Journal of Precision Agriculture

Automated Grassweed Detection in Wheat Cropping System: Current Techniques and Future Scope

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Research Article

Open Access &

Peer-Reviewed Article

DOI: 10.14302/issn.2998-1506.jpa-24-5058

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Keywords:

automated, grass weed, pests, detection, machine-learning, deep-learning, automated, Elsvier, Publons & Taylor & Francis

Received: April 04, 2024

Accepted: April 17, 2024

Published: May 07, 2024

Academic Editor:

Ancut,a Chetrariu, Faculty of Food Engineering, Stefan cel Mare University of Suceava

Citation:

Swati Shrestha, Grishma Ojha, Gourav Sharma, Raju Mainali, Liberty Galvin (2024) Automated Grassweed Detection in Wheat Cropping System: Current Techniques and Future Scope. Journal of Precision Agriculture - 1(1):19-37. https://doi.org/10.14302/issn.2998-1506.jpa-24-5058

Abstract

Wheat is a staple grain crop in the United States and around the world. Weed infestation, particularly grass weeds, poses significant challenges to wheat production, competing for resources and reducing grain yield and quality. Effective weed management practices, including early identification and targeted herbicide application are essential to avoid economic losses. Recent advancements in unmanned aerial vehicles (UAVs) and artificial intelligence (AI), offer promising solutions for early weed detection and management, improving efficiency and reducing negative environment impact. The integration of robotics and information technology has enabled the development of automated weed detection systems, reducing the reliance on manual scouting and intervention. Various sensors in conjunction with proximal and remote sensing techniques have the capability to capture detailed information about crop and weed characteristics. Additionally, multi-spectral and hyperspectral sensors have proven highly effective in weed vs crop detection, enabling early intervention and precise weed management. The data from various sensors consecutively processed with the help of machine learning and deep learning models (DL), notably Convolutional Neural Networks (CNNs) method have shown superior performance in handling large datasets, extracting intricate features, and achieving high accuracy in weed classification at various growth stages in numerous crops. However, the application of deep learning models in grass weed detection for wheat crops remains underexplored, presenting an opportunity for further research and innovation. In this review we underscore the potential of automated grass weed detection systems in enhancing weed management practices in wheat cropping systems. Future research should focus on refining existing techniques, comparing ML and DL models for accuracy and efficiency, and integrating UAV-based mapping with AI algorithms for proactive weed control strategies. By harnessing the power of AI and machine learning, automated weed detection holds the key to sustainable and efficient weed management in wheat cropping systems.

Introduction

Wheat is a major crop in the United States contributing significantly to nations economy. In the year 2022, United States planted approximately 45.8 million acres of wheat with a production value of 14.6 billion dollars (USDA-NASS, 2023). Weeds present major limitations to wheat growers and are barriers to progress in conservation tillage. Weeds compete with wheat crop for resources like sunlight, water, nutrients, and space diminishing yield, interfering harvest, and compromising grain quality. At times, growers may be docked at the elevator for excessive weed contamination in their grains. Weeds also may serve as hosts for insects and/or diseases injuring wheat crop and reducing yield. Potential yield loss due to weed infestation in winter wheat in the United States can reach upto 25.6% [1]. Grass weeds like Italian ryegrass (*Lolium perenne* spp. *multiflorum*), cheat grass (*Bromus spp*), jointed goatgrass (*Aegilops Cylindrica*), and wild oat, (*Avena fatua*) are among the most troublesome wheat weeds as they share phenological similarity with the crop thus competing with them throughout the season [2]. These grass weeds cause millions of dollars in economic loss every year and limit yield and harvest efficiency [3]. Thus, developing and implementing appropriate weed management practices for grass weed control is critical for profitable wheat production in the US and worldwide.

Most of the problematic grass weeds in wheat are winter annual weed species that emerge in the fall and remain relatively inconspicuous through the winter. However, as temperature starts rising in the spring, they become competitive and severely impacts wheat yield if not controlled early. Control of grass weeds at early/actively growing stage in early spring will maximize crop yield by reducing competition. Unfortunately, because of morphological similarity of these weeds to wheat, many times growers are unaware of these weeds in their fields until they start to bloom in the spring. By this time, the weeds already have a competitive advantage with well-developed root system and tillers and most crop damage has already occurred. This difficulty in weed identification is further magnified by area of the field as larger the field, more difficult it is to scout for these grass weeds in a timely manner. Therefore, developing a precise weed identification tool that can differentiate weed vs crop in the early growth stages would help in timely intervention when the weeds are small and easier to control thus benefitting growers and the country's economy at large.

Identifying the grass weeds in their early growth stage and determining severity of infestations in wheat fields is the key in deciding the appropriate weed management program. For profitable and efficient weed control, growers must scout the entire field, identify any areas of severe weed infestations, and determine what weed management practices need to be implemented. Conventionally, herbicides have been used as the most effective way of weed control. Wheat fields containing uniform infestations of these problematic grass weeds should be considered for herbicide application program to avoid yield loss and harvest interference problems. Likewise, fields that have fewer uniform infestations, but rather pockets of severe weeds should be managed to reduce weed seed bank and future infestations. In the case of patchy weed distribution, site specific weed management (SSWM) i.e. applying herbicides only where patches occur, should be considered for potential economic and environmental benefits.

Traditional farm practices rely on manual scouting for visual weed identification and back-up advice from herbicide representatives or county agents for development of herbicide programs. The manual scouting programs are tedious, time-consuming and have limited accuracy because of the difficulty to differentiate wheat and grass weeds in early growth stages leading to inappropriate grass-weed control strategies.

Inappropriate grass-weed control strategies are often related to:

a) Inaccurate application timing of the herbicides (weeds might already have well developed root system and tillers to be effectively controlled by the herbicide when growers identify the weeds and act).

b) Applying herbicides without considering the grass-weed threshold might have negative economic and environmental consequences.

c) Broadcasting entire field even when weed-free areas are present, or weeds occur in patches.

For developing an economic and environmental friendly grass control in wheat there is a requirement for a method of weed management that can gather and assess weed-related data within the field, while also taking appropriate measures to effectively control weed.

Because of recent advances in sensor technology, unmanned aerial vehicles (UAV) platforms, and artificial intelligence (AI), automated weed detection can be developed as a promising tool for early grass weed detection and management in wheat. The use of UAVs, popularly known as drones, based remote sensing can facilitate rapid weed detection by providing high spatial as well as temporal resolution and rapid data acquisition. UAVs or drones are preferred over satellite and manned aerial platforms for image acquisition/remote sensing due to their cost effectiveness, flexibility in data acquisition, ability to conduct low altitude operations, immunity to cloud covers, and ease of operation [4]. Optical sensors are the most preferred technology for data acquisition in UAV based automated weed detection systems [5]. The UAVs equipped with multispectral and hyperspectral sensors help in capturing spectral information of the crops in multiple wavelengths. Different vegetation indices can be used to distinguish weeds from crops using their unique spectral signatures. Thus, using UAV imagery and machine learning algorithms, it is possible to create UAV generated weed maps and prescription maps to implement variable rate herbicide application [6]. In addition to the UAVs, hand-held sensors can also be used for image acquisition, but the process is more time-consuming and not possible to use for large acres. However, hand-held sensors can be used when images of high resolution are required for the model development process.

Automated weed detection can mitigate inappropriate grass-weed control strategies by:

a) Precise identification of weed threshold and weedy areas in the fields.

b) Allowing growers to act in a timely and targeted manner.

In recent years, stakeholders have shown enhanced interest in automated grass weed detection and management techniques in wheat. However, existing literature lacks systematic compilation of current studies on automated grass weed detection specifically tailored for wheat crops. In response to this knowledge gap, the paper is a systematic review of the current techniques on automated weed detection system. The paper will also discuss various image acquisition and machine learning techniques currently available and prospects of automated grass weed detection in wheat with the evolution of artificial intelligence and machine learning.

