Machine Learning-Based Real-Time Detection of Apple Leaf Diseases: An Enhanced Pre-processing Perspective

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Abstract

Cedar, rust, spot, frogeye, and healthy leaf are the five general types of apple leaf diseases (ALDs). An early phase diagnosis and precise detection of ALDs can manage the extent of infection and confirm the well growth of the apple production. The previous analysis utilizes difficult digital image processing (DIP) and can't be sure of a high accuracy rate for ALDs. This article introduces a precise detecting method for ALDs based on the deep learning (DL) method. It contains creating efficient PATHOLOGICAL images and proposing a new framework of a DL method to detect ALDs. Utilizing a database of 3,174 images of ALDs, the researched DL model is trained to detect the five general ALDs. This proposed work specifies that the research segmentation, transformation, and feature extraction methods give an enhanced outcome in disease handle for ALDs with maximum performance of detection rate. This article has created an effort to implement an approach that can detect the disease of apple leaves using different pre-processing methods. ALDs framework is designed for filtration, and color space transformation methods using Median, Gaussian, HIS, and HSV models. Grey Level Co-occurrence Matrix (GLCM) is used for the texture-based feature extraction (FE) method and the image creation method implemented in this article can improve the robustness of the improved feature extraction method.

Keywords: Apple leaf diseases, Deep Learning, Feature Extraction (GLCM) Method, Segmentation, Transformation.

1. Introduction

It is widely acknowledged that the apple is among the most important fruits in the world [1]. China is the country that produces the most apples in the world. The practices of apple picking and cultivation require a significant amount of work. As a result of the continuous increase in both planting area and production, there is an immediate need for both mechanized apple harvesting and precision planting [2, 3]. The use of methods like as yield estimate, robot harvesting, and precision spraying is very necessary in order to achieve perfect planting [4]. One of the most important steps in these processes is the segmentation of apple pictures.
At the present time, the first successful identification of sick fruit leaves is a key difficulty in computer vision (CV) [5]. This is often owing to the fact that these leaves are very important in agriculture and agro-based economics. The crop and the quality of the fruits are both severely impacted by a number of different illnesses that damage crops. The data that may be obtained from the symptoms that are seen on apple leaves can be of use in the identification of illnesses that affect a variety of fruit plants [6]. When damaged leaves are identified during the early stages of the process, the quality of the fruits and the harvest are both significantly improved [7]. On the basis of the hue, form, texture, and color, it is possible to identify a number of different kinds of disorders.

lesions that have been found. The presence of these lesions is an essential characteristic for the diagnosis of apple illnesses [8]. According to what has been stated, the assaults or sounds of various illnesses, such as rust, scab, and black spot, have a direct influence on the quality of the fruit production [9]. The development of an autonomous computerized system that can recognize and classify sick apple leaves at an early stage is a significant endeavor that calls for serious consideration. Several experts in the field of computers have created a number of different ways for the automated identification of illnesses that affect apple leaves [10].

During the last several years, analysts have used a wide variety of algorithms in order to segment images of apple leaves (AL). Through the use of color, spectral, and thermal cameras, analysts were able to effectively obtain images of aerial lasers (ALs) in plantations. Through the use of these photos, they were able to distinguish ALs from other things that were included in the photograph [11]. It is possible for spectral and thermal cameras to record data in both spectral and thermal modes [12]. With the help of the collective color camera, it is possible to collect data on the color, surface quality, and shape of objects. There was a significant amount of use of it in the area of leaf image segmentation (IS). The threshold-based segmentation approach is used by some analyzers in order to differentiate between photographs that exhibit a discernible color difference from those of foliage. These processes are simple and effective in their functioning.

