http://www.jctjournals.com ISSN(ONLINE):2278 – 3814

Volume-13, Issue-05, May 2024
JOURNAL OF COMPUTING TECHNOLOGIES (JCT)
International Journal
Page Number: 01-08

PLANT LEAF DISEASES DETECTION USING MULTI SVM BASED ON MACHINE LEARNING

Archana Khemre [1], Prof. Arpita Dash[2],
M.Tech Scholar of CSE[1], Assistant Professor [2],
[1,2]Department of Computer Science Engineering
[1, 2] Vaishnavi Group of Institutions (VIST), Bhopal, (M.P), India
[1]archanakhemrearchu@gmail.com

***Abstract*— According to research and reviews, the bulk of India is a horticulture sector, which has earned the country the moniker "rural nation"; over 70% of the population depends on farming for their livelihood. Identifying leaf diseases early is a key area for research. Diseases in farming and cultivation crops, caused by various amounts of growths, microbes, nematodes, and so on, significantly reduce the quantity and quality of agribusiness products. The spread of disease across the whole crop is a direct consequence of the difficulty ranchers have in detecting early symptoms of illness and identifying ailment by unassisted vision. By collecting leaf shade data, automatic photo processing algorithms complete harvest discovery and security, especially in large farms. Expires identification in plants and yields in fields, such as doing suggested tasks, are presented in this. Other diseases include Alternaria alternata, anthracnose, bacterial blight, and others. As a means of detection, K-means clustering is used. The suggested approach has a very high detection rate across all test photos.**

Keywords*— Multi Class Support Vector Machine (SVM), Plant Leaf, Diseases, Bacteria, Virus, Fungal Infection, Detection, K-Mea. etc...

I. INTRODUCTION

Every gardener has planted plants with the hopes of receiving amazing fruits, flowers, or veggies, only to have their expectations dashed when the plants get sick and eventually die. It is thought that these plants are sick. Plant diseases may be caused by a variety of reasons, such as biotic (living) agents, abiotic (non-living) factors, or a mix of the two. Only living things-fungi, bacteria, viruses, nematodes, and parasitic plants-are the subject of this study.

There have been significant effects of some plant diseases on civilization. The Phytophthora fire blight, a fungal disease that led to a potato famine in Ireland in 1845, is perhaps the most significant of them. Two million people either starved to death or fled Ireland, many of them to the United States. Until the Bordeaux combination was under control, the French wine industry was severely impacted by powdery mildew and powdery mildew.

In the late 1800s, Chinese chestnut imports from China unintentionally brought fungus illness to New York City. American chestnut trees were not immune to fire blight, while Chinese ones were. Thirty million acres of chestnut trees have perished in less than forty years. The eastern United States continues to have a problem with chestnut burns. Additionally, Dutch elm disease was unintentionally brought in. The disease affects and destroys elms all around the nation fig.1 shows Fungal Disease in Plant Leaf.

Fig.1. Fungal Disease in Plant Leaf

Background

Pathogens are pathogenic organisms. Without magnification, they are either minuscule or very difficult to see or identify. On garden plants, harmful organisms might include nematodes, bacteria, viruses, fungi, and even plants. Typically, hosts provide nutrition, water, and other resources needed for pathogen reproduction. A parasitic connection is what is known as such. Certain viruses are capable of infecting several plant species, whereas others are host-specific.

A. Fungi

Fungi, the biggest category of plant diseases, may take many different forms. They are often multi cellular creatures with bodies fashioned like wires. The hyphae, or threads, possess cell walls. A mycelium is formed when many strands of thread come together. A mycelium's continued development may result in fruiting bodies, which are where asexual or sexual spores develop. Mycelium, fruit bodies, and spore features are utilized to detect and diagnose fungal issues. Some funguses don't need a live host to thrive and spread fig.2 shows fungi disease in plants.

Fig 2 Fungi Disease in Plants

B. Bacteria

Compared to plant cells, bacteria are significantly smaller, simpler mono cellular creatures. Many are as big as a chloroplast found in a plant. Bacteria may grow in very large quantities inside plant tissues. Certain bacteria may create slugs, which can attract insects and help the germs spread to healthy plants. Even in seeds, bacteria may survive harsh circumstances seen in plant detritus. By generating poisons or enzymes that degrade the plant's cell walls, bacteria induce illnesses in plants. In order to produce galls and amino acids, genetic crown bacteria genetically modify their host plant. This provides the bacteria with a better environment to live in as well as the nutrients they need to proliferate Fig.3 shows bacteria in plant.

