Deep Learning in Agriculture: A Review

ABSTRACT

Deep learning is a kind of sophisticated data analysis and image processing technology, with good results and great potential. DL has been applied to many different fields, and it is also being applied to the agricultural field. This paper presents a wide-ranging review of research with regards to how DL is applied to agriculture. The analyzed works were categorized in yield prediction, weed detection, and disease detection. The articles presented here illustrate the benefits of DL to agriculture through filtering and categorization. Farm management systems are turning into real-time AI-enabled applications that give in-depth insights and suggestions for farmer's decision support by using the proper utilization of DL and sensor data.

Keywords: *Deep learning, Machine learning, Yield prediction, Disease detection, Weed detection*

1. INTRODUCTION

In the global economy, agriculture plays a prominent role. As the world's population continues to grow, the agriculture sector's demands will significantly increase. Agricultural technology and modern agriculture have become new scientific research areas that increase agricultural productivity and minimize the impact on the environment by using data-intensive methods. The data produced in modern agricultural processes are provided by various sensors, which can help to understand the operating circumstances including the climatic conditions, soil, and interaction of dynamic crops and the operation itself, thereby improving accuracy and faster decision-making.

DL [1] along with big data technology [2, 3] and high-performance computing [4] has created new opportunities for revealing, quantifying, and understanding data-intensive workflows in agricultural operating contexts. Among other definitions, DL is defined as the field of science that empowers ML and it is also used in more and more scientific fields year after year, such as bioinformatics [5-8], biochemistry [9], medicine [10], meteorology [11], economics [12], robotics [13-16], aquaculture [17], food safety [18-21] and climatology [22].

In this paper, we comprehensively reviewed the application of DL in agriculture. Several relevant papers have been presented that highlight the distinct characteristics of conventional DL models. The purpose of the review paper is to observe the different models of DL that are successfully utilized in the agricultural sector. Researchers will be able to choose the most appropriate model for their research based on this information. In the future, we hope to develop an application that has a direct connection to agriculture and DL. Throughout this review, we have gained some insight into the DL models and their accuracy rate for agricultural applications. This will certainly help us to determine which model would be most suitable for our application.

The following is the structure of the current work: In section 2, there is a paper selection technique for the survey. Section 3 elaborate the definition, terminology, evolution, tasks of learning, and analysis of DL, as well as the most popular learning models. Section 4 describes the methods implemented for the compilation and classification of submitted papers. Last section presents the conclusion.

As there are many abbreviations used in relevant scientific papers. **Tables 1-3** list the abbreviations used in this work, which are classified as DL models/algorithms, statistical measures, and general abbreviations, respectively.

Abbreviation	**Models/Algorithms**
CNN	Convolution Neural Network
RNN	Recurrent Neural Network
GAN	Generative Adversarial Network
LSTM	Long Short-Term Memory Network
DBN	Deep Belief Network
DCNN	Deep Convolution Neural Networks
MCNN	Multilayer Convolution Neural Network
DNN	Deep Neural Network

ResNet	Residual Network
R-FCN	Region-based Fully Convolutional Network
R-CNN	Region Based Convolutional Neural Network
DRL	Deep Reinforcement Learning
DenseNet	Densely Connected Convolutional Networks
PSPNet	Pyramid Scene Parsing Network
IRRCNN	Inception Recurrent Residual Convolutional Neural Network
IRCNN	Inception Recurrent Convolutional Neural Network
DCRN	Densely Connected Recurrent Convolutional Network
R2U-Net	Recurrent Residual Convolutional Neural Network based on U-Net model
NLP	Natural Language Processing
DRQN	Deep Recurrent Q-Network
BPNN	Back-propagation Neural Network
IndRNN	Independently Recurrent Neural Network
DNN_JOA	Deep Neural Network with Jaya Algorithm
ConvXGB	Convolutional eXtreme Gradient Boosting
SDG	Stochastic Gradient Descent
MLNN	Multilayer Neural Network

Table 1: Abbreviations for DL algorithms/models

Abbreviation	**Models/Algorithms**
RMSE	Root Mean Square Error
MSE	Mean Squared Error
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
DBN	Deep Belief Network

Table 2: Abbreviations for the statistical measures

Abbreviation	**Models/Algorithms**
NDVI	Normalized Difference Vegetation Index
RGB	Red Green Blue
DL	Deep Learning
ML	Machine Learning
ANN	Artificial Neural Networks
UAV	Unmanned Aerial Vehicle
RL	Reinforcement Learning

Table 3: General abbreviations

2. RESEARCH METHOD

The general research method followed is presented in **Figure 1**. Initially, considering our specific review goals, 10 academic databases were used for keyword searches. Seven filters were used to pick the main objective of the review. A review of those DL models used in agricultural applications is presented here. Therefore, those DL models that do not apply to the agriculture sector are not considered here. Following the filtering of those models, we looked at how those models relate to DL. These models were then examined. In conclusion, the result is evident.

