Detection & Identification of Rice Leaf Diseases using Multiclass SVM and Particle Swarm Optimization Technique

Prabira Kumar Sethy, Nalini Kanta Barpanda, Amiya Kumar Rath

Abstract*: In India the economic, political and social stability depend directly as well as indirectly on the annual production of rice. The income of hundreds of millions of people depends only on rice production and nothing else. However, as per the report of International Rice Research Institute (IRRI), 37% of the rice yield loss is due to diseases. In this consequence, the farmer can take care of crop on-time with apposite treatment. The disease detection and identification in large field through automatic technique is really useful as it reduces the work, time and cost for observation and evaluation of disease symptoms. This paper reports a novel approach for detection and identification of rice leaf diseases by K-means clustering, multi class SVM and PSO. Gray Level Co-occurrence matrix (GLCM) is used for feature extraction. The disease classification is done using SVM classifier and the detection accuracy is improved by optimizing the data using PSO. The investigational outcomes exhibit the performance of planned methodology in terms of accuracy of disease detection is 97.91%. However, in case of K-Nearest Neighborhood (KNN), Feed Forward neural network (FFNN) and SVM is 77.96%, 85.64% and 90.56% respectively.

Index Terms: Disease detection, FFNN, GLCM, Image processing, KNN, Particle Swarm Optimization, SVM Classifier.

I. INTRODUCTION

As a crop, rice is the most significant humanoid nutrition in the world, which can be fed directly than any other harvest. Since, it is becoming increasingly important nutrition across Asia where upon most of the deprived people are living.

For developing country like India, agricultural productivity is the fountainhead of economic growth. Chronologically, the main objective of farming is to yield and feed food to the nation. So, these leaf diseases in any forms in rice crop tends to cause reduction in quality, yield and fiscal progression respectively. Therefore, looking to the current farming arena, instead of watching the crop through the naked eyes by designated specialist where it does needs lot of efforts to implicate. Hence, as a result the automation essentiality of leaf disease identification and its management has turned the pen paper calculation into the reality of high magnitude. Therefore, this work can describe towards the finding of solution for minimizing the cost by avoiding manual monitoring and expert requirement for automatic detection of leaf diseases in a large area [1]. The recognition and the cataloguing of the disease at each stage will be quicker using soft computing techniques. This is a best practical application of image processing in agricultural industry. The image processing techniques are used for automatic recognition of crop diseases and it takes less time, fewer efforts and more precise [2]. This is indeed the sightsees result of phase by phase adapted techniques which encompasses and signifies some form of research exposure for finding the plant leaf diseases of rice crop. Segmentation of image is a process of grouping or separating of the image into a different part. At present, different image segmentation methods are used to segregate and exhibit as an individual object. Here in this article for automatic green foliage of plant disease identification, K-means colour image segmentation technique which is an effective tool has been used to segment the diseased part in a proper way. So, from that segmented image essential information can be extracted using different feature extraction techniques. In this paper, GLCM feature extraction technique is considered.

The image processing & pattern recognition are the one of the intricate and significant processes ever involved in the process of image classification. Hence, machine learning can be the best solution for the segment organization, which is being used to allocate a class for the group of unsystematic data. In this article optimization-based classification method is achieved.

Evolutionary computing was first introduced in the 1960s by I. Rechenberg. His idea was then taken forward by other researchers. Occasionally evolutionary changes seem inconsequential at a first look, which indeed maintains a crucial part in the natural selection and classes subsistence. Stochastic optimization problem can be resulted using PSO algorithm which can be fit from the field of evolutionary algorithms. Generally, it can solve by following population-based hunt procedure which is based on the replication of the communal actions of birds inside a group. The preliminary objective is to replicate explicitly the beautiful and erratic composition of a bird group, aiming to discover patterns which directs the capability of birds to hover concurrently and abruptly shifting of path by reforming in a best structure [3]. Each particle in the population are randomly distributed in the search space and also represented as a solution. Each particle is having its velocity and position in the current population, which shows the current solution available in search space. PSO is a fastest growing field in every area and also a very powerful technique which can be utilized efficiently in the different field of image processing. When PSO is

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combined with other image processing technique such as segmentation, thresholding, enhancement, classification etc. performance of the method is significantly increased [4].

Some benefits of Particle Swarm Optimization algorithm are as follows:

- PSO is an inherently continuous optimization algorithm which optimizes variables efficiently.
- A huge quantity of variables can be managed concurrently.
- Ability of searching from a large test group of price surface.
- Ability to modify variables with highly composite cost surfaces.
- Provides manifold optimum solutions. So, dissimilar image dissection yields can be collected concurrently.