Fig 3 Bacteria in Plants Leaves

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 shows Viruses in Plant leaf's.

Fig 4 Viruses in Plant leafs

D. Nematodes

Nematodes are multi cellular 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 fig.5 shows the Nematodes in Plant leafs

Fig 5 Nematodes in Plant leafs

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 historian 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 south-eastern Alaska) 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) "Analysis of early tomato leaf condition symptoms using image and deep learning models Computer vision preprocessing methods include contour tracing, K-means clustering, Histogram Equalization (HE), and RGB to grayscale conversion. Well-known feature extraction methods extract important properties from leaf samples. These methods include Discrete Wavelet Transform, PCA, and GLM. Researchers use SVM, K-NN, and CNN to identify healthy and damaged leaves. With its proposed accuracy, the model is suitable for CNN machine learning classification compared to other modern methods. [1].

Mahesh T R et.al (2023) "The CNN model should be able to identify and predict plant disease from any field dataset and previous datasets. This predicts the following diseases: This approach covers several plant leaves, so a farmer can select which to grow and which to avoid. He may also list prospective departures. It helps farmers decide which crop leaves to grow. The technique uses a pre-trained base model and trainable head model. The suggested approach identifies plant diseases with 95% accuracy. Comparison of base model architecture indicates MobilnetV2 is more accurate than ResNet50V2 and InceptionV3. An average pooling layer followed by two fully linked layers improves accuracy and efficiency. This technology also helps farmers determine plant demand and price based on past production data. For this study to include more plant species, the dataset must be improved. These studies may be enhanced using a custom optimizer for resource-constrained situations [2].

Kulkarni, Priyanka,et.al..(2024) " Rice leaf disease detection using machine learning." Most farmers face rice diseases. Thus, early diagnosis is crucial. Science has reduced the time-consuming laborious process of searching rice leaves for illness signs. This study integrates numerous rice disease detection strategies based on classifiers. Image processing requires pattern detection, and the CNN classifier fared well. Our CNN-based approach demonstrates promising accuracy. describes a machine learning method for identifying rice leaf diseases. Machine learning methods for rice leaf disease detection were compared. Rice leaf disease prediction systems varied in accuracy. The decision tree obtained the highest test data accuracy of 95%. [3].

Yang Wu, et.al (2022) "Examining strong model networks improves deep learning research performance. Complex networks usually On low-performance terminals, storage and processing resources limit efficiency. Complex networks have redundant parameters. Recent research has extensively studied deep neural networks for agricultural leaf disease detection. Similar leaf disease images. The large variation within classes and little difference between classes makes class recognition difficult. Thus, fine-grained categorization requires reliable local feature representation. To overcome the shortcomings of deep neural networks in crop disease diagnosis, an attention deep neural network-based method was given to identify peach and tomato disease leaves. Train discriminates areas and traits using the "Reconstruction and Generation Model". This makes the network learn images instead of global characteristics. The classification network should focus on discriminate area differences to properly detect damaged pictures. An attention mechanism is introduced to the generic network classification model to decrease destruction noise, and adversarial loss is used to distinguish the produced image from the original. [4].

Singh, Paramjeet, et.al (2024) " Deep neural network-based cotton leaf disease detection." Research suggests 70% of rural communities consume farm food. India produces cotton, but environmental hazards cause many diseases, particularly in cotton plants. More than prior studies, this research includes 22 courses. The proposed approach is more productive and efficient than current techniques due to its 99.39% accuracy and extraordinarily low error rates on the testing set. Since the dataset was small, we used different data augmentation strategies to increase the picture collection and improve the model. We used data augmentation since deep learning models need plenty of data. Data collection, scarcity, labeling, and over fitting are reduced to boost sample size, model flexibility, and generalization. Poor learning with explicit regularization is a serious concern. However, considerable bias reduction and regularization Correct augmentation techniques or massive real-world data may also make it quicker and simpler. The main difficulty is that deep learning models can't handle real-world data since they evaluate smaller amounts. Simple changes may address new problems with new data instances [5].

