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Symptoms Based Image Predictive Analysis for Citrus Orchards Using Machine Learning Techniques: A Review

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Abstract— In Agriculture, orchards are the deciding factor in the country's economy. There are many orchards, and citrus and sugarcane will cover 60 percent of them. These citrus orchards satisfy the necessity of citrus fruits and citrus products, and these citrus fruits contain more vitamin C. The citrus orchards have had some problems generating good yields and quality products. Pathogenic diseases, pests, and water shortages are the three main problems that plants face. Farmers can find these problems early on with the support of machine learning and deep learning, which may also change how they feel about technology. By doing this in agriculture, the farmers can cut off the major issues of yield and quality losses. This review gives enormous methods for identifying and classifying plant pathogens, pests, and water stresses using image-based work. In this review, the researchers present detailed information about citrus pathogens, pests, and water deficits. Methods and techniques that are currently available will be used to validate the problem. These will include pre-processing for intensification, segmentation, feature extraction, and selection processes, machine learning-based classifiers, and deep learning models. In this work, researchers thoroughly examine and outline the various research opportunities in the field. This review provides a comprehensive analysis of citrus plants and orchards; Researchers used a systematic review to ensure comprehensive coverage of this topic.

Keywords- Machine Learning, Deep Learning, Pre-Processing intensification, Process on Segmentation, Feature Extraction, Feature Selection, Image Classification.

I. INTRODUCTION:

The agriculture sector is a prominent sector for all countries in the world. A country's self-sufficiency relies on the availability of food production and agricultural products that meet the needs of its people. The country would face an economic crisis when its agricultural needs are unmet, thereby depleting its foreign exchange. Large-scale agriculture depends on orchards like fruits, nuts, sugarcane etc. Growing large-scale orchards has its own set of challenges, such as the susceptibility of sugarcane fields to pathogens and pests, which can greatly reduce productivity. Climate change plays a major role in agriculture because the water deficit reduces the production of agriculture and its income. Reducing the income from cultivation affects the prosperity of the nation. This research article discusses machine learning techniques and methods to detect the symptoms of pest attacks, pathogens, and water deficits using images of plants. Fruit orchards play a crucial role in the economic growth of the state. The citrus plant, known for its high vitamin C content, is extensively used in the Indian subcontinent, Arabian Peninsula, and Africa, making it among the best-finding groups of fruit plant genera. Citrus fruits have been linked to numerous health benefits and are also used as raw ingredients in the food and beverage industries to make things like jams, candies, ice cream, food items, etc. In the Indian monetary year 2020, lemons brought around 7300 crore rupees to the economy. This number was substantially greater than the gross value for the year before.

The growing population demands agricultural products and food products, leading to a need for increased productivity and yield in the sector. To achieve this, agriculturists must address major flaws in food production, such as plant disease, pest and drought control, and improper irrigation systems. These flaws can negatively impact food security and economic status. Early detection and management of these flaws through precision agriculture can help achieve sustainable efficiency and yield in agriculture. By addressing these issues, farmers can ensure sufficient food balance and improve the overall quality of their agricultural products. Symptoms of pests, diseases, and dryness

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in plants most often appear on their leaves, fruits, buds, or young branches, so it loses many fruits and they rot or fall [1], [2]. Due to seasonal changes, these pests and pathogens cause new illnesses and spread disease. To prevent the disease from spreading to other trees, it is crucial to identify the pest or pathogen in advance. Therefore, protecting crops from diseases, pests, and drought is the most significant problem faced by farmers today.

Agricultural image processing has advanced significantly in recent years, addressing the negative impact of diseases on fruit production and quality. Automated technologies have been developed to detect and diagnose diseases, preventing disease spread. To combat pathogens, drought, and pests, AI is used to manage orchards [3]. Deep learning applies to recognising the images and putting them into groups. According to [4] Image processing techniques using AI algorithms can identify diseased plants using images. Image processing methods have been developed to provide a clearer perspective on plant pests, diseases, and drought [5]. Acquiring images using visible light, spectral, thermal, and fluorescence these methods enable more accurate data extraction. Machine learning algorithms are trained using these images, which are processed using various techniques [6]. However, previous work relied on standard machine learning processes for disease identification, which had efficiency limitations and restricted monitoring of specific crops, diseases, drought, and pests.

Deep learning is being used increasingly to improve automated processes, cover more crops and diseases, and make it possible to recognise diseases right away. Improvements in image recognition and graphical computing units have led to work on automatically extracting features and putting diseases into groups. The current research examines how RGB images are used in typical machine learning and deep learning designs. It shows their strengths, flaws, and problems when it comes to quickly and correctly identifying plant diseases, pests, and drought. In this review, Figure 1 shows how image recognition techniques can be utilised in order to find plant diseases, pests, and drought. (Abbreviation in manuscript are mentioned below).

II. METHODOLOGY

A. Planning for Research Article Selection

This research provides methodology of systematic review. The study provides comprehensive view of existing literature on plant diseases, pest or drought detection using image processing between 2018 to 2023. It categories, studies, and rates the processes and results of studies on detecting plant diseases, pests, and drought using an image processing approach that uses diverse preprocessing methods on machine learning, and deep learning techniques. By applying PRISMA standards, the study examines the articles chosen for the systematic review. The review gives the results of prior investigations, which will help to figure out where more research is needed in the study.

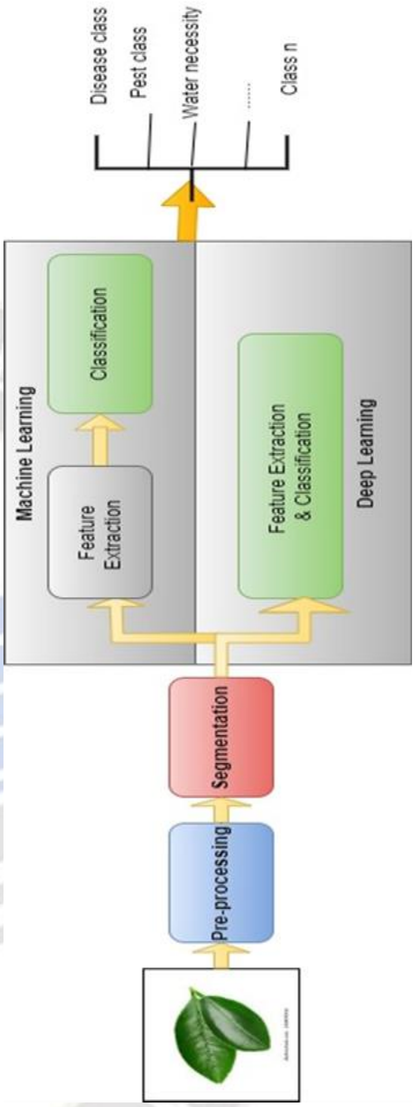

Figure 1. Diseases, pests and drought detection and classification using image recognition techniques.

B. Classification the research article

The paper distinguishes plant diseases, pest, and drought detection model in Computer vision by analysing the different pre-processing methods, segmentation, machine learning, and deep learning strategies utilised in Computer Visions. The following classes were researched and examined in the review work.

- Pre-processing for intensification.
- Processes of Segmentation.
- Feature Extraction and Selection.
- Machine Learning based classifier and Deep Learning models.

