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A Survey on Deep Learning in Agriculture

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Abstract: In multidisciplinary agricultural technology domain, deep learning opens up new possibilities for information research. This review paper presents 72 article and projects that use deep learning techniques to solve agricultural problems. We look at the agricultural problems being studied, the frameworks and models used, source of data, pre-processed data, and overall output based on the measurement that is used at the development process. We also compare deep learning to other common techniques to see if there are any variations in classification or regression results. In contrast to certain other widely used image processing methods, our results show that high accuracy are achieved by using deep learning.

Keywords: Agriculture, Deep Learning, Smart Farming, Convolutional Neural Networks

1. Introduction

Agriculture is important for the economic development. As human population continued to be increases, the pressure on agricultural system will increase. Agri-technology including predictive agriculture, commonly referred to as digital agriculture, are emerging as new field of scientific that employ immersive data methods to increase productivity of agriculture while reducing effect on environment. Digital Agriculture [1] is essential for tackling challenges in the production of the agricultural sector. By tracking, measuring, and evaluating different physical phenomena, the threats, complexities, univariate, and volatile agricultural environments can be better understood. Most of this considers the enormous amount of agricultural data and the use of computer technology, both for small-scale agricultural production and big farm observation[2], improving existing management and decision-making tasks through context, circumstance, and environment knowledge[3]. Spatial data, which uses images from satellites, helicopters, and unmanned aerial vehicles including drones, enables for relatively large surveillance. When it is used in cultivation, it has many benefits, including being an excellently, non-destructive method of obtaining data about soil features whereas data can be collected consistently.

In the agricultural domain, image processing is an important field of research, with intelligent data analysis, for classification or image recognition are methods to be used [5]. In Appendix A, a list of common techniques and applications, as well as the sensing methods used to acquire photographs. Machine learning (ML), Support Vector Machines (SVM), and other approaches are among the most common techniques for image analysis [6].

Deep learning (DL)[7] is another methodology that has recently gained popularity. DL is an area of machine learning algorithm which is equivalent to ANN. DL, on the other hand, is about "deeper" neural networks which use multiple convolutions to provide a hierarchical representation of data. This enables greater learning capacities and, as a result, improved efficiency and precision.

The key motivation for conducting this survey is that agriculture that uses DL is new, futuristic, and reassuring. DL's development and implementations in other domains, on the other hand, prove that it has a lot of promise.

2. Methodology

In the domain under investigation, the scholarly review consisted of few steps: (a) a compilation of similar work and (b) a thorough examination and

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investigation. The very first phase included performing a key phrase search of conference or journal papers in research articles such as ScienceDirect and IEEE XPLORE, as well as Google Scholar. As the keyword that we used are :

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

By doing so, we were able to exclude articles that listed DL but did not relate to the agriculture domain. The papers were then reviewed in the second phase, considering all of the research questions:

1. Which problem did agriculture and food-related are addressed?
2. Which method of DL models are applied and what are the approach?
3. What were the datasets and forms were used?
4. What were the researchers' frameworks for classes and labels? And are there any differences between them that the authors noticed?
5. Is there any data pre-processing or data augmentation methods are used?
6. Based on the metric used, what was the actual performance?
7. Does the authors measure their models' output on a variety of sets of data?
8. Does the writers equate the method used with other methods, if it is, was there any different?

Our key results are reported in Section (4), and Appendix B includes comprehensive information for each report.

3. DEEP LEARNING

Deep learning (DL) is becoming more and more relevant in our daily lives. Cancer detection, self-driving vehicles, precision medicine, speech recognition, and predictive forecasting are only a few of the fields where it has already made an impact. Feature learning, or the automated extraction of features from raw data, is a strong benefit of DL, with stronger features created by the features from lower-level composition [7]. Because of the more complex models, DL can handle more complicated situations especially well and quickly, allowing significant parallel processing[8]. If sufficiently large datasets representing the problem are available, these complicated models used in Deep Learning could improve the accuracy of classification or minimize the problem of regression. Based on the architecture used, Deep Learning contain vary component (e.g., convolution, layers of pooling, activation function, etc.).

Highly network model of DL models, as well as their strong learning power, enabled them to perform a wide range of complex problems using predictions and classifications[8]. Although DL is most commonly associated with image data, it could be extended many kinds of details, including natural language, voice, and audio, points data such as data forecast[9], soil chemistry[10], and others. Figure 1 shows the DL architecture, which depicts TensorFlow, a CNN that combines completely connected layers and convolutional.

