Review Article

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.

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 (Patterson & Gibson, 2017), along with big data technology (Jan et al., 2019; Santoso et al., 2017) and high-performance computing (Sterling, Brodowicz, & Anderson, 2017), 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 (Min et al., 2017; Li et al., 2019b, 2020; Cao et al., 2020), biochemistry (Sino, Farhan, & Seno, 2021), medicine (Ching et al., 2018), meteorology (Veillette, Samsi, & Mattioli, 2020), economics (Mosavi et al., 2020), robotics(Pierson & Gashler, 2017; Károly et al., 2020; Valipour, 2017; Sünderhauf et al., 2018), aquaculture (Sun, Yang, & Xie, 2020), food safety (Zhou et al., 2019; CHEN & YU, 2021; Haotian et al., 2021; Nogales et al., 2020) and climatology (Miller, 2018).

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 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.

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
BPNNs	Back-propagation Neural Networks
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	Measure
RMSE	Root Mean Square Error
MSE	Mean Squared Error
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error

Table 2: Abbreviations for the statistical measures.

Abbreviation	
NDVI	Normalized Difference Vegetation Index
RGB	Red Green Blue
DL	Deep Learning
ML	Machine Learning
ANNs	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.

Figure 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.

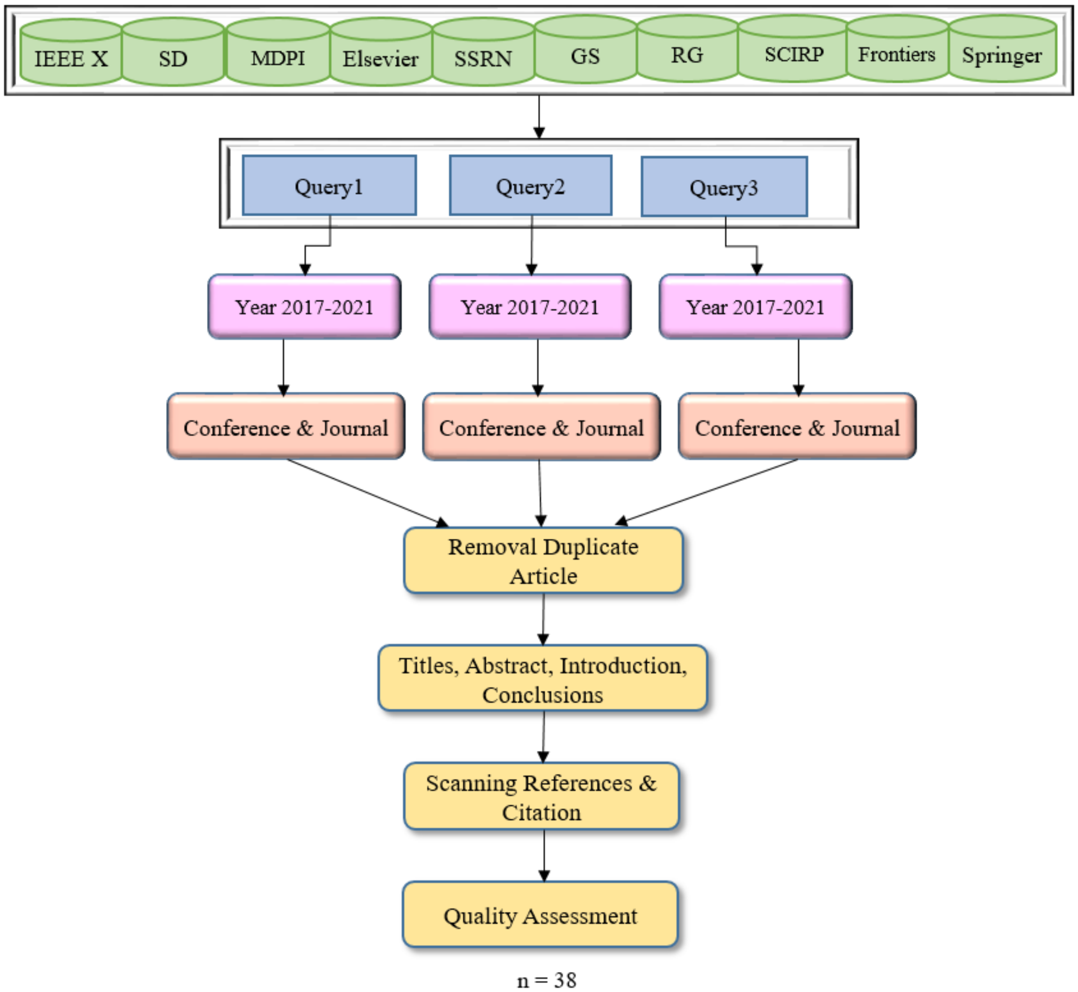

Figure 2: Filter and search the results: A. Query1 (Q1) = yield prediction, crops images, image processing, image classification, transfer learning, deep learning; B. Query2 (Q2) = disease detection, crops images, image processing, image classification, transfer learning, deep learning; C. Query3 (Q3)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

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.

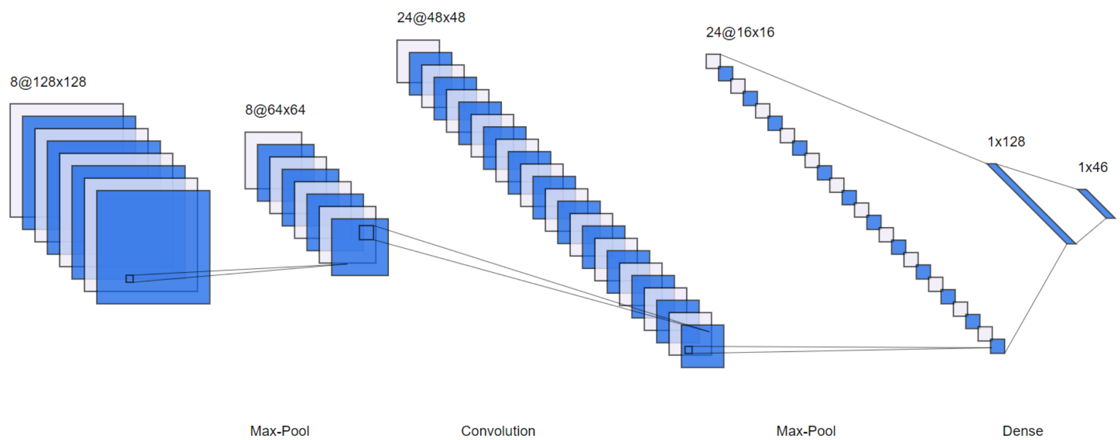

Figure 3: A typical deep learning procedure.