III. PROPOSED METHODOLOGY

Proposed Method – The proposed method is design to detect the Anthracnose in leaf's 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. Further process shown in steps.

Training and Data set Creation –

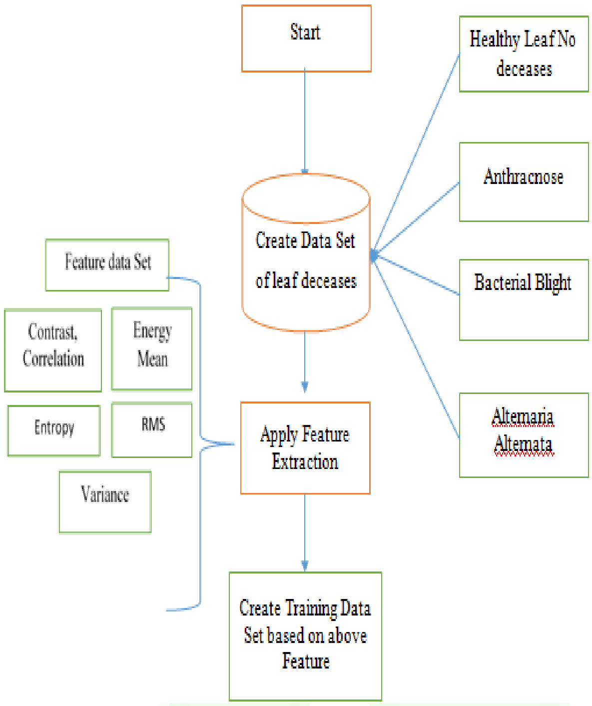


Fig.6. Create Training Data Set using Feature Extraction

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 this 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 6

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 types 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

One unsupervised learning approach for clusters is K-Means. The process of clustering a picture involves arranging its pixels based on shared attributes. The number k of clusters must first be defined in order to use the k Means technique. Next, k-cluster centers are selected at random. Calculated is the separation between each pixel and each cluster center. The distance might have a simple Euclidean function. Using the distance formula, a single pixel is compared to every cluster center. The pixel is relocated to the specific cluster that is the closest to it all. The centroid is then estimated once again. Every pixel is once again contrasted with every centroid. Up until the center converges, the process is ongoing. The divisive clustering that the K-means method achieves was initially described by Duda and Har. The method places each page into one of k clusters based on a similarity score. An average of every document inside each cluster is used to represent the clusters. Consider this average to represent the cluster's centroid.

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 image and structuring elements 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 Regions 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.

- 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:

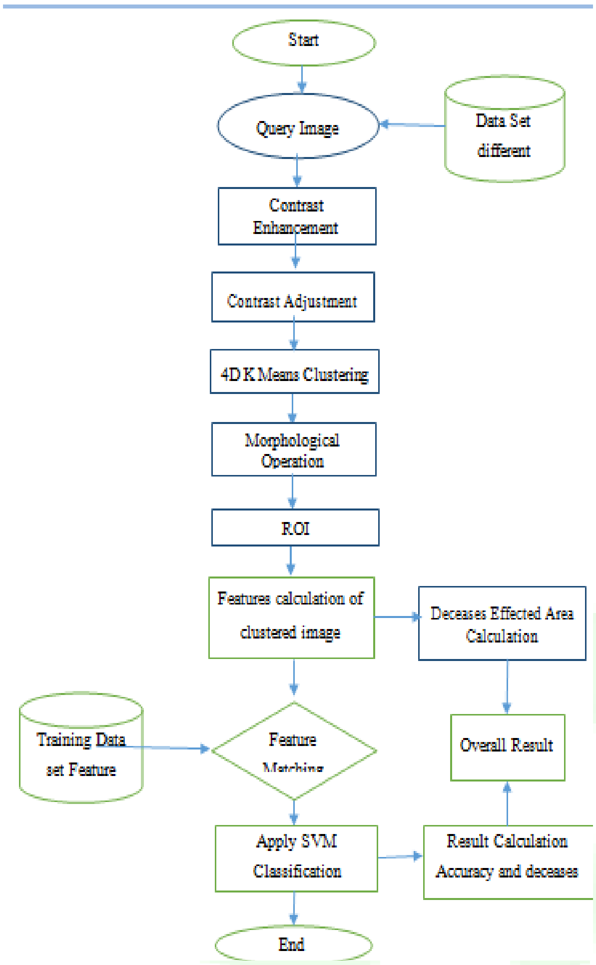


Fig. 7 Flow Chart of proposed algorithm

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.