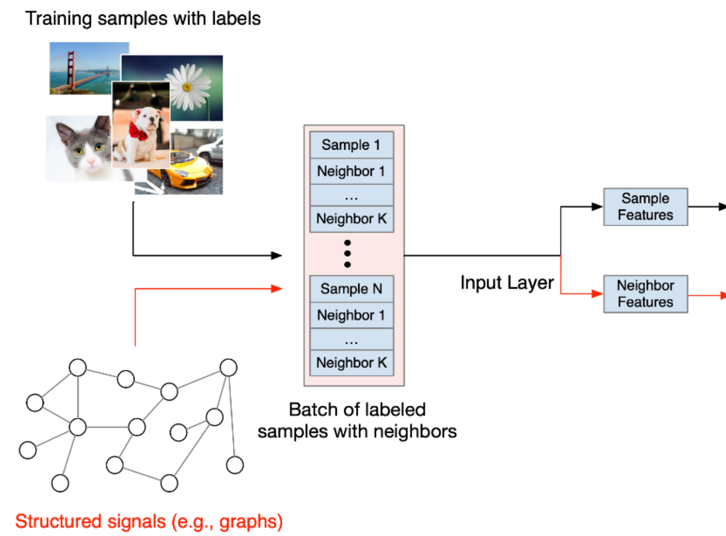

Figure 1 TensorFlow, illustrations of Framework of CNN Origin : Google Image

As shown in the diagram, different convolutions are applied to different network with different layer, resulting in different input of the learning dataset, beginning with common ones at the first bigger layers and progressing to higher detailed ones at the deeper layers. Before the dimensionality reduced by the pooling layer, removal of features is done by convolution layers from the input images. Multiple features at a lower level are encoded into further distinguishing characteristics in a spatially context-aware way by the convolutional layers. They can be thought of as a set of filters that turn an input data into a different one while highlighting particular patterns. The completely linked layers serve as classifiers in many situations near the model's output, using the to distinguish input images, greater features were taught into predetermined groups or predict numbering. It uses a variable as input and output it as another variable. Figure 2 shows presentation example of CaffeNet CNN processed cycle of leaf images, applied to a problem of recognizing plant diseases. We can see that because each processing stage progresses, the image elements that show the disease indication visibly known, specifically the last step.

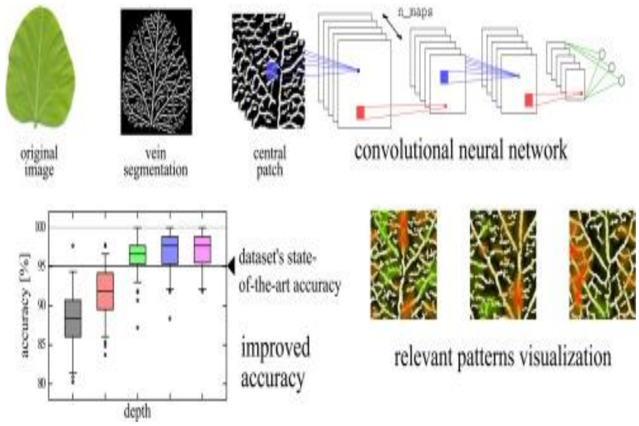

Figure 2 Visually explained of CNN output layer after processing images.

The reduced need for feature engineering is the most crucial benefits of using Deep Learning in processing of image (FE). Previously, hand-engineered features were used in image classification tasks, and their performance had an effect on the overall results. Time-consuming method is FE, dynamic procedure that must be adjusted if the dataset or problem evolves. However, DL does not need FE because it learns to find the essential features on its own.

The advantage of training DL, it is typically easier to evaluate than other ML-based approaches, but it is time-consuming. Other pitfalls including problems that may emerge using models that are pre-trained may encounter issues with optimization related to models' sophistication, and hardware limitations due to datasets that are minorly or substantially differ.

4. DEEP LEANRING IN AGRICULTURE

The 72 specified relevant studies are described in Appendix A, with details about the problem they solve, the agricultural-related field of research, the data sources used, the DL architectures and model used, the class and label of the data, preprocessed of data and/or augmented method used, and whole results achieved using the metrics.

4.1 Usage of Areas

There is area that turn out to be classify which are identification of plant disease(32 articles), plant and crop detection and classification(33 articles), and other article regarding deep learning in agriculture (7 articles). It is worth noting that all of the papers were written after2015, demonstrating how new and cutting-edge this methodology is in agriculture. Most of the research done uses with image recognition and area of interest identification, as well as obstacle detection. In a different light, the majority of articles focus on disease, with just a handful focusing on harvesting identification and seed detection.

4.2 Data Sources

When looking at the data sources DL model used to train in each post, images from big datasets are frequently used, with some cases uses thousands of images , some are real[11] or synthetically created by the authors [1]. A few datasets come from famous and publicly accessible datasets including PlantVillage, RiceLeafs, and Flavia, while others are a collection of actual photos gathered by the authors for their research purposes[12]. A significant number of photos are used in papers about land cover, crop type classification, and some disease detection articles. The far more complex the problem, hence more data is needed in particular. For instance, problems requiring a big number of images that are input for the model to train required a big amount of number for input images to identify a large number of classes or small variation among classes.

4.3 Pre-Processing of Data

Most of the research uses few pre-processing of image steps prior to images, or specific image characteristics/features/statistics were set to input of model of deep learning. To conform to the deep learning model's specifications, the famous pre-processing technique was resizing image, in famous problem to few scales. Image with sizes and pixels of 256 x 256, 128 x 128, 60 x 60 and 96 x 96 were standard. Segmentation of Image was famous to be used to increase size of datasets or by highlighting the region of interest to facilitate the learning process or by data annotating to make it easy for experts and volunteers. Foreground pixel extraction, background removal or removal non-green pixels using NDVI were used to removing the noise of datasets. Certain tasks included the construction of bounding lines to aid in the identification of weeds and the counting of fruits. Converting to grayscale of HSV color were also done by other datasets. Orthorectification calibration and terrain correction are one of the steps used for data pre-processing for satellite or aerial images.

4.4 Augmentation of Data

It is notable that augmentation of data method was applied in some of related work under study to add the total of images for training. By presenting the model with a variety of data, the overall learning procedure and results, as well as generalisation, are improved. This augmentation method is critical for articles with limited datasets to train their deep learning models, such as [13]. This step was critical in papers where the researchers used simulated images to train their models and then evaluated them on real data. Augmentation of data helped their models generalize and respond to actual problems more effectively in this case. Rotations, dataset partitioning/cropping, scaling, transposing, mirroring, translations and perspective transforms, adaptations of object strength in an object detection problem, and a PCA augmentation technique are all label-preserving transformations. Additional augmentation techniques were used in articles involving simulated data, for example by differing channels of HSV and inserting shadows that are random, or by using soil image to add simulated roots.