The reference [13] showed a research model that included other models in addition to denseNet-121 and efficientNet-B7, both of which had been adequately trained. This model makes an effort to categorize apple trees into a wide variety of categories by making use of photos obtained via active learning. These categories include scab, cedar rust, healthy, and a number of illnesses respectively. The database size is increased and the model's accuracy is improved by the use of this approach, which incorporates a multitude of picture segmentation methods. An accuracy percentage of 96.25 percent was achieved in the validation database by using the methods that was specified by the publisher. The approach that has been devised has successfully exhibited remarkable performance across a variety of parameters, and it has the potential to be used in the area of architecture for the purpose of providing an accurate and fast assessment of the health of plants. In the course of this research attempt, a method has been developed for the purpose of segmenting and extracting information from photographs of apple leaves. The final objective of this endeavor is to automate operations that are associated with this area. The suggested approach has been included into the procedures of feature extraction, segmentation, and filtering now being carried out. A further point to consider is that the classifier that AL pictures use allows them to be distinguished from other images. The combination of a number of different image processing (IP) techniques is what constitutes an AL image segmentation procedure or methodology. The following is a list of the objectives that this planned initiative aimed to accomplish:

- The objective is to assess and improve the accuracy of color and texture-based attributes for the purpose of artificial intelligence picture segmentation.
- To apply a feature extraction (FE) technique to extract reliable texture-based feature matrices.

Tracks are being developed for the remaining portions of this study paper: An in-depth investigation of the apple leaf image detection and classification models is presented in Section 2. In the third section, the research technique is discussed, which provides a summary of the planned work processes that were done to arrive at our approach. This section contains explanations that pertain to the database as well as the procedures that are used for preparing files. The pre-processing results that were obtained are discussed in Section 4, along with a comprehensive examination of the model that was suggested. Furthermore, the conclusion of this study piece may be found in section 5, which discusses the future scope.

2. Material and Methods

2.1 Apple Leaf Image Segmentation Method

The article [14] describes the construction of a system that uses machine learning (ML) and computer vision (CV) to identify illnesses that affect apples. Both automated apple disease detection (ADD) and leaf sign-based disease detection are used by the system. The applied method was comprised of three distinct components: (i) the identification of the sickness region, (ii) the extraction of features (FE), and (iii) the detection or categorization of the illness. In order to separate the susceptible area of the AL, they used a segmentation strategy that was based on the l*a*b color space. In order to classify each pixel of a picture as either healthy, ill, or background edge, the K-nearest neighbor (KNN) technique is used in conjunction with the utilization of average color generators in the a*b color space. The recovered features may be separated into two distinct categories: (i) the discrete wavelet transformation (DWT) technique that was used, and (ii) the l*a*b colorspace histogram feature sets. Both of these categories are distinct from one another. In order to diagnose a land rust infections in apple crops, the method that was suggested by [15] makes use of Mask R-CNN and instance segmentation. An assessment is carried out on three distinct Mask R-CNN network backbones, namely MobileNetV3-Large-Mobile, ResNet-50, and MobileNetV3- Large, in order to evaluate the efficacy of these backbones in terms of object detection (OD), segmentation, and the identification of AL illnesses. Using segmentation masks that were annotated on a subset of the Plant Pathology Challenge 2020 database, the authors trained and tested the recommended Mask R-CNN-based algorithms. This was done in order to determine their effectiveness. According to the findings, the Mask R-CNN approach, which makes use of a ResNet-50 framework, is capable of precisely and effectively identifying minor rust disease spots on apple leaves. Guava, jamun, mango, grapes, apple, tomato, and arjun were the seven different plant species that were segmented and categorized using a revolutionary approach that was published in [16]. This technique used pictures of the leaves of the plants in order to do this. The first step of the method is collecting and processing photographs from natural and crowdAI datasets in order to eliminate noise, resize, and improve contrast. Following the extraction of various features via the use of texture and color, the third phase includes the use of the k-means algorithm for the purpose of image segmentation. The testing process is carried out in the fourth stage, which comes after the SVM training has been finished. The segmentation and detection operations were both carried out with the help of particle swarm optimization (PSO), which was used in order to determine the optimum initialization parameter value. With a sensitivity (SN) of 0.9581%, a specificity (SP) of 0.9676%, a segmentation accuracy of 0.9759%, and a recognition accuracy of 95.23%, the methodology that was created exceeds other approaches that are already in use in terms of the results of investigations.

