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Fostering ayurvedic plant wellness: Innovative leaf disease detection using computer vision and machine learning

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ABSTRACT

Ayurveda is a conventional medicinal approach that has its roots in India and has been used for hundreds of years. It is still popular today since it is entirely natural and free of side effects. Although ayurvedic medicines are made from natural botanical substances, their safety depends on the way they are administered, taking into account the needs of the individual and the specific disease states they are treating. Diseases that affect the plants' leaves are regarded to be one of the main reasons for a decline in the output of ayurvedic plants in India's agricultural, economic, cosmetic, and pharmaceutical sectors. A plant exhibits signs of plant diseases in diverse sections of the plant, however, leaves are the most frequently observed component for spotting an infection. The objectives of this work are to modernize and innovate an autonomous ayurvedic plant leaf disease detection system by examining the scientific basis of computer vision. Additionally, a full analysis of computer vision techniques such as image pre-processing, segmentation, and feature extraction is covered to detect defects in plant leaves. This work investigates cutting-edge machine learning methods for identifying plant diseases that employ a variety of computer vision techniques. Based on the review, the article addresses the challenges and offers recommendations for changes that could be made in the future.

Keywords: ayurvedic plant disease; image processing; machine learning

1. INTRODUCTION

Since ancient times, plants have been used to flavor food, treat ailments, and prevent diseases. Their medicinal properties have been known across cultures. According to the WHO, around 80% of the world's population relies on traditional medical systems for their primary healthcare, with plants predominating over other natural resources (Jana et al., 2021). The therapeutic efficacy of plants reduces the risk of many human diseases, including cardiovascular diseases, hepatorenal diseases, diabetes, cancers, and neurodegenerative disorders (Ahmad Khan and Ahmad, 2018). Also, the pharmaceutical industry heavily relies on medicinal herbs to create the world's medications. An estimated, 18% of the top 150 prescription medications and 25% of modern pharmacopeia are made from traditional medical plants (Astutik et al., 2019). Over the years, there has been a steady rise in the export of value-added extracts of medicinal plants. In India, the market for medicinal plants was worth Rs. 4.2 billion (56.6 million USD) in 2019 and is anticipated to grow at a compound annual growth rate of 38.5% to reach 188.6 million USD by 2026. Out of the 7,500 species of higher plants in India that are known to have therapeutic uses, ayurveda uses about 2,000 with Siddha and Unani also contributing (Rajasekharan and Wani, 2020). Almost 90% of ayurvedic treatments are derived from plants (Kumar et al., 2017). The five botanical families that make up the ayurveda plants are Asteraceae, Apiaceae, Rosaceae, Fabaceae, and Lamiaceae. Due to various reasons, including the spread of disease or infection among medicinal plants, population growth, weather predictions, and a lack of economic stability, many nations and organizations have started adapting advanced methods for the enrichment of medicinal plant production. Studies show that the life cycle and distribution of vital medicinal plant resources are being significantly impacted by climate change. When studying crop ecosystems, plant nutrition, competition, soil-water connections, plant defence tactics, respiration, transpiration, and photosynthetic rates, a leaf is an essential component. When plants contract various diseases through their leaves, it will reduce agricultural output and cause a profitability loss. Fungus, bacterial, and viral diseases decrease agricultural production and impair the quality of plant components (fruits, roots, seeds, leaves, flowers, and bark) used to create medicines. The rapid growth of plants and increased agricultural output depend on leaves. Numerous investigations have been carried out to evaluate the damages caused by plant leaf disease severities in various regions including with uncertain climatic conditions. Various challenges, including plant diseases, climate change, and economic factors are driving the adaptation of advanced methods to enhance medicinal plant production. Diseases affecting plant leaves, such as the black spot caused by *Alternaria alternata*, can significantly reduce agricultural yield and quality (Liu et al., 2022). Consequently, early detection, diagnosis, and acknowledgment of disease in plants are essential to preventing plant loss, increasing plant quality and quantity, and boosting medical plant cultivation growth economically. Traditional plant disease identification methods like visual inspection by experts are often impractical due to their demands on labor and time. Consequently, researchers have developed computer vision systems that rapidly detect and classify plant diseases, often spotting symptoms before they are visible to the human eye (Wang et al., 2022). These systems, which utilize pattern recognition and machine learning, analyze leaf images to identify diseases, aiding in early diagnosis and treatment (Dhingra et al., 2019). The hardware for computer vision includes cameras and IoT devices, while the software processes the images (Orchi et al., 2022). Advancements in this field have significantly contributed to agricultural innovation, demonstrating the transformative impact of computer vision in the industry. The objective of the study is to understand the technological keystone of computer vision in modernizing and revolutionizing ayurvedic plant leaf disease detection. In addition, the study lists several illnesses or infections found in the leaves of ayurvedic plants, along with their causes and symptoms. To implement automated plant disease diagnosis using computer vision, this article highlights the significance of image acquisition, various image processing, and machine learning technologies. The paper concludes by highlighting the challenges and outlining recommendations for further work.

