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PLANT LEAF DISEASES DETECTION USING IMAGE PROCESSING BASED SEGMENTATION AND MORPHOLOGICAL OPERATION MULTI LEVEL SVM

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Abstract: As indicated by the examination and review nation India comprise its vast majority parts as a horticultural part, consequently given the name of rural nation and about 70% of individuals relies upon farming for their endurance. Early recognition of leaf malady is significant exploration point. Different quantities of ailment brought about by growths, microscopic organisms, and nematodes and so on Malady in farming/cultivation crops causes a noteworthy decrease in both amount and nature of agribusiness items. Early recognition of illness and recognizable proof of indications of malady by unaided eye is hard for rancher which results the spreading of sickness in entire yield. Discovery of harvests and its security particularly in enormous ranches is finished by utilizing automated picture handling strategies by taking shading data of leaves. In this introduced an expires identification in plants and yields in fields like performing proposed work. Alternaria Alternata, Anthracnose, Bacterial Blight and others. For the detection using segmentation by K mean clustering. The proposed method shows detected with an awfully high accuracy, in the different test images.

Keyword *- Multi Class Support Vector Machine(SVM), K Mean Clustering, Colour Features, Image processing, Leaf diseases, Texture features, Gray Level Co-Occurrence Matrix(GLCM),Search Engine Marketing(SEM), and Bacterial Blight*

I. INTRODUCTION

Each gardener has put in plants with hope of wonderful flowers, fruits or vegetables, only so that these hopes degrade when the plants fall ill and die. These plants are considered diseased. Many things can cause plant disease, including (living) biotic agents, abiotic (non-living) factors or a combination of both. This research focuses only on living agents - fungi, bacteria, viruses, nematodes and parasitic plants.

Certain plant diseases have had enormous repercussions on society. Perhaps the most important of these is the fire blight of Phytophthora, a fungal disease that caused potato famine in Ireland in 1845. About 2 million people starved or left Ireland, many For the United States. Powdery mildew and powdery mildew are fungal diseases that devastated the French wine industry until the Bordeaux mixture is controlled.

In the United States, fungal disease was accidentally introduced into New York City in the late 1800s on imported Chinese chestnut. Chinese trees were resistant to fire blight, but American chestnut trees were not. In less than 40 years, 30 million acres of chestnut trees have died. Chestnut burn remains a problem in the eastern United States. Dutch elm disease was also accidentally introduced. It infects and kills elms throughout the country.

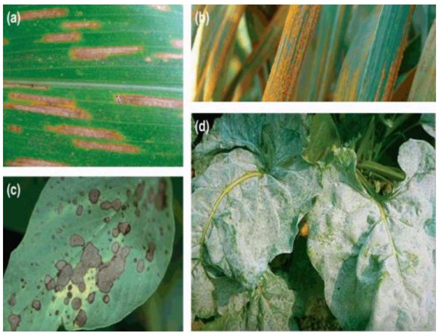

Fig. 1: Fungal Disease in Plant Leaf

Fig. 2: Fungi Disease in Plants

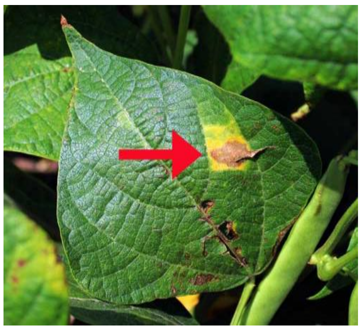

Fig. 3: Bacteria in Plants Leaves

1.2 Background

Pathogenic organisms are pathogens. They are microscopic or very difficult to see or recognize without magnification. Fungi, bacteria, viruses, nematodes and even plants can be pathogenic on garden plants. Pathogens usually get nutrients, water and everything they need to reproduce from their host. Such a relationship is called a parasite. Some pathogens can infect several types of plants; others require a specific host.

A. Fungi

The largest group of plant pathogens, fungi come in a wide variety of forms. In general, they are multicellular organisms with a wire-shaped body. These threads, called hyphae, have cell walls. When many yarns form together, they form a mycelium. The additional growth of a mycelium can produce fruiting bodies, where sexual or asexual spores form. The characteristics of spores, fruit bodies and mycelium are used to identify and diagnose fungal problems. Some fungi can survive and grow without a living host.

B. Bacteria

Bacteria are monocellular organisms which are much smaller and less complex than plant cells. Many have the size of a plant chloroplast. Bacteria can accumulate at high and exotic numbers of plant tissues. Some bacteria produce slugs that can attract insects that spread the bacteria in healthy plants. Bacteria can survive unfavorable conditions in plant debris or even in seeds. Bacteria cause plant diseases by forming toxins or producing enzymes that break down the cell walls of the plant. Genetic Crown bacteria genetically generate their host plant to create galls and amino acids, which gives bacteria a better place to live and the chemicals they need to grow and reproduce.

