A review of modern techniques for plant disease identification and weed detection in precision agriculture

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ABSTRACT

Plant disease identification and weed detection are critical components of precision agriculture, aimed at ensuring high crop yields and sustainable farming practices. These processes involve the use of advanced machine learning and deep learning techniques to automatically identify and classify plant diseases and distinguish between crops and weeds in agricultural fields. Traditional methods for managing these challenges are often labor-intensive, prone to errors, and environmentally unsustainable, necessitating the development of automated, accurate, and scalable solutions. This survey provides a comprehensive review of the state-of-the-art approaches, including pixel-based, region-based, and spectral-based methods, and evaluates their effectiveness in various agricultural contexts. Additionally, it identifies significant challenges such as data scarcity, model generalization, and computational constraints, while proposing potential research directions to address these gaps. The findings aim to guide future research in developing more robust and interpretable models that can be deployed in real-world agricultural environments, ultimately contributing to more efficient, precise, and sustainable farming practices.

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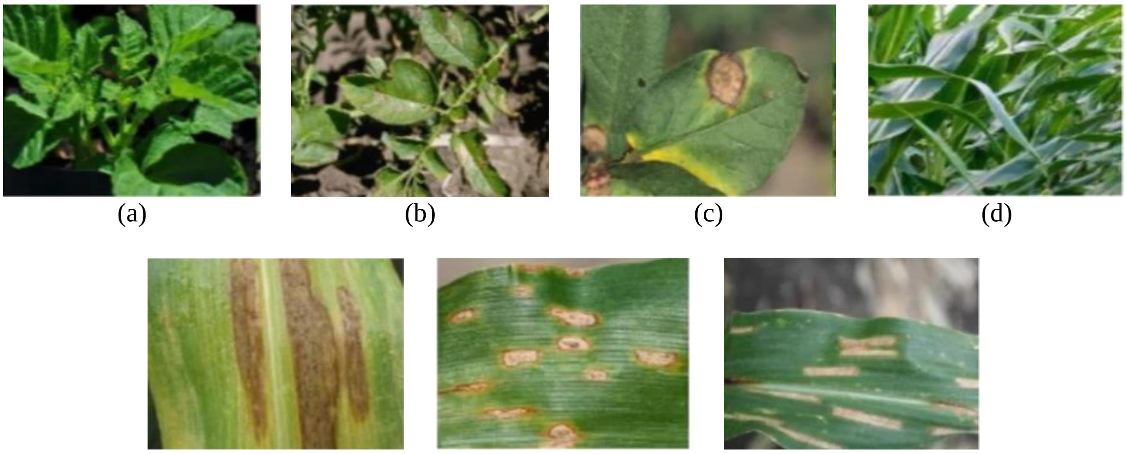
1. INTRODUCTION

Precision farming and plant phenotyping depend on the accurate diagnosis of plant diseases. A significant quantity of data, information, and technology are included in the two domains. Precision agriculture is not a good fit for traditional plant disease diagnosis and monitoring techniques since they are costly, time-consuming, and dependent on human visual examination. Furthermore, it is anticipated that human error and exhaustion will diminish the precision of these methods [1]. Studies investigating the use of image processing techniques with images of plants have been carried out in an effort to overcome the shortcomings of the disease detection methods that are now in use.

In 1983, an automated method using videos and black-and-white images was developed to detect plant diseases. It proved more accurate than visual checks, including in maize streak disease. Classical image processing has since been widely used for diagnosis [2], but it requires manual feature extraction, which is time-consuming and prone to bias. Traditional machine learning methods have been widely employed by the scientific community to identify plant diseases. Support vector machines (SVM) were utilized to detect tomato diseases [3]. To identify tomato illness, random forest (RF) algorithms were employed. K-nearest neighbors (KNN) were used to detect soybean diseases. The following lists a number of typical machine learning methods for classifying and identifying plant diseases. Because of its improved processing and storage capabilities as well as its ability to effectively handle large datasets, a kind of machine learning known as deep learning has gained popularity as a tool for sickness diagnosis. Since the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC), researchers from a wide range of disciplines have been using deep learning techniques more often. Convolutional neural networks (CNNs) are widely employed in deep learning applications for a number of tasks, including object recognition, photo classification, and semantic segmentation. The emergence of deep learning techniques, particularly CNN, has led to an increase in interest in plant disease identification research [4]. Since the creation of the PlantVillage dataset in 2015, this trend has been gradually growing. Projects requiring disease diagnosis, determining the severity of ailments, and creating different management methods commonly make use of PlantVillage data. Figure 1 presents a collection of plant leaf images from different datasets, showing both healthy and diseased conditions for potato and maize crops, where Figure 1(a) shows the potato healthy, Figure 1(b) shows the potato early bright, Figure 1(c) shows the potato late bright, Figure 1(d) shows the maize healthy, Figure 1(e) shows the maize late bright, Figure 1(f) shows the maize common rust, and Figure 1(g) shows the maize gray leaf spot.