2. OVERVIEW OF AYURVEDIC PLANT LEAF DISEASES

One of the key causes of deficits in the ayurvedic plant harvest is disease or environmental stress. The aberrant circumstances that negatively impact a plant's growth, development, or output are referred to as stress or illness in plants. There are two types of environmental stress/disease present: (a) abiotic stress and (b) biotic stress. Abiotic stress and disease are those that are brought on by external environmental (biological) inadequacies. Globally, factors such as low or high temperatures, UV radiation, salt, floods, droughts, heavy metals, inadequate or excessive soil moisture (bad soil pH), a lack of oxygen, over-watering, etc. are responsible for the substantial loss of crop plants. In contrast, biotic stress refers to damage caused by pests such as viruses, bacteria, fungi, algae, herbivores, nematodes, or insects. Figure 1 depicts the ailments that affect the ayurvedic plant aloe vera (Liliaceae family) and their underlying causes. Following are some basic manifestations of diseases caused by the fungus, bacterial and viral in ayurvedic plant leaves:

- Mildew: The powdery mildew, a fungus that grows on cherry, and sunflower leaf surfaces, is brought on by the fungus *Podosphaera clandestine* and hinders photosynthesis (Nayak and Bandamaravuri, 2018). On the underside of the leaves, the disease manifests as white to brown powdery patches. The area of a leaf covered by the powdery mildew prevents photosynthesis from occurring by blocking that area of the leaf (Sengar et al., 2018).
- Leaf spot: *Septoria helianthin*, which can be seed-borne and favours fairly high temperatures and copious rainfall, causes a septoria and Alternaria leaf spot on sunflower leaves. (Brand et al., 2020). *Alternaria alternata* is the primary culprit behind the aloe vera leaf spot disease reported in 2008 in the state of Tamil Nadu. *Alternaria alternata*, a fungus, has been observed to cause circular to sunken dots on the leaves that are round and dark brown. Cercospora leaf spot is also brought on by *Cercospora carotene* fungus in carrots.
- Blight: Carrot leaves are susceptible to Alternaria leaf blight, produced by *Alternaria dauci* fungus. Phoma blight is a fungal disease that appears as lesions on the leaves, the back of the head, the crown, or the base of the stalk and is brought on by *Phoma macdonaldii*. The tops of the leaves, where yellow water-soaked discolouration appears, are where symptoms first occur. The margins of the leaves also begin to yellow and extend gradually downward and inward of the leaves. Subsequently, the entire leaf blades begin to turn yellow and eventually wilt and perish (Saren et al., 2022).
- Rot: There are two potential causes of root rot. The first is continuing to be exposed to excessive moisture, which may result in the roots dying from a lack of oxygen. A fungus (Genera Phytophthora and Pythium) that lives in the soil could be the second factor (Okubara and Paulitz, 2005). The fungus remains latent in the soil, but if the aloe vera plant receives too much water, it may awaken. The roots will be attacked by the fungus, which will cause them to rot and die. Root rot causes the plant to gradually fade away.
- Rust: The fungus *Phakopsora pachyfhiza* and *P. meibomiae*, which cause aloe rust, appear as a yellow spot beneath the leaf's skin, where it then begins to expand. Following this, the skin of the leaf cracks, exposing the rust-colored spores (Avasthi et al., 2019) The wind can help the spores spread over a vast area.
- Mosaic virus: Distortion, mosaic, dwarfism, and yellowing of the leaves, along with occasionally a significantly smaller lettuce heart, are the typical symptoms in vulnerable lettuce cultivars (German-Retana et al., 2008).

Further detailed descriptions of various ayurvedic plant leaf diseases are mentioned in Table 1. According to the aforementioned study, the top three leaf diseases that typically affect various ayurveda plants are spots (produced by either fungi or bacteria), mildew, and rust.

