentation through PSPNet to generate pixel-wise segmentation masks on the bounding boxes, thereby identifying the exact locations of weeds in paddy fields.
- We introduced a Rectified Adam (RAdam) optimiser with a Sharpness-Aware Minimization (SAM) function that improved the training stability and convergence speed of the proposed model during training. This enhanced the ability of the model to detect and segment weeds in previously unseen fields correctly.

The remainder of this paper is organised as follows: Section 2 analyses existing works on weed detection and target-spraying system approaches; Section 3 defines the workflow of the weed detection and segmentation system; Section 4 presents the experimental results and a discussion; and Section 5 concludes the paper.

Literature survey

This section analyses existing studies on weed detection and segmentation approaches to identify the objectives and research gaps of existing works.

Object detection-based weed detection approaches

Ahmad *et al.* (2021) utilized three pre-trained convolutional classifiers to differentiate weed species from crop pixels. However, the effective controlled conditions, classification only approaches lack spatial localisation and limiting their utility for field-level spraying. Peng *et al.* (2022) introduced a WeedDet model based on RetinaNet to detect the complex information in the images through the extracted features using Det-ResNet. Guo *et al.* (2024) presented a multi-scale feature-enhanced DETR framework, termed RMS-DETR, which improved the detection performance of weeds in rice fields and identified the exact location of weeds. The model had limitations in detecting small-area targets, which affected its accuracy. Chen *et al.* (2025b) developed a GE-YOLO model to detect weeds in paddy rice fields, which utilised an enhanced version of the YOLOv8 object detection model. The model utilises the Efficient Multi-Scale Attention (EMA) mechanism to improve feature representation. However, the model could not cover the stringent weeds that generally affect rice fields. Ma *et al.* (2025) developed a YOLO-Crop Weed Detection (CWD) model that incorporates a hybrid attention mechanism to enhance its ability to differentiate between crops and weeds. The model requires improvements by adding advanced algorithms to the digital agricultural system to improve the accuracy of weed detection.

Segmentation-based weed detection approaches

Chen *et al.* (2024) suggested a Point-supervised Instance Segmentation Network (PIS-Net) to develop an effective method for segmenting weeds and provide effective support for future herbicide applications. However, this model utilised low-resolution mobile phone images for weed detection, which limited the segmentation performance. Similarly, Habib *et al.* (2024) introduced a segmentation model named DWUNet, which combines depth-wise convolutions with the UNet architecture for effective weed management in agriculture, thereby improving accuracy and speed in real-time applications. However, the model only utilised the digital camera of the smartphone, which limited the accuracy of weed detection. Zhang *et al.* (2024a) employed a lightweight weed localisation algorithm based on YOLO instance segmentation to accurately identify and localise weeds. However, the model requires improvements to enhance the algorithm's ability to identify weed spots, and thus, it cannot achieve a higher detection accuracy. To overcome this, Machidon *et al.* (2025) implemented a DL model, SqeeseSlimU-Net (SSU-Net), to enhance the abilities of UAVs in complex segmentation tasks. The model achieved real-time weed segmentation in precision agriculture by combining the semantic segmentation ability of the U-Net architecture. However, the model faced limitations owing to the need for high-quality datasets.

Hybrid approach combing weed detection and segmentation

Islam *et al.* (2025) developed a CNN-based models for object detection and semantic segmentation tasks in row crop production. The study demonstrated that object detection models achieve higher speed, while segmentation models provide spatial detail. However, the study limited the system's applicability to broader situations as other common weed species.

Thus, analysing the existing works, object detection models provide field-scale weed detection and segmentation approaches provide high-resolution masks for accurate spraying. Object detection model lacks pixel-level precision, and semantic segmentation is more resource-intensive. The existing approaches mostly rely on detection or segmentation rather than combining both for precise weed detection. This study aims to bridge these gaps by developing a YOLO11-PSPNet for weed detection and segmentation sequentially to support future targeted spraying, ensuring improved crop health and sustainable farming practices. The combined YOLO11-PSPNet model provides efficient real-time object detection and robust semantic segmentation in paddy fields.

Materials and methods

The proposed methodology detects weeds in rice paddy fields using the YOLO11-PSPNet framework, as illustrated in Figure 1. Initially, the videos captured by the UAV were converted into frames and stored as a raw dataset. The images were preprocessed to enhance the quality of the training dataset using histogram equalisation and data augmentation techniques. The proposed framework was trained sequentially. Initially, the YOLO11-s model detected weed-infested regions and generated bounding boxes. Then, the bounding box regions were segmented using PSPNet, which generated pixel-wise segmentation masks to identify the locations of the weeds. The introduced optimiser, RAdam with SAM, enhances the training stability and convergence speed of the proposed weed detection system. This supports targeted fertiliser or herbicide spraying in paddy fields, enhancing crop health and, consequently, the crop yield.

