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Review

A Survey on Deep Learning and Its Impact on Agriculture: Challenges and Opportunities

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Abstract: The objective of this study was to provide a comprehensive overview of the recent advancements in the use of deep learning (DL) in the agricultural sector. The author conducted a review of studies published between 2016 and 2022 to highlight the various applications of DL in agriculture, which include counting fruits, managing water, crop management, soil management, weed detection, seed classification, yield prediction, disease detection, and harvesting. The author found that DL's ability to learn from large datasets has great promise for the transformation of the agriculture industry, but there are challenges, such as the difficulty of compiling datasets, the cost of computational power, and the shortage of DL experts. The author aimed to address these challenges by presenting his survey as a resource for future research and development regarding the use of DL in agriculture.

Keywords: agriculture; deep learning; crop management; weed detection

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1. Introduction

In the contemporary era of globalization, the role and contributions of agriculture are crucially important. Over the years, agriculture has suffered from different challenges in fulfilling the ever-increasing needs of the world population, which has increased by twofold in the past five decades. There are different predictions for this unprecedented growth in the population, which is likely to reach approximately 9 billion people in the world by 2050 [1]. In addition, the estimates show an increase in the number of people living within urban areas, along with a significant drop in the percentage of the population who are retired or working [1,2]. This means that agricultural productivity around the world must be increased considerably, and there is a need for a human labor force. To address this sort of problem, technologies such as tractors were introduced into agriculture over a century ago. At present, mechanical technology is showing an incredible evolution, and a significant number of technologies are available. Existing technologies, such as remote sensing [3], robotic platforms [4], and the Internet of Things (IoT) [2], have recently become widespread in industry, particularly in the agricultural sector, leading to the phenomenon of smart and efficient farming [5,6]. Schmidhuber (2015) states that deep learning (DL) is a modern approach that is successfully being utilized as part of various machine-learning techniques [7]. It is comparable to artificial neutral networks (ANNs) but with enhanced learning capabilities; therefore, it has higher accuracy [8]. In recent years, DL technologies, such as generative adversarial networks (GANs), recurrent neutral networks (RNNs), and convolutional neutral networks (CNNs), have been widely implemented and investigated in different fields of research, including farming and agriculture. Agriculturalists and researchers often use different software systems without assessing the mechanisms and ideas of the techniques, such as GANs, RNNs, and CNNs, that are usually applied in DL algorithms. There are various sub-categories of DL algorithms, including deep convolutional generative adversarial networks (DCGANs), very deep convolutional networks (VGGNets), and long short-term memory (LSTM) networks; therefore, understanding these sub-categories of DL algorithms is important for understanding common DL algorithms [9]. According to Kamilaris and Prenafeta [10], DL is a modern and recent technique and system for data analysis and image processing with significant potential and promising results [10]. DL has been successfully used in different domains and has recently entered the agriculture field. Additionally, it has the potential to address complex problems more efficiently and quickly due to the use of complex models that enable massive parallelization. These multifaceted models used in DL are likely to increase classification accuracy and limit faults in regression problems, but only if there are sufficiently large databases that can be used to explain such problems.

The authors of [11] argued that DL using drone technology is significant for agriculture and farming as it provides a convenient way to monitor, assess, and scan crops through the use of high-quality and high-resolution images [11]. Such technology aids in recognizing advancements in fields and assessing quality. For example, with the help of images provided by drone technology, agriculturalists and farmers can determine whether crops are fully ready for harvesting. DL, along with machine-learning (ML) techniques, can help farmers understand the nature of the soil, thus aiding them in making timely decisions regarding farming. DL is also applied to assess how nutrients and water are to be managed and to make decisions about the suitable time for cropping and harvesting. Yields are higher and more efficient and the return on investment (ROI) for crops can be projected, considering the margin and cost in the market [12]. In addition, the efficiency of DL is recognized because it has been observed to outclass conventional methods, such as support vector machines (SVMs), random forest (RF) algorithms, and ANNs. Several technologies are being used together with DL to enhance performance in prediction and classification related to agricultural problems. The RNN and LSTM models have memory and time dimensions. As a result, they can be used to project animal and plant growth based on recorded data, evaluate water needs, and determine crop yield using the mining time dimensions and memory function [13,14]. They can also be utilized to estimate plant and animal growth based on previously recorded data to evaluate fruit yields or water requirements. Ren et al. [15], for example, used both models to forecast various phenomena and climate changes. Using hyperspectral images and infrared thermal imaging to provide data and information is the right direction for the prompt detection of diseases in crops. With the subsequent exponential growth in this field, it is necessary to provide an up-to-date review of the recent literature focusing on innovative research techniques implementing DL for agriculture. Hence, this study focused on providing an overview of the recent advancements linked to DL in the agricultural sector. The study aimed to describe the use of DL in agriculture; in particular, with respect to counting fruits, managing water, crop management, soil management, weed detection, seed classification, yield prediction, disease detection, and harvesting. The adoption of technology in the agriculture sector during the recent period has significantly transformed and assisted farming and crop cultivation. However, DL has been noted to have added efficiency to agriculture, which has motivated researchers to investigate how it can be helpful in farming and harvesting and in yield predictions.

This paper is categorized in the following way: Section 2 presents the research methodology. Section 3 provides a literature review by highlighting a brief history of the topic. Section 4 highlights the importance of DL in the agriculture sector. Section 5 discusses DL tools that can be used for model development. In addition, the same section describes the usage, purpose, significance, and implementation of DL in the agriculture sector. Section 6 provides the results and a discussion, drawing on previous studies that have discussed deep learning. Section 7 presents the overall conclusion of the study, together with some ideas for future research directions.

2. Research Method

The methodology of this study was based on secondary data and a comprehensive review of approaches linked to agricultural DL, including disease detection, yield prediction, and weed prediction, using databases such as Research Gate, IEEE Explore, Springer, Elsevier, Google Scholar, Frontier, and Science Direct. For this study, research papers published between 2016 and early 2022 were considered due to the increasing advancements in DL and its increasing use in agriculture. Additionally, the emphasis for data collection was on journal articles and conference papers. The inclusion criteria for research papers were that they were available in English with full access and were relevant to the research objectives with themes including development and agriculture. Studies that were published before 2016 were excluded from this study. The research method flowchart for this study is shown in Figure 1.

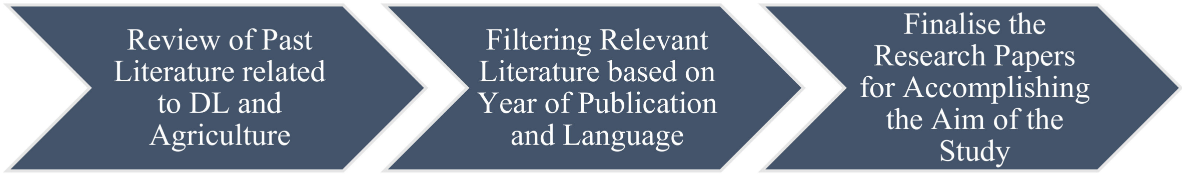

Figure 1. The research methodology.

