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Critical Review on Multi-Crops Leaves Disease Detection using Artificial Intelligence Methods

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Abstract— Nowaday's, plant diseases cause foremost losses in terms of quality, production economy, and production in agriculture field. Approximately, 70% of the world economy is dependent on agriculture; there is a need to overcome the loss suffered by crop diseases. There is a need to monitor the plants from initial level to overcome multiple diseases. A lot of researchers used different types of traditional approaches for multi-crop leaves disease detection, which are more complex and time taking. It's necessity of time to build an automatic diseases detection system to overcome the manual work. In this review paper, the focus on tomato and cotton leaves disease detection. A variety of research has already been conducted related to plant leaves disease of tomato and cotton using artificial intelligence methods. Real-time tomato and cotton leaves disease detection is one of the main issue in agriculture field. In this review paper, we present a literature review on different methods used to detect cotton and tomato leaves disease. This paper summarizes and reviews different methods based on artificial intelligence. The main objective of this paper is to analyze and review the limitations of previous research and suggest future directions for researchers.

Index Terms— Mutti-Crop Diseases, Artificial Intelligence; Image processing; Deep Learning; Machine Learning; Diseases Detection.

1 Introduction

In today world, agriculture plays a significant role in world economy where approximately, 70% of world economy based on agriculture. Quality of agriculture decrease due to the diseases of plants. To improve the economic growth, the plant leaves disease identification and recognition are the main tasks. Leaves is the most sensitive part of crops to show leaves disease symptoms at the intial stage. Initially, plants monitored with naked eyes for disease identification was time-consuming methodology. Manually monitored method for disease identification was replaced by automatic and semi-automatic techniques to monitor plants against diseases. These methods were less expensive and provide accurate result rather than manual monitoring. Thus this encourage researchers to develop more intelligent technologies that provide much accurate result and reduce human need with the passage of time.

The main purpose of this study is to review and analyze the automatic systems or frameworks developed based machine learning or deep learning for tomato and cotton leaves disease identification. A variety of research has already been conducted related plant leaves disease of tomato and cotton using image processing, machine and deep learning methods. Real-time tomato and cotton leaves disease detection one of the main issue in agriculture field.

In overall world cotton is the most significant crop that provides raw material for cotton textile industry [1] and [2]. Although, cotton plant diseases are main factors that reduced the productivity. Due to diseases, Cotton crop faces many problems that disturb its growth and not specify the disease by naked eye. The mainly affected fragment of plant is its leave that shows 80 to 90% of diseases [5]. Therefore, our major concern is leaves of the crop rather than entire cotton crop.

Tomato crop is produced in large quantities and having a high commercial values in the world market. Diseases are harmful to the health of plant that also disturbs its growth. By ensuring the slight losses of cultivated crop, it is critical to supervise its growth. There are various types of cotton and tomato diseases that determines the crop's health. The main concern of this study is to discover the ways of how we can detect leaves disease with easy approach to make the minimal usage of computer resources to meet the accurate results with modern AI techniques.

1.1 Classification of Multiple Plant Leaves Disease

In these days, tomato and cotton leaves affected by different kinds of diseases. The cotton and tomato leaves damaged by different types of fungal, bacterial and viral diseases. Fig. 1 shows that differents types of plant leaves disease [3].

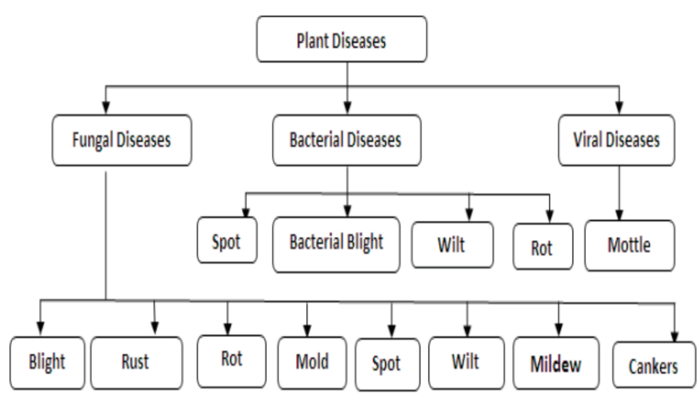

Fig. 1. Classification of Leaves Disease [3]

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1.2 Basic Key Issues and Challenges in Diseases Analysis

Recently, many researchers have conducted research on identification of plants diseases. Automatically identifying the plants are the major issues [4]. Some basic issuses and challenges on plant diseases recognition and classification ar key issues, challenges on disease detection and classification are as follows:

- Need good quality of crops leaves disease images.
- Required real-time and accurate dataset in huge amount
- Need to preprocessed dataset using latest preprocessing techniques
- Segmenting the exact spot in a leaves into meaningful disease. Prepare sample input dataset for training and testing.
- Need to implement an hybrid framework for classification
- Need regular base plants observations.
- Identifying the leaves diseases for multiple crops is the main challenge [4].

1.3 General Model of Plant Leaves Disease Detection

Different models have been introduced for detecting leaf disease in cotton and tomato plant. All these models are playing a collaborative effort for improving the process of leaf disease detection. Also these models have certain limitations that affect the efficiency level of these models, few of models are conceptual are for ideal case not easy to implement, few of models are working on a static dataset are not suitable for every kind of situations, few models are talking about learning but the term learning is ambiguous and not well refined. A General tomato and cotton leaves disease detection model is shown in Fig: 2 followed for literature review.

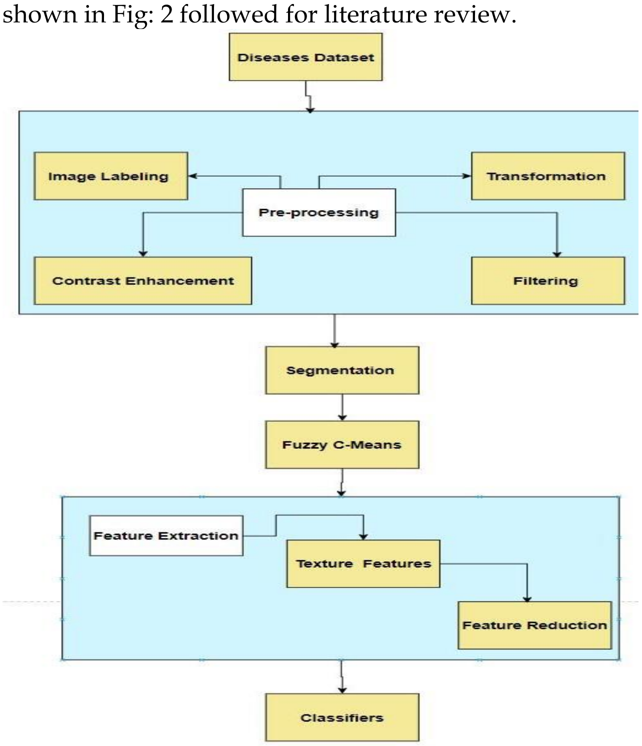

Fig. 2. Crops Disease Classification Framework

2 Significance of the Study

Now a days real-time multiple crops leaves disease recognition one of the main issue in agriculture industry. At a global scale, FAO estimates that agriculture economic production lost 20 to 40 percent annually due to crops diseases. Framers spend billions of dollars are on disease management system but there is no easiest way for framers to take decision behind crops diseases. Traditional systems are unable to classify real-time crops diseases. There is some major task needs to done in this study for multi-crop leaves disease classification:

- Need to develop an expert system for Real-time multiple crop leaves disease classification.
- Need to improve the economic production by using knowledge-based approach for automatic decision-making.
- Need to use latest image based pre-processing approaches used to enhance the image quality.
- The significance of a successful leaves disease recognition system can only achieved when related issues are fully measured and resolved.
- These challenges necessitate immediate attention by government agencies dealing with agriculture field.

3 Background

In the area of agricultural industry, multi-crop disease recognition are primarily step for good production. In agricultural field, Multi-crop leaves disease detection and classification is an essential field that gains lots of attention of researchers. To improve the quality of agriculture products, there is a need of automatic leaves disease recognition systems. The focus of this review paper is on recognition of cotton and tomato leaves disease frameworks. The structure of this review paper based on supervised, unsupervised and hybrid methods. General structure of our review paper shown in Fig 3.

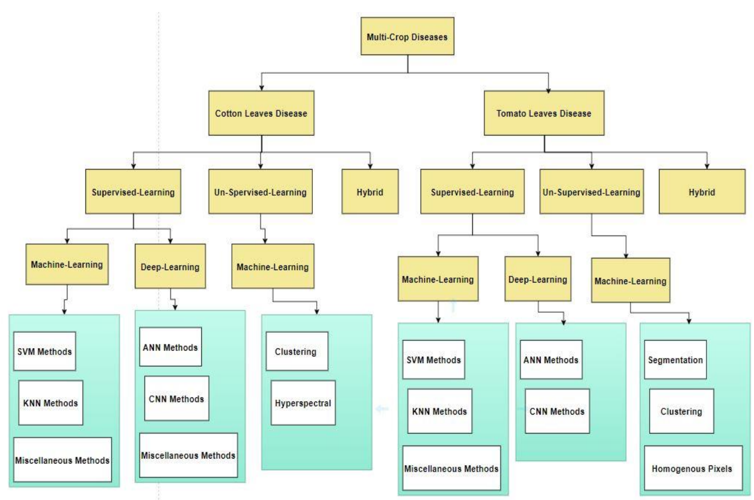

Fig. 3. Structur of Literature Review

3.1 Multi-Crop Diseases

Crop diseases recognition is the most important procedure to recognize the standard of the plants through which different factors such as richness of the grains, diseases recognition, and nutrition preservation evaluated. The main objective of this paper is to study the different types of AI techniques for crops diseases detection and classification.

3.1.1 Methods Used in Multi-Crop (Tomato & Cotton) Diseases Detection

There three types of different method are as follows:

- Supervised-Learning Methods
- Unsupervised-Learning Methods
- Hybrid-Learning Methods

1) Supervised Learning Methods:

Supervised leaning classification problems and regression problem both can be easily solved. It mainly consists of training data with labeled data are in it, so it easily compares the new data with it and predicts the output. Two types of supervised learning approaches used by many researchers given below:

a) Machine-Learning Based Supervised Approach
b) Deep-Learning Based Supervised Approach

a) Machine learning supervised classification methods

There are many machine learning supervised classification intelligent methods play a major role to achive the desired goals. Following machine learning supervised approaches used in different researches:

- Support Vector Machine (SVM) Approach
- K-nearest Neighbor Approach
- Random Forest Approach
- Fuzzy-Logic Approach

b) Deep Learning supervised methods

There are many deep learning supervised intelligent methods play a major role to achive the desired goals. Some major methods details given below:

- ANN Approach
- CNN based Framework
- CNN based Pre-trained Framework
- Deep Learning Miscellaneous Method

2) Un-supervised-Learning Method:

In un-supervised leaning classification problems and regression problem both can be easily solved. It mainly consists of training data with un-label data are in it, so it easily compares the new data with it and predicts the output.

a) Machine-Learning un-supervised classification methods for tomato Diseases Detection:

There are many machine learning based un-supervised classification intelligent methods play a major role to achive the desired goals. Many researchers used un-supervised based machine-learning approaches and these approaches given below:

- Clustering based Approaches
- Spectral based Approaches
- Segmentation Approaches
- Homogeneous Pixel Counting Approaches

3) Hybrid Learning Method:

In hybrid leaning classification problems and regression problem both can be easily solved. Many researchers used un-supervised based machine-learning approaches and these approaches given below:

- Segmentation Clustering based SVM Approach
- Clustering based CNN Approach

4 Literature Review

In past years, many researchers conduct reseach on tomato and cotton leaves disease classification by using artificial intelligence based machine or deep learning methods mention in previous setection III.

4.1 Tomato Diseases Classification

In this section, tomato diseases classification methods mentioned in previous setecion III will be discuss in details.

4.1.1 A Review on Supervised Machine-Learning Methods for Tomato Diseases Detection

In this section, Supervised Machine-Learning methods mentioned in previous section III will be discuss in details. Machine Learning has been very famous and used in past by many researchers [6], [7], [8], [9], [10], [11], [12], and [13].
Mokhtar et al [6] proposed an effective SVM based tomato leaves disease detection framework using different types of Kernel Functions like Invmult, Cauchy and Laplacian Kernels. The classification of tomato leaves disease accuracy founded to be 99.5%. While, Hassanien et al [7] discuss improved Moth-Flame framework using SVM classifier to identify leaves disease on rough tomato diseases dataset. However, proposed method still needs to improve the parameters selection approach for accurate values selection. Similarly, Hlaing and Maung Zaw [8] discussed a SIFT texture feature framework based on SVM classifier for image distribution using histogram matching approach to recognize leaves on tomato plant village dataset. Support Vector Machine approach used to evaluate the good performance of selected features and classify the leaves disease. The proposed classification average accuracy calculated using ten-Fold cross validation. The proposed approach achieves 85.1% accuracy results with 33.88sec time. Relatively, Hlaing and Zaw [9] worked on SVM classifiers based on Model-based statistical features used to extract texture, statistical features and Generalized Extreme values from tomato leaves disease plant village dataset. SVM approach applied to predict and recognize the tomato plant diseases where five diseases and healthy. Result accuracy for this research was 84%.
KNN and Random Forest methods has been very famous and used in past by many researchers [10], [11], [12], [13]. Oktaviana Rena Indriani et al [10] discuss KNN based classification approach used to identify the maturity level of tomato leaves disease by the combination of GLCM and HSV techniques, extracted values classified using the KNN approach. Whereas, Chuanqi Xie et al [11] discussed Hyperspectral-Imaging approach to identify healthy and gray mold tomato leaves disease on inoculated dataset collected from real-time environment. Collected dataset pre-processed using wave band width approach and Feature ranking (FR) used to reduce data volume. Comparatively, F.Jakjoud et al [12] deployed two-sub classifiers based on SVM and KNN with fuzzy decision maker

rules on internet tomato diseases dataset. The result of each classifier can reach over than 80% and the Fuzzy Combination of KNN Sub-classifier more than 98% gives the best accuracy. However, proposed SVM method still needs to improve the size and the type of data, with the statistical features, the dependence between parameters makes hyperplane tuning very difficult. On the other hand, Jagadeesh Basavaiah et al [13] worked on Multiple Feature Extraction approach using Decision-Tree and Random-Forest algorithms to recognize leaves disease on tomato crop by improving the recognition performance accuracy and reduce the computing time. Set of iportant features extracted using Color histograms, Hu Moments, Haralick and Local Binary Pattern methods and these extracted features used for training and testing. The proposed classification average accuracy is 90% for Decision Tree approach and 94% for Random Forest approach respectively.

Summary Table of Tomato Leaves Disease Detection Using Supervised Machine-Learning Methods

Ref	Author & Year	Pre-processing & Feature Extraction	Methods	Dataset	Results	Limitations
[6]	• Usama Mokhtar • Mona A. S. Ali • Aboul Ella Hassenian • Hesham Hefny & • 2016	• Leaf image isolation • Image resizing • Background removing. • Wavelet based features extracted • 402 texture feature extracted	• SVM • Cauchy kernel • Invmult Kernel and • Laplacian Kernel.	**Source** Different farms dataset in bani seef city at February, at temperature between 16 and 20 degree **Dimensions** Approximately 200 images record & Contains two disease categories	**Accuracy** 99.5%	• Need real-time dataset for classification.
[7]	• Aboul Ella Hassanien • Tarek Gaber • Usama Mokhtar • Hesham Hefny • 2017	• Eliminating noisy, irrelevant, and redundant data • Gabor filters	• MFORSFS algorithm • SVM	**Source** Different farms dataset **Dimensions** Contains two disease categories	**Accuracy** 89.3%	• Need to improve parameter selection approach.