C. Viruses

Virus particles are made up of a few strands of DNA and are even smaller than bacteria. Electronic microscopes reveal them to have many shapes, including long strands, short stems, and multi-sphere balls. Viruses use the cell organelles of a host plant to produce more viruses. The result can be strange colors of plants, shapes or structures. Some virus infections, however, do not cause any visible plant problems. Touching plant material infected with the virus, and then touching healthy plants can transmit certain viruses. For example, a smoker can transmit the tobacco mosaic virus from a cigarette to a plant. In Alaska, some viruses are transmitted by insects such as aphids, scales, leaf larvae and white flies. Mushrooms, mites, nematodes and even parasitic plants can also transmit viruses. Some viruses can also infect the seeds of a host plant and be transmitted to the next generation. Potato virus X can be transferred from one potato garden to another by a garden tool or a contaminated leg (anything that moves the sap).

Fig. 4: Viruses in Plant leafs

Fig. 5: Nematodes in Plant leafs

D. Nematodes

Nematodes are multicellular roundworms that may not exceed the letter "I" in the word DIME on an American coin. Because they are clear and live in the ground, they are impossible to see without magnification. All pathogenic plant nematodes have a mouth called stylus. The style is like a spear or hypodermic needle used by the nematode to pierce the plant cells and feed them. Some nematodes pass from the root to the root, while others establish a feeding site in a single root. Feeding can cause root lesions or galls that limit the flow of water and nutrients in the host plant. Other nematodes weaken the plant by mass feeding. Some foliar nematodes attack the parts of plants above the ground. Movement of infected soil or parts of plants can transmit nematode diseases.

E. Parasitic plants

Many Alaskans note that moss and lichen grow in trees; this vegetation is not parasitic, it simply uses the tree as a platform. Some plants are really parasites for other plants. Dodder, for example, produces flowers and seeds, but does not have chlorophyll. So he cannot make his own food. It has a yellow corpse like a thread squirting around its host. Root-like haustoria penetrate the host plant and remove food and water. Some parasitic plants, such as mistletoe, produce chlorophyll but do not have real roots and depend on their host (on hemlock in southeastern Alaksa) for water and nutrients. Seeds of parasitic plants are spread by contaminated birds or soils, or they can be thrown out of plant structures like small bombs.

