International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# Machine Learning Techniques Based on Ensemble Feature Selection for Disease Indentification and Classification in Plant Leaves

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**Submitted**: 04/02/2024 **Revised**: 13/03/2024 **Accepted**: 20/03/2024

**Abstract**: Farmers have a number of challenges when trying to examine vast regions for plant diseases manually. This is because it takes a lot of time and needs a big number of experienced labourers with a true grasp of plant diseases. In order to diagnose plant diseases accurately and quickly, image processing and machine learning models might be used. Agricultural specialists now use visual or microscopic examination of leaves or certain chemical methods to diagnose plant diseases. Large farms need a large crew of specialists and continual plant monitoring, both of which are prohibitively costly for the typical farmer. Managing plant diseases is essential for increasing crop yields and ensuring a healthy food supply. To begin with, GCMO, or Graph Cut-based Multi-level Otsu, is a variation of unsupervised multi-stage segmentation that this study suggests. It combines Graph Cut and Multi-Level Otsu algorithms. After that, several evaluation metrics are used to compare the segmentation performance of the proposed technique with current unsupervised segmentation algorithms. The pictures of rice, peanut, apple, and potato plant leaves are used for this purpose. When compared to preexisting unsupervised methods, the segmentation accuracies achieved by the suggested approach were much higher when evaluated on a variety of conventional and real-time datasets. This study's primary goals are to apply deep learning-based classification to pre-processed results and to adopt optimum Feature Selection (FS) to segmented ones. Kernel Fuzzy C Means (KFCM) is used for leaf image segmentation and the multi-level Otsu Thresholding approach is used for impacted area segmentation after the input pictures are pre-processed using a multiscale retinex algorithm.

***Keywords:*** *optimal Feature Selection, Graph Cut-based Multi-level Otsu, Kernel Fuzzy C Means, multiscale retinex algorithm*

## Introduction

The projected yearly loss due to rice plant leaf diseases, such as brown spot, bacterial leaf blight, rice blast, and tungro, is 60 billion dollars, and it's growing every day. Therefore, in order to prevent these monetary losses, plant disease identification is crucial [1]. The usual method for farmers to identify these illnesses is by physically examining the leaves and stems of plants. However, if they wait for symptoms to manifest on the plants, it would be too late to do anything about the significant yield harm that has already happened. Using digital image processing technology, farmers may detect infections before symptoms appear, allowing them to preserve plants from devastating disease damage [2]. Alternatively, farmers may consult an agricultural specialist, but this would be a laborious and potentially disease-spreading procedure [3]. To successfully manage the spread of plant diseases, it is vital to precisely identify the presence of the disease in its early stages [4]. For the purposes of predicting plant health and estimating production, leaf recognition and identification are very advantageous. The problem is that manual recognition is inefficient and takes too much time since there are hundreds of plant species and different plant leaf diseases in the world. As a result, studying plant diseases is crucial, and creating an autonomous system that

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can recognise them based on leaves calls for an emphasis on making the identification process as easy as possible for humans [5]. In order to reach this objective, it is necessary to address a number of real concerns, such as the spread of climate-related illnesses; Multi-feature images, complex backgrounds, occlusions, shadows in sunny weather, unexpected variations in camera settings, biological similarities between the subject and the image background, and many features all appearing on a single image can be challenging to photograph.

Every day, more and more people die from pesticide poisoning as a result of the overuse of harmful chemical pesticides, as is well known [7]. Both soil and groundwater are susceptible to environmental harm, and pesticide overuse makes them much more so. Consequently, in order to successfully control plant diseases, there is a need for precise and prompt disease detection, quantification, and categorization of plant leaf diseases throughout the incubation period. Incubation is a crucial step in this lengthy and intricate process because it allows for data collection, diagnosis, and interpretation [8]. On the other hand, it's crucial to identify plant illnesses early so that farmers don't lose money and harvests due to extensive damage. Around 3.5 million individuals were poisoned by pesticides in 2012, with 1,93,460 people losing their lives. Developing nations accounted for around 84% of these fatalities, according to the World Health Organisation [9].

