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Research Article

Deep Learning in Agriculture: Challenges and Opportunities – A Comprehensive Review

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Abstract
In this study, we have explored recent advancements in applying deep learning (DL) techniques within the agricultural sector. By reviewing studies published from 2015 to 2022, the research sheds light on the diverse applications of DL in agriculture. These applications encompass fruit counting, water management, crop, and soil management, weed detection, seed classification, yield prediction, disease identification, and harvesting. The study underscores the potential of DL in revolutionising agriculture, leveraging its ability to learn from extensive datasets. However, challenges such as data compilation, computational costs, and the scarcity of DL experts exist. We aim to mitigate these challenges by presenting this survey as a valuable resource. This resource aims to guide future research and development endeavours focused on integrating DL techniques in agricultural practices.

Keywords: deep learning, agriculture, soil management, seed classification.

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1. Introduction

In today's globalized world, the significance of agriculture and its contributions cannot be overstated. Throughout the years, agriculture has faced numerous difficulties in meeting the escalating demands of the world's population, which has doubled over the past five decades. Various projections indicate unprecedented growth, with the global population expected to reach approximately 9 billion by 2050 (Santos et al., 2020). Additionally, there is a noticeable rise in urbanization, accompanied by a substantial decrease in the percentage of retired or working individuals within the population

(Patil et al., 2016). This shift necessitates a substantial increase in agricultural productivity worldwide, requiring a robust human labour force. To tackle this issue, the agricultural sector implemented technological solutions over a century ago, including innovations like tractors. Today, mechanical technology has rapidly advanced, offering a wide array of options. Technologies like remote sensing (Atzberger, 2013), robotic platforms Santos et al., 2018), and the Internet of Things (IoT) (Patil et al., 2016) have become prevalent, especially in agriculture. This widespread adoption has ushered in an era of smart and efficient farming (Walter et al., 2017). According to Schmid Huber (2015), DL represents a modern approach that has found successful applications in various machine-learning techniques (Schmidhuber,2015). It shares similarities with artificial neural networks (ANNs) but possesses superior learning capabilities, resulting in higher accuracy (Kamilaris, 2018). In recent years, DL technologies like generative adversarial networks (GANs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs) have been extensively explored across different research domains, including agriculture. However, practitioners and researchers often utilize these technologies without a comprehensive understanding of their underlying mechanisms and concepts. DL encompasses several sub-categories of algorithms, including deep convolutional generative adversarial networks (DCGANs), very deep convolutional networks (VGGNets), and long short-term memory (LSTM) networks. Familiarity with these sub-categories is essential for comprehending common DL algorithms (Bouguettaya et al., 2022). As noted by Kamilaris and Prenafeta (Khan et al., 2022), DL represents a contemporary and potent technique for data analysis and image processing, displaying significant potential and promising results (Khan et al., 2022). Its successful integration into diverse domains, including agriculture, is notable. DL's strength lies in its ability to tackle complex problems swiftly and efficiently, owing to intricate models that facilitate massive parallelization. These sophisticated models, when applied in DL, have the potential to enhance classification accuracy and minimize errors in regression problems. However, this efficacy relies heavily on the availability of substantial databases capable of addressing such intricate problems. Its successful integration into diverse domains, including agriculture, is notable.

The authors (Kashyap, 2017) emphasized the significance of utilizing DL with drone technology in agriculture, providing a convenient method for monitoring, assessing, and scanning crops through high-quality, high-resolution images. This technology enables the recognition of advancements in fields and quality assessment. For instance, agricultural experts can determine crop readiness for harvesting by analysing images captured by drones. DL, in conjunction with machine learning (ML) techniques, aids farmers in understanding soil properties, facilitating timely farming decisions. It is also employed to manage nutrients and water efficiently, determining optimal cropping and harvesting times. This approach leads to higher yields, increased efficiency, and better projections of return on investment (ROI) for crops, accounting for market margins and costs (Magamadov, 2019). DL's efficiency surpasses traditional methods like support vector machines (SVMs), random forest (RF) algorithms, and ANNs. Various technologies combined with DL enhance predictive and classification performance in agricultural contexts. RNN and LSTM models, incorporating memory and time dimensions, predict plant and animal growth based on historical data. These models evaluate water requirements and crop yields, utilizing temporal data and memory functions (Jain et al., 2016). Additionally, they estimate growth and evaluate fruit yields or water needs using previously recorded data. (Ren and Kim, 2020) employed models to forecast phenomena and climate changes. Utilizing hyperspectral and infrared thermal imaging for data collection enables prompt disease detection in crops. With the exponential growth in this field, it is crucial to provide an updated review of recent literature focusing on innovative DL research techniques in agriculture. This study offers an overview of recent advancements related to DL in agriculture, specifically focusing on fruit counting, water management, crop, and soil management, weed detection, seed classification, yield prediction, disease detection, and harvesting. The adoption of technology in the agricultural sector has significantly transformed farming and crop cultivation. Notably, DL has enhanced agricultural efficiency, motivating researchers to explore its applications in farming, harvesting, and yield predictions.

This paper is structured as follows: Section 2 outlines the research methodology employed in this study. In Section 3, a literature review is presented, which includes a brief historical overview of the topic. Section 4 emphasizes the significance of DL in the agricultural sector. Section 5 explores DL tools suitable for model development, describing their usage, purpose, significance, and implementation within agriculture. Moving forward, Section 6 presents the study's results and engages in a discussion, drawing on insights from previous studies that have explored deep learning concepts. Finally, in Section 7, the paper concludes by summarising the overall findings and suggesting potential avenues for future research.

2. Research Methodology

The methodology employed in this study relied on secondary data and an extensive review of approaches associated with agricultural DL, encompassing areas like disease detection, yield prediction, and weed prediction. Various databases, including Research Gate, IEEE Explore, Springer, Elsevier, Google Scholar, Frontier, and Science Direct, were utilized for sourcing relevant literature. The study focused on research papers published between 2015 and early 2022, aligning with the period of significant advancements in DL and its growing application in agriculture. Data collection primarily centred around journal articles and conference papers that met specific criteria: they had to be in English, accessible in full, and directly relevant to the research objectives, particularly concerning development and agriculture themes.

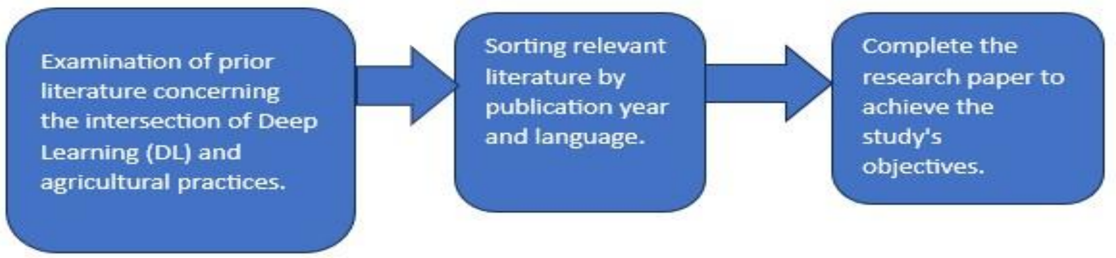

Fig. 1 The approach used for conducting the research

3. **Literature Review**

3.1 Deep Learning

The agricultural sector confronts numerous difficulties due to rising demand and a diminishing workforce in the fields. Smart farming, in this context, emerges as a solution to address critical issues like food security, sustainability, productivity, and environmental impact (Santos et al., 2022). Agriculture holds immense significance in the global economy, ensuring food security for nations and serving as a cornerstone for international trade (Kamilaris, 2018). In today's world, the automation wave, powered by artificial intelligence (AI), has touched various aspects of our lives, from home appliances to transportation services. Therefore, it is imperative for farming practices, the backbone of nations, to embrace technological advancements. To effectively address the intricate, multivariate, and unpredictable challenges of agricultural ecosystems, continuous monitoring, measurement, and analysis of various physical aspects and phenomena are crucial. Quick understanding and responses can be achieved through the insightful analysis of vast amounts of agricultural data, facilitated by new Information and Communication Technologies (ICTs). This necessity applies to both small-scale farms and large-scale ecosystem monitoring efforts. The implementation of DL with expansive networks offers a promising avenue to handle these difficulties, enabling the agricultural sector to make informed decisions based on data-driven insights.