II. LITERATURE SURVEY

Vinta, Surendra Reddy,et.al. .(2024) "Investigation of early symptoms of tomato leaf disorder by using analysing image and deep learning models" The approach suggested uses computer vision techniques for preprocessing, such as contour tracing, K-means clustering, Histogram Equalization (HE), and RGB to greyscale conversion. The leaf samples are subjected to feature extraction techniques that are well-known for their ability to extract valuable characteristics. Discrete Wavelet Transform, Principal Component Analysis, and Generalized Linear Model are some of these techniques. Researchers employ machine learning techniques including Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), and Convolutional Neural Networks (CNN) to discern between healthy and damaged leaves. When compared to other contemporary techniques, the suggested model has demonstrated that it is appropriate for the CNN machine learning classification approach, with its suggested level of accuracy [1**].Khalid, Munaf Mudheher et.al. (2024)** "Deep Learning for Plant Disease Detection"The need for early and accurate plant disease detection is especially important in the modern day, when demands for food security and environmental sustainability are growing. In our investigation, we utilized deep learning capabilities, particularly the CNN and MobileNet models, to address this enduring agricultural problem. Our results provide insightful light on these models' potential. Excellent results were obtained by the CNNs, with an accuracy of 89%, precision and recall of 96%, and an F1-score of 96%. By contrast, although the MobileNet design showed a higher accuracy of 96%, its precision, recall, and F1-score values were somewhat lower, coming in at 90%, 89%, and 89%, respectively. By adding a layer of interpretability to our models and providing visual insights into how these networks identify disease signs in plant photos, XAI employing GradCAM enhanced our analysis. These developments are in line with the revolutionary potential of DL models to improve plant disease diagnosis and proactive control. Although our study provides a hopeful glimpse into this emerging field, there are still many opportunities ahead [2]. **Kulkarni, Priyanka,et.al..(2024)** "Rice Leaf Diseases Detection Using Machine Learning." Most farmers deal with rice-related illnesses. Thus, early diagnosis is essential. The previously time-consuming manual technique of looking for symptoms of sickness on rice leaves has been greatly simplified by scientific developments. Based on the classifiers used, this study combines the many methods that researchers have utilized to detect disorders related to rice. In image processing, pattern identification is essential, and the CNN classifier did a good job at it. Utilizing CNN, our proposed model shows encouraging results in achieving excellent precision. explains a machine learning approach for diagnosing several diseases that impact rice leaves. A comparative analysis of machine learning techniques for rice leaf disease detection was conducted. The algorithms employed to predict diseases affecting rice leaves differed in their accuracy. The decision tree had the greatest accuracy rate of 95% on the test data. [3]. **Lakshmi, M. Dhana et.al..** "Analysis of Cotton Leaf Curl Diseases Using Advanced Learning Model"The advanced learning model (ALM), which was created to address a number of problems with cotton plant disease detection, is described in this work. MF is an automated method that uses the input photos to identify and detect a certain ailment. MF categorization using photos of disease-free and sick leaves. The most common application of the image filters is to reduce picture noise, which enhances the performance of the MF. Using photos from the plant disease dataset, the pre-trained model ResNet50 recognizes diseased areas, extracts features from the illness images, and trains the model. The suggested model produced results with 98.45% accuracy, 97.45% precision, 96.89% recall, 98.67% specificity, and 98.45% F1-Score. [4**]. Singh, Paramjeet ,et. al. .(2024**) "Cotton Leaf Net: cotton plant leaf disease detection using deep neural networks." According to data, almost 70% of rural households subsist on agricultural produce. India has a vast amount of crops, including cotton plants, however it has been reported that these crops suffer greatly from a variety of environmental risks that lead to a wide range of illnesses, particularly in cotton plants. Only 22 classes are covered by the current research, which is comparatively greater than the works that have already been published. When the suggested method is used on the testing set, it produces results with an accuracy of 99.39% and very low error rates, making it more productive and efficient than the current models. We used a variety of data augmentation approaches to expand the picture collection in order to improve the model's performance because the dataset was rather small. Since massive amounts of data are conducive to the effective operation of deep learning models, we have used data augmentation. It improves sample size, the model's flexibility, and the process of generalization by reducing data collection and scarcity, labeling, and overfitting. Still, it has a number of serious problems, such as inadequate learning if explicit regularization is used. Nonetheless, substantial regularization combined with counteracting the bias and It may also be accomplished by using the right augmentation techniques, or it can be accomplished with less work and time by just collecting massive amounts of real-world data. The main problem in this work is that deep learning models have trouble with real-world data since they evaluate smaller amounts of data. However, if new data instances are supplied, it may be easily modified to address new issues. [5]. **Wu, Yang et.al. (2022**) "Plant leaf diseases fine-grained categorization using convolutional neural networks"In deep learning research, powerful and complicated model networks must be studied in order to achieve improved performance. However, storage capacity and processing power are typically the limits of complicated networks, and they are hard to apply efficiently to low-performance terminals. Furthermore, redundant parameters are present in complicated networks. Recent years have seen a large amount of research on the use of deep neural networks for the detection of agricultural leaf diseases. The pictures of leaf diseases are quite similar to each other. The truth is that there is little variation across classes, but there is a lot of variation inside them. It makes the actual recognition extremely tough. As a result, in the fine-grained classification job, the small region of the target's exquisite feature representation is crucial. A fine-grained disease identification technique based on attentional deep neural network was presented for peach and tomato disease leaf detection in order to address the shortcoming of deep neural networks in crop disease identification. [7]. **Chowdhury, Muhammad EH,.(2021)**"Automatic and reliable leaf disease detection using deep learning techniques." We created a deep convolutional neural network (CNN) in this study using the EfficientNet CNN model, which was established lately. The model was adjusted and trained to distinguish between photos of healthy and diseased tomato leaves. The findings obtained using the most widely used publicly available Plant Village dataset demonstrate that our model performs better than several previous deep learning approaches [60,61]. Additionally, it was discovered that EfficientNet-B7 outperformed other architectures in extracting discriminative features from photos and that the Modified U-net was the most appropriate for separating leaf images from the background. Additionally, When more parameters were included during training, the networks' overall performance typically improved even more. Plant diseases may be automatically detected early with the use of trained models. While experts require years of training and experience to detect diseases early through visual examination, anybody may use our algorithm without any prior expertise. When a new user logs in, the network will start up in the background and begin receiving input from the visual camera. It will then promptly notify the user of the results so they may take the appropriate action. Preventive measures can thus be implemented sooner. Thanks to modern technology like cellphones, drone cameras, and robotic platforms, this effort can help detect tomato crop diseases early and automatically. Better agricultural yields may be ensured by integrating the suggested framework with a feedback system that provides insightful recommendations, fixes, disease management, and control techniques. The authors want to expand their work in order to verify the effectiveness of the suggested approach in a real-time application. This application will utilize microcontrollers equipped with cameras to monitor performance. [9].

III. PROPOSED METHODOLOGY

Proposed Method – The proposed method is design to detect the Anthracnose in leafs and fruits. The proposed method is used to detect the deceases in plants leaf and fruits. Anthracnose is the most common deceases in the plants. For the detection

of decease in plants, first create the data base of the plant deceases present in nature. There are different deceases are present in the plants create the data set of images.
In the proposed work calculate the accuracy of detected deceases. For the calculation of accuracy required both data training and testing data sets. In the first part of proposed method create training data set and in the second part apply image processing for effected area calculation. Father process shown in steps.

