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Cotton Leaf Spot Diseases Detection Utilizing Feature Selection with Skew Divergence Method

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Abstract - ***This research work exposes the novel approach of analysis at existing works based on machine vision system for the identification of the visual symptoms of Cotton crop diseases, from RGB images. Diseases regions of cotton crops are revealed in digital pictures, Which were amended and segmented. In this work Proposed Enhanced PSO feature selection method adopts Skew divergence method and user features like Edge,Color,Texture variances to extract the features. Set of features was extracted from each of them. The extracted feature was input to the SVM, Back propagation neural network (BPN),Fuzzy with Edge CYMK color feature and GA feature selection. Tests were performed to identify the best classification model. It has been hypothesized that from the given characteristics of the images, there should be a subset of features more informative of the image domain.To test this hypothesis, three classification models were assessed via cross-validation. To Evaluate its efficiency of six types of diseases have been accurately classified like Bacterial Blight, Fusariumwilt, Leaf Blight, Root rot, Micro Nurient, Verticilium Wilt.The Experimental results obtained show that the robust feature vector set which is an Enhancement of a feature extraction method (EPSO) has been afforded the performance assessment of this system.***

Keywords— ***SVM, BPN, Fuzzy, CMYK and Edge Features, Genetic Algorithm, Cotton leaf data sets., Enhance Particle swarm optimization, Skew divergences features.***

I. Introduction

Data mining is the process of extracting patterns from the data and to transform raw data into information.. It is commonly utilized in a broad range of profiling practices, such as marketing, surveillance, fraud detection, agriculture environment and scientific discovery. Among other things, the most prominent features of data mining techniques are clustering and predictive. The benefits of data mining are its capability to gain deeper perceptive of the patterns using current available exposure capabilities . In this work categorization of the cotton leaf diseases are done using data mining with image processing techniques.

The main target is to identify the disease in the leaf spot of the cotton crops. In this regard, It is discussed that about 80 to 90 percentage disease on the Cotton crops are on its leaf spot [1]. Consequently areas of interest is that identifying the leaf of the cotton tree rather than whole cotton plant the cotton leaf is mostly suffered from diseases like fungus, virus, Foliar leaf spot of cotton, Alternaria leaf spot of cotton. The machine visualization system right now is usually contained on computer, digital camera and application software. Various kinds of algorithms are incorporated in the application software. Image processing analysis is one significant method that helps to segment the image into objects and background. One of the key steps in image analysis is feature detection.Plant disease reduces the production and quality of food, fiber and biofuel crops.

Image processing has fascinated many researchers in the area of pattern recognition and technique combined with data mining are applied to trace out the leaf spots from the of plant leaves, which helps in diagnosing the cotton leaf spot diseases accurately The image processing techniques are extensively applied to agricultural science, and it has great perspective, especially in the plant protection field, which ultimately leads to crop management.
Image analysis can be applied for the following purposes:

1. To detect diseased leaf, stem, fruit, root
2. To enumerate affected area by disease.
3. To find the boundaries of the affected area.

A moreover leaf spot is a major component of the crops [2]. The diseases can be easily recognized with the help of the polluted vicinity of the crop. Usually the leaves will naturally going to focus the impure part in a clear way which can be easily identified. Generally by naked eyes we can easily identify the infected region. So we can say the transform in the crop color is the imperative feature for the notification. When the health of the crop is in good stage then the color of the crop is dissimilar but as soon as the crop is going to affected by some harming pathogens, the color transforms automatically. Crop diseases have turned into a dilemma because it may cause a diminution in productivity [3]. In this research work described that goal of identifying foliar diseases in cotton plantations. The primary goal of the developed system has been to identify the existence of pathogens in cotton fillers. Once a disease is identified it has to be automatically classified through further processing of the corresponding image. A survey conducted in one of south zone particular Tamil Nadu at Andhiyur district. During the investigation congregate from the farmers' side gathered the suggestion about the cotton crop diseases details.

In this work organized about the Section 2. Literature survey, Section 3. Motivation, Problem Analysis, Section 4. Material and Methods, Section 5. Comparative studies, Section 6. Result and Discussion, Section 7. Conclusion and Acknowledgment, References.

II. Literature Survey

The proposed work describes about the diagnosis of cotton leaves using various approaches suggesting that the various implementation ways as illustrated and discussed below. Hui Li et al., in the year 2011 has been implemented the Web-Based Intelligent Diagnosis System for Cotton Diseases Control system the author proposed a BP neural network for his system.

A research scheme was designed for the system test, in which 80 samples, including 8 main species of diseases, 10 samples in each sort were included. The result showed the rate of correctness that system could identify the symptom was 89.5% in average, and the average running time for a diagnosis was 900ms [4].Yan Cheng Zhang et al., (2007) proposed fuzzy feature selection approach - fuzzy curves (FC) and fuzzy surfaces (FS) – to select features and classification of cotton disease levels. [5].

Syed A. Health et al., In this research work discussed about the automated system that can identify the pest and disease affecting parts such as cotton leaf, boll or flower. In this work proposed a CMYK based image cleaning technique to remove shadows, hands and other impurities from images. The outcomes are tested over a database consisting of 600 images to classify the presented image as a leaf, boll or flower [6].