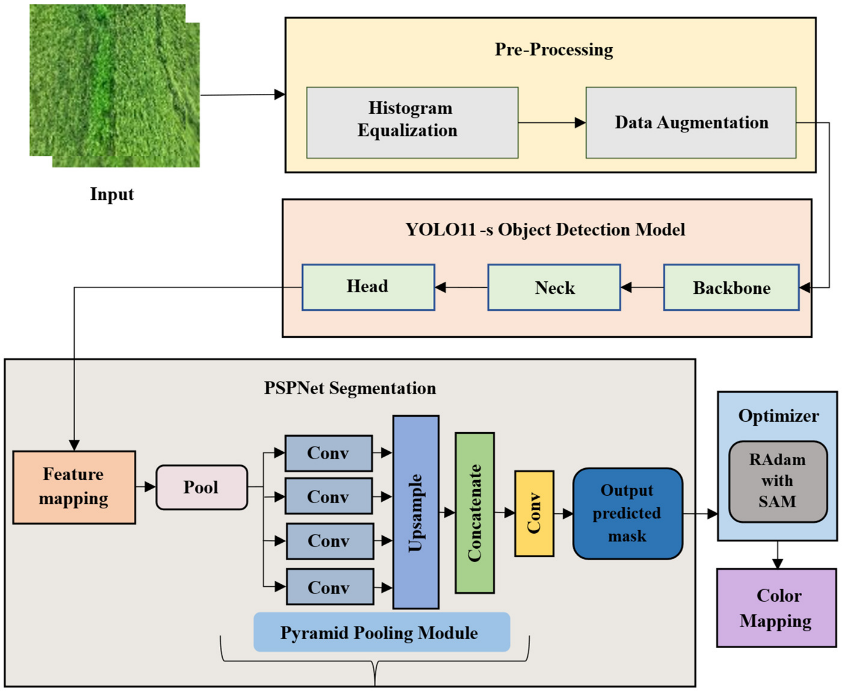

Figure 1. Overview of the proposed YOLO11-PSPNet detection-segmentation framework

Data acquisition

The data were collected from the study area located at Therakalputhoor, Kanyakumari District, India, between July and August 2024, and updated in a Roboflow repository (Dataset Link: https://app.roboflow.com/pest-i22ng/weed-ge616/1). We utilised a UAV to gather images of paddy rice fields at the tillering stage. The study area was 150 m in length and 85 m in width, with 12,750 total square meters, as shown in Figure 2. We utilised the EVO II Pro drone manufactured by Autel Robotics to capture the images, flying at an altitude of 5m to 25m with a CMOS lens with an efficient 20 million pixels, and the Ground Sampling Distance (GSD) was 0.225 cm/pixel. The drone tracked a determined path with 80% forward and

80% side overlap. The rice field data were obtained from a vertical perspective to cover the total study area. A total of 1215 rice field UAV images were collected, and the sample dataset images are shown in Figure 3. This represents the weed-infested regions and rice paddy fields in the UAV images. The dataset images were split into 70% for training, 20% for testing, and 10% for validation. For model training, the images were resized to 640 × 640 pixels.

Figure 2. Schematic representation of the experimental rice field captured at an altitude of 5m to 25m from the ground

Figure 3. Sample images from the UAV-captured dataset, displaying various weed-infested regions in rice fields

Data annotation and preprocessing

Preprocessing is an essential step in enhancing the quality of the dataset. The UAV rice field dataset was preprocessed using histogram equalisation and data augmentation techniques. We manually labelled the bounding boxes on the UAV images using the annotation tool Roboflow, as illustrated in Figure 4.

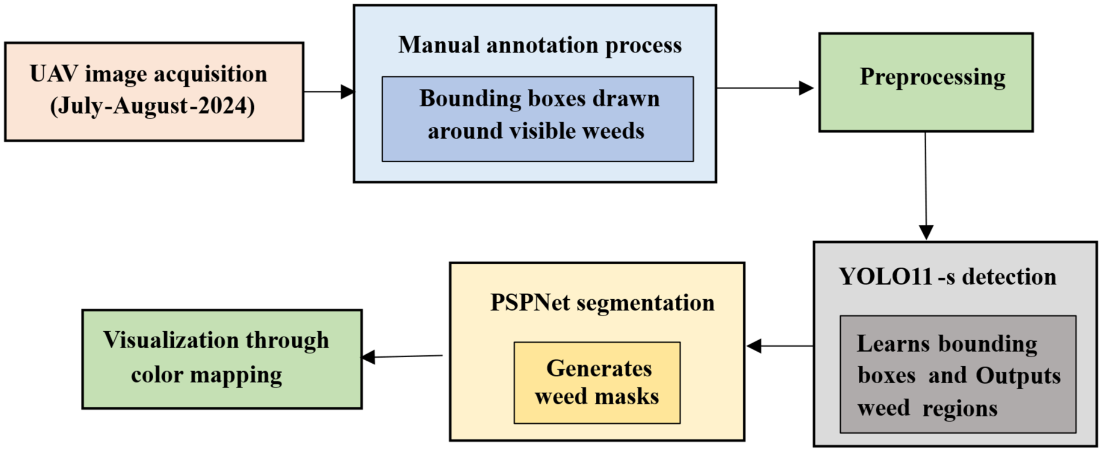

Figure 4. Overview of data creation and processing pipeline

Histogram equalization

Histogram equalisation was used to strengthen the colour and enhance the contrast of paddy-field weed images. This approach is applied by allocating a gray value level. The images were processed by improving the range of colours with a lower limit to the darkest point and by reducing the range of colours with an upper limit to the brightest point. This phase is essential for ensuring accurate visualisation of minor features and patterns. Histogram equalisation is achieved using Equation (1).

$$H = \sum_{i=0}^{c} \frac{n_i}{n} \tag{1}$$

Where n represents the number of images in the data, i signifies the range of grey values, which ranges from 0 to the current grey value c, and n_i represents the number of images on the grey value.

