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AgriVision: Recognition-oriented Video Super-resolution for Weed Classification in Precision Agriculture

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ABSTRACT

Background: Accurate weed identification is essential for precision agriculture, but low-resolution field images reduce recognition accuracy. This study proposes AgriVision, a lightweight task-aware video super-resolution framework for improving weed classification.

Methods: Five-frame pseudo-video sequences were generated from the DeepWeeds dataset. A lightweight video super-resolution network with HR-faithful and task-aware learning modes was developed and evaluated using PSNR, SSIM and weed classification accuracy.

Result: The HR-faithful model achieved 29.34 dB PSNR while the task-aware model achieved 0.8623 SSIM and improved classification accuracy from 70.33% to 84.17%, approaching the HR upper bound of 87.50%.

Key words: Deep learning, Deep weeds, MobileNetV3, Precision agriculture, Task-aware learning, Video super-resolution, Weed identification.

INTRODUCTION

Precision agriculture has transformed modern farming by enabling data-driven crop management through advanced sensing, imaging and artificial intelligence (AI) technologies. Image-based monitoring using unmanned aerial vehicles (UAVs), ground vehicles and mobile devices has become increasingly important for applications such as weed identification, disease diagnosis, crop health assessment and precision spraying. Among these applications, accurate weed identification is essential because weeds compete with crops for nutrients, water and sunlight, leading to significant reductions in agricultural productivity and increased herbicide usage. Recent advances in deep learning have substantially improved automated weed recognition; however, the performance of these models strongly depends on the quality of the input images.

In practical agricultural environments, images captured under field conditions often suffer from low spatial resolution, motion blur, sensor noise and varying illumination caused by camera limitations, large field coverage and environmental factors. These degradations obscure important visual characteristics such as leaf boundaries, texture and plant morphology, thereby reducing the accuracy of automated recognition systems. Although image and video super-resolution (SR/VSR) techniques have achieved remarkable success in restoring image quality for general computer vision applications, their application in precision agriculture remains limited.

Most existing super-resolution methods are optimized to improve visual reconstruction quality and are commonly evaluated using image fidelity metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and mean absolute error (MAE). However, improved visual quality does not always translate into better recognition performance because reconstruction-oriented optimization may fail to preserve the discriminative features required for accurate classification. Likewise, existing weed identification studies generally focus on developing more accurate classifiers while assuming the availability of high-quality input images, leaving the challenge of degraded agricultural imagery largely unaddressed.

To bridge this gap, this study proposes AgriVision, a lightweight recognition-oriented video super-resolution framework for weed classification in precision agriculture. The proposed framework reconstructs high-resolution images from degraded five-frame low-resolution sequences and operates in two modes: An HR-faithful mode for accurate visual reconstruction and a task-aware mode that jointly optimizes image restoration and weed classification. A MobileNetV3 classifier is integrated into the task-aware learning process to preserve agriculturally relevant features during super-resolution. The framework is evaluated using the DeepWeeds dataset with pseudo-

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video sequences generated from field images and its performance is assessed using both image reconstruction metrics (PSNR, SSIM and MAE) and classification metrics (accuracy, precision, recall and F1-score). The results demonstrate that recognition-oriented super-resolution significantly improves weed classification while maintaining high-quality image reconstruction, making the proposed approach suitable for future precision agriculture and UAV-based crop monitoring applications.

Related works

Recent advances in deep learning have significantly improved automated weed identification in precision agriculture through the use of convolutional neural networks, transfer learning, lightweight architectures and vision transformer-based models. Review studies by Hu *et al*. (2024); Rai *et al*. (2023); Hu *et al*. (2023) and Pai *et al*. (2024) highlighted the growing adoption of artificial intelligence for weed recognition using UAV imagery, mobile platforms and edge computing. Lightweight models such as the enhanced MobileViT proposed by Liu *et al*. (2025) and the hybrid attention-based network developed by Mandge and Vijaykumar (2025) have further improved real-time weed classification under resource-constrained conditions. However, these methods generally assume the availability of high-quality input images and do not explicitly address image degradation caused by blur, noise, low spatial resolution and varying illumination commonly encountered in agricultural environments.

