International Journal of Modern Agriculture, Volume 10 No. 2, 2021
ISSN: 2305-7246

A Review on Applications of Deep Learning in Agriculture

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Abstract:
Agriculture is one of the major industries in the world. As the global population has been continuously increasing, a large increase on food production must be achieved by maintaining at the same time availability and high nutritional quality across the globe, protecting the natural ecosystems by using sustainable farming procedures. However, traditional methods of farming are not enough to handle this huge food demand. This is driving farmers and agro companies to find newer ways to increase production and reduce agriculture waste. As a result, Information and communication technologies (ICT) are emerging as part of the agriculture industry's technological evolution. Such modern farming technology is called the Internet of Things (IoT) and it does not require the presence of a farmer to control various agricultural processes. IoT based farming system can be used for monitoring the crop field with the help of sensors (light, humidity, temperature, soil moisture, etc.) and automating the farming eco system. The automation in agriculture is the main concern and the emerging area of research across the world. Thus, new automated methods were introduced. These new methods satisfied the food requirements and also provided employment opportunities to billions of people. One of the most prominent technologies for agriculture automation is Deep learning.
The main objective of this paper is to find the various applications of Deep learning in agriculture such as for irrigation, weeding, Pattern recognition, crop disease identification etc. This article performs a survey of 27 research papers that employ different deep learning techniques applied to various agricultural problems, such as disease detection/identification, fruit/plants classification, Automation of irrigation and fruit counting among other domains. The paper reviews the specific employed deep learning models, the source of the data, the performance of each study, the employed hardware and the possibility of real-time application to study eventual integration with autonomous robotic platforms. The current study also compared deep learning with other existing techniques, in terms of performance. Our research findings indicate that deep learning offers better performance and outperforms traditional image processing techniques.

1. Introduction:

Agriculture plays a significant role in economic sector, as the requirement of foodstuff due to rise in population is constantly increasing. There is a huge requirement of advancements in the agriculture sector such as to make precise calculations regarding yield production, using best and latest farming equipment, in order to meet the increasing needs of crop. Because of these advancements modern farming is also referred as digital farming, precise farming, intelligent farming, intensive farming, continual farming, organic farming and agribusiness.
Traditionally, farmers have been following indigenous production methods and rely upon friends, relatives, fellow farmers and input dealers to get information regarding agriculture. Farming sector is facing various challenges such as unavailability of good quality of seeds, lack of modern equipment, poor irrigation facilities, small and fragmented holdings of land, dealing with local traders and middleman, lack of storage facilities. With advancement of agricultural science and technology, multiple options to access modern technologies have become available. Therefore agriculture

scientists and researchers have to think how science and technology can be used as a tool to empower Agriculture sector. With growing population and ever growing demand for food, the scientist and researchers across the globe are busy to find innovative ways to meet this ever surging demand. Agriculture is one industry where Machine Learning scientists and researchers are working with farmers to help them with their produce. Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabelled. It is also known as deep neural learning or deep neural network. Deep learning is a modern method that has been successfully applied in various domains. Deep learning has various applications such as image processing and text classification. Since the successful rate of deep learning is very high in other domains, so it is applied to agriculture methods also. Deep learning covers several layers of neural networks designed to perform more cultured tasks. Some of the deep learning models provide remarkable results, and in terms of scale they are not matched with humans. Each layer uses the outcome of previous result as input and whole network is trained as a single chain. Deep learning platform is a platform which helps users to build different deep learning architectures or facilitate users to apply deep learning to a wide range of agriculture applications with apps and services. Deep learning technologies play a crucial role in disseminating information to farmers enabling them to decide on the cropping pattern, use of high-yielding seeds, fertilizer application, pest management, marketing, etc. This Study begins with 3 research questions. The first research question is what are the various deep learning models available. Second research question is which deep learning method gives better performance for agriculture data. Finally the third question is what are the various applications of Deep learning in Agriculture.

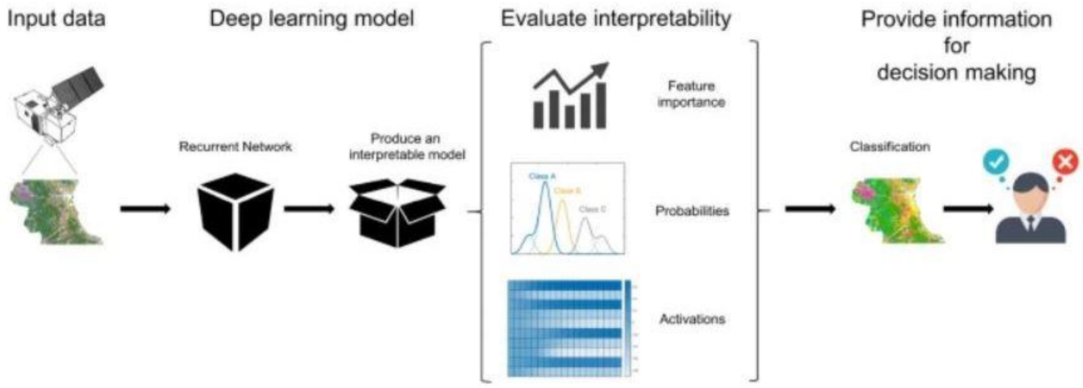

Figure 1.1: Deep learning in agriculture

This study is divided into five sections. Section 1 introduces the concept of deep learning in agriculture. Section 2 of this article presents review of existing literature. Section 3 explains the methodology used in the present study. Section 4 interpret and describe the significance of findings and scope of current study. Section 5 presents the conclusions of the work.