The basic steps of Particle Swarm Optimization Algorithm as shown in the Fig. 1 are as follows:

- Initialize any arbitrary location and speed set a value of elements.
- Estimate the appropriateness of individual element.
- Estimate for gbest.
- Estimate for pbest.
- Update velocity & position.
- Estimate the appropriateness for new location.

Upon fulfilling the condition, gbest is the solution else repeat the above steps.

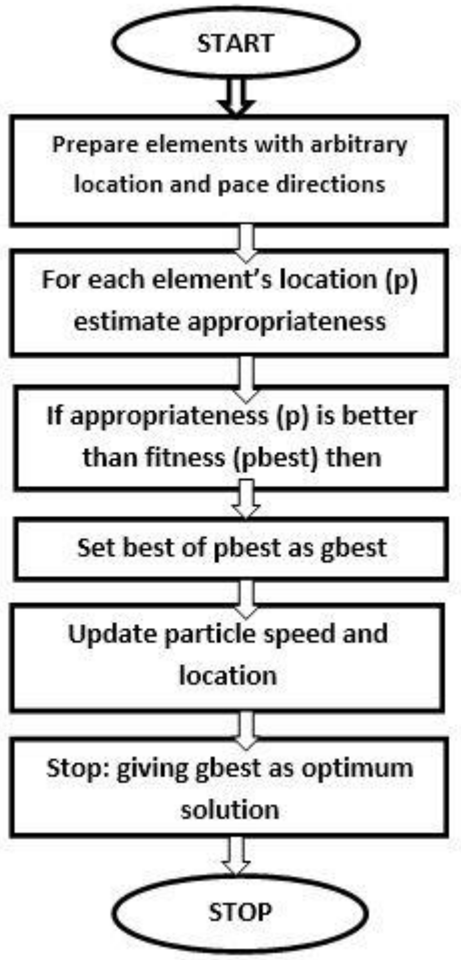

Fig.1: Steps of Particle Swarm Optimization Algorithm.

II. RELATED WORK

This section describes different works that have been already done by researchers for detection and identification of plant diseases based on image processing techniques.