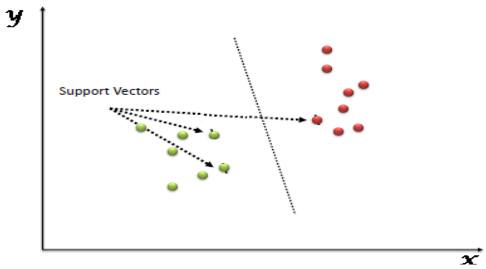


Fig. 8 SVM Based Clustering

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 area leaf 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. Therefore, correct deceases are 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 performs features matching between different deceases images with the help of support vector machine.

Table.1. Comparison of proposed method with different Previous Method

Ref. No.	Techniques	Accuracy
2024/ Proposed	MULTI SVM	Accuracy of 98%
Kulkarni, Priyanka, et.al (2024) [3]	CNN-based approach	Accuracy of 95%
Yang Wu, et.al (2022) [4]	CNN (convolutional neural network) method	Accuracy of 93.3 %.
Mahesh T R et.al (2023) [2]	CNN model	Accuracy of 95%

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 diseases 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 fruit's part calculation is known as an affected region. With the help of this calculated the percentage of effected area of plants and leaf by the different deceases.

Accuracy -In the work of detecting plant diseases, a leaf that is discovered as a decease is considered a true positive (TP), whereas a leaf that is not affected by the disease is considered a genuine negative (TN). In contrast, false negatives (FN) refer to affected regions of the leaf. The false negative (FN) is a crucial component in some industrial applications, such as weed or disease identification, since it directly impacts the overall accuracy of the detection system. A system that exhibits more accuracy but also exhibits a substantial number of false negatives (FN) may entail an elevated risk. This is due to the potential for weed or sick plants to rapidly propagate or proliferate, hence posing a threat to overall output, even after the implementation of a targeted 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 –

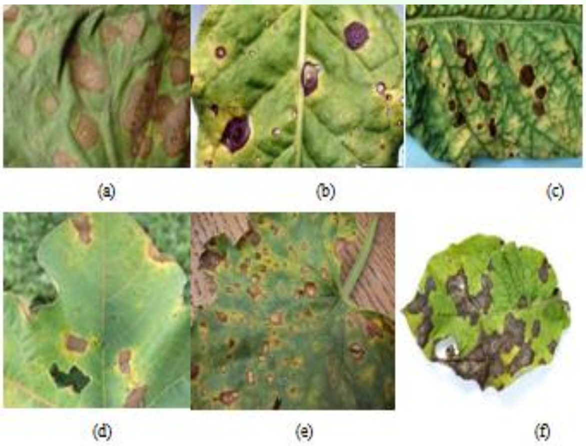


Fig. 9: Shows the Alternaria Alternata deceases data set

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

Anthracnose diseases data set –

Fig. 10 – Shows the Anthracnose deceases data set

In the above figure 10 shows the anthracnose deceases data set images. In the above figure shows only five images of these diseases. 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 12 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 14 shows the final GUI of proposed method with result.

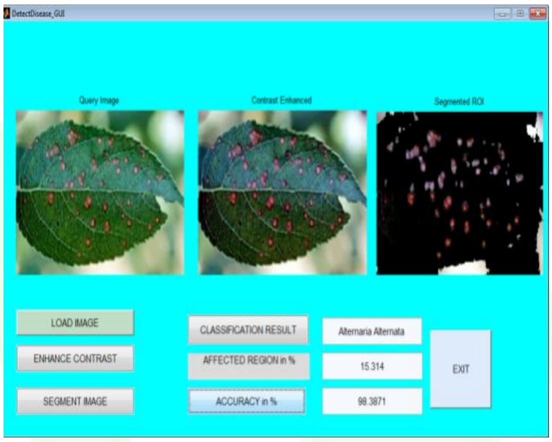


Fig. 11 Shows the GUI of Proposed Method (With Result)

In the figure 12 three figures are shown, in the back end of this GUI three axis windows.