2. Literature Review

This study have been classified into 5 agricultural domains namely Plant disease identification, identification of weeds, plant recognition, fruits counting and crop type classification. For this a purpose an intensive review of deep neural network efforts in the agriculture domain in the last 6 years (2015-2021) is performed.

Kamilaris A. et al. (2016) proposed a Agri-IoT framework, a semantic framework for IoT based smart farming applications, which supports reasoning over various heterogeneous sensor data streams in real-time. Agri IoT can integrate multiple cross-domain data streams, providing a complete semantic processing pipeline, offering a common framework for smart farming applications. Agri-IoT supports large-scale data analytics and event detection, ensuring seamless interoperability among sensors, services, processes, operations, farmers and other relevant actors, including online information sources and linked open datasets and streams available on the Web.

Nilay Ganatra et al. (2020) did comprehensive review of research dedicated to applications of deep 9 learning for precision agriculture is presented along with real time applications, 10 tools and available datasets. The findings exhibit the high potential of applying deep 11 learning techniques for precision agriculture.

Walter A. et al. (2017) discussed the role of Smart farming for sustainable agriculture. According to them Agriculture has seen many revolutions, whether the domestication of animals and plants a few thousand years ago, the systematic use of crop rotations and other improvements in farming practice a few hundred years ago, or the “green revolution” with systematic breeding and the widespread use of man-made fertilizers and pesticides a few decades ago. We suggest that agriculture is undergoing a fourth revolution triggered by the exponentially increasing use of information and communication technology (ICT) in agriculture.

Tamoor K et al. (2020) presented a novel approach to fruit production prediction using deep neural networks to build a fast and reliable prediction system for agricultural production. In this article, authors have considered different types of fruit production data (apples, bananas, citrus, pears, grapes, and total fruits), analysed this data, and predicted the future production of these fruits using deep neural networks. The data are taken from the National Bureau of Statistics of Pakistan and the production output of major fruits. Authors have implemented 3 different methods to predict the data for future fruit production. The first method is Levenberg-Marquardt optimization (LM), which was 65.6% accurate; the second method is called scale conjugate gradient back propagation (SCG), which had an accuracy of 70.2%, and the third method, is Bayesian regularization back propagation (BR), which was 76.3% accurate.

Mehta P. et al. (2015) incorporates the performance analysis of clustering algorithms when applied to FAO Soya bean dataset. The algorithms are compared on the basis of various parameters, such as time taken for completion, number of iterations, and number of clusters formed and the complexity of the algorithms. Finally, based on the analysis, the paper determines the best befitting algorithm for the FAO Soya bean dataset.

K. G. Liakos et al. (2018) did a comprehensive review of research dedicated to applications of machine learning in agricultural production systems. The works analyzed were categorized in (a) crop management, including applications on yield prediction, disease detection, weed detection crop quality, and species recognition; (b) livestock management, including applications on animal welfare and livestock production; (c) water management; and (d) soil management.

Chengjuan Ren et al. (2020) discussed advantages and disadvantages of deep learning and future research topics. The survey shows that deep learning-based research has superior performance in terms of accuracy, which is beyond the standard machine learning techniques nowadays.

Bahrampour S et al. (2016) presented a comparative study of five deep learning frameworks, namely Caffe, Neon, TensorFlow, Theano, and Torch, on three aspects: extensibility, hardware utilization, and speed. The study is performed on several types of deep learning architectures and we evaluate the performance of the above frameworks when employed on a single machine for both (multi-threaded) CPU and GPU (Nvidia Titan X) settings. The speed performance metrics used here include the gradient computation time, which is important during the training phase of deep networks, and the forward time, which is important from the deployment perspective of trained networks. For convolutional networks, we also report how each of these frameworks support various convolutional algorithms and their corresponding performance.

Leila Hashemi et al. (2020) examine the ability of deep learning methods for remote sensing image classification for agriculture applications. Unet and convolutional neural networks are fine-tuned, utilized and tested for crop/weed classification. The dataset for this study includes 60 top-down images of an organic carrots field, which was collected by an autonomous vehicle and labeled by experts. FCN8s model achieved 75.1% accuracy on detecting weeds compared to 66.72% of U-net using 60 training images. However, the U-net model performed better on detecting crops which is 60.48% compared to 47.86% of FCN-8s.