Automated weed detection

Automated weed detection is an area of growing significance because of pressing needs to enhance efficiency, reduce labor cost, and minimize negative impacts of herbicides in agricultural production system. The integration of robotics and information technology in agriculture has made automated weed detection possible, minimizing the need for manual scouting or intervention. Use of sensors in conjunction with proximal as well as remote sensing tools help in capturing information about crops growing in a field at a rapid rate with minimal disturbance to the crops. As plants can be distinguished from each other based on their optical, mechanical, thermal, or spectral properties, the sensors that can detect or sense such differences are used in automated weed detection systems [7]. Several types of sensors, including Light Detection and Ranging (LiDAR), thermal infrared, multispectral, hyperspectral, RGB cameras, can be used for automated weed detection depending on specific requirement [8]. The data collected by such sensors is further analyzed using several mathematical or probabilistic models like Machine Learning (ML) and Deep Learning (DL) models for automated weed detection that is aimed at saving time and labor costs, enhancing sustainability, and promoting precision farming practices [9]. The information collected by automated weed detection systems can be used as input in autonomous spraying systems that are designed for site-specific herbicide applications [10].

The use of sensor technologies, Internet of Things (IoT), and robotics has significantly improved the efficiency of weed detection and minimized the cost by allowing site-specific herbicide application (Emmi et al., 2014). Using such autonomous systems can also help in continuously monitoring crops, allow timely intervention, and prevent yield loss. Automation in weed detection also minimizes human intervention and avoids health hazards that can occur due to exposure to herbicides during application [11].

Modern weed detection systems like WEED-IT® and WeedSeeker® are widely used in site-specific herbicide applications using reflectance information in red and infrared bands with a high level of accuracy. These site-specific herbicide application systems use optical sensors that can trigger individual nozzles based on the detection of weeds, applying herbicide only to the weeds. They can be installed in existing spraying equipment and have integrated GPS that enable precise mapping of fields and recording areas of weed infestation. WEED-IT® and WeedSeeker® were used for site-specific or spot herbicide application in the dryland wheat growing regions to eliminate weeds such as Russian thistle (*Salsola tragus L.*) and Kochia (*Bassia scoparia L.*). It was observed that the use of such systems reduced the herbicide volume required in the field by 53% compared to traditional uniform application [12]. However, the use of WeedSeeker® and other similar technologies is not limited to the grain crop

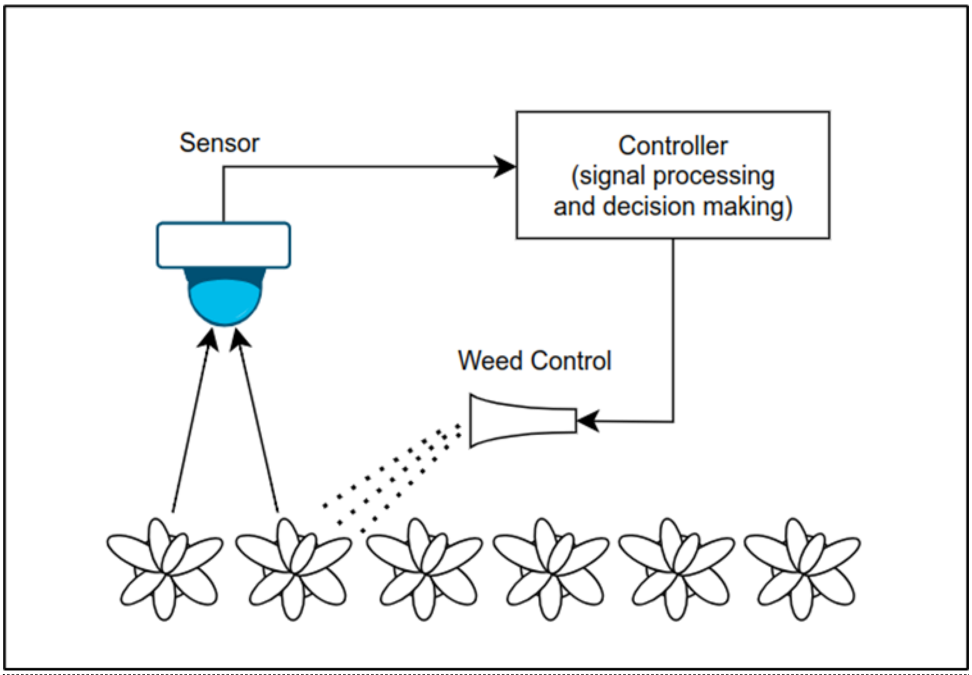

Figure 1. Intuitive Diagram of automated weed detection and site-specific herbicide Application

fields. WeedSeeker® technology was also used for the detection and spot treatment of weed in sugarcane and peanut respectively and resulted in the herbicide reduction of 18% to 54% throughout the season [13][14].

Completely autonomous or robotic systems for weed detection and control consist of three major components; a sensor unit consisting of sensors for weed detection, a control unit for data processing and decision making, and an actuator controlled mechanical spraying unit for site specific weed control (Figure 1) [15].

Sensors for automated weed detection

Sensors are defined as devices that can sensitively and selectively detect changes in the environment within their proximity and produce output signals that can be used by different computing systems [16]. Sensors can be of several types and have different modes of operation. They can produce several types of signals that are used as an input into a processing unit or signal processor. Sensors can be classified into distinct groups based on different criteria to differentiate them. Based on the type of signals they produce; sensors can be categorized as analog and digital sensors. Analog sensors generate a continuous stream of output or analog signal, whereas digital sensors produce output in digital or discrete form [17]. Similarly, based on the way they interact with the environment, they are further classified as active and passive sensors. Active sensors emit energy as a signal into the environment and detect the response from the target. Some examples of active sensors include RADAR, LiDAR, active infrared sensors, and ultrasonic sensors. Alternatively, passive sensors rely on external sources of energy that include sunlight, heat, sound waves, and electromagnetic radiation. Passive sensors include passive infrared sensors, optical sensors, and passive sonar sensors.

Sensors and sensing techniques used in automated grass weed detection

Precision agriculture heavily relies on the use of sensors and actuators to obtain information about different aspects of agriculture with high levels of accuracy. Sensors provide information about crop health, nutrient, and moisture levels in soil, and other climatic or environmental conditions that enable farmers and agronomists to take timely and targeted actions to optimize yields and minimize resource usage. Some of the most important aspects of crop growth in agriculture that can impact yield and profitability are soil, water, climate, weeds, pests, and diseases. These aspects of crop growth can be monitored and managed using various types of sensors. For example, soil moisture and pH sensors can be employed to measure moisture content and pH of the soil. Measuring soil moisture levels helps in employing variable rate irrigation (VRI) and reduce water usage for irrigation. A study conducted in 2020 found that a soil sensor-based irrigation scheduling technique was more effective compared to soil water balance (SWB) method and utilized 27 – 45% less water [18]. In a similar manner, sensors such as humidity sensors, temperature sensors, pressure sensors, and solar radiation sensors are used in climate monitoring purposes.

Proximal and Remote Sensing

Specific sensors can be used or designed in agriculture according to the needs of growers to ensure the efficiency and effectiveness of sensing tasks. In agriculture, proximal sensing and remote sensing are the two types of sensing techniques that are primarily used. In proximal sensing, the sensor is near the target of interest. This type of sensing technique is widely used in precision agriculture and the sensors are mostly mounted on vehicles or are hand-held. GreenSeeker® (Trimble Inc.) is one of the most popular hand-held optical sensors developed by researchers of Oklahoma State University which helps in the measurement of Normalized Difference Vegetation Index (NDVI) using red (660 nm) and near infrared (NIR) radiation in the electromagnetic spectrum to aid in variable rate nitrogen application in crops [19]. For automated weed detection, proximal sensing technique can be used by mounting cameras or other sensors on tractors or handheld devices. As most of the sensors used for automated weed detection are optical imaging sensors, this type of sensing technique is used if finer or higher spatial resolution is required [20].