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NAME	ABBREVIATION
RGB	Red Green Blue
LBP	Local Binary Pattern
AI	Artificial Intelligence
TL	Transfer Learning
HSV	Hue Saturation Value
ESD	Ensemble Subspace Discriminant
Q-SVM	Quadratic Support Vector Machine
Cascade R-CNN	Cascade Region-Based Convolutional Neural Networks
UAV	Unmanned Aerial Vehicle
CNN	Convolution Neural Network
SVM	Support Vector Machine
LDA	Linear Discriminant Analysis
CLAHE	Contrast Limited Adaptive Histogram Equalization.
CGAN	Conditional Generative Adversarial Network.
TGVFCMS	Total Generalised Variation Fuzzy C Means
FCM	Fuzzy C-Mean
R-CNN	Region-Based Convolutional Neural Networks
PCA	Principal Component Analysis
HSL	Hue Saturation Lightness
F-KNN	Fine K-Nearest Neighbour.
C-SVM	Cubic Support Vector Machines
GA	Genetic Algorithm
ImGA	Improved Genetic Algorithm
ResNet	Residual Neural Network
CCM	Color Co-Occurrence Method
VGG	Visual Geometry Group
GLCM	Grey Level Co-Occurrence Matrix
SGD	Stochastic Gradient Descent
WOA	Whale Optimisation Algorithm
DAGSVM	Directed Acyclic Graph Support Vector Machine
BPNN	Back-Propagation Neural Network
DL	Deep Learning
ML	Machine Learning
CSA	Crow Search Algorithm
CCDF	Correlation Coefficients and Deep Features
AIE-ALDC	AI Enabled Apple Leaf Disease Classification.
LR	Logistic Regression
RF	Random Forest
Bilstm	Bidirectional Long Short-Term Memory
SNN	Spiking Neural Network
RNN	Recurrent Neural Network
DCNN	Deep Convolutional Neural Network
LSTM	Long Short-Term Memory Networks
SLIC	Simple Linear Iterative Clustering
FCNN	Fully Convolutional Neural Network
YOLO	You Only Look Once
BNL	Batch Normalisation Layer
MPL	Max-Pooling Layer
PSPNet	Pyramid Scene Parsing Network
UNet	U-Shaped Encoder-Decoder Network Architecture
SSD	Single Short Detector.

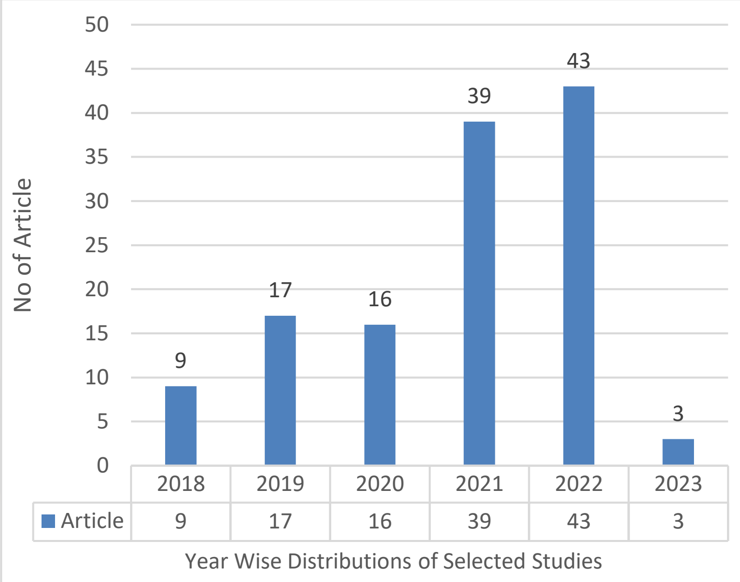

Figure. 2 Selected Articles Year wise split.

C. Norms for Information Providing

The research was done based on the norms of the systematic review and PRISMA (Included, Screening, Identification).

D. Search Strategy

Scopus, Web of Science and Springer database are used to find and classify the research articles. Researchers used a customised search for the years 2018 through 2023 to find papers about plant diseases, pests, and drought detection. Word combinations like ‘plant diseases’, ‘plant pests’, ‘plant drought’, ‘image processing’, ‘machine learning’, ‘deep learning’, [plant] AND [diseases OR pest OR smart irrigation] AND [image processing*] AND [Machine Learning OR Deep Learning] were entered as keywords in the databases. Figure 2 shows the annual distribution of collected sources articles.

III. AFFECTIVE FACTORS IN CITRUS ORCHARDS

In the agriculture sector, getting high yields and larger production of food products were in large-scale production units like orchards and big-scale farmers. These citrus orchards were producers and suppliers of more predominant scale citrus fruits and products. The plant pathogens, pets, and drought were causing the major issue of economic loss, inferior quality and less production rates compared to the demand. In this part, the detailed description of the affected orchards and how they will reflect on the leaves has been listed below.

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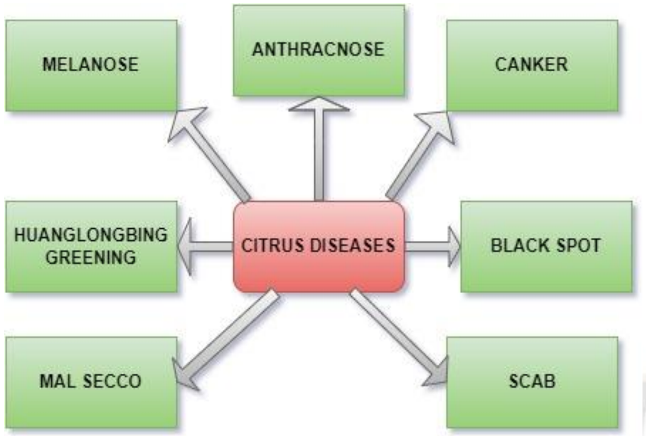

Figure 3. classification of citrus pathogens.

A. Citrus Pathogens

Citrus plants are in agricultural production, like lemons, oranges, grapefruits etc. These citrus orchards are affected by these citrus pathogens, which include citrus scab, black spot, anthracnose, citrus greening, melanoses, mal secco and citrus canker are presented in Figure. 3, [7] and those symptoms of the citrus pathogen on leaves are in Figure. 4.

Figure 4. Symptoms of sample plant pathogens [8], [9], [10], [11], [12].

B. Citrus Affecting Pest

Seasonal climate changes, insufficient nutrients in the soil, and fungicides cause citrus pathogens. These pathogens were major causes of affecting the plant's maturity and the production of fruits. There is also another factor that is damaging the plants and stopping their appropriate maturity. Even though the plants are not affected by any of the pathogens, those factors are pests and deficit conditions. The pests will totally stop the growth of plants because they affect the entire leaf structure, which leads to a lack of photosynthesis. The citrus caterpillars, citrus warm, leaf miner, citricola scale, and black and brown aphids are pests that are present in the citrus plants [13]. Pictures of those are presented in Figure. 5, and samples of pests in Figure. 6.

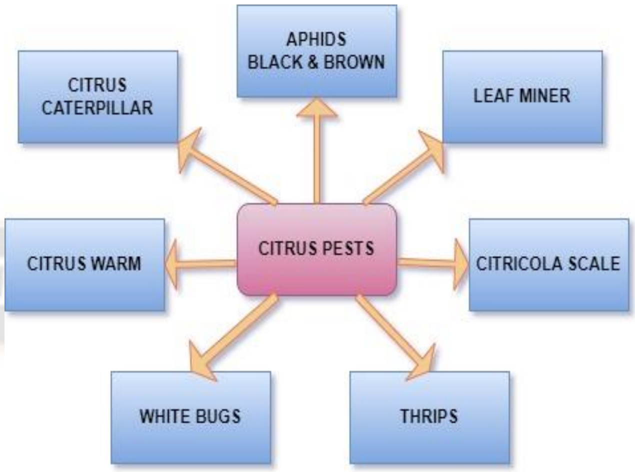

Figure 5. Categories of citrus pests.

C. Water Deficit Affecting the Orchards

Given the current environmental conditions and the growing scarcity of freshwater across the globe, it has become essential for agricultural irrigation systems to automate their scheduling, at least to some extent. By accurately assessing crop water deficit, it is possible to reduce water usage while improving the quality and yield of crops [2]. A Neural Network can help automate on-site monitoring and irrigation by classifying plant water deficit in immediate circumstances [14], [15]. The plant deficit will be recognised using the symptoms of plant leaves, and those symptoms are leaves drops at the immature stage, foliage to wilt, discolours on leaves, roots dying, and foliage discolour which has been mentioned in Figure. 7.

Figure 6. samples of citrus pests, [13].

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IV. PRE-PROCESSING TECHNIQUES FOR IMAGE INTENSIFICATION

This section provides a concise overview of image preprocessing techniques that are crucial for enhancing image contrast. When the image is captured from the image acquisition process with noises and poor background quality, it may affect the sharpness of the segmentation.