4.5 Metrics of Performance

In terms of performance evaluation techniques, the authors have used a variety of metrics, each of which is unique to the used model in every analysis. The list of metrics and the description of metrics including use of symbols in Table 1 as shown. From now on, we will refer to "DL results" as its point in one of the performance metrics mentioned in Table 1. The famously used performance metrics were CA followed by F1 Score. Few articles use CA, F1, P, or R for prediction of a model.

Table 1 Performance measurements that have been used in similar research are being investigated

Number	Performances Metric	Unit	Definition
1	Classification Accuracy	CA	The predictions percentage in which the top category (the one with the probability that are highest) is same as goal label as author annotated before using the DL model. CA is averaged across all classes of multi-class classification problems.
2	Precision	P	True positives (TP, accurate predictions) as a percentage of total applicable data, e.g the number of false positive(FP) and true positive. P is averaged over all classes of multi-class classification problems. P = (FP + TP)/(FP + TP)
3	Recall	R	The TP fraction from the summation of false negative(FN) and true positive. For classification that are multi-class, among all the classes that get averaged are R. TP/(FN + TP) = R
4	F1 Score	F1	Precision and recall are combined into a harmonic mean. F1 is summed over all classes in multi-class classification problems.
5	LifeCLEF metric	LC	A rating based on the right species' position in a data of collected specimen.
6	Quality Measure	QM	Calculated by multiplying precision and sensitivity. QM= ((FP + TP)(FN + TP))/((TP + FP)(TP + FN))/((FP + TP)(FN + TP))
7	Root Mean Square Error	RMSE	The discrepancy between expected and observed values' standard deviation
8	Mean Square Error	MSE	The square root errors between expected and value observed is the average.
9	Mean Relative Error	MRE	The percentage of mean error between observed value and predicted
10	L2 Error	L2	The root of the squares of the totals of the discrepancies between the model's expected and real fruit counts
11	Ratio of total fruits counted	RFC	The ratio of the model's estimated fruit count to the real number. The real number was calculated by averaging the number of people (experts or volunteers) who independently observed the photographs.
12	CA-IoU, F1-IoU, P-IoU or R-IoU	CA-IoU F1-IoU P-IoU R-IoU	These are common R, P, F1 and CA metrics as before, but with the addition of IoU to account for true/false positives and negatives. When dealing with problems involving bounding boxes, this function is used. These accomplished by setting a threshold that are minimum for IoU, so that above any value it is considered by the metric as positive
13	Intersection over Union	IoU	The ove+A10:O43rlap area between the ground truth boxes and expected is divided by the union of their area to test predicted bounding boxes.

5. Discussions

Our research show that DL outperforms the competition in most of relevant tasks. It is important to use the same experimental conditions when contrasting the efficiency of other technique compared with DL-based in each research. The majority of the articles used the related work under review to make direct, accurate, and price comparison between the method that use Deep Learning and other modern techniques for problem solving addressed in each paper. It is difficult to generalize and make comparisons between papers because each one used different datasets, pre-processing methods, measurements, models, and parameters. As a result, we restricted our comparisons to the techniques used in each post. As a result of these constraints, Deep Learning has surpassed the standard method such as Artificial Neural Network, Support Vector Machine and others.

While Deep Learning typically linked with computer vision and analyzing of images, we have seen several articles in which trained using Deep Learning based using field sensory data[14][15]. These articles show that DL can be used to solve a large range of problems in agriculture, not just those including images.

When it comes to agricultural applications of DL techniques, classification of leaf, disease identification of plant, recognition of plant, and counting of fruit are just a few of the papers that stand out. This is most likely due to the abundance sets of data in fields, most likely the difference in attribute of leaves that are sick or plant and picture of fruits[16].

We highlight a few that claim high performance when taking into account the problem's complexity in vast number of classes involved or terms of definition, without diminishing the journals or surveyed paper quality. These works are significant contributions to the Deep Learning community because they seek to address the issue of incomplete or non-existent datasets in a number of situations.

5.1 Deep Learning Advantages

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

DL models also appear to generalize well. In fruit counts, for example, the model learned to count directly[15][18]. The challenging condition made the model robust in the problem of banana leaf classification[19], such as different resolution, scale, and illumination, and complex context. Peaches, oranges, mangoes, and other circular fruits may all benefit from the same detection frameworks. For example, the DeepAnomaly model used the homogeneous features field of agriculture to recognize unknown objects, obstruct heavily, and distant, rather than just a merely a collection of predefined elements [20].

Peaches, oranges, mangoes, and other circular fruits may all benefit from the same detection frameworks. The

DeepAnomaly have a key aspect rather than just a predefined object which are able to recognize unexplained objects/ anomalies are the ability, which an agricultural field could detect unknown object, heavy occluded, and distant used the homogeneous features. [21].

While other approaches require less time compared with DL (e.g., RF, SVM), DL has a very quick testing time quality. In instance, obstacles and anomalies could be detected by the model that train longer[21], but it tested faster than SVM and KNN. Another benefit of deep learning is the ability to create virtual datasets to train the algorithm, so then be used on real-problem to be solved.

5.2 Deep Learning Disadvantages and Limitations

The significant downside during training process is the need of large dataset as input and obstacle to using DL. Lots of images are needed regardless of augmentation of data techniques, according to the problem (e.g., the precision required, number of classes, etc.). Some tasks are more difficult because data annotation is a mandatory process in most cases. Experts are required to label input images. Banana pathology has limited resources and expertise worldwide, as stated in [18].

Another drawback is that while Deep Learning models can be train exceptionally well, and even generalize in some ways, they could not identify further the "boundaries of the dataset's expressiveness”. In [22] performs, in instance, classification on a homogenous background with single leaves facing up. Disease images that occur on plant are able to distinguish by a real-world framework. Lots of top side of the leaves are not affected with diseases. Although the training collection have bigger picture size and the testing picture was substantially smaller, the model still failed to detect object. Time consuming procedure but required not just in DL but include computer vision are the pre-processing of data. This is particularly true when the involvement of aerial and satellite images.

