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Implementation of Plant Leaf Diseases Recognition by Image processing using Machine Learning

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ABSTRACT

In a developing country like India agriculture plays a noteworthy role. Agricultural intervention in the livelihood of rural India indulges by about 58%. Among the agricultural products, orange is one of the most used crops. Thus, preventing significant loss in quantity and yield of oranges is majorly dependent on the recognition and classification of diseases an orange plant leaf might possess. Initially, the leaves of an orange plant leaf get affected, when the plant develops a particular type of disease. In this research, four consecutive stages are used to discover the type of disease. The four stages include pre-processing, leaf segmentation, feature extraction, and classification. To remove the noise, we are doing the pre-processing and to part the affected or damaged area of the leaf, image segmentation is used. The Ensemble Bagging Classifier algorithm, which is a guided, supervised and advanced machine learning algorithm, is implemented to find solutions for both the problems related to classification and regression. During the terminal stage, the user is recommended the treatment. Mostly live plants are adversely affected by the diseases. This paper imparts a representation of leaf disease detection employing image processing that can identify drawbacks in orange plant leaf plants from images, based on color, bound, and texture to give brisk and reliable results to the farmer.

1. INTRODUCTION

In countries like India, it is of at most importance to bring technological advancement in the fields related to crop productivity. Research initiatives and tentative study processes in the important domain of qualitative farming are focused on improving the yield and food crop standard at low cost, with a greater monetary outcome. The agricultural building model stands as a result of a compound interlinking of soil with seeds and chemicals used to enhance growth. Vegetables and fruits exist as one of the present significant agricultural achieved outputs. In directive for getting surplus and effective worthy products, a product value examination and improvement has always been importantly imperative.

Diseases are disablement to the conventional state of the plant that translates or hinders its important roles such as transpiration, photosynthesis, fertilization, pollination, germination, etc. They distorting diseases are spawned by pathogens like fungi, bacteria, and viruses, because of unfavourable environmental situations. Accordingly, the preliminary stage for diagnosing plant disease is a significant task.

Farmers need periodic monitoring by professionals which might be prohibitively costly and time absorbing. Thence, looking for quick, less costly, and precise ways to smartly detect the diseases from the indicators that look to be on the plant leaf is of great pragmatic importance. In our study, we are proposing a system that can be used to identify the particular type of disease a tomato leaf might have. It is of major concern to identify the type of disease an important crop like orange can have, by implementing upbringing technologies like image recognition [11], which represent the application functioning visually and it is also an important reason for making digital technologies popular. Machine learning is used for detecting diseases in plants. Machine learning is one of the subparts of Artificial Intelligence to work automatically or give instructions to do a particular work. The main aim of machine learning is to understand the training data and fit that training data into models that should be useful to people. So, we can use machine learning to detect diseases in plants [12].

The major concern in the agriculture field is that the yield is proportional to the increasing population due to the limited natural resources. The big challenge here is to increase productivity irrespective of non-favouring natural conditions. Nowadays precision agriculture is introduced which uses the recent advanced technology in the agriculture field to increase its yield. The automatic leaf disease diagnosis system belongs to the precision agriculture stream which predicts the disease by analyzing the infected leaf disease images using Computer Vision, Image Processing, and Machine Learning algorithms. Due to the automatic disease detection system, the instant and accurate decision about the plant disease is available to the farmer which makes the diagnosis process faster. In the previous technique, the farmer had to submit the infected leaf to the pathology lab and then the pathologist confirmed the disease Motivation The major concern in the agriculture field is that the yield is proportional to the increasing population due to the limited natural resources. The big challenge here is to increase productivity irrespective of non-favouring natural conditions. Nowadays precision agriculture is introduced which uses the recent advanced technology in the agriculture field to increase its yield. The automatic leaf disease diagnosis system belongs to the precision agriculture stream which predicts the disease by analyzing the infected leaf disease images using Computer Vision, Image Processing, and Machine Learning algorithms. Due to the automatic disease detection system, the instant and accurate decision about the plant disease is available to the farmer which makes the diagnosis process faster. In the previous technique, the farmer had to submit the infected leaf to the pathology lab and then the pathologist confirmed the disease which proved to be a very time-consuming job. A delayed response results in low productivity of the crops. Hence it is essential to automate the disease detection system for faster diagnosis of the crop.

The major concern in the agriculture field is that the yield is proportional to the increasing population due to the limited natural resources. The big challenge here is to increase productivity irrespective of non-favouring natural conditions. Now a day precision agriculture is introduced which uses the recent advanced technology in agriculture to increase its yield. The automatic leaf disease diagnosis system belongs to the precision agriculture stream which predicts the disease by analyzing the infected leaf disease images using Computer Vision, Image Processing, and Machine Learning algorithms. Due to the automatic disease detection system, the instant and accurate decision about the plant disease is available to the farmer which makes the diagnosis process faster. In the previous technique, the farmer had to submit the infected leaf to the pathology lab and then the pathologist confirmed the disease which proved to be a very time-consuming job. A delayed response results in low productivity of the crops. Hence it is essential to automate the disease detection system for faster diagnosis of the crop. The early diagnosis leads to better disease control, less use of pesticides, less frequency of pesticide use, and higher yield of crops.

The primary goal of this research work is to design and develop a better machine learning system and to improve the classification accuracy of plant leaf disease and classification methods. To achieve this research goal, specific objectives are set. The research objectives of this thesis are comprised of the following components.