3.2 Evolution of Deep Learning

The whole DL evaluation (Saleem, Potgieter, & Arif, 2019) 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 (1943) gave a threshold logic to copy human thought processes. Then it laid the foundation for both ANN (Braspenning et al., 1995; Mishra & Srivastava, 2014; Kukreja et al., 2016; Zou et al., 2008) and DL. In 1957, the perceptron was created by by Frank Rosenblatt (1957). Rosenblatt (1958, 1960) demonstrated a novel McCulloch-Pitts neuron 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 exhibited by Henry J. Kelley (1960). His model is based on Control Theory (Glad & Ljung, 2018; Glasser, 1985), but it lays the groundwork for further improvement and will be employed in ANN in the future. Stuart Dreyfus (1962) displayed backpropagation with the chain rule instead of other general rules used in the early days. Kunihiko Fukushima (1982) proposed Neocognitron, which is the first CNN (O'Shea & Nash, 2015; Wu, 2017) architecture that can recognize visual patterns like handwritten characters. In 1986, Backpropagation was successfully implemented in the neural network by Geoffrey Hinton, Rumelhart, and Williams (1986). It paved the way for researchers to quickly train massive DNN (Sze et al., 2017), which had previously been a major roadblock. Yann LeCun (1998) trained a CNN to recognize handwritten numerals using backpropagation. The authors (Hinton, Osindero, & Teh, 2006) 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 (2009), a professor at Stanford, launched ImageNet. ImageNet consists of 14 million well-labelled images. AlexNet is a GPU-implemented CNN model designed by Alex Krizhevsky (2012), 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 (2014). 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 (Ak et al., 2019), art (Matsumura et al., 2018), and science (Paganini et al., 2018). In 2016, a game named Go (Chen, 2016) 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 (Jin et al., 2021) for their contributions to DL and AI. Figure 4 summarizes the above paperwork.

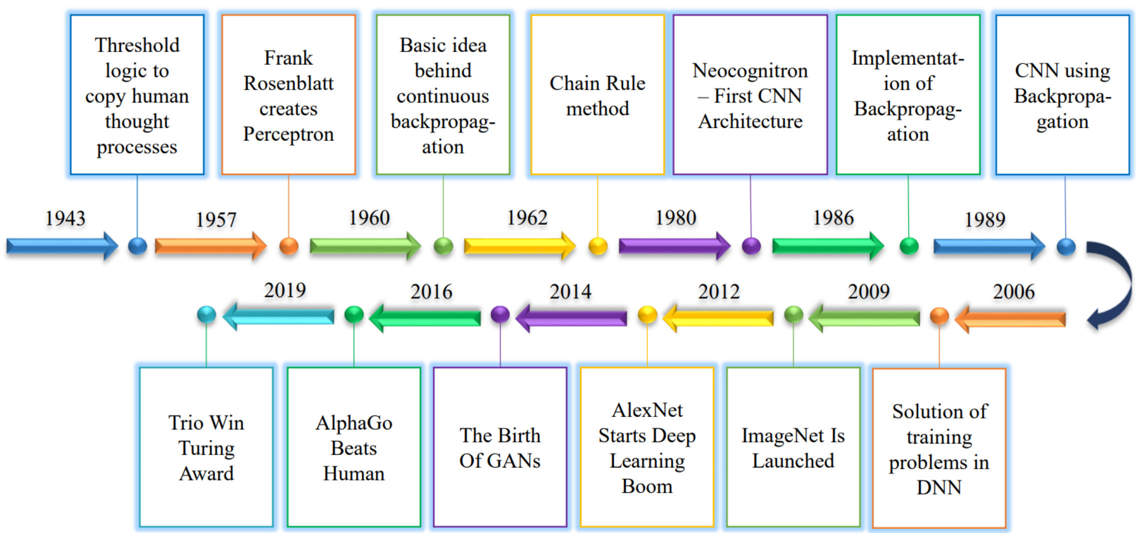

Figure 4: Summary of the deep learning evolution from 1943 to 2019.

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 highspeed GPU with a parallel architecture. By combining clusters and cloud computing, the development team can reduce DL network training time from weeks to hours.

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 Learning Models

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 (Li, Ding, & Chen, 2019a), CapsuleNet (Sabour, Frosst, & Hinton, 2017), IRCNN (Zahangir Alom et al., 2017; Alom et al., 2021), IRRCNN (Alom et al., 2019), RefineNet (Lin et al., 2017), PSPNet (Zhao et al., 2017), Mask-RCNN (He et al., 2017), Fast-RCNN (Wang, Shrivastava, & Gupta, 2017). The growth of the DL model also continues in 2018. In that year many notable models had been developed such as DCRN (Gao et al., 2019), R2U-Net (Alom et al., 2018), DeepLab (Chen et al., 2017a). After a year, EfficiantNet (Tan & Le, 2019; Marques et al., 2020) was developed by Google AI. Since then several researchers are interested in this model. In 2020, UnitedModel (Ji, Zhang, & Wu, 2020) was proposed based on CNN architecture. Researchers are still working on generating new models in 2021. ConvXGB (Thongsuwan et al., 2021), based on CNN and Chen et al.'s XGBoost was also introduced this year. Figure 5 summarizes the above paperwork.

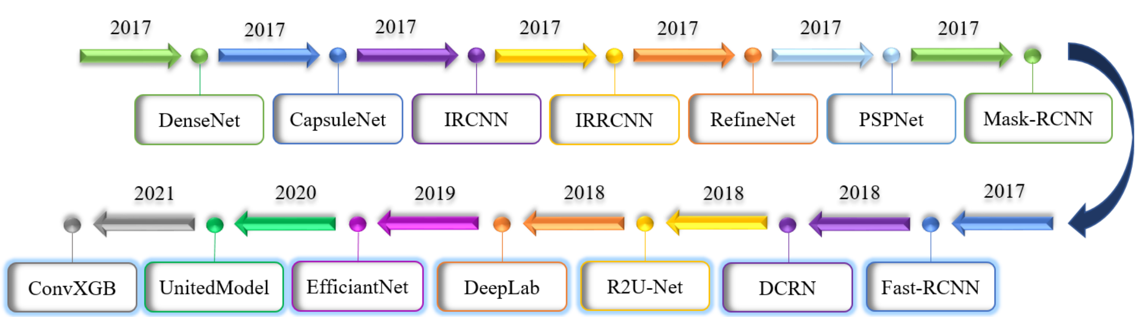

Figure 5: Visualization of the evolution of several DL models from 2017 to date.