Fig. 1: Research method flowchart

2.1. Selection of Articles

A comprehensive review of agricultural DL approaches, including yield prediction, disease detection, and weed prediction, was conducted using resources such as IEEE Xplore, Science Direct, Elsevier, Multidisciplinary Digital Publishing Institute, Social Science Research Network, Springer, ResearchGate, Scientific Research Publishing, Frontiers and Google Scholar. The following seven filters were used: (i) Target keyword, (ii) Year of publication, (iii) Type of publication, (iv) Duplicate check, v) Article title, Abstract and Keyword screening for article selection, (vi) Checked references of selected articles (vii) Final quality assessment of the selected article.

In this study, papers published between 2017 and 2021 were considered because of the rapid advancement of the field. After that, we focused our search on conference papers and journal articles. At the end of the selection process, we came across several similar articles based on the results from 10 different databases. After removing duplicates, carefully read the titles, abstracts and conclusions of the remaining publications. Finally, during a quality assessment, 38 papers were selected for the study. **Figure 2** shows the details of the process that was followed during our systematic analysis.

3. AN OVERVIEW ON DEEP LEARNING

In recent years, DL has been very successful in many fields including agriculture. As a learning algorithm, DL can make better use of datasets for feature extraction. Due to its practicality, DL is becoming increasingly popular with many researchers for research work. In this section, we mainly discuss the evolution of DL and introduced some state-of-the-arts models and algorithms.

3.1. Deep Learning Terminology and Definitions

DL is a ML technique that builds ANNs to imitate the way the brain functions. In practice, DL is also known as deep structured learning or hierarchical learning, and it uses layers of hidden data, usually more than six, although non-linear processing is generally greater to extract characteristics from data and to transform the data at various levels of abstraction (representation). **Figure 3** shows a typical DL procedure.

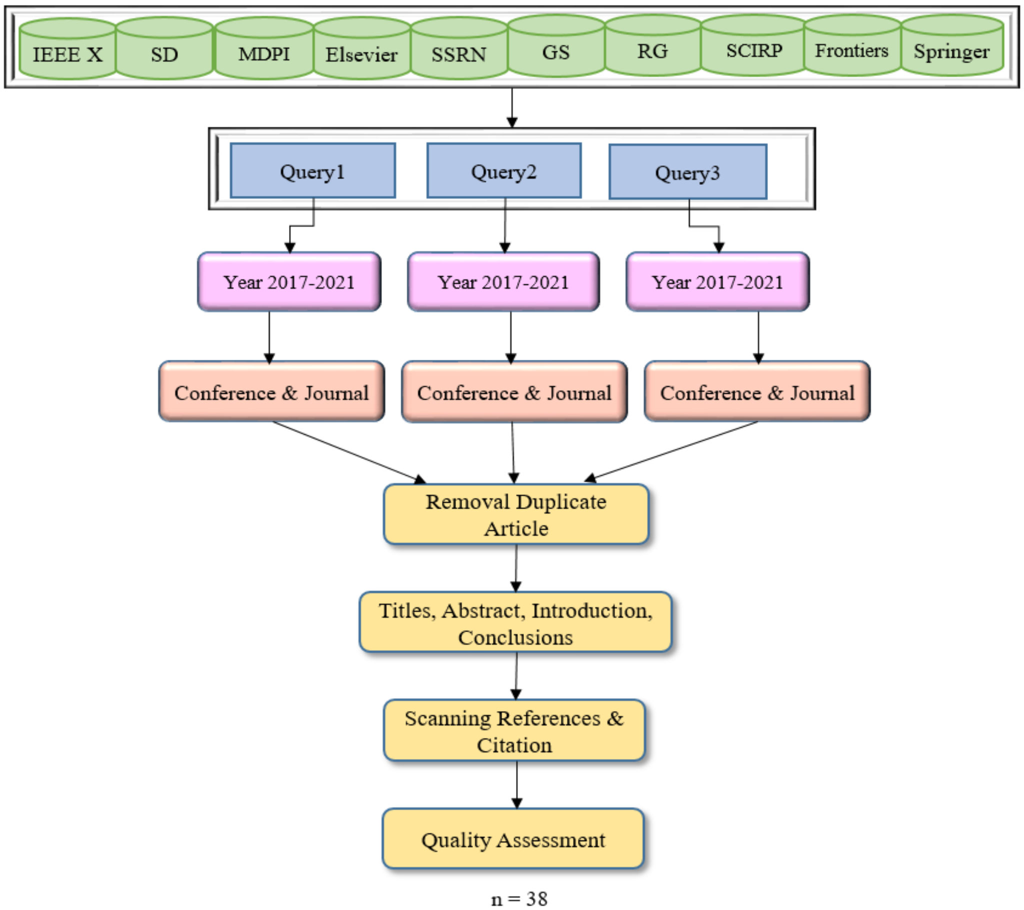

Fig. 2: Filter and search the results: A. Query1 (Q1) = yield prediction, crops images, image processing, image classification, transfer learning, deep learning; B. Query2 (Q2) = disease detection, crops images, image processing, image classification, transfer learning, deep learning; C. Query3 (Q3) = weed detection, crops images, image processing, image classification, transfer learning, deep learning.