Savita N. Ghaiwat et. al. [1] focused on dissimilar types of technique cataloguing on identification of green foliage of plant. For class estimation, k-nearest-neighbor technique is the best and unpretentious method, which may be preferable for a given ground of specimen. Sometimes, it is hard to control optimal parameters using SVM, if the training data cannot geometrically distinguishable then this may be considered as one of its downsides. Vijai Singh and Prof A. K. Misra [5], denotes a review on dissimilar automatic detection techniques like image segmentation for leaf disease classification and many more. Here for the best collection and classification of result genetic algorithm can be employed. Here the group of people also suggested that to improve the rate of recognition different classification processes are used like ANN, Bayes classifier, Fuzzy Logic and hybrid algorithms. Mrunalini R et. al. [6], anticipated various methods of plant disease categorization and detection of how the plants are affected. The author presented the contraption-based erudition and recognition scheme will be more effective in comparison to others since it consumes energies, time and expenses as well. Here the scholars presented a frame for the cluster extraction using the RGB concomitant method. However, for an instinctive programmed for recognition of leaf disease neural network is the best and suitable method. It supports precise identification of affected leaf disease which looks to be the worthwhile approach towards finding the solutions for stem and root diseases by putting less efforts in terms of computation. S. W. Zhang, Y. J. Shang and L. Wang [7], recommended a scheme using KNN classifier for plant disease identification where the developed algorithm can work for five dissimilar varieties of maize diseases. Here they have taken the help of various temporal parameters to produce a feature set like tint level (using colour moment method), outline and spatial based attributes. Also, to pull out the outline of shape they have taken the help of some other feature parameters like feature unconventionality, chubbiness, intricacy, and figure are to be assessed respectively to get a precise form of desired result. Simultaneously we need to calculate for the spatial based feature like energy, distinction, immobilization moment, relationship and part of degeneration. S. Arivazhagan et al. [8], presented schemes which is having four key steps for different disease identification they are first, an input RGB colour transformation model image is to be used, second masking from an explicit beginning mark point, third viridescent dots to be detached which is followed by segmentation process, and fourth texture information are to be calculated to get the useful sectors for the classification and identification of the precise disease. The approaches sturdiness has been verified by taking near about 500 investigational comments from the record. Bindushree H. B, Dr. Sivasankari G. G [9], have presented an idea using auto-program classification of green foliage of plant diseases taking the help of image processing techniques. Their proposed methodology consists of three stage i.e. First is segmentation of disease affected area, the second is its extraction using GLCM and the third is classification using SVM. Anand H. Kulkarni et al. [10], proposed an accurate method of early plant diseases recognition, by means of artificial neural network (ANN) and assorted image dispensation techniques. Here for disease classification ANN classifier along with Gabor filter method for feature extraction is used. It ensures about improved outcomes having the rate of recognition up to 91%. Sabah Bashir, Navdeep Sharma et al. [11], proposed a clustering scheme of disease detection for the orchard apple using a real technique like K-mean. By considering Color and texture features, it is possible to classify different plant diseases. In near future, it is very much apparent that for the purpose of plant disease classification, some different form of techniques is approached i.e. K-means clustering and Bayes classifier. Sanjeev S. Sannakki et al. [12], proposed system aims to classify the disease found on leaves of the grape plant using Neural Network. Gray Level Co-occurrence Matrix (GLCM) and spatial gray-level dependence matrices (SGDM) feature extraction techniques are used. They have considered two kind of grape leaves disease in their experiments i.e., downy mildew and powdery mildew. Piyush Chaudhary et al. [13], suggested a system of disease spot dissection in green foliage of plant using image processing techniques. Here this detection has done by likening the consequence of color space like HSI, CIELAB, and YCbCr. Median filter is the best filter to use for Image Soothing. Finally, Otsu technique is applied on a shaded element to find out the threshold diseased spot calculation. Using CIELAB colour model the background noise is removed. Pranjali B. Padol & Prof. Anjali A. Yadav et al. [14], approached a method for detection grape leaf disease using SVM classifier. They have used thresholding and Gaussian filtering for image pre-processing. For image segmentation, K-means clustering and GLCM method are used for texture feature extraction. In their paper, Linear Support Vector Machine (LSVM) is used for classification of leaf disease and the system gives 88.89% average accuracy for both Downey and Powderly grape leaf disease. Smita Naikwadi, Niket Amoda et al. [15], Plant disease identification can be done through histogram matching. Since, disease seems on the green foliage of plant therefore, using edge detection technique and colour feature which help us to find out the corresponding disease through the histogram matching. Using slice segregation method for the training development which has the ability to separate the individual films of the sample into primary spectrums like red, green, and blue layers. For the detection of ends of the incrusted images edge detection technique can be employed. For the evolvement of the colour co-occurrence texture investigation GLCM method can be useful. K. Muthukannan et al. [16], recommends different forms of Neural Network techniques which were duly tested by taking several parameters successfully for two different infected leaf image catalogues for the phaseolus vulgaris and momordica charantia. Out of all sorting techniques feedforward neural network (FFNN) analysis approach offers healthier and improved upshots. Prabhjeet Kaur and Dr. Sanjay Singla [17], design a prototype for plant leaf disease detection. Histogram equalization method is used to reduce the noise level found in the input image and by the help of K-means segmented method, the disease infected area will be segmented. Then statistical parameters are extracted as features and by using SVM final disease type will be declared. The summary of related work is illustrated in Table 1.

III. LIMITATION OF EXISTING WORK

The limitation of existing work are as follows:

- Still, the current execution needs more intensification and correctness towards the finding of results.
- An exact temporal evidence is highly desirable for an image dissection.
- In contemplation to achieve more correctness record extension is highly desirable.
- Less diseases have been uncovered. Hence, it is highly essential to extend the area of exertion to discover more diseases.
- The causal factors associated with incorrect orderings may be due to- (a) disease indications may fluctuate from shrub to shrub, (b) intensification of topographies is highly needed, (c) exercise samples reuired to foresee the plant disease precisely.

For the bridging of investigation gaps a new-fangled practice is used by means of image segmentation can be suggested for the auto programmed identification as well as cataloguing of green foliage of plant diseases.

The benefits of planned process are as follows:

- Users' involvement is zero at the time of image dissection.
- Enhanced and effective diagnosis.
- Fully automated technique in comparison to others.

For the recognized diseases, it offers natural recycle actions.

IV. MATERIALS AND METHODS

The proposed methodology for disease identification is explained in following sub-sections:

A. Image Procurement

It is the first and foremost step for the initialization of planned procedure. First, take the input leaf image of the rice crop, which has captured by the digital camera. The input image is in primary colour. Then, the primary colour is changed into an apt color space as needed.

B. Image Pre-treatment

In pre-treatment phase, the query image converted to suitable color space i.e. L*a*b color space on which the algorithm is implemented. To extract the required information from the image more efficiently by using image resizing and contrast enhancement image pre-treatment techniques.