Canziani A. et al. (2016) presented a comprehensive analysis of important metrics in practical applications: accuracy, memory footprint, parameters, operations count, inference time and power consumption. Key findings are: (1) power consumption is independent of batch size and architecture; (2) accuracy and inference time are in a hyperbolic relationship; (3) energy constraint is an upper bound on the maximum achievable accuracy and model complexity; (4) the number of operations is a reliable estimate of the inference time.

Zhang X. et al. (2018) proposed a model based on deep learning for leaf disease recognition. Two improved models that are used to train and test nine kinds of maize leaf images are obtained by adjusting the parameters, changing the pooling combinations, adding dropout operations and rectified linear unit functions, and reducing the number of classifiers. In addition, the number of parameters of the improved models is significantly smaller than that of the VGG and AlexNet structures. During the recognition of eight kinds of maize leaf diseases, the GoogLeNet model achieves a top-1 average identification accuracy of 98.9%, and the Cifar10 model achieves an average accuracy of 98.8%. The improved methods are possibly improved the accuracy of maize leaf disease, and reduced the convergence iterations, which can effectively improve the model training and recognition efficiency.

Amara J et al. (2017) proposed a deep learning-based approach that automates the process of classifying banana leaves diseases. In particular authors make use of the LeNet architecture as a convolutional neural network to classify image data sets. The preliminary results demonstrate the effectiveness of the proposed approach even under challenging conditions such as illumination, complex background, different resolution, size, pose, and orientation of real scene images.

Zhong L. et al. (2019) developed a deep learning based classification framework for remotely sensed time series. The experiment was carried out in Yolo County, California, which has a very diverse irrigated agricultural system dominated by economic crops. For the challenging task of classifying summer crops using Landsat Enhanced Vegetation Index (EVI) time series, two types of deep learning models were designed: one is based on Long Short-Term Memory (LSTM), and the other is based on one-dimensional convolutional (Conv1D) layers. Three widely-used classifiers were also tested for comparison, including a gradient boosting machine called XGBoost, Random Forest, and

Support Vector Machine. Although LSTM is widely used for sequential data representation, in this study its accuracy (82.41%) and F1 score (0.67) were the lowest among all the classifiers. Among non-deep-learning classifiers, XGBoost achieved the best result with 84.17% accuracy and an F1 score of 0.69. The highest accuracy (85.54%) and F1 score (0.73) were achieved by the Conv1D-based model, which mainly consists of a stack of Conv1D layers and an inception module.

Mariannie Rebortera et al. (2019) used the banana harvest data from agrarian reform beneficiary (ARB) cooperative in Davao del Norte, Philippines, proved that RNN-LSTM has the capability in forecasting harvest yields over conventional-based model like the famous autoregressive integrated moving average (ARIMA). Using the same set of training and testing data, experiment exhibits that RNN-LSTM obtains 43.69 in terms of root-mean-squared-error (RMSE) and ARIMA obtains 64.11respectively. This means that RNN-LSTM outperforms the ARIMA model with 32.31 percent reduction in error rates.

A Kamilaris (2018) et al. (2018) did a survey of 40 research efforts that employ deep learning techniques, applied to various agricultural and food production challenges. We examine the particular agricultural problems under study, the specific models and frameworks employed, the sources, nature and pre-processing of data used, and the overall performance achieved according to the metrics used at each work under study. Moreover, we study comparisons of deep learning with other existing popular techniques, in respect to differences in classification or regression performance. The findings indicate that deep learning provides high accuracy, outperforming existing commonly used image processing techniques.

Dyrmann M. et al. (2016) designed and trained a deep convolutional neural network that the convolution kernel size and the order of network connection are based on the high efficiency of the filter capacity and coverage. To evaluate the classification performance of the network, experiments were conducted using a public database Caltech256 and a homemade product image database containing 15 species of garment and 5 species of shoes on a total of 20,000 colour images from shopping websites.

Rahnemoonfar M. et al (2017) presented a simulated deep convolutional neural network for yield estimation. Knowing the exact number of fruits, flowers, and trees helps farmers to make better decisions on cultivation practices, plant disease prevention, and the size of harvest labor force. The current practice of yield estimation based on the manual counting of fruits or flowers by workers is a very time consuming and expensive process and it is not practical for big fields.

Ramos P. J. et al. (2017) proposed to count the number of fruits on a coffee branch by using information from digital images of a single side of the branch and its growing fruits. In order to do this, 1018 coffee branches at different ripening stages.

Bargoti S. et al. (2016) presented the use of a state-of-the-art object detection framework, Faster R-CNN, in the context of fruit detection in orchards, including mangoes, almonds and apples. Ablation studies are presented to better understand the practical deployment of the detection network, including how much training data is required to capture variability in the dataset.

Yalcin, H et al. (2016) propose a Convolutional Neural Network (CNN) architecture to classify the type of plants from the image sequences collected from smart agro-stations. First challenges introduced by illumination changes and deblurring are eliminated with some preprocessing steps.