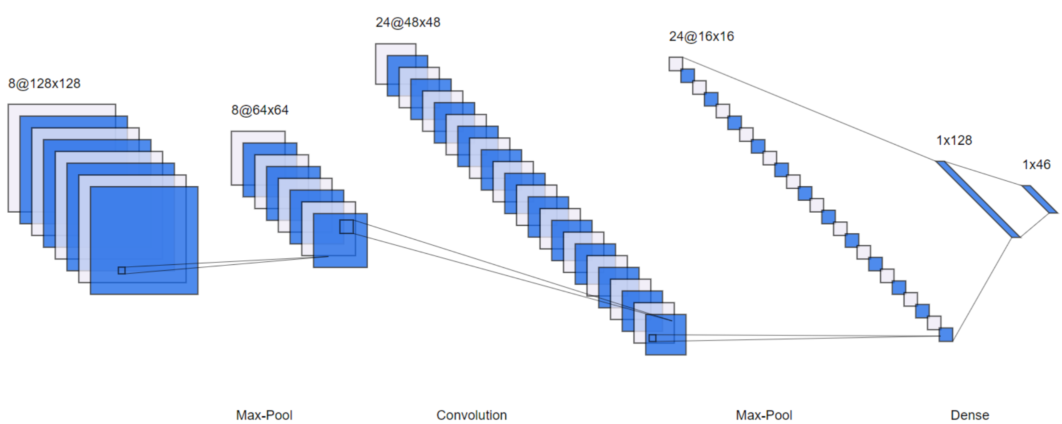

Fig. 3: A typical deep learning procedure.

3.2. Evolution of Deep Learning

The whole DL evaluation [23] can be divided into two phases. The first phase started from 1943 to 2006, and the second phase started from 2012 till now. In both phases, many new technologies and algorithms have been discovered. The year 1943 was the beginning of DL. Walter Pitts and Warren McCulloch gave a threshold logic [24] to copy human thought processes. Then it laid the foundation for both ANN [25-28] and DL. In 1957, the perceptron was created by Frank Rosenblatt [29]. Rosenblatt demonstrated a novel McCulloch-Pitts neuron [30,31] dubbed the 'Perceptron,' which had actual learning capabilities and could perform binary classification on its own. The first-ever version of the continuous backpropagation model [32] exhibited by Henry J. Kelley. His model is based on Control Theory [33, 34] but it lays the groundwork for further improvement and will be employed in ANN in the future. Stuart Dreyfus displayed backpropagation with the chain rule instead of other general rules [35] used in the early days. Kunihiko Fukushima proposed Neocognitron [36], which is the first CNN [37,38] architecture that can recognize visual patterns like handwritten characters. In 1986, Backpropagation [39] was successfully implemented in the neural network by Geoffrey Hinton, Rumelhart, and Williams. It paved the way for researchers to quickly train massive DNN [40], which had previously been a major roadblock. Yann LeCun [41] trained a CNN to recognize handwritten numerals using backpropagation. The authors of [42] published a paper in 2006, where they introduced DBN. It is much more efficient to train a large amount of data. The DL community has long struggled to find enough labelled data. For this reason, Fei-Fei Li, a professor at Stanford, launched ImageNet [43] back in 2009. ImageNet consists of 14 million well-labelled images. AlexNet is a GPU-implemented CNN model designed by Alex Krizhevsky in 2012 [44], that won the ImageNet image classification contest with an accuracy of 84%. It became the highest gain in accuracy compared with others. Then GAN was invented by Ian Goodfellow [45]. Since GAN can synthesize data similar to the real world, GAN opens a new door for the application of DL in the fields of fashion [46], art [47], and science [48] In 2016, a game named Go [49] was played between deepmind's DRL model and the human champion. Where the human champion was defeated by a deepmind's DRL model. This is a huge achievement for the DL society. Yoshua Bengio, Geoffrey Hinton, and Yann LeCun won the 2018 Turing Award [50] for their contributions to DL and AI. **Figure 4** summarizes the above paperwork.

3.3. Tasks of Learning

DL has achieved a higher level of recognition accuracy than ever before. Meeting user expectations, this technology supports safety-critical applications such as driver-less cars. With the latest advances in DL, computers are now able to perform certain tasks more efficiently than humans, such as classifying object images. DL requires a lot of labelled data. In addition, powerful computing power is required. DL runs efficiently using a high-speed GPU with a parallel architecture. By combining clusters and cloud computing, the development team can reduce DL network training time from weeks to hours.

