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Artificial Intelligence in Precision Agriculture: A Review

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ABSTRACT

Artificial intelligence (AI) has long been applied in agriculture and has become especially prevalent in recent years. AI especially deep learning technique have progressed to have much stronger learning ability to learn more useful features to handle even more complicated task in the field of precision agriculture. Challenges in agriculture such as disease, infestation, inadequate irrigation and soil treatment, and poor crop management have brought about crop losses and adverse effects on the environment. Not to mention, the ever-increasing demand of agricultural product due to the increasing global population and the limited amount of arable land. To be overcome, those challenges need innovative approaches, ones that could benefit from AI's flexibility, accuracy, cost-effectiveness, and generally superior efficiency. AI technology whose aim is to mimic the ability of humans to solve problems especially in decision making enables agricultural activities to be done more efficiently while reducing human interference. The use of AI in agriculture has evolved from the application of fuzzy logic, then into machine learning and deep learning. Some deep learning methods that have been applied in precision agriculture are convolutional neural network, transformer learning, meta deep learning, and lightweight deep learning. This paper presents a review of 100 research papers addressing the application of AI in overcoming challenges in agriculture from the year 2000 to 2023. The paper selection for this review paper is done by using the SALSA method to effectively identify relevant research papers. In the near future, AI will be ubiquitous in the global agricultural sector and will bring about new technologies, new knowledge, and endless possibilities.

Keywords: Fuzzy logic; artificial neural network; deep learning

INTRODUCTION

Over the past few decades, the global agricultural sector has been confronted with the rising demand for food while dealing with limited resources and environmental constraints (Ahmad Zakey et al. 2024). With the world's population forecast to be approximately 9.8 billion in 2050 ("World population projected to reach 9.8 billion in 2050, and 11.2 billion in 2100 | United Nations" n.d.), increased food resources will be needed to accommodate such unprecedented growth. Against those trends, natural disasters, and drought, along with decreases in available land and resources, can be anticipated to raise the value of agricultural food products. From the other direction, the increased demand for such products will mostly be met with the intensified use of agricultural inputs such as pesticides, fertilizers, and water due to the limited availability of arable land (Sishodia et al. 2020). By extension, the intensification of agricultural inputs will inevitably have adverse effects on the environment, including groundwater depletion, reduced surface flow, and eutrophication (Kleinman et al. 2011; Konikow 2015; Konikow & Kendy 2005; Sishodia et al. 2017, 2020; Wen & Chen 2006). Meanwhile, the excessive and/or inefficacious use of natural resources such as soil and water, pesticides, and fertilizers in agriculture not only lead to economic waste but also causes the loss of water and nutrients from the soil and, in turn, the deterioration of the environment (Hendricks et al. 2019; Sishodia et al. 2020). The development of techniques that can increase crop production by increasing the efficient use of agricultural inputs while minimizing adverse environmental impacts is crucial for an economically and environmentally feasible as well as sustainable agricultural system (Delgado et al. 2019; Sishodia et al. 2020).

In those efforts, precision agriculture (PA) will play an important role in elevating the quality of agriculture products and practices. PA allows the growth in productivity of agricultural practices, as well as reducing their production costs, optimizing their use of resources, and minimizing their environmental impact (Ishak et al. 2009). Increasingly recognized for making use of current technology and intelligence in order to automate various aspects of agricultural practices, PA involves applying management practices tailored to the needs of crops and site conditions in order to improve the management of fields from various perspectives (Mustaza et al. 2022). For example, PA can be applied in irrigation systems, soil nutrient maintenance, weed management, and even pest management.

Integrating PA into agricultural practices can help to supply crops with suitable amounts of water and nutrients, reduce wastage in the use of herbicides and pesticides, and provide optimal conditions for crops to grow. In turn, the practice can effectively increase crop yields based on more than farmers' expertise only and can thereby help to reduce the costs of field maintenance and adverse environmental impacts due to inadequate agricultural practices. In light of the current global food crisis, characterized by declining food material supplies and ever-higher prices for such supplies, PA that can increase the yields of agricultural food supplies is highly sought and desperately needed.

The agricultural sector has not been exempted from the impact of advances in information and communication technology occurring around the world. Artificial intelligence (AI), big data, the Internet of Things (IoT), the Global Positioning System (GPS), blockchain and remote sensing are among the most promising state-of-the-art technologies and are considered disruptive. However, AI is regarded as the most disruptive technology and has had an impact on many industries, including education, healthcare, business, urban planning, and agriculture. According to Pavaloaia et al., (Păvăloaia & Necula 2023) these technologies are referred to as disruptive since they significantly alter the way things are usually done without having any unfavorable effects. These technologies are also seen as disruptive because of their extraordinary computational power, enormous amounts of data, and ground-breaking technological advancements.

They are adopted to optimize agricultural production for cheaper, more efficient, and more environmentally friendly agricultural practices that simultaneously reduce input wastage and yield losses (Delgado et al. 2019; Elijah et al. 2018; Jha et al. 2019; Sishodia et al. 2020). Some AI-based approaches, including machine learning, also enable the estimation of soil moisture, evapotranspiration, and crop yields for the automation and application of appropriate amounts of water, fertilizer, herbicides, and insecticides in specific fields (Boursianis et al. 2022; Sishodia et al. 2020). Such technology enables farmers to not only identify aspects of spatial variability that negatively affect the growth and yield of their farms but also to understand how to counter those effects. As such, technology is an essential part of PA that enables the development and application of the localized or site-specific management of fields and farms (Aubert et al. 2012; Sishodia et al. 2020).

During the industrial revolution in the 19th century, machines were employed to replace human labor. Following the development of information technology in the 20th century and the later emergence of computer technology, the development of AI-powered machines has now begun in earnest. At present, AI is progressively substituting human labor. To be clear, AI encompasses all behaviors designed for machines developed to imitate human intelligence and behavior, especially in learning and problem-solving. On sometimes large scales, AI systems are employed to execute complex tasks in ways that humans would. Therein, machine learning, a subset of AI, is a technique used to identify, understand, and analyze patterns within data, one that equips machines with the capability to learn without being explicitly programmed. In the world of modern technology, AI is one of the most important areas of research in computer science and is readily increasing in prevalence owing to its rapid technological advancement and extensive scope of application. The robust implementation of AI in problem-solving, especially for problems that cannot be solved well by humans or traditional computing structures, has helped the technology to become even more pervasive (Ghosh et al. 2018).

Approximately 5 billion hectares, or approximately 38% of the world's land, is used in agriculture ("Land use in agriculture by the numbers | Sustainable Food and Agriculture | Food and Agriculture Organization of the United Nations" n.d.). However, agriculture faces a host of difficulties in the full process from sowing to harvesting. Among them are infestation and disease, the inefficacious application of chemicals (e.g., fertilizers, pesticides, and herbicides), poor weed management, poor yield management, and improper drainage and irrigation. With the rise in the world's population, it is crucial for agriculture activities to be reassessed with the goal of incorporating innovative approaches to realize improved and sustainable agricultural practices.

The assimilation of AI in agriculture sector will doubtlessly be facilitated by advanced modern technology such as robotics, broad Internet coverage (e.g., in fields and across farms), IoT, big data analytics, and drone technologies, supported by the availability of cheap sensors and cameras as well (Clara Eli-Chukwu 2019). In agriculture, circumstances or problems that arise cannot be overcome with common, one-size-fits-all solutions. Instead, the details of each circumstance need to be considered before landing on a solution that can best solve the particular problem. With the development of various AI techniques, complex problems are indeed being resolved, even if gradually. For example, by analyzing data such as temperature, weather, soil nutrient levels, moisture levels, and historic crop performance, AI systems can furnish insights into crops suitable to be planted in a given year and site-specific optimal times for sowing and harvesting, which can reduce the wastage of inputs (e.g., water, fertilizer, and pesticides) and improve crop yields (Clara Eli-Chukwu 2019). With the assimilation of AI technology into agriculture, harmful impacts on natural ecosystems can be reduced and worker safety increased. Food prices can also be controlled, and food production put on pace with the increase in the human population.

Based on the number of scientific papers indexed by Web of Science Core Collection, three analyses were conducted on the number of scientific paper of the topic (1) “digital agriculture” OR “precision agriculture” AND “artificial intelligence”; (2) “digital agriculture” OR “precision agriculture” AND “deep learning”; (3) ”digital agriculture” OR “precision agriculture” AND “machine learning” to provide a view of the adoption of PA and digital agriculture with deep learning, machine learning and AI in scientific research. In the figure, the term “digital agriculture” is abbreviated as “DA”, “precision agriculture” as “PA”, and “deep learning” and “machine learning” as “DL” and “ML” respectively. All the analyses conducted show an increasing trend from previous years approaching the year 2023 in the number of research in the topics. Figures 1, 2 and 3 show the trend in scientific paper of the topics.