Following the preprocessing step, Convolutional Neural Network architecture is employed to extract the features of images. The construction of the CNN architecture and the depth of CNN are crucial points that should be emphasized since they affect the recognition capability of the architecture of neural networks. In order to evaluate the performance of the approach proposed in this paper, the results obtained through CNN model are compared with those obtained by employing SVM classifier with different kernels, as well as feature descriptors such as LBP and GIST. The performance of the approach is tested on dataset collected through a government supported project, TARBIL, for which over 1200 agro-stations are placed throughout Turkey. The experimental results on TARBIL dataset confirm that the proposed method is quite effective.

Saeed K et al. (2020) presented a deep learning framework using convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for crop yield prediction based on environmental data and management practices. The proposed CNN-RNN model, along with other popular methods such as random forest (RF), deep fully connected neural networks (DFNN), and LASSO, was used to forecast corn and soybean yield across the entire Corn Belt (including 13 states) in the United States for years 2016, 2017, and 2018 using historical data.

Mythili K et al. (2021) proposed a model is to deliver direct advisory services to even the smallest farmer at the level of his/her smallest plot of crop, using the most accessible technologies using deep learning. It is a recommender model built using a classifier and an optimization of the classifier. Based on appropriate parameters, the system recommends crops as technology based crop recommendation system in agricultural decisions can be of great help to farmers in increasing their crop yields or cultivating suitable crops based on their land characteristics and climatic parameters. This work proposed MDNN where the weight matrices are calculated with L2 regularization and PSO utilized to tune the hyper parameters of MDNN and its network structure to improve the prediction accuracy.

Zhang Y et al. (2017) designed a 13-layer convolutional neural network (CNN). Three types of data augmentation method was used: image rotation, Gamma correction, and noise injection. We also compared max pooling with average pooling. The stochastic gradient descent with momentum was used to train the CNN with minibatch size of 128. The overall accuracy of our method is 94.94%, at least 5 percentage points higher than state-of-the-art approaches. We validated this 13-layer is the optimal structure. The GPU can achieve a 177× acceleration on training data, and a 175× acceleration on test data. We observed using data augmentation can increase the overall accuracy.

Khaki S. et al. (2019) designed a deep neural network (DNN) approach that took advantage of state-of-the-art modeling and solution techniques. Our model was found to have a superior prediction accuracy, with a root-mean-square-error (RMSE) being 12% of the average yield and 50% of the standard deviation for the validation dataset using predicted weather data. With perfect weather data, the RMSE would be reduced to 11% of the average yield and 46% of the standard deviation. We also performed feature selection based on the trained DNN model, which successfully decreased the dimension of the input space without significant drop in the prediction accuracy. Our computational results suggested that this model significantly outperformed other popular methods such as Lasso, shallow neural networks (SNN), and regression tree (RT).

3. Methodology

In order to answer the research questions a bibliographic analysis in the domain under study was done, it involved two steps:

- Collection of related works and,
- Detailed review and analysis of the works.

A survey is performed on various research papers on Applications of deep learning in agriculture. The research paper from 2015-2021 selected for study. In the first step, a keyword-based search using all combinations of two groups of keywords of which the first group addresses deep learning and the second group refers to application of deep learning in farming.

Deep Learning or Deep Neural network

Deep learning is one of the prominent methods by which we can overcome the challenges of feature extraction. A Deep neural network is a type of artificial neural network (ANN) used in image recognition, processing and classification that is specifically designed to process pixel data. Deep learning are powerful image processing technique that perform both generative and descriptive tasks, often using machine vision that includes image and video recognition, along with recommender systems and natural language processing (NLP). Most deep learning methods use neural network architectures, which is why deep learning models are often referred to as deep neural networks. The term "deep" usually refers to the number of hidden layers in the neural network. Traditional neural networks only contain 2-3 hidden layers, while deep networks can have as many as 150. Deep learning models are trained by using large sets of labelled data and neural network architectures that learn features directly from the data without the need for manual feature extraction. A perceptron receives multiple inputs, applies various transformations and functions and provides an output. In perceptron where neuron output value 0 and 1 based on, if the weighted sum $\sum_i w_i x_i$ is less than or greater than some threshold value respectively. It is a type of direct formal neural network organized into several hidden layers in which information flows from the input layer to the output layer only. In deep-learning networks, each layer of nodes trains on a distinct set of features based on the previous layer's output. The further you advance into the neural net, the more complex the features your nodes can recognize, since they aggregate and recombine features from the previous layer.

