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AI in the Field: A Review of Deep Learning Methods for Weed Identification in Wheat Crops

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Weed infestation is a major constraint in wheat production, causing yield losses and higher herbicide dependence. Traditional control methods often lack precision, highlighting the need for intelligent, sustainable solutions. Deep learning has recently emerged as a powerful tool for automated and accurate weed detection in precision agriculture. This review summarizes the latest advances in deep learning applied to wheat weed identification, emphasizing model architectures, datasets, and imaging techniques. Approaches such as YOLO variants, Faster R-CNN, U-Net, and transformer-based models have achieved high accuracy in distinguishing wheat from diverse weed species, even under complex field conditions. Integration of UAV imagery, multispectral sensors, and spectral indices further enhances detection at early growth stages. Recent innovations, including attention mechanisms, feature fusion, optimized loss functions, and lightweight designs, have improved precision, speed, and generalization. Key challenges remain in dataset quality, class imbalance, and cross-field applicability. This work outlines current trends, identifies gaps, and highlights future directions for scalable and sustainable deep learning-based weed detection in wheat agriculture.

Keywords: Weed detection, Wheat Crops, Smart farming, Artificial intelligence (AI) in Agriculture, Convolutional Neural Networks (CNN), YOLO Architecture, UAV-Based Weed Mapping

Introduction:

Wheat (Triticum aestivum L.) is one of the most widely cultivated crops worldwide, covering more than 237 million hectares annually and producing approximately 765 million tons [1]. In Pakistan, Punjab and Sindh are the major wheat-producing regions, with Sindh achieving slightly higher yields per hectare [2]. Wheat adapts to diverse climates, tolerating temperatures from 3–32 °C and rainfall from 250–1700 mm. It is a staple food, consumed globally more than rice, maize, and potatoes [3], and contributes 8.9% to agricultural value addition and 1.6% to Pakistan's GDP [4]. Meeting the growing food demand, especially with Pakistan's population projected to surpass 225 million by 2025, requires boosting wheat production. However, weeds pose a serious threat to wheat production because they compete with crops for vital resources like nutrients, light, and water. Moreover, weeds serve as hosts for pests and diseases, thereby further diminishing crop productivity [5]. Studies show that weeds, pests, and diseases together cause nearly 40% of annual global crop losses [6]. In wheat fields specifically, uncontrolled weed infestations can result in yield losses ranging from 40% to 50% [3]. Flowering plants (angiosperms) were traditionally classified into two groups: monocotyledons and dicotyledons, before being combined into a unified system [7]. As wheat belongs to the monocotyledons, broadleaf (dicotyledonous) weeds are more easily managed with selective herbicides, whereas grassy (monocotyledonous) weeds demand the use of specialized grass-targeting herbicides [8]. These grass weeds not only reduce yield and harvest efficiency but also cause annual economic losses amounting to millions of dollars [9]. Without appropriate control methods, weed damage can occasionally reach 100%, and technical failures have been known to result in yield losses of up to 20% in wheat production even when control measures are in place. Maintaining crop yield and minimizing financial losses requires the implementation of efficient weed management strategies. [10]. [11] reported that inadequate weed management in Northwestern Pakistan led to significant reductions in wheat yield. Their findings showed that adopting reduced or zero tillage practices along with suitable herbicides like Affinity enhanced weed control efficiency (up to 94.1%) and improved wheat productivity compared to conventional tillage. This highlights the importance of effective weed management strategies for sustaining wheat growth and yield.

In wheat fields, weeds are especially troublesome because, in their early stages of growth, they closely resemble wheat, making hand identification difficult. [12]. Recent advances in computer vision and machine learning have created new opportunities, with researchers making notable progress in developing and optimizing models for weed detection [13][14][15]. Furthermore, conventional weeding practices—mechanical, chemical, and manual—also carry inherent drawbacks. An example is chemical weeding, where herbicides are frequently applied uniformly across whole fields, leading to higher operational expenses and greater environmental hazards. Although it complies with sustainable farming techniques, mechanical weeding is not effective, time-consuming, and risky of causing damage to crops. [16]. Scholars have considered sophisticated methods such as deep learning and machine vision for automated weed detection to address such limitations. Deep learning (DL) is an aspect of machine learning and, in turn, artificial intelligence. Neural networks (NN) would be applied in deep learning applications to detect objects in images or classify images. [17]. Deep learning classification methods have been widely applied in fields like pattern recognition and computer vision. [18].

Nowadays, various farming practices enhance the precision of weed detection through cameras, drones, and deep learning techniques. High-end machine learning models, particularly Convolutional Neural Networks (CNNs) and object detection systems such as YOLO, have demonstrated promise in effectively determining the distinction between wheat and other weeds. Those advanced imaging technologies, such as 3D, spectral, and thermal sensors, contribute to higher accuracies of detection, though their potential in large-scale applications related to agriculture is limited due to their high costs and requirements for controlled environments. [19]. This highlights the need for affordable, adaptable solutions that can perform effectively across diverse outdoor environments. A deep learning-based approach to tackle issues of weed detection has been proposed in this study.

The research is concerned with the creation of an effective and dependable solution based on the use of image data and robust machine learning practices to increase the effectiveness of the weed identification and eradication processes. Recent advances in computer vision and deep learning (DL) offer potential solutions. Deep learning, a subset of machine learning, uses neural networks to classify and detect objects in images [17]. DL methods, especially Convolutional Neural Networks (CNNs) and object detection systems like YOLO, have shown high accuracy in distinguishing wheat from weeds [13][14]. Advanced imaging technologies such as spectral, 3D, and thermal sensors further improve detection accuracy but remain costly and impractical for large-scale field use [19]. Thus, there is a clear technology gap: while precision tools exist, they are either too expensive or impractical for widespread adoption. This study addresses that gap by proposing a deep learning-based, image-driven approach for effective and reliable weed detection, aimed at improving both efficiency and sustainability in wheat production.

