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REVIEW

Artificial Intelligence for Maximizing Agricultural Input Use Efficiency: Exploring Nutrient, Water and Weed Management Strategies

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ABSTRACT

Agriculture plays a crucial role in the economy, and there is an increasing global emphasis on automating agricultural processes. With the tremendous increase in population, the demand for food and employment has also increased significantly. Agricultural methods traditionally used to meet these requirements are no longer adequate, requiring solutions to issues such as excessive herbicide use and the use of chemical fertilizers. Integration of technologies such as the Internet of Things, wireless communication, machine learning, artificial intelligence (AI), and deep learning shows promise in addressing these challenges. However, there is a lack of comprehensive documentation on the application and potential of AI in improving agricultural input efficiency. To address this gap, a desk research approach was used by utilizing peer-reviewed electronic databases like PubMed, Scopus, Google Scholar, Web of Science, and Science Direct for relevant articles. Out of 327 initially identified articles, 180 were deemed pertinent, focusing primarily on AI's potential in enhancing yield through better management of nutrients, water, and weeds. Taking into account research findings worldwide, we found that AI technologies could assist farmers by providing recommendations on the optimal nutrients to enhance soil quality and determine the best time for irrigation or herbicide application. The present status of AI-driven automation in agriculture holds significant promise for optimizing agricultural input utilization and reducing resource waste, particularly in the context of three pillars of crop management, i.e., nutrient, irrigation, and weed management.

KEYWORDS

Agriculture; artificial intelligence; crop management; nutrient; irrigation; weed management; resource use efficiency

1 Introduction

As the world population grows, food production must increase to meet the ever-increasing needs of the growing population, which is estimated to reach 9.7 billion by 2050 [1]. Frequent irrigation as well as excessive resource consumption for crop production, are contributing factors to climate change and resource depletion [2]. In addition to increasing food production through the effective use of planning, decision-making, and management practices, digital urban farming can also help to reduce production losses through the increased resilience of farms and the reduction of their vulnerability to climate change [3]. Moreover, the agriculture sector is facing challenges in achieving optimal production due to labour shortages and the seasonal nature of the agriculture sector. Other reasons can be the movement of people from rural to urban for sustainable life balance and education and high wages provided by non-agricultural industries as compared to the agricultural sector. Climate change is a threat to agricultural production [4]. The worldwide agricultural environment is currently facing vagaries of climate such as drought, frequent heat waves, changes in rainfall patterns, floods, and attacks of insect pests [5]. As the growth and productivity of crops have decreased, irrigation and rainfall availability have reduced, and rainfall patterns have become increasingly erratic and intense over the last few decades [6]. After the green revolution, there was a tremendous increase in crop production, but there remains a significant challenge to preserve this increase and improve food and nutritional security in this era of climate change [7].

As a result of varying climate patterns, yield reductions in different crops varied between different regions [8]. Rising temperatures and erratic rainfall have negatively impacted crop growth and development [9]. The decline in soil fertility leads to a reduction in crop productivity. Continued use of fertilizers for increasing agricultural production has exacerbated soil degradation [10–13]. The major reasons behind the rapid soil fertility depletion may be listed as inadequate and non-judicious fertilizer use, complete removal of crop residues, continuous mono-cropping systems, adverse climate and soil types, lack of proper site specific cropping systems and accelerated soil erosion [14–16]. Therefore, to deal with these challenges, there is a need to harness the potential artificial intelligence (AI) technologies in agriculture. To fulfill the rising food demand, the agricultural industry needs to increase global food production by 70%. This has led to a tremendous responsibility on the agriculture sector to enhance crop production and increase yield per hectare. In many countries where expanding cropland is practically impossible, the adoption of agriculture automation has become essential and urgent. Agricultural automation can be defined as autonomous navigation by robotic devices without human intervention, providing precise information to help perform agricultural operations [17].

AI is the fundamental concept behind the development of technologies that mimic human brain functions [18]. This field of computer science uses algorithms for machine learning (ML) and deep learning (DL) to analyze data and replicate human intelligence [18]. Various learning algorithms assist farmers in identifying nutrient deficiencies, weed infestations, and water stress conditions, thereby enabling efficient nutrient management, irrigation practices, and weed control. These advancements in AI technologies have led to a new era of crop management. Convolutional neural network (CNN) and artificial neural network (ANN) are the most well-established deep learning techniques that are used to analyze the data [19,20]. These aid farmers in identifying nutrient and water stress conditions, facilitating improved nutrient and irrigation management.

DL models, particularly deep convolutional neural networks (DCNNs), have shown promising results in the diagnosis of plant nutrient status. These models leverage multiple processing layers to analyze and process data, particularly RGB images [21]. The DCNN has been demonstrated to be effective for performing a variety of tasks, including segmenting biological materials, recognizing plants, predicting leaf water content, and detecting disease in plants [22]. Moreover, AI has been increasingly utilized in various fields, including drought assessment and monitoring. Machine learning algorithms can be trained to identify drought stress [23]. This information helps in the early detection and monitoring of drought conditions [24]. An et al. [25] concluded that the ResNet50 CNN model with color images achieved maximum accuracy in identification of drought stress conditions in maize, yielding higher accuracy than grayscale images. Waheed et al. [26] observed that ANN outperformed other DL models such as CNN, MobileNetV2, and the visual geometry group (VGG16) in effectively differentiating between nutrient-deficient and healthy ginger plants. Butte et al. [27] concluded that the Retina-UNet-Ag model yielded the highest values of the Dice score coefficient (DOC) and Intersection over Union (IoU) for water stress identification in potatoes using aerial images.

Recognition of weeds still faces several challenges due to irregular growth patterns, significant occlusion, and difficulties in early detection [28]. To tackle this issue, a smart sprayer was created by leveraging machine vision and AI techniques [29,30]. This innovative system enables the identification of target weeds and precise spraying in specific locations as needed [31]. The development of hybrid models combining deep learning and traditional image processing is anticipated to improve weed recognition. However, the high cost of AI technologies currently poses a barrier to widespread commercialization [32].

The adoption of AI-based weed management technologies holds promise in addressing various challenges faced by the agricultural sector, such as the shift towards organic farming, labour shortages, food security, climate change, and issues related to excessive use of fertilizers, herbicides, and irrigation water. Through the integration of big data, AI concepts, and Internet of Things (IoT) devices in smart farming, real-time information on agricultural conditions can be provided, enabling farmers to make effective decisions [33]. Nevertheless, the adoption of complex technologies and the lack of experience with emerging technologies remain significant challenges in implementing AI-assisted agriculture. However, the application of AI in agriculture can greatly assist farmers in various aspects, technologies, and applications, offering the potential to accomplish more with fewer resources. Therefore, it is essential to focus on these areas and collect relevant local data to ensure that AI systems are well-suited to specific conditions [34].

Although the benefits and the potential of AI to accelerate input use efficiency and ensure farming sustainability are anticipated within the agricultural space systematic data-driven analysis and comprehensive documentation on automation in agriculture, have yet to take place [35]. The purpose of this study is to make a systematic review of the studies and research in agriculture that employ the recent AI technologies to solve several relevant problems in agronomic crop management, specifically for the three major pillars, i.e., nutrient, water, and weed management. Therefore, this study aims to address this gap through the following objectives:

1. Evaluate the potential application of AI to increase input use efficiency in agriculture.
2. Explore the use of AI in nutrient, water, and weed management for enhancing crop yield.

The outline of this paper proceeds with the research methodology, which follows the desk research approach with the selected criteria and data collected; Section 1 deals with the introduction of artificial intelligence for maximizing agricultural input efficiency. The approach utilized in the writing of this review study is explained in Section 2. Section 3 presents the revolution in agriculture; Section 4 presents the concept of AI technologies in agriculture; Section 5 presents the results and discussion; Section 6 shows limitations; Section 7 presents prospects. Finally, Section 8 shows conclusions.

2 Methodology

2.1 Review Principles

This review paper aims to explore recent studies on the application of AI techniques in agriculture, addressing specific questions through a two-fold approach (Fig. 1). Firstly, it provides a comprehensive overview of key AI concepts in agriculture and discusses a sustainable perspective for optimizing input use efficiency. Second, it carries out a desk research to provide a comprehensive literature analysis, focusing on the state of AI-driven automation in agriculture, encompassing nutrient stress, weed control, and irrigation. The review utilizes secondary documents to analyze the limitations and potential of AI for achieving sustainability in the context of agronomic management practices. The issue overview, literature sourcing, synthesis and discussion of the findings, and technique used in previous research are the three iterative phases of the desk study [3,36].

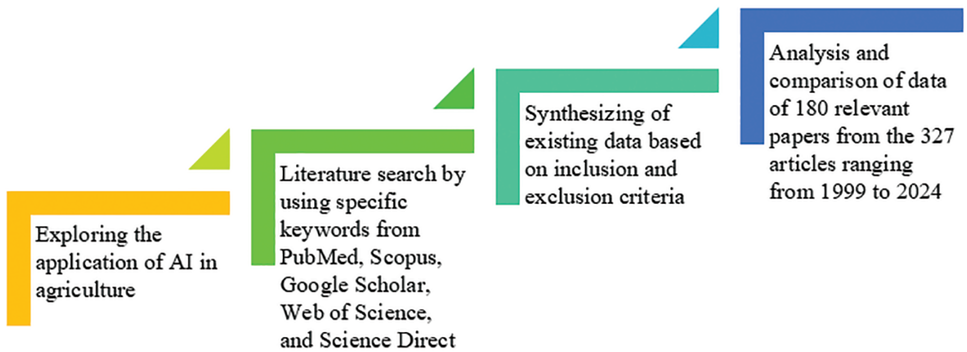

Figure 1: Methodology of literature review using desk study approach

2.2 Literature Search Strategy

We used reliable online resources like PubMed, Scopus, Google Scholar, Web of Science, and Science Direct to do a thorough internet search in order to conduct the literature survey. Other sources, such as the Food and Agriculture Organization of the United Nations (FAO) are also used for this study. The search employed specific key terms, including "artificial intelligence", "concept of machine learning", "deep learning in agriculture", "nutrient stress detection using AI", "irrigation management strategies using AI in different crops", "weed identification using AI", "weed control through AI", "challenges of AI" and "prospects". The articles included in this review were mainly selected based on the significance of their titles and abstracts of the research topic.

2.3 Inclusion and Exclusion Criteria

The inclusion criteria for this study were research that particularly studied advances in the use of AI to improve resource usage efficiency through real-time insights into fertiliser, water, and weed management. Papers that did not include AI applications in agriculture in their abstract, introduction, or conclusion were rejected at the eligibility stage. On the other hand, the exclusion criteria included articles that addressed topics other than the main three pillars of crop management such as nutrient, irrigation, and weed management and were written in any other language, contained incomplete or irrelevant data, irrelevant and duplicate articles or for which full-text access was unavailable.

2.4 Strengths and Limitations

We conducted a comprehensive literature search to identify studies that elucidate the potential of AI to increase agricultural input use efficiency by optimizing agricultural practices and minimizing resource wastage through sensors, drones, and satellite imagery, AI algorithms. This review included 180 relevant papers from the 327 articles that were initially collected. To address the existing knowledge gap in this subject, we collected studies ranging from 1999 to 2024, including both recent and historical data.

3 Revolution in Agriculture: Towards Smart Farming

Historically, agriculture was primarily focused on food production for human and animal survival, known as the traditional agriculture era 1.0 [37]. During this period, manual labour and simple tools like sickles and shovels were used, resulting in low productivity. The introduction of steam engines in the 19th century marked the agricultural era 2.0, characterized by the adoption of machinery and the use of chemicals. Agriculture 2.0 significantly increased farm efficiency and productivity but also led to harmful consequences such as chemical pollution, excessive power consumption, and environmental degradation [33,38]. In the 20th century, rapid advances in computation and electronics marked the beginning of the agricultural era 3.0 [39]. This era saw the utilization of robotic techniques, programmed machinery, and other technologies that improved agricultural efficiency. The problems from the previous era were addressed through precise irrigation, site-specific nutrient application, and efficient weed management technologies [40].

Agriculture is currently undergoing a revolutionary phase with the introduction of cutting-edge technology [41,42] (Fig. 2). Examples of these technologies include the Internet of Things, big data analytics, artificial intelligence, cloud computing, and remote sensing. This combination of new advancements is revolutionizing the agriculture industry (Fig. 2). These advancements have greatly enhanced agricultural activities by leveraging sensor and network platforms to optimize production efficiency, reduce water and energy usage, and minimize environmental degradation [43]. Based on epsilon-based measures and Tobit truncated regression models, Abbas et al. [44] investigated issues of economic and environmental inefficiencies impacting sunflower producers in Pakistan. According to the study, out of 240 sunflower growers, 69.9% were economically inefficient, whereas 56.3% were environmentally inefficient. Whereas, smart farming, facilitated by the integration of automation and sensor technology, has brought about a revolution in agricultural practices, including harvesting and crop yields, resulting in increased efficiency. The application of IoT, GPS, sensors, robots, drones, precision farming equipment, and data analytics has changed traditional agricultural operations [45]. This integration empowers farmers to address their specific requirements and discover suitable solutions. These innovations have improved decision-making accuracy and timeliness, leading to increased crop productivity. Smart farming plays a crucial role in addressing diverse challenges in crop production by monitoring soil characteristics, climate factors, soil moisture levels, and more [46]. This monitoring improves crop management practices to maintain optimum production while minimizing the excessive usage of fertilizers and herbicides [47]. It represents the advancement of precision agriculture through the adoption of modernization and the implementation of intelligent techniques for remote farm data collection, management, and real-time maintenance solutions.