2.2 Apple Leaves Disease Detection Model

According to [17], the agriculture industry has a crucial role in both the Saudi Arabian economy and food security. However, agricultural problems provide a significant barrier to this sector and have a substantial impact on the economic progress of many countries worldwide. Three separate IP approaches were used in each of the three classification models in this investigation to differentiate between healthy and sick apple plant leaves. The calculations were performed using the Kaggle New Plant Diseases repository. This project aims to assist agriculturalists in the detection and control of disease spread. The proposed methodology recommends suitable identifiers for each diagnosed plant ailment based on the results of the detection process. The identification of diseases in recent times was characterized in [18] as a process that takes a lot of time, is costly, and heavily depends on human observation. The use of ADD and segmentation techniques based on PLI (plant leaf images) may provide more reliability and practicality compared to their previous counterparts. This document offers techniques for obtaining, preparing, dividing, extracting characteristics from, and categorizing photographs of Apple Leaves. The current investigation used deep convolutional neural network (CNN) models, notably efficientNet and denseNet, to precisely categorize apple leaf pictures representing diseases on apple trees into four separate groups. The classifications included several diseases, such as Healthy, Scab, Rust, and Multiple Diseases, among others. To enhance ALDD, advanced approaches such as data argumentation and annotation were used, which included astute edge detection (ED), blurring, and inverting. [19] AppleNet was introduced as a highly accurate and resilient detection approach for ALD. It enhances the existing YOLOv5 network by including coordinate attention (CA) and feature enhancement module (FEM) approaches. The fusion of the feature pyramid and pan Utilizing YOLOv5 may lead to heightened semantic information (SI) and improved SI of low-level feature maps. However, it does not achieve the same degree of performance as using multiple-scale data. To enhance the results of data gathered at various levels, the Finite Element Method (FEM) was used, while the Cellular Automaton (CA) was used to enhance the detection efficiency (DE). According to the simulation findings, appleNet obtains a maximum mean average precision (mAP) of 95.9 percent and a precision of 93.1 percent. These values are greater than those obtained by four classic detection techniques. Consequently, appleNet attains more competitive outcomes on ALDD.

3. Research Methodology

The purpose of this part is to provide a detailed overview of our module from a methodological perspective in order to define the research model. Figure 3 is a block diagram that describes the steps that are being discussed. The flow work included in the study approach is shown in Figure 3. The study model will provide a description of the many components, which include (i) the collection of apple leaf image datasets, (ii) the pre-processing portion, and (iii) the feature extraction and selection portion. In the beginning, it was discovered that many various kinds of ailments are associated with apple leaf imagery. It is possible for the majority of research to get the apple leaf dataset from internet repository sources. Following the part on the collection of data, it uploaded the photographs of the apple leaves and checked the feasibility of the database to determine whether or not a dataset image would explore the 3D format. The next phase was the application of the picture pre-processing procedure, which included the development of the RGB, HSL, and HSV color spaces as well as the conversion of color to grayscale format. A degraded version of the information contained in the submitted picture has been shown by this format apple leave image. The study model has utilized the filtering technique in order to eliminate the undesired data from the apple leaf photos in the event that noisy information has been displayed in the image that was supplied. Following the completion of the filtering process, the study model proceeded to the subsequent step, which was the extraction of features. Through the use of feature-based approaches, the process of feature extraction has been able to extract more accurate feature sets. The evaluation of the value in the form of texture feature sets was the primary aim of the technique for feature extraction.

3.1 Collection of Apple Leave Image Dataset

It is possible for the research model to verify a greater number of classes or categories of ALDs in the natural backdrop as a result of the various datasets. This enhances the model's capacity to deal with fluctuations in the environment, which ultimately results in the research model being more robust. As a result, the dataset that is referred to as AppleLeaf9 was compiled by combining the data from the Plant Village dataset (PVD) [20], the apple leaf disease image segmentation dataset

(ALDISD), and the Kaggle apple leave illnesses dataset (Plant Pathology 2020) [21]. Agriculture disease experts were asked to review each photograph, and those that included erroneous labeling were eliminated from consideration. Figure 1 provides a summary of the AppleLeaf9 image sources and their respective divisions. The appleLeaf9 samples are specified in figure 2, which may be found here.