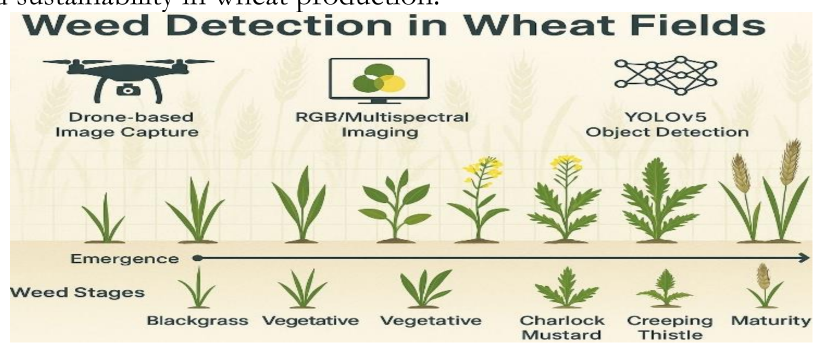

Figure 1. Visual representation of weed distribution within a wheat field during field monitoring. (author's own illustration)

Objectives:

The main objectives of this study are:

To review and synthesize recent deep learning approaches applied to weed detection in wheat fields.

To categorize and compare commonly used models, including YOLO variants, CNN-based classifiers, segmentation networks, transformer-based hybrids, and multimodal techniques.

To examine the role of imaging methods such as UAV-based sensing, multispectral/hyperspectral imaging, and mobile-based systems in enhancing weed detection.

To identify research gaps and limitations, particularly related to dataset diversity, weed–wheat similarity, occlusion challenges, and computational constraints.

To highlight future directions for developing lightweight, robust, and scalable AI-powered weed detection systems for precision agriculture.

Novelty Statement:

This study provides a focused and up-to-date review of deep learning-based methods for weed detection in wheat fields. Unlike earlier surveys that broadly address precision agriculture or general crop–weed detection, this work specifically examines the performance of recent deep learning architectures, including CNNs, YOLO variants, segmentation networks, and transformer-enhanced hybrids, alongside their integration with UAV and spectral imaging systems. By combining performance comparisons with an analysis of dataset challenges, model limitations, and deployment issues, this review uniquely bridges the gap between academic research and practical field applications, offering a roadmap for more intelligent and sustainable weed management in wheat agriculture.

Literature Review:

Introduction to Weed Detection Challenges:

Weed infestation poses a major challenge to wheat production, causing yield losses, increasing competition for resources, and raising dependence on herbicides. Traditional control methods, such as blanket herbicide application, are both expensive and associated with environmental contamination and the development of herbicide resistance. These challenges underscore the urgent need for sustainable, precise, and automated approaches to weed management. Recent advances in artificial intelligence (AI) and deep learning (DL) have opened new opportunities for site-specific, real-time weed detection. By enabling accurate crop–weed differentiation, these technologies support precision agriculture practices such as monitoring, mapping, and automated spraying. Current research emphasizes object detection frameworks like YOLO, pixel-level segmentation, multi-modal fusion, UAV-based imaging, and hyperspectral sensing, alongside efforts in dataset development and integrated spraying systems. Together, these innovations aim to make weed management more efficient, scalable, and environmentally friendly.

YOLO-Based Detection Models:

YOLO architectures have dominated wheat weed detection because of their balance of speed and accuracy. [20] tested YOLOv3 to YOLOv5 variants for early detection of Papaver rhoeas in wheat fields, finding YOLOv5 the most effective (mAP 76.2%, F1-score 75.3%). Similarly, [21] applied YOLOv5 to UAV images across 185 wheat fields in Turkey, covering five phenological stages of charlock mustard, creeping thistle, and forking larkspur. YOLOv5s achieved a peak precision of 0.96 for thistle during vegetative stages, but its performance declined at fruiting stages, highlighting the challenges of late-stage detection. To overcome issues such as occlusion and small-weed recognition, researchers have developed enhanced YOLO variants. [22] proposed CSCW-YOLOv7 with CARAFE upsampling, SE attention, a Contextual Transformer, and Wise IoU loss, achieving 97.7% accuracy and 94.4% mAP on a five-weed dataset. [23] By integrating MobileViTv3 for global–local feature extraction, BiFPN for multi-scale fusion, and a new MPDIOU loss function, the model achieved 92.7% accuracy, with precision, recall, and mAP values improving by nearly 10% over baseline YOLOv8s. These enhancements are architecture-dependent, as they result from changes in feature extraction, feature fusion, and loss optimization rather than dataset-specific factors. Compared with YOLOv5-based approaches, YOLOv8-MBM showed superior accuracy on single-weed detection, but its limited evaluation on only Artemisia reduced its generalizability. In contrast, other models, such as YOLOv5s (used by [21]), remained more versatile across multiple weed species and growth stages. Thus, while YOLOv8-MBM advanced performance, it traded generality for precision in a narrower setting. [24] introduced PMDNet, an improved YOLOv8-based model for weed detection in wheat fields. By integrating PKINet for multi-scale feature extraction, MSFPN for enhanced feature fusion, and DyHead for adaptive detection, PMDNet achieved notable improvements, raising mAP@0.5 to 85.8% and mAP@0.50:0.95 to 69.6%, with a precision of 94.5%. It outperformed Faster R-CNN, RetinaNet, and RT-DETR-L, while maintaining 87.7 FPS in real-time tests. However, compared to lighter models such as the YOLOv5s spraying system [25], PMDNet demanded higher computational power, limiting its suitability for embedded or mobile deployment. While its accuracy and speed were strong, its regional dataset and difficulty with very small weeds restricted scalability across diverse field conditions. This highlights a trade-off between PMDNet's high precision and the lightweight efficiency needed for farmer-ready solutions. [25] integrated a lightweight YOLOv5s model with a hysteresis control algorithm for precision spraying, reducing GFLOPs by 52.2% and achieving spraying accuracies of 99.8%–95.7% across field speeds. These efforts highlight the continued evolution of YOLO models toward real-time, scalable, and field-ready detection and control.