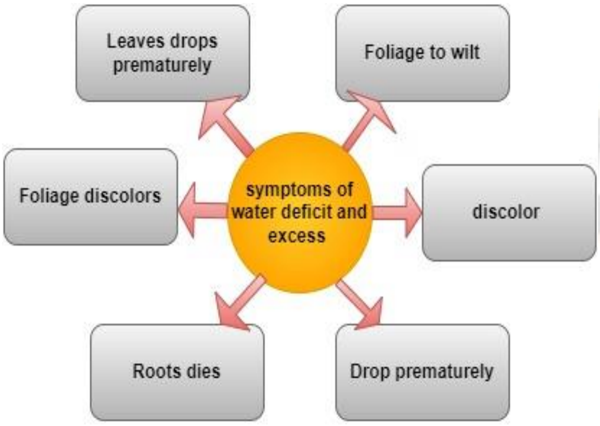

Figure 7. symptoms and effects of plant deficit.

Image pre-processing is the first step of image processing; some frequently used pre-processing techniques are compared in Table. 1.

[16] used to apply PCA on the data for dimensionality reduction, after these data augmentation is done through rotation, and for training, stochastic gradient descent with momentum (SGDM) optimizers are used. [17] has come up with spatial strong boost image filtering to sharpen and get rid of noise. Morphological improvement is done by contrast enhancement and resizing. It ensures the quality features for feature extraction and attain best in classification. By diving high-resolution images into low-level groups with super pixels during the preprocessing step, Image features has been made easy in the next step of image processing [18].

For citrus diseases matching, preprocessing methods are used to improve the contrast, brightness of the images to enhance the features in it. lateral flip, vertical flip are used to increase the dataset credibility [9]. These pictures are trained and learned by a deep learning network, which can then be used to quickly find and identify crop diseases. [19] made up a unique pattern by the pictures have been read, random 256x256-pixel pieces are cut out and then image filtering, distortion, flip, or rotation effects are added. [20] Each pixel in a certain area is the same in terms of things that can be measured, like colour, brightness, or structure. These features are enhanced by histogram equalization and thresholding on the grayscale images.

The contrast stretching method and CLAHE technique were used to fix images that were out of focus or fuzzy [21]. These preprocessing methods were used, and the classification got better. [22] method for changing the colour channel is used on the picture. converting RGB channels into a gray channel. Scaling, turning, shifting, adding noise, and making a mirror-image are the augmentation work use to increase the training and validation set on classification to improve its accuracy.

The RGB pictures of the plants are shrunk down to 227x 227x 3 and changed to HSV images. And then, Data augmentation of image with different brightness, different lighting, image are turned and its height or width changed [23]. The thresholding method for getting rid of noise gets rid of small things used for enhancing features. They provide some ways to increase the data by flip it horizontally, flip it vertically, rotate it 45 degrees, and rotate it 60 degrees for data augmentation, finally performance on classification are increased [24].

Enhanced the quality of the image by cropping it to draw focus to the area of interest, scaling it to make it smaller, or using the median filter to get rid of noise [25]. Contrast Stretching, Noise Filtering, or changing the Histograms [26]. Those filters such as low pass, high pass, etc. are used to remove various forms of noise. The area of interest is determined by thresholds the H band of the HSV colour area and cutting tiny parts of the image frame [27]. Datasets final training set has 3,468 shots that are augmented by rotation images into 0, 90, 180, and 270 degrees. The picture data set was moved from RGB field to HSV field, YCbCr, and grey colour scales transform [28]. Image rotation brings the number of photos in the set to 400 [29]. Through the process of changing the brightness, the number of pictures in the data set grows to 3600 by adding the augmented data into it.

TABLE 1. COMPARING THE TECHNIQUES FOR INTENSE PRE-PROCESSING.

Ref	Pre – processing techniques and usages	Performance metrics
[3]	Process "a" registers infrared and multispectral images, while process "b" registers infrared and RGB images. Then image resizing.	98.5% accuracy.
[16]	Principal component analysis's image was used to randomly crop, spin, reverse, and change the colour transform of the data.	accuracy of 94.3%.
[17]	Sharpen and get rid of noise with strong boost filtering the picture is cleaned up and its contrast is made better in the pre-processing step.	Overall Accuracy of canker is 97.4%,
[18]	Using super pixels to divide high-resolution pictures into small groups has made maths easier in long run.	96.24%, with 94.59% accuracy and 97.94% recall.
[9]	Brightness, contrast, horizontal, vertical, and both side flip.	87.53% accuracy.

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[19]	A random stretch, blur, brightness, and contrast change.	the model's success goes from 42.3% accuracy to 98.6%.
[20]	Using histogram equalization, thresholding on a grayscale picture.	accuracy 97 %.
[21]	Out of focus pictures or blurry rectified using the CLAHE algorithm.	95.3% accuracy
[22]	RGB channels into gray channel, Scaling, rotating, shifting, adding noise, and making a mirror-image.	Accuracy 98%.
[23]	Data augmentation. Original picture, image with different contrast, image with different lighting, image turning, image height or width changed.	F1 score of 0.88 and accuracy of 0.89.
[25]	Cropping the show area of desire, scaling to make the image smaller, utilising the median filter to achieve free of noise.	93.42%
[26]	Cleaning images as Contrast Stretching, Noise Filtering, and changing the Histogram. different kinds of noise, different filters, low pass, high pass used.	
[27]	Thresholding the H channel of HSV colour space. dataset rotations from 0, 90, 180, and 270 degree on augmentation.	Accuracy (96.82%).
[28]	RGB image dataset converted to HSV, YCbCr, and gray-colored metrics.	accuracy of 97.4%.
[29]	Through Image rotation and Through brightness alteration process, further, the data set is augmented.	98.08% accuracy
[30]	Sigma filter to get rid of noise and the CLAHE histogram Equalization.	accuracy of 98.76%
[31]	RGB images into HSV images.	accuracy of 96.96%.
[32]	Filter smoothing and improved the contrast.	Accuracy 98%.
[33]	1st process registers infrared and multispectral pictures, 2nd process registers RGB and infrared.	Training and test sets are 99.38% and 78.33%.
[34]	The bilateral image filtering and CGAN.	Accuracy of 96.4%.
[35]	RGB-HSV conversion. Saturation plane binary thresholding. hue-based segmentation works faster than K-Means.	86.58% accuracy
[36]	Resizing, enhancing, and converting into grayscale.	Accuracy of 98.39%.

V. SEGMENTATION PROCESS ON PLANT LEAVES

Image-based segmentation is the process of analysing information in an image and separating it with a similar combination of pixels. These combined similar pixels were to be noted as regions of interest in the input images. In this domain of agriculture, so many pathogens and pests were noted in the region of leaves and fruits. So, for this purpose, many segmentation techniques are discussed below and its comparison on techniques are mentioned in Table.2.

Region growing method for plant segmentation is to extend the area recursively from the seed part and it will joins neighbour pixels those are near identical, it stop on area of the contradict pixel rule [28]. [29], [38] with K-means clustering, each point is put into a cluster based on its local mean. This allows a pattern of groups to form. This method uses all of the groups given by k to find clusters. The minimum difference between classes is used to figure out the best cutoff [37]. A binary mask is a type of picture where the intensity of each pixel is either 1 or 0. The Otsu segmentation approach researchers utilized to getting the optimal value of the threshold those are present on the pixels [43], [46]. The K-Means method is used to separate parts of an image [47] [39].

The RGB image metrics were turned into HIS values for the segmentation model [40]. By finding the edge and spots, researcher can find the part of the leaf that is sick. The Unequal and Anti-Packing System with corners is used by the Set Pixel method to separate shades in a picture [48]. In image design, the NAMS are based on the following idea: If the researcher given the image (a wrapped texture) and some cubes (predefined sub-textures), select the shapes from the image. Semantic Segmentation is the process of grouping pixels in a picture that belong to the same class together [49]. Instance Segmentation goes beyond the problem of semantic segmentation by not only looking at whether the pixels of the objects belong to the same class but also dividing the pixels of each object instance [50].

