ESP-JETA
ESP Journal of Engineering & Technology Advancements
Volume 3 / Issue 1 Paper Id: JETA-V3I1P102, Page Count: 07-14

Segmentation and Classification of Leaf Disease Using Radial Basis Function neural Network

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Abstract: Finding plant leaves is a crucial step in preventing a major outbreak. The automatic diagnosis of plant disease is an important research area. Similar to humans and other animals, plants also experience the negative effects of sickness. These diseases affect the entire plant, including the leaf, stem, fruit, root, and flower. More often than not, when a plant's sickness is left untreated, the plant bites the ground or can also cause the loss of leaves, blooms, natural products, and so forth. For accurate identification and treatment of plant diseases, these disorders must be properly dedicated. The study of plant infections, their causes, and methods for containing and managing them is known as plant pathology. However, the modern strategy emphasises human inclusion for order and differentiating disease evidence. This strategy is time-consuming and expensive. Programmable disease detection from plant leaf images using a sensitive registration technique may be more valuable than the existing one. In this research, we present a method for identifying symptoms and characterising plant leaf illnesses organically called Bacterial looking development based entirely Radial Basis Function Neural Network (BRBFNN). We employ bacterial looking streamlining (BFO), which also increases the speed and accuracy of the device, to give Radial Basis Function Neural Network (RBFNN) the best possible weight when understanding various illnesses at the plant Leaf's. The suggested method improves recognition of evidence and infection characterisation.

Keywords: Neural Network (BRBFNN), Plant Pathology, Infection Characterisation, Image Processing, Analog and digital image processing, Digital Processing Techniques.

INTRODUCTION

A) Image Processing

In order to create a stronger image or to extract some useful information from it, an image might be transformed into a virtual shape and subjected to a number of processes. It is a type of sign distribution in which the input is a photo, such as a video body or image, and the output can be a photo or characteristics associated with that photo. Typically, an image processing system treats images as dimensional alerts while applying pre-established sign processing techniques to them. It is one of today's unexpectedly evolving technologies, with programmes in many different business-related areas. Within the fields of engineering and computer technology, image processing also has a middle studies position. The following three phases are essentially what image processing entails. The first step is importing the photo using an optical scanner or with the help of virtual photography. Second, analysing and modifying the image by using photo-enhancement, data compression, and other techniques that are invisible to the human eye, such as satellite photos. The final stage before the outcome can be changed by an image or report based on image analysis is output.

Analog and digital image processing are the two types of image processing techniques. For the more challenging copies, such as printouts and images, analogue or visible photo processing techniques may be used. Along with the use of those obvious tactics, image analysts also employ a number of basic principles of interpretation. Digital processing techniques help in computer-based alteration of virtual images. As raw data from satellite television for computers' imaging sensors contains flaws. It must go through several processing processes in order to remove these defects and obtain original statistics. Pre-processing, augmentation and display, and statistics extraction are the three standard processes that all forms of information must go through when using virtual techniques.

One of the many additional services that may be provided through a community of included teleradiology service providers is access to high-performance computing facilities to carry out computationally intensive picture processing and visualisation operations. In general, current products in the image processing (IP) field only partially satisfy the needs of diverse end user groups. They both aim to provide a full selection of ready-to-use software in a user-friendly and software-specific interface for those who use IP software, or they aim for the specialised IP researcher and developer, dispensing programmer's libraries and visual language tools. However, we now lack the common framework that will integrate all prior initiatives and trends within the field while at the same time providing additional, fee-based capabilities that support and ultimately recognise what we refer to as a "service." These capabilities include: Computational aid control and clever execution scheduling; clever and adaptable mechanisms for the description, control, and retrieval of picture processing software programme modules; mechanisms for the "plug-and-play" integration of already existing heterogeneous software programme modules; easy access and consumer transparency in terms of software, hardware, and network technologies; and others.

B) Plant Diseases Prediction:

Agrarian India is a nation. Farmers can choose from a wide selection of suitable fruit and vegetable crops. Through inflammatory images of various leaf patches, research work develops the advanced computer to identify diseases. Virtual digital cameras on mobile devices are used to capture images, which are then processed using image growing before being used as part of the leaf game for classification purposes in lessons and tests. Both image processing tactics and superior computing strategies are used in the device's sophisticated approach. The Following Are Some Uses for Image Analysis:

1. To identify fruit, stem, and leaf disease.
2. To quantify affected areas by disease.
3. To find the boundaries of the affected area.
4. To determine the color of the affected area.
5. To determine size & shape of leaf.
6. To identify the Object correctly. Etc.

