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Deep Learning Techniques in Tomato Plant – A Review

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Abstract. Deep learning establishes an ongoing, modern technique for image processing with large potential and promising results. After proving its efficiency in various applications DL has also entered into the domain of agriculture. Here, we surveyed 38 research works that applied deep learning techniques to various research problems in tomato plant. We examine the areas of tomato plant research where deep learning is applied, data preprocessing techniques applied, transfer learning and augmentation techniques used. Studied dataset information like data sources used, number of images, classes and train test validation ratio applied. In addition, we study comparisons done on various deep learning architectures and discussed the outcome. The finding showed that DL techniques outperformed all other image processing techniques but DL performs mainly depends on the dataset used.

1. Introduction

Recently, agriculture was playing a main role in global economy. The increase in the population along with urbanization that prompt a steady decrease in the total amount of cultivated land leads to the increased stress level on the agricultural system. Computer vision based intelligent systems are fetching a major part of agricultural product maintenance and it is increasingly used to boost yield and efficiency[1]. Machine learning a part of artificial intelligence (AI) which makes the systems capable of learning automatically and improves from experience without coding directly[2]. As DL shows a promising result in various applications, recently it has also entered into the domain of agriculture[3]. One of the DL architectures named CNN end up being the best in image classification and made extraordinary progress[4]. DL was effectively used in diverse tasks, such as object detection, text analytics, semantic segmentation and scene analysis. The CNN model works with two steps, first one is to capture the image of the crop or the fruit according to our interest and the second one is to feed the captured image into the developed model for further analysis and to get the result. Various algorithms and techniques are applied to the popular CNN architectures like AlexNet, VGGNet, GoogLeNet, ResNet and SqueezeNet to achieve the promising result[5]. The popular techniques are transfer learning, data augmentation, hyperparameter tuning, data preprocessing techniques, object detection and image segmentation. The popular data preprocessing techniques are resize, background removal, foreground pixel extraction, creation of bounding boxes, image space conversion, histograms, PCA, wavelet transformation, GLCM, shape and statistical feature[6].

The commonly used data augmentation techniques are rotation, dataset partitioning/cropping, scaling, transposition, mirroring, Random Rotation, Random Brightness and GAN[7]. The famous object detection models are YOLO, RCNN, DetectNet and SSD. Whereas the image segmentation architectures are FCN, SegNet and U-Net. The famous pre trained models available are ImageNet, Alexnet, ResNet and COCO dataset. The parameters and hyperparameters which helps to fine tune the DL models are weight, learning rate, total iterations, total hidden layers, units in each hidden layer, momentum, mini batch size and activation function[8].

The significance of this paper is to collect all the tomato plant related work, like disease identification, pest detection, tomato classification, tomato detection, macronutrient deficiency and weed detection, and analyze the works done. It may help the future researchers in creating a more precise and refined system to identify and solve research gaps in the agriculture domain is the motto. The remaining part of this paper is planned as Sect. 2 present the research methodology carried out during the review of existing work. Section 3 gives a clarification of the deep learning techniques used on tomato plant. Section 4 discussion on the result achieved on the works mentioned and suggestion for better implementation of further models and the conclusion in Sect. 5.

2. Methodology

2.1. Planning
The following analysis has been done based on the journal papers published between 2016 and 2020. We started our work based on the keyword based search conducted from the Google Scholar and downloaded the papers from reputed journals. The search was conducted using the query [Tomato] AND [Preprocess OR Disease OR Pest OR Crop Yield] AND [Deep Learning OR Machine Learning]. From the above query 38 papers are finalized for this review because of its meaningful findings and perfect scope of the research.

2.2. Conduction
After the collection of related research works using the above method, we started our detailed analysis of those papers and done a detailed review. While analyzing the papers individually we searched answers for the upcoming queries:

1. Which Data sources used?
2. What are the areas of use?
3. What type of data preprocessing techniques helped to improve the image quality?
4. What are all the data augmentation techniques used to improve the dataset size?
5. How pre-trained networks help to improve the overall accuracy of the model?

3. Deep learning techniques in tomato plant
In Table 3, we list the 38 identified research findings, indicating the article name, year, description of the dataset, DL architectures and algorithms implemented, transfer learning applied, data augmentation employed and on the whole performance achieved according to the metrics used, along with the comparisons with other techniques, wherever exist.

3.1. Data Sources
Observing the data sources used, many authors have used the popular available dataset like PlantVillage [9][10][11][12][13][14][15][16]. It consists of thirty nine classes of various crop images like tomato, apple, corn, potato, grapes and few more of which tomato plant constitutes 10 classes.