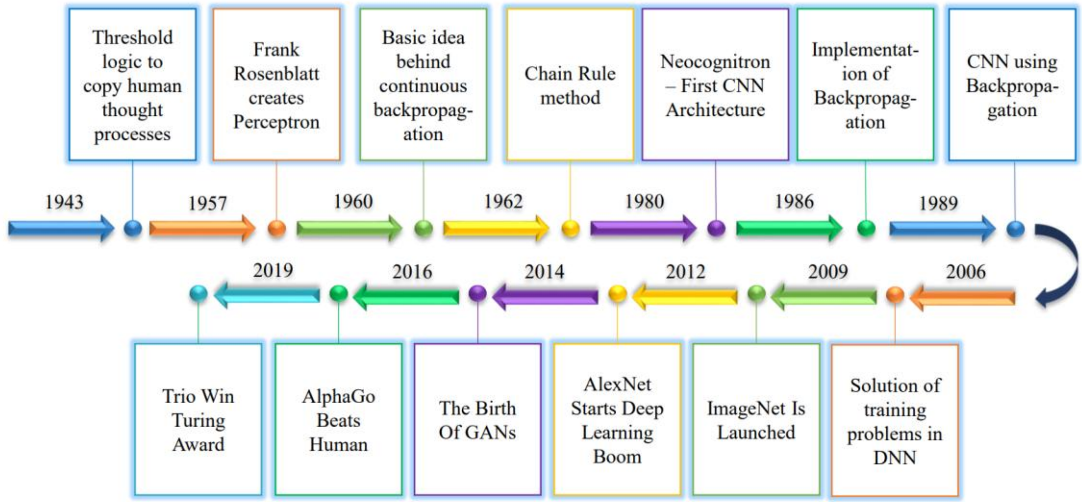

Fig. 4: Summary of the deep learning evolution from 1943 to 2019.

3.4. Analysis of Learning

DL, a subset of ML, uses a hierarchical neural network to analyze data. The neuron code is connected together within these hierarchical neural networks, similar to the human brain. Unlike other existing linear programs in the machine, the DL hierarchy allows a non-linear approach to process data in a series of layers to integrate additional information in each subsequent layer.

3.5. Analysis of Learning

In 1943, Walter Pitts and Warren McCulloch laid the foundation for DL. After that various DL models has developed. Here we have gathered the information on the models which are developed between 2017 to 2021. During that time period, many models were invented by researchers. We'll go through the most popular models. In 2017, several models were proposed by the authors such as DenseNet [51], CapsuleNet [52], IRCNN [53,54], IRRCNN [55], RefineNet [56], PSPNet [57], Mask-RCNN [58], Fast-RCNN [59], The growth of the DL model also continues in 2018. In that year many notable models had been developed such as DCRN [60], R2U-Net [61], DeepLab [62]. After a year, EfficientNet [63,64] was developed by Google AI. Since then several researchers are interested in this model. In 2020, UnitedModel [65] was proposed based on CNN architecture. Researchers are still working on generating new models in 2021. ConvXGB [66], based on CNN and Chen et al.'s XGBoost was also introduced this year. **Figure 5** summarizes the above paperwork.

In this review, the learning models of DL are limited specifically to those that have been used in the research

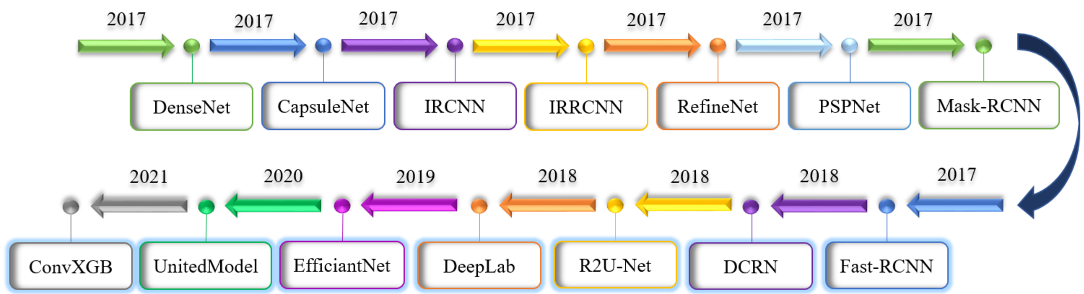

Fig. 5: Visualization of the evolution of several DL models from 2017 to date.

3.5.1. CNN

CNN [67] is a specialized type of ANN used for image recognition [68]. This network is a MLNN that contains two or more hidden layers. CNN's hidden layers generally consist of a series of convolutional layers. The convolutional layer is the primary component of CNN. It extracts the input signal's high-level characteristics. After the convolution layer, the pooling layer is applied. Pooling operations are set up based on the applications. The pooling operation is mostly used to decrease dimensionality and to select the most essential feature. The fully connected layer is the last layer in the CNN structure, which can be one or more layers, and is placed after a series of convolution and pooling layers.

3.5.2. DNN

DNN [69, 70] is usually a FFNN [71], in which data flows from the input layer to the output layer without moving backwards, and the link between layers is a forward path and never touch a node again. Compositional models are created by DNN architectures, in which the object is represented as a layered composition of picture primitives. The large datasets in the cloud allow additional large layers to capture high-level patterns and build more accurate models. The two stages of a neural network called training and inference, represent the production of development.

3.5.3. RNN

RNN [72] is a type of neural network containing loops that allow data to be stored inside the network. In short, RNN uses their reasoning from prior experiences to predict future events [73]. Recurrent models are useful because they can sequence vectors, allowing the API to execute more complex tasks. RNN is commonly used for ordinal or temporal problems, such as language translation [74], NLP [75], speech recognition [76].

3.5.4. DCNN

DCNN [77] is a type of DL method that differs from traditional CNN in terms of the number of hidden layers (typically more than 5), which are used to extract more features and enhance prediction accuracy. One type of DCNN increases the number of hidden layers, while the other increases the number of nodes in the hidden layer. The DCNN method is a supervised learning task that uses raw data to identify classification features. It has been widely and effectively utilized in computer vision [78] tasks such as object localization, detection [79], and image classification [80].