Managing diseases is a difficult endeavour. The majority of plant illnesses are visible on the leaves or stems. Because of the intricacy of visual patterns, precise quantification of these visually perceived illnesses, pests, and characteristics has not yet been studied. Consequently, there is a growing need for more accurate and complex visual pattern comprehension.

Various Types of Leaf Spot Diseases:

- Bacterial
- Fungal
- Viral

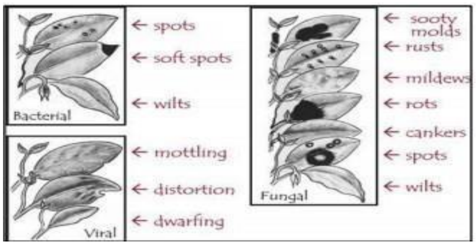

Fig 1.2.1 Types of Leaf Spot Diseases

Mushrooms can be distinguished primarily by their morphology, with a focus on their reproductive structures. In comparison to mushrooms, bacteria are thought to have more basic life cycles. With a few rare exceptions, bacteria are single cells that divide into two cells, or binary fission, to increase their population. There are very small, protein-based viruses that lack genetic material called companion proteins [9]. In the biological sciences, an experiment may produce tens of thousands of photos. For tracking tests like lesion categorization, quantitative feature scoring, area computation for insect consumption, etc., these photos could be necessary. Almost all of these duties are carried out manually or with the aid of different software programmes. It requires a lot of work, but it also has two major flaws: very long processing times, and subjectivity from various individuals. hence, transport a lot of data Powerful computer software is required for experiments involving plant biology in order to automatically extract and analyse pertinent data.

EXISTING WORK

Has crop identification historically been carried out by experts in taxonomy utilising a variety of plants? Other differentiating characteristics include the basic shape of a plant's leaves, the colour of its flowers, and the shape and colour of its fruit. several varieties. technology advancements in information and images The expanding trend towards automation is being driven by signal processing techniques, and traditional methods are progressively being supplanted by new approaches in industry, applied research, and other spheres of society. problem Recognition of plants is not an exception. presently accessible Insufficient taxonomists and financial hardship for these experts Service expansion. creation of a factory-specific automation system At a low or no cost, recognition from leaf photos can give both specialists and laypeople a useful tool. Such a system would have many benefits over conventional methods, including the ability to prevent subjective errors made by human operators once it uses quantitative analysis; the ability to provide a very affordable option to study and identify the sheets because it only requires the commonplace camera and computer processing technology and could enable construction and maintenance work. less effort specialist journal database.

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As a result, the RGB scheme is a reliant colour space. The disease detection and categorization method needs to be more accurate, hence a device independent colour space is necessary. In a colour space that is independent of the camera used to take the photographs, the coordinates used to determine the colour will result in the same colour. The mathematical morphology for the quasi-flat zone technique makes an effort to categorise things (in this example, pixels) based on a variety of properties. By reducing the sum of squares of distances between the objects and the relevant cluster or class centroid, classification is accomplished.

A. Features Extraction:

1. *Leaf Shape features:*

Shape attributes it typically consists of a set of measurements that characterise a particular Shape in terms of some of its fundamental geometric characteristics. Examples of often used features to characterise a specific form include its facets. Convexity, solidity, compactness, roundness, rectangle, and proportion. Although the nomenclatures can differ greatly, their general definitions and measurements are always included in all introductory books on image processing, as shown in [12]. The form attributes are heavily employed in image processing, though not always in contexts involving categorization. The ease with which shapes may be created and understood when quantifying the fundamental geometric properties that correlate to human visual perception is one of the most intriguing elements of shape analysis utilising shape features. The reader may easily infer what the instance under the property name implies when it says "rectangular" even though the precise description of the calculation procedure would not include some of the previously described shape attributes. Properties of the module are often a set of measurements that describe a particular entity. Following some of its fundamental geometrical characteristics. Examples of often used characteristics to define a specific form are its aspect ratio, squareness, roundness, strength, compactness, and convexity. Although nomenclatures might differ greatly, their general definitions and measures are often included in introductory books on image processing, such as [12]. The form attributes are heavily employed in image processing, though not always in contexts involving categorization. One of the most intriguing parts of shape analysis utilising shape features is how intuitive this method is, i.e. how simple it is to understand when the basic geometric properties that correlate to human visual perception are quantified. The reader can easily infer what the instance under the feature name signifies, such as the rectangular one, even though a precise description of the computation technique for some of the form attributes already described would not exist.