3. Literature Review

3.1. Deep Learning

Agriculture faces many challenges due to the increase in demand and the presence of fewer workers in the fields. In this context, smart farming can be used to address issues such as food security, sustainability, productivity, and environmental impact [16]. As is known, agriculture plays a vital role in the global economy [17]. This is because it ensures food security for countries, and most companies rely on it for their external trade. In the world today, most home appliances, travel means, and other commonly used services are becoming automated through the adoption of artificial intelligence (AI); thus, farming practices should too, since they are the backbone of a country. Achieving understanding and making quick responses with the help of data provided by continuous monitoring, measuring, and analysis of different physical aspects and phenomena would be helpful to overcome the complex, multivariate, and unpredictable challenges of agricultural ecosystems [18]. This would require the analysis of huge amounts of agricultural data and the use of new information and communication technologies (ICTs) and would be necessary for both small-scale farms and large-scale ecosystem monitoring [19]. It could be achieved using DL with a large network. DL is basically an aspect of machine learning that aims to build neural networks that can analytically learn by simulating the human brain. It acts like the human brain in that it works by reading data, such as pictures, videos, text, and sounds. With its continued development, DL has already been implemented in various complex tasks, such as image segmentation, image recognition, natural language processing, object detection, and image classification [18]. However, DL requires a huge dataset since the quality of the DL results entirely depends on the size of the dataset, and the model tends to learn from that data and then respond accordingly. Some computer and industrial advancements, such as image processing, IoT technologies, robotics, machine learning, deep learning, and computer vision, are very useful in the agricultural industry and even for local farmers. High-quality image processing makes AI based on drone technology a very helpful asset for farmers, since they can identify the progress of the crops and determine whether they are ready to harvest or not while sitting in one place rather than having to move long distances. This has been achieved just AI and a drone system; one can only imagine how beneficial it would be to implement DL in agriculture [18].

Figure 2 lists numerous advantages of using DL in agriculture. With the current increase in the population, there has also been an increase in the demand for agricultural goods [18]. The implementation of DL and other automation components could greatly benefit production outcomes, reduce the chances of ripening, reduce production costs, and increase income due to the increased production. Moreover, it would also make it possible to forecast climatic changes—for instance, if there is an incoming rainstorm, cyclone, etc.—so that the farmers could be ready and prepare before a disaster.

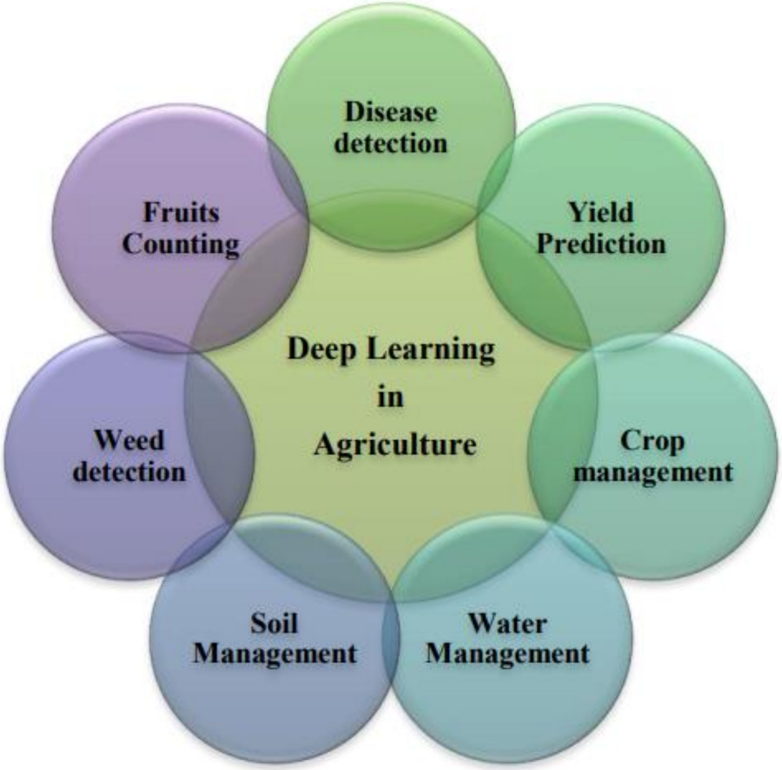

Figure 2. Deep learning applications in agriculture [18].

3.2. *Agriculture before Deep Learning*

Traditional agriculture was the main method of farming before the adoption of scientific advancements in agricultural industries. Traditional agriculture mainly involves the extensive use of traditional tools and organic fertilizers, indigenous knowledge of land use and natural resources, cultural beliefs, etc. [19]. Another way to describe it could be as the "primitive style" or "early style" of farming and food production. The traditional method of farming affects the environment in many ways, such as through the depletion of soil nutrients. For instance, slash and burn practices in traditional agriculture were one reason for decreased soil organic matter. Another problem caused by traditional farming was deforestation, as most deforestation has taken place in tropical rainforests to make space for other agricultural activities. Another significant issue relating to soil erosion is the removal of topsoil by water or wind. This topsoil is the most fertile, and it may take decades to replenish it once it is removed [19].

Agroforestry, crop rotation, intercropping, polycultures, and water harvesting are some of the most common types of traditional farming practices. The traditional farming method of constructing grain storage structures provided an incredible moisture-proof environment for grain storage. Compared to today's colossal warehouses, these small structures were cheap to fabricate and maintain. However, many different pesticides were used to keep the grains safe during storage periods, which later resulted in very bad effects on the environment [20]. The implementation of technology and the investment of huge sums of money in agricultural industries have helped to control other diseases, thereby making the amount of money spent worthwhile.

3.3. *Deep Learning Architecture*

Several nonlinear transformations are used to model higher-level abstractions in data, and these are the foundations of DL [21]. One of the main benefits of DL is the automatic extraction of features from raw data or feature learning. Producing features from lower-level components yields features in higher-level components [22]. Recurrent neural networks (RNNs) and CNNs are two types of DL networks that are often used in agriculture.

3.3.1. Convolutional Neural Networks (CNNs)

The CNN is a type of DL algorithm [23] composed of multiple convolutional layers, pooling layers, and fully connected layers. Two of the most common applications for CNNs are the recognition of handwritten characters and image processing. In the domain of computer vision, CNNs have been used for a variety of tasks, including object detection, image classification, voice recognition, image fragmentation, medical image analysis, and text and video processing. Convolutional, pooling, and fully connected layers are the typical architectural components of a CNN [24]. Figure 3 depicts the architecture of a CNN, and brief descriptions of each layer are provided below.