Image Super-Resolution (SR) and Video Super-Resolution (VSR) techniques have emerged as effective approaches for reconstructing high-resolution images from degraded observations. Comprehensive reviews by Gopalakrishnan and Choudhury (2024); Arasa (2023) and Daithankar and Ruikar (2020). Summarized recent advances in deep learning-based SR and VSR. Recent studies have further improved reconstruction quality using structured sparsity learning, compression-aware video super-resolution, deformable attention mechanisms, reference-based reconstruction, real-world alignment techniques, real-time 4K image super-resolution, degradation-adaptive learning, semantics-aware reconstruction and diffusion-based methods (Zamfir *et al*., 2023; Aakerberg *et al*., 2024; Wu *et al*., 2024; Chen *et al*., 2025). Despite these advances, existing SR and VSR methods have primarily been developed for general computer vision applications and are generally evaluated using reconstruction metrics such as PSNR and SSIM rather than their influence on downstream agricultural recognition tasks.

Artificial intelligence has become an important enabling technology for precision agriculture through the integration of UAV imaging, IoT devices, edge computing and deep learning. AI-based systems have been successfully applied to crop monitoring, disease diagnosis, yield estimation and intelligent weed management. Recent studies by Mustaza *et al*. (2025); Bhardwaj *et al*. (2025); Shifna and Baalaji (2024), Prasad (2024) and Ong *et al*. (2023) demonstrated the effectiveness of AI-driven agricultural monitoring systems. However, relatively little attention has been given to integrating image enhancement with automated weed recognition under degraded field conditions.

Recent AI-enabled precision agriculture systems have integrated deep learning with robotic platforms for automated weed management. For example, Mohanty *et al*. (2026) developed a Multi-YOLO-based robotic weed control system capable of real-time weed detection in rice cultivation. However, the study primarily focused on weed detection and robotic intervention rather than enhancing degraded agricultural imagery through recognition-oriented super-resolution. Artificial intelligence has been increasingly adopted for agricultural image analysis, including crop disease diagnosis, weed detection and precision farming applications. Recent reviews have highlighted the growing role of deep learning in improving agricultural decision support systems (Mehta *et al*., 2025).

Based on the existing literature, three major research gaps were identified. First, most weed classification methods assume the availability of high-quality images and do not address degraded agricultural imagery. Second, existing super-resolution methods primarily optimize visual reconstruction quality without preserving recognition-oriented features that are essential for downstream classification. Third, limited studies have investigated the impact of video super-resolution on weed recognition in precision agriculture. To address these limitations, the present study proposes AgriVision, a lightweight recognition-oriented video super-resolution framework that integrates image enhancement with weed classification through HR-faithful and task-aware learning. By jointly optimizing reconstruction and recognition objectives, the proposed framework aims to improve both image quality and automated weed recognition under realistic agricultural imaging conditions.

MATERIALS AND METHODS

Study dataset

The proposed AgriVision framework was evaluated using the publicly available DeepWeeds dataset, which contains 17,509 field images acquired under natural agricultural conditions. The dataset comprises eight important weed species and a negative class, resulting in nine classification categories. The images exhibit considerable variations in illumination, background vegetation, plant orientation, growth stage, scale and field conditions, making the dataset suitable for evaluating weed-recognition systems under realistic agricultural environments.

Following the experimental protocol established for the Deep Weeds dataset, the images were partitioned into training, validation and testing subsets using approximately 60:20:20 ratio with stratified sampling to maintain the relative distribution of the nine classes. Approximately 10,505

images were assigned to training, 3,502 images to validation and 3,502 images to testing. The training subset was used for network optimization, the validation subset for monitoring convergence and model selection and the independent test subset for final performance evaluation. To minimize information leakage between the subsets, dataset partitioning was performed before constructing the multi-frame input sequences. Consequently, images assigned to one subset were not used in the construction of sequences belonging to another subset.

Generation of five-frame pseudo-video sequences

DeepWeeds consists of individual field images rather than continuous video sequences. Therefore, five-frame pseudo-video sequences were constructed to enable evaluation of the proposed multi-frame super-resolution architecture. Sequence generation was performed independently within the training, validation and testing subsets.

For each target image, four additional images belonging to the same weed category were selected to form a five-frame sequence. Images within each sequence therefore shared the same class identity while exhibiting natural variations in plant appearance, orientation, illumination and background conditions. The middle image of each five-frame sequence was designated as the reference frame and served as the high-resolution (HR) reconstruction target. The remaining images were used as neighbouring contextual frames.