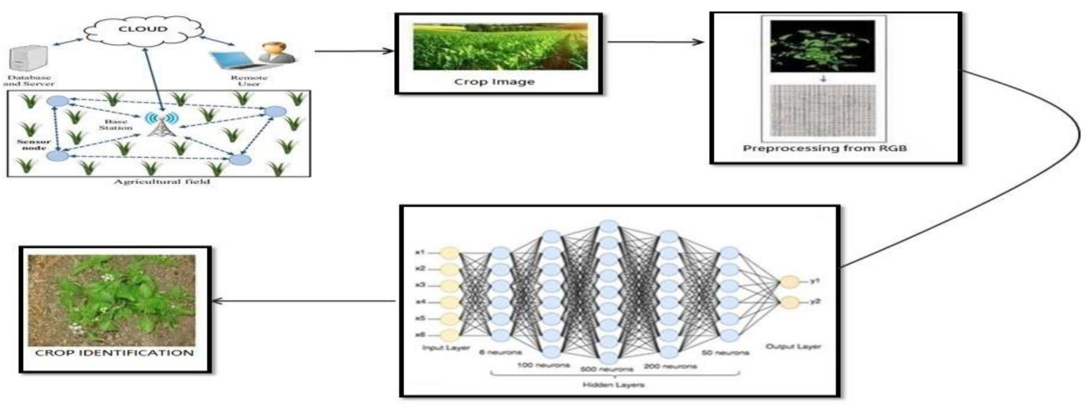

Figure 3.1: Deep neural network in agriculture

Deep learning framework – Tensorflow:

Tensorflow is the most popular and apparently best Deep Learning Framework. TensorFlow is a framework created by Google for creating Deep Learning models. TensorFlow is an open source software library for numerical computation using data flow graphs. Nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) that flow between them. This flexible architecture lets you deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device without rewriting code. For visualizing TensorFlow results, TensorFlow offers TensorBoard, suite of visualization tools.

Keras:

Keras is a high-level library that's built on top of TensorFlow. It provides a scikit-learn type API (written in Python) for building Neural Networks. Developers can use Keras to quickly build neural networks without worrying about the mathematical aspects of tensor algebra, numerical techniques, and optimization methods.

Deep learning Methods:

Deep learning (DL) algorithms have recently emerged from machine learning and soft computing techniques. Since then, several deep learning (DL) algorithms have been recently introduced to scientific communities and are applied in various application domains. Most popular deep learning models are

Xception:

Xception is a convolutional neural network architecture that relies solely on depthwise separable convolution layers. Xception Model is proposed by Francois Chollet. Xception is an extension of the inception Architecture which replaces the standard Inception modules with depthwise Separable Convolutions.

VGG 16: VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition". The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPUs.

VGG-19:
VGG-19 is a convolutional neural network that is trained on more than a million images from the ImageNet database. The network is 19 layers deep and can classify images into 1000 object categories, such as a keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images.
ResNet-50: ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database . The pretrained network can classify images into 1000 object categories, such as keyboard, mouse,

pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

ResNet-101: ResNet-101 is a convolutional neural network that is 101 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

Inception v3:

Inception v3 is a widely-used image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years. The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concats, dropouts, and fully connected layers. Batchnorm is used extensively throughout the model and applied to activation inputs. Loss is computed via Softmax.

MobileNet: In Dense-MobileNet models, convolution layers with the same size of input feature maps in MobileNet models are taken as dense blocks, and dense connections are carried out within the dense blocks. The new network structure can make full use of the output feature maps generated by the previous convolution layers in dense blocks, so as to generate a large number of feature maps with fewer convolution cores and repeatedly use the features.

MobileNetV2:

MobileNetV2 is very similar to the original MobileNet, except that it uses inverted residual blocks with bottlenecking features. It has a drastically lower parameter count than the original MobileNet. MobileNets support any input size greater than 32 x 32, with larger image sizes offering better performance.

DenseNet: DenseNet is one of the new discoveries in neural networks for visual object recognition. DenseNet is quite similar to ResNet with some fundamental differences. DenseNet was developed specifically to improve the declined accuracy caused by the vanishing gradient in high-level neural networks. In simpler terms, due to the longer path between the input layer and the output layer, the information vanishes before reaching its destination.

NASNetMobile

Google introduced NASNet, which framed the problem of finding the best CNN architecture as a Reinforcement Learning problem. Basically the idea was to search the best combination of parameters of the given search space of filter sizes, output channels, strides, number of layers etc. In this Reinforcement Learning setting, the reward after each search action was the accuracy for the searched architecture on the given dataset.

EfficientNets: EfficientNets rely on AutoML and compound scaling to achieve superior performance without compromising resource efficiency. The AutoML Mobile framework has helped develop a mobile-size baseline network, EfficientNet-B0, which is then improved by the compound scaling method to obtain EfficientNet-B1 to B7.

The bellow table represents performance of various deep learning models on the ImageNet. validation dataset. Depth refers to the topological depth of the network. This includes activation layers, batch normalization layers etc.