4 Artificial Intelligence

AI is a technology that aims at replicating human intelligence, encompassing learning, problem-solving, and behaviours similar to human cognition [48]. By studying the functioning of the human brain, including how it learns, makes decisions, and solves problems; intelligent software and systems are developed [49]. These systems are trained using data and provide desired outputs based on valid inputs, effectively imitating the human brain. AI incorporates various techniques such as ML, DL, robots, IoT, and wireless sensor networks (WSN) to tackle agricultural challenges [50]. With AI and ML algorithms, dynamic connections between input and output variables are leveraged to generate predictions that offer solutions for both simple and complex scenarios. These AI-powered technologies have become increasingly prevalent in our daily lives, evident in applications like facial recognition apps and self-driving cars [51]. While numerous industries have experienced notable productivity gains through AI and ML, the agricultural sector is also undergoing a digital transformation. AI has found diverse applications in agriculture, empowering farmers in tasks such as irrigation management, crop rotation planning, optimized harvesting, crop selection, precision planting, and pest control [52].

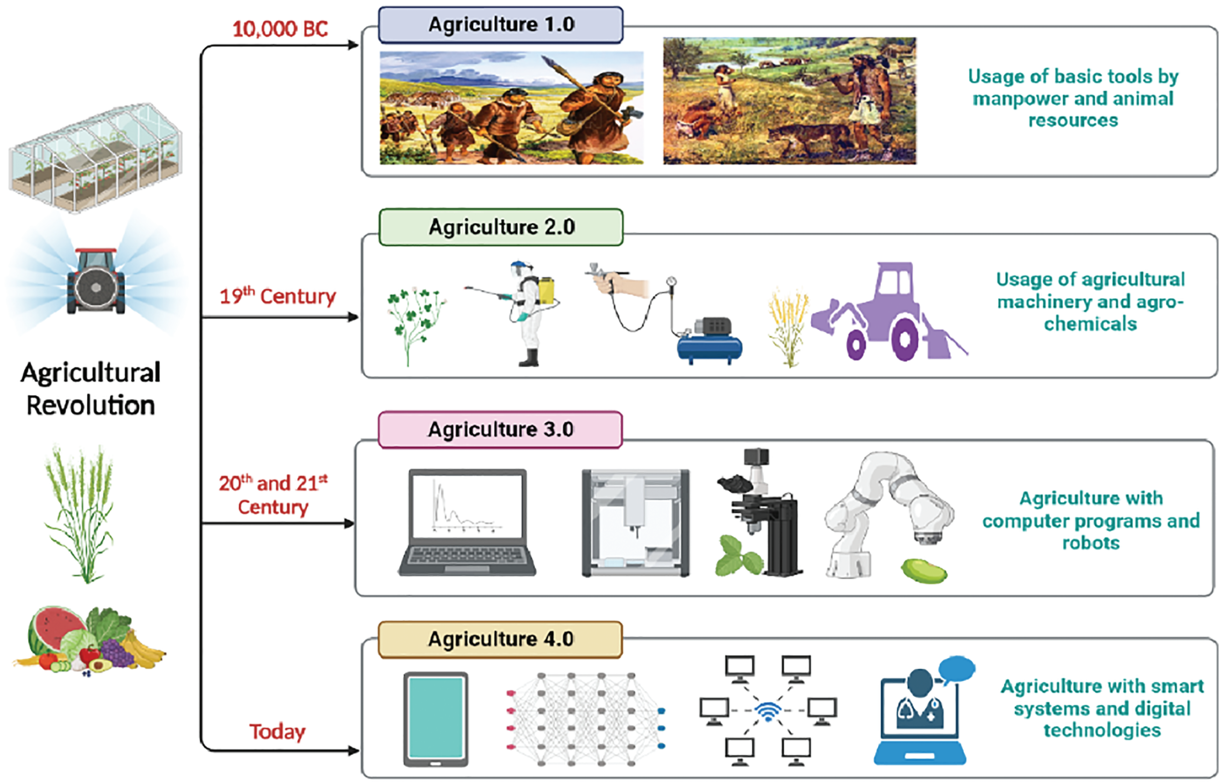

Figure 2: Development during agricultural revolution

AI has emerged as a promising technology in the field of digital agriculture, holding immense potential to transform farming practices [53]. Digital agriculture involves the utilization of digital technologies to collect, store, and analyze agricultural data electronically, employing AI techniques to facilitate enhanced reasoning and decision-making processes. Among the various applications within this field, precision agriculture stands out as a technique that monitors crucial factors such as soil moisture, composition, temperature, and humidity. By utilizing AI, precision agriculture determines optimal fertilizer and water requirements for specific crops and different sections of a farm, leading to more efficient resource allocation. Additionally, computer vision and ML techniques play a crucial role in identifying diseases and deficiencies in plants, as well as recognizing weeds [54]. This enables targeted spraying of disease-infected plants or weed-infested areas, eliminating the need to treat the entire field. The integration of AI in agriculture contributes to the development of innovative farming methods capable of increasing crop yields and addressing previously encountered challenges.

However, despite the merits of employing AI in agriculture, several issues need to be considered. Firstly, the implementation of AI techniques necessitates significant computational power, which can contribute to global warming concerns. AI (both in terms of training models and applications) may consume massive amounts of energy and emit greenhouse gases (GHGs) [55]. Following the introduction of DL, specialist hardware for training massive AI models became crucial to research. The increase in hardware efficiency can reduce the energy consumption involved with training larger models [56,57]. However, AI research can have large, severe environmental consequences dependent on where and how energy is generated, stored, and transported. Furthermore, in developing countries, there is a need for improved internet infrastructure to harness AI technologies. The cost associated with utilizing AI is also considerable, and countries must have access to AI experts to use these technologies. The fundamental goal of this review is to investigate how AI approaches might help increase crop yields while overcoming constraints such as global warming, excessive fertiliser use, and limited availability of natural resources, plant diseases, nutrient deficiencies, weeds, and water stress.

4.1 Machine and Deep Learning

There are mainly two subsets of AI namely ML and DL [58]. ML is a branch of AI that enables machines to learn from experiences and make more accurate predictions [59]. It uses multiple algorithms or the same algorithm multiple times to achieve better performance [60]. Through ML, computer programs can improve their performance by learning from problem-specific training data, allowing them to perform tasks such as object detection and natural language translation [61]. With machine learning algorithms, hidden insights and complex patterns can be identified without the need for explicit programming [62]. In order to make reliable and repeatable decisions, ML relies on previous computations and extracts patterns from large databases. AI is deployed using dedicated machines or systems that rely on ML technology. ML entails discovering patterns and characteristics within the machine through direct training using data. Computers learn from specific data provided by humans and conduct assessments and predictions based on the acquired knowledge during the learning process [63].

ML can be categorized into three primary learning methods: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, both the data and corresponding labels (answers) are provided to the learning algorithm. The objective of utilizing algorithms in machine learning is to enable them to acquire knowledge from labeled data and make accurate predictions for unlabelled data. This approach is frequently employed in various tasks, including object recognition, probability estimation, and regression analysis [64]. In contrast, unsupervised learning involves working with unlabelled data to identify inherent patterns, characteristics, and classes using learning algorithms. This type of learning is particularly useful for tasks like clustering, feature extraction, and dimensionality reduction. Lastly, reinforcement learning entails an agent interacting with an environment, perceiving its current state, and selecting actions or action sequences to maximize rewards or compensations based on available behaviours. This type of learning is often employed in fields like robotics and game-playing. Each of these learning methods has its unique applications and it is utilized depending on the specific problem and the available data.

DL is a specialized branch of machine learning that utilizes DCNN or CNNs. Unlike simple neural networks, deep neural networks have multiple hidden layers arranged in nested architectures. They also use advanced neurons and procedures like convolutions or multiple activations in a single neuron. These qualities allow deep neural networks to handle raw input data and automatically identify the representations required for the specific learning task [65]. The main distinction between ML and DL lies in their respective approaches. Research in machine learning typically involves identifying key features from the data using the researcher's experience or domain expertise. These features are extracted using manual or image processing algorithms, and then utilized for subsequent classification or regression analysis [66]. The DL algorithm, on the other hand, automatically extracts features from raw image data and performs classification and regression training without the need for explicit feature engineering.

4.2 Neural Networks Involved in AI

4.2.1 Convolutional Neural Networks (CNNs)

CNNs are a type of deep learning approach specifically designed for processing data with a grid pattern, such as images [67]. A typical CNN consists of three types of layers: convolution, pooling, and fully connected layers (Fig. 3). The convolution and pooling layers perform feature extraction, while the fully connected layer maps the identified features to the final output, such as classification [68]. The convolution layer is a crucial component of CNNs and involves applying mathematical computations, including convolutions, to a 2D grid of pixel values in a digital image. A small grid of parameters, known as a kernel or filter, is applied to each position in the image. This enables efficient and effective processing of images, as features can be detected in any part of the image. In image classification using CNNs, the workflow involves passing the captured images through a series of convolutional, pooling, and fully connected layers. A pre-processing component handles tasks such as resizing, color space transformation, and normalization. Then, segmentation is performed to separate plants from the background, followed by feature extraction, which encompasses extracting essential features related to morphology, spectral properties, visual textures, and spatial contexts [69]. To manage the increased dimensionality resulting from feature extraction, algorithms like Stepwise Linear Discriminant Analysis (SWLDA), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) are employed to select essential feature combinations. CNNs have been observed to outperform other classifiers in image analysis.

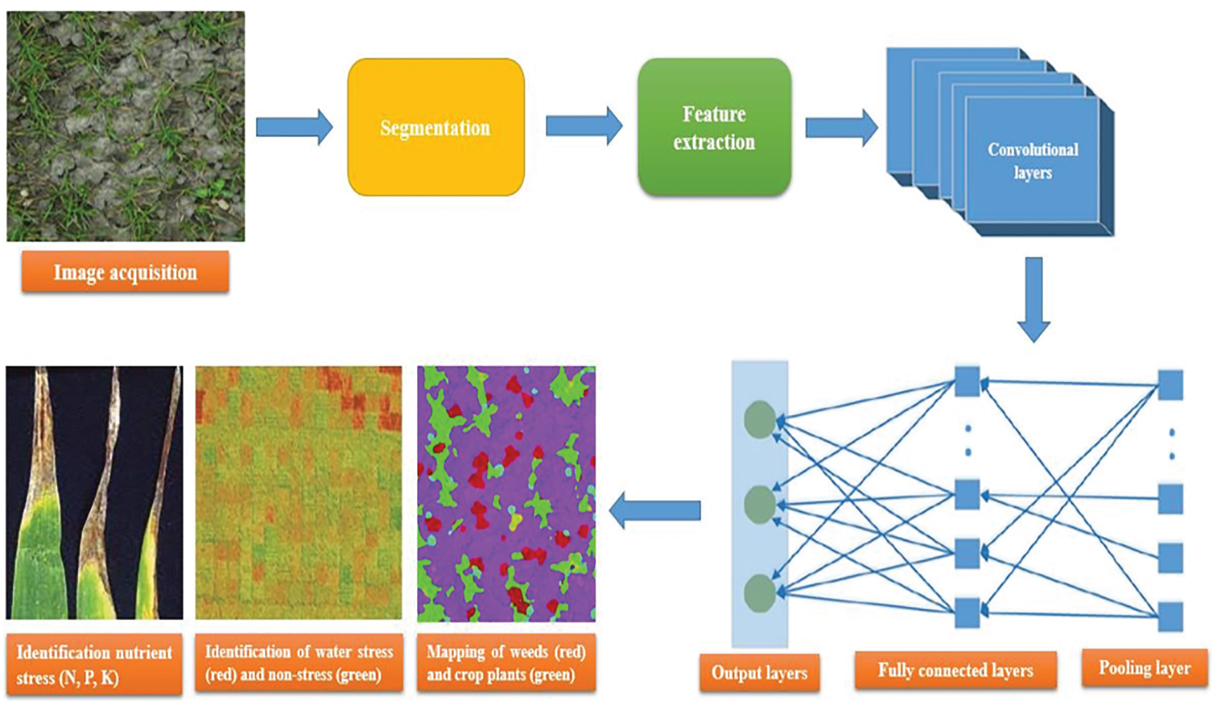

Figure 3: Identification of nutrient, water and weed stress using CNN

The SegNet architecture is a deep convolutional neural network (DCNN) architecture commonly used for segmenting color images. The architecture can strike a balance between computational efficiency and accuracy, outperforming some other DCNN architectures [70]. InceptionV3 is another notable architecture known for its ability to reduce the number of parameters used in calculations. It addresses challenges such as overfitting or underfitting by incorporating a greater number of layers, thereby enhancing the network's non-linear capabilities. ResNets, on the contrary, utilize a residual learning structure to improve error propagation across multiple layers of non-linear transformations. There have been limited research endeavours in utilizing DCNNs for detecting plant nutrient status. Using DL networks, including Inception-ResNetv2 and auto encoders, Tran et al. [71] classified calcium, nitrogen, and potassium deficits in tomato plants using DL networks. Furthermore, Abdalla et al. [72] developed a deep-learning model that categorizes oilseed rape plants into nine classes based on their nutritional status. Anami et al. [73] applied the pre-trained VGG16 CNN model to classify automatically stressed paddy crop images captured during the booting growth stage. The study used 30,000 field images of five different rice crop kinds with 12 different stress levels, including a healthy/normal category. The trained models attained an average accuracy of 92.89%, illustrating the viability of deep learning methods in automating field agriculture and resource management practices. These findings have potential applications in the development of decision support systems and mobile applications for crop management.

