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Revolutionizing Agriculture with Deep Learning Current Trends and Future Directions

Asar Khan[1], Syafeeza Ahmad Radzi[1]*, Muhammad Zaim Mohd Zaimi[1], Azureen Naja Amsan[1], Wira Hidayat Mohd Saad[1], Norazlina Abd Razak[1], Norihan Abdul Hamid[1], Airuz Sazura A. Samad[2]

[1] *Machine Learning and Signal Processing (MLSP) Research Group, Fakulti Teknologi dan Kejuruteraan Elektronik dan Komputer (FTKEK), Universiti Teknikal Malaysia Melaka, 76100, Durian Tunggal, Melaka, MALAYSIA*
[2] *Ges Venture Manufacturing Sdn. Bhd, Johor Bahru, Johor, MALAYSIA*

*Corresponding Author: syafeeza@utem.edu.my
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Abstract

Deep learning (DL) presents new opportunities for agricultural technologies, offering superior accuracy over traditional methods. This study reviews 61 publications employing DL to address various agricultural issues, including disease identification, plant and crop detection, and classification. Notable performances include the VGG model for plant disease detection with 99.53% accuracy, AlexNet and GoogleNet with 99.76% accuracy, and ResNet-152 with 99.75% accuracy. In plant and crop classification, AlexNet achieved 99.80% accuracy, while MobileNet achieved 99% accuracy in fruit detection for mango and pitaya. A fine-tuned VGG-16 model reached 99.75% and 96.75% accuracy in fruit classification using two datasets. Additionally, CNN achieved 98% accuracy in improving efficiency, and a modified Inception-ResNet model achieved 91% and 93% accuracy in fruit counting on real and synthetic images, respectively. By analyzing frameworks, data sources, pre-processing methods, and results, the survey reveals that deep learning significantly enhances learning capabilities and precision in agricultural applications through hierarchical data representation and convolutional layers. This review underscores DL's potential in promoting smarter, safer food production and sustainable farming practices, encouraging further exploration and adoption of DL in various unexplored agricultural domains.

1. Introduction

Agriculture plays a crucial role in economic growth. As the global population keeps growing, there will be more demands on the agricultural sector. Emerging scientific fields like agri-technology, often called digital agriculture, are gaining prominence. These fields use data-intensive methods to enhance agricultural productivity and minimize environmental impact. This includes predictive agriculture, which is becoming a key focus.

Digital Agriculture [1] is essential for tackling challenges in the production of the agricultural sector. Through tracking, measurement, and assessment of diverse physical phenomena, a more comprehensive knowledge of the complicated, unsteady, and dynamic agricultural contexts can be achieved. This encompasses the huge amount of agricultural data and the integration of computer technology, both for small-scale agricultural operations and comprehensive farm surveillance [2]. This convergence enhances existing management and decision-making processes, enriched by contextual, circumstance, and environmental knowledge [3].

Utilizing images captured by satellites, helicopters, and unmanned aerial vehicles, like drones, spatial data allows for extensive surveillance coverage. When applied in agriculture, this approach offers numerous advantages. It serves as an effective, non-invasive means of gathering information about soil characteristics, ensuring consistent data collection [4].

Within the realm of agriculture, image processing occupies a significant realm of research, involving the application of intelligent data analysis techniques for tasks such as image recognition and classification [5]. Notably, methods such as machine learning (ML), Support Vector Machines (SVM), and other strategies have emerged as common tools for image analysis [6].

A recent addition to this field is deep learning (DL) [7], which has rapidly gained traction. DL constitutes a subset of machine learning algorithms, comparable to Artificial Neural Networks (ANN). However, DL delves further into neural networks, utilizing multiple layers of convolutions to establish a hierarchical data representation. This results in enhanced learning capabilities, consequently leading to improved efficiency and precision.

The driving force behind this survey lies in the emergence of DL as a new, forward-looking, and promising tool in agriculture. Moreover, the documented progress and successful implementations of DL across various domains underscore its potential and reaffirm its relevance for exploration within the agricultural context.

2. Methodology

In the explored domain, the academic review encompassed a series of steps: (a) compilation of similar works and (b) conducting an in-depth investigation and analysis. The initial phase entailed executing a search for key phrases within conference or journal papers, sourced from platforms like IEEE Xplore, ScienceDirect, and Google Scholar. The employed keywords were:

["deep learning"] and ["agriculture"]

By doing so, exclusion of articles listing DL but lacking relevance to the agriculture domain was achieved. Subsequently, the papers underwent review in the second phase, encompassing all research questions:

- Which agricultural and food-related issues were addressed?
- What DL model methodologies were employed, and what were the associated approaches?
- Which datasets and formats were utilized?
- What frameworks did the researchers adopt for classes and labels, and were any disparities observed among them?
- Was data pre-processing or data augmentation implemented?
- How did the models perform based on the applied metrics?
- Did the authors assess their models' outputs across diverse datasets?
- Did the authors draw comparisons between their chosen method and alternative approaches, and if so, were there notable differences?

The key results are reported in Section (4).

3. Deep Learning: Relevance and Challenges

The relevance of deep learning (DL) is steadily growing in our day-to-day lives. It has already left its mark in numerous fields such as cancer detection, precision medicine, self-driving vehicles, predictive forecasting, and speech recognition. An advantageous aspect of DL is feature learning, which involves automatically extracting features from raw data. This process generates robust features by composing lower-level features [7]. DL's ability to handle complex situations well and quickly, coupled with its potential for significant parallel processing, is a notable advantage facilitated by its more complicated models [8]. In scenarios with sufficiently large datasets representing a problem, DL's complex models hold the potential to enhance classification accuracy or minimize the problem of regression. The architecture employed in DL encompasses various components, including convolution, layers of pooling, and activation functions, among others.

Highly network model of DL models, as well as their strong learning power, allow them to perform classification and predictions for a wide range of highly complex problems [8]. Although DL is most associated with image data, it can be extended to any kind of data, including audio, voice, and natural language, as well as more broadly to constant or points data such as forecast data [9], soil chemistry [10], and others.

The primary advantage of employing DL in image processing is the diminished requirement for feature engineering (FE). In the past, image classification tasks relied on hand-crafted features, which significantly impacted the overall outcomes. Feature engineering is a dynamic and time-intensive process, necessitating adjustments when the problem or dataset changes. Contrastingly, DL eliminates the need for FE as it autonomously learns to identify the essential features.

A drawback of DL is its relatively longer training duration, yet it often offers simpler evaluation compared to other machine learning (ML) methods. Additional challenges encompass the potential issues arising from using pre-trained models on datasets with minor or substantial differences, optimization concerns tied to the complexity of models, and limitations imposed by hardware capabilities.

4. Advanced Deep Learning Models for Agricultural Applications

The 61 specified relevant studies are described in Table 1, Table 2, and Table 3 with details about the agricultural-related field of research, the problem they solve, the DL models and architectures used, the data sources used, the class and label of the data, pre-processed of data and/or augmented method used, and whole results achieved using the metrics.

4.1 Applications of Deep Learning in Agriculture

The areas of focus that emerge in classification include the identification of plant diseases (33 articles) as listed in Table 1 [11-41], the detection and classification of plants and crops (21 articles) as listed in Table 2[36], [42-61], along with other articles discussing the application of DL in agriculture (7 articles) as listed in Table 3 [62-68]. Based on the analysis of Tables 1, Table 2, and Table 3, several deep learning techniques have reported significant achievements in terms of classification accuracy in agricultural applications.