Data augmentation

In this study, the data augmentation process improved the robustness and diversity of the training dataset. Data augmentation included processes such as horizontal and vertical flipping, scaling, rotation, translation, cropping, contrast adjustment, colour jitter, and adding noise to make the model more generalised to variations of the same object in rice weeds and improve robustness. Random flipping and translation were used to detect specific object locations. Efficient scaling and rotation allow the model to learn the different ways in which weed patterns appear from various angles and sizes. To ensure efficient detection in complex environments, colour jittering and contrast adjustments consist of varied lighting, occlusions, shading, and canopy density to improve model robustness and diverse field conditions. After preprocessing, the preprocessed images were sent for efficient weed detection using YOLO11.

Weed detection through YOLO11

YOLO11 is the latest version of the YOLO object detection model designed for high-speed and accurate object detection and classification. In this study, YOLO11-s was used for rice-weed detection in paddy fields. YOLO11-s was specifically chosen for this study because of its advanced multi-scale feature extraction, superior detection accuracy, and real-time inference capabilities, which make it highly suitable for weed detection in rice crops. Additionally, weed detection requires the ability to identify small, obstructed, and low-contrast objects in paddy fields, which is a major limitation of previous detection models. YOLO11-s addresses this issue through multi-scale feature extraction and anchor-free detection, thereby improving its ability to detect concealed objects effectively. In this study, we trained YOLO11-s on preprocessed images to detect weeds in paddy fields. The model detects weed-infested areas and generates bounding boxes on the images. The

YOLO11-s architecture includes three basic components: backbone, neck, and head. It introduces an effective architecture with C3K2 blocks, Spatial Pyramid Pooling Fast (SPFF), and an advanced attention mechanism, Cross-Stage Partial with Spatial Attention (C2PSA). The architectural diagram of YOLO11-s is shown in Figure 5. The backbone serves as a feature extractor, using convolutional layers to create multi-scale feature maps and reduce the spatial dimensions.

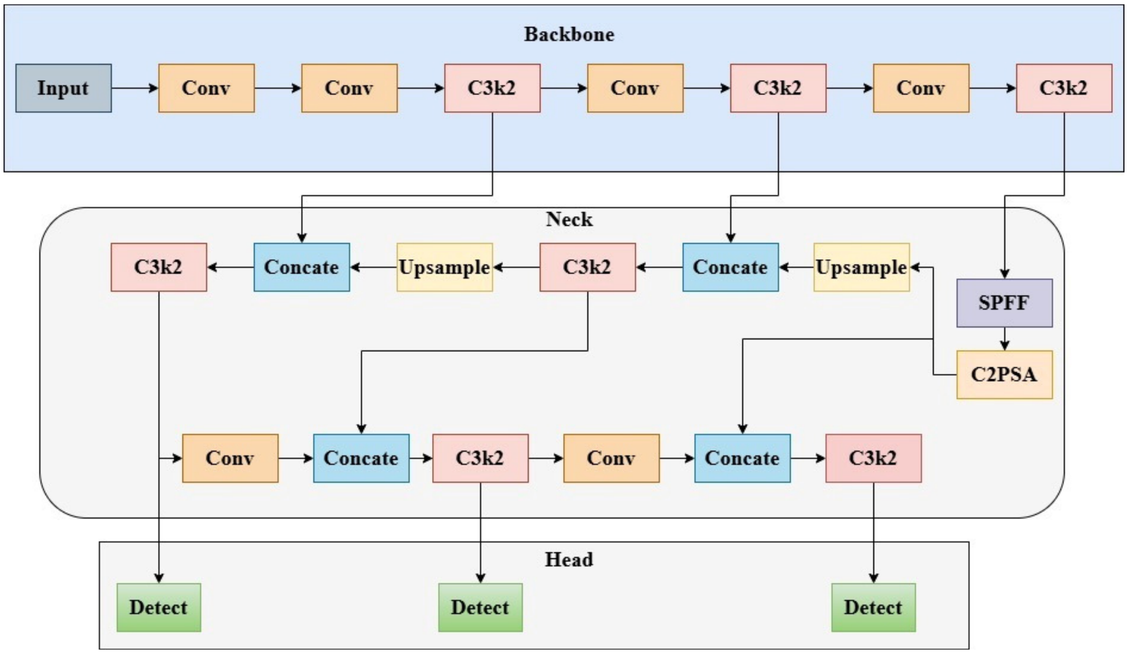

Figure 5. Architecture diagram of the YOLO11-s model, highlighting key layers and detection components

The C3k2 Cross Stage Partial (CSP) Bottleneck replaces the previous C2f block, utilising a smaller kernel size for faster processing while maintaining performance. The C2PSA block enhances spatial attention, allowing the model to focus on the critical image regions. The neck block integrates features at different scales and transforms them into the head block for final detection, employing C3k2 and C2PSA to improve feature aggregation and reduce the computational cost. The head block generates the final detection output through multiple Convolution-BatchNorm-Silu (CBS) layers after the C3k2 blocks. It acts as a basic element in both the feature extraction and detection process. Finally, the final detection output is generated for the rice-weed images based on the refined feature maps. The proposed framework was trained sequentially, YOLO11-s trained for weed object detection, and the resulting bounding-box regions then passed as PSPNet for semantic segmentation.