However, CNNs can become computationally intensive and require significant hardware resources when dealing with large features and a large number of parameters to learn. This challenge can be mitigated by utilizing pre-trained models, which offer state-of-the-art performance. The convolutional layer is a fundamental component of CNNs, and it plays a vital role in image processing. CNNs consist of kernels that independently perform convolution operations on the input image, resulting in a set of feature maps. Various parameters, including strides, depth, and zero paddings, are used to control the size or volume of the activation map [74]. The stride parameter determines the number of pixels the kernel moves over the input image, directly impacting the output size. The depth parameter signifies the number of kernels utilized for convolution, with each kernel generating a distinct feature map. Additionally, the pooling layer plays a crucial role in CNNs by reducing the spatial size representation of the image, thereby reducing the number of training parameters and computational costs. Additionally, pooling helps prevent overfitting during the training process by retaining essential information while discarding irrelevant details.

4.2.2 Artificial Neural Networks (ANNs)

ANNs are processing algorithms or hardware systems that are designed according to the functioning of the human brain [75]. These exhibit remarkable self-organization and adaptive learning capabilities, reflecting the complexity of the human brain. Electric signals flow through interconnected neural networks in our brains, facilitated by axons and synapses that pass signals between nodes. ANNs are constructed in a layered fashion, taking inspiration from biological neurons, and this architecture enables them to learn complex nonlinear relationships [76].

The architecture of an ANN typically consists of three layers:

1. Input layer
2. Hidden or middle layer
3. Output layer

One of the key advantages of neural networks is their ability to predict and forecast based on parallel reasoning. Instead of being extensively programmed, neural networks are trained through a learning process. Learning involves adapting to changes in the environment, allowing the ANN to adjust itself accordingly.

Crop yield prediction can be achieved through the implementation of an Artificial Neural Network (ANN) system, which consists of three primary modules: the Image Pre-processing Module (IPM), the Crop Disease Diagnosis Module (CDDM), and the Crop Yield Prediction Module (CYPM) [77]. The IPM acquires leaf images from various sources, such as web crawling, drone photography, AI Hub, and ImageNet. These images are subjected to normalization using the Google Vision API and are subsequently resized [78]. The normalized images are then stored on a server for further processing. In order to develop a CNN model, the CDDM uses the normalized images from the IPM. The model is trained using the normalized images obtained from the IPM and is employed for diagnosing crop diseases [79]. The CYPM utilizes an ANN to predict the expected crop yield. It takes into account the diagnosed crop diseases from the CDDM, current weather data obtained from sources like the National Weather Service (including factors such as precipitation and sunshine), and crop status information. The crop status information, which includes details like the crop name, sowing, and harvest dates, and applied fertilizers, is obtained from the farm server.

By integrating these modules and leveraging the power of ANN, the system can effectively predict crop yields based on various factors, enabling informed decision-making in agricultural practices.

5 Results and Discussion

To meet the increasing demand for food and overcome the limitations presented by limited land and labour resources, farmers need innovative solutions to enhance their agricultural output. It is crucial to develop strategies that help farmers reduce and manage risks effectively. Currently, many farmers struggle to control risks and threats to their crops, such as nutrient deficiencies, water scarcity, and weed infestations. These challenges are exacerbated by climate change, monoculture practices, and the widespread use of agrochemicals [80]. To meet our agricultural targets, the industry needs to undergo significant scaling up, and farm efficiency must double.

Chemical fertilizers are the major source of plant nutrients for increasing crop production. In the last 45 years, additional fertilizer applied to the crops has been responsible for the increase in crop productivity. The relationship between fertilizer consumption and cereal production in the world is strongly positive (Fig. 4). This is probably due to the planting of cultivars that have been developed for improved nutrient use efficiency with higher yield potential. In order to meet the growing need for food, fertilizer consumption has been increasing over the years which has led to heavy metal accumulation, water eutrophication, and air pollution which results in issues such as the greenhouse effect [81]. According to a case study on the assessment of greenhouse gas emissions from cotton farms, the total greenhouse gas emissions were 1106.12 kg CO_2 eq ha^{-1}, with diesel fuel (58%) being the leading contributor, followed by irrigation water (23%) and chemical fertilizers (9%) [82]. Crop growth and development can be significantly affected by macronutrient and micronutrient deficiencies [83]. Insufficient availability of critical nutrients such as nitrogen, potassium, calcium, phosphorus, and iron poses a serious difficulty in agriculture. It is crucial to detect and prevent nutrient deficiencies early to optimize crop production. Additionally, plant diseases caused by bacteria, fungi, insects, and viruses are significant factors that contribute to reduced crop yields [84]. Disease-infected crops exhibit symptoms like blight, spots, rots, root rots, dieback, and wilt. Early identification of abnormal crop growth is of utmost importance in agriculture. However, disease diagnosis through visual inspection requires extensive professional expertise and is time-consuming, especially for large farms that necessitate periodic monitoring. Therefore, an alternative method utilizing AI is needed for automated disease identification.

The agriculture sector currently consumes a significant portion, approximately 85%, of the world's available freshwater resources. This percentage is continuously growing due to population expansion and increased food demand. To ensure the efficient utilization of water resources in agriculture, the development of technologies that enhance water usage is necessary [85,86]. Water consumption will increase as the population grows and migration continues in already-stressed urban areas, putting further pressure on total freshwater supplies. Fig. 5 depicts the projected population increase and *per capita* water availability in India until 2050. The data indicate that the *per capita* water availability in 1951 was approximately 1.4 million gallons, which subsequently dropped to 0.6 million gallons in 1991. By 2011, it further declined to around 0.4 million gallons [87]. In the absence of measures to address these future water demands, agricultural, industrial, and domestic water users in India are likely to experience more frequent and severe water shortages.

Weed infestation causes significant yield losses in various crops, as illustrated in Fig. 6. The scarcity of labour and the high costs associated with manual weeding have driven the advancement of automated weed control systems, enabling real-time plant care in the field [88]. In large-scale cultivation, cost-effective and labour-saving techniques are crucial for effectively eliminating weeds from crops. Automatic weeding has emerged as an effective operation to ensure the sustainability of crop production [89]. While herbicides are commonly used for weed control, their excessive application poses risks of poisoning for individuals involved in handling and usage. Furthermore, it contributes to air, water, and soil pollution, with the possibility of residue presence in food [90].

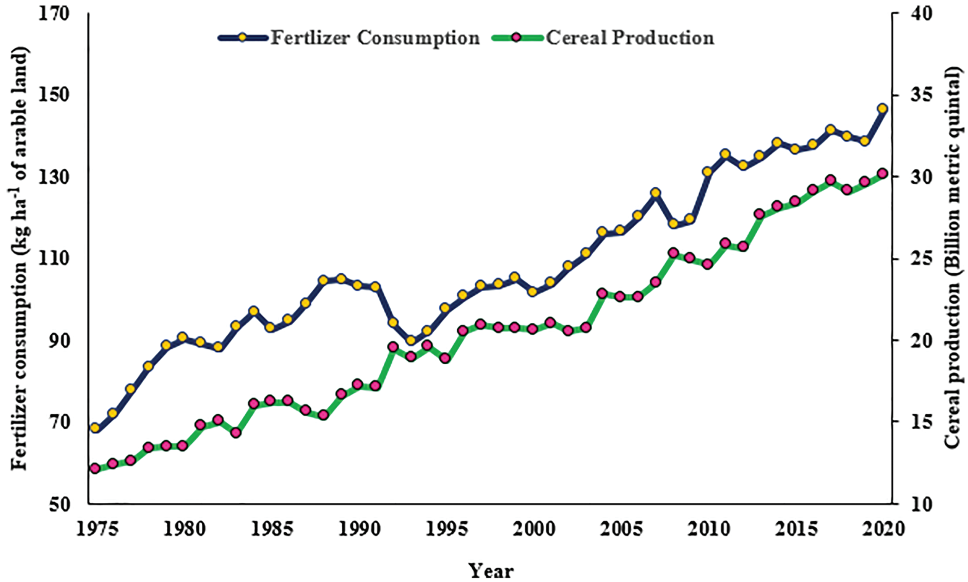

Figure 4: Cereal production and fertilizer consumption over the years. Data sources: data.worldbank.org/indicator/ (accessed on 19/04/2024)

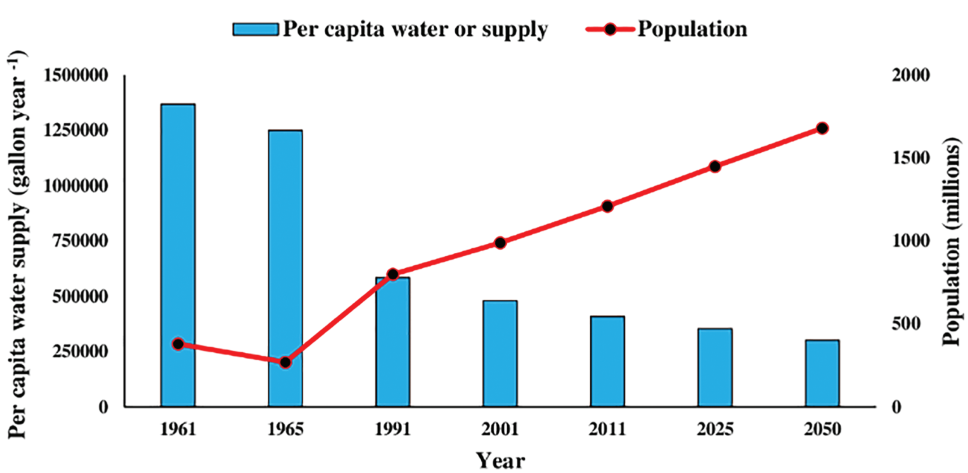

Figure 5: Population and *per capita* water supply per year in India. Data sources: KPMG International 2010; Office of the Registrar General & Census Commissioner, India

Considering the scale of the challenges and the need for agricultural expansion, AI can play a vital role in automating the major aspects of crop production, including nutrient management, water usage optimization, and weed control. By harnessing AI technologies, farmers can enhance their productivity, mitigate risks, and contribute to sustainable and efficient agriculture. Table 1 shows applications of various ML and DL techniques in crop management.

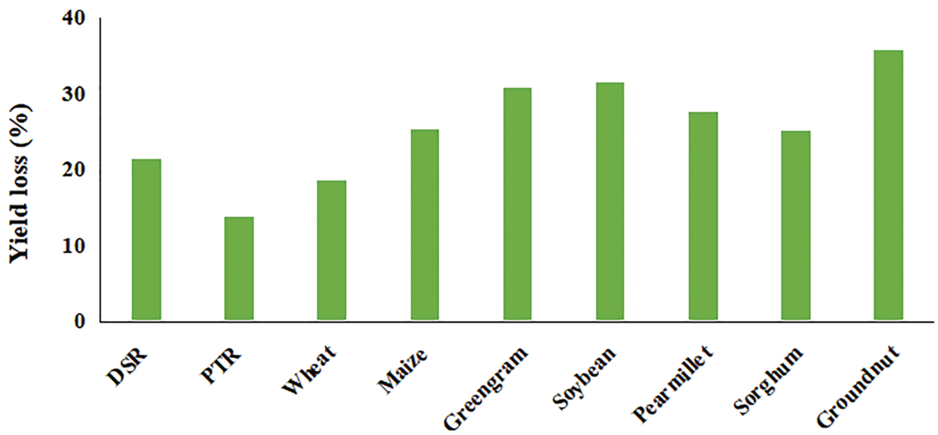

Figure 6: Actual yield losses (%) due to weeds in different crops

Table 1: Applications of various ML and DL techniques in agriculture

Model	Applications	Model performance	References
DQN, CNN	Irrigation scheduling based on weather forecast	When the DQN irrigation approach was compared to the results of the traditional irrigation system, a significant drop in irrigation water volume was noticed	[91]
SVM (Support vector machine)	Nitrogen deficiency detection in rice	Accuracy of the model was 88%	[91]
WeedDet model based on RetinaNet UNET, VGG16 and ResNet50 based SegNet Model	Weed detection in paddy field	WeedDet model has accuracy of 94.1%	[92]
DCNN	Identification and classification of maize drought stress	The accuracy is high in in the proposed model for the identification of stress	[25]
KNN	Boron defieciency detection in corn	Accuracy of the model is 80%	[93]
Mask RCNN	Irrigation system malfunctioning detection	Model perform better with different datasets	[94]
DQN, CNN	Irrigation mode for tomato fields	When compared to the threshold and fixed watering approaches, the DQN agent increases productivity by 11% and reduces wastage of water by 20%–30%	[95]
RF, KNN	Weed recognition in maize field	Accuracy of the model in distinguishing between weed and crop was 81%	[96]

(Continued)

Table 1 (continued)

Model	Applications	Model performance	References
ResNet18, linear iterative clustering	Detection of weeds in spinach and bean fields	An AC of 88.73% for spinach and 94.34% for beans were reached by CNN trained with unsupervised labelling, and an AC of 94.84% for spinach and 95.70% with supervised labelling (bean)	[97]
DS-CNN, ND-CNN	Improved model for rice plant stress detection	ND-CNN performed better than DS-CNN	[98]
AlexNet, GoogLeNet, Inception V3, Xception	Automatic identification of weeds	InceptionV3 outperformed other models	[99]
SVM (Support vector machine)	Weed detection in sugarbeet field	Accuracy of the model was 95%	[100]
CNN	Stress level in sorghum due to nitrogen deficiency	CNN models gives better accuracy and perform better	[101]

5.1 Drone Technology for Crop Management

Drones, also known as unmanned aerial vehicles (UAVs), have become indispensable tools for farmers in addressing various challenges and monitoring their fields [102]. These UAVs assist in observing crop health, detecting nutrient and water stress, and identifying diseases. They utilize a range of sensors including thermal, multispectral, hyperspectral, and RGB sensors. The integration of UAVs-based IoT technology is considered the future of remote sensing in precision agriculture. By flying at low altitudes, UAVs may gather pictures with ultra-high spatial resolution of up to a few centimetres, considerably boosting system performance. Furthermore, UAVs are less costly and easier to operate than manned aircraft, and they are more efficient than ground systems since they can cover large areas in less time and cause less damage. UAVs are now widely used for monitoring crop fields [103]. UAVs are equipped with multiple sensors that enable farmers to identify areas within their crops that require timely action for improvement. UAVs finds extensive applications in precision agriculture [104]. The deployment of multispectral and hyperspectral sensors on drones enables the collection of visible and non-visible wavelengths, such as near-infrared radiation (NIR) and short-wave infrared radiation (SWIR) with wavelengths ranging from 800 to 2500 nm and 1400 to 3000 nm, respectively [105]. These sensors are useful in managing plant health by identifying nutrient deficiencies; weed and drought stress [106].