Alternatively, remote sensing is another sensing technique in which the sensor is either mounted on a satellite, aircraft, or drones (UAVs). This technique enables the acquisition of data from a large geographical area in a short duration and is widely adopted in precision agriculture in areas such as crop growth monitoring, soil moisture estimation, and pest and disease detection [21], [22], [23]. However, the data collected by optical remote sensors are usually lower resolution compared to the data collected by proximal sensors [24].

Using satellite based remote sensing for weed detection is impractical for weed patch detection and mapping on a field scale whereas UAV based remote sensing has been found to be effective for automated weed detection as it offers better spatial, and temporal resolution compared to satellite [25]. Sensors used in remote sensing for weed detection are usually passive sensors as they do not emit energy and rely on sun as the source of illumination [26]. Remote sensing in precision agriculture began with using wavelengths in the visible and near infrared (NIR) ranges only and has gradually broadened to include almost all the wavelengths of radiation in the electromagnetic spectrum [27]. With this, it has been possible to identify and differentiate spectral signatures of weeds from crops thus enabling early detection and elimination of weeds in agricultural fields.

Multispectral and Hyperspectral Sensors

Multispectral and Hyperspectral sensors are unique types of optical sensors that can detect or capture electromagnetic radiation reflected or emitted by different objects under consideration in different bands of wavelengths. In precision agriculture, these sensors are usually mounted on remote sensing platforms such as satellites, aircraft, and drones and they capture information about the spectral reflectance of crop canopies and other objects in the region of interest. Multispectral sensors can capture data in only a few discrete bands (usually 3 to 10) whereas hyperspectral sensors can capture hundreds of contiguous bands with narrower spectral intervals. There are several multispectral sensors available in the market that include MicaSense RedEdge series, Parrot Sequoia, ACSL SOTEN, Sentera Quad, and MiniMCA6. Similarly, there are several hyperspectral sensors offered by companies that include Headwall Photonics, Specim, Telops, BaySpec, and others.

Use of hyperspectral and multispectral sensors are found to be highly effective in automated weed detection and timely weed management in a wide variety of crops. An automated weed detection and evaluation system was developed in a study conducted in 2005 using machine vision and hyperspectral imaging system to accurately detect weeds in cotton fields with an average false alarm rate of 15%. The hyperspectral images were acquired in wavelengths ranging from 500 to 1000 nm. The hyperspectral data-cube consisted of 100 individual wavelengths captured in steps of 5nm [28]. An automated weed detection and crop monitoring system was proposed in a study conducted in 2019 that used several vegetative indices and object-based image analysis on multispectral images to capture weed patches in wheat fields [29]. An RBG sensor and a Tetracam NIR sensor were used for data acquisition in that experiment. In another study in 2012, an automated weed control system with hyperspectral imaging was used to selectively apply hot food-grade oil for weed control in early growth tomatoes. The system used a multispectral Bayesian classifier to discriminate plant canopy from weed and successfully controlled 95.8% of Black nightshade (*S. Nigrum*) and 93.8% of redroot pigweed (*A. Retroflexus*) after 15 days of thermal treatment [30]. Similarly, Barrero and Perdomo (2018) used UAV based multispectral imaging to detect Gramineae weed in rice fields in Colombia using multispectral Micasense Rededge camera and RGB Canon Powershot D20 with impressive detection results [31]. These results from multiple studies have proven multispectral and hyperspectral imaging as highly effective tools for precision agriculture including automated weed detection.

Computer Vision and artificial intelligence in automated weed detection

Currently, various tasks in smart agriculture, such as identifying plant pests and diseases, predicting crop yields, and managing nutrient and water requirement, rely on computer vision technology for successful implementation [32]. Computer vision is a field of artificial intelligence that employs machine learning and neural networks to train computer systems on extracting valuable information from digital images, videos, and other visual data inputs. Computer vision works like human vision except that instead of retina and visual cortex a wide array of data and algorithms are used in the process. Two essential technologies that are used to accomplish computer vision include traditional machine learning (ML) and deep learning (DL).

With the advancement of computer technology, and increased computational capacity, it is now possible to process large volumes of data collected from the sensors efficiently using complex Machine Learning (ML) and Deep Learning (DL) algorithms for automated weed detection with high levels of accuracy and reliability. As image sensors are predominantly used in UAV based automated weed detection, computer vision techniques can be effectively used to process the high-resolution image data captured by such sensors. The upcoming section of the paper will discuss various types of ML and DL techniques and how they can be utilized in automated weed detection.

Machine Learning

Machine Learning (ML) is one of the major branches of Artificial Intelligence (AI) that uses algorithms and models based on statistical techniques to make predictions from the input features of dataset without being explicitly programmed. The concept of ML was proposed a long time ago and there were

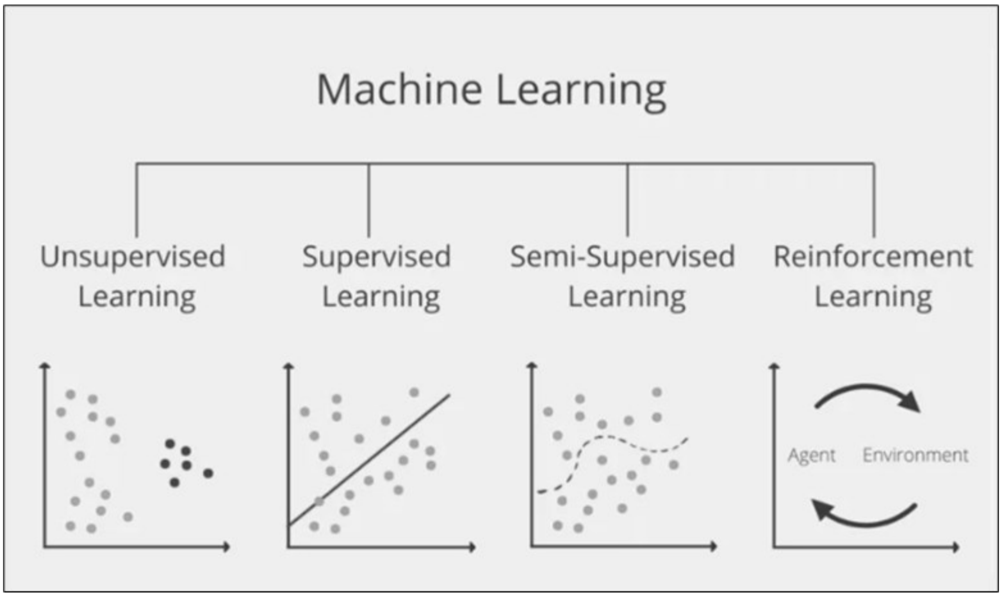

Figure 2. Four major types of machine learning techniques.

several research that laid the foundation for ML. One of the major contributions in this field was the study by Arthur Samuel (1959), where the focus was to develop programs that could learn to play the game of checkers through reinforcement learning [33]. This study was also a foundation for research on reinforcement learning and pattern recognition. A ML model is a statistical model based on linear algebra and probability theory that can find patterns on the data that was previously unseen and make informed decisions based on that data [34]. Hence, ML is a process of solving a problem by collecting the relevant data and building a statistical model to solve the problem using the collected dataset. There are different types of ML based on the raw data and statistical model used for predictions that are discussed below (Figure 2).

Types of Machine Learning

1. Supervised learning

Supervised learning is a process of using the dataset that consists of labeled examples in which all the feature vectors have a corresponding label or target variable. In the learning process, the algorithm learns to map input features to the corresponding target variable with a goal to predict accurate output for the unseen input data or features [35]. Some of the most popular supervised learning algorithms include Linear Regression, Support Vector Machine (SVM), Random Forest, K- Nearest Neighbors (KNN), and Neural Networks. Supervised learning is primarily used for two types of problems, classification, and regression. Most of the tasks associated with object detection and classification are performed using supervised learning algorithms.