(a) (b) (c) (d) (e) (f) (g)

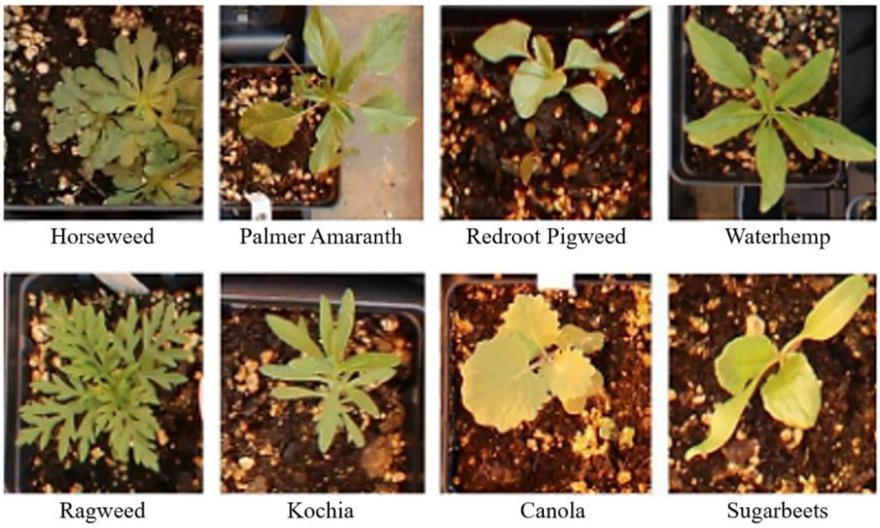
Figure 1. Images from other datasets showing healthy and diseased plant leaves of (a) potato healthy, (b) potato early bright, (c) potato late bright, (d) maize healthy, (e) maize late bright, (f) maize common rust, and (g) maize gray leaf spot

Deep learning models are constructed using various publicly available plant disease datasets, including those for rice, cassava, and coffee leaf rust diseases [5]. Using publicly accessible research data, several of these studies have concentrated on developing deep learning models for disease detection in various crops. The goal of these pieces is to investigate and resolve the yield loss issue. Custom datasets have been utilized in several studies using a range of methodologies. Using deep learning algorithms to identify plant diseases offers several benefits. These systems accurately diagnose various illnesses, differentiate disease symptoms, assess severity levels, and provide cost-effective solutions compared to manual methods [6].

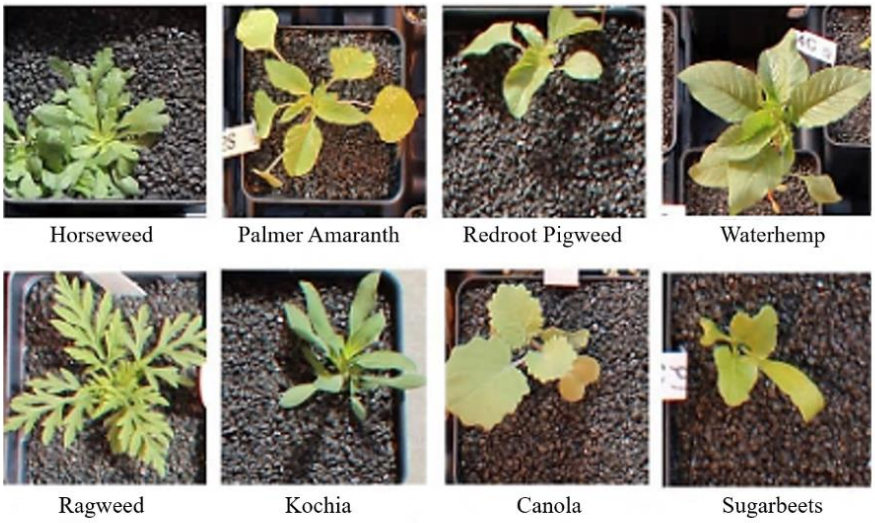
The presence of weeds in agricultural settings is a major concern since they reduce crop yields, raise production costs, and degrade crop quality overall. Two conventional weed management methods that are known to be labor-intensive and potentially harmful to the environment are the use of herbicides and hand weeding. The advancement of weed detecting technology in the last several years has made weed management more creative and long-lasting. Precision farming approaches can benefit from the use of weed-detecting technologies. These systems provide farmers with comprehensive awareness of weed species distribution and density patterns [7].