Additionally, the utilization of drones enables the collection of data for crop cultivation assistance. Subsequently, the acquired data can be analyzed through AI in farming, allowing farmers to make well-informed decisions. Drones equipped with sensors and capable of capturing multispectral photos facilitate crop health monitoring. The assistance of ML algorithms expedites and simplifies the process of data analysis. This integration enhances agricultural output efficiency and concurrently reduces crop loss.

Multispectral and hyperspectral imagery differ in the number and width of bands of light detected by each camera. Multispectral imagery typically refers to around five to ten bands, while hyperspectral imagery can have hundreds of bands. Hyperspectral sensors create images using much narrower bands in the range of 10–20 nm, employing an imaging spectrometer. This broader spectrum coverage makes hyperspectral sensors more sensitive and capable of capturing images in bandwidths that are not possible with multispectral sensors. The reflectance in the SWIR region, combined with reflectance in the visible or near-infrared (NIR) regions, has been found to monitor the status of nitrogen (N), phosphorus (P), sulphur (S), and potassium (K) in plants [107]. New spectral algorithms specifically developed and validated for N, P, S, and K can be utilized for site-specific management in wheat crops [108]. Additionally, drones can be used to observe and assess serious soil degradation, which poses a threat to soil productivity [109]. The introduction of drones in agriculture has revolutionized big-area inspections, smart targeted irrigation, and fertilization [110]. The ability to detect areas requiring significant irrigation or affected by weeds through drone-based infrared cameras helps agronomists save time, conserve water resources, and reduce the use of agrochemicals. Moreover, these advanced farming techniques have the potential to increase crop productivity and improve the overall quality of the produce [111].

AI-powered drones play an important role in assisting farmers with agricultural production and harvesting procedures. The incorporation of predictive analysis shows useful in early problem detection in the field [112]. This enables farmers and organizations to address concerns, reducing the likelihood of substantial crop loss or damage. AI technology has the ability to forecast and detect approaching flood or drought conditions before they occur [113,114]. Furthermore, AI simplifies the analysis of weedicide and pesticide requirements, allowing precise application in the field. The software aids in the timely detection of pest attacks and plant health concerns in real time [115], optimizes soil fertility management [116], and reduces the demand for pesticides and herbicides in specific fields [89]. In the domain of pesticide and weedicide application, AI contributes to the efficiency of spraying operations and crop monitoring. The utilization of drones for chemical spraying not only enhances effectiveness but also reduces human efforts and workforce demands [117].

5.2 Nutrient Stress Management Using AI Technology

AI presents an innovative approach to identifying nutrient deficiencies in plants, particularly through the rapid fluorescence of chlorophyll a. Kalaji et al. [118] conducted a study investigating the impact of deficiencies in certain macro (Ca, S, Mg, K, N, P) and micro (Fe) nutrients on the photosynthetic machinery of hydroponically grown tomato (*Solanum lycopersicum* L.) and maize (*Zea mays* L.) plants. A comparison was done between plants grown in a full nutrient solution (control) and those grown in a medium deficient in either a macro-or microelement. The physiological state of the photosynthetic apparatus *in vivo* was evaluated after 14 days of food shortage using JIP-test parameters generated from rapid chlorophyll fluorescence measurements. Most cases of nutritional insufficiency resulted in a decrease in photochemical efficiency, an increase in non-photochemical dissipation, and a reduction in the number of active photosystem II (PSII) reaction centers. However, individual nutrient deficits have a nutrient-specific influence on photochemical processes. Plants deficient in magnesium and calcium demonstrated a significant decrease in electron donation via the oxygen-evolving complex (OEC). Sulphur deficiency inhibited electron transport beyond PSI, most likely due to a decrease in PSI concentration or the activity of PSI electron acceptors. Conversely, Ca deficiency had an opposite effect, impacting PSII activity more than PSI. While distinct responses to nutrient deficiencies were noted between tomato and maize plants, the study's findings suggest that certain fluorescence parameters could serve as markers for the fluorescence phenotype [119]. The principal component analysis of selected JIP-test parameters was offered as a potential species-specific technique for diagnosing or forecasting nutritional deficiencies using fast chlorophyll fluorescence measurements.

Similarly, Aleksandrov [120] proposed a technique that evaluates the photosynthetic activity of leaves to assess mineral deficiency in nutrient solutions. Chlorophyll fluorescence is analyzed using the Joint Imaging Platform (JIP) test, which provides information regarding the function of photosystems I and II and the overall physiological condition of the photosynthetic apparatus. To detect nutritional deficits in bean plants, the researchers measured fluorescence transients from plants grown in nutrient solutions missing N, P, K, Ca, or Fe. These fluorescence transients served as input data for an artificial neural network trained to identify and forecast N, P, K, Ca, and Fe deficiencies in bean plants. The results indicated the potential of the ANN as a useful tool for recognizing and forecasting nutritional deficiencies in bean plants based on the rapid fluorescence of chlorophyll a [121].

In another study, Waheed et al. [26] utilized an Artificial Neural Network (ANN) to classify ginger plants with nutrient deficiencies, achieving a validation accuracy of 97% when compared to healthy plants. Furthermore, CNN models like MobileNetV2 and VGG16 demonstrated promising results with validation accuracies of 96% and 95%, respectively. The performance of the classification models was assessed using the Receiver Operating Characteristic (ROC) curve, with the ANN exhibiting a faster convergence rate in comparison to other techniques. These findings highlight the potential of the proposed deficiency detection methods to improve ginger yield and their relevance in developing real-time disease detection applications [122]. Kiratiratanapruk et al. [123] conducted a study focusing on the detection and classification of six major rice diseases using pre-trained models, including Faster R-CNN, RetinaNet, YOLOv3, and Mask R-CNN. The testing findings showed that YOLOv3 outperformed the other models for rice leaf disease detection and classification, with a mean average precision (mAP) of 79.19%. Mask R-CNN, Faster R-CNN, and RetinaNet attained accuracy values of 75.92%, 70.96%, and 36.11%, respectively. Furthermore, machine vision combined with DL techniques were evaluated for real-time identification of early blight disease in potatoes by creating a comprehensive database capturing images of healthy and diseased plants under various lighting conditions. Three Convolutional Neural Network (CNN) models, GoogleNet, VGGNet, and EfficientNet, were trained using the PyTorch framework. The CNNs and DL frameworks exhibited accurate classification of early blight disease at different stages [124].

5.3 Irrigation Management Using AI

Drought is a period of abnormally dry weather sufficiently prolonged for the lack of water to cause a serious hydrologic imbalance in the affected area. Unlike short-term natural disasters such as floods, earthquakes, and cyclones, drought can persist for extended periods, necessitating effective monitoring and forecasting using meteorological and remote sensing data for planning and decision-making. The accuracy and efficiency of drought forecasting models or methods are crucial for effective mitigation planning and adaptation strategies [125]. ML has emerged as a valuable tool for more accurate and efficient drought forecasting, contributing to drought disaster risk management [126,127]. To detect water stress in crops like maize, okra, and soybean, several deep-learning models were employed, including AlexNet, GoogLeNet, and InceptionV3. GoogLeNet had the highest accuracy rates at 98.3%, 97.5%, and 94.1% for maize, okra, and soybean, respectively [128].

Drought stress has a significant impact on the growth, development, and production of crops. While traditional machine learning techniques have made progress in detecting and diagnosing drought stress, their reliance on manual feature extraction processes limits their accuracy. To evaluate the accuracy of DCNN, a comparative experiment with standard machine learning on the same dataset was conducted. The overall identification and classification accuracies for drought stress were found to be 98.14% and 95.95%, respectively, for the entire dataset. Even in sub-datasets at the seedling and jointing stages, high accuracies were achieved, with color images outperforming grayscale images [129]. These comparative experiments on the same dataset demonstrate the superiority of DCNN over traditional machine-learning methods. The suggested deep learning-based technique shows potential in recognizing and categorizing drought stress in field maize using digital images [25]. Furthermore, the utilization of UAV imagery enables stress detection. Butte et al. [27] employed the Retina-UNet-Ag deep learning model to analyze aerial images of potato plants. The model achieved an average dice score coefficient (DSC) of 0.723 and

0.756 for healthy and stressed plants, respectively, demonstrating its ability to differentiate between the two in-field images captured by a Parrot Sequoia camera. Other studies have also addressed the localization of crop stress in aerial images using deep learning techniques [130,131].

Thermal imaging of plants has emerged as a non-destructive method for remotely monitoring water status. Melo et al. [132] conducted a study to predict the moisture status of sugarcane crops using thermal images. They employed an ANN model called Inception-ResNet-v2, which combines deep learning with transfer learning techniques to achieve high accuracy in a shorter time and at a lower cost compared to traditional methods [133]. A comparison was made between the recommended model's performance and a human evaluation of the identical set of thermal photos. The results demonstrated that the developed technique outperformed human evaluations and enabled non-destructive classification of water stress in plant thermal images. The deep learning model exhibited superior accuracy in differentiating between different levels of thermal stress, with accuracies of 23%, 17%, and 14% for the available water capacity classes of 25%, 50%, and 100%, respectively [134]. Modelling the hyperspectral response of vegetables is essential for assessing water stress using a non-invasive method. Osco et al. [135] conducted a study on water-stressed lettuce (*Lactuca sativa* L.) using hyperspectral data and ANN. The performance of the ANN technique was evaluated in comparison to other machine learning algorithms. The results revealed that the ANN technique obtained up to 80% accuracy in discriminating water-stressed lettuce from the non-stressed group at the start of the trial. The accuracy gradually increased, reaching 93% at the end of the trial. Absorbance data outperformed reflectance data in terms of water stress modelling [136,137].

Arif et al. [138] created two artificial neural networks (ANNs) to evaluate soil moisture in paddy fields. The first model used minimum, average, and maximum air temperature data to predict evapotranspiration, whereas the second model used solar radiation, precipitation, and air temperature information. These models offered accurate and dependable soil moisture predictions using minimum meteorological data, labour, and time. Furthermore, Behmann et al. [139] claimed that close range hyperspectral imaging can identify stress-related processes non-destructively in their early stages, which are invisible to the naked eye. Their method combines unsupervised and supervised techniques to identify progressive stress buildup in barley (*Hordeum vulgare*) during drought conditions. These fingerprints can appear in both well-watered and drought-stressed plants, but their distribution varies. Ordinal classification using Support Vector Machines (SVM) quantifies and visualizes the distribution of senescence stages, distinguishing between well-watered and drought-stressed plants. Distinctive sets of relevant Vegetation Indices (VIs) are identified for each senescence stage. The method, applied to potted barley plants in greenhouse experiments, detects drought stress up to ten days earlier than NDVI. Additionally, certain VIs exhibit general relevance, while others are stage-specific. The study demonstrates the method's effectiveness in visualizing leaf senescence and its efficiency in the early detection of drought stress.

Hinnell et al. [140] addressed the usage of neuro-drip irrigation systems, which used artificial neural networks (ANNs) to forecast the geographical distribution of subsurface water. The ANNs enabled fast decision-making processes, leading to efficient water management. The combination of precision agriculture and wireless sensor network (WSN) applications represents a promising area of research that can improve crop production, precision irrigation, and cost reduction. WSN systems offer easy deployment, system maintenance, and monitoring, which can contribute to the widespread adoption of precision agriculture.

5.4 AI for Detection and Management of Weed Stress

The presence of weeds poses a significant threat to crop growth as they compete with crops for essential resources and space. Weeds have the potential to reduce crop production and quality by competing for resources [141]. Farmers employ various weed control strategies to mitigate yield reduction. However, current approaches primarily rely on chemical herbicides, leading to the rapid evolution of herbicide-resistant weeds and posing serious environmental risks. Due to manpower constraints, high human weeding expenses, and rising demand for organic food, the development of automated weed control devices for real-time field management has gained attention. Large-scale cultivation necessitates cost-effective and labor-saving solutions for efficient weed management. Automated weeding is an excellent approach for ensuring the sustainability of agricultural production systems. While herbicides are commonly employed for weed control in agriculture, their usage leads to environmental pollution along with risks of poisoning for individuals involved in their application [142,143]. To address the negative impacts mentioned, advancements in spraying technologies have been made to improve efficiency and safety. These advancements incorporate developments in electronics, AI, and automation [144–146]. However, it is important to note that most agrochemicals, including herbicides, are still applied uniformly across fields, regardless of the uneven distribution of pests, pathogens, and weeds. This uniform application leads to the wastage of agrochemicals in areas where there is little or no issue, resulting in increased costs, and risk of crop damage, pest resistance, environmental pollution, and contamination of edible products [147]. Weeds are known to grow quickly and spread over the field, competing with crops for important resources like space, nutrients, sunshine, and water. While herbicides are commonly used in agriculture to suppress weeds, improved sensor-based herbicide spraying can provide a long-term solution to offset the negative effects of indiscriminate herbicide use. Sensor-based spraying is categorized into two categories based on the application place [148] (Table 2). Spraying systems are divided into two categories: "green on brown" (GoB) and "green on green" (GoG). The GoB technique uses spectral information in the near-infrared and visible wavelengths in order to discriminate among green vegetation and soil or agricultural leftovers. The GoG technique employs powerful image algorithms to distinguish between green crops and green weeds, allowing plant species to be classed as crops, grass weeds, broadleaved weeds, and perennial weeds [149].