Bernardes A. A. et al., (2011) proposed method for automatic classification of cotton diseases through feature extraction of leaf symptoms from digital images. Wavelet transform energy has been used for feature extraction while SVM has been used for classification. The image set of supposedly adulterated leaves was classified within one of the four other sub-classes, namely: MA, RA, AS, and NONE. Finally obtained were: 96.2% accuracy for the SA class, 97.1% accuracy for the MA class, 80% accuracy for the RA class, and 71.4% accuracy for the AS class [7].

Meunkaewjinda. A, et al., (2008). In his work the cotton leaf disease segmentation is performed using modified self organizing feature map with genetic algorithms for optimization and support vector machines for classification. Finally, the resulting segmented image is filtered by Gabor wavelet which allows the system to analyze leaf disease color features more efficiently [8].

Gulhane. V. A et al. (2011) This work described Self organizing feature map together with a back-propagation neural network is used to recognize the color of the image. Finally find out the classification of the cotton diseases [9].

Viraj A. Gulhane. e tal., (2012).This proposed work addresses about the disease analysis is possible for the cotton leaf disease recognition, the analysis of the various diseases present on the cotton leaves can be effectively detected in the early stage before it will injure the whole crops, initially we can be able to detect three types of diseases of the cotton leaves by the methodology of Eigen feature regularization and extraction technique. In this method 90% of detection of Red spot i.e. fungal disease is detected, it is most dangerous disease; it can highly affect the productivity of the cotton crop in more extent. And if it detects in early stage we can say that, we able to make better manufacture [10].

Qinghai He et al., (2013). In this paper the author described RGB color model, HIS color model, and YCbCr color model for extracting the injured image from cotton leaf images were developed.. The ratio of damage (γ) was chosen as feature to measure the degree of damage which caused by diseases or pests. In this work shows the comparison of the results obtained by implementing in different color models, the comparison of outcomes shows good accuracy in both color models and YCbCr color space is considered as the best color model for extracting the damaged image [11].

III. Motivation

This research work address on solving various problems like boosting up the precision rates and diminish the error rates using the Proposed Enhanced PSO which make use of Skew divergences to calculate the features correctly from the image.This method increases the accuracy and reduce the information gap to farmers. Creating a complicated agricultural environment to support the farmers to easily identify the diseases and get control of it using the Pest Recommendation module.

- Deployed the automatic disease classification processes using advanced Data mining and Image processing techniques.
- Augment the profit and safety of the farmer's life and diminish their burden.
- Time consuming (less).
- Enhance the economic status of our country.

Problem Credentials

- Ancient days crop disease identification process through the laboratory condition.
- However, this requires continuous monitoring of experts which might be prohibitively expensive in large farms.
- Further, in some developing countries, farmers may have to go long distances to contact experts, this makes consulting experts too expensive and time consuming.
- Existing learning techniques discussed yields low precision rates, high dimensionality, identification of disease consumes more time.
- The basic problems regarding high error rate and low accuracy, a fast and accurate recognition and classification of the diseases is required by inspecting the infected leaf spot images and identifying the severity of the diseases.

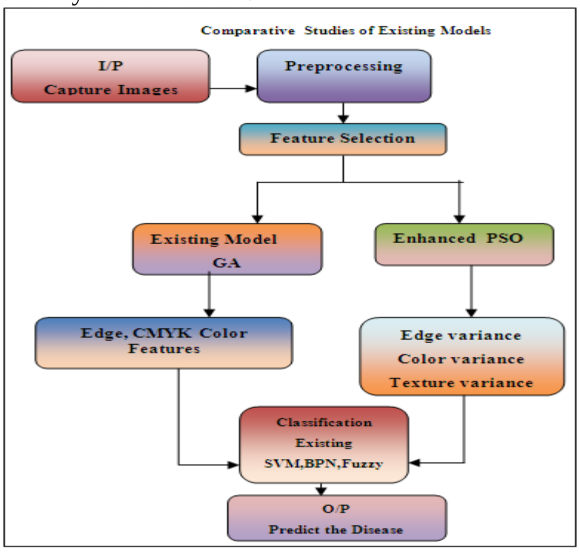

Fig 1: Architecture diagram flow for Existing Classifiers and Proposed features models

This work focuses on classification approach with a proposed feature selection has been detected to identify six types of diseases.In this work 270 images has been used to train and

120 images are tested and finally the performance evaluation of each image is obtained.

Second,In this work classification has been performed using the existing classifiers like SVM, BPN, Fuzzy to investigate the results of cotton leaf disease identification. The accuracy of this system has been evaluated and compared.

First, In this work subset of feature selection has been used in feature extraction of cotton leaf disease like GA with Edge, CMYK color features and *Proposed EPSO Feature extraction method has been used to statistically analyze for the affected part of the poission distributions are* like (Edge, color, texture variance features). After that score level fusion method has been used in combination-based method is like the product rule, sum rule are often used to determine the final score. Matching score-level fusion which combines the matching scores from the individual matchers of 16 *16 block vise (JFV) feature variance is calculated by the affected part of the leaf region. The following method has been used to increase the accuracy rate from existing features.