Collectively, these studies demonstrate YOLO's dominance while highlighting ongoing refinements for robustness in complex field conditions.

Table 1 presents YOLO-based weed detection methods in wheat fields. [26] enhanced YOLOv8 using MobileViTv3 and BiFPN to achieve higher accuracy; however, their evaluation was limited to Artemisia. The performance gains were architecture-dependent, as they came from changes in feature extraction (MobileViTv3), feature fusion (BiFPN), and loss optimization (MPDIOU), not from dataset-related factors. [24] introduced PMDNet, achieving top precision and speed, but limited by heavy computation and regional data. [25] integrated a lightweight YOLOv5s into a spraying system, ensuring high accuracy, though performance dropped at higher speeds. [21] applied YOLOv5s on UAV imagery, effective in early stages but less accurate at fruiting. Overall, the table shows a clear shift from YOLOv5 to YOLOv8-based models, improving accuracy and real-time applicability but still facing limits in weed diversity and scalability. In comparative terms, YOLOv8-based variants such as MBM and PMDNet demonstrate higher detection accuracy, particularly for small or occluded weeds, while YOLOv5 remains more lightweight and better suited for real-time field spraying. This contrast highlights the trade-off between accuracy and deployability, an issue that future research must address.

CNN and Two-Stage Models:

While YOLO dominates, CNNs and two-stage detectors remain valuable. [27] Applied ResNet50 on mobile devices in Indian wheat fields, achieving a validation accuracy of 93.25% across five weed types, showing the feasibility of farmer-accessible tools. [28] compared PyTorch and TensorFlow on 6,000 wheat field images, reporting that PyTorch was faster (9.43 ms per image) and more accurate, with weed removal accuracy ranging from 0.89 to 0.91, though performance was constrained by limited weed diversity. Additionally, two-stage models such as Faster R-CNN have demonstrated strong effectiveness. [29] Applied an enhanced Faster R-CNN with transfer learning and preprocessing, which outperformed baseline models under MS COCO evaluation metrics. Although the exact accuracy value was not reported in the summary, the study demonstrated improved detection rates in complex wheat field conditions. However, computational cost and lack of hardware integration restricted real-world deployment. While CNNs and two-stage models offer strong classification performance, their slower inference speed makes them more suitable for offline analysis or mobile-specific applications.

Segmentation and Pixel-Level Approaches:

Segmentation-based models provide pixel-level precision for canopy mapping. [30] evaluated U-Net, DeepLabV3, and PSPNet on UAV images at wheat jointing and booting stages. PSPNet achieved the best accuracy (80%), outperforming U-Net (75%) and DLV3 (56.5%). While effective for canopy distribution and quantifying weed pressure, these models struggled with fine species differentiation—U-Net underclassified minor weeds, while PSPNet blended overlapping classes. Segmentation thus excels at canopy-scale analysis but is less suited for species-specific detection.

Table 1. YOLO-Based Wheat Weed Detection Studies

Study	Model/Variant	Dataset (images/species)	Key Features	Performance
[20]	YOLOv3–YOLOv5 YOLOv5s best	Field images of Papaver rhoeas	Early-stage, high-precision, UAV + ground images	mAP 76.2%, F1 75.3%
[21]	YOLOv5s	Charlock mustard, creeping thistle, forking larkspur	UAV dataset: 185 fields, 145,792 objects, 15 growth-stage scenarios	Mean precision 0.86; best precision 0.96 (seedling–vegetative stages); lower at the fruiting stage
[22]	CSCW-YOLOv7	5 weed species	CARAFE upsampling, SE attention, CoT, WIoU loss	Accuracy 97.7%, mAP 94.4%
[23]	YOLOv8-MBM	Artemisia (single weed)	MobileViTv3, BiFPN, MPDIOU	Precision 93.2%
[24]	PMDNet (YOLOv8-based)	5,967 images / 8 weeds	PKINet, MSFPN, DyHead	Precision 94.5%, 87 FPS
[25]	YOLOv5s (lightweight) + hysteresis control algorithm	Tillering-stage wheat	Hysteresis algorithm, solenoid valve control	GFLOPs ↓52.2%, mAP 91.4%, spraying 99.8–95.7%

UAV-Based Imaging and Field Monitoring:

UAVs provide a scalable solution for weed monitoring across large fields. [26] integrated UAV imagery with DeepLabV3+, achieving detection precision of 91.27% in scattered fields and 87.51% in drilled fields. Beyond weed detection, [26] also quantified weed-induced yield losses of up to 60% under heavy infestations. However, weeds at the regrowth stage were challenging to distinguish due to occlusion, while the use of high-resolution hyperspectral sensors substantially increased costs. Similarly, [21] used UAV imagery across multiple growth stages, though reliance on 2D RGB limited late-stage accuracy. UAV-based systems thus provide valuable spatial variability insights but face trade-offs in cost, resolution, and annotation effort.