2. ***Leaf texture analysis:***

Applying standard image texture analysis methods to photographs of plant leaves is what the leaf texture analysis entails. This can be helpful when the texture demonstrates the textural properties of a certain species, especially when used in conjunction with other leaf analysis techniques like B. Sheet forming procedures. Several publications have claimed that integrating texture analysis methods into cinema classification systems has produced positive results; however, given the varying volumes of the databases utilised as well as the nature of the methodologies employed, the lack of consistent results in this area is apparent. This method has certain qualities.

Table 2.1.1 various feature extraction process on existing methods

Reference	**Technique**	**Features**	**Pros and Cons**
Wu et al. (2007b)	It is pioneer research reporting the design of Flavia dataset and classifying proposed work with the help of Probabilistic neural network (PNN) classifier (PCA used for preprocessing)	7 Shape Features: smooth factor, aspect ratio, form factor, rectangularity, narrow factor, perimeter ratio of diameter, perimeter ratio of physiological length and width	Pros: High accuracy, simple and easy to apply, general purpose Cons: Improvement is required in the selection of feature set
Krishna et al. (2010)	It reports the use of three different classification techniques. It has been shown that the SVM classifier with binary decision tree gives the highest accuracy	Shape Features: Diameter, physiological length, physiological width, perimeter feature, and vein features	Pros: High accuracy Cons: Lacks novelty
ArunPriya et al. (2012)	This work is based on the use of kernelized support vector machine for classification to identify plants. The system has been evaluated on two datasets of 10 different plant species	Basic geometric, and digital morphological features	Pros: Good computational results, high performance, Cons: A limited number of features

PROPOSED WORK

Applying standard image texture analysis methods to photos of plant leaves is what the leaf structure analysis entails. This can be helpful when the texture demonstrates the textural properties of a certain species, especially when used in conjunction with other leaf analysis techniques like B. Sheet forming procedures. Several publications have claimed that integrating texture analysis methods into cinema classification systems has produced positive results; however, given the varying volumes of the databases utilised as well as the nature of the methodologies employed, the lack of consistent results in this area is apparent. There are positive aspects to this strategy. Over 65% of the population of India is reliant on agriculture, making it an agricultural nation. Disease-related crop losses range from 10 to 30 percent. Farmers make judgements on diseases based on their personal experience, but this is not the precise and correct method. Farmers occasionally consult experts However, it also takes a while to detect diseases. Diseases affect plants' leaves and stems more frequently. On plants, illnesses include viral, bacterial, fungal, insect, rust, nematode, and more. Plant disease lowers output. What restricts plant growth also causes a decline in plant quality and quantity. The greatest method for identifying and diagnosing the illness is image processing. Which area was first affected by different characteristics like colour, consistency, etc. In order to identify diseases, a classification technique is used.

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A. Modules description:

1) Image acquisition
2) Preprocessing
3) Image segmentation
4) Radial basis function neural network (RBFNN)
5) Disease prediction
6) Evaluation criteria

1) Image Acquisition:

Plants They have developed into a significant energy source and a crucial piece of the puzzle for addressing the issue of global warming. There are a number of illnesses that can harm crops and cause financial, social, and ecological consequences. Punctuality and correct disease diagnosis are crucial in this regard. There are numerous methods for identifying plant disorders. Some diseases exhibit no symptoms at all, or they do so when it is too late to take any action. In these situations, it is frequently essential to conduct a few different types of complex analyses using strong microscopes. In certain instances, the characters are only partially visible in the electromagnetic spectrum that is invisible to humans. Remote sensing methods are applied in this situation, which study the multi and hyper eerie images. This strategy frequently uses digital imaging techniques to help you reach your objectives.