DL represents a subset of machine learning focused on constructing neural networks that emulate the human brain's analytical learning process. Like the human brain, DL interprets data from various sources such as images, videos, text, and sounds. Its ongoing development has enabled its application in complex tasks like image segmentation, recognition, natural language processing, object detection, and image classification (Thai-Nghe et al., 2022). However, the efficacy of DL hinges on extensive datasets; the model learns and responds based on the information within these datasets. In the realm of agriculture, technological advancements such as image processing, the Internet of Things (IoT), robotics, machine learning, and computer vision have proven invaluable. Particularly, high-quality image processing integrated with drone technology offers farmers an efficient means to monitor crop progress and assess readiness for harvest remotely, eliminating the need for extensive travel. The synergy of AI and drones has already demonstrated significant benefits. Considering these advancements, implementing DL in agriculture could revolutionise the industry (Thai-Nghe et al., 2022). Figure 2 outlines the numerous advantages of incorporating DL in agricultural practices. Given the growing global population, the demand for agricultural products continues to rise (Thai-Nghe et al., 2022). Implementing DL and other automated components holds the potential to significantly enhance production outcomes. It can minimize crop spoilage, decrease production costs, and boost income by increasing overall production. The integration of DL stands poised to revolutionize agriculture, making processes more efficient and ensuring higher yields in response to the escalating demands of our expanding population.

Furthermore, it would enable the prediction of climate variations, such as impending rainstorms or cyclones, allowing farmers to be adequately prepared and take preventive measures before a potential disaster occurs.

3.2 Era Preceding the Emergence of Deep Learning

Traditional agriculture, predating scientific advancements in the agricultural sector, primarily relied on conventional methods. It involved the extensive use of traditional tools, organic fertilizers, indigenous knowledge of land use, natural resources, and cultural practices (Traditional Agriculture: An Efficient and Sustainable Farming Method. Stories.pinduoduo-global.com. 2021).

Described as the "primitive style" or "early style" of farming, traditional agriculture had significant environmental impacts, including soil nutrient depletion. Practices like slash and burn led to reduced soil organic matter, while deforestation, especially in tropical rainforests, occurred to make room for agricultural activities. Soil erosion, exacerbated by the removal of fertile topsoil by water or wind, posed another critical issue, as replenishing this topsoil could take decades (Traditional Agriculture: An Efficient and Sustainable Farming Method. Stories.pinduoduoglobal.com. 2021). Agroforestry, crop rotation, intercropping, and polycultures, along with water harvesting, represent some of the typical traditional farming practices. In traditional grain storage methods, small structures provided a moisture-proof environment, unlike today's large warehouses. These structures were cost-effective to build and maintain. However, during storage, various pesticides were employed to protect grains, leading to adverse environmental effects later on (Sahila and Begum, 2021). Technological advancements and substantial investments in agricultural industries have aided in disease control, justifying the significant financial investments made.

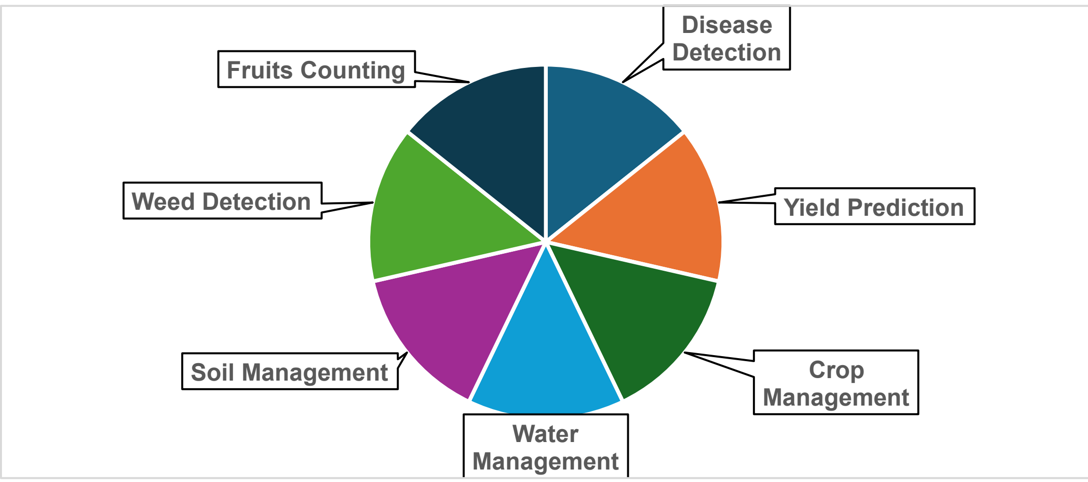

Fig. 2 Deep Learning Application in Agriculture

4. Deep Learning Architecture

DL relies on several nonlinear transformations to capture intricate patterns in data, forming the fundamental basis of this approach (Dargan et al., 2020). One of DL's key advantages is its ability to automatically extract features from raw data through a process called feature learning. This involves generating higher-level features from lower-level components (LeCun et al., 2015). In agricultural applications, DL networks such as RNNs and CNNs are commonly employed to leverage these transformative techniques.

4.1 Convolutional Neural Networks (CNNs)

The Convolutional Neural Network (CNN) is a type of Deep Learning algorithm (Abdullahi et al., 2017) that consists of multiple convolutional layers, pooling layers, and fully connected layers. CNNs find widespread applications in areas like handwritten character recognition and image processing. Within computer vision, CNNs are utilised for diverse tasks such as object detection, and image. classification, voice recognition, image segmentation, medical image analysis, and text and video processing. The standard components of a CNN architecture include convolutional layers, pooling layers, and fully connected layers (Ajit et al., 2020). Figure 3 illustrates the structure of a CNN, with brief explanations of each layer provided below. In a CNN, the convolutional layer serves as a fundamental and crucial component. It captures the distinctive features of images while allowing for the simultaneous processing of data in a more manageable way. Following this, pooling operations aggregate various dimensions of an image, enabling the recognition of objects even when they are distorted or positioned at different angles. This process reduces the number of learnable features in the model, effectively mitigating the risk of overfitting. Pooling can be achieved through methods such as average pooling, maximum pooling, and stochastic pooling. Finally, the fully connected layer, the last stage, is responsible for feeding the neural network (Ajit et al., 2020).