In the identification of plant diseases, some of the most notable performances include the VGG model for plant disease detection (Table 1), which achieved an impressive accuracy of 99.53%. Similarly, AlexNet and GoogleNet also demonstrated remarkable performance in plant disease detection, achieving a accuracy of 99.76%. Another high-performing model, ResNet-152, reached an accuracy of 99.75% for plant disease detection. For the detection and classification of plants and crops (Table 2), the AlexNet model showed exceptional performance in plant classification by neural network models, achieving an accuracy of 99.80%. In the domain of fruit detection, MobileNet achieved a accuracy of 99% when used for detecting mango and pitaya. Additionally, a fine-tuned VGG-16 model for fruit classification using two datasets achieved accuracy of 99.75% and 96.75% respectively. In other applications of deep learning in agriculture (Table 3), notable achievements include the use of CNN for improving efficiency in deep learning, which achieved a accuracy of 98%. Furthermore, a modified Inception-ResNet model for fruit counting achieved accuracy of 91% on real images and 93% on synthetic images.

The three tables collectively illustrate that deep learning techniques significantly outperform traditional methods in various agricultural applications. The high classification accuracies achieved by these models demonstrate their potential to revolutionize agriculture by enabling precise disease detection, effective crop classification, and versatile problem-solving capabilities. This can lead to smarter, safer food production and more sustainable farming practices, ultimately contributing to increased agricultural productivity and reduced environmental impact. The bar chart in Fig. 1 summarizes the deep learning model accuracies reported in Table 1, Table 2, and Table 3 in different agricultural applications.

Table 1 *Detection or classification of plant diseases*

No.[Ref]	Agriculture Area	Problem Description	Dataset Used	Classes and Labels	Variation among Classes	DL Model
1 [11]	Crop Disease Classification	Classify 14 crops species and 26 diseases	Public dataset of 54306 images consists of diseased and healthy plant	40 Classes: 14 Crop Species and 26 Diseases include healthy leaves	N/A	ResNet-50 Accuracy = 99.24%
2 [12]	Crop Disease Classification	Classify 3 Diseases of	Obtain from AI Challenger	3 Classes: Spot Blight, Late Blight,	N/A	ResNet-50 Accuracy = 98%

		Tomato Crops	consists of 300 test images	and Yellow Leaf Curl Disease		
3 [13]	Crop Disease Detection	Compare the performance of DL and classify rice leaf diseases	Artificial Pakistani Dataset contains 3000 images	4 Classes: Hispa, Healthy, Brown Spot, and Leaf Blast	Confusion between Hispa and Leaf Blast	Comparison between VGG-19, ResNet-50 V2, ResNet-101 V2. ResNet101V2 was the best performing model with an accuracy of 86.799
4 [14]	Plant Disease Detection	Detect plant disease which in two classes diseased and healthy	Obtain online which contain 87,848 images	2 Classes: Healthy and Diseased	N/A	AlexNet, GoogleNet, Overfeat and VGG Accuracy = 99.53% through VGG
5 [15]	Plant Disease Detection	Detect rice diseases in 10 classes	Not stated	10 Classes: Rice Blast, Brown Spot, Bakanae, Sheath, Blight, Sheath Rot, Leaf Blight, Bacterial Sheath Rot, Seedling Blight, Bacterial Wilt	Some classes show almost the same disease as the disease look alike such as Rice Blast and Sheath Blight	Deep CNN, SVM Accuracy = 95.48% through deep CNN
6 [16]	Plant Disease Detection	Detect diseases in tomato plant in 7 classes including healthy	Dataset taken from Vegetable Crops Research Institute, Jawa Barat consists of 1400 images	7 Classes: Early Blight, Late Blight, Healthy, Calcium Deficiency and others	The accuracy training result increases as the number of epochs increases	Squeeze Net Accuracy = 86.92%
7 [17]	Plant Disease Detection	Detect rice disease in Bangladesh with 6 classes	Dataset taken from BRRI with 600 images	6 Classes: Leaf Blight, Sheath Rot, False Smut and others	N/A	InceptionV3, MobileNetV1, ResNet-50 Accuracy = 98%
8 [18]	Plant Disease Detection	Plant disease detection to classify 4 classes of health	PlantVillage dataset of 4 classes with 10,000 images	4 Classes: Healthy, Early, Middle, End	The result of detection mixed between Early and Middle because of the	VGG-16, VGG-19, Inception-V3, ResNets0 Accuracy = 90.4% through VGG-16

					quality of image	
9 [19]	Plant Disease Detection	Detection of tomato leaf disease in 9 classes	Open access dataset with 5,500 images	9 Classes: Early Blight, Late Blight, Virus disease and others	N/A	AlexNet, GoogleNet, ResNet Accuracy = 97.28% through ResNet
10 [20]	Plant Counting and Disease Detection	Fruit counting and disease detection in apple tree	5 datasets obtain from University of Minnesota with not stated number of images.	Labels: Red Apples, Yellow Apples, Green Apples, Red apples with patches	N/A	Gaussian Mixture Models (GMM) + CNN CA = 96-97%
11 [21]	Plant Disease Detection	Detection of Cassava Disease in food	Leaflet cassava dataset which contain 15,000 images	6 Classes: Healthy, Brown Leaf Spot, Cassava Mosaic Disease and others	N/A	Inception-V3 Accuracy = 93%
12 [22]	Plant Disease Detection	Detection of strawberry diseases	Dataset created by author with a total image of 2098	4 Classes: Crown Leaf Blight, Gray Mold, Powdery Mildew, Fruit Leaf, Blight and Leaf Blight	Detection of disease vary because of lighting in the image	VGG16, G-ResNet50 Accuracy = 98.67% through G-ResNet50
13 [23]	Plant Disease Classification	Classification of diseased tomato with 9 classes	Plantvillage dataset with 14,828 images	9 Classes: Early Blight, Late Blight, Target Spot, others	N/A	AlexNet, GoogLeNet Accuracy = 99.18%
14 [24]	Plant Detection	Early detection of disease in leaf	Saitama Agricultural Technology dataset consist of 1.44Million images	3 Classes: Fully Leaf, Not Fully Leaf, None Leaf	Some identification of not fully leaf class are mistaken for fully leaf as the shape of the leaf disturbs the result	CNN but the model is not stated Detection performance of 78.0% in F1-measure at 2.0 fps.
15 [25]	Plant Disease Detection	Early detection of disease in banana leaf	PlantVillage dataset of banana leaves with 3,700 images	3 Classes: Healthy, Black Sigatoka, and Black Speckle	N/A	LeNet Accuracy = 94.44%