A. Genetic algorithm

Genetic algorithm (GA) is a class of optimization procedures inspired by the biological mechanism of reproduction. In the past, it has been used to solve various problems including target recognition [12, 13], object recognition [14,15], face recognition [16], and face detection/verification [17]. GA operates iteratively on a population of structures, each one of which represents a candidate solution to the problem at hand, properly encoded as a string of symbols (e.g., binary). A randomly generated set of such strings forms the initial population from which the GA starts its search. Three basic genetic operators guide this search: selection, crossover, and mutation. In this work existing GA has been used for randomly feature selection subset with edge features, color CMYK feature techniques. Then analyzed the best fitness of the feature vector to classify the diseases. Due to gain the optimal result.

B. Proposed Particle Swarm Optimization

The process of PSO algorithm in finding optimal values follows the work of this animal society. Particle swarm optimization consists of a swarm of particles, where particle represents a potential solution [18]. In this work proposed EPSO feature selection is performed using Skew divergences of (Edge, color, texture Variance) features that helps to identify the diseases matching pixels more randomly. Finally the best matching of the features is obtained to classify the diseases; the final outcome is the optimal solution.

C. *Support Vector Machine Stratagem*

The goal of SVM is to determine a suitable hyperplane with maximum margin which can be computed as an optimization problem [19]. In this investigation SVM has been used to test the performance of cotton leaf disease data sets to classify the six types of diseases. Finally, the obtained results have been compared to evaluate the existing features.

D. Fuzzy method

This approach affords a way to translate a linguistic model of the human thinking process into a mathematical framework for developing the computer algorithms for computerized decision-making processes. The theory has grown very quickly [20, 21, 22, 23, and 24]. In this paper we analyze the possibility of identifying the correct diagnosis using the present fuzzy algorithm.

E. Feature Selection

For classical pattern recognition techniques, the patterns are generally represented as a vector of feature values. The feature selection can have a significant impact on the competence of the consequential classification algorithm [25].

The vital role of feature selection techniques utilized in image processing, pattern matching, data mining environment. The most significant purpose of feature selection is to reduce the number of features used in classification while maintaining acceptable classification accuracy. Low discriminatory features are eliminated, leaving a subset of the original features which retains adequate information to discriminate well among classes. Several search algorithms have been used for feature selection. GA has attracted more and more attention in the feature selection area [26]. In this work features selection has been used to reduce the dimensionality and gain the optimal solution, at the same time reduce the computational complexity.

Enhance Particle Swarm Optimazation based Feature Extraction Method (EPSO)

Enhanced Particle Swam Optimization using the Skew divergence method is applied for feature extraction from diseased cotton images. Feature extraction is performed by splitting the input image into pixels value, then set the color variance and quantization value of edge detector. Existing method works only with canny edge detector and color splitting; it will not check the individual pixel wise or block wise of color variance and text variance. Initially simple edge detection is carried out and blocks with edge pixels inside are judged into the structural category. Then, the color variance is calculated in the remaining blocks. Find the variation across the edge with canny edge detector and color splitting methods. Variations in the gray level in a region in the neighborhood of a pixel are a measure of the texture. Then calculate the feature level fusion to combine the Edge, color and texture features sets after normalization in order to yield a joint feature vector (JFV). Instead of using GA for selection of the best features in the feature vector we used proposed EPSO to select the best parameters from both global and local features results. Initially select the feature vectors for training; we define the decision function (W) to classify the feature vectors W, based on decision function. We classify the training samples into -1 or +1. If the objective or decision function f (W) is greater than zero, then we define the class label as +1 otherwise it is considered as class label of -1. Finally the regions are classified by using the SVM classifier.

Enhanced Particle Swam Optimization (EPSO)

Input: Acquisition of segmented leaf images

Output: Feature extraction result
Split (SI)
Initialize =2000
Set
Perform classification (Cv,Ev)
Existing color variance
Calculate color_var

$$C_v = \sum_{y=1}^{S}\sum_{x=1}^{S}\left[\left(R_{xy}-\bar{R}\right)^2+\left(G_{xy}-\bar{G}\right)^2+\left(B_{xy}-\bar{B}\right)^2\right]$$

Where,

$$\bar{R}=\frac{1}{s^2}\sum_{y=1}^{S}\sum_{x=1}^{S}R_{xy}\ ,\bar{G}=\frac{1}{s^2}\sum_{y=1}^{S}\sum_{x=1}^{S}G_{xy}\ ,\bar{B}=\frac{1}{s^2}\sum$$

Proposed Calculate color_var CDOV (Color divergence oriented variance)

$$C_{v1}=\sum_{y=1}^{S}\sum_{x=1}^{S}\left[\left(R_{xy}-\bar{R}\right)^2\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$C_{v2}=\sum_{y=1}^{S}\sum_{x=1}^{S}\left[\left(G_{xy}-\bar{G}\right)^2\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$C_{v3}=\sum_{y=1}^{S}\sum_{x=1}^{S}\left[\left(B_{xy}-\bar{B}\right)^2\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where,

$$\bar{R}=\frac{1}{s^2}\sum_{y=1}^{S}\sum_{x=1}^{S}R_{xy}\ ,\bar{G}=\frac{1}{s^2}\sum_{y=1}^{S}\sum_{x=1}^{S}G_{xy}\ ,\bar{B}=\frac{1}{s^2}\sum$$