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

3.5.1 CNN

CNN (Albawi, Mohammed, & Al-Zawi, 2017) is a specialized type of ANN used for image recognition (Lee et al., 2020). 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 (Liu et al., 2017a; Cheng et al., 2017) is usually a FFNN (Bebis & Georgiopoulos, 1994), 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 (Medsker & Jain, 1999) 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 (Choi et al., 2016). 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 (Cho et al., 2014), NLP (Nadkarni, Ohno-Machado, & Chapman, 2011), speech recognition (Hori, Cho, & Watanabe, 2018).

3.5.4 DCNN

DCNN (Xu et al., 2014) are 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 (Hongtao & Qinchuan, 2016) tasks such as object localization, detection (Cai et al., 2016), and image classification (Rawat & Wang, 2017).

3.5.5 AlexNet

AlexNet is a CNN that was created by Alex Krizhevsky (2012). It achieved the best results among the other modern technology to classify images from the ImageNet (You et al.,

2018) 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 (Targ, Almeida, & Lyman, 2016) 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 (Ayyachamy et al., 2019), ResNet-34 (Koonce, 2021), ResNet-50 (Wen, Li, & Gao, 2020), ResNet-101 (Demir, Yilmaz, & Kose, 2019), ResNet-110 (He et al., 2016), ResNet-152 (Reenadevi, Sathiya, & Sathiyabhama, 2021), ResNet-164 (Liu et al., 2017b), and ResNet-1202 (He et al., 2016).

3.5.7 CaffeNet

One type of AlexNet is CaffeNet (Alfarisy, Chen, & Guo, 2018). 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 (Sam et al., 2019), inception V2 (Bose & Kumar, 2019), inception V3 (Wang et al., 2019; Guan et al., 2019), inception V4 and inception ResNet (Szegedy et al., 2017).

3.5.9 R-FCN

The R-FCN (Tang et al., 2020) is a region-based object detector (Rasmussen, Nasrollahi, & Moeslund, 2017). Unlike prior region-based object detectors such as Fast/Faster R-CNN (Jiang & Learned-Miller, 2017; Chen & Gupta, 2017), R-FCN is fully convolutional. The computation is shared across the entire image, unlike earlier per-region network detectors.

3.5.10 VGG16

VGG16 (Qassim, Verma, & Feinzimer, 2018), 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 (2014) 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 (Jaworek-Korjakowska, Kleczek, & Gorgon, 2019) 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 (Li, 2017) is a rapidly developing field that combines RL (Kaelbling, Littman, & Moore, 1996) 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 (Greff et al., 2016) are a type of RNN created by Sepp Hochreiter and Juergen Schmidhuber in the 1990s and are now frequently utilized for image (Chen et al., 2017b), sound (Hayashi et al., 2017), and time series analysis (Karim et al., 2017) because they employ memory gates to address the vanishing gradient problem.

3.5.14 LeNet

LeNet is the CNN structure proposed by (LeCun et al., 1998). Generally speaking, LeNet refers to LeNet5 (LeCun et al., 2015), which is a simple CNN. LeNet5 is a MLNN (Sartori & Antsaklis, 1991) and is trained using a backpropagation algorithm. The main purpose of this architecture is to recognize handwritten (El-Sawy et al., 2016) 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 (Elavarasan

& Vincent, 2020) 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 reducing the error and increasing the forecast accuracy, resulting in better food production. In another study of yield prediction, the authors (Nevavuori et al., 2019) 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. The authors (Anami et al., 2020) 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 (Khaki et al., 2020) 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 (Terliksiz & Altỳlar, 2019). In this study, the RMSE is 0.81 and the % error is 2.70. The authors (Chu & Yu, 2020) 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 (Khaki & Wang, 2019) 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. The authors (Sun et al., 2019) 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 (Nevavuori et al., 2020) 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 (Islam et al., 2018) developed a DNN-based model for crop selection and yield prediction. This model aims to get better output and prediction. Table 4 demonstrate the above paperwork in terms of yield prediction.

Authors	**Crop**	**Models /Algorithms**	**Results**
(Elavarasan & Vincent, 2020)	Paddy	DRL	93.7% accuracy
(Nevavuori et al., 2019)	Wheat and Barley	CNN	8.8% error rate
(Anami et al., 2020)	Paddy	VGG16	92.89% accuracy

Authors	Crop	Models /Algorithms	Results
(Khaki et al., 2020)	Corn and Soybean	CNN-RNN	Corn: RMSE = 9% Soybean: RMSE = 8%
(Terliksiz & Altŷlar, 2019)	Soybean	DNN/CNN and LSTM based	2.70% error rate
(Chu & Yu, 2020)	Rice	BBI	Summer: MAE = 0.0044 RMSE = 0.0054 Winter: MAE = 0.0074 RMSE = 0.0192
(Khaki & Wang, 2019)	Corn	DNN	RMSE = 12%
(Sun et al., 2019)	Soybean	CNN-LSTM	RMSE = 8.24%
(Nevavuori et al., 2020)	Wheat, Barley, Oats	CNN-LSTM and 3D-CNN	MAE = 218.9 kg/ha MAPE = 5.51%
(Islam et al., 2018)	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 (Tiwari et al., 2020) 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, the authors (Ashqar & Abu-Naser, 2018) identify 5 kinds of tomato leaves diseases using CNN. They achieved 99.84% accuracy. The authors (Rangarajan et al., 2018) 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, the authors (Zhang et al., 2018a) 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, the authors (Hasan et al., 2019) 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 (Hussain et al., 2018) 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, the authors (Arivazhagan & Ligi, 2018) 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, an MCNN was proposed by authors (Singh et al., 2019) 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, the authors (Baranwal et al., 2019) 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 f 98.54% accuracy. The authors (Wallelign et al., 2018) 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 , a DCNN was designed to operate symptom-wise recognition of cucumber diseases by authors (Ma et al., 2018). 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 (Tm et al., 2018) 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 (Andrianto et al., 2020) 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. The authors (Zhang et al., 2018c) 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 (Lu et al., 2017b) 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, a weakly supervised DL framework was proposed by the authors (Lu et al., 2017a) 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. The authors (Matin et al., 2020) 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. The authors (Senan et al., 2020) 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%. The authors (Shrivastava et al., 2019) 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, the authors (Atole & Park, 2018) 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 (Alfarisy et al., 2018) 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, the authors (Ramesh & Vydeki, 2020) 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, the authors (Ji et al., 2020) 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 (Ferentinos, 2018) 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.