Finally, in the field of agriculture, researchers must use their own collections of datasets although there is freely available database for researchers. If not several days, it would take several hours to complete this task.

6. DISCUSSIONS

The aim of this article is to provide a research effort on survey of deep learning-based agricultural. We found 72 important articles by looking at the topic and issue they address, as well as model’s technical details, pre-processing tasks, data sources use, and overall performance as measured by each article's performance metrics. Our findings show that deep learning outperforms other common image processing techniques in terms of efficiency. In the future, we hope to extend the best practices and general concepts of deep learning, to other areas of agriculture where this new technology has yet to be utilized as outline in this survey. The discussion section has listed some of these fields.

Our goal is for the researchers to experiment with deep learning and encourage them to use it to solve variety of prediction or classification agricultural problem, including data analysis, computer vision, and image processing. Deep learning's overall benefits are promoting its use in more intelligent, more safe food production and sustainable farming.

Appendix A. Agriculture Applications on Deep Learning

No.	Agriculture Area	Problem Description	Data Used	Classes and Labels	Variation among Classes	DL Model Used
1	Crop Disease Classification	Classify 14 crops species and 26 diseases	Public dataset of 54306 images consist of diseased and healthy plant	40 Classes: 14 Crop Species and 26 Diseases include healthy leaves	N/A	ResNet-50 CNN
2	Crop Detection	Detect 3 classes of rice plant	Authors-created dataset contain 600 images	3 Classes : Normal, Unhealthy and snail-infested	N/A	AlexNet CNN
3	Crop Disease Classification	Classify 3 Disease of Tomato Crop	Obtain from AI Challenger consist of 300 images	3 Classes : Spot Blight, Late Blight and Yellow Leaf Curl Disease	N/A	ResNet-50 CNN
4	Plant Disease Classification	Classify 3 Disease of Paddy Leaf and Healthy leaf	RiceLeaf Dataset contain 3355 images	4 Classes : Healthy, Brown Spot, Leaf Blast, and Hispa	N/A	N/A
5	Crop type Classification	Classification of rice field and non rice field	Public dataset from Google	2 Classes : Rice field and Non rice field	Confusion when the paddy is not in transplanting season	SVM
6	Crop Disease Detection	Compare the performance of DL model and classify disease of rice leaf	Artificial Pakistani Dataset contain 3300 images	4 Classes : Hispa, Healthy, Brown Spot and Leaf Blast	Confusion of between Hispa and Leaf Blast	VGG19, ResNet-50, ResNet50 V2, ResNet101V2
7	Crop Detection	Detect Oil Palm Tree with Remote Sensing Images	Authors created dataset	2 Classes : Palm tree and not detect	Detection of Palm Tree is hard because of the ground colour	SVM
8	Plant Disease Detection	Detect plant disease which in two classes diseased and healthy	Obtain online which contain 87,848 images	2 Classes : Healthy and Diseased	N/A	AlexNet, GoogLeNet, Overfeat and VGG
9	Crop Detection	Detect Bakanae Disease in Rice seedlings in 2 classes Diseased and Healthy	Acquire using flatbed scanner. Number of image acquire did not mention	2 Classes : Diseased and Healthy	N/A	SVM
10	Plant Disease Detection and Classification	Detect disease in rice plant and classify the disease in 3 classes	Author created the dataset itself	3 Classes : Bacterial Leaf Blight, Brown Spot and Leaf Smut	N/A	SVM
11	Plant Recognition	Detect Plant using 360 images and classify the plant into	Author created which contain 42,337 images	64 Fruit categories such as Tomato, Dates, Kiwi etc.	N/A	SVM Linear Regression Gaussian Naïve Bayesian Linear Discriminant Analysis
12	Plant Disease Detection	Detect disease in Sigatoka Disease in Banana Leaf	Author captured the image and it contain 799 images	2 Classes : Infected and Non-affected	N/A	SVM
13	Plant Disease Detection	Detect rice disease in 10 classes	Not stated	10 classes : Rice Blast, Brown Spot, Bakanae, Sheath Blight, Sheath Rot, Leaf Blight, Bacterial Sheath Rot, Seedling Blight, Bacterial wilt	Some classes show almost the same disease as the disease look alike such as Rice Blast and Sheath Blight	CNN SVM
14	Pest Detection	Detect pest in plant	71 types of 35,000 images of pest	71 classes : whitefly, grub, sawfly, aphid and others	N/A	GoogLeNet, Inception-V3, Inception-V4
15	Plant Disease Detection	Detect diseases in Tomato Plant in 7 classes including healthy	Dataset taken from Vegetable Crops Research Institute, Jawa Bara consist of 1400 images	7 classes : Early Blight, Late Blight, Healthy, Calcium Deficiency and others	The accuracy training result increases as the number of epoch increases	Squeezenet CNN Keras
16	Plant Disease Detection	Detect rice disease in Bangladesh with 6 Classes	Dataset taken from BRRI with 600 Images	6 Classes : Leaf Blight, Sheath Rot, False Smut and others	N/A	Inception-v3 MobileNet-v1 ResNet-50
17	Plant Disease Detection	Detection of rice disease in 2 classes	Dataset created by the author but the number of images not stated	2 classes : Healthy and Diseased	N/A	SVM
18	Plant Disease Detection	Detection of rice disease in 4 classes	Dataset collected from Kaggle, Dataquest and manually by author in total of 3000 images	4 classes : Healthy, Hispa, Brownspot, and Leaf Blight	N/A	DL not stated which model it uses
19	Plant Crop and Disease Detection	Detection of Crop and Diseases in plant	PlantVillage dataset consist of 54,306 images	40 classes : 14 crop species and 26 diseased	Training using coloured images and segmented images produce higher accuracy compared with grayscale images	AlexNet, GoogLe Net,
20	Fruit Counting	Predict number of tomatoes in the images	Author produce 24,000 images	Estimate the number of tomato fruits	N/A	Modified Inception-ResNet CNN

