A Comprehensive Review of Deep Learning Approaches for Automated Farm Weed Classification

Francis Amaechi Okoye., *Njoku Camillus Ekene., Ebere Uzoka Chidi

Department of Computer Engineering, Enugu State University of Science and Technology, Enugu, Nigeria

Corresponding Author

DOI: https://doi.org/10.51584/IJRIAS.2026.11070118

Received: 22 July 2026; Accepted: 27 July 2026; Published: 08 August 2026

ABSTRACT

One of the biggest obstacles to agricultural output is weed infestation, which causes a significant drop in crop production, increases production costs, and affects food security. Conventional ways of controlling weeds, such as hand weeding and using herbicides, are usually very laborious, expensive, and unsustainable. In recent years, deep learning has become an attractive option in automated weed detection and classification in precision agriculture. This paper is a review of the extensive classification of farm weeds through deep learning models with special emphasis on object detection networks, convolutional neural networks (CNNs), transfer learning models, transformer-based models and data augmentation techniques. Applicable literature was methodically evaluated with reference to datasets, model structures, and performance parameters, including accuracy, F1-score, and mean average precision (mAP). The review indicates that other models, such as YOLO variants, ResNet, EfficientNet, and Vision Transformers, have demonstrated high classification accuracy under controlled conditions. Nevertheless, issues such as limited dataset diversity, inadequate real-world generalisation, excessive computational complexity, and standardised evaluation schemes continue to impede at-scale implementation. The research results have concluded that, in the future, lightweight models, larger-scale, more diverse data, and the integration of deep learning with IoT and autonomous systems should be the subject of research to make the processes of monitoring and controlling weeds in modern agriculture fully automated and sustainable.

Keywords: Farm Weeds, Deep Learning, Precision Agriculture, Weed Classification, Object Detection

INTRODUCTION

Weeds are a significant challenge in agriculture, as they are unwanted plants that grow among crops and compete for essential resources such as sunlight, water, and nutrients. Their presence is ubiquitous across various types of farming systems, from small-scale subsistence farms to large commercial agricultural enterprises (Morellos et al., 2024). Weeds can emerge due to several factors, including soil disturbance, seed dispersion through wind and water, and farming practices that inadvertently promote their growth. Managing weeds effectively is crucial because their unchecked proliferation can lead to substantial reductions in crop yields and quality, ultimately affecting food supply and economic stability (Alahmad et al., 2023).

Weeds impose a considerable economic burden on agriculture by necessitating additional labor, herbicides, and machinery to control their spread. The costs associated with weed management can be substantial, often comprising a significant portion of the overall production expenses for farmers (Alahmad et al., 2023). For instance, the need for frequent herbicide applications not only increases operational costs but also can lead to the development of herbicide-resistant weed species, further complicating management efforts (Senoo et al., 2024). Additionally, the presence of weeds can lower the market value of crops, as contaminated or lower-quality produce is less desirable to consumers and buyers. Therefore, effective weed management strategies are vital for maintaining the profitability and sustainability of agricultural operations (Pukrongta et al., 2024).

The economic impact of weeds on maize production is considerable. Farmers must invest heavily in weed management practices, including the use of herbicides, mechanical removal, and labor-intensive weeding (Thotho and Macheso, 2023). These costs can significantly increase the overall production expenses, reducing the profitability of maize farming. Moreover, if weeds are not effectively controlled, they can cause substantial yield losses, further diminishing economic returns. For instance, heavy weed infestations can reduce maize yields by up to 70%, leading to financial strain for farmers who rely on maize as a primary source of income (Nguyen et al., 2024).

The reliance on chemical herbicides to manage weeds in maize fields poses several environmental risks (Gladju et al., 2022). Herbicides can contaminate soil and water bodies, affecting non-target plant and animal species and leading to biodiversity loss. Additionally, the repeated use of herbicides can lead to the development of herbicide-resistant weed species, complicating future weed management efforts (Aworka et al., 2022). These resistant weeds can proliferate, requiring even more intensive and costly management strategies. Sustainable weed management practices, such as crop rotation, cover cropping, and integrated pest management, are crucial to mitigate these environmental impacts and promote ecological balance (Cedric et al., 2022).

According to Zhang et al. (2022), weeds can also affect the health and productivity of maize plants by acting as hosts for pests and diseases. Certain weed species harbor insects and pathogens that can transfer to maize, causing infestations and infections that further reduce crop health and yield. For example, weeds like Johnson grass can host the maize dwarf mosaic virus, which can then infect maize plants, leading to severe yield reductions (Islam et al., 2022). The presence of weeds can also create a more humid microenvironment, fostering conditions favorable for fungal diseases. Consequently, effective weed management is essential not only for maintaining high maize yields but also for producing healthy, high-quality maize crops (Shah et al., 2021).

To address these challenges, there is a growing shift toward sustainable and intelligent weed management strategies. Traditional methods are increasingly being complemented or replaced by advanced technologies such as computer vision and deep learning. These approaches enable automated weed detection and classification, facilitating precision agriculture practices that improve efficiency while minimising environmental impact.

LITERATURE REVIEW

Recent advances in deep learning and computer vision have significantly improved weed detection and classification in precision agriculture. Existing studies can be broadly categorised into Deep Learning architectures for weed classification, Comparative studies of CNN models, Transfer Learning and Model Optimisation, Emerging approaches using transformers and alternative classifiers, and Challenges with Limited Dataset for weed classification, as shown in Figure 1.