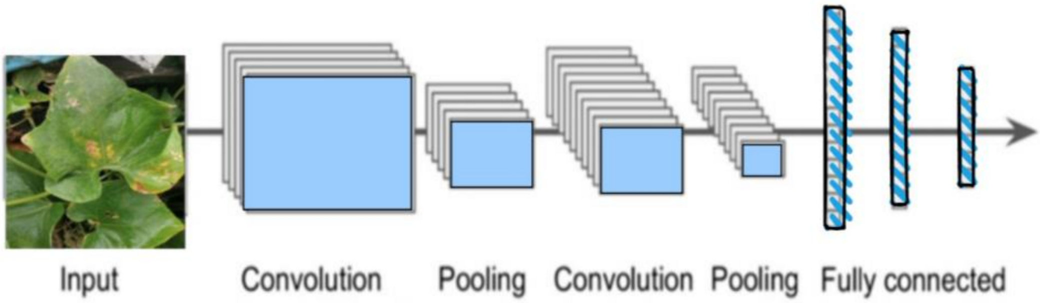

Figure 3. Convolutional neural network architecture.

In a CNN, the convolutional layer is the most fundamental and significant. It stores all of the images' distinguishing characteristics while making it possible to limit the amount of data that must be simultaneously processed. Then, pooling enables a CNN to aggregate all the different dimensions of an image and recognize the object, even if its form is distorted or it is positioned at an angle. Thus, the number of learnable features in the model is reduced, helping to address the overfitting issue. Pooling can be accomplished in a variety of ways, including average pooling, maximum pooling, and stochastic pooling. The fully connected layer is the final layer, which is used to feed the neural network [24].

3.3.2. Recurrent Neural Networks (RNNs)

An RNN is a type of neural network model capable of performing exceptionally well in fundamental tasks such as machine translation, language modeling, and speech recognition [25]. Unlike traditional neural networks, RNNs use the network's sequential information. This feature is essential in many applications because the data sequence's inherent structure contains valuable information that can be extracted from it. Figure 4 depicts the fundamental structure of a recurrent neural network [25].

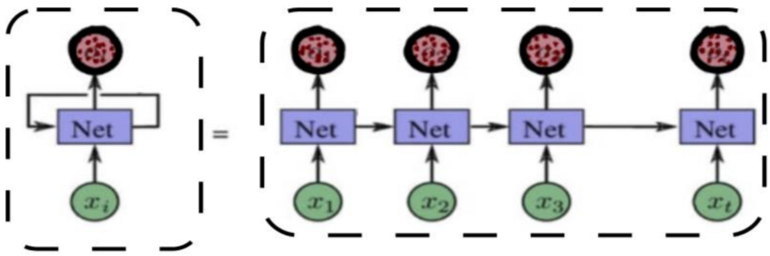

Figure 4. Recurrent neural network generic structure.

4. Significance of Deep Learning in Agriculture

4.1. Counting of Fruit

Counting fruit is an essential task for growers because it makes it possible to estimate the yield, which can be helpful in the management of yards. According to [26], counting fruit using automated fruit detection and algorithms can optimize agriculture production and help in managing the harvest process effectively. For automated fruit counting and detection, the authors provided a method that uses a pipeline for the DL algorithms consisting of part 0, part 1, part 2, and part 3. In part 0, the algorithms learn ground truths. They use the Bob detection neural network in part 1 and count the fruit through the neural network in part 2. In part 3, the linear regression is run for the final count [26]. The authors of [27] proposed automatic yield estimation using robotic agricultural techniques to improve the manual counting of fruit. The authors used Inception-ResNet to achieve a high accuracy ratio with a lower computational cost as a deep simulated learning technique. The significance of the technique proposed in [27] is that it does not require thousands of images to train the neural networks. Instead, the network can be trained with synthetic images to test the authenticity of images, achieving an accuracy rate of 91%. This novel DL method can facilitate farmers' abilities to efficiently count fruit and make decisions with great precision [27]. Similarly, the authors of [28] trained a Fast R-CNN DL model to detect, count, and predict the right size for citrus fruit. The authors also used the long short-term memory detection method to calculate the number of fruit on each tree, as shown in Figure 5. Hence, DL methods, such as automated yield detection, DL simulation, and Fast R-CNN, can be helpful in the counting of fruit. Table 1 presents the most recent methods for counting fruits.

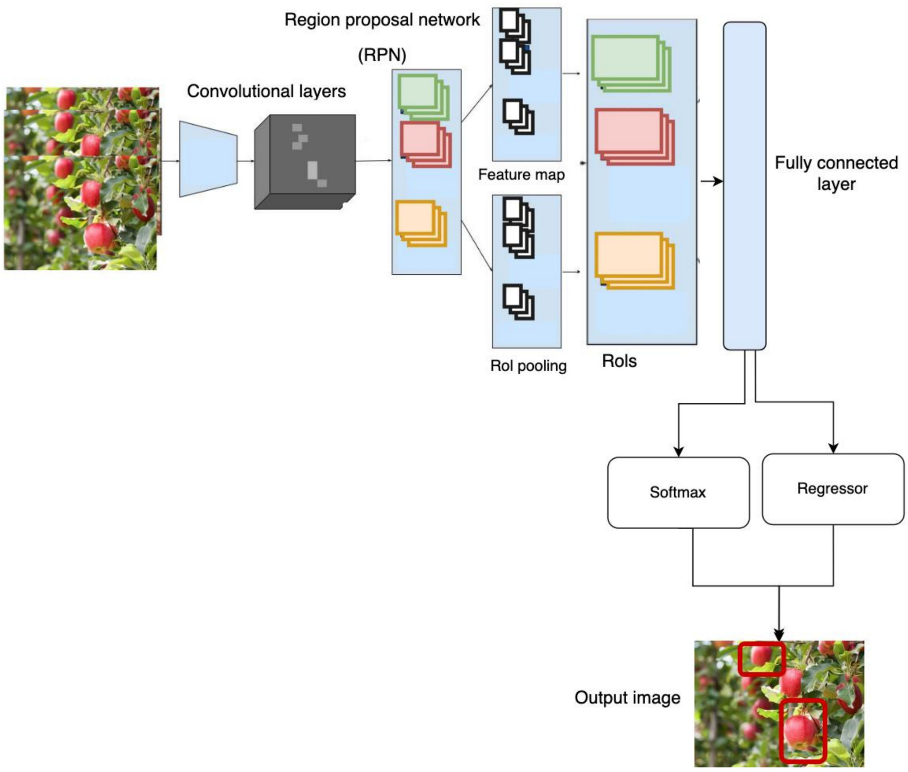

Figure 5. Flowchart for Faster R-CNN [28].