Authors	Crop	Models /Algorithms	Results
(Tiwari et al., 2020),)	Potato	VGG19	97.8% accuracy
(Ashqar & Abu-Naser, 2018)	Tomato	CNN	99.84% accuracy
(Rangarajan et al., 2018)	Tomato	AlexNet	97.29% accuracy
		VGG16 net	97.49% accuracy
(Zhang et al., 2018a)	Tomato	ResNet	97.28% accuracy
(Hasan et al., 2019)	Tomato	Inception-v3	99% accuracy
(Hussain et al., 2018)	Wheat	CNN	84.54% accuracy
(Arivazhagan & Ligi, 2018)	Mango	CNN	96.67% accuracy
(Singh et al., 2019)	Mango	MCNN	97.13% accuracy
(Baranwal et al., 2019)	Apple	CNN	98.54% accuracy
(Wallelign et al., 2018)	Soybean	CNN	99.32% accuracy
(Ma et al., 2018)	Cucumber	DCNN	93.4% accuracy
(Tm et al., 2018)	Tomato	LeNet	94% accuracy
(Andrianto et al., 2020)	Rice	VGG16	60% accuracy
(Zhang et al., 2018c)	Maize	GoogLeNet	98.9% accuracy
		Cifar10	98.8% accuracy
(Lu et al., 2017b)	Rice	DCNN	95.48% accuracy
(Lu et al., 2017a)	Wheat	VGG-FCN-VD16	97.95% accuracy
		VGG-FCN-S	95.12% accuracy
(Matin et al., 2020)	Paddy	AlexNet	99.42% accuracy
(Senan et al., 2020)	Paddy	CNN	93.6% accuracy
(Shrivastava et al., 2019)	Paddy	DCNN	91.37% accuracy
(Atole & Park, 2018)	Rice Plant	DCNN/AlexNet	91.23% accuracy
(Alfarisy et al., 2018)	Paddy	CaffeNet	87% accuracy
(Ramesh & Vydeki, 2020)	Paddy	DNN_JOA	Bacterial Blight: 95.7% accuracy
			Blast: 98.9% accuracy
			Sheath rot: 92% accuracy
			Brown spot: 94% accuracy
			Normal leaf: 94% accuracy
(Ji et al., 2020)	Grape	UnitedModel	99.17% accuracy
(Ferentinos, 2018)	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 the first study, the authors (Tiwari et al., 2019) uses the inception model (V2) to the detecting of weeds in crops. Their approach model can detect weed with 98% of accuracy. In the second study, the authors (Zhang et al., 2018b) detects weed on broad-leaf using CNN algorithms with 96.88% accuracy. In the third study, the authors (Sarker & Kim, 2019) 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 (Teimouri et al., 2018) of the fourth study 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.

Authors	**Functionality**	**Models /Algorithms**	**Results**
(Tiwari et al., 2019)	Effective in detecting weeds in crops.	Inception model (V2)	98% accuracy
(Zhang et al., 2018b)	Detecting weed on Broad-leaf	CNN	96.88% accuracy
(Sarker & Kim, 2019)	Object detection of weeds	R-FCN	81% accuracy
(Teimouri et al., 2018)	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.

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

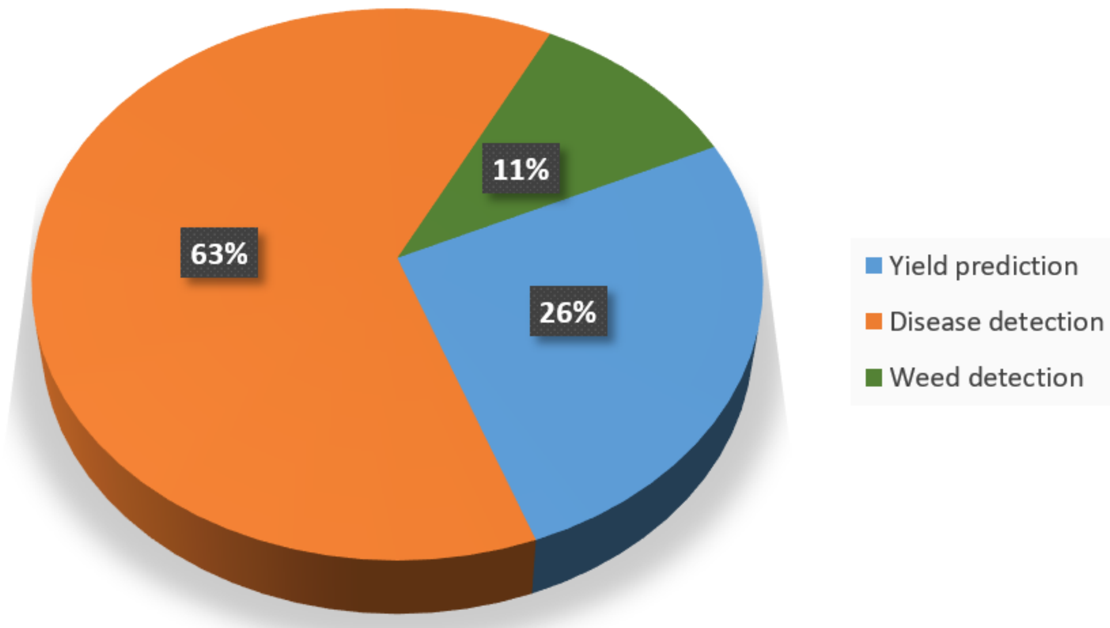

Figure 6: The distribution of articles according to the selection is represented via a pie chart.

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.