[8]	• Chit Su Hlaing • Sai Maung Maung Zaw & • 2018	• Image enhancement • Texture features • Color features • Statistical Analysis • Histogram Matching	• SIFT texture feature Model • SVM	**Source** Plant Village Dataset **Dimensions** Approximately 3535 images record	**Accuracy** 85.1%	• Need to improve proposed model accuracy and computing time.
[9]	• Chit Su Hlaing • Sai Maung Maung Zaw & • 2017	•Background Removal •SIFT features extracted •Extreme Values extraction •Statistical texture features extraction	• SVM classifier • Quadratic SVM	**Source** Plant dataset **Dimensions** Approximately 3k images record	**Training Accuracy** 83.4% **Training Time duration** 55.9 sec to 56.8 sec	• Need to build real-time application for diseases detection.
[10]	• Oktaviana Rena Indriani • Christy Atika Sari • Edi Jaya Kusuma	• Grayscale conversion • texture and color analysis • Gray Level Co-occurrence Matrix (GLCM) • Hue, Saturation, Value (HSV).	• K-Nearest Neighbor (K-NN)	**Source** Experimental dataset **Dimensions** Approximately 100 images record	**Accuracy** 89%	• Need to improve proposed framework accuracy using latest deep learning methods.
[11]	• Chuanqi Xie a • Ce Yang a • Yong He b • 2016	• Region of interest • Color conversion • PCA	• Hyperspectral imaging technique • KNN	**Source** Internet data **Dimensions** Approximately 210 images record	**Training Accuracy** 99.29% **Testing Accuracy** 94.44%	• Spray inoculation method could be considered in order to make the whole leaf infected.
[12]	• F.Jakjoud • A.Hatim • A.Bouaddi • 2019	• Color filter • Extract Leaves from background • Threshold • 14 Haralick approach	• KNN • SVM • Fuzzy Decision Maker	**Source** Internet **Dimensions** Approximately 200 images record Contains two disease Categories	**Accuracy** 80%	• Need to improve size and the type of data, with the statistical features, the dependence between parameters makes hyperplane tuning very difficult.
[13]	• Jagadeesh Basavaiah • Audre Arlene Anthony & • 2020	• Color histograms • Hu Moments • Haralick • Local Binary Pattern features	• Random forest • Decision tree	**Source** Database **Dimensions** Approximately, 500 images record	**Decision-Tree Accuracy** 90% **Random-Forest** 94%	• There are no texture features selection approach used.

4.1.2 A Review on Supervised Deep-Learning Methods for Tomato Diseases Detection:

ANN approach has been very famous and used in past by many researchers [14], [15]. G. K. Vianna et al [14] discussed ANN computational approach, based on MLP to detect different types of tomato leaves disease. The Red/Green filter is a simple technique to process massive amount of digital images if compared to more sophisticated digital images algorithms, such as edge detection treatments or trimming the bottom, among others, but it has showed to be strong enough to overcome the focus, blur, and lightning and definition limitations of the digital images. Analyzed each network of all 50 with this configuration, they found networks that has achieved an accuracy rate of 94.12%. While, Gizelle K. Vianna et al [15] presents a system to identify the late blight leaves disease from tomato plant dataset using Artificial Intelligence based Multilayer perception Neural Network framework and achieves 97% recognition accuracy results in classification.

Tomato diseases classification and detection using Deep-Learning famous CNN framework conducted by many researchers [16], [17], [18], and [19]. Belal A. M. Ashqar et al [16] proposed a CNN based framework that used to detect or classify healthy tomato leaves and five diseases. CNN used an abbreviation of Multilayer Perceptron's implement to required minimal preprocessing techniques on collect public tomato leaves dataset as compared to other image processing methods and achieved 99.84% accuracy results in diseases classification. While, Claudio Cevallos et al [17] build a vision-based system using Convolutional Neural Network (CNN) to recognize and classify the different types of tomato leaves disease and apply data augmentation technique on greenhouse tomato diseases dataset. The proposed model achieves overall 86.57% accuracy for diseases classification. Whereas, Mohammed Brahimi et al [18] proposed that, Convolutional Neural Network approach used to identify nine different types of tomato leaves diseases and extract features automatically from raw images. The proposed model achieves overall 99.18% accuracy for diseases classification. Similarly, Jun Sun et al [19] discussed Feature Pyramid Network (FPN) approach based on CNN framework used to recognition tomato diseases agricultural university of greenhouse. Feature Pyramid Network (FPN) approach used to extract multiscale features and the mean average precision (mAP) founded to be 90.7% to 99.5%.

Tomato diseases classification and detection using DLCNN framework conducted by many researchers [20], [21], [22], and [23]. Thair A. Salih, Ahmed J. Ali et al [20] presents a DLCNN based system based on different types of layers like input, convolution, batch normalization, active function, pooling, fully connected and classification layers used to recognition tomato leaves diseases on tomato plant village. The classification or recognition performance accuracy achieved by proposed framework are 96.34%, while the achieved training accuracy are 99.36%. The main drawback of proposed framework there is no rules defined for recognizing images in training phase. While, Azeddine Elhassouny et al [21] proposed a novel framework based on DLCNN used to extract texture or color features from ten different type tomato leaves disease framers plant dataset and achieved high performance accuracy 90%. Whereas, QIUFENG WU et al [22] discussed a CNN based DCGAN classification framework to classify tomato leaves diseases from large amount of dataset for training of neural networks, and improved the proposed framework recognition accuracy. After training and testing model, the average accuracy founded to be 94.33%. Similarly, Onyeka Emebo, Barka Fori et al [23] proposed a system to classify and detect tomato leaves diseases based on DCNN framework. DCNN has the ability to detect automatically important features using plant vil-lage dataset collected form. DCNN based layers used for leaves diseases classification with high accuracy 99.01% results.

CNN based Pre-trained frameworks has been very famous and used in past by many researchers [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51]. Robert G. de Luna et al [24] proposed a CNN based novel pre-trained such as Alexnet and F-RCNN framework used to train for anomaly detection and the Transfer Learning ap-proach used for disease recognition with achieving the aver-age accuracy 91.67%. While, Jun LiU et al [25] worked on improved recognition based approach for gray tomato leaves spot diseases detection based on MobileNetv2 and YOLOv3 lightweight Neural Network using digital camera based captured tomato leaves diseases images for testing. Whereas, Iftikhar Ahmad et al [26] proposed a CNN based different types of architectures such as ResNet, Inception, VGG-16 and VGG-19 used for identification of tomato leaves disease. Preprocessing and features extraction approaches applied on laboratory or field dataset. Parameter tuning layer used to enhance model accuracy. Similary, Suryawati et al [27] works on different CNN based architectures like VGGNet, AlexNet, and GoogleNet for tomato leaves disease identifica-tion two layers of CNN approach applied on plant village dataset. However, proposed model just work on predefined tomato leaves dataset variations. Likewise, Halil Durmuú et al [28] proposed CNN based AlexNet and SqueezeNet framework used to detect tomato leaves disease from plant village dataset and collected dataset preprocessed using segmenta-tion approach. AlexNet approach achieves the high accura-cy as compared to SqueezeNet approach. Comparatively, Lilian Mkonyi et al [29] describe a system for tomato leaves disease recognition using CNN based framework (VGG16, VGG19, and ResNet50) on agricultural lab dataset. CNN based fully connected layers used to train the preprocessed images for classification with achieving 91.1% average accu-racy results. While, Jia Shijie et al [30] works on CNN based hybrid framework to predict tomato leaves disease with good performance such as for training 62.5%, for validation 25% and for testing 12.5%.VGG16 approach used for feature extraction and SVM approach used for classification of to-mato pests and leaves disease. Relatively, Ding Jiang et al [31] used pre-trained CNN framework with Resnet-50 algo-rithm in tomato plant leaves disease detection. The identifi-cation of tomato leaves diseases performed using CNN based 11x11 layers and achieved the training and testing accuracy are 98.3% or 98.0% respectively. The limitation with their model was there is no multiple diseases detected. Moreover, need to combine the segmentation or localization diseas-

es results.
While, Siti Zulaikha Muhammad Zaki et al [32] authors introduced a pre-trained CNN approach based on existing DL approach such as MobileNet V2. The introduced framework evaluated on a plant village dataset, which consists three types of tomato leaves diseases in terms of healthy and unhealthy. The MobileNet V2 approach achieves good performance results as compare to other deep learning approaches. Whereas, L. Zhang et al [33] build an automatic tomato leaves diseases diagnosis system using CNN based Enhanced Su-per-Resolution Network (EDSR) approach to preprocess the collected tomato plant diseases dataset. The proposed classification framework achieved 81.11% accuracy. Relatively, Batool et al [34] discussed a deep learning based pre-trained classification approaches. The pre-trained ap-proach used to extract important features from images and KNN approach used to classify leaves diseases. The pro-posed framework achieved 76.1% accuracy. Whereas, Chena et al [35] works on BARNet framework used to recog-nition tomato leaves diseases and achieves an efficient accu-racy results with a detection rate 91%. Binary Wavelet De-composition (BWD) approach used to extract important tex-ture features from pre-processed images. While, T. Zhang et al [36] build a leaves diseases recognition system using CNN based SE-ResNet framework on plant diseases dataset col-lected from AI challenger website. Image based prepro-cessing techniques such as image enhancement, Gaussian filtering and contrast enhancement applied to enhance the quality of images. On the other hand, Hidayatuloh et al [37] proposed a novel framework based on transfer learning approach with SqueezeNet model to train a large amount of dataset in order to achieve better accuracy results to detect or classify disease in tomato plants through its leaves with 86.92% accuracy. While, Gharghory et al [38] works on CNN based pre-trained models such as AlexNet, SqueezeNet and VGG-16 used for classification leaves diseases detection on plant village dataset. The pro-posed model for classification achieves accuracy 99%.
Relatively, Liu et al [39] proposed DNN based DenseNet framework to solve disease detection problems in complex tomato leaves images. Feature propagation approach used to overcome the amount of storage data. Network convolu-tion kernel used to train the tomato leaves diseases dataset collected from agricultural university. The proposed classifi-cation approach achieves 21% higher accuracy as compare to other models. Comparatively, Sun et al [40] focusing on the detection of key organs of tomato leaves diseases using CNN based architectures. CNN based architectures such as R-CNN and Resnet-50 used for classification of leaves diseases symptoms and provide op-timal solution to user. Resnet-50 approach used to improve the Mean Average Precision (MAP). Likewise, V. Tsironis et al [41] discussed two different types of Deep learning based framework such as AlexNet and SqueezeNet used to identify ten different types of tomato leaves diseases classes including healthy images on plant village dataset. The average accuracy of these frameworks is achieved 0.97%. While, Adhikari et al [42] works on CNN based multiple layers model such YOLO used for classification of tomato leaves diseases and the CNN based framework Mean Average Precision (MAP) found to be 0.76. Similarly, Nithish et al [43] proposed a ResNet framework used to detect and classify diseased tomato leaves from the healthy plants leaves and data augmentation approach applied on collected dataset for extracting features. The overall accuracy of proposed model founded to be 97.01%. The ma-jor drawback of proposed framework is too much time con-suming process. Need to improve fine-tune parameters in training time. Whereas, Agarwal et al [44] implement a real-time detection and classification framework of a tomato leaves diseases using CNN based architectures like VGG16, Incep-tion V3 and GoogleNet introduced as a training or testing model. The average of proposed model founded to be 91.2% for tomato plant leaves dataset.
Comparatively, Llorca et al [45] works on CNN based transfer-learning frameworks such as GoogleNet and Incep-tion-V3 to solve the tomato leaves diseases detection and classification problem. The recognition of tomato leaves dis-eases accuracy founded to be 88.9%. While, Aversano et al [46] works on public plant village dataset to classify diseas-es symptoms in tomato leaves. They used three types of CNN based pre-trained (VGG-19, Xception and ResNet-50) networks for classification and detection of leaves diseases. On the other hand, Ouhami et al [47] build an automat-ic disease detection using Deep Learning pre-trained models such as DensNet161, DensNet121 and VGG16 used for training the tomato leaves diseases dataset. The DensNet161 model achieves high accuracy as compare other used models. Similarly, Kumar and Vani [48] built a mobile application based system for automatically detect tomato leaves diseas-es using CNN based architectures such as LeNet, VGGNet, ResNet50 and Xception on plant village dataset. CNN approach used to train collected dataset and achieved 99.25% overall system accuracy. While, Y.ZHANG et al [49] works on improved Faster RCNN based framework to recognize the multiple tomato leaves disease on laboratory dataset collected from AI-Challenger website. Depth Residual Network used to replace VGG16 framework for diseases feature extraction and image annotation technique used to label the images. Likewise, Prajwala TM et al [50] describes novel framework based on LeNet approach, which helps in diseases classification of tomato leaves from tomato plant healthy or infected images dataset. The extracted features input to the Neural Network ap-proach to train the dataset that determines the type of dis-ease of the infected tomato leave and achieves 94% to 95% accuracy results in diseases classification. While, Ngugia et al [51] presents a CNN approach used to subtract background from plant village leaves diseases dataset. Segmentation network approach used to remove unnecessary background noises from dataset. CNN based KijaniNet network approach used to detect leaves diseases and achieves 0.97% results.
Tomato diseases classification using LTSM and MLP methods research has been conducted by [52], [53]. Hang et al [52] discussed an LSTM model with classification approaches based on vectors to assist the tasks of classification of tomato leaves disease from natural language using 1.12G crawling dataset based on NLP collected from internet agriculture website. While, Abdulridha et al [53] proposed that, UAV-based hy-

perspectral imaging technique that used to recognize and differentiate between TS and BS infected tomato leaves dis-ease on laboratory dataset. Both TS and BS leaves disease has similar symptoms and it's difficult to differentiate the both diseases symptoms. MLP approach applied to classify tomato leaves disease and achieve high performance accu-racy rate 97% to 99%.