16 [23]	Plant Disease Classification	Classification of diseased tomato with 9 classes	Plantvillage dataset with 14,828 images	9 Classes: Early Blight, Late Blight, Target Spot, others	N/A	AlexNet, GoogLeNet Accuracy = 99.18%
17 [26]	Plant Disease Detection	Detection of plant disease by leaf classification	Author created the dataset consist of 33,469 images	15 Classes: Healthy Leaf, Peach, Pear, Apple and others	N/A	CaffeNet Accuracy = 96.3%
18 [27]	Plant Disease Detection	Detection of plant disease and saliency map visualization	PlantVillage dataset consist of 54,323 images of 14 crop with 34 classes	34 Classes: Apple Healthy, Apple Scab, Blueberry Healthy and others	N/A	AlexNet, GoogleNet Accuracy = 99.76%
19 [28]	Plant Disease Detection	Disease detection of Corn Plant using CNN with 3 types of disease	PlantVillage dataset with 3,854 images of maize diseases	3 Classes: Common Rust, Gray Leaf Spot, and Northern Leaf Blight	N/A	CNN Accuracy = 99%
20 [29]	Plant Disease Detection	Disease detection of tomato plant	PlantVillage dataset but not stated how many images was used	10 Classes including Healthy	N/A	AlexNet, SqueezeNet 94.3% through SqueezeNet
21 [30]	Plant Disease Detection	Disease detection of apple Leaf using CNN	Author created with 13,689 images	4 Classes: Mosaic, Rust, Brown Spot, and Alternaria	N/A	AlexNet Accuracy = 97.62%
22 [31]	Plant Disease Detection	Identification of maize leaf diseases using CNN	Plantvillage and several google images in total of 500 images	9 Classes: Heatlhy, Rust, Brown Spot, Round Spot and others	N/A	GoogLeNet, Cifar10 Accuracy = 98.9% through GoogLeNet
23 [32]	Plant and Pest Disease Detection	Identification of plant disease and pest using DL	Author created dataset with 1,965 images	8 Classes: Walnut Leaf, Apricot Monilia laxa, Erwinia amylovora	During testing, only certain image of Brown Spot are detected as Round Spot since the disease have almost	AlexNet, VGG-16, VGG-19 Accuracy = 96.92% through VGG-16

					the same specifications	
24 [33]	Plant Disease Detection	Plant leaf disease detection with 4 classes	Plant Photo Bank of China with 1,000 images	4 Classes: Black Rot, Bacteria Plaque, Rust and Healthy	N/A	VGG-16 Accuracy = 83.57%
25 [34]	Plant Disease Detection	Plant disease detection of 56 Classes with detection of lesions and spots	Not stated but total images are 46,409 images	14 Classes: Soybean, fuji, Coffee, and others	N/A	GoogLeNet Accuracy = above 75%
26 [35]	Plant Disease Classification	Plant leaf classification with 32 kinds of leaf	Flavia Dataset with 4,800 images	32 Classes: Tangerine, Oleander, Wintersweet and others	N/A	10-layer CNN Accuracy = 87.92%
27 [36]	Real-Time Disease Detection	Real-time detection of apple leaf disease using DL	Author created dataset with 26,377 images	5 Classes: Rust, Gray Spot, Mosaic, Brown Spot and others	N/A	GoogLeNet, Inception 78.80% mAP
28 [37]	Plant Disease Detection	Recognition of apple leaf disease in DL	Challenger-Plant-Disease-Recognition dataset but not stated number of images	6 Classes: Healthy, Apple Scab, Gray Spot and others	N/A	DenseNet Accuracy = 93.51%
s29 [38]	Plant Disease Detection	Tomato disease detection and classification with 10 classes including healthy	Plantvillage dataset of Tomato Disease with 13,112 images	10 Classes: Healthy, mildew general, mildew serious, and others	N/A	ResNetS0, Xception, MobileNet, ShuffleNet, DenseNet21_Xception Accuracy = 83.68% through ShuffleNet
30 [39]	Plant Disease Detection	Plant disease detection using DL with 14 crops and 26 diseases	PlantVillage dataset of 54,306 images	40 Classes: Apple Scab, Apple black rot and others	The test was done with 3 variation of grayscale images, coloured and leaf segmented	AlexNet, GoogleNet Accuracy = 99.35%
31 [40]	Plant Disease Detection	Comparative study of DL	PlantVillage dataset	38 Classes: Apple, Pear,	ResNet-152 show the	VGG16, Inception V4, ResNet-50 101

		models for plant disease detection with 26 diseases and 14 crops	with 54,306 images	Banana, Maize and others	greatest accuracy among others model	ResNet-152, DenseNet-121 Accuracy = 99.75%
32 [24]	Plant Leaf Detection	Plant leaf disease detection on early stage with 3 classes	Author created dataset with 1.14million images	3 Classes: Fully Leaf, Not Fully Leaf and None Leaf	N/A	CNN 78.0% in F1-measure at 2.0 fps
33 [41]	Plant Disease Identification	Disease identification of plant using hyperspectral image with 2 classes	Author created dataset with 539 images	2 Classes: Healthy, Infected	N/A	3D-CNN Accuracy = 95.73%, F1 score of 0.87

Table 2 *Detection and classification of plants and crops*

No.[Ref]	Agriculture Area	Problem Description	Dataset Used	Classes and Labels	Variation among Classes	DL Model
1 [42]	Crop Detection	Detect 3 classes of rice plant	Authors-created dataset contain 600 images	3 Classes: Normal, Unhealthy, and snail-infected	N/A	AlexNet Accuracy = 91.23%
2 [43]	Plant Detection	Detect maturity of crop in ripe and unripe	Dataset created by authors consist of 4,427 images	6 Classes: Based on maturity stage	N/A	AlexNet, VGG-16, VGG-19, ResNet50, ResNext50, MobileNet MobileNetV2 F1-score = 0.90
3[44]	Plant Detection	Detection of cotton fields from remote sensing images.	Author created the dataset with samples of 5,500 images	Detection of cotton field with remote sensing images	N/A	ResNet, VGG, SegNet, Deeplab v3+ precision was 0.948, F1 score was 0.953
4 [45]	Plant Detection	Identification of plant leaf counting	Dataset created by the author images of 600	Detection of number of leaves in tree	Identification of plant leaf vary as the algorithm still not fit with the model	YOLO-V3 and DarkNet F1 Score is over 0.94

Penerbit UTHM

5 [46]	Plant Classification	Fruit classification of using 2 datasets to classify 10 classes of fruits	2 datasets: 1st dataset contain 3,158 images of 10 fruits and 274 dataset 5,946 images of 10 classes	10.Classes: Pineapple, Avocado, Banana, Carrot, Kiwi and others	N/A	Light Architecture and VGG-16 fine tuned Dataset 1 = 0.9975 Dataset 2 = 0.9675
6 [47]	Fruit Classification	Classification of date fruit of 7 classes.	Authors created the dataset which contains 8,072 images	7 Classes: Immature-1, Immature-2, Khalal, Tamar and others	N/A	CNN, AlexNet, VGGNet Accuracy = 96.98%
7 [48]	Plant Species Classification	Plant Species Classification using Leaf Vein Morphometric	Author created the dataset with 1,200 images	43 Species but not stated in the paper which species	N/A	Fine Tuned AlexNet using CNN, SVM, ANN as the classifiers Accuracy = 94.88%
8 [49]	Plant Detection	Plant Identification in Natural Environment with 100 plants	BIFU100 dataset with 10,000 images	100 Classes: Chinese Buckeye, metasequoia, ginkgo biloba and others	N/A	ResNet26 Accuracy = 91.78%
9 [50]	Plant Detection	Detection of mildew disease in pearl millet using transfer learning	124 images but after augmentation composed of 711 images. Own dataset.	2 Classes: Diseased and healthy	N/A	VGG-16 Accuracy = 95%
10 [51]	Fruit Defect Detection	Detection of Mangosteen surface detection to avoid human error	Author created dataset with 500 images	2 Classes: Fine and Defect	N/A	CNN Accuracy = 97%
11 [52]	Real-time Fruit Detection	Real-time fruit detection in apple orchard	Author created dataset consist of 1,200 images	Labels: Apples	An apple that is too small is hard to detect and cause an error of detection	LedNet Accuracy = 0.853