First window or Axis Shows the test image in which applies proposed method. For this first we select the input image by press push button “LOAD IMAGE”.

The subsequent stage involves the use of a contrast enhancement procedure to accentuate the afflicted region of the leaf. By using contrast enhancement methods

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 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.

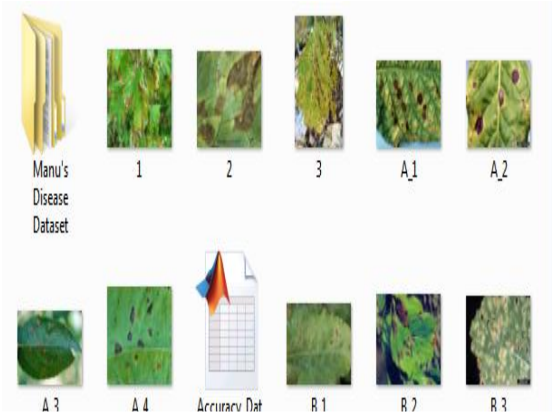


Fig.12 Loaded image data set

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

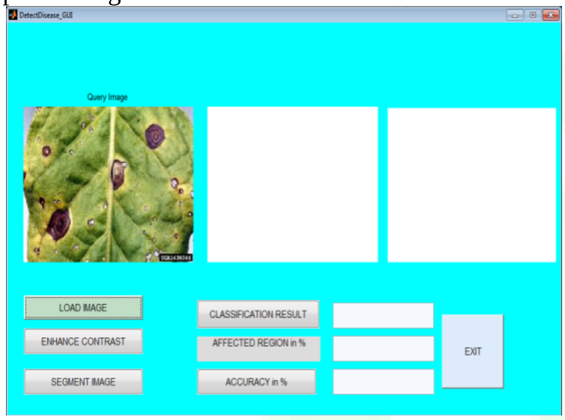


Fig.13 shows the query image

E. Analysis on different Images –

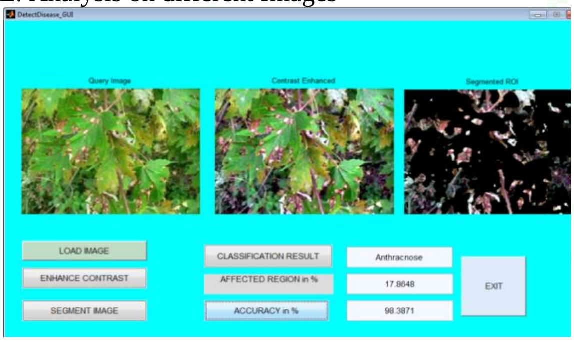


Fig.14 Final Output of different test image 1

In the below fig Final Output of different test image.

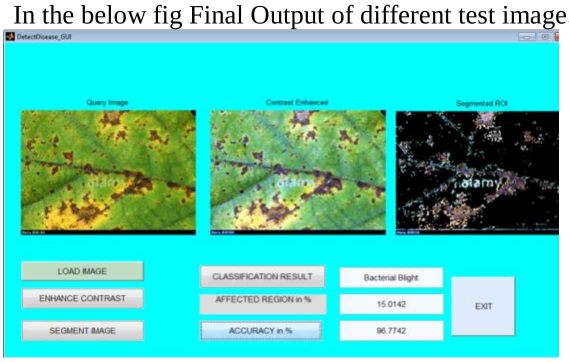


Fig.15 Final Output of different test image 2

In the below shows Clustering output of the image.