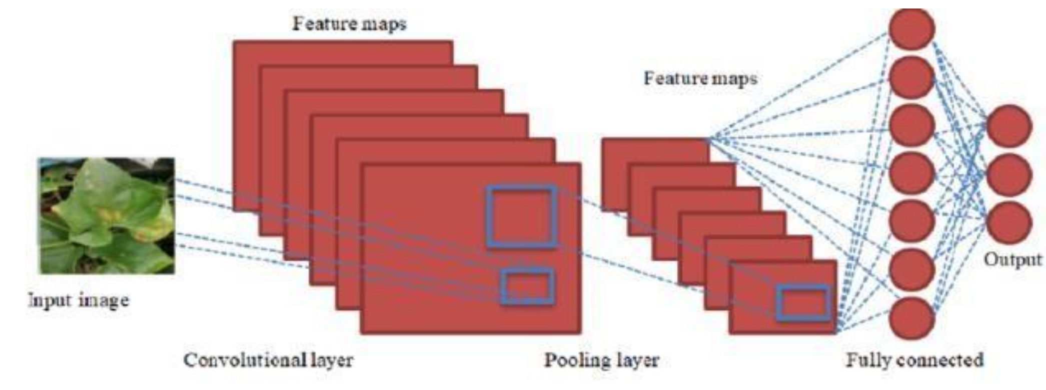

Fig. 3 Convolutional Neural Network Architecture

4.2 Recurrent Neural Networks (RNNs)

An RNN stands for Recurrent Neural Network, which is a specialized type of neural network model known for its outstanding performance in essential tasks like machine translation, language modelling, and speech recognition. (Zaremba, 2014). Unlike conventional neural networks, RNNs leverage the sequential information within the data. This sequential aspect is crucial in numerous applications as it allows the network to capture the inherent structure of the data sequence, extracting valuable information from it. Refer to Figure 4 for an illustration of the fundamental architecture of a recurrent neural network (Zaremba, 2014).

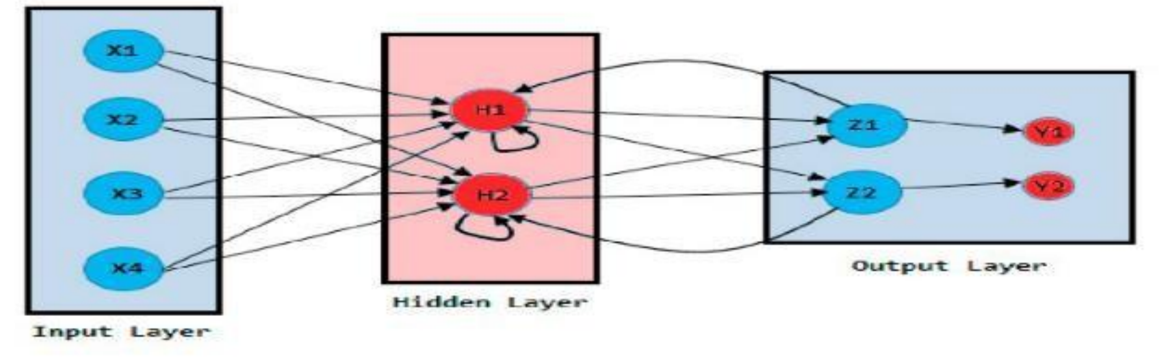

Fig. 4 Recurrent neural network architecture

5. Importance of Deep Learning in Agriculture

5.1 Counting of fruit

Accurately tallying fruits is crucial for growers as it enables them to estimate yields, aiding in efficient yard management. According to (Chen et al., 2017), automated fruit detection and algorithms play a pivotal role in optimizing agricultural production and enhancing harvest management. The authors introduced a method employing a DL algorithm pipeline comprising parts 0 to 3. In part 0, algorithms learn ground truths, followed using the Bob detection neural network in part 1 and fruit counting via a neural network in part 2. The final count is obtained through linear regression in part 3 (Chen et al., 2017). In another study, detailed in (Rahemoonfur and Sheppard, 2017), researchers proposed automatic yield estimation utilizing robotic agricultural techniques to enhance manual fruit counting. They utilized Inception-ResNet, a deep simulated learning technique, achieving high accuracy with minimal computational cost. Notably, their approach doesn't demand a vast dataset for neural network training; instead, it can be trained using synthetic images, resulting in a remarkable 91% accuracy. This innovative DL method empowers farmers to efficiently count fruits and make precise decisions (Rahemoonfur and Sheppard, 2017). Similarly, (Apolo-Apolo et al., 2020), authors trained a Fast R-CNN DL model to detect, count, and predict the appropriate size for citrus fruits. Additionally, they employed the LSTM detection method to calculate the number of fruits on each tree, as depicted in Figure 5. DL methods, such as automated yield detection, DL simulation, and Fast R-CNN, prove invaluable in fruit counting. Table 1 outlines the most recent techniques for fruit tallying.

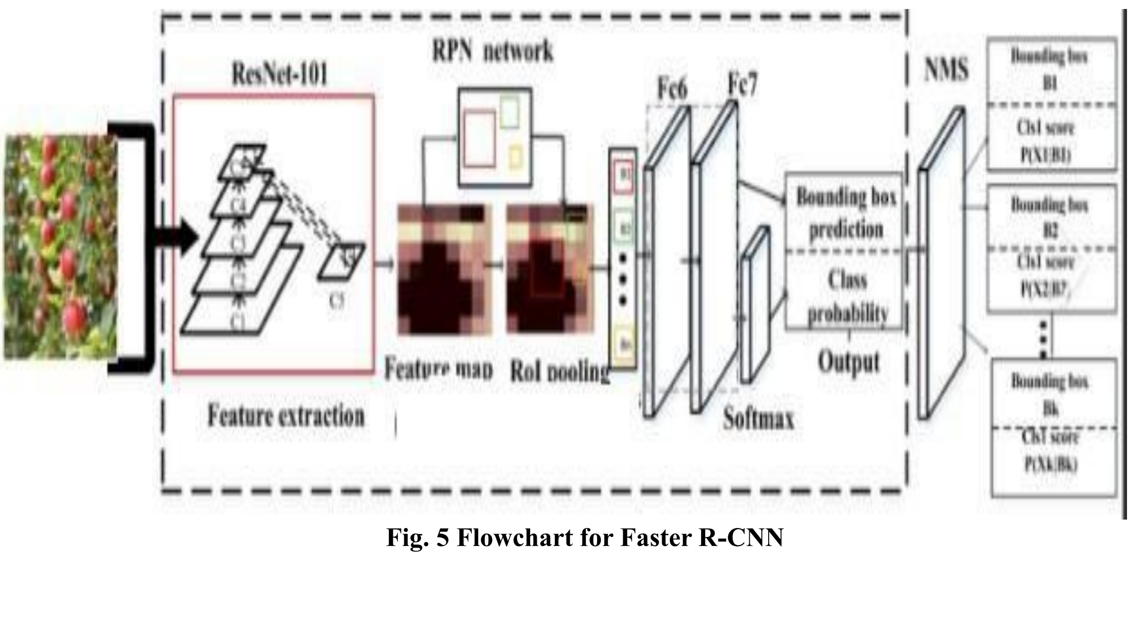

Fig. 5 Flowchart for Faster R-CNN

Table 1: Summary of different DL methods for counting fruit

Ref	DL Technique	Dataset	Accuracy
(Sa et al., 2016)	Faster R-CNN	TL	0.83 F1-score
(Krizhevsky et al., 2012)	Inception-Resnet-v4	ILSVRC	N/A
(Bargoti & Underwood, 2017)	VGG-16	Orchard	95%
(Fu et al., 2018)	CNN	Kiwifruit	89.2%
(Katarzyna and Pawel, 2019)	YOLO V3	PT+WGISD	………
(Villacres & Auat, 2020)	Faster R-CNN +Iv2	Cherries	85%
(Chung & Van Tai, 2019)	E-Net	Fruit #60	94%
(Wang & Chen, 2018)	8-layer CNN Model	Own Collection	95.67%
(Santos et al., 2020)	YOLO V3	PT+WGISD	97%