Summary Table of Tomato Leaves Disease Detection Using Supervised Deep–Learning Methods

Ref	Author & Year	Pre-processing & Feature Extraction	Methods	Dataset	Results	Limitations
[14]	• G. K. Vianna • S.M.S. Cruz	• Color Filtering • Gray Scale Filtering	• ANN • MLP	**Source** Plant village dataset **Dimensions** Multiple Diseases Class	**Accuracy** 94.24%	N/A
[15]	• Gizelle K. Vianna • Gabriel V. Cunha • Gustavo S. Oliveira & • 2017	• Color Conversion • Mean-Filtering • Normalization • Noise Removal • Background Subtraction	• Pattern Recognition • ANN	**Source** Database images **Dimensions** Approximately 60 images record	**Accuracy** 90%	• Need to improve propose model accuracy
[16]	• Belal A. M. Ashqar • Samy S. Abu-Naser & • 2018	• Multilayer perceptrons designed to require minimal preprocessing • Full-Color Intermediate Activation • Gray-Scale Intermediate Activation	• Deep convolutional neural network	**Source** Public Tomato leaves Data **Dimensions** Approximately 9k images record & Contains five disease categories	**Accuracy** 99.84%	N/A
[17]	• Claudio Cevallos • Hiram Ponce • Ernesto Moya-Albor • Jorge Brieva & • 2020	• Contrast enhancement • Image Resize • Data Augmentation	• Convolutional neural network	**Source** Plant dataset **Dimensions** Approximately 596 images record & Contains four disease categories	**Accuracy** 86.57%	• Need to increase the number of images in the training set to study the robustness of the CNN-model.
[18]	• Mohammed Brahimi • Kamel Boukhalfa • Abdelouahab Moussaouic & • 2017	• Fine-Tuning • Remove Background • Color Space conversion • Gabor Wavelet Transform (GWT) • Gray-Level Co-occurrence Matrix (GLCM)	• CNN	**Source** Plant dataset **Dimensions** Approximately 14,828 images record & Contains Nine disease categories	**Accuracy** 99.18%	• Need to reduce the computation and the size of deep models for small machines like mobiles.
[19]	• Jun Sun • Xiaofei He • Minmin Wu • Xiaohong Wu • Jifeng Shen • Bing Lu & • 2020	• Improved Feature Pyramid Network • Multi-scale feature fusion	• CNN • FPN	**Source** Agricultural greenhouse of Jiangsu University **Dimensions** Approximately 8929 images record	**MAP** 90.7 to 99.5%,	• The technique based on multichannel image fusion will be considered to solve the above problems

[20]	• Thair A. Salih • Ahmed J. Ali • Mohammed N. Ahmed & • 2020	• Color, leaves edge Features • Image Resizing • Normalization	• Deep Convolutional Neural Network	**Source** Plant Village Dataset **Dimensions** Approximately 5k images record & Contains Five disease categories	**Accuracy** 96.43%	• There is no rule for determining the number of images to the training network, but a lot of images in the dataset will increase network efficiency.
[21]	• Azeddine Elhassouny • Florentin Smarandache & • 2019	N/A	• Deep Convolutional Neural Network	**Source** Database **Dimensions** Approximately 7176 images record & Contains Ten disease categories	**Accuracy** 90.03%	• To improve tomato diseases identification accuracy, we still need to provide thousands of high quality tomato diseases images samples.
[22]	• QIUFENG WU • YIPING CHEN • JUN MENG & • 2020	• Data Augmentation • Fine-Tuning	• Deep convolutional generative adversarial networks (DCGAN)	**Source** Plant Village Dataset **Dimensions** Approximately 1500 images record & Contains Ten disease categories	**Average Accuracy** 94.33%	N/A
[23]	• Onyeka Emebo • Barka Fori • Geteloma Victor • Temidayo Zannu & • 2019	• Image Labeling • Contrast Enhancement	• Deep Convolutional Neural Network	**Source** Plant Village Dataset **Dimensions** Approximately 643 images record	**Training Accuracy** 99.02% **Validation Accuracy** 99.01%	• Build a tensorflow lite versions of such models so they can run on mobile devices as this will give these farmers the tools at their hands to make diagnosis in a familiar interface and assuming the cost of good smart phones drops to compete with the raspberry pi.
[24]	• Robert G. de Luna • Elmer P. Dadios • Argel A. Bandala & • 2020	• Image Enhancement • Normalization • Color Conversion • Anomaly Detection	• CNN • F-RCNN • Alexnet	**Source** Tomato plant leaves **Dimensions** Approximately 4,923 images record & Contains four disease categories	**Accuracy** 91.67%	• Need to improve the overall system accuracy.
[25]	• Jun LiU • Xuewei Wang & • 2020	• Data Annotation • Color Conversion	• MobileNetv2-YOLOv3 neural network	**Source** China Agriculture Field Data **Dimensions** Approximately 2,385 images records	**F1 Source** 93.24% **AP values** 91.32%	• This work only detect tomato gray leaf spot disease. Other kinds of common diseases exist in tomato.

[26]	• Iftikhar Ahmad • Muhammad Hamid • Suhail Yousaf • Syed Tanveer Shah • Muhammad Ovais Ahmad & • 2020	• Histogram Equalization • Parameter-Tuning • subtraction of the mean RGB value • Contrast Enhancement	• CNN • VGG-16 • VGG-19 • ResNet • Inception V3	**Source** Laboratory Data **Dimensions** Approximately 2,364 images record & Contains four disease categories	**F1 Score** 0.995% **Recall Score** 0.994%	• A natural extension of our work will be to optimize these models for better performance on real-world field based data.
[27]	• Endang Suryawati • Rika Sustika • R. Sandra Yuwana • Agus Subekti • Hilman F. Pardede & • 2018	N/A	• Convolutional neural network(two layers) • AlexNet (five layers) • VGGNet (13 layers) • GoogleNet	**Source** Plant Village Dataset **Dimensions** Approximately 18k images record & Contains Ten plant disease categories	**Base-line** 84.58% **Alex-Net** 91.52% **Google-Net** 89.68% **VGG-Net** 95.24%	• Need to implement the knowledge transfer process from the tomato model to the other plants model.
[28]	• Halil Durmuú • Ece Olcay Güneú • Mürvet KÖrcÖ • 2017	• Image Segmentation • Noise Removal	• CNN • AlexNet • SqueezeNet	**Source** Plant Village Dataset **Dimensions** Approximately 54.309 images record & Contains Ten disease categories	**AlexNet Accuracy** 0.9565% **SqueezeNet Accuracy** 0.943%	• Need to extract leaf from the complex background to complete the system.
[29]	• Lilian Mkonyi • Denis Rubanga • Mgaya Richardc • Never Zekeya • 2020	• Image labeling • Image Resizing • Augmentation	• CNN • VGG16 • VGG19 • ResNet50	**Source** Plant dataset **Dimensions** Approximately 2145images record & Contains four disease categories	**Accuracy** 91.9%	• Need to collect real-time for disease classification.
[30]	• Jia Shijie • Jia Peiyi • Hu Siping • Liu Haibo • 2017	• Fine-Tuning • Contrast Enhancement	• CNN • VGG16 • SVM	**Source** China dataset **Dimensions** Approximately 7040 images record & Contains 11 disease categories	**Accuracy** 89%	• Need to detect tomato pests and diseases based on relative low quality leaf images.
[31]	• Ding Jiang • Fudong Li • Yuequan Yang • Song Yu • 2020	• Image Enhancement • Gaussian noise and Affine transformation	• CNN • Resnet-50 • Leaky-ReLU activation function	**Source** AI Challenger dataset **Dimensions** Approximately 6794 images record & Contains three disease categories	**Training Set Accuracy** 98.3% **Testing Set Accuracy** 98%	• Need to use a multiple diseases classification model.

[32]	• Siti Zulaikha Muhammad Zaki • Mohd Asyraf Zulkifley • Marzuraikah Mohd Stofa • 2020	• Fine-Tune	• CNN • MobileNet V2	**Source** Plant Village dataset **Dimensions** Approximately 4,671 images record & Contains three disease categories	Accuracy 90%	• Need to use different classes in the Plant Village instead of just three diseases.
[33]	• Li Zhang • Jingdun Jia • Yue Li • Wanlin Gao • Minjuan Wang • 2019	•Image Labeling •Data Augmentation •EDSR	• CNN • Super-resolution network (EDSR) model	**Source** Plant Dataset **Dimensions** Approximately 1000 images record & Contains 11 disease categories	**Accuracy** 81.11%	• Need to optimize the CNN based identification architecture of improved identification accuracy and reduce model size.
[34]	• Ayesha Batool • Syeda Basmah Hyder • Aymen Rahim • 2020	• Image Segmentation • Texture Features • Normalization • GLCM	• Convolutional layer • KNN • AlexNet	**Source** Plant dataset **Dimensions** Approximately 450 images record & Contains nine disease categories	**Accuracy** 76.1%	• Ned to use another pre-trained model to evaluate the performance of the proposed algorithm.
[35]	• Xiao Chena • Guoxiong Zhoua • Aibin Chena • Jizheng Yia • 2020	• Binary Wavelet Transform • Image Enhancement • Noise Removal • Texture Feature	• ABCK-BWTR • B-ARNet	**Source** Plant Dataset **Dimensions** Approximately 8,616 images record & Contains five disease categories	**Accuracy** 89%	• Improve the recognition effect of tomato diseases especially similar diseases under the complicated background
[36]	• Tao Zhang • Xiankun Zhu • Yiqing Liu • Kun Zhang • Azhar Imran & • 2018	• Augmentation • Gaussian distributed additive noise	• CNN • ResNet • SE-ResNet	**Source** AI Challenger dataset **Dimensions** Approximately 11k images record & Contains disease 27 categories	**Accuracy** 88.83%	N/A
[37]	• Akbar Hidayatuloh • M. Nursalman • Eki Nugraha & • 2018	• Scaling and normalization	• CNN • Squeezenet architecture	**Source** Vegetable Crops Research Institute (Balitsa) in Lembang **Dimensions** Approximately 1400 images record & Contains Seven disease categories	**Accuracy** 86.92%	• Increasing the number of epochs or adjusting the configuration parameters used and by increasing the amount of data used to improve data quality better.

[38]	• Sawsan Morkos Gharghory & • 2020	• Image Enhancement • Color Conversion • Filtering	• CNN • SqueezeNet • VGG -16 Net • AlexNet	**Source** Plant Village Dataset **Dimensions** Multiple Diseases Classes	**Accuracy** 97.4%	• Internet of Things and mobile applications are suggested with the deep learning CNN to identify and classify the plant diseases type.
[39]	• Jun Liu • Jie Pi • Liru Xia • 2020	• Image Resizing • Image Labeling	• DenseNet deep neural network architecture • Focal loss function	**Source** Northwest Agricultural University **Dimensions** 712 positive samples and 812 negative samples	**Accuracy** 91%	• Need to transplant the network model under the existing hardware platform.
[40]	• Jun Sun • Xiaofei He • Xiao Ge • Xiaohong Wu • Jifeng Shen • Yingying Song • 2018	• Image Labeling • Normalization • Texture Features	• CNN • RCNN • Resnet-50	**Source** Agricultural digital greenhouse of Jiangsu University **Dimensions** Approximately 5624 images record	**MAP** 85.2% to 90.7%	• Need to use a real-time dataset.
[41]	• V. Tsironis • S. Bourou • C. Stentoumis • 2020	• Object Detection • Statistical Analysis • Histogram	• CNN • R-CNN • Fast RCNN • Mask R-CNN • YOLOv3	**Source** Internet Dataset **Dimensions** 277 images and 2418 annotations	**MAP** 66.66%	N/A

[42]	• Santosh Adhikari • Bikesh Shrestha • Bibek Baiju • 2018	• Region of Interest • Data Annotation • Data Augmentation	• CNN • YOLO • Alexnet	**Source** authenticated online source **Dimensions** Approximately 520 images record & Contains three disease categories	**Accuracy** 89%	• Detect all types of plant diseases, not only detection but also suggesting remedies for diseases.
[43]	• Nithish kannan E, • Kaushik M, • Prakash P, • Ajay R, • Veni S • 2020	• Data Augmentation • Fine-Tuning • Contrast Enhancement • Color Conversion • Scaling	• CNN • ResNet-50	**Source** vast repository of PlantVillage **Dimensions** Approximately 12,206 images record	**Accuracy** 97%	• However, the training of the model requires high configuration hardware due to the number of layers present in the ResNet 50 model.
[44]	• Mohit Agarwala • Abhishek Singhb • Siddhartha Arjariac • Amit Sinhad • Suneet Guptaa & • 2019	• Data Augmentation	• CNN • VGG16, • InceptionV3 • MobileNet	**Source** Online Plant Village Dataset **Dimensions** Approximately 10k images record & Contains Ten disease categories	**Average Accuracy** 91.2%	• Need to improve the same model on same dataset, as testing accuracy is less.
[45]	• Charmaine Llorca • May Elsbeth Yares • Christian Maderazo & • 2018	• Data Augmentation	• CNN • Google's Inception-V3	**Source** Cornell's College of Agriculture and Life Sciences **Dimensions** Approximately 2,779 images record	**Average Accuracy** 88.9%	• Improving some of the steps in retraining the model such as increasing the number.

[46]	• Lerina Aversano • Mario Luca Bernardi • Marta Cimitile & • 2020	• Image Enhancement • Normalization	• CNN • VGG-19 • ResNet-50 network • Xception	**Source** Public Plant Village Dataset **Dimensions** Approximately 16k images record	**Xception Accuracy** 0.94% **VGG-19 Accuracy** 0.97%	• Extend the dataset to work on, using a greater number of classes, and improve the precision of the models.
[47]	• Maryam Ouhami • Youssef Es-Saady • Mohamed El Hajji & • 2020	• Fine-Tune	• CNN • DensNet-161 and 121 • VGG16	**Source** Database Images **Dimensions** Approximately 666 images record & Contains Multiple Diseases Class	**DensNet-161 Accuracy** 95.65% **DensNet-121 Accuracy** 94.93% **VGG16 Accuracy** 90.58%	• In our future works, we will try to improve the results, increase the dataset size and address more challenging diseases detection problems.
[48]	• Akshay Kumar • Vani M. • 2019	• Segmentation • Color Conversion	• CNN • LeNet model (2 convolution layers) • VGG16 (13 convolution layers) • ResNet50 • Xception (36 convolution layers)	**Source** Plant Village Dataset **Dimensions** Approximately 14,903 images record	**LeNet** 91.50% **VGG16** 99.11% **ResNet-50** 97.55% **Xception** 97.11%	• The training consumes much time and requires high-end hardware configuration.
[49]	• YANG ZHANG • CHENGLONG SONG • DONGWEN ZHAN & 2020	• Image annotation tool LabelImg	• F-RCNN • Depth residual network • K-mean clustering algorithm	**Source** AIChallenger Laboratory Data **Dimensions** Approximately 4,178 images record & Contains four disease categories	**Probability** 0.995%	• Need to include images of natural plants that should be collected for detection.
[50]	• Prajwala TM • Alla Pranathi • Kandiraju Sai Ashritha • Nagaratna B. Chittaragi & • 2018	• Noise Removal • Image Resizing • Normalization	• Convolutional Neural Networks	**Source** Plant Village repository **Dimensions** Approximately 18160 images record	**Average Accuracy** 94-95%	N/A
[51]	• Lawrence C. Ngugia • Moataz Abelwahaba • Mohammed Abo-Zahhada & • 2020	• Segmentation • Background subtraction • Noise Removal • Gray Scale Conversion • Normalization • Data Augmentation	• Convolutional neural network	**Source** Field Dataset **Dimensions** Approximately 1,408 images record & Contains five disease categories	**mwIoU** 0.97% **mBFScore** 0.94%	• Need to extend the capability of the proposed CNN models to perform background removal on leaf images for other crops

[52]	• Xiao Hang • Hongju Gao • Shaopeng Jia & • 2020	• Statistical Analysis	• Skip-gram algorithm • LSTM	**Source** Internet data **Dimensions** Approximately data set of 1.12G pathological and healthy tomatoes crawled record	**Accuracy** 60%	• Need to improve propose model accuracy.
[53]	• Jaafar Abdulridha • Yiannis Ampatzidis • Sri Charan Kakarla • Pamela Roberts & • 2020	• Image Enhancement • Filtering • Noise Removal • Texture Features	• UAV-based hyperspectral imaging technique • MLP	**Source** Laboratory Dataset **Dimensions** Approximately 2k images record	**MLP Average Accuracy** 97–99%	• Need to use segmentation approach

4.1.3 A Review on Un-Supervised Machine-Learning Methods for Tomato Diseases Detection

Un-Supervised Machine Learning Clustering and Spectral methods has been very famous and used in past by many researchers [54], [56], [57], [58], [60], [62]. K. Tian et al [54] discussed an improved K-means framework based on adaptive clustering approach for the segmentation of tomato leaves disease on greenhouse tomato leaves dataset. The proposed approach highly improved performance accuracy of K-means clustering method. Similarly, Y. W. TIAN et al [56] build a tomato leaves disease detection system based on android application using Fuzzy C-means clustering approach used to extract tomato leaves disease spot. Experiment results proves that the system of greenhouse tomato leaves disease index measured accurate, non-destructive, and error was small and saved time. Whereas, Jeong-Hyeon Park et al [57] proposed the novel framework based on enhanced k-means clustering, which enables to investigate and analyze the tomato leaves image taken by image camera and detect or classify the infected area within the image. The edge detection and edge-tracking scheme used to decide whether the extracted areas are located in inside of leaf or not. Comparatively, Wang et al [58] discussed an OR-AC-GAN based multiple tomato leaves disease recognition system on plant village dataset collected from internet. Set of important texture features extracted using statistical analysis and MVPCA approach. While, Xu et al [60] discussed a near-infrared based spectroscopy system that used to detect leave miner diseases on tomato plants collected from chine Greenhouse University. SW-NIR approach applied to train and test dataset. The proposed system achieves 60% accuracy results. On the other hand, Lu et al [62] works on hyperspectral image based system to recognize yellow tomato leaves disease from plant diseases dataset. COR_MEAN thresholding approach used to validate the dataset. The proposed system gives 100% accurate results.