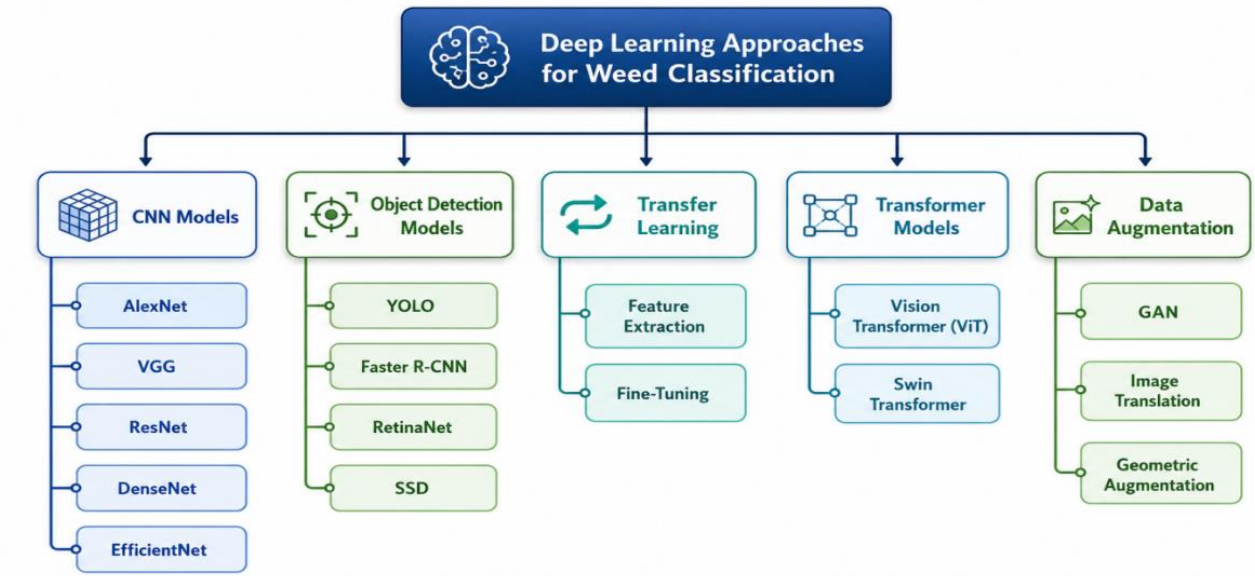

Figure 1: Classification of Deep Learning Approaches for Farm Weed Classification

Review of Machine Learning Techniques for Weed Classification

Lopez-Corea et al. (2022) created an intelligent weed management system to monitor tomato crops based on the use of object detection neural networks. They applied the deep learning model, RetinaNet, created to detect objects, and trained it on 1,713 tomato images and five weed species photographed in different light conditions. Two other object detection frameworks were also tested with the help of the dataset: Faster R-CNN and YOLOv7. Results in terms of mean average precision (mAP) indicated that RetinaNet was more effective than the others with mAP scores of 0.900 to 0.977, based on the weed species. Faster R-CNN and YOLOv7 also performed satisfactorily, but were not as precise when it comes to differentiating monocot weed species.

Espejo-Garcia et al. (2021) developed a study aimed at testing the appropriateness of automated machine learning (AutoML) to identify weeds. The effectiveness of open-source AutoML systems was investigated as the means of accelerating and streamlining the implementation of machine and vision solutions in the agricultural sector, the goal being to find out whether the integration of AutoML methods could be as effective as manually-designed architectures (ResNet, VGGNet, etc.). Also, two datasets, the Early Crop Weeds dataset and the Plant Seedlings dataset, were trained and tested with the open-source AutoML system, which consisted of 504 and 960 RGB images, respectively. The model assessments that were conducted based on the metrics of F1 scores indicated positive performances of 93% and 90.74, respectively, based on the dataset.

Divyanth et al. (2022) evaluated image-to-image translation-based data augmentation to enhance crop and weed classification models to use in precision agriculture applications. Information was gathered based on the image data on Kaggle of crop and weed seedlings on various development stages which included 200 RGB images of five classes comprising of maize (Zea mays) and four common weeds (charlock, fat hen, shepherd's purse and small flowered cranesbill). Conditional generative adversarial networks (cGANs) were used to generate artificial images of the same features and classes to limit the use of a large image dataset. The faithfulness of such synthetic images was evaluated by t-distributed stochastic neighbor embedding (t-SNE) visualization plots of both real and artificial images of both classes. Later, the accuracy of this approach as a data augmentation method was confirmed by the results of classification using the transfer learning of the fixed CNN architecture AlexNet. Two classifiers, which are SVM and LDA were adapted after extracting the features of the pooling layer of AlexNet (pool 5 layer). Findings reported based on F1 score measures revealed that AlexNet improved between 0.97 and 0.99 when it was trained on an artificial dataset. Similarly, the F1-scores of the SVM were raised by 0.93 to 0.96 and 0.94 to 0.96 of the LDA model.

Comparative Studies of CNN Models

Corceiro et al. (2024) did research on machine learning as an opportunity to apply it to weed management and crop improvement regarding vineyard flora classification, aiming at the understanding of how various models of neural networks in image classification function and which of them are most effective. There were 172 images of vineyard flora that were used to collect data with a Sony RGB camera. The photographs were of five weed species, including Centaurea melitensis, Echium plantagineum, Lolium rigidum, and Ornithopus compressus. The findings showed that the three best models, including MaxVit, ShuffleNet, and EfficientNet, were able to reach the highest accuracies of 96, 99.3, and 99.3, respectively, in the initial set of experiments. The three models in the second experiment had a 96% accuracy rate. But in the third experiment when long dataset was tested, EfficientNet_B1 and EfficientNet_B5 performed better with 95.13% and 94.83 respectively. The two models again came out in the fourth experiment to be highly accurate with the two models having an accuracy of 96.1.

Fatima et al. (2023) tested the development of a lightweight deep learning-based weed detection system of a commercial autonomous laser weeding robot. The information was obtained through field surveys on six fields of agriculture in Pakistan. The data were captured as videos, and 12,000 frames were cut out. The data gathered has predominantly cultivated crops such as okra, sponge gourd and bitter gourd and four weed species that are widely used in these crops, such as horseweed, herb Paris, grasses and small weeds. Object detection models (YOLOv5s and SSD-ResNet50) were trained and tested on the dataset. It has been reported that the YOLOv5 model reached a mAP of 0.88 at IOU 0.5, which means that the model was able to predict a high number of true positives with a high number of false positives and false negatives. SSD-ResNet50 had a mAP of 0.53 at IOU 0.5, which is why YOLOv5 is more adapted to weeds and crops detection and classification in fields.