Training and Data set Creation –

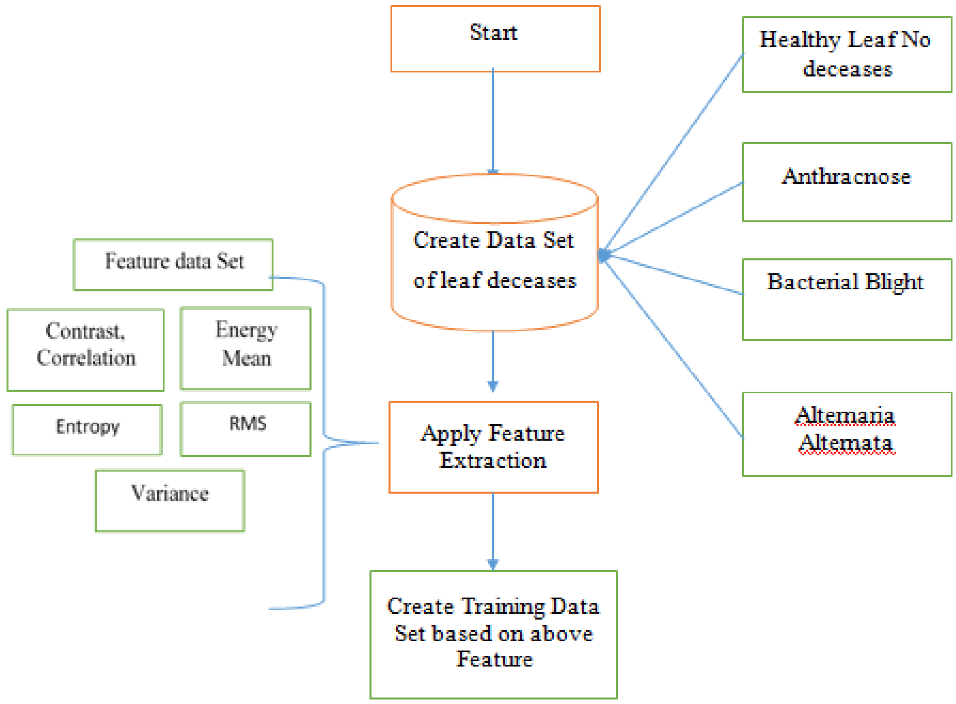

Fig. 6: Create Training Data Set using Feature Extraction

The above figure 6 shows the data set creation and feature excretion of different deceases images also the healthy images.

Steps of Training Data Set creation
Step 1 – First collect the different type of image which contain different deceases. Create different classes deceases wise and create a class of healthy leaf. Collect all type of image and make a data set.
Step 2 –Apply feature execration techniques of these image and create a training data set. Which is used to detection the type of deceases in the plants.
The diagram of above steps also explained in the above figure 4.1.

Proposed Algorithms Flow Chart Effected Area detection and Area Calculation of Effected Part-

Step 1 – Query Image Selection:
First select the image from data set. The data set is the combination of the three types of images. Three type of images are pure sugar beet images, pure creeping thistle images and mixture of both creeping thistle and sugar beet. For selecting the image form data set using a matlab function that is uigetfile. Uigetfile is the predefined function in matlab for selecting dataset of the image. Also select the directory of image with the help cd command.
[file name, pathname, filterindex] = uigetfile(... {'*.m;*.fig;*.mat;*.mdl', 'All MATLAB Files (*.m, *.fig, *.mat, *.mdl)';

Step 2 – Contrast Enhancement of Query Image:
After the select of image, apply this image into the preprocessing block. In this step enhance the contrast of the image using *stretchlim(I)* function. After stretch the contrast of the image now apply contrast adjustment using *imadjust* function. The preprocessing tasks are completed now discuss the third step in which apply segmentation.

Step 3- Apply K Mean Cluster
Segmentation using K means Algorithm
K-Means is the one of the unsupervised learning algorithm for clusters. Clustering the image is grouping the pixels according to the same characteristics. In the k Means algorithm initially we have to define the number of clusters k. Then k-cluster center are chosen randomly. The distance between the each pixel to each cluster centers are calculated. The distance may be of simple Euclidean function. Single pixel is compared to all cluster centers using the distance formula. The pixel is moved to particular cluster which has shortest distance among all. Then the centroid is re-estimated. Again each pixel is compared to all centroids. The process continuous until the center converges. The K-means algorithm implements a divisive clustering and was first discussed by Duda and Har. The algorithm uses a similarity metric to assign all documents to one of *k* clusters. The clusters are represented as an average of all documents contained within the cluster. This average can be thought of as the centroid of the cluster.

The 2D continuous image *f(x, y)* is divided into N rows and M columns. The intersection of a row and a column is called as pixel. The value assigned to the integer coordinates [*m, n*] with {*m*=0,1, 2,...,*M*-1} and {*n*=0,1,2,...,*N*-1} is *f*[*m, n*]. In fact, in most cases *f(x, y)* which we tend to could consider to be the physical signal that impinges on the face of a sensor. Typically an image file like BMP, JPEG, TIFF etc., has some header and picture information. A header usually includes details like format identifier (typically first information), resolution, number of bits/pixel, compression type, etc.

