Artificial Intelligence for Weed Detection: A Comprehensive Review

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Abstract

Weed invasion is a major constraint for agricultural production worldwide, leading to significant crop losses, increased production costs and over-reliance on herbicides. Manual inspection and blanket spraying of herbicides for weed control are labor intensive, environmentally damaging, and economically inefficient. Recent advances in artificial intelligence (AI), computer vision and precision agriculture have led to automated weed detection systems that are able to accurately identify weed species across a wide range of field conditions. Good progress is being made in weed recognition accuracy, in reducing computational complexity and in reducing herbicide use with machine learning, deep learning, object detection, semantic segmentation and vision transformer models. In addition, the application of unmanned aerial vehicles (UAVs), edge computing, Internet of Things (IoT) devices, and autonomous agricultural robots has enabled the deployment of intelligent precision farming systems. In this paper, we present a comprehensive survey on AI-based weed detection techniques, including publicly available datasets, machine learning algorithms, convolutional neural networks, object detection methods, semantic segmentation architectures, vision transformers, and emerging edge intelligence technologies. Critical discussions on the current research challenges such as dataset limitations, model generalization, computational constraints, and real-time deployment. Finally, future research directions on foundation models, explainable AI, federated learning, and autonomous precision agriculture are outlined to boost the development of sustainable weed management systems.

Keywords— Weed Detection, Artificial Intelligence, Precision Agriculture, Deep Learning, Machine Learning, Computer Vision, Vision Transformer, Edge AI, Autonomous Agriculture.

Introduction

Weed Incursion is a big problem in agricultural production worldwide. It reduces crop yield, increases input cost and overuses herbicides. Manual inspection and blanket spraying pesticides for weed management is laborious, environmentally destructive and inefficient. Recent advances in AI, computer vision, and precision agriculture have enabled the creation of automated weed identification systems that can reliably recognize beneficial species in diverse field environments. Machine learning, deep learning, object detection, semantic segmentation and vision transformer models enhance the accuracy of weed recognition, decrease computational complexity and reduce herbicide usage. Intelligent precision farming systems are enabled by UAVs, edge computing, IoT and autonomous agricultural robots. The work focuses on AI-based weed detection technologies, the emerging edge intelligence technology, the use of publicly available datasets and machine learning methods such as convolutional neural networks (CNNs), object detectors, semantic segmentation architectures, and vision transformers. Critical discussions address dataset limitations, model generalizability, real-world applications, and computational costs for current research issues. Demand for food, population growth, climate change and loss of arable land are driving a digital transition in agriculture. Among the most damaging biotic pressures to agricultural output are weeds. This is because they compete with crops for nutrients, sunlight, moisture and space. Weed species, infestation intensity and environmental conditions may lead to yield loss of 20-50% [1], [2].
Traditional weed control includes manual field scouting and blanket pesticide application. These techniques have been used for decades, but they have disadvantages such as high labor costs, inaccurate weed detection, excessive use of herbicides, environmental contamination and the

appearance of herbicide-resistant weeds [3], [4]. Unnecessary chemical contamination of healthy crops and ecosystems increases the cost of production and decreases agricultural sustainability. Precision agriculture has emerged as a sustainable solution for crop management through integration of cutting-edge sensing technologies, computer vision, artificial intelligence, robots and IoT platforms. With precision agriculture, herbicides are only applied where the weeds are, not over the whole field. Chemical use Precision agriculture [5], [6]. , reduces chemical use, improves crop yield, reduces operational expenses, and reduces environmental impacts. One of the most promising technologies in computer vision is automated weed detection. Hand-held cameras, UAVs, agricultural robots and tractor-mounted imaging systems can be used to automatically perform weed and crop identification. Early computer vision systems were based on hand-crafted techniques, including color histograms, texture descriptors, morphological features, and edge detection. These features were identified through traditional machine learning methods such as SVM, decision tree models, random forests, logistic regression, and k-nearest neighbors. These methods have been successful in controlled laboratory conditions, but they have been degraded under variable illumination, different backgrounds, overlapping vegetation and growth stages [7], [8], [13], [14].

Lately, Transformer based computer vision models have outperformed CNNs. Vision Transformers (ViTs), Swin Transformers, DETR, and Segment Anything Models (SAM) [15], [16] are examples of self-attention mechanisms that have been employed to model long-range spatial relationships in complex field environments characterized by variations in weed morphology, lighting conditions, and occlusions. These advances have pushed AI-based weed detection from image classification to scene understanding and decision support [17, 18].