Model	**Size**	**Top-1 Accuracy**	**Top-5 Accuracy**	**Parameters**	**Depth**
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.713	0.901	138,357,544	23
VGG19	549 MB	0.713	0.900	143,667,240	26
ResNet50	98 MB	0.749	0.921	25,636,712	-
ResNet101	171 MB	0.764	0.928	44,707,176	-
InceptionV3	92 MB	0.779	0.937	23,851,784	159
InceptionResNetV2	215 MB	0.803	0.953	55,873,736	572
MobileNet	16 MB	0.704	0.895	4,253,864	88
MobileNetV2	14 MB	0.713	0.901	3,538,984	88
DenseNet121	33 MB	0.750	0.923	8,062,504	121
DenseNet169	57 MB	0.762	0.932	14,307,880	169
DenseNet201	80 MB	0.773	0.936	20,242,984	201
NASNetMobile	23 MB	0.744	0.919	5,326,716	-
NASNetLarge	343 MB	0.825	0.960	88,949,818	-
EfficientNetB0	29 MB	-	-	5,330,571	-
EfficientNetB1	31 MB	-	-	9,177,569	-
EfficientNetB2	36 MB	-	-	9,177,569	-

EfficientNetB3	48 MB	-	-	12,320,535	-
EfficientNetB4	75 MB	-	-	19,466,823	-
EfficientNetB5	118 MB	-	-	30,562,527	-
EfficientNetB6	166 MB	-	-	43,265,143	-
EfficientNetB7	256 MB	-	-	66,658,687	-

Table 1: Performance of various deep learning models

Keras and TensorFlow are top two frameworks that are preferred by Data Scientists and researchers in the field of Deep Learning. The key differences between a TensorFlow and Keras are as follows:

- Keras is a high-level API that runs on the top of TensorFlow. For its simple usability and its syntactic simplicity, it has been promoted, which enables rapid development.
- The performance of Keras is comparatively slow, while Tensorflow delivers a similar pace that is fast and efficient.
- The architecture of Keras is plain. It is easier to read and briefer. On the other hand, TensorFlow is not easy to use, although it provides Keras as a system that facilitates working.
- For keras, the debugging of simple networks is typically much less difficult. Whereas, debugging is very difficult for Tensorflow.
- Keras is usually used as a slower comparison with small datasets. TensorFlow, on the other hand, is used for high-performance models and large data sets requiring rapid implementation.

Thus in terms of flexibility, Tensorflow's eager execution allows for immediate iteration along with intuitive debugging. Keras offers simple and consistent high-level APIs and follows best practices to reduce the cognitive load for the users. Both frameworks thus provide high-level APIs for building and training models with ease. Keras is built in Python which makes it way more user-friendly than TensorFlow.

Online datasets for agriculture research using deep learning:

Datasets are an integral part of the agricultural research using deep learning. To apply deep learning technology in various agricultural situations, a large number of agriculture domain specific dataset available.

PlantVillage: The PlantVillage dataset consists of 54303 healthy and unhealthy leaf images divided into 38 categories by species and disease. Note: The original dataset is not available from the original source (plantvillage.org), therefore we get the unaugmented dataset from a paper that used that dataset and republished it.

ImageNet: ImageNet is an image database organized according to the WordNet hierarchy in which each node of the hierarchy is depicted by hundreds and thousands of images. The project has been instrumental in advancing computer vision and deep learning research. The data is available for free to researchers for non-commercial use.

LeafSnap: This dataset consists of images of leaves taken from two different sources, as well as their automatically-generated segmentations. 23147 Lab images, consisting of high-quality images taken of pressed leaves, from the Smithsonian collection. These images appear in controlled backlit and front-lit versions, with several samples per species. 7719 Field images, consisting of "typical" images taken by mobile devices (iPhones mostly) in outdoor environments. These images contain varying amounts of blur, noise, illumination patterns, shadows, etc.

Urban Trees: This dataset contains urban tree growth data collected over a period of 14 years (1998-2012) in 17 cities from 13 states across the United States: Arizona, California, Colorado, Florida, Hawaii, Idaho, Indiana, Minnesota, New Mexico, New York, North Carolina, Oregon, and South Carolina. Measurements were taken on over 14,000 urban street and park trees.

Flowers 102: This dataset consisting of 102 flower categories. The flowers chosen to be flower commonly occuring in the United Kingdom. Each class consists of between 40 and 258 images.

iNaturalist dataset: It is an image classification benchmark consisting of 675,000 images with over 5,000 different species of plants and animals. It features many visually similar species, captured in a wide variety of situations, from all over the world. Images were collected with different camera types, have varying image quality, have been verified by multiple citizen scientists, and feature a large class imbalance.

VegFru: VegFru categorizes vegetables and fruits according to their eating characteristics, and each image contains at least one edible part of vegetables or fruits with the same cooking usage. Particularly, all the images are labelled hierarchically. The current version covers vegetables and fruits of 25 upper-level categories and 292 subordinate classes. And it contains more than 160,000 images in total and at least 200 images for each subordinate class.

CropDeep: This dataset, consisting of 31,147 images with over 49,000 annotated instances from 31 different classes. In contrast to existing vision datasets, images were collected with different cameras and equipment in greenhouses, captured in a wide variety of situations. It features visually similar species and periodic changes with more representative annotations, which have supported a stronger benchmark for deep-learning-based classification and detection.