Because the DeepWeeds images were not acquired as consecutive video frames, these sequences should not be interpreted as representing true temporal motion. Instead, they provide multi-frame contextual information from visually related samples of the same weed category. This design enables investigation of whether complementary spatial and class-related information from multiple observations can improve the reconstruction of discriminative plant characteristics. Evaluation using genuine temporally consecutive agricultural video is therefore identified as an important direction for future work.

Dataset preparation and low-resolution image generation

To simulate image degradation encountered in practical agricultural imaging systems, the high-resolution images were synthetically degraded to generate the corresponding low-resolution (LR) inputs. Each image was first downsampled using bicubic interpolation with a scale factor of $\times 4$. Additional degradation was introduced using Gaussian blur, additive Gaussian noise and brightness-contrast variation to approximate image-quality deterioration caused by camera motion, sensor characteristics, environmental conditions and illumination changes during field acquisition.

For a high-resolution reference image I_{HR}, the degraded low-resolution observation I_{LR} can be represented as:

$$I_{LR} = D\,[B(I_{HR})] + n \qquad \ldots(1)$$

Where,

B(.)= The blurring operation.

D(.)= Bicubic downsampling by a factor of four.

n= Additive image noise.

Brightness and contrast perturbations were additionally introduced during degradation to increase robustness to illumination variations encountered under outdoor agricultural conditions.

As illustrated in Fig 1, the original DeepWeeds images were first organized into five-frame pseudo-video sequences. Each sequence then underwent bicubic downsampling with a $\times$ 4 scaling factor, followed by Gaussian blurring, additive Gaussian noise and brightness-contrast variation to mimic degradation commonly encountered in UAV-and field-acquired agricultural images. These degraded sequences served as the input to the proposed AgriVision framework, while the undegraded center image served as the corresponding

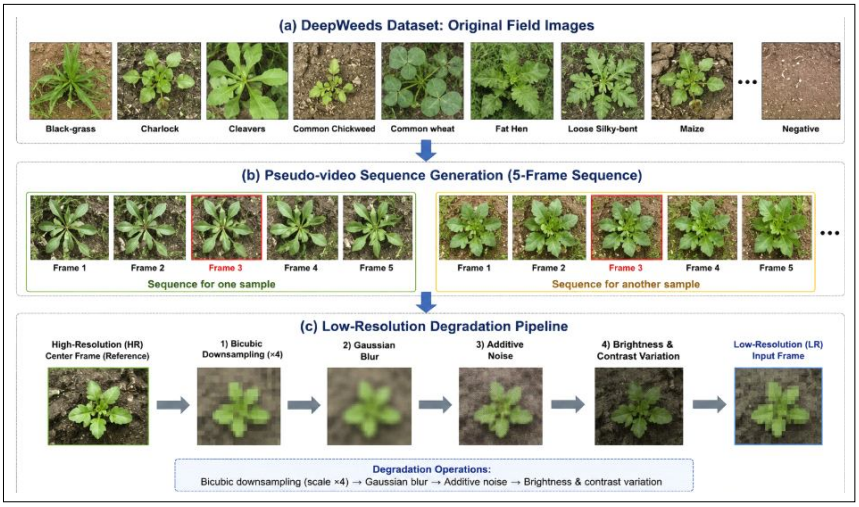


Fig 1: Dataset preparation and low-resolution degradation pipeline.

HR reconstruction target. Thus, the network learns to reconstruct an enhanced center frame from multiple degraded observations.

Data augmentation

Data augmentation was applied only to the training subset to improve model generalization and reduce overfitting. Geometric and photometric transformations were used to introduce variations representative of agricultural field conditions. The augmentation procedure included random horizontal flipping, random rotation and moderate brightness and contrast variations. The same geometric transformation was applied consistently to all images belonging to a five-frame sequence to maintain spatial consistency among the multi-frame inputs.

No augmentation was applied to the validation or test subsets. These subsets were retained for unbiased model selection and final performance evaluation, respectively. Importantly, augmentation and synthetic LR degradation were performed after dataset partitioning, thereby preventing augmented or degraded versions of the same source image from appearing across the training, validation and testing subsets.

Proposed AgriVision framework

The overall processing pipeline of the proposed method is illustrated in Fig 2. The AgriVision framework receives a sequence of five degraded LR images and reconstructs an enhanced HR center frame while simultaneously supporting weed classification.