2. Unsupervised Learning

Unsupervised learning involves analyzing unlabeled data to find the underlying patterns in the dataset, which can assist in tasks like clustering or association. There is no explicit guidance or information to the model to find the patterns in the dataset. This approach is useful when there is uncertainty about the inherent properties of the dataset. The most popular unsupervised learning techniques include clustering, dimensionality reduction, and association rules. Clustering involves grouping similar data points together based on their similarity in features. Popular algorithms for clustering include hierarchical, k-means, and gaussian mixture models. In dimensionality reduction, the algorithm focuses on representing the data into a lower dimensional space without compromising the characteristics of the data. These algorithms are widely used in image recognition, natural language processing, and anomaly detection [36].

3. Semi-supervised Learning

This ML approach uses the features of both supervised and unsupervised learning techniques by using both labeled and unlabeled dataset during model training. This technique is highly beneficial in conditions where there are not enough labeled datasets available for training. Usually, the unlabeled examples are higher in quantity compared to the labeled examples. The unlabeled dataset is used to refine the model by improving its understanding of the hidden patterns in the data [37]. Some of the examples of semi-supervised learning involve co-training, self-training, and multi-view learning. This learning technique is utilized in different domains that include computer vision and natural language processing [38].

4. Reinforcement Learning

In this domain of ML, the learning is based on simulation of an environment where the machine can learn to achieve an optimal result perceiving the state of that environment and learning by trial and error. This approach is based on reward and punishment, and the machine can execute actions in every state. The best course of action is selected by achieving the maximum cumulative rewards from each state. Reinforcement learning is used in situations involving sequential decision-making with long-term objectives, such as game playing, robotics, resource management, and logistics [39].

Traditional Machine Learning (TML) for Automated Weed Detection

Automated weed detection using TML involves using ML algorithms along with a series of image processing techniques. Image processing techniques that involve segmentation, edge detection, texture analysis, shape analysis, and principal component analysis (PCA) are used to extract features from the dataset and use them to train the ML model. Some of the major criteria for distinguishing weeds from crops are features that include color, shape, texture, height, and distribution in the field. All these features can be detected using vision-based or optical sensors and computer vision techniques including traditional machine learning. These criteria also serve a critical role in feature engineering for TML tasks, where algorithms like support vector machines (SVM), random forests, or neural networks can leverage these features to classify weeds from plants. TML algorithms have been implemented to detect weeds in a wide range of crops with high levels of effectiveness and reliability. A study by Islam et al. (2021) have used algorithms like random forest, SVM, and KNN and compared their effectiveness for detecting weeds in a chili field in Australia, where SVM and RF performed well with an accuracy of more than 90% [40]. Similarly, a real time weed detection system was designed in a 2020 study using random forest for classification task [41]. The system was proven to be effective for automated weed detection and variable rate application of herbicides. In another study, SVM was used to identify six types of weeds in a data set that consisted of 224 relevant images. Through optimization of feature extraction methods, the system achieved an impressive accuracy of about 97% [42]. Similarly, a study conducted in 2006 used SVM for weed detection in maize and achieved an accuracy of up to 83 % [43]. Random forest classifier was used in a 2023 study for early season Blackgrass weed detection in wheat using ground-based imagery as well as UAV-based aerial imagery and an accuracy of 88% and 72% was achieved respectively [44]. Su et al. (2022) also detected blackgrass weed in wheat fields with 93% accuracy using UAV based multispectral imagery along with random forest classification algorithm [45]. In a similar study, several types of grass weeds in wheat fields were detected using AdaBoost algorithm, that is an ensemble of multiple classification algorithms [46]. Although TML algorithms have been widely used in the field of automated weed detection, their limitations including dependence on feature engineering, poor generalization, and lack of scalability hinder their effectiveness in this domain. Using TML for large and high-resolution datasets such as multispectral and hyperspectral images can be computationally intensive and inefficient [47]. With the advancement in computing power and reduced cost of computer hardware's, deep learning (DL) algorithms have been gaining popularity in the field of precision agriculture and crop vs weed detection wherein feature extraction and classification processes are merged [48]. These DL algorithms can extract multidimensional semantic feature information of crops and weeds because of their enhanced data exploration capabilities thus overcoming the disadvantages of traditional machine learning techniques (Figure 3) [49]. The upcoming section discusses DL techniques and their usage in automated weed detection in detail.

Deep Learning

DL is a subset of ML that focuses on algorithms that mimic the brain's neural networks. It utilizes multiple layers of artificial neurons, typically arranged in neural networks, to model and learn from complex data. These neural networks are designed to mimic the functioning of biological neurons,

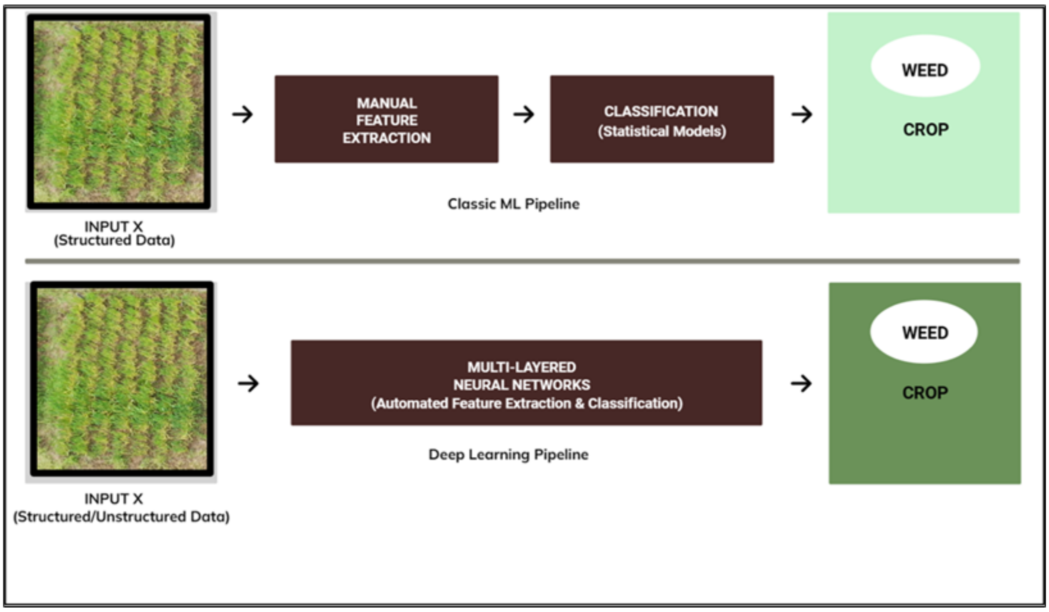

Figure 3. Comparison of traditional machine learning (ML) and advanced deep learning (DL) pipeline for automated weed detection in agriculture. With the advancement in artificial intelligence and computing technologies, DL techniques can facilitate accurate and efficient weed vs crop distinction in agricultural fields.

allowing them to learn and recognize patterns in data at multiple levels of abstraction [50]. This hierarchical learning process enables deep learning models to automatically extract features from raw data and enable end-to-end learning, making them effective for a wide range of tasks including image recognition and natural language processing. DL involves training multiple layers of Artificial Neural Networks (ANNs), which is why it is referred to as “deep” learning. A neuron or node is the smallest unit of ANN that can take an input and perform computation (a weighted sum of input followed by an activation function) and produce an output. Frank Rosenblat (1958) proposed the simplest form of a neural network unit that could take multiple binary inputs, perform computations, and apply a step function to produce a binary output [51]. The term “perceptron” was used to define such artificial neurons and they were primarily used for linearly separable binary classification tasks (Figure 4). This was one of the earliest neural network architectures that influenced further research in the field of DL.

