[1]Manjot Kaur

[2]Someet Singh

[3]Anita Gehlot

[4]Rajesh Singh

Unveiling the Potential: Machine Learning and Image Processing for Early Disease Detection in Tulsi Herb

Journal of Electrical Systems

Abstract: - Tulsi (Ocimum tenuiflorum) herb is very much predisposed to infections that influence the growth of the plant and impact the farmer's ability to learn about the environmental factors affecting the plant. To discover any type of plant infection at a very preliminary stage, a prediction model employing machine learning and image processing techniques can be developed to accelerate the method of disease detection and classification with high-performance metrics. The deployment of various variable preprocessing methods and distinctive factors in the feature extraction process appeared to enhance the implementation of infection recognition and categorization. This article intends to assess and explore the application and implementation of numerous approaches and developments regarding leaf infection categorization and classification. A thorough analysis is provided for disease infection and classification implementation upon examination of formerly recommended avant-garde methods. Finally, challenges and some commendations in this space are considered for the real-time implementation of numerous image computational algorithms for disease detection and recognition of Ocimum tenuiflorum.

Keywords: Avant-garde methods; Disease detection; Image processing technique; Machine learning; Plant infection; Ocimum tenuiflorum

1. Introduction

Ocimum tenuiflorum, 'The Embodiment of Herbaceous plant', the prominent 'Exceptional one' 'Tonic of Life', stands as an annual delicate herb [1]. It is grown at a large scale in the tropical climate and warm regions of India. It is an aromatic shrub, grown throughout the eastern world tropics. It is widely planted all over India in kitchen gardens and as indoor plants for religious and traditional medicine purposes and is famous for its essential oils. India remains a developing country, and the domain of agriculture is the backbone of the country's continuous growth and development. The field of agriculture faces lots of hurdles like a huge loss in crop production and the traditional method of plant leaf disease identification is also exceedingly difficult in the agricultural field [2].

The traditional manual method of identifying the infection in plants is variable and unpredictable; hence it cannot be considered a reliable systematic strategy to crop control. The consumer challenge for increased protection and superiority in agricultural products is what's required right now. Therefore, it will be crucial in the future to develop an automated, accurate, inexpensive, and effective model to identify plant infection in leaf, stem, and root. [3-4].

The investigators have proposed image processing and classification model work on various medicinal plants *Ocimum tenuiflorum*, bael(*Aegle marmelos*), peppermint(*Mentha × piperita*), catnip(*Nepeta cataria*), lemon balm(*Melissa officinalis*), and stevia(*Stevia rebaudiana)* [5-8]. *Ocimum tenuiflorum* is an important medicinal plant in day-to-day life and to identify the infections at an early stage for increasing the production quality and quantity, novel image processing and machine learning classifier models are required. The prediction model for plant leaf infection recognition and classification utilizes fast computer vision software and machine learning methods [11-13]. The symptoms of *Ocimum tenuiflorum* infection can decide the placement of dataset of infected leaves in training model under appropriate categorization labels. In image processing features like shape, texture, colour, vein, and many more are extracted and processed [14-15]. Machine learning classifiers like k-nearest neighbour, support vector machine, random forest, decision tree and artificial neural network are compared for better accuracy model [16-17].

[1] [1]Lovely Professional University, School of Electrical and Electronics Engineering, Phagwara, India manjotkaur.hpk@gmail.com

[2]Lovely Professional University, School of Electrical and Electronics Engineering, Phagwara, India someet.17380@lpu.co.in

[3]Uttaranchal University, Uttaranchal Institute of Technology, Dehradun, India anita.ri@uttaranchaluniversity.ac.in

[4]Uttaranchal University, Uttaranchal Institute of Technology, Dehradun, India, rajeshsingh@uttaranchaluniversity.ac.in

The key aspect of the paper is to discuss the novel procedures required in different stages of image processing and the machine learning classifier model for categorizing healthy and unhealthy leaves with maximum accuracy score, better precision, and recall rate [18-19]. The classification model of machine learning will employ the categorization of infected and healthy leaves which will indirectly help in increase in crop productivity. When the disease or herbivore is not severe enough or persistent enough to elicit diagnostic symptoms, it is difficult to physiologically identify plant infections and herbivory. Herbivory, physiological plant stress, and many plant diseases all share early symptoms. Even at their most acute and advanced phases, some diseases and herbivores can be challenging to diagnose. The classified infected leaves at an early stage can help farmers to provide the optimum requirements for plant growth. This study focuses mainly on leaves infected either due to pathogens or lack of optimum plant requirement. The application aims to increase productivity of the tusli crop by categorization of health and infected leaves at an early stage [20]. At every phase the existing algorithms important elements are discussed, compared and recommendations are presented.

The paper is organized into eight sections. Section one gives the preliminary introduction about *Ocimum tenuiflorum* leaf infections and machine learning model. Section two commences with the background, benefits, and various infections in *Ocimum tenuiflorum* leaves. Section three describes and discusses the various steps involved in the prediction model for healthy and unhealthy *Ocimum tenuiflorum* Leaves. Section four focuses on research on various image processing techniques, their uses, and the selection of right and appropriate algorithms for infection classification. Section five provides a comparison of various machine learning classifier models used for infection detection. Section six discusses various performance parameters which can be used to analyse the performance of classifier models. In sections seven and eight, recommendations and conclusions of paper are drawn, and some suggestions are provided for future work.

2. Significance of *Ocimum tenuiflorum*

Ocimum tenuiflorum is native to Southeast Asia and has a history within Indian medicine as a treatment for many conditions [21-22]. Many studies have recommended the use of the entire plant of *Ocimum tenuiflorum* for therapeutic, values, and human use [23]. It is an important herb to be used as first aid in the treatment of respiratory disorders, digestive disorders, heart diseases, skin diseases, anti-aging cure, kidney stress, headaches, acne fight, fever, eye, and oral health. Ayurveda also recognizes the use of the herb for curing diseases that range up to numerous growth [24]. The experimental studies show that the herb is highly cytoprotective, immune-modulator, and high as an anti-cancer agent. According to the Journal of Ayurveda & Integrative Medicine, it has antianxiety and antidepressant properties comparable to antidepressant drugs [25]. Bearing in mind, the significance of resistance increasing processes in the aftermath of the COVID-19 epidemic, and SARS-CoV-2 variant, the Department of AYUSH, Government of India, in conjunction with an understanding of healthiness advancement of the hordes, commends the ayurvedic medicine ‘Ayush Kwath’ [27], which contain four therapeutic herbs *Ocimum tenuiflorum*, ginger, cinnamon, and black pepper. It is widely used in Ayurveda because of its incredible medicinal uses [28]. It has fungal resistant and bacterial resistant features which benefit in cleaning the body fluid and retain skin, facial and body hair nourishing and glowing. Badri tulsi - *Ocimum tenuiflorum* or *Origanum vulgare* is an important form of herb for all reasons. Dr. Madhusudan Deshpande (Ayurveda Expert), a member (from 2017-2022) of the Central Council of Indian Medicine (Ministry of AYUSH), says that badri tulsi is advantageous in the therapy of various illnesses. It is found in snowy plains of the Himalayas and living in a cold environment, will absorb more carbon, and will become more powerful as the temperature rises. It has a 12% higher carbon absorption capacity and hence more tendency of releasing oxygen. It is widely used to cure skin diseases, diarrhoea, diabetes, wounds, hair loss, headaches, infections, fever, cancer, heart problems, digestion, cold, malaria, obesity, beauty, and many more [29].

Commercial production of the plant by-products has connotation owing to useful aroma elements obtained from vital oil of the plant leaf and flowers. A large volume of pasturage is accumulated during the time of year and is exported throughout the nation and worldwide. At an average score, *Ocimum tenuiflorum* generates nearly 10,000 kgs of new herbage per hectare annually. The basil produce is almost 0.1 to 0.23 percentage of oil and just about 10-20 kilograms of necessary oil per hectare [26]. Watered plant provides better herbage produce which is around 20 tonnes and the oil produce around 40kg/hectare [26]. The herb is mostly extracted in the form of oil, powder, and capsule. In the global market, it is extensively used in personal care, pharmaceuticals, and the food and beverage industry.

Ocimum tenuiflorum utilization is growing day by day and should be considered as a prominent and valuable type of herb. The consumption is increasing yearly, but crop damage is also increasing substantially. As per the survey of Chamoli district at Uttarakhand, India, exercised the ordinary least square approach to investigate the correlation between aggregate harvest revenue and the revenue from the crop for 2016 and 2017 [36]. The outcomes recommend as shown in Figure 1 that the gathering and farming of *Ocimum tenuiflorum* supplied an essential resource of green environmental substitute supplementary money revenue to rural populations particularly intended for women [37].

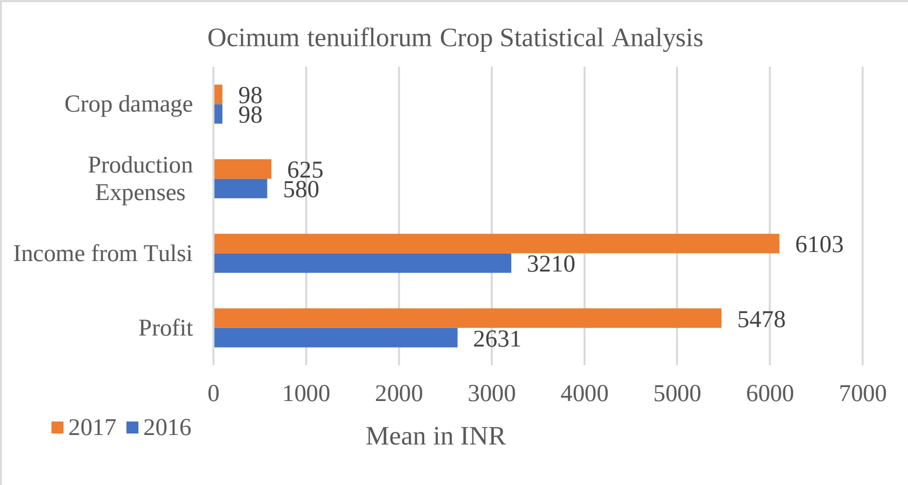

Figure 1. *Ocimum tenuiflorum* crop statistical analysis for the year 2016-17.