Table 1. Summary of different DL methods for counting fruit.

Ref	DL model	Dataset	Accuracy
[29]	Faster R-CNN	TL + field farm	0.83 F1-score
[30]	Inception-ResNet-v4	ILSVRC-2010&2012	N/A
[31]	VGG-16	Orchard	95%
[32]	CNN	Kiwifruit	89.29%
[33]	YOLO V3	PT + WGISD	—
[34]	Faster R-CNN + Iv2	Cherries	85%
[35]	E-Net	Fruit 360	93.7%
[36]	8-layer CNN model	Self collecting	95.67%
[37]	M-Net	Mango orchard	73.6%
[38]	YOLO V3	PT + WGISD	97.3% for test

4.2. Management of Water

Water is an essential natural resource for agriculture that needs recycling for the continued and sustainable development of agriculture. The authors of [39] stated that water is essential for agriculture production but the chemicals from industries and the wastewater from daily usage increase water pollution. Therefore, the agriculture field needs a DL technique to protect agriculture from water pollution. The authors of [39] proposed a near-infrared (NIR) spectroscopy method that can be used to assess water demand, protection, and recycling. The NIR system is used as one layer along with an improved convolutional neural network (CNN) layer that employs decision tree analysis to depict informative data helpful for making decisions relevant to water management. The authors of [40] posited that agriculture is the backbone of the economy in India and requires water as a significant resource. Traditional irrigation methods waste water due to excessive water use and unplanned water management. Therefore, the authors provided an integrative approach that uses DL methods to improve the irrigation system in India's agriculture (see Figure 6). The system consists of sensors that detect the soil's humidity and predict the irrigation needs of the soil. The authors of [41] stated that water is a critical resource for which evapotranspiration assessment is very beneficial. Evapotranspiration assessment uses DL techniques to predict upcoming water needs and to provide clues that can be helpful for real-time irrigation management. Thus, DL techniques can help farmers precisely manage their irrigation systems.

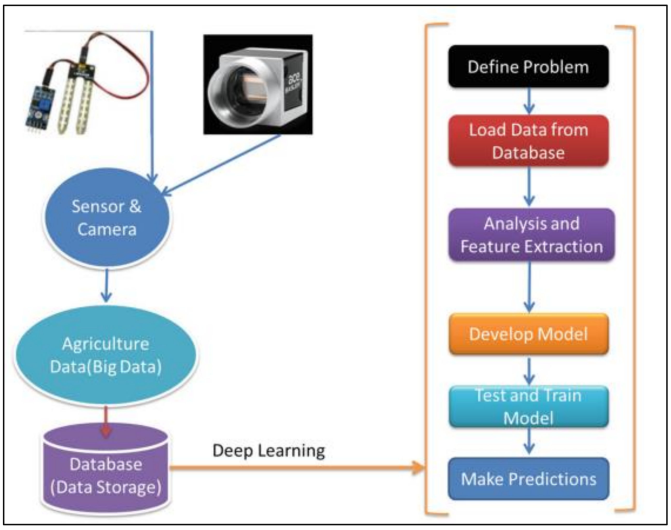

Figure 6. Deep learning approach for water management [40].

4.3. Crop Management

The significance of DL frameworks is increasing in crop management, a subfield of agriculture. The authors of [42] asserted that DL technology is beneficial for crop planting. Crop planting is the first step in crop production and needs to be managed efficiently to increase crop production. The authors discussed the various DL crop planting techniques, including ViSeed, which has been used for soybean production; Fast R-CNN, which has been used to count and measure the stalks of sorghum plants; CNN, which has been used for the identification of localized features of roots and shoots; and VGG-16, which has been used for categorization of crops and weeds. According to the authors of [43], there are different types of deep learning networks that can be used for crop prediction. These different types include ANNs, for which the regression method and crop species and images and climatic and soil properties can be used to predict wheat, barley, sugarcane, sunflower, and potato crop production. Other DL techniques discussed in [43] include two-layered DNN LSTM, which has been used to predict tomato, soybean, and corn crop production using the regression method, a vegetative index, environmental characteristics, and soil. In addition, the authors of [44] stated that intelligence plays a crucial role in precisely managing crops. The authors introduced the CropDeep approach, which classifies and detects different classes of crops. CropDeep provides crop management services through cameras and models; it classifies crops and provides analysis that is helpful for decision making and includes real-world challenges; e.g., weather uncertainty (see Figure 7). Table 2 presents the most recent methods for crop management.

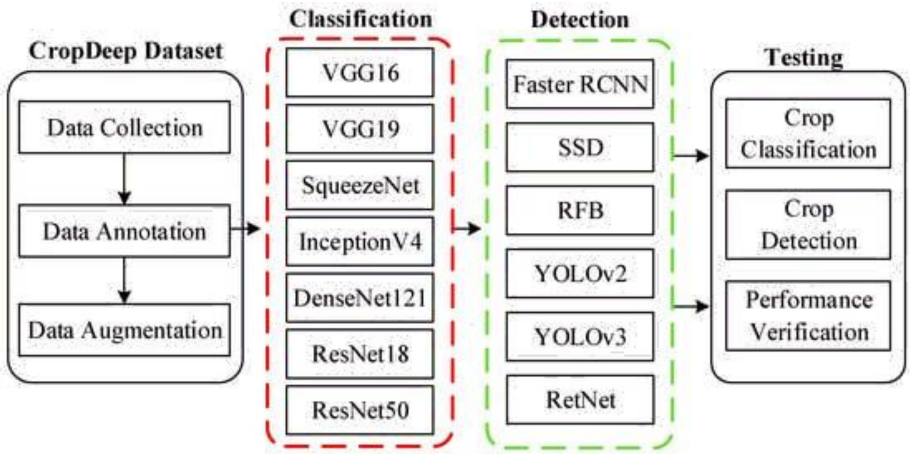

Figure 7. CropDeep deep-learning detection and classification models [44].

Table 2. Summary of different DL methods for crop management.

Ref	DL Model	Application	Accuracy
[45,46]	FCN architecture/Stem-seg-S	Joint stem detection and crop/weed classification	mAP, 85.4% (stem detection) 69.7% (segmentation)
[47]	AgroAVNET	Crop/weed classification	98.23%
[48]	AlexNet, VGG-19, GoogLeNet, ResNet-50, ResNet-101, Inception-v3	Crop/weed classification	96% (VGG-19)
[49]	1D/2D/3D CNN	Crop mapping	94% (3D CNN)

4.4. Soil Management

Soil management refers to the practices, operations, and treatments that protect soil and increase an agricultural field's production. The authors of [50] stated that DL techniques can help manage soil moisture. According to the authors, developing a mathematical model is difficult for soil moisture, so the accuracy, predictions, and generalization of existing models could be improved. The authors improved the DL regression model by fitting it with large datasets, making it possible to precisely determine soil moisture.

