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Need of Feature Extraction in Coconut Tree Disease Detection: A Review

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Abstract
Agriculture has served as the primary means of sustenance for mankind for thousands of years. Even in the present day, it continues to support approximately 50% of the global population. Plant diseases pose a significant threat to crop production, resulting in substantial losses each year on a global scale. To mitigate the financial impact of these diseases, it is crucial to maintain the health of plants throughout their growth and development. The symptoms of infections are predominantly visible on plant leaves, making them a common indicator for disease detection and identification. However, visually observing and identifying diseases is a challenging task that requires extensive human expertise. To provide farmers with improved assistance in disease detection, image processing techniques combined with computational intelligence or soft computing techniques can be employed. These methods offer a more effective approach to disease detection. By extracting features from the symptoms of a disease, it becomes possible to identify and detect the presence of a disease in plants. Therefore, feature extraction techniques play a vital role in such systems. This paper focuses on reviewing the feature extraction methods, highlighting their advantages and disadvantages. It provides a comprehensive discussion on various image features, including color, texture, and shape, for different types of disorders found in diverse agricultural practices.
Keywords: *Agriculture, Image Feature, Feature Extraction, Disease Detection.*

1. Introduction
Advanced technologies like IoT, Data Mining, Artificial Intelligence, and Data Science play a crucial role in enhancing precision agriculture. The Internet of Things (IoT) consists of interconnected computational devices such as sensors and smart gadgets that are capable of communicating with each other and exchanging data.Coconut (Cocos nucifera Linn.) is a significant plantation crop in India, cultivated for its oil and raw materials used in the coir industry. It is a globally cultivated palm tree, found in approximately 93 countries, including India where it covers an area of 2.1 million hectares (2015-16, 3rd estimates). The production of coconuts in India reached 14,075 million nuts with an average productivity of 6,702 nuts per hectare per year (CDB, 2016).Coconut exhibits remarkable versatility, serving as a fruit, a source of milk and oil, a staple in the diets of many individuals in tropical and subtropical regions, a seed nut, a fuel, and much more [1]. In terms of coconut production, India ranks as the third-largest producer globally [2]. Similar to other palm trees, coconut plants are susceptible to various damages caused by pest infestations. Early detection of coconut pests and diseases is feasible in laboratory settings. Additionally, plant pathologists can assist cultivators in identifying and addressing plant pests and diseases. However, these methods are not practical for rural cultivators residing in remote areas due to the lack of access to laboratories and experts. In recent years, several computerized methods utilizing machine learning techniques have been developed to identify and classify plant diseases. Researchers have employed computer vision, machine learning, and deep learning techniques to detect pests and diseases in plants such as tomatoes, potatoes , maize , and citrusp[3][4]. the authors review recent research on machine learning and deep learning techniques for image-based plant

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disease classification in the context of industrial farming systems[5]. The analysis indicates that deep learning-based approaches outperform machine learning-based approaches However, the utilization of machine and deep learning for identifying coconut damages remains limited [6]. Utilizing image processing techniques in conjunction with computational intelligence or soft computing techniques can enhance the assistance provided to farmers in detecting diseases[7]. By extracting features from plant symptoms, diseases can be identified. This paper presents the detailed literature survey based on feature selection methods based on texture, colour and shape of the coconut tree leaf disease detection in subsections of the paper.

2. Types of Coconut Diseases

Coconut leaf diseases encompass a range of disorders and conditions that affect the leaves of coconut trees, exerting a significant impact on the overall health and productivity of the tree. Among the most prevalent coconut leaf diseases are leaf spots, leaf blight, leaf rot, leaf wilt, and leaf necrosis. Leaf spots, caused by fungal infections, manifest as small, circular, or irregular-shaped spots on the leaves[8]. These spots can lead to discoloration, wilting, and premature shedding of the leaves, ultimately reducing productivity and rendering the tree more susceptible to other diseases. Leaf blight, on the other hand, results from bacterial infection and can cause severe defoliation, thereby diminishing the growth and yield of the coconut tree. Affected leaves may exhibit a brown or yellow hue and display a distinct blight pattern[9]. Leaf rot, caused by fungal infections, induces yellowing or browning of the leaves, eventually leading to their demise. This disease thrives in humid and wet conditions, spreading rapidly to other parts of the tree. Leaf wilt, caused by the Fusarium oxysporum fungus, triggers wilting and discoloration of the leaves, ultimately culminating in the death of the entire tree[10]. Lastly, leaf necrosis, influenced by various factors such as nutrient deficiencies and exposure to extreme weather conditions, causes the leaves to turn brown. Proper management of coconut leaf diseases is crucial to prevent them from turning black and dying[11]. It is important to consistently monitor the health of the leaves and intervene promptly to prevent the spread of infections. This may involve utilizing fungicides, trimming infected leaves, and enhancing the overall health of the trees through appropriate nutrient management and cultural practices. Some of the different types of coconut diseases are listed in Table 1{Appendix 1) Accurate diagnosis of the disease is also vital, as each disease may require a different approach for effective management. Caterpillar assaults on coconut trees can cause critical harm to the tree's clears out, driving to decreased development and abdicate. Caterpillars are insatiable eaters and can rapidly defoliate a coconut tree on the off chance that not controlled in time. The indications of a caterpillar assault on a coconut tree incorporate the appearance of irregular-shaped gaps in the clears out and the nearness of caterpillars or their droppings on the tree[12]. Compelling administration of caterpillar assaults includes the utilize of bug sprays, pruning contaminated clears out, and moving forward in general tree well-being through appropriate supplement administration and social hones. Customary checking of the tree's well being can too offer assistance distinguish any potential issues some time recently they gotten to be serious.