Weed identification systems are built on the foundation of machine learning techniques. Two well-liked ideas in artificial intelligence (AI) are deep learning and artificial neural networks (ANN). The algorithms are able to recognize the visual traits of various weed species and successfully differentiate them from crops. Their thorough training on enormous databases that include pictures of weeds and crops allows them to accomplish this [8]. The development of more accurate and successful weed management techniques may be made possible by weed detection systems. The sustainability of horticulture and agricultural activities may be significantly increased by optimizing the use of resources like water and fertilizer. A computer vision-based technology called the weed identification system can automatically identify and classify weeds in agricultural regions. With machine learning techniques and image analysis algorithms, farmers can successfully eradicate weed infestations. With the help of this method, crops and weeds may be accurately distinguished, allowing for focused intervention. By using this technique, farmers may save time and money while increasing agricultural output and decreasing their need on pesticides. The area of agriculture might undergo a huge upheaval with the introduction of a breakthrough technology known as machine learning for weed detection.

With the use of cutting-edge technology, farmers are able to locate and recognize weeds in their fields and take specific action to eradicate them. Gathering photos of a field, processing and analyzing them with machine learning algorithms, and finally determining whether photos have weeds in them are the steps in the process. This process may be completed using a variety of techniques, including item identification, segmentation, and classification. To solve this problem and correctly identify the weeds, a number of approaches are presently being researched. In order to evaluate the image and identify the weeds in a way that mimics an analysis, the CNN approach was selected [9]. Figure 2 illustrates the stages involved in weed detection using CNN, including the input image as in Figure 2(a) and segmented output as in Figure 2(b).



(a)



(b)

Figure 2. Illustrative stages in the weed detection process using CNN-based classification of (a) example of weed-infested crop image input for model training and (b) segmented and classified weed output using CNN inference

The topic of weed identification has been extensively studied using a variety of machine vision techniques. In study [10] developed a weed-crop classifier using fuzzy decision-making and form descriptors, achieving 92.9% accuracy on 66 field images. During the initial stages of the growth season, crops typically exhibit a notable advantage over weeds. The height attribute was utilized to establish a methodology for differentiating between weeds and crops through the implementation of a binocular stereo vision system. The differentiation between weeds and crops was achieved by employing a height-based segmentation technique and conducting depth dimension analysis. The plant spacing data was employed to differentiate between the crops and the weeds, specifically the weeds that were relatively taller.

A typical weed detection system comprises four essential processes, image pre-processing, feature extraction, weed identification and classification, and image collection [11]. The successful completion of these phases has been facilitated by the utilization of various state-of-the-art technologies. The process of sorting and identifying weeds is an essential step in these procedures. In recent times, there has been a notable rise in the utilization of embedded processors and machine learning methodologies for the purpose of autonomous weed species identification. The primary reason for this can be attributed to the progress made in computer technology, specifically in the domain of graphics processing units (GPU) [12].

A significant subset of machine learning is deep learning. Deep learning techniques offer several advantages for various machine learning tasks, including object identification, recognition, and image classification. For the purposes of this study, traditional machine learning methods will be designated as "machine learning." The application of machine learning algorithms for the differentiation of weeds and crops presents challenges due to the inherent similarities between the two categories. The advanced feature learning capabilities of deep learning algorithms offer a viable solution to the problem. While systematic review papers remain relatively scarce, deep learning research specifically targeting weed detection has seen exponential growth since 2020, driven by CNN advancements [13].

The urgent need to solve the difficulties in contemporary agriculture, particularly with regard to the identification of weeds and plant diseases, served as the impetus for this study. High expenses and substantial time commitments are features of traditional methods for weed management and disease diagnosis. These techniques are also prone to human error, which may provide less-than-ideal results that have a negative impact on crop output and quality.

