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Advancements in deep learning methods for precise weed and rice classification from UAV imagery: a comprehensive review

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Abstract
Weed invasion poses a significant threat to global rice production, causing substantial yield losses and environmental degradation from excessive herbicide use. Unmanned Aerial Vehicles (UAVs), combined with advanced remote sensing and deep learning techniques, offer a transformative approach for precise weed and rice classification, supporting site-specific weed management. This review not only synthesizes recent advancements in deep learning methods using UAV-acquired data, diverse vegetation indices, and multiple sensor modalities (RGB, multispectral, hyperspectral, thermal, and LiDAR) but also provides a critical perspective on the evolution of model architectures, highlighting key trends and challenges in real-world agricultural applications. We discuss persistent issues, including data scarcity, limited model generalizability across varying environmental conditions, and the computational demands for real-time deployment. Furthermore, we propose future research directions informed by our perspective on the field's development, emphasizing synthetic data generation via generative adversarial networks, advanced attention mechanisms, and the integration of UAVs with ground-based robotic platforms to enable more autonomous, efficient, and sustainable agricultural practices. This review thus offers both a comprehensive synthesis and a forward-looking viewpoint on advancing UAV-based precision weed management in rice cultivation. By integrating these insights, we provide a roadmap for translating UAV-based weed detection from experimental research to scalable, field-ready solutions.

Keywords Agricultural remote sensing, Crop identification, Precision agriculture, Rice mapping, Weed management

1 Introduction

1.1 Global significance of rice production and weed management challenges

Rice stands as a cornerstone of global food security, serving as a primary staple for a significant portion of the world's population [1]. Despite its critical role, rice production faces determined threats, with weed invasion being a major limiting factor. Direct rice yield losses attributable to weeds are substantial, ranging from an estimated 16% to a confounding 86% [2], depending on multiple factors such as rice type, cultivar, weed species and density, cropping season, management practices, fertilizer application rates, and local environmental conditions [3]. Even a conservative estimate of a 16% yield loss can dramatically affect farmers' profitability and overall food security. This considerable variability in yield reduction underscores the universal and severe impact of weeds on rice productivity.

Existing weed control methods predominantly rely on uniform, blanket application of herbicides across entire fields [4]. This indiscriminate approach, while effective to a degree, leads to excessive chemical usage, which has profound negative consequences. Biologically, it contributes to soil and water pollution, impacts biodiversity, and can foster herbicide resistance in weed populations. Economically, it increases input costs for farmers, weakening profitability. Furthermore, the presence of weeds often triggers over-spraying, exacerbating these issues [5]. A fundamental challenge in moving towards more sustainable and efficient weed management is the inherent difficulty in accurately mapping weed distribution. This complexity arises primarily from the striking visual and spectral similarity between rice crops and various weed species, particularly during their early growth stages, making precise differentiation a challenging task. The substantial yield loss and environmental degradation associated with ongoing herbicide practices highlight an urgent global need for advanced, sustainable solutions. This situation frames the entire discussion within a critical agricultural and environmental context, emphasizing that the technological advancements reviewed are not merely academic curiosities but essential tools for global food security and environmental stewardship.

1.2 Evolution of precision agriculture and the role of unmanned aerial vehicles

Precision agriculture represents an archetype shift in contemporary farming practices, emphasizing the integration of data-driven approaches to enhance resource efficiency and reduce environmental impact. In this evolving landscape, remote sensing technology has emerged as a pivotal enabler, with Unmanned Aerial Vehicles (UAVs) proving to be a transformative strength [6]. Traditional ground-based surveying methods for weed detection are inherently labor-intensive, time-consuming, and inefficient, especially when dealing with large agricultural areas. They are also susceptible to human error, limiting their scalability and accuracy [7]. Satellite-based remote sensing, while offering broad coverage, suffers from critical limitations such as low spatial and temporal resolution [8], poor timeline, and susceptibility to cloud cover, which can severely hinder data acquisition and analysis. These constraints can significantly hinder the effectiveness of weed detection, as they may not provide the necessary detail for accurate mapping of weed populations, especially in dynamic agricultural environments.

These inherent shortcomings of existing weed management and monitoring approaches have directly boosted the rapid development and adoption of UAV technology in precision agriculture [9]. UAVs overcome these limitations by offering a compelling array of advantages: their ability to cover large zones in a brief amount of time, their payload capacity to carry diverse optical sensors, high flexibility, relatively low hardware cost, and ease of operation. UAVs are not affected by cloud cover in the same way satellites are, providing greater flexibility in terms of temporal resolution and enabling rapid, non-destructive extraction of crop growth information [10]. The integration of multi-sensor payloads (e.g., RGB, multispectral, hyperspectral, thermal, and LiDAR) on UAV platforms provides exceptional spectral, spatial, and temporal resolution, marking a paradigm shift in agricultural monitoring. This capability has transformed weed detection from traditional methods to highly precise, data-driven approaches [11]. Additionally, integrated with deep learning models, UAV enables automated, accurate, and scalable weed identification, paving the way for real-time, site-specific management in complex field conditions [6].

1.3 Scope and contributions of this review

This review provides a comprehensive synthesis of recent advancements in UAV-based remote sensing and deep learning methodologies published between 2018 and 2025. Specifically, it focuses on approaches tailored for precise weed and rice classification, offering an integrated perspective on technological progress and application trends (Fig. 1). It critically examines the evolution of UAV platforms and the diverse sensor technologies deployed, delving into the nuances of spectral differentiation and the development of specialized vegetation indices. A significant focus is placed on exploring various vegetation indices and UAV data adaptation that enhance classification accuracy for weed mapping. Furthermore, a substantial portion of this survey paper is dedicated to a comprehensive comparative analysis of prominent deep learning models, outlining their typical pipelines and evaluating their accuracies within the context of rice field applications. Ultimately, this review identifies the prevailing challenges in the field and proposes concrete future research directions, aiming to guide the development of more robust, generalizable, and practical solutions for sustainable rice production globally.

1.4 UAV types and operational advantages for agricultural monitoring

UAVs have emerged as pivotal tools in modern precision agriculture due to their operational flexibility, rapid deployment, and cost-effectiveness [12, 13]. Their capacity to operate across heterogeneous agricultural landscapes with minimal human intervention has facilitated high-throughput field phenotyping and monitoring over large spatial

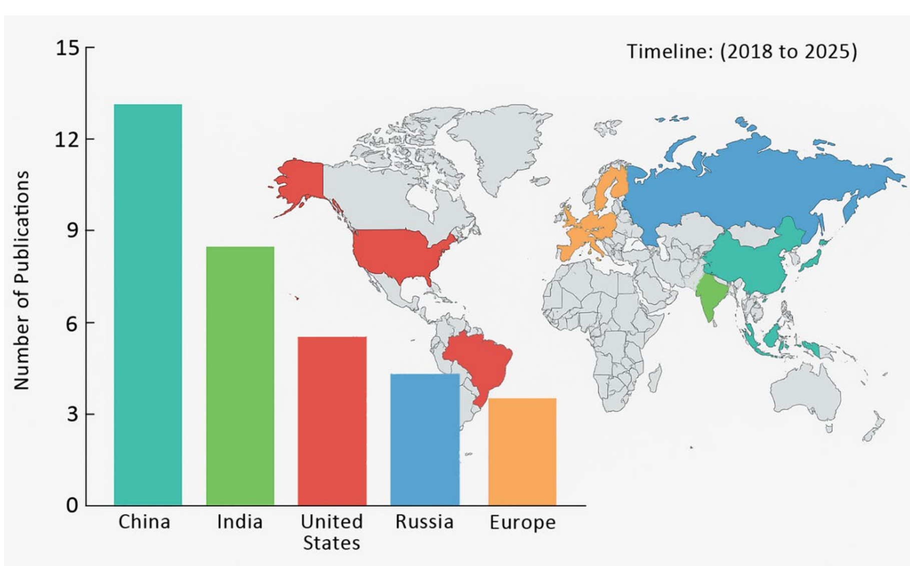

Fig. 1 Spatial Distribution of the Rice-weed research from 2018 to 2025

extents. The ease of maintenance and relatively low operating costs compared to manned systems make UAVs particularly smart for routine agricultural assessments [14].

UAV platforms used in agricultural applications are generally classified into coaxial, single-rotor, and multi-rotor configurations [2]. These UAVs support a broader spectrum of agricultural tasks, including crop health monitoring, growth analysis, disease detection, and yield estimation [15]. Future advancements are expected to focus on improving their energy efficiency, autonomous flight stability, and sensor integration capabilities [16].