3. General Architecture of a Plant Disease Detection System

Plant pathology can benefit from the application of soft computing and computational intelligence in computer vision and image processing [13]. An adequate set of high-quality images is a prerequisite for these kinds of systems. To identify plant diseases through image processing, one must first create a dataset by taking pictures of various plant parts, such as leaves, roots, and so on. Because of factors like lighting, device calibration, and atmosphere, the captured images might have some undesirable features. As a result, photos are typically pre-processed to ensure they are suitable for the intended uses. Color space conversion, contrast stretching, scaling, rotation, smoothing, and background removal are a few of the preprocessing operations[14]. Because leaves indifferent to disease typically have similar spectral characteristics, raw image data may not always be helpful in

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differentiating between healthy and diseased leaves or identifying the precise illness. Feature extraction is carried out over the input images in order to derive discriminating data. various characteristics, including color, texture, and shape, among others. may prove helpful in identifying particular plant diseases[15]. Once the classifier receives the set of features, it can identify the disease and/or classify the leaves as healthy or unhealthy. The accuracy of classification plays a major role in the efficacy and applicability of these systems. This work discusses and provides an overview of the main feature extraction methods that have been proposed in the literature. The plant disease detection/classification system is shown in general in Figure 1.

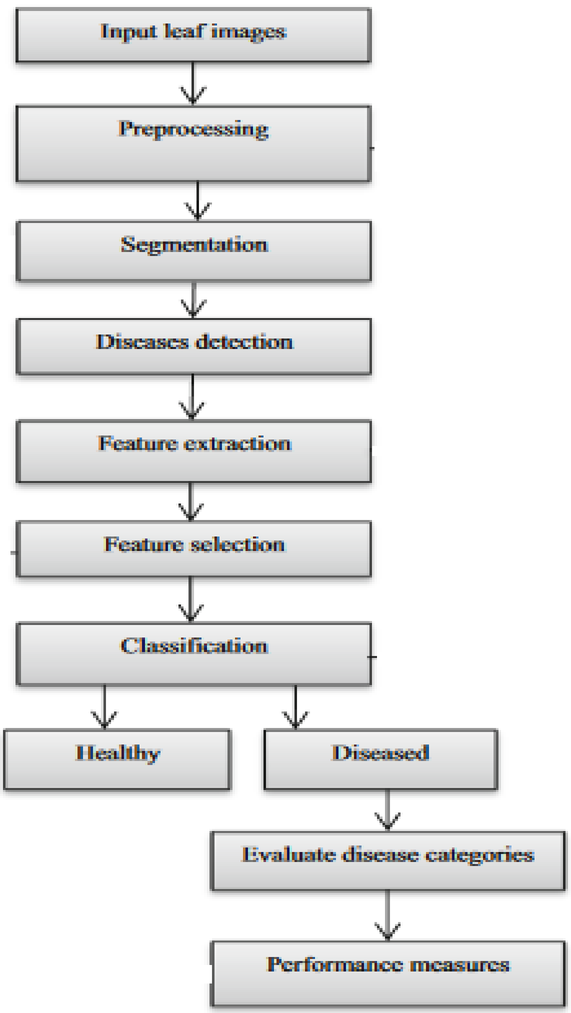

Figure 1 General Steps for Plant Disease Detection System Using Learning System

3.1 Image Acquisition

The quality of the images obtained, whether they are retrieved from the repository or directly taken from fields, has an impact on the disease detection system's performance, making the image acquisition phase crucial. Imaging techniques and tools, such as camera orientation, have an impact on the quality of the image. Unwanted features like distortion, blur, shadows, artifacts, and complicated backgrounds could be present in the raw photos. These undesirable aspects of the image often degrade the system's functionality. Additionally, a significant problem that can be resolved by taking pictures of plants exhibiting a variety of symptoms or by adding images to create a true and complete dataset is the variation in symptoms of a single infection. A single disorder's symptoms can differ depending on the plant's genotype, age of leaves, growth stages, and environmental conditions [16]. The imaging system becomes more complex due to the effects of illumination and the ensuing factors. As such, it necessitates greater attention to device details such as resolution and camera orientation when taking pictures. Researchers use their own plant image datasets because they are self-created and because there are no benchmark datasets available for their particular crop or culture.