The authors of [51] proposed that agriculture has been an essential aspect of the lives of human beings since even before civilization. Soil yield plays a key role in crop production and efficient agriculture. Therefore, the authors discussed how implementing the Keras API in Python can help protect soil from herbicide toxicity while also retaining moisture. Moreover, using a first-order agriculture simulator that employs discrete time, the Richard equation can help determine the precise moisture level in soil [52]. The authors explained that using an agriculture simulator can help in obtaining aerial images with a particular soil moisture information dataset. The dataset was analyzed using seven methods, including constant prediction baseline, SVM, and NN, which showed that using a CNN could reduce water consumption by 52% [52]. Thus, the authors showed that DL techniques can help maintain soil moisture.

4.5. Weed Detection

Weeds are undesirable plants that can reduce crop production. DL techniques can help detect weeds. According to [51], a "weed" is a plant that grows in an unfavorable environment. They have negative effects on crop production because they compete with plants for water, sunlight, and soil minerals. Weed detection can be undertaken by using DL techniques, such as first-order agriculture simulation with Richard's equation. This approach reduces the use of weedicides, thus protecting the soil from toxicity and ensuring the plants achieve suitable production yields. In addition, the authors of [53] raised the concern that the production and utilization of herbicides have made weeds resistant to these herbicides. Therefore, developing precision techniques to detect weeds is important to increase crop production. Researchers have discussed the revolution in computing technology and how it can help in better understanding weed biology and ecology. DL is the most helpful technique, as it aids in categorizing weeds in crop categories and getting rid of them. In a similar context, the authors of [54] found that DL techniques, such as classification SVMs and CNNs, can reduce the burden on farmers. The techniques can help farmers detect weeds. The authors described various weed detection and categorization techniques. In such techniques, the camera first takes images of weeds and then uses a gray-level occurrence matrix to identify homogeneity among the images. The color identified through the hue saturation value (HSV) describes the mellowness of the weeds, as shown in Figure 8. Hence, DL techniques are helpful for weed detection, reducing the burden on farmers and increasing crop yield.

4.6. Seed Classification

In the agriculture sector, crop production strongly relies on seeds. According to [55], seeds are a significant part of crop production, without which production and harvesting of crops are impossible. The increased level of population growth has put pressure on agriculture growth due to the precision needed when identifying and classifying seeds. The authors proposed a CNN to increase the efficiency of the classification of seeds. In this technique, the methods used included decayed learning points.

4.7. Classification of Plant Diseases

Plants can produce decreased crop yields due to the presence of fungi, microbes, and bacteria. If the disease is not diagnosed in time, it can cause significant economic losses for farmers. The pathogen-killing pesticides that are used to restore crop functionality and remove pests come at a high cost. Excessive use of pesticides is detrimental to the environment and can disrupt the water and soil cycles [56]. As plant diseases stunt growth, identifying them in their early stages is essential. DL models have been applied in the process of recognizing and categorizing various plant diseases. Several DL architectures have been proposed to improve detection accuracy [57]. In [58], the authors proposed a method for identifying and categorizing banana diseases based on a CNN. The proposed model processes pictures of leaves to help farmers detect two banana diseases (sigatoka and speckle) quickly. In addition, the authors of [59] used AlexNet to accurately classify plant diseases based on leaf images. The DL hybrid model described in [60] identified and categorized diseases that affect sunflowers, such as Verticillium wilt, Phoma rot, downy mildew, and Alternaria leaf rot. The authors of [61] developed a mobile app that utilizes machine learning to diagnose diseases that affect plant leaves. The app can classify 38 different diseases. The authors amassed 96,206 images, including both healthy and diseased plant leaf specimens, for training, testing, and validation of the model. In [62], the authors proposed a pre-trained, transfer-learning deep neural network model that could predict crop disease by learning leaf characteristics from input data. They extensively investigated different DL and CNN topologies, such as ResNet, MobileNet, Wide ResNet, and DenseNet. The result showed that the proposed method was superior in terms of accuracy and memory to previous methods in the literature. Another CNN-based method for detecting, classifying, and identifying plant diseases was proposed in [63]. The accuracy for the identification of 13 different plant diseases ranged from 91 to 98%. Furthermore, the proposed model was able to distinguish between unhealthy and healthy leaves, as well as their backgrounds. Using 500 different leaf images, the authors of [64] proposed a model based on an SVM classifier. The proposed model could accurately identify plant diseases, achieving an accuracy of 94%. Table 3 presents the most recent methods for classifying plant diseases.

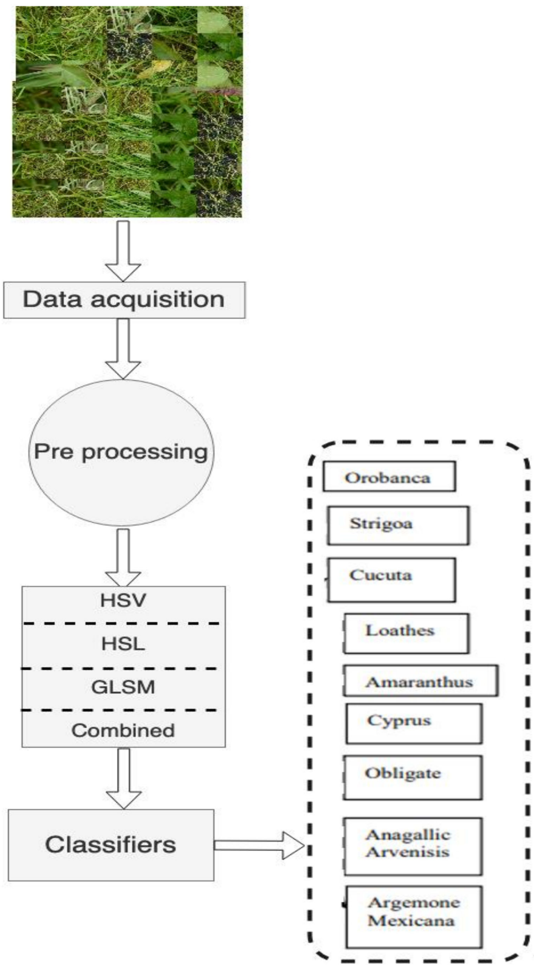

Figure 8. Flowchart for weed detection and classification [54].

Table 3. Summary of different DL methods for classifying plant diseases.