Hyperspectral and Multispectral Imaging:

Spectral imaging expands detection by capturing reflectance differences. [31] applied hyperspectral data and ML classifiers (PLS-DA, SVM, MLP) to ryegrass and clover pastures, with MLP achieving 89.1% accuracy after SNV preprocessing. [32] used UAV multispectral imagery to identify Italian ryegrass in wheat, achieving >70% accuracy, with NIR bands most effective. [33] combined multispectral sensing with CNN and transformer models for blackgrass detection in Europe, approaching 90% accuracy on previously unseen field images. Despite the promise, these methods remain limited by sensor cost, dataset transferability, and scalability under field variability.

Transformer and Attention-Based Enhancements:

Attention mechanisms and transformers are increasingly integrated into detection pipelines. [22]'s CSCW-YOLOv7 included SE and CoT modules, while [23]'s YOLOv8-MBM embedded MobileViTv3 for global attention. These hybrid CNN-transformer designs improved recognition of small, overlapping, and morphologically similar weeds, reflecting a shift toward architectures that balance local detail with contextual awareness.

Dataset Contributions:

High-quality datasets are essential for training robust models. [34] released Weed25, a dataset of 14,035 images across 25 species, achieving over 92% accuracy with YOLOv5. [24] curated 5,967 images of eight weed species for PMDNet. Despite these efforts, many datasets remain limited in species diversity, geographic coverage, and phenological stages, restricting model generalization.

Multi-Modal Fusion Techniques:

Integrating multiple data modalities improves discrimination between visually similar weeds. [35] combined RGB and depth image features with AdaBoost, achieving 88% accuracy at the tillering stage (0.2 s processing) and 81.1% at the jointing stage (0.69 s). This approach surpassed RGB-only detection but remained limited by segmentation errors, occlusion, and noisy depth data in low-light settings. To address these issues, [35] introduced a three-branch CNN framework that independently processes RGB and depth inputs before fusing them at the decision stage. Depth images are converted into an RGB-like three-channel format for CNN feature extraction, and multi-scale feature fusion enhances model robustness.

The model reached a mean average precision of 36.1% for grass weeds, 42.9% for broadleaf weeds, and an IoG accuracy of 89.3%, with fusion weights of 0.4 (RGB) and 0.3 (depth). Despite surpassing RGB-only methods, challenges remained, including manual weight tuning, high computational load, and occlusion from overlapping leaves. Future work emphasized automated weight optimization, model compression, and multi-perspective imaging to improve precision and efficiency.

Hybrid ML–DL Frameworks:

Combining ML and DL enhances classification accuracy. [36] Extract statistical features (Hu moments, entropy, GLCM) for ML classifiers such as SVM and ANN, while DL models (VGG16, DenseNet, ConvNeXtBase) provide feature learning. YOLOv8m is applied for detection before classification. SVM achieves 99.5% accuracy on the Early Crop–Weed dataset, while ConvNeXtBase combined with Random Forest achieves 98% on other datasets. Despite high accuracy, reliance on SMOTE balancing and sensitivity to lighting limits field readiness. This hybrid design illustrates the complementary strengths of ML and DL in addressing complex crop–weed detection scenarios.

Low-Cost and Embedded Systems:

To enhance accessibility, researchers have investigated the use of low-cost hardware for weed detection. [37] implemented CNN-based detection and spraying on Raspberry Pi, enabling real-time control but restricted to only two weed species. While embedded solutions help reduce costs, they face challenges of scalability and limited computational capacity, underscoring the need for lightweight yet versatile models.

Spraying and Actuation Systems:

The integration of detection and spraying is essential for effective site-specific management. [25] integrated a lightweight YOLOv5s with a hysteresis control algorithm, achieving a 52% reduction in GFLOPs and a 42% decrease in model size. The system achieved a mAP of 91.4% and an F1-score of 85.3%, with spraying rates of 99.8%, 98.2%, and 95.7% at speeds of 0.3, 0.5, and 0.6 m/s, respectively. However, performance declined at higher speeds due to velocity feedback limitations. These results demonstrate the feasibility of coupling lightweight DL models with actuation systems for precise and efficient herbicide application.

Region-Specific Weed Detection:

Several studies highlight region-specific challenges. [33] focused on blackgrass in Europe, integrating spectral and transformer models to achieve ~90% accuracy, while [27] built a mobile system for Indian wheat fields. These examples highlight both adaptability and the importance of broader validation across geographies and environments.

Mobile and Farmer-Friendly Solutions:

Mobile-based platforms improve accessibility. [27]'The ResNet50 mobile app achieved 93.25% accuracy, showing potential for smallholder farmers despite limited weed coverage and grayscale imagery constraints. Such tools represent early steps toward democratizing AI in agriculture, bridging gaps between research and practice.

Synthesis and Research Gaps:

Across studies, YOLO-based models dominate due to their efficiency, with extensions such as CSCW-YOLOv7, YOLOv8-MBM, and PMDNet offering improvements in accuracy and robustness. Segmentation models are valuable for canopy mapping but face limitations in fine species-level classification, whereas CNNs and hybrid ML–DL frameworks offer complementary strengths. UAV-based imaging expands monitoring capabilities but remains constrained by cost and scalability challenges. Several gaps remain unaddressed. Dataset limitations, especially the scarcity of diverse weed species and balanced samples, restrict the generalizability of models across regions. Detecting small, overlapping, or partially occluded weeds continues to be problematic, especially in early growth stages. Current models often demand high computational resources, which restricts their use in real-time, field-ready applications. While multimodal sensing (hyperspectral, LiDAR, depth fusion) shows promise, practical approaches increasingly emphasize RGB imagery due to its accessibility, cost-effectiveness, and scalability in real farming environments. Current research focuses on developing high-resolution, diverse RGB datasets, designing lightweight yet robust architectures, and advancing early-stage multi-species detection under real-world field conditions. Addressing these gaps forms the foundation for intelligent, real-time, and scalable weed detection systems in wheat fields.