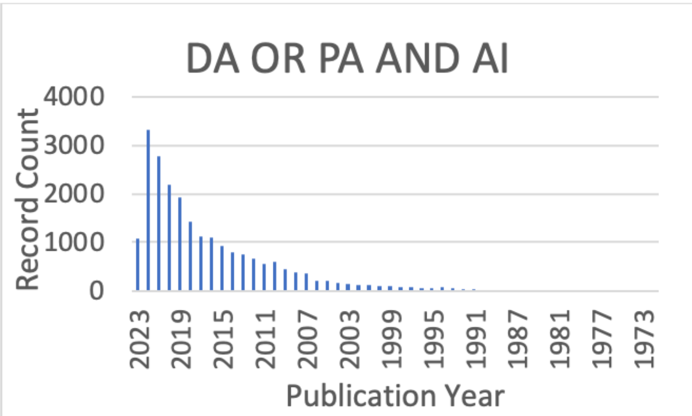

FIGURE 1. The record counts based on publication years for the topic “digital agriculture” OR “precision agriculture” AND “artificial intelligence”.

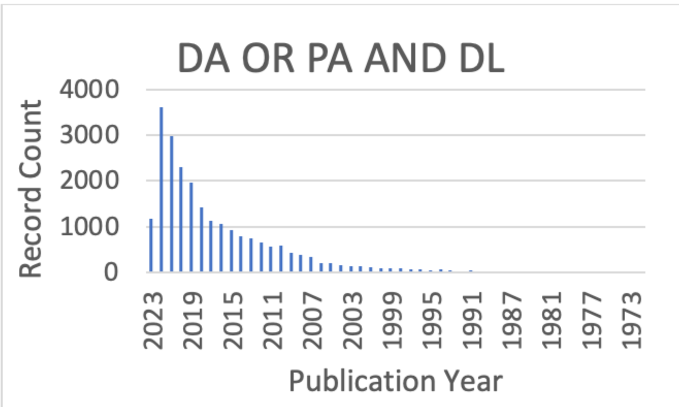

FIGURE 2. The record counts based on publication years for the topic “digital agriculture” OR “ precision agriculture” AND “deep learning”.

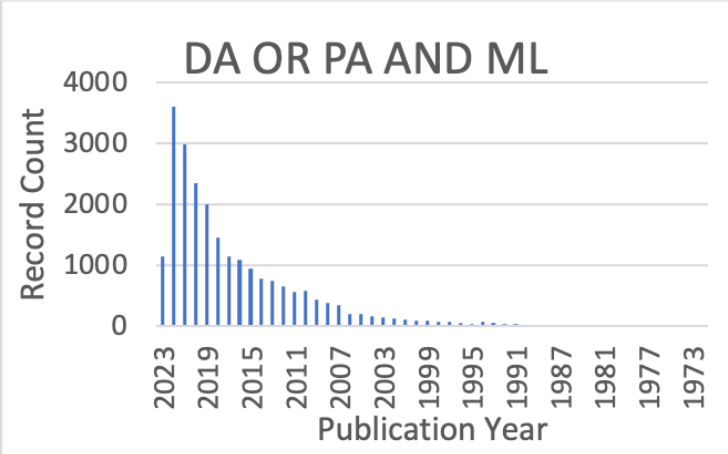

FIGURE 3. The record counts based on publication years for the topic "digital agriculture" OR "precision agriculture" AND "machine learning".

Addressing the period from 2000 to 2023, which encapsulates the gradual development of smart agricultural systems to date, this review considers 100 published articles that have contributed to current understandings of how AI techniques can be used to overcome challenges in agriculture. The database, methodologies and results of the studies cited in this review were analyzed, the research gaps were identified, and novelties of each study are highlighted. The studies have been systematically grouped and categorized based on their application of AI across different facets of precision agriculture, offering a comprehensive overview of the field. This structured approach not only synthesizes existing knowledge but also underscores emerging trends and future directions for each application, making the review a valuable resource for researchers and practitioners alike.

RESEARCH METHOD

The methodology used in the writing of this review paper are as follows. This review paper uses the SALSA framework which is the acronym for Search, Appraisal, Synthesis and Analysis, a systematic method for identifying relevant studies. The method used is described in the Table 1 below.

TABLE 1. Summary of the steps used to identify relevant studies using SALSA framework

Steps	Outcome	Methods
Search	Define search strategy	Searching string such as PA, DA with AI, ML and DL
	Search studies	The database used for this study is the Web of Science and Google Scholar
	Selecting studies	Inclusion: Studies from the year 2000 until 2023 The paper should be relevant to the topic of AI in Precision Agriculture and its subsections Exclusion: Language other than English Papers which cannot be fully accessed
Appraisal	Quality Assessment	Significant contribution and high performance (mostly accuracy)
Synthesis	Categorize data	Categorize the study to 6 different category of agriculture aspects
	Data Analysis	The studies involving deep learning which involve disease management and weed management were tabulate to summarize the studies
Analysis	Result and Discussion	The limitations of the studies for each agricultural aspects/section are provided at the end of the section
	Conclusion	Summarization of each aspect and its technology is provided at the end of the section

Firstly, several review papers of the same area of research were studied as an example and to identify the basic structure of review papers. Next, the objectives of the research paper were identified which is to review the methods used and identify the trend of the research of AI in precision agriculture.

Following the SALSA framework, articles were collected with the keyword such as 'precision agriculture', and 'digital agriculture' with 'artificial intelligence', 'machine learning' and 'deep learning' in the Web of Science and Google Scholar database. After that, based on the inclusion and exclusion criteria mentioned in TABLE 1, and after appraising the articles in terms of contribution and performance, relevant articles on the applications of precision agriculture were identified, and further research is conducted with respective applications. These include crop disease management, irrigation and soil management, pest management, weed management, yield management and general crop management.

Then, the AI technology used and its evolution in precision agriculture is identified where based on the articles, fuzzy logic, machine learning, artificial neural networks deep learning, meta deep learning, lightweight deep learning, vision transformer and convolutional neural networks were utilized. The method, novelty, challenges, and issues for each method presented in the paper were identified. Each subsection summarizes the findings and the application. The techniques used and their accuracies were summarized. The recent papers where deep learning and CNN was applied, were summarized in tables (disease management and weed management).

RESEARCH QUESTIONS

1. What are the activities in agriculture that could benefit from using AI technology?
2. What are the applications of AI in precision agriculture used in previous research?
3. How did the selected AI techniques improve the agricultural activities?
4. What are the challenges and limitations of the applications of AI in agriculture?

STRUCTURE OF THE PAPER AND THE CONTRIBUTION

This paper has four parts. The first part is the introduction to precision agriculture and the use of AI in precision agriculture. The second section focuses on the research method. The next section focuses on the application of various AI techniques, including expert systems (ESs), fuzzy systems, artificial neural networks (ANNs), deep learning, lightweight deep learning, meta deep learning and transformer learning in the agricultural activities of general crop management, crop disease management, irrigation and soil management, pest management, weed management, yield management and prediction. The year 2021 to 2023 shows a significant increase in the number of papers in the area. The paper will highlight these activities in these recent years as well as the overall landscape of AI application from among the earliest time it was applied in the area of precision agriculture. Finally, the fourth and final section summarizes the paper and provides an outlook on the application of AI in agriculture.

APPLICATION OF ARTIFICIAL INTELLIGENCE IN PRECISION AGRICULTURE

Since computer technology was first used in agricultural activity in 1983 (Ghosh et al. 2018), different methods have been proposed to solve problems in agriculture, beginning with databases (Ghosh et al. 2018; Martiniello 1988), followed by decision support systems (Ghosh et al. 2018; Thorpe et al. 1992). By comparison, however, systems that employ AI have shown superior accuracy and robustness (Ghosh et al. 2018). This paper identifies six categories of agricultural practices: (1) crop disease management, (2) irrigation and soil management, (3) pest management, (4) weed management, (5) yield management and prediction and (6) general crop management as depicted in Figure 4 below.

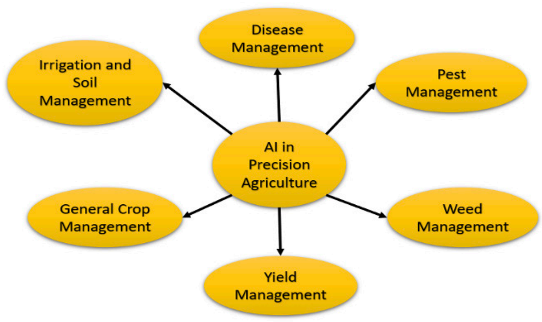

FIGURE 4. Agricultural practices which utilize AI identified in this paper.

CROP DISEASE MANAGEMENT

As the agricultural sector strives to meet a growing world population's increasing demand for agricultural products, plant disease, whether in crops or livestock, may impede that effort by causing yield loss. To produce an optimal yield at harvest, crop disease management is imperative. Several factors can cause diseases in crops and/or livestock, including genetics, soil type, rainfall, aridity, wind, and temperature (Clara Eli-Chukwu 2019). Owing to those factors and the inconsistent nature of causes of diseases, crop disease management is a major hurdle to overcome, especially in large-scale agriculture. In such management, AI largely focuses on the diagnosis and early detection of disease as shown in leaves, branches, and fruits.