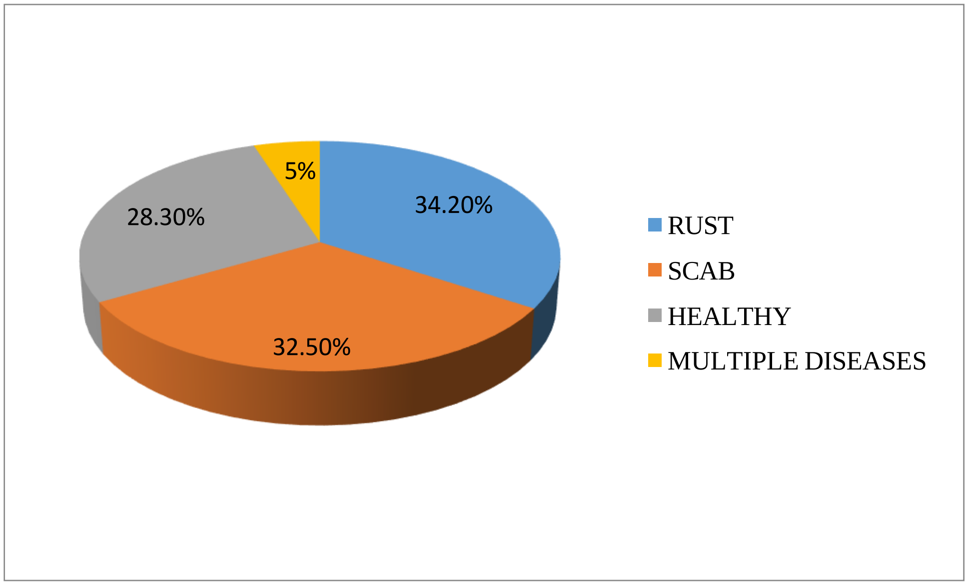


Fig 1. Division of Image Sources in Apple Leave Dataset

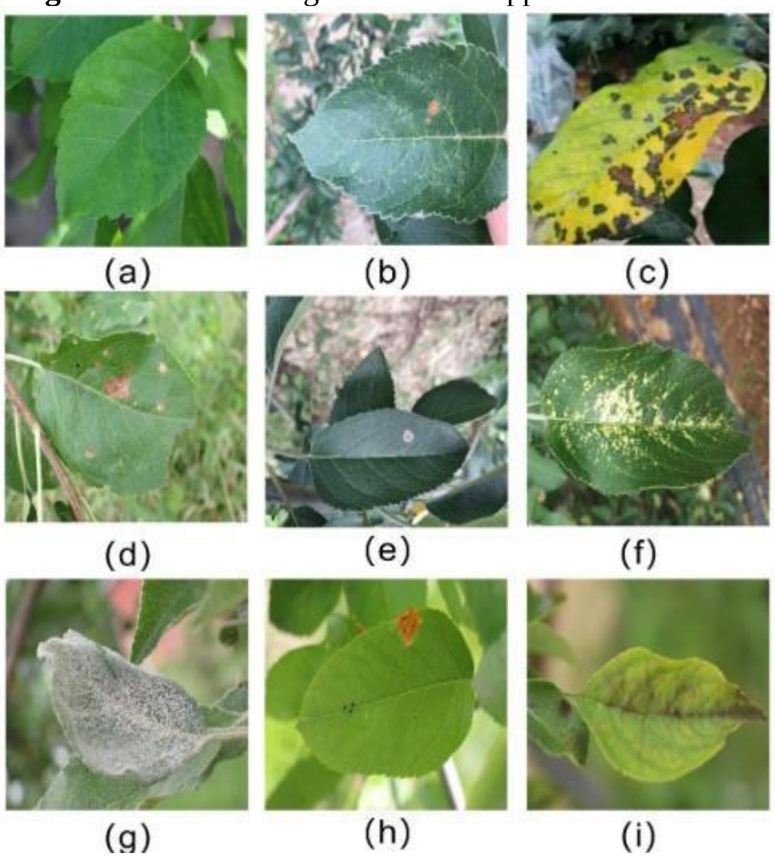


Fig 2. Samples of Apple Leave Images (a) Healthy, (b) ALS (Alternaria leaf spot), (c) BS (brown spot), (d) FLS (frogeye leaf spot), (e) GS (grey spot), (f) Mosaic, (g) PM (powdery mildew), (h) Rust, and (i) Scab.

