Deep Learning Techniques in Tomato Plant – A Review

S Mohana Saranya¹, R R Rajalaxmi¹, R Prabavathi², T.Suganya³, S.Mohanapriya¹, K.Tamilselvi¹

¹ Department of CSE, Kongu Engineering College, India.
² Department of CSE, SRM Institute of Science and Technology, India.
³ Department of CSE, Sri Krishna College of Technology, India.

Email: mohanasaranya.cse@kongu.edu

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 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].

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 SqueezeNet, 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 | Classes | Images | Train/ Test/ Validation ratio | Data Augmentation | Transfer Learning | Architecture/ Algorithm | Result | Comparison with other technique |
|---------------|-------------|---------|--------|------------------------------|------------------|-------------------|-------------------------|--------|-------------------------------|
| 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] |
| Rangarajan 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] |
| Authors           | Year | Dataset Size | Training Time | Improved FRCNN | k-means Clustering | Highest Accuracy | Shortest Detection Time | Accuracy Comparison | Details |
|-------------------|------|--------------|---------------|----------------|-------------------|------------------|------------------------|---------------------|---------|
| Zhang et al. 2020 | 5    | 4,178        | 60/10/30      | No             | No                | 2.71% higher     | ResNet-101, MobileNet  | FRCNN,              | [18]    |
| Wang et al. 2019 | 11   | 286          | 60/20/20      | No             | No                | Highest accuracy | ResNet-101, VGG 16    | FRCNN, Mask R-CNN   | [19]    |
| Sun et al. 2018   | 3    | 5624         | 80/20/0       | No             | No                | Accuracy:         | With various architectures and NMS | Improved FRCNN [Customized], k-means clustering, Soft-NMS | [35]    |
| Liu et al. 2020   | N/AP | 3460         | 80/10/10      | Yes            | No                | SSD with Inception V2 | SSD with VGG16, MobileNet, Inception V2 and SSD with varying image size | Accuracy-98.85% | [36]    |
| Tran et al. 2019  | 3    | 571          | 80/20/0       | Yes            | No                | Ensemble Averaging | Inception-ResNet V2, Autoencoder | Accuracy-91%. | [43]    |
| Luna et al. 2018  | 4    | 4,923        | 80/20/0       | Yes            | Yes              | FRCNN             | N/C                    | Accuracy-95.75%   | [20]    |
| Liu et al. 2020   | 12   | 15,000       | N/A           | No             | No                | Improved Yolo V3  | SSD, FRCNN, original Yolo V3 | Accuracy-92.39% | [21]    |
| Gadekallu et al. 2020 | 10  | 16,419       | N/A           | No             | No                | PCA, WOA          | N/C                    | Accuracy-94%     | [12]    |
| Zhang et al. 2019 | 11   | 2000         | N/A           | Yes            | Yes              | Deep super-resolution network [Customized] | Varying augmented datasets | Accuracy-81.11% | [44]    |
| Liu et al. 2019   | 2    | 1,594        | N/A           | No             | No                | Customized        | SDD, DenseNet and ResNet | Architecture and focal loss function | Accuracy-91.26% | [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    | FRCNN with VGG, RFCN with ResNet-50 | Average precision- 83% | RFCNN, RFCN, SSD with VGG Net and ResNet | [22]    |
| 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]    |
| 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/A | P 958 | 70/15/15 | RBF-SVM | Accuracy-97.06% | Linear, Quadratic and Cubic SVM, Bayesian-ANN | [31] |
| Name et al. Year | N/A | SSD | Accuracy-flower | RCNN |
|------------------|-----|-----|-----------------|------|
| Luna et al. 2020 | 3   | N/A | 95.99%         | ANN, KNN |
| Wan et al. 2018  | 3   | 68/32/0 | 99.91% | N/C |

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