In 2005, Fang et al. employed computer vision and ANNs trained with a genetic algorithm to identify tomato crops exhibiting physiological disease with astonishing 100% accuracy (Wang & Zhang 2005). In 2007, Huang proposed an application of neural network and image-processing techniques to detect and classify diseases in Phalaenopsis seedlings by using features such as color and texture (Huang 2007). Wang et al (Wang et al. 2008) also proposed using an ANN for the spectral prediction of Phytophthora infestants (e.g., late-blight fungus) on tomatoes, in which the ANN is designed as a backpropagation (BP) neural network using a gradient descent learning algorithm.

Other research has involved using fuzzy logic in developing AI-based systems for crop disease management. In 2011, Sannaki et al (Sannakki et al. 2011) proposed using machine vision in combination with fuzzy logic to grade leaf disease. Kolhe (Kolhe et al. 2011a, 2011b) also employed fuzzy logic in developing a web-based intelligent system for diagnosing disease in oilseed crops, while in 2013 Tilva et al applied fuzzy logic in developing a weather-based forecasting system for forecasting plant disease in corn crops (Tilva V. et al. 2013). In 2015, Muthukannan et al proposed using a feedforward neural network (FNN), learning vector quantization (LVQ), and a radial basis function network (RBF) to process the shape and textural features of leaves for classifying plant diseases (Muthukannan et al. 2015). The following year, Mohanty et al proposed the image-based detection of plant diseases by using a deep convolutional neural network (CNN) trained using more than 54,306 images from a public data set. Able to identify 14 crop species and 26 diseases, their system demonstrated 99.35% accuracy (Mohanty et al. 2016). Along with that, Patil and Thorat (Suyash S. Patil & Sandeep A. Thorat 2016) employed machine learning and a hidden Markov model to identify the probability of early-stage diseases in grapes.

Since 2018, studies examining the use of deep learning in crop disease management have become increasingly prevalent. That year, Ferentinos (Ferentinos 2018) developed CNN models to detect and diagnose plant diseases by using images of leaves and deep learning methods. The training of the models made use of 87,848 images from an openly available data set comprising 25 plant species in 58 distinct classes. In 2019, Shrivastava et al (Shrivastava & Pradhan 2021) developed an image-based machine learning approach to detect and classify diseases in rice plants. Using a pretrained deep CNN to extract features and a support vector machine (SVM) to classify the images, their system managed to achieve 91.37% accuracy for a 80%–20% training–testing partition. The same year, Picon et al proposed a crop conditional CNN architecture for the multi-crop (wheat, barley, corn, rice and rape-seed) classification of plant diseases by using pictures taken with cell phones in fields (Picon et al. 2019). On top of that, Barbedo et al (Arnal Barbedo 2019) employed a deep learning technique (CNN) to identify plant diseases with reference to individual lesions and spots. After that, Coulibaly et al used deep neural networks and transfer learning with images of millet crops to classify diseases while using a small amount of data and achieved 95.00% accuracy (Coulibaly et al. 2019).

In 2020, Lee et al. evaluated and compared the performance of several transfer learning processes based on pretraining tasks (i.e., in the plant-specific domain and the general object domain) and network topologies. (Lee et al. 2020). Along with that, Pham et al (Pham et al. 2020) proposed a feedforward neural network and hybrid metaheuristic feature selection approach for early illness detection in mango leaves. Among their results, the feedforward neural network proposed outperformed popular CNN models with simple network structure (i.e., AlexNet, VGG16, and ResNet-50) enhanced with transfer learning (i.e., 89.41% vs 78.64%, 79.92%, and 84.88%, respectively). In 2021, Thanjaivadivel and Suguna (Thanjaivadivel & Suguna 2021) analyzed and compared various techniques for detecting plant diseases by classifying plant leaves into three categories according to texture, shape, and color. The proposed enhanced learning method managed to achieve impressive 99.76% accuracy for diseases in tomatoes. By extension, Gajjar et al proposed the real-time detection and identification of plant leaf diseases by employing CNN techniques in embedded hardware (i.e., NVIDIA Jetson TX1) and were able to achieve 96.88% accuracy (Gajjar et al. 2022). In 2022, Raouhi et al (Raouhi et al. 2022) proposed a technique for optimization using fine-tuning based on MobileNet model architecture in deep CNNs for the classification of diseases in olive trees. The trained model achieved the highest rate (i.e., 100%), whereas the highest rate in experiments without data augmentation was 92.59% (i.e., evaluated according to accuracy and other performance metrics). Figure 5 shows the sample data set of diseases in olive trees considered in their experiment.

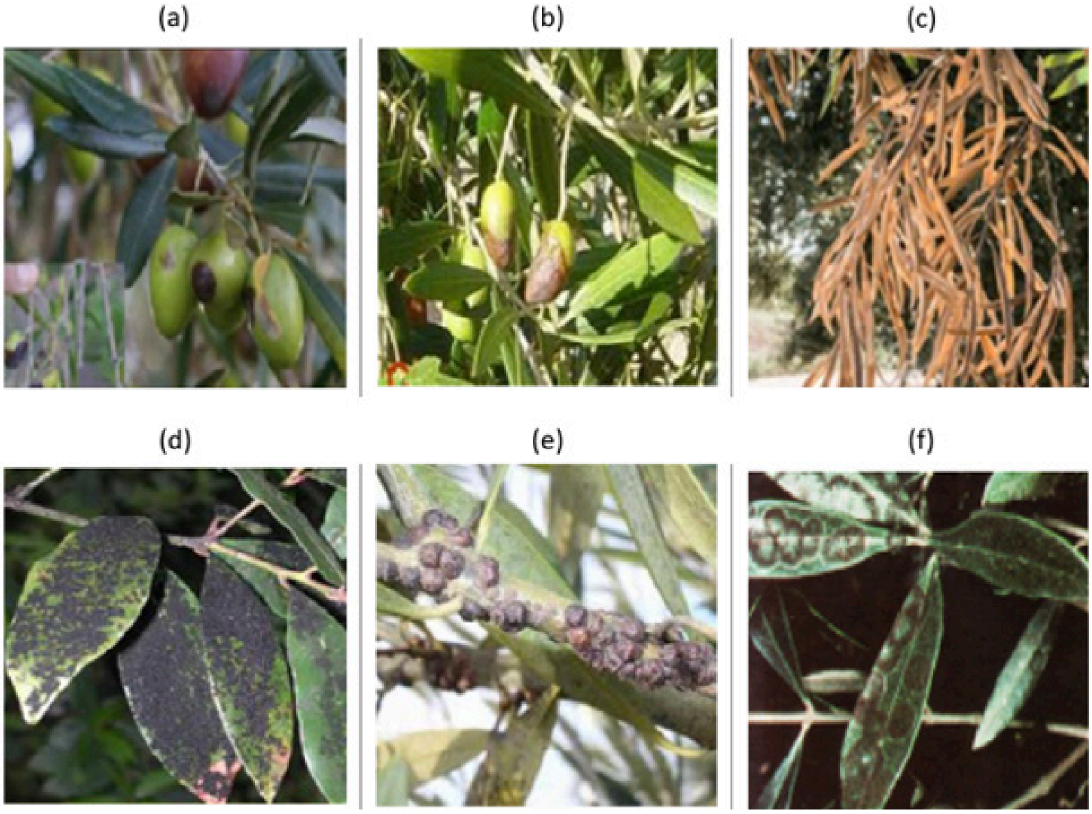

FIGURE 5. Data sets of diseases in olive trees (Raouhi et al. 2022), including (a,b) Anthracnose (c) Verticilliose, (d) Fumagina, (e) Saissetia oleae, (f) Cycloconium OP

In recent studies, Paymode and Malode proposed using transfer learning in a CNN-based VGG16 model to classify leaf diseases in multiple crops (Paymode & Malode 2022). Their model achieved 98.40% accuracy for grapes and 95.71% accuracy for tomatoes. Beyond that, Harakannanavar et al (Harakannanavar et al. 2022) proposed combining computer vision and a machine learning system to identify leaf illnesses in tomato plants. In their model, samples of tomato leaves are resized, the quality of the samples is improved, and the boundary of the samples and their informative features are extracted. The extracted features are subsequently classified using the machine learning approaches of SVM, CNN, and K-Nearest Neighbor (K-NN), which in the proposed model managed to achieve accuracy rates of: SVM (88%), K-NN (97%) and CNN (99.6%). Then, Memon et al (Memon et al. 2022) proposed a model based on meta deep learning to identify numerous cotton leaf diseases, which outperformed custom CNN, VGG16, and ResNet50 and achieved an accuracy of 98.53%. In another work, Borhani et al (Borhani et al. 2022) Borhani developed a lightweight deep learning solution based on vision transformer (ViT) for plant disease classification that was tested on three different datasets: wheat rust classification dataset, rice leaf disease dataset, and Plant Village dataset. The ViT approach was compared with CNN similar complexity and combination of CNN and ViT however the proposed ViT approach outperformed the others. Divyanth et al (Divyanth et al. 2023) developed a two-stage semantic segmentation approach based on deep learning (SegNet, UNet, DeepLabV3+) for corn disease identification and severity estimation. The UNet in stage one and DeepLabV3+ in stage two shows promising result. Next, Latif et al (Latif et al. 2022) propose a deep convolutional neural network transfer learning-based approach to detect and classify rice leaf disease. The proposed approach achieved an average accuracy of 96.08% on the non-normalized, augmented dataset. Sanida et al (Sanida et al. 2023) proposed a diagnostic tool for diseases or disorders that affect tomato leaf based on a robust hybrid CNN. This hybrid techniques which comprise of CNN and an inception module managed to achieve an accuracy of 99.17%.