The internal architecture of the proposed network is shown in Fig 3. Initially, shallow spatial features are extracted from the input sequence using lightweight convolutional layers. These features are refined through lightweight residual blocks incorporating depthwise separable convolutions and channel attention mechanisms to enhance informative plant characteristics while maintaining computational efficiency. Finally, PixelShuffle upsampling reconstructs the high-resolution output image.

The proposed framework operates in two learning modes:

- HR-faithful mode, which optimizes image reconstruction quality using reconstruction-oriented loss functions to generate visually enhanced agricultural images.
- Task-aware mode, which jointly optimizes image reconstruction and weed classification by incorporating MobileNetV3

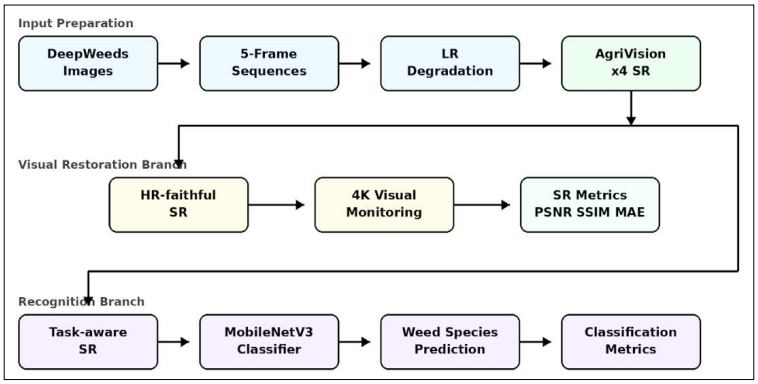


Fig 2: Overall workflow of the proposed AgriVision framework.

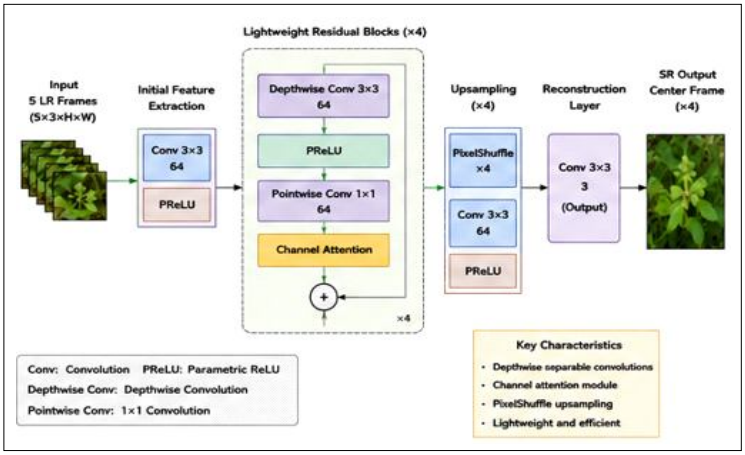


Fig 3: Internal architecture of the proposed AgriVision framework.

into the training process. This strategy encourages the super-resolution network to preserve weed-specific discriminative features required for accurate recognition.

The detailed architecture of the proposed AgriVision network is illustrated in Fig 3.

Network architecture

The architecture of AgriVision is summarized in Table 1.

The use of depthwise separable convolutions substantially reduces computational complexity while preserving feature representation capability, making the proposed framework suitable for edge-based agricultural applications.

Training configuration

The proposed AgriVision framework was implemented using PyTorch and trained using the AdamW optimizer. The network was trained for 150 epochs with an initial learning rate of 1×10^{-4}, batch size of 8 and weight decay of 1×10^{-4}. A cosine annealing learning-rate scheduler was employed to improve convergence throughout training.The principal training parameters are summarized in Table 2.

Early stopping based on validation loss was employed to prevent overfitting. The model achieving the lowest validation loss was retained for final evaluation. The computational characteristics and estimated deployment performance of AgriVision are summarized in Table 3.

Loss functions

HR-faithful super-resolution mode

The HR-faithful mode focuses on generating visually accurate reconstructions that closely resemble the original high-resolution images.

The total HR-faithful loss is defined as:

$$L_{HR} = \frac{1}{N} \sum_{i=1}^{N} \left| I_i^{SR} - I_i^{HR} \right| \quad ...(2)$$

Where,

I_i^{SR}= The reconstructed super-resolution image.