- Develop new pre-processing techniques to improve the image quality and selection of Region of Interest (ROI).
- Usage of machine learning classifier to classify the ROI images and to show the performance analysis of classifier, to find the classification accuracy, sensitivity, and specificity.

2. RELATED WORK

This Section describes the background of plant disease detection. Various techniques available for plant disease detection are reviewed based on the various machine learning techniques.

Trivedi J. et. al. (2020), proposed in a paper titled “Plant Leaf Disease Detection Using Machine Learning”, a Convolutional Neural Network (CNN) architecture for plant leaf disease detection using techniques of Deep Learning. A CNN model is trained with the help of the Plant Village Dataset consisting of 54,305 images comprising of 38 different classes of both unhealthy and healthy leaves. The disease classification accuracy achieved by the proposed architecture is up to 95.81% and various observations were made with different hyperparameters of the CNN architecture. The experiment results achieved are comparable with other existing techniques in the literature [1].

S. Ramesh et al. (2018), in a paper titled "Plant Disease Detection using Machine Learning", proposed a Random Forest algorithm in identifying between healthy and diseased leaves from the data sets created. Our proposed paper includes various phases of implementation namely dataset creation, feature extraction, training the classifier, and classification. The created datasets of diseased and healthy leaves are collectively trained under Random Forest to classify the diseased and healthy images. For extracting features of an image, we use a Histogram of an Oriented Gradient (HOG). Overall, using machine learning to train the large data sets available publicly gives us a clear way to detect the disease present in plants on a colossal scale [2].

G. Geethaet. al. (2020), proposed in a paper titled "Plant Leaf Disease Classification and Detection System Using Machine Learning", four consecutive stages are used to discover the type of disease. The four stages include pre-processing, leaf segmentation, feature extraction, and classification. To remove the noise are doing the pre-processing and to part the affected or damaged area of the leaf, image segmentation is used. The k-nearest neighbors (KNN) algorithm, which is a guided, supervised, and advanced machine learning algorithm, is implemented to find solutions for both the problems related to classification and regression. During the terminal stage, the user is recommended the treatment. Mostly live plants are adversely affected by the diseases. This research imparts representation of leaf disease detection employing image processing that can identify drawbacks in tomato plants from images, based on color, bound, and texture to give brisk and reliable results to the farmer [3].
Chowdhury et. al. (2021), in a paper titled "Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques", proposed the use of a deep learning architecture based on a recent convolutional neural network called Efficient Net on 18,161 plain and segmented tomato leaf images to classify tomato diseases. The performance of two segmentation models i.e., U-net and Modified U-net, for the segmentation of leaves is reported. The comparative performance of the models for binary classification (healthy and unhealthy leaves), six-class classification (healthy and various groups of diseased leaves), and ten-class classification (healthy and various types of unhealthy leaves) are also reported. The modified U-net segmentation model showed accuracy, IoU, and Dice scores of 98.66%, 98.5%, and 98.73%, respectively, for the segmentation of leaf images. EfficientNet-B7 showed superior performance for the binary classification and six-class classification using segmented images with an accuracy of 99.95% and 99.12%, respectively. Finally, EfficientNet-B4 achieved an accuracy of 99.89% for ten-class classification using segmented images. It can be concluded that all the architectures performed better in classifying the diseases when trained with deeper networks on segmented images. The performance of each of the experimental studies reported in this work outperforms the existing literature [4].
Srdjan Sladojevic et. al. (2016), proposed in a paper titled "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification" developed of plant disease recognition model, based on leaf image classification, by the use of deep convolutional networks. A novel way of training and the methodology used to facilitate a quick and easy system implementation in practice. The developed model can recognize 13 different types of plant diseases out of healthy leaves, with the ability to distinguish plant leaves from their surroundings. According to our knowledge, this method for plant disease recognition has been proposed for the first time. All essential steps required for implementing this disease recognition model are fully described throughout the paper, starting from gathering images to creating a database, assessed by agricultural experts. Caffe, a deep learning framework developed by Berkley Vision and Learning Centre, was used to perform the deep CNN training. The experimental results on the developed model achieved precision between 91% and 98%, for separate class tests, on average96.3% [5].
Monalisa Saha et. al. (2020), proposed in a paper titled "Identification of Plants leaf Diseases using Machine Learning Algorithms", a machine learning used for detecting diseases on plants. Machine learning is one of the subparts of Artificial Intelligence to work automatically or give instructions to do a particular work. The main aim of machine learning is to understand the training data and fit that training data into models that should be useful to people. So, we can use machine learning to detect diseases in plants. It has been assisting good decisions making and predicting the large amount of data produced. The color of leaves, amount of damage to leaves, area of the unhealthy plant leaf is used in classification. In this, we overviewed different machine learning algorithms

to identify different plant leaves diseases and identify the best accuracy [6].

Paramasivam Alagumariappan et. al. (2020), proposed in a paper titled "Intelligent Plant Disease Identification System Using Machine Learning", the designed and developed algorithm for identification of plant disease in a real-time decision support system integrated with a camera sensor module. Furthermore, the performance of three machine learning algorithms, such as Extreme Learning Machine (ELM) and Support Vector Machine (SVM) with linear and polynomial kernels was analyzed. Results demonstrate that the performance of the extreme learning machine is better when compared to the adopted support vector machine classifier. It is also observed that the sensitivity of the support vector machine with a polynomial kernel is better when compared to the other classifiers. This work appears to be of high social relevance because the developed real-time hardware is capable of detecting different plant diseases [7].