There are roughly 1,75,000 fatalities every year in China alone. Poisoning by pesticides is becoming a major issue in India's healthcare system. People in southern India, especially in the state of Andhra Pradesh [10], are trying to make the most of a small plot of land by using chemical pesticides to their fullest potential. The state of Andhra Pradesh has India's highest incidence of pesticide poisoning incidents due to extensive agricultural output. If we can identify the signs of the illness early enough, we can restrict the use of highly dangerous pesticides, which will lower the number of fatalities [11].

Critical challenges such as pesticide poisoning fatalities, economic loss in agricultural output, nutritional insufficiency and famine [12], and infections spreading over a broad region may be effectively addressed with early identification. Estimation or assessment of plant diseases is necessary for a variety of reasons. Consequently, early diagnosis of plant diseases is essential:

1. In monitoring plant's health, and to manage disease epidemics in different stages of disease development, and to avoid the spread of pathogens [13] over a wide area.
2. It also helps to reduce the excessive usage of pesticides and thereby improves the nutritional value of plants through the proper usage of pesticides [14].
3. The type and quantity of disease knowledge are highly pertinent for decisionmaking in situations like the disease directly related to crop loss and disease[15].

**Types of Plant Leaf Diseases**

Recognising plant diseases is essential in agriculture since they cannot be prevented [16]. Various microorganisms, including bacteria, fungus, viruses, and others, cause plant diseases. These micro infections are often very small and can only be seen under a microscope [17][18]. The spores produced by fungi may infect plants and can be transmitted from one place to another by many means such as air, water, insects, and even equipment [19]. During the wet and muggy seasons, fungal diseases are common. While most of these diseases show up on the leaves of plants, they may also impact the stems, roots, and even the fruits when they appear [20]. There may be a number of distinct symptom categories used to categorise leaf diseases, but it's important to remember that no two are ever identical [21]. There are a lot of other names for plant leaf diseases that might be perplexing, in addition to the ones already listed.

**Leaf Spots:** Leaf spots are typically recognized by shape, size, and colour spots. Almost usually, a significant border exists. Sometimes a yellow halo surrounds the lesion [22], possibly due to fungus or bacteria. This growth of fungus might be tiny structures that look like pimples and are often black in colour, or it could be a mouldy growth of spores[23].

**Leaf Blights:** In comparison to leaf spots, leaf blights often have more significant, irregularly shaped infected regions. Sometimes a large number of tiny dots combine to give leaves a "blighting" effect . Common names often include the term "blight," for example, Southern corn leaf blight or early blight[24].

**Rusts:** The spots produced by rusts are typically leaf spots; however, these spots are termed "pustules." Pustules caused by rust may appear in a variety of colours, including faded yellow, orange-red, reddish-brown, or even black . Pustules may be identified by their colour; the leaf quickly wilts and falls off when the condition is severe[24].

**Powdery Mildew:** Powdery mildew is a surface growth disease that appears powdery to mealy and may be seen on leaves, stems, and flowers. It can range in colour from white to a light grey colour. This issue is prevalent in vegetables of the cucurbittype family as well as on grains of a smaller size.

**Downy Mildew**: Symptoms of downy mildew include light grey to purple mould growing on the leaf's bottom and spots of mild yellow-green to yellow spots on the upper side of the leaf surface

**Computer Vision in Plant Leaf Disease Detection**

If you want to know how healthy a plant is and how much it will produce, you need to know how to spot plant leaf diseases. In contrast, the globe is home to more than half a million plant species, each with its own unique set of leaf diseases. Attempts at human identification in such cases are often futile and tedious [25]. Consequently, studying how to identify plant species is crucial, and the automated leaf-based recognition method it employs highlights the need of developing and deploying identification mechanisms that are easy for humans to utilise. The fact is that professionals need to understand the genetics of rice plant illnesses in order to protect these species and reverse the loss of biodiversity caused by recent urbanisation [26]. Fruits and flowers are not easy to identify with precision. Therefore, leaves are considered the best alternative due to their accessibility and longevity [27]. The leaves may be collected at any stage of their development and have a nearly two-dimensional shape. Developing a computerised system that can automatically identify and categorise different kinds of plant leaves is both necessary and advantageous [28].