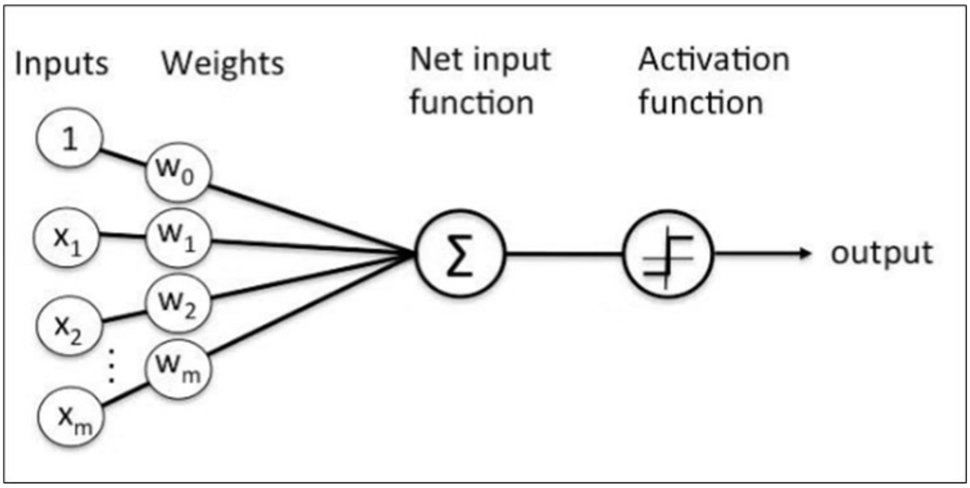

Figure 4. Perceptron: one of the simplest neural network architectures

At present, Convolutional Neural Network (CNN), which was used for the first time by LeCun for Handwritten Zip Code Recognition, is one of the most popular deep learning algorithms for computer vision applications [52]. Deep Learning algorithms are used for a wide variety of tasks ranging from facial recognition, microbial detection, driving assistance systems, medical image analysis, environmental monitoring, agriculture, and so on [53], [54], [55], [56]. Some of the most popular CNN based DL architectures are LeNet, AlexNet, ZFNet, GoogleNet, VGGNet, ResNet, etc. Other popular DL algorithms that can be implemented for computer vision tasks are Recurrent Neural Networks (RNNs), Vision Transformers (ViTs), and U-Net.

Convolutional Neural Networks (CNN)

CNN is a type of feed forward neural network architecture that has been proven to be formidable tool for image analysis because of its effectiveness in image recognition and processing. The main feature of CNN architecture is the convolutional layer that performs convolution operation to the input data (Figure 5). This architecture is influenced by the perception through visual cortex [57]. A typical CNN architecture should consist of convolutional layers where the convolution operations to the input data is performed, activation functions that introduce non-linearity to the network, pooling layers that are used to down sample the feature maps created by the convolutional layers, and fully connected layers that flatten the output from the previous layer to perform either classification or regression tasks.

One of the major differences in the architecture of CNNs compared to other neural network architectures is the presence of neurons that are organized into three dimensions, height, width, and depth. Additionally, the neurons in CNN are also not fully connected with each other from one layer to the other which reduces the number of parameters in the network and allows the network to handle large input data such as high-resolution images [58]. There are several deep learning architectures based on CNN used today that have performed exceptionally well in the popular benchmarking datasets such as ImageNet. One such CNN architecture was proposed for image classification using the ImageNet dataset and achieved a top-5 error of 18.9% on the test data which was a groundbreaking achievement in image classification at that time [59].

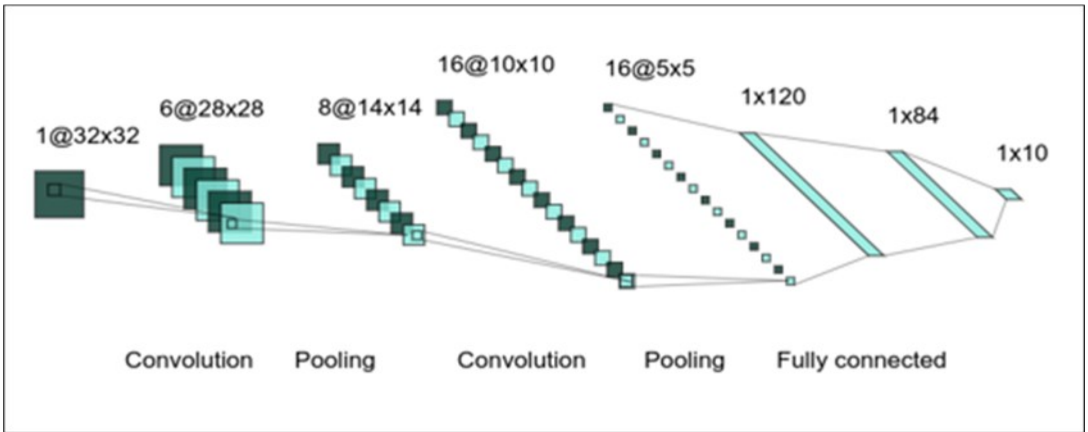

Figure 5. An example of Convolutional Neural Network Architecture (LeNet 5)

Deep Learning for Automated Weed Detection

With the improvements in hardware resources and continuous refinement of deep learning techniques, a widespread use of DL techniques has been observed across various domains. Automated weed detection is one such field that has also benefited from the use of DL techniques, particularly CNNs, as they have demonstrated remarkable accuracy in weed detection and classification. The challenge of extraction and selection of features in traditional ML has been addressed by DL methods that can learn features from the dataset on their own. DL methods have also been found to be effective in handling higher dimensional multispectral and hyperspectral imagery that provide rich and detailed information about the objects. For instance, a 2018 study evaluated multiple research papers that used DL techniques in agriculture, found that DL methods are more efficient compared to TML in most of the agricultural image processing scenarios [60]. As the volume of data available has significantly grown with the use of hyperspectral and multispectral imaging in agriculture, the TML methods have reached saturation and DL methods have emerged as superior performers that can train efficiently on large datasets for weed detection. Consequently, DL methods are being used to detect different kinds of weeds in a wide variety of crops. In a study, CNN was used with unsupervised data labeling on UAV captured imagery to detect weeds in row crops and achieved accuracy difference of 1.5% in spinach field and 6% in the bean field [61]. Similarly, Etienne et al (2021) used YOLOv3, a CNN based DL model with UAS imagery to detect monocot and dicot weeds and achieved an average precision of 91.48% and 86.13% respectively [62]. A survey by Hasan et al. (2021) searched and enumerated the number of research papers in the field of automated weed detection using DL from 2010 to 2020 using relevant keywords across multiple academic research databases [63]. They found about 1650 relevant papers that included the keywords used for the search. Hence, there is a substantial amount of research in the field of automated weed detection using DL methods.

Current status of automated grass weed detection in wheat cropping system

Even though, use of computer vision and artificial intelligence has been gaining popularity in the field of precision agriculture and automated weed detection, majority of ML and DL architecture for crop vs weed distinction have been tested in vegetable crops like tomato, radish, carrot, lettuce, sugar beets and onions to name a few [63], [64]. There have been comparatively fewer studies on implementation of artificial intelligence methods specifically for grass weed detection in wheat crops [63]. Table 1 Summarizes all the studies that have been conducted in the past decade for automated grass weed detection in wheat cropping system using machine learning and deep learning techniques.

The search for articles was performed via keywords: “automated, grass weed, pests, detection, machine-learning, deep-learning and automated”, carried out directly in google scholar, Elsvier, Publons and Taylor & Francis.