The *Ocimum tenuiflorum* herb is jam-packed with antioxidants as well as immune-boosting traits, the phytochemicals in the leaf defend the human body from harms affected by unrestricted radicals [30]. It relieves in improving the metabolic rate which facilitates in kilograms loss once combined with enhanced bodily combat & a nourishing low-fat food intake. The plant is also capable to enhance the sensitivity of insulin, which results in a reduction in blood sugar and thus curing diabetes [31]. Thus, the herb has been observed to focus on physical, metabolic chemical and psychosomatic anxiety through a distinctive blend of pharmacologic measures [32]. The herb can safeguard the vital organs and soft tissue against chemical and physical stress. Therefore, the antimicrobial *Ocimum tenuiflorum* has many health subsidies which can assist kill pathogenic microorganisms superficially and internally [33].

2.1 Ocimum tenuiflorum Leave Infections

The valuable *Ocimum tenuiflorum* plant requires ideal husbandry, mowing, conservation, and storage processes for therapeutic and sacred values. The problem is important to ensure the quality standards and processes for healthy leaves. It becomes important to distinguish the healthy and infected leaves and take necessary measurements to improve the production quality and crop yield. The plant, [34] is cultivated naturally in wet soil, temperate climate, and it can be easily affected by fungal, bacterial, and nematodes. Irregular dark spots and circular spots on leaves with dim light centers, yellow, wilting leaves, stunning growth, dying leaves plunging from the plant, stem lesions are caused due to fungus. Yellowing leaves are normally considered as nutrient deficient, but they are spread by contamination of seeds. Intermittent brown or black water-drenched marks or angular spots on leaves and stems having streaks are caused due to bacteria. The main diseases which can affect plant growth are powdery mildew, seedling blight, and Root Rot. [35] The *Ocimum tenuiflorum* leaves, stems, and roots are infected due to 50% fungal, 40 % insects, pests, and nematodes, and 10 % due to bacteria.

Though, several infections can affect leaf harm heading towards harvest dropped, particularly in high moisture circumstances when leaves have been extremely delicate. Undeniably, exceedingly only some pesticides and fungicides are usually applied on basil. Hence, be educated about the common diseases by an automated process will help in preventing them and thus increasing the crop yield promptly. Figure 2 and Table 1 depict different types of infections and diagnostic symptoms due to different types and causes of infections in various parts of *Ocimum tenuiflorum* herb.

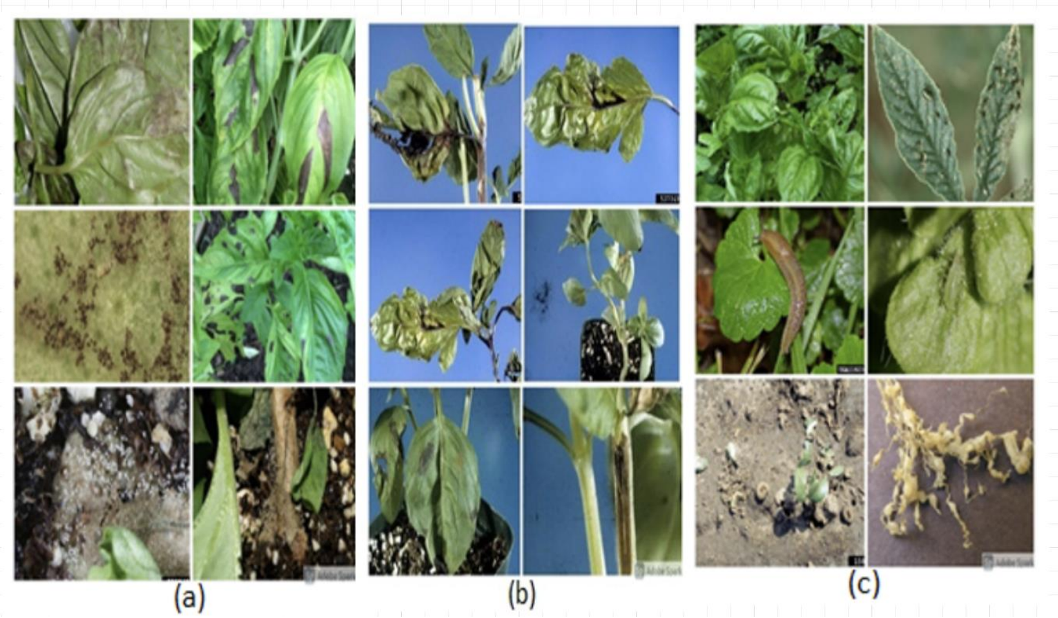

Figure 2. (**a**) Fungal, (**b**) Bacterial, (**c**) Insects infected *Ocimum tenuiflorum* leaves

Table 1. *Ocimum tenuiflorum* herb infection types and symptoms

Infection	Cause	Diagnostic Symptoms	Causal Agent	Part
Cercospora leaf spot Cercospora ocimicola	fungal	round to crooked dark marks, light centers	overhead irrigation	leaves
Downy Mildew Peronospora belbahrii	fungal	yellowing, discoloration across the central vein, gray hazy or fluffy development on the low downside of the leaves, brown, black sharp stains	improper air circulation	leaves
Fusarium wilt Fusarium oxysporum	fungal	yellow, fading leaves, brown stripes on the lower side of leaves, underdeveloped growth	contaminated seeds while planting	leaves
Gray Mold Botrytis cinerea	fungal	dark, brown-gray hazy development on stems and leaves, Severe lacerations on stem	overhead irrigation	stems leaves
Leaf spot Pseudomonas cichorii	bacterial	gawky or unusual brown or black water-drenched marks on leaves, stains on stems	narrow space field, improper air circulation	stems leaves
Root rot Rhizoctonia solani	fungal	seizure of seeds to sprout, sprouted seedlings fall, a tanned, withered region at bottom of the stem root's tan and water-saturated	improper air circulation, high-level humidity	roots stem
Slugs & snails Decoratus reticulatum	mollusc	unevenly formed cracks in leaves and stems, flowers and bear fruit damage, shredded leaves	high moisture	leaves stem
Pests	insects	yellow leaves, necrotic spots on leaves, dirty blight	intolerant variety of planting	leaves

Cutworms, loopers, owlet moths, and underwings Spodoptera exigua	insects	skeletonized leaves, cut sapling stem close to the bottom	wide host variety	leaves stem
Flea beetle Phylotreta spp.	insects	tiny gaps or hollows - "shothole"	improper quantity of insecticides	leaves
Grasshoppers Various sp.	insects	circular holes	improper quantity of insecticides	leaves
Root-knot nematode Meloidogyne spp.	nematode	lesions around 3.3 cm, a decline in plant vigor, yellowing plants	soil solarizing is not through	roots

3. Prediction model for *Ocimum tenuiflorum* herb infection detection and classification

Predictive modelling is a measurable method utilizing AI and information mining to foresee and figure likely future results with the guide of verifiable and existing information. The image processing methods are best intended for the recognition and categorization of plant infections with the latest appropriate tools. But with recent advances in technology, machine learning as an application or subset of Artificial Intelligence (AI), enables machines to learn from data without being explicitly programmed. AI is a larger idea that aims to build intelligent machines that can replicate human thinking capabilities and behavior. In the last 25 years, many advances have been made to enhance parameters like accuracy, reliability and precision of image analysis for herb infection identification, categorization, classification, combined with manipulation. Including the use of machine learning and computer vision technologies, calculations, training, and testing data have become more and more accurate. The amalgam of image processing with AI tools is magnificent and gives good quality, accurate, and desired results [38]. The different classifier models used in AI are meant for individual application, the rate and probability of choosing a particular type of machine learning or deep learning set of rules are very much significant for the prediction prototype to work during ambient conditions. A leaf is an important part of a plant, which has got many features like color, texture, and veins to identify the infected leaf in different conditions and different environments. AI-powered tools are highly efficient in empowering such systems [39]. Image quality is of utmost importance while studying the leaf under testing. High-resolution images are preferred but AI algorithms can identify and classify images that are of low resolution as well [40].

Hence, AI-empowered image processing model is required for identifying the healthy leaves in *Ocimum tenuiflorum* herb plant. Through image processing and machine learning algorithms, the process aims to classify the plant leaf diseases and generate a prediction model that would provide an easy and accurate way of determining the plant disease through a click of an image of the affected plant leaf [39]. The system will not only be beneficial to farmers, in saving the crops, but also in saving money by buying only the specific kind of pesticides suitable to treat the infected disease. Since the system does not involve any heavy types of machinery and electricity, the system proves to be not only cost-effective but also an environmentally friendly one [40]. The latest image processing techniques can be applied for uncovering and identification of plant leaf infections by applying various methods through Open Computer Vision (CV) tool and then sample images can be tested with different classifiers to obtain the best accuracy [41-44]. The system will depend on six different processes as shown in the proposed methodology step down process in Figure 3.