Region-specific segmentation using PSPNet

In the field of semantic segmentation tasks, specifically for complex paddy environments, such as rice field segmentation from UAV images, YOLO11-s as a backbone architecture significantly impacted the model performance, as illustrated in Figure 6.

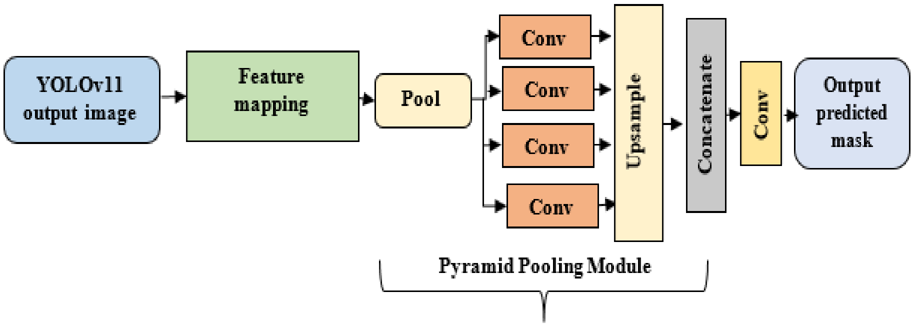

Figure 6. Structural overview of the PSPNet segmentation model used for precise weed localisation

In this study, we utilised PSPNet as the segmentation model with the attention of our experimentation, choosing an effective and accurate backbone. The bounding box weed regions from YOLO11-s were sent to the PSPNet for fine-grained segmentation. The model applies pixel-wise segmentation masks to highlight the weeds in the paddy fields. The PSPNet utilised a YOLO11-s output image as an input image that was sent for feature extraction through a pretrained ResNet model with a dilated network that supports the extraction of comprehensive details through YOLO11-s bounding box images. The feature map size was one-eighth of the input image. Then, the Pyramid Pooling Module (PPM) is utilised to collect appropriate details on top of the extracted feature map. A four-level pyramid was generated to cover all weed-detected images. The pooling kernel captures several contextual scales at diverse levels. Details from the pyramid are shared with the original feature map through a process known as fusion. The PPM fuses features at four pyramid scales represented by 1×1, 2×2, 3×3, and 6×6, which distinguishes the feature map into several sub-regions and generates pooled images for diverse positions. Each pyramid level is diminished using a 1×1 convolution to retain the global feature weights. The resulting low-dimensional feature maps were then upsampled using bilinear interpolation to match the size of the original feature map. Finally, the features from the four levels were concatenated to produce the final global feature for the PPM. A convolution layer processes this combined detail to create the final prediction map, which enhances the integrated details and provides a comprehensive prediction of rice-field weeds by generating the masks.

RAdam with SAM optimiser

The combined model for object detection through YOLO11-s and segmentation through PSPNet simultaneously can lead to unstable gradients and slow convergence, particularly with noisy UAV images. To overcome these issues, we utilised the Rectified Adam (RAdam) optimiser with Sharpness-Aware Minimization (SAM) to produce a training process. This leads to a more effective and reliable weed-detection system. The SAM improves model generalisation by simultaneously minimising the loss value and loss sharpness. RAdam optimiser is expressed in Equations (2) and (3).

$$a_s = \frac{a_s}{1-\alpha_1^s}, b_s = \frac{b_s}{1-\alpha_2^s}, \tag{2}$$

$$\vartheta_{s+1} = \vartheta_s - \rho . \frac{a_s}{\sqrt{b_s + \epsilon}} . r_s \tag{3}$$

Where a_s, b_s denotes the training samples, α signifies the learning rate, and r_s represents the rectified factor that stabilises early updates. The SAM allows the optimiser to find parameters in the flatter regions of the loss. This was performed using a two-step update. Firstly, perturb the weights ϑ slightly in the gradient direction. Then, we optimise for the worst-case increase in the loss.

This ensures that the model is good at the training set and is also robust against small variations, such as lighting or field condition changes in UAV images. This ensures that the proposed RAdam with SAM ensures stable and smooth convergence, particularly in the early training phases.

Color mapping

Colour mapping is a process that uses colours to assign values to images. Colour mapping delivers a simple method for attaining complex colour variations in rice field images by permitting the colour palette and other characteristics of an image to be changed through another image as a reference. In this study, the segmentation mask was overlaid on the original UAV image for better visualisation of weeds through colour mapping, as illustrated in Figure 7. Colour-map visualisation is typically used to highlight variations in intensity or texture.