References

Ak, K. E., Lim, J. H., Tham, J. Y., & Kassim, A. A. (2019). Attribute manipulation generative adversarial networks for fashion images. In *Proceedings of the IEEE/CVF*

International Conference on Computer Vision, pp. 10541–10550.

Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. In *2017 International Conference on Engineering and Technology (ICET)*, pp. 1–6. Ieee.

Alfarisy, A. A., Chen, Q., & Guo, M. (2018). Deep learning based classification for paddy pests & diseases recognition. In *Proceedings of 2018 International Conference on Mathematics and Artificial Intelligence*, pp. 21–25.

Alom, M. Z., Hasan, M., Yakopcic, C., Taha, T. M., & Asari, V. K. (2018). Recurrent residual convolutional neural network based on u-net (r2u-net) for medical image segmentation..

Alom, M. Z., Hasan, M., Yakopcic, C., Taha, T. M., & Asari, V. K. (2021). Inception recurrent convolutional neural network for object recognition. *Machine Vision and Applications*, *32*(1), 1–14.

Alom, M. Z., Yakopcic, C., Nasrin, M. S., Taha, T. M., & Asari, V. K. (2019). Breast cancer classification from histopathological images with inception recurrent residual convolutional neural network. *Journal of digital imaging*, *32*(4), 605–617.

Anami, B. S., Malvade, N. N., & Palaiah, S. (2020). Deep learning approach for recognition and classification of yield affecting paddy crop stresses using field images. *Artificial Intelligence in Agriculture*, *4*, 12–20.

Andrianto, H., Faizal, A., Armandika, F., et al. (2020). Smartphone application for deep learning-based rice plant disease detection. In *2020 International Conference on Information Technology Systems and Innovation (ICITSI)*, pp. 387–392. IEEE.

Arivazhagan, S., & Ligi, S. V. (2018). Mango leaf diseases identification using convolutional neural network. *International Journal of Pure and Applied Mathematics*, *120*(6), 11067–11079.

Ashqar, B. A., & Abu-Naser, S. S. (2018). Image-based tomato leaves diseases detection using deep learning..

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.

Ayyachamy, S., Alex, V., Khened, M., & Krishnamurthi, G. (2019). Medical image retrieval using resnet-18. In *Medical Imaging 2019: Imaging Informatics for Healthcare, Research, and Applications*, Vol. 10954, p. 1095410. International Society for Optics and Photonics.

Baranwal, S., Khandelwal, S., & Arora, A. (2019). Deep learning convolutional neural network for apple leaves disease detection. In *Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), Amity University Rajasthan, Jaipur-India*.

Bebis, G., & Georgiopoulos, M. (1994). Feed-forward neural networks. *IEEE Potentials*, *13*(4), 27–31.

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Bose, S. R., & Kumar, V. S. (2019). Efficient inception v2 based deep convolutional neural network for real-time hand action recognition. *IET Image Processing*, *14*(4), 688–696.

Braspenning, P. J., Thuijsman, F., & Weijters, A. J. M. M. (1995). *Artificial neural networks: an introduction to ANN theory and practice*, Vol. 931. Springer Science & Business Media.

Cai, Z., Fan, Q., Feris, R. S., & Vasconcelos, N. (2016). A unified multi-scale deep convolutional neural network for fast object detection. In *European conference on computer vision*, pp. 354–370. Springer.

Cao, Y., Geddes, T. A., Yang, J. Y. H., & Yang, P. (2020). Ensemble deep learning in bioinformatics. *Nature Machine Intelligence*, *2*(9), 500–508.

Chen, J. X. (2016). The evolution of computing: Alphago. *Computing in Science & Engineering*, *18*(4), 4–7.

Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017a). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE transactions on pattern analysis and machine intelligence*, *40*(4), 834–848.

Chen, M., Ding, G., Zhao, S., Chen, H., Liu, Q., & Han, J. (2017b). Reference based lstm for image captioning. In *Thirty-first AAAI conference on artificial intelligence*.

CHEN, T.-C., & YU, S.-Y. (2021). Research on food safety sampling inspection system based on deep learning. *Food Science and Technology*.

Chen, X., & Gupta, A. (2017). An implementation of faster rcnn with study for region sampling. *arXiv preprint arXiv:1702.02138*.

Cheng, Y., Wang, D., Zhou, P., & Zhang, T. (2017). A survey of model compression and acceleration for deep neural networks. *arXiv preprint arXiv:1710.09282*.

Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., Ferrero, E., Agapow, P.-M., Zietz, M., Hoffman, M. M., et al. (2018). Opportunities and obstacles for deep learning in biology and medicine. *Journal of The Royal Society Interface*, *15*(141), 20170387.

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*.

Choi, E., Bahadori, M. T., Schuetz, A., Stewart, W. F., & Sun, J. (2016). Doctor ai: Predicting clinical events via recurrent neural networks. In *Machine learning for healthcare conference*, pp. 301–318. PMLR.

Chu, Z., & Yu, J. (2020). An end-to-end model for rice yield prediction using deep learning fusion. *Computers and Electronics in Agriculture*, *174*, 105471.

Demir, A., Yilmaz, F., & Kose, O. (2019). Early detection of skin cancer using deep learning architectures: resnet-101 and inception-v3. In *2019 Medical Technologies Congress (TIPTEKNO)*, pp. 1–4. IEEE.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. (2009). Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pp. 248–255. Ieee.

Dreyfus, S. (1962). The numerical solution of variational problems. *Journal of Mathematical Analysis and Applications*, *5*(1), 30–45.

El-Sawy, A., Hazem, E.-B., & Loey, M. (2016). Cnn for handwritten arabic digits recognition based on lenet-5. In *International conference on advanced intelligent systems and informatics*, pp. 566–575. Springer.

Elavarasan, D., & Vincent, P. D. (2020). Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications. *IEEE Access*, *8*, 86886–86901.

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, *145*, 311–318.

Fukushima, K., & Miyake, S. (1982). Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition. In *Competition and cooperation in neural nets*, pp. 267–285. Springer.

Gao, S., Miao, Z., Zhang, Q., & Li, Q. (2019). Dcrn: densely connected refinement network for object detection. In *Journal of Physics: Conference Series*, Vol. 1229, p. 012034. IOP Publishing.

Glad, T., & Ljung, L. (2018). *Control theory*. CRC press.

Glasser, W. (1985). *Control theory*. Harper and Row New York.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems*, *27*.