Haqu et al. (2023) used real-time measurements of unwanted plants in wheat fields to train and verify deep learning detection models. The data was gathered on the PMAS agricultural university research farm and comprises 6,000 RGB photos. YOLOv5s, YOLOv5m, YOLOv5l, YOLOv4 and YOLOv3 versions were trained and evaluated on the weed dataset. Comparative analysis using accuracy as a measure revealed that YOLOv4 has a better performance than other methods, with an F1-score value of 0.92 in the TensorFlow framework, and YOLOv3 has a value of 0.90. The YOLOv5s, YOLOv5m, and YOLOv5l in the PyTorch platform had F1-score values of 0.51, 0.57 and 0.54, respectively.

Overall, the CNN methods that were tested showed incredible results in controlled testing environments, with the classification accuracy typically being above 95%. The most commonly used architectures were models based on EfficientNet, ResNet, and VGG, as they have excellent feature extraction properties. Nonetheless, the majority of studies were based on limited and small datasets, limiting the ability of models to generalise to different agricultural contexts. In addition, the computational requirements of deeper CNN technologies prevent their successful use on resource-constrained edge devices in precision agriculture.

Transfer Learning and Model Optimization

In the precision agriculture study conducted by Pauzi et al. (2024), CNN and two approaches based on transfer learning, VGG16 and VGG16_BN, were used to classify and detect weeds. The models were trained and validated on images of 2,377 dataset images of an oil palm plantation in Malaysia, which comprised three classes (broad weed, mixed weed, and narrow weed). Optimisers used were Adam, Adadelta, Adagrad, AdamW, Adamax, ASGD, NAdam, RAdam, RMSprop, Rprop and SGD. Findings show that the VGG models are more accurate than the baseline CNN. Of the two VGG models, VGG16_BN using Adagrad optimiser (learning rate 0.001, weight decay 1e-4) had an average accuracy of 97.6% and the maximum accuracy of 99%.

Bah et al. (2018) suggested drone images based on deep learning to detect weeds automatically. Two fields of beans and spinach were surveyed using a UAV to gather data. A total of 673 weed samples and 4,861 crop samples were obtained in the bean field; 4,303 crop samples and 3,626 weed samples were labelled without supervision in the spinach field. A pre-trained algorithm was used (ResNet18), which was trained using the dataset, and feature extraction models (SVM and RF) were applied to compare the algorithms. When AUC was used as a metric, ResNet18 was found to be superior to SVM and RF, with the highest results of 94.84% on supervised and 88.73% on unsupervised bean fields and 95.70% on supervised and 94.34% on unsupervised spinach fields.

The data presented by Peteinatos et al. (2020) consisted of three crop species (maize, potato, and sunflower) and 9 weed species in a total of 93,130 images in an experimental field. Three CNNs, including VGG16, ResNet50, and Xception (Extreme Inception), were modified and trained on the data. Accuracy was used as a metric, with ResNet50 and Xception outperforming VGG16 at 97% and 98%, respectively.

In their study, Aaron et al. (2023) used the quantisation technique to downsize the size of a light deep learning model called InceptionNetV3, which was trained on the identification of weeds in corn and soybean crops. Two publicly available datasets (soybean weed dataset and corn weed dataset) were used to collect 13,177 samples, comprising 7,404 images of soybean, 4,573 images of weed and 1,200 images of corn. Findings indicate that the InceptionV3 model obtained an accuracy of 97% with a size of 183.34 MB and an accuracy of 87% with a size of 23.38 MB when quantised.

Collectively, the reviewed studies demonstrate that transformer networks have come to the fore as an alternative to traditional CNN-based architectures, due to their remarkable ability to learn long-range spatial relationships. While Vision Transformers showed remarkable classification results, their high computational cost and reliance on large, well-annotated datasets are significant challenges for real-world use. Hence, the hybrid CNN-transformer models are an interesting approach for future intelligent weed classification systems.

Emerging Approaches: Transformers and Alternative Classifiers

Reedha et al. (2022) published an article that outlines weed and crop classification based on high-resolution UAV-acquired images using a transformer neural network. The data consisted of five classes (weed, beet,

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue VII July 2026

parsley, spinach and off-type beet), and each class had 4,000 images except off-type beet (3,265 images). ResNet and EfficientNet CNN-based architectures were trained with ViTB16 and ViTB32 to allow for comparing their performance. Findings indicate that the ViTB-16 model scored the highest F1-score of 99.4%.

Moldvai et al. (2024) compiled a publicly available dataset of 3,000 images from six plant classes (bluegrass, white goosefoot, lettuce, sledge, corn, cirsium, and setosum) to train and test a computer vision model for weed identification and classification. The dataset was split into different subsets (4, 10, 20, 40, 80 and 160 images) used to train six classifier types: Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbours (KNN), Artificial Neural Network (ANN), Naive Bayes (NB), and Gradient Boosting Machine (GBM). Findings described, with 160 images per weed, produced a 94.5% recall rate. A comparative analysis of the represented deep learning models for weed classification reviewed in this section is presented in Table 1.

Table 1: Comparative Analysis of Representative Deep Learning Models for Weed Classification

Author	**Dataset**	**Model**	**Accuracy/F1/mAP**	**Strength**	**Limitation**
Lopez-Corea et al. (2022)	Tomato Weed Dataset	RetinaNet	mAP 97.7%	Excellent object detection	Computationally intensive
Fatima et al. (2023)	Pakistan Field Images	YOLOv5	mAP 88%	Lightweight	Moderate recall
Peteinatos et al. (2020)	Multi-crop Dataset	ResNet50	97% Accuracy	Robust classification	Large model size
Reedha et al. (2022)	UAV Dataset	ViT-B16	F1 = 99.4%	Highest accuracy	High computation
Pauzi et al. (2024)	Oil Palm Dataset	VGG16_BN	99% Accuracy	Transfer learning	Limited dataset diversity
Khan et al. (2022)	Potato Weed Dataset	Tiny-YOLOv4	49.4% Accuracy	Fast inference	Small dataset

Challenges with Limited Datasets

Khan et al. (2022) suggested a weed detection model in a potato crop based on the techniques of deep learning and computer vision. Training and validation of the Tiny-YOLOv4 model were performed using a small dataset of 5 potato weeds (including Piyazibooti, Canada thistle, jungle gajjar, bathu, and billibooti) captured with a Logitech camera in a potato field in the Potohar region. The findings show that testing accuracy on the small dataset is 49.4%, indicating that both the model and the dataset size can be improved.