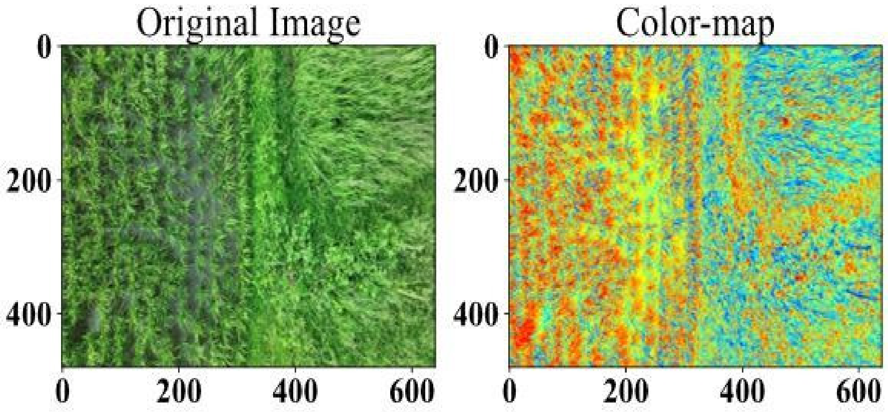

Figure 7. Visualisation of detected weeds, demonstrating the effectiveness of YOLO11-PSPNet in identifying weed regions, showing variations through a colour map

The red and yellow regions indicate higher feature intensities, and the blue and green regions signify lower intensities

Training configuration and experimental setup

The YOLOv11-PSPNet model was trained using the preprocessed UAV dataset with 70% training, 20% testing, and 10% validation splits. During the training process, we employed various data augmentation transformations, such as flipping, colour adjustment, rotation, and scaling, to prevent overfitting and ensure generalisation. The proposed model uses several hyperparameters to balance the model performance and computational efficiency, as illustrated in Table 1.

Table 1. Hyperparameters used for the YOLO11-PSPNet framework

Hyperparameter	Definition	Values
YOLO11-s		
Learning rate	Controls the step size for updating model weights during training.	0.001
Batch size	Number of training samples processed before the model's weights are updated.	16
Momentum	Stabilize gradient updates.	0.937
Weight decay	Controls the strength of the regularization technique to prevent overfitting	0.0005
Epochs	Total number of times the training dataset is passed through the model.	50
Optimizer	Minimize the loss function during training.	Stochastic Gradient Descent
PSPNet		
Segmentation	Backbone	ResNet-50
Pyramid pooling module	Captures contextual information at different spatial scales	Adaptive average pool
Pooling type	Aggregate features in the pyramid pooling module	Average pooling
Loss function	Quantifies the difference between predicted segmentation masks and ground truth.	Cross-entropy loss

Evaluation metrics

The rice weed detection and segmentation performance were examined using metrics including the Dice Similarity Coefficient (DSC), Intersection over Union (IoU), mean Average Precision (mAP), and mean IoU (mIoU).

DSC: The DSC calculates the similarity between the segmented and ground-truth regions. The values ranged from 0 to 1, and a higher value represented more accurate segmentation results. The DSC formulation is expressed as follows:

$$DSC = \frac{2 * TP}{FP + 2 * TP + FN} \tag{4}$$

In equation (4), TP denotes the true positive, FP and FN signify the false positive and false negative.

IoU: This metric evaluates the overlap between the segmented and ground truth areas. The IoU values ranged from 0 to 1. The segmented and ground-truth regions are denoted by S_R and G_T as represented in equation (5).

$$IoU = \frac{S_R \cap G_T}{S_R \cup G_T} \tag{5}$$

mAP: This is a measure of the object detection. To estimate the mAP, the Average Precision was computed for all object classes. The mathematical representation of the mAP metric is given by Equation (6).

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{6}$$

Results

Performance analysis of the proposed model

This section presents the performance metrics of the proposed model, as illustrated in Table 2. The proposed YOLO11-PSPNet model attained a precision of 99.4 % and a recall of 98.2 %. The model accurately detected weeds in the paddy field, with an mAP50 of 99.56 %, an IoU of 99.61 %, and a DSC score of 83.2 %. The proposed model accurately detected and segmented weeds in rice fields using YOLO11-s and PSPNet models. Figure 8 shows the loss curves of the proposed weed detection model. The model performance was evaluated through training and validation. The graph shows the model performance during training and validation. The loss graph records the value of learning from the data and decreases the error as it learns from the data. Figure 9 illustrates the detection performance based on the IoU and the number of epochs. This graph in weed detection visually represents how the IoU metric evaluates predicted bounding boxes corresponding to the actual ground-truth boxes with respect to the changes as the model is trained through each epoch based on the trained dataset. This graph shows the pixel-level overlap accuracy between predicted masks and ground truth labels, reflecting segmentation quality in dense paddy vegetation

Table 2. Performance metrics of the proposed YOLO11-PSPNet framework

Metrics	Values
Precision (%)	99.4
Recall (%)	98.2
mAP50	99.56
mAP50-95	99.03
IoU (%)	99.61
mIoU (%)	98.27
DSC (%)	83.2