3.2 Image Pre-Processing

Unwanted information like shadows, noise, unclear distortion, and complicated backgrounds are frequently present in image sets that are created and taken in real time. At a lower level of abstraction, preprocessing images is therefore practically necessary. In order to lessen the impact of undesirable characteristics, pre-processing is used. It would be better to process the pre-processed image further [17]. In order to simplify such complicated systems, techniques like cropping and resizing can be applied. Colors space conversion, histogram equalization, contrast enhancement, cropping, noise removal, and smoothing are examples of basic pre-processing operations whose applicability varies depending on the type of acquired images.

3.3 Region of Interest Identification Based on Image Segmentation

Region of interest (ROI) detection in

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images is done automatically through a process called image segmentation. The goal of ROI detection is to distinguish the areas with lesions from those that are not. The image's segmented version is more useful for differentiating between the healthy and diseased leaf areas.There are several approaches for segmentation, including methods based on thresholding [18], region growing [19], and edge detection [20]. The chosen approach will vary depending on the application and dataset. The prevalent, conventional methods for plant disease detection applications are edge-based and threshold-based segmentation. These methods, which work best with images that have good object contrast, are based on pattern discontinuities in images. The high number of edges and the presence of noise in the image affect edge-based methods. Since threshold-based techniques operate on the peaks of the histogram, they neglect to take into account important spatial information. Consequently, high color heterogeneity (variation) in the plant leaf image can occasionally go unnoticed. In this technique, choosing the threshold value is important because it can lead to poor segmentation. Lately, methods based on soft computing have also been applied to image segmentation. Compared to conventional methods, these strategies outperformed them [21]. By using a genetic algorithm, [19] segments data. Pujari & Co. Pantazi et al. [22] used the lesion segmentation algorithm's grab-cut exploit Clustering is a crucial method for identifying ROI, with K-means clustering being particularly effective in extracting ROI from plant leaf images. Compared to edge-based and thresholding-based approaches, K-means clustering has shown to be more efficient when multiple diseases' symptoms are present in the leaf images. However, it is important to note that K-means clustering's performance is influenced by the number of clusters and initial centroid selection, as well as the visual complexities in infected leaf images[23]. As a result, a combination of K-means clustering and other techniques is often used to accurately identify ROI. In some studies, Canny edge operator and Otsu's thresholding have been combined with K-means clustering for ROI identification. Additionally, fuzzy c-means clustering has been preferred for segmenting infected areas in plant disease detection, highlighting the challenges faced in the image segmentation process.

4. Feature Extraction and Selection Methods for Plant Disease Detection Features

A component that aids in the unique identification of an object or piece of content is called an image feature. After the object's features are considered, an appropriate class label is assigned. Learning the features automatically is the main function of feature extraction in the detection of plant diseases. Plant infections are primarily identified using characteristics of plant leaves, such as color, texture, and shape [24]. These attributes require the proper application of the appropriate feature extraction algorithm. Selecting an effective extraction technique and determining which attribute among a set of attributes is the best are difficult tasks. Here is a list of frequently asked questions concerning the feature extraction process. Not all of the feature set's features are suitable for all applications. Irrelevant attributes have the potential to aggravate the overfitting and computational complexity of the classification algorithms[25]. Therefore, it's crucial to choose the best features from the available set in ML-based applications. The PCA (Principle Component Analysis) scores for entropy, covariance, and features can be used to solve this problem [24]. Other techniques for selection include fuzzy curves, surface methods, relief-F method, and information gain [26]. Moreover, feature selection makes use of fuzzy histograms to select the right features, additional methods such as particle swarm optimization (PSO) and genetic algorithms (GA) are employed [27]. Most frequently, disease detection applications use classification techniques like artificial neural networks (ANN), support vector machines (SVM), and k-nearest neighbor (k-NN). A variety of artificial neural network (ANN) models are widely used in plant disease detection, including feed-forward neural networks, error back-propagation networks, Kohonen's self-organizing maps, and multi-layer perceptrons (MLP). Moreover, plant disease management and control are also accomplished through the use of fuzzy logic-based systems like the rule-based system, Sugeno

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fuzzy inference, and adaptive neuro fuzzy inference system (ANFIS)[28]. Classification techniques based on deep learning have recently shown impressive success, outperforming other techniques in accuracy [27]. While using leaf images to identify diseases, convolutional neural networks (CNNs) can be a useful substitute for other classifiers. Mohanty and colleagues. employed a transfer learning technique to identify plant diseases in multiple cultures utilizing the Plant Village dataset and pre-trained CNN models like Google Net and Alex Net [29]. Typically, there are two applications of CNN: one is for classification, and the other is for feature extraction [30]. Convolution and pooling layers of CNN's layered architecture are used to extract features for deep feature extraction, from which different classification algorithms can be applied. In Section 3, the numerous feature extraction methods for identifying distinct plant diseases are thoroughly examined and discussed.