Overall, research on AI-driven solutions in agriculture has primarily focused on crop disease management, with deep learning emerging as the predominant technique in recent years. A significant number of studies, as summarized in Table 2, have utilized CNNs and other deep learning models to detect and classify crop diseases based on visual data, typically images of diseased plants. These models have shown great potential, with improvements in disease detection accuracy over time. While these models have demonstrated promising results, the reliance on image-based inputs alone poses limitations. Certain diseases may exhibit similar visual symptoms, leading to potential misclassification. Therefore, a more comprehensive approach is required, one that integrates multiple data sources—such as environmental factors, soil health, and crop physiology—alongside image analysis. In addition, further research should consider the inclusion of laboratory-based techniques to validate AI-generated diagnoses and address the challenge of diseases with overlapping or confusing symptomatology. This multifaceted approach could enhance the accuracy and robustness of AI applications in crop disease management.

TABLE 2. Summary of research utilizing CNN and deep learning models for crop disease management.

Source	Plant	Disease	Data set	Accuracy (%)
Mohanty et al (2016)	14 crop species	26 diseases	54,306 images of diseased and healthy plants collected from PlantVillage	99.35
Ferentinos (2018)	25 plant species	58 classes of plants and diseases	87,848 photographs of diseased and healthy plants from an open database	99.53
Shrivastava (2019)	Rice	Rice blast, bacterial leaf blight, sheath blight	619 images from rice fields at Indira Gandhi Agricultural University in Raipur, Chhattisgarh, India	91.37
Picon et al (2019)	Barley, wheat, corn, rice, grapeseed	17 diseases	More than 100,000 images taken in real field conditions	Not specified
Barbedo (2019)	14 crop species	10 diseases	1383 original images, 46 135 expanded	MD[a] (70.00), ModD[b] (80.00), SD[c] (85.00)
Coulibaly et al (2019)	Pearl millet	Mildew disease	124 images from Image Net	95.00
Gajjar et al (2021)	Apples, corn, potatoes, tomatoes	16 diseases	21,978 images from PlantVillage's data set and a manually collected data set	96.88
Raouhi et al (2022)	Olives	6 diseases	5,571 images of different plant leaves classes taken from an olive grove	90.20
Paymode and Malode (2022)	Grapes, tomatoes	12 diseases	4,449 original photographs from PlantVillage	Grapes (98.40), tomatoes (95.71)
Harakannanavar et al (2022)	Tomatoes	6 diseases	Taken from PlantVillage's data set, 600 samples for testing	SVM (88.00), K-NN (97.00), CNN (99.60)
Memon et al (2022)	Cotton	6 diseases	2,384 images of cotton leaves taken in the Pakistani city of Matiari located in Sindh Province	98.53
Borhani et al (2022)	Wheat, Rice and 14 (Plant village) other crop species	26 infections (Plant Village), yellow rust and brown rust (wheat) and bacterial leaf disease, brown spot, and leaf smut (Rice)	3 dataset which are the wheat rust classification dataset (3,679 images), rice leaf disease dataset (120 images) and Plant Village (54,306 images)	Not specified
Divyanth et al (2023)	Corn	Gray leaf spot, northern leaf blight and northern leaf spot	1,050 images of diseased leaf were collected at Purdue University's Agronomy Center for Research and Education (ACRE).	Average accuracy of 97.31% (UNet) in stage one and 92.37% (DeepLabV3+ in stage two.

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Source	Plant	Disease	Data set	Accuracy (%)
Latif et al (2023)	Rice	5 diseases	Rice Leaf Diseases Dataset by Ade F. which consist of 2,710 images from www.kaggle.com.	96.08
Sanida et al (2023)	Tomato	9 diseases	18,160 images of tomato leaves from Plant Village dataset	99.17

a Mildly Diseased
b Moderately Diseased
c Severely Diseased.

IRRIGATION AND SOIL MANAGEMENT

Soil is the source of nutrients, water, and proteins that help to ensure proper crop growth and development. As a result, soil and irrigation management challenges are critical in agriculture. Understanding different soil types and conditions can help increase agricultural yields and conserve soil resources. Furthermore, placing compost and manure on soil is required to improve its quality. In contrast, incorrect irrigation and soil management can result in yield losses and crop quality degradation. To date, the application of AI in irrigation and soil management has generally focused on the classification of soil types, nutrient maintenance, and predicting moisture and rainfall for optimal crop yields.

In 2000, Chang and Islam (Chang & Islam 2000) proposed using a self-organizing feature map (SOFM) and a three-layered ANN(TFNN) to remotely sense brightness, temperature, and soil moisture in order to classify soil into three textural types—coarse, medium, and fine—and further into six classes: (1) sand, (2) loamy fine sand, (3) fine sandy loam, (4) loam, (5) silty loam, and (6) silty clay loam or clay loam. In 2005, Sicat et al proposed the fuzzy modeling of farmers' knowledge (FK)to classify the suitability of agricultural land using GIS (Sicat et al. 2005). Their results suggest the effectiveness of fuzzy modeling in that classification, which can be useful to optimize land use planning. In 2009, Zhao et al proposed employing artificial neural networks (ANNs) to forecast the distribution of soil textures (i.e., sand, clay, and silt content) based on soil attributes from an existing coarse-resolution soil map and hydrographic parameters produced from a digital elevation model. (Zhao et al. 2009). The following year, Hinnell et al (Hinnell et al. 2010) developed Neuro-Drip, an Excel-based ANN that rapidly depicts soil-wetting patterns from surface drip irrigation emitters. Neuro-Drip is intended to estimate findings from various numerical models with sufficient precision to allow decision-making concerning irrigation system design and management without the use of numerical models directly. Drip irrigation system design and management that is effective allows for the efficient supply of water and nutrients, which boosts agricultural yields.

In 2011, Bilgili (Bilgili 2011) proposed using a three-layer feedforward ANN to forecast monthly mean soil temperatures in Adana, Turkey, trained using a backpropagation algorithm. Mean soil temperature was predicted using various monthly mean meteorological variables and can be used in other agricultural applications, including to predict frost. That same year, Dai et al (Dai et al. 2011) developed a simulation of crop yield response to soil moisture and salinity using ANNs, and the results were compared to multiple linear regression (MLR) results. The response of sunflower yields to salt and soil moisture was simulated using ten and six input variables, respectively, including soil moisture and salinity at various phases of crop growth. The results showed that utilising ANNs is more appropriate. In 2012, Arif et al (Arif et al. 2012) Arif proposed employing artificial neural networks (ANNs) with minimal meteorological data to estimate soil moisture in paddy fields for irrigation scheduling as well as water resource allocation, management, and planning. Their findings indicate that ANNs are reliable in measuring soil moisture in rice fields, even with minimal meteorological data and without the need for specialized, expensive tools, heavy labor, or an abundance of time. In 2016, Manek and Singh (Manek A. H. & Singh P. K. 2016) proposed a comparative study of neural network architecture (i.e., a backpropagation neural network (BPNN), a generalized regression neural network, (GRNN) and a radial basis neural network) (RBNN) to predict rainfall for agricultural activities. After training and testing were completed, the RBNN produced the most accurate predictions.

Most recently, in 2022 Dhal et al (Dhal et al. 2022), used augmented error estimation methodologies and a machine learning classifier to manage nutrient concentration in aquaponic environments depending on plant demands, for the optimization of plant development in aquaponic irrigation, due to limited data sets. The results demonstrated that the semi-bolstered resubstitution error estimation technique performs best when linear SVM is used as the classifier. Then, Wei et al (Wei et al. 2022) estimates the annual amount of irrigation water in the Kansas High Plains by using random forest regression integrated with pumping record, remote sensing tools and climate data. The random forest regression model managed to achieve a satisfactory accuracy in capturing the spatial and temporal variability of irrigation amount. Sami et al (Sami et al. 2022) proposed using a neural network based on long short-term memory (LSTM) in a smart irrigation system. A physical sensor is substituted by a neural sensor throughout the test, and the proposed neural network-based sensor predicts real-time results with high accuracy. In order to improve soil moisture prediction, Li et al (Li et al. 2022b) proposed an encoder-decoder deep learning model with residual learning based on LSTM (EDT-LSTM). During testing, the model produced promising outcomes for predicting soil moisture with a lead time of up to 10 days. In another work, Ibrahim et al (Ibrahim et al. 2023) developed two machine learning models, adaptive neuro-fuzzy inference system (ANFIS) and SVM, to predict eight irrigation water quality indices (IWQIs) such irrigation water quality index, sodium absorption ratio, and so on. The produced ANFIS and SVM models were able to simulate the IWQIs with reasonable accuracy. Bertocco et al (Bertocco et al. 2023) proposed using ML-based techniques to increase the accuracy of a LoRaWAN-based wireless soil-moisture-sensing system to detect volumetric water content (VWC), indicating an ensemble-tree-based algorithm (i.e., XGBoost) as the best model.