Aliyu M. Abdu et. al. (2020), in a paper titled "Machine learning for plant disease detection: an investigative comparison between support vector machine and deep learning", presented comparative analysis through the model implementation of the two renowned machine learning models, the support vector machine (SVM) and deep learning (DL), for plant disease detection using leaf image data. Until recently, most of these image processing techniques had been, and some still are, exploiting what some considered as "shallow" machine learning architectures. The DL network is fast becoming the benchmark for research in the field of image recognition and pattern analysis. Regardless, there is a lack of studies concerning its application in plant leaves disease detection. Thus, both models have been implemented in this research on a large plant leaf disease image dataset using standard settings and in consideration of the three crucial factors of architecture, computational power, and amount of training data to compare the duos. Results obtained indicated scenarios by which each model best performs in this context, and within a particular domain of factors suggests improvements and which model would be more preferred. It is also envisaged that this research would provide meaningful insight into the critical current and future role of machine learning in food security [8].

Nilam Bhise et. al. (2020) proposed in a paper titled "Plant Disease Detection using Machine Learning" the detection of diseases of plants by getting their images of leaves, stems, and fruits and also discuss the use of image extraction and image pre-processing which has been used [9].

Vijay Borate et. al. (2018) in a paper titled "Plant Leaf Disease Detection Using Machine Learning " proposed a processing scheme that uses machine learning and a dynamic plant image model to predict diseases related to the leaf. Using machine learning makes the platform generic and useful. Adding and updating new diseases and datasets is easy if machine learning is used. Using cloud computing for storing retrieving and serving data from the machine learning model is an efficient choice and both technologies can be used to create a system [10].

PROPOSED METHODOLOGY

The three methods are used for feature extraction and for leaf detection, machine learning approaches are used in this work. The focus is on extracting features using MATLAB and image processing libraries and using machine learning algorithms for prediction. Our implementation is divided into three parts. The first part is image pre-processing, Feature extraction, and leaf disease detection. For leaf disease detection, inbuilt methods available in the MATLAB library are used. Once the leaf disease is detected, the region of interest and important leaf disease features are extracted from it. There are various features that can be used for leaf disease detection. The entire working process of the presented method is shown in Figure 1. The presented model consists of a series of processes which are discussed below.

As computers have started becoming a part of our living spaces and workspaces, and began to interact more and more with humans, the systems are supposed to be more accurate in understanding the emotional states and moods of humans. Having an intelligent facial expression recognition system makes the creation of good visual interfaces easier and helpful for human and computer interactions. The communication among humans is effective as they can give responses according to the other persons expression, so for interacting effectively with the humans, the computers are also supposed to gain this ability. Human Computer Interfaces and robotics are not the only applications of facial expressions recognition systems, it rather finds its applications in several distinct areas like Video Games, Animations, Psychiatry, Educational Software, Sensitive Music, Medical science, Forensics, Criminal Interview etc. As the facial expressions recognition systems are becoming robust and real time, many other innovative applications and uses are yet to be seen.

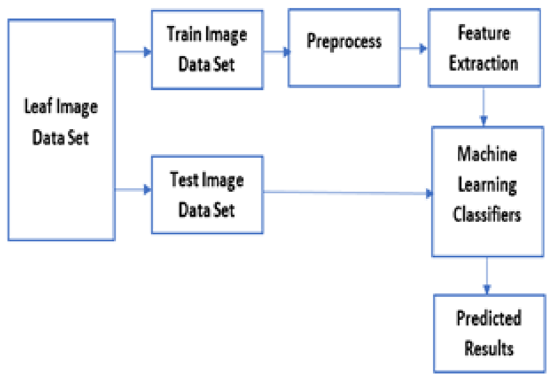

Figure 1: Proposed Methodology of System

A. Database Image / Input Image

Image acquisition is the process of getting images of infected leaves. It needs to prepare an image database on our own, which requires image acquisition from a live farm. In this process, images are captured from the farm using a digital camera to get them directly in digital form, so that digital image processing operations can be applied. In this project, a standard benchmark dataset from Kaggle is used for experimentation of orange leaf disease classification with 3 disease and one healthy.