Greff, K., Srivastava, R. K., Koutník, J., Steunebrink, B. R., & Schmidhuber, J. (2016). Lstm: A search space odyssey. *IEEE transactions on neural networks and learning systems*, *28*(10), 2222–2232.

Guan, Q., Wan, X., Lu, H., Ping, B., Li, D., Wang, L., Zhu, Y., Wang, Y., & Xiang, J. (2019). Deep convolutional neural network inception-v3 model for differential diagnosing of lymph node in cytological images: a pilot study. *Annals of translational medicine*, *7*(14).

Haotian, H., Jinfeng, J., Dongbo, W., & Sanhong, D. (2021). An integrated platform for food safety incident entities based on deep learning. *Data Analysis and Knowledge Discovery*, *5*(3), 12–24.

Hasan, M., Tanawala, B., & Patel, K. J. (2019). Deep learning precision farming: tomato leaf disease detection by transfer learning. In *Proceedings of 2nd International Conference on Advanced Computing and Software Engineering (ICACSE)*.

Hayashi, T., Watanabe, S., Toda, T., Hori, T., Le Roux, J., & Takeda, K. (2017). Duration-controlled lstm for polyphonic sound event detection. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *25*(11), 2059–2070.

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pp. 2961–2969.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778.

Hinton, G. E., Osindero, S., & Teh, Y.-W. (2006). A fast learning algorithm for deep belief nets. *Neural computation*, *18*(7), 1527–1554.

Hongtao, L., & Qinchuan, Z. (2016). Applications of deep convolutional neural network in computer vision. *Journal of Data Acquisition and Processing*, *31*(1), 1–17.

Hori, T., Cho, J., & Watanabe, S. (2018). End-to-end speech recognition with word-based rnn language models. In *2018 IEEE Spoken Language Technology Workshop (SLT)*, pp. 389–396. IEEE.

Hussain, A., Ahmad, M., & Mughal, I. A. (2018). Automatic disease detection in wheat crop using convolution neural network. In *The 4th International Conference on Next Generation Computing*.

Islam, T., Chisty, T. A., & Chakrabarty, A. (2018). A deep neural network approach for crop selection and yield prediction in bangladesh. In *2018 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, pp. 1–6. IEEE.

Jan, B., Farman, H., Khan, M., Imran, M., Islam, I. U., Ahmad, A., Ali, S., & Jeon, G. (2019). Deep learning in big data analytics: a comparative study. *Computers & Electrical Engineering*, *75*, 275–287.

Jaworek-Korjakowska, J., Kleczek, P., & Gorgon, M. (2019). Melanoma thickness prediction based on convolutional neural network with vgg-19 model transfer learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pp. 0–0.

Ji, M., Zhang, L., & Wu, Q. (2020). Automatic grape leaf diseases identification via unitedmodel based on multiple convolutional neural networks. *Information Processing in Agriculture*, *7*(3), 418–426.

Jiang, H., & Learned-Miller, E. (2017). Face detection with the faster r-cnn. In *2017 12th IEEE international conference on automatic face & gesture recognition (FG 2017)*, pp. 650–657. IEEE.

Jin, Y., Yuan, S., Shao, Z., Hall, W., & Tang, J. (2021). Turing award elites revisited: patterns of productivity, collaboration, authorship and impact. *Scientometrics*, *126*(3), 2329–2348.

Kaelbling, L. P., Littman, M. L., & Moore, A. W. (1996). Reinforcement learning: A survey. *Journal of artificial intelligence research*, *4*, 237–285.

Karim, F., Majumdar, S., Darabi, H., & Chen, S. (2017). Lstm fully convolutional networks for time series classification. *IEEE access*, *6*, 1662–1669.

Károly, A. I., Galambos, P., Kuti, J., & Rudas, I. J. (2020). Deep learning in robotics: Survey on model structures and training strategies. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *51*(1), 266–279.

Kelley, H. J. (1960). Gradient theory of optimal flight paths. *Ars Journal*, *30*(10), 947–954.

Khaki, S., & Wang, L. (2019). Crop yield prediction using deep neural networks. *Frontiers in plant science*, *10*, 621.

Khaki, S., Wang, L., & Archontoulis, S. V. (2020). A cnn-rnn framework for crop yield prediction. *Frontiers in Plant Science*, *10*, 1750.

Koonce, B. (2021). Resnet 34. In *Convolutional Neural Networks with Swift for Tensorflow*, pp. 51–61. Springer.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*, 1097–1105.

Kukreja, H., Bharath, N., Siddesh, C., & Kuldeep, S. (2016). An introduction to artificial neural network. *Int J Adv Res Innov Ideas Educ*, *1*, 27–30.

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278–2324.

LeCun, Y., et al. (2015). Lenet-5, convolutional neural networks. *URL: http://yann. lecun. com/exdb/lenet*, *20*(5), 14.

Lee, S., Kim, H., Lieu, Q. X., & Lee, J. (2020). Cnn-based image recognition for topology optimization. *Knowledge-Based Systems*, *198*, 105887.

Li, H., Tian, S., Li, Y., Fang, Q., Tan, R., Pan, Y., Huang, C., Xu, Y., & Gao, X. (2020). Modern deep learning in bioinformatics. *Journal of molecular cell biology*, *12*(11), 823–827.

Li, S., Ding, Z., & Chen, H. (2019a). A neural network-based teaching style analysis model. In *2019 11th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC)*, Vol. 2, pp. 154–157. IEEE.

Li, Y., Huang, C., Ding, L., Li, Z., Pan, Y., & Gao, X. (2019b). Deep learning in bioinformatics: Introduction, application, and perspective in the big data era. *Methods*, *166*, 4–21.

Li, Y. (2017). Deep reinforcement learning: An overview. *arXiv preprint arXiv:1701.07274*.

Lin, G., Milan, A., Shen, C., & Reid, I. (2017). Refinenet: Multi-path refinement networks for high-resolution semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1925–1934.

Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y., & Alsaadi, F. E. (2017a). A survey of deep neural network architectures and their applications. *Neurocomputing*, *234*, 11–26.

Liu, Z., Li, J., Shen, Z., Huang, G., Yan, S., & Zhang, C. (2017b). Learning efficient convolutional networks through network slimming. In *Proceedings of the IEEE international conference on computer vision*, pp. 2736–2744.