These studies suggest that there is a great scope of using artificial intelligence in automated grass weed detection in the future, but researchers should focus on enhancing the efficiency and accuracy of the current grass-weed detection techniques, Current literature lacks comparison of various machine learning and deep learning techniques in terms of their accuracy and memory efficiency. Investigating on wide range of computer vision techniques that are available currently and deploying the best model that has acceptable accuracy and efficiency specifically in terms of memory usage would be a valuable resource for wheat growers and researchers. The ability to identify grass weed in initial stages could help growers take pro-active measures for weed control minimizing yield and resource loss. The use of UAVs with appropriate sensors can be used for creating accurate maps of weeds with DL and ML

Table 1. List of all the studies conducted worldwide in the past two decades on automated grass weed detection in wheat cropping system.

S.N.	Study Title	Sensor Platform	Image processing Technique	Model Used	Model Type (TML/ DL)	Weeds used in the study	References
1	On-farm evaluation of UAV-based aerial imagery for season-long weed monitoring under contrasting management and pedoclimatic conditions in wheat.	UAV based	Segmentation and Classification	Watershed Segmentation and Random Forest Classifier	TML	Ryegrass	Anderegg et al., 2023 (Switzerland) [44]
2	Detection of Italian Ryegrass in Wheat and Prediction of Competitive Interactions Using Remote-Sensing and Machine-Learning Techniques.	UAV based	Classification	Custom (Multilayer Perceptron (MLP))	DL	Ryegrass	Sapkota et al., 2020) (United States) [65]
3.	Real time detection of inter-row ryegrass in wheat farms using deep learning.	Ground-Based	Segmentation	(Encoder-decoder) Based on EFRNet	DL	Ryegrass	Su et al., 2021 (Australia) [66]
4.	Multi-Modal Deep Learning for Weeds Detection in Wheat Field Based on RGB-D Images.	Ground Based	Detection	CNN	DL	Meadow foxtail, Annual Bluegrass, Japanese Chess, Cockspur grass	Xu et al., 2021 (China) [67]
5.	Spectral analysis and mapping of blackgrass weed by leveraging machine learning and UAV multispectral imagery.	UAV Based	Classification	Random Forest Classifier	TML	Blackgrass	Su et al., 2022 (United Kingdom) [45]
6.	Automating Agriculture: Using UAS and machine learning to monitor weed populations.	UAV Based	Classification	CNN	DL	Blackgrass	Lambert, 2018 (United Kingdom) [68]
7.	Testing the ability of unmanned aerial systems and machine learning to map weeds at sub-field scales: a test with the weed *Alopecurus myosuroides* (Huds).	UAV Based	Classification	CNN	DL	Blackgrass	Lambert et al., 2019 (United Kingdom) [69]
8.	WeedsNet: a dual attention network with RGB-D image for weed detection in natural wheat field.	Ground Based	Detection	WeedsNet (Custom CNN)	DL	Blackgrass, Japanese brome, Kentucky bluegrass	Xu et al, 2023 (china) [70]

9.	Recognition of Weeds in Wheat Fields Based on the Fusion of RGB Images and Depth Images.	Ground Based	Classification	AdaBoost (ensemble)	TML	Foxtail grass, annual blue-grass, brome, barnyard grass, red-root pig-weed, shep-herd's purse	Xu et al., 2020 (China) [46]
10.	Using a fully convolutional neu-ral network for detecting loca-tions of weeds in images from cereal fields.	Ground Based	Detection	CNN	DL	Monocot and Dicot weeds	Dyrmann et al., 2018 (Denmark) [71]

algorithms. These UAV's can not only be used for understanding the spatial distribution of weed but can for spot spraying. Combining these two techniques of automated grass-weed detection and site-specific management can revolutionize management of grass weeds in wheat cropping system in the future.

Conclusion

Accurate detection of grass weed at early growth stage of wheat and their management is critical for profitable wheat production. However, accurate identification of grassweeds at early growth stage is difficult for growers because of the morphological similarity of grass weeds to wheat. By the time growers identify the weeds, they have developed strong tillers, are difficult to control and already impacted the crop yield negatively. In today's era where artificial intelligence and computer vision are widely used in the fields of precision agriculture, it is possible to use various computer algorithms to distinguish crops vs weeds and take pro-active measures to control them before they impact crop productivity. The paper discusses current research on automated grass weed detection systems in wheat and the future scope of using artificial intelligence for weed management.

References

1. M. L. Flessner *et al.*, "Potential wheat yield loss due to weeds in the United States and Canada," *Weed Technol.*, vol. 35, no. 6, pp. 916–923, 2021.
2. K. Jabran, K. Mahmood, B. Melander, A. A. Bajwa, and P. Kudsk, "Weed dynamics and management in wheat," *Adv. Agron.*, vol. 145, pp. 97–166, 2017.
3. D. A. Ball and C. J. Peterson, "Herbicide Tolerance in Imidazolinone-Resistant Wheat for Weed Management in the Pacific Northwest U.S.A.," in *Wheat Production in Stressed Environments*, vol. 12, H. T. Buck, J. E. Nisi, and N. Salomón, Eds., in Developments in Plant Breeding, vol. 12. , Dordrecht: Springer Netherlands, 2007, pp. 243–250. doi: 10.1007/1-4020-5497-1_31.
4. J. Albetis *et al.*, "Detection of Flavescence dorée Grapevine Disease Using Unmanned Aerial Vehicle (UAV) Multispectral Imagery," *Remote Sens.*, vol. 9, no. 4, Art. no. 4, Apr. 2017, doi: 10.3390/rs9040308.
5. S. Christensen, M. Dyrmann, M. S. Laursen, R. N. Jørgensen, and J. Rasmussen, "Sensing for Weed DetectionWeed detection," in *Sensing Approaches for Precision Agriculture*, R. Kerry and

A. Escolà, Eds., Cham: Springer International Publishing, 2021, pp. 275–300. doi: 10.1007/978-3-030-78431-7_10.

6. F. Castaldi, F. Pelosi, S. Pascucci, and R. Casa, "Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize," *Precis. Agric.*, vol. 18, no. 1, pp. 76–94, Feb. 2017, doi: 10.1007/s11119-016-9468-3.
7. E. Anastasiou *et al.*, "Precision farming technologies for crop protection: A meta-analysis," *Smart Agric. Technol.*, vol. 5, p. 100323, Oct. 2023, doi: 10.1016/j.atech.2023.100323.
8. J. Gao, D. Nuyttens, P. Lootens, Y. He, and J. G. Pieters, "Recognising weeds in a maize crop using a random forest machine-learning algorithm and near-infrared snapshot mosaic hyperspectral imagery," *Biosyst. Eng.*, vol. 170, pp. 39–50, Jun. 2018, doi: 10.1016/j.biosystemseng.2018.03.006.
9. R. Katarya, A. Raturi, A. Mehndiratta, and A. Thapper, "Impact of Machine Learning Techniques in Precision Agriculture," in *2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE)*, Feb. 2020, pp. 1–6. doi: 10.1109/ICETCE48199.2020.9091741.
10. J. E. Hunter III, T. W. Gannon, R. J. Richardson, F. H. Yelverton, and R. G. Leon, "Integration of remote-weed mapping and an autonomous spraying unmanned aerial vehicle for site-specific weed management," *Pest Manag. Sci.*, vol. 76, no. 4, pp. 1386–1392, 2020, doi: 10.1002/ps.5651.
11. F. Dankhara, K. Patel, and N. Doshi, "Analysis of robust weed detection techniques based on the Internet of Things (IoT)," *Procedia Comput. Sci.*, vol. 160, pp. 696–701, Jan. 2019, doi: 10.1016/j.procs.2019.11.025.
12. N. G. Genna, J. A. Gourlie, and J. Barroso, "Herbicide efficacy of spot spraying systems in fallow and postharvest in the pacific northwest dryland wheat production region," *Plants*, vol. 10, no. 12, p. 2725, 2021.
13. E. Fillols, C. Baillie, S. Underdown, and T. Staier, "Integrating the Weedseeker® technology into weed management strategies in sugarcane.," 2013, Accessed: Apr. 02, 2024. [Online]. Available: https://www.cabidigitallibrary.org/doi/full/10.5555/20133284208
14. K. Rizzardi, E. Prostko, G. Rains, G. Vellidis, and F. Morari, "Selective spraying of weeds in peanut," in *Sixth European Conference on Precision Agriculture (6ECPA), vol. Poster, Skiathos, Greece*, 2007, p. 6. Accessed: Apr. 02, 2024. [Online]. Available: https://www.researchgate.net/profile/Glen-Rains/publication/237447174_Selective_Spraying_of_Weeds_in_Peanut/links/00b7d5268467ff1da6000000/Selective-Spraying-of-Weeds-in-Peanut.pdf
15. K. Asha, A. Mahore, P. Malkani, and A. K. Singh, "Robotics-automation and sensor-based approaches in weed detection and control: A review," *Intern J Chem Stud*, vol. 8, pp. 542–550, 2020.
16. J. Vetelino and A. Reghu, *Introduction to sensors*. CRC press, 2017. Accessed: Apr. 02, 2024. [Online]. Available: https://www.taylorfrancis.com/books/mono/10.1201/9781315218274/introduction-sensors-john-vetelino-aravind-reghu
17. K. Kumar, A. Sharma, and S. L. Tripathi, "Chapter 9 - Sensors and their application," in *Electronic Devices, Circuits, and Systems for Biomedical Applications*, S. L. Tripathi, V. E. Balas, S. K. Mohapatra, K. B. Prakash, and J. Nayak, Eds., Academic Press, 2021, pp. 177–195. doi: 10.1016/