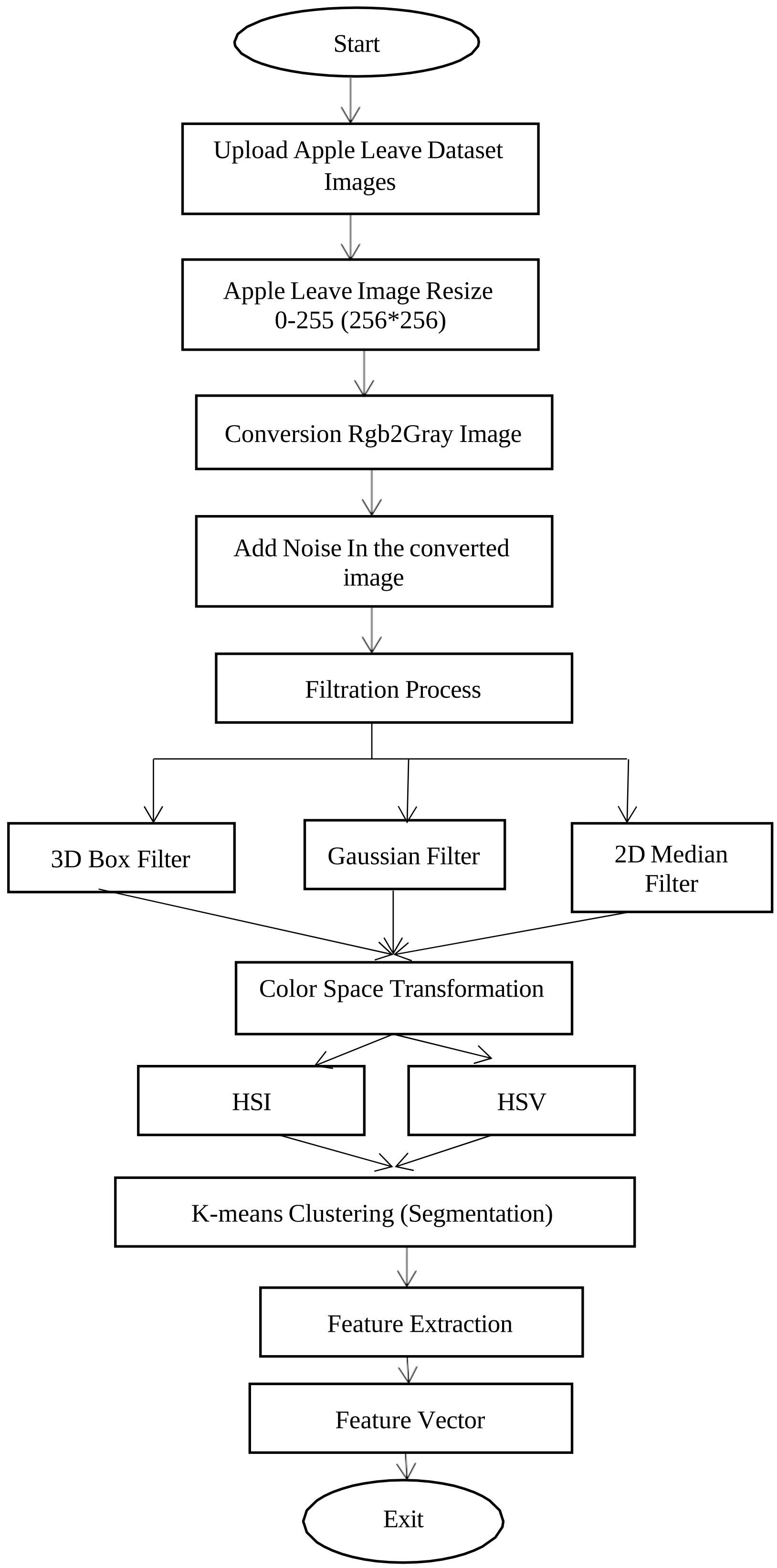


Fig 3. Research Methodology

3.2 Pre-processing Steps

This stage refers to the process of preparing our database in order to include photos of apple leaves. This is accomplished via the use of a variety of procedures, including the incorporation of noise, the filtering of noise attacks, the transformation of color space, the detection of edges, segregation, and the technique of feature extraction.