Step 4 Morphological Operations

Morphological operators often take a binary imageand a structuring elementas input and combine them using a set operator (intersection, union, inclusion, complement). They process objects in the input image based on characteristics of its shape, which are encoded in the structuring element.

Step 5 Region of Interests (ROI)

A region of interest (ROI) is a subset of an image or a dataset identified for a particular purpose. The dataset could be any of the following: Waveform or 1D dataset: The ROI is a time or frequency interval on the waveform (a graph of some quantity plotted against time). Image or 2D dataset: The ROI is defined by given boundaries on an image of an object or on a drawing.

- Volume or 3D dataset: The ROI is the contours or the surfaces defining a physical object.

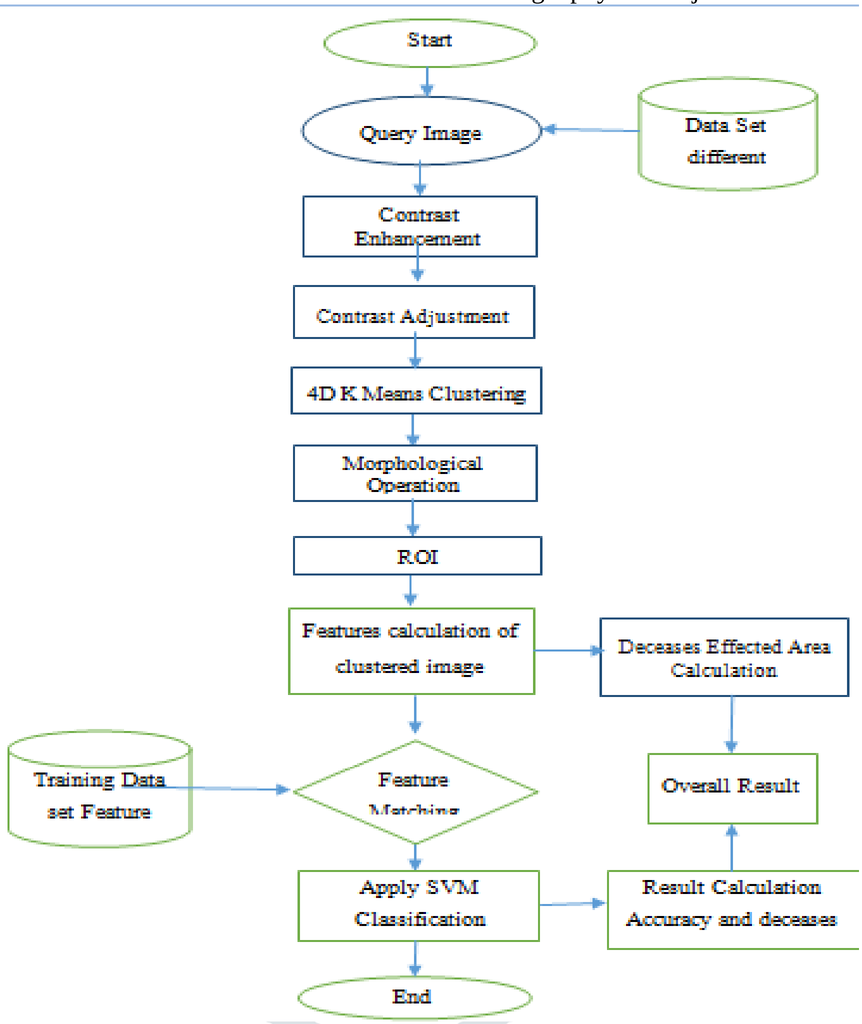

Fig. 7: Flow Chart of proposed algorithm

- Time-Volume or 4D dataset: Concerning the changing 3D dataset of an object changing in shape with time, the ROI is the 3D dataset during a specific time or period of time.

  There are three fundamentally different means of encoding a ROI:

  Step 6 – Apply Support vector machine on calculated features and training data set features. Shown in below flow chart.

  Support Vector Machine (SVM)

  SVM is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate.