Soil and irrigation management are critical components of sustainable agriculture, as adequate nutrient availability and water supply are fundamental to healthy crop growth. AI-based predictions for soil and irrigation, using current environmental data combined with historical trends and climate information, have proven to be valuable tools for optimizing these resources. However, while these models are effective, there is a growing need to account for uncertainties and environmental contaminants that could affect their accuracy. Factors such as declining water quality, increased soil salinity, and high soil acidity can significantly influence the efficiency of AI models and crop productivity.

In addition to these natural variables, human activities—such as industrial operations, nearby farming practices, and improper environmental management—can exacerbate the challenges of maintaining soil and water health. Factories or farms that implement inadequate waste management or use excessive chemicals may contaminate local water sources, contributing to soil degradation and water pollution. Therefore, AI models for soil and irrigation management must also factor in these anthropogenic influences to provide more comprehensive predictions and strategies. By integrating real-time monitoring of environmental pollutants, human activities, and water quality data into AI systems, more resilient and adaptive solutions can be developed, ensuring long-term agricultural sustainability and improved crop yields.

PEST MANAGEMENT

Insect infestations are one of the gravest problems in agriculture and generally lead to losses in crop yields. Such insects harm crops by eating parts of the plant (e.g., leaves, stems, roots and flowers) and can cause disease as well as infestation. Over the years, various researchers have developed computerized systems that can identify pests and provide consultation about courses of action for pest management. The application of AI in that domain has generally been based on consultations on pest management and detection.

In 2012, Samanta and Ghosh (Samanta & Ghosh 2012) developed an automatic diagnosis system to detect insect pests in tea plants based on ANNs using correlation-based feature selection and an incremental backpropagation network applied on a database comprising records of tea gardens of North Bengal, India. The results of classification with and without dimension reduction achieved correct classification of 100% in both cases. In 2015, Peixoto et al (Peixoto et al. 2015) proposed an approach by utilizing fuzzy systems for the dynamics and control of soybean aphids. The study uses a method based on fuzzy sets theory to describe the interaction between soybean aphids and its natural predators and to propose a means of chemical control for the aphids. The model includes biotic (i.e., predator) and abiotic (i.e., temperature) factors that affect the population dynamics of soybean aphids and is very useful in predicting the timing and number of predators to release in order to control the pests.

Most recently, in 2022 Sourav proposed the intelligent identification of jute pests based on transfer learning and deep CNNs (Sourav & Wang 2022). The model used, the VGG19 CNN pretrained network using the ImageNet database, managed to achieve 95.86% accuracy and has been integrated into Android and iOS applications for practical use. Ahmad et al (Ahmad et al. 2022) developed an object recognition system for detecting insect pests and classifying them in the form of smartphone IP-camera by utilizing deep learning-based detector YOLOv5. The developed system works efficiently and is able to correctly identify insect pests and can be employed for use in the field. Gomes and Borges (Gomes & Borges 2022) proposed the use of few-short learning (FSL) for detecting insect pests at different maturity stages and the best result achieved an accuracy of 86.33% for adult insects and 87.91% for early stages. In (Li et al. 2022c), Li et al compared several deep learning models which are faster-RCNN, mask-RCNN and YOLOv5 for insect pest detection by testing with 2 datasets. By using the first dataset, Baidu AI insect detection dataset, the experimental result shows that YOLOv5 achieve the highest accuracy above 99%

while with IP102 dataset which has more complex background, the faster-RCNN and mask-RCNN produce higher accuracy, reaching 99%. Then, Kumar et al (Kumar et al. 2023) proposed using YOLOv5, which includes five cutting-edge object identification algorithms, to identify insect pests with minimal differences between subcategories. The addition of channel and spatial attention modules improves the network's detection capabilities. In the detection of insect pests (fall armyworms), Obasekore et al (Obasekore et al. 2023) proposed a deep learning-based extensible and robot-centered technique. To catch insect pest larvae, the robot employs RGB data from a camera sensor split into peripheral and foveal line-of-sight vision. The VGG19 classifier (with 99% accuracy) and the faster-RCNN detector using VGG16 as the base network were used for peripheral and foveal vision, respectively.

Pest infestations affect crop growth and quality as consumer prefer perfect appearance on their agricultural food product and product with defects are usually hardly sold. Other than appearance, pest also spreads diseases from crop to crop. Therefore, pest management are a very important aspect in agriculture. Most pest can be recognized through images however, symptoms on the crop also plays an important role in recognizing pest infestation as the pest are not always present on the crop for identification. It also important to identify symptoms on the crop for effective pest management.

WEED MANAGEMENT

Weeds, defined as undesirable plants that compete with productive crops for space, water, and soil nutrients, are a major challenge in agricultural activities and can result in significant output losses. Weed control is thus a critical element of farming and agriculture. Many benefits of effective weed management include increased safety and route clearance for drivers and agricultural workers, less natural resources for unwanted weeds, and fewer alternate hosts for insect pests and illnesses. Although the excessive application of herbicides has dire consequences for both humans and the environment, mechanically removing weeds requires considerable effort and a large team of workers. Against those trends, modern AI technology can be applied to minimize the application of herbicides and make weed management more efficient, specifically by way of selective herbicide spraying.

In 2001, Gliever and Slaughter proposed using ANNs for weed and crop recognition in cotton crops (Gliever & Slaughter D. C. 2001). The algorithm for weed detection, designed for robotic weed control, managed to successfully map 93% of weeds and 91% of cotton plants that respectively received or did not receive herbicide. The following year, Yang et al (Yang et al. 2002) developed ANNs for weed recognition in corn fields. The images taken from corn fields were preprocessed, and the resulting images were used as inputs for learning vector quantization (LVQ) ANNs. The system successfully distinguished 90% of corn from weeds and 80% of four weed species from corn. In 2003, Yang et al (Yang et al. 2003) used image-processing technologies, ANNs, and fuzzy logic to develop a herbicide application map for the PA of corn crops. Following the development of ANNs to recognise weeds from corn plants, images of weeds were processed to obtain information for weed coverage and weed patchiness maps, and a fuzzy logic controller was used to compute variable rates of herbicide administration based on the maps. In subsequent work, Aitkenhead (Aitkenhead et al. 2003) compared the use of image analysis and neural network-based methods in discriminating weeds from carrot crops. Although image analysis was found to be nearly as accurate as the neural network-based method, it is time consuming and ill-suited for practical use in fields. By contrast, the neural network-based method is relatively flexible and needs no human intervention following initial training. In 2005, Burks et al (Burks et al. 2005) evaluated the design parameters of three neural network models, backpropagation (BP) and radial basis function (RBF) using MATLAB, and counter propagation (CP) using the Stuttgart Neural Network Simulator (SNNS) by using image data from six different class. They also employed a stepwise variable selection approach to choose the appropriate input parameter for neural networks used to categorise weed species, which simplified the process of detecting redundant texture variables and lowered the model's processing requirements. When compared to other neural network-based methods, the BP method produced a relatively high classification accuracy (i.e., 96.7%) with fewer computational requirements, and removing the intensity feature from the BP-network data model lowered the processing requirements. Other findings indicated that the HS (i.e., hue and saturation) feature was robust for a neural network classifier. In 2006, Karimi et al (Karimi et al. 2006) investigated the effectiveness of SVM in classifying hyperspectral images captured above a cornfield with respect to rates of nitrogen application and practices of weed management practices. Ultimately, the results of the SVM application were more accurate than those produced by the ANN model.

In 2011, Burgos-Artizzu et al (Burgos-Artizzu et al. 2011) developed a real-time image processing computer vision system for identifying crops from weeds in maize fields. The system, which can distinguish weed patches from crop rows in real time under uncontrolled lighting, is made up of two independent subsystems: fast image processing (FIP) that delivers results in real time and slower but more accurate processing using robust crop row detection (RCRD) that corrects the first subsystem's mistakes. The system detected 95% of weeds and 80% of crops under various settings such as illumination, soil humidity, and weed and crop growth when tested on various videos of maize fields filmed in different fields and years. In 2014, Tobal and Mokhtar (Tobal & Mokhtar 2014) proposed a self-organizing map neural network capable of recognizing and classifying image patterns of various plant leaves, including weeds. The evolution process maximized the neural network's performance in classification and utilized the basic strategy of genetic algorithms (GA). That same year, Haug et al (Haug et al. 2014), propose a machine vision-based approach for a plant classification system without segmentation in regard to crop and weed discrimination. The system can discriminate weeds from crops growing close together and even handle overlap between plants. The system utilizes a random forest classifier and a Markov random field to process and classify the images of carrot farms, for an average accuracy of 93.8%.