3.2.1 Apple Leave GrayScale Image

Figure 4(i) displays the picture of the test apple leaf illness that was submitted. Converting the picture that was submitted into a grayscale apple leaf image is the first step in the conversion process. A grayscale format or channel, as illustrated in figure 4(ii), is created from an image that has been uploaded and contains two or more RGB channels.

(i) (ii)

Fig 4. (i) Input Image (ii) Grayscale Image

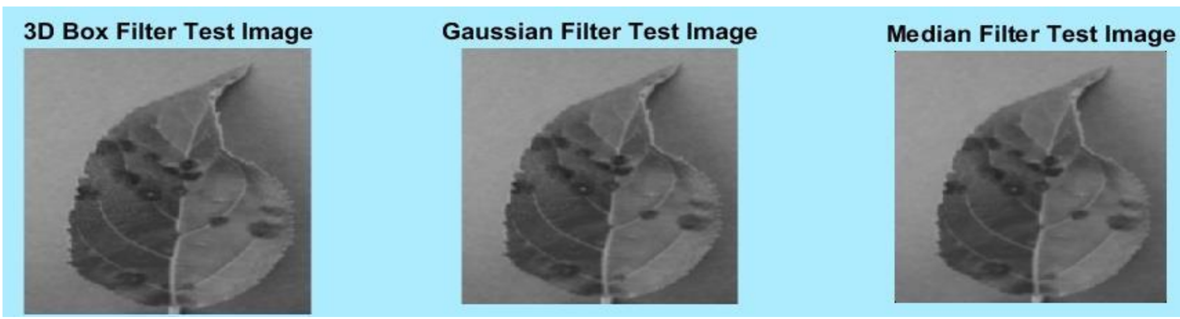
3.2.2 Apple leave Image Resizing

It not only resizes the picture but also alters its size and, if desired, scales it to certain dimensions, such as 0-255 or 256*256, as illustrated in figure 5.

Fig 5. Resizing Image

3.2.3 Filtration Process of Apple leave Images

The 3D-Box filter has been created as part of the planned work. To accomplish it in a similar manner, a neighborhood of pixels with four sides is weighted in three major parts: first, the filter size is computed, then padding values are added, and lastly, the normalization factor is predicted. The final picture that was produced using the 3Dbox filter is seen in Figure 6 (i). A Gaussian filter is a linear smoothing filter, as shown in figure 6 (ii), that chooses the values that allow the framework of the Gaussian function to be implemented. This filter is an efficient low-pass form that is used to remove sounds that are susceptible to different frequencies, whether they are in the spatial or frequency domain. This is the normal division. It thus offers a wide range of potential applications in the field of image processing. After that, we will move on to the median filter. It differs from the primary filter in that it is non-linear. Along the same lines as the main filter, the median filter is responsible for monitoring the moving window standard. The pixel standards that represent the median in the window are computed, and the pixel that represents the center of the window is replaced with the approximately approximated median. During the process of median filtering and initial arrangement, the absolute pixel values from the surrounding neighborhood are arranged in a statistical order. After that, the value of the middle pixel is used to determine how an individual pixel should be changed. The picture that was used for the median filter test is shown in Figure 6 (iii).

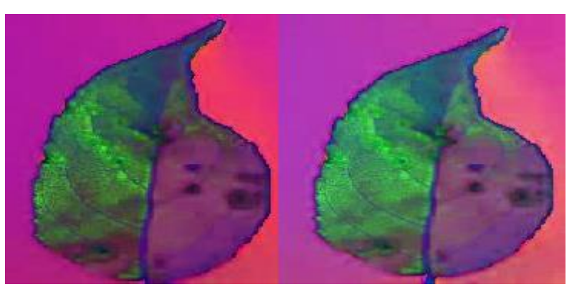


(i) (ii) (iii)

Fig 6. Filtered Image (i) 3D Box filter (ii) Gaussian Filter, and (iii) median Filter Image