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Table 1: Summary of Related Works

No.	References	Goals	Remarks
1	1	Performance analysis of SVM, ANN, Self-organising map, PNN and Fuzzy Logic for plant leaf disease classification	In a neural network, it's difficult to understand the structure of algorithm and to determine optimal parameters when training data is not linearly Separable.
2	5	K-means segmentation method, Genetic Algorithm, SVM	To improve recognition rate in classification process Artificial Neural Network, Bayes classifier, Fuzzy Logic and hybrid algorithms can also be used.
3	6	K-means clustering algorithm with Neural Network for automatic detection of leaves diseases	Artificial Neural Network and Fuzzy Logic with other soft computing technique can be used to classify the crop diseases.
4	7	Thresholding based segmentation with KNN classifier	Further improvement in the plant disease identification rate at various stages, need to increase the training samples and extract the effective features.
5	8	Colour co-occurrence method with SVM classifier	The training samples can be increased and shape feature and colour feature along with the optimal features can be given as input condition of disease identification.
6	9	Gray Level Co-occurrence Matrix (GLCM) for feature extraction and SVM for classification.	Not Available
7	10	Gabor filter for feature extraction and ANN classifier for classification	Recognition rate can be increased.
8	11	Texture segmentation by co-occurrence matrix method and K-means Clustering Technique	Principal component classifier, K-means clustering, and Bayes Classifier can be used to classify various plant diseases.
9	12	Co-occurrence matrix for feature extraction and Feed forward neural network for classification	Instead of K-means, other segmentation techniques can be used to extract the lesion more accurately.
10	13	Median filter is used for image smoothing and threshold can be calculated by applying Otsu method.	Disease spot area can be computed for assessment of loss in agriculture crop. The disease can be classified by calculating dimensions of disease spot.
11	14	The Gaussian filter is used for image de-noising and Linear Support Vector Machine (LSVM) is used for classification of leaf disease.	Design an automated system with the help of embedded system and develop more algorithms technique to improve the detection rate of the classification process.
12	15	The colour co-occurrence texture analysis method was developed through the use of Spatial Gray-level Dependence Matrices.	A better result of detection can be obtained with the large database and advance feature of colour extraction.
13	16	Feed Forward neural network (FFNN), learning vector quantization (LVQ) and radial basis function network (RBF) used for classifications.	Develop hybrid algorithms for achieving better classification result & extract colour features of leaf image for better classification result.
14	17	Particle Swarm Optimization for the optimization of results and SVM for Classification of disease type.	Not Available.

C. K-Means Based Segmentation Method

This step includes the segmentation of an image using K-Means algorithm. It is quite helpful method for an entity recognition using a group of K-classes [18]. The capability of finding the thought-provoking fragment of the source image can be done by curtailing the square summation distance between the equivalent cluster and an entity. In K-Means clustering techniques, the clusters are determined by the groupings

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of pixels having the same value present in an image. Practically, the computational speed of this new image processing technique is very fast as well as gives more accurate output. The input dataset is partitioned into K number of clusters and each cluster is considered by a cluster center which is adaptive by nature. Initially considered values are known as seed points and inputs are also known as data points. Estimation of the distances between the centers, inputs, and allocate inputs to the nearest center is only possible by using K-Means clustering technique.

Following are the steps for K-means grouping:

Step 1: Image confirmation.

Step 2: Image transformation from primary colour space to L*a*b* Colour Space, which helps in the findings of pictorial transformations that present in the primary colour space.

Step 3: Here the colours classification can be done in 'a*b*' Space using K-means. Here single entity occupied and allotted with single location in the space. It helps in finding cluster divisions as by identifying entities from a cluster, which may distant to another in a near proximity. Hence the colour information of 'a*b*' space, can be represented by taking active dot particles with 'a*' and 'b*' values, which return a cluster set of [index, centre].

Step 4: From the results, pixel ordering, and labelling can be render using K-means by maintaining a return index to the corresponding each cluster.

Step 5: Afterwards, the original image is partitioned on the basis its k- number of colour segmentation.

This process has already been implemented in leaf image segmentation of rice crop onto more than one groups having the respective diseases [19]. After the successful implementation K-Means cluster-based segmentation, the percentage of the infected area calculated, and features are extracted.

D. Computing the features using Gray Level Co-occurrences Matrix

Feature extraction plays a vital role in the process of facsimile cataloguing. Hence, GLCM could be an effectual and right resourceful technique for statistical parameter extraction on the basis of texture mining [20]. The image features include Correlation, Entropy, Variance, Homogeneity, Contrast, Energy and Mean are computed as given in equations from (1) to (7). The resulted topographies using the monochrome concentration and positioning can be indicated by the association of active dotted particles whose numerical relatives can be reckoned in Table 2. The graphical representation of extracted feature is shown in Fig.2.