5.2 Water Management

Water, a vital natural resource for agriculture, necessitates efficient recycling to sustain agricultural development. According to researchers (Chen et al., 2020), while water is essential for agriculture, pollutants from industries and daily wastewater contaminate it. To safeguard agriculture from water pollution, a DL technique is imperative. The authors (Chen et al., 2020) introduced a near-infrared (NIR) spectroscopy method for assessing water demand, protection, and recycling. This approach integrates the NIR system with an enhanced convolutional neural network (CNN) layer, employing decision tree analysis to extract informative data crucial for water management decisions. In India, agriculture serves as the backbone of the economy, relying significantly on water as a resource (Garg et al., 2020). Conventional irrigation methods often lead to water wastage due to excessive usage and unplanned management. To address this, the authors proposed an integrated approach utilizing DL methods to enhance the country's irrigation system, as depicted in Figure 6. The system incorporates sensors detecting soil humidity and predicting soil irrigation requirements efficiently. Moreover, researchers emphasized the critical role of water as a resource, particularly in assessing evapotranspiration (Mohan and Patil, 2018). Evapotranspiration assessment, employing DL techniques, accurately predicts future water needs, offering valuable insights for real-time irrigation management. Consequently, DL techniques empower farmers to precisely regulate their irrigation systems, ensuring optimal water usage.

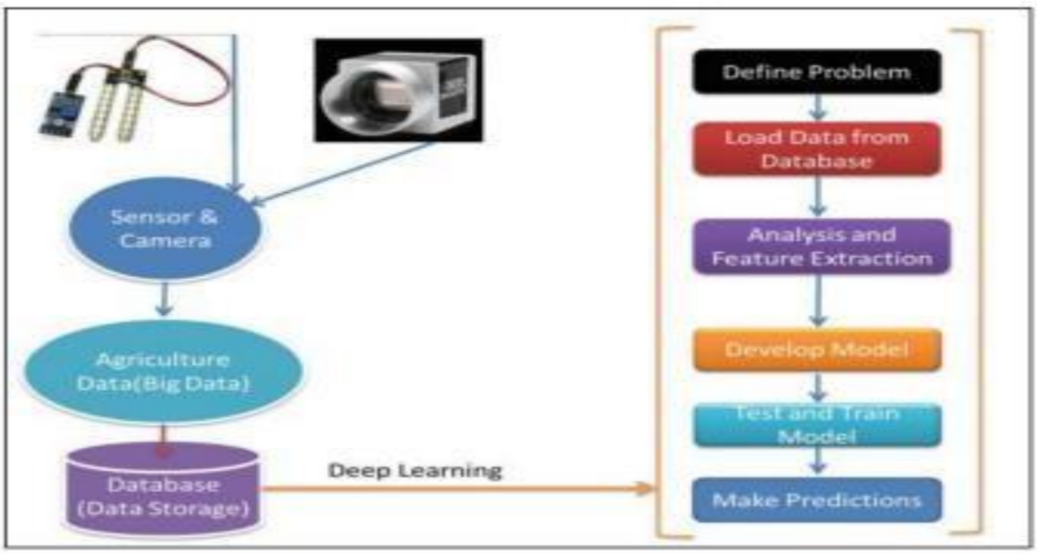

Fig. 6 Deep learning approach for water management [40]

5.3 ***Crop Management***

Deep learning frameworks have become increasingly vital in crop management, a pivotal subfield of agriculture. Researchers (Yang and Sun, 2019) emphasized the benefits of employing DL technology in crop planting, the initial and crucial stage of crop production that requires efficient management to enhance yields. The authors explored diverse DL techniques for crop planting, such as VI Seed for soybean production, Fast R-CNN for counting and measuring sorghum plant stalks, CNN for identifying localized features of roots and shoots, and VGG-16 for categorizing crops and weeds. In the realm of crop prediction, various deep-learning networks have proven valuable, as outlined in (Dharani et al., 2021). These networks, including ANNs, utilize regression methods along with crop species, images, and climatic, and soil properties to predict the production of crops like wheat, barley, sugarcane, sunflower, and potato. Additionally, (Dharani et al., 2021) discussed techniques such as two-layered DNN LSTM, employed to forecast tomato, soybean, and corn production. This approach integrates regression methods with vegetative indices, environmental characteristics, and soil properties. Furthermore, the critical role of intelligence in precise crop management was highlighted by researchers (Zheng et al., 2019). They introduced the Crop Deep approach, which classifies and detects various crop classes. Using cameras and models, Crop Deep delivers crop management services, offering valuable analyses for decision-making, even amid real-world challenges like weather uncertainties (refer to Figure 7). Table 2 provides an overview of the most recent methods in crop management.

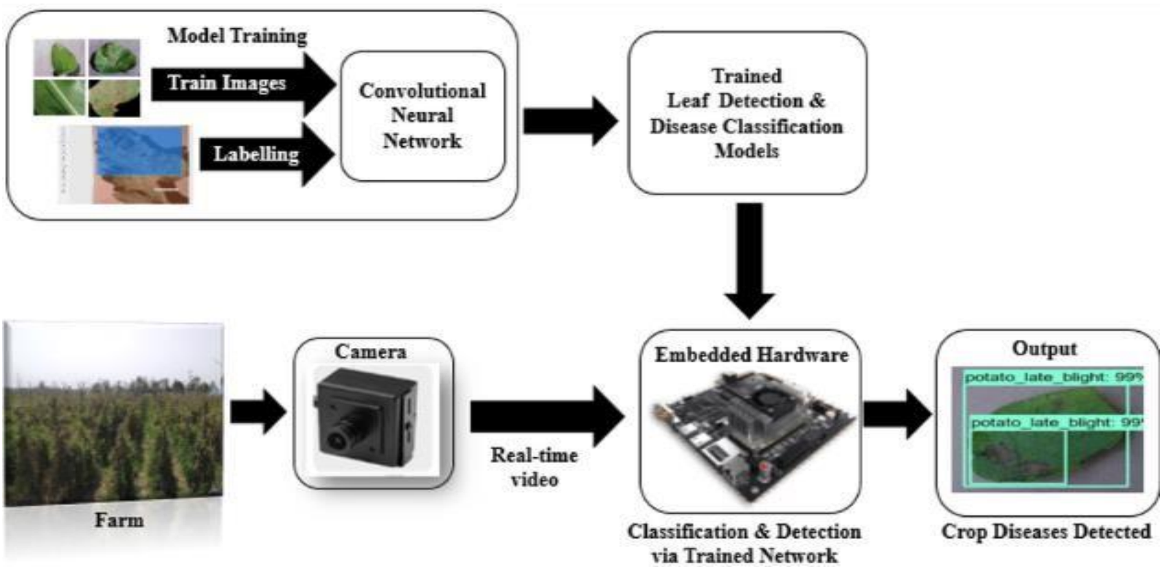

Fig. 7 Crop plant deep-learning detection and classification models [44]