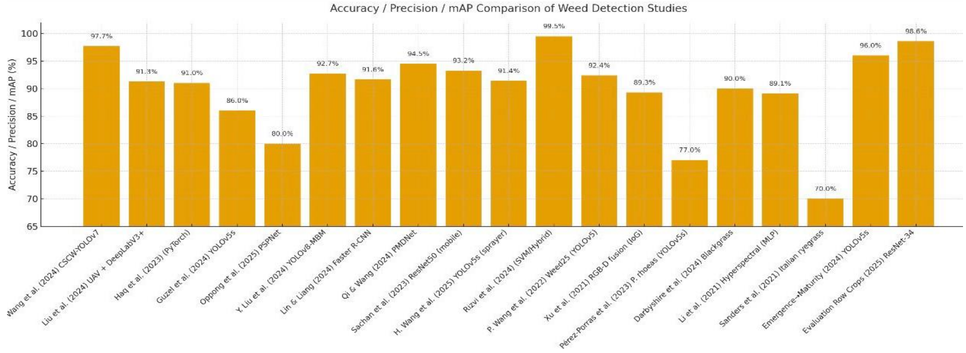

Figure 2. Reported Accuracy of Deep Learning Models for Weed Detection in Wheat Fields (2021–2025).

As shown in Figure 2, the reported accuracy of deep learning models for wheat weed detection between 2021 and 2025. The Figure compares results from a wide range of architectures, including YOLO variants (v3–v9, MBM, PMDNet), CNN-based classifiers (ResNet, VGG, DenseNet), segmentation networks (U-Net, DeepLabV3, PSPNet), and transformer-integrated hybrids. Most studies consistently achieved accuracy levels above 85%, with YOLOv7/YOLOv8 and transformer-enhanced models pushing performance closer to 95% under complex field conditions. Earlier CNN approaches performed reliably but were slower, while segmentation models excelled in canopy mapping rather than species-specific classification. The trend shown in Figure 2 reflects the steady improvement of deep learning techniques in balancing accuracy, real-time speed, and adaptability to field variability.

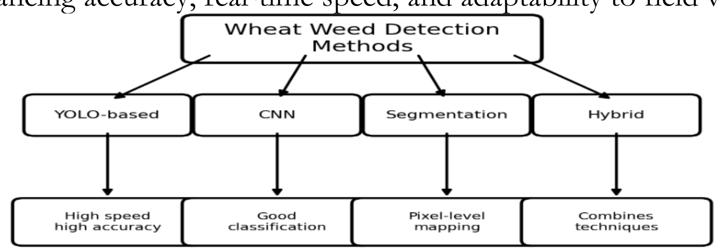

Figure 3. Flowchart of Wheat Weed Detection Methods

Figure 3: Flowchart of Wheat Weed Detection Methods. The diagram provides an overview of the principal strategies used in recent studies. YOLO-based detectors dominate due to their speed and strong object-level recognition capabilities, making them suitable for UAV imagery and real-time spraying. CNN classifiers are widely used in mobile and low-cost systems for species recognition, but are less efficient in real-time detection. Segmentation methods such as U-Net, DeepLabV3, and PSPNet are effective for canopy-scale mapping and quantifying weed pressure but struggle with fine-grained species identification. Hybrid and multimodal techniques combine RGB imagery with depth, hyperspectral, or transformer-based features, improving robustness under occlusion and visual similarity. As shown in Figure 3, the flowchart highlights the evolution of these methods and how each contributes differently to precision agriculture by balancing trade-offs between accuracy, computation, and practical deployment in real field conditions.

Table 2. Overview of deep learning-based methods for weed detection in wheat crops.

Dataset	Method	Performance	Limitation
Weed Detection in Wheat Crops Using Image Analysis and AI (2023) 6000 RGB images of Cirsium arvense collected via mobile and HD webcam, labeled, and preprocessed	DL: YOLOv3-Tiny, YOLOv4-Tiny, YOLOv5s/m/l (TensorFlow & PyTorch); Transfer Learning; Preprocessing: resizing, cropping, augmentation	YOLOv5l: Highest precision in PyTorch (0.84). YOLOv4-Tiny: Highest accuracy overall (0.97). Inference time: 9.43 ms (YOLOv4-Tiny), 12.38 ms	Only one weed type was used. Images from one location only. Might not generalize to other weeds, crops, or weather conditions
Harnessing UAVs and DL for Grass Weed Detection (2024) 8wheat plots: 6 infested, 2 weed-free, UAV imaging of Grass weeds: Alopecurus aequalis (Meadow foxtail), Poa annua (Annual bluegrass), Biomass & yield measured	DeepLabV3+ (best segmentation); NDVI, SAVI, RVI; SVR for biomass; ResNet-50 backbone, Python + LabelMe for training	Weed detection accuracy:91.27% (broadcast fields), 87.51% (drilled fields). Yield loss due to weeds: up to 60%. Biomass estimation $R^2 > 0.85$. NDVI bands showed a high correlation with weed biomass	Hard to distinguish weeds during the regrowth stage due to occlusion. DeepLabV3+ can't estimate the amount of weeds, only presence/absence. High-resolution hyperspectral cameras are still limited. Mislabeling edges of wheat/weed in the dataset
Deep Learning-Based Target Spraying Control of weeds on wheat field at tillering stage 2025). Wheat fields, four weeds: Silene conoidea, Malcolmia africana, Descurainia sophia, Capsella bursa-pastoris; real-time sprayer system	YOLOv5-SGS (improved YOLOv5s) - Ghost Module - GSConv - SimAM attention - Target spraying decision algorithm - Hysteresis delay compensation algorithm..	GFLOPs reduced by 52.2%, model size reduced by 42.4%. Accuracy: mAP 91.4%, F1 score 85.3% Spraying accuracy: 99.8% at 0.3–0.4 m/s, 98.2% at 0.4–0.5 m/s, 95.7% at 0.5–0.6 m/s. Coverage rate: over 93% at slower speeds; slightly drops at higher speeds	Slight drop in performance at higher sprayer speeds (e.g., above 0.5 m/s). Needs higher-frequency speed feedback hardware for improved accuracy at fast operation speeds
Weed25: A Deep Learning Dataset for Weed Identification (2022) – 14,035 images of 25 weed species from 14 families, annotated and split into train/val/test sets	Object detection models: YOLOv3, YOLOv5, Faster R-CNN; Training with 100 epochs, batch size 4, IoU 0.5	YOLOv5 achieved the best performance with a 92.4% mAP and strong precision–recall tradeoff, while YOLOv3 and Faster R-CNN were slightly lower. Still, overlapping leaves and background interference caused reduced accuracy for species like crabgrass and green foxtail.	The study was limited to 25 species, with misclassification issues arising from background noise, morphological similarity among grass weeds, and environmental factors like lighting and leaf overlap. Such challenges reduced accuracy and occasionally caused false predictions.
YOLOv8 Model for Weed Detection in Wheat Fields Based on a Visual Converter and Multi-Scale Feature Fusion (2024). Custom dataset with wheat and Artemisia weed images.	Improved YOLOv8s-MBM: MobileViTv3 (backbone), BiFPN (feature fusion), MPDIoU (loss function); Grad-CAM for visual interpretation	Precision: 92.7%- Recall: 87.6%- mAP@0.5 (mAP1): 89.7%- mAP@0.5–0.95 (mAP2): 85.2%- FPS (speed): 35.5- Outperforms YOLOv3–YOLOv9 and Fast R-CNN models.	Only one weed species was used (Artemisia)- Limited weed diversity and growth stages- Detection performance drops slightly for occluded or very small weeds.