3.5.5. AlexNet

AlexNet is a CNN that was created by Alex Krizhevsky [44]. It achieved the best results among the other modern technology to classify images from the ImageNet [81] in the ILSVRC 2010 competition. AlexNet is made up of eight layers, five of which are convolutional and three of which are completely connected. It has some features like ReLU Nonlinearity, Multiple GPUs, Overlapping Pooling. AlexNet is a sophisticated model that can achieve high accuracy on even the most challenging data sets. Its performance suffers dramatically when the convolutional layer is removed. It is the main architecture for all object retrieval tasks, and it has a lot of potential applications in computer vision and artificial intelligence. AlexNet has the potential to be more adopted than CNN for working with AlexNet images in the future.

3.5.6. ResNet

ResNet [82] was likely the most breakthrough development in the recent few years in the DL community. ResNet permits clients to prepare hundreds or even a huge number of layers while as yet accomplishing magnificent results. The performance of many computer vision applications such as image recognition has improved thanks to its powerful representational ability. There are several types of ResNet, including ResNet-18 [83], ResNet-34 [84], ResNet-50 [85], ResNet-101 [86], ResNet-110 [87], ResNet-152 [88], ResNet-164 [89], and ResNet-1202 [87].

3.5.7. CaffeNet

One type of AlexNet is CaffeNet [90]. AlexNet is the name of a classification CNN that competed in the 2012 ImageNet Large Scale Visual Recognition Challenge. The primary difference between CaffeNet and AlexNet is that CaffeNet does not train with relighting data-augmentation, and pooling occurs before normalization

3.5.8. Inception Model

The Inception module is used for CNN to achieve more efficient calculations and deeper networks by stacking 1 × 1 convolutional dimensionality reduction. These modules are designed to solve problems such as computational overload and overfitting. In short, the solution is to use multiple kernel filter sizes on CNN, rather than sequentially stacking them and ordering them to run at the same level. It has some versions like inception V1 or GoogLeNet [91], inception V2[92], inception V3 [93, 94], inception V4 and inception ResNet [95].

3.5.9. R-FCN

The R-FCN [96] is a region-based object detector [97]. Unlike prior region-based object detectors such as Fast/Faster R-CNN [98,99], R-FCN is fully convolutional. The computation is shared across the entire image, unlike earlier per-region network detectors.

3.5.10. VGG16

VGG16 [100], also known as OxfordNet, is a CNN architecture that won the 2014 ILSVR (Imagenet) competition. This model was proposed by K. Simonyan and A. Zisserman [101] from the University of Oxford in an article titled ``Very deep convolutional networks for large-scale image recognition". It is one of the best model architectures to date. Similar to its name VGG16, it has 16 weighted layers.

3.5.11. VGG19

VGG19 [102] is a CNN architecture. This architecture was developed by the Visual Geometry Group back in 2014. Similar to its name VGG19s, it consists of 19 layers where 16 act as convolution layers and 3 fully connected layers. It is also known for its simpleness. All the convolution layers have a kernel size of 3x3. Although the model is simple, it has achieved significant accuracy for classification.

3.5.12. DRL

DRL [103] is a rapidly developing field that combines RL [104] and DL. It's also the most popular sort of ML since it can handle a wide range of complicated decision-making tasks that were before unsolvable by a machine with human-like intelligence.

3.5.13. LSTM

LSTM [105] is a type of RNN created by Sepp Hochreiter and Juergen Schmidhuber in the 1990s and are now frequently utilized for image [106] sound [107], and time series analysis [108] because they employ memory gates to address the vanishing gradient problem.

3.5.14. LeNet

LeNet is the CNN structure proposed by [108]. Generally speaking, LeNet refers to LeNet5 [109], which is a simple CNN. LeNet5 is a MLNN [110] and is trained using a backpropagation algorithm. The main purpose of this architecture is to recognize handwritten [111] and machine-printed characters.

4. REVIEW

We have reviewed several articles which consist of yield prediction, disease detection and weed detection using DL. Here we have discussed their learning models and how it works as well as its accuracy.