1.5 Sensor modalities: RGB, multispectral, hyperspectral, thermal, and lidar

UAVs support a variety of sensors RGB, multispectral, hyperspectral, thermal, and LiDAR, each contributing uniquely to precision agriculture [17–19]. RGB cameras provide affordable, high-resolution imaging for vegetation mapping and canopy analysis [13, 20]. However, multispectral sensors extend into the near-infrared range, enabling vegetation indices such as NDVI, which are valuable for mapping crop vigour and detecting early-stage weeds [21, 22]. Comparatively, hyperspectral sensors capture hundreds of contiguous bands, facilitating fine-grained discrimination of plant species with similar spectral features, such as rice and weeds [23]. Whereas, thermal sensors measure canopy temperature and are effective for monitoring crop water stress and irrigation efficiency [24]. To generate dense 3D point clouds, supporting biomass estimation, canopy height modeling, and terrain reconstruction can be achieved using LiDAR systems [25]. However, the integration of advanced sensors such as thermal and LiDAR also increases payload and power requirements, which can reduce UAV flight time and pose deployment challenges [19]. The integration of these complementary sensor modalities enables multimodal data fusion, which significantly improves classification accuracy and robustness, especially in environments where spectral confusion between crops and weeds is high [26, 27].

1.5.1 Low-cost UAV platforms for resource-limited farming systems

In addition to advanced UAVs equipped with hyperspectral or LiDAR sensors, recent studies emphasize the role of low-cost UAVs as accessible alternatives for smallholder farmers and local cooperatives [28]. Such UAVs often equipped with RGB or low-cost multispectral sensors enable affordable, repeatable field surveys with sufficient accuracy for crop monitoring, yield estimation, and weed mapping (Fernández et al., 2024). Their use can democratize precision agriculture, particularly in developing regions where investment in high-end UAVs remains prohibitive. Integration with open-source photogrammetry software such as OpenDroneMap and Pix4Dmapper further supports low-cost photogrammetric workflows, making them suitable for sustainable and scalable deployment.

Low-cost UAV systems increasingly support precision agriculture in regions where access to high-end sensors is limited. The Table 1 lists representative UAV models frequently used for photogrammetric crop and weed mapping, with indicative price ranges, sensor types, flight endurance, spatial resolution, and agricultural use cases.

Table 1 **A** Summary of representative Low-Cost UAV platforms for agricultural remote sensing and Weed-Rice mapping applications

Model	Sensor type	Approx. cost (USD)	Flight time (min)	Spatial resolution / GSD	Typical agricultural use	References
DJI Mini 3 Pro	RGB	900–1100	34	1.6–2.0 cm/pixel @50 m	Field mapping, weed detection	[29]
Parrot Anafi	RGB/Multispectral	800–1200	25	2–3 cm/pixel	Crop canopy monitoring	[29]
eBee SQ	Multispectral (Sequoia+)	5000–6000	50	3–5 cm/pixel	Large field mapping, NDVI, GNDVI	[29]
DJI Phantom 4 RTK	RGB	3500	30	2 cm/pixel	High-accuracy weed and crop classification	[12]
WingtraOne Gen II	Multispectral	10,000+	59	1–2 cm/pixel	Regional-scale agricultural surveys	[18]

1.5.2 Data acquisition and pre-processing considerations

UAV-based agricultural imaging is typically conducted at low altitudes, offering ultra-high spatial resolution that is important for detecting small-scale vegetation features such as early weeds [30]. Environmental variability, e.g., lighting changes from fluctuating sunlight and cloud shadows, can negatively affect image quality and reduce model performance [31, 32]. As a result, pre-processing becomes critical for model accuracy and generalization. Standard procedures include geometric correction, radiometric normalization, resizing imagery to conform to neural network input dimensions, and splitting datasets into training, validation, and testing subsets [33]. Data augmentation strategies such as rotation, flipping, and zooming help expand training data volume, reduce overfitting, and improve robustness across varying imaging conditions [34]. Furthermore, pre-processing steps are essential for preparing UAV imagery for deep learning models. These include orthorectification, mosaicking, normalization of spectral bands, and contrast enhancement to mitigate illumination variability. Such preprocessing ensures that datasets are standardized and compatible with neural network input requirements, improving model generalization and reducing training bias [35].

The altitude at which UAV images are captured directly affects ground sampling distance (GSD) and image clarity. Lower flight altitudes (e.g., 30–50 m) yield finer resolution suitable for early-stage weed detection and small-plot studies, whereas higher altitudes (100–150 m) support broader spatial coverage but risk spectral mixing and reduced feature separability [30, 36]. Consequently, selecting an optimal altitude involves balancing resolution, coverage, and processing efficiency.

2 Spectral signatures and vegetation indices for Weed-Rice mapping

Accurate weed-rice discrimination relies heavily on the spectral reflectance characteristics captured by remote sensing. This section reviews key vegetation indices (VIs) and spectral features used in UAV-based monitoring, highlighting their strengths, limitations, and applicability across different rice growth stages. While rice–weed classification presents unique challenges due to the high spectral similarity between seedlings, it is important to note that the performance of VIs can vary significantly across different cropping systems. For instance, indices such as NDVI and GNDVI have been widely applied in maize and soybean fields for weed detection [37], but their effectiveness is often reduced in rice fields because of the dense canopy and early-stage spectral overlap with weeds. Conversely, indices specifically tailored for paddy environments, such as WDVINIR, demonstrate higher reliability in discriminating weeds from rice compared to their performance in upland crops [38].

This comparative perspective underscores that VI selection is not crop-agnostic; rather, it must be aligned with crop morphology, canopy structure, and field conditions. Incorporating lessons from other crops (e.g., maize, wheat, soybean) reveals that while some indices show broad utility, rice–weed mapping often requires customized or combined VIs due to the water background, spectral similarity at seedling stages, and rapid canopy closure [39].

2.1 Differentiating rice and weed species based on spectral characteristics

Distinguishing rice from visually similar weed species, especially during early growth stages, poses a significant challenge in agricultural remote sensing. While visual similarities complicate manual identification, hyperspectral imagery offers a solution by enabling physiological and biochemical differences that manifest as distinct spectral signatures. Hyperspectral sensors effectively enable the discrimination of crops from weeds and among various weed species. Notably, specific spectral bands have been identified as critical for effective differentiation [40]. For instance, Table 2 provides the details of articles published in recent years with a focus on spectral characteristics and bands.

Regardless of these advancements, early-stage classification remains challenging due to the high spectral similarity between seedlings. To address this, recent research has explored deep learning approaches. A researcher claimed that incorporating multiple spectral pre-processing techniques and traditional machine learning achieved a maximum classification accuracy of 93.94% [42]. Furthermore, a deep learning-based framework for extracting hyperspectral features attained 98.18% accuracy in distinguishing seedling barnyard grass from rice [42].

These findings underscore the importance of precise sensor calibration and band selection in exploiting nuanced spectral differences. The integration of advanced deep

Table 2 Machine and deep learning research work focused on spectral characteristics

Year	Spectral bands (nm)	Classification method	Accuracy achieved	Summary	References
2021	415, 561, 687, 705, 735, 1007	Support Vector Machine (SVM)	> 90%	Used SVM with six optimal bands to distinguish barnyard grass and weedy rice from rice.	[41]
2025	unspecified	Deep Learning	98.18%	Developed a deep learning model for extracting hyperspectral features for rice–weed discrimination.	[42]
2022	400–2500 (range)	Review	Not available	Reviewed spectral bands and classification methods used in hyperspectral weed detection.	[43]
2024	Not specified	Ground-based Hyperspectral Imaging	75–95%	Used ground-based hyperspectral sensing for weed identification in rice fields.	[44]
2018	Full spectrum	Spatio-Spectral Deep CNN	+ 11.9% over SVM	Applied spatial-spectral deep CNN to improve rice classification accuracy.	[45, 46]
2020	Selected via band ranking	Gaussian Processes Regression	Not available	Developed a GPR-based tool to select informative spectral bands for vegetation traits.	[47]

learning techniques further enhances classification accuracy, offering promising avenues for targeted weed management in precision agriculture.

2.2 Vegetation indices and their application in weed discrimination

This section elaborates on the Vegetation Indices (VIs) used in recent years and their achieved accuracy in rice mapping. Vegetation indices are radiometric values derived from combinations of spectral bands that are designed to enhance specific vegetation characteristics while minimizing background interference from soil or non-vegetative elements. They play a crucial role in monitoring crop growth and health. Figure 2 illustrates both widely used vegetation indices and newly developed indices introduced over the past decade for weed–rice discrimination. One of the most effective vegetation indices recently developed for weed identification in rice fields is the Weed Discrimination Vegetation Index in Near-Infrared ($WDVI_{NIR}$). Utilizing reflectance from the Green, Red Edge, and NIR bands, $WDVI_{NIR}$ demonstrated 93.47% maximum accuracy and a Kappa coefficient of 0.859 in distinguishing weeds from rice fields. Despite its promising results, the index was constructed primarily through statistical modelling, limiting its generalizability across different ecological conditions and crop varieties due to the lack of integration of agronomic mechanisms or environmental variability [48].