Table 1. PlantVillage Dataset summary

Classes(Tomato Plant)	Images
Tomato Bacterial spot disease	2127
Tomato Septoria leaf spot disease	1723
Mosaic virus disease	325
Leaf mold disease	904
Target spot disease	1356
Early blight disease	952
Yellow leaf curl virus disease	4032
Tomato Late blight disease	1781
Two spotted spider mite	1628
Healthy	1591

Table 2. Agricultural Pest and Disease Dataset summary

Classes(Tomato Plant)	Images
Healthy tomato fruit	64
Malformed tomato fruit	38
Dehiscent tomato fruit	36
Blossom-end rot tomato	18
Puffy tomato fruit	16
Blotchy ripening tomato	16
Sunscald tomato fruit	12

Agricultural Pest and Disease Database was also used[17]. Open dataset available in AIChallenger competition was used in[18]. Many authors have used the real dataset collected by them for their own research needs.

3.2. Areas used
Usage of DL for tomato plant was mainly used in six areas. They are disease detection in tomato leaves (15 papers), pest detection (3 papers), classification of tomato as ripe or unripe using sorting machine (5 papers), detecting tomato fruit (10 papers), macronutrient deficiency (2 papers), weed detection (1 paper).

3.2.1. Disease Detection
The architecture build with residual deep CNN, along with the attention mechanism applied on top of it, was used to classify the three diseased and one healthy category from 1,20,000 tomato leaf images. The work was conducted with the popular public dataset PV. The class labels are early blight, late blight, leaf mold and healthy. It achieves an overall accuracy of 98% [9]. AlexNet and VGG16 net architectures are used to detect the six diseased and a healthy class images from the PV dataset of selected 13,262 segmented images. The AlexNet achieves an accuracy of 97.49% with the pre trained deep learning model [10]. AlexNet, SqueezeNet and Inception V3 architectures are used to evaluate the severity of tomato Late Blight plant disease as Early, Middle and End Stage using the open PV dataset. The experiment was conducted using 1909 diseased images and 433 healthy images with 80:20 train test ratio. AlexNet provides the accuracy of 89.69% for transfer learning model and 93.4% for feature extraction model where extracted feature was classified using SVM [11]. Improved FRCNN replaceVGG16 with ResNet101 for feature extraction whereas k-means clustering technique was used to classify healthy tomato leaves from four diseases namely tomato powdery mildew, tomato blight, tomato leaf mold disease and tomato mosaic virus using the open dataset available in AIChallenger competition 2018. Totally 4,178 images are used with 60:30:10 of training, validation and test set ratio. This method provides the 2.71% higher accuracy than normal FRCNN method [18].

FRCNN was used to classify ten types of tomato disease and the healthy one from the 286 images collected from internet. Then Mask R-CNN was used for detection and localization of the infected area. In this experiment 60:20:20 was the training, test and validation set ratio used. To find the best accuracy the object detection model Faster RCNN are combined with different CNN architectures like ResNet 101, ResNet 50, VGG 16 and MobileNet. Whereas Mask R-CNN was combined with ResNet 50 and ResNet

101. ResNet 101 consume the longest time for training and classification but gave the highest accuracy. In turn MobileNet gave the shortest classification time with low accuracy than ResNet 101[19].

The 3 diseases was identified using 4,923 tomato leaf images of good and disease affected leaves collected by their own using automatic image capturing system. The experiment was conducted with 80:20 train test ratio. The model was built using pre trained Alexnet architecture and FRCNN was used on top of it to acquire an accuracy of 95.75%[20]. The SSD, FRCNN, Yolo V3(original) and improved Yolo V3 algorithms are used to spot tomato diseases and identify pests. Used a dataset with 15,000 images collected under different scenarios containing 12 class labels including the diseases and insect pests. Improved Yolo V3 architecture used image pyramid based multi-scale feature detection, bounding box mechanism, dimension clustering technique and multi-scale learning. It gives highest overall accuracy of 92.39% with very less detection time of 20.39 ms[21].

The model was designed to classify the ten tomato diseases and pests classes in the popular Plant Village dataset. The principal component analysis algorithm is used for dimensionality reduction and on top of it an optimization algorithm called Whale is used to extort the essential features of the images. Then these extracted features are given as input to deep neural network for further classification. The model provided an accuracy of 94%[12]. FRCNN, RFCN, and SSD architectures are combined with VGG net and ResNet on their self collected dataset of 5000 images from various Korean tomato farms. The system effectively recognizes the 9 types of tomato diseases, insect pests and nutritional problems. FRCNN with VGG-16 and RFCN with ResNet-50 provides the better average precision of 83% and 85.98% respectively[22].

A light weight CNN model comprising of 8 hidden layers was used classify 9 indistinguishable varieties of diseases in crop from the PV dataset. 1400 images of 10 classes are given for training, testing used 100 images and validation took the 300 images. The model achieves an overall best accuracy of 98.7% using the augmented dataset images[13]. The efficiency of architectures like AlexNet, Inception V3, GoogleNet, ResNet 50 and ResNet 18 are compared using the PV dataset for the identification of ten classes of tomato diseases and pests. The experiment was with 80:20 train test ratio. AlexNet provides the accuracy of 98.93%. whereas GoogleNet outperforms all the other with 99.72% of area under the curve and 99.12% of sensitivity[14]. The shallow models like SVM and Random forest are compared with deep learning models like AlexNet and GoogleNet with the help of PV dataset. Google Net has emerged with a highest accuracy of 99.18%[15].