Examining Deep Learning Pixel-Based Classification Algorithms for Mapping Weed Canopy Cover in Wheat Production Using Drone Data (2025). Drone-based multispectral images at 4 wheat growth stages (Mayweed, Speedwell, Hairy Buttercup, Common Vetch, others); 2012 & 2205 training polygons	Deep Learning: U-Net, DeepLabV3 (DLV3), PSPNet (all using ResNet34 backbone)	PSPNet: 80% accuracy (best overall) - U-Net: 75% accuracy (best generalization) - DLV3: 56.5% accuracy (best precision for species-specific weeds)	DLV3 struggled with underclassification and fine detail detection - PSPNet tended to blend weed classes - U-Net underclassified some less dominant weeds
Weed Detection and Recognition in Complex Wheat Fields Based on an Improved YOLOv7 (2024) 2,614 field images from Henan, China; 5 weed species (Descurainia sophia, Thistle, Golden saxifrage, Shepherd's purse, Artemisia argyi*)	YOLOv7 enhanced using CARAFE, SE, CoT, and WIoUv3, then trained on an 80/20 split with validation from the training set.	Precision: 97.7%- Recall: 98%- mAP: 94.4%- Reduced parameters by 10.7%- Lower FLOPs by 10%- Outperformed YOLOv5m, YOLOv7, Faster RCNN	Model limited to 5 weed species- A. argyi detection less accurate due to fewer samples- Background occlusion caused some false positives (e.g., wheat leaves misidentified as thistle)- High similarity between wheat and some weeds caused detection errors.
PMDNet: An Improved Object Detection Model for Wheat Field Weed (2025) 5,967 wheat field images; 8 weed species (Artemisia capillaris, Agropyron cristatum, Chenopodium album, Bassia scoparia, Cirsium arvense, Kali collinum, Raphanus raphanistrum, Thermopsis lanceolata)	YOLOv8-based PMDNet: PKINet (multi-scale backbone), MSFPN (feature fusion), DyHead (attention head); data augmentation; ablation studies	mAP@0.5 ↑ from 83.6% to 85.8%. mAP@0.5:0.95 ↑ from 65.7% to 69.6%. Precision: 94.5%. Speed: 87.7 FPS. Outperformed YOLOv5n, YOLOv10n, Faster-RCNN, RetinaNet	Heavy model—not suitable for low-power devices. The dataset is from a single region. It struggles with thin/small weeds. Limited weed species coverage
Identification of Weeds in Wheat Crop Using Artificial Intelligence Techniques (2023) Collected 1,869 weed images from ICAR-IARI wheat fields of 5 weeds (Chenopodium album, Coronopus didymus, Convolvulus arvensis, Malva neglecta, Medicago polymorpha)	ResNet-50 CNN with transfer learning; Fine-tuning on image preprocessing; deployed on an Android mobile app.	Accuracy: 93.25%- Precision: 92.79%- Recall: 93.10%- F1-score: 92.90%	Only five weed species were used. Not generalized to other crops. No testing under complex field conditions or multiple locations. Grayscale input may limit color-based detection precision.
Identification and Classification Model of Wheat and Weed Based on Improved Faster R-CNN (2024)	Image dataset creation (web scraping), augmentation (RGB patching, flipping, blurring), model	AP: 91.64%, AR: 75.87%, real-time: 0.44s/image, better than VGG16 & MobileNetV2	Only software-level; no hardware (IoT) deployment yet due to time and budget constraints