20	Plant Detection	Detect maturity of crop in ripe and unripe	Dataset created by author consist of 4,427 images	6 classes based on maturity stage	N/A	AlexNet, VGG-16, VGG-19, ResNet50, ResNext50, MobileNet and MobileNetV2
21	Plant Detection	Detection of weeds	Early Crop Weeds and Plant Seedlings dataset	4 seedlings and 13 classes	N/A	AutoML
22	Plant Detection	Detection of Cotton Fields from Remote Sensing Images	Author created the dataset with samples of 5,500 images	Detection of Cotton Field with Remote Sensing Images	N/A	ResNet, VGG, SegNet, and DeepLab v3+
23	Plant Disease Detection	Detection of Strawberry Diseases	Dataset created by author with a total images of 2098	4 classes : Crown Leaf Blight, Gray Mold, Powdery mildew, fruit leaf blight and leaf blight	Detection of disease vary because of lighting in the image.	VGG16 ResNet50
24	Plant Detection	Identification of Plant Leaf Counting	Dataset created by the author with images of 600	Detection of number of leaves in tree	Identification of plant leaf vary as the algorithm still not fit with the model	YOLO-V3 and DarkNet
25	Plant Detection	Early detection of disease in leaf	Saitama Agricultural Technology dataset consist of 1.44Million images	3 Classes : Fully leaf, not fully leaf, none leaf	Some identification of not fully leaf class are mistaken for fully leaf as the shape of the leaf disturb the result	CNN but the model is not stated
26	Plant Disease Detection	Early detection of disease in banana leaf	PlantVillage dataset of banana leaves with 3,700 images	3 Classes : Healthy, Black Sigatoka, and Black Speckle	N/A	LeNet
27	Plant Classification	Fruit classification of using 2 datasets to classify 10 classes of fruits	2 datasets : 1st dataset contain 3,158 Images of 10 fruits and 2nd dataset 5,946 images of 10 classes	10 classes : Pineapple, Avocado, Banana, Carrot, Kiwi and others	N/A	Light Architecture and VGG-16 fine tuned
28	Plant Disease Detection	Plant disease detection to classify 4 classes of health	PlantVillage dataset of 4 classes with 10,000 images	4 classes : Healthy, Early, Middle, End	The result of detection mixed between Early and Middle because of the quality of image	VGG-16, VGG-19, Inception-V3 and ResNet50
29	Plant Disease Detection	Detection of Tomato Leaf Disease in 9 classes	Open access dataset with 5,500 images	9 Classes : Early Blight, Late Blight, Virus disease and others	N/A	AlexNet, GoogLeNet, and ResNet
30	Plant Counting and Disease Detection	Fruit counting and disease detection in apple tree	5 datasets obtain from University of Minnesota with not stated number of images	Labels : Red Apples, Yellow Apples, Green Apples, Red apples with patches	N/A	GMM
31	Fruit Counting	Counting Apples and Oranges	2 datasets consist of 5,000 images	Labels: apple and orange	The performance of the two datasets vary as it differ in lighting condition, occlusion level, resolution and camera type	Caffe Net
32	Fruit Classification	Classification of date fruit of 7 classes	Authors created the dataset which contain 8,072 images	7 Classes : Immature-1, Immature-2, Khalal, Tamar and others	N/A	CNN, AlexNet and VGGNet
31	Plant Disease Detection	Detection of Cassava Disease in food	Leaflet cassava dataset which contain 15,000 images	6 Classes : Healthy, Brown Leaf Spot, Cassava Mosaic Disease and others	N/A	Inception-v3
32	Crop Improvement	Identify functional variants in natural populations using deep learning model	Plant genomics dataset but not state the total images	Not stated	N/A	CNN, DeepNovo
33	Plant Species Classification	Plant Species Classification using Leaf Vein Morphometric	Author created the dataset with 1,290 Images	43 Species but not stated in the paper which species	N/A	Fine Tuned AlexNet using CNN, SVM, ANN as the classifiers
34	Plant Detection	Plant Identification in Natural Environment with 100 plant	BJFU100 dataset with 10,000 images	100 classes : Chinese Buckeye, metasequoia, ginkgo biloba and others	N/A	ResNet26
35	Plant Detection	Detection of mildew disease in pearl millet using transfer learning	124 images but after augmentation composed of 711 images. Own dataset.	2 classes : Diseased and Healthy	N/A	CNN model of VGG-16
36	Plant Disease Classification	Classification of diseased tomato with 9 classes	PlantVillage dataset with 14,828 images	9 Classes : EarlyBlight, LateBlight, Target Spot and others	N/A	AlexNet and GoogLeNet
37	Fruit Defect Detection	Detection of Mangosteen surface detection to avoid human error	Author created dataset with 500 images	2 Classes : Fine and Defect	N/A	CNN