GANs a new method for data augmentation was used here along with popular architectures like AlexNet, VGG16, GoogLeNet and ResNet. GoogLeNet acheives an average identification accuracy of 94.33% when combined with DCGAN than with BEGAN. 1500 images are used for this work which belongs to five different classes from the popular PlantVillage dataset which are then increased using GAN method and worked with 80:20 train test ratio[16]. FRCNN, SSD and MobileNetv2-YOLOv3 algorithms are used in this work to detect the tomato gray leaf spot disease using 2385 images collected on real time. MobileNetv2-YOLOv3 outperformed all the model with the F1 score as 93.24%, average precision value as 91.32% and 86.98% average IOU value[23].

An improved moth-flame approach, the MFO algorithm was combined with the rough set algorithm to choose the significant features, used here to solve the dimensionality reduction problem. Further classification was done with the SVM. This method was tested with the popular open datasets from UCI machine learning repository proves that it outperforms the PSO and GA with rough sets. It provides an accuracy of 90.5%[24]. YOLOv2 was used to detect the pests and diseases in tomato plant using an augmented dataset of 1000 images. The non augmented images were taken from Agricultural Pest and Disease Database. 97.24% of mean Average Precision was achieved[17].

Extreme Learning Machine (ELM) algorithm was used here with the real dataset collected by them for their own research needs named Tomato Powdery Mildew Disease (TPMD) dataset. Various techniques for resampling like SMOTE, IMPS, RUS, and ROS are used to balance the dataset. Dataset has been partitioned with 70:30 train test ratio. ELM along with IMPS provided the 89.19% classification accuracy and 88.57% area under curve[25]. This model was developed using PyTorch that uses DCNNs. PV

dataset with 12,206 images containing five diseased classes was taken for the experiment. The pre trained model provides an accuracy of 97%[26].

3.2.2. Pest Detection

The machine learning approaches, multilayer perceptron and K-nearest neighbor, are compared with the deep learning approaches, Faster RCNN and SSD, for the detection of two pests. Finally the deep learning approaches performed the best for the real images collected by the authors[27]. Other papers also dealt with the pest detection techniques which are discussed already in disease detection[21][22].

3.2.3. Tomato Classification- sorting machines

ResNet101, ResNet34 and ResNet50 architectures are used to detect the external defects in tomato fruit with the help of a dataset with 43,843 images belonging to two classes. Dataset has been partitioned with 50:25:25 train test and validation ratio. ResNet50 model achieves an average precision of 94.6%[28]. CNN, SOM, ANN, LVQ and SVM are used to classify the 3 classes with labels unripe, ripe and defective which includes overripe and rotten. 60 images are used with 70:30 train test ratio. CNN model performs the best with an accuracy of 100%[29]. Calyx and stalk scar detection algorithm used here came up with an accuracy of 95.1% with histogram thresholding. RBF-SVM classifier was used to detect the defected regions along with LAB color-space pixel values achieved the accuracy of 98.9%. This model proved that texture and color features combined together always provided the better results. Dataset with 500 images used with 70:30 train test ratio[30].

RBF-SVM, Linear SVM, Quadratic SVM, Cubic SVM and Bayesian-ANN algorithms are used in this model to forecast the volume and mass of tomato fruit. Dataset was created with 958 samples of which 70% images given for training and 30% images given for test and validation. Out of all the above methods RBF-SVM gave the highest accuracy of 97.06% for 2D features and 96.94 for all features[31]. The dataset was formed with 150 tomato fruit images with 50 samples for each three classes red, orange and green. In which 102 samples are considered for training and remaining 48 samples for testing. The BPNN classification technique was combined with the feature color value and applied to this dataset which provided an accuracy of 99.31%[32].

3.2.4 Tomato Detection

FRCNN was used to localize the ripe tomato regions and then density based Gaussian function was used to eliminate the image background. In that IFS edge was obtained using the edge detection method and then connection of edge breakpoints and removal of repeated edge points are done using the contour detection method. Author collected 800 sample images including adjacent tomatoes, separated tomatoes, overlapping tomatoes and shaded tomatoes with training of 600 images and testing of 200 images. The accuracy of 95.5% for separated, 93.8% adjacent, 78.4% overlapped and 81.9% shaded tomatoes was achieved[33]. An improved YOLOv3-tiny method was proposed which enhanced the depth wise separable CNN and replaced the standard CNN with a residual structure in the original network. On top of it image enhancement algorithm was applied to improve the contrast in turn which improves the detection ability. Using data augmentation 5500 images are formed from 1000 real images for training and 336 images used for testing. This model achieved 91.92% f1-score which is 12% higher than the original version[34]. Improved FRCNN, original FRCNN use VGG16 which was replaced with Resnet-50, and K-means clustering are applied on a dataset with 5624 images with 80:20 train test ratio. The above architecture along with soft non-maximum suppression algorithm to preserve the generated bounding boxes helps to get better accuracy of tomato flowers from 76.8% to 90.5%, immature green tomatoes from 88.4% to 90.8% and mature red tomatoes from 90.4% to 90.9% respectively[35].