Additionally, several traditional vegetation indices (VIs), such as NDVI, LCI, NDRE, and OSAVI, are also widely used in crop monitoring and physicochemical inversion but often show lower accuracy in discriminating weeds in rice fields. Recent studies highlight the need for more specialized indices to improve specificity in weed-rice classification [43].

In addition to $WDVI_{NIR}$, other VIs, such as RGB-based indices (e.g., ExG, ExR, VARI), are sensitive to vegetation greenness but susceptible to illumination variability. Multispectral-based indices (e.g., CI_{red} edge, $CI_{green,}$ NDVI, GNDVI) influence discrete bands, including NIR and red edge, and offer improved sensitivity to plant biochemical traits. SAVI and GSAVI, when combined with unsupervised clustering, have achieved

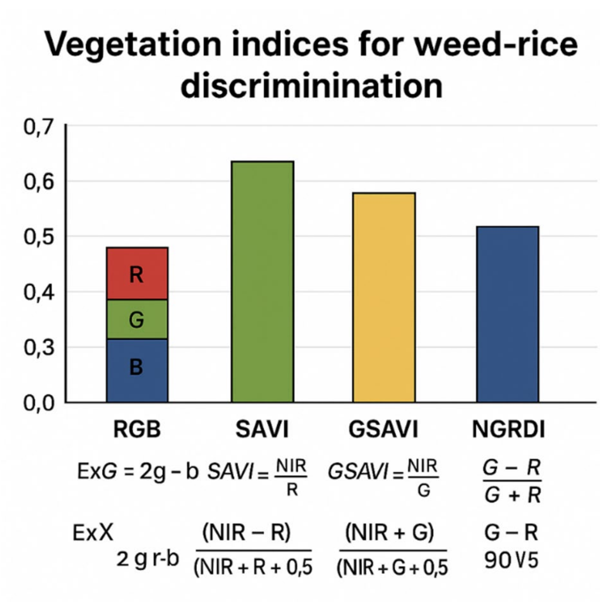

Fig. 2 Renowned vegetation indices used for weed-rice perception

over 94% accuracy in early-stage weed detection. NGRDI, fused with visible band data, reported M/MGT index values of 80–108% and MP values of 70–85% for effective weed detection.

Table 3 summarizes key vegetation indices used for weed–rice mapping, detailing each index's name, formula, spectral bands utilized, primary characteristics or intended purpose, and reported effectiveness or accuracy in discriminating between weed and rice.

However, many spectral indices face saturation issues in mid-to-late rice growth stages, where dense canopies hinder reflectance signals, reducing correlation with biomass and limiting their utility for continuous Leaf area Index (LAI) estimation and temporal weed monitoring [56, 57]. These limitations underscore the importance of integrating specialized indices with advanced data fusion or deep learning approaches to enhance robustness and adaptability across diverse rice-growing scenarios.

3 Deep learning models for weed and rice perception

Deep learning has become the backbone of UAV-based weed and rice classification, offering significant advantages over traditional machine learning in handling high-dimensional, heterogeneous datasets. However, the utility of these methods is not solely determined by their architectural evolution (from CNNs to Transformers) but by their suitability for specific UAV sensor modalities, field conditions, and operational demands.

3.1 Typical model development pipeline: from data acquisition to deployment

The development of deep learning models for UAV-based weed and rice classification typically follows a structured, multi-stage pipeline designed to ensure robustness and accuracy in real-world agricultural settings. While the evolution from CNNs to Transformer-based models reflects the broader deep learning trajectory, a critical analysis reveals important nuances in their applicability to UAV-based weed and rice classification. CNNs have demonstrated strength in spatial feature extraction for high-resolution UAV imagery but often struggle with spectral similarity between rice and weeds, particularly at early growth stages. Transformer-based architectures, with their self-attention mechanisms, improve contextual understanding and long-range dependencies, yet they demand larger annotated datasets and higher computational resources, limiting field scalability. Furthermore, multimodal UAV data introduce additional challenges: CNNs handle multispectral and RGB inputs effectively, whereas hyperspectral and LiDAR data often require hybrid architectures that combine spectral and spatial attention mechanisms. Despite performance improvements, both CNN and Transformer approaches remain constrained by issues of transferability across environments, annotation burdens, and real-time operational feasibility. Future work should therefore focus less on architecture alone and more on task-driven hybrid approaches that integrate domain-specific constraints, such as planting geometry, crop phenology, and environmental variability. The process commences with image acquisition, where high-resolution RGB images of rice fields are systematically captured by UAVs at various critical growth stages of both crops and weeds. Figure 3 shows that the initial stage provides the essential visual input for downstream analysis. Furthermore, Table 4 presents a detailed breakdown of each step in the model.

Table 3 Comparative analysis of key spectral indices used for UAV-based rice mapping

Index	Formula	Bands	Key characteristics/purpose	Effectiveness/accuracy for weed-rice discrimination	References
WDVI_NIR	log(G/NIR) / (RE/NIR)	Green, Red Edge, Near-Infrared	Specifically designed for weed-rice discrimination; sensitive to weed presence.	93.47% accuracy, Kappa 0.859 for weed identification in rice fields.	[4]
NDVI	(R800nm - R670nm) / (R800nm + R670nm)	Red, Near-Infrared	General vegetation health; widely used for biomass and LAI.	Fewer accurate for rice weed identification when used alone	[49]
NDRE	(R800nm - R720nm) / (R800nm + R720nm)	Red Edge, Near-Infrared	Sensitive to chlorophyll content; less prone to saturation than NDVI in dense canopies.	Moderate performance (80–85% accuracy); useful for mature canopies, but limited in early-stage weed detection.	[50]
OSAVI	1.16(R800nm - R670nm) / (R800nm + R670nm + 0.16)	Red, Near-Infrared	Optimized Soil Adjusted Vegetation Index; reduces soil background effects.	Performs well in sparse vegetation areas (85% accuracy), but is less effective for distinguishing weeds from rice.	[51]
GNDVI	(R800nm - R550nm) / (R800nm + R550nm)	Green, Near-Infrared	Sensitive to chlorophyll content; similar to NDVI but uses the green band.	Generally good for biomass estimation (82–88% accuracy), but lacks precision for weed-specific detection.	[52]
ExG	2 g - r - b	Red, Green, Blue (normalized)	Excess Green highlights green vegetation against the background.	Effective for identifying green vegetation; it can be affected by illumination.	[53]
VARI	(g - r) / (g + r - b) (RGB) or (R550nm - R670nm) / (R550nm + R670nm) (MCA)	Red, Green, Blue (normalized) or Green, Red (MCA)	Visible Atmospherically Resistant Index; minimizes atmospheric effects.	Used for vegetation monitoring; effectiveness varies with specific application.	[50]
CI_red edge	R800nm / R720nm − 1	Red Edge, Near-Infrared	Chlorophyll Index Red Edge; directly related to chlorophyll content.	(87–90% accuracy); useful for differentiating stressed weeds from healthy rice.	[54]
CI_green	R800nm / R550nm − 1	Green, Near-Infrared	Chlorophyll Index Green related to chlorophyll content.	Used for plant physiological status; potential for discrimination based on health.	[54]
SAVI / GSAVI	(Formulas not provided in snippets)	Spectral information	Soil-Adjusted Vegetation Index reduces soil background effects.	Overall accuracy > 94% for weed classification in early growth stages when combined with clustering.	[38]

Table 3 (continued)

Index	Formula	Bands	Key characteristics/purpose	Effectiveness/accuracy for weed-rice discrimination	References
NGRDI	(Formula not provided in snippets)	Visible light bands (Green, Red)	Normalized Green-Red Difference Index; highlights green vegetation.	M/MGT index 80–108%, MP 70–85% for weed detection in rice fields when fused with visible light.	[55]
Specific Bands (SVM)	N/A	415, 561, 687, 705, 735, and 1007 nm	Direct use of specific spectral bands for classification.	Less accurate for rice weed identification compared to specialized indices.	[41, 48]