AI includes learning, reasoning, and perception of the real-time problem and their adaptive, corrective solution [45]. In machine learning, a file is trained to identify specific categories of designs. A template is prepared for a set of information data, an algorithm is given, tested and results are analyzed concerning various important parameters. Deep learning is the vital component of the machine learning domain, correspondingly machine learning is an integral part of AI [46-48]. The domain of machine learning is considered as AI, although not the entire AI is considered the same as machine learning. It is significant to consider some factors like model performance, accuracy, interpretability, computational power while selecting and choosing the right AI model as per Figure 5 for the given problem statement.

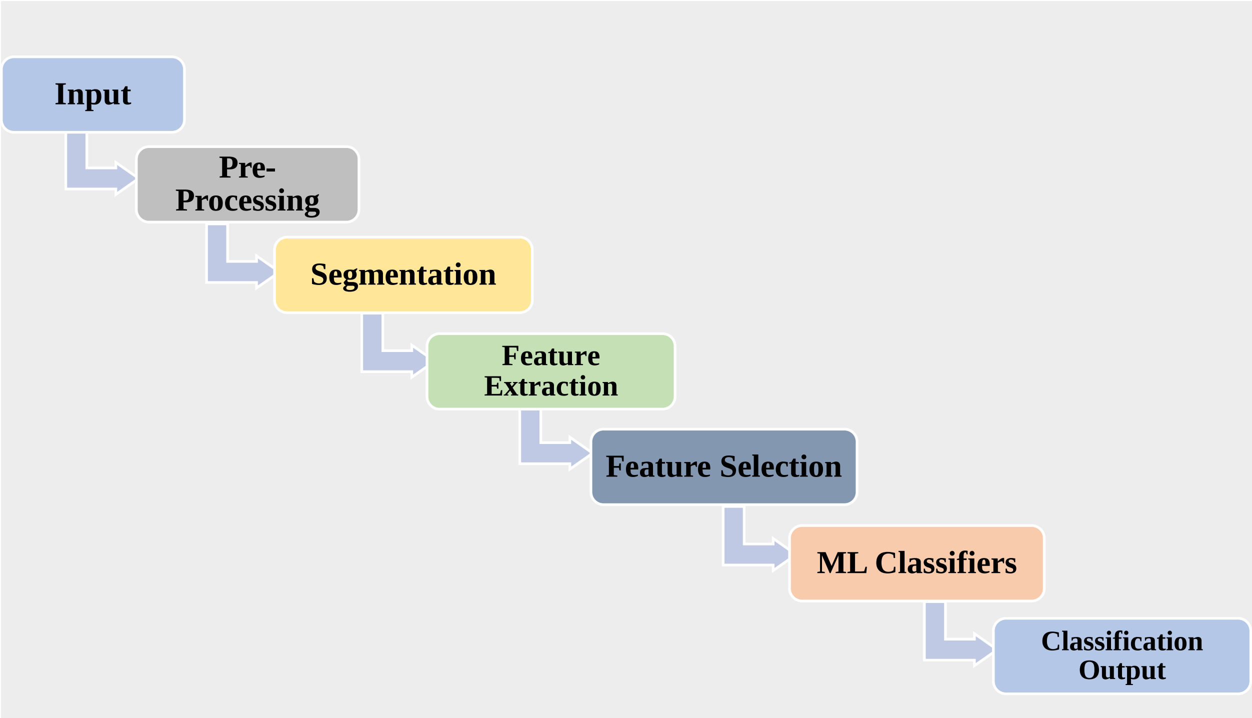

Figure 3. Proposed methodology for prediction outcome.

AI includes learning, reasoning, and perception of the real-time problem and their adaptive, corrective solution [45]. In machine learning, a file is trained to identify specific categories of designs. A template is prepared for a set of information data, an algorithm is given, tested and results are analyzed concerning various important parameters. Deep learning is the vital component of the machine learning domain, correspondingly machine learning is an integral part of AI [46-48]. The domain of machine learning is considered as AI, although not the entire AI is considered the same as machine learning. It is significant to consider some factors like model performance, accuracy, interpretability, computational power while selecting and choosing the right AI model as per Figure 5 for the given problem statement.

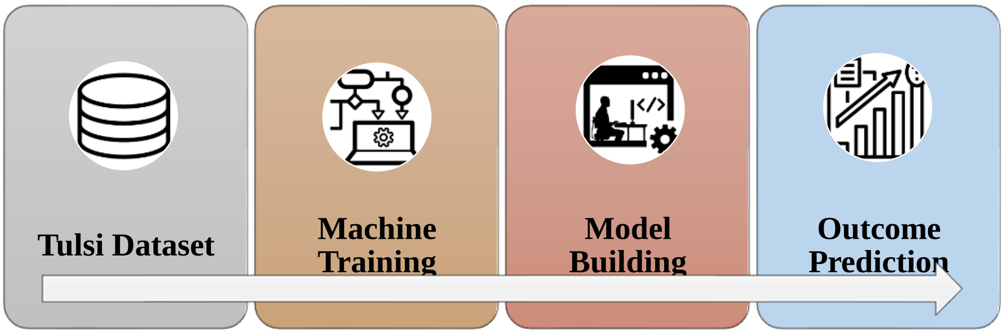

Figure 4. Intelligence model for leaf infection prediction.

The method of identifying diseases in plants in the agriculture field is by visualization by which an agricultural expert can identify diseases in the plant. Machine learning models with automation, computational skills can easily take an image of a leaf and conclude whether the plant is infected with a particular disease or not. The model can identify and segregate healthy and infected *Ocimum tenuiflorum* leaves [47]. Artificial Intelligent Model will aim at identifying and classifying the diseases and infected parts of the leaf and will take necessary actions to improve the growth of the plant and hence the productivity [49]. AI mathematical models replicate a decision process that enables automation and understanding. It is a progressive innovation as it focuses on accuracy cultivating and prescient investigation, mechanization, higher harvest yield, better quality, assessing and planning the yields, better satisfy need without excess, rating decisions, and find and treat plant contaminations with targeted resolutions.

4. Infection recognition by image processing techniques

Image processing is a preliminary stage in the proposed intelligence model as depicted in Figure 3. Digital Image Processing is a technique of manipulating and converting digital images by using various algorithms into enhanced images for desirable output at a particular stage. It involves image importing through image acquisition tools, analyze and enrich the image and provide the output report analysis. The process includes the alteration of the images as stored for infection identification and classification. This includes enhancement of image quality, information content as per features to be studied, and compression of image data for further processing [16]. The various techniques are described in sequence to be performed before applying the classifier model to identify healthy and infected leaves. All through the last four to five decades, economical and robust digital computers have become extensively available and utilized for a variety of tasks. Digital image processing provides significant benefits over analogue image processing. Digital image processing aims to improve the image data (features) by suppressing unwanted distortions and/or enhancing some key image features so that our AI-Computer Vision models can take advantage of this improved data to work on. This broadens the range of algorithms that can be applied to the input data. Digital image processing occurs as a constantly fascinating area because it provides enhanced illustrative data for treating the image documents for storing communication, and depiction for machine assessment [56].

4.1. Pre-processing

It is a process for the advancement of image data that represses any kind of undesirable deformations and aims for enhancing some selected or wanted features. It involves cropping leaf region into Gray Level transformation i.e., red, green, blue (RGB) to gray level [50]. Different methods can be applied to sharpen the image features depending upon the requirement of the dataset chosen. Table 2 and 3. highlights some of the common methods and algorithms and the features being enhanced by them. Image-based machine learning varies on how well the feature of a specific image is obtained from pre-processing stage [51]. Image pre-processing techniques are used to recognize the comprehensive features of interest from the image. The aim of image preprocessing is to enhance the vision data by suppressing undesirable misrepresentations or improving certain image features vital for additional processing in machine learning classifier stage.

Table 2. Image Pre-Processing Methods

Methods	Enhanced Features
Local Binary Pattern (LBP) and Oriented Fast & Rotated Brief (ORB)	Corrections in Illumination, Blur & Focus, Noise Removals, Filtering
Scale Invariant Feature Transform (SIFT) and Speeded up Robust Feature Detector/ Descriptor (SURF)	Corrections in Illumination, Blur & Focus, Noise Removals, Filtering, Edge Enhancements, Point Processing, Math & Statistical Processing, Color Spacing Conversions, Region Processing & Filters
Basic Space Fast Fourier Transform (FFT) Codes	Corrections in Illumination, Blur & Focus, Noise Removals, Filtering, Region Processing & Filters, Color Spacing Conversions
Blob Metrics	Corrections in Illumination, Blur & Focus, Noise Removals, Filtering, Thresholding, Edge Enhancements, Morphology, Segmentation, Region Processing & Filters, Point Processing, Math & Statistical Processing, Color Spacing Conversions

Here are many types of image preprocessing techniques which may involve image data resize, image data enhancement, noise exclusion, segmentation, grayscale shifting, and image binarization. The image preprocessing stage has taken raw image as input and produce an enhanced image as an output [52]. Once the leaf image diseases have been enhanced and filtered, the next process is to segment an image and find the appropriate region. In this study, there are different preprocessing techniques used to get appropriate features from the image. These are enhancement, noise removal, segmentation, color transformation, and binarization, some of which are demonstrated in Figure 5. Conventionally, most image processing detection algorithms assume that the background is black and that the object to be detected is white. However, as most of the text in the actual world is white lettering on black backgrounds, many real-world images will need to be inverted in order to conform to the image identification algorithm's presumptions.