Gallo et al. (2023) introduced a new weed and crop dataset called Chicory Plant (CP) and a publicly available dataset, Lincoln Beet (LB), to train and validate the YOLOv7 model to detect weeds and crops. The CP dataset comprises 3,000 RGB images taken at various growth stages with the help of a UAV system, and the LB dataset consists of 4,405 images. To make a comparison, the single-shot detector (SSD), YOLOv3, and YOLOvF detectors were used on the CP dataset. YOLO v7 was also found to be superior to other variants of YOLO with a mean average precision of 56.6% mAP at 0.5, a recall of 62.1% and a precision of 61.3% on the CP dataset.

Mckay et al. (2024) used three datasets (T1 miling, T2 miling and YC) of canola plant images in different field states together with other plants in order to train three models, namely, ResNet18, ResNet34 and VGG-16, as the canola recognition and classification models. T1miling and T2miling T1miling and T2miling datasets comprise 72 and 71 RGB images, respectively, whereas the YC dataset comprises 167 images. Average precision, recall, Jaccard index (IoU) and macro F1 scores were used to evaluate the models, with ResNet34 ranking as the highest-performing model, with an average precision of 0.84, a recall of 0.87, an IoU of 0.77, and a macro F1 score of 0.85.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue VII July 2026

The reviewed studies have shown that, dataset quality and diversity are still key factors affecting the performance of weed classification using deep learning models. While there are a number of publicly available datasets that have assisted in algorithm development, many existing studies still use relatively small datasets, crop-specific datasets, or geographically limited datasets. Consequently, the lack of large-scale, standardised benchmark datasets limits model generalisation and makes direct comparison among different deep learning architectures difficult. The creation of detailed multi-crop and multi-environment datasets for robust model assessment and application in actual farm contexts should be prioritized in future research.

RESEARCH METHODOLOGY

This review adopted a systematic literature review (SLR) methodology to critically analyse recent developments in deep learning techniques for automated farm weed classification. A structured search strategy was employed to ensure comprehensive coverage of relevant literature published between 2018 and 2024, a period during which deep learning experienced rapid advancement within precision agriculture. The establishments of the literature review were done using reliable scientific databases, including the IEEE Xplore, ScienceDirect, SpringerLink, MDPI, Scopus, Web of Science, Google Scholar, and others. Words and phrases searched included combinations of the words weed classification, weed classification, deep learning, convolutional neural networks, transfer learning, YOLO, Vision Transformers precision agriculture, computer vision, artificial intelligence in agriculture. The beginning search yielded approximately 186 documents. After duplicates were removed, 155 papers needed screening by their title and abstract. Studies not applicable to deep learning, papers in not English, duplicates of review publications, abstracts from conferences lacking complete papers, and the publications that did not contain the experimental evaluation were removed. After assessing full texts, 42 main articles were chosen for qualitative analysis.

The studies selected were separated into categories according to the specific deep learning methods used, including CNNs, object detection methods, transfer learning systems, transformer structures, lightweight architectures, and data augmentation approaches. Each research was evaluated taking into account the type of data, models used, evaluation metrics, computational complexity, positive sides of the study, limitations, and practical ways of using. Finally, comparative analysis and thematic synthesis were conducted to identify emerging research trends, current limitations, unresolved challenges, and promising future research directions for intelligent weed classification systems. Figure 2 presents the flow diagram of the PRISMA approach to our literature selection process.

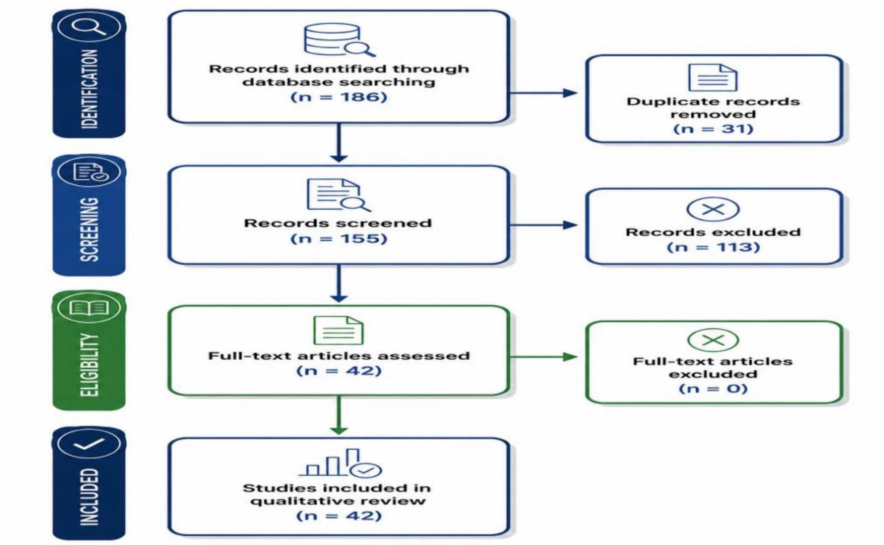

Figure 2: PRISMA Flow Diagram of the Literature Selection Process

A Study On Maize Plant Weeds

Weeds present a significant challenge to maize cultivation by competing for essential resources such as light, water, and nutrients. Maize plants, particularly in their early growth stages, require optimal conditions for rapid development (Shukla et al., 2023). The presence of weeds during this critical period can severely inhibit maize growth, as weeds often have more aggressive root systems and faster growth rates, allowing them to outcompete maize for resources. This competition can lead to stunted maize plants, reduced leaf area, and diminished photosynthetic capacity, ultimately impacting overall crop yield and quality (Soussi et al., 2024).