4.1 Texture Based Feature Extraction Methods

A small-area patch of an image that has a high tonal variation is considered to have dominant texture [31-33]. It essentially depicts the image's spatial arrangements and color patterns. Factors influencing texture perception include light, contrast, distance, and orientation. Entropy, contrast, skewness, variance, homogeneity, and other parameters can all be used to describe the texture of an image.

4.2 Color Based Feature Selection Methods

Color features reflect sensor response for various wavelengths and give colors their physical and visual characteristics. Color features are relatively invariant to orientation and scale and resilient against complex backgrounds. Photometric information such as illumination, shadowing, shading, and optical density of color channels are provided by color features. As was covered in earlier sections, the color features can be represented in a variety of color spaces, including Luv, RGB, HSI, YCbCr, HSV, and L*a*b*. It is possible to use the grayscale values in the various bands just as features[34].

4.3 Shape Based Feature Selection Methods

Shape features, such as perimeter boundaries, circular, triangular, and rectangular shapes, give an object in an image its visual characteristics. The properties of statistical independence, scale invariance, translation, rotation, and identifiability are followed by shape featureextraction techniques [35-37]. The type of pathogen, crop species, and disease type all affect how an infection appears on plant leaves. The diameter, solidity, eccentricity, centroid, area, extent, major axis length, convex hull, and minor axis length can be used to characterize the shape features.

5. Review on Texture, Color, and Shape Based Feature Extraction Techniques

Plant diseases are also analyzed using a variety of features combined together. Different types of features can be combined to enhance the performance of disease detection systems. Two methods exist for identifying plant diseases based on leaf images: (i) deep learning, which utilizes intricate architectures to autonomously learn features, and (ii) feature-based, which involves extracting manually crafted features like color and texture to train a traditional machine learning model. While deep learning approaches offer superior accuracies, they demand more computational resources, making them unsuitable for mobile or handheld devices with restricted memory and processing capabilities. The field of plant disease identification is witnessing a surge in the popularity of artificial intelligence tools such as Deep learning and Convolutional Neural Network (CNN), as they offer an optimal solution for accurately identifying plant diseases. These pairings may be helpful if various feature kinds offer complementary data. The identification of plant diseases has been the subject of numerous studies up to this point. We address various approaches that researchers have suggested in this section for the identification of various plant diseases. It is discovered that color, shape, texture, and deep learning models can be used to classify machine learning-based disease detection methods. Color properties basically decide the visual characteristics of an question [38]. It does not speak to objects over diverse wavelength values. Color histogram and color co-occurrence network characterize the color show as cruel, kurtosis, skewness and standard deviation. Surface properties speak to surface

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properties of an question such as smoothness, entropy, vitality, differentiate, relationship etc. And surfaces can utilize LBP, Gabor channel and GLCM procedures. Shape highlights speak to a picture based on protest forms. They can be measured by heading, zone, flightiness and center of gravity etc. Hu minutes can be utilized for this reason. The combination of color, surface and shape highlights can progress the execution of a malady classification framework. List of feature extraction techniques that were used in coconut disease are listed in Table 2(Appendix 2) Now and then a single property may not be sufficient to legitimately characterize an question. Moreover, MPEG-7-based visual descriptors can be utilized for highlight extraction since they give surface, color and shape highlights together. In expansion, profound learning-based include extraction can be another elective to manual shape highlights [39].

Conclusion

This article displayed a survey of include extraction methods utilized to create programmed plant malady location and classification frameworks. The major components of an programmed edit disease location framework such as picture procurement, pre-processing, locale of intrigued recognizable proof, include extraction, and classification were examined with accentuation on include extraction. There are different highlight descriptors based on the ghostly and spatial properties of the pictures such as shape, surface, and color etc. Different frameworks are created based on one or more such characteristics. All such methods were checked on in this work and summarized in unthinkable frame. On the premise of exactness, it can be concluded that a combination of complementary highlights professional wide superior exactness compared to single highlight sorts. In later times, profound learning procedures are effectively connected for highlight extraction in agrarian applications. These strategies have the capacity to memorize both color and spatial characteristics at the same time. In spite of the fact that, profound learning procedures have their claim restrictions counting tall computational complexity.

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