12 [53]	Fruit Detection	Detection of fruit of mango and pitaya	Author created dataset	2 Classes: Mango and Pitaya	The colour of non-ripe mango effects the accuracy of the test	MobileNet Accuracy = 99%
13 [54]	Fruit Detection	Detection of strawberry based on masked R-CNN	Author created dataset with 2,000 images but only 1,900 used for training	Only label of strawberry	N/A	Mask R-CNN, ResNet50 Average detection precision rate was 95.78%
14 [55]	Real-Time Fruit Detection	Real-time fruit detection within the tree of apple and pear	Author created dataset with 5,000 images	2 Labels: Apple and Pear	N/A	YOLO Darknet Accuracy = 90%
15 [56]	Plant Classification	Plant classification by neural network models	Flavia, Swedish, UCI Leaf, and PlantVillage	Comparing all the DL model	N/A	AlexNet, VGG-16 but using LDA and SVM Accuracy = 99.80% through VGG-16 model and PlantVillage dataset
16 [57]	Crop Pest Classification	Classification of pest in plant with 40 classes in first dataset, 24 classes in second dataset and 40 classes in third dataset	NBAIR, Xie1 and Xie2 dataset	40 Classes: 1st dataset 24 Classes: 2nd dataset 40 Classes: 3rd dataset	N/A	AlexNet, ResNet, GoogLeNet, VGGNet Accuracy = 96.75%
17 [58]	Plant Detection	Detection of apple trees on trellis wires	Author created dataset with 509 images	4 Classes: Background, Trunk, Branch and Trellis Wire	The detection of trellis wires and brunch cause a small error as the brunch and wires are almost the same look	CNN, SegNet Trunk and branch segmentation accuracy of 0.92 and 0.93
18 [59]	Real-Time Fruit Detection and Yield Estimation	Real-Time fruit detection and load estimation using MangoYoLo	Author created dataset with total images of 1,400	Labels: Orchard	The higher the number of training images the higher the	R-CNN(VGG), R-CNN(ZF) and YOLOV3

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					training accuracy	
19 [60]	Leaf Classification	Classification of coffee leaf biotic stress with classes including healthy	Author created dataset with 1,685 images	4 Classes: Rust, Brown Leaf Spot, Cercospora Leaf Spot and Leaf Miner	N/A	CNN, AlexNet, VGG-16, GoogLeNet, ResNet50, MobileNetV2 Accuracy = 95.24% through ResNet50
20 [61]	Plant Species Detection	Multiclass weed species detection using DL with 9 classes	DeepWeeds dataset with 17,509 labelled images	9 Classes: Parthenium, Rubber vine, Siam weed, and others	Chinese Apple and Snake Weed showed a low F1 score as the leaf material is strikingly similar to each other	CNN, ResNet50, InceptionV3 Accuracy = 95.7% through ResNet50
21 [36]	Real-Time Fruit Detection	Real-time detection of apple fruit on apple tree in apple orchard	Author created dataset with 1,100	1 Labels: Apple	Detection of Apple are low for very small apple	LedNet 78.8 mAP

Table 3 *Other applications of DL in agriculture*

No.[Ref]	Agriculture Area	Problem Description	Dataset Used	Classes and Labels	Variation among Classes	DL Model
1 [62]	Crop Yield Prediction	Prediction of crop yield using remote sensing data	Author acquires data in Argentina and Brazil	Predicted area Argentina and Brazil	N/A	Not stated but it uses Deep Learning framework
2 [63]	Improving Efficiency in Deep Learning	Improving efficiency by using classification in DL with 2 classes	Author created dataset with 4,752 images	2 Classes: Carrots, Weeds	N/A	CNN Accuracy = 98%
3 [64]	Agriculture Monitoring	Monitoring agriculture using DL with satellite images	Author created real-world paddy datasets from Landsat 8 images in Vietnam	1 Label: Paddy field	N/A	SVM, CNN, Threshold and Spectral

4 [65]	Pest Detection	Detect pest in plants	71 types of 35,000 images of pest	71 Classes: Whitefly, Grub, Sawfly, Aphid, and others	N/A	Google Net, InceptionV3, InceptionV4
5 [66]	Fruit Counting	Predict number of tomatoes in the images	The author produced 24,000 images	Estimate the number of tomato fruits	N/A	Modified Inception-ResNet Accuracy = 91 % on real images and 93% on synthetic images
6 [67]	Fruit Counting	Counting apples and oranges	2 datasets consist of 5,000 images	Labels: apple and orange	The performance of the two datasets vary as it differs in Lighting condition, occlusion level, resolution and camera type	Caffe Net
7 [68]	Crop Improvement	Identify functional variants in natural populations using deep learning model	Plant genomics dataset but not state the total images	Not stated	N/A	CNN, DeepNovo

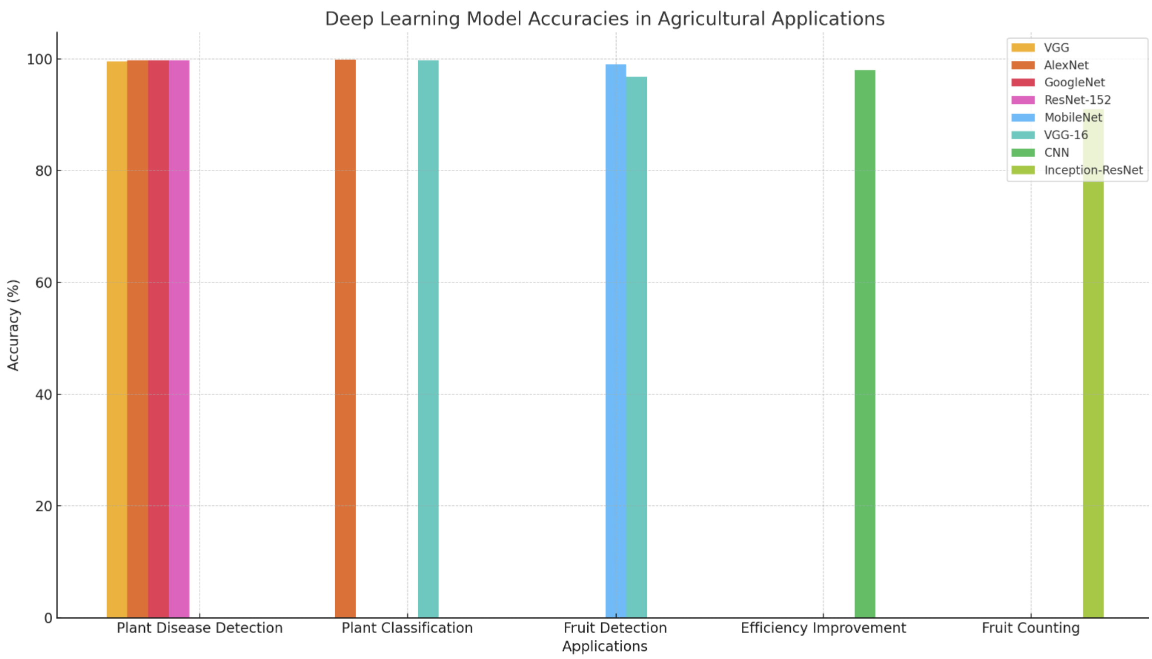

Fig. 1 *Deep learning model accuracies across different agricultural applications*