Table 2: Overview of commercially available spot spraying systems [148]

Product	Company	Technology	Sensors	Herbicide reduction
Robotti	Agrointelli (Aarhus N, Denmark)	Combining deep learning and big data	RTK-GPS, autonomous, Lidar, camera	40%–60%
Bilberry	Bilberry (Gentilly, France)	AI-based weed detection and spot spraying	RGB camera	More than 80%
Weedseeker	Trimble agriculture (Colorado, USA)	Infrared sensors	High-resolution blue LED-spectrometer	60%–90%
Weed-It	Weed-It (CJ Steenderen, Netherlands)	Detection of green vegetation	Blue LED-lighting and spectrometer	95% (only in crop-free areas)
Blue river's see and spray	Blue-river technologies dimensions agri technologies (New York, USA)	CNN-based weed detection in cotton and spot spraying	RGB cameras	Up to 90%

(Continued)

Table 2 (continued)

Product	Company	Technology	Sensors	Herbicide reduction
Smart spraying	BASF, (Mumbai, India) Bosch, (Renningen, Germany)	Camera-based weed coverage measurement and spot spraying	Bi-spectral camera	70%
H-sensor	AgriCon (Jahna, Germany)	AI-based weed detection in cereals and maize	Bi-spectral camera	50%

Using patch spraying or spot spraying techniques, these systems use precise sprayers to target areas with high levels of weed infestations [150]. Patch spraying involves the utilization of georeferenced weed maps to identify regions with significant weed infestations. Herbicides are selectively sprayed in these infested areas, while the boom sprayer is kept off in areas with reduced weed infestations that do not surpass the economic weed threshold. Spot spraying systems, on the other hand, have a narrower field of application and aim to target individual weed plants or smaller weed patches. This approach reduces the number of sprayed areas, allowing for more precise and targeted weed control [151]. Patch and spot spraying both require sensor-controlled spraying systems, which incorporate sensors to detect weeds and crops, expert systems to determine herbicide dosages and weed control requirements, and application systems to apply the herbicides [152]. Patch spraying uses georeferenced weed maps to determine areas for herbicide application based on weed infestation levels, while spot spraying can target even smaller areas for precise weed control. These targeted spraying techniques help minimize herbicide usage and reduce the environmental impact associated with excessive application [153].

Patch spraying and spot spraying are viable options for reducing herbicide usage and enhancing weed control in crops, serving as alternatives to uniform herbicide applications. Patch spraying is typically employed in extensive arable crops like cereals, maize, and soybeans, utilizing large boom sprayers for implementation [154]. Conversely, spot spraying is better suited for high-value crops like vegetables and sugar beets. However, spot spraying may have lower speeds due to the complexity of weed/crop classification using CNNs, but commercial robot systems have successfully implemented spot spraying [155].

The automation of weed sprayers has gained significant interest in recent years [156]. Incorporating computer vision technologies in agricultural operations has been found to reduce operator stress levels. An effective smart sprayer system should be capable of real-time weed spot detection and precise application of chemicals to the intended locations. Various sensors and techniques, including machine vision, spectral analysis, remote sensing and thermal imaging, have been analyzed for weed detection [157]. Machine vision, which enables the differentiation of vegetation from the soil background based on colour differences, has been used for weed detection, but earlier systems were limited in distinguishing between crop plants and weeds [158].

Researchers have developed and evaluated smart sprayer systems capable of distinguishing between weed leaves and crop plants. For example, Lee et al. [159] developed a system that could differentiate between weed leaves and tomato plants, although the processing speeds were slower at that time. Recent advancements in commercial spraying technologies have integrated AI to differentiate between crop plants and various weeds. Examples include the H-Sensor by Agricon GmbH and the See and Spray system by Blue River Technology, both designed for row crops. These precision spray technologies significantly reduce herbicide usage compared to traditional broadcast sprayers that treat the entire field regardless of weed presence [147].

In [160], three distinct deep-learning image-processing methods were employed to estimate weed presence in lettuce crops. These methods were compared to visual estimations made by experts. The first method employed was support vector machines (SVM) with histograms of oriented gradients (HOG) as feature descriptors, while the other or the second method used was YOLOV3 in order to detect objects. The third approach used Mask R-CNN for segmenting individual weeds. To remove non-photosynthetic items, a normalized difference vegetation index (NDVI) was utilized as a background subtraction. For crop detection, both machine learning and deep learning approaches received high F1 scores of 88%, 94%, and 94%, respectively. The observed crops were paired with the NDVI background subtractor to indirectly identify weeds. The coverage percentage of weeds was determined using classical image processing methods, resulting in improved accuracy compared to human-estimated data [161]. Furthermore, a method was created to distinguish weeds from crops using image analysis and neural networks, with an accuracy of more than 75% without prior plant knowledge. Shahzadi et al. [162] created an expert systems-based smart agricultural system that used IoT technology to relay data to a server, allowing implements in the field to make informed decisions. The system used temperature, humidity, leaf wetness, and soil sensors to provide information about the field, but it was not actively involved in processing.

The key weed control time has been identified for a variety of crops, notably annual species, taking into account crop type, cultivar, production system, management approaches, and environmental variables. Numerous research have looked at the interactions between crops, weed communities, and the environment. However, the applicability of these models as decision-making tools is limited due to their low generalization capacity, as they often struggle to interpret scenarios beyond experimental conditions. Complex relationships exist between agricultural systems and weed infestations, but recent advancements in computational development, particularly in machine learning models, have facilitated the understanding of these complex relationships. Machine learning models, such as ANNs, have exhibited the ability to learn and comprehend correlations between dependent and independent variables, enabling pattern detection and prediction under various conditions [163,164]. ANNs have been used effectively in weed research to identify weed species, determine spatial distribution for herbicide administration, and estimate herbicide sorption and desorption in agricultural soils [165]. ANNs offer great prediction accuracy for novel instances, but they must be thoroughly trained and evaluated to guarantee generalizability during validation and testing. The selection of appropriate inputs is crucial for generating high-performance models, which can be challenging when studying the weed control period due to the numerous variables influencing weed-crop competition [166,167]. Table 3 shows the identification of weed patches by different types of multispectral, RGB, and hyperspectral cameras.

Table 3: Weed patches identification by different types of camera (multispectral, RGB, hyperspectral)

Crop	Weed (Scientifc name)	Type of camera	Application	References
Beta vulgaris	*Cirsium arvense*	Multispectral camera	Discriminate crop *vs.* weeds	[168]
Glycine max	*Echinochloa crusgalli*	Multispectral camera	Assessment of crop injury from dicamba	[169]
Hordeum vulgare	*Cirsium arvense*	RGB camera	Discriminate crop *vs.* weeds	[170]

(Continued)

Table 3 (continued)

Crop	Weed (Scientifc name)	Type of camera	Application	References
Sorghum spp.	*Portulaca oleracea*	Hyperspectral camera	Discriminate crop *vs.* weeds	[171]
Zea mays	*Sorghum halepense*	Multispectral camera	Discriminate crop *vs.* weeds	[172]
Triticum aestivum	*Alopecurus myosuroides*	RGB and multispectral camera	Discriminate crop *vs.* weeds	[173]
Zea mays	*Echinochloa crusgalli* and *Abutilon theophrasti*	RGB and multispectral camera	Evaluation of resistant weeds	[174]

The imperative task of weed monitoring and control in agriculture is underscored by Wakchaure et al. [175]. In the context of precision farming, Cho et al. [176], and Dorrer et al. [177] have harnessed standalone ANN for vision intelligence. However, the existing classification system encounters limitations, notably its need for individual testing in each operational field. Addressing this challenge, Hall et al. [178] have proposed a classification model incorporating low-dimensional features, utilizing DCNN algorithms for data collection. Their application on cotton plants via a mobile platform successfully delineated cotton and weeds.

6 Limitations

Although AI improves the agriculture industry in many remarkable ways, there are many concerns regarding the application of AI in agriculture sector. Agriculture employs over 1.5 billion people, which is 20% of the world's population and there are predictions of there being millions of unemployed field workers in the next decades primarily due to the impact of AI in the agriculture industry [17,179]. On the other hand, AI algorithms require large and diverse datasets for effective training. In agriculture, obtaining such datasets can be challenging due to factors like limited historical data, variability in farming practices, and differences in environmental conditions. Agriculture practices vary widely across regions and even within the same region. The lack of standardization in data collection methods, equipment, and farming techniques can make it difficult to develop universal AI solutions that work seamlessly across different agricultural contexts. In many rural areas, where agriculture is a primary industry, there may be inadequate infrastructure and poor internet connectivity [53,180]. This can impede the deployment and operation of AI technologies that rely on real-time data transmission and cloud computing. Furthermore, the initial cost of implementing AI technologies in agriculture, including the purchase of advanced equipment and systems, can be high. This may limit the adoption of AI solutions, especially for small-scale farmers with limited financial resources. Moreover, farmers and agricultural workers may lack the necessary skills and knowledge to use effectively AI technologies. Hence, training programs and educational initiatives are essential to bridge this gap and ensure that end-users can leverage the full potential of AI technologies.

7 Future Research Direction

AI has the potential to revolutionize farming practices by providing solutions for pest control, weather prediction, and other agricultural tasks. In the future, AI will enable farmers to become agricultural scientists by utilizing data to optimize yields. AI companies are developing robots that can perform various tasks in the field, addressing the challenges encountered by agricultural labour. The rapid advancement of AI techniques led to their use in concurrently recognizing different weeds using computational networks such as convolutional neural networks (CNN) and recurrent neural networks (RNN).

AI-equipped drones surveil the farm, providing ongoing real-time field data. This allows farmers to identify areas with insufficient water and selectively start irrigation, hence avoiding flooding or scarcity. In order to ensure a consistent water supply to crops, these measures contribute to optimal crop growth. Various integrated AI approaches will be employed to create a conducive environment for crops, ultimately enhancing overall crop growth. However, for AI to have a widespread impact in agriculture, it is crucial to focus on providing universal access. Currently, advanced technology is predominantly accessible to large, well-connected farms. Ensuring connectivity and extending the reach of AI to small farms in remote regions worldwide is essential for the future of AI-driven automated agriculture.

8 Conclusion

This study reviews the existing literature on the implementation of AI technologies in agriculture by assessing various research findings. The integration of artificial AI in nutrient, weed, and water management within the agricultural domain marks a significant advancement in precision farming practices. The reviewed literature underscores the efficacy of AI-driven solutions in optimizing resource allocation, enhancing crop yield, and mitigating environmental impact. As evidenced by the diverse applications discussed, ranging from machine learning algorithms for crop deficiency detection to autonomous systems for precision irrigation and weed management, AI demonstrates its versatility in addressing complex challenges across agricultural sectors. While acknowledging the promising outcomes, it is imperative to emphasize the need for continued research, technological refinement, and widespread adoption to harness fully the potential benefits of AI in agriculture. This review underscores the transformative role of AI in shaping the future of smart farming, offering not only increased input use efficiency but also contributing to the overarching sustainable development goals to maintain global food security.

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References

1. FAO. The State of Food and Agriculture 2021. Making agrifood systems more resilient to shocks and stresses. Rome FAO; 2021.