- Correlation is a measure of Gray level linear dependence between the pixels at the specified positions relative to each other. It is a measure of how correlated a pixel is to its neighbour over the whole image.

$$\text{Corelation}\,(f_1) = \frac{\sum_i \sum_j (ij)p(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y} \qquad (1)$$

- Homogeneous scene has high entropy while inhomogeneous scenes have a low first-order entropy. Maximum entropy is reached when all probabilities are equal.

$$\text{Entropy}(f_2) = \sum_i \sum_j p(i,j)\log(p(i,j)) \qquad (2)$$

- The variance is a measure of how far a set of numbers is spread out. It is one of several descriptors of a probability distribution, describing how far the numbers lie from the mean (expected value).

$$\text{Variance}(f_3) = \sum_i \sum_j (i-\mu)^2 p(i,j) \qquad (3)$$

- Homogeneity returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\text{Homogeneity}\,(f_4) = \sum_{i,j=0}^{N-1} \frac{p_{ij}}{1+(i-j)^2} \qquad (4)$$

- Contrast is also called sum of squares variance. This measure of contrast or local intensity variation will favour contributions from $P(i, j)$ away from the diagonal; that is, $i \neq j$. It is a measure of the intensity contrast between a pixel and its neighbour over the whole image.

$$\text{Contrast}(f_5) = \sum_{i,j=0}^{N-1} p_{ij}(i-j)^2 \qquad (5)$$

- Energy returns the sum of squared elements in the GLCM. The range is in [0 1]. Energy is 1 for a constant image.

$$\text{Energy}(f_6) = \sum_{i,j=0}^{N-1} (p_{ij})^2 \qquad (6)$$

- Mean compute the average value of matrix elements.

$$\text{Mean}(f_7) = \sum_{i,j=0}^{N-1} i p_{ij} \qquad (7)$$

E. Optimization of data using Particle Swarm Optimization Algorithm

At times PSO may be wearisome to understand but then again, an unfussy algorithm to use with. On reiterations the closest actual to expected result can be achieved by adjusting the set of variables concurrently. The fundamental of this algorithm is based on by conjuring up a herd of birds approaching and finding an unseen food place whereby chirping and spinning over an area and this constriction form lasts till one of the birds ensues upon the target.

The PSO system serves direct results in the exploration space. On defining the problem using a single particle, the optimization looks and assesses for the aptness by giving some direct solutions for the explorations space. [21].

Here, the method is PSO to optimize large feature dataset to provide an improved set of solutions. By means of dataset optimization, the efficiency and accuracy of the classifier can be upgraded than the existing.

Table 2: Extracted Features Vector Using GLCM.

SI No.	Contrast	Correlation	Energy	Homogeneity	Mean	Standard Dev.	Entropy	RMS	Variance	Smooth-ness	Kurtosis	Skewness	IDM
1	0.52	0.82726	0.81	0.956992	11.42	42.14	1.088	3.194	1523.1	1	17.921	1.8645	255
2	0.453	0.88268	0.741	0.942985	18.26	51.96	1.6572	4.679	2206.1	1	10.582	2.3426	255
3	1.1950	0.76266	0.570	0.931926	25.981	60.49	2.1984	7.044	3429.7	1	7.2729	1.8866	255
4	0.6984	0.91896	0.602	0.955868	35.465	71.82	2.3910	7.347	4946.8	1	4.3601	2.3403	255
5	1.2426	0.68088	0.78	0.939879	12.649	46.03	1.0954	3.338	1823.7	1	16.636	3.0963	255
6	1.2304	0.80841	0.376	0.932311	36.484	61.36	3.7752	9.044	3009.9	1	5.7770	2.3511	255
7	0.7108	0.87418	0.655	0.929282	24.433	58.77	2.0447	4.267	2085.4	1	7.2405	3.2904	255
8	0.9014	0.90097	0.576	0.927381	35.759	71.94	3.6071	7.978	3948.0	1	5.0127	3.1041	255
9	1.1222	0.86510	0.698	0.943924	28.194	69.98	2.4453	6.015	3597.8	1	6.7964	3.0347	255
10	1.3610	0.73879	0.724	0.935854	18.952	55.79	1.9201	5.197	2359.1	1	11.386	4.1726	255
11	0.7258	0.86020	0.614	0.928567	23.879	56.00	2.1350	5.346	2258.1	1	7.4625	3.7641	255
12	0.4065	0.91903	0.750	0.94786	17.785	56.20	1.5335	4.562	2827.8	1	12.644	0.8359	255
13	1.2210	0.70682	0.734	0.923988	15.923	48.57	1.4202	4.269	2039.3	1	11.61158	1.6122	255
14	0.7435	0.85764	0.757	0.938948	18.945	56.55	1.8782	4.812	2798.3	1	10.949	2.8360	255
15	0.2743	0.91649	0.823	0.976112	13.225	44.84	2.1005	5.519	1703.5	1	20.069	1.3342	255
16	0.2681	0.92901	0.786	0.962688	14.843	47.85	2.0682	4.844	1490.1	1	16.601	1.3215	255
17	0.6847	0.92833	0.378	0.906731	59.880	78.53	4.5886	9.207	2859.6	1	2.1288	4.2210	255
18	1.1217	0.87307	0.480	0.896516	40.152	73.24	3.1530	7.711	4661.7	1	4.0614	3.0734	255
19	0.5468	0.84231	0.723	0.947347	17.922	49.77	1.6294	4.534	2052.4	1	10.111	0.4327	255
20	1.8418	0.81905	0.478	0.883095	45.042	77.61	2.9739	7.068	4540.2	1	3.1090	0.7450	255
21	1.5751	0.86446	0.471	0.903862	47.808	80.98	3.1664	7.936	5354.2	1	3.0829	1.8645	255
22	0.8019	0.76745	0.843	0.96402	12.901	46.13	2.0809	5.212	2015.2	1	19.969	2.3426	255
23	0.3280	0.86944	0.709	0.944129	16.123	44.55	1.6311	2.662	352.88	1	12.241	1.8866	255
24	1.4987	0.87351	0.237	0.877284	77.399	84.80	4.791627	11.2647	6629.51	1	1.5772	2.3403	255
25	1.3460	0.86976	0.270	0.912759	62.05059	74.62	4.5629	10.71	4388.6	1	2.1224	3.0963	255