2) Preprocessing:

In this lesson, we will use pre-processing techniques to remove picture noise and transform an RGB image to grayscale. Preprocessing has been implemented to improve dataset manipulation and image display. In order to thin out the data set and improve the presentation, resample the image to change the number of pixels in the dataset. The resultant colour image is first transformed into a grayscale image. pursuit Image segmentation is used to separate the background from the leaf pixels in order to do this. After segmentation, the image is binary transformed, the holes are filled in and small portions are removed. The leaf's interior is then subtracted. leaves a trace of the leaf's outline in an image.

3) Image Segmentation:

1. Region Growing Algorithm (RGA) For Feature Extraction

RGA is a straightforward method that starts with a set of seed points and expands by adding neighbouring pixels to each seed that have similar qualities to the seed, such as intensity level, colour, or scalar properties for grayscale images. The RGA approach offers the advantage of selecting a seed point from a variety of measurements. This approach has two fundamental schemes known as 4-neighborhood and 8-neighborhood. While the 8-neighborhood chooses both neighbouring and diagonal regions while expanding, the 4-neighborhood leaves diagonally related regions.

2. Bacterial foraging optimization (BFO) for training the Network

The BFO is a brand-new optimization algorithm that Kevin Passino presented in 2002. BFO was created as a result of the group foraging behaviour of bacteria like M. Xanthus and E. Coli. Chemotaxis serves as an inspiration for the BFO algorithm. virtual bacteria's movement patterns in response to various signals, either moving in their direction or away from them Another crucial idea for BFO is to move slowly when looking for nutrients in the problem search region. BFO has proven to be a successful and significant optimization method with high accuracy and convergence speed employed in a variety of real-world applications. The four fundamental BFO processes that were used to train the suggested approach are listed below:

i. Chemotaxis

Chemotaxis is the process by which E. coli uses its flagella to move as it looks for areas that are nutrient-rich (locomotory organelles). When the searching is done in the same direction as the step before it, the process is known as swimming, and when it is done in the opposite direction, the process is known as tumbling. Refer to for a definition of the chemotactic movement of the bacterium. (1).

$\varphi i(x+1,y,z)= \varphi i(x,y,z)+ C(s)\Delta(s)\sqrt{}\Delta T(s)\ .\ \Delta(s)$ (1)

where(x,y,z) = s bacterium at xth chemotactic, y = reproductive, z = elimination- dispersal step, C(s) = size of the unit step taken in the random direction, Δ(s) = indicates a vector in the arbitrary direction

ii. Swarming

Bacteria like E. Coli and S. Typhimurium, when stimulated by a high level of succinate, shows an interesting group behavior by releasing an attractant aspartate.

These aspartates help the nutritional gradient that has a specific pattern move the swarm up at a fast rate of speed. Using attractants and deterrents to facilitate swarm communication between cells

$Jcc(\varphi(s,x,y,z))= \quad \Sigma Jcc(\varphi,\varphi s(x,y,z))Ss=1 \quad = \Sigma[-battractant\exp(-cattractant$

$\Sigma(\varphi m-\varphi ms)2pm=1)]Ss=1+$

$\Sigma[drepellant\exp(-crepellant\Sigma(\varphi m-\varphi m$
$s)2pm=1)]Ss=1$

where $Jcc(\varphi(s,x,y,z))$ is an objective function, S is the total number of bacteria population, p is no. of variables to be optimized, φ= [φ1, φ2, … , φp]T is point in the p-dimensional search domain, battractant, cattractant, repellent, and crepellant are measure of quantity and diffusion rate of the attractant signal and the repellent effect magnitude.

iii. Reproduction

The technique by which the healthy bacteria crossover asexually split into two bacteria having the same direction helps to keep the population to be constant reproduction. The fitness value of the st bacteria after Nc chemotactic steps, where Jhealths reflects the st bacterium's health.

$Jhealths= \Sigma(x,y,z)Nc+1x=1.$

iv. Dispersal and elimination

There are several factors that could have an impact on the local environment and possibly create changes in the bacterial population where they are found. All of the bacteria in a location are either killed or transported to another region as a result of the high concentration of nutrient gradients or events that the rise in temperature generates. To manage these scenarios, the new replacements are initialised at random over the search space, with a very small likelihood that some germs will be eliminated at random.