Dataset	**Description**
EPFL, Plant village dataset	Images of variety of crops and their diseases

ImageNet dataset	Plants images like trees, vegetables and flowers
Leafsnap dataset	185 spices of leaves from Northeastern United States
Urban Trees	This dataset contains urban tree growth data collected over a period of 14 years (1998-2012) in 17 cities of United States
iNaturalist dataset	It contains of 675,000 images with over 5,000 different species of plants and animals.
VegFru	This dataset contains vegetables and fruits according to their eating characteristics
CropDeep	This dataset, consisting of 31,147 images with over 49,000 annotated instances from 31 different classes.

Table 2: Online dataset in Agricultural domain

Deep learning applications in Agriculture:

Deep Learning (DL) is the state-of-the-art machine learning technology, which shows superior performance in computer vision, bioinformatics, natural language processing, and other areas. Deep learning has great capability in image processing, which makes it widely used in agriculture research. Generally speaking, most applications of DL in agriculture can be categorized as plant or crop classification, which is vital for pest control, robotic harvesting, yield prediction, disaster monitoring etc.

- Plant disease detection is very time consuming when it is done manually. Fortunately, with the development of deep learning plant disease detection can be accomplished through image processing. CNN architectures like AlexNet, GoogLeNet and ResNet can be used for identifying the plant leaf diseases. Amara, J et al. [1] presented a deep learning-based approach for banana leaf diseases classification.
- Deep neural network can also be used in weather forecasting, which is key problem to agriculture. Crop yield prediction before harvest is crucial to farmers, consumers, and the government in their efforts to design strategies for selling, purchasing, market intervention, and food shortage relief. Deep Learning methods such as Conditional Restricted Boltzmann Machine (CRBM) and Convolutional Neural Network (CNN) offers the accurate representation, classification and prediction of rainfall with adequate accuracy level. Khaki S et al. [14] did a study on crop yield prediction using deep neural networks.
- Deep learning is also used in Land cover classification (LCC) is considered as a vital and challenging task in agriculture, and the key point is to recognize what class a typical piece of land is in. Deep learning methods such as CNN, GAN and RNN are able to be used for land cover classification of remote sensing image data. Manuel Campos-Taberner et al. [19] explained deep learning applications in land use classifcation based on Sentinel-2 time series.
- Agriculture Companies are leveraging computer vision and deep-learning algorithms to process data captured by drones and/or software-based technology to monitor crop and soil health.

Convolutional neural network is particularly well-known for its effectiveness in handling vision-based tasks such as image classification, object detection, semantic segmentation, and scene understanding. Bargoti S. et al. [3] performed a study on Deep Fruit Detection in Orchards.

- Deep learning is also used to track and predict various environmental impacts on crop yield such as weather changes. Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these kind of studies, and the other widely used deep learning algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN). Mariannie Rebortera et al.[9] performed a research on Forecasting Banana Harvest Yields using Deep Learning
- Deep learning techniques CNN, RNN, VGGnet are used for image-based anomaly detection solution to detect crop diseases from visual inspection of leaves. CNN model of physiological signals anomaly detection and we test our algorithm on eight physiological signals on DEA. Rahnemoonfar M et al. [18] performed a research on fruit counting based on deep simulated learning.

- Deep Neural network are used for speech recognition of animals. For the animal speech classification RNN, CNN and VGGnet are found to give better and accurate result. Tuomas Oikarinen et al. [27] performed a study on deep convolutional network for animal sound classification and source attribution using dual audio recordings.
- Deep learning algorithms, take decades of field data to analyse crops performance in various climates and new characteristics developed in the process. Based on this data they can build a probability model that would predict which genes will most likely contribute a beneficial trait to a plant. Tamoor Khan et al. [4] did a study on Agricultural Fruit Prediction Using Deep Neural Networks
- Deep learning algorithms like Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Stacked Auto-Encoders, Deep Boltzmann Machine (DBM), Deep Belief Networks (DBN) are widely used to monitor soil moisture and temperature to understand the dynamics of ecosystems and the impingement in agriculture. Kamilaris A et al. [12] developed a framework for Internet of Things-enabled smart farming applications. In 3rd World Forum on Internet of Things (WF-IoT).
- Deep learning algorithms viz. feedforward neural network, CNN, RNN are connected with estimation of daily, weekly, or monthly evapotranspiration allowing for a more effective use of irrigation systems and prediction of daily dew point temperature, which helps identify expected weather phenomena and estimate evapotranspiration and evaporation. Leila Hashemi-Beni et al. [16] performed a research on Deep Learning For Remote Sensing Image Classification For Agriculture Applications.
- Deep learning methods viz. CNN, RNN, LSTM can be used to provide accurate prediction and estimation of farming parameters to optimize the economic efficiency of livestock production systems, such as cattle and eggs production. Walter A et al. [21] performed a study on smart farming is key to developing sustainable agriculture.