In a short amount of time, this will help both scientists and the average person identify leaves accurately. Therefore, it is crucial to create machine learning methods that allow for precise leaf species identification [29]. In order to study the leaf in its entirety, there are cameras with very high resolutions and dimensions. It takes a specialist in the field to determine whether the leaf of the rice plant is impacted or not. A regular individual couldn't afford to buy a high-end camera for each inquiry under these conditions. Consequently, it is critical to photograph the leaves and utilise a machine learning model to determine their species using a smartphone's camera.[30].

**Digital Image Processing in Plant Leaf Disease Detection**

Crop diseases come in many forms, and each one has the potential to drastically lower harvest yields. The security of the food supply is at risk because of this. This highlights the critical need for precise disease categorization of plant leaves. Conventional approaches, such as visual inspection and laboratory testing, have many drawbacks, such as a lengthy testing period and the possibility of inaccurate findings [31]. Consequently, deep learning models based on Computer-Aided Detection (CAD) are often employed to attain better performance. Conventional categorization techniques have certain challenges, but they have tackled and, to a large part, overcome these challenges [32].

In order to identify and categorise diseases in plant leaves, the basic architectural style is shown in Fig. 1.

A pre-processing procedure is first performed to standardise the dataset and enhance the picture quality. Segmentation, HFE, and HFS are the subsequent steps that are carried out using deep learning models and image processing operations. Furthermore, the correlations between various problematic traits may be discovered utilising optimisation techniques and HFS methodologies [50]. The best features are also selected by these methods. In addition, the classification operation is carried out using deep learning and transfer learning models to classify the many illnesses that might impact different types of plants