Image preprocessing is the major technique to extricate suitable features from the image. The images, which have noise are always not acceptable irrespective of what image acquisition devices are used [10]. The following figures show some of the pre-processing techniques carried out on *Ocimum tenuiflorum* infected leaves: fungal, bacterial and nymphs on Jupyter Notebook in Python 3 version. Figure 6 shows the gray intensity levels, brightness control and histogram representation which can be used for understanding and manipulating images. A plot is shown as a bar graph, the pixel intensities are represented on x axis and the number of times of occurrences on y axis, that the corresponding pixel intensity value on x axis occurred. In figure 7 bacterial infected leaves are taken and histogram in terms of RGB is plotted and red, green, blue histograms represent various intensity levels.

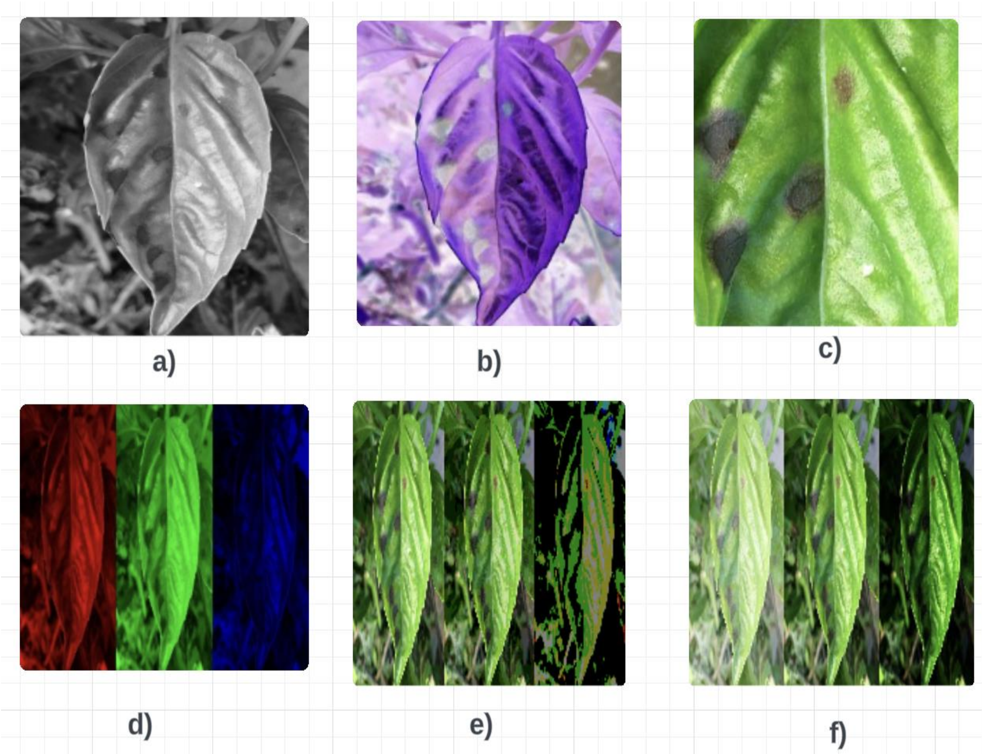

Figure 5. Pre-processing methods: a) Gray Scale b) Negative / positive inversion (invert pixel value) c) Trimming with slice d) Generation of single-color image and concatenation e) Color reduction f) Gamma correction.

Table 3. Pre-Processing Algorithms

Pre-Processing Techniques	Features
Gabor Filter	Uniqueness, Specific to period & Scale, Fast FFT, Quantification of Stationary Signals
Adaptive Median Filter	Smooth non repulsive noise, Retain edge information in high-density impulse noises
Morphological Operations	Detection of lesions of various sizes and shapes
Mean Filter/Average Filter	Reduce the variance and easy to carry out
Image Normalization	Consistent among different pages in the dataset, prevent printing problems
Histogram Equalization	Simple & Enhance Image Contrast

Weighted Median filter	Salt & Pepper noise Removal
Weiner Filter	MSE Minimization, Degradation Function & Noise Handling

Figure 6 shows the gray intensity levels, brightness control and histogram representation which can be used for understanding and manipulating images. A plot is shown as a bar graph, the pixel intensities are represented on x axis and the number of times of occurrences on y axis, that the corresponding pixel intensity value on x axis occurred. In figure 7 bacterial infected leaves are taken and histogram in terms of RGB is plotted and red, green, blue histograms represent various intensity levels.

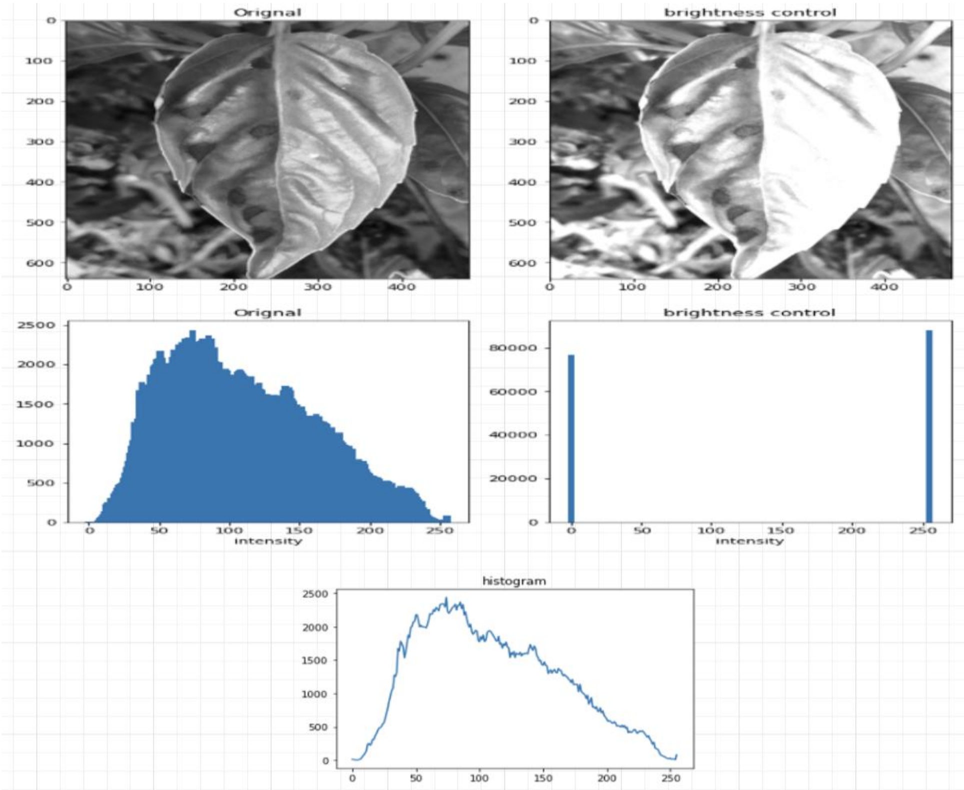

Figure 6. Histogram and brightness control on fungal infected

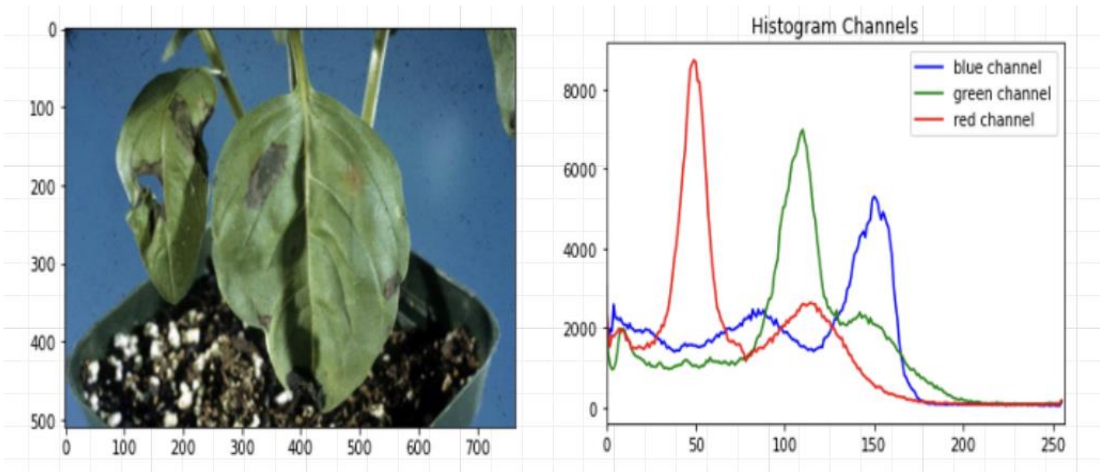

Figure 7. Histogram channels for bacterial infected leaves

Histogram Equalization enhances the contrast of pictures, by stretching out the range of the grayscale pixels by flatting the histogram. The contrast of the nymph infected leaves image is improved as shown in figure 9 after applying histogram equalization function by stretching it out.

The histogram's equalization distributes the intensity levels over a larger range of values. Since contrast enhancement affects brightness values rather than color values, it cannot be used directly in the RGB color space. Images must therefore be transformed to either grayscale or a color system with a brightness component, like the hue saturation value (HSV) as illustrated in figure 8. The analysis of the machine learning system's output scores is enhanced by histograms.