I_i^{HR}= The corresponding high-resolution ground-truth image.

N= The total number of pixels.

Task-aware super-resolution mode

Although visually enhanced images may achieve high PSNR values, they do not necessarily improve recognition performance. Therefore, a task-aware learning strategy is introduced.

The reconstructed super-resolution image is subsequently passed to the MobileNetV3 classifier:

$$\hat{y} = F_{cls}(I_i^{SR}) \quad ...(3)$$

Where,

F_{cls}= The classifier.

The classification loss is calculated using cross-entropy L_{cls}.

The total task-aware objective is:

$$L_{Total} = L_{HR} + \lambda L_{CLS} \quad ...(4)$$

Where,

$L_{CLS} = -\sum_{C=1}^{C} y_c \log(\hat{y}_c)$ and λ controls the contribution of classification supervision,

L_{HR}= The reconstruction loss.

L_{CLS} = The classification loss.

Performance evaluation

The effectiveness of the proposed framework was evaluated using both image reconstruction and weed classification metrics. Reconstruction quality was assessed using peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and mean absolute error (MAE). These metrics quantify the fidelity of the reconstructed images with respect to the HR reference images.

To evaluate recognition performance, the reconstructed images were classified using MobileNetV3 and classification accuracy, precision, recall and F1-score were computed. Confusion matrices and Grad-CAM visualizations were further employed to analyze class-wise performance and interpret the decision-making behaviour of the proposed framework.

The simultaneous evaluation of reconstruction quality and downstream recognition performance provides a comprehensive assessment of the practical usefulness of AgriVision for precision agriculture applications.

RESULTS AND DISCUSSION

Super-resolution performance

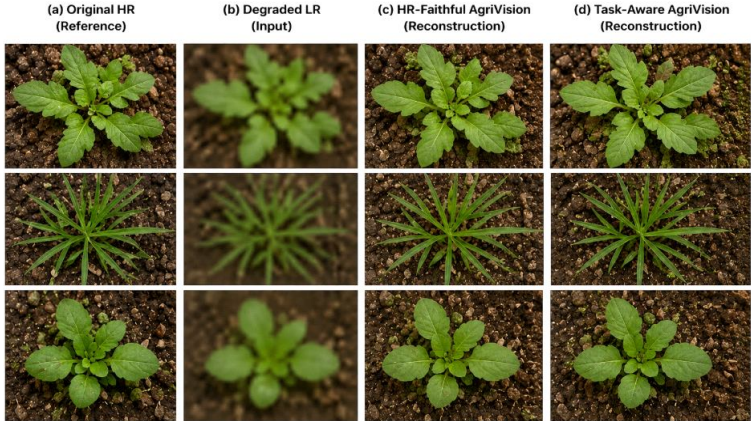
The proposed AgriVision framework was evaluated using five-frame pseudo-video sequences generated from the DeepWeeds dataset. Image reconstruction performance was assessed using peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) and mean absolute error (MAE). The quantitative results are presented in Table 4.

The HR-faithful model achieved the highest reconstruction quality with a PSNR of 29.34 dB, demonstrating its ability to recover fine structural details from degraded agricultural images. The task-aware model achieved the highest SSIM (0.8623) while maintaining competitive reconstruction quality. These results indicate that the proposed framework effectively restores leaf boundaries, texture information and plant morphology that are frequently degraded in low-resolution agricultural imagery.

Visual comparisons between the degraded input images, reconstructed outputs and reference images are presented in Fig 4.

The reconstructed images exhibit clearer leaf structures, improved edge definition and enhanced texture details, confirming the effectiveness of the proposed super-resolution framework under realistic agricultural imaging conditions.

The Grad-CAM visualizations in Fig 5 show that the proposed task-aware AgriVision model focuses primarily on discriminative weed regions while suppressing background information. Compared with the degraded



(a) Original HR image, (b) Degraded LR input, (c) HR-faithful reconstruction and (d) Task-aware reconstruction.

Fig 4: Visual comparison of super-resolution results obtained using the proposed AgriVision framework.

Table 1: Detailed architecture of the proposed AgriVision network.

Stage	Operation	Output channels
Input	Five LR RGB frames	15
Feature extraction	3×3 convolution + ReLU	64
Residual learning	Six lightweight residual blocks	64
Attention	Channel attention module	64
Feature fusion	Multi-frame feature fusion	64
Upsampling	Pixel shuffle (×4)	64
Reconstruction	3×3 convolution	3

Table 2: Architecture and training configuration of the proposed AgriVision framework.