Types of Weeds that Affect Maize Plants

Managing these diverse and competitive weed species is crucial for maintaining high maize yields and ensuring the sustainability of maize farming. Integrated weed management strategies, combining chemical, mechanical, and cultural practices, are essential to effectively control these weeds and minimise their impact on maize crops. Figure 3 depicts the weeds that affect maize plants

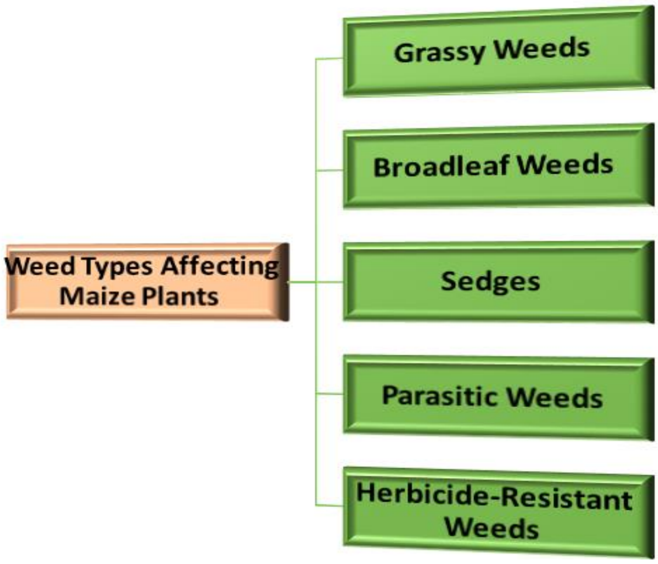

Figure 3: Types of Weeds Affecting Maize Plants

a. Grassy Weeds

Barnyardgrass (Echinochloa crus-galli): This annual grass weed is highly competitive and can significantly reduce maize yields. It grows rapidly, has a robust root system, and can reach heights that overshadow maize plants, limiting their access to sunlight and nutrients (Cedric et al., 2022). Johnson Grass (Sorghum halepense): A perennial grass weed, Johnson grass spreads through seeds and rhizomes. It is particularly problematic because it competes aggressively with maize for nutrients and water and can also harbour pests and diseases that affect maize (Zhang et al., 2022). Foxtail Species (Setaria spp.): Including giant foxtail (Setaria faberi), green foxtail (Setaria viridis), and yellow foxtail (Setaria pumila), these annual grasses are common in maize fields. They grow quickly and densely, competing with maize for light and soil nutrients (Shah et al., 2021).

b. Broadleaf Weeds

Pigweed (Amaranthus spp.): Species such as redroot pigweed (Amaranthus retroflexus) and Palmer amaranth (Amaranthus palmeri) are notorious for their fast growth and high seed production. These broadleaf weeds can outcompete maize and are difficult to control, especially as some species have developed herbicide resistance (Islam et al., 2021). Common Lambsquarters (Chenopodium album): This broadleaf weed is prevalent in many maize-growing regions. It grows rapidly and competes with maize for light, water, and nutrients, particularly during the early stages of maize growth (Shah et al., 2021). Velvetleaf (Abutilon theophrasti): Known for its large leaves and tall stature, velvetleaf can overshadow maize plants, limiting their access to sunlight and nutrients. It also produces a large number of seeds, making it persistent and difficult to manage.

c. Sedges

Yellow Nutsedge (Cyperus esculentus): Although not a true grass, this sedge is a significant weed in maize fields. It reproduces through tubers and can form dense stands that compete with maize for water and nutrients.

Yellow nutsedge is particularly troublesome because it thrives in a variety of soil conditions (Shah et al., 2021). Purple Nutsedge (Cyperus rotundus): Similar to yellow nutsedge, purple nutsedge spreads through underground tubers and can be highly competitive. It is difficult to eradicate once established and can significantly impact maize yield and quality (Zhang et al., 2022).

d. Parasitic Weeds

Striga (Striga spp.): Also known as witchweed, Striga is a parasitic weed that attaches to the roots of maize plants, extracting water and nutrients. This weed can severely stunt maize growth and reduce yields. It is particularly problematic in sub-Saharan Africa and other tropical regions.

e. Herbicide-Resistant Weeds

Waterhemp (Amaranthus tuberculatus): A member of the pigweed family, waterhemp has developed resistance to multiple herbicides, making it a significant challenge for maize growers. Its rapid growth and high seed production enable it to effectively outcompete maize plants (Shah et al., 2021).

4.2 Methods of Weed Management

Effective weed management is essential for maintaining healthy crops and ensuring high yields. Here are several methods used to manage weeds in agricultural systems:

a. Chemical Control

Herbicides: Chemical herbicides are among the most common methods of weed control. Herbicides can be classified by their mode of action and the types of weeds they control. Pre-emergent herbicides are applied before weed seeds germinate, while post-emergent herbicides are used after weeds have emerged. Selective herbicides target specific weed species without harming crops, whereas non-selective herbicides kill all plant types. However, the overuse of herbicides can lead to resistance in weed populations and environmental issues (Zhang et al., 2022).

b. Mechanical Control

Tillage: Tilling the soil can help control weeds by uprooting them and burying weed seeds. It is effective in reducing weed populations but can also cause soil erosion and affect soil structure. Hand Weeding: Manual removal of weeds is labour-intensive but effective, especially for small-scale farms or in areas where chemical use is restricted. It is a precise method that minimises damage to crops (Shah et al., 2021). Mowing and Cutting: Regular mowing or weed cutting can prevent weeds from flowering and setting seed. This method is often used in conjunction with other weed management strategies.

c. Cultural Control

Crop Rotation: Rotating different crops in a field can disrupt weed life cycles and reduce weed populations. Different crops compete with weeds in various ways, making it harder for weeds to establish.

Cover Cropping: Planting cover crops, such as clover or rye, can suppress weed growth by outcompeting weeds for light, water, and nutrients. Cover crops also improve soil health and reduce erosion (Islam et al., 2021).

Mulching: Applying organic or synthetic mulches to the soil surface can suppress weed growth by blocking light and reducing the temperature fluctuations that promote weed germination.

d. Biological Control

Natural Enemies: Utilising natural predators, such as insects, fungi, or bacteria, can help control weed populations. For example, certain beetles or moths can feed on specific weed species, reducing their spread (Osorio et al., 2020).

Allelopathy: Some crops release chemicals that inhibit weed growth. Utilising allelopathic crops can provide a natural means of weed suppression. For instance, the residue of crops like rye can suppress the germination and growth of weeds.

e. Integrated Weed Management (IWM)

Combination of Methods: IWM involves using chemical, mechanical, cultural, and biological control methods to manage weeds. This approach aims to reduce reliance on any single method, thereby minimising the risks of resistance development and environmental harm (Shah et al., 2021).

f. Precision Agriculture Techniques

Remote Sensing and GIS: Using drones, satellites, and geographic information systems (GIS) to monitor weed populations and map their distribution. This data helps farmers target specific areas for treatment, thereby reducing overall herbicide use (Mu et al., 2022).