Summary Table of Tomato Leaves Disease Detection Using Un-Supervised Machine-Learning Methods

Ref	Author & Year	Pre-processing & Feature Extraction	Methods	Dataset	Results	Limitations
[54]	• Kai Tian • Jiuhao Li • Jiefeng Zeng • Asenso Evans • Lina Zhang & • 2019	• Image Segmentation • Background Removal • K-means • Fuzzy C-means Feature extraction	• Adaptive clustering • K-means algorithm	**Source** China Agricultural University Greenhouse dataset **Dimensions** Approximately 1k images record	**F1 Score** 0.765% **Entropy** 0.643%	• The main drawback of this method is that it requires more computation to calculate the validity index
[56]	• YOU-WEN TIAN • PENG-HUI ZHENG • RUI-YAO SHI & • 2016	• Image segmentation • Adopted threshold segmentation • Iterative threshold segmentation	• Fuzzy C-means cluster algorithm • Segmentations	**Source** NO.22 greenhouse of North Mountain vegetable base in Shenyang Agricultural University **Dimensions** Approximately 43 images record	**Accuracy** 0.87%	N/A
[57]	• Jeong-Hyeon Park • Sung-Keun Lee & • 2019	• Edge detection and edge tracking scheme • Thresholding • Segmentation • Filtering	• Enhanced k-means clustering	**Source** Tomato farm near Suncheon Bay **Dimensions** Contains Multiple diseases Classes	**Mean Average Precision (MAP)** 0.84%	• Need to improve disease recognition accuracy.
[58]	• DongyiWang • RobertVinson • Maxwell Holmes • YangTao & • 2019	• MVPCA • Segmentation • FDPC • Noise Removal	• Generative adversarial nets (GAN) • OR-AC-GAN	**Source** Plant dataset **Dimensions** Contains Multiple disease categories	**Accuracy** 96.26%	N/A
[60]	• H.R. Xu • Y.B. Ying • X.P. Fu • S.P. Zhu & • 2007	• Wavelet composition • Texture features • Statistical analysis	• Near-infrared Spectroscopy • SW-NIR	**Source** Greenhouse university Dataset **Dimensions** Multiple disease categories	**Accuracy** 60%	N/A
[62]	• Jinzhu Lu • Mingchuan Zhou • Yingwang Gao & • 2017	• Image Enhancement • Background noise Removal • Segmentation • 24 texture features extracted using GLCM	• COR_MEAN Thresholding • ROC • AUC	**Source** Plant dataset **Dimensions** Multiple diseases classes	**Accuracy** 100% good results	• Need to develop multiple spectral imaging system for tomato diseases detection.

4.1.4 A Review on Hybrid Methods for Tomato Diseases Detection

Tomato leaves disease detection using hybrid approach conducted by many researchers [63], [64], and [65]. M. Z. Din et al [63] describe hybrid framework based on clustering and SVM for identification of tomato leaves disease. Image based segmentation applied using k-means clustering approach. After segmentation, set of texture features extracted using GLCM. SVM classifier used to classify four different types of tomato leaves disease from database with high accuracy 98.3%. While, C. K. Sampoorna et al [64] works on image processing based framework used for differentiating the plant leaves disease. The collected dataset pre-processed using Otsu segmentation approach and then CNN, SVM & K-means applied for diseases classification. The proposed system accuracy were increasing 15% as compared to other systems. Whereas, Madhavi Patil et al [65] discussed a CNN based classification framework to classify tomato leaves diseases. Image based segmentation applied on preprocessed tomato leaves images and divided into different number of clusters using K-means clustering approach. Then CNN approach used to train and test the collected pre-processed dataset. After the training and testing model, the Mean Average Precision (MAP) founded to be 0.76.

Summary Table of Tomato Leaves Disease Detection Using Hybrid Methods

Ref	Author & Year	Pre-processing & Feature Extraction	Methods	Dataset	Results	Limitations
[63]	• M. Z. Din • S. M. Adnan • W. Ahmad • S. Aziz , J. Rashid • W. Ismail • M. J. Iqbal & 2018	• Image Segmentation • Filtering • Multi- • Thresholding • Texture feature extraction • GLCM feature Extraction	• SVM Classifier	**Source** Online Plant Village dataset **Dimensions** Approximately 200 images record & Contains four disease classes Healthy, Bacterial Spot Images, Early Blight Images, and Spider Mites.	**Accuracy** 98.3%	• Need to include shape and color based features along with texture features in order to get even better performance.
[64]	• C. K. Sampoorna, K. Rasadurai & • 2020	• Noise Removal • Image segmentation • Otsu segmentation • K-means Clustering • Color feature extraction	• K-means Clustering • Neural network • SVM	**Source** Database images **Dimensions** Contains four Diseases Categories	**Recall** 13.82% **Sensitivity** 13.78% **Specificity** 100%	N/A
[65]	• Prof. Madhavi Patil • Gaurav Langar • Purvi Jain • Nikhil Panchal & • 2020	• Color Conversion • Filtering • Image Segmentation • Image Smoothing • K-means clustering	• Convolutional Neural Networks(CNNs)	**Source** Database **Dimensions** Approximately 520 images record & Contain Two Diseases Categories	**Mean Average Precision (MAP)** 0.76%	• Need to develop a mobile-based app, which is useful for farmers as proper guide to do agriculture.

4.2 Cotton Diseases Classification

In this section, cotton diseases classification methods mentioned in previous setecion III will be discus in details.

4.2.1 A Review on Supervised Machine-Learning Methods for Cotton Diseases Detection

In this section, Supervised Machine-Learning methods mentioned in previous section III will be discuss in details. Machine Learning has been very famous and used in past by many researchers [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83].

Prashar et al [66] proposed hybrid framework based on ACDR and SVM to identify and classify cotton leaves diseases present on the cotton plants. Robust automatic cotton crop diseases recognition approach has been proposed using the different invariant feature descriptors with the support vector machine. The performance comparison has been completed by submitting the query image randomly selected from the train-

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ing database and using the standard training database created for the disease recognition. The experimental results have proved the efficiency of the various feature descriptors in terms of rate of accurately detected samples. While, Dubey et al [67] proposed a novel framework based on Machine Learning SVM method for cotton leaves diseases classification and recognition using iterative clustering and roughness measure concept. The dataset are individually input and trained using SVM approach. Preprocessed images are stored into database for classification and achieved good accuracy 94% results. Whereas, Sarangdhar and Pawar [68] built a mobile application for cotton leaves diseases recognition and classification using Machine Learning based Regression approach. SVM based regression used to detect five different types of cotton leaves diseases. The overall accuracy of SVM classifier for cotton diseases classification are 83.26%. Similarly, Patil and SZambre [69] discussed a novel framework based on Machine Learning SVM approach for identification and classification of the cotton leaves spot disease present on the cotton plants. Cotton leaves images preprocessed by using Image Processing techniques such as Grayscale conversion, segmentation, and Morphological operations. From these preprocessed images, features were extracted using Shape features, color features, Statistical analysis and Texture features. SVM approach used for identification of cotton leaves diseases and achieved 97% accuracy results. Comparatively, Prashar and Talwar [70] described a novel framework based on SVM to identify and classify which of the cotton leaves disease on digital camera images. Propose model overall achieved 85% accuracy for each image disease detection. However, the proposed approach still need to improve the classification result by using latest deep learning pre-trained methods.

On the other hand, Sivasangar and Indira [71] proposed novel framework based on SVM with genetic algorithm to identify and classify of the cotton leaves disease on digital camera images. Adaptive thresholding morphological operations used to detect edges of diseases images. The separation of feature vectors separated by using SVM and classified by using genetic algorithm. Then features extracted images are stored into database and classified using Backpropagation Neural Network. . The proposed framework successfully implemented with an accuracy of more than 99.3 % for leaves disease classification and detection. While, Thara et al [72] works on mobile-based system for recognition and controlling the cotton leaves diseases using Machine Learning framework. Image based segmentation and Gaussian based filtering techniques applied on collected dataset from database images. The overall accuracy of SVM classifier for cotton diseases classification are 83.26%. Relatively, Rothe and Kshirsagar [73] described a novel framework based on Machine Learning SVM approach for identification of cotton leaves diseases in cotton plant dataset. Dataset images are preprocessed using Otsu's Segmentation approach and then classified using SVM classifier. The overall accuracy of SVM classifier for cotton diseases classification are 90%. Likewise, Patki and Sable [74] proposed a novel framework based on Machine Learning classifier such as Multi-Support Vector Machine to identify and classify cotton leaves diseases. The database images divided into training and testing phase according to 60-40 pattern for each class. The overall recognition and classification accuracy obtained for the system are 87.5%.

KNN method has been very famous and used in past by many researchers [75], [76], [77], [78]. Prashar et al [75] built an expert system to solve the agriculture related problems more accurately and efficiently. KNN classifier used to recognize cotton leaves diseases. MLP technique utilized for overlapping pooling with different layers to classify infected leaves diseases. Overall classification accuracy for diseases detection more than 96%. Whereas, V. A. Gulhane and Kolekar [76] proposed a hybrid framework based on Principle Component Analysis (PCA) and Nearest Neighborhood Classifier (KNN) to diagnose related diseases problems in cotton leaves. PCA classifier used to extract most useful features from diseases images. The classification accuracy of leaves diseases are 95%. Similarly, Parikh et al [77] proposed a novel framework based on Neural Networks approaches such as Backpropagation neural network and a Multi-layered feed-forward network for cotton leaves disease classification. Image-based segmentation used to remove background from images. Set of texture features extracted using local statistical analysis approach. On the other hand, Sabah Afroze et al [78] discussed a novel framework based on KNN classifier to identify and classify which of the cotton leaves disease present on the cotton plants. Dataset images pre-processed using adaptive histogram equalization approach and normalization process, Difference of Gaussian (DoG) approach applied on equalized images.

Fuzzy-logic and Decision-tree methods has been very famous and used in past by many researchers [79], [80], [81] [82], [83]. Mr.Chandrakant et al [79] works on pattern based recognition system for identification of leaves disease. Image based Segmentation applied using Active Contour approach and features are extracted using Hus moments. Adaptive Neuro-Fuzzy system used for training the diseases dataset. The overall pattern recognition system achieves 85% accuracy. While, Rothe and Kshirsagar [80] discussed an Adaptive neuro fuzzy inference system to identify and classify the cotton leaves disease on digital camera images collected from research center. The important objects separated from preprocessed images using segmentation Graph cut method and the color features are extracted using Zigzag scanning. Then neural network used to classify diseases with the help of the training dataset and improved the system performance. Relatively, Yan-Cheng Zhang et al [81] discussed fuzzy selection based Fuzzy-Curves (FC) and Surfaces (FS) approaches used to recognize cotton diseases. Fuzzy feature-selection technique used to extract best set of features and Fuzzy curves used to isolate the important features and reduce incorrect features. Then Fuzzy surfaces used to gather the important dependent features for leaves diseases classification. Whereas, Chopda et al [82] discussed a novel framework based on Machine Learning Decision Tree classifier to identify which of the cotton crop leaves disease present on the cotton plants. User provide real-time data to server and then server authenticates the received data. After authentication, Decision Tree classifier used to predict cotton diseases and display it to user panel. On the other hand, Ajay A. Gurjar [83] proposed a novel approach based on regularizes and extracts eigenfeature to recognize the cotton leaves disease present on the cotton plants. Scatters matrix used within class type and these matrixes decomposed into various subspaces. Propose model overall achieved 90% accuracy for each image disease detection.