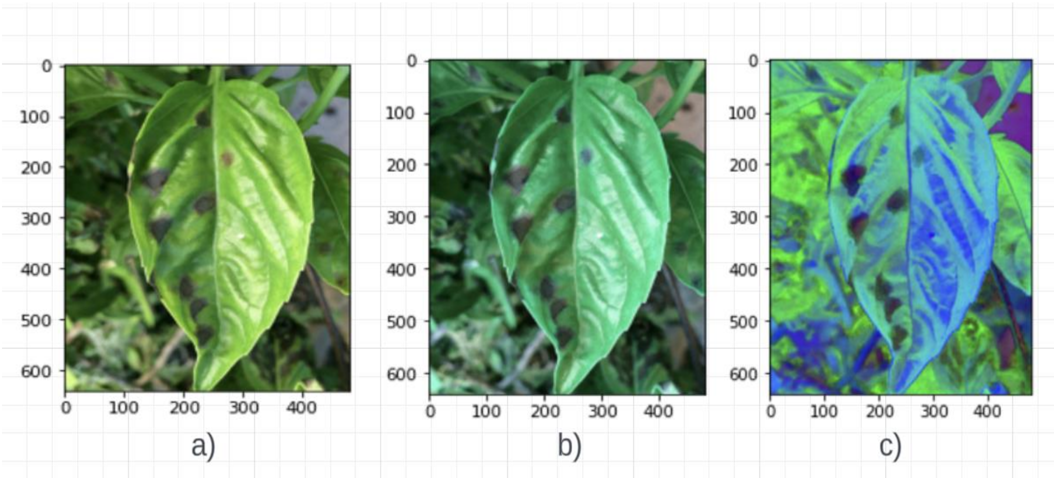

Figure 8. Histogram Equalization Pre-processing: a) original image b) BGR to RGB image c) HSV image

4.2. Image Segmentation

It is a method of segregating digital images into various significant or centered features required for a particular problem area. The process intends at distinguishing and isolating the foreground from the backdrop of the image under testing under edge or line detection as depicted in Table 4.

Table 4. Image Segmentation Algorithms

Algorithms	Technique
Pixel Based	Region Uniformity Criterion, Easy to Define
Edge Based	Computationally Fast, no prior Image content is required
Region-Based	Easier to categorize & execute
Deformable Model-Based	Generate surface from Images
Texture Based	Complex problems using training data
ANN Based	Parallel nature of Neural net
Fuzzy Theory-Based	Feature-Based & Spatial Information
Genetic Algorithm Based	Contrast Enhancement, Solve Complex Optimization Problems

Image segmentation stays as an indispensable element of the image testing method that defines the worth of the outcome [53]. It is the process of splitting or categorizing an image into various elements. The amount to which this section division is carried out hinges on the problem statement to be resolved. During segmentation, the picture usually is partitioned up until the items of significance were separated from their backdrop. There are presently numerous methods of doing data image segmentation, varying from the easy thresholding technique to enhanced color data image segmentation techniques.

These components usually relate to somewhat that beings can simply split and perceive as distinct entities. The image segmentation method is established on various characteristics discovered in the data image. This may be color data, borders, or a portion of an image [12]. Segmentation methods employ two techniques that perform on gray level values. The first one is centered on the incoherence of gray-level values which separates an image established on unpredicted alterations in gray level whereas the second is centered on the resemblance of the gray-level values that utilize thresholding and region growing. The threshold value, which is expected to be steady in all data set images through the identical lighting requirements, was generated on basis of the conclusions of the histogram graphical analysis. An easy and straightforward method for segmenting images is intensity thresholding. Each pixel is assigned a group (for example, healthy or ill) based on its value. Images are typically first converted to gray-scale when employing this method, and then the threshold is set using the value of the grey intensity. A sample of a gray scaled image is shown in Figure 6. An illustration of removal of background is displayed in Figure 9 using Otsu's threshold algorithm [52].

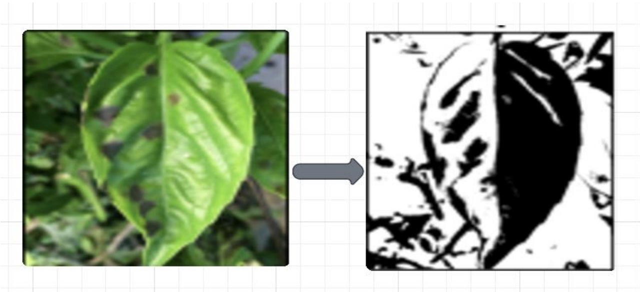

Figure 9. Threshold Segmented Image

It can be concluded from Table 4 that edge-based segmentation performs well for images with more significant object contrast. It can be recommended that edge detection, texture detection, and region-based detection algorithms can be applied to achieve quality images for leaf categorization [54].

4.3. Feature extractions

Features can be considered as measurable properties obtained from the various focus on portions of image, color, and moments [55]. It creates fused data set for different feature kinds like texture, shape, and vein of a leaf under analysis. It can be accomplished by contour-based or region-based extraction. Contour-based extraction is articulated in length, aspect ratio, width, and leaf diameter as signifiers. The region-based technique uses the signifiers such as shape, area, compactness, rectangularity, and eccentricity [9]. It performs an essential role in establishing the accuracy and precision of the machine learning classifier model [5]. If the matter feature is properly recognized, feature extraction would be simpler. The various features useful for leaf infection classification are texture, color and morphology [38]. The method of separating the features as shown in Table 5 is effective when you have a significant data set and need to decrease the number of resources without missing any vital or relevant information [56]. This is a decent decision because expanding the distance between the method for each class while extending the information in a lower-layered space can prompt better classification results. While utilizing LDA, is expected that the info information follows a Gaussian Distribution, subsequently applying LDA to not Gaussian information might potentially prompt unfortunate characterization results. LDA is undoubtedly, a supervised learning dimensionality reduction technique that can be used for infected leaf relevant information extraction. Hence the diminution of the training/testing/validation data aids to build the model by a reduced amount of system's efforts and enhance the rate of understanding and simplification measures in the given machine learning method.

Table 5. Feature Extraction Algorithms

Algorithms	Technique	Features
Principal Component Analysis (PCA)	Simplify a dataset, identify patterns with similarities and differences, Powerful Tool for analyzing data	Data Compression, Low Noise Sensitivity, Decreased Requirement for Capacity and Memory

Discrete Cosine Transform (DCT)	Spatial to Frequency Domain, Correlation with neighboring pixels	De-correlation, Energy Compaction, Concentrating Energy into lower-order coefficients
Linear Discriminant Analysis (LDA)	Data reduction, dimensionality reduction, class scatter measure	No illumination problems
Independent Component Analysis (ICA)	Second-order and higher-order dependencies, statistically independent variables	Reconstructs data better than PCA in n-dimensional space

4.4. Feature selection

Selecting the feature is one of the vital processes for image processing as shown in Table 6. It is used to choose the most valid and appropriate features and eliminates the additional or unwanted features with a minimum number of column features from a data source that is considerable in building a classifier model [57].

Table 6. Feature Selection Algorithms

Algorithms	**Technique**	**Features**
Filter	Statistical Measure	High Computational Efficiency & Time, Cheaper, Low Complexity, Useful as Preprocessor, Less Computational Space, High Dimensional Data
Wrapper	Optimization algorithm	Slow Computational Time, Expensive, More Computational Space, High Complexity, High Classification Accuracy, Increased Runtime
Embedded	Combination of Filter & wrapper	Slow Computational Time, Expensive, More Computational Space, High Complexity, Classifiers Dependencies

The table compares various parameters like efficiency, time, complexity, accuracy rate and model price for filter, wrapper, and embedded feature selection algorithms. The models established on regression slopes and intercepts, will approximate parameters for every term in the model [9]. Since the occurrence of non-informative variables can increase uncertainty to the predictions and decrease the total efficacy of the model.

Filter methods calculate the significance of the predictors outside of the predictive models and consequently, the model only the predictors that bypass certain criteria [15]. Wrapper methods assess multiple models utilizing techniques that add or delete predictors to locate the optimal blend that increases model performance. Wrapper methods are perhaps the most excellent methodology to select the features in consideration to accuracy and precision parameters, but then again, they also involve numerical resources. The method employs training a prototype numerous times using distinct sets of features and subsequently evaluate the resultant prototypes through the overlap accuracy of validation. Whereas in the filter methods, the features are calculated against a substitute instead of cross-validation accuracy [58]. Though, such alternatives are often much faster to calculate and do not need reorienting the entire model at every phase in the repetition. The word embedded method is only a no-win situation-each for selecting the features in artificial intelligence discovering methods that do not plunge into the previous dualistic approaches. It functions around a method analogous to selecting the features since the L1 standard consequence promotes sparseness on the prototype weights. Hence feature selection for leaf disease infection classification can be well performed either by filter method or by wrapper method.

5. Infection Prediction Using Classifiers

Predictive Modeling develops a model that uses test data for which category is known and it then classifies new interpretations. The main objective is to classify diseases into one of the classes either healthy or infected leaves. The various supervisor machine learning models, as illustrated in Figure 10, compare the models, with 3 signifying the highest parameter response, 2 the average response, and 1 the least performance response. The parameters for the basis of comparison are accuracy rate, classification speed and precision rate. The model can be employed over any open-source or licensed machine learning tool and output can be analyzed in terms of performance metrics [15]. Though, every minute we add up or remove a feature or subset of features on or after the given data, it is necessary to re-educate the model and assess the set to be validated. The mathematical models imitate a conclusion process which aids automation and comprehension [39]. ML models with computerization, computational skills can effortlessly take vision of a leaf and determine whether the plant is infested with a specific disease or not [42,43]. A system can be proposed where different classifier models can be combined to make decisions attained from a multi-functional approach to achieve better accuracy and recognition success rate [64].