3. Radial Basis Function Neural Network (RBFNN)

Three layers make up the RBFNN: the input layer, the hidden layer, and the output layer. The system is a feed-forward system. The input layer functions similarly to that of other networks, taking input and producing output. The main distinction for every network is how the hidden layers function. The Radial Basis Function-specific activation functions are present in this network's hidden layer (RBF). In addition, the output layer has linear neurons, while the hidden layer also includes radial kernel functions.

The network is made up of neurons with "local" or "tuned" receptive fields, such as somatosensory cells that respond to specific body locations or orientation-selective cells in the visual cortex. The response of RBF is said to drop or rise monotonically with distance from a central point, making it a distinct type of linear function with a distinguishing property. In order to predict the expected outcomes, the hidden layer must execute non-linear transformation of the input and output layers while performing linear regression. When compared to other networks, RBF has more hidden layers functioning simultaneously. The Gaussian and Multiquadric are widely utilised, despite the fact that there are numerous radial kernels that can be used for RBF. A Multiquadric RBF that monotonically increases with distance from the centre and a Gaussian RBF that monotonically decreases with distance from the centre.

4. Disease Prediction:

A collection of interconnected supervised learning methods used for regression and classification are known as support vector machines (RBFNNs). Making predictions about the labels of upcoming, unlabeled data requires analysing a specified set of labelled observations (the training set) (the test set). The goal is to identify a function that explains how observations and labels relate to one another. In multiclass RBFNN, labels are assigned to instances using support vector machines, and the labels are selected from a limited number of different elements. The most common way to achieve this is to break down a single multiclass problem into a number of binary classification problems. Common methods for this reduction include creating binary classifiers that distinguish between I one of the labels and the rest (one-versus-all) or (ii) between every pair of classes (one-versus-one). In the one-versus-all example, new examples are categorised using a winner-takes-all strategy, with the class being assigned by the classifier with the highest output function. Utilizing the multiclass classifier, illness predictions can be made from images of leaves.

4) Evaluation Criteria:

MATLAB 2012b was used to do the proposed job, along with an i3 processor and 4GB of RAM. To assess the success of this attempt, we have two sets of images. The second dataset comprises of around 270 photos from crowdAI.org's PlantVillage Disease Classification Challenge that are divided into the same six disease categories as the first collection, which featured six different images of diseases from planet nature and six different diseases. Two categories of results are shown in the results section: (A) correctly segmenting and identifying the diseased region on a plant leaf; and (B) recognising the various leaf illnesses. To evaluate the effectiveness of the suggested work for precisely detecting the afflicted area or illness on the plant leaf, two quantitative assessment criteria based on the statistical performance of the ground truth picture and segmented image are used. The standards are sensitivity and specificity. Watch (9) and (10). The most crucial phase is the classification of diseases according to certain traits associated with them. The proposed work performs the task of appropriately categorising illnesses by using two entropy functions, Validation evaluation partition coefficient Vpc and Validation evaluation partition entropy Vpe..

$Specificity{=}TNTN{+}FP$

$Sensitivity{=}TPTP{+}FN$

where True Positive (TP) is the number of pixels that were correctly classified, False Positive (FP) is the number of pixels that were incorrectly classified, True Negative (TN) is the number of precisely misclassified pixels, and False Negative (FN) is the number of incorrectly misclassified pixels. When the result is equal to 1, it signifies that the segmentation is perfect. The values of specificity and sensitivity range from 0 to 1..

$Vpc{=}\ \Sigma\Sigma uik2NNi{=}1Kk{=}1$

$Vpe{=}\quad -\Sigma\Sigma uik\log$

$(uik){=}1Kk{=}1$

where uik is the number of clusters, N is the total number of image pixels, and uik is the membership value of pixels belonging to the k-th cluster. Both functions have values between 0 and 1, and when Vpc is high and Vpe is low, it indicates that the segmentation results have lower membership values and that the tissues have been appropriately classified.