Table 2: Different literature on DL methods for crop management

Ref	DL Method	Application	Accuracy (%)
(Lottes et al., 2020) (Lottes& Behley, 2018)	FCN architecture	crop classification	84.5
(Chaven & Nandedkar, 2018)	AgroAVNET	Crop/weed classification	98.23
(Suh et al., 2018)	AlexNet, VGG-19, GoogleNet, ResNet-50, ResNet-101, Inception-v3	Crop/weed classification	96(VGG-19)
(Suh et al., 2018)	AlexNet, VGG-19, GoogleNet, ResNet-50, ResNet-101, Inception-v3	Crop/weed classification	96(VGG-19)
(Meng et al., 2021)	1D/2D/3D CNN	Crop mapping	94 (3D CNN)

5.4 Soil Management

Soil management encompasses a range of practices and treatments designed to safeguard soil and enhance agricultural field productivity. Researchers (Cai et al., 2019) pointed out that DL techniques offer valuable assistance in managing soil moisture levels. Creating accurate mathematical models for soil moisture proves challenging, but the authors improved DL regression models by utilizing extensive datasets, enabling precise determination of soil moisture content. In a broader historical context, agriculture has been a vital part of human life since ancient times, even predating civilization, as emphasized by scholars (Yashwant et al., 2020). Soil yield significantly influences crop production and overall agricultural efficiency. To safeguard soil from herbicide toxicity while retaining moisture, the authors explored the implementation of the Keras API in Python. Additionally, they utilized a first-order agriculture simulator based on discrete-time and the Richard equation to precisely assess soil moisture levels. This simulator, combined with aerial images containing specific soil moisture information, underwent analysis through seven methods, including constant prediction baseline, SVM, and (Neural Network) NN. The results indicated that employing a CNN led to a remarkable 52% reduction in water consumption (Tseng et al., 2018). This research underscores the potential of DL techniques in effectively managing soil moisture levels. proves challenging, but the authors improved DL regression models by utilizing extensive datasets, enabling precise determination of soil moisture content. In a broader historical context, agriculture has been a vital part of human life since ancient times, even predating civilization, as emphasized by scholars (Yashwant et al., 2020). Soil yield significantly influences crop production and overall agricultural efficiency. To safeguard soil from herbicide toxicity while retaining moisture, the authors explored the implementation of the Keras API in Python. Additionally, they utilized a first-order agriculture simulator based on discrete-time and the Richard equation to precisely assess soil moisture levels. This simulator, combined with aerial images containing specific soil moisture information, underwent analysis through seven methods, including constant prediction baseline, SVM, and (Neural Network) NN. The results indicated that employing a CNN led to a remarkable 52% reduction in water consumption (Tseng et al., 2018). This research underscores the potential of DL techniques in effectively managing soil moisture levels.

Additionally, scholars expressed concerns about herbicides leading to weed resistance (Westwood et al., 2018). Precision techniques for weed detection are pivotal to enhancing crop production. Advancements in computing technology have revolutionized our understanding of weed biology and ecology. Among these techniques, DL stands out for its ability to categorize weeds within crop varieties and eliminate them effectively. In a related study, researchers (Mishra and Gautam, 2021) emphasized that DL techniques, including classification SVMs and CNNs, alleviate the burden on farmers by enabling accurate weed detection. These techniques involve capturing weed images through cameras, followed by analysis using a Gray-level occurrence matrix to identify homogeneity among the images. The colour information obtained through the hue saturation value (HSV) helps describe the weed's characteristics, as illustrated in Figure 8. Hence, DL techniques play a crucial role in weed detection, lightening the load on farmers and promoting increased crop yield.

5.5 Seed Classification

In agriculture, the cornerstone of crop production lies in seeds. Researchers emphasized by (Gulzar et al., 2020) that seeds are pivotal to crop cultivation; without them, the production and harvesting of crops would be utterly impossible. The escalating population growth has intensified the demand for precision in seed identification and classification, placing significant pressure on agricultural processes. To enhance the efficiency of seed classification, the authors introduced a CNN-based technique. This method incorporated advanced strategies, including the utilization of decayed learning points.

5.6 Classification of Plant Diseases

The presence of fungi, microbes, and bacteria can lead to reduced crop yields in plants. If left undiagnosed, these diseases can cause significant economic losses for farmers. To counteract these issues, farmers often resort to using pathogen-killing pesticides, but these solutions come at a high cost. Additionally, the excessive use of pesticides can harm the environment and disrupt water and soil cycles (Sharma et al., 2020). Detecting plant diseases in their early stages is crucial, as these diseases hinder plant growth. Deep Learning (DL) models have been employed to recognize and categorize various plant diseases, and multiple DL architectures have been proposed to enhance the accuracy of disease detection (Saleem et al., 2019). In their study (Amara et al., 2017), the authors introduced a novel approach to address this challenge. A method for swiftly identifying and categorizing banana diseases has been devised based on CNN. This innovative model processes leaf images, aiding farmers in promptly detecting two specific banana diseases, namely Sigatoka and speckle. Additionally, researchers (Dipali and Deepa, 2021) utilized AlexNet to precisely classify plant diseases based on leaf images. Another breakthrough was the development of a DL hybrid model described in (Akash and Malik, 2021), capable of identifying and categorizing diseases affecting sunflowers, such as Verticillium wilt, Phoma rot, downy mildew, and Alternaria leaf rot. To simplify disease diagnosis, the authors (Ahmed and Reddy, 2021) created a mobile app employing machine learning techniques to recognize diseases affecting plant leaves. Remarkably, this app can classify a diverse array of 38 plant diseases. To bolster their approach, they collected a substantial dataset of 96,206 images, encompassing both healthy and diseased plant leaf samples, for rigorous training, testing, and validation of the model.

Additionally, researchers (Pallagani et al., 2019) introduced a pre-trained, transfer-learning deep neural network model proficient in predicting crop diseases by learning distinctive leaf characteristics from input data. Their comprehensive exploration involved various DL and CNN topologies, including ResNet, MobileNet, Wide ResNet, and DenseNet. The results demonstrated that their method surpassed previous approaches in terms of both accuracy and memory efficiency.

Furthermore, a CNN-based methodology for detecting, classifying, and identifying plant diseases was proposed by (Sladojevic et al., 2016). This model exhibited remarkable accuracy in identifying 13 different plant diseases, ranging from 91 to 98%. Notably, it could differentiate between unhealthy and healthy leaves as well as their backgrounds. In a different approach, authors (Arivazhagan et al., 2013) leveraged a dataset of 500 diverse leaf images to propose a model based on a Support Vector Machine (SVM) classifier. This model demonstrated exceptional accuracy, achieving a rate of 94% in accurately identifying plant diseases. For a detailed overview of the most recent methods in plant disease classification, please refer to Table 3.