Lu, J., Hu, J., Zhao, G., Mei, F., & Zhang, C. (2017a). An in-field automatic wheat disease diagnosis system. *Computers and electronics in agriculture*, *142*, 369–379.

Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017b). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing*, *267*, 378–384.

Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. *Computers and electronics in agriculture*, *154*, 18–24.

Marques, G., Agarwal, D., & de la Torre Díez, I. (2020). Automated medical diagnosis of covid-19 through efficientnet convolutional neural network. *Applied soft computing*, *96*, 106691.

Matin, M. M. H., Khatun, A., Moazzam, M. G., Uddin, M. S., et al. (2020). An efficient disease detection technique of rice leaf using alexnet. *Journal of Computer and Communications*, *8*(12), 49.

Matsumura, N., Tokura, H., Kuroda, Y., Ito, Y., & Nakano, K. (2018). Tile art image generation using conditional generative adversarial networks. In *2018 Sixth International Symposium on Computing and Networking Workshops (CANDARW)*, pp. 209–215. IEEE.

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, *5*(4), 115–133.

Medsker, L., & Jain, L. C. (1999). *Recurrent neural networks: design and applications*. CRC press.

Miller, J. (2018). *A Satellite-Based Climatology of Transverse Cirrus Band Occurrence Using Deep Learning*. The University of Alabama in Huntsville.

Min, S., Lee, B., & Yoon, S. (2017). Deep learning in bioinformatics. *Briefings in bioinformatics*, *18*(5), 851–869.

Mishra, M., & Srivastava, M. (2014). A view of artificial neural network. In *2014 International Conference on Advances in Engineering & Technology Research (ICAETR-2014)*, pp. 1–3. IEEE.

Mosavi, A., Faghan, Y., Ghamisi, P., Duan, P., Ardabili, S. F., Salwana, E., & Band, S. S. (2020). Comprehensive review of deep reinforcement learning methods and applications in economics. *Mathematics*, *8*(10), 1640.

Nadkarni, P. M., Ohno-Machado, L., & Chapman, W. W. (2011). Natural language processing: an introduction. *Journal of the American Medical Informatics Association*, *18*(5), 544–551.

Nevavuori, P., Narra, N., Linna, P., & Lipping, T. (2020). Crop yield prediction using multitemporal uav data and spatio-temporal deep learning models. *Remote Sensing*, *12*(23), 4000.

Nevavuori, P., Narra, N., & Lipping, T. (2019). Crop yield prediction with deep convolutional neural networks. *Computers and electronics in agriculture*, *163*, 104859.

Nogales, A., Morón, R. D., & García-Tejedor, Á. J. (2020). Food safety risk prediction with deep learning models using categorical embeddings on european union data. *arXiv preprint arXiv:2009.06704*.

O'Shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*.

Paganini, M., de Oliveira, L., & Nachman, B. (2018). Accelerating science with generative adversarial networks: an application to 3d particle showers in multilayer calorimeters. *Physical review letters*, *120*(4), 042003.

Patterson, J., & Gibson, A. (2017). *Deep learning: A practitioner's approach.* " O'Reilly Media, Inc.".

Pierson, H. A., & Gashler, M. S. (2017). Deep learning in robotics: a review of recent research. *Advanced Robotics*, *31*(16), 821–835.

Qassim, H., Verma, A., & Feinzimer, D. (2018). Compressed residual-vgg16 cnn model for big data places image recognition. In *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 169–175. IEEE.

Ramesh, S., & Vydeki, D. (2020). Recognition and classification of paddy leaf diseases using optimized deep neural network with jaya algorithm. *Information processing in agriculture*, *7*(2), 249–260.

Rangarajan, A. K., Purushothaman, R., & Ramesh, A. (2018). Tomato crop disease classification using pre-trained deep learning algorithm. *Procedia computer science*, *133*, 1040–1047.

Rasmussen, C. B., Nasrollahi, K., & Moeslund, T. B. (2017). R-fcn object detection ensemble based on object resolution and image quality. In *International Joint Conference on Computational Intelligence*, pp. 110–120. SCITEPRESS Digital Library.

Rawat, W., & Wang, Z. (2017). Deep convolutional neural networks for image classification: A comprehensive review. *Neural computation*, *29*(9), 2352–2449.

Reenadevi, R., Sathiya, T., & Sathiyabhama, B. (2021). Breast cancer histopathological image classification using augmentation based on optimized deep resnet-152 structure. *Annals of the Romanian Society for Cell Biology*, *25*(6), 5866–5874.

Rosenblatt, F. (1957). *The perceptron, a perceiving and recognizing automaton Project Para.* Cornell Aeronautical Laboratory.

Rosenblatt, F. (1958). The perceptron: a probabilistic model for information storage and organization in the brain.. *Psychological review*, *65*(6), 386.

Rosenblatt, F. (1960). Perceptron simulation experiments. *Proceedings of the IRE*, *48*(3), 301–309.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *nature*, *323*(6088), 533–536.

Sabour, S., Frosst, N., & Hinton, G. E. (2017). Dynamic routing between capsules. *arXiv preprint arXiv:1710.09829*.

Saleem, M. H., Potgieter, J., & Arif, K. M. (2019). Plant disease detection and classification by deep learning. *Plants*, *8*(11), 468.

Sam, S. M., Kamardin, K., Sjarif, N. N. A., Mohamed, N., et al. (2019). Offline signature verification using deep learning convolutional neural network (cnn) architectures googlenet inception-v1 and inception-v3. *Procedia Computer Science*, *161*, 475–483.

Santoso, L. W., et al. (2017). Data warehouse with big data technology for higher education. *Procedia Computer Science*, *124*, 93–99.

Sarker, M. I., & Kim, H. (2019). Farm land weed detection with region-based deep convolutional neural networks. *arXiv preprint arXiv:1906.01885*.

Sartori, M. A., & Antsaklis, P. J. (1991). A simple method to derive bounds on the size and to train multilayer neural networks. *IEEE transactions on neural networks*, *2*(4), 467–471.

Senan, N., Aamir, M., Ibrahim, R., Taujuddin, N., & Muda, W. (2020). An efficient convolutional neural network for paddy leaf disease and pest classification. *Int. J. Adv. Comput. Sci. Appl*, *11*(7), 116–122.