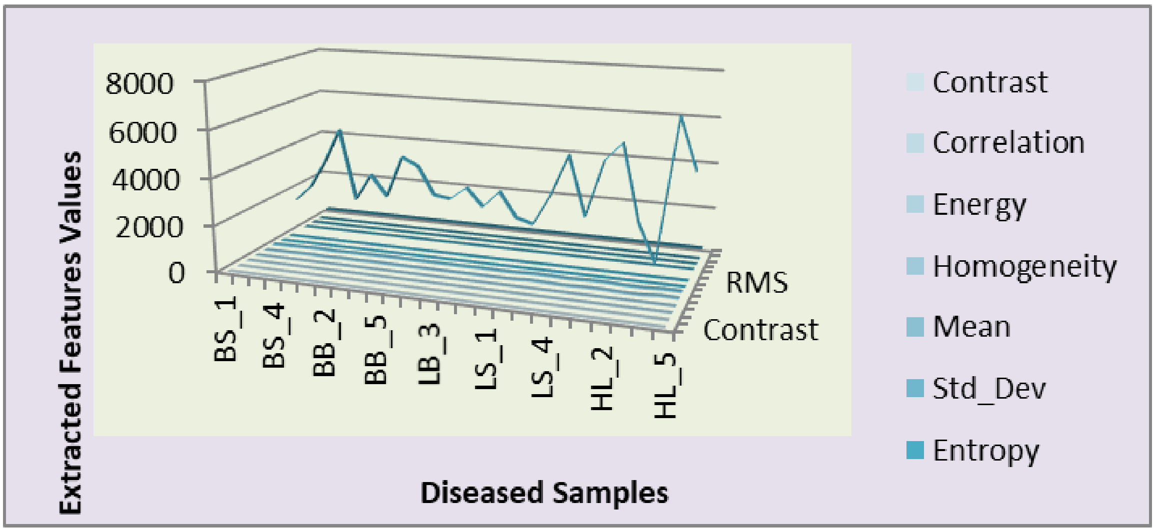

Fig. 2 Graphical Representation of Extracted Features Vector.

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The used quasi cypher in the PSO System:

Load the amount of elements
Load the individual element arbitrarily with their spot and speed
Load m_1 ,m_2, a_1, a_2 , *k*, k_{max} , and break the current state
While (unbreak state)
  For (elements spots)
    For (Insertion of whole exercise sets)
      Implement the inserted exercise sets
      Anticipated results process control
      upgrade suitability point *epsum*
    End for
    If (*epsum* _ *pbest*)
      upgrade *pbest* value point
      upgrade *pbest* direction
    End if
  End for
  For (Whole element positions)
    upgrade gbest value point with least pbest value
    upgrade gbest direction
    upgrade element speed direction s_i^k
    upgrade element spot direction y_i^k
  End for
End while

Where m1, m2 are momentum constant coefficients, a1, a2 are arbitrary quantities between 1 and 2, s_i^k the speed of j_{th} element at repetition n, y_i^k present location of j_{th} element at repetition n.