4.2 Data Sources

In the examination of data sources employed for training DL models in each study, a common trend emerges wherein substantial datasets of images are frequently utilized. In certain instances, these datasets comprise thousands of images, encompassing both real images [69] and those synthetically generated by the authors [1]. Several datasets are drawn from well-known and publicly accessible repositories like PlantVillage, RiceLeafs, and Flavia. Conversely, some researchers assemble their own collections of real images tailored to their research objectives [70]. A notable concentration of images is observed in papers addressing topics such as land cover, crop type classification, and certain disease detection investigations. Notably, the complexity of the problem at hand corresponds directly to the volume of data required. For instance, challenges demanding numerous input images for effective model training necessitate the availability of a substantial number of input images to accurately discern a wide array of classes or minor variations within classes.

4.3 Data Pre-processing

A predominant approach across much of the research involves limited pre-processing steps applied to images prior to their utilization, or the specification of distinct image characteristics, features, or statistics as inputs for deep learning models. Adhering to the requisites of DL models, a common pre-processing technique involves resizing images to specific dimensions, often adapting them to a few standardized scales. Common sizes include 256 × 256, 128 × 128, 96 × 96, and 60 × 60 pixels. Image segmentation is widely adopted, serving to augment dataset size or facilitate the learning process by highlighting regions of interest or annotating data to aid experts and volunteers. Techniques like foreground pixel extraction, background removal, or the elimination of non-green pixels based on Normalized Difference Vegetation Index (NDVI) are employed to mitigate dataset noise. In certain cases, tasks encompass the creation of bounding lines to assist in weed identification and fruit counting. Some datasets undergo conversion to grayscale from HSV color space. For satellite or aerial images, pre-processing steps such as orthorectification calibration and terrain correction are often employed.

4.4 Augmentation of Data

It is worth highlighting that certain studies within the examined body of work employed data augmentation methods to increase the quantity of training images. This approach introduces diversity into the dataset, leading to improvements in the overall learning process, outcomes, and generalization capability. Notably, data augmentation proves to be critical for articles working with limited datasets for training their DL models, as exemplified in [71]. This augmentation step was particularly pivotal in cases where researchers employed simulated images to train their models, subsequently assessing their performance on real-world data. The augmentation of data played a crucial role in enhancing the models' capacity to generalize and effectively address real-world challenges. Techniques such as rotations, dataset partitioning/cropping, scaling, transposing, mirroring, translations, perspective transforms, adjustments of object properties in object detection tasks, and a PCA-based augmentation method all fall under label-preserving transformations. Furthermore, additional augmentation strategies were embraced in articles involving simulated data. For instance, they incorporated variations in different channels of the HSV color space and introduced random shadows, or employed soil images to simulate the addition of roots.

4.5 Performance Metrics

In terms of performance evaluation techniques, the authors have employed a variety of metrics, each tailored to the specific model used in each analysis. Table 1 displays these metrics, along with their definitions/descriptions and the use of symbol in this survey by referring to them. From now on, the "DL results" is referred as one of the performance metrics mentioned in Table 4. The most commonly utilized performance metrics were accuracy, followed by the F1 Score. Some articles used CA, F1, P, or R for model prediction, as detailed in Table 1, Table 2, and Table 3.

Table 4 *Performance measurements used by other researchers*

Performance Metrics	Symbol	Description
Classification Accuracy	CA	The percentage of accurate predictions in which the top class (the one with the highest probability) is the same as the goal label as annotated by the authors before using the DL model. CA is averaged across all multi-class classification problems.

Precision	P	True positive (TP, accurate predictions) as a percentage of total applicable data, i.e the number of TP and false positives (FP). P is averaged over all classes of multi-class classification problems. P = (TP + FP)/ (TP + FP)
Recall	R	The fraction of TP from the total amount of TP and false negatives (FN). For multi-class classification problems, R gets averages among all the classes. R = TP/ (TP + FN)
F1 Score	F1	Precision and recall are combined into a harmonic mean. F1 is summed over all classes in multi-class classification problems.
LifeCLEF metric	LC	A rating based on the right species' position in the list of collected species.
Quality Measure	QM	Calculated by multiplying sensitiity (the percentage of pixels that were classified correctly) by precision (the percentage of pixels that were correctly detected) (which proportion of detected pixels are truly correct). QMI= ((TP + FPKTP + FN)I/((TP + FPITP + FN)/((TP + FPYTP + FN)
Mean Square Root	MSE	The square root of the errors between expected and observed values is the mean.
Root Mean Square Error	RMSE	The discrepancy between expected and observed values' standard deviation.
Mean Relative Error	MRE	The mean error between predicted and observed values, in percentage.
Ratio of Total Fruits Calculated	RFC	The ratio of the model's estimated fruit count to the real number. The real number was calculated by averaging the number of people (experts or volunteers) who independently observed the Photographs.
L2 Error	L2	The root of the squares of the totals of the discrepancies between the model's expected and real fruit counts.
Intersection over Union	IoU	The area of overlap between the expected 2nd ground truth boxes is divided by the area of their union to test predicted bounding boxes.
CA-IoU, F1-IoU, P-IoU, R-IoU	CA-IoU F1-IoU P-IoU R-IoU	These are the same CA, FL, P, and R metrics as before, but with the addition of loU to account for true/false positives and negatives. When dealing with problems involving bounding boxes, these functions are used. This 5 accomplished by setting a minimum threshold for loU, so that any value above it is considered positive by the metric.

5. Comparative Analysis and Challenges of Deep Learning in Agricultural Applications

DL outperforms in most tasks, but fair comparisons demand identical experimental conditions when contrasting it with other techniques. Articles primarily draw from the reviewed work to accurately compare DL and contemporary techniques, considering problem-specific contexts. Generalization and comparisons are challenging due to varying datasets, methods, measurements, models, and parameters. Thus, the assessments are limited to each article's employed techniques, where DL consistently surpasses standard methods like Support Vector Machines and Artificial Neural Networks.

While DL often aligns with computer vision, some articles employ it for field sensory data analysis [72][64], showcasing its broad applicability in agriculture beyond images. In agricultural DL applications, remarkable focus is placed on leaf classification, plant disease identification, recognition, and fruit counting, driven by abundant field data and distinct visual attributes [73].

Noteworthy articles highlight exceptional performance considering complex problems or numerous classes, without diminishing the surveyed papers' quality. These contributions tackle incomplete or absent datasets, adding significance to the DL community.