Shrivastava, V. K., Pradhan, M. K., Minz, S., & Thakur, M. P. (2019). Rice plant disease classification using transfer learning of deep convolution neural network. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

Singh, U. P., Chouhan, S. S., Jain, S., & Jain, S. (2019). Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease. *IEEE Access*, *7*, 43721–43729.

Sino, N. I., Farhan, R. N., & Seno, M. E. (2021). Review of deep learning algorithms in computational biochemistry. In *Journal of Physics: Conference Series*, Vol. 1804, p. 012135. IOP Publishing.

Sterling, T., Brodowicz, M., & Anderson, M. (2017). *High performance computing: modern systems and practices*. Morgan Kaufmann.

Sun, J., Di, L., Sun, Z., Shen, Y., & Lai, Z. (2019). County-level soybean yield prediction using deep cnn-lstm model. *Sensors*, *19*(20), 4363.

Sun, M., Yang, X., & Xie, Y. (2020). Deep learning in aquaculture: A review. *J. Comput*, *31*, 294–319.

Sünderhauf, N., Brock, O., Scheirer, W., Hadsell, R., Fox, D., Leitner, J., Upcroft, B., Abbeel, P., Burgard, W., Milford, M., et al. (2018). The limits and potentials of deep learning for robotics. *The International Journal of Robotics Research*, *37*(4-5), 405–420.

Sze, V., Chen, Y.-H., Yang, T.-J., & Emer, J. S. (2017). Efficient processing of deep neural networks: A tutorial and survey. *Proceedings of the IEEE*, *105*(12), 2295–2329.

Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. A. (2017). Inception-v4, inception-resnet and the impact of residual connections on learning. In *Thirty-first AAAI conference on artificial intelligence*.

Tan, M., & Le, Q. (2019). Efficientnet: Rethinking model scaling for convolutional neural networks. In *International Conference on Machine Learning*, pp. 6105–6114. PMLR.

Tang, C., Chen, S., Zhou, X., Ruan, S., & Wen, H. (2020). Small-scale face detection based on improved r-fcn. *Applied Sciences*, *10*(12), 4177.

Targ, S., Almeida, D., & Lyman, K. (2016). Resnet in resnet: Generalizing residual architectures. *arXiv preprint arXiv:1603.08029*.

Teimouri, N., Dyrmann, M., Nielsen, P. R., Mathiassen, S. K., Somerville, G. J., & Jørgensen, R. N. (2018). Weed growth stage estimator using deep convolutional neural networks. *Sensors*, *18*(5), 1580.

Terliksiz, A. S., & Altỳlar, D. T. (2019). Use of deep neural networks for crop yield prediction: A case study of soybean yield in lauderdale county, alabama, usa. In *2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)*, pp. 1–4. IEEE.

Thongsuwan, S., Jaiyen, S., Padcharoen, A., & Agarwal, P. (2021). Convxgb: A new deep learning model for classification problems based on cnn and xgboost. *Nuclear Engineering and Technology*, *53*(2), 522–531.

Tiwari, D., Ashish, M., Gangwar, N., Sharma, A., Patel, S., & Bhardwaj, S. (2020). Potato leaf diseases detection using deep learning. In *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, pp. 461–466. IEEE.

Tiwari, O., Goyal, V., Kumar, P., & Vij, S. (2019). An experimental set up for utilizing convolutional neural network in automated weed detection. In *2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU)*, pp. 1–6. IEEE.

Tm, P., Pranathi, A., SaiAshritha, K., Chittaragi, N. B., & Koolagudi, S. G. (2018). Tomato leaf disease detection using convolutional neural networks. In *2018 eleventh international conference on contemporary computing (IC3)*, pp. 1–5. IEEE.

Valipour, S. (2017). Deep learning in robotics..

Veillette, M., Samsi, S., & Mattioli, C. (2020). Sevir: A storm event imagery dataset for deep learning applications in radar and satellite meteorology. *Advances in Neural Information Processing Systems*, *33*.

Wallelign, S., Polceanu, M., & Buche, C. (2018). Soybean plant disease identification using convolutional neural network. In *The thirty-first international flairs conference*.

Wang, C., Chen, D., Hao, L., Liu, X., Zeng, Y., Chen, J., & Zhang, G. (2019). Pulmonary image classification based on inception-v3 transfer learning model. *IEEE Access*, *7*, 146533–146541.

Wang, X., Shrivastava, A., & Gupta, A. (2017). A-fast-rcnn: Hard positive generation via adversary for object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2606–2615.

Wen, L., Li, X., & Gao, L. (2020). A transfer convolutional neural network for fault diagnosis based on resnet-50.. *Neural Computing & Applications*, *32*(10).

Wu, J. (2017). Introduction to convolutional neural networks. *National Key Lab for Novel Software Technology. Nanjing University. China*, *5*(23), 495.

Xu, L., Ren, J. S., Liu, C., & Jia, J. (2014). Deep convolutional neural network for image deconvolution. *Advances in neural information processing systems*, *27*, 1790–1798.

You, Y., Zhang, Z., Hsieh, C.-J., Demmel, J., & Keutzer, K. (2018). Imagenet training in minutes. In *Proceedings of the 47th International Conference on Parallel Processing*, pp. 1–10.

Zahangir Alom, M., Hasan, M., Yakopcic, C., & Taha, T. M. (2017). Inception recurrent convolutional neural network for object recognition. *arXiv e-prints*, arXiv–1704.

Zhang, K., Wu, Q., Liu, A., & Meng, X. (2018a). Can deep learning identify tomato leaf disease?. *Advances in Multimedia*, *2018*.

Zhang, W., Hansen, M. F., Volonakis, T. N., Smith, M., Smith, L., Wilson, J., Ralston, G., Broadbent, L., & Wright, G. (2018b). Broad-leaf weed detection in pasture. In *2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC)*, pp. 101–105. IEEE.

Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018c). Identification of maize leaf diseases using improved deep convolutional neural networks. *IEEE Access*, *6*, 30370–30377.

Zhao, H., Shi, J., Qi, X., Wang, X., & Jia, J. (2017). Pyramid scene parsing network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2881–2890.

Zhou, L., Zhang, C., Liu, F., Qiu, Z., & He, Y. (2019). Application of deep learning in food: a review. *Comprehensive Reviews in Food Science and Food Safety*, *18*(6), 1793–1811.

Zou, J., Han, Y., & So, S.-S. (2008). Overview of artificial neural networks. *Artificial Neural Networks*, 14–22.