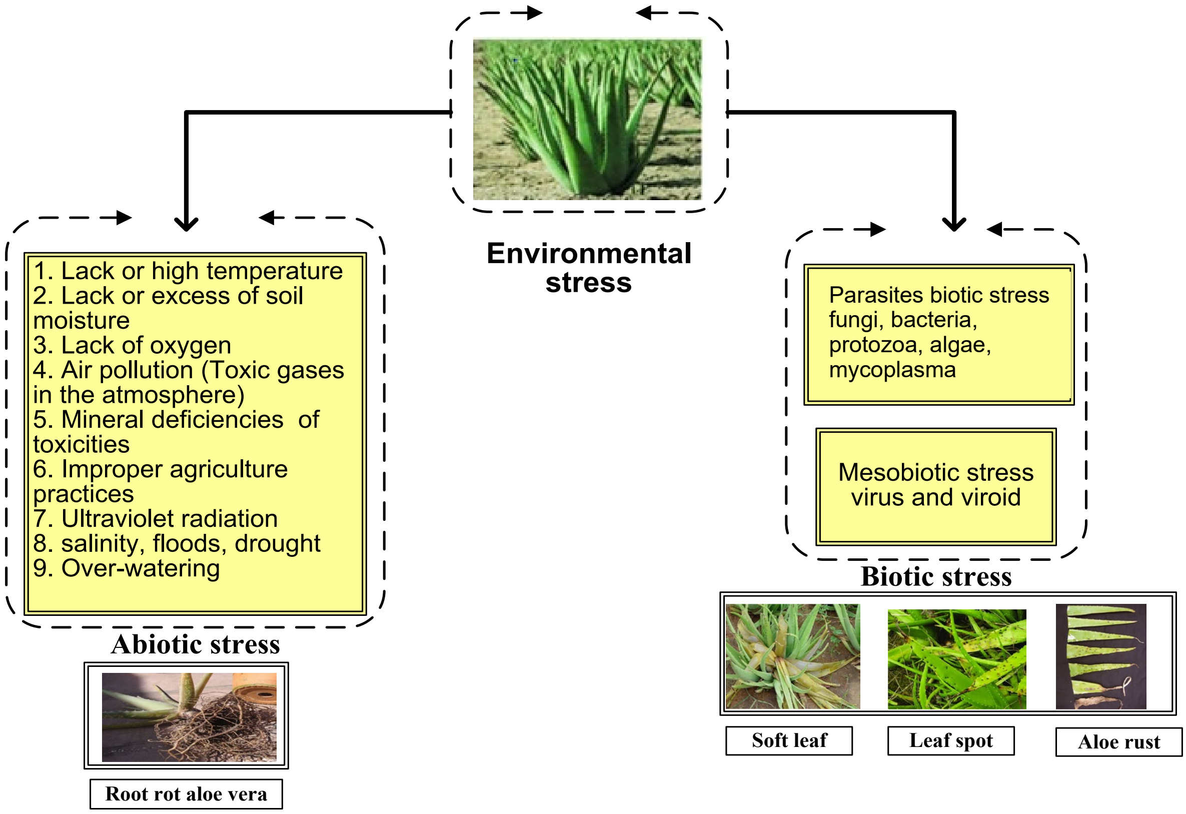


Figure 1. Differentiation between the environmental stresses

3. COMPUTER VISION ENABLED TECHNIQUES FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATION USING MACHINE LEARNING

The integration of various technologies for detecting plant diseases through computer vision was examined. This involves steps from acquiring leaf images to classifying them as healthy or unhealthy using machine learning. Key steps like image acquisition, pre-processing, segmentation, classification, detection, and prediction form a systematic approach to identifying plant diseases, outlined in Figure 2. In the training phase, leaf images captured by IoT sensors are processed and segmented to extract features for classifier training. In testing, these methods are used on new leaf images to determine their health status. In this research paper, all phases are covered along with a succinct overview of the various methods used to identify plant leaf diseases. Accuracy is a common performance metric used to evaluate the usefulness and competence of plant leaf disease recognition systems. In addition, other performance measures such as precision, recall, ROC categorization rate, recognition rate, and success rate also utilized to assess the overall performance of these systems.

3.1 Data repository for plant leaf acquisition phase

Image acquisition, essential for machine learning in plant disease detection, can be performed by sourcing from standard repositories or directly capturing with high-tech equipment. Key repositories include Plant Pathology 2020-FGVC7 and PlantVillage, Kaggle (PlantVillage Dataset | Kaggle), BIFROST (PlantVillage Dataset | Kaggle), APS Image Databases (apsnet.org), IPM Images (The Source for Agriculture and Pest Management Pictures), OSF (Image set for deep learning: Field images of maize annotated), Swedish leaf dataset (liu.se). High-quality images are critical, as real-time collection can contain noise and variations that affect accuracy. IoT vision sensors are particularly useful for capturing detailed images necessary for identifying subtle plant health indicators. Field-collected plant images are sent to a cloud server via IoT gateways like the Raspberry Pi (Soetedjo and Hendriarianti, 2021), facilitating disease analysis and decision-making. An innovative disease detection system utilizing compressed sensing has been tested with Raspberry Pi to identify leaf diseases efficiently (Gayathri Devi et al., 2019). This system uses IoT for real-time identification and classification of medicinal plants, contributing to advancements in smart agriculture. Large datasets from agricultural sensors, managed via cloud computing, enhance plant disease detection capabilities (Ouhami et al., 2021).

Table 1. List of ayurvedic plants along with their causes and symptoms

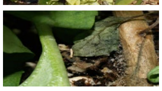
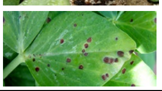
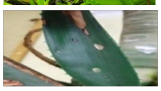
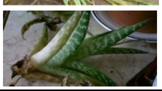
Plant name	Plant disease /stress	Image with symptoms	Causes	Symptoms
Sunflower	Powdery mildew		Fungus (*Erysiphe graminis*)	White powdery spots on leaves
	Downy mildew		Fungus (*Plasmopara halstedii*)	Yellow and brown spots
	Septoria leaf spot		1. Fungus (*Septoria helianthin*) (Biotic stress) 2. Higher air humidity and wetness (Abiotic)	Brown leaf spots
	Alternaria leaf spot		1. Fungus (*Septoria helianthin*) (Biotic stress) 2. Higher air humidity and wetness (Abiotic)	Black leaf spots
	Verticillium wilt		Fungus (*Verticillium dahliae* Klebahn)	Plant wilt
	Phoma blight		Fungus (*Phoma macdonaldii*)	Huge dull sore on the stem begins from the leaf and reaches the petiole
False Daisy	Alternanthera yellow vein virus (AlYVV)		Virus (Begomovirus)	Vein yellowing and swelling on leaves
	Mosaic virus		Virus (Mosaic virus)	Distortion, mosaic, dwarfism, and yellowing of the leaves
	Big-vein		Fungus (*Olpidium brassicae*)	Discoloration, enlargement of the veins running through the leaves
Celery	Leaf curl		Fungus (*Colletotrichum acutatum*)	Curled, distorted leaves
Carrot	Alternaria leaf blights		Fungus (*Alternaria dauci*)	Brown irregular spots
	Cercospora leaf blights		Fungus (*Cercospora carotae*)	Circular tan spots
	Bacterial leaf blight		Bacteria (*Xanthomonas campestris* pv. Carotae)	Yellow to light brown, angular spots
Coriander	Stem gall		Fungus (*Protomyces macrospores* Unger)	Swelling of leaf veins and leaf stalks
Basil	Cercospora leaf spot		Fungus (*Cercospora beticola*)	Light brown circular spots
	Alternaria leaf spot		Fungus (*Alternaria alternata*)	Black mottled lesions
	Downy mildew		Fungus (*Peronospora belbahrii*)	Grey/black spores, yellowing of upper leaf surface
	Fusarium wilt		Fungus (oil-borne pathogenic)	Brown streaks on the stem, defoliated plants
	Gray mold		Fungus (*Botrytis cinerea*)	Gray mold symptoms on leaves and stems
Pea	Asocochyta blight		Fungus (*Ascochyta pisi*, *Mycosphaerella pinodes* and *Phoma pinodella*)	Yellow foliage with brown blotches