38	Plant Disease Detection	Detection of plant disease by leaf classification	Author created the dataset consist of 33,469 images	15 classes : Healthy Leaf, Peach, Pear, Apple and others	N/A	CaffeNet
39	Plant Disease Detection	Detection of plant disease and saliency map visualization	PlantVillage dataset consist of 54,323 images of 14 crop with 34 classes	34 Classes : Apple Healthy, Apple Scab, Blueberry Healthy and others	N/A	AlexNet, GoogLeNet
40	Plant Disease Detection	Disease detection of Corn Plant using CNN with 3 types of disease	PlantVillage dataset with 3,854 images of maize diseases	3 Classes : Common Rust, Gray Leaf Spot, and Northern Leaf Blight	N/A	CNN
41	Plant Disease Detection	Disease detection of tomato plant	PlantVillage dataset but not stated how many image was use	10 Classes including Healthy	N/A	AlexNet, SqueezeNet
42	Plant Disease Detection and Classification	Disease detection of plant and classification using CNN	PlantVillage dataset which contain 54,303 images	38 Classes : Tomato, Maize, Tomato Leaf Blight and others	N/A	CNN, AlexNet, GoogLe Net, ResNet, LeNet
43	Real-time Fruit Detection	Real-time fruit detection in apple orchard	Author created dataset consist of 1,200 images	Labels : Apples	An apple that is too small is hard to detect and cause an error of detection	LedNet
44	Fruit Detection	Detection of fruit of mango and pitaya	Author created dataset	2 Classes : Mango and Pitaya	The colour of non-ripe mango effect the accuracy of the test	MobileNet
45	Fruit Detection	Detection of strawberry based on masked R-CNN	Author created dataset with 2,000 images but only 1,900 used for training	Only label of strawberry	N/A	Mask R-CNN, ResNet 50
46	Plant Disease Detection	Disease detection of Apple Leaf using CNN	Author created with 13,689 images	4 Classes : Mosaic, Rust, Brown Spot, and Alternaria	N/A	AlexNet
47	Plant Disease Detection	Identification of Maize leaf diseases using CNN	PlantVillage and several google images in total of 500 images	9 Classes: Heatlhy, Rust, Brown Spot, Round Spot and others	During testing, only certain image of Brown Spot are detection as Round Spot as the disease have almost the same specs	GoogLeNet and Cifar10
48	Plant and Pest Disease Detection	Identification of plant disease and pest using DL	Author created dataset with 1,965 images	8 Classes : Walnut Leaf, Apricot Monilia laxa, Erwinia amylovora	N/A	AlexNet, VGG16, and VGG19
49	Plant Disease Detection	Plant leaf disease detection with 4 classes	Plant Photo Bank of China with 1,000 images	4 Classes : Black Rot, Bacteria Plaque, Rust and Healthy	N/A	VGG-16
50	Plant Disease Detection	Plant disease detection of 56 Classes with detection of leasions and spots	Not stated but total images are 46,409 images	14 Classes : Soybean, Citrus, Coffee, and others	N/A	GoogLeNet
51	Plant Disease Classification	Plant leaf classification with 32 kinds of leaf	Flavia Dataset with 4,800 images	32 Classes : Tangerine, Oleander, Wintersweet and others	N/A	10-layer CNN
52	Plant Disease Detection	Detection of plant disease by using leaf classification with 15 classes	Author created dataset with 4,483 images	15 Classes : Healthy, Apple(Rust), Apple(powdery mildew) and others	N/A	CaffeNet
53	Real-Time Disease Detection	Real-time detection of apple leaf disease using DL	Author created dataset with 26,377 images	5 Classes : Rust, Gray Spot, Mosaic, Brown Spot and others	N/A	GoogLeNet, Inception
54	Plant Disease Detection	Recognition of apple leaf disease in DL	Challenger-Plant-Disease-Recognition dataset but not stated number of images	6 Classes : Healthy, Apple Scab, Gray Spot and others	N/A	DenseNet
55	Real-Time Fruit Detection	Real-time fruit detection within the tree of apple and pear	Author created dataset with 5,000 images	2 Labels : Apple and Pear	N/A	YOLO Darknet
56	Plant Disease Detection	Tomato disease detection and classification with 10 classes including healthy	PlantVillage dataset of Tomato Disease with 13,112 images	10 Classes : Healthy, mildew general, mildew serious, and others	N/A	ResNet50, Xception, MobileNet, ShuffleNet, DenseNet21_Xception
57	Plant Disease Identification	Maize and rice disease detection with 9 classes	Fujian Institute dataset with 1,966 images	9 Classes : Rice Stackburn, Rice leaf smut and others	When the number of epoch increase from 10 to 30 the accuracy increase 3%-5%	VGGNet-19, Inception-V3, ResNet-50, DenseNet-201
58	Plant Disease Detection	Plant disease detection using DL with 14 crops and 26 diseases	PlantVillage dataset of 54,306 images	40 Classes : Apple Scab, Apple black rot and others	The test was done with 3 variation of grayscale images, coloured and leaf segmented	AlexNet, GoogLeNet,