The first step is to pull out three kinds of colour features: RGB, HSV, and YCbCr [51]. For each channel, the mean, range, variance, kurtosis, and skewness are all determined, and then these features are added to the texture features. The features with a least similar to each other are thought to indicate the sick area, whereas the remaining features indicate the healthy leaves and backdrop. GrabCut's segmentation is based on a programme [52]. The target area is surrounded by a rectangle. The pixels inside the rectangle are marked as unknown, while the pixels on the outside are marked as known. Using the Orchard-Bouman clustering algorithm, the foreground and background of a picture are modelled as Gaussian Mixture Models (GMMs). After pre-processing is done, the segmenting is done [53]. The TGVFCMS method is resistant to noise and keeps the edges Regularising TGV images up to a certain order of separation is helpful for judging things like noise removal and how sharp the edges are [54]. To improve the result of the segmentation, researchers will

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use the K-means algorithm on the object component that researchers get after the EDP breaks up the picture.

TABLE 2. COMPARING THE TECHNIQUES OF SEGMENTATION.

Ref	**Crop /parts use**	**Segmentation techniques**	**Performance metrics and result**
[24]	Plant leaves	Fuzzy C-Mean (FCM) is an unsupervised segmentation method.	Accuracy 98.43%.
[28]	Ginseng plant	Region growing method for plant segmentation	F1 score accuracy 0.88 and 0.89.
[37]	Potato	the segmentation algorithm using the thresholding method (Otsu method)	CNN classifiers, SVM classifiers accuracy. 93.2% and 87.5%.
[38]	Plant leaves	Blended Watershed Segregation Using Enhanced Kernel Means Clustering.	Accuracy 98.2%.
[39]	Paddy leaves	To identify sets of HSV pictures, the technique of k-means clustering was applied. This strategy depends only on tone of the image.	Accuracy 96.96%, precision 95.92%, recall 96.41%.
[40]	Plant leaves	Otsu, k-means, RGB Image conversion in HIS. Here HIS is used.	Accuracy 98%.
[43]	Tomato leaves	Otsu segmentation approach	Accuracy 96.4%
[46]	Paddy	Otsu's binary mask is used to separate the leaf area from the rest of the picture.	accuracy 99.20%.
[47]	Plant Leaves	Image segmentation is by K-Means algorithm.	Accuracy 96%.
[48]	Plant leaves	For RGB picture segmentation, the setpixel method uses the non-symmetry along with Anti-packing System using Squares.	
[49]	Coffee leaves	In instance segmentation, researchers utilise Mask R-CNN. In the subsequent phase of this U Net, PSP Net structures are used to do semantic segmentation.	UNet, PSPNet were found to have a mean intersection union with 94.25% and 93.54%.
[51]	fruit crops	correlation coefficient-based segmentation	Accuracy 98.6%.
[52]	Cucumber leaves	GrabCut algorithm-based segmentation	Accuracy 95%.
[53]	banana leaf	A hybrid segmentation called total generalized variation fuzzy C means.	89.04% of SE, 96.38% of SP, and 93.45% of AC
[54]	Pepper and tomato	the K-means algorithm based on the original image and object component.	accuracy
[55]	Citrus leaves	Markov random field MRF, graph cuts, and 2D histograms are all examples of higher-order statistics. The leaf pixels were split into rectangular areas.	Accuracy 91%.
[56]		FCM is used to find the spots on the leaf that are affected.	Accuracy (up to 95%).
[57]	Plant leaves	K-Means Clustering Algorithm for Image Segmentation	accuracy of 92.6%.

VI. METHODS FOR EXTRACTING THE FEATURES AND SELECTING THE FEATURES

Feature extractions are more important in classification because, using this feature, only classes can be differentiated. Every sample contains its own set of features like shape, size, colour, texture, etc. After feature extraction, the feature selection process is to select the best features from the extracted things. This best feature will make the recognition and classification of pathogens and pests more accurate. In this literature, several features, extraction techniques, and selection processes are mentioned below. Its comparison are mentioned in Table.3.

Getting strong features from an image makes it possible to classify it properly [16]. In this work, researcher deal with Machine Learning as well as deep learning parameters, like LBP. ResNet-18 has an eighteen-layer deep neural network framework that utilises an improved form of Genetic Algorithm for determining the characteristics. Additionally, it adds the concept of residual learning [20]. The best way to choose features is to cut down on the time it takes to do calculations. The global average pool layer is used to pull out features, and the size of the extracted features 2048. The mean size corresponding to the characteristic vectors for MobileNetv2 and DenseNet201 is 1280 and 1920, accordingly [35]. When the feature sets from MobileNetv2 and Densenet201 are combined, a big feature set is created. Whale Optimisation Technique was deployed to obtain a collection of distinct features from an entire collection of features.

[30] Each in the three Hue Saturation Lightness features got its own co-occurrence matrix. Then, 13 Haralick descriptors were

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calculated for each grid, giving a total of 39 extracted features (3 x 13).

Getting features out of an item is a key part of identifying it [40]. The local binary pattern and a grey-level co-occurrence matrix is utilised [44]. As it was originally suggested, the LBP feature would be used to get the intensity pattern from the segmented images. The colour-cooccurrence Method is made up of a grid of pixel values that are spread out in the same way across all of the pictures at the given offsets. New saliency method for separating diseased parts in an improved picture [51]. There are three primary areas to the saliency structure:

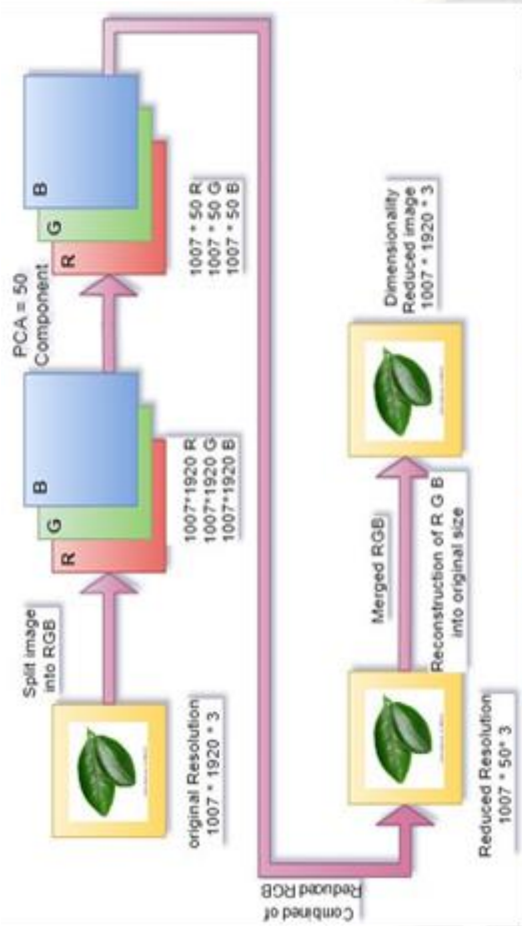

Figure 1. Working of PCA. [38], [58]

Extracting texture, colour characteristics, by Segmentation-based Nonlinear Texture Evaluation and local binary patterns. First, LBP and SFTA are utilised to find up the picture's texture and colour details.

[56] dark scales or colours. Colour, texture, shape, and edges can all be used to figure out what's wrong with a plant. LBP doesn't change in colour or rotation [58]. [59] uses colour and deep characteristics generated by the ResNet50 model that has already been trained. It shows how the pattern of strength changes locally. Using the Colour Co-occurrence Matrix (CCM) method, texture analysis was used to pull out features from pictures in a training dataset [60]. The basic parts of CapsNet are capsules [61]. Capsule makes vectors that have the same size but are in different places. This layer has feature extractors, classification layers, and dimensionality reduction layers.

TABLE 3. COMPARING FEATURE EXTRACTION AND FEATURE SELECTION TECHNIQUES.

Ref	**Features**	**Methods for extracting the features and selection.**	**Performance/result**
[16]	Obtained LBP and intense features.	ResNet50 and altered threshold-based GA are used to improve this vector. This GA also selects the characteristics in it.	ESD and Q-SVM, the precision is 99%.
[20]	ResNet-18 adds residual learning and ImGA or Improved Genetic Algorithm.	The average pooling is being used to retrieve features. For feature selection and improved computation, ImGA is suggested.	achieves the best accuracy in hybrid dataset of 99%.
[30]	Haralick texture feature, uniformity, variance, sum average, entropy, and entropy	the colour Co-occurrence Matrix approach used for texture mapping. feature selection using Pearson's correlation technique.	93.42% of accuracy.
[35]	MobileNetv2 and DenseNet201 features	For feature retrieval, MobileNetv2 and DenseNet201 were used.	95.90 % of accuracy
[40]	colour, texture, morphology, edges.	Color Co-occurrence Method (CCM).	98% accuracy.
[43]	new vector routing algorithm		96.4% of accuracy.
[44]	colour, shape, and structure features.	LBP and Gray-level matrix are used.	86.58% accuracy
[51]	Various Deep features.	By VGG16, Caffe AlexNet, is used to extract and select characteristics.	98.6% accuracy.
[56]	shape, and structure features.	Fast GLCM could be very helpful for confirming the high quality of the structure.	accuracy (up to 95%).