Automated Weeding Machines: Robotic weeders and automated machinery can identify and remove weeds with high precision. These technologies reduce labour costs and minimise crop damage (Shah et al., 2021).

IoT and Smart Sensors: Integrating Internet of Things (IoT) devices and smart sensors in fields can provide real-time data on weed growth and environmental conditions, enabling timely and targeted interventions (Qu et al., 2024).

Deep Learning for Weed Management

Deep learning, a subset of artificial intelligence, is revolutionising weed management by providing precise, automated, and scalable solutions. By utilising convolutional neural networks (CNNs) and other advanced deep learning architectures, these systems can accurately identify and classify weed species in real time from images captured by drones, satellites, or ground-based sensors (Lopez et al., 2022). Trained on vast datasets of annotated images, these models learn to distinguish between weeds and crops with high accuracy (Shah et al., 2021). This precision enables targeted herbicide application, reducing chemical use and promoting sustainable farming practices. Moreover, deep learning models can adapt to diverse environmental conditions and crop growth stages, making them versatile tools across agricultural settings (Garcia et al., 2024b).

Implementing deep learning in weed management offers several significant benefits. Firstly, it reduces the labour-intensive process of manual weed identification and removal, freeing up valuable time for farmers and lowering labour costs. Secondly, the ability to apply herbicides only where needed minimises environmental impact and delays the development of herbicide-resistant weed populations (Saleem et al., 2022). Additionally, integrating deep learning with other precision agriculture technologies, such as IoT sensors and automated machinery, creates a synergistic effect that enhances overall farm management efficiency (Shah et al., 2021). As deep learning algorithms continue to evolve, they are expected to become even more effective, contributing to higher crop yields, lower production costs, and more sustainable agricultural practices.

Challenges of Deep Learning for Weed Management

The challenges of weed management in deep learning arise from the inherent similarities between weeds and crops, the variability in appearance due to environmental and species differences, and the complex visual environments created by dense and overlapping vegetation. Addressing these challenges requires sophisticated algorithms, extensive and diverse training data, and advanced image processing techniques (Shah et al., 2021). By overcoming these issues, deep learning models can become more effective in accurately identifying and managing weeds, leading to improved crop yields and more sustainable agricultural practices. Some of the challenges are presented in Figure 4;

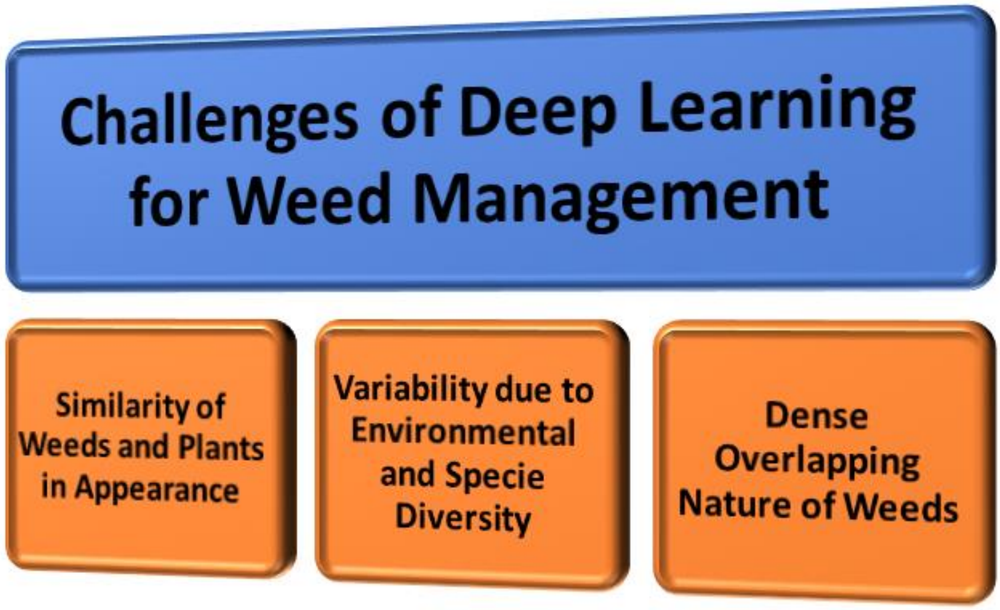

Figure 4: Deep Learning Challenges for the Management of Plant Weeds

a. Similarity of Weeds and Plants in Appearance

One significant challenge in weed management with deep learning is the similarity in appearance between weeds and crops. Weeds often closely resemble the crops they compete with, especially during certain growth stages (Mu et al., 2022). This similarity can make it difficult for deep learning models to accurately distinguish between weeds and desirable plants. The fine-grained differences between weeds and crops require high-resolution images and advanced algorithms to capture subtle visual cues. Misclassification can lead to incorrect herbicide application, damaging crops and reducing the effectiveness of weed control measures (Lopez et al., 2022).

b. Variability Due to Environmental and Species Diversity

The appearance of weeds and crops can vary widely due to environmental conditions, growth stages, and species diversity. Factors such as soil type, weather, and light conditions can alter plant morphology, making it challenging to maintain consistent model performance across different settings. For instance, a weed that looks distinct in one region may appear very similar to crops in another area due to changes in growth conditions (Haq et al., 2023). Deep learning models must be trained on diverse datasets that account for this variability, which requires extensive and representative image collection. Failure to address this variability can result in models that are either too generalised to specific conditions, limiting their effectiveness in real-world applications (Fatima et al., 2023).

c. Dense and Overlapping Nature of Weeds

Weeds often grow densely and overlap with crops, creating a complex visual environment that can be difficult for deep learning models to analyse accurately. This dense growth can obscure individual plants and make it challenging to segment and identify weeds. Overlapping vegetation increases the likelihood of occlusion, where parts of weeds or crops are hidden from view, complicating the task of distinguishing between them (Shah et al., 2021). Deep learning models need to incorporate advanced image segmentation techniques and robust feature extraction methods to handle such complex scenarios. Moreover, real-time processing of high-resolution images is required to manage the densely packed vegetation effectively, which demands significant computational resources and processing power (Qu et al., 2024).