Summary Table of Cotton Leaves Detection Using Supervised Machine-Learning Methods

Ref	Author & Year	Pre-processing	Features	Methods	Dataset	Results	Limitations
[66]	• Kapil Prashar • Dr. Rajneesh Talwar • Dr. Chander Kant & • 2017	• Matrix form conversion • Resize image • Grayscale conversion • Diagnosing Filter • Gaussian filter	• Color oriented feature descriptor • Histogram of oriented gradients (HoG)	• SVM • Automatic Cotton Disease Recognition (ACDR)	**Source** cotton farms **Dimensions** Approximately 200 images record	**Accuracy** 85%	• Need to enhance proposed model for the multipurpose and multi-level supervised classification by using the multiple machine learning models for the ACDRs.
[67]	• Yogita K. Dubey • Milind M. Mushrif • Sonam Tiple & • 2018	• Histogram • Roughness Measure • Super pixel Segmentation • Simple linear iterative clustering (SLIC) algorithm	• Texture extract • Extract patterns • Gray level co-occurrence matrix (GLCM)	• SVM (supervised ML approach)	**Source** Database **Dimensions** Approximately 100 images record Contains four diseases classes	**Accuracy** 94%	N/A
[68]	• Adhao Asmita Sarangdhar • Prof. Dr. V. R. Pawar & • 2017	• Remove noisy data • Image Enhancement • Resizing and filtering images • Segmentation • Thresholding • Color mapping	• Region of interest (ROI) • Partial least square regression(PLSR) • Eight color and texture features extracted • Color feature extraction	• SVM based regression approach (supervised ML approach) • IOT devices	**Source** Database **Dimensions** Approximately 900 images record & Contains five diseases classes	**Accuracy** 83.26%	N/A
[69]	• Prof. Sonal P. Patil • Ms. Rupali S.Zambre & • 2017	• Image Enhancement • Grayscale conversion • Image segmentation • Gray-level Thresholding • Morphological operations	• Shape feature extraction • Color feature extraction • Statistical analysis • Texture feature extraction-GLCM(not confirm)	• Support vector Machine (SVM)	**Source** Database **Dimensions** Multi class diseases	**Accuracy** 97.2%	• Need to use hybrid model for real-time classification

[70]	• Kapil Prashar • Rajneesh Talwar • Chander Kant • P.P.S.Pannu & • 2018	• Difference of Gaussian (DoG) • Difference of Hessians (DoH) • Histogram of oriented gradients (HoG)	• Color, Shape and texture features • Scale Invariant Feature Transform (SIFT) • Speeded Up Robust Features (SURF) and Fast Retina Keypoints (FREAK)	• SVM Classifier	**Source** Database **Dimensions** Approximately 200 images record & Contains three diseases classes	**Accuracy** 85%	• Need to improve the deep learning using the neural network along with the shape and curve based features, which can further improve the performance of the script recognition.
[71]	• A.Sivasangari • K.priya & • 2017	• Adaptive thresholding • Morphological operators(edge detection) • HSV model • Segmentation	• Feature selection using Edges, color and shape	• SVM with genetic algorithm • A genetic algorithm determines the number of clusters.	**Source** Mobile camera images **Dimensions** Multiple Disease classes	**Accuracy** 0.993%	N/A
[72]	• Thara D.K • Sehla Saba • Vaishnavi S & • 2018	• Remove unwanted data • Color conversion • Median filter (remove noise) • Segmentation • Thresholding • Region Of Interest (ROI)	• Total eight color and texture features are extracted in present system using Partial Least Square Regression (PLSR).	• SVM based regression technique with non-linear Gaussian kernel	**Source** Database **Dimensions** Approximately 900 images record & Contains three disease classes	**Accuracy** 83.26%	N/A
[73]	• P.R. Rothe • Dr. R. V. Kshirsagar & • 2014	• Un-sharp filtering • Otsu's segmentation method	• Color • Shape • Texture	• SVM Classifier	**Source** Database **Dimensions** Multiple Disease Classes	**Accuracy** 90%	• Need to improve propose model efficiency by using hybrid model for real-time classification
[74]	• Supriya S. Patkil • Dr. G. S. Sable & • 2016	• Image Enhancement • Image Segmentation • Thresholding	• Extract color and texture features • Color-co-occurrence • Gray Level Co-occurrence Matrix (GLCM)	• Multi-SVM	**Source** Database images **Dimensions** Approximately 103 images record & Contains four diseases classes	**Accuracy** 87.5% and 2.1sec time.	N/A

[75]	• Kapil Prashar • Rajneesh Talwar • Chander Kant • & • 2019	• Image Enhancement • Labeling data • Image segmentation of color variations	• Extract GLCM features • Extract HOG features • Binarized mask • Feature intensities • Extract Histogram features	• Support Vector Machine (SVM) • Neural Network with Multi-layer Perceptron's • K-nearest Neighbor (KNN)	**Source** Database **Dimensions** Approximately 40 images record	**Accuracy** 96%	• Need to improve the time parameter, which is significantly higher and can increase the overall classification delay in the real-time systems.
[76]	• Viraj A. Gulhane • Maheshkumar H. Kolekar & • 2014	• Image enhancement • Gray Scale Conversion	• By using PCA extract most significant features from images	• PCA classifier • KNN Classifier	**Source** Database **Dimensions** Approximately 110 images record & Contains Six Disease classes	**Accuracy** 95%	• Need to design more robust classifier considering features like texture, leaf shape.
[77]	• Aditya Parikh • Mehul S. Raval • Chandrasinh Parmar • Sanjay Chaudhary & • 2016	• Leaves Segmentation • Hue and luminance from HSV colour space • Adaptive Thresholding	• Local statistical features • Texture features • Gray-level Co Occurrence matrix	• KNN Classifier	**Source** University Lab **Dimensions** Approximately 200 images record	**Accuracy** 82.5% **Classification Time** 155 sec per image	• One of the main issues plaguing the research in this direction is lack of available labelled data set in unconstrained conditions.
[78]	• A.Sabah Afroze • M. Parisa Beham • R. Tamilselvi • S.M. Seeni Mohamed Aliar Maraikkayar & • 2019	• Reduce noise • Adaptive histogram equalization (AHE) • Difference of Gaussians (DoG)	• Local Binary Pattern • Histogram of Gradient (HoG) • Local Binary Pattern(LBP) • Histogram of oriented gradient (HoG)	• K-NN classifier	**Source** Internet images **Dimensions** Approximately 185 images are collected & Contains five disease classes	**Accuracy** 99.6%	• Need large set of database used to validate the efficiency of algorithm.
[79]	• Mr. Chandrakant Deelip Kokane • Prof. N.L.Bhale & • 2017	• Image Segmentation • Active contour model	• Hus moments	• Adaptive neuro-fuzzy inference system	**Source** Central Institute of Cotton Research Nagpur **Dimensions** Multiclass disease Classes	**Accuracy** 85%	• Need to improve propose model accuracy.

[80]	• P.R. Rothe • Dr. R. V. Kshirsagar & • 2014	• Image enhancement • Un-sharp filter • Laplacian filter • Image segments • Graph cut approach	• Color feature extraction • Image partitioning • Representative color selection • DCT transformation and Zigzag scanning.	• Adaptive neuro fuzzy inference system	**Source** Digital camera images **Dimensions** Multiple Disease Classes	**MAP** 0.78%	N/A
[81]	•YAN-CHENG ZHANG •HAN-PING MAO •BO HU •MING-XI LI & •2007	N/A	• Statistical analysis • Texture features	•Fuzzy Feature Selection •Fuzzy curves (FC) and Surfaces (FS)	**Source** Database images **Dimensions** Multiple Disease Classes	**MSE** 0.139	• Need to develop real-time application by using hybrid model.
[82]	• Jayraj Chopda • Hiral Raveshiya • Sagar Nakum & • 2018	•Image Enhancement •Transformation	N/A	• Decision tree classifier • Machine Learning	**Source** Real time temperature data to server **Dimensions** Multi class diseases	Performed statistical experiments	• Need to build an Android Application.
[83]	• Ajay A. Gurjar • Viraj A. Gulhane & • 2012	•Color Conversion •Filtering	• Eigenfeature regularization • Eigen space • Transformation • Extraction matrix • Texture feature	• EIGEN SPECTRUM	**Source** Database **Dimensions** Approximately 50 images record August to December 2011	**Accuracy** 90%	N/A

4.2.2 A Review on Supervised Deep-Learning Methods for Tomato Diseases Detection

ANN approach has been very famous and used in past by many researchers [84], [85], [86], [87], [88], [89]. M. Gulhane and Gurja [84] described a novel framework based on ANN to identify and classify the cotton leaves disease. Color-based segmentation technique used to extract the intensity of pattern to several leaves disease consequently and then it's used to analyze the N numbers of cotton diseases. The overall recognition accuracy of proposed approach founded to be 85% to 91%. Relatively, Malvika Ranjan et al [85] proposed a novel framework based on ANN that help to detect and classify the multiple diseases of cotton leaves and provide an optimal solution to farmers. Color feature such as HSV features extracted from result of segmented images. ANN approach used to train the collected dataset and classification accuracy founded to be 80%. Whereas, Shah and Jain [86] works on cotton leaves diseases detection and classification using ANN framework. In the proposed solution, Image preprocessing techniques used for image segmentation then set of important texture and shape features extracted from the preprocessed images. The proposed solution provides accuracy up to 90%. Comparatively, Wankhade and Agrawal [87] discussed a novel framework based on Generalized Feed Forward (GFF) Neural Networks to detect the cotton leaves diseases. Cotton leaves images preprocessed by using image-processing techniques and set of important features were extracted using WHT or statistical techniques. Then GFFNN approach used for classification of disease and achieved 100% accuracy results. Likewise, Revathi and Hemalatha [88] proposed a novel framework based on Neural Network to automatically recognize the leaves diseases from tomato plant dataset collected from internet. PSO approach applied to extract important features (i.e. shape, texture, color). The feature selection approach used to detect the injured leaves spot of cotton. The overall accuracy of proposed approach for classification of leaves disease founded to be 95%. On the other hand, Rothe and Kshirsagar [89] proposed a novel framework based on Neural Networks to recognition the multiple types of leaves disease on database images collected form Research Center. The classification method performed by using Back Propagation Neural Networks and Feed-Forward Back Propagation Network. These Neural Network approaches used to solve the multiple class problem without using any type of explicit function. The average accuracy of classification method is 85.52%.

Tomato diseases classification and detection using Deep-Learning famous CNN framework conducted by many researchers [90], [91], and [92]. Kumbhar et al [90] developed a web based application using CNN approach to recognize crop diseases and displays user the results as detected disease, pesticides recommended and cost of pesticides recommended, and for that user have to upload an image then, Image processing are used to digitized the color image of the diseased leaves. While, Udawant and Srinath [91] discussed a novel framework based on CNN approach used for classification of the diseased portion of cotton plant images. Dataset images preprocessed by using image-processing techniques such as image enhancement, color transformation, object detection, and so on. Propose model overall achieved 97% accuracy for each image disease detection. Similarly, Jenifa et al [92] proposed a novel framework based on Deep Convolutional Neural Network to identify cotton leaves disease automatically. The data individually input and trained in this method. Propose model overall achieved 96 % accuracy. However, the proposed approach are not able to classify all types of leafs disease. Moreover, the proposed model is unable to detect real-time leaf disease.

Summary Table of Cotton Leaves Disease Detection Using Supervised Deep-Learning Methods

Ref	Author & Year	Pre-processing	Features	Methods	Dataset	Results	Limitations
[84]	• Mr. Viraj A. Gulhane • Dr. Ajay A. Gurjar & • 2011	•Image Enhancement •Color conversion •Segmentation	• Texture feature • Shape feature	• Image processing • ANN	**Source** Database **Dimensions** Approximately 200 images record	**Average Accuracy** 90.5%	• Need to develop a real-time application using this method
[85]	• Malvika Ranjan • Manasi Rajiv Weginwar • Neha Joshi • Prof. A.B. Ingole & • 2015	•Image Enhancement •Gray scale conversion •Thresholding	• Color feature • Shape features • RGB to HSV • HSV feature extraction • Feature matrix	• ANN classifier	**Source** Database images **Dimensions** Multiple disease classes	**Accuracy** 80%	• Need to improve propose model accuracy.
[86]	• Nikhil Shah • Sarika Jain & • 2019	•Image enhancement •Color conversion •Image segmentation	• Color and texture feature extracted	• ANN Classifier	**Source** Camera images **Dimensions** Approximately 20 images record	**Average Accuracy** 90%	• Need to improve propose system efficiency.
[87]	• Darshana S.Wankhade • Mr.Vijay L. • Agrawal & • 2017	•Image enhancement •Filtering	• WHT feature Extraction • WHT transformed	• GENERALIZED FEED FORWARD (GFF) NEURAL NETWORK	**Source** Database **Dimensions** Multiple Disease Classes	**Training Accuracy** 75% **Cross-Validation Accuracy** 100%	• Need to improve propose model accuracy by using hybrid approach.
[88]	•P.Revathi •M.Hemalatha & •2014	•Image enhancement •Color conversion Edge detection	• PSO Feature Selection • Color feature variance, shape and texture feature variance	• Gain_Deep Forward Neural Network Classifier	**Source** Database images **Dimensions** Approximately 270 images record & Multi-class diseases	**Accuracy** 95%	N/A
[89]	• P. R. Rothe • R. V. Kshirsagar & • 2015	•Smoothing •Remove Noise •Low Pass filter •Gaussian Filter •Image Segmentation •Object detection •Active contour model •Snake Evolvement	• Seven invariant moments • Object measurable quantities • Deformation of objects	• Back propagation neural networks • Back propagation learning rule • Feed-forward back propagation network	**Source** Research Center **Dimensions** Multiple Disease Classes	**Accuracy** 85.52%	• Need to develop a real-time application using this method. • Also, improve propose model accuracy.

[90]	• Shantanu Kumbhar • Amita Nilawar & • 2019	•Gray Scale conversion •Segmentation	• GLCM feature extraction	• CNN (use convolutional hidden layers pooling and flattening layer) • CNN based Soft-max layer	**Source** User input images Or Database images **Dimensions** 513 images record	**Training Accuracy** 80% **Testing Accuracy** 89%	• Need to improve propose model accuracy by using hybrid approach.
[91]	• Prashant Udawant • Pravin Srinath & • 2019	•Activation Function •Image Enhancement	N/A	• Convolution neural network (CNN)	**Source** Database images **Dimensions** Multiple disease classes	**Accuracy** 89.6%	N/A
[92]	•A. Jenifa •R. Ramalakshmi •V.Ramachandran & •2019	• Image enhancement • Grey level conversion • Noise coefficient Morphological • Image segmentation	N/A	• DEEP CONVOLUTION NEURAL NETWORK (CNN)	**Source** Cotton plant dataset **Dimensions** Approximately 500 images record	**Accuracy** 96%	• Need to add many more images and works with many other categories of disease, which will helps to many farmers to identify the diseases in the cotton leaves.

4.2.3 A Review on Un-Supervised Machine-Learning Methods for Cotton Diseases Detection

Un-Supervised Machine Learning Segmentation method has been very famous and used in past by many researchers [93], [94], [95], [96], [98]. P. Revathi and M. Hemalatha [93] works on Advance Computing system to help farmer to take good decision about cotton leaves spot diseases on plant village dataset. Image based segmentation applied to extract useful features such as pixel counting function and Texture Statistics Computation that are necessary for further analysis. While, Kamble et al [94] build a mobile application based on Segmentation approach. Image analysis one of the important approach that help to segment the images into different number of objects and remove the background noise. Content Based Image Retrieval (CBIR) used to retrieval the image data from collected dataset. Image representation based on certain features that used in retrieval process. Relatively, P. Revathi et al [95] proposed a novel framework based on Homogeneity-based edge detector segmentation to extract the useful features from cotton leaves spot diseases images. They used multiple digital camera based cotton leaves spot disease images and these leaves disease classified using Neural-Network approach. Gathered images converted into grayscale and edges detected using the Sobel and Canny Edge detection approach. Whereas, Niu et al [96] works on segmentation based Improved Watershed approach for leaves diseases classification on plant village dataset. Canny operators used to extract features from preprocessed images. Improved Watershed algorithm used to classify leaves disease and achieve 97% accuracy results. Comparatively, J. Zhang et al [98] proposed a novel hybrid framework based on PCNN and Immune approach for classification of leaves disease. The dataset images was preprocessed using thresholding, Gaussian filters, and segmentation techniques to extract useful features.

Un-Supervised Machine Learning Clustering and Homogenous methods has been very famous and used in past by many researchers [99], [100], [101], [103], [104]. Warne and Ganorkar [99] discussed novel framework based on K-means Clustering to identify and classify the cotton leaves disease on digital camera images. Moreover, preprocessed the input images using histogram equalization approach applied to increase the image contrast level, K-means clustering approach was used for segmentation that classifies different numbers of K features objects and them Neural Network are used for leaves diseases. While, Bharathi and Santosh [100] discussed a novel framework based on K-means clustering approach for classification of cotton leaves that are affected on cotton plant. Images of multiple leaves disease collected using a digital camera. The identification of diseases leaves types done using color histogram and edge histogram approaches. Similarly, Bhong and Pawar [101] proposed a novel framework based on image processing to identify and classify which of the cotton leaves diseases on the cotton plants dataset. K-means clustering approach used for segmentation that classifies different objects based different set of features. Then neural network used to leaves classification. Overall recognition accuracy for K-Mean Clustering approach using Euclidean distance founded to be 89.56%.