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[57]	second-order texture features	grey level co-occurrence matrix (GLCM)	accuracy of 92.6%.
[58]	Colour features.	LBP was utilised to retrieve features, and dimensionality was reduced by PCA.	Accuracy is 95% overall in it.
[61]	various similar group features in image.	CapsNet model with water wave optimizer (WWO).	higher accuracy of 0.9920.

VII. MACHINE LEARNING BASED CLASSIFIER TECHNIQUES

Machine learning-based classifiers are used for analysing the important features of basic patterns with many multiples of data were show in table. 4, 5. The basic work for getting the image data into processed data involves using pre-processing, segmentation, feature extraction, and feature selection to process the features into the input for the classifiers. Using these features of input, the classifier will classify the data into the specified classes that are mentioned in the classifiers. In this literature, many classifier techniques are discussed below.

[16] thought of a method that could use deep learning to find plant diseases. When researcher look at a model that has already been taught (deep ResNet50), it is then improved using a genetic algorithm (GA) with a converted harmonic limit. In Transfer learning work, TL needs to teach a model that has already been trained for a new job with less data, so a Convolution always needs a lot of pictures to learn using stochastic gradient descent (SGD) [20]. [30] colour matrix generated from HSL colour, and various Haralick texture characteristics were extracted. Texture characteristics were chosen as significant factors for training backpropagation neural network using Pearson's correlation method. As a consequence, 0.9146 kappa value with accuracy of 93.42% was obtained.

MobileNetv2 is trained on the orange set with ImageNet's already-trained weights to make it easier to learn about features [35]. The study uses another deep learning technique (DesnseNet201) has 201 layers and is a thick model. In the recommended study, the best features are found by using the Whale Optimisation Algorithm (WOA). With a 95.7% success rate. The efficiency of each technique was evaluated using data sets to train the SVM with a linear kernel, CNN based AlexNet architecture [37]. With 93.2% accuracy, the CNN classifier was the most accurate, while the SVM classifiers were the least accurate with 87.5%.

The whole classifier was put to the test, and when the ESD and Q-SVM classifiers were used, the best result was 99%. DAGSVM (Directed Acyclic Graph Support Vector Machine) is one way to solve multi-class SVM [45]. The suggested framework can tell the difference between sick and healthy leaves with 98.39% accuracy. [47] PCA could help with data processing and compression by using a linear method to reduce the number of dimensions and it will be shown in figure. 8. Set up the GA settings in ImGA, then check the health. The Hybrid dataset was 99.5% accurate, while the Fruit dataset was 94% accurate, and the Leaf dataset was 97.7% accurate. This study shows that 97% of the time, sick leaf spots are found using fuzzy c-means grouping [56]. Grey-level co-occurrence matrix (COLCM) is used to find the features, and progressive neural architecture search is used to put them into groups. Real time with up to 98.43% accuracy. [62] made by a classification algorithm called Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel. The tomato leaf disease detection system had an average performance measure of 90.37% accuracy. [63] used an LDA classifier learned on segmented trees from five-band multispectral stacks to find a disease sensitivity of 98%. SVM works better when it is built on an RBF kernel. show that the BPNN algorithm and the SVM algorithm are the most accurate at classifying the test set, at 86.57% and 86.30%, respectively [64].

TABLE 4. COMPARING MACHINE LEARNING CLASSIFIERS AND USES OF THE CLASSIFIERS.

Ref	Classifiers	Performance metrics
[20]	LDA, L-SVM, fine Kernal-Nearest Neighbor.	Hybrid dataset 99.5%, Fruit, Leave dataset 94%, 97.7%.
[25]	Spot Tagging early pathogen detect ML algorithm.	classification accuracy 97%.
[30]	Backpropagation neural network	Accuracy 93.45%.
[35]	Linear discriminant, SVM linear, quadratic, cubic and Ensemble subspace discriminant	Accuracy 95.4, F1-score 0.97.
[37]	SVM model supervised learning algorithm	Accuracy 87.5%.
[38]	Recursive Backpropagation process of Neural Network-trained MLP utilizing GA-based PSO algorithm	Accuracy 98.76%.
[39]	Utilizing a crow search strategy on deep neural networks.	Accuracy 96.96%, precision 95.92%, recall 96.41%.
[47]	RBF-SVM	Accuracy 95%.
[54]	MULTI CLASS SVM	95.90 % of accuracy.

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[56]	progressive neural architecture search (PNAS).	Accuracy 98%.
[65]	SVM and DL	Accuracy 96.33%

In order to differentiate between several varieties of cocoa beans researchers tested a Deep vision network and a traditional network [32]. Researcher using Resnet 18 as the framework. These deep vision networks had the highest accuracy of 96.82% compared with ML algorithms. This DNN deep neural network (CSA crow search algorithm) architecture makes it possible to use simple statistical learning methods with less work for the computer [39]. A GLCM was used to pull out parts of an image's texture it shown accuracy of 96.96%.

A linear and polynomial kernel multi-hidden extreme machine (MELM) and SVM have been used to see how well they work [40]. When it comes to classifying leaf diseases, the multi-hidden layer extreme machine classification does a better job than SVM classification, which gets a score of 98%. CNN's logistic regression create a novel way for extracting features that uses attention-based expanded CNN to find the most important features faster [43]. In this suggested method, they use bilateral filtering and Otsu segmentation to prepare the image. Finally, the selected features from the already-processed data are put together, and a fast and simple LR classifier is used to classify them. The results of the experiments show 96.6% accuracy for validation for multiclass dataset. The hue threshold in [44] is used to divide up places where there are diseases. The segmented pictures are used to find 12 colour features. As textural feature markers, they choose a GLCM and LBP. Extreme gradient boost (XGBoost) is used to sort things into groups. With only 26 features, the test sample can be predicted with an accuracy of 86.58%.

This article [51] is mostly about how CCDF can be used to find and group different fruit illnesses. Certain features are extracted using two deep, pre-trained models (VGG16 and caffeAlexNet). A parallel feature fusion step is put in before the max-pooling step to combine the features that have been retrieved. The characteristic vector is enhanced using GA. The core predictor are Multi-SVM. The score improved to 98.60% in multi-SVM. LBPs help to obtain features, the GrabCut algorithm is used for segmentation, and for categorization one-class categorization is implemented. The overall success percentage for 46 plant-condition combinations that were tested was 95% [52].

These papers talk about illnesses that affect tomato and pepper plants [54]. Colour, texture, shape, and vein are the four most popular ways to describe it. Colour characteristics can be found in many ways, such as with a colour chart. From the well-known Grey Level Co-occurrence Matrix, steps will be taken. A new method for precision agriculture called AIE-ALDC, which uses AI to classify diseases on apple leaves [61]. The suggested AIE-ALDC method uses orientation-based data enhancement and Gaussian filtering to get rid of noise. Capsule Network is a characteristic generator that can produce useful feature vectors. Lastly, BiLSTM architecture is employed to determine where the images of leaves should be categorised. The results of the experiments show that the AIE-ALDC method is better accuracy of 0.9920.

The suggested hybrid model [57] uses k-means clustering to find the diseased area on the leaf and [66] an enhanced CNN to categorise the diseases by comparing sampled and validated inputs. Then, the infected areas were separated using an algorithm called k-means clustering. The GLCM method get the needed features from affected parts. This study proposes an accuracy of 92.6%. [45] Image processing methods and feature extraction are used in the framework. The K-Means method can be used to figure out how to do this job. Then, the sorting of images will be done by putting together a supervised learning model and a support vector machine. The suggested framework of sick and healthy leaves had 98.39% accuracy.