5.1 Deep Learning Advantages in Agriculture

Except for the differences in the results of identification problem in the assessed articles, several of the papers demonstrated the value of DL in terms of reduced feature engineering effort. Hand-engineered components take a long time to create, but in DL, this is done automatically. Furthermore, finding good feature extractors by hand is not always a simple or obvious job.

DL models also appear to generalize well. In fruit counts, for example, the model learned to count directly [66]. The model was robust under challenging conditions in the banana leaf classification problem, such as illumination, complex context, and different resolution, scale, and orientation of the images [74].

Peaches, oranges, mangoes, and other circular fruits may all benefit from the same detection frameworks. The Deep Anomaly have a key aspect rather than just a predefined object which are able to recognize unexplained objects/ anomalies are the ability, which an agricultural field could detect unknown object, heavy occluded, and distant used the homogenous features [75].

While DL require more time than other conventional approaches (e.g., SVM, RF), it has a very fast inference time quality. For example, the model took much longer to train in order to detect obstacles and anomalies [75], but once it did, it performs faster than SVM and KNN. Another benefit of DL is the ability to create virtual datasets to train the algorithm, which can then be used to solve real-world problems.

5.2 Deep Learning Disadvantages and Limitations in Agriculture

A significant training downside is the demand for large input datasets, a common DL obstacle. Even with data augmentation, tasks necessitate sufficient images depending on factors like precision and the number of classes. Some tasks are more challenging due to mandatory data annotation, requiring expert labeling. This resource scarcity is evident in banana pathology, highlighted in [76][25].

Another drawback is that while DL models can be train exceptionally well, and even generalize in some ways, they could not identify further the "boundaries of the dataset's expressiveness". For example, [48] achieves homogenous background classification of up-facing single leaves but falters in real-world settings distinguishing diseases on plants. Diseased portions are often limited to certain leaf sides. Despite larger training images and smaller test images, detection fails. Pre-processing data is time-consuming, crucial not only in DL but also in computer vision, particularly for aerial and satellite images.

In agriculture, researchers frequently create their datasets despite available databases. This time-consuming endeavour could take hours or even days.

6. Conclusions

This paper presents a comprehensive survey of deep learning (DL) applications in agriculture, analyzing 61 significant articles. The findings clearly illustrate that DL surpasses other prevalent image processing techniques in terms of efficiency and accuracy. Specifically, DL models have shown remarkable performance in plant disease detection, plant and crop classification, and fruit detection and counting. For instance, the VGG model achieved an impressive accuracy of 99.53% in plant disease detection, while AlexNet and GoogleNet both reached 99.76% accuracy. ResNet-152 also performed exceptionally well with 99.75% accuracy in the same domain.

In plant and crop classification, the AlexNet model achieved 99.80% accuracy, highlighting its effectiveness in this area. MobileNet demonstrated a 99% accuracy in detecting mango and pitaya fruits, while a fine-tuned VGG-16 model reached 99.75% and 96.75% accuracy in fruit classification using two different datasets. Moreover, CNN improved efficiency with a 98% accuracy, and a modified Inception-ResNet model achieved 91% and 93% accuracy in fruit counting on real and synthetic images, respectively.

These results underscore the potential of DL in revolutionizing agricultural practices by enabling precise disease detection, effective crop classification, and versatile problem-solving capabilities. This can lead to smarter, safer food production and more sustainable farming practices, ultimately contributing to increased agricultural productivity and reduced environmental impact. The study encourages further exploration and adoption of DL in various unexplored agricultural domains to foster smarter and more sustainable farming practices.

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References

[1] Li, W., Fu, H., Yu, L., & Cracknell, A. (2017). Deep learning based oil palm tree detection and counting for high-resolution remote sensing images. *Remote Sensing*. https://doi.org/10.3390/rs9010022

[2] Lateef, F., & Ruichek, Y. (2019). Survey on semantic segmentation using deep learning techniques. *Neurocomputing*. https://doi.org/10.1016/j.neucom.2019.02.003

[3] Bastiaanssen, W. G. M., Molden, D. J., & Makin, I. W. (2000). Remote sensing for irrigated agriculture: Examples from research and possible applications. *Agricultural Water Management*, *46*(2), 137–155. https://doi.org/10.1016/S0378-3774(00)00080-9

[4] Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture*, *143*(September), 23–37. https://doi.org/10.1016/j.compag.2017.09.037

[5] Teke, M., Deveci, H. S., Haliloglu, O., Gurbuz, S. Z., & Sakarya, U. (2013). A short survey of hyperspectral remote sensing applications in agriculture. *RAST 2013 - Proceedings of 6th International Conference on Recent Advances in Space Technologies*, 171–176. https://doi.org/10.1109/RAST.2013.6581194

[6] Anup Vibhute, & Bodhe, S. K. (2012). Applications of Image Processing in Agriculture: A Survey. *International Journal of Computer Applications*, *52*(2), 34–39.

[7] Lee, S. H., Chan, C. S., Wilkin, P., & Remagnino, P. (2015). Deep-plant: Plant identification with convolutional neural networks. *Proceedings - International Conference on Image Processing, ICIP*. https://doi.org/10.1109/ICIP.2015.7350839

[8] Pan, S. J., & Yang, Q. (2010). A survey on transfer learning. In *IEEE Transactions on Knowledge and Data Engineering*. https://doi.org/10.1109/TKDE.2009.191

[9] Sehgal, G., Gupta, B., Paneri, K., Singh, K., Sharma, G., & Shroff, G. (2018). Crop planning using stochastic visual optimization. *2017 IEEE Visualization in Data Science, VDS 2017*, 47–51.

[10] Song, X., Zhang, G., Liu, F., Li, D., Zhao, Y., & Yang, J. (2016). Modeling spatio-temporal distribution of soil moisture by deep learning-based cellular automata model. *Journal of Arid Land*, *8*(5), 734–748. https://doi.org/10.1007/s40333-016-0049-0

[11] Pallagani, V., Khandelwal, V., Chandra, B., Udutalapally, V., Das, D., & Mohanty, S. P. (2019). DCrop: A deep-learning based framework for accurate prediction of diseases of crops in smart agriculture. *Proceedings - 2019 IEEE International Symposium on Smart Electronic Systems, ISES 2019*. https://doi.org/10.1109/iSES47678.2019.00020

[12] Jiang, Di., Li, F., Yang, Y., & Yu, S. (2020). A Tomato Leaf Diseases Classification Method Based on Deep Learning. *Proceedings of the 32nd Chinese Control and Decision Conference, CCDC 2020*, 1446–1450. https://doi.org/10.1109/CCDC49329.2020.9164457

[13] S. A. Burhan, S. Minhas, A. T. and M. N. H. (2020). Comparative Study Of Deep Learning Algorithms For Disease And Pest Detection In Rice Crops. *12th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Buchares,*. https://doi.org/10.1109/ECAI50035.2020.9223239

[14] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, *145*(September 2017), 311–318. https://doi.org/10.1016/j.compag.2018.01.009

[15] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing*, *267*, 378–384. https://doi.org/10.1016/j.neucom.2017.06.023

[16] A. Hidayatuloh, M. N. and E. N. (2018). Identification of Tomato Plant Diseases by Leaf Image Using Squeezenet Model. *2018 International Conference on Information Technology Systems and Innovation (ICITSI)*, 199–204. https://doi.org/10.1109/ICITSI.2018.8696087