Whereas, Revathi and Hemalatha [103] discussed a novel framework based on Homogeneous Pixel Counting technique for Cotton Diseases Detection (HPCCDD). Classification approach applied to train collected dataset and achieve intelligent farming, including early recognition of diseases. Homogenize techniques like Sobel and Canny filter used to detect the edges; these extracted edge features used in classification to identify the disease spots. Propose model overall achieved 98.1% accuracy for each image disease detection. Relatively, Dr. P. Revathi [104] proposed a novel framework based on Enhanced HPCCDD to detect cotton leaves disease on digital camera images collected from Agriculture University. Cotton leaves disease analysis done using Image-processing techniques. The Enhanced HPCCDD approach for classification and multiple features are extracted using PSO technique.

Summary Table of Cotton Leaves Disease Detection Using Un-Supervised Machine-Learning Methods

Ref	Author & Year	Pre-processing	Features	Methods	Dataset	Results	Limitations
[93]	• P. Revathi • M. Hemalatha & • 2018	• Color transformation • Image enhancement • Color filtering • Edge detection • Image segmentation	• Pixel counting function • Texture Statistics Computation • Shape features • Color Features	• Advance computing architecture • Homogeneous Pixel counting technique for Cotton Diseases Detection (HPCCDD)	**Source** Mobile images **Dimensions** Multiple Disease Classes	Just propose model	• Experiments not performed yet.
[94]	• Ms Swarupa Kamble • Atul V. Kondekar • Swapnil Mane • Mukul Wanjare & • 2016	• Image enhancement • Image resizing • Color conversion	• Color feature extraction • Histogram based extraction • Texture feature extraction	• GLCM/CCM (gray-level co-occurrence matrix/color co-occurrence)	**Source** Database images **Dimensions** Multiclass disease	N/A	• The System accepts any photo upload if it's valid format and process and finds no match.
[95]	• P. Revathi • M. Hemalatha & • 2012	• Edge detection • Gray scale conversion • Canny and Sobel Edge detection	• Color and shape feature	• Segmentation based Edge Detection • HOMOGENEOUS SEGMENTATION BASED EDGE DETECTION (HSBED) METHOD	**Source** database **Dimension** Approximately 200 images record	N/A	• Need to develop a real-time application using this method.
[96]	• Chong Niu • Han Li • Yuguang Niu & • 2015	• Thresholding • Lifting Wavelet Algorithm • Morphological operations • Segmentation	N/A	• Improved Watershed Algorithm	**Source** Laboratory **Dimensions** Multiple class diseases	**Accuracy** 98%	N/A
[98]	• Jianhua Zhang • Fantao Kong • Zhifen Zhai • Jianzhai Wu • Shuqing Han & • 2018	• Leaves Segmentation • Otsu algorithm • K-Means algorithm	•17 Color features extracted	• Immune algorithm Pulse coupled neural networks (PCNN) • FCM algorithm	**Source** Natural captured images **Dimensions** Approximately 1200 images record	**Average MAE** 6.5%	• Depend on the iteration step, and its real-time performance is relatively poor.

[99]	• Pawan P. Warne • Dr. S. R. Ganorkar & • 2015 Cited 19	• Contrast Enhancement • Image segmentation • K-means clustering • Histogram equalization	• Color feature variance	• Neural Network • K-mean clustering	**Source** Camera or web cotton leaf images **Dimensions** Approximately 2000 images record	**Accuracy** 89.5% And Euclidean distance is 436.95 second	• Need to develop a real-time application using these methods.
[100]	• Bharathi N • Santosh K. & • 2018	• Image enhancement • Transformation • Gray scale conversion • Edge detection	• Color Histogram • Euclidian Distance • Intersection Distance	• Image processing • Segmentation • K-mean clustering	**Source** Camera images **Dimensions** Multiple disease classes	**Accuracy** 0.877%	• Proposed model not working well when clusters are separated.
[101]	• Vijay S.Bhong • Prof.B.V.Pawar & • 2016	• Color conversion • Image segmentation • K-means clustering	• Color feature variance	• Image processing • Neural Network	**Source** Database **Dimensions** Multiclass disease	**Accuracy** 89.56% Euclidean distance is 436.95 second	N/A
[103]	• P.Revathi • M.Hemalatha & • 2012	• Color transformation • Image Segmentation • Edge Detection • Canny and Sobel edge detection	• Statistical Analysis • Texture statistics computation	• Homogeneous Pixel Counting technique for Cotton Diseases Detection (HPCCDD)	**Source** Digital mobile camera **Dimensions** Multiclass Disease	**Accuracy** 98.1%	• Real time disease not detected.
[104]	• Dr. P. Revathi & • 2017	• Image enhancement • Color conversion • Thresholding	• GLCM feature extraction	• HPCCDD (Homogeneous Pixel Counting Algorithm for Cotton Diseases Detection) Algorithm • Improved HPCCDD algorithm	**Source** Database **Dimensions** Multiclass Disease	**Accuracy** 98% **Sensitivity** 57.69% **Specificity** 98.01%	• Need to develop a real-time application using these methods.

4.2.4 A Review on Hybrid Methods for Cotton Diseases Detection

Cotton leaves disease detection using hybrid approach conducted by many researchers [105], [106], [107], [108], [109], [110], [111], [112], [113], and [114]. Jenifa et al [105] proposed a novel framework based on Machine learning approach such as Multi-Support Vector Machine to classify cotton leaves diseases. SVM approach used to recognition the pattern. By using K-Means segmentation approach, the set of color and texture feature extracted. The average accuracy of proposed approach founded to be 93.63%. Similarly, Batmavady et al [106] proposed a novel framework based on image processing and Neural Network approaches used to identifying cotton leaves diseases from plant village dataset. Image based segmentation applied using Fuzzy C-Means Clustering approach. Then set of important features extracted from segmented images using Radial Basis Function (RBF) Neural Network approach. SVM and Neural Network approaches used to train and test large number of samples preprocessed dataset. The average accuracy of proposed classification methods founded to be 85.44% and 90% respectively. Whereas, Bhimte and Thool [107] proposed a Hybrid framework based on image processing and machine learning to automatically classify the cotton leaves diseases. Color-based segmentation applied using K-means Clustering approach. From segmented image, texture features are extracted using Gray Level Co-occurrence Matrix (GLCM) approach for leaves diseases classification.

While, Sushma S. Patil et al [108] proposed an Advance Computing based System using image preprocessing and SVM classifiers. Color, shape and texture features extracted from segmented images. Comparatively, Usha Kumari et al[109] presents an automatic leaves diseases recognition system in cotton crop for different three types of leaves diseases. K-means clustering approach applied for leaves diseases segmentation. Since, 30 texture features given to ANN and SVM methods for leaves diseases recognition. Average accuracy of ANN and SVM classifiers founded to be 85.1% and 92.06% respectively. On the other hand, Rothe and Kshirsagar [110] discussed a novel framework based on image processing for leaves diseases classification. Graph cut based approach used for segmentation of diseased leaves images. Gaussian filter technique applied to remove the background noise from images before segmentation. The Color, Shape and Texture fea-

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tures extracted and trained using SVM classifier. While, T Srujana et al [111] works on Advance Image Processing approach to detect the pest and different type of leaves diseases on cotton plants. Images of leaves affected with some diseases done using preprocessing. Images are then subject find Edge detection. Edge detected images was given to Advanced fuzzy K-means clustering for the segmentation. Comparatively, K. Praveen Choudhary et al [112] discussed a novel framework based on image processing and machine-learning approaches to identify and classify the cotton leaves diseases such as Bacterial Blight, Leaf Crumple and Alternaria. Based on the extracted features, Machine Learning techniques such as Multi-SVM, KNN Algorithm and ANN approach used to classify the cotton leaf disease. Disease identified and the farmer can take precautionary measures to save the cotton yield. While, Nirmal Chowdhary et al [113] proposed a hybrid framework based on Machine learning and image processing used to detect and classify cotton leaf diseases. K-Means Segmentation approach used for background subtraction and from these segmented images, features were extracted such as Shape, Texture and Color. On the other hand, Vivek Chaudhari et al [114] proposed a novel framework based on Neural Networks approaches such as Backpropagation neural network and a Multi-layered feed-forward network to detect cotton plant leaves diseases. Preprocessed images segmented by using the K-means Clustering approach. From these clustered images, features were extracted using discrete wavelet transform. Then Neural Network approach used to train the preprocessed images and achieved 97% accuracy for each image disease detection.

Summary Table of Cotton Leaves Disease Detection Using Hybrid Methods

Ref	Author & Year	Pre-processing	Features	Methods	Dataset	Results	Limitations
[105]	• A.Jenifa; • R. Ramalakshmi • V.Ramachandran & • 2019	• Median Filter • Smoothing filter • Enhancement • Thresholding • K-means segmentation	• Color Co-occurrence • HIS color space representation • Texture feature	• Multi-SVM • PSNR(Peak signal to Noise ratio)	**Source** Mobile camera **Dimensions** Approximately 60 images record	**Accuracy** 93.63%	• Unable to classify real-time leaves diseases.
[106]	• S. Batmavady • S. Samundeeswari & • 2019	• Grayscale conversion • Median filter(Nosie remove) • Histogram enhancement • Morphological- • Fuzzy C-Means algorithm	• Twelve statistical features are extracted • Statistical features of segmented image	• SVM classifier • RBF neural network classifier.	**Source** Village plant dataset **Dimensions** Multiclass disease	**SVM Accuracy** 85.44% **RBF-NN Accuracy** 90%	• Need to focused on real time implementation of the proposed algorithm for continuous monitoring and detection of plant diseases
[107]	• Namrata R. Bhimte • V. R. Thool & • 2018	• Image enhancement • Image segmentation • K-means clustering	• Seven Texture feature • Gray Level Co-occurrence Matrix(GLCM) • Statistical features extraction	-SVM classifier	**Source** Camera images **Dimensions** Approximately 130 images record	**Accuracy** 98.46%	• Need to develop a more efficient, robust machine vision system for early automatic detection of various type of diseases in plants.
[108]	• Sushma S. Patil • Mr. Suhas K. C & • 2014	• Image enhancement • Sobel and canny Edge detection • Segmentation • K-means clustering	• Color, shape and texture features	•Advance Computing system •SVM Classifier	**Source** Digital Camera images **Dimensions** Four disease classes	**MAP** 0.78%	• Need to improve proposed model accuracy.
[109]	• Ch. Usha Kumari • N. Arun Vignesh • Asisa Kumar Panigrahy • L. Ramya & • 2019	• Segmentation • K-means Clustering	• Mean , Contrast, Energy, Correlation, Standard Deviation, Variance , Entropy, and Kurtosis are extracted	• Neural Network • SVM	**Source** Database images **Dimensions** Approximately 200 images record	**Accuracy** 82%	N/A

[110]	• P.R. Rothe • Dr. R. V. Kshirsagar & • 2014	• Low pass filter • Gaussian filter • Image Segmentation • Graph cut technique • K-means clustering	• Color Feature • Color layout descriptor (CLD) • Image partitioning • Representative color selection • DCT transformation • Zigzag scanning • Shape-based feature extraction	• Support vector machines • Back propagation neural network • Adaptive fuzzy inference system	**Source** Database images **Dimensions** Multiclass diseases	N/A	• Need to implement a hybrid using segmentation approach.
[111]	• T Srujana1 • Divya • Md.Javeed & • 2018	• Image enhancement • Edge Detection • Segmentation • Using clustering	• Color features: Correlation, entropy • Texture features : Energy, contrast, edges	• Image processing • K-means clustering • FUZZY C-MEANS CLUSTERING • Hybrid fuzzy K-means cluster acronym (AFKM)	**Source** Database **Dimensions** Multiclass Diseases	**Process** 0.18 **Frequency** 5 **Power** 0.060	• Need to use different latest neural network architectures for classification.
[112]	• K. Praveen Chowdhary • Sainath • Yaratapalli Sukumar Reddy • M. Yashas Kumar & • 2020	• Background Subtraction • K-means Segmentation • Gray level conversion • Adaptive histogram equalization	• Extract background noise • Feature vector • Texture features • Color features • Shape features	• Image processing • Machine learning methods • KNN • SVM • ANN	**Source** Database cotton leave images **Dimensions** 40 images of each type disease	**ANN** 90% **KNN** 85% **SVM** 70%	• Need to develop real-time expert system for disease detection
[113]	• Nirmal Chowdhary K. • Nithin Y. M. • Srikanta P. • Prof. Rekha B. S. & • 2018	• Background Subtraction Using K-Means Segmentation • Grayscale conversion	• Extracting the Shape, Texture and Color feature Extraction • Adaptive histogram equalization	• K Nearest Neighbor Algorithm • Multi class support vector machine • K Nearest Neighbor Algorithm • Artificial Neural Network	**Source** Dataset is imbalanced and lacks geometric variances of Cotton Leaves **Dimensions** Approximately 500 plus images record	**Multi-Class SVM** 70% **KNN** 86% **ANN** 86%	• The system cannot be used for an image consisting of a cluster of leaves. • Experimenting with noisier and the distorted images can be tried.

[114]	• Vivek Chaudhari • C. Y. Patil & • 2014	• Image Segmentation • K-means clustering • Transformations of image colors • Extract image objects	**Feature extraction** • Wavelet transformation • Extraction of coefficients from decomposition vectors • Wavelet decomposition **Feature Reduction** • Principal Component Analysis (PCA)	• Back Propagation Neural Network • Multi-layered feed forward network	**Source** Camera images **Dimensions** Contains two main disease	**Accuracy** 97%	• Need to develop a real-time application using this method. • Real time disease not detected.

5 Limitations & Future Work

Lots of work has been done by researchers in the area of agriculture to detecting leaves disease. But, there are still some issues that are needed to be addressed like still need an optimal solution for real-time disease detection. From the above critical literature review, we have found some limitations such as there is a big need to use the latest feature selection or segmentation techniques to reduce the computational time. A need for developing an algorithm that can be cost-efficient for the farmer users and profit efficient for the service providers at the same time. Still needs to address the issue of real-time crop leaves detection.

For future directions, recommended to create a more robust and hybrid framework for accurate leaves disease detection. We also recommend, to work on multi classes on a different dataset of crop diseases using different types of AI techniques.

6 Conclusion

This paper summarizes and reviews different methods based on supervised, unsupervised, and hybrid for multi-crop leaves disease detections and classification. The different leaves disease detection approaches for multi-crops have been proposed in the area of the agricultural industry. Most of these approaches are talking about the accuracy of a dataset and most of the approaches are claiming the learning based on a dataset but there is a big ambiguity in most of the algorithm that this data set is maintained only once and then is just utilized means no update in the dataset so learning is also stopped. In the past few years, many researchers use these approaches to recognize diseases in plants like tomato and cotton. Image processing, machine learning, and deep learning are the few latest approaches that many researchers used to detect leaves disease in multi-crops (tomato & cotton). Through complex images captured from outdoor lightning and natural environment, many challenges arise while detecting diseases in multi-crops (tomato & cotton). This review paper determines that these leaves disease classification approach disease gives an accurate result because these techniques can run the application build for the detection of leaves disease also having some limitations. Need to upgrade and enhance the existing diseases recognition system. In future, we can use a more intelligent approach of AI and develop a hybrid framework-based expert system for real-time multi-crops leaves disease recognition.