Despite these advances, many research questions remain to be answered. Weed datasets are scarce and they provide little diversity in crop species, weed morphology, climate and imaging sensors. Algorithms used in deep learning are computationally intensive and may not generalize well across different regions and farming practices. Explainability, robustness, model compression, continuous learning and real-time deployment are still research areas [19], [20]. work. The last research directions are foundation models, explainable AI, federated learning and autonomous precision agriculture for better sustainable weed management system.

A summary of the main contributions of this review is as follows: ·

- A detailed survey of AI algorithms for weed detection, from traditional machine learning to the latest transformer-based architectures.
- Comparative analysis of public datasets for weed detection and their applications.
- In-depth discussion on CNN, object detection, semantic segmentation and transformer vision models.
- A survey on UAV, edge AI, IoT and autonomous robotic systems for precision agriculture
- Challenges in present research and future directions on intelligent weed management identification

Evolution of AI-Based Weed Detection Technologies

Automatic weed detection has evolved from image processing to intelligent deep learning and transformer-based systems. Transition from computer vision to AI in precision agriculture. During the first generation of weed detection systems (1995-2005), researchers used handcrafted image features (e.g., color indices, texture descriptors, edge information, and morphological features). These manually designed features were computationally cheap but sensitive to illumination changes, soil background heterogeneity and plant growth stages [21], [22]. This constrains their use in large scale agriculture.

Between 2005 and 2012 machine learning (ML) algorithms improved automated weed identification . ML classifiers learned discriminative patterns on retrieved image features, not on manual judgement rules. Common classifiers are SVM, DT, RF, LR and KNN. Colour histograms, Local Binary Patterns (LBP), Grey-Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and Scale-Invariant Feature Transform (SIFT) have been widely employed to increase classification accuracy [21–24]. These methods performed better than standard thresholding methods, but they required careful tuning of hand-crafted features and parameters.

Since 2012, deep learning has transformed agricultural computer vision. Convolutional neural networks (CNNs) learned hierarchical visual representation from raw data, eliminating the requirement for feature engineering. Many landmark CNN architectures as AlexNet, VGGNet, GoogLeNet, ResNet, DenseNet, EfficientNet, and MobileNet have improved weed classification on agricultural datasets [25–28]. Deep feature learning is more robust to illumination, plant morphology, soil texture, and background clutter than typical machine learning.

Research has been conducted on object identification algorithms that can simultaneously identify weed species and estimate their spatial locations in agricultural areas. Faster R-CNN is a two-stage detector with high accuracy in region proposal networks, while SSD and the YOLO family are one-stage detectors that infer faster for real-time applications [29], [30]. YOLOv3 to YOLOv11 can be applied in agricultural robots, UAVs and embedded edge devices as it leads to increased detection precision and reduced processing complexity. Transformer-based computer vision models may represent the next generation of intelligent agricultural systems. Vision transformers (ViTs) leverage self-attention mechanisms to model the long-range spatial dependencies in the images, which enhances robustness in complex agricultural scenarios. Swin Transformer, DETR and SAM versions were shown to be useful for crop monitoring, weed segmentation and precision farming [23], [24]. Research trends are AI, edge computing, IoT, cloud computing, and autonomous agricultural machinery. AI models on embedded platforms like the Google Coral TPU , Raspberry Pi and NVIDIA Jetson provide real-time inference in the field reducing bandwidth and communication latency [25] . Next-generation autonomous precision agriculture will require UAV, robots, edge intelligence, and cloud analytics.

Public Datasets for Weed Detection

Weeds databases vary in terms of image acquisition platforms, annotation methods, imaging sensors, environmental conditions, and target crop species. Field sensors can be handheld, unmanned aerial, tractor-mounted, robotic, and stationary and can image. Annotations may be image class labels, bounding boxes for object detection, or pixel segmentation masks depending on the application [26]. A widely used dataset is DeepWeeds which includes over 17,000 RGB images of various invasive weed species in real-field conditions and is often employed for image classification and object detection tasks [27]. WeedMap [38] is used to benchmark the semantic segmentation of aerial images recorded by UAV systems. Commonly used to evaluate segmentation architectures are the U-Net and DeepLabV3+. The benchmark dataset PlantSeedlings [29] contains images of crops and weeds at early stages of growth in controlled conditions. New datasets such as Weed25, CropWeed, and GZ-Weed [20]–[22] have larger image sets, more complete annotations, and better environmental diversity. The datasets allow for AI applications such as picture classification, object detection, semantic segmentation and multi-class weed recognition. Geographic coverage, annotation quality and consistency, seasonal volatility, and the relatively fewer publicly available photos compared to large-scale computer vision datasets like ImageNet remain challenges.