4.1. Yield Prediction

Yield prediction is the most essential aspect of proper agriculture for yield mapping, yield estimation, supply of grain including crop management, and demand to enhance productivity. Some studies have been discussed regarding yield prediction. The authors of [112] proposed an agriculture framework based on supervised smart farming that is used to construct a comprehensive yield prediction framework that maps the raw data to the paddy productivity prediction values. In this proposed work they construct a model which is an RNN DL algorithm called DRQN over the Q-Learning RL algorithm to determine the crop yield. The main goal of this work was to reduce the error and increase the forecast accuracy, resulting in better food production. In another study of yield prediction, the authors of [113] used a DL methodology of yield prediction to develop a model for wheat and barley crops based on NDVI and RGB data acquired from UAVs. The main aim of the model was to improve performance and provide accurate yield estimation using RGB images. In paper [114], the authors use the field images to develop a DCNN framework for automatically recognizing and classifying several biotic and abiotic paddy crop stressors. To classify automatically distorted paddy crop images acquired throughout the growing stage, the work used the pre-trained VGG16 CNN model. The trained model gained an average accuracy of 92.89%. In another study, the authors [115] proposed a DL framework to predict the yield basis on environmental data and optimization techniques that use CNNs and RNNs. To predict yields for both corn and soybean this model achieved an RMSE of 9% and 8% of their average yields, respectively. A DNN model, CNN, and LSTM are proposed for soybean crop yield prediction by the authors [116]. In this study, the RMSE is 0.81 and the % error is 2.70. The authors of [117] proposed a model that fuses two BPNNs with an IndRNN which is called BBI-model. This model can make accurate predictions in different seasons. In another study of yield prediction, the authors of [118] proposed a DNN based model is used to predict yield. This model has excellent accuracy for predicting corn, which has achieved 12% RMSE of average yield. In paper [119], the authors developed a combined model which includes CNN and LSTM to predict yield. This model performed well, with an RMSE of 8.24%. In the future, the proposed method has the potential to enhance yield prediction accuracy for additional crops such as corn, wheat, and potatoes more precisely. Also, in the next work, the authors [120] developed a model Using CNN and LSTM networks. They trained CNN-LSTM, convolutional LSTM, and 3D-CNN architectures with the captured images. With the 3D-CNN model, they have achieved 218.9 kg/ha MAE and 5.51% MAPE. Finally, the authors of [121] developed a DNN-based model for crop selection and yield prediction. This model aims to get better output and prediction. **Table 4** demonstrates the above paperwork in terms of yield prediction.

Author	**Crops**	**Model/Algorithm**	**Result**
[112]	Paddy	DRL	93.7% accuracy
[113]	Wheat and Barley	CNN	8.8% error rate
[114]	Paddy	VGG-16	92.89% accuracy
[115]	Corn and Soybean	CNN-RNN	Corn: RMSE=9%
			Soybean: RMSE = 8%
[116]	Soybean	DNN/CNN, LSTM based	2.70% error rate

[117]	Rice	BBI	Summer: MAE = 0.0044 RMSE = 0.0054
			Winter: MAE = 0.0074 RMSE = 0.0192
[118]	Corn	DNN	RMSE = 12%
[119]	Soybean	CNN-LSTM	RMSE = 8.24%
[120]	Wheat, Barley, Oats	CNN-LSTM, 3D-CNN	MAE = 218.9 kg/ha MAPE = 5.51%
[121]	6-various crops	DNN	Aus rice: Accuracy = 97.7% MSE = 2.3%
			Aman rice: Accuracy = 94.6% MSE = 5.4%
			Boro rice: Accuracy = 96.7% MSE = 3.3%
			Potato: Accuracy = 97.3% MSE = 2.7%
			Wheat: Accuracy = 96% MSE = 4%
			Jute: Accuracy = 94.1% MSE = 5.9%