In this study [67], using EfficientNet Sailfish Optimizer, Images of apple plant leaves are located and categorised by Adam optimizer, features are obtained by Efficient Net, then Spiking neural net categorization. Accuracy of 0.9969, this approach can place a cases in the HY class. These Color-Kernal-clustering and CHT used in [68] to identify potential fruit areas. LBP AdaBoost classifier is designed to eliminate false positives. 85.6% of the validation is right overall.

The RelieF algorithm detects the restrictive reliance between used features. [69] also use multi-class categorisation is to connect labelled input with the appropriate outputs. This method achieves 95.90% accuracy. [65] used support vector machines (SVM) and deep learning (DL) to find plant diseases using leaf picture data. For SVM and DL, these splits were 50% train, 20% optimise, and 30% test, and 60% train, 20% optimise, and 20% test. With its advanced design that uses deep layers of convolutional neural networks, the DL model outperforms the SVM by a fairly large margin when it comes to how well it can classify things [70]. For linear and RBF kernels, the accuracy was 96.33% and 97%, respectively, which was even closer to that of DL.This algorithm needs data to learn from the training data, which comes from feature vectors and data outputs, which

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are called labels [71]. These features and labels are used to teach the SVM, which is also called the prediction model.

TABLE 5. CLASSIFIERS USED ON MACHINE LEARNING CLASSIFICATION.

Ref	Classifiers	Performance metrics
[32]	Support Vector Machine (SVM), and Random Forest (RF).	Accuracy 85.71%.
[40]	support vector machine and extreme learning machine.	Accuracy 98%.
[43]	logistic regression classifier	Validation accuracy 96.4%.
[44]	Extreme gradient boosting or XGBoost	Accuracy 86.58%
[45]	Multi-Class SVM.	Accuracy 98.2%.
[51]	Multi-class SVM.	Accuracy 98.60%.
[52]	one-class categoriser using LBP inputs.	Accuracy 95%.
[57]	CNN for classification only	Accuracy 92.7%
[61]	Bidirectional Long Short-Term Memory (Bilstm) Model	Accuracy 0.9920.
[67]	Spiking Neural Network (SNN)-based classification	Accuracy 99.36%.
[68]	Color-Kernal-clustering and CHT used for identify fruits. The LBP AdaBoost as a classifier.	accuracy 85.6%.

VIII. MANIPULATION OF DEEP LEARNING MODELS AND ITS WORKING

Deep learning does complex calculations on vast volumes of data using artificial neural networks. It is a form of computational intelligence that is based in the way the human brain is organised and functions. Machines are trained using deep learning algorithms by learning through examples. Deep learning is frequently used in sectors like healthcare, eCommerce, entertainment, agriculture, and advertising. Layers of neural networks are used to train deep learning models. These models do not require manual feature extraction; they learn from direct input. In the work, researchers discuss many DL models, including CNN, RNN, Mask R-CNN, DCNN, and LSTM, and their processes. Then some CNN architectures (AlexNet, ResNet, GooLeNet, VGG, etc.) are also discussed here. Then these techniques are plotted in Table. 6.

[16] came up with the idea for a deep learning system that could be used to find plant diseases. The deep learning features are found by looking at a model that has already been taught (deep ResNet50). In this, the best performance was found at 99% at ESD, and Q-SVM classifiers were used. Using a deep neural network [17], For feature extraction, they used the Swin Transformer Neural Network, and for classification, they featured Cascade R-CNN-Swin. With stochastic weight averaging (SWA) methods, it is possible to get more accurate results. [18] stochastic gradient descent with momentum optimizer is utilised for training. AlexNet and VGG19 models for different datasets AlexNet classifiers are better than VGG19 classifiers at putting things into groups. On AlexNet, the accuracy is 91.4%, the precision is 90.7%, the sensitivity is 90.6%, the specificity is 90.4%, and the F-score is 90.9%.

When researcher use the AlexNet and ResNet models of traditional neural networks with and without data augmentation, researcher change the current data to add more data points [21]. ResNet and AlexNet got 95.83% and 97.92% accuracy, respectively. On hard datasets from the real world, Capsule Networks do better than other deep learning methods [8]. The Gabor CapsNet was better than the other models on both sets of data in terms of accuracy. MobileNetV2 is the main network model for the project [9]. The accuracy of MobileNetV2's ranking is 87.28%, which is higher than that of its competitors. ResNet50 is correct 86.53% of the time; DenseNet201 was right 87.53% of the time with an accuracy of 88.52%. Using a basic CNN technique and super pixels created by a Simple Linear Iterative Clustering method, citrus trees and other agricultural trees were identified in UAV pictures [22]. The workflow worked well and was very accurate (overall accuracy = 96.24%, Precision (positive predictive value) = 94.59%, and Recall (sensitivity) = 97.94%).

The first one was made from a set of pictures of whole leaves with different backgrounds and stages of disease [23]. From now on, this model will be called F-CNN. The second model, which is called S-CNN, was trained with the same pictures that were used to train the first model, which is called F-CNN. The average and middle amounts of confidence for S-CNN went up by 0.093, which is a big step up from F-CNN. CNN's accuracy was 98.6%, while earlier CNN said it was 42.3%. LSTM is better than a fully linked layer because it looks at all data sources instead of just one. This makes it more powerful. With a very high accuracy of 98.43% in real time [24]. [26] advanced CNN systems available today. using a technique known as depth-wise separable convolution, which involves first performing a 33 convolution at the depth level and then an 11 convolution at the point level. has a 96.5% validation rate and a 95.3% testing rate. The CNN model has hidden layers that make up the design of the deep network [46]. These are BNL, the RL, MPL, and so on. The suggested model has a classification rate of 99.20%.

The CRUN-MP method is suggested; using this, the part of the leaf that was infected was cut out [27]. The U-Net is used to separate the broken part of the leaf from the healthy part. A morphological treatment is done on the area to figure out exactly where the sick part is. Through the Entropy-ELM technique, features are taken from the chosen fine-tuned model and made better [29]. The ELM method was used to combine the characteristics of all four fine-tuned models, and the characteristic selected, merged the initial step. For the final classification, machine learning classifiers are used to recognise the combined traits. The trial process is done on five different sets of data. The best accuracy that can be reached on these datasets is 98.4%. In these convolutional layers, features are pulled out of the different levels of VGG16 that have already been trained and fed into the M-SVM [33].

CNN's K-fold cross validation is a way to divide a set of data into K values, where K+1 must be found so that the data can be split up even more [72]. The model is learned with the Keras, Version 2.2.4-TF, deep learning toolkit that works with TensorFlow. Based on the confusion matrix, the model for spotting leaf diseases and pests on cotton plants is 96.4% accurate overall. The DenseNet201 model had the best results, with numbers for all metrics higher than 99% [36]. But the SqueezeNet model learned the fastest. The transfer learning method is more credible and easier to understand. mean of 99.3% accuracy, 99.2% F1 score, 99.1% memory, and 99.4% precision. In this suggested work, the Sequential model and the smaller VGG model were used [73]. The accuracy of the smaller VGG model was 87%, while the accuracy of the sequential model was only 65%. In this study, researchers trained Efficient NetB0 and Dense Net121. These are used to pull deep features from images of maize plants [74]. Using the concatenation method, the detailed characteristics taken from every CNN, after combined to make a more complicated set of features that the model can use to learn more about the dataset. The model has accuracy of 98.5 %.

Faster R-CNN, YOLO version 4, and SSD Mobilenet version2 object detection CNN models have been refined [75]. The training accuracy of Inception version2 is 95%, Mobilenet version2 is 73%, and YOLO is 85%. This VGG-19 design is used to look for diseases in peaches. Mask R-CNN is used to figure out where diseases are happening [76]. Different ways of judging the suggested method have shown that it is accurate 94% of the time. [77] came up with a model based on the Mask R-CNN design that works well for segmenting these seven diseases into their different types. This gives a final mean average accuracy of 82.43%. RNNs are another type of neural network that is used to solve hard machine learning problems that involve a series of inputs [78]. The training accuracy reached 97.58%. With a value of 96.40% on the predictions. In the study [79], researchers evaluated the effectiveness of AlexNet-based transfer learning and enhancing methods. worked when they were used to identify grape varieties. The trial validation accuracy is 77.30%. When this classifier network was used on the well-known Flavia leaf dataset, an accuracy of 89.75% was achieved. Deep learning models are a good bet, and AlexNet is one of these models [80]. In this paper, a GPDCNN is suggested for identifying plant diseases by combining dilated convolution with global pooling. This network is meant to solve the problems of the AlexNet model having too many parameters and a single scale of features.