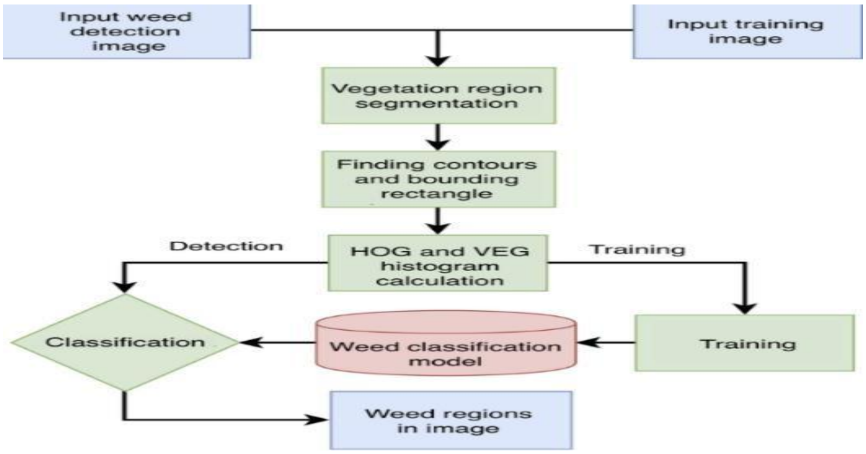

Fig. 8 Flow chart for Weed detection and classification. [54]

Table 3: Outline of different DL techniques for detecting plant diseases

Ref	Class of Leaf	Method	Accuracy (%)
(Chen et al., 2020)	Rice	VGGNet	92.00
(Sharma et al., 2020)	Tomato	F-CNN & S-CNN	98.30
(Atila et al., 2021)	Plant leaf	Efficient Net	96.18
(Kaur et al., 2022)	Grapes	Hy-CNN	98.70
(Ji et al., 2020)	Grapes	United model	98.20
(Gadekallu et al., 2021)	Plant leaf	Whale and DL	95.10
(Azimi et al., 2021)	Crop	FCNN and SCNN	92.01
(Joshi et al., 2021)	Coffee	Deep CNN	98.00

5.7 Yield Prediction

Accurate yield predictions for each crop are crucial and require meticulous attention. Agricultural machine learning and deep learning (DL) algorithms play a central role in predicting crop yields, providing valuable insights to farmers regarding cultivation readiness and harvest timing (Kavitha, 2022).

Manjula and colleagues (Josephine et al., 2022) proposed a model based on an RF classifier that achieved an impressive 99.74% accuracy in predicting millet crop yield. However, predicting crop yield remains challenging due to the intricate interplay of various factors. Representing genotype information demands high-dimensional marker data, encompassing millions of markers for each plant. The influence of genetic markers must be estimated, considering the multitude of environmental conditions and field management techniques. In recent studies, a range of machine-learning models, including association rule mining, Artificial Neural Networks (ANNs), decision trees, and multivariate regression, have been explored for crop yield prediction. Notably, both machine learning (ML) and DL models treat the output as an implicit function of input variables, often resulting in highly nonlinear and complex functions ((Khaki and Wang, 2019). In-depth research has been conducted in this field (Deepika and Kaliraj, 2022) employing a neural network with a single hidden layer to predict corn yield using weather, soil, and management data. Similarly, (Deepika and Kaliraj, 2022) utilized neural networks, projection pursuit regression, and stepwise multiple linear regression to forecast crop yield. Their findings indicated the superior performance of the neural network method over traditional regression approaches. Additionally, (Deepika and Kaliraj, 2022) predicted soybean varieties' yields using weighted histogram regression, surpassing the effectiveness of conventional regression algorithms.

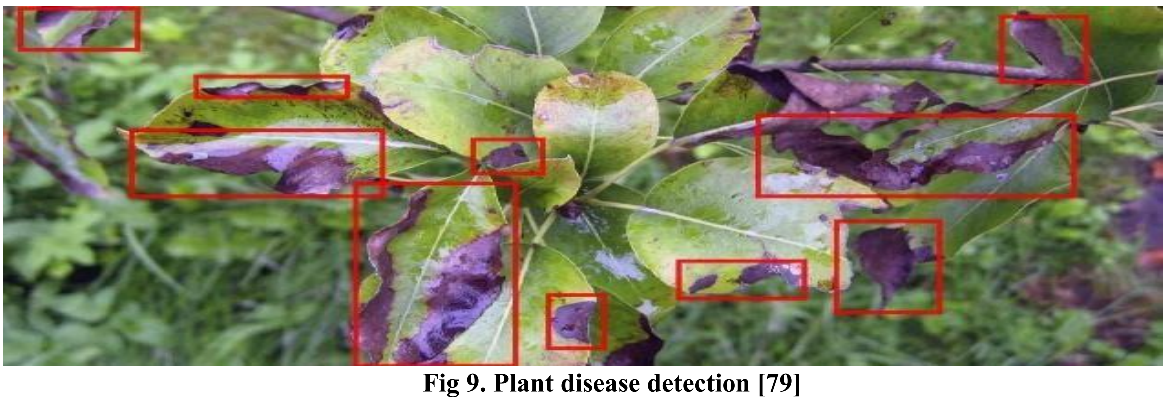

Fig 9. Plant disease detection [79]

5.8 Disease Detection

In the realm of agriculture, a significant concern for farmers is the occurrence of crop diseases. Thanks to advancements in Artificial Intelligence (AI) and DL technologies applied in agricultural sectors, detecting crop diseases has become a much simpler process. Before the integration of advanced technology in agriculture, identifying diseases in crops during their early stages was a time-consuming and laborious task that required manual intervention (Ale et al., 2022). Plant diseases not only hamper plant growth and population but also profoundly impact a country's economy. Therefore, it is imperative to adopt automatic and precise techniques for predicting and detecting the severity of plant diseases. This is crucial for disease management, ensuring food safety, and estimating potential financial losses. In many developing countries, farmers often must travel long distances to consult with experts, leading to substantial expenses and time consumption (Deepika and Kaliraj, 2022). This challenge can be mitigated by developing a robust and user-friendly system for plant or crop disease detection. Such a system would require an extensive database of sample images of diseased crops, which could be uploaded to the cloud. The system could operate on IoT devices, such as smartphones and tablet PCs, equipped with suitable computational capabilities. Efforts have been made to address this issue of crop diseases, indicating progress in this field.

Nikhil Patil and colleagues introduced a crop disease detection system utilizing a CNN, as outlined in their study (Zhu et al., 2018). This system exhibited an impressive accuracy rate of 89% compared to conventional methods of crop disease detection. Consequently, CNN systems are highly dependable in image processing, especially in agricultural research, where they find widespread application.

In the realm of agriculture, most applications of DL and AI can be categorized under plant or crop classification. This classification is pivotal for various purposes such as disaster monitoring, robotic harvesting, pest control, and yield prediction. Recognition models for plant and crop diseases primarily rely on pattern recognition and leaf images (Zhu et al., 2018). Therefore, DL and AI models are capable of automatically identifying diseased plants and triggering alerts to farmers for prompt action. Figure 9 provides an illustrative example of how DL and AI technologies can effectively detect plant diseases.

In their study, (Zhu et al., 2018) introduced a crop disease detection system utilizing a CNN, which exhibited an impressive accuracy rate of 89% compared to traditional methods. Therefore, in the realm of image processing, CNN systems stand out as dependable tools, especially in agricultural research where they are extensively employed. DL applications in agriculture mainly revolve around plant or crop classification, serving critical purposes such as disaster monitoring, robotic harvesting, pest control, and yield prediction. Recognition models for plant and crop diseases are primarily grounded in pattern recognition and leaf images. Consequently, DL and AI models possess the capability to automatically identify diseased plants, triggering alerts for farmers to take early action. An illustrative example of this capability is presented in Figure 9, demonstrating how DL and AI technologies excel at detecting plant diseases.

6. Application of Deep-Learning Models in Agriculture

Different approaches have been explored in the development of DL tools, as outlined in (Zhao and Koch, 2013). Python tools, for instance, emphasize the concept of saliency in images. Saliency, in this context, refers to unique features such as pixels or image resolution crucial in visual processing.