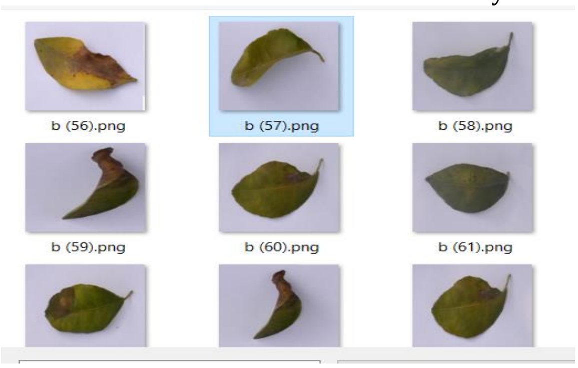

Figure 2: Sample Dataset of Orange Leaf

B. Image Pre-processing

A three-dimensional representation of the HSV color space is hexacore, where the central vertical axis represents the Intensity. Hue is defined as an angle in the range [0,2π] relative to the red axis with red at angle 0, green at 2π/3, blue at 4π/3, and red again at 2π. Saturation is the depth or purity of the color and is measured as a radial distance from the central axis with a value between 0 at the center to 1 at the outer surface. For S=0, as one moves higher along the Intensity axis, one goes from Black to White through various shades of gray. On the other hand, for a given Intensity and Hue, if the Saturation is changed from 0 to 1, the perceived color changes from a shade of gray to the purest form of the color represented by its Hue. Looking from a different angle, any color in the HSV space can be transformed to a shade of gray by sufficiently lowering the Saturation. The value of Intensity determines the particular gray shade to which this transformation converges. When Saturation is near 0, all pixels, even with different Hues look alike and as we increase the Saturation towards 1, they tend to get separated and are visually perceived as the true colors represented by their Hues as shown in figure 1. Thus, for low values of Saturation, a color can be approximated by a gray value specified by the Intensity level while for higher Saturation; the color can be approximated by its Hue. The Saturation threshold that determines this transition is once again dependent on the Intensity. For low intensities, even for a high Saturation, a color is close to the gray value and vice versa. Saturation gives an idea about the depth of color and the human eye is less sensitive to its variation compared to variation in Hue or Intensity. We, therefore, use the Saturation value of a pixel to determine whether the Hue or the Intensity is more pertinent to the human visual perception of the color of that pixel and ignore the actual value of the Saturation. It is observed that for higher values of intensity, a saturation of 0.2 differentiates between Hue and Intensity dominance. Assuming the maximum Intensity value to be 255, we use the following threshold function to determine if a pixel should be represented by its Hue or its Intensity as its dominant feature.

$$th_{sat}(V) = 1.0 - \frac{0.8\,V}{255}$$

In the above equation, see that for V=0, th(V) = 1.0, meaning that all the colors are approximated as black whatever be the Hue or the Saturation. On the other hand, with increasing values of the Intensity, the Saturation threshold that separates Hue dominance from Intensity dominance goes down.

C. Image Segmentation

Binary images may contain countless defects. In some circumstances, binary regions constructed by simple thresholding are buckled by noise and textures. Morphology is a vast extent of image processing operations that modifies the images based on shapes. It is considered to be one of the data processing methods useful in image processing. It has many applications like texture analysis, noise elimination, boundary extraction, etc. Morphological image processing follows the goal of eliminating all these defects and maintaining the structure of the image. Morphological operations are confident only in the associated ordering of pixel values, rather than their numerical values, so they are focused more on binary images, but it can also be applied to grayscale images such that their light transfer functions are unknown and thus their absolute pixel values are not taken into consideration.

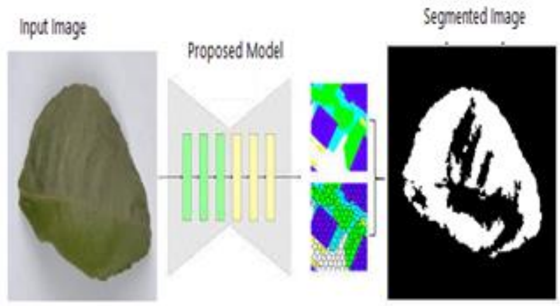

Figure 3: Image Segmentation

Morphological techniques verify the image with a small template called the structuring element. This structuring element is applied to all possible locations of the input image and generates the same size output. In this technique, the output image pixel values are based on similar pixels of the input image with its neighbors. This operation produces a new binary image in which if the test is successful, it will have a non-zero-pixel value at that location in the input image. There is various structuring element like diamond-shaped, square-shaped, cross-shaped, etc.

The base of the morphological operation is dilation, erosion, opening, and closing expressed in logical AND, OR notation and described by set analysis. Dilation adds pixels while erosion removes the pixels at the boundaries of the objects. This removal or adding of pixels depends on the structuring element used for processing the image.

D. Feature Extraction

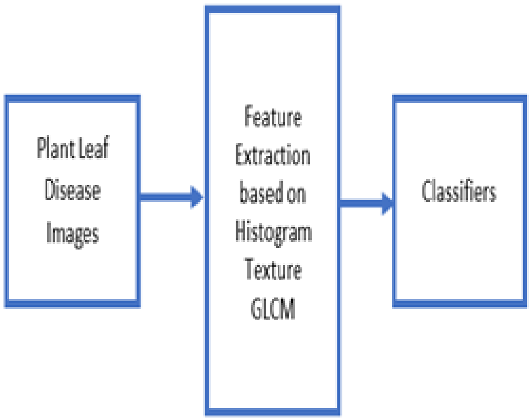

Figure 4: Feature Extraction

Figure 4 shows the figure extraction process of the proposed machine learning model. Following are the feature extraction methods described.

E. Histogram Features

The histogram of an image refers to the intensity values of pixels. The histogram shows the number of pixels in an image at each intensity value. Figure 10 shows the histogram of an image and it shows the distribution of pixels among those grayscale values. The 8-bit grayscale image is having 256 possible intensity values. A narrow histogram indicates the low contrast region. Some of the common histogram features are mean, variance, energy, skewness, median, and kurtosis are discussed.

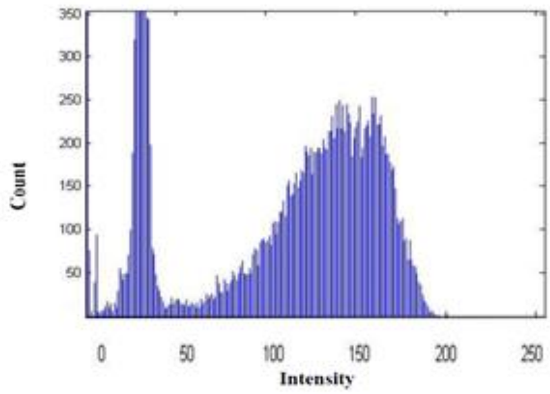

Figure 5: Histogram of an Image

F. Texture Features

The texture is a repeated pattern of information or arrangement of the structure at regular intervals. In a general sense, texture refers to the surface characteristics and appearance of an object given by the size, shape, density, arrangement, and proportion of its elementary parts. A basic stage to collecting such features through the texture analysis process is called texture feature extraction. Due to the signification of texture information, texture feature extraction is a key function in various image processing applications like remote sensing, medical imaging, and content-based image retrieval.