5) Evaluation Metrics for our Proposed System

Table 3.1 Specificity

Disease	K-Means	Genetic Algorithm	RBFNN
Common Rusts	0.767	0.778	0.879
Late Blight	0.760	0.772	0.884
Cedar Apple Rust	0.769	0.781	0.894
Leaf Curl	0.769	0.776	0.889

Leaf Spot	0.769	0.767	0.865

Table 3.2 Sensitivity

Disease	K-Means	Genetic Algorithm	RBFNN
Common Rusts	0.606	0.732	0.808
Late Blight	0.649	0.721	0.798
Cedar Apple Rust	0.628	0.701	0.778
Leaf Curl	0.628	0.711	0.787
Leaf Spot	0.628	0.732	0.834

Table 3.3 VPC

Disease	K-Means	Genetic Algorithm	RBFNN
Common Rusts	0.813	0.830	0.846
Late Blight	0.815	0.832	0.884
Cedar Apple Rust	0.820	0.836	0.894
Leaf Curl	0.813	0.825	0.889
Leaf Spot	0.804	0.821	0.853

Table 3.4.VPE

Disease	K-Means	Genetic Algorithm	RBFNN
Common Rusts	0.186	0.170	0.153
Late Blight	0.184	0.167	0.151
Cedar Apple Rust	0.180	0.163	0.146
Leaf Curl	0.186	0.174	0.157
Leaf Spot	0.195	0.178	0.146

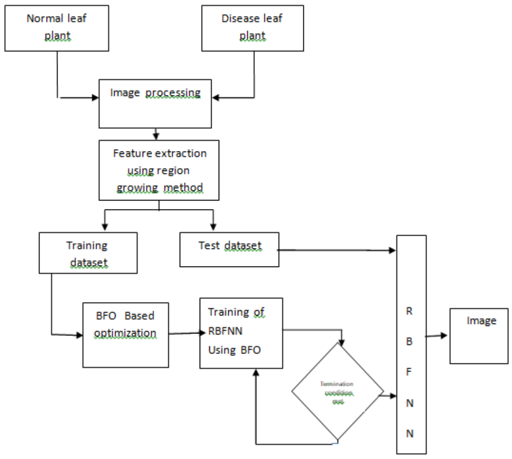

Fig 3.1 Flow Chart of BFO based RBFNN

RESULT AND DISCUSSION

Below image is the result of late blight disease after classification.

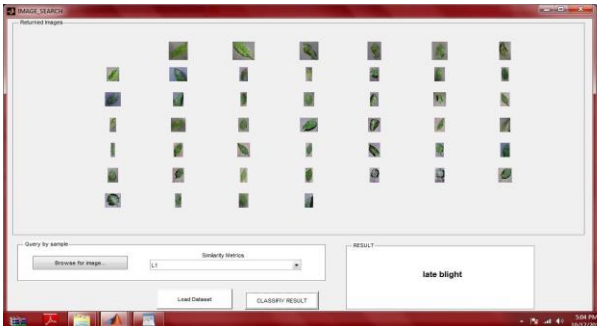

Fig: 4.1 Late blight disease

Below is the result of Cedar Apple Rust Disease after classification.

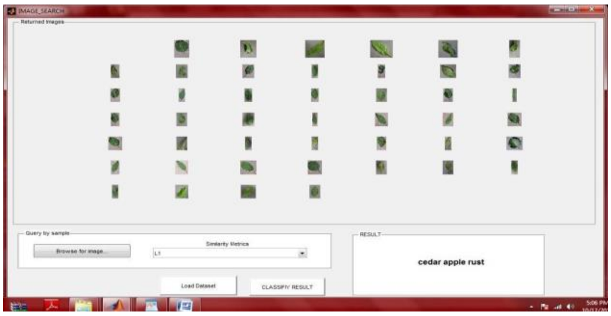

Fig: 4.2 Cedar Apple Rust Diseases

Below is the result of Common Rust Disease after

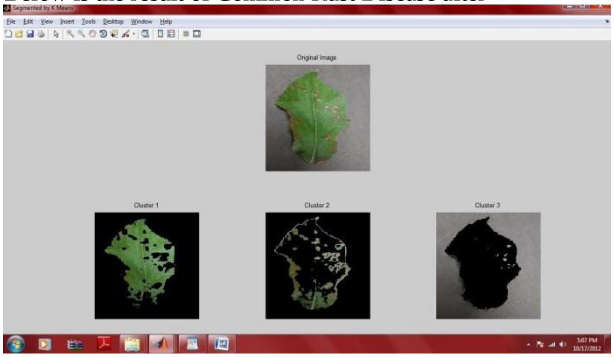

Fig: 4.3 Common Rust Disease

Below is the result of Leaf Spot Disease after classification.