The development of deep learning and machine learning technologies offers a singular chance to improve existing processes by putting automated, accurate, and scalable solutions into place. The purpose of this review is to examine and compile the most recent developments in deep learning methods for weed and plant disease identification. It draws attention to how these techniques might improve the sustainability of agricultural operations and lessen dependency on dangerous chemicals like pesticides. By reviewing and analyzing the current state of the art, this paper seeks to identify research gaps and propose directions for future work, ultimately contributing to the development of more efficient, precise, and environmentally friendly agricultural technologies.

In the context of agricultural technology, plant disease identification and weed detection share several interrelated challenges that influence their effectiveness when using deep learning techniques. Both fields require extensive data collection efforts, often facing issues such as limited availability of annotated datasets, variability in species appearances, and the impact of environmental conditions on data quality. The challenges of class imbalance, where certain diseases or weed species are underrepresented, are prevalent in both areas, complicating model training and leading to potential biases. Generalization across different crops, regions, and environmental conditions is another common hurdle, as models trained on one dataset may not perform well when applied to new scenarios. Furthermore, both plant disease identification and weed detection encounter difficulties in model interpretability, where the complexity of deep learning models makes it challenging to explain decisions, reducing trust among end-users like farmers.

Finally, the deployment of these models in real-world agricultural settings involves overcoming obstacles related to computational requirements, scalability, and integration with existing farming practices, all while adhering to regulatory standards and considering ethical implications. These interrelated challenges highlight the need for comprehensive approaches that address both domains to enhance agricultural productivity and sustainability. Table 1 (in Appendix) summarizes and contrasts the challenges encountered in both plant disease identification and weed detection across multiple aspects. The contributions of this are:

i) Comprehensive review of state-of-the-art techniques: this survey provides a detailed examination of the latest machine learning and deep learning approaches for plant disease identification and weed detection, covering various methods, datasets, and evaluation metrics used in recent research. It offers a consolidated resource for researchers and practitioners in the field.
ii) Identification of challenges and research gaps: by analyzing the current literature, this paper identifies key challenges such as data scarcity, model generalization, and computational requirements. It also highlights specific research gaps, particularly in the integration of multi-modal data and the need for real-time, scalable solutions, and guiding future research efforts.

iii) Proposed directions for future research: the survey suggests potential directions for advancing the field, including the exploration of hybrid models combining traditional and deep learning techniques, the development of more reliable and comprehensible models, alongside the application of these technologies in diverse agricultural settings to enhance their utility.

2. RELATED WORK

The models and techniques employed in these investigations, as well as the body of literature now available on the many classifications and diagnoses of plant leaf diseases, have all been carefully reviewed by the author. According to research, deep learning techniques for the real-time identification and detection of insects in soybean cultivation are successful. To determine the viability and dependability of the suggested approach for insect identification and detection, a performance study of many transfer learning (TL) models was carried out. The accuracy values of the suggested approach were 98.75% for you only look once version 5 (YOLOv5), 97% for CNN, and 97% for InceptionV3. With a processing speed of 53 frames per second, the YOLOv5 approach shows great efficacy in the given scenario and is appropriate for real-time detection applications. By combining photographs from various devices, a collection of agricultural insects was put together and categorized. The suggested research was less complicated, required less work from the manufacturer, and produced better results.

A deep learning-based system may be able to identify and classify plant leaf diseases [14], [15]. The website offers the ability to download images from the PlantVillage dataset. CNN were used to classify plant leaf diseases in accordance with the recognized approach. Twelve of the fifteen groups studied plant illnesses caused by bacteria, fungus, and other pathogens, while three focused on healthy foliage. Across all used data sets, the training accuracy was 98.029%, while the testing accuracy was 98.29%. The accuracy levels attained throughout training and testing are noteworthy.

In study [16] analyzing the size, shape, and color of lesions shown in leaf photos can be a useful method for identifying illnesses in rice plants. The purpose of this technique is to make illness diagnosis more effective. Through picture binarization, the suggested model effectively eliminates background noise from images by utilizing Otsu's global threshold approach. A fully connected CNN architecture is used in the suggested approach.

The CNN network was trained using a dataset that included 4,000 samples of photos showing both healthy and damaged rice leaves. Enabling the model to correctly identify the three different kinds of rice illnesses was the aim of the training process. The results show that the suggested fully connected CNN method outperformed the others in terms of speed and efficiency, achieving an accuracy rate of 99.7% on the dataset. When compared to existing techniques for identifying and categorizing plant diseases, our methodology shows a notable boost in accuracy.