There are four major application domains related to texture analysis namely texture classification, segmentation, synthesis, and shape from texture. Texture classification produces a classified output of the input image where each texture region is identified with the texture class it belongs. Texture segmentation makes a partition of an image into a set of disjoint regions based on texture properties so that each region is homogeneous with respect to certain texture characteristics.

GLCM: The basic of GLCM texture considers the relation between two neighboring pixels in one offset, as the second-order texture. The gray value relationships in a target are transformed into the co-occurrence matrix space by a given kernel mask such as 3 3, 5 5, 7 7, and so forth. In the transformation from the image space into the co-occurrence matrix space, the neighboring pixels in one or some of the eight defined directions can be used; normally, four directions such as 0°, 45°, 90°, and 135° are initially regarded, and its reverse direction (negative direction) can be also counted into account. It contains information about the positions of the pixels having similar gray level values.

Energy: Energy (E) can be defined as the measure of the extent of pixel pair repetitions. It measures the uniformity of an image. When pixels are very similar, the energy value will be large. It is defined in Equation as

$$E = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} M^2(i,j)}$$

Contrast: The contrast (Con) is defined in Equation, is a measure of intensity of a pixel and its neighbor over the image. In the visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view.

$$Con = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2 M(i,j)$$

Correlation: Correlation is a measure of gray level linear dependence between the pixels at the specified positions relative to each other. On behalf a perfectly positively or negative correlated image, the correlation value is 1 and -1. On behalf of constant image its value is NaN.

Range = [-1, 1] and the formula is

$$Cor = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} M(i,j)\frac{(i-\mu i)(j-\mu j)}{\sqrt{\sigma i^2 \sigma j^2}}$$

Homogeneity: Homogeneity is going by the name of HOM. It passes the value that calculates the tightness of distribution of the elements in the GLCM to the GLCM diagonal. For diagonal GLCM its value is 1 and its range is [0, 1]. Opposite of contrast weight is homogeneity weight values, with weight decreases exponentially loose from the diagonal. The weight employed in contrast is (i-j) ^2 and in homogeneity, it is 1/1+ (i-j) ^2. The equation is

$$Cor = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} M(i,j)/R$$

G. Machine Learning Classification

Machine learning is a subset of artificial intelligence in the field of computer science that often uses statistical techniques to give computers the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed.

Ensemble Bagging Classifier: Ensemble bagging classifier which mainly named as Random Forest Tree Bagger which is a supervised classification algorithm. As the name suggest, this algorithm creates the forest with a number of trees. In general, the more trees in the forest the more robust the forest looks like. In the same way in the random forest classifier, the higher the number of trees in the forest gives the high accuracy results.

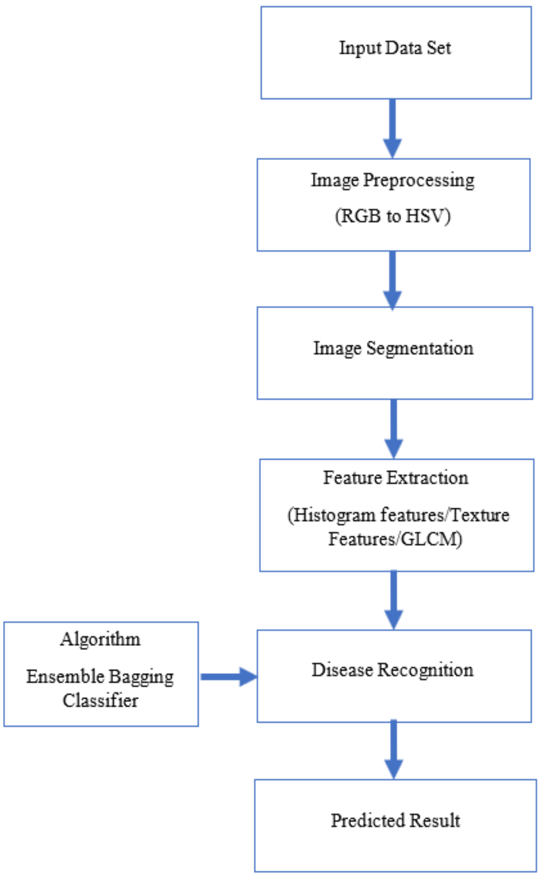

Figure 7: Flowchart of Proposed System

RESULTS ANALYSIS

The proposed work is implemented on Intel CORE processor i5, 8 GB RAM Laptop configuration and the operating system is Windows 10. MATLAB R2018b software was used to write the programming code in this we used Image processing, Statistics and Machine Learning toolbox, and Deep Learning toolbox. The input images are taken from LIDC and Radiopedia Dataset for experimentation.

A. Performance Metrics

This presents the experimental results and performance metrics for different models. Accuracy is one of the common performance metrics. It is the measure of all the correctly identified cases. It is mostly used when all the classes are equally important. Accuracy is the proportion of correctly classified examples to the total number of examples, while the error rate is incorrectly classified instead of correctly.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP is True-positive, TN is True-negative, FP is False-positive and FN is False-negative.