Here Rxy be the color value of the x and y coordinates that is x is the horizontal and y be the vertical axis value R¯ be the value of color variance found from the original values of the image for red, similarly we calculate the blue and green values also .Instead of calculating color variation for RGB, each color it becomes less result when compare to after adding the divergence to the values between red, green and blue
Similarly the color variance of the skew divergence between red and blue

$$s_\alpha(C_{v1},C_{v2}) = D(C_{v1}||\alpha C_{v2}+(1-\alpha)C_{v2})$$

Similarly the color variance of the skew divergence between green and blue

$$s_\alpha(C_{v2},C_{v3}) = D(C_{v2}||\alpha C_{v3}+(1-\alpha)C_{v3})$$

Similarly the color variance of the skew divergence between blue and red

$$s_\alpha(C_{v3},C_{v1}) = D(C_{v3}||\alpha C_{v1}+(1-\alpha)C_{v1})$$

Then

Color variance CV=Sα (Cv1, Cv2) + Sα (Cv2, Cv3) +Sα (Cv3, Cv1)…… ……. (4)

In general color variance RGB (Red, Green and Blue) colors on a screen are created by adding light to change a black appearing screen. Measuring the color variance between three colors with two different types of system is used. These two different systems are called additive color and subtractive color. The screen is additive color because light is added to create color. The press uses subtractive color because inks are used to partially block the reflection of light.

But these color variance system are less result when comparing to the variance of the system with color divergence of variance (CDOV) .The color divergence of variance performs better when comparison of variance results with the color such as. In proposed color variance CV=Sα (Cv1, Cv2) + Sα (Cv2, Cv3) +Sα (Cv3, Cv1) are calculated additionally when comparing to the existing system.

Calculate edge_var (Ev, El)
Do canny_sobel

a. Gaussian filter noise removal
b. Choose width
c. Grad(SI)
d. A Roberts mask or a Sobel mask can be used

$$|G| = \sqrt{Gx^2+Gy^2} \approx |Gx|+|Gy|$$

e. Find the edge direction

$$\theta = \tan^{-1}\left(\frac{Gy}{Gx}\right)$$

f. Resolve to edge direction
g. Non-maxima suppression
h. Use

Calculate edge variance - EDOV (Edge divergence oriented variance)

𝒗^(e^)=𝒗^1(𝒖|e^(x,y)<0))+𝒗^2(𝒖|e^(x,y)>0))…………… (5)

Edge variation measuring the variance values between the different images.In existing edge variance only measuring the variance of the edges between the images. After calculation of the edge variance between the edge points, perform the edge points with skew divergence becomes a more efficient result variation than the normal variation of the edge points

$$s_\alpha\left(\hat{v}_1 \mathrm{u}\left(\hat{e}_{(x,y)}\right),\hat{v}_2 \mathrm{u}\left(\hat{e}_{(x,y)}\right)\right) = D\left(\hat{v}_1 \mathrm{u}\left(\hat{e}_{(x,y)}\right)||\alpha\hat{v}_2 \mathrm{u}\left(\hat{e}_{(x,y)}\right)+(1-\alpha)\hat{v}_2 \mathrm{u}\left(\hat{e}_{(x,y)}\right)\right)$$

Where, α is the skew parameter

Where $_e$^(x, y) = 0 (detected edge location) & V^1, V^2(Edge variance)
Calculate tex_var (Tv) (TDOV)

$$T_v = \frac{1}{m\times n}\sum_{s=-2}^{2}\sum_{t=-2}^{2}|g(x+s,y+t)-\bar{g}|^2$$

Where

$$\bar{g} = \frac{1}{m \times n} \sum_{s=-2}^{2} \sum_{t=-2}^{2} g(x+s, y+t)$$

In total variation also we consider the skew divergence between the x, y points

$s_\alpha(x,y) = D(x||\alpha y + (1-\alpha)y)$……………… (6)

Calculate feature level fusion
Do joint feature vector (JFV) ()
Calculate score level fusion

i. Apply Sum rule= Cv+V^(e^)+Tv

j. Apply product rule=Cv.V^(e^).Tv

Classification using EPSO-SVM

k. Feature selection using PSO

i. Initialize the particle's best known position to its initial position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$

ii. Parameter selection

iii. For each particle evaluate the fitness value

iv. If $(f(\mathbf{p}_i) < f(\mathbf{g}))$ update the swarm's best known position: $g \leftarrow p_i$

v. Set pbest as gbest g

vi. Update particle values

- Update the particle's velocity: $v_{i,d} \leftarrow \omega\, v_{i,d} + \varphi_p\, r_p\, (p_{i,d}-x_{i,d}) + \varphi_g\, r_g\, (g_d-x_{i,d})$ // update the particle velocity to choose other particles
- Update the particle's position: $x_i \leftarrow x_i + v_i$
- If $(f(\mathbf{x}_i) < f(\mathbf{p}_i))$ do:
- Update the particle's best known position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$
- If $(f(\mathbf{p}_i) < f(\mathbf{g}))$ update the swarm's best known position: $\mathbf{g} \leftarrow \mathbf{p}_i$
- best global solution

vii. Get best as the optimal solution

viii. Obtain optimized parameters and feature selection

ix. Else

x. Goto step i

Input: Edge detected feature vector as input data point for SVM classification
Output: Classification result and prediction

Procedure Muticlass_SVM ( )
Begin
Initialize C=0
Get input file W for training
Read the number of input feature vectors W from the edge point result
Procedure Muticlass_SVM ( )
Begin
Initialize C=0
Get input file for training Read the number of input feature vectors W from the result
Decision function
If Xi*W+b=0 for is the first class
Else
For Xi *W+b=1 is the first class
The predicted result for (i=1… n) number of features

Display the result.