Dube *et al*. [17] have introduced a CNN-based model for the detection and categorization of tomato leaf diseases. This model uses a publicly available dataset and photos taken in agricultural areas throughout the country. Generative adversarial networks (GAN) were used to generate samples that faithfully mirrored the training set in order to lower the chance of overfitting. The results showed that the suggested model outperformed the test and training datasets by more than 99%. This demonstrates the model's capacity to precisely detect and categorize tomato leaf diseases.

Yusuf and Niswar [18] use the PlantVillage dataset was to demonstrate classification of one mite-associated disease, two viral infections, two fungal infections, and four bacterial diseases across multiple crop species. Images of the healthy foliage of twelve different crop kinds were displayed. Grey-level co-occurrence matrices (GLCMs), SVMs, and CNNs were among the machine learning techniques used to build prediction models. As AI has advanced for classification tasks, backpropagation techniques in ANNs have also progressed. In order to detect diseases, real-time leaf photos taken during a K-means clustering operation were examined. For tomato plants, the corresponding overall accuracy was 96%, 94%, 95%, and 97%. For rice trees, the accuracy was 99%, while for apple trees, it was 98%.

The following are the outcomes produced by the suggested process. This study evaluated multi-class classification problems using f-measure, precision, and recall measures. The dataset used for these results includes a single symptom pool for each class. An improved CNN approach is suggested for the detection of rice illnesses. Deep neural networks (DNNs) are remarkably adept in picture categorization tasks. The application of DNNs for the categorization of plant disease photos is demonstrated in this study. This article assesses the precision of existing methods. TL, CNN+TL, ANN, and enhanced convolutional neural network (ECNN)+GA are among the methods examined; their respective accuracies are 80%, 85%, 90%, and 95%.

Comparative studies evaluated traditional machine learning methods (SVM, KNN, RF, and linear regression (LR)) against CNNs for plant disease prediction using PlantVillage dataset, typically showing RF ~97% and CNNs ~98% accuracy [19]. Photographic backdrops limited rice leaf disease identification accuracy, but TL models achieved DenseNet169 at 90% and other CNNs >94% testing accuracy [20]. Ant colony optimization (ACO) integrated with CNNs has demonstrated superior performance for hyperparameter optimization in plant leaf disease classification, outperforming traditional SVM and standalone CNN approaches [21].

To remove the effects of color, texture, and geometry on the plant leaf configurations in the given photos, a CNN classifier was used. Numerous indications show that the suggested approach outperforms earlier techniques in terms of accuracy rate. Metrics are used in the analysis and recommendation-making process. The methods discussed above are comparatively summarized in Table 2, which provides an overview of approaches used for plant disease identification, along with their respective strengths, limitations, and research gaps.

Andrea *et al*. [22] describes a pixel-based weed detection system that distinguishes between weeds and crops by using plant occlusion and overlap. A weed identification system will be put in place to reduce and stop the use of pesticides in the field. The collection consists of RGB-formatted pictures of sugar beets and carrots taken with a JAI 130-GE camera under ambient light. Ten decision trees are used in the RF method's development to categorize the type of plant. To evaluate the RF model's performance, cross-validation with a computing-fold technique is used. To guarantee improved classification model results, accuracy, precision, and recall values are evaluated. The investigation came to the conclusion that the pixel-based classification might be improved by using the attribute profile to create more intricate variants. In order to improve crop and weed classification and segmentation and optimize the process overall, the proposal combines region-based and pixel-based morphological approaches.