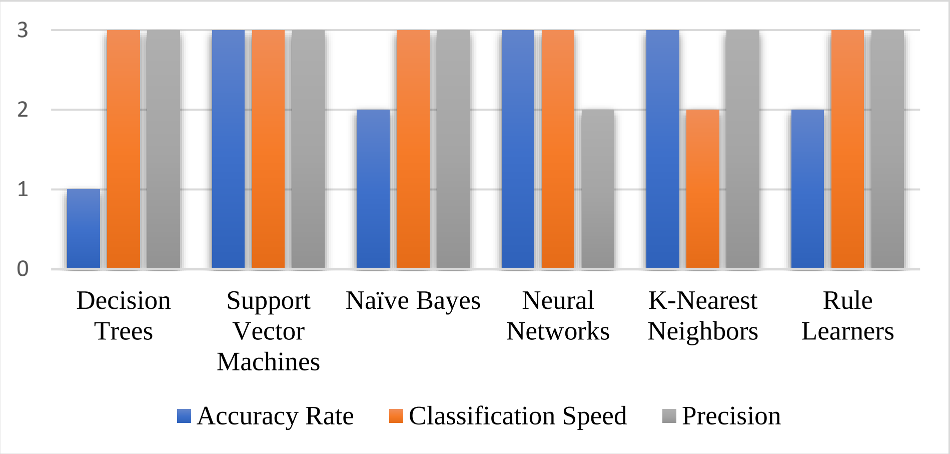

Figure 10. Supervised Machine Learning Classifier Models Comparison

Table 7 gives the review of different algorithms employed for various image processing and classifier models through Machine Learning, deep learning, and neural networks. The table also highlights features and tools used for study and research purposes. The comparison is made based on the last 10 years of research carried out for leaf disease identification, categorization, classification, and thus finally prediction for the best accuracy model. The dataset is a blend of work carried out on different plant leaves, fruits, and vegetables including stems, leaf, and roots. The various combination of algorithms is used when image processing and artificial intelligence are fused giving better output performance.

Studies discovered attaining results that are quite acceptable while using a small number of images for training and testing. The study revealed that SVM, discriminant analysis, especially linear discriminant analysis, and backpropagation neural networks perform significantly better than others. Naive Bayes, random forest, k-nearest neighbor, and multilayer perceptron follow. However, with recently established advanced deep neural networks, state-of-the-art outcomes are much enhanced [6].

Table 7. Review of Algorithms for Image Processing and AI Models

Reference Paper	Dataset	Pre-processing	Features	Training Model	Tools	Average Accuracy
[3]	38 Classes, 14956 Images	Average, Linear, Median, Adaptive	Shape, Colour, Texture, Vein	Random Forest, SVM, K-Nearest Neighbour	Matlab 2020, GUI	AA-73.88%, FScore-71.98% Recall-72.90%

						Precision-72.88%
[5]	Medicinal Plants-900	HSV, YCbCr	Colour, Edge, Texture	SVM, RBENN	Matlab, ANN Tool	AA-90% Combined
[7]	Medicinal Plant Leaves-`6	Cropping Leaf Region, RGB to GL	Multispectral, Texture, Runlength	MLP,LB,B, RF,SL	Computer Vision Laboratory Setup, Open CV	99.10% Ocimum tenuiflorum-AA
[10]	Crop Pests & disease	image resizing, filtering, colour space conversion and histogram equalization.	Texture, shape, size, and colour.	SVM,PCA, MLC, Knn, NB,DT,RF, ANN	Compute Unified Device Architecture(CUDA) from Nvidia corporation, GPUs, Alexnet, Googlenet. Matlab 2019b	98.5%-AA
[14]	Medicinal Leaves	RGB-Grayscale-Binary	Morphological, Filtering	Multilayer Perception	Matlab, SPSS	Recoginition Rate-70.87%
[16]	Plants	Image Re-orientation, cropping, gray scaling, binary thresholding, noise removal, contrast stretching, threshold inversion, edge recognition	Shape, size, and colour	ANN, PNN, CNN, K-Nearest, SVM	Previous Data	Comparison of classifiers
[44]	Leaf Flower Fruit Bark Flavia dataset 1907 ICl dataset 16848	BOF, LLC, SPM	Shape, Texture, Colour, BOF_DP, BOF_SC	Dual-Output Pulse-Coupled Neural Network	Machine Learning Tools	96%-AA
[51]	Flavia dataset, 32 types-1907 images	RGB to Grayscale	Centroid minor axis major axis solidity perimeter orientation	k-NN, Decision Tree, Multilayer Perceptron Adaboosting	Machine Learning Model	95.42% Precision rate 95.38% Accuracy

[52]	560 Plant Images	Resize, Filter, Histogram Equalization	GLCM & LBP	SVM, KNN, Ensemble	MATLAB, GUI	98.2%-SVM
[53]	500 Flowers & Plants	boundary enhancement, smoothening, filtering, noise removal	Leaf Contour, Length & Width	PIS	Matlab	Classification Images
[54]	52 plant species, Folio Leaf Dataset	ISC-MRCNN Vertical Flipping, Horizontal Rotation, Brightness Enhan	Instance Segmentation	APS-DCCNN	VIA-VGG Image Attenuator	96.37%-AA
[55]	Legumes-433	Hit/Miss Transform, Adaptive Thresholding	Veins	SVM, PDA, Random Forests	Matlab	PDA-98%
[57]	391-Fruits & vegetables	Segmentation	GCH,CCV, BIC, LBP, CLBP, UNSER, ISADH	MSVM, KNN	Matlab	Avg Classification Error-1%,3%
[60]	13 Types of Diseases-4483 images	Cropping, High resolution	Colour analysis, Thresholding	Caffe, CNN	Python, Open CV, Matlab, C++, GPU	AA-96.3%
[63]	Plant Village & Crowd AI 5406 Citrus Leaf Images with HLB Disease	Image Cropping Transforming & Normalizing Images	The ratio of Yellowing Area, Leaf Vein, Leaf's Yellowing Level	AlexNet, VGG, ResNet, Inception V3, Squeezenet, Densenet	Deep Convolutional Generative Adversarial Networks	92.6%-AA
[65]	AI challenger Dataset, 13185 Tomato Leaves	SVM, K-means	Shape, Texture, and colour of leaves	RRDN, Deep CNN	Ubuntu18.04, Tensorflow2.3.1 Cuda10.1, Python 3.8, SeeTaas Deep Learning Cloud Platform	95%-AA

6. Performance metrics

After performing the normal feature extraction, selection, and employing a model, and obtaining some output in types of a probability or a category, the subsequent action is to discover out how efficient is the model created on some metric utilizing test datasets. Various systems of measurement is used to assess different Machine Learning Processes. The Classification performance metrics for example Accuracy, Area under Curve, precision, recall, can be used for classifying algorithms mostly used by search engines [65]. The Confusion matrix happens as an instinctive and simplest metric utilized for realizing the performance parameters of the prototype. The matrix is generally applied for classification problems where the output is of two or more types of categorizations [66,67]. The Confusion matrix is not treated as a performing measure, but nearly all the performance metrics are based on the Confusion Matrix and the figures within it. It is truly based on positive and negative values as shown in the matrix which is the tabular vision of model prediction vs base truth labels [68].

Table 7. Confusion matrix representation

Confusion Matrix		Actual	
		healthy	unhealthy
Predicted	healthy	True Positive	False positive
	unhealthy	False Negative	True Negative

Table 8. Performance Metrics Parameters

Parameters	Description	Calculations	Range
Accuracy	Correctly classified data based on the total amount of real time data.	Accuracy = (True Positive + True Negative) / (True Positive + True Negative + False Positive + False Negative)	0-100%
Precision	Class predictions are classified as positive; how many are positive.	Precision (P) = True Positive / (True Positive + False Positive)	0≤ P≤1
Recall	Correctly classified as True Positive based on the all-positive data.	Recall (R) = True Positive / (True Positive + False Negative)	0≤ R≤1
F-Measure	Single score/ Harmonic Mean for precision & Recall	F-Measure = (2 x Precision x Recall) / (Precision + Recall)	0≤ F ≤1
Specificity	Negative Rate which is True	Specificity=True Negative/ (True Negative + False Positive)	0≤ S ≤1
ROC	Receiver Operating Characteristics	Plot showing Binary classifier as a function of cut-off Threshold	AOC (0,0) to (1,1)

In situations where False positives and False negatives do not have the same impact, picking the appropriate metric is significant. However, with machine learning models, there is usually a difference between accurately detecting False Positives or False Negatives. Preferably, we would prefer to have a prediction that is accurate in terms of both False positive and False negative. For instance, it may be argued that False positives are more significant if our model determines whether a leaf is unhealthy. If that leaf has the condition, we want to make sure we accurately recognize them. To properly evaluate models, it is essential to choose the appropriate performance indicator for the problem statement [69].

7. Recommendations

To prevail over the complexities of a manual process, numerous techniques based on image processing together with artificial intelligence have been established in modern times to detect and distinguish leaf infection identification and classification. Though the prominence of the issue of detecting leaf infections applying digital image processing is enormous, also the research is beneath analysis since the previous twenty-five years, however, the developments seem to be a bit timorous. Some indicators take the lead to this inference:

Disease identification- Ocimum tenuiflorum herb needs to be properly classified for types of infection. Infection identification should aim at automatically detecting the severity of detected diseases.

Dataset- Dataset for training and testing purposes is limited. Higher quality datasets to be used. Ensemble learning methods to be explored on the dataset.

Computational Effort- High computational complexity and cost to be surmounted. Easier & faster implementation of results to be carried out.