VI. Result and Discussion

The cotton leaf disease dataset was collected from south zone of Tamil Nadu at Andhiyaur district in the month of June 2012. Surabi varites from maximum incidence was recorded during upto one week the diseases images 270 data sets collected from the field. Directly met the farmers and get the suggestion from them. In this study dataset captured and collected by camera mobile (Nokia) in the above said areas.Six types of diseases such as Bacterial Blight, Fusariumwilt, Leaf Blight, Root Rot, Micronutrient, Verticillium wilt were used for analysis.

First, Initialize the training database; resize the images 150*150 size. Next Edges detected by using Canny with Sobel techniques are combined, finally find out edge features. Mean (or) average filter was used to remove the noise. Features extracted from the test image (new features) are compared with the features available in the training set (features). RGB2 CMYK color features are extracted and stored in GG, RGB2 IND features are extracted and stored in II.Rgb2 gray features are extracted and stored. The histogram was obtained and stored in the variable Imgh1.Here skew divergence distance measurement has been used to find out the color, Edge and texture features.

The Existing Algorithms BPN, Fuzzy logic and SVM Classifiers with Edge, CMYK Color splitting model features has been combined and tested with our own collected cotton leaf data sets. In this investigation, the existing models have been analyzed to have low accuracy rates and error rates are augmented. The proposed Skew divergences method given increased accuracy rate.

Results

Table 1.Performance Evaluation of Edge Feature with SVM, BPN, Fuzzy Classifiers in diseases vise

Class	SVM			BPN			Fuzzy		
Diseases Name	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity
Bacterial blight	0.61	1.00	0.93	0.61	1.00	0.93	0.80	1.00	0.97
Fusarium wilt	0.62	0.65	0.91	0.62	0.65	0.91	0.74	0.85	0.93
Leaf blight	0.67	0.60	0.93	0.67	0.60	0.93	0.70	0.70	0.93
Root rot	0.78	0.70	0.96	0.82	0.70	0.97	0.82	0.70	0.97
Micronutrient	0.62	0.80	0.89	0.65	0.85	0.90	0.71	0.85	0.92
Verticillium wilt	1.00	0.50	1.00	1.00	0.55	1.00	1.00	0.65	1.00
Accuracy		0.68%			0.70%			0.78%	

The Results from table 1 show that Edge features Extraction method when used with SVM, BPN and Fuzzy classifiers gives the accuracy of only 68%, 70%, 78%.

Table2. Performance Evaluation of Edge Feature with CYMK Color Feature with SVM, BPN, Fuzzy Classifiers in diseases vise

Class	SVM			BPN			Fuzzy		
Diseases Name	Precision	Sensitity	Specificity	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity
Bacterial blight	0.69	1.00	0.95	0.73	1.00	0.96	0.80	1.00	0.97
Fusarium wilt	0.65	0.75	0.91	0.73	0.80	0.93	0.74	0.85	0.93
Leaf blight	0.67	0.60	0.93	0.70	0.70	0.93	0.70	0.70	0.93
Root rot	0.82	0.70	0.97	0.82	0.70	0.97	0.82	0.70	0.97
Micronutrient	0.68	0.85	0.91	0.71	0.85	0.92	0.71	0.85	0.92
Verticillium wilt	1.00	0.60	1.00	1.00	0.65	1.00	1.00	0.65	1.00
Accuracy		0.73%			0.77%			0.78%	

The Results from table 2 show that Edge with CYMK Features Extraction method when used with SVM, BPN and Fuzzy classifiers gives the accuracy of only 73%, 77%, 78%.

Table 3. Performance Evaluation of Edge Feature with GA with SVM, BPN, Fuzzy Classifiers in diseases vise

Class	SVM			BPN			Fuzzy		
Diseases Name	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity
Bacterial blight	0.81	1.00	0.97	0.81	1.00	0.97	0.81	1.00	0.97
Fusarium wilt	0.81	0.85	0.96	0.81	0.85	0.96	0.81	0.85	0.96
Leaf blight	0.73	0.80	0.94	0.73	0.80	0.94	0.73	0.80	0.94
Root rot	0.88	0.70	0.98	0.88	0.70	0.98	0.88	0.70	0.98
Micronutrient	0.75	0.90	0.94	0.75	0.90	0.94	0.78	0.90	0.95
Verticillium wilt	1.00	0.70	1.00	1.00	0.70	1.00	1.00	0.75	1.00
Accuracy		0.81%			0.81%			0.82%	

The Results from table 3 show that Edge features with GA feature Extraction method when used with SVM, BPN and Fuzzy classifiers gives the accuracy of only 81%,81%,82%.

Table 4. Performance Evaluation of Edge Feature with CMYK Color feature combined with GA Feature Selection using SVM, BPN, and Fuzzy Classifier in diseases vise

Class	SVM			BPN			Fuzzy		
Diseases Name	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity
Bacterial blight	0.81	1.00	0.97	0.83	1.00	0.97	0.83	1.00	0.97
Fusarium wilt	0.81	0.85	0.96	0.81	0.85	0.96	0.81	0.85	0.96
Leaf blight	0.73	0.80	0.94	0.76	0.80	0.95	0.76	0.80	0.95
Root rot	0.93	0.70	0.99	0.94	0.75	0.99	0.94	0.75	0.99
Micronutrient	0.79	0.95	0.95	0.83	0.95	0.96	0.83	0.95	0.96
Verticillium wilt	1.00	0.75	1.00	1.00	0.80	1.00	1.00	0.80	1.00
Accuracy		0.83%			0.85%			0.85%	

The Results from table 4 show that Edge with CYMK Color features and GA feature Extraction method when used with SVM, BPN and Fuzzy classifiers gives the accuracy of only 83%, 85%, 85%.