Table 2. Summary of plant disease identification

Reference	Method	Advantage	Disadvantage	Research gap
[13]	YOLO series, Mask R-CNN, U-Net, DeepLab, and transformer-based models	Typical mAP 80-95%; focus on real-time challenges and field deployment.	Dataset imbalance; small weed objects; and lighting variation.	Weed detection in various crops; gaps: UAV integration, data-efficient models, and precision spraying.
[4]	Deep CNN	Accuracy 99.35% (lab/controlled) and 31-65% natural images	Controlled conditions dataset and poor generalization to the real world.	Need for validation on more diverse datasets and real-world scenarios.
[2]	CNN/DL model) + CV preprocessing	Accuracy ~97.3% and fast diagnoses.	Specific to rice and may not generalize well to other crops.	Generalization of method to other crops and real-world environments.
[14]	Expert curation, controlled photography, and crowdsourcing platform PlantVillage	54,309 expertly labeled leaf images; open access; covers 14 crops; and 26 diseases.	Controlled conditions (lab-like) and less representation of field variability.	Real field data+ongoing crowdsourcing are needed to expand coverage.
[9]	SVM, RF, KNN, CNN, ResNet, EfficientNet, vision transformers, TL, and data augmentation	High accuracy for multi-class classification (up to 99% for some crops).	Mixed results across different crops and complexity in combining multiple machine learning approaches.	Data scarcity; real-world deployment; edge computing; and multi-modal data.
[21]	ACO-CNN	High accuracy plant disease detection.	ACO has high computational overhead and training time is longer than standard CNNs.	Real-time deployment; validation of diverse field conditions; and extension to multi-crop/multi-disease scenarios.
[16]	TL AlexNet and SVM classifier	Accuracy of 91.37% with AlexNet features and SVM.	Small dataset (619 images) and field condition variability	Comparison of models on more varied and challenging datasets.
[11]	CNN, Faster R-CNN, Mask R-CNN, YOLO, SegNet, and U-Net	DL excels at weed-crop discrimination; fine-tuning pre-trained models is effective; high accuracy on large labeled datasets.	Limited by image background and acquisition conditions, and may not generalize well.	Improved robustness of models under varying conditions and dataset diversity.
[12]	Robotics, machine vision, precision spraying, AI automation, and sensor fusion	Future tech vision (robotics; AI; and precision spraying)	High initial investment; technical complexity; regulatory hurdles; and farmer adoption barriers	Integrated robot fleets; real-time decision systems; economic viability; and farmer training programs.

Two methods were used by Andrea *et al*. [21] to extract strong features that enable trustworthy identification. Soybean seedlings and the weeds they were connected with were gathered during the investigation. Because the manually extracted features produced poor feature quality and inconsistent identification, the author intends to use feature learning approaches for the first feature extraction. CNN and the K-means feature learning algorithm were used to create the weed detection model. The dataset was created by hand using a Canon EOS 70D camera to take pictures of soybean fields which are situated on Northwest A&F University's North Campus. In the pre-processing phase, data whitening and standardization techniques were used to retrieve high-quality data for the feature learning approach. The K-means clustering approach is used to arrange the data items according to their closeness to the closest data points. By using K-means, the classification model successfully learns features and trains rapidly. One fully connected layer, four downsampling layers, and five convolutional layers make up the CNN. Lastly, there are four lakh parameters in the model. The accuracy attained by the random initialization approach was surpassed by the 92.89% model accuracy obtained by using K-means as a pre-training methodology.

Due to their striking similarities in characteristics, it can be difficult to distinguish between weeds and crops. Andrea *et al*. [22] investigated two methods that make use of form traits to create a weed detection system in order to address this problem. In order to create a pattern-based system for weed detection, the study applied ANN and SVM. Shiraz University's sugar beet fields were photographed by hand in order to compile the dataset. To evaluate the plant's morphological traits, pictures of it were taken when it was at the four-leaf development stage. The resolution of the pictures was 960 by 1,280 pixels. The 600 images in the collection are arranged into groups of 120 images apiece. The RGB format was used to capture the photographs. Analyzing photographs to identify their green features is part of the pre-processing step. To make feature extraction easier, the RGB pictures in the dataset are converted to greyscale format. For plant analysis, the SVM and ANN classification methods were applied and assessed.

With hidden layers, the ANN functions as a feed-forward architecture. Data was transferred between the hidden layers using the tangent sigmoid and logarithm sigmoid functions. While texture features are incorporated into the ANN to improve the discriminating process, principal component analysis (PCA) is used to lower the dimensionality of the input data. A SVM is used to classify the types of plants. The root mean square error (RMSE) and R^2 values are evaluated in order to determine the accuracy of the SVM. To assess the ANN performance, the confusion matrix was computed. SVM reach an accuracy of 88%, while ANN attain an accuracy of 86%. According to the results, the SVM outperforms an ANN in classification when a shape feature is used for model training.

For efficient area-specific weed control in agriculture, weed identification and categorization are essential. Biswas and Aslekar [23] used spatial resolution and spectral bands to study weed detection systems. Because herbicides have detrimental effects on crop health and human health, the author's main goal is to decrease their use in agricultural contexts. The CNN and histogram of oriented gradient (HOG) approaches are compared and evaluated in order to determine the effectiveness of weed detection. Table 3 compiles different weed detection methods, comparing their performance and identifying areas needing further investigation.