In 2016, Lottes et al (Lottes et al. 2016)developed a machine learning-based classification system for differentiating sugar beets from weeds. The system also combines a random forest classification and a Markov random field. In 2017, Andrea et al (Córdova-Cruzatty Andrea et al. 2017) proposed a CNN capable of accurately classifying weeds and maize, with a model trained on data obtained during the segmentation stage. Several CNN architectures were examined, and the network with the best results was a computer network of 16 filters, with 97.23% training accuracy on 4,580 segmented images from both classes. Ferreira et al (dos Santos Ferreira et al. 2017) also utilized CNNs to detect weeds in images of soybean crops and classify the weeds as grasses and broadleaves for specific herbicide applications. The database's images, taken by drone over a soybean farm, number over 15,000 and show soil, soybeans, broadleaf and grass weeds. The system also achieved more than 98% accuracy in detecting broadleaf and grass weeds in relation to soil and soybeans, with the average accuracy of 99% between all images. Dyrmann et al (Dyrmann et al. 2017a) proposed using a CNN in detecting the location of weeds in leaf-occluded cereal crops based on a modified version of GoogLeNet architecture. With a network trained on more than 17,000 annotations of weed images, the system can detect 46% of weeds in a field even when large portions of the weeds overlap with the wheat plants. Dyrmann et al (Dyrmann et al. 2017b) also proposed the pixel-wise classification of weeds and crops in images by utilizing a fully CNN. To overcome the issue of plant foliage overlap, the CNN was trained to create the pixel-wise classification of crops, weeds, and soil in RGB images from fields to determine the exact position of plants. The model showed a pixel accuracy exceeding 94% and 100% accuracy in detecting both maize and weeds when tested on real images and while keeping a high intersection union. In 2018, Sa et al (Sa et al. 2018) also demonstrated a CNN-based classification for detecting weeds by using aerial multispectral images taken from a micro aerial vehicle. The encoder–decoder cascaded deep neural network that they used was trained on data sets from herbicide-controlled sugar beet fields.

In 2020, Wu et al (Wu et al. 2020) developed a computer vision-based weed management system that uses a non-overlapping multi-camera system to compensate for the delay produced by the plant detection algorithm. To improve the detection system, the system employs a naïve biased Bayesian classifier in with a biased probabilistic model. That same year, Raja et al (Raja et al. 2020) developed a crop signaling-based real-time in-row weed and crop identification and classification method for automatically regulating weed-spraying among lettuce plants. Crop signaling has a machine-readable visual signature, which simplifies weed and crop classification and ensures success. The technology also makes use of computer vision capabilities to locate lettuce plants and weeds. In 2021, Islam et al (Islam et al. 2021) proposed a system for the early detection of weeds using image processing and machine learning on a chili pepper farm in Australia. The images, taken by unmanned aerial vehicle (UAV), undergo preprocessing and feature extraction, and the authors compared the use of random forest (RF), SVM, and K-NN as classifiers. MATLAB simulation revealed that the RF and SVM were efficient and practical for detecting weeds from UAV images with 96% and 94% accuracy, respectively. Also that year, Chen et al (Chen et al. 2021) proposed the in-field detection of weeds and corn seedlings based on multi-feature fusion and SVM, namely in 18 fusion methods with six features compared to identify the optimal fusion strategy. Principal component analysis (PCA) was used to reduce dimensionality, which improved the experiment's accuracy, especially when rotation-invariant local binary pattern (LBP) features and a gray level-gradient co-occurrence matrix (GGCM) were combined. In 2022, Mustaza et al (Mustaza et al. 2022) used a modified line filter technique in directional shape feature extraction for classifying weeds, in which the classifier was a multilayer perception neural network (MLPNN) with 50 hidden layers. Ultimately, the technique managed to achieve more than 97% accuracy. Figure 6 presents some data sets used in the study.

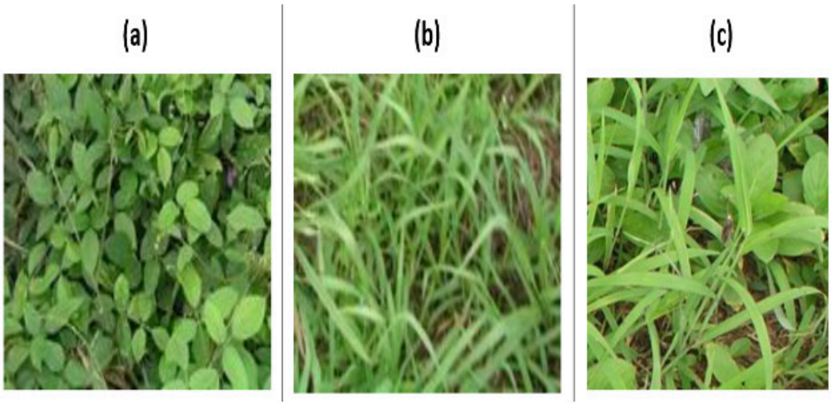

FIGURE 6. Data sets from (Mustaza et al. 2022) showing (a) broadleaf weeds, (b) narrow weeds, and (c) mixed weeds.

Reedha et al (Reedha et al. 2022) utilized transformer neural network for the classification of weed and crops using high resolution images taken using UAVs. The ViT model were used to learn and classify images of crop and weed in beet, parsley and spinach fields and managed to outperform the other CNN-based model like ResNet and EfficientNet. Garibaldi-Marquez et al (Garibaldi-Márquez et al. 2022) compared the use shallow and deep learning for weed classification in natural corn field-multi plant images. The images were classified between narrow-leaf weeds, broadleaf weeds, and crops. The region of interest (ROI) was extracted using connected component analysis (CCA), and the ROI classification is based on CNN and is compared to a shallow learning technique (SVMs). The CNN-based approaches were considered the best with 97% accuracy. Then, Lopez-Martinez et al (López-Martínez et al. 2023) implemented a high-performance computing cluster (HPCC) where the image processing and analysis were done using deep learning (VGG16 and InceptionV3 models) techniques. Fatima et al (Fatima et al. 2023) developed a YOLOv5-based lightweight weed detection mechanism to aid laser weeding robots. Next, Almalky & Ahmed (Almalky & Ahmed 2023) developed deep learning networks to detect and classify the growth stages of Consolida regalis weeds which are YOLOv5, RetinaNet and faster-RCNN. Overall, RetinaNet is accurate and precise, while YOLOv5 has the shortest real-time inference time for detecting weeds and classifying their growth phases.

Recent studies in weed management utilized computer vision, ANNs, CNNs, and other machine learning techniques such as K-NN, SVM and RF. However, in image classification for weed management, CNN and deep learning are among the techniques frequently used. Table 3 summarizes studies that use CNN and deep learning models in weed management.

As with other precision agriculture applications, the advancement of AI methods, particularly in image classification and detection, has significantly improved weed management strategies. Over the years, classification and detection accuracy have approached near-perfect levels, with some models nearing 100%. These advancements have primarily focused on detecting weeds for herbicide application and robotic weeding systems. The use of AI-driven image analysis enables precise identification of weeds, allowing for targeted herbicide use, reducing chemical waste, and minimizing environmental impact. However, an often-overlooked aspect in weed management is the need to distinguish between live and dead weeds. This is crucial in avoiding unnecessary herbicide application or activating other weeding mechanisms, which could lead to wasted resources and higher operational costs. Despite the progress in AI-based detection, few studies have focused on developing algorithms that can accurately detect the status of weeds post-treatment, such as their vitality or level of decay.

Furthermore, while many studies have achieved high accuracy in controlled environments, real-world, real-time implementation remains limited. There is a significant gap in research concerning hardware integration and the deployment of AI models in dynamic, field-based scenarios. Future work should prioritize the development of robust hardware systems capable of processing real-time data for weed detection and classification in diverse environmental conditions. This shift towards practical, in-field applications will mark a substantial leap forward in achieving more sustainable and efficient weed management solutions.

TABLE 3. Summary of research utilizing CNN and deep learning models for weed management.