Ref.	Leaf Type	Method	Accuracy
[65]	Rice	VGGNet	92.00
[66]	Tomato	S-CNN and F-CNN	98.30
[67]	Plant leaf	EfficientNet	96.18
[68]	Grape	Hy-CNN	98.70
[69]	Grape	United model	98.20
[70]	Plant leaf	Whale and DL	95.10
[71]	Crop	FCNN and SCNN	92.01
[72]	Coffee	Deep CNN	98.00

4.8. Yield Prediction

It is essential to focus on and carefully manage yield predictions for each crop. Agricultural machine-learning and DL algorithms are primarily concerned with crop yield prediction. They inform the farmer about whether the crop is ready for cultivation and predict when it will be [73]. Manjula et al. [74] proposed a model based on an RF classifier that could predict millet crop yield with an accuracy of 99.74%. The prediction of crop yield is notoriously difficult due to the presence of numerous complex factors. For example, high-dimensional marker data are required to represent genotype information, consisting of the data for millions of markers for each individual plant. The final effect of the genetic markers must be estimated because it is affected by numerous environmental conditions and field management techniques. Recently, a variety of machine-learning models, including association rule mining, ANNs, decision trees, and multivariate regression, have been applied in the field of crop yield prediction. The most notable characteristic of ML and DL may be that the output is treated as an implicit function of the input variables and may be a highly nonlinear and complex function [75].

Extensive research has been conducted on crop yield prediction. Liu et al. [76] employed a neural network with one hidden layer for the prediction of corn yield using input data on weather, soil, and management. In the same context, Drummond et al. [76] worked on predicting crop yield by using neural networks, projection pursuit regression, and stepwise multiple linear regression. As a result, they found that both regression methods were outperformed by the neural network method. In addition, Marko et al. [76] predicted the crop yields of different soybean varieties by using weighted histogram regression. They obtained better performance than the conventional regression algorithms.

4.9. Disease Detection

In the agricultural field, one major threat to farmers is crop disease. With the developments in the fields of AI and DL and their implementation in agricultural industries, crop disease detection has become one of the easiest processes. Before the adoption of advanced technology in agriculture, the detection of diseases in crops at an early stage was a time-consuming and tedious task that had to be performed manually [77]. Plant disease not only affects plant growth and the population but also seriously affects the economy of countries. Hence, it is essential to adopt automatic and accurate techniques for the prediction and detection of plant disease severity for disease management and food safety and to predict losses in returns. In most developing countries, farmers are usually required to travel huge distances to contact experts, which can consume huge amounts of money and time [76]. This could be handled by developing a robust and easy-to-use plant or crop disease detection system, which would require many sample images of crops that have diseases that could be uploaded to the cloud, and the system could run on IoT devices, such as smartphones and tablet PCs with appropriate computational capabilities. Some work has been done in order to tackle this issue of crop diseases. Nikhil Patil et al. [78] proposed a crop disease detection system using a CNN. The system achieved an accuracy rate of 89% compared to the traditional crop disease detection system. Hence, when it comes to image processing, CNN systems can be relied upon due to the fact that they are widely used in agricultural research. Most DL applications in agriculture can be categorized as plant or crop classification, which is important for disaster monitoring, robotic harvesting, pest control, and yield prediction. Plant and crop disease recognition models are mostly based on pattern recognition and leaf images [78]. Hence, DL and AI models could automatically determine which plants are diseased and send alerts to the farmer for early action. Figure 9 shows an example of how DL and AI can detect plant diseases.

Figure 9. Plant disease detection [79].

5. Application of Deep-Learning Models in Agriculture

According to [80], there are different points of view about the creation of DL tools for model development. Python tools are used to emphasize the concept of saliency in images. Saliency is typically defined by unique features, including pixels, or the resolution of the image in visual processing. Another DL tool is the gradient explanation technique, which employs the gradient-based attribution method. In this method, each gradient quantifies each of the input dimensions that can change the predictions around the input. The integrated gradient is a gradient-based attribution that allows predictions to be formed by a deep neural network. It is created via attributions related to the network's input features [81]. Deep label-specific feature (DeepLIFT) is another tool designed to ensure the accuracy of deep neural network predictions. It is also known as the gradient + input method, and it is used to enhance the gradient with the input signal. It has quite a few advantages over gradient-based methods, especially when it is implemented into models that are usually trained with natural images and genomics data [82]. Typically, activation of each neuron takes place with reference to the contribution scores calculated by the system. These calculations are based on comparisons between various outputs and a certain benchmarked output and the differences in the inputs from their reference inputs. Another model is guided backpropagation, also known as guided saliency, which is a type of deconvolution approach. This tool and approach is often employed in a range of network structures, such as in max pooling in CNNs [83]. The purpose is to substitute the max-pooling layers with a convolutional layer. Similarly, the authors of [84] claim that deconvolution is a technique for visualizing CNNs that uses quite similar aspects, such as deconvolutional networks. Furthermore, the authors of [85] proposed class activation maps (CAMs) for the identification of images. With this tool, analysts may inspect a particular image and then its specific parts or pixels are used to form the final output. In other words, CAMs are used to study the discriminative regions of an image, as with a CNN. A final softmax-loss layer is formed after obtaining the weighted sum of the vector. Finally, layer-wise relevance propagation (LRP) is a tool for decomposing nonlinear classifiers that aims to improve DL interpretability [86]. It is based on deep neural networks formed by propagating predictions backward, fulfilling the requirement for the conservation property. All the abovementioned DL tools are currently available for model development.

According to [87], the deep neural network (DNN) can be employed using a CNN for the assessment of the quality of seeds in agriculture. The model can be used to study the quality of seeds in soybean pods, along with the sorting of haploid seeds. Assessments of the shape, phenotypic expression, and embryonic pose are undertaken [88]. CNNs have also been used in the classification plant seedlings into 12 species. Furthermore, the authors of [89] used an image analysis technique to create a principal component analysis (PCA) that can be used to place seeds in different clusters in a cost- and time-effective manner. The authors of [90] claimed that DL algorithms, such as Inspection-v3, VGG-16, and VGG-19, are more efficient in citrus plant disease detection than other innovations. In [91], the authors claimed that DL methods aid in the identification of plant diseases from individual lesions and spots. This makes it possible to focus on other aspects rather than only considering the entire leaf in disease detection. This DL application is good at detecting multiple diseases on the same leaf and provides 12% greater accuracy. DL methods can also be used to identify various plant diseases [92]. The authors of [93] claimed that apple leaf and fruit diseases can be detected using a CNN model, implying that the use of DL models for disease detection is quite effective. There are also harvesting techniques that use DL. The authors of [94] formed a shot-detector (YOLO) algorithm for on-tree fruit detection and used the BBox-Label-Tool to label images. Likewise, two deep learning models were utilized for images of pears and apples fruits, and it was found that the deep learning models were quite effective for harvesting purposes. The authors of [95] revealed that having a robust DL model can be helpful in the harvesting process, as it showed promising results due to its employment of bio-inspired features. As shown by these studies, DL is becoming one of the most useful techniques and models in harvesting since it employs mature features in comparison to other agricultural techniques. This recent survey also shows that CNNs have promising results in agriculture and increase efficiency. In other words, CNNs have increased accuracy and improved learning capacities when DL mechanisms are employed in agriculture.