Wu *et al*. [24] suggested to enable yield calculation and autonomous herbicide spraying, an image processing system was created to distinguish between crops and weeds based on texture and size features. For crop detection, five texture attributes are used. Energy, entropy, inertia, local homogeneity, and contrast are the five attributes. Additionally, traits based on morphological size are used in crop and weed identification. A thorough assessment of all results led to the establishment of the majority selection for crop and weed detection. To extract a cell from an image, image segmentation uses a range of image processing techniques. The decision-making mechanism determines which cells will be sprayed. By figuring out the coordinates required for selective herbicide treatment, a Cartesian robot manipulator is created to locate weeds in an actual field.

TL improves weed detection accuracy while lowering the amount of data and computing resources needed for DNN training. This is especially important because the swin transformer network needs a lot of training data. The input for a two-stage TL approach is a swin transformer network that has already been trained on the ImageNet dataset. In order to improve recognition accuracy in weed recognition tasks and further reduce the requirement for training data quantity, this method was suggested for network training in this study.

All of the swin transformer network's parameters—aside from those in the last completely connected layer-are obtained by the feature extraction network. The feature extraction network is then adjusted using the plant seedlings dataset to create a task-specific pre-trained network that improves relevance for weed identification tasks. Using our maize/weed field image (MWFI) dataset, the task-related pre-trained network is fine-tuned to produce the final weed recognition network [25].

Table 3. Comparative analysis of weed detection approaches

Method	Advantages	Disadvantages	Research gap
Pixel-based classification using RF with 10 decision trees.	Effective in handling occlusion and overlapping of plants.	Limited to pixel-based classification, which may miss contextual information.	It is advisable to integrate region-based and pixel-based morphological segmentation to improve categorization.
Dataset: sugar beet and carrot images captured under natural light.	High precision, recall, and accuracy due to cross-validation.	May not generalize well to other crops or environmental conditions.	Exploring attribute profiles to enhance complex variants in pixel-based classification.
Combined K-means clustering and CNN for feature extraction and classification.	Robust feature extraction leading to stable weed identification.	Manual dataset preparation is time-consuming and labor-intensive.	Improving feature extraction methods to reduce manual intervention and enhance scalability.
Dataset: soybean seedlings and weeds, captured with Canon EOS 70D camera.	High accuracy (92.89%) achieved with K-means pre-training.	May require significant computational resources for large-scale deployment.	Integrating other machine learning methods for further enhancement and testing in diverse agricultural settings.
Shape feature-based classification using SVM and ANN.	SVM demonstrated better accuracy (88%) compared to ANN (86%).	Shape features alone may not be sufficient for accurate classification in complex environments.	Incorporating additional features such as texture or spectral data to improve classification accuracy.
Dataset: sugar beet fields at four-leaf stage, images in RGB format.	ANN includes texture features and PCA for dimensionality reduction.	Potential overfitting due to high similarity between crop and weed features.	Exploring the combination of SVM and ANN with other deep learning approaches for better generalization across different weed species.
Weed detection using spectral bands, spatial resolution, CNN, and HOG.	Allows area-specific weed control, reducing herbicide use, and minimizing health risks.	High dependency on the spectral and spatial resolution of images, which may vary across datasets.	Further analysis on the integration of multi-spectral data and deep learning models for real-time, in-field weed detection systems.
Dataset: not specified.	Effective in identifying weeds in specific areas of the field, improving targeted herbicide application.	CNN may require significant computational power, limiting its use in real-time applications.	Examining the effectiveness of different spectral bands and spatial resolutions in diverse agricultural contexts to optimize weed detection systems.
Texture and size feature-based detection, with automatic herbicide spraying.	generated a method for image processing to identify yield and control weeds.	Complexity in real-time application due to the requirement of accurate Cartesian coordinates.	Improvement of real-time detection and spraying accuracy using advanced robotics and real-time image processing algorithms.
Morphological features: energy, entropy, inertia, local homogeneity, contrast.	Combines multiple features for robust decision-making in crop and weed identification.	High complexity in feature extraction and decision-making process.	Further research on integrating advanced decision-making algorithms with robotic systems for precision agriculture and automated weed control.

3. CONCLUSION

The survey concludes by highlighting the growing significance of machine learning and deep learning techniques in transforming weed detection and plant disease diagnosis in precision agriculture. These technologies provide fascinating solutions to the drawbacks of traditional methods, but they also present issues that require attention, such processing requirements, model generalization, and data scarcity. The evaluation of existing methods, such as pixel-, region-, and spectral-based methods, demonstrates the capabilities and limitations of existing models. The identification of research gaps, particularly in the areas of data integration, real-time processing, and model interpretability, emphasizes the need for more innovation and collaboration in this area. Future research may yield more precise, scalable, and sustainable solutions by addressing these problems, which will ultimately increase agricultural productivity and advance global food security.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

DATA AVAILABILITY

No dataset is utilized in this research.