Table 1. List of ayurvedic plants along with their causes and symptoms (Continued)

Plant name	Plant disease /stress	Image with symptoms	Causes	Symptoms
Pea	Bacterial blight		Bacteria (*Pseudomonas syringae*)	Shiny, dark green water spots
	Powdery mildew		Fungus (*Erysiphe cichoracearum* DC)	Powdery white patches
Lavender	Root rot		1. Fungus (*Fusarium* spp., *Phytophthora* spp., *Pythium* spp. and *Rhizoctonia* spp.) 2. Wet and waterlogged soils	Wilted, yellowed, or browned leaves, dieback stem
	Septoria leaf spot		1. Fungus (*Septoria lavandulae*) 2. High humidity and water sitting on lavender leaves	Black spots
Bean	Bean rust		Fungus (*Uromyces appendiculaters*)	Leaves turn yellow, wilt
	Anthracnose		Fungus (*Colletotrichum lindemuthianum*)	Dark, brick-red to black lesions on leaves
Peach	Bacterial leaf spot		Bacteria (*Xanthomonas campestris* pv. Pruni)	Leaf lesions with black edges
Cactus	Cactus dry rot		Fungus (*phyllosticta concave*)	Black and yellow spots
Strawberry	leaf blight		Fungus (*Phomopsis obscurans*)	Large round spots
	Leaf spot		Fungus (*Mycosphaerella fragariae*)	Small yellow spots
	Leaf scorch		Fungus (*Diplocarpon earliana*)	Small purplish blemishes on leaf surface
Mint	Powdery mildew		Fungus (*Erysiphe cichor-acearum*)	Powdery white patches
	Stem rot		Fungus (*Homa stasserti*)	Upper leaves sickle-shaped, chlorotic or crimson
	Verticillium wilt		Fungus (*Verticillium dahlia*)	Plant wilt
	Mint anthracnose (leopard spot)		Fungus (*Anthracnose colletotrichum*)	Dark brown or black spots on leaves
	Mint rust		Fungal (*Puccinia menthae*)	Black brown patches
Aloe vera	Leaf spot		Fungus (*Alternaria alternata*)	Black leaf spots
	Aloe rust		Fungal (*Phakopsora pachyfhiza* and *P. smeibomiae*)	Circular, dark black or brown patches
	Soft rot		Bacteria (*Pectobacterium chrysanthemi*)	Water-soaked spots
	Root rot		1. Overwatering (abiotic stress) 2. Fungus (Phytophthora, Pythium genera) (biotic stress)	Yellow leaf, black and soft roots

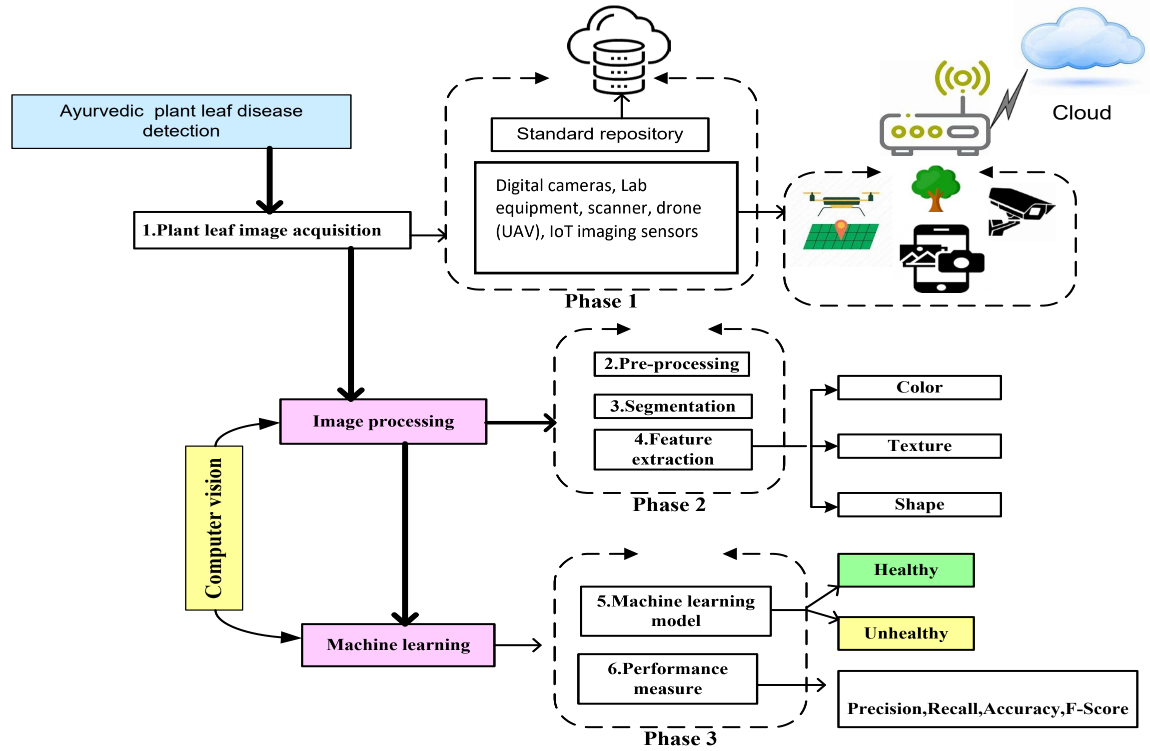


Figure 2. General structure of the identification and classification of plant leaf diseases

3.2 Image processing in plant leaf detection

This section is separated into three subsections. The first sub-section emphasizes the influence of acquired image pre-processing techniques to eradicate noise, background, and shadow from the collected images. The second subsection illustrates the various segmentation techniques. The third subsection presents the method for extracting features from an image, such as an object's edge, shape, size, or color.