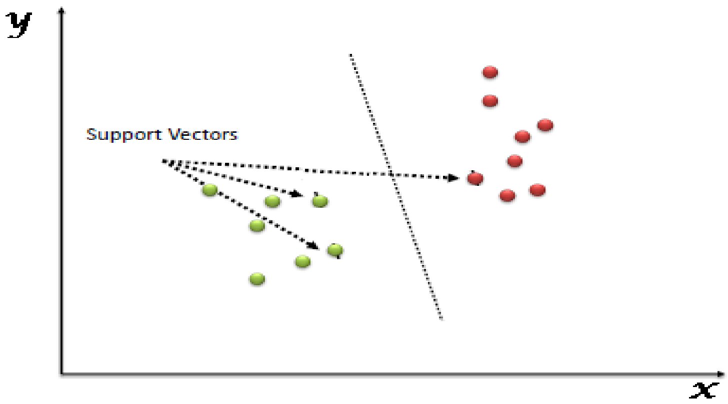

Fig. 8: SVM Based Clustering

IV. SIMULATION AND RESULT

The result of proposed method for different deceases detection in plants using images processing shown in this section, simulation of our proposed method and result calculation. We have done proposed work with the help the MATLAB R2013b software and simulate our whole proposed methodology in graphical user interface (GUI). The performance of the proposed algorithm is tested for different gray scale images that is shown in below figure. Basic configuration of our system is: Processor: Intel (R) Quad Core (VM) i5–3110 Central Processing unit @, 2.40 GHz with 4GB RAM: System type: 64-bit Operating System. MATLAB based simulation result shows good classification of deceases between different decease images and also calculate affected arealeaf by decease.

A. Result Parameters

There are different result parameters in decease detection in plants like classification of decease, in this proposed work on different decease. Therefor correct deceases is the major task of the proposed work. Second result parameter is affected regions or affected area from deceases and the last one is accuracy for that perform features matching between different deceases images with the help of support vector machine.

Classification –

The major task of proposed work is separate by machine learning the plant disease recognition and classification method by using image processing and soft computing techniques. Methods/Analysis: The proposed method examined the three types of plant diseases using natural outdoor images in the study. The tomato plant images categorized into six categories including four disease infected that are bacterial leaf spot, fungal septoria leaf spot, bacterial canker, fungal , leaf curl and one non-infected (healthy)

Affected Region (Area)–

Affected area of plants leaf and fruits part calculation is known as a affected region. With the help of this calculated the percentage of effected area of plants and leaf by the different deceases.

Accuracy –In the plant decease detection task, a detected as a decease is a true positive (TP) whereas a real negative (TN) is a non-effected leaf of plant detected. The false negatives (FN), on the other hand, are effected parts of leaf. In some industrial applications, such as weed or disease detection, and the overall accuracy of the detection system, the FN is also an important factor. Any system with higher precision but a considerable number of FN may mean a higher risk because if the weed or diseased plants are left out they can quickly spread or multiply, jeopardizing net production even after Application of a specific treatment:

Accuracy = (TP + TN) / S (3.1)

When S is the total number of samples in the test set, FP is the number of false positives (deceases detected as plants) and FNR is the false negative rate. Sensitivity is the probability of a positive test, given the plant in view is the decease detected.

B. Data Sets –

There are different deceases data set are taken for performing proposed work. Alternaria Alternata, Anthracnose, Bacterial Blight, Leaf Spotand healthy leaf.

Alternaria Alternata deceases data set –

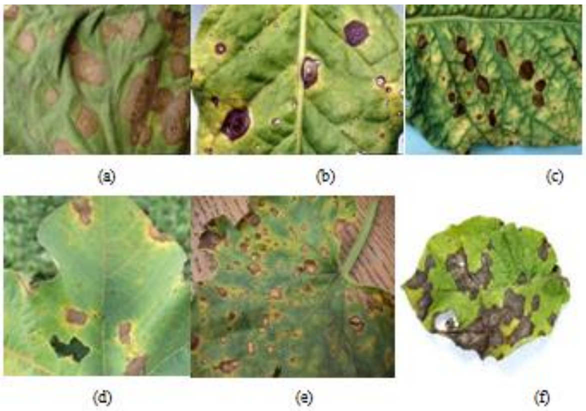

Fig. 9: Shows the Alternaria Alternata deceases data set

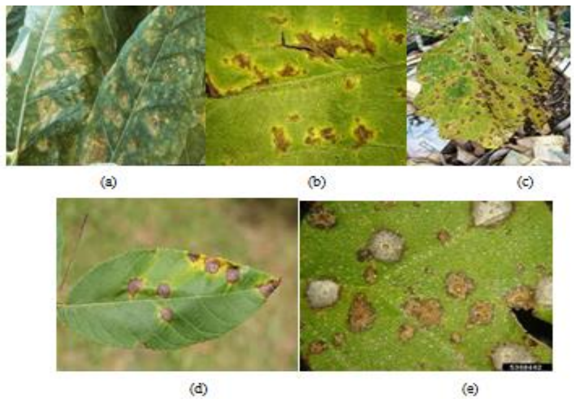

Fig. 10: Shows the Anthracnose deceases data set

In the above figure 9 shows the alternaria alternata deceases data set images. In the above figure shows only six image of this deceases. Similar that 20 images are taken in the data set for processing.

Anthracnose deceases data set –

In the above figure 10 shows the anthracnose deceases data set images. In the above figure shows only five image of this deceases. Similar that 20 images are taken in the data set for processing. Anthracnose is a group of fungal diseases that affect a variety of plants in warm, humid areas. Commonly infecting the developing shoots and leaves, anthracnose fungi (usually *Colletotrichum* or *Gloeosporium*) produce spores in tiny, sunken, saucer-shaped fruiting bodies known as acervuli.