B. Experimental Result and Process

In the experimental results and process, let us be discussed form proposed GUI i.e., graphical user interface of the system all about it shows the graphical representation then follow the steps for respective training and testing given leaf image to load number of samples database then how to extract database features.

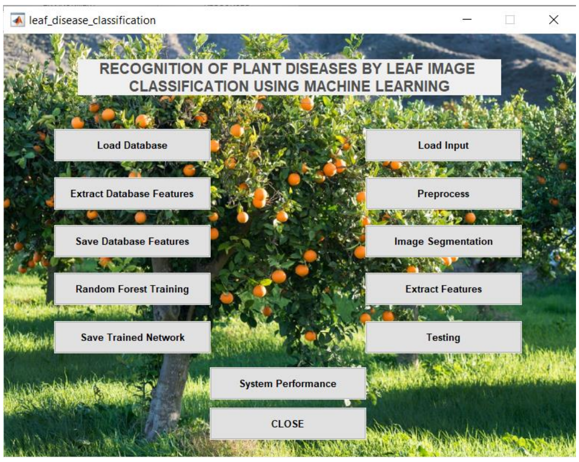

Figure 8: Proposed GUI of System

C. Training Phase

The training phase is first process to do for leaf disease detection , in the training phase whatever leaf disease we have to detect a disease first we have to train system on that step we have to load the database which is to be stored database then follow the next step i.e. extract database features Feature extraction is a part of the dimensionality reduction process, in which, an initial set of the raw data is divided and reduced to more manageable groups then save this database features Random forest and then save this trained network and training accuracy score the steps of all above description has been showed in pictorial representation. Training accuracy score is to calculated along with error plot.