6. Results and Discussions

The findings from the studies show that DL mechanisms have helped farmers in different areas of agricultural production. These include counting fruit, management of water, crop management, soil management, weed detection, seed classification, yield prediction, disease detection, and even harvesting. A summary of the key findings is presented in Table 4.

Table 4. Summary of different DL methods used in agriculture.

Ref	Method Used	Purpose of Employing Method	Key Insights
[20]	Automated fruit detection and algorithms using a DL algorithm pipeline consisting of part 0, part 1, part 2, and part 3	Counting fruit	Optimization of agriculture production Promising harvesting results
[27]	Inception-ResNet	Counting fruit	Provides high accuracy in the counting of fruit Uses synthetic images to test authentic images, achieving a 91% accuracy rate
[26]	Near-infrared (NIR) spectroscopy	Management of water	Increased water protection and recycling Provides information that helps make effective decisions in water management

Table 4. *Cont.*

Ref	Method Used	Purpose of Employing Method	Key Insights
[41]	Evapotranspiration	Management of water	Allows the prediction of water specifications for real-time irrigation management
[42]	R-CNN for counting and measuring crop plantings	Crop management	The CNN helps in identifying localized features of roots and shoots CGG-16 allows categorization of crops and weeds
[43]	Two-layered DNN LSTM	Crop management	Highlights soil and environmental characteristics Prominent vegetative index used to create estimations of crop production for tomato, soybean, and corn
[51]	Keras API through Python	Soil management	Helps in preventing the harmful effects of herbicides and toxicity in soil and in retaining moisture
[52]	First-order agriculture simulator using discrete time	Soil management	Improves aerial images and provides soil moisture information
[51]	First-order agriculture simulation with Richard equation	Weed detection	Increases protection of soil from toxicity and ensures plants achieve good production yields
[54]	SVM and CNN	Weed detection	The camera is used to take an image of a weed, and then the gray-level occurrence matrix is employed to determine the homogeneity among the images Reduces burden on farmers
[55]	CNN	Seed classification	Increased efficiency in seed classification
[74]	Random forest (RF)	Yield prediction	Provides the best yield prediction accuracy
[76]	Histogram regression	Yield prediction	Offers accuracy in the determination of soybean varieties
[78]	CNN	Disease detection	Achieved an 89% accuracy rate when compared to other traditional crop disease detection methods Improves pest control and makes robotic harvesting possible with increased yield prediction and disaster monitoring abilities for crops
[95]	Bio-inspired methods	Harvesting	Increases harvesting efficiency Improves accuracy for harvesting in agriculture
[96]	Canopy-attention-YOLOv4	Fruit detection	Precision = 94.89% Recall = 90.08% F1 = 92.52%
[97]	YOLOv5-CS (citrus sort)	Fruit detection and counting	Recall = 97.66% Precision = 86.97% mAP = 98.23%

The key findings from the literature review show that there are various ways in which DL has benefited the agriculture industry. Agriculture faces numerous barriers as a result of increased demand and fewer workers in the sector. However, the implementation of smart farming can help address issues such as productivity, environmental impact, food security, and sustainability and increase the efficiency of agricultural production [16]. Agriculture, as is well-known, plays an important part in the global economy [17] as it ensures food security for regions and is used by the majority of businesses for external commerce. The implementation of deep-learning methods has helped the agricultural sector grow and develop, employing the latest prediction analyses and tools. There are various tools that have been used by scholars to prove the efficiency of deep-learning methods in agriculture. According to [18], the size of the dataset used for deep-learning methods may determine the quality of the results. The accuracy of the results obtained using deep learning in agricultural production and processes may lead to improved decisions. Traditional farming practices result in a wide range of environmental consequences, including soil nutrient depletion. Deforestation is another issue produced by traditional farming, as most deforestation has occurred in tropical rainforests to make room for other agricultural activities. Soil erosion, which occurs as a result of the erosion of topsoil by water or wind, is another issue associated with traditional farming. This topsoil is the most productive portion of the soil and, once removed, it can take decades to restore it [19]. This implies that traditional agricultural production methods are insufficient to promote the efficiency of the sector. Agriculture must become more brilliant and progressive in order to meet future demands and utilize emerging technologies, such as deep learning, remote sensors, and distributed computing [98]. The current study's key findings highlight that the use of various DL tools in agriculture has improved farming outcomes and production. According to [95], the real parameters for agriculture are now obtained through cutting-edge technology and DL mechanisms. DL methods have proven their ability to increase efficiency in agriculture, showing improved results and accuracy in all domains. Despite the employment of DL mechanisms in agriculture, it was identified that there are also certain challenges that accompany the use of this technology, such as dataset creation, the time required to train staff, and having skilled labor to increase production. Furthermore, system development and hardware maintenance, as well as the deployment of large models and software on small devices, such as mobile phones, may have an impact on system efficiency [99]. Moreover, developing awareness among staff members when DL methods are employed is also challenging in agriculture. According to [100], transfer learning is a technique that can be employed to minimize the emerging challenges that may arise when employing deep learning in agriculture. It is typically used to address problems when there is a small dataset and minimal time is required to test the accuracy of the model. As shown in [101,102], AI is useful to minimize the challenges affecting agricultural production when DL and robotics are used. In the same context, automated machine learning (AutoML) is another technique that helps increase agriculture production through innovation. When DL methods are employed in agricultural production mechanisms, AutoML can be useful to minimize the challenges. Thus, the literature shows that DL methods have been extremely useful in increasing production in the agricultural sector. However, in order to minimize the challenges that come with employing DL techniques, it is important to consider employing other emerging technologies, such as robotics, the Internet of Things, and distributed computing.