C. Proposed Method GUI –

The above figure 3.5 shows the basic GUI of proposed method. In this GUI shows the blank axis windows and empty results. That is initial part of GUI and below figure 3.5 shows the final GUI of proposed method with result.

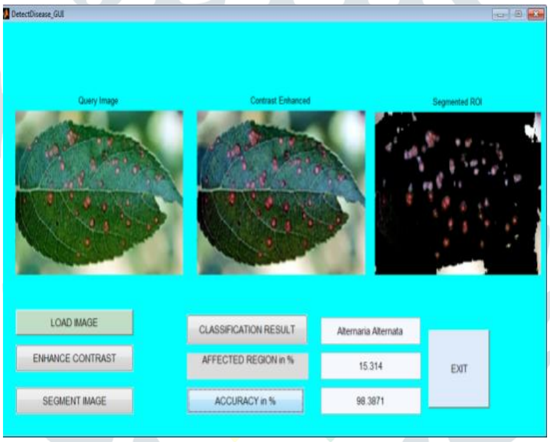

Fig. 10: Shows the GUI of Proposed Method (With Result)

In the figure 5.6 three figures are shown, in the back end of this GUI three axis windows.

First Step – window or Axis Shows the test image in which apply proposed method. For this first we select the input image by press push button “LOAD IMAGE”.
Second Step – apply contrast enhancement process to highlight the affected area of leaf. With the help contrast enhancement techniques.
Third Step – Perform the segmentation of the image. For the segmentation of the image apply K- Mean clustering process and find the outcomes. Select the appropriate cluster and segment the affected area by a particular deceases.
Fourth Step – Find the classification of the deceases, which type of deceases it is. Then calculate the affected area in leaf and shows the effected percentage area.
Fifth Step – At last with the help of SVM calculates the accuracy of proposed method.
Now discuss the making GUI and its internal structure of proposed method or Back end of the proposed method.

D. Simulation of Proposed Method Step by Step –

Step 1 – Load testing image – Click on the load image then open this window for selected the leaf. Click on testing leaf and further proceed on the image.

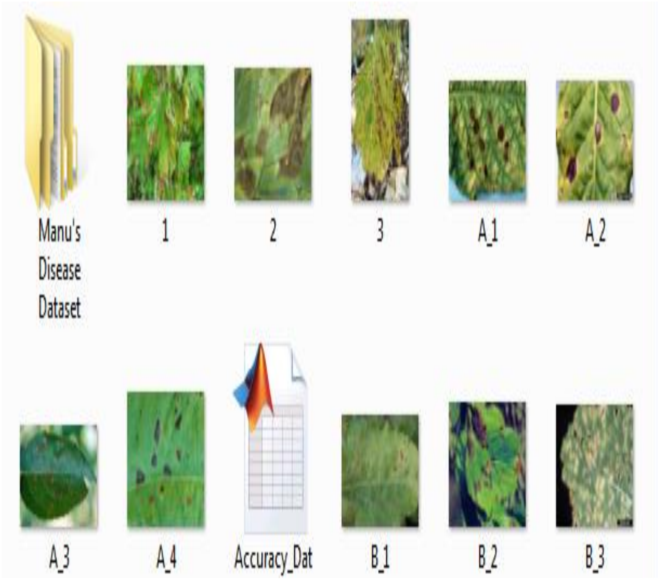

Fig 11: Loaded image data set

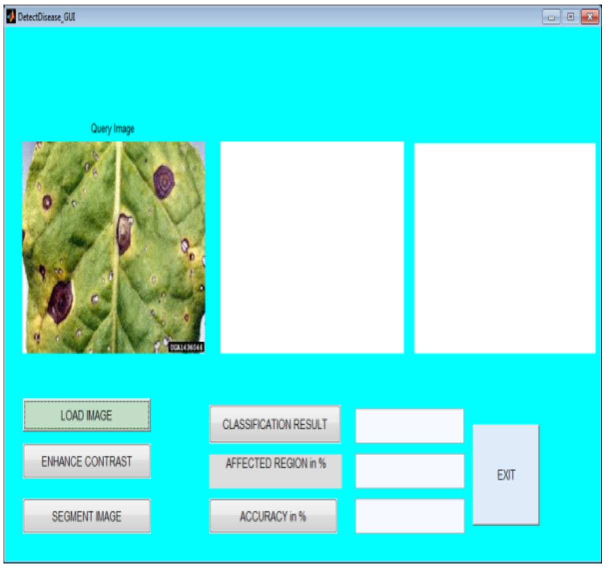

Fig. 12: shows the query image

Step 2 – Shows the selected on image on the axis 1. That title is query image. This query image is further proceed for contrast enhancement.