[17] Kamrul, M. H., Paul, P., & Rahman, M. (2019). Machine vision based rice disease recognition by deep learning. *2019 22nd International Conference on Computer and Information Technology, ICCIT 2019*, 1–6. https://doi.org/10.1109/ICCIT48885.2019.9038350

[18] Wang, G., Sun, Y., & Wang, J. (2017). Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning. *Computational Intelligence and Neuroscience*. https://doi.org/10.1155/2017/2917536

[19] Zhang, K., Wu, Q., Liu, A., & Meng, X. (2018). Can deep learning identify tomato leaf disease? *Advances in Multimedia*. https://doi.org/10.1155/2018/6710865
[20] Häni, N., Roy, P., & Isler, V. (2018). Apple Counting using Convolutional Neural Networks. *IEEE International Conference on Intelligent Robots and Systems*, *February 2019*, 2559–2565. https://doi.org/10.1109/IROS.2018.8594304
[21] Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017). Deep learning for image-based cassava disease detection. *Frontiers in Plant Science*. https://doi.org/10.3389/fpls.2017.01852
[22] Wenchao, X., & Zhi, Y. (2022). Research on Strawberry Disease Diagnosis Based on Improved Residual Network Recognition Model. *Mathematical Problems in Engineering*, *2022*, 6431942.
[23] Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep Learning for Tomato Diseases: Classification and Symptoms Visualization. *Applied Artificial Intelligence*. https://doi.org/10.1080/08839514.2017.1315516
[24] Cap, H. Q., Suwa, K., Fujita, E., Kagiwada, S., Uga, H., & Iyatomi, H. (2018). A deep learning approach for on-site plant leaf detection. *Proceedings - 2018 IEEE 14th International Colloquium on Signal Processing and Its Application, CSPA 2018*. https://doi.org/10.1109/CSPA.2018.8368697
[25] Amara, J., Bouaziz, B., & Algergawy, A. (2017). A deep learning-based approach for banana leaf diseases classification. *Lecture Notes in Informatics (LNI), Proceedings - Series of the Gesellschaft Fur Informatik (GI)*.
[26] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. *Computational Intelligence and Neuroscience*. https://doi.org/10.1155/2016/3289801
[27] Brahimi, M., Arsenovic, M., Laraba, S., Sladojevic, S., Boukhalfa, K., & Moussaoui, A. (2018). *Deep Learning for Plant Diseases: Detection and Saliency Map Visualisation*. https://doi.org/10.1007/978-3-319-90403-0_6
[28] Hidayat, A., Darusalam, U., & Irmawati, I. (2019). Detection of Disease on Corn Plants Using Convolutional Neural Network Methods. *Jurnal Ilmu Komputer Dan Informasi*, *12*(1), 51. https://doi.org/10.21609/jiki.v12i1.695
[29] Durmus, H., Gunes, E. O., & Kirci, M. (2017). Disease detection on the leaves of the tomato plants by using deep learning. *2017 6th International Conference on Agro-Geoinformatics, Agro-Geoinformatics 2017*. https://doi.org/10.1109/Agro-Geoinformatics.2017.8047016
[30] Liu, B., Zhang, Y., He, D. J., & Li, Y. (2018). Identification of apple leaf diseases based on deep convolutional neural networks. *Symmetry*, *10*(1). https://doi.org/10.3390/sym10010011
[31] Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018). Identification of maize leaf diseases using improved deep convolutional neural networks. *IEEE Access*. https://doi.org/10.1109/ACCESS.2018.2844405
[32] Türkoğlu, M., & Hanbay, D. (2019). Plant disease and pest detection using deep learning-based features. *Turkish Journal of Electrical Engineering and Computer Sciences*. https://doi.org/10.3906/elk-1809-181
[33] Guo, Y., Zhang, J., Yin, C., Hu, X., Zou, Y., Xue, Z., & Wang, W. (2020). Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming. *Discrete Dynamics in Nature and Society*, *2020*. https://doi.org/10.1155/2020/2479172
[34] Arnal Barbedo, J. G. (2019). Plant disease identification from individual lesions and spots using deep learning. *Biosystems Engineering*, *180*(2016), 96–107. https://doi.org/10.1016/j.biosystemseng.2019.02.002
[35] Liu, J., Yang, S., Cheng, Y., & Song, Z. (2019). Plant Leaf Classification Based on Deep Learning. *Proceedings 2018 Chinese Automation Congress, CAC 2018*. https://doi.org/10.1109/CAC.2018.8623427
[36] Jiang, P., Chen, Y., Liu, B., He, D., & Liang, C. (2019). Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. *IEEE Access*. https://doi.org/10.1109/ACCESS.2019.2914929
[37] Zhong, Y., & Zhao, M. (2020). Research on deep learning in apple leaf disease recognition. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2019.105146

[38] Hong, H., Lin, J., &Huang, F. (2020). Tomato Disease Detection and Classification by Deep Learning. *Proceedings - 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering, ICBAIE 2020*, 25–29. https://doi.org/10.1109/ICBAIE49996.2020.00012
[39] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*. https://doi.org/10.3389/fpls.2016.01419
[40] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, *161*(March), 272–279. https://doi.org/10.1016/j.compag.2018.03.032
[41] Nagasubramanian, K., Jones, S., Singh, A. K., Sarkar, S., Singh, A., & Ganapathysubramanian, B. (2019). Plant disease identification using explainable 3D deep learning on hyperspectral images. *Plant Methods*. https://doi.org/10.1186/s13007-019-0479-8
[42] Atole, R. R., & Park, D. (2018). A multiclass deep convolutional neural network classifier for detection of common rice plant anomalies. *International Journal of Advanced Computer Science and Applications*, *9*(1), 67–70. https://doi.org/10.14569/IJACSA.2018.090109
[43] Garillos-Manliguez, C. A., & Chiang, J. Y. (2021). Multimodal Deep Learning and Visible-Light and Hyperspectral Imaging for Fruit Maturity Estimation. *Sensors*. https://doi.org/10.3390/s21041288
[44] Li, H., Wang, G., Dong, Z., Wei, X., Wu, M., Song, H., & Amankwah, S. O. Y. (2021). Identifying cotton fields from remote sensing images using multiple deep learning networks. *Agronomy*, *11*(1). https://doi.org/10.3390/agronomy11010174
[45] Buzzy, M., Thesma, V., Davoodi, M., & Velni, J. M. (2020). Real-time plant leaf counting using deep object detection networks. *Sensors (Switzerland)*, *20*(23), 1–14. https://doi.org/10.3390/s20236896
[46] Shamim Hossain, M., Al-Hammadi, M., & Muhammad, G. (2019). Automatic Fruit Classification Using Deep Learning for Industrial Applications. *IEEE Transactions on Industrial Informatics*. https://doi.org/10.1109/TII.2018.2875149
[47] Nasiri, A., Taheri-Garavand, A., & Zhang, Y. D. (2019). Image-based deep learning automated sorting of date fruit. *Postharvest Biology and Technology*. https://doi.org/10.1016/j.postharvbio.2019.04.003
[48] Tan, J. W., Chang, S. W., Abdul-Kareem, S., Yap, H. J., & Yong, K. T. (2020). Deep Learning for Plant Species Classification Using Leaf Vein Morphometric. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, *17*(1), 82–90. https://doi.org/10.1109/TCBB.2018.2848653
[49] Sun, Y., Liu, Y., Wang, G., & Zhang, H. (2017). Deep Learning for Plant Identification in Natural Environment. *Computational Intelligence and Neuroscience*. https://doi.org/10.1155/2017/7361042
[50] Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., & Traore, D. (2019). Deep neural networks with transfer learning in millet crop images. *Computers in Industry*. https://doi.org/10.1016/j.compind.2019.02.003
[51] Azizah, L. M. rifatul, Umayah, S. F., Riyadi, S., Damarjati, C., & Utama, N. A. (2018). Deep learning implementation using convolutional neural network in mangosteen surface defect detection. *Proceedings - 7th IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2017*. https://doi.org/10.1109/ICCSCE.2017.8284412
[52] Kang, H., & Chen, C. (2020). Fast implementation of real-time fruit detection in apple orchards using deep learning. *Computers and Electronics in Agriculture*, *168*(November), 105108. https://doi.org/10.1016/j.compag.2019.105108
[53] Basri, H., Syarif, I., & Sukaridhoto, S. (2019). Faster R-CNN implementation method for multi-fruit detection using tensorflow platform. *International Electronics Symposium on Knowledge Creation and Intelligent Computing, IES-KCIC 2018 - Proceedings*. https://doi.org/10.1109/KCIC.2018.8628566
[54] Yu, Y., Zhang, K., Yang, L., & Zhang, D. (2019). Fruit detection for strawberry harvesting robot in non-structural environment based on Mask-RCNN. *Computers and Electronics in Agriculture*, *163*(April), 104846. https://doi.org/10.1016/j.compag.2019.06.001
[55] Bresilla, K., Perulli, G. D., Boini, A., Morandi, B., Corelli Grappadelli, L., & Manfrini, L. (2019). Single-shot convolution neural networks for real-time fruit detection within the tree. *Frontiers in Plant Science*. https://doi.org/10.3389/fpls.2019.00611