B978-0-323-85172-5.00021-6.

18. A. G. El-Naggar, C. B. Hedley, D. Horne, P. Roudier, and B. E. Clothier, “Soil sensing technology improves application of irrigation water,” *Agric. Water Manag.*, vol. 228, p. 105901, 2020.
19. E. Rutto and D. B. Arnall, “History of the GreenSeeker sensor,” Oklahoma Cooperative Extension Service, 2009. Accessed: Apr. 02, 2024. [Online]. Available: https://shareok.org/bitstream/handle/11244/317964/oksa_pss_2260_2009-08.pdf?sequence=1
20. F. López-Granados, “Weed detection for site-specific weed management: mapping and real-time approaches,” *Weed Res.*, vol. 51, no. 1, pp. 1–11, Feb. 2011, doi: 10.1111/j.1365-3180.2010.00829.x.
21. P. S. Thenkabail, J. G. Lyon, and A. Huete, “Advances in hyperspectral remote sensing of vegetation and agricultural crops,” in *Fundamentals, Sensor Systems, Spectral Libraries, and Data Mining for Vegetation*, CRC press, 2018, pp. 3–37. Accessed: Apr. 02, 2024. [Online]. Available: https://www.taylorfrancis.com/chapters/edit/10.1201/9781315164151-1/advances-hyperspectral-remote-sensing-vegetation-agricultural-crops-prasad-thenkabail-john-lyon-alfredo-huete
22. D. Entekhabi *et al.*, “The soil moisture active passive (SMAP) mission,” *Proc. IEEE*, vol. 98, no. 5, pp. 704–716, 2010.
23. A.-K. Mahlein, “Plant Disease Detection by Imaging Sensors – Parallels and Specific Demands for Precision Agriculture and Plant Phenotyping,” *Plant Dis.*, vol. 100, no. 2, pp. 241–251, Feb. 2016, doi: 10.1094/PDIS-03-15-0340-FE.
24. M. H. M. Roslim *et al.*, “Using Remote Sensing and an Unmanned Aerial System for Weed Management in Agricultural Crops: A Review,” *Agronomy*, vol. 11, no. 9, Art. no. 9, Sep. 2021, doi: 10.3390/agronomy11091809.
25. D. W. Lamb and R. B. Brown, “PA—Precision Agriculture: Remote-Sensing and Mapping of Weeds in Crops,” *J. Agric. Eng. Res.*, vol. 78, no. 2, pp. 117–125, Feb. 2001, doi: 10.1006/jaer.2000.0630.
26. R. P. Sishodia, R. L. Ray, and S. K. Singh, “Applications of Remote Sensing in Precision Agriculture: A Review,” *Remote Sens.*, vol. 12, no. 19, Art. no. 19, Jan. 2020, doi: 10.3390/rs12193136.
27. D. J. Mulla, “Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps,” *Biosyst. Eng.*, vol. 114, no. 4, pp. 358–371, Apr. 2013, doi: 10.1016/j.biosystemseng.2012.08.009.
28. V. Alchanatis, L. Ridel, A. Hetzroni, and L. Yaroslavsky, “Weed detection in multi-spectral images of cotton fields,” *Comput. Electron. Agric.*, vol. 47, no. 3, pp. 243–260, Jun. 2005, doi: 10.1016/j.compag.2004.11.019.
29. A. Mateen and Q. Zhu, “Weed detection in wheat crop using UAV for precision agriculture,” *Pak J Agric Sci*, vol. 56, pp. 809–817, 2019.
30. Y. Zhang, E. S. Staab, D. C. Slaughter, D. K. Giles, and D. Downey, “Automated weed control in organic row crops using hyperspectral species identification and thermal micro-dosing,” *Crop Prot.*, vol. 41, pp. 96–105, Nov. 2012, doi: 10.1016/j.cropro.2012.05.007.
31. O. Barrero and S. A. Perdomo, “RGB and multispectral UAV image fusion for Gramineae weed detection in rice fields,” *Precis. Agric.*, vol. 19, no. 5, pp. 809–822, Oct. 2018, doi: 10.1007/s11119

-017-9558-x.

32. E. Mavridou, E. Vrochidou, G. A. Papakostas, T. Pachidis, and V. G. Kaburlasos, “Machine Vision Systems in Precision Agriculture for Crop Farming,” *J. Imaging*, vol. 5, no. 12, Art. no. 12, Dec. 2019, doi: 10.3390/jimaging5120089.
33. A. L. Samuel, “Some Studies in Machine Learning Using the Game of Checkers,” *IBM J. Res. Dev.*, vol. 3, no. 3, pp. 210–229, Jul. 1959, doi: 10.1147/rd.33.0210.
34. G. Kumar, R. Banerjee, D. Kr Singh, and N. Choubey, “Mathematics for machine learning,” *J. Math. Sci. Comput. Math.*, vol. 1, no. 2, pp. 229–238, 2020.
35. P. Cunningham, M. Cord, and S. J. Delany, “Supervised Learning,” in *Machine Learning Techniques for Multimedia: Case Studies on Organization and Retrieval*, M. Cord and P. Cunningham, Eds., Berlin, Heidelberg: Springer, 2008, pp. 21–49. doi: 10.1007/978-3-540-75171-7_2.
36. C. M. Bishop, “Pattern recognition and machine learning,” *Springer Google Sch.*, vol. 2, pp. 5–43, 2006.
37. O. Chapelle, B. Scholkopf, and A. Zien Eds., “Semi-Supervised Learning (Chapelle, O. et al., Eds.; 2006) [Book reviews],” *IEEE Trans. Neural Netw.*, vol. 20, no. 3, pp. 542–542, Mar. 2009, doi: 10.1109/TNN.2009.2015974.
38. X. Zhu and A. B. Goldberg, *Introduction to Semi-Supervised Learning*. Springer Nature, 2022.
39. R. S. Sutton and A. G. Barto, *Reinforcement Learning, second edition: An Introduction*. MIT Press, 2018.
40. N. Islam *et al.*, “Early Weed Detection Using Image Processing and Machine Learning Techniques in an Australian Chilli Farm,” *Agriculture*, vol. 11, no. 5, Art. no. 5, May 2021, doi: 10.3390/agriculture11050387.
41. M. Alam, M. S. Alam, M. Roman, M. Tufail, M. U. Khan, and M. T. Khan, “Real-Time Machine-Learning Based Crop/Weed Detection and Classification for Variable-Rate Spraying in Precision Agriculture,” in *2020 7th International Conference on Electrical and Electronics Engineering (ICEEE)*, Apr. 2020, pp. 273–280. doi: 10.1109/ICEEE49618.2020.9102505.
42. F. Ahmed, H. A. Al-Mamun, A. S. M. H. Bari, E. Hossain, and P. Kwan, “Classification of crops and weeds from digital images: A support vector machine approach,” *Crop Prot.*, vol. 40, pp. 98–104, Oct. 2012, doi: 10.1016/j.cropro.2012.04.024.
43. Y. Karimi, S. O. Prasher, R. M. Patel, and S. H. Kim, “Application of support vector machine technology for weed and nitrogen stress detection in corn,” *Comput. Electron. Agric.*, vol. 51, no. 1, pp. 99–109, Apr. 2006, doi: 10.1016/j.compag.2005.12.001.
44. J. Anderegg *et al.*, “On-farm evaluation of UAV-based aerial imagery for season-long weed monitoring under contrasting management and pedoclimatic conditions in wheat,” *Comput. Electron. Agric.*, vol. 204, p. 107558, Jan. 2023, doi: 10.1016/j.compag.2022.107558.
45. J. Su *et al.*, “Spectral analysis and mapping of blackgrass weed by leveraging machine learning and UAV multispectral imagery,” *Comput. Electron. Agric.*, vol. 192, p. 106621, 2022.
46. K. Xu, H. Li, W. Cao, Y. Zhu, R. Chen, and J. Ni, “Recognition of Weeds in Wheat Fields Based on the Fusion of RGB Images and Depth Images,” *IEEE Access*, vol. 8, pp. 110362–110370, 2020,