Classification Model- Combination of multiclass algorithms is to be employed. More hybrid feature analysis and segmentation techniques are to be applied.

Performance Metrics- Recognition rate, precision rate, and classification accuracy to be increased. Performance parameters to be analyzed combinedly for better results.

Therefore, machine intelligence, condition testing, and computer vision are still in comparatively initial phases of real-time advancement. Solution of image investigation challenges is considered as empirical tactics. Although these methodologies are certainly wide-ranging, nearly all of them contribute to a considerable ground of techniques that are specifically included in this paper. The investigators need to dedicate additional time in preparing the researchers to recognize the tools proposed to apply for classification models.

8. Conclusions and Future Scope

Ocimum tenuiflorum herb is highly susceptible to diseases that affect the development of the plant which in turn affects the ecosystem of the farmer. To detect a plant infection at the exceedingly initial phase, it is necessary towards improving computational approaches utilizing machine learning and digital image processing which will make this method of disease detection and classification automated with high-performance metrics. Accurately and appropriately characterized identification and classification of infections stays effective towards enhancing the growth and harvest of the plant. Thus, it can be concluded that performance parameters are an essential criterion for better understanding and identifying the tools to be meant to recognize, distinguish, and categorize plant infections employing digital image processing and classification models.

In this article, *Ocimum tenuiflorum* leaf has been considered for the classification model, but in the future other medicinal plants can also be taken for investigation of different types of infections. The main objective for future research is to apply image processing for classification of infection in leaves, develop the training model for prediction of infection in leaves and test the designed prediction model. The implementation of the prediction model in the real-time scenario is an added potential direction. The immediate results can be readily accessible to cultivators by creating mobile-centered applications. Web gateways can be utilized to give virtual solutions. Current research work could be extended to attain improved pace and accuracy by creating superior algorithms. It is thus relevant that through this paper it is easy to understand the principal areas covering the field of digital image processing and machine learning for the classification of plant infections.

References

1. Mishra: T., Rai, A. (2021). Antimicrobial potential of Ocimum santum and Adhatoda vasica: The Medicinal Herbs. International Journal of Pharmacy and Biological Sciences 1191, 17-28. doi:10.21276/ijpbs.2021.11.1.3.
2. Lavanya, V., Ganapathy, D., Visalakshi, R.M. (2019). Antioxidant and free radical scavenging activity of Ocimum basilicum - An in vitro study. Drug invention Today 12(5), 1004-1007.
3. Ganatra, N., Patel, A. (2020). A Multiclass Plant Leaf Disease Detection using Image Processing and Machine Learning Techniques. International Journal on Emerging Technologies 11(2), 1082-1086.
4. Jamshidi, N., Cohen, M.M. (2017). The Clinical Efficacy and Safety of Ocimum tenuiflorum in Humans: A Systematic Review of the Literature. Evidence-Based Complementary and Alternative Medicine 9217567, 13. https://doi.org/10.1155/2017/9217567.

5. Anami, B.S., Nandyal, S.S., Govardhan, A. (2010). A combined color texture and edge features-based approach for identification and classification of Indian medicinal plants. International Journal of Computer Applications 6(12), 45-51.
6. Begue, A., Kowlessur, V., Singh, U., Mahomoodally, F., Sameerchand, P. (2017). Automatic Recognition of Medicinal Plants using Machine Learning Techniques. International Journal of Advanced Computer Science and Applications 8(4), 166-175. doi:10.14569/IJACSA.2017.080424.
7. Naeem, S., Ali, A., Chesneau, C., Tahir, M. H., Jamal, F., Sherwani, R. A. K., & Ul Hassan, M. (2021). The Classification of Medicinal Plant Leaves Based on Multispectral and Texture Feature Using Machine Learning Approach. Agronomy, 11(2), 263. http://dx.doi.org/10.3390/agronomy11020263.
8. Vijayashree, T., Gopal, A. (2015). Classification of Ocimum tenuiflorum Leaves Based on Texture Analysis. Middle East Journal of Scientific Research 23 (Sensing, Signal Processing and Security). 102-107.
9. Bantan, R.A., Ali, A., Naeem, S., Jamal, F., Elgarhy, M., Chesneau, C. (2020). Discrimination of sunflower seeds using multispectral and texture dataset in combination with region selection and supervised classification methods. Chaos Interdiscip. J. Nonlinear Sci. 30, 113142.
10. Ngugi, L.C., Abelwahab, M., Abo-Zahhad, M. (2021). Recent advances in image processing techniques for automated leaf pest and disease recognition – A review. Information Processing in Agriculture 8(1), 27-51. https://doi.org/10.1016/j.inpa.2020.04.004.
11. Gomathi, M. & Vijayashree, T. (2015). Development of novel neural networks for the identification of types of Ocimum tenuiflorum leaves. Research Journal of Pharmaceutical, Biological and Chemical Sciences 6 (3). 1252-1259.
12. Ji, M., Zhang, L., Wu, Q. (2020). Automatic grape leaf diseases identification via United Model based on multiple convolutional neural networks. Information Processing in Agriculture 7(3), 418-426. https://doi.org/10.1016/j.inpa.2019.10.003.
13. Jiang, P., Chen, Y., Liu, B., He, D., & Liang, C. (2019). Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. IEEE Access 7, 59069-59080.
14. Ananthi, C., Periyasamy, A., & Muruganand, S. (2014). Pattern Recognition of Medicinal Leaves Using Image Processing Techniques. Journal of Nanoscience and Nanotechnology, 2(2), 214-218.
15. Dhingra, G., Kumar, V., Joshi, H.D. (2017). Study of digital image processing techniques for leaf disease detection and classification. Multimed Tools Appl 77, 19951–20000. https://doi.org/10.1007/s11042-017-5445-8.
16. Azlah, M. A. F., Chua, L. S., Rahmad, F. R., Abdullah, F. I., & Wan Alwi, S. R. (2019). Review on Techniques for Plant Leaf Classification and Recognition. Computers, 8(4), 77. http://dx.doi.org/10.3390/computers8040077.
17. Bao,Q.T., Kiet, N.T.T., Dinh, T.Q., Hiep, H.K. (2020) Plant species identification from leaf patterns using histogram of oriented gradients feature space and convolution neural networks. Journal of Information and Telecommunication 4(2), 140-150. doi: 10.1080/24751839.2019.1666625.
18. Roopashree, S.,Anitha, J. (2020). Enrich Ayurveda knowledge using machine learning techniques. Indian Journal of Traditional Knowledge 19(4), 813-820.
19. Saleem, M. H., Potgieter, J., Arif, K. M. (2020). Plant Disease Classification: A Comparative Evaluation of Convolutional Neural Networks and Deep Learning Optimizers. Plants, 9(10), 1319. doi:10.3390/plants9101319.
20. Sharma, P., Berwal, Y.P.S., Ghai, W., (2020). Performance analysis of deep learning CNN models for disease detection in plants using image segmentation. Information Processing in Agriculture 7(4), 566-574. https://doi.org/10.1016/j.inpa.2019.11.001.
21. Rhoades, H. (April 2021). Diseases And Problems with Growing Basil. https://www.gardeningknowhow.com/edible/herbs/basil/basil-diseases.htm.
22. Tewari, D., A N, S., H K, P., H S, M. (2012). A Review of Phytoconstituents of Ocimum (Ocimum tenuiflorum). International journal of Ayurvedic medicine. 3(1), 1-9. doi:1-9. 10.47552/ijam. v3i1.103.
23. Pattanayak, P., Behera, P., Das, D., & Panda, S. K. (2010). Ocimum sanctum Linn. A reservoir plant for therapeutic applications: An overview. Pharmacognosy reviews 4(7), 95–105. https://doi.org/10.4103/0973-7847.65323.