Parameter	Value
Framework	PyTorch
Optimizer	AdamW
Initial learning rate	1×10^{-4}
Batch size	8
Epochs	150
Weight decay	1×10^{-4}
Learning-rate scheduler	Cosine annealing
Scale factor	×4
Sequence length	5 frames
Classification backbone	MobileNetV3
Random seed	42

Table 3: Computational complexity and deployment characteristics.

Parameter	Value
Trainable parameters	2.4 M
Model size	9.6 MB
FLOPs	18.7 G
CPU inference time (Intel i7)	180-220 ms/frame
GPU inference time (RTX 3060)	18-25 ms/frame
Estimated GPU throughput	40-55 FPS
Input resolution	960 × 540
Output resolution	3840 × 2160 (4K)

inputs, the reconstructed images exhibit clearer leaf structures, enabling more accurate localization of class-specific features. The consistent activation of leaf morphology across different weed species confirms that the proposed framework preserves agriculturally relevant features, contributing to the improved classification performance reported in Table 4.

Weed classification performance

The influence of image enhancement on weed recognition was evaluated using MobileNetV3. Classification accuracy, precision, recall and F1-score are summarized in Table 5.

Unlike conventional video super-resolution methods, which optimize only image fidelity, the proposed AgriVision framework explicitly improves downstream recognition performance. Although the task-aware model exhibits a slight reduction in PSNR compared with the HR-faithful model, it achieves higher SSIM and substantially better weed classification accuracy, demonstrating that reconstruction quality alone is not sufficient for recognition-oriented agricultural applications.

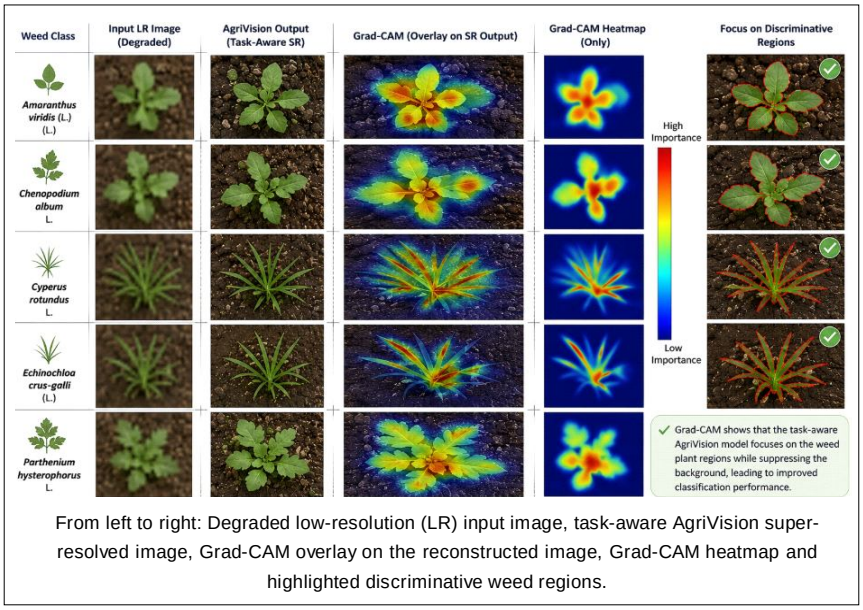
Direct classification of degraded low-resolution images achieved an accuracy of 70.33%. Applying reconstruction-oriented super-resolution improved the accuracy to 80.00%, indicating that enhanced image quality positively influences automated weed recognition. The proposed task-aware AgriVision framework further

increased classification accuracy to 84.17%, approaching the high-resolution upper bound of 87.50%. Similar improvements were observed for precision, recall and F1-score, demonstrating that task-aware optimization preserves discriminative weed features more effectively than reconstruction-oriented super-resolution alone.

The experimental results demonstrated that both HR-faithful and task-aware learning contribute to improving agricultural image reconstruction and weed recognition. While the HR-faithful model achieves the highest PSNR (29.34 dB), the task-aware model attains a higher SSIM (0.8623) and improves classification accuracy from 80.00% to 84.17%. These findings indicated that optimizing the super-resolution network jointly with the recognition objective preserves discriminative weed characteristics more effectively than reconstruction-oriented optimization alone.