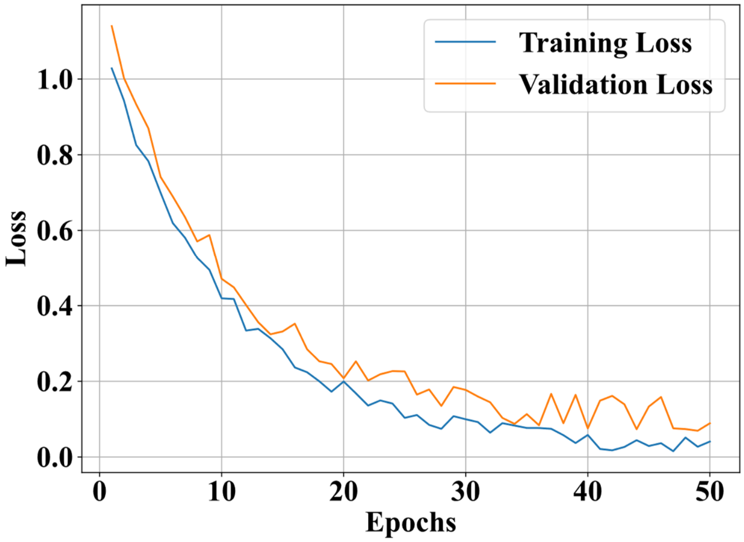

Figure 8. Training and validation loss curves, showcasing model convergence and learning stability

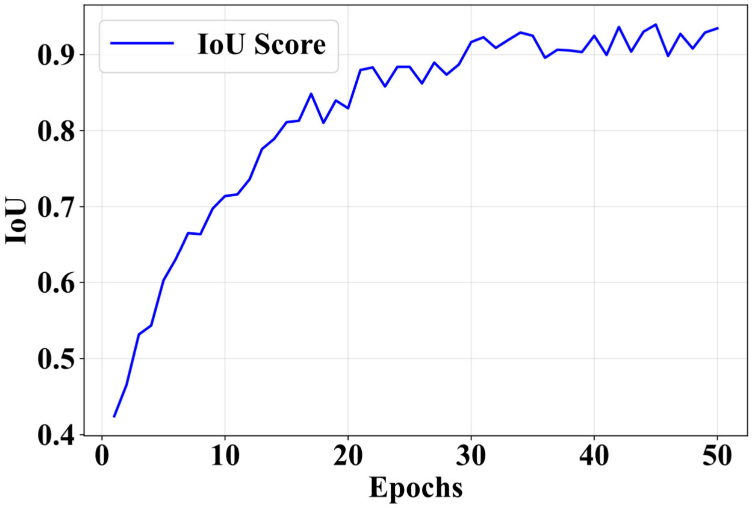

Figure 9. IoU performance evaluation of PSPNet segmentation across validation samples

Performance analysis on weed detection

The YOLO11-s model detected the weeds and generated bounding boxes that identified the weeds and paddy fields separately. This figure shows that the red boxes specify the paddy fields, and the blue boxes signify the weed-infested areas in the paddy fields, as demonstrated in Figure 10.

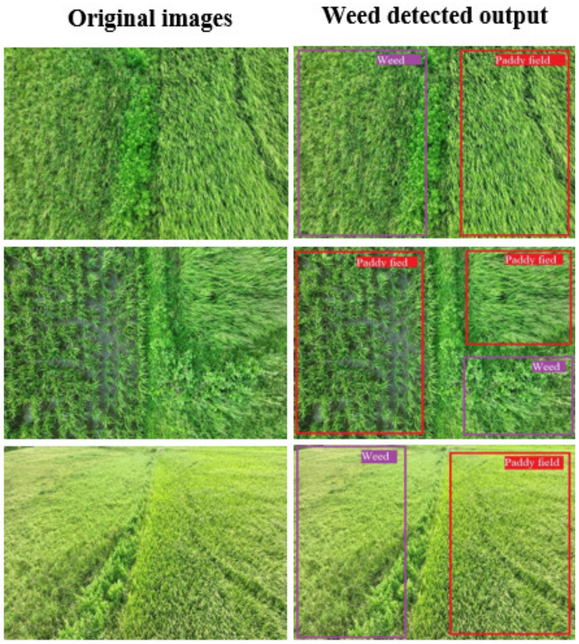

Figure 10. Bounding boxes on the UAV high-resolution images, detecting weeds shown in blue colour bounding boxes for the sample three input images

Performance analysis on weed segmentation

The PSPNet segmentation model generates pixel-wise segmentation masks that accurately identify weed locations. The model detected weeds from the bounding boxes of YOLO11-s and then generated a segmented mask, as shown in Figure 11. This figure shows examples of weed images with annotation masks and PSPNet predictions. This analysis demonstrated that rice crop and weed coverage can be accurately predicted in rice paddy field weeds.