The gradient explanation technique utilizes a gradient-based attribution method, where each gradient quantifies input dimensions that can influence predictions around the input. Integrated gradient, a gradient-based attribution, forms predictions in deep neural networks by considering attributions related to the network's input features (Kummerer, 2015).

Deep label-specific feature (Deep LIFT) is another tool designed to ensure the accuracy of deep neural network predictions. Also known as the gradient + input method, it enhances the gradient with the input signal, particularly useful in models trained with natural images and genomics data (Shrikumar, 2017). Neuron activation occurs based on contribution scores calculated by the system, involving comparisons between different outputs, benchmarked outputs, and input differences from their reference inputs. Guided backpropagation, or guided saliency, employs a deconvolution approach and is commonly used in various network structures, including max pooling in CNNs (Springerberg and Dosovitskiy, 2022). Its purpose is to substitute max-pooling layers with a convolutional layer, enhancing visualization. Additionally, deconvolution, a technique for visualizing CNNs, and deconvolutional networks share similar aspects, as suggested by the authors (Zeiler and Fergus, 2014).

Furthermore, Class Activation Maps (CAMs) were proposed for image identification (Zhou et al., 2016). Analysts can inspect specific images, and their parts or pixels are utilized to form the final output, enhancing the interpretability and understanding of DL models. In simpler terms, Class Activation Maps (CAMs) are employed to examine specific regions of an image, a technique commonly used with CNNs. After obtaining a weighted sum of the vector, a final SoftMax-loss layer is formed. Additionally, layer-wise relevance propagation (LRP) serves as a tool for dissecting nonlinear classifiers, enhancing the interpretability of DL models (Bach and Binder, 2015). These DL tools are readily available for model development.

According to recent studies (Uzal et al., 2018), Deep Neural Networks (DNN) can be harnessed, especially with CNNs, to assess seed quality in agriculture. These models can evaluate the quality of seeds within soybean pods, including sorting haploid seeds. Assessments encompass shape, phenotypic expression, and embryonic pose (Nkemelu et al., 2022). CNNs have also been instrumental in classifying plant seedlings into 12 distinct species. Moreover, researchers (Amiryousefi et al., 2017) utilized an image analysis technique to create a Principal Component Analysis (PCA) for clustering seeds efficiently and economically. In the realm of disease detection, DL algorithms like Inspection-v3, VGG-16, and VGG-19 have proven more efficient in detecting citrus plant diseases compared to other innovations (Sujatha et al., 2021). DL methods facilitate the identification of plant diseases from individual lesions and spots, enabling focus on specific areas rather than analysing the entire leaf (Arnal, 2019). This approach, noted in (Liu et al., 2017), enhances accuracy by 12% and is adept at detecting multiple diseases on the same leaf. DL models have also revolutionized disease detection in plants, including apple leaf and fruit diseases, through CNN models (Bresilla et al., 2019). These studies demonstrate the effectiveness of DL in agriculture, extending to harvesting techniques. Researchers (Altaheri et al., 2019) devised a shot-detector (YOLO) algorithm for on-tree fruit detection, employing deep-learning models for apples and pears. The robustness of these DL models, as evidenced by (Meshram et al., 2021), offers promising results in the harvesting process, utilizing bio-inspired features. In summary, DL, particularly CNNs, has emerged as a pivotal technique in agriculture, showcasing enhanced accuracy and improved learning capacities when incorporated into various agricultural applications. These advancements underscore the pivotal role of DL in boosting efficiency across agricultural practices.

7. 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.

The comprehensive literature review reveals the manifold ways in which DL has positively impacted the agriculture industry. The sector, faced with challenges like increased demand and a decreasing workforce, has found solutions through smart farming, which addresses concerns related to productivity, environmental impact, food security, and sustainability, consequently enhancing agricultural efficiency (Santos et al., 2022). Agriculture's pivotal role in the global economy cannot be overstated, ensuring food security for regions and serving as the backbone of numerous businesses involved in international trade (Kamilaris, 2018). DL methods have played a transformative role in agriculture, employing cutting-edge prediction analyses and tools to foster sector growth. Scholars have utilized various tools to demonstrate the efficacy of DL methods. Notably, the size of the dataset used in DL methods significantly influences the quality of the results obtained, with accurate predictions leading to informed decision-making in agricultural processes (Thai Nghe et al., 2022). Traditional farming practices have led to environmental consequences such as soil nutrient depletion, deforestation, and soil erosion (Traditional Agriculture: An Efficient and Sustainable Farming Method. Stories.pinduoduo-global.com. 2021). Traditional agricultural methods are insufficient to promote sector efficiency. To meet future demands and embrace emerging technologies like DL, remote sensors, and distributed computing, agriculture must evolve intelligently (Khan et al., 2022).

The study's findings emphasize the substantial improvements in farming outcomes and production due to the implementation of various DL tools. Advanced technologies and DL mechanisms have redefined the parameters for agriculture, increasing efficiency and accuracy across domains (Meshram et al., 2021). However, the integration of DL techniques in agriculture is not without challenges. Issues like dataset creation, staff training time, the need for skilled labour, system development, hardware maintenance, and deploying large models on small devices, such as mobile phones, present obstacles. Moreover, raising awareness among staff when DL methods are utilized proves to be a challenge in agricultural settings (Wang et al., 2021).

Table 4: Application of different DL methods in Agriculture

Ref	Model Used	Objective of application	Outcomes
(Shaila and Begum, 2021)	Fruit detection and DLalgorithm pipeline	Counting fruit	Optimisation of agriculture output, Good Harvesting outcome
(Rahnemoonfur & Sheppard, 2017)	Inception-ResNet	Counting fruit	Obtaining 91% accuracy using synthetic images
(Chen et al., 2017)	Near-infrared spectroscopy	Water management	Enhances water recycling and safeguard
(Moha &Patil, 2018)	Evapotranspiration	Water management	Acute prediction of water specification in irrigation management
(Yang & Sun, 2019)	R-CNN	Measuring Crop planting	CNN finds localized features of roots and shoots.
(Dharani et al., 2021)	DNN LSTM	Crop regulation	Focused environmental and soil features. Accurate prediction of tomato, corn &soybean production.
(Yashwant et al., 2020)	Keras API	Soil handling	Aids in mitigating the detrimental impact of herbicides and soil toxicity, while also preserving essential moisture content.
(Yang & Sun, 2019)	R-CNN	Measuring Crop planting	CNN finds localized features of roots and shoots.
(Tseng et al., 2018)	Agriculture simulator with discrete time	Soil handling	Aids in mitigating the detrimental impact of herbicides and soil toxicity, while also preserving essential moisture content.
(Yashwant et al., 2020)	Agriculture simulation using Richard equation	Weed identification	Enhances soil protection against toxins and promotes optimal plant yields for higher production.
(Mishra & Gautam, 2021)	SVM & CNN	Detection of weed	Utilizing a camera to capture weed images, followed by analysing the grey-level occurrence matrix to assess image homogeneity, lightens the workload for farmers.
(Gulzar et al., 2020)	CNN	Classification of seed	Efficient classification
(Josephine et al., 2022)	Random forest	Yield prediction	Offers unparalleled precision in predicting crop yields.
(Deepika & Kaliraj, 2022)	Histogram regression	Yield prediction	Provides precise identification of soybean varieties.
(Zhu et al., 2018)	CNN	Disease identification	Attained an accuracy rate of 89%, surpassing other conventional methods for

			detecting crop diseases. Enhances pest management, enables robotic harvesting, and boosts crop yield forecasts and disaster monitoring capabilities.
(Meshram et al., 2021)	Bio-inspired methods	Harvesting	Enhances harvesting productivity and enhances precision in agricultural harvesting.
(Lu et al., 2022)	Canopy-attention-YOLOv4	Fruit detection	Precision = 94.89%, Recall = 90.08% ,F1 = 92.52%
(Lyu et al., 2022)	Citrus sort	Fruit detection and counting	Recall = 97.66% Precision = 86.97% mAP = 98.23%