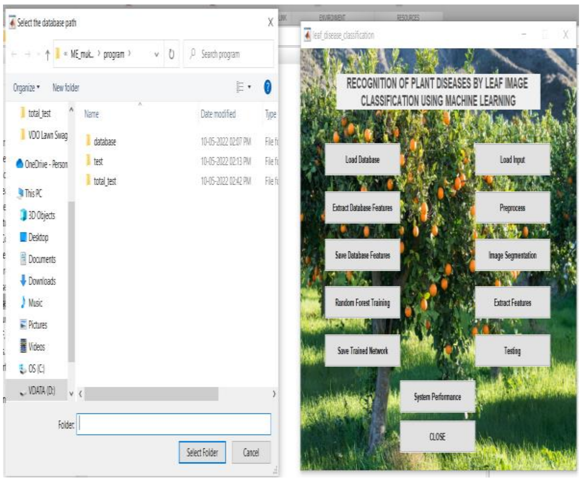

Figure 9: Database Loading

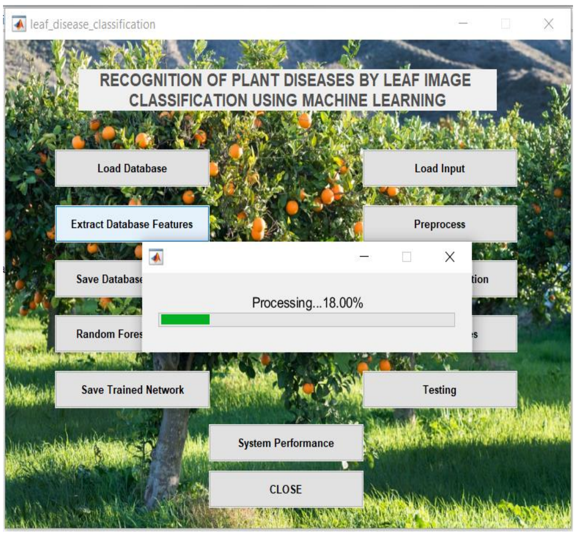

Figure 10: Preprocessing Process

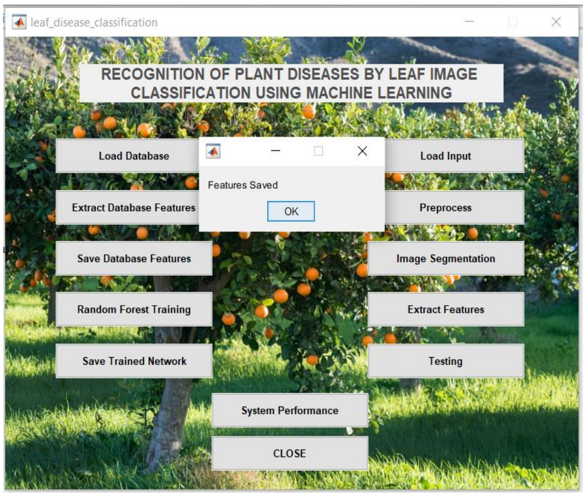

Figure 11: After Preprocessing extracted feature are saved

Figure 12: Training accuracy score

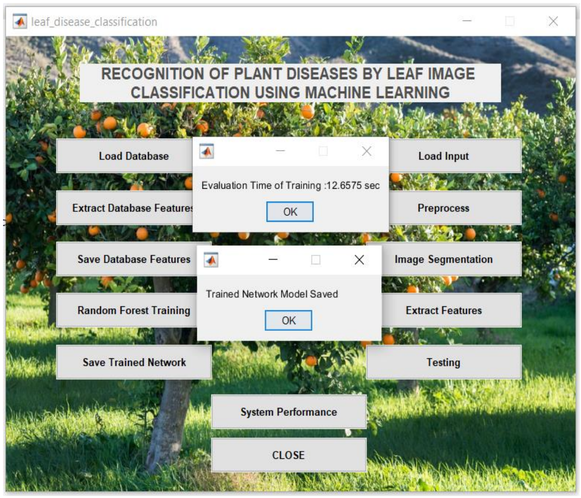

Figure 13: Shows the Training time of model

D. Testing Phase

Testing for Black spot disease: The second part is testing phase in that phase first we have tested for Black spot disease in that testing part first we have to take Sample dataset of orange leaf to test model then select next part i.e. Select and Input the orange leaf to test model then that leaf image for preprocessing part after that Segmented Image of Input image is done along that there is Extracted the feature of Input image essential part next step is to Predicted Result of leaf disease it will calculate evaluation time for testing RF along with respective leaf detection will displayed in GUI i.e. these are the steps follow for checking which type of disease that leaf have and it will result to Black spot disease. These all the steps have been showed in pictorial representation.