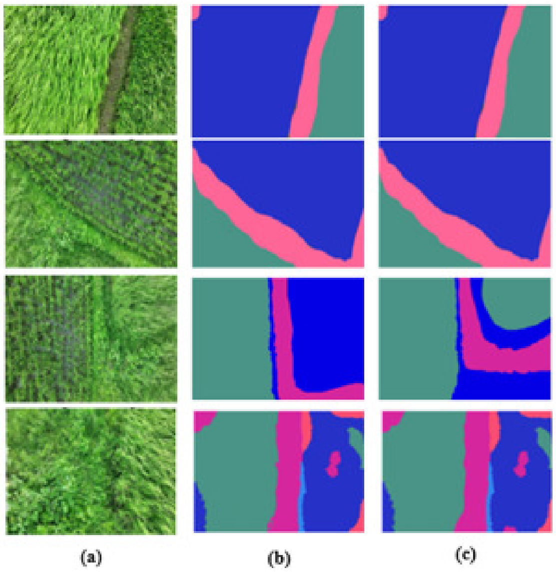

Figure 11. Weed detection results: (a) four sample input images, (b) ground truth annotation masks, (c) the predictions of PSPNet for the input image

Analysis of the performance of RAdam optimiser with the SAM

Figure 12 illustrates the performance curve of the RAdam optimiser with the SAM. As shown in this figure, the epochs are adjusted from large to small with the number of training iterations of the model. The optimiser updates and calculates the network parameters that affect the model training and output to reach the optimal value, thereby minimising the loss function. Thus, it is important to select an appropriate optimiser to train the proposed model. The proposed RAdam optimiser with SAM had the best fitting effect, and the fluctuation of the gradient descent curve was the most stable. Here, RAdam with SAM was used as the optimiser when training the proposed model YOLO11-PSPNet. Table 3 compares the convergence behaviours of various optimisers, including Adam, AdamW, and Adamax, with the proposed RAdam with SAM, based on key performance metrics. The Epochs to convergence indicate how quickly each learning rate reaches a high accuracy, with fewer epochs reflecting faster convergence. Loss variance represents the model's fit on the training and unseen data, with lower values indicating better performance and minimal overfitting. This confirms its robustness, faster convergence, and higher efficiency. The results show that the proposed RAdam with the SAM optimiser outperforms both the constant learning rate and step decay with a lower epoch to convergence value of 50 and a lower loss variance value of 0.014.

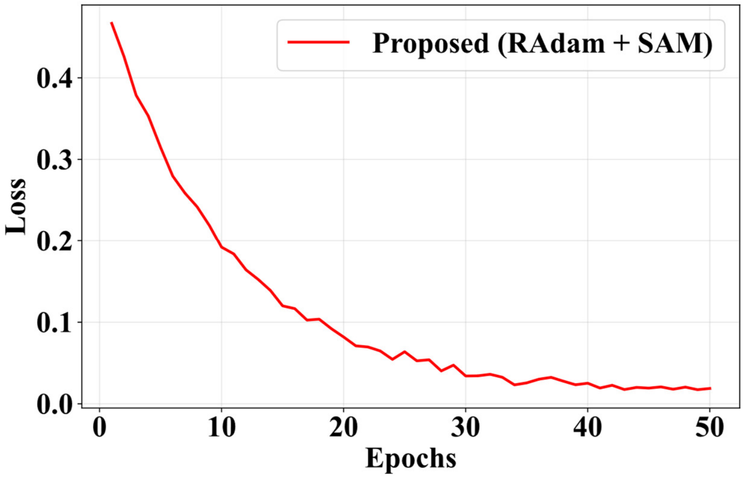

Figure 12. Impact of the proposed RAdam optimiser with SAM function on model performance

Table 3. Convergence analysis of different optimisers

Optimizer	Precision (%)	Recall (%)	Epochs to Converge	Loss Variance
AdamW	96.8	95.3	61	0.023
Adam	97.2	95.4	57	0.018
Adamax	96.6	94.9	55	0.027
Proposed (RAdam + SAM)	99.4	98.2	50	0.014

Comparative analysis

Table 4 compares the existing weed detection approaches and the proposed model in terms of precision, recall, and mAP50. The existing YOLOv3-tiny, YOLOv8n, and YOLO-CWD models achieved precisions of 87%, 96.5%, and 86.2%, respectively. In comparison, the proposed model achieved a precision of 99.4%, a recall of 98.2%, and a mAP of 99.56%, demonstrating that the proposed YOLO11-PSPNet framework effectively detects weeds in rice fields.

Table 4. Comparative analysis of weed detection performance between YOLO11-PSPNet and existing state-of-the-art approaches

References	Methods	Precision (%)	Recall (%)	mAP50
Farooque *et al.*, 2023	YOLOv3-tiny	87	75	76.4
Zhang *et al.*, 2024a	YOLOv8n	96.5	96.4	98.2
Ma *et al.*, 2025	YOLO-CWD	86.2	74.3	75.1
Proposed	YOLO11-PSPNet	99.4	98.2	99.56

Table 5 compares the existing weed segmentation approaches and the proposed model in terms of mAP50 and IoU. The existing PIS-Net, SSU-Net, and F-YOLOv8n-Seg-CDA approaches achieved mAP50 of 68.29%, 63.50%, and 98.4%, respectively. In comparison, the proposed model obtains a mAP value of 99.56% and IoU of 99.61%. This highlights the proposed YOLO11-PSPNet framework efficiently segments weeds in rice fields.