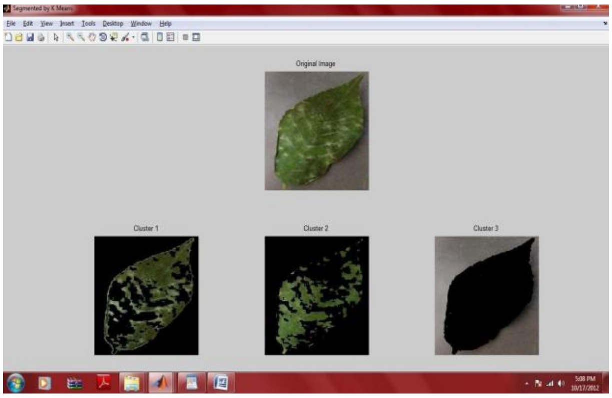

Fig: 4.4 Leaf Spot Disease

Below is the result of Cedar Apple Rust Disease after classification.

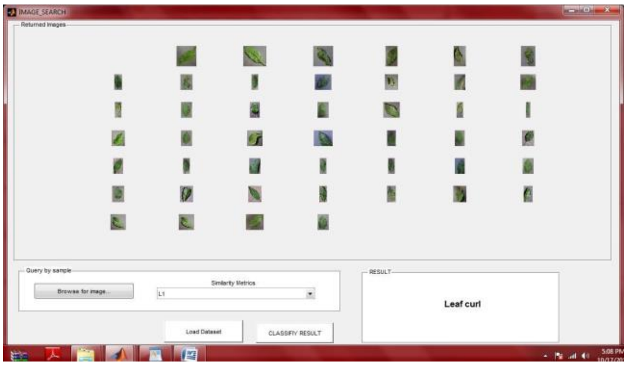

Fig: 4.5 Leaf Curl Disease

Below image visualize the leaf image retrieval process based on three classes.

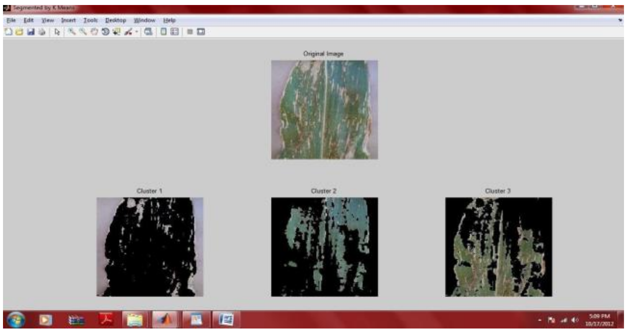

Fig: 4.6 Leaf Image Retrieval

Below are the numerical representation of Classification metrics which we used in our project.

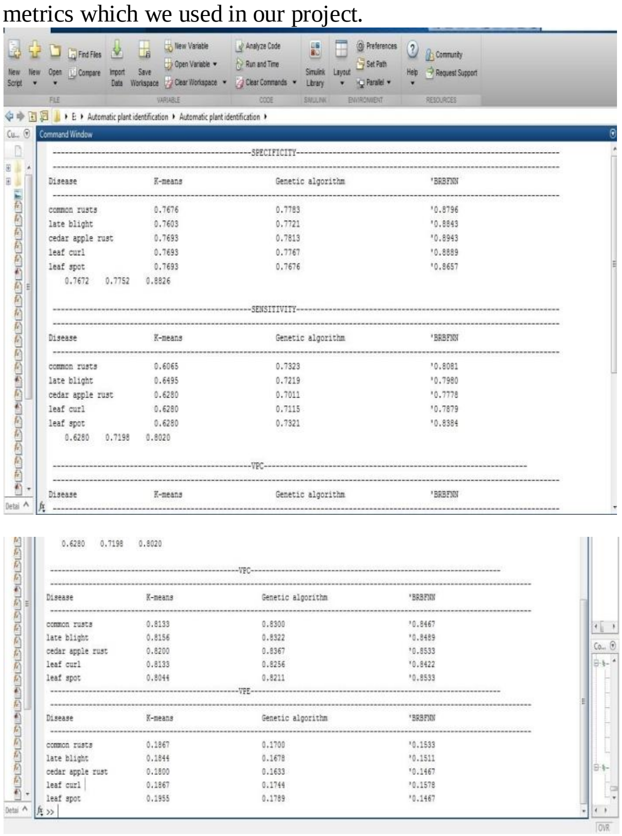

Fig: 4.7 Metrics Report

Comparative analysis of k-mean & Genetic algorithms on sensitivity against RBFNN based on various diseases.