In mitigating these challenges, techniques like transfer learning have been explored, particularly useful when there's a limited dataset and time for model accuracy testing (Coulibaly et al., 2019). AI, combined with DL and robotics, has proven effective in overcoming challenges faced in agricultural production (Sahni et al., 2021 Khan et al., 2021). Automated machine learning (AutoML) is another innovative technique enhancing agricultural production. When integrated with DL methods, AutoML minimizes challenges, demonstrating its utility in agricultural contexts. While DL methods have significantly enhanced agricultural production, addressing challenges requires a holistic approach. Combining DL with other emerging technologies such as robotics, the IoT, and distributed computing holds promise. This synergy ensures a comprehensive and effective response to the challenges faced in the agriculture sector, ushering in a new era of efficiency and sustainability.

Most Deep Learning (DL) techniques in agriculture presently employ straightforward algorithms and network structures. This is primarily because the integration of deep learning with precision agriculture is still in its nascent stage. The limited collaboration between the computer science and agriculture communities further exacerbates this issue. While Table 1 illustrates that several DL algorithms achieved accuracy rates of 90% or more with specific datasets, it's crucial to note that these results lack generalizability. When these networks are applied to different datasets or real farmland environments, their accuracy and speed often fall short of benchmarks. This disparity arises due to the significant differences in complexity, quality, and quantity between agricultural datasets and actual farmland environments.

Numerous innovative approaches have been proposed to reduce the dependence of DL models on agricultural datasets. These include strategies like transfer learning (Kaya et al., 2019 and Sharma et al., 2022), few-shot learning (Argueso et al. 2020 and Zhong et al., 2020), graph convolutional networks (Jiang et al., 2020), and semi-supervised learning (Khaki et al., 2021). However, comprehensive evaluations of these methods are still pending. Only a handful of recent studies have concentrated on tailoring deep-learning algorithms and neural network architectures specifically for agricultural applications. For instance, some studies have focused on optimizing the parameters utilized in DL models. Additionally, researchers have dedicated efforts to enhancing DL algorithms and frameworks. A notable example is the work by authors (Sa et al., 2017 and Sa et al., 2018, who developed WeedMap and WeedNet to achieve large-scale dense semantic segmentation of weeds using aerial images. Their modifications to the decoder enabled the utilization of a customized version of the VGG16 architecture in place of the original encoder.

Jiao and colleagues (Jiao et al., 2020) developed a convolutional neural network known as Anchor-Free RCNN (AFRCNN) 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 (Eunice et al., 2022) utilized 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 Plant Village 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 (Wu et al., 2020) 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 (Hammouch et al., 2021) proposed the use of a 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.

8. Future Difficulties and Possibilities in the Agricultural Domain

Deep learning has the potential to revolutionize the agricultural industry by enhancing crop production efficiency, enabling precision agriculture, and refining crop monitoring and forecasting techniques. However, realizing this potential in agriculture comes with its set of challenges that must be effectively addressed.

One significant challenge is the scarcity of high-quality labelled data within the agricultural domain. Overcoming this challenge necessitates the development of novel data collection methods and the creation of extensive labelled datasets tailored for training deep learning models (Hammouch et al., 2021). Additionally, the computational demands associated with deep learning pose a hurdle, especially in resource-limited environments like rural areas (Sourav and Emanuel, 2021). Moreover, deep-learning models in agriculture must demonstrate robustness and adaptability across diverse environments, varying crop types, imaging conditions, and sensor modalities. Achieving this requires the formulation of models that can generalize effectively across different scenarios and exhibit resilience to data variations (Bharma et al., 2022 Goodfellow et al., 2014). Furthermore, given the often incomplete, noisy, or corrupted nature of agricultural data, methods capable of handling missing or incomplete data are crucial (Liu et al., 2019). Recent research efforts have explored robust deep-learning techniques, such as robust optimization, adversarial training (Liu et al., 2019), and metalearning (Madry et al., 2018 Finn et al., 2017), yet further research is essential in this domain.

Interpretability and explainability are equally vital challenges facing deep-learning models in agriculture, as these factors are integral for decision-making processes and building trust among stakeholders. Ongoing research focuses on developing methods that shed light on the inner workings of deep-learning models. Techniques like explainable AI, such as Local Interpretable Model-Agnostic Explanations (LIME) (Ribeiro et al., 2016) and Shapley Additive Explanations (SHAP) (Lundberg and Lee, 2017), as well as interpretable deep learning methods like decision trees and rule-based systems (Caruana, 2015), are emerging to enhance model transparency.

Additionally, integrating multiple data modalities, such as image, sensor, and weather data, is pivotal for enhancing the performance and accuracy of deep-learning models in agricultural applications. This integration allows for a more comprehensive understanding of agricultural systems and contributes to the refinement of deep learning techniques in this sector. The adoption of multistream neural networks, particularly those employing attention mechanisms (Vaswami et al., 2017), is imperative in handling diverse data modalities and providing a holistic understanding of agricultural systems. Few-shot learning, a machine learning technique enabling models to generalize to new classes with minimal examples, holds promise in agriculture. It accelerates learning from limited data, enhancing efficiency and reducing the volume of required training data (Snell et al., 2017).

In summary, while deep learning holds immense potential for revolutionizing the agricultural industry, several challenges must be surmounted for its full realization. Addressing issues related to model robustness, interpretability, incorporation of multiple data modalities, and embracing few-shot learning techniques is essential. Further research in these areas is critical to overcoming these challenges and harnessing the full power of deep learning in agriculture.

9. Conclusions and Future Work

The main objective of this study was to present a comprehensive overview of recent developments in the application of Deep Learning (DL) in the agricultural sector. The review encompassed various aspects of agricultural DL, including disease detection, yield prediction, weed identification, and other related studies published between 2015 and early 2022. The findings highlighted the diverse applications of DL tools in agriculture, ranging from fruit counting to harvesting, along with associated challenges.

The study revealed that while DL processes have been integrated into agriculture, several challenges persist. Compiling datasets, training staff, and securing expertise in DL remain formidable obstacles. Additionally, issues such as system development, hardware requirements, and the deployment of large models on small devices like smartphones can impact system efficiency. Despite its potential, DL's application in agriculture is limited due to the high costs associated with hardware and software. Future research should focus on developing cost-effective DL methods for widespread use. Furthermore, efforts are needed to enhance the accuracy and effectiveness of DL techniques. Another hindrance to DL implementation in agriculture is the availability of computational resources. Training models necessitates significant computing power, which poses a challenge as datasets grow larger and DL networks become more complex. Continuous improvement in Graphics Processing Units (GPUs) and Central Processing Units (CPUs) performance is crucial for
DL's widespread adoption. Cloud computing services, such as the Google Cloud Platform, have accelerated DL development, but stringent computation requirements mean that current agricultural DL

applications are primarily offline. Addressing these challenges is vital for the seamless integration of DL into agricultural practices.

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