59	Plant Disease Detection	Comparative study of DL models for plant disease detection with 26 diseases and 14 crops	PlantVillage dataset with 54,306 images	40 Classes : Apple, Pear, Banan, Maize and others	ResNet-152 show the greatest accuracy among others model	VGG16, Inception V4, ResNet-50 101 and 152, DenseNet-121
60	Plant Leaf Detection	Plant leaf disease detection on early stage with 3 classes	Author created dataset with 1.14million images	3 Classes : Fully Leaf, Not Fully Leaf and None Leaf	N/A	CNN
61	Plant Classification	Plant classification by neural network models	Flavia, Swedish, UCI Leaf, and Plant Village	Comparing all the DL model	N/A	AlexNet, VGG-16 but using LDA and SVM
62	Crop Pest Classification	Classification of pest in plant with 40 classes in first dataset, 24 classes in second dataset and 40 classes in third dataset	NBAIR, Xie1 and Xie2 dataset	40 classes : 1st dataset 24 classes : 2nd dataset 40 classes : 3rd dataset	N/A	AlexNet, ResNet, GoogLeNet, and VGGNet
63	Plant Detection	Detection of apple trees on trellis wires	Author created dataset with 509 images	4 Classes : Background, Trunk, Branch and Trellis Wire	The detection of Trellis wires and Brunch causes a small error as the Brunch and wires are almost the same look	CNN, SegNet
64	Real-Time Fruit Detection and Yield Estimation	Real-Time fruit detection and load estimation using MangoYOLO	Author created dataset with total images of 1,400	Labels : Orchard	The higher the number of training images the higher the training accuracy	R-CNN(VGG), R-CNN(ZF) and YOLOv3
65	Crop Yield Prediction	Prediction of crop yield using remote sensing data	Author acquire data on Argentina and Brazil	Predicted area : Argentina and Brazil	N/A	Not stated but it uses Deep Learning framework
66	Leaf Classfication	Classification of coffee leaf biotic stress with 5 classes including healthy	Author created dataset with 1,685 images	4 Classes : Rust, Brown Leaft Spot, Cercospora Leaf Spot and Leaf Miner	N/A	CNN, AlexNet, VGG-16, GoogLeNet, ResNet50 and MobileNetV2
67	Plant Disease Identification	Disease identification of plant using hyperspectral image with 2 classes	Author created dataset with 539 images	2 classes : Healthy and Infected	N/A	3D-CNN
68	Plant and Pest Disease Detection	Detection of plant and pest disease using DL 8 classes	Author created dataset with 1,965 images	8 Classes : Coryneum beijerinckii, Apricot monilia laxa and others	N/A	GoogLeNet, ResNet50, ResNet101, InceptionV3, and others
69	Plant Species Detection	Multiclass weed species detection using DL with 9 classes	DeepWeeds dataset with 17,509 labelled images	9 Classes : Parthenium, Rubber vine, Siam weed, Snake weed and others	Chinee Apple and Snake Weed showed a low F1 score as the leaf material are strikingly similar to each other	CNN, ResNet-50, Inception-v3
70	Real-Time Fruit Detection	Real-time detection of apple fruit on apple tree in apple orchard	Author created dataset with 1,100 images	1 Labels : Apples	Detection of Apple are low for very small apple	LedNet
71	Improving Efficiency in Deep Learning	Improving efficiency by using classification in DL with 2 classes	Author created dataset with 4,752 images	2 Classes : Carrots and Weeds	N/A	CNN
72	Agriculture Monitoring	Monitoring agriculture using DL with satellite images	Author created real-world paddy datasets from Landsat 8 images in Vietnam	1 Labels : Paddy field	N/A	SVM, CNN, Threshold and Spectral

No.	FW Used	Data Pre-Processing	Data Augmentation	Data for Training vs Testing	Performance Metric Used	Value of Metric Used	Ref.
1	TensorFlow	The images from the dataset were annotate	N/A	Same	CA	99.24%	[23]
2	Keras	Image segmentation, background and shadow removal	N/A	Same	CA	86.799%	[24]
3	Developed by author	Cropping on target area only	N/A	Same	CA	95.00%	[25]
4	TensorFlow	Image resolution scaled to 224x224 pixels	Gaussian Noise and Affine transformation	Same	CA	98.3% ± 0.6%	[26]
5	TensorFlow	N/A	Affine transformation and perspective transformation	Same	CA	93.00%	[27]
6	Not stated	Image was resized to 227x227 pixels	Cropping and rotations done manually	Same	CA	91.23%	[28]
7	TensorFlow	Image was resized to 128x128 pixels	N/A	Different dataset	RMSE	1.16	[29]
8	Deep Learning Toolbox	Resized the images to 224x224	Images were rotated and flips	Same	CA	98.00%	[30]
9	Deep Learning Toolbox	Images was resized to 64x64. Converted to grayscale and remove noise	N/A	Same	F1	72.00%	[31]
10	Developed by author	Background and noise removal. Images resize to 897x3081 pixels	N/A	Same	CA	93.33%	[32]
11	Torch7	Cropping and resized image to 256x256 pixels	N/A	Same	CA	99.53%	[33]
12	Deep Learning Toolbox	N/A	N/A	Same	CA	87.90%	[34]
13	Developed by author	Images was resized to 17x17 pixels	N/A	Same	CA	96.00%	[35]
14	VGG	Enhancing images, RPC Orthorectification, annotation and resized to 224x224 pixels	Flipping, rescaling, and changing image color	Same	F1	0.953	[36]
15	Not stated	Image segmentation was applied	N/A	Same	CA	97.30%	[13]
16	TensorFlow	Images was resized to 224x224 and change image value between 0.255 to 0 to 1	N/A	Same	CA	86.92%	[37]
17	Deep Learning Toolbox	Images resized to 512x512 pixels then rescale data to [0,1] then apply ZCA whitening	N/A	Same	CA	95..48%	[38]
18	Deep Learning Toolbox	Convert RGB to Grayscale and resized. Image segmentation was applied	N/A	Same	CA	96.00%	[39]
19	TensorFlow	Resized the image to 299x299, 224x224	Flipped and rotated the images	Same	CA	96% ± 3%	[40]
20	Caffe	Image resized to 256x256pixels and background removal	N/A	Same	CA	99.35%	[41]
21	TensorFlow	Removing background	N/A	Same	F1	0.90	[42]
22	TensorFlow/ Keras	Image Segmentation	N/A	Different	F1	90.74% ± 3%	[43]
23	Author Developed Model	N/A	N/A	Same	CA	90.00%	[44]
24	YOLOv3	Image was resized, cropped and labelled	N/A	Same	F1	0.94	[45]
25	Deep Learning Toolbox	Image was labelled, resized and convert to grayscale	N/A	Same	CA	70.00%	[46]
26	Developed by authors	Images resize 64x64 pixels	N/A	Same as it uses 2 datasets	CA	99.75% and 96.75%	[47]
27	Developed by authors	Image resized to 227x227 and 224x224	N/A	Same	CA	99.00%	[48]
28	Keras	Images resized to 224x224 and 299x299. Then, normalization of images.	N/A	Same	CA	99.75%	[49]
29	Developed by authors	Image resized to 64x64 pixels and converted to grayscale	N/A	Same	F1	0.9294 for RGB and 0.8636 for grayscale	[50]
30	Developed by authors	Images resized to 200x150 pixels	Cropping center images and clockwise rotation	Same	F1	78.00%	[51]
31	Developed by authors	Images resized to 200x150 pixels	Cropping center images and clockwise rotation	Same	CA	96.30%	[52]
32	TensorFlow	Image was labelled, and resized to 250x250 pixels	Images was flipped left and right	Same	CA	95.96%	[53]
33	Caffe	Images resized to 320x240 pixels	Images was flipped randomly	Same	F1	0.76	[54]
34	Developed by authors	Image sharpening, and brightness adjustment	Image was flipped left to right, top to bottom, and diagonally. Images was rotated	Same	CA	97.28%	[55]
35	Keras	Images resize to 256x256 pixels and 299x299 pixels	N/A	Same	CA	90.40%	[56]
36	Developed by authors	Images resized to 227x227 pixels and 224x224 pixels	Images were reflected horizontal and vertical	Same	CA	99.01%	[57]
37	TensorFlow	Images were cropped	N/A	Same	CA	98% BLS 96% RMD 95% GMD	[58]
38	Developed by author	RGB convert to grayscale and Canny Edge Detection was applied	N/A	Same	CA	96.75, 97.47, and 95.97%	[59]
39	PyTorch	Image resized to 224x224 pixels	Mirroring of the images and color variation. Mix-up method was applied	Same	CA	95.24%	[60]
40	Deep Learning	Background removal	N/A	Same	F1	0.93	[61]
41	PyTorch	Image Labelling, resizing to 224x224 and 299x299, contrast and brightening	Rotation, horizontal and flipping	Same	CA	99.76%	[62]
42	OpenCV	Image was resized 256x256	Affine transformation	Same	CA	96.30%	[63]
43	Developed by authors	N/A	N/A	Same	RMSE	0.70	[64]
44	Keras	Resized images to 224x224	N/A	Same	CA	91.78%	[19]
45	Keras/Tensor Flow	Resized images to 224x224 pixels	Rotation and flipping	Same	F1 and CA	91.75% and 95.00%	[65]
46	Developed by authors	Resized images to 512x512	N/A	Same	CA	97.00%	[66]
47	Deep Learning Toolbox	Image resized to 250x250 pixels	N/A	Same	CA	94.88%	[67]
48	Developed by authors	N/A	N/A	Same	Not stated	Not stated	[68]