[56] Kaya, A., Keceli, A. S., Catal, C., Yalic, H. Y., Temucin, H., & Tekinerdogan, B. (2019). Analysis of transfer learning for deep neural network based plant classification models. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2019.01.041

[57] Thenmozhi, K., & Srinivasulu Reddy, U. (2019). Crop pest classification based on deep convolutional neural network and transfer learning. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2019.104906

[58] Majeed, Y., Zhang, J., Zhang, X., Fu, L., Karkee, M., Zhang, Q., & Whiting, M. D. (2018). Apple Tree Trunk and Branch Segmentation for Automatic Trellis Training Using Convolutional Neural Network Based Semantic Segmentation. *IFAC-PapersOnLine*. https://doi.org/10.1016/j.ifacol.2018.08.064

[59] Wang, A. X., Tran, C., Desai, N., Lobell, D., & Ermon, S. (2018). Deep transfer learning for crop yield prediction with remote sensing data. *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, COMPASS 2018*. https://doi.org/10.1145/3209811.3212707

[60] Esgario, J. G. M., Krohling, R. A., & Ventura, J. A. (2020). Deep learning for classification and severity estimation of coffee leaf biotic stress. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2019.105162

[61] Olsen, A., Konovalov, D. A., Philippa, B., Ridd, P., Wood, J. C., Johns, J., Banks, W., Girgenti, B., Kenny, O., Whinney, J., Calvert, B., Azghadi, M. R., & White, R. D. (2019). DeepWeeds: A Multiclass Weed Species Image Dataset for Deep Learning. *Scientific Reports*. https://doi.org/10.1038/s41598-018-38343-3

[62] Wang, A. X., Tran, C., Desai, N., Lobell, D., & Ermon, S. (2018). Deep transfer learning for crop yield prediction with remote sensing data. *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, COMPASS 2018*. https://doi.org/10.1145/3209811.3212707

[63] Knoll, F. J., Czymmek, V., Poczihoski, S., Holtorf, T., & Hussmann, S. (2018). Improving efficiency of organic farming by using a deep learning classification approach. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2018.08.032

[64] Park, S., Im, J., Park, S., Yoo, C., Han, H., & Rhee, J. (2018). Classification and mapping of paddy rice by combining Landsat and SAR time series data. *Remote Sensing*. https://doi.org/10.3390/rs10030447

[65] Song, Y., Duan, X., Ren, Y., Xu, J., Luo, L., & Li, D. (2019). Identification of the agricultural pests based on deep learning models. *Proceedings - 2019 International Conference on Machine Learning, Big Data and Business Intelligence, MLBDBI 2019*, 195–198. https://doi.org/10.1109/MLBDBI48998.2019.00044

[66] Rahnemoonfar, M., & Sheppard, C. (2017). Deep count: Fruit counting based on deep simulated learning. *Sensors (Switzerland)*, *17*(4), 1–12. https://doi.org/10.3390/s17040905

[67] Chen, S. W., Shivakumar, S. S., Dcunha, S., Das, J., Okon, E., Qu, C., Taylor, C. J., & Kumar, V. (2017). Counting Apples and Oranges with Deep Learning: A Data-Driven Approach. *IEEE Robotics and Automation Letters*. https://doi.org/10.1109/LRA.2017.2651944

[68] Wang, H., Cimen, E., Singh, N., & Buckler, E. (2020). Deep learning for plant genomics and crop improvement. In *Current Opinion in Plant Biology*. https://doi.org/10.1016/j.pbi.2019.12.010

[69] Krizhevsky, B. A., Sutskever, I., & Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. *Communications of the ACM*, *60*(6), 84–90.

[70] Lim, M. G., & Chuah, J. H. (2019). Durian types recognition using deep learning techniques. *2018 9th IEEE Control and System Graduate Research Colloquium, ICSGRC 2018 - Proceeding*. https://doi.org/10.1109/ICSGRC.2018.8657535

[71] Saleem, M. H., Potgieter, J., & Arif, K. M. (2019). Plant disease detection and classification by deep learning. In *Plants*. https://doi.org/10.3390/plants8110468

[72] Schmidhuber, J. (2015). Deep Learning in neural networks: An overview. In *Neural Networks*. https://doi.org/10.1016/j.neunet.2014.09.003

[73] Fangfang Gao, Longsheng Fu, Xin Zhang, Yaqoob Majeed, Rui Li, Manoj Karkee, Q. Z. (2020). Multi-class fruit-on-plant detection for apple in SNAP system using Faster R-CNN. *Computers and Electronics in Agriculture*, *176*. https://doi.org/10.1016/j.compag.2020.105634

[74] Barnea, E., Mairon, R., & Ben-Shahar, O. (2016). Colour-agnostic shape-based 3D fruit detection for crop harvesting robots. *Biosystems Engineering*, *146*, 57–70. https://doi.org/10.1016/j.biosystemseng.2016.01.013

[75] Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., & Wierstra, D. (2016). Continuous control with deep reinforcement learning. *4th International Conference on Learning Representations, ICLR 2016 - Conference Track Proceedings*, *September*.

[76] Mesa, A. R., & Chiang, J. Y. (2021). Multi-input deep learning model with rgb and hyperspectral imaging for banana grading. *Agriculture (Switzerland)*, *11*(8). https://doi.org/10.3390/agriculture11080687