3.2.4 Color Space Transformation

HSI and HSV are two examples of the color space transformation algorithms that are used by this. When it comes to displaying color pictures, HSI, which stands for Hue, Saturation Intensity, is an excellent choice since it is well-suited to employing a strong human graphical model.The human senses are able to perceive a variety of emotions via the use of hue. A higher saturation level is comparable to brighter colors. Saturation is a criterion that determines the color and clarity. The illumination of the color is referred to as its intensity. HSI is shown in Figure 7(i), which is the image. HSV, on the other hand, is a color prototype that is formed like a cylinder that replicates the RGB primary or fundamental colors into magnitudes that are simpler for folks to perceive. The picture that has been modified using HSV is shown in Figure 7(ii).

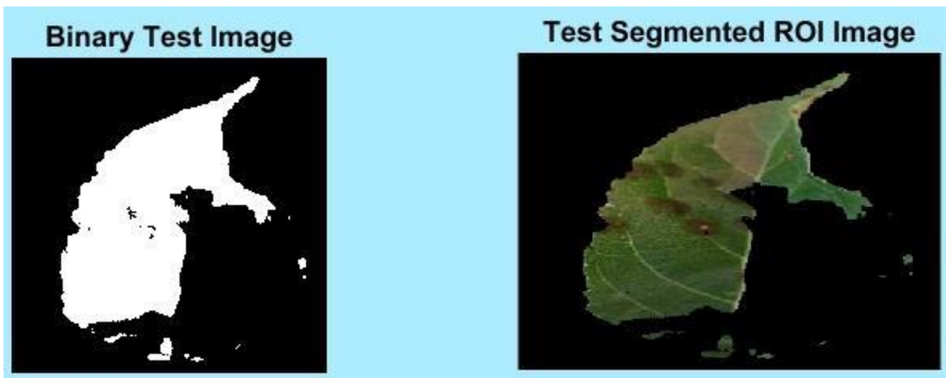


(i) (ii)

Fig 7. (i) HSI image (ii) HSV color space model image

3.2.5 Segmentation using K-means Clustering method

This section illustrates the process of picture segmentation achieved via the use of the K-means clustering technique. The subtraction of the background is a class of approaches that is often used for the purpose of segmenting items of interest within a picture. A binary picture is shown in Figure 8(i), and the segmented image is shown in Figure 8(ii). This type of clustering is an iterative process that makes an effort to filter the dataset into Kpre-defined sub-clusters that are distinct from one another and do not overlap. In this method, all of the data points are grouped together into a single collection. It makes an effort to safeguard the clusters to the greatest extent possible while simultaneously attempting to build the intra-group data points as comparable as possible. It does this by assigning data points to a group in such a way that the sum of the aligned distances between the data points and the centroid of the group is the smallest possible addition.



(i) (ii)

Fig 8.(i) Binarize Image and (ii) Region of Interest Image

3.2.6 Feature Extraction Using GLCM and SIFT algorithm

The abbreviation for the grey-level co-occurrence technique is GLCM. In the GLCM matrix, the relation between two adjacent image pixels at the same time is measured. One of the pixels is referred to as the reference pixel, and the other pixel is also referred to as the closest pixel [22]. After that, it does an analysis on the texture data, and it requires a symmetric matrix. This particular matrix is constructed using the identical parts of values that are located on the opposite sides of the diagonal. In order to facilitate further processing, GLCM is converted into this form. Values for the GLCM matrix are shown in Table 1.

- Energy
- Contrast
- Correlation
- Standard Deviation
- RMSE
- Variance
- Smoothness
- Homogeneity
- Skewness, and Mean.