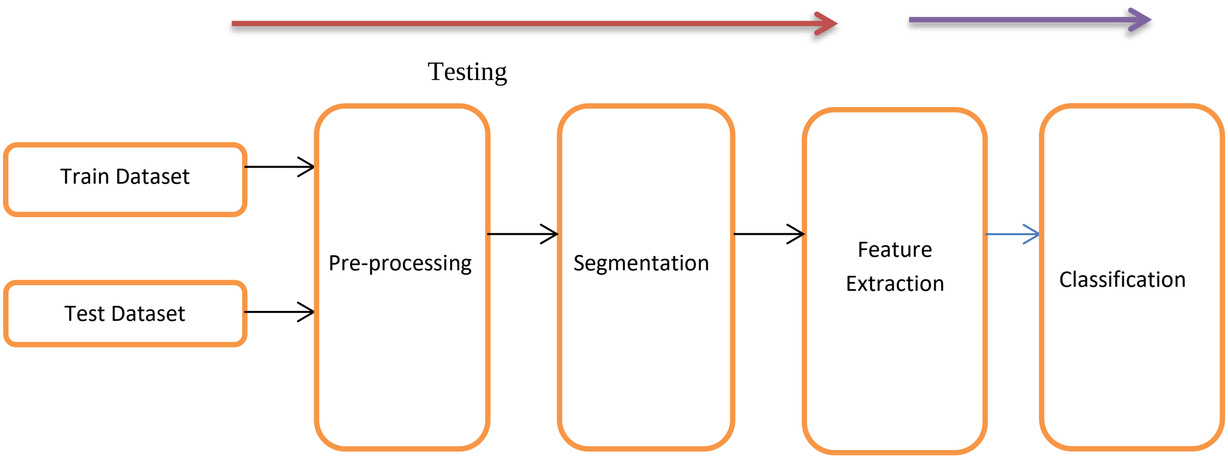


**Fig 1:** The Basic Architecture for Plant Leaf Disease Detection and Classification

**Image Pre-processing**

Adjusting the intensities of the input and output picture pixels is a typical pre-processing step for actions performed with images at the most fundamental level of abstraction. The pixel level describes this degree of abstraction. The main goal of pre-processing is to improve certain picture attributes that are crucial for further processing or to remove undesirable distortions from the image data. Intensity images are often shown using a brightness matrix that contains the values of image functions. Additionally, pre-processing techniques include geometric picture modifications including scaling, translation, and rotation..

**Image Segmentation**

Digital image processing tasks such as attribute detection, picture visualisation, and image interpretation all begin with segmentation. Digital image processing and machine learning methods are used to analyse the properties retrieved from captured pictures in order to detect illness kinds. Proper segmentation is used to acquire these characteristics. One method of processing images is segmentation, which basically involves breaking the picture down into its relevant pieces. The efficacy of the segmentation determines the degree of segmentation of certain components or areas of interest. In order to correctly identify the sick area on a green leaf, for example, this autonomous segmentation algorithm must segment the provided picture until the items or areas of interest have been identified. Selecting the best segmentation method increases the likelihood of correct segmentation, which is particularly important when dealing with plant photos captured in real-time. One of the hardest jobs in our application is the segmentation of nontrivial plant photos. Intensity value discontinuity and similarity are the two most fundamental characteristics that all segmentation algorithms adhere to. picture segmentation, in particular, involves labelling each pixel in a picture in such a way that related pixels have common characteristics.

**Feature Extraction (FE)**

It is common practice to split dimension reduction techniques into two subcategories: feature extraction and feature selection. In feature extraction, merging the original features into a smaller dataset via feature transformations reduces the number of feature sets needed.

Applications where model interpretation is not crucial, such as signal processing, image analysis, and information retrieval, often use these FE approaches. The item is given a suitable class name so that its attributes may be used to describe it. The feature extraction model's principal role in the plant leaf disease detection framework is to automatically learn the features.

Typically, plant illnesses are diagnosed by analysing photographs of leaves based on their shape, texture, and colour. An appropriate feature extraction approach has to be appropriately applied based on these features.Deciding which feature set is superior and selecting the optimum extraction technique will be the two most challenging tasks.

**Classification**

The first step in classifying plant leaf diseases is to identify them. More and more categorization jobs are being handled by deep learning algorithms recently [59]. To train the classification model, which employs several convolution layers, Deep Convolution Neural Networks (DCNN) are used.

In order for this convolutional layer to apply the convolutional operation to certain characteristics, it needs a set of filters. In order to distinguish between the several varieties of plant leaves, this architecture uses a series of convolutional layers, with each layer learning a unique set of characteristics that capture discriminatory patterns. Every time a batch of input data undergoes a gradient update, Deep Neural Networks (DNNs) learn something new about the data's characteristics.

Due in part to the frequent modification of the parameters of the preceding layers during training, the data distribution on this input feature map is quite soft. Because of this, training time has been cut in half, and different optimisation methods are required to determine how the parameters in the training set should be initialised.