It was found that most DL-based farming techniques use very simple algorithms and network structures. The primary cause of this is that the combination of deep learning and precision agriculture is still in its infancy. The lack of collaboration between the computer-science and agriculture communities is also a contributing factor. Table 1 shows that many of the deep-learning algorithms tested had an accuracy of 90% or more with some datasets, but it should be noted that these results are not generalizable. The accuracy and speed of these networks typically fall short of the benchmarks when they are employed with other datasets or a real farmland environment. This is mainly due to the fact that the complexity, quality, and quantities of agricultural datasets are still very different from actual farmland environments. Many novel approaches have been proposed to lessen the reliance of DL models on agricultural datasets, including transfer learning [103,104], few-shot learning [105,106], graph convolutional networks [107], and semi-supervised learning [108]. However, their entire performances are still unavailable. Only a few recent studies have focused on tailoring deep-learning algorithms and neural network architectures to the needs of agricultural applications. Some studies, for instance, have aimed to find the most effective ways to optimize the parameters used in DL models. Enhancing DL algorithms and frameworks has been the focus of other research. With the aim of large-scale dense semantic segmentation of weeds using aerial images, the authors of [109,110] presented WeedMap and WeedNet. They made changes to the decoder that allowed them to use a modified version of the VGG16 architecture in place of the original encoder. Jiao et al. [111] created an anchor-free convolutional neural network (AF-RCNN) to achieve a balance between speed and accuracy in deep-learning algorithms applied to the detection of multiclass agricultural pests. To improve recognition accuracy in leaf disease detection, the authors of [112] utilized convolutional neural networks (CNNs) and pre-trained models to identify plant diseases. The study focused on fine-tuning popular pre-trained models, such as DenseNet-121, ResNet-50, VGG-16, and Inception V4, using the PlantVillage dataset, which contains 54,305 images of plant diseases in 38 classes. The performance of the models was evaluated through various metrics. The results showed that DenseNet-121 achieved the highest classification accuracy of 99.81%, outperforming other state-of-the-art models. In the same context, the authors of [113] proposed a new method for data augmentation utilizing generative adversarial networks (GANs) for tomato leaf disease recognition. By utilizing deep convolutional generative adversarial networks (DCGANs) to augment the original images and GoogLeNet as the input, the proposed model was able to achieve the top average identification accuracy of 94.33%. The model was further improved by adjusting the hyper-parameters, modifying the architecture of the convolutional neural networks, and experimenting with different GANs. The use of DCGAN to augment the dataset not only increased its size but also improved its diversity, leading to better generalization of the recognition model. In addition, the authors of [114] proposed the use of a deep convolutional generative adversarial network (DCGAN) to augment an original dataset and trained a convolutional neural network (CNN) in the task of regression by utilizing the DCGAN to generate synthetic images that were realistic enough to be included in the training set. They employed a two-stage scheme where the baseline CNN, trained with the original dataset, was utilized to predict the regression vectors for each image generated by the DCGAN. These regression vectors served as the ground truth for the augmented dataset, enabling the CNN to make more accurate predictions.

7. Future Challenges and Opportunities in the Agricultural Domain

Deep learning has the potential to revolutionize the agricultural industry by enabling more efficient crop production, precision agriculture, and improved crop monitoring and forecasting. However, there are several challenges that need to be addressed to fully realize the potential of deep learning in agriculture. One major challenge is the lack of high-quality labeled data in the field of agriculture. This can be addressed by developing new data collection methods and creating large labeled datasets that can be used to train deep-learning models [114]. Another challenge is the high computational cost associated with deep learning, which can make it difficult to implement these models in resource-constrained environments, such as rural areas [115].

Additionally, there is a need for deep-learning models in agriculture to attain robustness and adaptability to different environments, crop types, imaging conditions, and sensor modalities. This requires the development of models that can be generalized well across different scenarios and are robust to variations in the data [116,117]. Furthermore, as the data in the agricultural domain is often incomplete, noisy, or corrupted, there is a need for methods that can handle missing or incomplete data [118]. In recent years, research on robust deep-learning techniques, such as robust optimization, adversarial training [118], and meta-learning [119,120], has been undertaken to address this challenge, but more research is still needed in this area.

Another important challenge is the need for deep-learning models in agriculture to be interpretable and explainable, as this is essential for decision making and to gain trust from stakeholders. There is a growing interest in developing methods that can provide insight into the inner workings of deep-learning models, such as explainable AI techniques—for instance, Local Interpretable Model-Agnostic Explanations (LIME) [121] and Shapley Additive Explanations (SHAP) [122]—and interpretable deep learning—for instance, decision trees and rule-based systems [123]. Moreover, the integration of multiple modalities of data, such as image, sensor, and weather data, is crucial to improving the performance of deep-learning models in agriculture. There is a need for multistream neural networks, such as those based on attention [124], that can handle multiple modalities of data and provide a more comprehensive understanding of the agricultural system.

Few-shot learning is a form of machine learning that allows models to be generalized to previously unseen classes with a small number of examples. This is beneficial in agriculture, as it allows such models to learn more quickly and accurately from a limited amount of data. Furthermore, it is more data-efficient, meaning that fewer data points are required to train the model [125].

In conclusion, deep learning has the potential to revolutionize the agricultural industry, but there are several areas that need to be addressed to fully realize its potential. These include the need for robustness, interpretability, integration of multiple modalities of data, and few-shot learning. Further research in these areas is crucial to overcoming these challenges and fully harnessing the power of deep learning in agriculture.

8. Conclusions and Future Work

The primary aim of the present study was to provide an overview of the recent advancements linked to DL in the agricultural sector. This study employed a comprehensive review of approaches linked to agricultural DL, including disease detection, yield prediction, and weed prediction, in studies published between 2016 and early 2022. The key findings of this paper indicated that a range of DL tools, employed for counting fruit, managing water, crop management, soil management, weed detection, seed classification, yield prediction, disease detection, and even harvesting, have been identified. It was also revealed that, despite the employment of DL processes in agriculture, there are certain obstacles that come with the use of this technology. It involves difficulties such as the compilation of datasets, the time necessary for staff training, and the presence of DL experts to ensure high production. Furthermore, system development and hardware requirements, as well as the deployment of large models and software on small devices, such as smartphones, may have impacts on system efficiency. Thus, it can be concluded that, with the support of the most recent prediction analyses and tools, the application of DL methods has assisted the agriculture industry in growing and developing. It can be noted that DL has great potential in the field of agriculture. However, the high cost of hardware and software makes its application very limited. Therefore, there is a need to work on research and development around cost-effective DL methods in the future to enhance large-scale applications. Furthermore, DL methods are limited in terms of accuracy and effectiveness. Thus, more research is needed in this direction to enhance the accuracy and effectiveness of DL methods.

The availability of computational capacity is yet another barrier that inhibits the implementation of DL in agriculture. The training of models necessitates ever-increasing amounts of computing resources due to the growing number of datasets, as well as the increasing complexity of deep-learning neural networks. It is very important that the performance of graphics processing units (GPUs) and central processing units (CPUs) continues to improve, as this is a very important accelerator for the widespread popularity of deep learning. In addition, the development of DL has been sped up by the availability of cloud computing services, such as the Google Cloud Platform, offered by private businesses. However, because of stringent requirements regarding computation capacity, current uses of DL in agriculture are typically offline. This means that the collection and analysis of images of farmland is undertaken in an asynchronous manner. Consequently, companies have paid some attention to this issue.

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