Table 5. Performance Evaluation of Edge Feature with Color Texture features Combined with a GA feature selection With SVM, BPN, Fuzzy Classifiers in diseases vise

Class	SVM			BPN			Fuzzy		
Diseases Name	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity
Bacterial blight	0.88	1.00	0.98	0.88	1.00	0.98	0.89	1.00	0.98
Fusarium wilt	0.82	0.90	0.96	0.86	0.90	0.97	0.86	0.90	0.97
Leaf blight	0.76	0.80	0.95	0.85	0.85	0.97	0.89	0.85	0.98
Root rot	0.94	0.75	0.99	0.94	0.85	0.99	0.95	0.90	0.99
Micronutrient	0.83	0.95	0.96	0.83	0.95	0.96	0.90	0.95	0.98
Verticillium wilt	1.00	0.80	1.00	1.00	0.80	1.00	1.00	0.90	1.00
Accuracy		0.86%			0.89%			0.91%	

The Results from table 5 show that Edge with Color, texture features and GA feature Selection method when used with SVM, BPN and Fuzzy classifiers gives the accuracy of only 86%,89%, 91%.

Table 6. Performance Evaluation of Edge Feature with Edge Feature with Color Texture features Combined with a PSO feature selection With SVM, BPN, Fuzzy Classifiers in diseases vise

Class	SVM			BPN			Fuzzy		
Diseases Name	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity	Precision	Sensitivity	Specificity
Bacterial blight	0.89	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00
Fusarium wilt	0.86	0.90	0.97	0.87	1.00	0.97	0.87	1.00	0.97
Leaf blight	0.89	0.85	0.98	0.89	0.85	0.98	0.94	0.85	0.99
Root rot	0.95	0.90	0.99	0.95	0.90	0.99	0.95	0.95	0.99
Micronutrient	0.90	0.95	0.98	0.90	0.95	0.98	0.90	0.95	0.98
Verticillium wilt	1.00	0.90	1.00	1.00	0.90	1.00	1.00	0.90	1.00
Accuracy		0.91%			0.93%			0.94%	

The Results from table 6 show that Edge with Color,texture features and PSO feature Selection method when used with SVM, BPN and Fuzzy classifiers gives the accuracy of only 91%, 93%,94%.

V.Conclusion

In this work the new feature extraction method has been proposed using Enhance PSO with Skew divergence technique.The obtained features has been classified using SVM, BPN and Fuzzy classifiers. The Experimental result has been obtained by testing all the existing and proposed method with our own dataset. The results obtained showed higher accuracy when our proposed EPSO algorithm is combined with fuzzy classifiers.When comparing all the results, the experimental results clearly shows that. Our proposed EPSO feature method gives better performance when combined with fuzzy classifier. The accuracy of 94% is obtained using our proposed EPSO feature extraction which extracts Edge, Color and texture features and a feature vector is constructed using Skew divergence distance methods. The performance of Fuzzy classifier is compared with SVM and BPN classifiers.

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Bacterial Blight disease

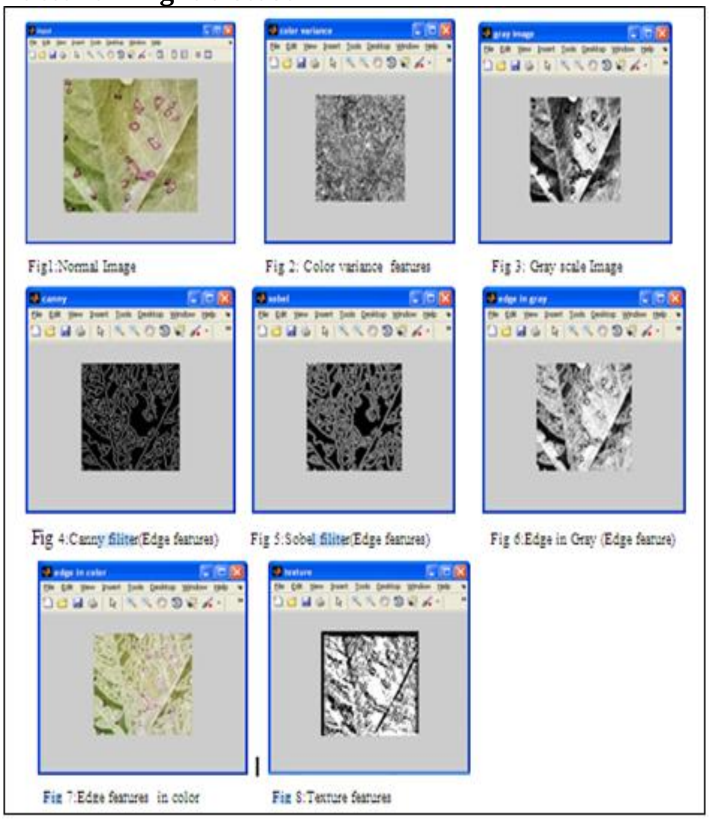

Fig1:Normal Image; Fig 2: Color variance features; Fig 3: Gray scale Image; Fig 4:Canny filiter(Edge features); Fig 5:Sobel filiter(Edge features); Fig 6:Edge in Gray (Edge feature); Fig 7:Edge features in color; Fig 8:Texture features

Fig 2: Enchance the color,Edge,texture feature a extraction process of Bacterial Blight disease.