Dataset of wheat + 5 weed types (e.g., Setaria viridis, Echinochloa crus-galli); images collected via web scraping and augmented (RGB patching, flipping, blurring)	training using ResNet-50+FPN as backbone in Faster R-CNN, transfer learning		
Revolutionizing Agriculture: Machine and Deep Learning Solutions for Enhanced Crop Quality and Weed Control (2024) – Two datasets: Early-Crop-Weed (Black Nightshade, Velvetleaf) and CottonWeedID15 (15 species, including Carpetweed, Crabgrass, Goosegrass, Morning Glory, others); images annotated and class-balanced via SMOTE	Manual & deep feature extraction: GLCM, LBP, Hu moments, statistical features; Deep: VGG16, VGG19, Xception, DenseNet, ConvNeXt (transfer learning); Object detection: YOLOv8-M; Classification via ANN, SVM, Random Forest	ANN: 89.26% (CottonWeedID15). SVM (poly kernel): 99% (Early-Crop-Weed). ConvNeXt + RF: 98% (Early-Crop-Weed), 89% (CottonWeedID15). YOLOv8-M: mAP 89%	Datasets are unbalanced. Detection is difficult due to similar weed-crop texture and lighting conditions. Need for more real-time capable models and larger datasets.
Multi-Modal Deep Learning for Weeds Detection in Wheat Field Based on RGB-D Images (2021) – 1,228 field images captured with an RGB-D camera; Broad-leaf weeds: Amaranthus retroflexus, Capsella bursa-pastoris; Grass weeds: Alopecurus aequalis, Poa annua, Bromus japonicus, Echinochloa crusgalli; images manually labeled and augmented	RGB-D image fusion, PHA image recoding; Faster R-CNN with VGG16 backbone; multiscale object detection; ensemble learning	mAP: 42.9% (broad-leaf), 36.1% (grass); IoG: 89.3%; PHA improved detection 1.35× over depth	Manual weight tuning in ensemble learning; high computational load; occlusion from overlapping leave
Early and On-Ground Image-Based Detection of Poppy (Papaver rhoeas) in Wheat Using YOLO Architectures (2022) – On-ground RGB images of wheat fields; annotated for early-stage P. rhoeas detection (BBCH 12–14)	Six YOLO models (YOLOv3, YOLOv4-P5, YOLOv4-CSP, YOLOv5s, YOLOv5m, YOLOv5l) image cropping and preprocessing	YOLOv5s performed best F1-score: 75.3%, mAP@0.5: 76.2%, accuracy: 77%; Fastest inference (83 FPS GPU, 7 FPS CPU	Small weed size caused information loss when resizing; Only RGB images were used (no multispectral); YOLOv4-P7 and P9 were not tested due to memory limits.
Evaluation of Weed Infestations in Row Crops Using Aerial RGB Imaging and Deep Learning (2025) – UAV-based RGB images over maize fields; annotated ROI; 10	UAV imaging; DeepLabV3 with ResNet/DenseNet/VGG backbones; ArcGIS pixel-based classification	ResNet-34 performed best (Precision, Recall, F1: 0.986); classified 4.1% of area as weed-infested; model robust against shadow interference	limited to RGB imaging (spectral limitations), not generalized to other crops/weeds, small scattered weeds not detected, not integrated into real-time farming workflows

backbone models for DeepLabV3 training; weeds: Chenopodium album, Cirsium arvense, Polygonum aviculare, Sorghum halepense			
Deep Learning for Image-Based Detection of Weeds from Emergence to Maturity in Wheat Fields (2024) – Drone-based RGB images of 185 fields; 145,792 annotated weed instances; 5 growth stages (seedling to fruiting); weeds: Charlock mustard, Creeping thistle, Forking larkspur)	YOLOv5 (nano, small, medium, large, xlarge); trained 80/20 split; evaluated using precision, recall, F1, AUC	YOLOv5s gave the best results: up to 96% precision in early stages; worst for FL at fruiting (0.45); YOLOv5n performed worst (21% lower precision); strong correlation across metrics ($R^2 \geq 0.95$)	YOLOv5s-based weed detection was limited by 2D RGB imagery and a single model, with reduced accuracy at later growth stages, suggesting future improvements through 3D tools, advanced sensors, and newer deep learning models.
Multi-Modal Deep Learning for Weeds Detection in Wheat Field Based on RGB-D Images (2021) Dataset: 1,228 RGB-D images (field experiment); broadleaf weeds (Amaranthus retroflexus, Capsella bursa-pastoris) and grass weeds (Alopecurus aequalis, Poa annua, Bromus japonicus, Echinochloa crusgalli); manually labeled and augmented.	Method: RGB-D image fusion; PHA image recoding; Faster R-CNN with VGG16 backbone; multiscale object detection; ensemble learning	mAP: 42.9% (broad-leaf), 36.1% (grass); IoG: 89.3%; PHA improved detection 1.35× over depth	Manual weight tuning in ensemble learning; high computational load; occlusion from overlapping leaves
Multispectral Fine-Grained Classification of Blackgrass in Wheat and Barley Crops (2024) Dataset: 15,929 multispectral images (RGB + NIR + Red Edge) from 51 wheat and barley fields; dataset split by field for generalization testing. Target weed: Alopecurus myosuroides (Blackgrass).	Method: Deep learning classifiers – ResNet-50, EfficientNet-B4, Swin Transformer B; evaluated across spectral band combinations and dataset sizes.	Swin B achieved the best accuracy: 87.7%, followed by ResNet-50 (87.3%) and EfficientNet B4 (83.0%). The NIR band was most effective. Performance plateaued after 6,000 training images. Barley is harder to classify than wheat.	Should focus on expanding barley image data, optimizing spectral band selection, and developing more robust, generalizable models, possibly integrating **temporal crop stage features** for improved detection across growth stages.
Identification of Weeds Based on Hyperspectral Imaging and Machine Learning (2021) Dataset: 120 hyperspectral samples (greenhouse-grown weeds); grass	Method: Machine learning models (PLS-DA, SVM, MLP) with SNV preprocessing; compared pixel-level vs. superpixel spectra.	MLP with Sp data gave the best results (up to 90% accuracy); well (70–100%); specific spectral regions identified (550–750, 995–1,005, 1,110–1,220, 1,380–1,470 nm)	Pixel-level classification had lower accuracy; manual patch selection in