doi: 10.1109/ACCESS.2020.3001999.

47. M. Ahmad *et al.*, “Hyperspectral image classification—Traditional to deep models: A survey for future prospects,” *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 15, pp. 968–999, 2021.
48. Z. Wu, Y. Chen, B. Zhao, X. Kang, and Y. Ding, “Review of weed detection methods based on computer vision,” *Sensors*, vol. 21, no. 11, p. 3647, 2021.
49. M. Abdulsalam and N. Aouf, “Deep weed detector/classifier network for precision agriculture,” in *2020 28th Mediterranean Conference on Control and Automation (MED)*, IEEE, 2020, pp. 1087–1092. Accessed: Apr. 02, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9183325/
50. Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *nature*, vol. 521, no. 7553, pp. 436–444, 2015.
51. F. Rosenblatt, “The perceptron: A probabilistic model for information storage and organization in the brain,” *Psychol. Rev.*, vol. 65, no. 6, pp. 386–408, 1958, doi: 10.1037/h0042519.
52. Y. LeCun *et al.*, “Backpropagation applied to handwritten zip code recognition,” *Neural Comput.*, vol. 1, no. 4, pp. 541–551, 1989.
53. C. Potena, D. Nardi, and A. Pretto, “Fast and Accurate Crop and Weed Identification with Summarized Train Sets for Precision Agriculture,” in *Intelligent Autonomous Systems 14*, W. Chen, K. Hosoda, E. Menegatti, M. Shimizu, and H. Wang, Eds., Cham: Springer International Publishing, 2017, pp. 105–121. doi: 10.1007/978-3-319-48036-7_9.
54. B. D. Shrestha Gurung *et al.*, “Transformer in Microbial Image Analysis: A Comparative Exploration of TransUNet, UNet, and DoubleUNet for SEM Image Segmentation,” in *2023 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Dec. 2023, pp. 4500–4502. doi: 10.1109/BIBM58861.2023.10385974.
55. G. Ojha, D. Poudel, J. Khanal, and N. Pokhrel, “Design and analysis of computer vision techniques for object detection and recognition in ADAS,” *J. Innov. Eng. Educ.*, vol. 5, no. 1, pp. 47–58, 2022.
56. B. Kayalibay, G. Jensen, and P. van der Smagt, “CNN-based Segmentation of Medical Imaging Data.” arXiv, Jul. 25, 2017. doi: 10.48550/arXiv.1701.03056.
57. D. H. Hubel and T. N. Wiesel, “Receptive fields, binocular interaction and functional architecture in the cat’s visual cortex,” *J. Physiol.*, vol. 160, no. 1, pp. 106-154.2, Jan. 1962.
58. K. O’Shea and R. Nash, “An Introduction to Convolutional Neural Networks.” arXiv, Dec. 02, 2015. doi: 10.48550/arXiv.1511.08458.
59. A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” in *Advances in Neural Information Processing Systems*, Curran Associates, Inc., 2012. Accessed: Apr. 02, 2024. [Online]. Available: https://proceedings.neurips.cc/paper/2012/hash/c399862d3b9d6b76c8436e924a68c45b-Abstract.html
60. A. Kamilaris and F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” *Comput. Electron. Agric.*, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.
61. M. D. Bah, A. Hafiane, and R. Canals, “Deep Learning with Unsupervised Data Labeling for Weed Detection in Line Crops in UAV Images,” *Remote Sens.*, vol. 10, no. 11, Art. no. 11, Nov. 2018, doi: 10.3390/rs10111690.

62. A. Etienne, A. Ahmad, V. Aggarwal, and D. Saraswat, "Deep Learning-Based Object Detection System for Identifying Weeds Using UAS Imagery," *Remote Sens.*, vol. 13, no. 24, Art. no. 24, Jan. 2021, doi: 10.3390/rs13245182.

63. A. S. M. M. Hasan, F. Sohel, D. Diepeveen, H. Laga, and M. G. K. Jones, "A survey of deep learning techniques for weed detection from images," *Comput. Electron. Agric.*, vol. 184, p. 106067, May 2021, doi: 10.1016/j.compag.2021.106067.

64. B. Espejo-Garcia, N. Mylonas, L. Athanasakos, S. Fountas, and I. Vasilakoglou, "Towards weeds identification assistance through transfer learning," *Comput. Electron. Agric.*, vol. 171, p. 105306, 2020.

65. Sapkota, B., Singh, V., Neely, C., Rajan, N., & Bagavathiannan, M. (2020). Detection of Italian ryegrass in wheat and prediction of competitive interactions using remote-sensing and machine-learning techniques. Remote Sensing, 12(18), 2977.

66. Su, D., Qiao, Y., Kong, H., & Sukkarieh, S. (2021). Real time detection of inter-row ryegrass in wheat farms using deep learning. Biosystems Engineering, 204, 198-211.

67. Xu, K., Zhu, Y., Cao, W., Jiang, X., Jiang, Z., Li, S., & Ni, J. (2021). Multi-modal deep learning for weeds detection in wheat field based on RGB-D images. Frontiers in plant science, 12, 732968.

68. Lambert, J. (2018). Automating Agriculture: Using UAS and machine learning to monitor weed populations (Doctoral dissertation, University of Sheffield).

69. Lambert, J. P., Childs, D. Z., & Freckleton, R. P. (2019). Testing the ability of unmanned aerial systems and machine learning to map weeds at subfield scales: a test with the weed Alopecurus myosuroides (Huds). Pest management science, 75(8), 2283-2294.

70. Xu, K., Yuen, P., Xie, Q., Zhu, Y., Cao, W., & Ni, J. (2024). WeedsNet: a dual attention network with RGB-D image for weed detection in natural wheat field. Precision Agriculture, 25(1), 460-485.

71. Dyrmann, M., Skovsen, S., Laursen, M. S., & Jørgensen, R. N. (2018, June). Using a fully convolutional neural network for detecting locations of weeds in images from cereal fields. In The 14th International Conference on Precision Agriculture (pp. 1-7). International Society of Precision Agriculture.