A. Acquired image pre-processing techniques

After image acquisition, pre-processing transforms images for machine learning recognition, removing noise, background, and shadows for enhanced model performance (Singh and Misra, 2017). Techniques include noise reduction, cropping, smoothing, and color space conversion (Vishnoi et al., 2022). Filters like mean, median (Zamani et al., 2022), and histogram equalization improve image clarity and sharpness (Kurmi and Gangwar, 2022). Color spaces such as the hue-saturation-value (HSV), hue-saturation-intensity (HIS), and red-green-blue (RGB) are adjusted for accurate representation (Sinha and Shekhawat, 2020). Figure 3 illustrates these pre-processing methods.

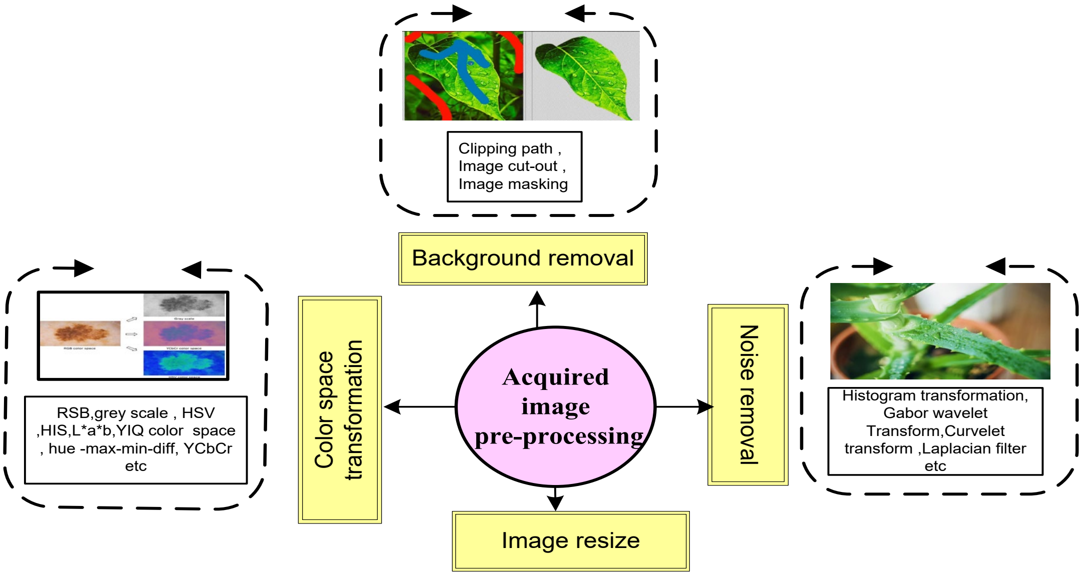


Figure 3. Pre-processing based techniques

B. Image segmentation

Image segmentation is crucial for isolating areas of interest, such as diseased regions on plant leaves, to facilitate feature extraction for machine learning models. This technique divides a digital image into parts, highlighting the segments necessary for further analysis. Recent advancements have improved segmentation methods (Patil and Burkpalli, 2022), allowing for more precise disease identification on leaves with complex backgrounds. These improvements are pivotal for enhancing the accuracy of plant leaf disease detection. The segmentation techniques are illustrated in Figure 4. The traditional and soft segmentation techniques are explained below.

- Edge-based segmentation: This technique makes use of pattern discontinuities in photos and work best with images that have strong object contrast (Vishnoi et al., 2022). The edge detectors are capable of identifying both horizontal and vertical edges. This method seeks to locate the boundaries of leaves inside an image.
- Region-based segmentation: This technique uses pixel similarities in intensity, color, and texture to group pixels or subregions into larger segments (Deenan et al., 2020). It starts from a point and clusters pixels with similar attributes, utilizing techniques like region growing, region merging, region splitting, and watershed to define object edges.
- Thresholding-based segmentation: Image segmentation by thresholding uses histogram-based threshold values to convert images into binary format, isolating the objects of interest. The OSTU algorithm, introduced by OTSU in 1979, has undergone further refinements (Zhao et al., 2015), including the development of a disease segmentation algorithm and the integration of the fruit fly optimization algorithm (FOA) to expedite the process (Huang et al., 2021).
- Clustering-based segmentation: In pixel-level clustering-based segmentation, the *K*-means algorithm facilitates grouping by pixel intensity (Kaur et al., 2018). Further, hybrid clustering methods enhance segmentation, with the Fuzzy C-means (FCM) and chameleon swarm algorithm (FCM-CSA) addressing FCM's limitations in segmenting diseased plant leaves (Umamageswari et al., 2023). Additionally, the combination of super-pixel clustering and *K*-means has been proposed for plant disease recognition within IoT frameworks (Zhang et al., 2018), and a novel technique merging color balancing with superpixel technology has been developed for identifying tomato plant diseases (Khan and Narvekar, 2022).