SSD was combined with various CNN architectures like VGG16, MobileNet and Inception V2 as one case. As an another case SSD was used with varying image size of 300X300 pixels and 512X512 pixels. The dataset was formed with 3460 images after applying data augmentation. The dataset was divided with 80:10:10 train, test and validation ratio. Finally SSD with Inception V2 outperformed the other

combinations and provided an average precision of 98.85%[36]. Here the author used a structured sparse operation where convolution layer kernel is separated into several groups which gradually reduce the unimportant parameter and Focal loss function is introduced in the last classification layer which enhanced the system's generalization ability. Dataset consists of 712 matured and 812 non matured tomato fruit images. Various combinations of new datasets are created with above samples under different environmental conditions and results are compared. The proposed architecture outperformed all the other architectures like SDD, DenseNet and ResNet. It gave the highest accuracy of 91.26% for dataset under strong light and illumination interference[37].

HOG, SVM classifier, proposed FCR and NMS algorithms are used to detect tomatoes in different scenarios. Dataset comprises of 247 images in which 100 images given for training, 72 images for validation and 75 images for testing. Finally it came up with recall, precision, and F1 score as 90.00%, 94.41 and 92.15%, respectively[38]. CNN model was trained and validated with varying augmented datasets and optimal augmentation method was identified. Various augmentation techniques used are geometric transformations, random noise and combination of both. Dataset formed with rotation, scaling and salt noise gave an accuracy of 91.9%. Five maturity levels of tomato are identified with 200 samples[39]. FRCNN was combined with various CNN architectures like Resnet-101, Resnet 50 and Inception ResNet v2. The models were pretrained with COCO dataset and then again trained with the dataset of 640 samples with 28,835 tomatoes which are labeled manually. R-CNN architecture when combined with Resnet-101 gave the AP of 87.83%[40].

YOLOv2, YOLOv3, Faster R-CNN and proposed YOLO-Tomato algorithms are compared in this work by training and testing them on a dataset of 966 images with 725 images for training which contained 2553 tomatoes and 241 images for testing included 912 tomatoes. In YOLO-Tomato dense architecture for feature extraction was implemented and rectangular detection box was replaced with a proposed circular detection box which better matches the tomato shape and provides more precise IoU for the NMS process in turn reducing prediction coordinates. It provides an accuracy of 94.58%[41]. RCNN and the SSD are used for the detection of fruits and flowers when applied on a dataset of 277 images with 231 images used for training and 46 images for validation. In the above two SSD registered accuracy of 100% for flower and 95.99% for fruit detection. Whereas ANN, KNN and SVM are used for the maturity classification. In comparing all these SVM gave 99.81% accuracy on the dataset of 450 samples with 150 samples for each class such as green tomato, turning tomato and red tomato maturity[42].

3.2.5. Macronutrient Deficiency
Inception-ResNet v2, Autoencoder and EA of above two architectures are used in this work. The proposed EA method provides an accuracy of 91%. In a dataset of 571 images 80% was used for training and 20% was used for testing[43]. An EDSR model was used to detect the eleven trace elements for calculating the nutrient deficiency in tomato plant. Dataset consists of 2000 images. The model was trained and validated with varying augmented datasets and optimal augmentation method was identified as dataset augmented with SR-Rotation gave the highest accuracy of 81.11%[44].

3.2.6. Weed Detection
YOLOv3-tiny model was pre-trained with the COCO dataset and it was trained and tested with the help of Darknet infrastructure. The F-score was 0.56 for the entire plant and 0.65 for the selected regions of the leaf blade derived networks for the recognition of the weed goosegrass [45].

3.3 Image Preprocessing
The commonly used pre-processing procedure was image resize with the intention of adjusting to the requirements of the DL architecture. In some works image size modified to 227×227 for the AlexNet model, 224×224 for the VGG16 net[10], 416×416 for YOLOv3-tiny[46], 64×64[38] and resize to half of its original size[40]. Image segmentation was done in order to enlarge the volume of the dataset, to highlight the regions of interest and to allow easier data annotation by researchers[40], using calyx and stalk scar [30], using threshold segmentation[32]. Some datasets used adaptive histogram equalization for

image enhancement[46]. Various resampling techniques are used to balance the imbalanced dataset like IMPS, SMOTE, RUS and ROS[25]. Background removal was done in [31], using Gaussian density function[33], using histogram thresholding technique[30] and noise cancellation algorithm[32] to reduce the overall noise of the dataset. Other operations like bounding box creation to facilitate weed detection or fruits counting or to classify the multiple objects present. Few datasets used Image space conversion, converted from RGB to HIS color model[46][38][32] or to the other color models like HSV [24]. Furthermore, some papers applied features extraction techniques on the images and extract features like shape and statistical features[30][31], histograms[38], PCA filters[12], Gabor filter[24] and GLCM feature[30].