E. Analysis on different Images –

Fig. 13: Final Output of different test image 1

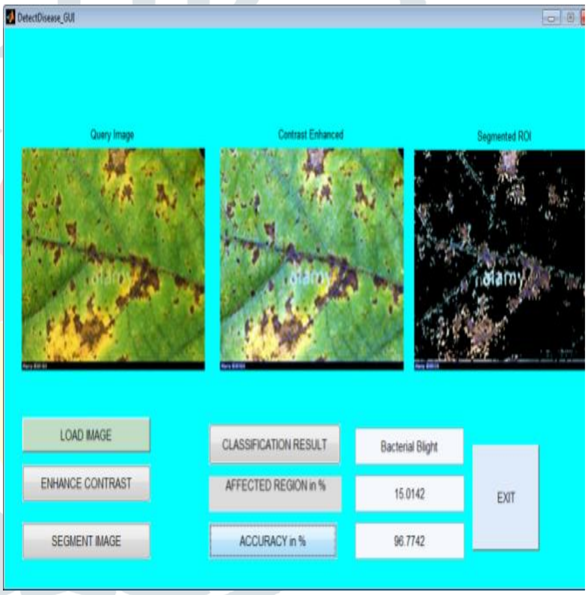

Fig. 14: Final Output of different test image 2

3.8 Clustering output of the image

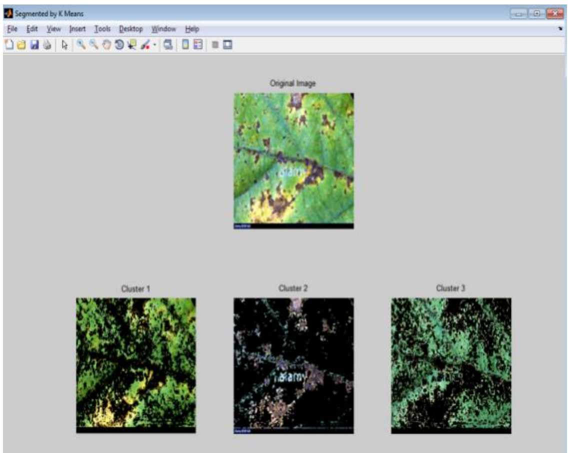

Fig. 3.11: Clustering output of test image 2

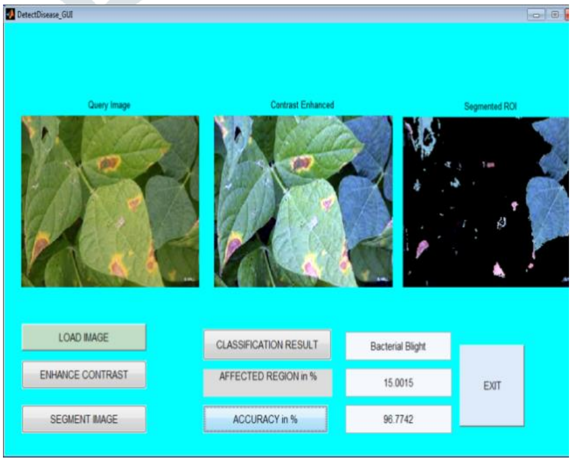

Fig. 3.12: Analysis of test image 3

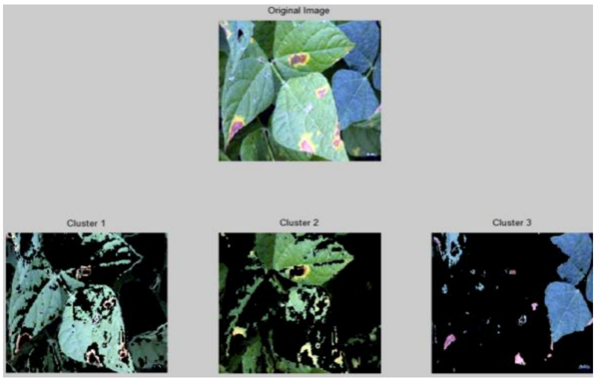

Fig. 3.13: Clustering output of test image 3

V. CONCLUSION

Deep learning has proven to be a valuable tool in the field of brain tumor detection. By leveraging deep neural networks and advanced image processing techniques, researchers and medical professionals have developed accurate and efficient methods for detecting and classifying brain tumors from medical imaging data, The Convolutional Neural Network (CNN) based classification is equipped for the classification and detection of tumors. The identification of brain tumor location is also done using a CNN-based model by segmenting the brain tumor is presented in research work. The proposed model is based on modified ResNet 50. ResNet 50 model shows better accuracy and other result parameters as compare to other deep learning model such CNN as well as VGG 16 model. The use of deep learning in brain tumor detection has several benefits. It enables automated and objective analysis of medical images, reducing human error and variability. Deep learning models can process large amounts of data quickly, allowing for faster and more efficient diagnoses. They can also handle complex features and patterns in the images, leading to improved accuracy in tumor detection.

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