PSO uses a population of randomly created parameter vectors, called particles and assigns a movement vector to each of them which represents the update for the next iteration step in the optimization at the globally best position and is terminated after 50 iteration steps. The gbest value and optimized data output are plotted in Fig. 3 and Fig. 4. The optimum solutions which plot gbest fitness value Vs iteration steps are shown in Fig.5. The extracted feature dataset is optimized using PSO and then SVM classifier is use for classification. The optimized feature vector and its graphical representation is given in Table 3 and Fig.6 respectively.

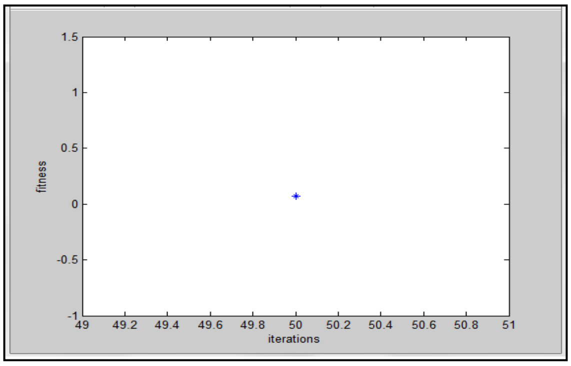

Fig. 3: gbest value of Dataset

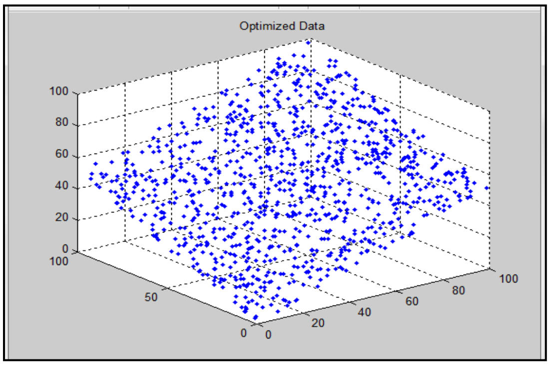

Fig. 4: Optimized Dataset

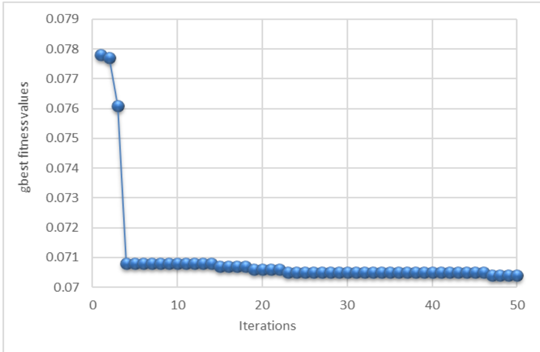

Fig. 5: Optimum Solutions

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Table 3: Optimized Features Vector using PSO