Source	Plant	Data set	Accuracy (%)
Lottes et al (2016)	Sugar beet	Dataset A (1024 images), Dataset B (694 images) and Dataset C (974 images) where A and B are collected on the same field with a temporal difference of one week while C is collected on another field.	Not specified
Andrea et al (2017)	Maize	A total of 34222 images of maize and 10762 images of weed were obtained as dataset after being processed and extended by applying geometric transformation. The original images were obtained from maize fields in Pilaro in Tungurahua Province, in the center of the Ecuadorian Highland region.	LeNet (86.48), AlexNet (93.86), cNET (96.40), sNET(80.40)
Ferreira et al (2017)	Soybean	Over 15,000 images of soil, soybean, broadleaf and grass weeds were taken in soybean plantation in Campo Grande, Matto Grosso do Sul, Brazil.	98% accuracy for broadleaf and grass weeds detection with an accuracy average between all images above 99%
Dyrmann et al (2017)	Cereal crops	More than 17,000 annotations of images from winter wheat fields using camera mounted on ATVs	Not specified
Dyrmann et al (2017)	Maize	301 images of soil and 8430 images of segmented plant	Over 94%
Sa et al (2018)	Sugar beet	Annotated 132, 243 and 90 multispectral images	Not specified
Reedha et al (2022)	Beet, parsley, and spinach	19,265 images from beet, parsley and spinach crop field taken by UAV	Not specified
Marquez et al (2022)	Corn, broadleaf weed and narrow leaf weed	13,000 images taken from five cornfields located in different region within Aguascalientes, Mexico	VGG16 (97.93), VGG19 (97.44), Xception (97.24)
Martinez et al (2023)	Weed	DeepWeeds dataset consist of 17,509 images of different plant species from northern Australia	65
Fatima et al (2023)	Okra, bitter gourd, sponge gourd and weed	9,000 images taken on different agriculture farms in Pakistan	Not specified
Almalky & Ahmed (2023)	Consolida regalis weed	3,731 images from videos taken by UAV from multiple weed field in Turkey	Not specified

YIELD MANAGEMENT

Yield prediction and management are among the most challenging tasks in agricultural activities. Even if crop growth is optimal, yield loss will occur unless proper yield management is in place. Predicting crop yields also helps in estimating agricultural costs and devising marketing strategies. Factors affecting such yields can be analyzed by employing prediction models.

Technologies such as AI, satellite images, machine learning, cloud computing, and advanced analytics are increasingly being used in agricultural activities. The result has been more efficient, sustainable, smart, and cost-effective agriculture, and farmers have been able to obtain maximum average yields and increase the amount of food products. AI applications in that category are generally based on the storage, classification and prediction of the amount of yields.

In 2003, Gottschalk et al (Gottschalk et al. 2003) proposed using fuzzy controllers to improve the climate control in potato stores. Among their results, using fuzzy controllers optimized with GA lowered the energy consumption during the test period. The following year, Kavdir and Guyer proposed using fuzzy logic for grading apples based on color, size, and defects, for results that showed good (89%) general agreement with human experts. In 2005, Liu et al (Liu et al. 2005) proposed using backpropagation ANNs to estimate the effect of soil parameters such as soil moisture, nitrogen (N), phosphorus (P), potassium (K), soil organic matter (SOM), and NTotal on crop yield. The results of training included a correlation coefficient of .916 and an average error value of 2.8 × 102, which indicate that the model can precisely describe the effect of soil parameters on crop yields. In 2007, Ji et al (Ji et al. 2007) employed ANNs for predicting rice yields in a mountainous region. ANN parameters such as learning rate and the number of hidden nodes were found to affect the accuracy of the prediction. Compared with the multiple linear regression, the ANNs consistently predicted yields more accurately. The following year, Singh and Prajneshu (Krishna Singh & Prajneshu 2008) utilized MLFANN a multilayered feedforward ANN for modeling and forecasting maize yields. Among the maize crop data used as predictors were crop yield data, total human labor, fertilizer consumption, and pesticide consumption. MATLAB's neural network toolbox was used in training, and the proposed MLFANN showed superiority over the multiple linear regression (MLR) analysis. In 2009, Mustafa et al (Mustafa et al. 2009) proposed using SVM and fuzzy logic (FL) for sorting and grading agricultural products. The developed system first captures the fruit's image, which is subsequently sent to processing involving feature extraction, classification, and grading in MATLAB. The agricultural products are then classified using the SVM based on fruit shape and graded by using FL.

In 2010, Rahman and Bala (Rahman & Bala 2010) proposed using backpropagation ANN (BPANN) in modeling the production of jute. The six input variables used were day of the Julian calendar, solar radiation, maximum temperature, minimum temperature, rainfall, and type of biomass, whereas the output was plant dry matter. They conducted two sets of experiments in 2006 to train the model, and also conduct two sets of experiments in 2007 to validate it. Ultimately, the models correctly predicted the growth of different components of jute plants. In 2011, Papageorgiou et al (Papageorgiou et al. 2011) proposed using the soft computing technique of fuzzy cognitive mapping (FCM) to predict yields in cotton crop production. Fuzzy cognitive maps integrate fuzzy logic and cognitive map theory, where each map developed consists of nodes connected by directed edges. The nodes represent the primary factors affecting cotton crop production such as texture, organic matter, pH, different types of minerals and cotton yield, while the edges show the cause-and-effect relationship between the soil properties and cotton yields. The advantages of that approach are its simple structure and flexibility, as well as that it represents knowledge visually and is more descriptive. In 2012, Shantaiya and Ansari (SHANTAIYA & Ansari 2012) developed an algorithm to identify rice seeds based on morphological features, nine of which, along with six color features, could be extracted from the images, and a neural network was used to classify the seeds into several varieties. The following year, Punn and Bhalla (Punn & Bhalla 2013) employed two types of machine learning algorithms (i.e., SVM and a neural network) to classify wheat grains, the images of which were captured using a digital camera and underwent thresholding. Once features of wheat were extracted and the SVM and neural network applied, the neural network achieved 94.5% accuracy but the SVM only 86.8% accuracy. By some contrast, in 2017, Pandey and Mishra (Pandey & Mishra 2017) used two forms of ANNs to estimate the yields of potato crops that were differently sown: a generalized regression neural network (GRNN) and a radial basis function neural network (RBNN). Crop metrics like leaf area index, biomass, and plant height were employed as input, whereas potato field yields were used as output. Among the results, although both neural networks were able to predict accurately, GRNN was generally superior due to its quick learning capability and lower spread constant. In 2019, to predict maize yields using genotype and environment and historical data, Khaki and Wang (Khaki & Wang 2019) developed a deep neural network (DNN) that can learn nonlinear, complex relationships between genes and environmental conditions, as well as their interactions, and predict yields for new hybrid plants in new locations with known weather conditions.

Sun et al (Sun et al. 2022b) in his paper present the use of random forest algorithm with satellite data, climatic data, and spatial information to estimate winter wheat yield in China (2014–2018). The result shows that random forest accuracy outperformed multiple linear regression method. Li et al (Li et al. 2022a) utilized R and Python open-source systems integrated with an automated hyperspectral narrowband vegetation index and AI-based automated machine learning (AutoML) to estimate yields of spring wheat, pea and oat mixture, and spring barley with red clover. Cao et al (Cao et al. 2022) uses three dataset which are satellite data, observational climate data and subseasonal-to-seasonal (S2S) atmospheric prediction data to predict winter wheat yield (2005 to 2014) by utilizing machine learning algorithm which are XGBoost, random forest and support vector regression (SVR) and multiple linear regression. XGBoost shows promising results and the use of S2S dynamical prediction in crop yield forecasting outperform observational climate data. Bian et al (Bian et al. 2022) used machine learning approaches (including Gaussian process regression, SVR, and random forest regression) to build a wheat yield forecast model utilising multispectral UAV data in Xuzhou City, Jiangsu Province, China in 2021. The results reveal that machine learning and multi-spectral UAV data can accurately estimate crop yield. Batool et al (Batool et al. 2022) evaluated the use of a simulation model compared to machine learning for tea crop production prediction utilizing data from weather, crop, soil, and agro-management. The result shows that XGBoost outperformed other machine learning models and it also concludes that machine learning performs better than simulation models in yield prediction.

Yield management and prediction is very important as agricultural products marketing and management (e.g: future resources allocation and sales) depends on the yield. Therefore, it is important to not only do prediction based on factors such as water, climate, and soil, but it is also important to integrate all aspects of agriculture in predicting yield and its management.

GENERAL CROP MANAGEMENT

Crop management includes all agricultural practices executed to enhance the development, growth, and yields of crops, including the preparation, sowing, and maintenance of crops, as well as harvesting, storage, and marketing. Because increased crop production and productivity can contribute significantly to a country's economic development, placing greater emphasis on such production is typically beneficial. In crop management, AI is applied mostly in the general management of fields and farms. The category also refers to all other studies not grouped in the foregoing categories.

In 2001, Shahin and Symons (Shahin & Symons 2001) developed an online classification system based on machine vision to grade lentils using a neural classifier and that achieved more than 90% accuracy. In 2004, Li et al developed a machine recognition based on a backpropagation neural network for features of wheat crops (Li et al. 2004). Next, in 2016, Ravichandran and Koteeshwari developed a smartphone-based crop predictor and advisor using an ANN with an overall prediction accuracy of 90% (Ravichandran & R. S. Koteeshwari 2016). More recently, Bargoti and Underwood proposed the deep detection of fruit in orchards using an object detection framework (i.e., Faster R-CNN) for fruits such as mangoes, almonds, and apples (Bargoti & Underwood 2017). Nkemelu et al (Nkemelu et al. 2018) have also proposed using deep CNNs to classify 12 species of plant seedlings, in a system that achieved approximately 93% accuracy.