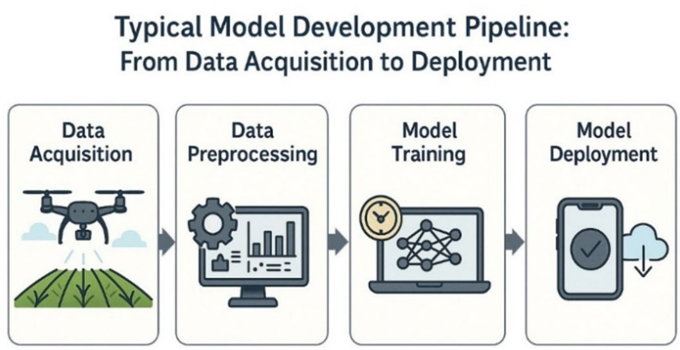

Fig. 3 Deep Learning Model Development Pipeline

Table 4 Decomposition of structural design

Stage	Key Activities	Tools/Examples
1. Dataset Preparation	- Use curated datasets (e.g., WeedNet v3) with diverse weed species and growth stages- Annotate rice and weed accurately	WeedNet v3, LabelImg, CVAT
	- Standardize images (e.g., 224 × 224 × 3 for GoogLeNet)- Split dataset: 70% train, 15% validation, 15% test	Python, OpenCV
	- Apply augmentation (rotation, flip, scale) to improve generalization	Augmentations, Keras
2. Model Selection	- Choose CNN architectures (e.g., GoogLeNet, U-Net, RMS-DETR)- Apply transfer learning by modifying pre-trained models	PyTorch, TensorFlow, MATLAB
	- Use hybrid models combining CNNs and Transformers for multi-scale feature fusion	RMS-DETR
3. Training	- Train models on annotated images using backpropagation- Monitor loss and accuracy across epochs	Adam/SGD Optimizer, BatchNorm
4. Validation & Evaluation	- Test model on unseen data- Evaluate with metrics: Accuracy, Precision, Recall, F1-score, IoU, mAP	% Accuracy (GoogLeNet example)
5. Optimization	- Tune hyperparameters and transfer models across platforms (e.g., Python to MATLAB) to boost performance	Learning rate, epochs, batch size

3.2 Prominent deep learning architectures and comparative analysis of models

Deep learning has significantly advanced image analysis in agriculture, with Convolutional Neural Networks (CNNs) playing a pivotal role in the classification of weeds and rice. CNNs offer hierarchical feature extraction capabilities that eliminate the need for manual feature engineering, enabling efficient and automated processing of high-resolution UAV imagery. Their strong generalization ability across diverse environmental conditions makes them particularly effective in complex agricultural landscapes, where accurate weed-crop differentiation is critical. However, the effectiveness of CNNs is often contingent upon the availability of large annotated datasets and may be influenced by real-world variables such as variable lighting conditions, shadows, and occlusions.

Among CNN-based architectures, GoogLeNet has been widely adopted due to its deep structure and inception modules, which facilitate multi-scale feature extraction, an essential attribute for capturing the varying size and morphology of weeds. Similarly, ResNet and VGG architectures have shown high classification accuracy in diverse crop-weed scenarios due to their robust feature learning capabilities and ease of transfer learning.

Segmentation-based architectures such as U-Net and its lightweight derivatives—including MobileNetV2-U-Net and FFB-BiSeNetV2 treat weed identification as a pixel-level classification task. These models are particularly well-suited for UAV-based RGB imagery, offering high precision in delineating crop and weed regions, even under real-time operational constraints. More recent advances include Detection Transformers (DETR) and their agricultural adaptations, such as RMS-DETR, which integrate Transformer-based global context modeling with CNN-driven local feature extraction. These hybrid models excel in identifying small, sparse, or partially occluded weed scenarios that often challenge traditional CNNs.

The YOLO family of object detection models, including YOLOv7-FWeed and YOLO-sesame, has also gained traction due to their real-time processing capabilities and high detection accuracy. These models are particularly effective when deployed on UAVs for rapid field surveillance. Furthermore, hybrid approaches combining CNNs with traditional machine learning classifiers, such as VGG-SVM, have been explored for enhancing classification stability and computational efficiency. To rigorously evaluate model performance, standard metrics such as Accuracy, Precision, Recall, F1-Score, mean Average Precision (mAP), Intersection over Union (IoU), and Dice Score are commonly employed. These metrics provide a comprehensive assessment of detection quality and guide model selection and optimization for operational deployment in precision agriculture.

The high reported accuracies, often exceeding 90%, across various deep learning architectures for weed-rice classification, particularly with specialized models like RMS-DETR and UNet variants, unequivocally demonstrate the significant progress achieved in the field. However, the variability in performance metrics and the diversity of datasets used across different studies (e.g., general weed classification versus rice-specific classification versus segmentation tasks) highlight an ongoing challenge regarding direct comparability. This situation underscores the need for standardized benchmarks and more comprehensive real-world datasets to enable more definitive comparative analyses and to better generalize model performance across different agricultural contexts. A detailed comparison of deep learning models, datasets, performance indicators, and findings related to crop and weed mapping is presented in Table 5.

Table 5 Performance metrics of deep learning models for UAV-based weed and rice differentiation and some for other crops

Model architecture	Weed/crop target	Data source/sensor	Key performance	Specific findings/context	References
Vision Transformers	Beet, parsley, spinach, weed	RGB Images	Accuracy: 97%	Effective in multi-species weed classification using high-level feature extraction	[58, 59]
YOLOv7-FWeed	Soybean vs. weed	UAV RGB imagery	Accuracy: 93.07%;	Real-time detection with strong accuracy-performance trade-off	[60, 61]
ConvNets with SLIC Superpixel	Soybean vs. weed	RGB (SLIC segmentation)	Accuracy: 98.33%	Combines spatial context with CNNs for enhanced feature localization	[62]
Mask R-CNN	Cotton vs. weed	UAV or ground RGB	Unavailable	Instance segmentation capability suitable for overlapping objects	[63]
Improved U-Net	General weed segmentation	UAV RGB imagery	Accuracy 84.29%	High segmentation accuracy in a complex background with class imbalance	[64]
Various Deep Learning Models (AlexNet, GoogLeNet, InceptionV3, Xception)	General crop/weed classes	RGB images	Accuracy: 97.7%	Comparative study showing strong generalization of deeper models	[65, 66]
Deep Belief Networks	Rice weeds	Fusion features	Recognition Rate: 91.13%	Utilizes fusion features for improved recognition.	[67]
Fine-tuned DenseNet + SVM	Weeds (Echinochloa colona, Cyperus difformis), Healthy Rice	Natural field condition images	Micro F1 score: 99.29%	High performance in real-world conditions.	[68]
WeedDet	Weeds in paddy fields	(Not specified)	Mean Average Precision: 94.1%, FPS: 24.3	Exceptional accuracy and impressive inference time.	[69]
Deformable DETR	Barnyard grass/Rice	UAV Remote Sensing Imagery	mAP50: 0.775	Improved over the original DETR, but less than RMS-DETR.	[70, 71]
Anchor DETR	Barnyard grass/Rice	UAV Remote Sensing Imagery	mAP50: 0.755	Lower performance compared to RMS-DETR.	[72]
CNN LVQ	Weeds (Soybean, Grass, Broadleaf)	UAV Imagery	Overall Accuracy: 99.44%	High accuracy after hyperparameter refinement.	[73]
VGG-16	Cotton weed	(Not specified)	Accuracy: 95.4%	Baseline CNN can have lower accuracy with large datasets.	[74]
ResNet-101	Cotton weed	(Not specified)	Accuracy: 97.1%	High-performing CNN.	[75]
DenseNet-121	Cotton weed	(Not specified)	Accuracy: 96.9%	High-performing CNN.	[76, 77]
XceptionNet	Cotton weed	(Not specified)	Accuracy: 96.1%	High-performing CNN.	[78, 79]

Table 5 (continued)

Model architecture	Weed/crop target	Data source/sensor	Key performance	Specific findings/context	References
Customized CNN	Cotton weed	(Not specified)	Accuracy: 98.3%	Outperformed other CNNs in the specific cotton weed task.	[80]
One-class classifier	Weeds	Unsupervised UAV data	Accuracy: Up to 90%	Reduces the need for manual annotation.	[81, 82]
Swin Transformer	Maize and Weed	UAV multispectral	Accuracy: 97.8%	Strong spectral-spatial attention and generalization in dense canopy	[83]
EfficientFormer	Mixed crops	UAV RGB imagery	Accuracy: 96.5%	Lightweight architecture suitable for edge deployment	[84]

4 Challenges and future research directions

Despite the remarkable advancements in UAV-based remote sensing and deep learning for weed and rice classification, several significant challenges persist, necessitating focused future research to transition these technologies from experimental success to widespread practical application. One key area for future development is the integration of mechanized farming features, such as row spacing and planting patterns, into existing weed detection models. Incorporating these features can provide valuable spatial context, enabling models to better distinguish crops from weeds, particularly in structured farming systems. By leveraging row alignment and inter-row spacing, models can reduce false positives and improve precision in weed localization. This integration also offers practical benefits for precision agriculture, as it allows automated weed management systems to align detection outputs with machinery operations, enhancing operational efficiency.