**Multi-Scale Retinex Algorithm for Image Pre-processing**

The goal of image enhancement is to raise the picture quality so that it can be better used for classification and segmentation. Most pattern recognition and image processing activities performed under computer vision employ this step before going on to the segmentation and classification stages of image processing. The main goal of this stage is to enhance the picture by eliminating unnecessary data from the host image and focusing on the pertinent information for the current job. The segmentation and classification procedures rely heavily on this improvement. The main objective of the retinex algorithm is to define realistic colour perception. Through its simulations, effective techniques for improving local picture contrast have been developed, which enables the capacity to highlight objects in shadows and other aspects. From these modified methods, Multi-Scale Retinex stands out as a center-surround image filter that performs well. Digital cameras tend to pick up ambient noise, such as dust, fog, and haze, which might alter the original or host picture. It is also necessary to fix the picture sensors' erratic colour, contrast, and brightness changes. Light, contrast, and shadow problems plague plant leaf images captured when plants were in direct sunlight. As a result, the multi-scale retinex image-enhancing technique has the potential to fix such problems. In this investigation's pre-processing step, an MSR method is used to enhance the plant leaf picture. Pictures taken in real time when the sun is directly above might suffer from lighting and shadow problems. A colour restoration technique that use the relative reflectance components of the picture may fix these errors. The retinex algorithm takes into account all pixels while determining the brightness value. For every intensity value of the edge pixels that follow in the route, it is required to compute this brightness value. The lighting conditions of the picture determine whether the technique has to be applied to each colour individually for a colour balance or only to the brightness alone for local contrast enhancement.

**GCMO Segmentation**

One potential top goal for machine vision research is the persistently challenging task of unsupervised picture segmentation. Methods that use regions or their borders as their basis are included in this group. The objective of the first segmentation step is to decouple the leaf image from the backdrop; hence, two segmentation steps are necessary.

To begin segmentation, we suggested a hybrid graph-based N-cut method with a value of 2 for N, which would allow us to separate the background from the leaf chunk. The next step in segmentation is to divide the image into healthy and diseased areas. This will help with disease severity estimation. To achieve accurate segmentation for different images, the cluster numbers are chosen based on the segmentation preview shown by MATLAB. Before comparing the four segmentation outputs for each image-based K value, we begin by choosing four clustering numbers, K=5,6,7, and 8. After considering these four possibilities, we settle on one K value.

Finding cuts in a graph representation of the picture is one way to tackle the picture segmentation issue. Finding the edge between adjacent pairs of pixels is the next step after treating each pixel as a vertex in the picture. A graph G with vertices V and edges E, where each edge is given a weight, is the resulting notation. Therefore, the degree of closeness or affinity between any two vertices or pixels gives each edge a weight. The vertices between two pairs of pixels are chopped using the following principles by Min-Graph-chopped. To begin, it is desirable for a pair of vertices within the same sub-graph to have a high affinity, but a pair of vertices outside of the same sub-graph should have a low affinity. Lastly, every subgraph in the picture is a segment, and there must be a minimal cost associated with all of the cuts added together. One major drawback of Min-Cut is that it tends to segment the unwanted part of the picture instead of the desired part if the cost of the intended cut is greater than the other cut. This is why we used a normalised cut to get around it.

We propose a hybrid approach to plant leaf picture segmentation that works for both simple and complicated backgrounds. By utilising both regional and boundary data, GCMO-based segmentation is able to achieve optimal results when it comes to separating BG and FG information in an image. This is achieved by dividing the graph into multiple sub-graphs, with each sub-graph serving as an object of interest in the image. By dividing the graph into many sub-graphs, graph cut-based segmentation also produces excellent results when it comes to identifying foreground and background information in an image. The graph cut method divides the picture into sections by first grouping the sections according to perspectival grouping rules, such as continuity and similarity, and then by determining the degree of dissimilarity between each section. The first step is to group the picture sections, and the second is to trim them.