The Efficient B7 model, which is based on CNN, has been tried and proven to be able to find lesions on plant leaves [3]. Each of these is used for data enrichment and CNN. With a classification accuracy of 98.7%. The proposed model has two key steps: ResNet101 as the feature extractor, region proposal network, and limiting the number of viable areas, the ROI pooling helps reduce the possibility of false-positives with incorrect categorization [10]. The suggested model has an average detection accuracy of 95.8% and a detection accuracy of 94.37%. [81] In this study, well-known learners like ResNet-50, SqueezeNet, SqueezeNet-MOD2, AlexNet, GoogLeNet, and SqueezeNet-MOD1 were improved and tested. The six methods of DL employed in this research had a classification accuracy (CA) of more than 92% on average. With a CA of 98.11%, ResNet-50 was the best at telling the difference between healthy and infected leaves. Scaled YOLOv4 P7 is used to predict diseases quickly and early, and CenterNet2 with Res2Net 101 DCN-BiFPN is better than other new and efficient models at predicting citrus leaf diseases in their early stages [11].

The actual instances are initially divided into groups using Mask R-CNN network [49]. The next stage, it arranges the occurrences according to their importance using the UNet and PSPNet. It classifies the instances in the final step using a ResNet. In the instance segmentation job, researchers got a precision of 73.90% and a recall of 71.90% for the Mask R-CNN network. got a mean overlap over the union of 94.25% on the UNet network and 93.54% for the PSPNet network. To correctly find citrus diseases, it suggests a patch categorization network with an embed system, a cluster module, and a neural network model [12]. Stochastic gradient descent optimizer was used to train [82]. They used MobileNet v2, Inception v3, Xception, and VGG-16, which are all popular deep-learning network architectures. The Xception-based model achieved accuracy of 98.3%.

[83] dataset was used to fine-tune a VGG model that had already been trained. The "Caffe" deep learning structure was

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used to teach our system how to work. Using VGG-based transfer learning, these models get an average of 93.6% accuracy. A sequential VGGNet16 design is used to evaluate the four severity levels of the citrus fruit illness [84]. [85] design has VGG Neural Network, and using this DCDM architecture did very well and accuracy of 98.78%. The 2-Class CNN looked at a stage of sick and a stage of a healthy leaves [86]. Then 4-Class CNN needed for two stages of a sick leaves with two stages of a healthy leaves. These 6-Class CNN needed for three diseased leaves and three healthy leaves, at the same time to correctly and reliably tell healthy potato plants from diseased plants. PyTorch utilised for, validation, training and testing. Three CNNs were chosen to find early blight disease at different stages: GoogleNet, VGGNet, and EfficentNet. With a score of 0.99, EfficientNet had the best accuracy.

Using RGB images, these, DenseNet201, ResNet101, GoogleNet and AlexNet had classification accuracy of 97.45%, 99%, 97.75%, and 99.8%. Convolutional neural networks, the learning models Resnet50 and GoogleNet were able to get an accuracy of 89.2% and 86.6% [87]. This method uses detailed features obtained from deep convolutional network [88]. The deep features are used with the algorithm to make it easier to find symptoms that are similar. Each cropped image is sent into the refined, detailed feature obtained during testing procedure. After that, it goes to the trained KNN method, which outputs k vector-space ill leaf image that are similar to the input.

TABLE 6. COMPARING DEEP LEARNING MODELS.

Ref	DL model	Performance metrics
[3]	Deep Transfer Efficient-Net B7 model	Accuracy 98.5%
[16]	ResNet50	the precision, sensitivity, and F1 score
[17](pest)	Swin-Transformer and Cascade R-CNN.	Average Precision 0.5 of IoU is 91.5%.
[18]	Stochastic gradient descent momentum optimizer is used on AlexNet and VGG19 models	accuracy of 94.3%.
[21]	AlexNet, ResNet50.	Accuracy 95.83% and 97.92%
[8]	Gabor Capsule network	Accuracy 93.33% and 98.13% on citrus and tomato Datasets.
[22]	Simple Linear Iterative Clustering (SLIC) algorithm and CNN	Accuracy 96.24%, Precision 94.59%, Recall 97.94%.
[9]	MobileNetV2	Accuracy 87.53%
[23]	SCNN	accuracy moved on to 98.0% from 96.3% of F-CNN.
[24]	LSTM	accuracy of 98.4% on Kaggle dataset.
[26]	CNN architecture based on depth wise separable convolution.	Own dataset Accuracy 95.3%.
[27]	Region-Based Convolutional Neural Network (RCNN) and U-Net.	Kaggel, Accuracy 98%.
[29]	VGG16, ResNet50, ResNet101, and Densenet201.	Cucumber leaf diseases scan dataset, accuracy 98%.
[28]	Structured Convolution layers	Ginseng National Research Center in Daejeon. F1 score 0.88 and accuracy 0.89.
[31]	Deep CNN	Plant Village, APS 3700 images.
[32]	ResNet 18	Own dataset, accuracy 96.82%.
[33]	VGG16 model	Accuracy 99.8%.
[34]	CNN MODEL	By using Adam optimizer and Tanh activation function, 98.08% accuracy.
[36]	Transfer learning using eleven CNN models.	Plant village dataset 18,160 images. 50%, 70%, and 90%. Training subset, Accuracy 99.4% using 90% for training.
[37]	Alex Net model	Own dataset, 2456 images, CNN classifier highest accuracy 93.2%.
[41]	VGG16 convolutional layers as well as the combination of Squeeze-and-Excitation (SE) module and Inception structure	library of plant leaf diseases (https://challenger.ai/), accuracy 91.7%.
[46]	fully connected Convolution Neural Network (CNN)	The Rice leaf dataset is acquired from Kaggle, accuracy 99.20%.
[49]	Mask R-CNN network, PSPNet and UNet.	MIoU of 94.25% and 93.54% was obtained.
[53]	CNN MODEL	sensitivity 89.04%, specificity 96.38% and accuracy 93.45%.
[72]	CNN architecture	Own dataset, accuracy is 96%.
[73]	Sequential and Smaller VGG	The dataset of PlantVillage and Sequential CNN which gave 87%.
[74]	EffcientNetB0, and DenseNet121	Own dataset, accuracy 98.56%.
[75]	Faster R-CNN, SSD, Mobilenet v2, and YOLO v4.	95% accuracy of RCNN.
[76]	VGG-19 and Mask R-CNN.	Plant Village or Fruit-360. mean Average Precision (mAP) 94%.

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[77]	Mask R-CNN	Own dataset, mean average precision 82.43%.
[79]	Alex Net transfer learning scheme	Own dataset. the four-corners-in-one method, achieved a test accuracy score of 77.30%
[80]	global pooling convolutional network.	
[10]	two-stage deep CNN model	Kaggle Website, accuracy 86.2%, 97.2% and 94.6% for black spot, citrus canker, Huanglongbing
[81]	CNN constructed from the extracted features. AlexNet, SqueezeNet, GoogLeNet, and ResNet-50.	Accuracy 98.11%.
[11]	Scaled YOLOv4 P7.	YOLOv4 P7 with high recall and precision.
[12]	DCNN Model.	Accuracy 94%.
[82]	Inception v3, VGG-16, MobileNet v2, Xception	Accuracy 98.3%.
[83]	VGG-model	Accuracy 93.6%.
[86]	GoogleNet, VGGNet, and EfficentNet	Efficient-Net achieved precision score of 0.99.
[87]	GoogleNet and Resnet50 using convolutional neural networks	a precision 86.6% and 89.2%
[88]	k-nearest neighbors and deep neural network.	accuracy 98.83%.
[89]	CNN model	Own dataset accuracy 95.29%.
[90]	CNN model	Own and specialist dataset, Accuracy 94%.
[91]	VGG and ResNet, Mask R-CNN	Plant village dataset, accuracy 98.49%.
[92]	CNN with two layers.	Plant village dataset, accuracy 95.65%.
[93]	several layers of the Deep CNN.	Plant village dataset, accuracy 96.46%.
[94]	Faster R-CNN and Mask R-CNN.	mAP value 99.64%.