Future research should focus on developing hybrid approaches that combine spectral, textural, and mechanized farming information, as well as validating these methods across diverse crop types, growth stages, and field conditions. Addressing these challenges will facilitate the transition of UAV-based weed detection systems from experimental studies to scalable, field-ready applications.

4.1 Present accuracies of DL, ML and vis

A review of accuracy trends from 2018 to 2025 (Fig. 4) reveals deep learning's increasing dominance, with a significant rise in accuracy post-2020. Vegetation indices show steady, moderate improvements, and machine learning accuracy has seen a sharp increase due to the integration of hybrid models like DenseNet + SVM. This highlights the growing refinement and superiority of deep learning in remote sensing-based crop-weed classification. Vegetation Indices (VIs) often outperform traditional Machine Learning (ML) methods like SVMs and DBNs in weed–rice discrimination, with indices such as WDVI_NIR, SAVI/GSAVI, and CI_red edge achieving higher or comparable accuracies above 90%, especially in specific field conditions.

Furthermore, deep learning models, particularly CNN LVQ, DenseNet + SVM, and customized CNN architectures (Fig. 5), consistently achieved the highest accuracies (over 98%) in weed-rice discrimination, outperforming traditional machine learning methods like SVM and Deep Belief Networks (around 90% accuracy). While vegetation indices such as WDVI_NIR, SAVI/GSAVI, and CI_red edge also showed strong performance (above 90%), they generally trailed behind deep learning.

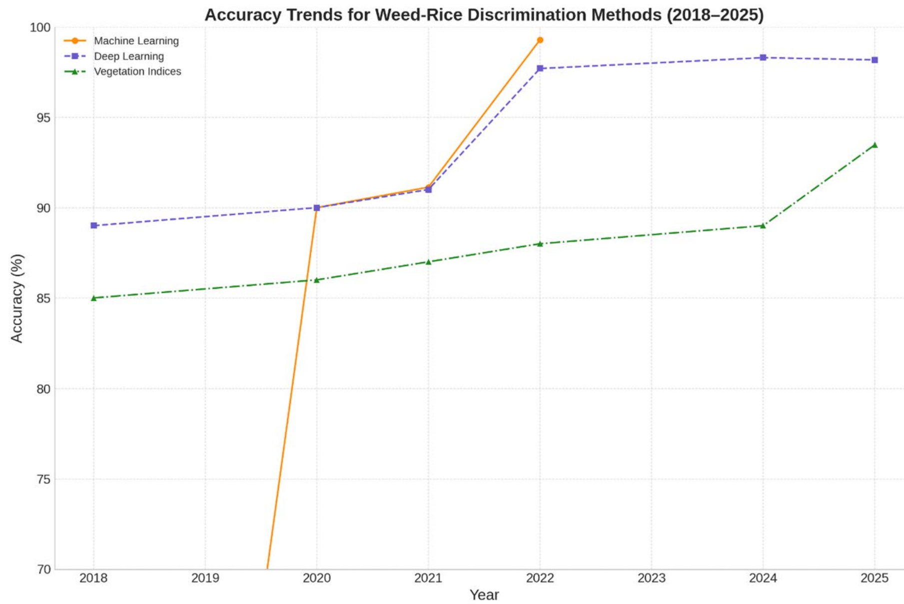

Fig. 4 Trend of implementation of DL, VIs and ML from 2018 to 2025

4.2 Data availability, annotation, and generalizability issues

A fundamental challenge in the development of robust deep learning models is their "data-starving" nature. Training these models to achieve high accuracy and reliability requires vast quantities of high-quality, meticulously labeled data [33]. The acquisition and annotation of such datasets in real-world agricultural environments are inherently time-consuming, labor-intensive, and costly. Furthermore, many publicly available datasets, while valuable, may not fully capture the immense diversity and variability encountered in actual field conditions, such as different rice varieties, weed species, growth stages, soil types, and environmental factors [34]. Currently, no unified dataset exists for rice-weed differentiation.

This data scarcity and lack of representativeness directly impact the generalizability of trained models. Models developed and validated in one specific environment (e.g., a particular region, a single rice cultivar, or a narrow range of growth stages) frequently exhibit a noticeable decrease in recognition accuracy when applied to different field datasets or under varying environmental conditions. Real-world images are also perpetually affected by dynamic environmental factors, including illumination variations (e.g., direct sunlight, overcast conditions), shadows cast by clouds or surrounding objects, and occluded leaves due to dense canopy cover [85]. These factors are major obstructions to accurate vegetation analysis and can lead to significant errors in weed detection, further limiting model robustness.

To address this, future research must prioritize the acquisition of more diverse and representative datasets and the development of robust data collection strategies. Synthetic data generation through methods like Generative Adversarial Networks (GANs) offers an effective approach to augment real datasets, especially in cases where certain weed types or growth stages are underrepresented [86]. Domain adaptation techniques offer significant potential for improving model performance across diverse field conditions.

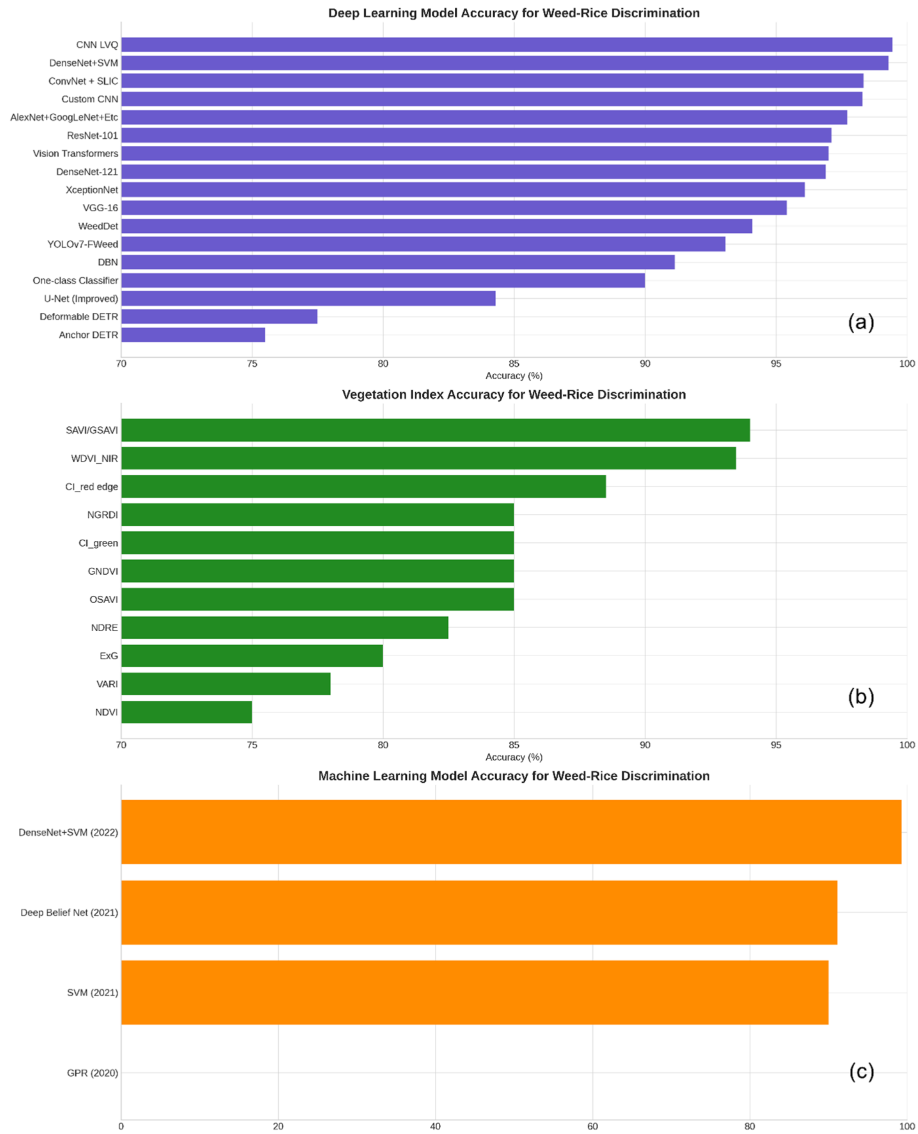

Fig. 5 Comparison of **a** Deep learning **b** Vegetation Indices **c** Machine Learning

4.3 Environmental factors and real-time processing constraints

The dynamic and often unpredictable nature of agricultural environments poses insistent challenges for UAV-based weed classification. Unpredictable weather conditions, including fluctuating cloud cover, wind, and varying sunlight intensity, directly impact the quality of image acquisition and subsequently affect the performance and reliability of classification algorithms. Furthermore, real farm environments are inherently complex, characterized by the presence of small-sized, occluded, and densely distributed weed instances, which complicates the discrimination process [87].