Micro Nutrient Disease

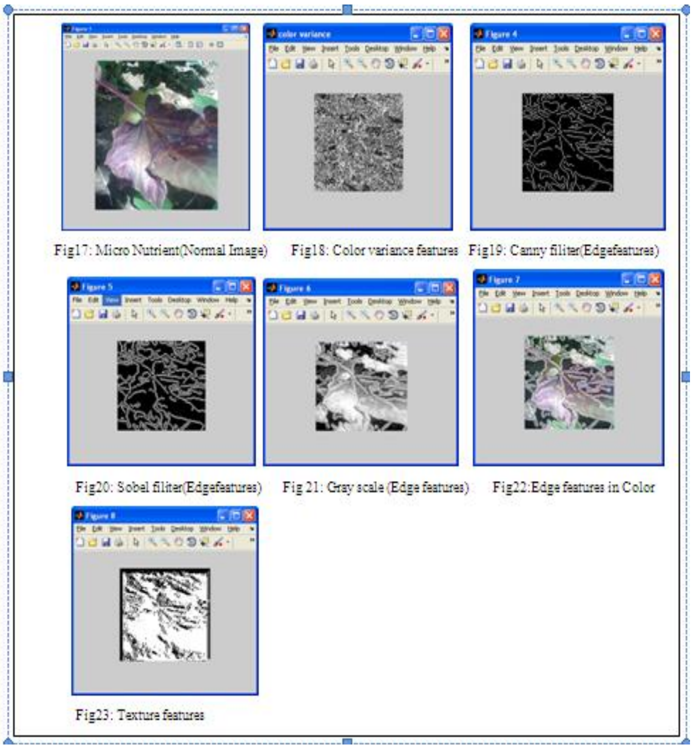

Fig17: Micro Nutrient(Normal Image); Fig18: Color variance features; Fig19: Canny filiter(Edgefeatures); Fig20: Sobel filiter(Edgefeatures); Fig 21: Gray scale (Edge features); Fig22:Edge features in Color; Fig23: Texture features

Fig 3: Enhance the color, Edge, texture feature a extraction process of Micro Nutrient disease

Root rot Disease

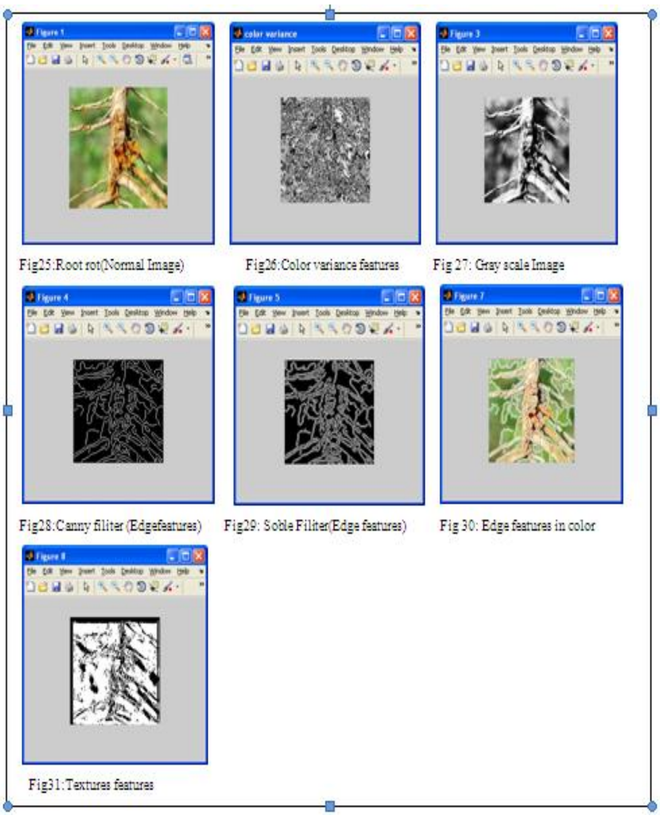

Fig25:Root rot(Normal Image); Fig26:Color variance features; Fig 27: Gray scale Image; Fig28:Canny filiter (Edgefeatures); Fig29: Soble Filiter(Edge features); Fig 30: Edge features in color; Fig31:Textures features

Fig 4: Enchance the color, Edge, texture feature a extraction process of Root rot disease