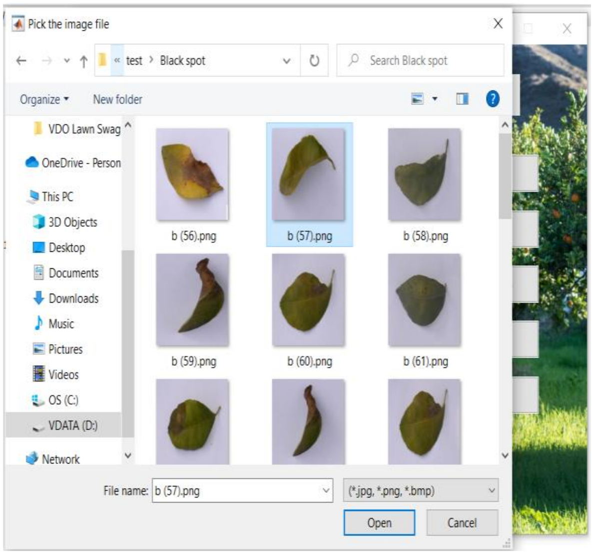

Figure 14: Sample dataset of orange leaf to test model

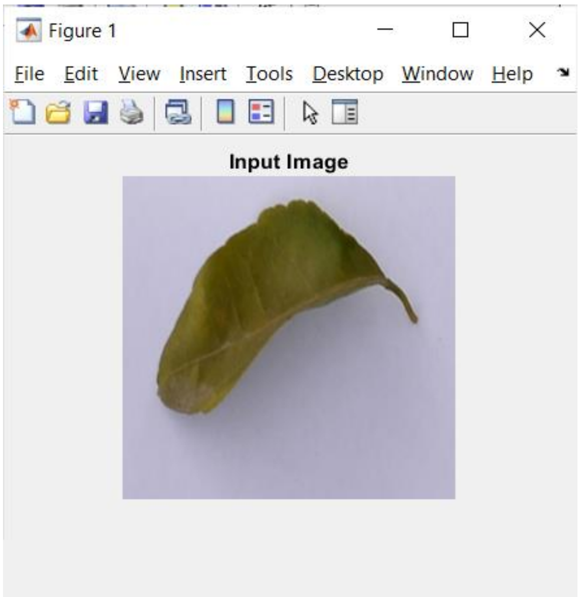

Figure 15: Select and Input the orange leaf to test model

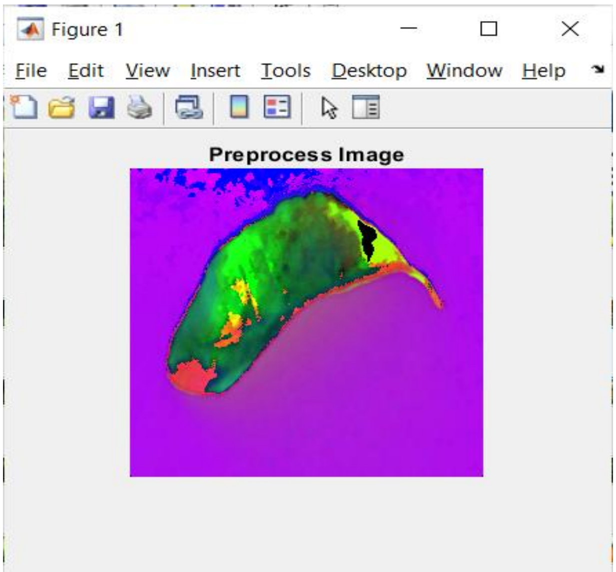

Figure 16: preprocessing

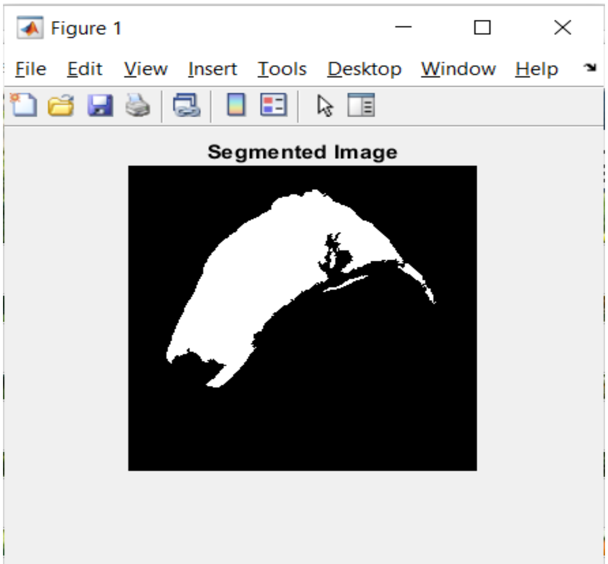

Figure 17: Segmented Image of Input image

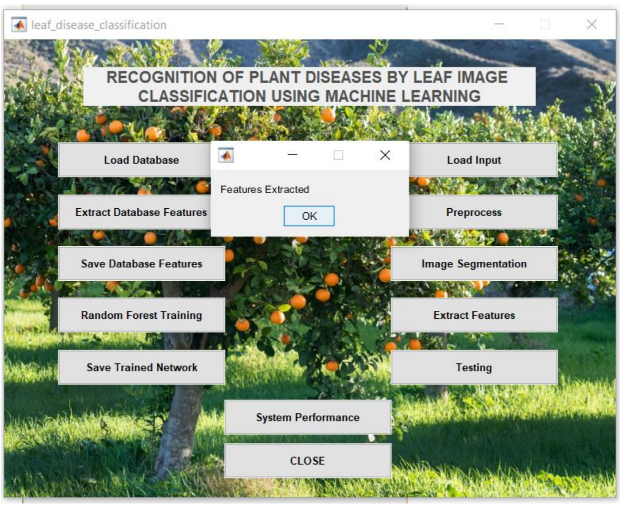

Figure 18: Extracted the feature of Input image

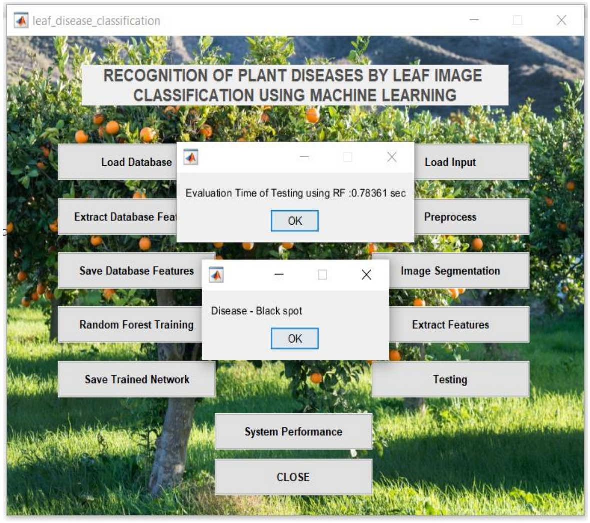

Figure 19: Predicted Result of leaf disease

E. Evaluation Phase

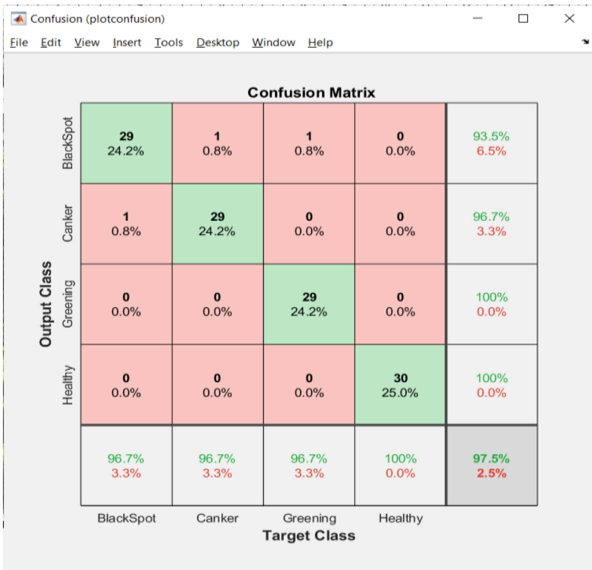

Figure 20: Accuracy Score of the proposed model

Conclusion and Future Scope

There are many developed methods in the detection and classification of plant diseases using diseased leaves of plants. However, there is still no efficient and effective commercial solution that can be used to identify the diseases. The proposed technique is concluded in the thesis to improve the performance of an expert system to detect and identify orange leave diseases. This approach depends on DIP for the first detection and classifies the orange leaves according to the diseases is used. In this research work, collection of the various types of categories in the orange leaves such as green, healthy, black spot, and canker leaves. The knowledge base design by the proposed method, image pre-processing phase has implemented to identify the error in the uploaded image, smooth image calculated, region detection to detect the background and image region in the orange leave image and convert the rgb2gray scale format. Research work has implemented a GLCM method which is used for the extraction of the features. GLCM method to identify the unique or genuine properties of the uploaded images and obtain the features of the disease symptoms. A morphological technique is used to segment the image. Ensemble Bagging Classifier has been implemented to classify the disease in the orange leaves based on the GLCM tricks. This proposed method is to resolve the detection problem in orange leaves disease. In the research proposal phase, Ensemble Bagging Classifier is implemented with GLCM and K Morphological technique to enhance the disease detection results.

The Graphical User Interface system for calculated consequences and accuracy are shown in the accuracy rate of the proposed model is of 97.5%. So, the proposed image processing concept is effective to consider and calculate the orange leaf diseases. The performance of existing method was calculated by its accuracy rate. The proposed method to improve the performance is calculated by its accuracy rate

In the future, the research methodology can be integrated with Ant Lion Optimization Approach to select the extracted feature with the help of a fitness function. It will implement a classification and detection using color space and texture analysis to design a system for early plant disease prediction and performance analysis of the system can enhance in the future by using background division approaches to divide the fruit leave object from a difficult background and improve the image Quality Factor.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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