Research Gaps

Although the deep learning-based farm weed classification has made tremendous progress, a number of research gaps that restrict real-world application and consistency of performance in various agricultural settings still exist.

The following are the main research gaps in the field of farm weed classification based on deep learning techniques:

Limited and Non-Diverse Datasets: The vast majority of currently available research is based on limited datasets, small datasets, or region-specific datasets, which restricts the generalisation of the model to the conditions of a variety of real-world agricultural settings, particularly in underrepresented regions like sub-Saharan Africa.

Poor Real-World Deployment of Models: The majority of models cannot be efficiently implemented in the actual farming settings, regardless of high-reported accuracies, because of changes in lighting, weather, crop stage and field conditions.

Computational Complexity of Models: Some deep learning models (CNNs, YOLO variants, transformers) are resource-intensive, thus not suitable to be run in real-time on edge devices like drones, robots, and IoT systems.

Limited Use of Lightweight and Optimised Models: The body of research on lightweight architectures to balance accuracy and performance in real-time agricultural systems is limited.

Insufficient Exploration of Transformer-Based Models: The majority of the research is in the form of CNN and YOLO architectures, whereas new models like Vision Transformers (ViTs) and hybrid ones are under-investigated and under-researched in the context of weed classification.

Lastly, despite the growing adoption of precision agriculture technologies, including drones and IoT systems, there remains a gap in end-to-end automated weed management systems that integrate detection, classification, and the autonomous application of herbicides within a complete pipeline. This gap would bring the field closer to full-autonomous, sustainable weed management systems in modern agriculture.

Future Research Directions

Future work should be directed towards the development of efficient real-time deep learning architecture with low weight on resource constrained agricultural devices that classify weed. While current CNNs and transformer-based models have achieved outstanding accuracy in classification tasks, many require substantial computational resources that limit their deployment in practical farming environments. On the other hand, emerging lightweight architectures such as MobileViT, EfficientFormer, EdgeNeXt, and Tiny Vision Transformers have also shown potential to deliver efficient performance while maintaining strong classification accuracy to meet the stringent requirements of deploying at the edge, on drones, and mobile devices.

Another interesting research direction is to enhance the transparency and reliability of deep learning models by incorporating the concepts of Explainable Artificial Intelligence (XAI). Given that agricultural practitioners need to be able to read the predictions from the system to make weed management decisions, these explainability techniques, such as attention visualization and feature attribution, can boost the confidence of the user, improve decision-making and foster broader adoption of the intelligent weed classification system. Furthermore, the development of large scales, geographically representative and publicly accessible benchmark datasets should be prioritised in order to enhance the robustness of the models and enable fair comparisons of their performance at various agricultural sites.

In addition, emerging learning paradigms such as self-supervised, federated, domain adaptation and continual learning could gain a lot from minimizing the reliance on annotated datasets and enhancing the generalisation of the model in different field scenarios. The development of deep learning models and their integration with agricultural autonomous robots, unmanned aerial vehicles (UAVs), Internet of Things (IoT) sensor networks and precision spraying technologies are also areas for future research. Interdisciplinary solutions will help to develop intelligent, autonomous, and environmentally friendly weed management systems to support next generation precision agriculture.

CONCLUSION

The review has analysed the latest developments in the field of farm weed classification with the help of deep learning methods, with special focus on object detection models, convolutional neural networks, transfer learning methods, transformer-based networks, and data augmentation methods. The literature review indicates that deep learning has greatly enhanced the accuracy and efficiency of weed detection and classification in precision agriculture compared to traditional manual and machine learning methods. Models such as YOLO variants, ResNet, EfficientNet, and Vision Transformers have shown good performance in detecting and classifying weeds across different agricultural settings, with various studies reporting high accuracy and mean average precision.

Nevertheless, despite these innovations, issues such as the lack of diversity in datasets, the inability to extrapolate to real-world settings, excessive computational demand, and the absence of standardised frameworks for assessment remain barriers to implementation. Moreover, the current systems remain mostly experimental in nature and have not yet been fully developed into end-to-end automated weed management systems for real-world farming operations.

Further development of lightweight and efficient deep learning models that can be used in real-time on edge devices, and the enhancement of dataset diversity by collecting large quantities of region-specific data, should be the focus of future research. Hybrid models that combine CNNs and transformers should be developed to achieve superior performance. In addition, the combination of deep learning models with smart farming systems that use IoT and autonomous farming equipment will play a pivotal role in developing fully automated, precise, and sustainable weed-handling systems.

ACKNOWLEDGEMENT

The authors would like to acknowledge the assistance of an artificial intelligence agent (Google Gemini, Copilot, and Anthropic) in the creation and refinement of the figures and diagrams presented in this manuscript. The AI tool helped generate initial drafts of the architectural illustrations and block diagram, which were subsequently reviewed, modified using the Microsoft PowerPoint application and approved by the authors. The authors take full responsibility for the final content and integrity of all figures.

Language Editing Declaration

The authors used Grammarly solely to improve the grammar, spelling, punctuation, sentence clarity, and readability of the manuscript. The tool was not used to generate scientific content, interpret results, perform data analysis, or formulate the study's conclusions. The authors take full responsibility for the accuracy, originality, and integrity of the manuscript.