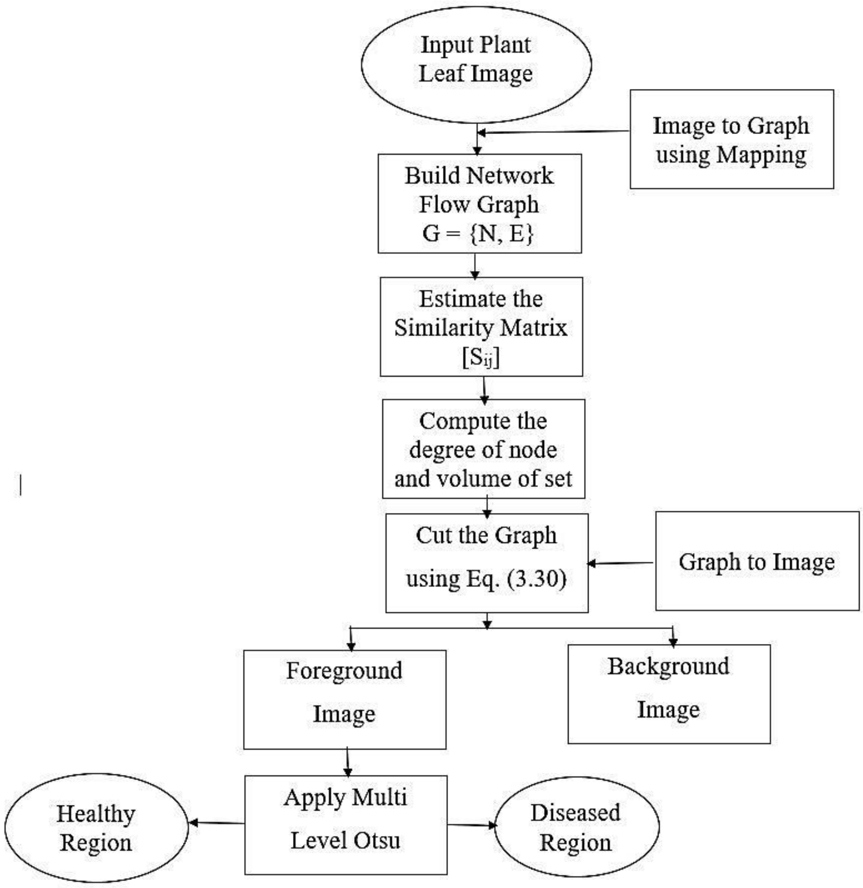


**Fig 2:** Proposed GCMO Algorithm Flowchart.

It could be difficult to handle, analyse, and organise data with a high dimensionality. In the context of machine learning in particular, it may lead to the dimensionality curse and is computationally costly and difficult to explain. When an image dataset has too many samples and features, a problem called "the curse of dimensionality" could arise, leading to a poor prediction model and a lot of computational work needed for training.

Using feature extraction and feature selection methods, we may improve the classification model's accuracy by selecting only the most relevant features and discarding the rest.

Despite the availability of several tried-and-true techniques for feature extraction and feature selection, there is no universally accepted "optimal approach" due to the inherent limitations of each. Our understanding of the relevant domain, our skill in selecting the optimal method to achieve the goal, and the metrics we want to employ all contribute to feature selection's efficacy. Because of this, there is a need for an affordable, precise, and automated method for detecting plant diseases. We have also developed a robotized system [80] to facilitate the effective completion of our tasks. Several academics in the agricultural sector have spent over twenty years studying leaf disease detection extensively. Despite the abundance of prior work, some questions remain unanswered and need more investigation.

Our research has resolved frequent problems, such as how to determine which plant leaves are diseased. We are proud of the fact that our work is more efficient and precise. When building a deep learning model, transfer learning has the potential to cut down on training time, generalisation error, and processing cost. This study advances our understanding of how to detect diseases in different types of plant leaves.

## Conclusion

Improved agricultural yields are dependent on the ability to identify and categorise plant leaf diseases; this study fills that need. For this study, researchers drew on two datasets: one from PlantVillage and the other a real-time dataset harvested from rice and peanut plants. The seven-step procedure is as follows: acquisition of images, preprocessing of images, segmentation, HFE, EFS, feature ranking, and classification. To begin with, the preprocessing procedures that eliminate various forms of noise from the datasets were carried out using the MSR technique. The GCMO segmentation technique was used to recover ROI regions once the images were adequately preprocessed.

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