Table 1. GLCM Matrix values

GLCM Matrix	Values
Contrast	0.086
Correlation	0.98
Energy	0.33
Standard Deviation (SD)	70.9
RMSE	10.9
Variance	3063
Smoothness	1
Homogeneity	0.98
Skewness	0.17
Mean	70.16

4. Result Discussion

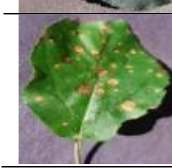
Validation of this method has been performed on the PVD [20,23]. Pre-processing techniques are used in order to divide the results of the study methodology into distinct portions. These techniques include the following: (i) the filtering method, (ii) the segmentation method, and (iii) the feature extraction methods. Filtration technique and segmentation method results of the picture contrast enhancement and GLCM algorithm, as well as SIFT algorithm in the given image. Utilizing MATLAB 2018a, the suggested work was responsible for the development and training of the proposed model. Additionally, the GUIDE includes a number of frameworks and libraries that are used in our research activity, in addition to MATLAB. Using the PVD of GUIDE, we created a dataset from the input photographs of apple leaves, and then we applied the transformation, filtering, segmentation, and feature extraction process to the data. A number of characteristics were collected from the picture of the apple leaf for the study project. With the use of the formula in table 2, the GLCM approach was able to extract features such as energy, contrast, RMS, and entropy. One of the most effective approaches to surface examination is this strategy. It is the co-occurrence characteristics that we get via the use of the GLCM matrix that constitute the primary notion. All of the picture pixels in the matrix are counted and saved thereafter. This histogram equalization (HE) approach was applied by us in order to verify that the information included inside the picture pixels in that matrix was same. All of these characteristics, including standard deviation, mean, and skewness, were calculated by using this method. Figure 3 provides a breakdown of the many classifications of apple leaf pictures.

Table 2. GLCM Features

GLCM Matrix	Formula's
Contrast	$\sum_a \sum_b (a-b)^2 h_{ab}$
Correlation	$\frac{\sum_a \sum_b (ab)\, hab - \mu_X \mu_Y}{\sigma_X \sigma_Y}$
Energy	$\sum_a \sum_b hab^2$
Standard Deviation (SD)	$\sqrt{\sum_{a=0}^{l-1} h(a) - m^2 p(h(a))}$
RMSE	$\sqrt{\frac{1}{l*l} \sum_{a=0}^{l-1} \sum_{b=0}^{l-1} h(a,b) - i)^{\wedge}2}$

Homogeneity	$\sum_{a}\sum_{b}\frac{1}{1+(a+b)^2}\ hab$
Skewness	$\frac{1}{s^3}\sum_{a=0}^{l-1} h((a)-m)\text{^}3\ p(h(a))$
Mean	$\sum_{a=0}^{l=1} h(a)p(h(a))$

Table 3. Proposed Apple leaf Image with Categories

Apple Leaf Images	**Categories**
	Scab
	Cedar and Rust
	Healthy
	Forgeye and Spot

5. Conclusions

Through the use of the DL approach, simulation analysis is carried out in this article with the purpose of identifying and categorizing illnesses based on photographs of ALDs in a manner that is both effective and efficient. The detection of ALDs at an early stage is the most important objective that research needs to accomplish. In this work that has been suggested, we have devised and implemented methods that are based on the primary notion of DL in order to identify ALDs by using the characteristics or attributes of their leaves. A dataset that comprises various apple leaf pictures that have been afflicted by a variety of illnesses has been extracted from the PVD dataset for the purpose of conducting experiments on ALDs that have been investigated. However, our attention has been directed on other classifications of ALDs, such as scab, spot, cedar, and others. The research work on ALD detection systems has been carried out in a variety of steps prior to the development of the DL. These stages include feature extraction, image augmentation, color-space transformation, segmentation in a pre-processing step, and feature extraction using a GLCM matrix. The accuracy of the ALDs that were investigated has been improved as a result of the use of all of these features. As a result of the simulations, it has been determined that the accuracy of the research model using GLCM grows in proportion to the growth in the feature extraction approach. Our suggested approach will be analyzed and calculated in the work that will be done in the future. The implementation of further deep learning techniques, such as enhanced SIFT (scale invariance feature transformation) and MSVM (multi-support vector machine), is proposed for the purpose of identifying ALDs in real time. Additionally, other types of ALDs as well as certain high-quality photos of ALDs are still necessary to be gathered on the plantation in order to identify additional illnesses in a timely and accurate way inside the plantation.

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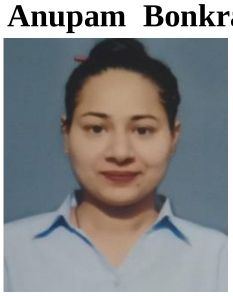

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