2. Maitra S, Sahoo U, Sairam M, Gitari H, Rezaei-Chiyaneh E, Battaglia L, et al. Cultivating sustainability: a comprehensive review on intercropping in a changing climate. Res Crops. 2023;24:702–15.
3. Balogun AL, Adebisi N, Abubakar IR, Dano UL, Tella A. Digitalization for transformative urbanization, climate change adaptation, and sustainable farming in Africa: trend, opportunities, and challenges. J Integ Environ Sci. 2022;19(1):17–37. doi:10.1080/1943815X.2022.2033791.
4. Habib-ur-Rahman M, Ahmad A, Raza A, Hasnain MU, Alharby HF, Alzahrani YM, et al. Impact of climate change on agricultural production; Issues, challenges, and opportunities in Asia. Front Plant Sci. 2022;13:925548. doi:10.3389/fpls.2022.925548.
5. Benedetti I, Branca G, Zucaro R. Evaluating input use efficiency in agriculture through a stochastic frontier production: an application on a case study in Apulia (Italy). J Clean Prod. 2019;236:117609. doi:10.1016/j.jclepro.2019.117609.
6. Aryal JP, Sapkota TB, Khurana R, Khatri-Chhetri A, Jat ML. Climate change and agriculture in South Asia: adaptation options in smallholder production systems. Environ Dev Sustain. 2019;20:1–31.
7. Ahmad S, Abbas G, Ahmed M, Fatima Z, Anjum MA, Rasul G, et al. Climate warming and management impact on the change of phenology of the rice-wheat cropping system in Punjab, Pakistan. Field Crops Res. 2019;230:46–61. doi:10.1016/j.fcr.2018.10.008.
8. Majeed Y, Fiaz S, Teng W, Rasheed A, Gillani SFA, Zhu X, et al. Evaluation of twenty genotypes of wheat (*Triticum aestivum* L.) grown grown under heat stress during germination stage. Not Bot Horti Agrobot Cluj Napo. 2023;51(2):13207. doi:10.15835/nbha51213207.
9. Ochieng' IO, Ranjani S, Seleiman MF, Padhan SR, Psiwa R, Sow S, et al. Increasing rainwater use efficiency, gross return, and grain protein of rain-fed maize under nitrate and urea nitrogen forms. Not Bot Horti Agrobot Cluj Napo. 2023;51(3):13293. doi:10.15835/nbha51313293.
10. Mosier S, Córdova SC, Robertson GP. Restoring soil fertility on degraded lands to meet food, fuel, and climate security needs via perennialization. Frontier Sustain Food Syst. 2021;5:706142. doi:10.3389/fsufs.2021.706142.
11. Aleminew A, Alemayehu M. Soil fertility depletion and its management options under crop production perspectives in Ethiopia: a review. Agric Rev. 2020;41(2):91–105.
12. Muchai SWK, Mucheru-Muna MW, Ngetich FK, Gitari HI, Nungula EZ, Baaru M. Interactive effects of zai pits and conventional practices with soil amendments on soil physico-chemical properties. Int J Biores Sci. 2023;10(2):173–83.
13. Nungula EZ, Mugwe J, Nasar J, Massawe HJ, Karuma AN, Maitra S, et al. Land degradation unmasked as the key constraint in sunflower (*Helianthus annus*) production: role of GIS in revitalizing this vital sector. Cog Food Agric. 2023;9(2):2267863. doi:10.1080/23311932.2023.2267863.
14. Mugo NJ, Karanja NN, Gachene CK, Dittert K, Gitari HI, Schulte-Geldermann E. Response of potato crop to selected nutrients in central and eastern highlands of Kenya. Cog Food Agric. 2021;7:1898762. doi:10.1080/23311932.2021.1898762.
15. Ashoka N, Harshavardhan M, Hongal S, Meti S, Raju R, Patil GI, et al. Farmers' acuity on climate change in the central dry zone of Karnataka. Indian J Ext Educ. 2022;58(3):136–41. doi:10.48165/ijee.
16. Heydarzadeh S, Arena C, Vitale E, Rahimi A, Mirzapour M, Nasar J, et al. Impact of different fertilizer sources under supplemental irrigation and rain-fed conditions on eco-physiological responses and yield characteristics of dragon's head (*Lallemantia iberica*). Plants. 2023;12(8):1693. doi:10.3390/plants12081693.
17. Lowenberg-DeBoer J, Behrendt K, Ehlers M, Dillon C, Gabriel A, Huang I, et al. Lessons to be learned in adoption of autonomous equipment for field crops. Appl Econ Perspect Pol. 2020;44(2):848–64.
18. Xu Y, Liu X, Cao X, Huang C, Liu E, Qian S, et al. Artificial intelligence: a powerful paradigm for scientific research. The Innov. 2021;2(4):100179.
19. Baweja HS, Parhar T, Mirbod O, Nuske S. StalkNet: a deep learning pipeline for high-throughput measurement of plant stalk count and stalk width. In: Field and service robotics. Springer; 2018. p. 271–84.
20. Debnath O, Saha HN. An IoT-based intelligent farming using CNN for early disease detection in rice paddy. Microprocess Microsyst. 2022;94:104631. doi:10.1016/j.micpro.2022.104631.

21. Dyrmann M, Karstoft, Midtiby HS. Plant species classification using deep convolutional neural network. Biosyst Eng. 2016;151:72–80. doi:10.1016/j.biosystemseng.2016.08.024.
22. Taha MF, Abdalla A, ElMasry G, Gouda M, Zhou L, Zhao N, et al. Using deep convolutional neural network for image-based diagnosis of nutrient deficiencies in plants grown in aquaponics. Chemosens. 2022;10(2):45. doi:10.3390/chemosensors10020045.
23. Gupta A, Kaur L, Kaur G. Drought stress detection technique for wheat crop using machine learning. PeerJ Comput Sci. 2023;9:e1268. doi:10.7717/peerj-cs.1268.
24. Abdourahamane ZS, Acar R. Fuzzy rule-based forecast of meteorological drought in western Niger. Theor Appl Climatol. 2019;135(1–2):157–68.
25. An J, Li W, Li M, Cui S, Yue H. Identification and classification of maize drought stress using deep convolutional neural network. Symmetry. 2019;11(2):256. doi:10.3390/sym11020256.
26. Waheed H, Zafar N, Akram W, Manzoor A, Gani A, Islam SU. Deep learning based disease, pest pattern and nutritional deficiency detection system for “Zingiberaceae” crop. Agriculture. 2022;12(6):742. doi:10.3390/agriculture12060742.
27. Butte S, Vanski A, Duellman K, Wang H, Mirkouei A. Potato crop stress identification in aerial images using deep learning-based object detection. Agron J. 2021;113(5):3991–4002. doi:10.1002/agj2.v113.5.
28. Su WH. Advanced machine learning in point spectroscopy, RGB-and hyperspectral-imaging for automatic discriminations of crops and weeds: a review. Smart Cit. 2020;3(3):767–92. doi:10.3390/smartcities3030039.
29. Charles GW, Sindel BM, Cowie AL, Knox OG. Determining the critical period for grass control in high-yielding cotton using Japanese millet as a mimic weed. Weed Technol. 2020;34(2):292–300. doi:10.1017/wet.2019.113.
30. Vijayakumar V, Ampatzidis Y, Schueller JK, Burks T. Smart spraying technologies for precision weed management: a review. Smart Agric Technol. 2023;6:100337. doi:10.1016/j.atech.2023.100337.
31. Olsen A, Konovalov DA, Philippa R, Wood P, Johns JJ, Banks W, et al. Deep weeds: a multiclass weed species image dataset for deep learning. Sci Rep. 2019;9:1–12.
32. Zhang J. Research on digital image processing and recognition technology of weeds in maize seedling stage based on artificial intelligence. J Phy Conf Ser. 2020;1648(4):42058. doi:10.1088/1742-6596/1648/4/042058.
33. Dhanaraju M, Chenniappan P, Ramalingam K, Pazhanivelan S, Kaliaperumal R. Smart farming: internet of things (IoT)-based sustainable agriculture. Agriculture. 2022;12(10):1745. doi:10.3390/agriculture12101745.
34. González-Calatayud V, Prendes-Espinosa P, Roig-Vila R. Artificial intelligence for student assessment: a systematic review. Appl Sci. 2021;11(12):5467. doi:10.3390/app11125467.
35. Linaza MT, Posada J, Bund J, Eiser P, Quartulli M, Döllner J, et al. Data-driven artificial intelligence applications for sustainable precision agriculture. Agronomy. 2021;11(6):1227. doi:10.3390/agronomy11061227.
36. Abubakar IR, Ain YA. The prospects and challenges of developing more inclusive, safe, resilient and sustainable cities in Nigeria. Land Use Pol. 2019;87:104105. doi:10.1016/j.landusepol.2019.104105.
37. Padhy S, Alowaidi M, Dash S, Alshehri M, Malla PP, Routray S, et al. AgriSecure: a fog computing-based security framework for Agriculture 4.0 via blockchain. Processes. 2023;11(3):757. doi:10.3390/pr11030757.
38. Hemathilake DMKS, Gunathilake DMCC. Agricultural productivity and food supply to meet increased demands. In: Bhat R, editor. Future foods. Academic Press; 2022. p. 539–53.
39. Yang X, Shu L, Chen J, Ferrag MA, Wu J, Nurellari E, et al. A survey on smart agriculture: development modes, technologies, and security and privacy challenges. IEEE/CAA J Aut Sin. 2021;8(2):273–302. doi:10.1109/JAS.6570654.
40. Sahoo S, Seleiman MF, Roy DK, Ranjan S, Sow S, Jat RK, et al. Conservation agriculture and weed management effects on weed community and crop productivity of a rice-maize rotation. Heliyon. 2024;10(10):e31554. doi:10.1016/j.heliyon.2024.e31554.
41. Javaid M, Haleem A, Khan IH, Suman R. Understanding the potential applications of artificial intelligence in agriculture sector. Adv Agrochem. 2022;2(1):15–30.

42. Nungula EZ, Mugwe J, Massawe BHJ, Seleiman MF, Ali N, Gitari HI. GIS-AHP based approach in land evaluation and suitability assessment for sunflower (*Helianthus annus*) production. Cogent Food Agric. 2024;10(1):2309831. doi:10.1080/23311932.2024.2309831.
43. Nungula EZ, Massawe BJ, Chappa LR, Nhunda DM, Seleiman MF, Gitari HI. Multicriteria land suitability assessment for cassava and bean production using integration of GIS and AHP. Cogent Food Agric. 2024;10(1):2333316. doi:10.1080/23311932.2024.2333316.
44. Abbas A, Mushtaq Z, Ikram A, Yousaf K, Zhao C. Assessing the factors of economic and environmental inefficiency of sunflower production in Pakistan: an epsilon-based measure model. Front Environ Sci. 2023;11:1186328. doi:10.3389/fenvs.2023.1186328.
45. Akhter R, Sofi SA. Precision agriculture using IoT data analytics and machine learning. J King Saud Univ Comput Infor Sci. 2022;34(8):5602–18.
46. Durai SKS, Shamili MD. Smart farming using machine learning and deep learning techniques. Decis Anal. 2022;3:100041.
47. Sisinni E, Saifullah A, Han S, Jennehag U, Gidlund M. Industrial internet of things: challenges, opportunities, and directions. IEEE Trans Ind Inf. 2018;14:4724–34. doi:10.1109/TII.2018.2852491.
48. Siemens G, Marmolejo-Ramos F, Gabriel F, Medeiros K, Marrone R, Joksimovic S, et al. Human and artificial cognition. Comput Educ: Artif Intell. 2022;3:100107.
49. Fan J, Fang L, Wu J, Guo Y, Dai Q. From brain science to artificial intelligence. Eng. 2020;6(3):248–52. doi:10.1016/j.eng.2019.11.012.
50. Khanna A, Kaur S. Evolution of internet of things (IoT) and its significant impact in the field of precision agriculture. Comput Elect Agric. 2019;157:218–31. doi:10.1016/j.compag.2018.12.039.
51. Sharma N, Sharma R, Jindal N. Machine learning and deep learning applications—A vision. Glob Trans Proc. 2021;2(1):24–8. doi:10.1016/j.gltp.2021.01.004.
52. Ferentinos KP. Deep learning models for plant disease detection and diagnosis. Comput Elect Agric. 2018;145:311–8. doi:10.1016/j.compag.2018.01.009.
53. Talaviya T, Shah D, Patel N, Yagnik H, Shah M. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artif Intell Agric. 2020;4:58–73. doi:10.1016/j.aiia.2020.04.002.
54. Dhanya VG, Subeesh A, Kushwaha NL, Vishwakarma DK, Kumar TN, Ritika G, et al. Deep learning based computer vision approaches for smart agricultural applications. Artif Intell Agric. 2022;6:211–29. doi:10.1016/j.aiia.2022.09.007.
55. García-Martín E, Rodrigues CF, Riley G, Grahn H. Estimation of energy consumption in machine learning. J Parallel Distrib Comput. 2019;134:75–88. doi:10.1016/j.jpdc.2019.07.007.
56. Cao F, Liu C, Li D, Qian Y, Zhang C, Zhang H. Local and global feature adaptive adjustment network for remote sensing image scene classification. In: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); 2024; Seoul, Republic of Korea. p. 5580–4.
57. Wheeldon A, Shafik R, Rahman T, Lei J, Yakovlev A, Granmo OC. Learning automata based energy-efficient AI hardware design for IoT applications. Math Phy Eng Sci. 2020;378:20190593.
58. Aceto G, Persico V, Pescapé A. A survey on information and communication technologies for Industry 4.0: state-of-the-art, taxonomies, perspectives, and challenges. IEEE Commun Surv. 2019;21(4).
59. Soori M, Arezoo B, Dastres R. Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cogn Rob. 2023;3:54–70:3467–501.
60. Uddin S, Ong S, Lu H. Machine learning in project analytics: a data-driven framework and case study. Sci Rep. 2022;12:15252. doi:10.1038/s41598-022-19728-x.
61. Sreekanth M, Hakeem AH, Peer QJA, Rashid I, Farooq F. Adoption of recommended package of practices by rice growers in district baramulla. J Appl Nat Sci. 2019;11:188–92. doi:10.31018/jans.v11i1.1748.
62. Jani K, Chaudhuri M, Patel H, Shah M. Machine learning in films: an approach towards automation in film censoring. J Data Inf Manage. 2019;2:55–64. doi:10.1007/s42488-019-00016-9.