Thilakarathne et al (Thilakarathne et al. 2022) proposed cloud-based machine learning crop recommendation platform to help farmers decide in harvesting crop based on known parameters. The study compares 5 different machine learning algorithms which are K-NN, decision tree, random forest, XGBoost and SVM and based on the result, accuracy of random forest model outperformed the other with accuracy of 97.18%. Sozzi et al (Sozzi et al. 2022) compared the use of YOLO object detection deep learning algorithm which are YOLOv3, YOLOv4 and YOLOv5 for autonomous Bunch detection in white grape varieties. The result shows that best accuracy and speed were obtained by YOLOv4-tiny. Rokade et al (Rokade et al. 2022) proposed a smart greenhouse system that integrates IoT and regressor machine learning algorithm. The combined use of SVM regressor and ANN in this work managed to achieve 92% accuracy. Lin et al (Lin et al. 2022) developed a multitask spatiotemporal deep learning model named long short-term memory based multi-task learning (LSTM-MTL) for large scale rice mapping using satellite image time series data. The model shows promising results in rice classification with an overall accuracy of 98.3%. Casado-Garcia et al (Casado-García et al. 2022) applied and compared semi-supervised deep learning in semantic segmentation of natural images in viticulture. Three semi-supervised learning methods were proposed which are PseudoLabelling, Distillation and Model Distillation and, in the result, the DeepLabV3+ architecture with ResNet50 backbone managed to achieve the highest overall accuracy of 84.78%.

Some of the studies in this subsection, general crop management, uses classification of image using machine learning and deep learning to classify crop stages and type. However, RGB image classification and detection also has its limitations and could not grasp the overall characteristics of crops. Instead, multispectral images make precise agricultural management possible by providing comprehensive information on the traits and health of plants. Multispectral image data can be used to monitor nutrient status, identify illnesses, estimate crop health, and classify crops better. The use of AI with multispectral images enables improvement in general crop management, and with other state-of-the-art technologies, so much more can be done as knowledge and opportunities are endless.

CONCLUSION

AI has been applied in research concerning agriculture since the 1980s, largely to empower what is currently referred to as precision agriculture. This paper considers 100 research articles published since 2000 that together show the evolution of AI-based research in agriculture. In early research on the topic, rule-based ESs were developed using expert knowledge to provide consultation for agricultural activities. In time, such research began to apply fuzzy logic and, in turn, machine learning. Researchers have also applied computer vision and ANNs as classifiers, which led to the use of deep learning, CNNs, lightweight deep learning, meta deep learning and transformer learning to classify images for applications such as weed management and pest management. Aside from consultation, the research seems to signal a shift toward automation and real-time application in agricultural activities.

CHALLENGES AND LIMITATION

Although AI can help in optimizing agricultural production and processes, there are a few challenges in adopting AI in agriculture and its limitations. First, the farm using AI face the risk of cyberattack which can cause disruption in agriculture processes by data poisoning, shutting down harvesting machine, drones or water sprayers. For example, the world's largest meat processing company, JBS, has to pay $11m in ransom due to ransomware cyberattack in 2021 ("Meat giant JBS pays $11m in ransom to resolve cyber-attack - BBC News" n.d.). In order to better mitigate this problem, companies should employ the assistance of white hat hackers and ensure that during the development phase, any securities failing of their IT systems are uncovered and solved to safeguard against real hackers.

Second, the use of AI system programmed to achieve the best crop yield in short term, may ignore the detrimental effect it brought towards the environment, although unintended. In order to achieve an increase in crop production, this can lead to overuse of fertilizers and pesticides which can poison the ecosystem and pollute the soil and the surrounding waterways and in the long term, can cause soil erosion.

Next, the use of precision agriculture can reduce the agricultural sector dependency on hired labor and autonomous machines can relieve farmers of manual labor which can improve working conditions. Without inclusive technology, however, socioeconomic inequities would persist since an AI agricultural system that ignores the complexity of labor inputs could continue to exploit underprivileged populations.

The majority of farms around the world are cultivated by small-scale growers, who are therefore likely to be excluded from AI-related benefits. Due to marginalization, poor internet penetration rates, and the digital divide, these smallholders may be unable to employ cutting-edge technologies, widening the gap between commercial and subsistence farmers.

Furthermore, some of the case studies reviewed in this paper are limited to farms with controlled environments such as weed detection in fields with rows using autonomous machines. Therefore, the developed technologies are not flexible enough to be used in other settings.

Moreover, AI technologies are very dependent on availability of the data which is usually obtained by a network of sensors which can be a challenge to mount or setup in. Most of the study use images from online databases such as PlantVillage or images taken by themselves on fields or farms.

FUTURE RESEARCH PATH

In recent years, the research on Artificial Intelligence of Things (AIoT) technology, a convergence between AI and IoT has become more prominent. Artificial intelligence (AI) and the internet of things (IoT) are two technologies among others that have played critical roles in modernizing the agriculture industry during the epidemic, and their combination has recently generated renewed interest. (Adli et al. 2023; Zhang & Tao 2021). An IoT system produces data for AI techniques for image analysis and data prediction as well as data integration and interpretation. AIoT technology has been used to address several agricultural processes and issues such as pest management (Chen et al. 2020) and post-harvest management issues. The deployment of AIoT technology drastically changes the traditional agricultural environment and it is expected that more research will be done based on this technology.

Aside from AIoT, vertical farming has also been garnering attention from the masses. In metropolitan settings with a shortage of land and space, vertical farming is the practice of growing plants and livestock on vertically inclined surfaces such as in skyscrapers (Kalantari et al. 2018). This strategy, which uses soil-free growth techniques, aims to reduce the load on traditional agricultural land by farming upwards rather than outward. (Beacham et al. 2019) It is especially appealing for usage in urban environments. Increasing food production while maintaining high standards of quality and safety and promoting sustainable urban farming are all possible benefits of vertical farming. Growing food in urban areas is beneficial towards the environment, society, and economy. Additionally, vertical farms have the potential to improve global food security (Kalantari et al. 2018; Salim Mir et al. 2022). If AI can be integrated into large scale vertical farming which can monitor and assess crop condition and environment, it can improve crops production, reduce manual labor, and makes farming easier.

Other than that, Satellite Image Time Series (SITS) monitoring has also garnered interest from researchers. SITS in agriculture are commonly used to monitor agriculture fields or farms for a long period of time to study the vegetation whether in visible band or infrared band. The satellite images used were taken by satellites such as Sentinel-1 and Sentinel-2. Some examples are (Picoli et al. 2018; Wang et al. 2020) and (Xu et al. 2021). In agriculture, SITS can be very helpful in providing crop health, growth, and production data. Farmers can make informed and educated decisions regarding irrigation, fertilization, and other management practices by evaluating changes in the vegetation over time. Crop monitoring, yield forecasts, irrigation management, pest and disease detection, and land use planning are among key applications of SITS. AI can be used to analyses SITS's images and farmers will be able to observe their farm over a long period of time and make informed decisions with help from the AI based on the data gathered through SITS.

Furthermore, phenotype data-assisted breeding (Sun et al. 2022a) has captured the interest of researchers in agricultural fields in recent years. Data on the anatomical, historical, physiological, and biochemical characteristics of the plant are provided via plant phenotyping. Plant phenotyping plays a key role in the discovery of new genetic variations (Bhat & Yu 2021) as well as the intensity and accuracy of selection. Non-invasive imaging, spectroscopy, image analysis, robotics, high performance computing capabilities, and phenomics databases can all be used to capture these characteristics. (Mir et al. 2019). These platforms and tools attempt to collect data on hundreds to thousands of plants in a single day on factors such as plant development, architecture, growth, and biomass productivity. This revolution, with the help of AI, is expected to provide plant scientists with the skills and resources they need to decipher the information stored in plant genomes. Another rising topic in the agricultural research sector is blockchain. Without the need for an intermediary, electronic recordkeeping, validation, and verification are possible with blockchain. All participants have access to the data, everything is made open and available, and the records are unchangeable and cannot be altered or deleted. Blockchain technology in agriculture is used in maintaining food quality and traceability, preventing counterfeit products, and modernizing and optimizing yield (L.B 2022) which can be supported by AI.

Due to the global population expected increment to approximately 9.8 billion by 2050, the demand for food products is bound to increase. In response, the agricultural productions need to be increased by approximately 70%; however, only approximately 10% of that increase can be expected to come from unused land, whereas the remainder will need to be covered by the intensification of current production (Clara Eli-Chukwu 2019). Given those trends and forecasts, it is crucial that agricultural activities are made to be more efficient, sustainable, and low-cost in order to meet rising demands and to keep agricultural products affordable for the general public. State-of-the-art technology such as AI, robotics, and autonomous systems is transforming global industries and gradually becoming ubiquitous. Such technology will significantly impact industries, especially manufacturing and agriculture. In the near future, even underdeveloped and developing nations are expected to commence or increase the adoption of smart technology and AI in their agricultural sectors. However, the introduction, proof of benefits, and consultation regarding such technology should be expanded, especially for farmers without technology savvy. If those farmers can be persuaded to use such state-of-the-art technology, then they will no doubt benefit from it, and the technology's global integration in the agricultural sector will no longer be a dream but a reality.

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DECLARATION OF COMPETING INTEREST

None

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