This review classifies the application of deep learning into 5 agricultural domains namely Plant disease identification, identification of weeds, plant recognition, fruits counting and crop type classification. For this a purpose an intensive review of deep neural network applications in the agriculture domain.

Agriculture Area	Problem Statement	Data Used	Deep Learning Architecture	Overall Accuracy	Hardware	Rederence
Plant disease deduction	Banana Leaf Diseases Classification	Dataset of banana diseases obtained from the PlantVillage project containing l 3700 images	LeNet architecture as a convolutional neural network	92	GPU	[1]
	Identification of 8 kinds of maize leaves diseases	500 images collected from public sources (Plant Village dataset	Modified GoogleNet and Cifar10	98.9%	GPU	[23]
Fruit classification	Classification of 18 types of fruit	3600 images acquired by authors and downloaded from public websites	13-layer convolutional neural network (CNN)	94.94%	GPU	[24]
	multi-temporal crop classification	remotely sensed time series data	One-dimensional convolutional neural network	84.17%	GPU	[25]
	Plant classification using convolutional neural networks	agricultural plants images are acquired by cameras mounted on agro-meteorological smart stations equipped with many sensors.	deep-learning based approach, SVM based classifier using features such as LBP and GIST is also implemented.	97.47%	GPU	[22]
	REMOTE SENSING IMAGE CLASSIFICATION	60 top-down images of an organic carrots field, which was	U-Net and FCN-8s	75.2%	GPU	[16]

		collected by an autonomous vehicle and labeled by experts				
	Plant species classification	total of 10,413 images containing 22 weed and crop species at early growth stages.	convolutional neural network	86.2%	GPU	[7]
Fruit Detection	Deep Fruit Detection in Orchards	Three fruit varieties: apples, almonds and mangoes, captured during daylight hours at orchards in Victoria and Queensland. Images taken under controlled conditions with regard to camera stabilisation and illumination, and images shot with hand-held mobile phones in fields with changing lighting conditions and different soil types.	Faster R-CNN	F1-score of > 0.9 achieved for apples and mangoes	GPU	[3]

Crop Yield Prediction	deep learning-based approach for crop yield prediction	The soil data was acquired from Gridded Soil Survey Geographic Database for the United States	CNN-RNN model	94.99%	GPU	[15]
Fruit Counting	Fruit counting based on deep simulated learning	Set of 2400 synthetic images and 100 randomly-selected real tomato images from Google Images are used	M odified version of Inception-ResNet	91%	NVidia 980Ti GPU.	[18]

Table 3: Applications of Deep Learning in Agriculture

4. Discussion and recommendations:

Smart farming is an emerging concept that refers to managing farms using deep learning technologies to increase the quantity and quality of products while optimizing the human labour required by production. This research presents applications of deep learning technologies in various agriculture problems like Soil health monitoring , Yield prediction, Pest and diseases detection, Weed detection, How to recognize a plant, How to manage quality of crop, management of irrigation, Welfare of animals, Forecasting livestock etc. Current research findings indicate that deep learning offers better performance and outperforms traditional image processing techniques. By applying deep learning to sensor data, farm management systems are evolving into real intelligence systems, providing richer recommendations and insights for the subsequent decisions and actions with the ultimate scope of production improvement. The objective of this paper is to encourage more researchers to study deep learning to settle agricultural issues such as recognition, classification or prediction, relevant image analysis, and data analysis, or more general computer vision tasks. For this scope, in the future, it is expected that the usage of various deep learning models will be even more widespread, allowing for the possibility of integrated and applicable tools. The major barrier to deep learning is the need of huge dataset, which is used input to train any deep learning model. In spite of technique like data augmentation which augments the dataset in label-preserving mode, for real life problem minimum some hundreds of images are required, according to the complexity of the given problem. With the advances in computer's processing capabilities, it is accepted that deep learning will receive more attention and broader applications in future research. Deep learning methods can combine with other project management techniques like PERT (Program evaluation review technique) and CPM (Critical path method) to Optimizing routes on agricultural fields minimizing water wastage in irrigation. The dream of smart agriculture can become be smarter if we combine the feature of deep learning with IoT for Sensing temperature of soil, nutrients and humidity, controlling and analysing water consumption for growth of plant.

5. Conclusion

In this study, a survey is performed in development of deep neural network efforts in the agriculture domain in the last 6 years (2015-2021). We have analysed 27 research papers on the applications of deep learning and the technical details of their implementation. Each work was compared with existing techniques for performance. This article presents concise summary of major Deep algorithms, including concepts, limitations, implementation to help researchers and agriculture scientists in agriculture to gain a holistic picture of major Deep learning techniques quickly. Research on DL applications in agriculture is summarized and analysed, and future opportunities are discussed in this paper. This study demonstrates various applications of deep learning in agriculture. Various Deep Learning (DL) models have been widely studied and their performance is evaluated. The aim is for the current survey to motivate researchers and agriculture scientists to experiment with deep learning in general, applying them to solve various agricultural problems involving classification or prediction, related not only to computer vision and image analysis, but more generally to data analysis.

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