63. Parekh V, Shah D, Shah M. Fatigue detection using artificial intelligence framework. Augment Hum Res. 2020;5:5. doi:10.1007/s41133-019-0023-4.
64. Grinblat GL, Uzal LC, Larese MG, Granitto PM. Deep learning for plant identification using vein morphological patterns. Comput Elect Agric. 2016;127:418–24. doi:10.1016/j.compag.2016.07.003.
65. Filippi P, Jones EJ, Wimalathunge NS, Somarathna PDSN, Pozza LE, Ugbaje SU, et al. An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning. Prec Agric. 2019;20(5):1015–29. doi:10.1007/s11119-018-09628-4.
66. Dadashzadeh M, Abbaspour-Gilandeh Y, Mesri-Gundoshmian T, Sabzi S, Hernández-Hernández JL, Hernández-Hernández M, et al. Weed classification for site-specific weed management using an automated stereo computer-vision machine-learning system in rice fields. Plants. 2020;9(5):559. doi:10.3390/plants9050559.
67. Asad MH, Bais A. Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network. Inf Process Agric. 2020;7(4):535–45.
68. Bajwa AA, Mahajan G, Chauhan BS. Nonconventional weed management strategies for modern agriculture. Weed Sci. 2015;63:723–47. doi:10.1614/WS-D-15-00064.1.
69. Lezoche M, Hernandez JE, Díaz MDMEA, Panetto H, Kacprzyk J. Agri-food 4.0: a survey of the supply chains and technologies for the future agriculture. Comput Ind. 2020;117(3):103187.
70. Badrinarayanan V, Kendall A, Cipolla R. Segnet: a deep convolutional encoder-decoder architecture for image segmentation. IEEE Trans Pat Anal Machine Intell. 2017;39:2481–95. doi:10.1109/TPAMI.34.
71. Tran TT, Choi J, Le TTH, Kim JW. A comparative study of deep CNN in forecasting and classifying the macronutrient deficiencies on development of tomato plant. Appl Sci. 2019;9(8):1601. doi:10.3390/app9081601.
72. Abdalla A, Cen H, Wan L, Mehmood K, He Y. Nutrient status diagnosis of infield oilseed rape via deep learning-enabled dynamic model. IEEE Trans Ind Inf. 2021;17:4379–89. doi:10.1109/TII.9424.
73. Anami BS, Malvade NN, Palaiah S. Deep learning approach for recognition and classification of yield affecting paddy crop stresses using field images. Artif Intell Agric. 2020;4:12–20.
74. Noon SK, Amjad M, Qureshi MA, Mannan A. Use of deep learning techniques for identification of plant leaf stresses: aa review. Sustain Comput: Inf Sys. 2020;28:100443.
75. Shah K, Patel H, Sanghvi D, Shah M. A comparative analysis of logistic regression, random forest and KNN models for the text classification. Augment Hum Res. 2020;5:12. doi:10.1007/s41133-020-00032-0.
76. Abdipour M, Younessi-Hmazekhanlu M, RezaRamazani SH, Omidi AH. Artificial neural networks and multiple linear regression as potential methods for modeling seed yield of safflower (*Carthamus tinctorius* L.). Ind Crops Prod. 2019;127:185–94. doi:10.1016/j.indcrop.2018.10.050.
77. Jeong YN, Son S, Lee SS, Lee BK. A total crop-diagnosis platform based on deep learning models in a natural nutrient environment. Appl Sci. 2018;8(10):1992. doi:10.3390/app8101992.
78. Alves DP, Tomaz RS, Laurindo BS, Laurindo RDS, Silva FFE, Cruz CD, et al. Artificial neural network for prediction of the area under the disease progress curve of tomato late blight. Sci Agric. 2017;74:51–9. doi:10.1590/1678-992x-2015-0309.
79. Barbedo JGA. Plant disease identification from individual lesions and spots using deep learning. Biosys Eng. 2019;180:96–107. doi:10.1016/j.biosystemseng.2019.02.002.
80. Cowls J, Tsamados A, Taddeo M, Floridi L. The AI gambit: leveraging artificial intelligence to combat climate change-opportunities, challenges, and recommendations. AI Soc. 2023;38:283–307. doi:10.1007/s00146-021-01294-x.
81. Sairaam M, Maitra S, Praharaj S, Nath S, Shankar T, Sahoo U, et al. An insight into the consequences of emerging contaminants in soil and water and plant responses. In: Aftab T, editor. Emerging contaminants and plants. Cham: Springer; 2023.
82. Abbas A, Zhao C, Waseem M, Ahmed K, Ahmad R. Analysis of energy input-output of farms and assessment of greenhouse gas emissions: a case study of cotton growers. Front Environ Sci. 2022;9:826838. doi:10.3389/fenvs.2021.826838.

83. Nasar J, Khan W, Khan MZ, Gitari HI, Gbolayori JF, Moussa AA, et al. Photosynthetic activities and photosynthetic nitrogen use efficiency of maize crop under different planting patterns and nitrogen fertilization. J Soil Sci Plant Nut. 2021;21:2274–84. doi:10.1007/s42729-021-00520-1.
84. Kabir M, Ekici S. Energy-agriculture nexus: exploring the future of artificial intelligence applications. Energy Nex. 2024;13:100263. doi:10.1016/j.nexus.2023.100263.
85. Chauhan U, Sharma D, Saleem S, Kumar M, Singh SP. Artificial intelligence-based sustainable agricultural practices. In: Artificial intelligence applications in agriculture and food quality improvement. IGI Global; 2022. p. 1–16.
86. Gitari HI, Gachene CKK, Karanja NN, Kamau S, Nyawade S, Sharma K, et al. Optimizing yield and economic returns of rain-fed potato (*Solanum tuberosum* L.) through water conservation under potato-legume intercropping systems. Agric Water Manage. 2018;208:59–66. doi:10.1016/j.agwat.2018.06.005.
87. Chakraborti R, Kaur J, Kaur H. Water shortage challenges and a way forward in India. Am Water Works Ass. 2019;111:42–9. doi:10.1002/awwa.v111.5.
88. Elstone L, How KY, Brodie S, Ghazali MZ, Heath WP, Grieve B. High speed crop and weed identification in lettuce fields for precision weeding. Sensors. 2020;20(2):455. doi:10.3390/s20020455.
89. Alhammad BA, Roy DK, Ranjan S, Padhan SR, Sow S, Nath D, et al. Conservation tillage and weed management influencing weed dynamics, crop performance, soil properties, and profitability in rice-wheat-greengram system in Eastern Indo-Gangetic Plains. Agron. 2023;13(7):1953. doi:10.3390/agronomy13071953.
90. Partel V, Costa L, Ampatzidis Y. Smart tree crop sprayer utilizing sensor fusion and artificial intelligence. Comput Elect Agric. 2021;191:106556. doi:10.1016/j.compag.2021.106556.
91. Chen M, Yuanlai CY, Wang X, Xie H, Liu F, Luo T, et al. A reinforcement learning approach to irrigation decision-making for rice using weather forecasts. Agric Water Manage. 2021;250:106838. doi:10.1016/j.agwat.2021.106838.
92. Peng H, Li Z, Zhou Z, Shao Y. Weed detection in paddy field using an improved RetinaNet network. Comput Elect Agric. 2022;199:107179. doi:10.1016/j.compag.2022.107179.
93. Luz PHC, Marin MA, Devechio FFS, Romualdo LM, Zuñiga AMG, Oliveira MWS, et al. Boron deficiency precisely identified on growth stage V4 of maize crop using texture image analysis. Comm Soil Sci Plant Anal. 2018;49(2):159–69. doi:10.1080/00103624.2017.1421644.
94. Albuquerque CKG, Polimante S, Torre-Neto A, Prati RC. Water spray detection for smart irrigation systems with Mask R-CNN and UAV footage. In: 2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor); 2020; Trento, Italy. p. 236–40.
95. Nyawade S, Gitari HI, Karanja NN, Gachene CKK, Schulte-Geldermann E, Parker M. Yield and evapotranspiration characteristics of potato-legume intercropping simulated using a dual coefficient approach in a tropical highland. Field Crops Res. 2021;274:108327. doi:10.1016/j.fcr.2021.108327.
96. Gao J, Nuyttens D, Lootens P, He Y, Pieters JG. Recognising weeds in a maize crop using a random forest machine-learningalgorithm and near-infrared snapshot mosaic hyperspectral imagery. Biosys Eng. 2018;170:39–50. doi:10.1016/j.biosystemseng.2018.03.006.
97. Dian BM, Hafiane A, Canals R. Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. Rem Sens. 2018;10(11):1–22.
98. Zhu Y, Abdalla A, Tang Z, Cen H. Improving rice nitrogen stress diagnosis by denoising strips in hyperspectral images via deep learning improving rice nitrogen stress diagnosis by denoising strips in hyperspectral images via deep learning. Biosys Eng. 2022;219:165–76. doi:10.1016/j.biosystemseng.2022.05.001.
99. Subeesh A, Bhole S, Singh K, Chandel NS, Rajwade YA, Rao KVR, et al. Deep convolutional neural network models for weed detection in polyhouse grown bell peppers. Artif Intell Agric. 2022;6:47–54. doi:10.1016/j.aiia.2022.01.002.
100. Bakhshipour A, Jafari A. Evaluation of support vector machine and artificial neural networks in weed detection using shape features. Comput Elect Agric. 2018;145:153–60. doi:10.1016/j.compag.2017.12.032.
101. Azimi S, Kaur T, Gandhi TK. A deep learning approach to measure stress level in plants due to nitrogen deficiency. Measurement. 2020;173(15):108650. doi:10.1016/j.measurement.2020.108650.

102. Tsouros DC, Bibi S, Sarigiannidis PG. A review on UAV-based applications for precision agriculture. Information. 2019;10(11):349. doi:10.3390/info10110349.

103. Zhang L, Niu Y, Zhang H, Han W, Li G, Tang J, et al. Maize canopy temperature extracted from UAV thermal and RGB imagery and its application in water stress monitoring. Front Plant Sci. 2019;10:1270. doi:10.3389/fpls.2019.01270.

104. de Castro AI, Shi Y, Maja JM, Peña JM. UAVs for vegetation monitoring: overview and recent scientific contributions. Rem Sens. 2021;13(11):2139. doi:10.3390/rs13112139.

105. Awais M, Li W, Cheema MJM, Hussain S, AlGarni TS, Liu C, et al. Remotely sensed identification of canopy characteristics using UAV-based imagery under unstable environmental conditions. Environ Technol Innov. 2021;22:101465. doi:10.1016/j.eti.2021.101465.

106. Andriolo U, Gonçalves G, Bessa F, Sobral P. Mapping marine litter on coastal dunes with unmanned aerial systems: a showcase on the Atlantic Coast. Sci Total Environ. 2020;736:139632. doi:10.1016/j.scitotenv.2020.139632.

107. Castaldi F, Castrignanò A, Casa R. A data fusion and spatial data analysis approach for the estimation of wheat grain nitrogen uptake from satellite data. Int J Rem Sens. 2016;37(18):4317–36. doi:10.1080/01431161.2016.1212423.

108. Sagan V, Maimaitijiang M, Sidike P, Eblimit K, Peterson K, Hartling S, et al. UAV-based high-resolution thermal imaging for vegetation monitoring and plant phenotyping using ICI, 8640 P, FLIR Vue Pro R 640, and thermoMap cameras. Rem Sens. 2019;11(3):330. doi:10.3390/rs11030330.

109. Bian J, Zhang Z, Chen J, Chen H, Cui C, Li X, et al. Simplified evaluation of cotton water stress using high-resolution unmanned aerial vehicle thermal imagery. Rem Sens. 2019;11(3):267. doi:10.3390/rs11030267.

110. Mc Evoy JF, Hall GP, Mcdonald PG. Evaluation of unmanned aerial vehicle shape, flight path and camera type for waterfowl surveys: disturbance effects and species recognition. PeerJ. 2016;4:e1831. doi:10.7717/peerj.1831.

111. López A, Jurado JM, Ogayar CJ, Feito FR. A framework for registering UAV-based imagery for crop-tracking in precision agriculture. Int J Appl Earth Observ Geoinf. 2021;97:102274.

112. Ennouri K, Smaoui S, Gharbi Y, Cheffi M, Braiek OB, Ennouri M, et al. Usage of artificial intelligence and remote sensing as efficient devices to increase agricultural system yields. J Food Qual. 2021;2021(3):6242288. doi:10.1155/2021/6242288.

113. Chougule MA, Mashalkar AS. A comprehensive review of agriculture irrigation using artificial intelligence for crop production. In: Kumar K, Kakandikar G, Davim JP, editors. Computational intelligence in manufacturing. Woodhead Publishing; 2022. p. 187–200.

114. Adede C, Oboko R, Wagacha PW, Atzberger C. A mixed model approach to vegetation condition prediction using artificial neural networks (ANN): case of Kenya's operational drought monitoring. Rem Sens. 2019;11(9):1099. doi:10.3390/rs11091099.

115. Orchi H, Sadik M, Khaldoun M. On using artificial intelligence and the internet of things for crop disease detection: a contemporary survey. Agriculture. 2022;12(1):9.

116. Helfer GA, Barbosa JLV, dos Santos R, da Costa AB. A computational model for soil fertility prediction in ubiquitous agriculture. Comput Elect Agric. 2020;175:105602. doi:10.1016/j.compag.2020.105602.

117. Spanaki K, Karafili E, Sivarajah U, Despoudi S, Irani Z. Artificial intelligence and food security: swarm intelligence of AgriTech drones for smart AgriFood operations. Prod Plan Cont. 2021;33(16):1498–516. doi:10.1080/09537287.2021.1882688.

118. Kalaji HM, Oukarroum A, Alexandrov V, Kouzmanova M, Brestic M, Zivcak M, et al. Identification of nutrient deficiency in maize and tomato plants by *in vivo* chlorophyll a fluorescence measurements. Plant Physiol Biochem. 2014;81:16–25. doi:10.1016/j.plaphy.2014.03.029.

119. Condori RHM, Romualdo LM, Bruno OM, de Cerqueira Luz PH. Comparison between traditional texture methods and deep learning descriptors for detection of nitrogen deficiency in maize crops. In: Proceedings of the Workshop of Computer Vision (WVC); 2017; Venice, Italy. p. 7–12.

120. Aleksandrov V. Identification of nutrient deficiency in plants by artificial intelligence. Acta Physiol Plant. 2022;44:29. doi:10.1007/s11738-022-03363-0.

121. Hernández S, Lopez JL. Uncertainty quantification for plant disease detection using Bayesian deep learning. Appl Soft Comput. 2020;96(8):106597. doi:10.1016/j.asoc.2020.106597.

122. Jung J, Maeda M, Chang A, Bhandari M, Ashapure A, Landivar-Bowles J. The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. Curr Opin Biotechnol. 2021;70:15–22. doi:10.1016/j.copbio.2020.09.003.

123. Kiratiratanapruk K, Temniranrat P, Kitvimonrat A, Sinthupinyo W, Patrapuwadol S. Using deep learning techniques to detect rice diseases from images of rice fields. In: Trends in artificial intelligence theory and applications. Artificial intelligence practices; 2020. p. 225–37. doi:10.1007/978-3-030-55789-8_20.

124. Afzaal H, Farooque AA, Schumann AW, Hussain N, McKenzie-Gopsill A, Esau T, et al. Detection of a potato disease (Early Blight) using artificial intelligence. Rem Sens. 2021;13:411. doi:10.3390/rs13030411.