3.4. Data Augmentation
Data Augmentation methods are used to enlarge the volume of the dataset artificially. This technique is mainly applied to the works with small datasets. It helps to provide more number of images for training purpose and also solves the problem of over fitting. The data augmentation techniques used are contrast, crop after random zoom and central zoom[9]. Resizing of the image, image translation, image scaling, image flipping, image rotation, perspective transformations, and intensity transformations are used in[27][22]. The hue range was modified from 1 to 1.5 times, the exposure was modified from 1 to 1.5 times and the total number of colors was modified from 0.9 to 1.1 times[34]. The dataset applied with illumination change, images rotation and noise enhancement[36][39]. Shift, rotation, and resizing in[43][44]. Changing the picture intensity over few regions of the image in the random choice of 20 to 30[13]. Scaling and cropping are used in[41]. RandomRotation and RandomResizedCrop methods are used in[26]. GANs are group of networks which can generate plausible new samples from unlabeled original samples. DCGAN and BEGAN models are used to increase the dataset size[16].

3.5. Transfer Learning
Transfer learning is the way of inheriting the knowledge from one problem and using it in another problem similar to it. Transfer learning can be applied variously in three cases like small, medium and large enough dataset size. The transfer learning concept was applied to the models and got promising results in many works[11][27][44][45]. The models were pretrained for object classification on the ImageNet dataset [28][10][46][14][15]. In few works Alexnet was used as pre-trained network[20]. In some other works models used COCO dataset for transfer learning technique[40][23] and few models are trained with ResNet 50 model[26].

4. Discussion
Our analysis on this review proved that DL offers enhanced performance in the huge majority of associated work. Owing to the fact that each work used different datasets, train test ratio, performance metrics, preprocessing techniques, architectures, parameters and hyper parameters, it is difficult to compare between papers. Thus our evaluations have been restricted with the methods used at reviewed work. But a common observation is that DL architecture has showed better performance than traditional approaches and shallow models used such as PSO, SVM, GA, ANN, KNN and others. Whereas the automatic extraction of features was well done by DL models when comparing with other traditional approaches such as background removal, foreground pixel extraction, image space conversion, histograms, PCA, wavelet transformation, GLCM, shape and statistical feature and other manual feature extraction techniques.

From this review it is observed that PV dataset for disease and pest identification was commonly used by 8 papers. Though the number of classes and images varies according to their research needs, a few observations are seen like AlexNet was used in 5 papers[10][11][14][15][16], among which [14] gave the highest accuracy of 98.93% with 10 classes. VGGNet was used in 2 papers [10][16], among which [10] gave the highest accuracy of 97.29% with 7 classes. ResNet was used in 3 papers [9][14][16], in which [14] gave the highest accuracy of 99.15% for ResNet 50. GoogleNet was used in 3 papers[14][15][16] in

which highest accuracy of 99.39% was given by[14]. Other architectures like SqeezeNet, Inception V3 and few others are not preferred much by the researchers.

The commonly used preprocessing technique in most of the work was resize, with the intention of adjust to the requirements of the DL architecture, and image space conversion. The most preferred pre training model for object classification was ImageNet dataset. From these observations some of the future works were identified like most of the researchers mainly concentrated on the disease and pest identification, the other areas such as macronutrient deficiency and weed detection in tomato plant can be taken for a future research scope. As like tomato these works can also be extended to other plants. The hyper parameter tuning technique can be utilized for a better result improvement as like the other techniques like transfer learning and image augmentation.

5. Conclusion

Our aim of this survey is to encourage new researchers to work with deep learning, using it for working out various agricultural related problems particularly related to tomato plant image analysis involving classification or prediction or generally related to data analysis. The future development of DL technology still has diverse challenges and obstacles which encourages for its additional use towards smarter, highly sustainable agricultural and safer food yield.

Table 3. List of significant contributions related to tomato plant using Deep Learning

Author & Year	Data Source			Data Augmen tation	Trans-fer Lear ning	Architec-ture/ Algorithm	Result	Comparison with other technique	Ref
	Classes	Images	Train/ Test/ Validati on ratio						
da Costa et al. 2019	2	43,843	50/25/25	No	yes	ResNet50	Precision-94.6%	ResNet101, ResNet34,	[28]
Karthik et al. 2020	4	1,20,000	N/A	yes	No	Residual deep CNN [customized]	Accuracy - 98%	N/C	[9]
Rangaraja n et al. 2018	7	13,262	N/A	No	yes	AlexNet	Accuracy - 97.49%	VGG16	[10]
Verma et al. 2020	3	2342	80/20/0	No	yes	AlexNet	Accuracy - Transfer learning 89.69% Feature extraction 93.4%	SqueezeNet, Inception V3	[11]
Gutierrez et al. 2019	3	N/A	N/A	yes	yes	FRCNN & SSD	N/A	KNN, MLP, FRCNN, SSD	[27]
Hu et al. 2019	N/AP	800	75/25	No	No	FRCNN	Accuracy: separated 95.5% adjacent 93.8% overlapping 78.4% shaded 81.9%	N/C	[33]
Xu et al. 2020	N/AP	5836	94/6/0	yes	yes	Improved YOLOv3-tiny [Customized]	F1-score 91.92%	YOLOv3-tiny	[34]