To improve classification accuracy, recent models have integrated complex architectures and multi-scale feature extraction techniques (e.g., RMS-DETR), yet this often increases computational load and slows down inference speeds [88]. This trade-off is critical, especially for real-time applications such as UAV-guided precision spraying, where rapid response is required. Thus, there is a growing need for lightweight, computationally efficient models capable of fast, in-field performance [89].

4.3.1 Computational infrastructure and data management constraints

UAV-based image acquisition generates large data volumes that require robust computational resources for preprocessing, model training, and inference. High-resolution orthomosaics, particularly from multispectral and hyperspectral sensors, demand high-performance computing (HPC) or GPU-enabled servers. For operational scalability, cloud-based solutions (e.g., Google Earth Engine, AWS, or Microsoft Azure) offer viable alternatives, though their cost may limit accessibility for small-scale farmers [90, 91]. Establishing data management pipelines covering compression, tiling, and metadata indexing is essential to optimize processing time and maintain reproducibility.

4.4 Integration with robotic systems and variable-rate application

The ultimate goal of UAV-based weed detection is not limited to mapping but extends to actionable outcomes in site-specific weed management (SSWM). Precision spraying systems rely on accurate weed maps to guide herbicide application, thereby reducing chemical usage and environmental impact [92]. Deep learning models provide technical support for these applications, yet achieving seamless integration with robotic systems remains a challenge.

This integration requires synchronized operations between UAVs and ground-based sprayers, as well as real-time communication protocols, robust georeferencing, and decision-making control systems [93]. Transitioning from detection to action is a multidisciplinary challenge that involves image analysis, robotics, and networked communication infrastructure.

4.5 Emerging technologies and methodologies

Several emerging technologies have been highlighted in this systematic review, which shows promise in addressing the challenges described below:

1. **Synthetic data generation**: GANs can generate realistic plant imagery to augment existing datasets and help reduce reliance on labor-intensive annotation [94, 95].
2. **Advanced deep learning techniques**: Attention mechanisms, which allow models to prioritize salient features in the imagery, can improve the discrimination of visually similar crops and weeds [96].
3. **Unsupervised and semi-supervised learning**: These techniques reduce dependence on labeled data by leveraging large volumes of unlabeled imagery for training [97].
4. **Multi-modal data acquisition and fusion**: Integrating RGB, multispectral, hyperspectral, thermal, and LiDAR data provides a richer representation of the field environment, enhancing detection accuracy and robustness [90].
5. **Edge deployment and real-time optimization**: Lightweight models optimized for real-time inference on edge devices (e.g., onboard UAV systems or field-side processors) can support in-situ decision-making and reduce latency [89, 92].

Emerging technologies present transformative opportunities for UAV-based weed and rice classification, yet their application remains in its infancy. Generative adversarial networks (GANs) and diffusion models can generate realistic synthetic UAV datasets, alleviating annotation burdens and enhancing model robustness across varied environments.

Advanced attention mechanisms, including Swin Transformers and spectral–spatial attention modules, are particularly promising for handling the high dimensionality of multispectral and hyperspectral UAV data, enabling more precise discrimination between rice and spectrally similar weeds. Federated and transfer learning approaches can further support cross-regional generalizability while mitigating the challenges of data scarcity and privacy restrictions in agricultural research. Finally, the integration of UAV platforms with ground-based robotics (e.g., autonomous sprayers) and edge computing frameworks offers a pathway toward real-time, autonomous weed management systems. Together, these emerging methodologies not only extend beyond traditional deep learning pipelines but also chart a roadmap for scaling UAV-based weed detection from experimental studies to operational agricultural practice.

Synthetic data generation methods such as generative adversarial networks (GANs), diffusion models, and variational autoencoders (VAEs) offer promising solutions to overcome annotation bottlenecks and improve model robustness. While GANs have been widely applied and are relatively mature, diffusion models and VAEs are emerging as mainstream approaches, capable of producing more stable and diverse synthetic UAV datasets that enhance training and generalization in rice–weed classification tasks.

The conjunction of these advanced architectures, methodologies, and multi-modal sensor strategies offers a path toward robust, autonomous, and scalable weed management systems. Future research should focus on bridging the laboratory field divide through integrated, adaptive systems capable of delivering real-time solutions in dynamic agricultural landscapes.

4.6 Socioeconomic barriers and farmer resistance to UAV adoption

Despite proven agronomic benefits, adoption of UAV-based precision agriculture technologies remains limited in many regions. Key reasons include the high initial cost of equipment, lack of technical training, and uncertainty about return on investment [98]. Cultural factors and risk aversion also contribute to resistance, particularly among traditional farmers accustomed to manual practices. Moreover, the perceived complexity of UAV operation, data interpretation, and regulatory compliance act as deterrents [99]. Overcoming these barriers requires targeted extension programs, financial incentives, and demonstration projects that emphasize the practical and economic benefits of UAV-assisted weed management.

5 Conclusions

Weed infestation in rice farming remains a major threat to crop yield and sustainability, especially due to the environmental and economic costs of conventional herbicide use. UAVs, equipped with advanced sensors and deep learning, offer a powerful solution for precise weed-rice classification and site-specific weed management. UAV-based systems surpass traditional and satellite methods through superior spatial-temporal resolution and sensor versatility, enabling accurate discrimination of spectrally similar vegetation. Deep learning models such as RMS-DETR and U-Net variants have achieved high classification accuracy, especially when coupled with data fusion techniques. However, practical implementation faces key challenges: deep learning's need for large, labeled datasets, environmental variability affecting image quality, limited model generalizability, and the computational demands of real-time deployment. Future research should prioritize synthetic data generation (e.g., GANs), attention-based and lightweight models, unsupervised learning, multi-modal data fusion (especially thermal and LiDAR), and edge computing. Expanding dataset diversity and optimizing for real-time performance will be essential for deploying robust, scalable, and sustainable weed management systems in rice agriculture. Beyond technical improvements, UAV-based deep learning offers tangible economic and environmental benefits. Field trials demonstrate potential reductions of up to 40% in herbicide use and 25% in operational costs through site-specific spraying [93, 100]. Moreover, timely detection of weed stress supports improved resource allocation, contributing to higher yields and sustainability. These outcomes highlight the broader socioeconomic impact of integrating UAV technologies into precision agriculture systems. This review underscores a critical path forward for robust weed and crop discrimination, advocating for a paradigm shift towards data-efficient learning (weakly/semi-supervised, self-supervised) to alleviate annotation bottlenecks. Enhanced model performance will stem from multi-modal and temporal data fusion, yielding richer insights. Crucially, the practical deployment of these solutions demands lightweight AI architectures for edge computing and seamless robotics integration, enabling autonomous field operations. Finally, standardized benchmarking datasets are indispensable to drive consistent evaluation and rapid advancements in the field.

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References

1. Asma J, Subrahmanyam D, Krishnaveni D. The global lifeline: A staple crop sustaining twothirds of the world's population. Agric Arch, 2023.
2. Rosle R et al. Weed detection in rice fields using UAV and multispectral aerial imagery, Chem Proc. 2022;10(1):44.
3. Dass A, et al. Weed management in rice using crop competition-a review. Crop Prot. 2017;95:45–52.
4. Yu F, et al. Research on weed identification method in rice fields based on UAV remote sensing. Front Plant Sci. 2022;13:1037760.
5. Small C et al. Optimizing weed control for progressive reclamation: literature review. InnoTech Alta Edmont Alta, 2018.
6. Harle S, Bhagat A, Dash AK. Remote sensing revolution: mapping land productivity and vegetation trends with unmanned aerial vehicles (UAVs). Curr Appl Mater. 2024;3(1):e070224226752.