Table I. Representative Public Weed Detection Datasets

Dataset	Year	Images	Annotation	Sensor	Primary Task
DeepWeeds	2018	17,509	Bounding Boxes	RGB	Classification, Detection

WeedMap	2018	2,182	Segmentation Masks	RGB (UAV)	Semantic Segmentation
Plant Seedlings	2015	4,750	Class Labels	RGB	Classification
Weed25	2020	25,000+	Bounding Boxes	RGB	Detection
CropWeed	2021	14,000+	Bounding Boxes + Masks	RGB	Detection, Segmentation
GZ-Weed	2022	7,463	Bounding Boxes	RGB	Detection

Algorithms for weed detection AI

Machine Learning Techniques

The first generation of weed detection systems was developed using machine learning (ML) algorithms. These algorithms use hand-crafted image features extracted from crop images such as color histograms, texture descriptors, edge information and shape characteristics. Then, the extracted features are classified by using supervised learning algorithms, such as Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), and k-Nearest Neighbors (KNN) [21]–[24].

Table II. Comparison of Classical Machine Learning Algorithms

Algorithm	Advantages	Limitations	Typical Application
SVM	High classification accuracy	Sensitive to parameter tuning	Weed classification
Random Forest	Robust and interpretable	Large memory requirement	Species identification
Decision Tree	Simple implementation	Overfitting	Crop–weed separation
KNN	Easy to implement	Slow on large datasets	Small-scale classification
Logistic Regression	Fast training	Linear decision boundary	Binary weed detection

Deep Learning-Based Weed Detection

Deep learning has revolutionized the computer vision in agriculture by directly learning discriminative feature representations from raw images. Convolutional Neural Networks (CNNs) have been found to outperform traditional machine learning methods in difficult field conditions without the necessity of manual feature engineering [25], [26]. Convolutional layers, activation functions, pooling layers and fully connected classifiers are the building blocks of CNN architectures. Convolutional filters for automatically learning hierarchical visual representations from edges and textures for the weeding of morphological semantic characteristics. Pooling operations reduce the amount of computation and increase translation invariance. Finally, the extracted deep features are classified using fully connected layers. Several CNN architectures have been successful in weed detection. Deep convolutional learning, as used by AlexNet, surpassed handcrafted feature-based image classification. The VGGNet feature extraction was improved by deeper network topologies, and the problem of very deep network degradation was solved by ResNet with residual learning. DenseNet improved feature propagation by connecting convolutional layers densely. EfficientNet and MobileNet now provide good accuracy-computational efficiency trade-offs for edge devices and embedded agriculture platforms [27–30].

Models for detecting objects

Two-stage and one-stage object detection methods are common today. Two-stage approaches like Faster R-CNN use a Region Proposal Network (RPN) to produce candidate areas and classify detected objects. Despite of their great detection accuracy, these approaches are limited by their computational cost for real-time implementation [21]. However, one-stage detectors such as SSD [12] and YOLO family [13, 14] directly predict object category and bounding box in one pass, resulting in faster inference. YOLOv5, v8 and v11 provide good real-time weed detection through a trade-off between detection accuracy, inference speed and computing efficiency [22], [23],[25], [30].

Vision Transformer

Vision Transformers (ViTs) are cutting-edge agricultural computer vision AI architectures. Transformers capture long-range dependencies across the image using self-attention mechanisms, unlike CNNs that convolutionally analyze local receptive fields [27].
The ViT separates an input image into fixed-size patches, converts each patch to an embedding vector, then feeds the vector sequence into many transformer encoder layers. Swin Transformer, DETR, and SAM perform well for weed categorization, object detection, and semantic segmentation [28], [29].

Conclusion

The artificial intelligence has changed the weed detection from image processing to real time crop monitoring and precise weed management with computer vision technologies. The machine learning algorithms classified the weeds automatically, and the deep learning algorithm made the feature extraction and recognition easier. Recent advances in object detection models, semantic segmentation architectures and vision transformers can achieve reliable weed localization in challenging agricultural conditions. In this review, publicly available weed datasets, machine learning approaches, deep learning architectures, object detection models, semantic segmentation approaches and transformer based weed detection are presented. The assessment noted precision agriculture is increasingly using edge AI, UAV-based monitoring, cloud computing and autonomous agricultural robots. However, these gains come with problems of dataset diversity, computing efficiency, model generalization, explainability and real-time deployment. The challenges will be tackled through lightweight AI models, foundation models, federated learning, edge intelligence and autonomous farming technologies to build sustainable, efficient and environmentally friendly weed management systems.

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