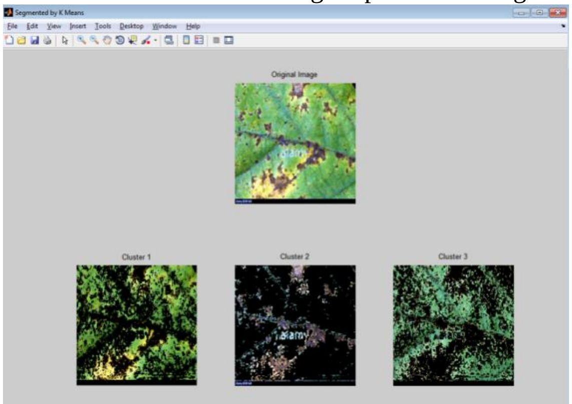


Fig.16 Clustering output of test image 2

In the below figure Shows Analysis of test image.

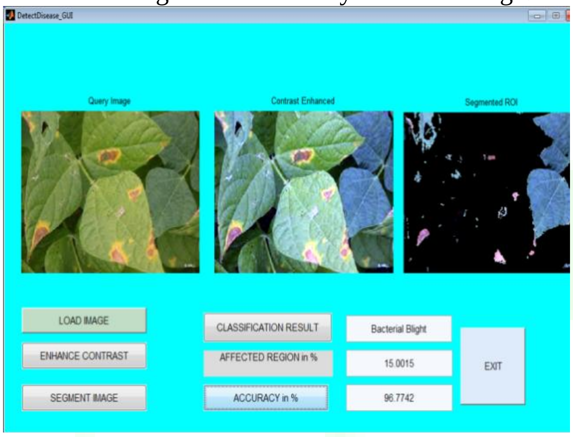
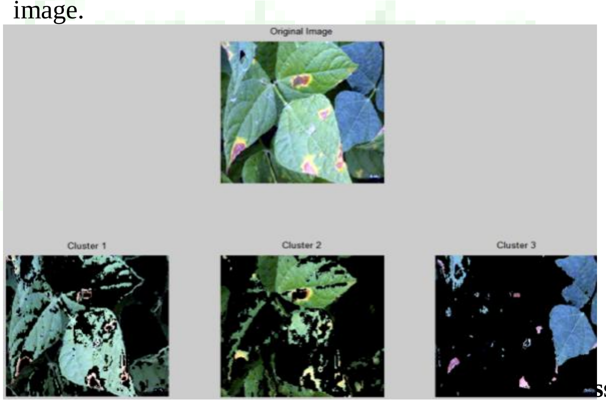


Fig.17 Analysis of test image 3

In the below figure shows Clustering output of test image.



sss

Fig.18 Clustering output of test image 3

Different result is shown in the above figure on different testing images.

IV. CONCLUSION

In This research presents a method for detecting diseases in plants and crops in fields similar to the proposed work. The plant species mentioned include Alternaria Alternata, Anthracnose, Bacterial Blight, Leaf Spot, and healthy leaf. Segmentation using K mean clustering is used for the purpose of detection. It has been shown that diseases may be recognized with a very high level of accuracy, reaching up to 98% across several test photos. The validation experiments demonstrated the ability to identify plant deaths without the need for 3D sensing. Color-based categorization places great emphasis on the accuracy of color perception, necessitating the use of cameras equipped with finely calibrated and labeled color filters. The identification of many diseases is still mostly hindered by environmental conditions, particularly sunshine. The presented study also identifies several diseases.

REFRENCES

[1] Vinta, Surendra Reddy, Ashok Kumar Koshariya, and Annantharao Gottimukkala. "Investigation of early symptoms of tomato leaf disorder by using analysing image and deep learning models." *EAI Endorsed Transactions on Internet of Things* 10 (2024).

[2] Mahesh, T. R., R. Sivakami, I. Manimozhi, N. Krishnamoorthy, and B. Swapna. "Early predictive model for detection of plant leaf diseases using MobileNetV2 architecture." International Journal of Intelligent Systems and Applications in Engineering 11, no. 2 (2023): 46-54.

[3] Kulkarni, Priyanka, and Swaroopa Shastri. "Rice Leaf Diseases Detection Using Machine Learning." *Journal of Scientific Research and Technology* (2024): 17-22.

[4] Wu, Yang, Xian Feng, and Guojun Chen. "Plant leaf diseases fine-grained categorization using convolutional neural networks." IEEE Access 10 (2022): 41087-41096.