7. Vijayakumar S, Shanmugapriya P, Saravanane P, Ramesh T, Murugaiyan V, Ilakkiya S. Precision weed control using unmanned aerial vehicles and robots: assessing Feasibility, Bottlenecks, and recommendations for scaling. NDT. 2025;3(2):10.
8. Wu B, et al. Challenges and opportunities in remote sensing-based crop monitoring: a review. Natl Sci Rev. 2023;10(4):nwac290.
9. Monteiro A, Santos S. Sustainable approach to weed management: the role of precision weed management. Agronomy. 2022;12(1):118.
10. Zhang C, Marzougui A, Sankaran S. High-resolution satellite imagery applications in crop phenotyping: an overview. Comput Electron Agric. 2020;175:105584.
11. Roslim MHM, et al. Using remote sensing and an unmanned aerial system for weed management in agricultural crops: A review. Agronomy. 2021;11(9):1809.
12. Mohsan SAH, Ahmad I, Zhang Y, Wang X. Agricultural applications of UAVs and AI: current landscape and future directions. Sensors. 2022;22(7):2564.
13. Roth GA, et al. Global, regional, and National age-sex-specific mortality for 282 causes of death in 195 countries and territories, 1980–2017: a systematic analysis for the global burden of disease study 2017. Lancet. 2018;392(10159):1736–88. https://doi.org/10.1016/S0140-6736(18)32203-7.
14. Zhang Y, Zhang Y, Liu Y, Guo Z. Hyperspectral UAV monitoring for crop growth and weed discrimination. Remote Sens. 2021;13(1):117.
15. Lan Y, et al. Real-time identification of rice weeds by UAV low-altitude remote sensing based on improved semantic segmentation model. Remote Sens. 2021;13(21):4370.
16. Hashim HA. Advances in UAV avionics systems architecture, classification and integration: A comprehensive review and future perspectives. Results Eng, p. 103786, 2024.
17. Primicerio J. A flexible unmanned aerial vehicle for precision agriculture. Precis Agric. 2012;13(4):517–23.
18. Aasen H, Burkart A, Bolten A, Bareth G. Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: from camera calibration to quality assurance. ISPRS J Photogramm Remote Sens. 2018;145:54–70.
19. Shahhosseini M, Martínez-Feria RA, Hu G, Archontoulis SV. Maize yield and nitrate loss prediction with the APSIM model under variable N management strategies: A big data approach. F Crop Res. 2020;246:107686.
20. Bendig J, Bolten A, Bennertz S, Broscheit J, Eichfuss S, Bareth G. Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging. Remote Sens. 2015;6(11):10395–412.
21. Hunt ER. Multispectral remote sensing of row and within-row corn leaf chlorophyll contents. Agric Meteorol. 2013;177:128–35.
22. Garcia-Ruiz F. Comparative assessment of crop yield prediction from UAV imagery using orthomosaic, vegetation indices and crop surface models. Precis Agric. 2015;16(2):273–89.
23. Gonzalez-Dugo MP. Using high-resolution UAV thermal imagery to assess crop water stress. Remote Sens. 2013;5(10):5167–82.
24. Jones HG, Serraj R, Loveys BR, Xiong L, Wheaton A, Price AH. Thermal infrared imaging of crop canopies for the remote diagnosis and quantification of plant responses to water stress in the field. Funct Plant Biol. 2009;36(11):978–89.
25. Wallace L. Evaluating the use of UAV-mounted lidar for precision agriculture applications. Remote Sens. 2016;8(9):709.
26. Lu Y, He Y. Multisource data fusion for crop classification using UAV imagery. Remote Sens. 2017;9(11):1183.
27. Feng Q, Liu J, Gong J. UAV remote sensing for urban vegetation mapping using random forest and texture analysis. Remote Sens. 2021;7(1):1074.
28. Sohl MA, Mahmood SA. Low-cost UAV in photogrammetric engineering and remote sensing: Georeferencing, DEM accuracy, and Geospatial analysis. J Geovisualization Spat Anal. 2024;8(1):14.
29. Fernández J, Gómez D, Morales M. Assessment of low-cost UAV photogrammetry for agricultural mapping. Geo-Spatial Inf Sci. 2024. https://doi.org/10.1007/s41651-024-00176-2.
30. Torres-Sánchez J, Peña JM, de Castro AI, López-Granados F. Multi-temporal mapping of the vegetation fraction in early-season wheat fields using images from UAV. Comput Electron Agric. 2015;103:104–13.
31. Gao Y. Effects of varying sunlight on remote sensing-based crop monitoring. Remote Sens. 2018;10(6):928.
32. Jiang H. Environmental factors affecting UAV image quality in field-based phenotyping. Front Plant Sci. 2021;12:648611.
33. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: A survey. Comput Electron Agric. 2018;147:70–90.
34. Ferentinos KP. Deep learning models for plant disease detection and diagnosis. Comput Electron Agric. 2018;145:311–8.
35. Angel Y, Turner D, Parkes S, Malbeteau Y, Lucieer A, McCabe MF. Automated georectification and mosaicking of UAV-based hyperspectral imagery from push-broom sensors. Remote Sens. 2019;12(1):34.
36. Jiang X, Ma J, Xiao G, Shao Z, Guo X. A review of multimodal image matching: methods and applications. Inf Fusion. 2021;73:22–71.
37. Yuan Z, Chen W, Yang A, Shao W. Remote sensing crop classification model integrating 1D convolutional residual blocks and temporal attention, in *Fourth International Conference on Machine Learning and Computer Application (ICMLCA 2023)*, SPIE, 2024, pp. 519–524.
38. Stroppiana D, Boschetti M, Brivio PA, Carrara P, Crema A, Musacchio M. Early season weed mapping in rice crops using multi-spectral UAV data. Remote Sens. 2018;10(3):381. https://doi.org/10.3390/rs10030381.
39. Pérez-Ortiz M, Peña JM, Gutiérrez PA, Torres-Sánchez J, Hervás-Martínez C, López-Granados F. Selecting patterns and features for between-and within-crop-row weed mapping using UAV-imagery. Expert Syst Appl. 2016;47:85–94.
40. Li H, Huang J, Zhang C, Ning X, Zhang S, Atkinson PM. An efficient and generalisable approach for mapping paddy rice fields based on their unique spectra during the transplanting period leveraging the CIE colour space. Remote Sens Environ. 2024;313:114381.
41. Zhang Y, Wang L, Liu Z, Chen Y. Hyperspectral imaging-based classification of rice and weeds using SVM with optimal bands. Comput Electron Agric. 2021;185:106131. https://doi.org/10.1016/j.compag.2021.106131.
42. Tan X, Li R, Huang B, Chen X. Deep learning-based hyperspectral feature extraction for rice and weed discrimination at early growth stages. Remote Sens. 2025;17(4):872. https://doi.org/10.3390/rs17040872.
43. Sulaiman N, Che'Ya NN, Mohd Roslim MH, Juraimi AS, Noor NM, Fazlil Ilahi WF. The application of hyperspectral remote sensing imagery (HRSI) for weed detection analysis in rice fields: A review. Appl Sci. 2022;12(5):2570.