Zhang et al. 2020	5	4,178	60/10/30	No	No	Improved FRCNN [Customized], k-means clustering	2.71% higher accuracy than FRCNN	FRCNN,	[18]
Wang et al. 2019	11	286	60/20/20	No	No	FRCNN, Mask R-CNN	Highest accuracy-ResNet-101, Shortest detection time-MobileNet	ResNet 50, MobileNet, ResNet 101, VGG 16	[19]
Sun et al. 2018	3	5624	80/20/0	No	No	Improved FRCNN [Customized], k-means clustering, Soft-NMS	Accuracy: tomato flowers 90.5%, immature green tomatoes 90.8% , mature red tomatoes 90.9%	With various architectures and NMS	[35]
Liu et al. 2020	N/AP	3460	80/10/10	yes	No	SSD with Inception V2	Accuracy-98.85%	SSD with VGG16, MobileNet, Inception V2 and SSD with varying image size	[36]
Tran et al. 2019	3	571	80/20/0	yes	No	Ensemble Averaging	Accuracy-91%.	Inception-ResNet v2, Autoencoder	[43]
Luna et al. 2018	4	4,923	80/20/0	yes	yes	FRCNN	Accuracy-95.75%	N/C	[20]
Liu et al. 2020	12	15,000	N/A	No	No	Improved Yolo V3 [Customized]	Accuracy-92.39%	SSD, FRCNN, original Yolo V3	[21]
Gadekallu et al. 2020	10	16,419	N/A	No	No	PCA, WOA	Accuracy- 94%	N/C	[12]
Zhang et al. 2019	11	2000	N/A	yes	yes	Deep super-resolution network [Customized]	Accuracy-81.11%	Varying augmented datasets	[44]
Liu et al. 2019	2	1,594	N/A	No	No	Customized Architecture and focal loss function	Accuracy-91.26%	SDD, DenseNet and ResNet	[37]
Sharpe et al. 2019	N/A	N/A	N/A	yes	yes	YOLOv3-tiny, Darknet infrastructure	F-score- 0.56 for entire plant and 0.65 for partial sections	N/C	[45]
Fuentes et al. 2017	10	5,000	N/A	yes	No	FRCNN with VGG	Average precision- 83%	FRCNN, RFCN,SSD with VGG Net and ResNet	[22]
						RFCN with ResNet-50	85.98%		
Liu et al. 2019	N/AP	247	40/30/30	yes	No	FCR and NMS	Precision-94.41% and F1 score 92.15%	HOG,SVM classifier	[38]

Agarwal et al. 2020	10	1800	77/6/ 17	yes	No	A light weight CNN model [Customized]	Accuracy-98.7%	N/C	[13]
Maeda-Gutiérrez et al. 2020	10	16,419	80/20/0	No	yes	GoogleNet	Area under the curve 99.72% and sensitivity 99%	AlexNet, Inception V3, ResNet 18, ResNet 50	[14]
Brahimi et al. 2017	10	14,828	N/A	No	yes	Google Net	Accuracy-99.18%	SVM, Random forest , AlexNet	[15]
Zhang et al. 2018	5	1000	N/A	yes	No	Dataset augmented	Accuracy-91.9%	Various augmentation techniques	[39]
Wu et al. 2020	5	1500	80/20/0	yes	No	GAN with GoogLeNet	Accuracy-94.33%	GAN with AlexNet, VGG16, ResNet	[16]
Mu et al. 2020	N/AP	640	N/A	No	yes	FRCNN with Resnet-101	Average precision-87.83%	FRCNN with Resnet-101, Resnet 50, Inception ResNet v2	[40]
Liu et al. 2020	N.AP	966	N/A	yes	No	YOLO-Tomato [Customized]	Accuracy-94.58	YOLOv2, YOLOv3, Faster R-CNN	[41]
Haggag et al. 2019	3	60	70/30/0	No	No	CNN	Accuracy-100%	ANN, SOM, LVQ and SVM	[29]
Liu et al. 2020	2	2385	N/A	No	yes	MobileNetv2-YOLOv3	Average Precision-91.32%	RCNN, SSD	[23]
Hassanien et al. 2017	Tested with 6 public dataset from UCI repository			No	No	Improved MFA [Customized]	Accuracy-90.5%	PSO and GA with rough sets	[24]

Table 4. List of significant contributions related to tomato plant using Machine Learning