weeds (Setaria pumila, Wind grass), broadleaf weeds (Ranunculus acris, Carduus tenuiflorus); spectral segmentation via thresholding and superpixel.			Sp segmentation was limited to four weed species.
Deep Learning-Based Decision Support System for Weeds Detection in Wheat Fields (2022) Dataset: 1,318 real RGB images captured in wheat fields (Nikon D7000) under varying lighting; weeds: Convolvulus arvensis (dicot) and Phalaris paradoxa (monocot).	Method: YOLOv5 object detection with CNN backbone (CSP, FPN, PAN); augmentation (flip, crop, exposure); GIoU loss; deployed on Raspberry Pi.	Precision: 83%- Recall: 93%- mAP@0.5: 94.4%- Accurate real-time detection- Efficient localized spraying	Only two weed species included- Model may need reprogramming for more weed types- Raspberry Pi may limit scalability for larger farms
Remote Sensing for Italian Ryegrass Detection in Winter Wheat (2021) Dataset: Field experiments (2016–2017, two sites); UAV-based multispectral imagery (5-band) of winter wheat fields; simulated weed densities with herbicide variations; target weed: Lolium perenne ssp. multiflorum (Italian ryegrass).	Method: UAV imaging; supervised classification; NIR reflectance analysis; compared across dates and altitudes.	Supervised classification achieved >70% accuracy; NIR band showed strong differentiation across densities, altitudes, and dates	Inconsistent lighting conditions between dates made unsupervised classification unreliable; reflectance values varied too much to be reused across dates

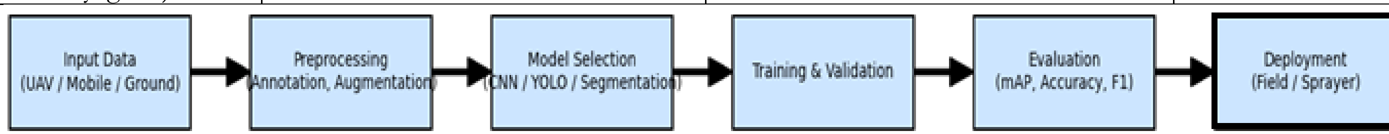

Figure 4. Conceptual Flowchart of Deep Learning-Based Weed Detection Pipeline in Wheat Fields

As shown in Figure 4, the flowchart illustrates the typical research pipeline adopted in recent studies on deep learning–based weed detection in wheat. The process begins with input data collection using UAVs, ground cameras, or mobile devices. The acquired images undergo preprocessing steps such as annotation, augmentation, and normalization to prepare training datasets. Next, an appropriate model architecture (e.g., CNNs, YOLO variants, or segmentation networks) is selected and optimized. The chosen model is then subjected to training and validation to learn discriminative features for crop–weed differentiation. Performance is assessed during the evaluation stage using metrics such as accuracy, mean Average Precision (mAP), and F1-score. Finally, successful models are integrated into deployment systems, including UAV-based monitoring, field robots, or precision sprayers, for real-time weed management in precision agriculture.

Challenges and Prospects for AI-Powered Weed Detection in Wheat Fields:

Although deep learning has greatly advanced automated weed detection, several persistent challenges still limit large-scale adoption in wheat production. A key difficulty lies in the high visual similarity between wheat and certain weeds, particularly during early growth stages, which leads to frequent misclassification. Dataset limitations remain another major bottleneck, as many studies rely on region-specific or imbalanced collections that reduce generalizability across diverse environments and weed species. Environmental variability—including differences in illumination, soil texture, crop density, and seasonal changes—further degrades model robustness. Detecting small, overlapping, or partially occluded weeds continues to pose difficulties, even for state-of-the-art models. Moreover, many deep architectures demand heavy computational resources, which constrain their practical deployment for real-time applications in wheat fields.

Looking forward, progress will depend on a multipronged strategy. Incorporating multiple weed categories into the dataset will enhance training and support more accurate classification. The development of lightweight yet accurate deep learning architectures is essential to enable real-time detection on resource-constrained devices such as UAVs, mobile platforms, and smart sprayers. Enhancing robustness under complex environmental conditions, together with optimizing early detection of weeds, will further strengthen field-ready systems. Collectively, these advances will enable robust, efficient, and sustainable AI-driven weed detection systems, contributing to higher wheat yields and supporting cost-effective and environmentally responsible farming practices.

Conclusion:

This review highlights the rapid evolution of deep learning approaches for weed detection in wheat fields, shifting from conventional image-based approaches to highly efficient models capable of operating under complex field conditions. These developments highlight the transformative role of deep learning in precision agriculture, where accurate weed identification is central to reducing herbicide use, preserving crop yield, and supporting sustainable farming. Despite impressive detection accuracies reported across many studies, several barriers remain before large-scale deployment can be realized. Current research is still constrained by the limited availability of diverse and openly accessible datasets, challenges in detecting small or occluded weeds, and the computational burden of running advanced models on lightweight devices suitable for field applications. Future progress will depend on open and standardized datasets, developing architectures that balance accuracy with efficiency, and exploring multimodal integration of UAV imagery, multispectral sensing, and IoT platforms. Beyond technical improvements, attention should also be directed toward practical implementation, including cost-effective hardware, user-friendly interfaces for farmers, and strategies for reducing reliance on chemical herbicides. By addressing these gaps, deep learning has the potential not only to improve weed detection but also to fundamentally reshape wheat production into a more precise, resource-efficient, and environmentally sustainable practice.

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