Table 4: Yield prediction table

4.2. Disease Detection

The control of pests and diseases outdoors (on arable land) and in greenhouses is among the most important issues in agriculture. Spraying insecticides uniformly throughout the planting area is the most common way to control pests. Although this approach is effective, it comes up at a high price and is environmentally harmful. Impacts on the environment can be surplus in agricultural production, secondary damage in groundwater pollution, impacts on wildlife and local ecosystems, etc. DL methods can reduce the problems to a manageable level. The authors [122] are presented with pre-trained models like VGG19 for classifying diseases such as early blight, late blight, and healthy in potato leaves. They have achieved 97.8% accuracy. In another study [123], the authors identify 5 kinds of tomato leaves diseases using CNN. They achieved 99.84% accuracy. The authors of [124] detect tomato crop disease and classification using two pre-trained DL architectures, AlexNet and VGG16. They obtained 97.49% accuracy for AlexNet and 97.29% accuracy for VGG16 net in their tests. In another work [125], the authors compared three DL models: AlexNet, GoogLeNet, and ResNet to identifying tomato leaf disease. Then they worked with ResNet and the SGD optimization algorithm and achieve the best accuracy of 97.28%. In another study [126], the authors use Google's pre-trained CNN model known as inception-v3 to detecting tomato leaf disease. Leaf pesticide intensity is divided into three categories: good, average and bad. They achieved 99% accuracy. The authors of [127] detect wheat crop diseases using CNN because it has automatically extract features by processing the raw images directly. Their proposed method obtained 84.54% accuracy. In another work [128], the authors adopted a CNN model for detecting diseased leaves in the Mango plant. Their proposed model can detect five kinds of mango leaf disease: anthracnose, Alternaria leaf spots, Leaf Gall, Leaf Webber, and Leaf burn with 96.67% accuracy. In next paper [129], an MCNN was proposed to classify the mango leaves that have been infected by the Anthracnose fungal disease. Their proposed model can classify infected leaves from a fungal disease named Anthracnose with 97.13% of accuracy. In the next study [130], the authors detect apple leaves diseases like apple black rot, apple cedar apple rust, healthy apple, and apple scab with their proposed model CNN and they achieved 98.54% accuracy. The authors of [131] developed a CNN model based on a Lenet architecture for soybean plant disease recognition and classification. This model performed well and achieved a 99.32% accuracy. In the next paper [132], a DCNN was designed to operate symptom-wise recognition of cucumber diseases by authors. Cucumber leaf images captured in the field were segmented to create the symptom images. This model had a significant recognition result, with an accuracy of 93.4%. The authors of [133], proposed a slightly modified CNN model named LeNet. This model was mainly used to detect and identify diseases in tomato leaves using the simplest approach. This model has achieved an average accuracy of 94-95%. The authors of [134], developed a DL system with VGG16 architecture to detect rice plant diseases. Due to the small dataset, the accuracy of the detection was not high enough. This model only achieved a 60% test accuracy. In paper [135], the authors proposed GoogLeNet and Cifar10 models based on DL are proposed for leaf disease recognition. This model aims to enhance maize leaf disease recognition accuracy and reduce the number of network parameters. The GoogLeNet and Cifar10 models achieved an average accuracy of 98.9%, and 98.8% respectively. The authors of [136], proposed a DCNN based method to identify rice diseases. Images of diseased and healthy rice leaves and stems were collected from the rice experimental field to make the dataset. This proposed model has achieved 95.48% of accuracy. In next study [137], a weakly supervised DL framework was proposed by the authors for the recognition and identification of wheat diseases. Two different architectures that are VGG-FCN-VD16 and VGG-FCN-S was implemented to train the dataset. The system achieved the recognition accuracy of 97.95% and 95.12% respectively. Paddy is one of the most important crops all over the world. Lots of farmers are not aware of paddy leaf disease. Here, some studies have been introduced on the application of DL to detect and classify paddy leaf diseases. In another study [138], the authors of proposed a special classification technique of DL which is AlexNet. This model is used to detect paddy leaf diseases like bacterial leaf blight, brown spots, and leaf smut. Their proposed model has achieved 99.42% accuracy. According to [139], the authors proposed an effective image processing and ML technique are used to identify and classify diseases and the classification of pests. Five layers of the CNN technique are applied to classify the images. Their proposed model can detect four kinds of leaves: healthy, leaf blast, brown spot, and hispa. The model achieved an accuracy of 93.6%. In paper [140], the authors proposed a DCNN model to classify rice plant diseases. AlexNet was used for feature extraction and SVM was used for classification. A total of 619 images of rice diseases were collected from the real field conditions belonging to the four classes: (a) Rice Blast, (b) Sheat Blight, (c) Bacterial Leaf Blight and (d) Healthy Leave. For 80% - 20% training-testing partitions, the proposed model has 91.37% accuracy of rice disease classification. In the next paper [141], the authors proposed a DCNN model for the classification of rice plants according to health status based on leaves images. The three classes of classifiers were applied through transfer learning from an Alexnet Deep network representing normal, snail-infested, and unhealthy plants. The network has performed well, with an accuracy rate of 91.23%. The authors of [90], proposed an open-source DL framework named the CaffeNet model. Due to limitations in GPU memory, they have fine-tuned CaffeNet with a small amount of training and testing image batch size. CaffeNet architecture consists of eight learning layers: five convolutional layers and three fully connected layers. The developed model can classify 13 types of paddy pests and diseases with an accuracy rate of 87%. In next study [142], the authors suggested an optimized DNN using Jaya Algorithm to identify and classify diseases of paddy leaves. They have compared their model with ANN, DNN and DAE. The accuracy of the proposed method is 98.9% for the blast affected, 92% for the sheath rot, 95.78% for the bacterial blight, 94% for the brown spot and 90.57% for the normal leaf image. In another study [65], the authors proposed a joint CNN architecture based on InceptionV3 and ResNet50 called UnitedModel, which is capable of classifying grape images into 4 categories, including 3 different symptom images, namely black rot, isariopsis leaf spot, esca and healthy images with an average of 99.17% validation accuracy and test accuracy of 98.57%. Finally, the authors of [143] proposed a CNN-based disease detection and diagnosis method which is based on basic leaf images that can discriminate between the uninfected and diseased leaves of diverse plants with sufficient accuracy. **Table 5** highlights the above papers for the case of disease detection.

Author	**Crops**	**Model/Algorithm**	**Result**
[122]	Potato	VGG19	97.8% accuracy
[123]	Tomato	CNN	99.84% accuracy
[124]	Tomato	AlexNet	97.29% accuracy
		VGG16 net	97.49% accuracy
[125]	Tomato	ResNet	97.28% accuracy
[126]	Tomato	Inception-v3	99% accuracy
[127]	Wheat	CNN	84.54% accuracy
[128]	Mango	CNN	96.67% accuracy
[129]	Mango	MCNN	97.13% accuracy
[130]	Apple	CNN	98.54% accuracy
[131]	Soybean	CNN	99.32% accuracy
[132]	Cucumber	DCNN	93.4% accuracy
[133]	Tomato	LeNet	94% accuracy
[134]	Rice	VGG16	60% accuracy
[135]	Maize	GoogLeNet	98.9% accuracy
		Cifar10	98.8% accuracy
[136]	Rice	DCNN	95.48% accuracy
[137]	Wheat	VGG-FCN-VD16	97.95% accuracy