REFERENCES

1. Aaron, A., Hassan, M., Hamada, M., & Kakudi, H. (2023). A lightweight deep learning model for identifying weeds in corn and soybean using quantization. Engineering Proceedings, 56, 318. https://doi.org/10.3390/ASEC2023-15811
2. Alahmad, T., Neményi, M., & Nyéki, A. (2023). Applying IoT sensors and big data to improve precision crop production: A review. Agronomy, 13, 2603. https://doi.org/10.3390/agronomy13102603
3. Bah, M. D., Hafiane, A., & Canals, R. (2018). Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. Remote Sensing, 10, 1690.
4. Corceiro, A., Alibabaei, K., Assunção, E., Gaspar, P. D., & Pereira, N. (2024). Leveraging machine learning for weed management and crop enhancement: Vineyard flora classification. Algorithms, 17, 19. https://doi.org/10.3390/a17010019
5. Divyanth, L. G., Guru, D. S., Soni, P., Machavaram, R., Nadimi, M., & Paliwal, J. (2022). Image-to-image translation-based data augmentation for improving crop/weed classification models for precision agriculture applications. Algorithms, 15, 401. https://doi.org/10.3390/a15110401

6. Espejo-Garcia, B., Malounas, I., Vali, E., & Fountas, S. (2021). Testing the suitability of automated machine learning for weeds identification. AI, 2, 34–47. https://doi.org/10.3390/ai2010004
7. Fatima, H. S., ul Hassan, I., Hasan, S., Khurram, M., Stricker, D., & Afzal, M. Z. (2023). Formation of a lightweight deep learning-based weed detection system for autonomous laser weeding robot. Applied Sciences, 13, 3997. https://doi.org/10.3390/app13063997
8. Gallo, I., Rehman, A. U., Dehkord, R. H., Landro, N., La Grassa, R., & Boschetti, M. (2023). Deep object detection of crop weeds using YOLOv7 on UAV images. Remote Sensing, 15, 539. https://doi.org/10.3390/rs15020539
9. Haq, S. I. U., Tahir, M. N., & Lan, Y. (2023). Weed detection in wheat crops using image analysis and artificial intelligence. Applied Sciences, 13, 8840. https://doi.org/10.3390/app13158840
10. Islam, M. P., Hatou, K., Aihara, T., Seno, S., Kirino, S., & Okamoto, S. (2022). Performance prediction of tomato leaf disease by convolutional neural networks. Smart Agricultural Technology, 2, 100054. https://doi.org/10.1016/j.atech.2022.100054
11. Khan, F., Zafar, N., Tahir, M. N., Aqib, M., Saleem, S., & Haroon, Z. (2022). Deep learning-based approach for weed detection in potato crops. Environmental Science Proceedings, 23, 6. https://doi.org/10.3390/environsciproc2022023006
12. López-Correa, J. M., Moreno, H., Ribeiro, A., & Andújar, D. (2022). Intelligent weed management based on object detection neural networks in tomato crops. Agronomy, 12, 2953. https://doi.org/10.3390/agronomy12122953
13. Mckay, M., Danilevicz, M. F., Ashworth, M. B., Rocha, R. L., Upadhyaya, S. R., Bennamoun, M., & Edwards, D. (2024). Canola identification for precision weed management using deep learning. Remote Sensing, 16, 2041. https://doi.org/10.3390/rs16112041
14. Moldvai, L., Mesterházi, P. Á., Teschner, G., & Nyéki, A. (2024). Weed detection and classification with computer vision using a limited image dataset. Applied Sciences, 14, 4839. https://doi.org/10.3390/app14114839
15. Morellos, A., Dolaptsis, K., Tziotzios, G., et al. (2024). IoT transfer learning-based service for grapevine health monitoring. Applied Sciences, 14, 1049. https://doi.org/10.3390/app14031049
16. Mu, Y., Feng, R., Ni, R., et al. (2022). Faster R-CNN-based model for weed seedling identification. Agronomy, 12, 2867. https://doi.org/10.3390/agronomy12112867
17. Nguyen, H. H., Shin, D. Y., Jung, W. S., Kim, T. Y., & Lee, D. H. (2024). IoT sensor-camera system for smart greenhouse farming. Agriculture, 14, 489. https://doi.org/10.3390/agriculture14030489
18. Olaniyi, O., et al. (2022). Maize-weed image dataset (Version 2). Mendeley Data. https://doi.org/10.17632/jjbfcckrsp.2
19. Osorio, K., Puerto, A., Pedraza, C., Jamaica, D., & Rodriguez, L. (2020). Deep learning for weed detection in lettuce crops using multispectral images. AgriEngineering, 2, 471–488. https://doi.org/10.3390/agriengineering2030032
20. Pauzi, N. A. M., Mustaza, S. M., Zainal, N., & Bukhori, M. F. (2024). Transfer learning-based weed classification and detection for precision agriculture. International Journal of Advanced Computer Science and Applications, 15(6), 440–448.
21. Peteinatos, G. G., Reichel, P., Karouta, J., Andújar, D., & Gerhards, R. (2020). Weed identification in maize, sunflower, and potatoes using CNNs. Remote Sensing, 12, 4185. https://doi.org/10.3390/rs12244185
22. Qu, H. R., & Su, W. H. (2024). Deep learning-based weed-crop recognition for smart agriculture: A review. Agronomy, 14, 363. https://doi.org/10.3390/agronomy14020363
23. Reedha, R., Dericquebourg, E., Canals, R., & Hafiane, A. (2022). Transformer neural network for weed and crop classification of UAV images. Remote Sensing, 14, 592. https://doi.org/10.3390/rs14030592
24. Senoo, E. E. K., et al. (2024). IoT and AI technologies for precision agriculture: Challenges and opportunities. Electronics, 13, 1894. https://doi.org/10.3390/electronics13101894
25. Shah, T. M., Nasika, D. P. B., & Otterpohl, R. (2021). Plant and weed identifier robot using neural networks. Agriculture, 11, 222. https://doi.org/10.3390/agriculture11030222
26. Shukla, B. K., Maurya, N., & Sharma, M. (2023). Sensor-based technologies for precision agriculture. Engineering Proceedings, 58, 22. https://doi.org/10.3390/ecsa-10-16051
27. Shoaib, M., Shah, B., et al. (2023). Deep learning-based plant disease detection: A review. Frontiers in Plant Science, 14, 1158933. https://doi.org/10.3389/fpls.2023.1158933

28. Soussi, A., Zero, E., Sacile, R., Trinchero, D., & Fossa, M. (2024). Smart sensors and smart data for precision agriculture. Sensors, 24, 2647. https://doi.org/10.3390/s24082647
29. Thotho, D., & Macheso, P. S. (2023). IoT, ML, and AI in precision agriculture: A survey. Tanzania Journal of Engineering and Technology, 42, 30–45. https://doi.org/10.52339/tjet.v42i4.922
30. Zhang, H., He, L., Gioia, F., et al. (2022). LoRaWAN IoT system for precision irrigation. Smart Agricultural Technology, 2, 100053. https://doi.org/10.1016/j.atech.2022.100053