24. Kulkarni, K.V., Adavirao, B.V. (2018). A review on: Indian traditional shrub Ocimum tenuiflorum (ocimum sanctum):The unique medicinal plant. Journal of Medicinal Plant Studies 6(2),106-110.
25. Cohen, M.M. (2014). Ocimum tenuiflorum - Ocimum sanctum: A herb for all reasons. Journal of Ayurveda & Integrative Medicine 5(4), 251-259.
26. Kumar, A., Rahal, A., Chakraborty, S., Tiwari, R., Latheef S.K., Dhama, K. (2013). Ocimum sanctum (Ocimum tenuiflorum): a miracle herb and boon to medical science - A Review. International Journal of Agronomy and Plant Production 4(7), 1580-1589.
27. Gautam, S., Gautam, A., Chhetri, S., & Bhattarai, U. (2020). Immunity Against COVID-19: Potential Role of Ayush Kwath. Journal of Ayurveda and integrative medicine. Advance online publication. https://doi.org/10.1016/j.jaim.2020.08.003
28. Hemalatha, R., Babu, K. N., Karthik, M., Ramesh, R., Kumar, B. D., & Kumar, P. U. (2011). Immunomodulatory activity and Th1/Th2 cytokine response of Ocimum sanctum in myelosuppressed swiss albino mice. Trends Med Res, 6, 23-31.
29. Prakash, P. A. G. N., & Gupta, N. (2005). Therapeutic uses of Ocimum sanctum Linn (Ocimum tenuiflorum) with a note on eugenol and its pharmacological actions: a short review. Indian journal of physiology and pharmacology, 49(2), 125.
30. Gautam, M. K., & Goel, R. K. (2014). Toxicological study of Ocimum sanctum Linn leaves: hematological, biochemical, and histopathological studies. Journal of toxicology.
31. Manzano, S.,Garrido-Cardenas JA, Manzano-Agugliaro F. (2020). Worldwide Research Trends on Medicinal Plants. International Journal of Environmental Research and Public Health 17(10), 3376. doi: 10.3390/ijerph17103376.
32. Mohan, Lalit, M. V. Amberkar, and Meena Kumari. (2011). Ocimum sanctum linn. (OCIMUM TENUIFLORUM)-an overview. Int J Pharm Sci Rev Res 7.1, 51-53.
33. Tiwari, A. K., Mishra, R., Chaturvedi, A., Sadan, A., Arogyadham, J. R. D., & Ayurveda, I. (2014). Traditional uses of Ocimum sanctum (Ocimum tenuiflorum). Int. J. Glob. Sci. Res, 1(2), 126-131.
34. Gowans M. (April 2021). Brownish Yellow Spots on a Holy Basil Plant. https://homeguides.sfgate.com/brownish-yellow-spots-holy-basil-plant-71343.html
35. Nilamudeen, M., Girija V.K., Nandakumar, C. (2013). Colletotrichum leaf spot of holy basil (Ocimum tenuiflorum L.)- A new report from Kerala. Progressive Horticulture 45(2), 383-384.
36. Shah, G.-M., Ahmad, F., Panwar, S., Khadka, M. S., Ali, A., & Bisht, S. (2019). Ocimum Sanctum [Ocimum tenuiflorum]—An Alternative Additional Livelihood Option for the Poor and Smallholder Farmers. Sustainability 11(1), 227. http://dx.doi.org/10.3390/su11010227.
37. Sharma, Suresh & Verma, Deepak & Kumar, Yogesh & Kumar, Sanjay & Srivastava, Ramesh. (2019). Comparative economic study of Ocimum tenuiflorum and paddy cultivation in Sitapur district of Uttar Pradesh. Agricultural Science Digest - A Research Journal. 39. doi:10.18805/ag. D-4890.
38. S. Y. Liu. (2020). Artificial Intelligence (AI) in Agriculture. IT Professional. 22(3), 14-15. doi: 10.1109/MITP.2020.2986121.
39. Bharathan, K., & Deepasree, V. P. (2018, December). Ocimum tenuiflorum Leaves Classification System. In 2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), 1-5. IEEE.
40. Malvankar, Shubham. (2020). Plant Disease Detection using Image Processing. International Journal for Research in Applied Science and Engineering Technology 8(5). 2685-2690. doi:10.22214/ijraset.2020.5450.
41. Zhang, W. (2020). imageprocAnal: A novel Matlab software package for image processing and analysis. Network Pharmacology 5(1-2), 1-32.
42. Zhang, S., Wu, X., You, z., Zhang, L. (2017). Leaf image-based cucumber disease recognition using sparse representation classification. Computers and Electronics in Agriculture 134, 135-141. https://doi.org/10.1016/j.compag.2017.01.014.
43. Zhang, X., Qiao, Y., Meng, F., Fan, C., Zhang, M. (2018). Identification of Maize Leaf Diseases Using Improved Deep Convolutional Neural Networks. IEEE Access 6, 30370-30377. doi: 10.1109/ACCESS.2018.2844405.
44. Zhang, Y., Cui, J., Wang, Z., Kang, J., & Min, Y. (2020). Leaf Image Recognition Based on Bag of Features. Applied Sciences, 10(15), 5177. doi:10.3390/app10155177.

45. Jabal, M. F. A., Hamid, S., Shuib, S. & Ahmad, I. (2013). LEAF FEATURES EXTRACTION AND RECOGNITION APPROACHES TO CLASSIFY PLANT. Journal of Computer Science 9(10), 1295-1304. https://doi.org/10.3844/jcssp.2013.1295.1304.
46. Tsaftaris, S., Minervini, M., Scharr, H. (2016). Machine Learning for Plant Phenotyping Needs Image Processing. Trends in plant science 21(12), 989–991. https://doi.org/10.1016/j.tplants.2016.10.00.
47. Wang, S., Li, Y., Yuan, J., Song, L., Liu, X., Liu,X. (2020). Recognition of cotton growth period for precise spraying based on convolution neural network. Information Processing in Agriculture, 2214-3173. https://doi.org/10.1016/j.inpa.2020.05.001.
48. Wang, Z., Sun, X., Zhang, Y. (2016). Leaf recognition based on PCNN. Neural Computing & Applications 27, 899–908. https://doi.org/10.1007/s00521-015-1904-1.
49. Konstantinos P. F. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture 145, 311-318. https://doi.org/10.1016/j.compag.2018.01.009.
50. Ji, M., Yang, Y., Zheng, Y., Zhu, Q., Huang, M., Guo, Y. (2021). In-field automatic detection of maize tassels using computer vision. Information Processing in Agriculture 8(1), 87-95. https://doi.org/10.1016/j.inpa.2020.03.002.
51. Malhotra, N., Rani, G.(2020). Plant's Leaf Analysis Using Pattern Recognition Algorithm. Journal of Computational and Theoretical Nanoscience, 17, 5167-5173. https://doi.org/10.1166/jctn.2020.9359.
52. Oo, Y.M., & Htun, N. (2018). Plant Leaf Disease Detection and Classification using Image Processing. International Journal of Research and Engineering 5, 516-523.
53. Valliammal, N., Geethalakshmi, S.N. (2011). Automatic recognition system using preferential image segmentation for leaf and flower images. Comput. Sci. Eng. Int. Journal 1(4), 13-25.
54. Yang, X., Chen, A., Zhou, G., Wang, J., Chen, W., Gao, Y., Jiang, R. (2020). Instance Segmentation and Classification Method for Plant Leaf Images Based on ISC-MRCNN and APS-DCCNN. IEEE Access 8, 151555-151573. doi: 10.1109/ACCESS.2020.3017560.
55. Larese. M.G., Namías, R., Craviotto, R.M., Arango, M.R., Gallo C., Granitto, P.M. (2014). Automatic classification of legumes using leaf vein image features. Pattern Recognition 47 (1), 158-168.
56. Kumar, M., Gupta, S., Gao, X., Singh, A. (2019). Plant Species Recognition Using Morphological Features and Adaptive Boosting Methodology. IEEE Access 7, 163912-163918. doi: 10.1109/ACCESS.2019.2952176.
57. Dubey, S., Jalal, A.S. (2015). Application of Image Processing in Fruit and Vegetable Analysis: A Review. Journal of Intelligent Systems, 24(4), 405 - 424. doi:10.1515/jisys-2014-0079.
58. Muneer, A., Fati, S.M. (2020). Efficient and Automated Herbs Classification Approach Based on Shape and Texture Features using Deep Learning. IEEE Access 8, 196747-196764. doi: 10.1109/ACCESS.2020.3034033
59. Yun, S., Xianfeng, W., Shanwen, Z., Chuanlei, Z. (2015). PNN based crop disease recognition with leaf image features and meteorological data. International Journal of Agricultural & Biological Engineering 8(4), 60-68. doi: 10.3965/j.ijabe.20150804.1719
60. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., Stefanovic, D. (2016). Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. Computational Intelligence and Neuroscience 2016, 3289801, 11. https://doi.org/10.1155/2016/3289801.
61. Sun, J., Yang, Y., He, X., Wu, X. (2020) Northern Maize Leaf Blight Detection Under Complex Field Environment Based on Deep Learning. IEEE Access 8, 33679-33688. doi: 10.1109/ACCESS.2020.2973658.
62. Tavakoli, H., Alirezazadeh, P., Hedayatipour A., Banijamali Nasib, A.H., Landwehr, N. (2020). Leaf image-based classification of some common bean cultivars using discriminative convolutional neural networks. Computers and Electronics in Agriculture. 181, 105935.
63. Perera, H., & Costa, L. (2023, July 28). Personality Classification of Text Through Machine Learning and Deep Learning: A Review (2023). International Journal for Research in Advanced Computer Science and Engineering, 9(4), 6–12. Https://Doi.Org/10.53555/Cse.V9i4.2266.
64. Zeng, Q., Ma, X., Cheng, B., Zhou, E., Pang, W. (2020) GANs-Based Data Augmentation for Citrus Disease Severity Detection Using Deep Learning. IEEE Access 8, 172882-172891. doi: 10.1109/ACCESS.2020.3025196.
65. Zhou, C., Ye, H., Xu, Z., Hu, J., Shi, X., Hua, S., Yue, J., et al. (2019). Estimating Maize-Leaf Coverage in Field Conditions by Applying a Machine Learning Algorithm to UAV Remote Sensing Images. Applied Sciences, 9(11), 2389. http://dx.doi.org/10.3390/app9112389.

66. Zhou, C., Zhou, S., Xing, J., Song, J (2021). Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network. IEEE Access 9, 28822-28831. doi: 10.1109/ACCESS.2021.3058947.
67. Rahmani, M.E., Amine, A., Hamou, R.M. (2020). Supervised machine learning for plants identification based on images of their leaves. Cognitive Analytics: Concepts Methodologies Tools and Applications Hershey PA, 1314-1330.
68. Kaur, S., Kaur, P. (2019). Plant Species Identification based on Plant Leaf Using Computer Vision and Machine Learning Techniques. Journal of Multimedia Systems 6(2), 49-60. https://doi.org/10.33851/JMIS.2019.6.2.49.
69. Mingqiang, Ji., Yang, Yu., & Zheng, Y., Zhu, Q., & Huang, M., & Guo, Ya. (2020). In-field automatic detection of maize tassels using computer vision. Information Processing in Agriculture 8, 87-95. https://doi.org/10.1016/j.inpa.2020.03.002.