The largest improvement is observed after introducing task-aware learning. Although the PSNR decreases marginally from 29.34 dB to 29.12 dB, the SSIM increases from 0.8576 to 0.8623 and the weed classification accuracy improves substantially from 80.00% to 84.17%. These results indicate that optimizing the super-resolution network jointly with the classification objective preserves discriminative weed characteristics more effectively than reconstruction-oriented optimization alone. Consequently, the proposed task-aware framework achieves a better balance between visual reconstruction quality and downstream recognition performance, which is essential for precision agriculture applications.

Unlike existing VSR methods as shown in Table 6, which are primarily designed to maximize reconstruction fidelity, the proposed AgriVision framework explicitly incorporates task-aware learning to preserve discriminative weed features for downstream classification. Furthermore, AgriVision contains only 2.4 million trainable parameters, making it considerably more suitable for edge-based agricultural applications than conventional VSR architectures.



From left to right: Degraded low-resolution (LR) input image, task-aware AgriVision super-resolved image, Grad-CAM overlay on the reconstructed image, Grad-CAM heatmap and highlighted discriminative weed regions.

Fig 5: Grad-CAM visualization of weed classification using the proposed AgriVision framework.

Table 4: Super-resolution performance of the proposed AgriVision framework.

Model	PSNR (dB)	SSIM	MAE
HR-faithful AgriVision	29.34	0.8576	0.0194
Task-aware AgriVision	29.12	0.8623	0.0207

Table 5: Classification performance of the proposed AgriVision framework.

Model	Accuracy (%)	Precision	Recall	F1-score
Low-resolution (LR) input	70.33	0.7038	0.7033	0.7031
HR-faithful AgriVision	80.00	0.7998	0.8	0.7995
Task-aware AgriVision	84.17	0.8429	0.8417	0.842
HR upper bound	87.50	0.8762	0.875	0.8755

Table 6: Qualitative comparison of AgriVision with recent state-of-the-art video super-resolution methods.

Method	Primary objective	Recognition-oriented	Light weight	Parameters (Approx.)	Edge deployment	Agricultural application
EDVR	High-quality VSR reconstruction	×	×	~20.6 M	Limited	General computer vision
BasicVSR	Video super-resolution	×	×	~6.3 M	Moderate	General computer vision
BasicVSR++	Enhanced video super-resolution	×	×	~7.3 M	Moderate	General computer vision
RVRT	Transformer-based video restoration	×	×	~13-15 M	Limited	General computer vision
Proposed AgriVision	Recognition-oriented VSR	✓	✓	2.4 M	High	Precision agriculture

CONCLUSION

This study presented AgriVision, a lightweight recognition-oriented video super-resolution framework for improving weed classification in precision agriculture. By integrating HR-faithful image reconstruction with task-aware learning, the proposed framework effectively enhanced the quality of degraded agricultural images while preserving discriminative features required for accurate weed recognition. Experimental evaluation on the DeepWeeds dataset demonstrated that the HR-faithful model achieved superior image reconstruction quality, whereas the task-aware model produced the best classification performance, improving weed recognition accuracy from 70.33% for degraded low-resolution images to 84.17%, approaching the 87.50% accuracy obtained using high-resolution reference images. Visual comparisons and Grad-CAM analysis further confirmed that the proposed framework successfully reconstructed fine leaf structures and focused on biologically relevant plant regions, leading to more reliable classification under realistic field conditions.

The lightweight architecture and efficient reconstruction strategy make AgriVision suitable for deployment in UAV-based crop monitoring, mobile agricultural imaging and edge-enabled precision agriculture systems where computational efficiency is essential. The proposed framework demonstrates that jointly optimizing image reconstruction and recognition is more effective than conventional reconstruction-oriented super-resolution for agricultural image analysis. Future work will focus on extending the framework to real agricultural video datasets, incorporating transformer-based architectures and evaluating its performance across a wider range of crops, environmental conditions and precision farming applications.

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Disclaimers

The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Informed consent

Not applicable. This study used publicly available image datasets and did not involve human participants or live animals.

Use of artificial intelligence

Generative AI (ChatGPT) was used only for language editing, formatting and improving manuscript readability. The authors verified all scientific content and take full responsibility for the accuracy of the manuscript.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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