Fusarium Wilt Disease

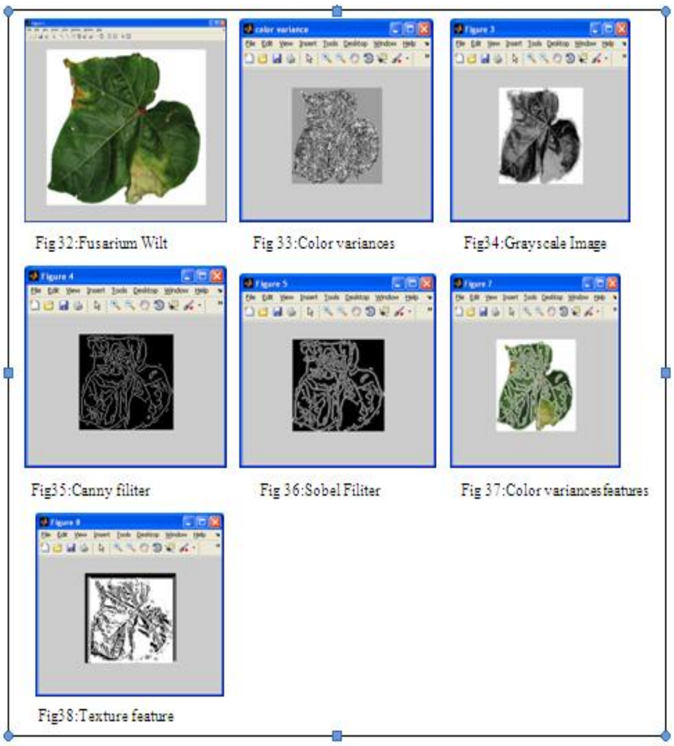

Fig 32:Fusarium Wilt; Fig 33:Color variances; Fig34:Grayscale Image; Fig35:Canny filiter; Fig 36:Sobel Filiter; Fig 37:Color variances features; Fig38:Texture feature

Fig 5: Enchance the color, Edge, texture feature a extraction process of FusariumWilt disease

Leaf Blight

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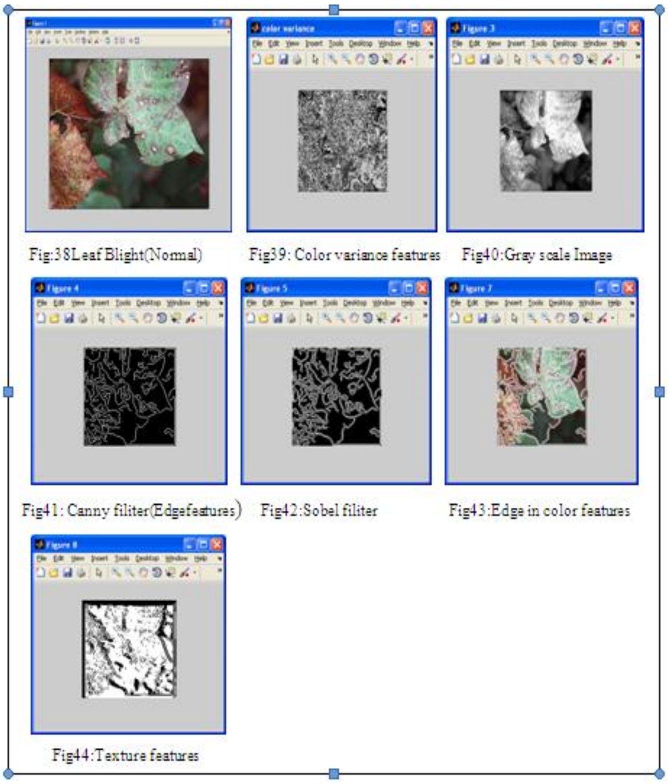

Fig 6:: Enchance the color, Edge, texture feature a extraction process of FusariumWilt disease.

Veritcelium Wilt

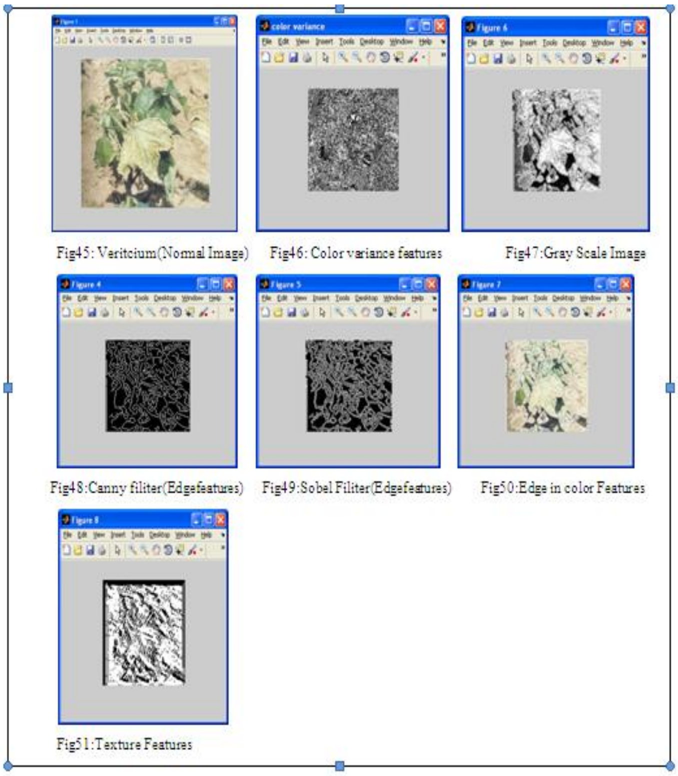

Fig 7: Enchance the color, Edge, texture feature a extraction process of Veritcelium Wilt disease

Figure 2, 3, 4, 5, 6, 7 Represent the EPSO Feature Extraction Method used to analysised the six types diseases in cotton leaf images.