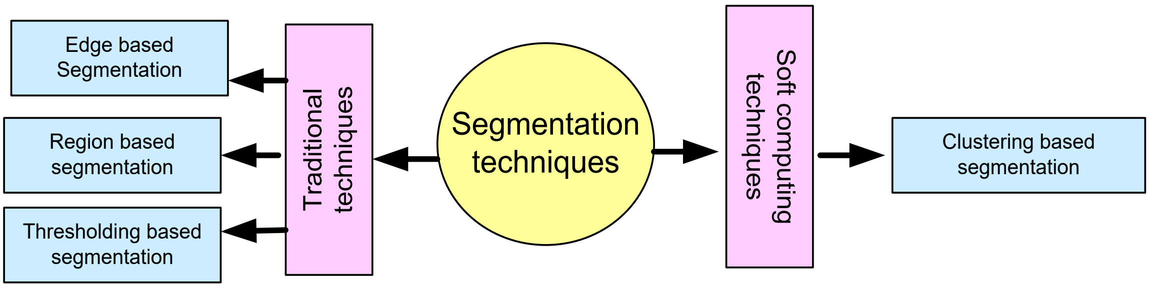


Figure 4. Segmentation-based techniques

C. Feature extraction and selection

Since each object has a distinctive shape, size, color, and texture, feature extraction is utilized to categorize the retrieved object into the correct class (Sachar and Kumar, 2021). The leaf's chosen features are used to create the input feature vector, which is then provided to the machine learning model. The primary purpose of feature extraction in plant disease diagnosis is to automatically learn the features. The effectiveness of the disease detection system can be improved through the combination of color, texture, and shape properties. A single type of attribute might not always be adequate to define an object accurately. Sujith and Neethu (2021) proposed method gives efficient hybrid feature extraction using shape and texture features. Figure 5 illustrates all the common methods for feature extraction in terms of shape, color, and texture. The following list includes some frequent information concerning the feature extraction procedure:

1. Texture based feature extraction: In texture-based feature extraction for plant disease detection, the key texture-based feature attributes employed in the identification of plant leaf diseases are entropy, variance, homogeneity, correlation, contrast, skewness, and moment. Gray-level co-occurrence matrices (GLCM)/Haralick features (Rajiv et al., 2021), shift-invariant feature transforms (SIFT), discrete wavelet transforms (DWT) (Dhingra et al., 2021) and local binary patterns (LBPs) (Sulc and Matas, 2015). Speeded-up robust features (SURF) and Gabor filter have all been utilized extensively in research to extract texture characteristics. Naeem et al. (2021) proposed leaf recognition using texture features for herbal plant identification where GLCM is utilized. Kurtosis, the inverse moment difference between the train and test picture sets, contrast, correlation, mean, energy, homogeneity, variance, smoothness, and root mean square are among the characteristics of GLCM. The features extracted in Gayathri Devi and Neelamegam (2019) suggested a system utilizing a hybrid approach that combines the discrete wavelet transform, scale-invariant feature transform, and grayscale co-occurrence matrix approach.

2. Color-based feature extraction: The representation of color feature exclusion is typically done using terminologies like color, saturation, chroma, brightness, histogram, etc. The color histogram shows the frequency with which various pixel intensities appear in an image. This allows the descriptor to understand how each color is used across the image. In addition, three distinct color spaces—RGB, normalized RGB (nRGB), and HSI color space—are utilized to produce color histograms.

3. Shape-based feature extraction: Using the region's properties, one can determine shape characteristics such as centroid, equivalent diameter, area, eccentricity main axis length, perimeter, minor axis length, and orientation. Hu's moment and center moment hog (histogram of oriented gradients) are two frequently used methods for acquiring these qualities (Basavaiah and Anthony, 2020).

3.3 Segmentation of plant leaf diseases using machine learning techniques

ML is pivotal in simulating plant ecology, factoring in disease impacts and environmental variables. The architecture of ML models is shaped by features derived during the image processing stage of plant disease detection. These models, trained on leaf images, categorize diseases in test images. A typical ML approach involves dividing data into training and testing sets using classification to differentiate infected from healthy leaves. Supervised learning utilizes well-labelled datasets for training (Esgario et al., 2022), while unsupervised learning seeks patterns in unlabelled data (Yan and Wang, 2022). Naeem et al. (2021) used various ML models, with s multi-layer perceptron showing the highest accuracy. The hybrid model combining ML with optimization algorithms offers real-time disease classification with reduced complexity (Yağ and Altan, 2022). Feature fusion and classification methods, like in Zhang et al. (2021), bypass the need for manual pre-processing, and a CNN-SVM combination effectively predicts disease severity (Turkoglu et al., 2022).

The effectiveness of a plant leaf disease classification model is assessed using a confusion matrix. The TF (true positive), FN (false negative), FP (false positive) and TN (true negative) were used to find the average precision, recall, and F1 score for multi-class classification (true negative). Table 2 is the manifestation of the different computer vision approaches used across the globe to simulate the process of plant leaf disease using machine learning. The research reveals that ayurvedic medicinal plants have received very little overall attention, while food grain plants have been studied the most.