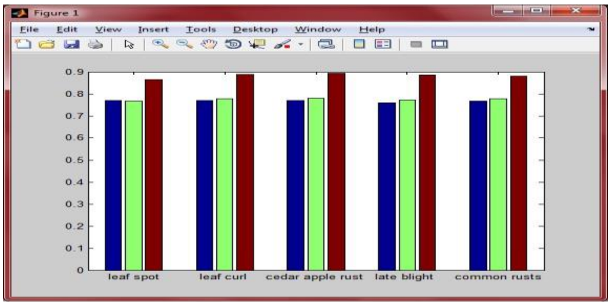

Fig: 4.8 Sensitivity

Comparative analysis of k-mean & Genetic algorithms on specificity against RBFNN based on various diseases.

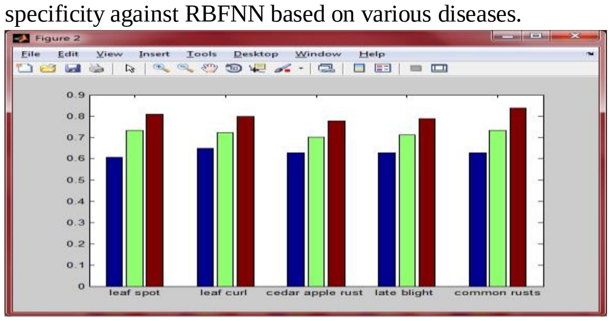

Fig: 4.9 Specificity

Comparative analysis of k-mean & Genetic algorithms on VPE against RBFNN based on various diseases.

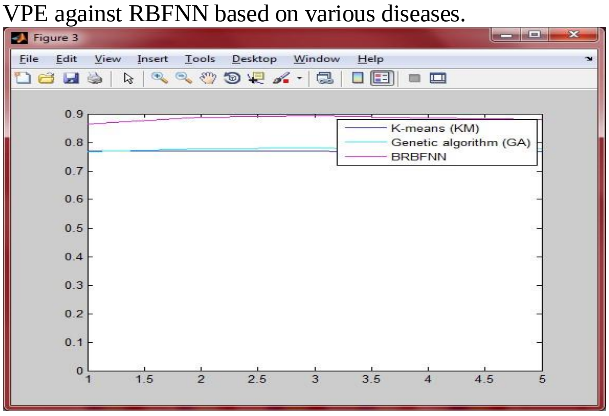

Fig: 4.10 VPE

Comparative analysis of k-mean & Genetic algorithms on VCE against RBFNN based on various diseases.

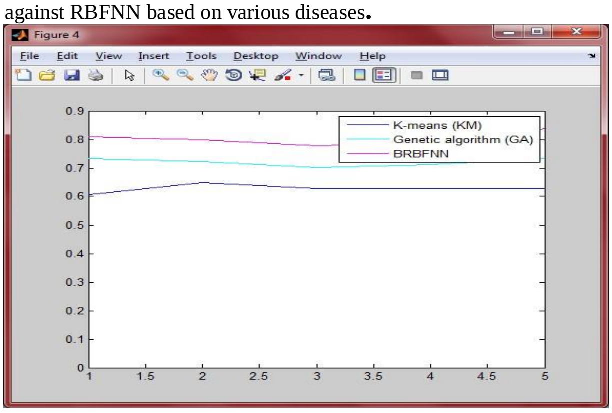

Fig: 4.11 VCE

CONCLUSION

For the purpose of identifying and categorising plant leaf diseases, we have put forth a brand-new technique known as Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN). The approach makes it simpler and more intelligent to identify plant leaf diseases, with an average classification accuracy of 87.6%. The results demonstrate that the proposed method performs better than previous methods in terms of both identifying and categorising plant leaf diseases.

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