44. Ramli Z et al. Weed management using UAV and remote sensing in Malaysia paddy field: A review. Pertanika J Sci Technol. 2024;33:3.
45. Chatnuntawech I, Tantisantisom K, Khanchaitit P, Boonkoom T, Bilgic B, Chuangsuwanich E. Rice classification using spatio-spectral deep convolutional neural network, arXiv Prepr. arXiv1805.11491, 2018.
46. Saragadam V, DeZeeuw M, Baraniuk RG, Veeraraghavan A, Sankaranarayanan AC. SASSI—super-pixelated adaptive spatio-spectral imaging. IEEE Trans Pattern Anal Mach Intell. 2021;43(7):2233–44.
47. Verrelst J, Rivera JP, Gitelson A, Delegido J, Moreno J, Camps-Valls G. Spectral band selection for vegetation properties retrieval using Gaussian processes regression. Int J Appl Earth Obs Geoinf. 2016;52:554–67.
48. Zhang Y, Yu X, Li H. Identification of weeds and rice using hyperspectral imaging and SVM. Precis Agric. 2021;22(3):785–800. https://doi.org/10.1007/s11119-020-09753-3.
49. Huang S, Tang L, Hupy JP, Wang Y, Shao G. A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing, J For Res. 2021;32(1). https://doi.org/10.1007/S11676-020-01155-1
50. Gitelson AA, Stark R, Grits U, Rundquist D, Kaufman Y, Derry D. Vegetation and soil lines in visible spectral space: a concept and technique for remote Estimation of vegetation fraction. Int J Remote Sens. 2002;23(13):2537–62.
51. Rondeaux G, Steven M, Baret F. Optimized soil-adjusted vegetation index. Remote Sens Environ. 1996;55(2):95–107. https://doi.org/10.1016/0034-4257(96)00018-7.
52. Gitelson AA, Kaufman YJ, Stark R, Rundquist D. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sens Environ. 1996;58(3):289–98. https://doi.org/10.1016/0034-4257(96)00072-9.
53. Woebbecke DM, Meyer GE, Von Bargen K, Mortensen DA. Color indices for weed identification under various soil, residue, and lighting conditions, in *Proceedings of the ASAE*, 1995, pp. 259–269. https://doi.org/10.13031/2013.27476
54. Gitelson AA, Gritz Y, Merzlyak MN. Remote Estimation of leaf area index and green leaf biomass in maize canopies. Remote Sens Environ. 2003;84(1):93–106. https://doi.org/10.1016/S0034-4257(02)00069-7.
55. Barrero LS, Perdomo SP. RGB and multispectral UAV image fusion for Gramineae weed detection in rice fields, Agric Eng Int CIGR J. 2018;20(2):136
56. Mensah B, Rai N, Betitame K, Sun X. Advances in weed identification using hyperspectral imaging: a comprehensive review of platform sensors and deep learning techniques. J Agric Food Res, p. 101388, 2024.
57. Che'Ya NN, Dunwoody E, Gupta M. Assessment of weed classification using hyperspectral reflectance and optimal multi-spectral UAV imagery. Agronomy. 2021;11(7):1435.
58. Lin F et al. Mmst-vit: Climate change-aware crop yield prediction via multi-modal spatial-temporal vision transformer, In: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 5774–5784.
59. Pacal I. Enhancing crop productivity and sustainability through disease identification in maize leaves: exploiting a large dataset with an advanced vision transformer model. Expert Syst Appl. 2024;238:122099.
60. Li J, Zhang W, Zhou H, Yu C, Li Q. Weed detection in soybean fields using improved YOLOv7 and evaluating herbicide reduction efficacy. Front Plant Sci. 2024;14:1284338.
61. Ding Y, Jiang C, Song L, Liu F, Tao Y. RVDR-YOLOv8: a weed target detection model based on improved YOLOv8. Electronics. 2024;13(11):2182.
62. Behera TK, Bakshi S, Nappi M, Sa PK. Superpixel-based multiscale CNN approach toward multiclass object segmentation from UAV-captured aerial images. IEEE J Sel Top Appl Earth Obs Remote Sens. 2023;16:1771–84.
63. Valicharla SK. Weed recognition in agriculture: A mask R-CNN approach. West Virginia University; 2021.
64. Liu Z, Su B, Lv F. Intelligent Identification Method of Crop Species Using Improved U-Net Network in UAV Remote Sensing Image, *Sci. Program.*, vol. 2022, no. 1, p. 9717843, 2022.
65. Prasetyo SY. Rice Variety Classification via Deep Learning: Unveiling InceptionV3 and Xception Pretrained Models, In: 2024 2nd International Symposium on Information Technology and Digital Innovation (ISITDI), IEEE, 2024, pp. 119–123.
66. Çiçek Y, GÜLBANDILAR E, Çiray K, ULUDAĞ A. Classifying weed development stages using deep learning methods: classifying weed development stages with DenseNET, Xception, SqueezeNET, GoogleNET, EfficientNET CNN models using ROI images. Int J Adv Comput Sci Appl, 16, 2, 2025.
67. Hua Y, Guo J, Zhao H. Deep belief networks and deep learning, In: Proceedings of 2015 international conference on intelligent computing and internet of things, IEEE, 2015, pp. 1–4.
68. Kaur A, Kukreja V, Kumar M, Choudhary A, Sharma R. A Fine-Tuned DenseNet Model for an Efficient Maize Leaf Disease Classification, In: 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), IEEE, 2024, pp. 1–5.
69. Peng H, Li Z, Zhou Z, Shao Y. Weed detection in paddy field using an improved retinanet network. Comput Electron Agric. 2022;199:107179.
70. Wang D, Li Z, Du X, Ma Z, Liu X. Farmland obstacle detection from the perspective of uavs based on non-local deformable detr, Agriculture, 2022;12(12):1983.
71. Liu Q, Meng H, Zhao R, Ma X, Zhang T, Jia W. Green Apple detector based on optimized deformable detection transformer. Agriculture. 2024;15(1):75.
72. Wei C, Li H, Shi J, Zhao G, Feng H, Quan L. Row anchor selection classification method for early-stage crop row-following. Comput Electron Agric. 2022;192:106577.
73. Meena RS, Solanki S. Citrus Plant Leaves Disease Detection Using CNN and LVQ Algorithm, In: International Conference on Data Analytics & Management, Springer, 2023, pp. 175–188.
74. Depuru S, Amala K, Supriya P, Reddy AB, Gireesh RS. VGG-16 technique to reduce the global food crises and enhance the crop yields: deep learning approaches, In: 2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), IEEE, 2024, pp. 596–599.
75. Ajayi OG, Olufade OO. Drone-based crop type identification with convolutional neural networks: an evaluation of the performance of RESNET architectures. ISPRS Ann Photogramm Remote Sens Spat Inf Sci. 2023;10:991–8.
76. Swaminathan A, Varun C, Kalaivani S. Multiple plant leaf disease classification using densenet-121 architecture. Int J Electr Eng Technol. 2021;12(5):38–57.
77. Arathi B, Dulhare UN. Classification of cotton leaf diseases using transfer learning-densenet-121, in *Proceedings of third international conference on advances in computer engineering and communication systems: ICACECS 2022*, Springer, 2023, pp. 393–405.

78. Sutaji D, Yıldız O. LEMOXINET: lite ensemble MobileNetV2 and Xception models to predict plant disease. Ecol Inf. 2022;70:101698.
79. Ghous U, Sarfraz MS, Ahmad M, Li C, Hong D. EXNet:(2 + 1) D extreme Xception net for hyperspectral image classification. IEEE J Sel Top Appl Earth Obs Remote Sens. 2024;17:5159–72.
80. Samala S et al. Optimizing Crop Management: Customized CNN for Autonomous Weed Identification in Farming, In: 2024 International Conference on Integrated Circuits and Communication Systems (ICICACS), IEEE, 2024, pp. 1–5.
81. Pantazi XE, Moshou D, Tamouridou AA. Automated leaf disease detection in different crop species through image features analysis and one class classifiers. Comput Electron Agric. 2019;156:96–104.
82. Lei L, Wang X, Zhong Y, Zhao H, Hu X, Luo C. DOCC: deep one-class crop classification via positive and unlabeled learning for multi-modal satellite imagery. Int J Appl Earth Obs Geoinf. 2021;105:102598.
83. Lin M, Wu J, Zou J, Meng J, Wang W, Wu J. Retired battery screening based on Markov transition field and Swin transformer. IEEE Trans Transp Electrif. 2023;10(2):4217–27.
84. Chen J, Dai H, Wang S, Liu C. Improving accuracy and efficiency in time series forecasting with an optimized transformer model. Eng Lett, 2024;32(1).
85. Singh A, Ganapathysubramanian B, Singh AK, Sarkar S. Machine learning for high-throughput stress phenotyping in plants. Trends Plant Sci. 2016;21(2):110–24.
86. Goodfellow I, et al. Generative adversarial networks. Commun ACM. 2020;63(11):139–44.
87. Milioto A, Lottes P, Stachniss C. Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs. ISPRS Ann Photogramm Remote Sens Spat Inf Sci. 2018;4:465–72.
88. Chollet F. Xception: Deep learning with depthwise separable convolutions, Proc IEEE Conf Comput Vis Pattern Recognit., pp. 1251–1258, 2017.
89. Xu X, Li M, Wang J, Liu Y. Lightweight convolutional neural network with multi-scale features for real-time crop and weed recognition. Comput Electron Agric. 2022;194:106738.
90. Maimaitijiang M, et al. Crop classification with fused RGB-deep and multispectral data using two-branch convolutional neural network and data fusion strategy. Remote Sens. 2020;12(3):350.
91. Meng T, Jing X, Yan Z, Pedrycz W. A survey on machine learning for data fusion. Inf Fusion. 2020;57:115–29.
92. Zhang Y, Ma R, Li J, Liu Z. UAV-assisted weed mapping and site-specific spraying: advances and challenges. Agric Syst. 2023;205:103565.
93. Rey J, Rodriguez A, Costa C, Oliver A. Precision agriculture in practice: remote sensing and ground robotics for site-specific weed control. Sensors. 2021;21(9):2996.
94. Goodfellow I et al. Generative adversarial Nets. in Adv Neural Inf Process Syst, 2014, pp. 2672–80.
95. Frid-Adar M, Klang E, Amitai M, Goldberger J, Greenspan H. GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification. Neurocomputing. 2018;321:321–31.
96. Vaswani A et al. Attention is all you need. in Adv Neural Inf Process Syst, 2017, pp. 5998–6008.
97. Zhou Y, Wu Q, Zhang J, Yang Z. Semi-supervised learning for precision agriculture: a review. Comput Electron Agric. 2022;199:107133.
98. Bian L, Li B, Wang J, Gao Z. Multi-branch stacking remote sensing image target detection based on YOLOv5. Egypt J Remote Sens Sp Sci. 2023;26(4):999–1008.
99. Piovani B, Monteiro-Neto C, de Oliveira LL, Guimaraes SM. Use of unmanned aerial system for monitoring sea turtles in coastal areas. Reg Stud Mar Sci. 2025;81:104002.
100. Wang W, Zhang J, others. Non-Destructive monitoring of rice growth key indicators based on Fixed-Wing UAV multispectral images. Sci Agric Sin. 2023;56(21):4175–91.

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