		VGG-FCN-S	95.12% accuracy
[138]	Paddy	AlexNet	99.42% accuracy
[139]	Paddy	CNN	93.6% accuracy
[140]	Paddy	DCNN	91.37% accuracy
[141]	Rice Plant	DCNN/AlexNet	91.23% accuracy
[90]	Paddy	CaffeNet	87% accuracy
[142]	Paddy	DNN_JOA	Blight: 95.7%
			Blast: 98.9%
			Sheath rot: 92%
			Brown spot: 94%
			Normal leaf: 94%
[65]	Grape	UnitedModel	99.17% accuracy
[143]	Generalized procedure for different crops (25 in total)	DNN/CNN	99.53% accuracy

Table 5: Disease detection table

4.3. Weed Detection

Another key issue in agriculture is weed detection and management. Weeds are cited by many farmers as the greatest serious hazard to agricultural productivity. Weed identification is crucial for sustainable agriculture since weeds are difficult to recognize and distinguish from crops. Similarly, the combination of sensors and DL algorithms can achieve accurate weed recognition and discrimination at a low cost without adversely affecting the environment. Weed detection using DL could lead to the development of equipment and robots to eradicate weeds, eliminating the demand for herbicides. Four studies have been introduced on the application of DL to the detection of agricultural weeds. In paper [144], the authors use the inception model (V2) to the detecting of weeds in crops. Their approach model can detect weed with 98% of accuracy. In next study [145], the authors detect weed on broad-leaf using CNN algorithms with 96.88% accuracy. In paper [146], the authors proposed a new model using R-FCN with ResNet-101. They also compare their proposed model with Faster R-CNN and R-FCN. Their model gets an overall better result than Faster R-CNN and R-FCN with 81% of accuracy detecting farmland weed. The authors of [147] employ the DCNN method to estimate the growth stage of several weed species in terms of the number of leaves with 70\% overall accuracy and 96% accuracy while accepting a two-leaf variance. **Table 6** shortens the above papers for the case of weed detection.

Author	**Functionality**	**Models/Algorithms**	**Results**
[144]	Effective in detecting weeds in crops.	Inception model (V2)	98% accuracy
[145]	Detecting weed on Broad-leaf	CNN	96.88% accuracy
[146]	Object detection of weeds	R-FCN	81% accuracy
[147]	Weed Growth Stage Estimator	DCNN	70% accuracy

Table 6: Weed detection table

5. CONCLUSION

In this review, the number of articles included was 38 in total. Twenty-four of the articles are about DL applications in disease detection, ten are about DL applications in yield prediction, and four are about weed detection. Among these three sections, the largest number of articles are related to applications of DL in disease detection. **Figure 6** illustrates the appearance of articles based on their proportion of selection.

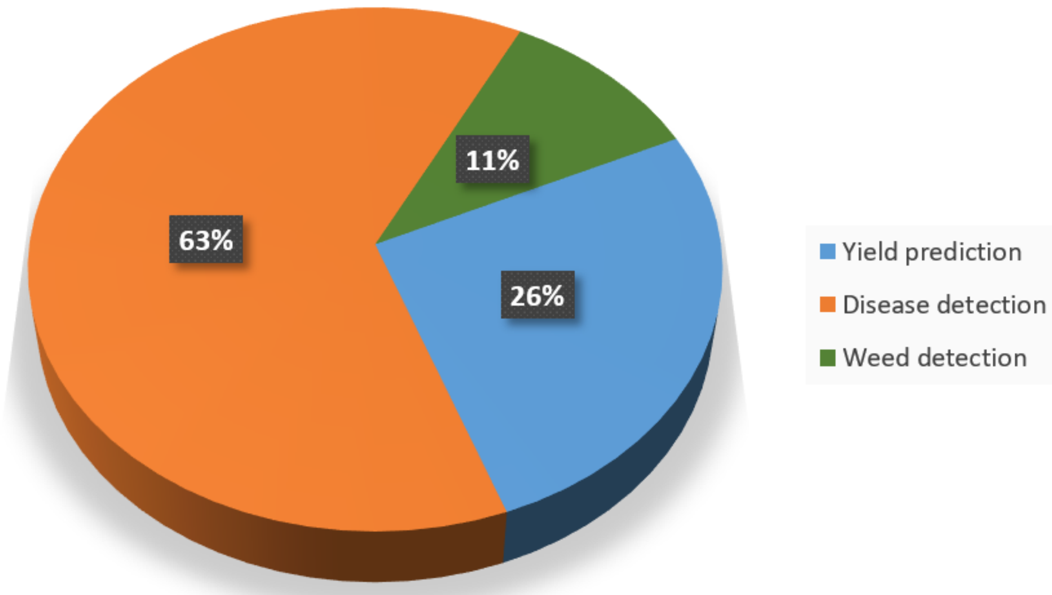

Fig. 6: The distribution of articles according to the selection is represented via a pie chart.

We have performed a survey of DL based technologies and their applications in the field of agriculture. DL has been utilized in several agricultural applications, including yield prediction, disease detection, and weed detection. In recent years, DL has become a popular research topic, and numerous applications have been developed. Nevertheless, DL still has a lot more potential for agriculture that needs to be fully exploited. Our goal is for this survey to encourage more researchers to explore DL and apply it to solve various agricultural problems. In future work, we plan to apply the general concepts and DL best practices outlined in this survey to other agricultural fields that have not yet fully utilized this modern technology. The overall advantages of DL are encouraging and can be further used to achieve smarter, more sustainable agriculture and safer food production.

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