Table 5. Weed segmentation performance between YOLO11-PSPNet and existing state-of-the-art approaches

References	Methods	mAP50	IoU
Chen *et al.*, 2024	PIS-Net	68.29	64.31
Machidon *et al.*, 2025	SSU-Net	63.50	58.27
Zhang *et al.,* 2024	F-YOLOv8n-Seg-CDA	98.4	96.4
Proposed	YOLO11-PSPNet	99.56	99.61

Table 6 compares the inference time of the proposed model with that of existing approaches, including RMS-DETR (Guo *et al.*, 2024), DWUNet (Habib *et al.*, 2024), a single-stage DL model (Rai and Sun, 2024), and an improved UNet (Li *et al.*, 2025). The existing approaches achieved inference times of 8.1, 8, 82.1, and 55.9 ms per image, respectively. The proposed model achieved an inference time of 6.2 ms per image, demonstrating that the proposed YOLO11-PSPNet framework outperforms existing approaches.

Table 6. Inference time comparison per image between the proposed model and existing weed detection methods

References	Methods	Inference time (ms)
Guo *et al.*, 2024	RMS-DETR	8.1
Habib *et al.*, 2024	DWUNet	8
Rai and Sun, 2024	Single-stage DL model	82.1
Li *et al.*, 2025	Improved UNet	55.9
Proposed	YOLO11-PSPNet	6.2

Discussion

The proposed YOLO11-PSPNet architecture effectively addresses the challenges of weed localisation in paddy fields by integrating block-wise detection with pixel-level segmentation. The model utilised UAV images for rice field weed detection to achieve fine-grained weed localisation in paddy fields. The proposed model addresses the limitations of existing approaches that rely on either detection or segmentation, enabling the precise identification of weed-infested regions through weed detection and segmentation for spraying applications. The YOLO11-s model demonstrated excellent capability to accurately detect weed-infested areas, whereas PSPNet provided fine-grained segmentation, enabling the separation of weed areas. Pixel-level segmentation enables precise mapping of weed distribution, which can be used to guide selective spraying tactics, reduce chemical inputs, and improve overall crop quality.

Additionally, the RAdam optimiser with SAM produced a training process that was both stable and robust, leading to a more effective and dependable weed detection system. The system achieved a high mAP of 99.56% and an mIoU of 98.27% with an inference time of 6.2 ms, indicating the potential for real-time deployment. The proposed YOLO11-PSPNet demonstrated significant improvements in the agricultural field by achieving accurate weed localisation. The colour mapping method enhanced the interpretability of the results for humans, facilitating accurate and targeted spraying. Existing works (Rai *et al*., 2024; Singh *et al*., 2025) shows strong object detection performance but limited to precise mask generation of dense canopy conditions. Segmentation approaches, U-Net++ and DeepLabV3+-based architectures perform segmentation tasks but require higher compute resources. Compared to these approaches, proposed YOLOv11-PSPNet sequential pipeline achieves both high mAP and high IoU while maintaining inference efficiency suitable for UAV-based spraying. The proposed YOLO11-PSPNet was primarily developed to detect and segment weeds in rice fields using UAV images for site-specific weed management. These two networks result in a more efficient and lightweight design suitable for deployment on edge devices. The integrated YOLO11-PSPNet model provides efficient real-time object detection and robust semantic segmentation in paddy fields. The PSPNet components support YOLO11-s in challenging detection cases, such as small or partially occluded objects. This contextual information helps to classify and localise objects more accurately in complex environments. In our study, the primary weed species observed and annotated in the dataset included *Echinochloa*, *Cyperus difformis*, and *Echinochloa colona*, as these are among the most widespread and problematic weed types in rice fields in our study region. Although our training focused on these common species, the proposed YOLO11-PSPNet was designed to learn general weed characteristics based on shape, texture, and spatial patterns, enabling it to effectively detect other weed types that were not labelled during training. In our trials, very few detection errors were observed when locating weeds. We reduced the misclassification rates using advanced data augmentation processes and high-resolution UAV images. Future work will focus on integrating these detection outputs with automated spraying and analysing the real-world benefits. This ensures that the integration of advanced deep learning models and UAV technology provides a comprehensive solution for precision weed management.

Conclusion

The proposed YOLO11-PSPNet intelligent weed detection system effectively utilises YOLO11-s and PSPNet for targeted fertiliser and herbicide spraying in precision agriculture. The approach enabled efficient weed localization and weed boundary extraction, resulting in highly accurate weed identification and mapping. This study contributes to precision agriculture by offering an automated weed detection and segmentation system that optimises herbicide use, reduces costs, and enhances crop health. The experimental results demonstrate that the proposed model outperforms existing approaches, with a precision and recall of 99.4% and 98.2%, respectively. The findings confirm that combining detection with targeted semantic segmentation can reduce processing overhead while maintaining high spatial accuracy. This ensures accurate weed detection at the early stages of crop growth. In the future, including multispectral UAV images across multiple growth stages and environmental conditions could expand weed classification by detecting variations in weeds and enhancing model robustness.

Authors' Contributions

Conceptualization: R.C; Data curation: R.C, S.R; Formal analysis: R.C, V.M; Investigation: R.C, S.R; Methodology: R.C, V.M; Project administration: R.C; Resources: S.R, V.M; Software: S.R; Supervision: V.M;

Validation: R.C; Visualization: S.R; Roles/Writing - original draft: R.C, S.R, V.M; and Writing - review & editing: R.C, V.M.

All authors read and approved the final manuscript.

Availability of Data and Materials

https://universe.roboflow.com/jeho/weed-lkwvk/

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Conflict of Interests

The authors declare that there are no conflicts of interest related to this article.

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