49	Caffe	Image resized 256x256 pixels	N/A	Same	CA	99.18%	[69]
50	Darknet	Images resized to 300x300 pixels and 416x416 pixels. Images were labelled	Adjust hue, saturation, rotation, jitter and multiscale	Same	F1	0.936 Faster R-CNN, 0.951 YOLOv3, 0.967 MangoYOLO	[70]
51	Developed by authors	Image resized to 500x500 pixels	N/A	Same	F1, CA, Precision	99.6, 99.3 and 99.1	[71]
52	OpenCV	Image resized to 224x224 pixels	Images were rotated	Same	CA	98.9%	[72]
53	Caffe	Images was resized but not stated,	N/A	Same	CA	97.62%	[73]
54	Mask R—CNN	Image resized to 640x840 pixels	N/A	Same	Precision and Recall	95.78% and 95.41%	[74]
55	TensorFlow	Image resized to 600x600 pixels	N/A	Same	CA	99.00%	
56	Developed by authors	Images was resized to 320x320 pixels	Several images were cropped and amplify	Same	Recall and CA	0.821 and 0.853	[75]
57	Caffe	N/A	N/A	Same	CA	97.22%	[76]
58	Developed by authors	Image resized to 320x320 pixels	Amplification was applied	Same	CA	85.00%	[77]
59	Developed by authors	N/A	N/A	Same	CA	99.00%	[78]
60	TensorFlow	Image resized to 256x256 pixels	Images were flipped horizontally	Same	CA	95.1%	[79]
61	Keras	Image resized to 224x224 pixels	Horizontal and vertical flipping, rotating, shearing and size scaling	Same	CA	93.78%	[80]
62	Developed by authors	Image resized to 256x256 pixels	N/A	Same	CA	99.35%	[81]
63	Developed by authors	Image resized 224x224, and convert to grayscale	N/A	Same	CA	97.10%	[82]
64	Keras	Image resized to 608x608 pixels	Image flipping, rotation, and transformation	Same	F1	0.81	[83]
65	Developed by authors	Image resized 128x128 pixels	Random rotation, random translation, random scaling	Same	CA	93.71%	[84]
66	OpenCV	Image resized to 256x256 pixels	Affine transformation	Same	CA	96.30%	[85]
67	Caffe	Image resized to 512x512 pixels	Rotation transformation,	Same	CA	97.14%	[86]
68	Developed by authors	Image resized to 64x64 pixels	Horizontal flip, vertical flip, noise, color jittering and rotation	Same	CA	87.92%	[87]
69	Developed by authors	N/A	N/A	Same	F1	0.93	[88]
70	Developed by authors	N/A	N/A	Same	CA	83.57%	[89]
71	Developed by authors	Images resize to 224x224 pixels	N/A	Same	CA	97.86% ± 1.56%	[90]
72	Developed by authors	N/A	Convert to HSV images	Same	F1 and CA	0.87 and 95.73%	[91]

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