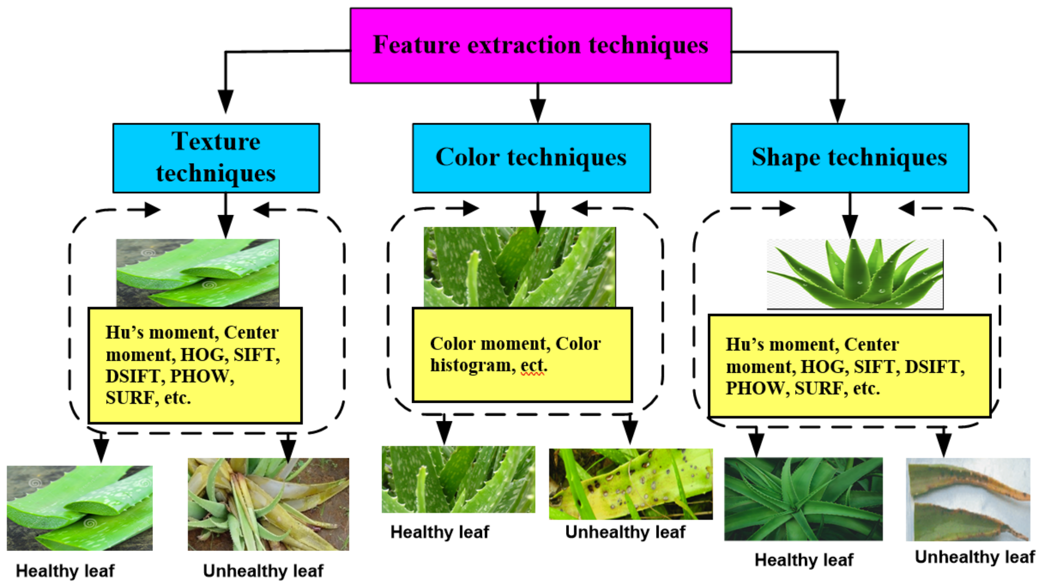


Figure 5. Feature extraction technique

4. CHALLENGES

The key issues and challenges are identified by the researchers and the scientists while analyzing the ayurvedic leaf diseases of plants.

4.1 Publicly available dataset requirements specify all disease information related to ayurvedic plants

Any disease information about ayurvedic herbs must be specified in a publicly accessible dataset. The knowledge about ayurvedic medicinal herbs and leaf diseases that have been discovered over time has to be accessible through a platform that enables integrated access. Numerous databases in India offer information about Indian medicinal plants. These significant databases include the Medicinal Plants Database (http://nmpb-mpdb.nic.in/user/index); Indian Medicinal Plants, Phytochemistry, and Therapeutics (IMPPAT) (imsc.res.in), which is a comprehensive online database for drug development based on the phytochemistry of Indian medicinal herbs (Mohanraj et al., 2018); the IMPLAD database, with the goal to make collated, classified, and intelligently analyzed data on Indian medicinal plants (Rajasekharan and Wani, 2020); the RAACFDb rheumatoid arthritis ayurvedic classical formulations database (Mohamed Thoufic Ali et al., 2017); and InDiaMed, an extensive database of diabetes medicinal herbs from India (http://www.indiamed.info). These databases do, however, include broad details about the origins of medicinal plants, common applications, standards for processing, and preservation techniques. Surprisingly, there is not a complete database of ayurvedic plants that includes information on leaf ailments and pictures of affected leaves.

Table 2. Comparison of several computer vision approaches in terms of various phases of image processing using machine learning from 2020 to 2022

Reference	Disease	Image dataset	Pre-processing	Segmentation	Feature extraction	Supervised classification	Performance result
Yağ and Altan (2022)	Black rot, cedar rust, scab disease	1,100 diseased leaf images	Feature extraction with signal processing will act as pre - processing	N/A	Two-dimensional discrete wavelet transform	Flower pollination algorithm (FPA) support vector machine (SVM), and a convolutional neural network (CNN) classifier	Accuracy: 99%
Habib et al. (2020)	Brown spot, black spot, Anthracnose powdery mildew, Phytophthora blight	Self-captured	Histogram m equalizatio, L*a*b* color Space, resizing	*K*-means	GLCM, SURF	SVM	90%
Dhivya (2022)	Anthracnose, *Alternaria Alternata*, and Cercospora leaf spot, bacterial blight	Manu's disease data set	K-SVD DWT	Advanced *K*-means clustering	PCA	BRBFNN[10 3] AKNN methods (advanced KNN)	BRBFNN> AKNN
Shrivastava and Pradhan (2021)	Leaf blight, Rice blast, Sheath blight	619 Self-captured images	RGB to 13 different color spaces (HSI, YCbCr, H SV, CIE RYZ)	N/A	Mean, standard deviation, Kurtosis, skewness	SVM, NB, DC, DT, RF, KNN, LR	SVM (94.65 %)>
Patil and Burkpalli (2021)	Alternaria, Cercospora leaf spot, grey mildew	Self-captured from field	_	Modified factorization-based active contour method (MFACM)	Color and texture feature extraction	Multilayer perceptron, SVM, Naïve Bayes, Random Forest, AdaBoost, K-NN	Multilayer perceptron (96.69%)>
Yogeshwari and Thailambal (2021)	Leaf disease	_	Adaptive mean adjustment (AMA), 2D adaptive anisotropic diffusion filter (2D AADF)	Adaptive Otsu (AO) thresholding, Fast fuzzy C means clustering (IFFCMC)	GLCM	DCNN K-NN, BPNN, Naïve Bayes, SVM	DCNN (97.43%) SVM (91.73 BPNN (94.92) Naïve Bayes (90.5) KNN (87.24)
Suganya Devi et al. (2020)	Bud necrosis rust, leaf spot, leaf blight	Self-captured	RGB to binary image	HSV color space	HOG, Harris corner detector	H2K (fusion of Harris corner detector), KNN classifier, HOG (histogram on oriented gradient)	97.67%.
Narmilan et al. (2022)	White leaf disease	Self-captured (UAV)				XGB, RF, DT, and KNN	XGB: 94 RF: 92 DT: 92 KNN: 91
Hamdani et al. (2021)	Muara Wahau, East Borneo, Indonesia	Anthracnose, Curvularia leaf spot, Cercospora leaf spot, Pestalotiop estalotiopsis	Resizing, conversion to RGB to L*a*b color	*K*-means clustering algorithm	Color: RGB to L*a*b, RGB to HSI, RGB to HSV	SVM and ANN	99.67%