References

[1] Supriya S. Patki, G. S. S. (2016). "A Review : Cotton Leaf Disease Detection". IOSR Journal of VLSI and Signal Processing (IOSR-JVSP), 6(3), 78–81. https://doi.org/10.9790/4200- 0603017881

[2] Zadokar, A. R., Bhagat, D. P., Nayase, A. A., & Mhaske, S. S. (2017). "Leaf disease detection of cotton plant using image processing techniques: a review". International Journal of Electronics, Communication and Soft Computing Science & Engineering (IJECSCSE), 53-55.

[3] Sherly Puspha Annabel, L., Annapoorani, T., & Deepalakshmi, P. (2019). "Machine learning for plant leaf disease detection and classification - A review". Proceedings of the 2019 IEEE International Conference on Communication and Signal Processing, ICCSP 2019, 538–542. https://doi.org/10.1109/ICCSP.2019.8698004

[4] Santhosh Kumar, S., & Raghavendra, B. K. (2019). "Diseases Detection of Various Plant Leaf Using Image Processing Techniques: A Review". 2019 5th International Conference on Advanced Computing and Communication Systems, ICACCS 2019, 313–316. https://doi.org/10.1109/ICACCS.2019.8728325

[5] Ganatra, N., & Patel, A. (2018). "A survey on diseases detection and classification of agriculture products using image processing and machine learning". International Journal of Computer Applications, 180(13), 1-13.

[6] Mokhtar, U., Ali, M. A. S., Hassenian, A. E., & Hefny, H. (2016). "Tomato leaves diseases detection approach based on Support Vector Machines". 2015 11th International Computer Engineering Conference: Today Information Society What's Next?, ICENCO 2015, 246–250. https://doi.org/10.1109/ICENCO.2015.7416356

[7] Hlaing, C. S., & Maung Zaw, S. M. (2018). "Tomato Plant Diseases Classification Using Statistical Texture Feature and Color Feature". Proceedings - 17th IEEE/ACIS International Conference on Computer and Information Science, ICIS 2018, 1, 439–444. https://doi.org/10.1109/ICIS.2018.8466483

[8] Jakjoud, F., Hatim, A., & Bouaddi, A. (2019). "Detection of diseases

on tomato leaves based on sub-classifiers fuzzy combination". International Journal of Innovative Technology and Exploring Engineering, 8(5), 735–739.

[9] Hlaing, C. S., & Zaw, S. M. M. (2018). "Model-based statistical features for mobile phone image of tomato plant disease classification". Parallel and Distributed Computing, Applications and Technologies, PDCAT Proceedings, 2017-December, 223–229. https://doi.org/10.1109/PDCAT.2017.00044

[10] Indriani, O. R., Kusuma, E. J., Sari, C. A., Rachmawanto, E. H., & Setiadi, D. R. I. M. (2018). "Tomatoes classification using K-NN based on GLCM and HSV color space". Proceedings - 2017 International Conference on Innovative and Creative Information Technology: Computational Intelligence and IoT, ICITech 2017, 2018-January, 1–6. https://doi.org/10.1109/INNOCIT.2017.8319133

[11] Xie, C., Yang, C., & He, Y. (2017). "Hyperspectral imaging for classification of healthy and gray mold diseased tomato leaves with different infection severities". Computers and Electronics in Agriculture, 135, 154–162. https://doi.org/10.1016/j.compag.2016.12.015

[12] Hassanien, A. E., Gaber, T., Mokhtar, U., & 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. https://doi.org/10.1016/j.compag.2017.02.026

[13] Basavaiah, J., & Arlene Anthony, A. (2020). "Tomato Leaf Disease Classification using Multiple Feature Extraction Techniques". Wireless Personal Communications, 115(1), 633– 651. https://doi.org/10.1007/s11277-020-07590-x

[14] Vianna, G. K., & Cruz, S. M. S. (2014). "Using multilayer perceptron networks in early detection of late blight disease in tomato leaves". Proceedings of the 2014 International Conference on Artificial Intelligence, ICAI 2014 - WORLDCOMP 2014, 516–522

[15] Vianna, G. K., Cunha, G. V., & Oliveira, G. S. (2016). "A Neural Network Classifier for Estimation of the Degree of Infestation by Late Blight on Tomato Leaves". International Journal of Computer and Information Engineering, 11(1), 18-24.

[16] Ashqar, B. A. M., & Abu-Naser, S. S. (2018). "Image-Based Tomato Leaves Diseases Detection Using Deep Learning". International Journal of Academic Engineering Research, 2(12), 10– 16. www.ijeais.org/ijaer

[17] Cevallos, C., Ponce, H., Moya-Albor, E., & Brieva, J. (2020). "Vision-Based Analysis on Leaves of Tomato Crops for Classifying Nutrient Deficiency using Convolutional Neural Networks". Proceedings of the International Joint Conference on Neural Networks, 0–6. https://doi.org/10.1109/IJCNN48605.2020.9207615

[18] Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). "Deep Learning for Tomato Diseases: Classification and Symptoms Visualization". Applied Artificial Intelligence, 31(4), 299–315. https://doi.org/10.1080/08839514.2017.1315516

[19] Sun, J., He, X., Wu, M., Wu, X., Shen, J., & Lu, B. (2020). "Detection of tomato organs based on convolutional neural network under the overlap and occlusion backgrounds". Machine Vision and Applications, 31(5), 1–13. https://doi.org/10.1007/s00138-020-01081-6

[20] Salih, T. A., Ali, A. J., & Ahmed, M. N. (2020). "Deep Learning Convolution Neural Network to Detect and Classify Tomato Plant Leaf Diseases". OALib, 07(05), 1–12. https://doi.org/10.4236/oalib.1106296

[21] Elhassouny, A., & Smarandache, F. (2019). "Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks". Proceedings of 2019 International Conference of Computer Science and Renewable Energies, ICCSRE 2019, 1–4. https://doi.org/10.1109/ICCSRE.2019.8807737

[22] Wu, Q., Chen, Y., & Meng, J. (2020). "Dcgan-based data augmentation for tomato Leaf disease identification". IEEE Access, 8, 98716–98728. https://doi.org/10.1109/ACCESS.2020.2997001

[23] Emebo, O., Fori, B., Victor, G., & Zannu, T. (2019). "Development of Tomato Septoria Leaf Spot and Tomato Mosaic Diseases Detection Device Using Raspberry Pi and Deep Convolutional Neural Networks". Journal of Physics: Conference Series, 1299(1). https://doi.org/10.1088/1742-6596/1299/1/012118

[24] De Luna, R. G., Dadios, E. P., & Bandala, A. A. (2019). "Automated Image Capturing System for Deep Learning-based Tomato Plant Leaves Disease Detection and Recognition". IEEE Region 10 Annual International Conference, Proceedings/TENCON, 2018-October(October), 1414–1419. https://doi.org/10.1109/TENCON.2018.8650088

[25] Liu, J., & Wang, X. (2020). "Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model". Plant Methods, 16(1), 1–16. https://doi.org/10.1186/s13007- 020-00624-2

[26] Ahmad, I., Hamid, M., Yousaf, S., Shah, S. T., & Ahmad, M. O. (2020). "Optimizing pre-trained convolutional neural networks for tomato leaves disease detection". Complexity, 2020. https://doi.org/10.1155/2020/8812019

[27] Suryawati, E., Sustika, R., Yuwana, R. S., Subekti, A., & Pardede, H. F. (2019). "Deep structured convolutional neural network for tomato diseases detection". 2018 International Conference on Advanced Computer Science and Information Systems, ICACSIS 2018, 385– 390. https://doi.org/10.1109/ICACSIS.2018.8618169

[28] Durmus, H., Gunes, E. O., & Kirci, M. (2017). "Disease detection on the leaves of the tomato plants by using deep learning". 2017 6th International Conference on Agro-Geoinformatics, Agro-Geoinformatics 2017. https://doi.org/10.1109/Agro-Geoinformatics.2017.8047016

[29] Mkonyi, L., Rubanga, D., Richard, M., Zekeya, N., Sawahiko, S., Maiseli, B., & Machuve, D. (2020). "Early identification of Tuta absoluta in tomato plants using deep learning". Scientific African, 10, e00590. https://doi.org/10.1016/j.sciaf.2020.e00590

[30] Shijie, J., Peiyi, J., Siping, H., & Haibo, Sl. (2017). "Automatic detection of tomato diseases and pests based on leaf images". Proceedings - 2017 Chinese Automation Congress, CAC 2017, 2017-January, 3507–3510. https://doi.org/10.1109/CAC.2017.8243388

[31] Jiang, Di., Li, F., Yang, Y., & Yu, S. (2020). "A Tomato Leaf Diseases Classification Method Based on Deep Learning". Proceedings of the 32nd Chinese Control and Decision Conference, 85 CCDC 2020, 1446–1450. https://doi.org/10.1109/CCDC49329.2020.9164457

[32] Zaki, S. Z. M., Zulkifley, M. A., Mohd Stofa, M., Kamari, N. A. M., & Mohamed, N. A. (2020). "Classification of tomato leaf diseases using mobile-net v2". IAES International Journal of Artificial Intelligence, 9(2), 290–296. https://doi.org/10.11591/ijai.v9.i2.pp290-296

[33] Zhang, L., Jia, J., Li, Y., Gao, W., & Wang, M. (2019). "Deep learning based rapid diagnosis system for identifying tomato nutrition disorders". KSII Transactions on Internet and Information Systems, 13(4), 2012–2027. https://doi.org/10.3837/tiis.2019.04.015

[34] Batool, A., Hyder, S. B., Rahim, A., Waheed, N., Asghar, M. A., & Fawad. (2020). 82 "Classification and Identification of Tomato Leaf Disease Using Deep Neural Network". 2020 International Conference on Engineering and Emerging Technologies, ICEET 2020. https://doi.org/10.1109/ICEET48479.2020.9048207

[35] Chen, X., Zhou, G., Chen, A., Yi, J., Zhang, W., & Hu, Y. (2020)." Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet". Computers and Electronics in Agriculture, 178(August), 105730. https://doi.org/10.1016/j.compag.2020.105730

[36] Zhang, T., Zhu, X., Liu, Y., Zhang, K., & Imran, A. (2020). "Deep Learning Based Classification for Tomato Diseases Recognition". IOP Conference Series: Earth and Environmental Science, 474(3). https://doi.org/10.1088/1755-1315/474/3/032014

[37] Hidayatuloh, A., Nursalman, M., & Nugraha, E. (2018). "Identification of Tomato Plant Diseases by Leaf Image Using Squeezenet Model". 2018 International Conference on Information Technology Systems and Innovation, ICITSI 2018 - Proceedings, 199–204. https://doi.org/10.1109/ICITSI.2018.8696087

[38] Gharghory, S. M. (2020). "Performance analysis of efficient pre-trained networks based on transfer learning for tomato leaves diseases classification". International Journal of Advanced Computer Science and Applications, 11(8), 230–240. https://doi.org/10.14569/IJACSA.2020.0110830

[39] Liu, J., Pi, J., & Xia, L. (2020). "A novel and high precision tomato maturity recognition algorithm based on multi-level deep residual network". Multimedia Tools and Applications, 79(13–14), 9403–9417. https://doi.org/10.1007/s11042-019-7648-7

[40] Sun, J., He, X., Ge, X., Wu, X., Shen, J., & Song, Y. (2018). "Detection of key organs in tomato based on deep migration learning in a complex background". Agriculture (Switzerland), 8(12). https://doi.org/10.3390/agriculture8120196

[41] Tsironis, V., Bourou, S., & Stentoumis, C. (2020). "Tomatod: Evaluation of object detection algorithms on a new real-world tomato dataset". International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 43(B3), 1077–1084. https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-1077-2020

[42] Adhikari, S., Unit, D., Shrestha, B., & Baiju, B. (2018). "Tomato Plant Diseases Detection System". I, 81–86

[43] Nithish, E. K., Kaushik, M., Prakash, P., Ajay, R., & Veni, S. (2020). "Tomato leaf disease detection using convolutional neural network with data augmentation". Proceedings of the 5th International Conference on Communication and Electronics Systems, ICCES 2020, Icces, 1125–1132. https://doi.org/10.1109/ICCES48766.2020.09138030

[44] Agarwal, M., Singh, A., Arjaria, S., Sinha, A., & Gupta, S. (2020). "ToLeD: Tomato Leaves Disease Detection using Convolution Neural Network". Procedia Computer Science, 167(2019), 293–301. https://doi.org/10.1016/j.procs.2020.03.225

[45] Llorca, C., Yares, M., & Maderazo, C. (2018). "Image-Based Pest and Disease Recognition of Tomato Plants Using a Convolutional Neural Network". E-Jikei.Org.

[46] Aversano, L., Bernardi, M. L., Cimitile, M., Iammarino, M., & Rondinella, S. (2020). "Tomato diseases Classification Based on VGG and Transfer Learning". 2020 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2020 - Proceedings, 129–133. https://doi.org/10.1109/MetroAgriFor50201.2020.9277626

[47] Ouhami, M., Es-Saady, Y., Hajji, M. El, Hafiane, A., Canals, R., & Yassa, M. El. (2020). "Deep transfer learning models for tomato disease detection". Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12119 LNCS, 65–73. https://doi.org/10.1007/978-3-030-51935-3_7

[48] Kumar, A., & Vani, M. (2019). "Image Based Tomato Leaf Disease Detection". 2019 10th International Conference on Computing, Communication and Networking Technologies, ICCCNT 2019, 1–6. https://doi.org/10.1109/ICCCNT45670.2019.8944692

[49] Zhang, Y., Song, C., & Zhang, D. (2020). "Deep Learning-Based Object Detection Improvement for Tomato Disease". IEEE Access, 8, 56607–56614. https://doi.org/10.1109/ACCESS.2020.2982456

[50] Tm, P., Pranathi, A., Saiashritha, K., Chittaragi, N. B., & Koolagudi, S. G. (2018). "Tomato Leaf Disease Detection Using Convolutional Neural Networks". 2018 11th International Conference on Contemporary Computing, IC3 2018, 2–4. https://doi.org/10.1109/IC3.2018.8530532

[51] Ngugi, L. C., Abelwahab, M., & Abo-Zahhad, M. (2020). "Tomato leaf segmentation algorithms for mobile phone applications using deep learning". Computers and Electronics in Agriculture, 178(August), 105788. https://doi.org/10.1016/j.compag.2020.105788

[52] Hang, X., Gao, H., & Jia, S. (2020). "Identification of Tomato Diseases using Skip-gram and LSTM Based on QA(Question-Answer) System". Journal of Physics: Conference Series, 1437(1). https://doi.org/10.1088/1742-6596/1437/1/012048

[53] Abdulridha, J., Ampatzidis, Y., Kakarla, S. C., & Roberts, P. (2020). "Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques". Precision Agriculture, 21(5), 955–978. https://doi.org/10.1007/s11119- 019-09703-4

[54] Tian, K., Li, J., Zeng, J., Evans, A., & Zhang, L. (2019). "Segmentation of tomato leaf images based on adaptive clustering number of K-means algorithm". Computers and Electronics in Agriculture, 165, 104962.

[55] Hong, H., Lin, J., & Huang, F. (2020, June). "Tomato Disease Detection and Classification by Deep Learning". In 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE) (pp. 25-29). IEEE.

[56] Tian, Y. W., Zheng, P. H., & Shi, R. Y. (2016). "The Detection System for Greenhouse Tomato Disease Degree Based on Android Platform". Proceedings - 2016 3rd International Conference on Information Science and Control Engineering, ICISCE 2016, 706–710. https://doi.org/10.1109/ICISCE.2016.156

[57] Park, J. H., & Lee, S. K. (2019). An Image Processing Mechanism for Disease Detection in Tomato Leaf. The Journal of the Korea institute of electronic communication sciences, 14(5), 959-968.