Author & Year	Data Source			Architecture/ Algorithm	Result	Comparison with other technique	Ref
Ireri et al. 2019	2	500	70/30/0	Calyx and stalk scar detection algorithm	Accuracy-95.1%	Linear, Quadratic, Cubic SVM classifier, ANN	[30]
				RBF-SVM classifier	Accuracy- 98.9%.		
Bhatia et al. 2020	2	244	70/30/0	ELM with IS	Accuracy-89.19%	SMOS, RUS, ROS	[25]
Nyalala et al. 2019	N/AP	958	70/15/15	RBF-SVM	Accuracy-97.06%	Linear, Quadratic and Cubic SVM, Bayesian-ANN	[31]

Luna et al. 2020	N/A P	277	83/0/17	SSD	Accuracy-flower 100% fruit 95.99%	RCNN	
	3	456	N/A	SVM	Accuracy-99.81%	ANN, KNN	[42]
Wan et al. 2018	3	150	68/32/0	BPNN with feature color value	Accuracy-99.31%	N/C	[32]

References

[1]   Tian H, Wang T, Liu Y, Qiao X, and Li Y 2020 Computer vision technology in agricultural automation-A review *Information Processing in Agriculture* **7** 1–19

[2]   Expert System [Internet]. Expert System [updated 2020 May 06; cited 2020 Sep 20]. Available from: https://expertsystem.com/machine-learning-definition/

[3]   Kamilaris A and Prenafeta-Boldu F X 2018 Deep learning in agriculture: A survey *Computers and Electronics in Agriculture* **147** 70–90

[4]   Nagaraju M and Chawla P 2020 Systematic review of deep learning techniques in plant disease detection *International Journal of System Assurance Engineering and Management* **11** 547–60

[5]   Siddharth Das [Internet]. Medium [updated 2017 Nov 16; cited 2020 Sep 21]. Available from: https://medium.com/analytics-vidhya/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5

[6]   Ali Masri [Internet]. MarkTechPost [updated 2019 Jun 14; cited 2020 Sep 21]. Available from:https://www.marktechpost.com/2019/06/14/data-pre-processing-for-deep-learning-models-deep-learning-with-keras-part-2/

[7]   Jason Brownlee [Internet]. Machine Learning Mastery [updated 2019 Apr 12; cited 2020 Sep 21]. Available from: https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/

[8]   Pulkit sharma [Internet]. Analytics Vidhya [updated 2018 Oct 22; cited 2020 Sep 21]. Available from: https://www.analyticsvidhya.com/blog/2018/10/introduction-neural-networks-deep-learning/

[9]   Karthik R, Hariharan M, Anand S, Mathikshara P, Johnson A, and Menaka R 2020 Attention embedded residual CNN for disease detection in tomato leaves *Applied Soft Computing J.* **86**

[10]   Rangarajan A K, Purushothaman R, and Ramesh A 2018 Tomato crop disease classification using pre-trained deep learning algorithm *Procedia Computer Science* **133** 1040–47

[11]   Verma S, Chug A, and Singh A P 2020 Application of convolutional neural networks for evaluation of disease severity in tomato plant *Journal of Discrete Mathematical Sciences and Cryptography* **23** 273–82

[12]   Gadekallu T R, Rajput D S and Praveen kumar M 2020 A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU *Journal of Real-Time Image Processing*

[13]   Agarwal M, Gupta S K and Biswas K K 2020 Development of Efficient CNN model for Tomato crop disease identification *Sustainable Computing: Informatics and System* **28** 100407

[14]   Maeda-Gutierrez V, Galvan Tejada E and Zanella-Calzada A 2020 Comparison of convolutional neural network architectures for classification of tomato plant diseases *Applied Sciences* **10**

[15]   Brahimi M, Boukhalfa K, and Moussaoui A 2017 Deep Learning for Tomato Diseases: Classification and Symptoms Visualization Engineering *Applications of Artificial Intelligence* **31** 299–315

[16]   Wu Q, Chen Y, and Meng J 2020 Dcgan-based data augmentation for tomato leaf disease identification *IEEE Access* **8** 98716–28

[17]   Zhao J and Qu J 2019 Detection method for tomato fruit common physiological diseases based on

YOLOv2 *Proc. - 10th Int. Conf. Information Technologies in Medical and Education* 559–63

[18] Zhang Y, Song C, and Zhang D 2020 Deep Learning-Based Object Detection Improvement for Tomato Disease *IEEE Access* **8** 56607–14

[19] Wang Q, Qi F, Sun M, Qu J, and Xue J 2019 Identification of Tomato Disease Types and Detection of Infected Areas Based on Deep Convolutional Neural Networks and Object Detection Techniques *Computational Intelligence and Neuroscience*

[20] De Luna R G, Dadios E P, and Bandala A A 2019 Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON* 1414–19

[21] Liu J and Wang X 2020 Tomato Diseases and Pests Detection Based on Improved Yolo V3 Convolutional Neural Network *Frontiers in Plant Science* **11** 1–12