[5] Singh, Paramjeet, Parvinder Singh, Umar Farooq, Surinder Singh Khurana, Jitendra Kumar Verma, and Munish Kumar. "CottonLeafNet: cotton plant leaf disease detection using deep neural networks." *Multimedia Tools and Applications* (2023): 1-26.

[6] Tugrul, Bulent, Elhoucine Elfatimi, and Recep Eryigit. "Convolutional neural networks in detection of plant leaf diseases: A review." *Agriculture* 12, no. 8 (2022): 1192.

[7] Wu, Yang, Xian Feng, and Guojun Chen. "Plant leaf diseases fine-grained categorization using convolutional neural networks." *IEEE Access* 10 (2022): 41087-41096.

[8] Li, Lili, Shujuan Zhang, and Bin Wang. "Plant disease detection and classification by deep learning—a review." *IEEE Access* 9 (2021): 56683-56698.

[9] Chowdhury, Muhammad EH, Tawsifur Rahman, Amith Khandakar, Mohamed Arselene Ayari, Aftab Ullah Khan, Muhammad Salman Khan, Nasser Al-Emadi, Mamun Bin Ibne Reaz, Mohammad Tariqul Islam, and Sawal Hamid Md Ali. "Automatic and reliable leaf disease detection using deep learning techniques." *AgriEngineering* 3, no. 2 (2021): 294-312.

[10] Kumar, Santhosh S., and B. K. Raghavendra. "Diseases detection of various plant leaf using image processing techniques: a review." 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS). IEEE, 2019.

[11] Chouhan, Siddharth Singh, et al. "Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology." IEEE Access 6 (2018):8852-8863.Advanced Computing & Communication Systems (ICACCS). IEEE, 2019.

[12] Nema, Sumit, and Aarju Dixit. "Wheat Leaf Detection and Prevention Using Support Vector Machine." *2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET)*. IEEE, 2018.

[13] Thorat, Apeksha, Sangeeta Kumari, and Nandakishor D. Valakunde. "An IoT based smart solution for leaf disease detection." *2017 International Conference on Big Data, IoT and Data Science (BID)*. IEEE, 2017.

[14] K.Swetha, Veena Venkataraman, Sadhana.G.D, R.Priyatharshini,“Hybrid approach for Anthracnose detection using intensity and size features”, International Conference on Technological Innovations in ICT For Agriculture and Rural Development, IEEE, 2016.

[15] B.Brendon J. Woodford Nikola K. Kasabov and C.Howard Wearing, “Fruit Image Analysis using Wavelets”,Department of Information Science, University of Otago, PO Box 56, Dunedin, New Zealand, HortResearch Clyde Research Centre, Clyde, Central Otago, New Zealand.

[16] Sandeep B. Patil ,Santosh Kumar Sao ,“An Improved Leaf Disease Detection Using Collection of Features And SVM Classifiers”,International Journal for Research in Applied Science & Engineering Technology (IJRASET),2015.

[17] Jagadeesh D. Pujari, Rajesh Yakkundimath, Abdulmunaf S.Byadgi, “Identification and Classification of Fungal disease Affected on Agriculture/Horticulture Crops using Image Processing Techniques”, IEEE International Conference on Computational Intelligence and Computing Research, 2014.

[18] Erick SALDAÑA,Raúl SICHE,Mariano LUJÁN,Roberto QUEVEDO, “Review: computer vision applied to the inspection and quality control of fruits and vegetables”, brazilian journal of food technology,2013**.**

[19] Piyush Chaudhary, Anand K. Chaudhari, Dr. A. N. Cheeran and Sharda Godara, “Color Transform Based Approch For Disease Spot Detection on Plant Leaf”, International Journal of Computer Science and Telecommunications, 2012.

[20] Shiv Ram Dubey, Anand Singh Jalal, “Detection and Classification of Apple Fruit Diseases using Complete Local Binary Patterns”, International Conference on Computer and Communication Technology IEEE, 2012.

[21] B.M.A De coninck, O. Amand, S. L. Delaure, S. Lucas, N.Hias, G.Weyens, J. mathys, E. De Bruyne and B.P.A. Cammue, “The use of digital image analysis and real time PCR fine-tune bioassays for quantification of cercospora leaf spot dieses in sugar beet breeding”, plant pathology, 2012.