[58] Wang, D., Vinson, R., Holmes, M., Seibel, G., Bechar, A., Nof, S., & Tao, Y. (2019). "Early Detection of Tomato Spotted Wilt Virus by Hyperspectral Imaging and Outlier Removal Auxiliary Classifier Generative Adversarial Nets (OR-AC-GAN)". Scientific Reports, 9(1), 1– 14. https://doi.org/10.1038/s41598-019-40066-y

[59] Raza, S. E. A., Prince, G., Clarkson, J. P., & Rajpoot, N. M. (2015). "Automatic detection of diseased tomato plants using thermal and stereo visible light images". Plos One, 10(4), 1-20.

[60] Xu, H. R., Ying, Y. B., Fu, X. P., & Zhu, S. P. (2007). "Near-infrared Spectroscopy in detecting Leaves Miner Damage on Tomato Leaf". Biosystems Engineering, 96(4), 447–454. https://doi.org/10.1016/j.biosystemseng.2007.01.008

[61] Muludi, K., Suharjo, R., Syarif, A., & Ramadhani, F. (2018). "Implementation of forward chaining and certainty factor method on Android-based expert system of tomato diseases identification". (IJACSA) International Journal of Advanced Computer Science and Applications, 9(9), 451-459.

[62] Lu, J., Zhou, M., Gao, Y., & Jiang, H. (2018). "Using hyperspectral

imaging to discriminate yellow leaves curl disease in tomato leaf". Precision Agriculture, 19(3), 379–394. https://doi.org/10.1007/s11119-017-9524-7

[63] Zaka-ud-din, Muhammad Aziz, Sumair Rashid, Junaid Ismail, W. (2018). "Classification of Disease in Tomato Plants Leaf Using Image Segmentation and SVM". Technical Journal, University of Engineering and Technology (UET), 23(2), 81–88.

[64] Sampoorna, C. K., & Rasadurai, K. (2020). "Tomato Leaf Disease Detection using K-Means, SVM Classifier & Neural Networks". International Journal of Recent Technology and Engineering, 8(5), 461–466. https://doi.org/10.35940/ijrte.e4898.018520

[65] Langar, G., Jain, P., & Panchal, N. (2020). "TOMATO LEAF DISEASE DETECTION USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING". INTERNATIONAL JOURNAL, 5(7).

[66] Prashar, K., Talwar, R., & Kant, C. (2017). "Robust Automatic Cotton Crop Disease Recognition (ACDR) Method using the Hybrid Feature Descriptor with SVM". International Conference on Computing on Sustainable Global Development, March.

[67] Dubey, Y. K., Mushrif, M. M., & Tiple, S. (2018). "Superpixel based roughness measure for cotton leaf diseases detection and classification". Proceedings of the 4th IEEE International Conference on Recent Advances in Information Technology, RAIT 2018, 1–5. https://doi.org/10.1109/RAIT.2018.8388993

[68] Sarangdhar, A. A., & Pawar, V. (2017). "Machine learning regression technique for cotton leaf disease detection and controlling using IoT". Proceedings of the International Conference on Electronics, Communication and Aerospace Technology, ICECA 2017, 2017- January, 449–454. https://doi.org/10.1109/ICECA.2017.8212855

[69] Patil, S. P., & SZambre, R. (2014). "Classification of Cotton Leaf Spot Disease Using Support Vector Machine". Journal of Engineering Research and Applications Www.Ijera.Com, 4(5), 92–97. www.ijera.com

[70] Prashar, K., & Talwar, R. (2018). "A Novel Shape and Texture based Analysis of the American Cotton Leaves Diseases with SVM Classification". Journal of Advanced Research in Dynamical and Control Systems, January

[71] Sivasangari, A., & Indira, K. (2017). Cotton Leaf Disease Detection and Recovery Using Genetic Algorithm. 117(22), 119–123.

[72] Thara, D. K., Saba, S., & Vaishnavi, S. (2018). "Detection of Cotton Leaves Diseases Using Machine Learning Regression Techniques".

[73] Rothe, P. R., & Kshirsagar, R. V. (2014c). "SVM-based Classifier System for Recognition of Cotton Leaf Diseases". International Journal of Emerging Technologies in Computational and Applied Sciences, 427–432

[74] Patki, S. S., & Sable, G. S. (2016). "Cotton Leaf Disease Detection & Classification using Multi SVM". 5(10), 165–168. https://doi.org/10.17148/IJARCCE.2016.51034

[75] Prashar, K., Talwar, R., & Kant, C. (2019). "CNN based on Overlapping Pooling Method and Multi-layered Learning with SVM KNN for American Cotton Leaf Disease Recognition". 87 2019 International Conference on Automation, Computational and Technology Management, ICACTM 2019, 330–333. https://doi.org/10.1109/ICACTM.2019.8776730

[76] Gulhane, V. A., & Kolekar, M. H. (2015). "Diagnosis of diseases on cotton leaves using principal component analysis classifier". 11th IEEE India Conference: Emerging Trends and Innovation in Technology, INDICON 2014. https://doi.org/10.1109/INDICON.2014.7030442

[77] Parikh, A., Raval, M. S., Parmar, C., & Chaudhary, S. (2016). "Disease detection and severity estimation in cotton plant from unconstrained images". Proceedings - 3rd IEEE International Conference on Data Science and Advanced Analytics, DSAA 2016, 594–601. https://doi.org/10.1109/DSAA.2016.81

[78] Bhong, V. S., & Pawar, P. B. V. (2016). "Study and Analysis of Cotton Leaf Disease Detection Using Image Processing". International Journal of Advanced Research in Science, Engineering and Technology, 3(2), 1447–1454.

[79] Kokane, M. C. D., & Bhale, N. L. (2017). "To Detect and Identify Cotton leaf disease based on pattern recognition technique".

[80] Rothe, P. R., & Kshirsagar, R. V. (2014a). "Adaptive neuro-fuzzy inference system for recognition of cotton leaf diseases". Proceedings of the International Conference on Innovative Applications of Computational Intelligence on Power, Energy and Controls with Their Impact on Humanity, CIPECH 2014, November, 12–17. https://doi.org/10.1109/CIPECH.2014.7019039

[81] Zhang, Y. C., Mao, H. P., Hu, B., & Li, M. X. (2007). "Features selection of cotton disease leaves image based on fuzzy feature selection techniques". Proceedings of the 2007 International Conference on Wavelet Analysis and Pattern Recognition, ICWAPR '07, 1, 124– 129. https://doi.org/10.1109/ICWAPR.2007.4420649

[82] Chopda, J., Raveshiya, H., Nakum, S., & Nakrani, V. (2018). "Cotton Crop Disease Detection using Decision Tree Classifier". 2018 International Conference on Smart City and Emerging Technology, ICSCET 2018, c, 1–5. https://doi.org/10.1109/ICSCET.2018.8537336

[83] Gurjar, A. A., & Gulhane, V. A. (2012). "Disease detection on cotton leaves by eigenfeature regularization and extraction technique". International Journal of Electronics, Communication and Soft Computing Science & Engineering (IJECSCSE), 1(1), 1.

[84] Gulhane, M., & Gurjar, A. (2011). "Detection of diseases on cotton leaves and its possible diagnosis". International Journal of Image …, 5, 590–598. http://www.cscjournals.org/csc/manuscript/Journals/IJIP/volume5/Issue5/IJIP-478.pdf

[85] Ranjan, M., Weginwar, M. R., Joshi, N., & Ingole, A. B. (2015). "Detection and classification of leaf disease using artificial neural network". International Journal of Technical Research and Applications, 3(3), 331-333.

[86] Shah, N., & Jain, S. (2019). "Detection of Disease in Cotton Leaf using Artificial Neural Network". Proceedings - 2019 Amity International Conference on Artificial Intelligence, AICAI 2019, 473–476. https://doi.org/10.1109/AICAI.2019.8701311

[87] Wankhade, D. S. (2017). "Classification of Diseases on the Leaves of Cotton Using Generalized Feed Forward (Gff) Neural Network". 5(3), 182–188.

[88] Revathi, P., & Hemalatha, M. (2013). "Identification of cotton diseases based on cross information gain_deep forward neural network classifier with PSO feature selection". International Journal of Engineering and Technology, 5(6), 4637–4642.

[89] Rothe, P. R., & Kshirsagar, R. V. (2015). "Cotton leaf disease identification using pattern recognition techniques". 2015 International Conference on Pervasive Computing: Advance Communication Technology and Application for Society, ICPC 2015, 00(c). https://doi.org/10.1109/PERVASIVE.2015.7086983

[90] Kumbhar, S., Nilawar, A., Patil, S., Mahalakshmi, B., & Nipane, M. (2019). "Farmer Buddy-Web Based Cotton Leaf Disease Detection Using CNN". International Journal of Applied Engineering Research, 14(11), 2662–2666

[91] Udawant, P., & Srinath, P. (2019). "Diseased portion classification & recognition of cotton plants using convolution neural networks". International Journal of Engineering and Advanced Technology, 8(6), 3492–3496. https://doi.org/10.35940/ijeat.F9526.088619

[92] Jenifa, A., Ramalakshmi, R., & Ramachandran, V. (2019b). "Cotton Leaf Disease Classification using Deep Convolution Neural Network for Sustainable Cotton Production". 2019 International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development, INCCES 2019, 2019–2021. https://doi.org/10.1109/INCCES47820.2019.9167715

[93] Revathi, P., & Hemalatha, M. (2012, July). "Advance computing enrichment evaluation of cotton leaf spot disease detection using image edge detection". In 2012 Third International Conference on Computing, Communication and Networking Technologies (ICCCNT'12) (pp. 1-5). IEEE.

[94] Journal, I., Engineering, O. F., Detection, D., Cotton, O. N., & Solutions, I. T. S. P. (2015). International journal of engineering sciences & research technology "disease detection on cotton leaves and its possible solutions". 4(11), 613–616.

[95] Revathi, P., & Hemalatha, M. (2012). "Homogenous segmentation based edge detection techniques for proficient identification of the cotton leaf spot diseases". International Journal of Computer Applications, 47(2), 875-888.

[96] Niu, C., Li, H., Niu, Y., Zhou, Z., Bu, Y., & Zheng, W. (2016). "Segmentation of cotton leaves based on improved watershed algorithm". IFIP Advances in Information and Communication Technology, 478, 425–436. https://doi.org/10.1007/978-3-319-48357-3_41

[97] Godara, S., Khurana, S. P., & Biswas, K. K. (2017). "Three variants of cotton leaf curl begomoviruses with their satellite molecules are associated with cotton leaf curl disease aggravation in New Delhi". Journal of plant biochemistry and biotechnology, 26(1), 97-105.

[98] Zhang, J., Kong, F., Zhai, Z., Wu, J., & Han, S. (2018). "Robust Image Segmentation Method for Cotton Leaf under Natural Conditions Based on Immune Algorithm and PCNN Algorithm". International Journal of Pattern Recognition and Artificial Intelligence, 32(5), 1– 23. https://doi.org/10.1142/S0218001418540113

[99] Warne, P. P., & Ganorkar, S. R. (2015). "Detection of diseases on cotton leaves using k-mean clustering method". International Research Journal of Engineering and Technology (IRJET), 2(4), 425-431.

[100] Bharathi, N., & Santosh, K. C. (2018). "Implementation of K-Means Clustering Approach for the Identification and Edge Detection of Cotton Leaves Image Processing Technique". 8(1), 135–144.

[101] Bhong, V. S., & Pawar, P. B. V. (2016). "Study and Analysis of Cotton Leaf Disease Detection Using Image Processing". International Journal of Advanced Research in Science, Engineering and Technology, 3(2), 1447–1454.

[102] ZHANG, J. H., KONG, F. T., WU, J. Z., HAN, S. Q., & ZHAI, Z. F. (2018). "Automatic image segmentation method for cotton leaves with disease under natural environment". Journal of Integrative Agriculture, 17(8), 1800-1814.

[103] Revathi, P., & Hemalatha, M. (2014). "Classification of cotton leaf spot diseases using image processing edge detection techniques". IEEE Proceedings of the International Conference On Emerging Trends in Science Engineering and Technology: Recent Advancements on Science and Engineering Innovation, INCOSET 2012, 169–173. https://doi.org/10.1109/incoset.2012.6513900

[104] Revathi, P. (2017). "Classification of cotton leaf spot disease using enhanced HPCCDD algorithm". International Journal for Research in Applied Science and Engineering Technology, 5(6), 2493-2503.

[105] Jenifa, A., Ramalakshmi, R., & Ramachandran, V. (2019a). "Classification of Cotton Leaf Disease Using Multi-Support Vector Machine". IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing, INCOS 2019, 1–4. https://doi.org/10.1109/INCOS45849.2019.8951356

[106] Batmavady, S., & Samundeeswari, S. (2019). "Detection of cotton leaf diseases using image processing". International Journal of Recent Technology and Engineering, 8(2 Special Issue 4), 169–173. https://doi.org/10.35940/ijrte.B1031.0782S419

[107] Bhimte, N. R., & Thool, V. R. (2019). "Diseases Detection of Cotton Leaf Spot Using Image Processing and SVM Classifier". Proceedings of the 2nd International Conference on Intelligent Computing and Control Systems, ICICCS 2018, Iciccs, 340–344. https://doi.org/10.1109/ICCONS.2018.8662906

[108] Patil, S. S., & Suhas, K. C. (2014). "Identification and classification of cotton leaf spot diseases using SVM classifier". Int. J. Eng. Res. Technol., 3(4), 1511-1544.

[109] Usha Kumari, C., Arun Vignesh, N., Panigrahy, A. K., Ramya, L., & Padma, T. (2019). "Fungal disease in cotton leaf detection and classification using neural networks and support vector machine". International Journal of Innovative Technology and Exploring Engineering, 8(10), 3664–3667. https://doi.org/10.35940/ijitee.J9648.0881019

[110] Rothe, P. R., & Kshirsagar, R. V. (2014b). "Automated extraction of digital images features of three kinds of cotton leaf diseases". 2014 International Conference on Electronics, Communication and Computational Engineering, ICECCE 2014, 67–71. https://doi.org/10.1109/ICECCE.2014.7086637

[111] Srujana, T., Divya, D., & Javeed, M. (2018). "FPGA Implementation for Detection Disease on Cotton Plants Using Advanced Image Processing Algorithm".

[112] Chowdhary, K. P., Sainath, Y. S. R., Kumar, M. Y., & Girish, B. G. (2020). "Detection of Cotton Leaf Diseases Using Image Processing and Machine Learning Approach".

[113] Nirmal Chowdhary K. Nithin Y. M. Srikanta P. Prof. Rekha B. S. (2018). "A Machine Learning Approach for Detection of Cotton Leaf Disease". A Machine Learning Approach for Detection of Cotton Leaves Disease, 6(03), 4.

[114] Vivek Chaudhari1, C. Y. P., & Abstract. (2014). "Disease Detection of Cotton Leaves Using Advanced Image Processing". International Journal of Advanced Computer Research, 4(15), 653–659.

[115] Pechuho, N., Khan, Q., & Kalwar, S. (2020). "Cotton Crop Disease Detection using Machine Learning via Tensorflow". Pakistan Journal of Engineering and Technology, 3(2), 126-130.