4.2 Noisy data affecting the leaf samples

The IoT sensors-captured plant photos feature a complicated structure with numerous normal zones, spot regions, and complex backgrounds. Moreover, the photos include properties related to shape irregularity, color dispersion, and texture fuzziness (Zhang et al., 2018). To acquire the best and quickest results from the machine learning-based simulation step, the quality of the leaf image must be high. To accomplish that, the simulation setup must incorporate the best-integrated image processing step.

5. RECOMMENDATION

The importance of the plant leaf disease autonomous system based on computer vision and the integration of several image processing phases for a higher result in machine learning classifiers have been covered in the previous sections. Based upon the analysis, we have discussed the challenges and suggested further recommendations for future enhancement below.

In the study depicted in Table 2, numerous researchers offered a variety of methods to address the issue of leaf disease. However, analogous standards for ayurvedic herbs are still lacking. According to the study, food grain plants are the ones that are most closely examined, while ayurvedic plants are rarely explored. According to the study, almost all plants and the components of those plants are prone to disease. While selecting a plant for a plant leaf disease recognition simulation system, it is important to take into account the plant's relevance to both the environment and the economy. Ayurvedic plants like mint, coriander, aloe vera, bean, marjoram should be taken into consideration for future research to boost the production of the corresponding ayurvedic plants, as they contribute to the worldwide market at a high scale, according to the study reported in section 1 via Table 1.

It has been found that the acquisition of plant images must be done effectively. If it is observed in real-time, that is, in an uncontrolled environment, its (acquisition of plant images) acceptance will surely rise if it is captured in real time, that is, in an unregulated setting (not in lab condition, real time data capturing). It has been highlighted that the types of datasets used in research investigations, such as real-time or lab-required condition datasets, have a major impact on the experimental results or performance. Researchers must prioritize developing a hybrid acquisition model capable of recognizing numerous images based on real-time circumstances. For plant image collection, IoT devices and sensors like web cameras, sensor-based systems, and UAV devices (drones) can be deployed in agricultural fields. The image-capturing sensors can be spread out over diverse lands at varying ranges to make the IoT environment suitable for vast agriculture fields.

To provide connectivity, wireless multimedia sensor networks can be deployed. It is advised to use an automatic and intelligent data collector, such as a single-board computer of small size like the Raspberry Pi (Shailendra et al., 2022) ARDUINO INTEL (GALILEO)[3], LIBELIUM (Suciu et al., 2019), or the Raspberry Pi with IBM + ARM (Chouhan et al., 2021), which helps in setting up the data communication for small computing and serving as a central hub point for all IoT sensors. Contrarily, cloud computing can be added as a solution for massive computing and to cover wide-area simulation (Ammad Uddin et al., 2014). Additionally, edge computing can be adopted to minimize latency, advance privacy and reduce bandwidth costs in cloud computing (Liu et al., 2021).

A suitable strategy, which is highly sought to fulfil the high-performance criteria, is chosen considering several ways to carry out specific tasks in each step of image processing, such as acquisition, pre-processing, segmentation, and feature extraction. According to the study, the type of image taken affects the appropriate strategies or methods for each phase of image processing. It was seen that most studies have employed the soft computing technique known as the *k* mean to complete the segmentation task. The feature extraction function is an additional crucial step in the diagnosis of plant diseases. The feature traits are often chosen based on shape, color, and texture. However, integrating color, texture, and shape features throughout the feature extraction process can also produce good results. The researchers should focus on establishing a feature selection phase that will consider all three features of a leaf.

A variety of ML categorization techniques can be looked into and used to categorize and recognize ayurvedic plant leaf diseases using leaf images. The researchers should focus on establishing an ML model for diagnosing ayurvedic plant leaves that take all the symptoms as input. To perform the classification assignment, a range of classification approaches have been made available. A few of the techniques that have been frequently used for this purpose are support vector machines, artificial neural networks, and K-NN clustering. As a result, these algorithms can be used to treat ayurvedic plant diseases, and comparison analysis can be done to determine which algorithm is the most successful. Following training, a testing database can be used to assess how well the classifier performed in identifying and categorizing the disease from a photo of an ayurvedic plant leaf.

6. CONCLUSION

To reduce ayurveda plant production losses, it is in dire need of an effective and automated system for detecting plant diseases at an early stage. In this study, the notional foundations of computer vision have been investigated to revolutionize and invent an autonomous ayurvedic plant leaf disease detection system. Many studies that have automated the process for diagnosing and categorizing plant leaf diseases have been summarised in this article associating ML, and image processing. Many extensively used techniques for image acquisition, pre-processing, segmentation, feature extraction, and classifiers are also addressed in this study. Notably, the study has found that ML algorithms, including SVM and K-NN, combined with cross-validation prediction measures, regularly demonstrate greater performance in plant disease detection automation systems. The review also outlines the optimal approaches for the various stages of image processing, and it contends that adopting IOT-based hybrid architectures for image acquisition will produce efficient computational results. The article also emphasizes the need for an in-house database on ayurvedic plant leaf disease to simplify the application of ML models for simulations.

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