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APPENDIX

Table 1. Challenges in plant disease and weed detection

Aspect	Challenges in plant disease identification	Challenges in weed detection
Data collection	Limited availability of annotated datasets for rare diseases.	Variability in weed species across regions and seasons.
	Capturing diverse disease symptoms across different growth stages.	Challenges in consistent weed image capture due to plant density.
	Difficulty in accessing disease samples during specific seasons.	Difficulty in capturing early-stage weeds that resemble crops.
Data quality	Presence of noise, shadows, and overlapping leaves.	Inconsistent image quality due to varying camera angles and heights.
	Impact of soil, dust, and debris on image clarity.	Variations in weed appearance due to different soil backgrounds.
Class imbalance	Imbalance in the number of healthy vs. diseased plant images.	Imbalance between dominant and less common weed species.
	Over-representation of certain disease classes in public datasets.	Skewed distribution of weeds in certain crop fields.
Model generalization	Difficulty in generalizing models across different climatic zones.	Generalization issues across different crop-weed combinations.
	Overfitting to specific disease symptoms, leading to poor performance on unseen data.	Overfitting to specific field conditions or weed types.
Disease symptom similarity	Visual similarity between abiotic stress symptoms and disease symptoms.	Similarity between weeds and crops at specific growth stages.
	Confusion between symptoms caused by pests vs. diseases.	Difficulty in distinguishing between broadleaf and grass weeds.
Computational requirements	High computational costs for processing large-scale agricultural datasets.	Real-time processing challenges for in-field weed detection systems.
	Need for extensive GPU resources for model training and inference.	Energy constraints for deploying models on mobile or drone platforms.
Environmental factors	Variability in disease appearance due to weather, humidity, and temperature.	Impact of weather conditions on weed visibility and identification.
	Effects of nutrient levels on disease expression in plants.	Seasonal changes affecting weed growth and detectability.
Model interpretability	Black-box nature of deep learning models complicating disease diagnosis.	Limited transparency in model decisions for weed identification.
	Challenges in explaining decisions to farmers and agronomists.	Difficulty in building trust with end-users due to lack of interpretability.
Multi-class classification	Handling multiple diseases occurring simultaneously on the same plant.	Detecting and classifying multiple weed species within a single image.
	Confusion between similar diseases, leading to misclassification.	Difficulty in accurately identifying overlapping weeds.
Cross-species adaptability	Difficulty in transferring models trained on one plant species to another.	Challenges in adapting models to detect weeds across different crop types.
	Need for retraining or fine-tuning models for different agricultural settings.	Inconsistency in weed morphology across regions, requiring adaptation.

Table 1. Challenges in plant disease and weed detection *(continued)*

Aspect	Challenges in plant disease identification	Challenges in weed detection
Annotation and labeling	Labor-intensive and time-consuming annotation process, especially for large datasets.	High complexity in accurately labeling various weed species in diverse environments.
	Need for expert knowledge to accurately label disease symptoms.	Difficulty in annotating images with overlapping or mixed weed species.
	Inconsistencies in annotations due to subjective judgment by annotators.	Need for crowd-sourced or automated labeling tools to reduce time and cost.
Field deployment	Scaling issues when deploying models across large and varied agricultural areas.	Challenges in integrating models with existing precision agriculture tools.
	Real-time deployment challenges in resource-constrained environments.	Need for robust models that can operate under variable field conditions.
	Adaptation to different crop management practices and farming techniques.	Calibration and tuning of models for different machinery and sensors.
Cost and accessibility	High costs associated with acquiring and processing large datasets.	Financial constraints for smallholder farmers to adopt advanced detection systems.
	Limited accessibility of advanced technology in developing regions.	Challenges in making weed detection technology affordable and scalable.
Ethical and privacy concerns	Privacy issues related to the collection and use of farm data.	Ethical considerations in the deployment of automated weed control methods.
	Need for policies ensuring fair access to disease detection technology.	Concerns about data ownership and sharing among farmers and companies.
Regulatory compliance	Adhering to agricultural regulations and standards for disease management.	Compliance with herbicide application guidelines based on weed detection outcomes.
	Need for certification and validation of models before deployment.	Navigating legal frameworks related to the use of artificial intelligence in agriculture.

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