[22] Fuentes A, Yoon S, Kim S C and Park D S 2017 A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition *Sensors (Switzerland)* **17**

[23] Liu J and Wang X 2020 Early recognition of tomato gray leaf spot disease based on MobileNetv2 YOLOv3 model *Plant Methods* 1–16, 2020

[24] Hassanien A E, Gaber T, Mokhtar U and Hefny H 2017 An improved moth flame optimization algorithm based on rough sets for tomato diseases detection *Computers and Electronics in Agriculture* **136** 86–96

[25] Bhatia A, Chug A, and Prakash Singh A Application of extreme learning machine in plant disease prediction for highly imbalanced dataset *Journal of Statistics and Management Systems* 1–10

[26] Nithish E, Kaushik M, Prakash P, Ajay R, and Veni S 2020 Tomato Leaf Disease Detection using Convolutional Neural Network with Data Augmentation *5th Int. Conf. on Communication and Electronics Systems* 1125–32

[27] Gutierrez A, Ansuategi A, Susperregi L, Tubio C, Rankic I, and Lenza L 2019 A Benchmarking of Learning Strategies for Pest Detection and Identification on Tomato Plants for Autonomous Scouting Robots Using Internal Databases *Journal of Sensors*

[28] da Costa A Z, Figueroa H E H and Fracarolli J A Computer vision based detection of external defects on tomatoes using deep learning *Biosystems Engineering* **190** 131–44,

[29] Haggag M, Abdelhay S, Mecheter A, Gowid S, Musharavati F and Ghani S 2019 An Intelligent Hybrid Experimental-Based Deep Learning Algorithm for Tomato-Sorting Controllers *IEEE Access* **7** 106890–98

[30] Ireri D, Belal E, Okinda C, Makange N, and Ji C 2019 A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing *Artificial Intelligence*

[31] Nyalala I 2019 Tomato volume and mass estimation using computer vision and machine learning algorithms: Cherry tomato model *Journal of Food Engineering* **263** 288–98

[32] Wan P, Toudeshki A, Tan H, and Ehsani R 2018 A methodology for fresh tomato maturity detection using computer vision *Computer and Electronics in Agriculture* **146** 43–50

[33] Hu C, Liu X , Pan Z, and Li P 2019 Automatic detection of single ripe tomato on plant combining faster R-CNN and intuitionistic fuzzy set *IEEE Access* **7** 154683–96

[34] Xu Z F, Jia R S, Liu Y B, Zhao C Y and Sun H M 2020 Fast method of detecting tomatoes in a complex scene for picking robots *IEEE Access* **8** 55289–99

[35] Sun J, He X, Ge X, Wu X, Shen J and Song Y 2018 Detection of key organs in tomato based on deep migration learning in a complex background *Agriculture* **8** 12

[36] Yuan T, Lv L, Zhang F and Fu J 2020 Robust cherry tomatoes detection algorithm in greenhouse scene based on ssd *Agriculture* **10**

[37] Liu J, Pi J, and Xia L 2020 A novel and high precision tomato maturity recognition algorithm based on multi-level deep residual network *Multimedia Tools and Applications* **79** 9403–17

[38] Liu G, Mao S, and Kim J H 2019 A mature-tomato detection algorithm using machine learning and color analysis *Sensors (Switzerland)* **19** 1–19

[39] Zhang L, Jia J, Gui G, Hao X, Gao W and Wang M 2018 Deep Learning Based Improved

Classification System for Designing Tomato Harvesting Robot *IEEE Access* **6** 67940–50

[40] Mu Y, Chen T S, Ninomiya S, and Guo W 2020 Intact detection of highly occluded immature tomatoes on plants using deep learning techniques *Sensors (Switzerland)* **20** 1–16

[41] Liu G, Nouaze J C, Mbouembe P L T, and Kim J H 2020 YOLO-tomato: A robust algorithm for tomato detection based on YOLOv3 *Sensors (Switzerland)* **20** 1–20

[42] de Luna R G, Dadios E P, Bandala A A, and Vicerra R R P 2020 Tomato growth stage monitoring for smart farm using deep transfer learning with machine learning-based maturity grading *Agrivita* **42** 24–36

[43] Tran T T, Choi J W, Le T T H and Kim J W 2019 A comparative study of deep CNN in forecasting and classifying macronutrient deficiencies on development of tomato plant *Applied Sciences* **9**

[44] Zhang L, Jia J, Li Y, Gao W and Wang M 2019 Deep learning based rapid diagnosis system for identifying tomato nutrition disorders *KSII Trans. Internet Inf. Syst.* **13** 2012–27

[45] Sharpe S M, Schumann A W and Boyd N S 2020 Goosegrass Detection in Strawberry and Tomato Using a Convolutional Neural Network *Scientific Reports* **10** 1–8

[46] Xu Z F, Jia R S, Liu Y B and Zhao C Y 2020 Fast method of detecting tomatoes in a complex scene for picking robots *IEEE Access* **8** 106890–98