125. Alizadeh MR, Nikoo MR. A fusion-based methodology for meteorological drought estimation using remote sensing data. Rem Sens Environ. 2018;211:229–47. doi:10.1016/j.rse.2018.04.001.

126. Mallya G, Zhao L, Song X, Niyogi D, Govindaraju R. Midwest drought in the United States. J Hydrol Eng. 2013;18(7):37–745.

127. Azizi E, Tavakoli M, Karimi H, Faramarzi M. Evaluating the efficiency of the neural network to other methods in predicting drought in arid and semi-arid regions of western Iran. Arab J Geosci. 2019;12(15):489. doi:10.1007/s12517-019-4654-z.

128. Chandel NS, Chakraborty SK, Rajwade YA, Dubey K, Tiwari MK, Jat D. Identifying crop water stress using deep learning models. Neur Comput Appl. 2020;33(10):5353–67.

129. Rasti S, Bleakley CJ, Silvestre GC, Holden NM, Langton D, O'Hare GM. Crop growth stage estimation prior to canopy closure using deep learning algorithms. Neur Comput Appl. 2020;33(2):1733–43. doi:10.1007/s00521-020-05064-6.

130. Cruz AC, Luvisi A, de Bellis L, Ampatzidis Y. X-FIDO: an effective application for detecting olive quick decline syndrome with novel deep learning methods. Front Plant Sci. 2017;8:1741. doi:10.3389/fpls.2017.01741.

131. Zhao H, Xu Z, Zhao J, Huang W. A drought rarity and evapotranspiration-based index as a suitable agricultural drought indicator. Ecol Indicat. 2017;82:530–8. doi:10.1016/j.ecolind.2017.07.024.

132. Melo LL, Melo VGML, Marques PAAM, Frizzone JA, Coelho RD, Romero RAF, et al. Deep learning for identification of water deficits in sugarcane based on thermal images. Agric Water Manage. 2022;272:107820. doi:10.1016/j.agwat.2022.107820.

133. dos Santos LH, da Silva LR, Leal F, de Carvalho NA. Scenario analysis of Brazilian soybean exports via discrete event simulation applied to soybean transportation: the case of Mato Grosso State. Res Trans Bus Manage. 2017;25:66–75.

134. Zhuang S, Wang P, Jiang B, Li M. Learned features of leaf phenotype to monitor maize water status in the fields. Comput Elect Agric. 2020;172:105347. doi:10.1016/j.compag.2020.105347.

135. Osco LP, Ramos APM, Moriya É.AS, Bavaresco LG, Lima BC, de Estrabis N, et al. Modeling hyperspectral response of water-stress induced lettuce plants using artificial neural networks. Rem Sens. 2019;11(23):2797. doi:10.3390/rs11232797.

136. Delloye C, Weiss M, Defourny P. Retrieval of the canopy chlorophyll content from Sentinel-2 spectral bands to estimate nitrogen uptake in intensive winter wheat cropping systems. Rem Sens Environ. 2018;216:245–61. doi:10.1016/j.rse.2018.06.037.

137. Gao J, Meng B, Liang T, Feng Q, Ge J, Yin J, et al. Modeling alpine grassland forage phosphorus based on hyperspectral remote sensing and a multi-factor machine learning algorithm in the east of Tibetan Plateau, China. ISPRS J Photogram Rem Sens Geoinf Sci. 2019;147(6):104–17.

138. Arif C, Mizoguchi M, Setiawan BI. Doi R. Estimation of soil moisture in paddy field using artificial neural networks. Int J Adv Res Artif Intell. 2012;1(1):17–21.

139. Behmann J, Steinrücken J, Plümer L. Detection of early plant stress responses in hyperspectral images. ISPRS J Photogram Rem Sens Geoinf Sci. 2014;93:98–111. doi:10.1016/j.isprsjprs.2014.03.016.

140. Hinnell AC, Lazarovitch N, Furman A, Poulton M, Warrick AW. Neuro-drip: estimation of subsurface wetting patterns for drip irrigation using neural networks. Irr Sci. 2010;28(6):535–44. doi:10.1007/s00271-010-0214-8.

141. Soltani N, Dille JA, Burke IC, Everman WJ, VanGessel MJ, Davis VM, et al. Perspectives on potential soybean yield losses from weeds in North America. Weed Technol. 2017;31(1):148–54. doi:10.1017/wet.2016.2.
142. Amato-Lourenco LF, Ranieri GR, de Oliveira SVC, Junior FB, Saldiva PHN, Mauad T. Edible weeds: are Urban environments fit for foraging? Sci Total Environ. 2020;698:133967. doi:10.1016/j.scitotenv.2019.133967.
143. Wayayok A, Soom MAM, Abdan K, Mohammed U. Impact of mulch on weed infestation in system of rice intensification (SRI) farming. Agric Agric Sci Proc. 2014;2:353–60. doi:10.1016/j.aaspro.2014.11.049.
144. Ampatzidis Y, Kiner J, Abdolee R, Ferguson L. Voice-controlled and wireless solid set canopy delivery (VCW-SSCD) system for mist-cooling. Sustainability. 2018;10(2):421. doi:10.3390/su10020421.
145. Abdulridha J, Ampatzidis Y, Ehsani R, de Castro A. Evaluating the performance of spectral features and multivariate analysis tools to detect laurel wilt disease and nutritional deficiency in avocado. Comput Electron Agric. 2018;155:203–11. doi:10.1016/j.compag.2018.10.016.
146. Luvisi A, Ampatzidis Y, Bellis LD. Plant pathology and information technology: opportunity and uncertainty in pest management. Sustainability. 2016;8(8):831. doi:10.3390/su8080831.
147. Nasar J, Ahmad M, Harun G, Tang L, Chou X. Maize/soybeans intercropping increases nutrient uptake, crop yield and modifies soil physio-chemical characteristics and enzymatic activities in a subtropical humid region based in Southwest China. BMC Plant Biol. 2024;24:434. doi:10.1186/s12870-024-05061-0.
148. Allmendinger A, Spaeth M, Saile M, Peteinatos GG, Gerhards R. Precision chemical weed management strategies: a review and a design of a new CNN-based modular spot sprayer. Agronomy. 2022;12(7):1620. doi:10.3390/agronomy12071620.
149. Torres-Sánchez J, López-Granados F, de Castro AI, Peña-Barragán JM. Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management. PLoS One. 2013;8(3):e58210. doi:10.1371/journal.pone.0058210.
150. Zhang W, Miao Z, Li N, He C, Sun T. Review of current robotic approaches for precision weed management. Curr Robot Rep. 2022;3:139–51. doi:10.1007/s43154-022-00086-5.
151. Espejo-Garcia B, Mylonas N, Athanasakos L, Fountas S. Improving weeds identification with a repository of agricultural pre-trained deep neural networks. Com Electro Agric. 2020;175:105593. doi:10.1016/j.compag.2020.105593.
152. Jha G, Sihi D, Dari B, Kaur H, Nocco MA, Ulery A, et al. Rapid and inexpensive assessment of soil total iron using Nix Pro color sensor. Agri Env Lett. 2021;6(3):e20050. doi:10.1002/ael2.v6.3.
153. Weiss M, Jacob F, Duveiller G. Remote sensing for agricultural applications: a meta-review. Rem Sens Environ. 2020;236:111402. doi:10.1016/j.rse.2019.111402.
154. Villette S, Maillot T, Guillemin JP, Douzals JP. Simulation-aided study of herbicide patch spraying: influence of spraying features and weed spatial distributions. Comput Elect Agric. 2021;182:105981. doi:10.1016/j.compag.2020.105981.
155. Jin X, Bagavathiannan M, Maity CY, Yu J. Deep learning for detecting herbicide weed control spectrum in turfgrass. Plant Method. 2022;18:94. doi:10.1186/s13007-022-00929-4.
156. Fernandez-Quintanilla C, Peña-Barragán JM, Andújar D, Dorado J, Ribeiro A, López-Granados F. Is the current state-of-the-art of weed monitoring suitable for site-specific weed management in arable crops? Weed Res. 2018;58:259–72. doi:10.1111/wre.2018.58.issue-4.
157. Sa I, Chen Z, Popovic M, Khanna R, Liebisch F, Nieto J, et al. WeedNet: dense semantic weed classification using multispectral images and MAV for smart farming. IEEE Robot Autom Let. 2018;3:588–95. doi:10.1109/LRA.2017.2774979.
158. Binch A, Fox CW. Controlled comparison of machine vision algorithms for Rumex and Urtica detection in grassland. Comput Elect Agric. 2017;140:123–38. doi:10.1016/j.compag.2017.05.018.
159. Lee WS, Slaughter DC, Giles DK. Robotic weed control system for tomatoes. Precis Agric. 1999;1:95–113. doi:10.1023/A:1009977903204.
160. Osorio K, Puerto A, Pedraza C, Jamaica D, Rodríguez L. A deep learning approach for weed detection in lettuce crops using multispectral images. Agri Eng. 2020;2:471–88. doi:10.3390/agriengineering2030032.

161. Rosset JD, Gulden RH. Cultural weed management practices shorten the critical weed-free period for soybean grown in the Northern Great Plains. Weed Sci. 2020;68(1):79–91.
162. Shahzadi R, Tausif M, Ferzund J, Suryani MA. Internet of things based expert system for smart agriculture. Int J Adv Comput Sci Appl. 2016;7(9):341–50. doi:10.14569/issn.2156-5570.
163. Price AJ, Williams JP, Duzy LA, McElroy JS, Guertal EA, Li S. Effects of integrated polyethylene and cover crop mulch, conservation tillage, and herbicide application on weed control, yield, and economic returns in watermelon. Weed Technol. 2018;32:623–32. doi:10.1017/wet.2018.45.
164. Shen E, Weidong Y, Wang X, Kang B, Mao S. TagSense: robust wheat moisture and temperature sensing using RFID. IEEE J Radio Freq Identif. 2024;8:76–87. doi:10.1109/JRFID.2024.3389868.
165. Kiala Z, Odindi J, Mutanga O. Determining the capability of the tree-based pipeline optimization tool (TPOT) in mapping parthenium weed using multi-date Sentinel-2 image data. Rem Sens. 2022;14(7):1687. doi:10.3390/rs14071687.
166. Chu H, Zhang C, Wang M, Gouda M, Wei X, He Y. Hyperspectral imaging with shallow convolutional neural networks (SCNN) predicts the early herbicide stress in wheat cultivars. J Hazard Mater. 2021;421:126706. doi:10.1016/j.jhazmat.2021.126706.
167. Sow S, Ranjan S, Kumar N, Nilanjaya, Gitari H, Dayal P, et al. Sustainable fodder production in South Asia through silvopastoral systems. Curr Sci. 2024;126(10):1217–24.
168. Garcia-Ruiz FJ, Wulfsohn D, Rasmussen J. Sugar beet (*Beta vulgaris* L.) and thistle (*Cirsium arvensis* L.) discrimination based on field spectral data. Biosys Eng. 2015;139:1–15. doi:10.1016/j.biosystemseng.2015.07.012.
169. Huang H, Deng J, Lan Y, Yang A, Deng X, Zhang L. A fully convolutional network for weed mapping of unmanned aerial vehicle (UAV) imagery. PLoS One. 2018;13:196302.
170. Rasmussen J, Nielsen J, Garcia-Ruiz F, Christensen S, Streibig JC. Potential uses of small unmanned aircraft systems (UAS) in weed research. Weed Res. 2013;53:242–8. doi:10.1111/wre.2013.53.issue-4.
171. Norasma N, Ya C, George D. Spectral discrimination of weeds using hyperspectral. In: Proceedings of the 5th Asian Conference on Precision Agriculture (ACPA), 2013 Jun 25–28; Jeju, Republic of Korea. p. 325–33.
172. Peña JM, Torres-Sánchez J, de Castro AI, Kelly M, López-Granados F. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. PLoS One. 2013;8(1):1–11.
173. Cox J, Li X, Fox C, Coutts S. Black-grass (*Alopecurus myosuroides*) in cereal multispectral detection by UAV. Weed Sci. 2023;71(5):444–52. doi:10.1017/wsc.2023.41.
174. Xia F, Quan L, Lou Z, Sun D, Li H, Lv X. Identification and comprehensive evaluation of resistant weeds using unmanned aerial vehicle-based multispectral imagery. Front Plant Sci. 2022;13:938604. doi:10.3389/fpls.2022.938604.
175. Wakchaure M, Patle BK, Mahindrakar AK. Application of AI techniques and robotics in agriculture: a review. Artif Intell Life Sci. 2023;3:100057.
176. Cho SI, Chang SJ, Kim YY, An KJ. Development of a three-degrees-of-freedom robot for harvesting lettuce using machine vision and fuzzy logic control. Biosys Eng. 2022;82(2):143–9.
177. Dorrer MG, Popov A, Tolmacheva AE. Building an artificial vision system of an agricultural robot based on the Dark Net system. IOP Conf Ser: Earth Environ Sci. 2020;548:032032. doi:10.1088/1755-1315/548/3/032032.
178. Hall D, Dayoub F, Kulk J, McCool C. Towards unsupervised weed scouting for agricultural robotics. In: 2017 IEEE International Conference on Robotics and Automation (ICRA); 2017; Singapore. p. 5223–30.
179. Hertzberg J, Kisliuk B, Krause JC. AI in current and future agriculture. KI-Künstliche Intelligenz; Künstl Intell. 2024;37:113–5. doi:10.1007/s13218-024-00838-9.
180. Uddin M, Chowdhury A, Kabir MA. Legal and ethical aspects of deploying artificial intelligence in climate-smart agriculture. AI Soc. 2024;39:221–34. doi:10.1007/s00146-022-01421-2.