IX. IMAGE BASED WATER STRESS AND IRRIGATION FINDINGS WITH DEEP LEARNING MODELS

Precision watering based on how much water stress a plant is under is needed to consistently grow high-quality fruits. This helps experts make decisions about stress cultivation. In the usual method, single, low-cost data, called single-modal data, is used. But for more advanced farming, researchers need data from more than one source, such as physiological and weather data. Because there isn't enough water in the world for farmland, optimising the irrigation system has become an important part of any semi-automatic irrigation scheduling system. Using good methods to figure out how much water a crop needs can reduce the amount of water used and improve the quality and quantity of the crop. By classifying the plant's water stress in real time, using a neural network can help with automatic, constant monitoring and irrigation.

$$d_{srt} = \max(stem_{t-n}, stem_{t-n+1}, stem_t) - stem_t$$

The key input features for the suggested method are leaf wilting and the environment [14]. The water stress is clear from the way the plants are dying. The things in the surroundings have to do with breathing, which is what causes stress. A multiple uni-neural network with RNN as one of its LSTM layers is used to build the water stress prediction model. These architectures can use the suggested method, which has well-designed input characteristics and Neural Clusters fall. Neural Clusters fall encourages a multiple uni-neural network that can combine characteristics well by taking the whole world into account. Neural Clusters fall is a method for modelling neural networks that is based on clustering environmental factors. Based on the results of the clustering, it creates multiple network segment on neural network. They took pictures of the plants, took notes on the surroundings (humidity, scattered light, VPD, temperature), and measured the diameter of the stems of three tomato plants that had been pinched and grown in a dense crop. the variation in the stem's circumference that was discovered using the most recent irrigation (DSR) as a gauge of water deficit. DSR are the difference between current stem circumference and largest stem circumference on last watering. The state of the fruit after watering by real DSR and projected DSR must be compared to assess the current accuracy of measuring water deficit.

Deep Neural Networks for the Multinomial Classification of Tomato Plants' Water Stress Based on Thermal and Optical Aerial Pictures [15]. The thermal and optical pictures that the UAV system takes are processed and broken up into different parts. First, the pictures are cleaned up by getting rid of any that aren't very good. For segmentation, the spectral grouping technique is used. Two different VGG-19 classifiers are pre-trained for thermal and optical images and merged in the final layer. Softmax will be used for classification. There were 6600 thermally segmented images and 6600 optically segmented images in the finished dataset. These segmented pictures were given to the following classes: 2468 normal plants (38%), 1723 plants with too little water (26%), and 2409 plants with too much water (36%). The best accuracy (0.805) is achieved when the

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image resolution is 512 pixels and the SGD method is used to optimise.

TABLE 7. DEEP LEARNING ON PLANT WATER STRESS.

Ref	**Dataset and types**	**Models used in Deep learning**	**Performance metrics/ result**
[14]	Plant image and environmental data (temperature, relative humidity, UPD, commercial scattered light) Green house in fukuroi, Japan.	Multiple uni-neural network using Clusters fall.	21% reduced for Mean Absolute Error and Root Mean Square Error.
[15]	6600 thermal and 6600 optical images collected and pre-processed UAV data by their own.	Two pretrained VGG-19.	Accuracy is .805 is achieved.

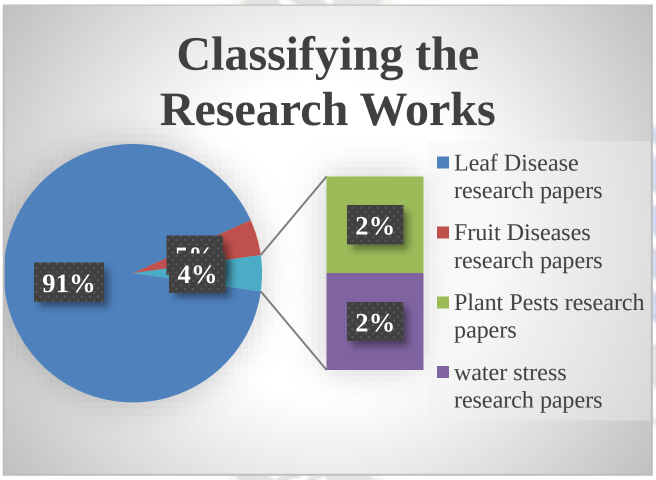

Figure. 8 Categorizing the gathered Articles.

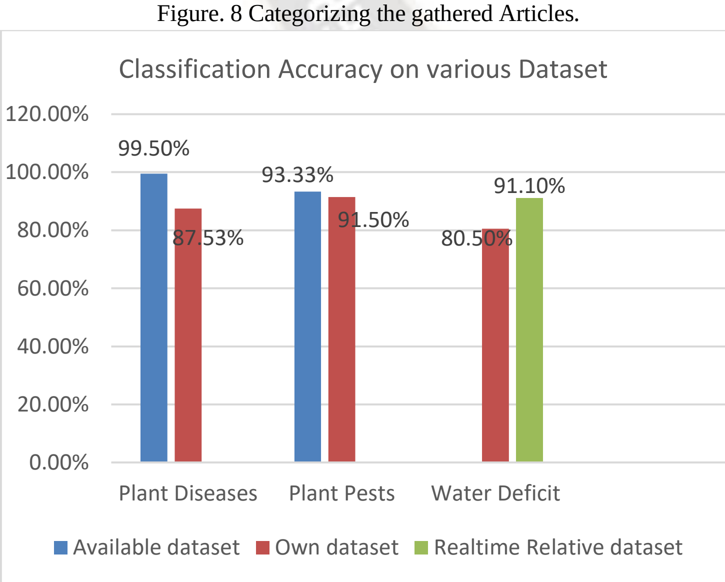

Figure. 9 Comparing the Classification Accuracy of Datasets.

X. DISCUSSION

In this review, several varieties of methodologies in image processing using machine learning, deep learning mechanisms were utilised to identifying, classifying the extensive review work on diseases, pests, and water stress on plants. This review leads to some important aspects such as pre-processing for intensifications comparison in Table. 1, the process of segmentation and its comparison on Table. 2, methods for extracting and selecting features in Table. 3, machine learning classifiers in Table. 4, Table. 5, and deep learning models and their comparison is in Table. 6. In this work, researchers discussed many aspects of comparison made for every step by models' working, performance, datasets, techniques, and various diseases of plants. The entire process of reviewing, including the pre-processing step, is important for segmentation and classification techniques. The deep learning model has more features and information than the traditional machine learning models for plant diseases, pests, and water stress identification processes in Table. 7, with a more accurate and wide range of detection in plant species. Then the use of various imaging processes for accruing high accuracy and fine-tuned information for problem detection and identification is discussed in the review. They were using numerous types of images, among which RGB images are the most familiar and easiest way to acquire them. The very first part of the research is gathering details about the datasets, like Kaggle, Mendely, and the PlantVillage dataset. The datasets, like the PlantVillage dataset, datasets from studies, and datasets from the internet, were used for the research. These dataset categorization in these review shows dependency of dataset on pest and water stress are very high, it is represented in the Figure. 9. The separation accuracy of various datasets are spotted in Figure. 10.

XI. CONCLUSION

In this review, most of the reviewed works focused on pre-processing images, segmentation, machine learning classifier techniques, and deep learning models. In order to find solutions for problems in citrus orchards, a comprehensive analysis of 94 research papers was conducted. The analysis identified machine learning, deep learning technic as effective methods on improving performance in this agricultural field. From the review, we draw the conclusion thus preprocessing approaches supports improving segmentation, and that combined preprocessing and segmentation work will enhance classification accuracy. When it comes to segmenting diseases and pests these instance, semantic, correlation coefficient segmentation is the most preferred method. Also, the colour and the deep features are the important features for knowing diseases in images. We draw the conclusion from this review that the Multi Model and Deep Neural Network are more effective at classifying diseases and water deficit from the images. Thus, researchers are trying to get the fast, effective, accurate system, it works for diseases, pests, and water stress predictive identification on the plants of healthy citrus orchards.

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