Sl.	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13
1	0.0008	0.0039	0.0005	0.0421	1.5232	0.0032	0.255	0.0008	0.0011	0.001	0.001	0.0114	0.0179
2	0.0009	0.0029	0.0005	0.052	2.2061	0.0047	0.255	0.0007	0.0017	0.001	0.0009	0.0183	0.0106
3	0.0008	0.0023	0.0012	0.0605	3.4297	0.007	0.255	0.0006	0.0022	0.001	0.0009	0.026	0.0073
4	0.0009	0.0017	0.0007	0.0718	4.9468	0.0073	0.255	0.0006	0.0024	0.001	0.001	0.0355	0.0044
5	0.0007	0.0038	0.0012	0.046	1.8237	0.0033	0.255	0.0008	0.0011	0.001	0.0009	0.0126	0.0166
6	0.0008	0.0019	0.0012	0.0614	3.0099	0.009	0.255	0.0004	0.0038	0.001	0.0009	0.0365	0.0058
7	0.0009	0.0023	0.0007	0.0588	2.0854	0.0043	0.255	0.0007	0.002	0.001	0.0009	0.0244	0.0072
8	0.0009	0.0019	0.0009	0.0719	3.948	0.008	0.255	0.0006	0.0036	0.001	0.0009	0.0358	0.005
9	0.0009	0.0023	0.0011	0.07	3.5978	0.006	0.255	0.0007	0.0024	0.001	0.0009	0.0282	0.0068
10	0.0007	0.0031	0.0009	0.0558	2.3592	0.0052	0.255	0.0007	0.0019	0.001	0.0009	0.019	0.0114
11	0.0009	0.0024	0.0011	0.07	2.2582	0.0053	0.255	0.0006	0.0021	0.001	0.0009	0.0239	0.0075
12	0.0009	0.0033	0.0014	0.0558	2.8279	0.0046	0.255	0.0008	0.0015	0.001	0.0009	0.0178	0.0126
13	0.0007	0.0031	0.0007	0.056	2.0393	0.0043	0.255	0.0007	0.0014	0.001	0.0009	0.0159	0.0116
14	0.0009	0.003	0.0004	0.0562	2.7984	0.0048	0.255	0.0008	0.0019	0.001	0.0009	0.0189	0.0109
15	0.0009	0.0042	0.0003	0.0448	1.7035	0.0055	0.255	0.0008	0.0021	0.001	0.001	0.0132	0.0201
16	0.0007	0.0038	0.0003	0.0479	1.4902	0.0048	0.255	0.0008	0.0021	0.001	0.001	0.0148	0.0166
17	0.0009	0.0008	0.0007	0.0785	2.8597	0.0092	0.255	0.0004	0.0046	0.001	0.0009	0.0599	0.0021
18	0.0009	0.0016	0.0011	0.0732	4.6618	0.0077	0.255	0.0005	0.0032	0.001	0.0009	0.0402	0.0041
19	0.0009	0.0028	0.0005	0.0498	2.0524	0.0045	0.255	0.0007	0.0016	0.001	0.0009	0.0179	0.0101
20	0.0009	0.0013	0.0018	0.0776	4.5403	0.0071	0.255	0.0005	0.003	0.001	0.0009	0.045	0.0031
21	0.0009	0.0013	0.0016	0.081	5.3542	0.0079	0.255	0.0008	0.0032	0.001	0.0009	0.0478	0.0031
22	0.0008	0.0042	0.0008	0.0461	2.0153	0.0052	0.255	0.0007	0.0021	0.001	0.001	0.0129	0.02
23	0.0009	0.0031	0.0003	0.0446	0.3529	0.0027	0.255	0.0002	0.0016	0.001	0.0009	0.0161	0.0122
24	0.0009	0.0004	0.0015	0.0848	6.6295	0.0113	0.255	0.0003	0.0048	0.001	0.0009	0.0774	0.0016
25	0.0009	0.0007	0.0013	0.0746	4.3887	0.0107	0.255	0.0003	0.0046	0.001	0.0009	0.0621	0.0021

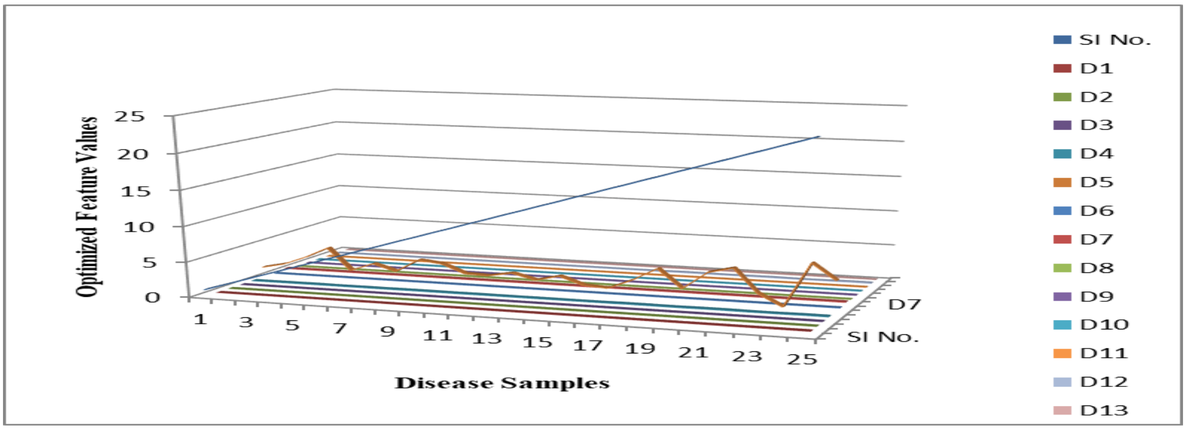

Fig 6. Graphical Representation of Optimized Features Vector

V. CLASSIFICATION OF DISEASE

In this phase, the classification and comparison for the leaf diseases of rice crop has done through by storing the corresponding feature set of values to their respective dataset. Here a fully controlled learning method of classification is used that is none other than support vector machines (SVM) with high dimension spaces, efficient memory and versatile decision function. Generally, SVM is categorize as two types: Linear SVM and Multiclass SVM. Linear SVM is used to classify two kind of data set and multiclass SVM is used to classify more than two kind of data set. So multiclass SVM is used to classify four types of rice leaf diseases. First, the extracted feature dataset is optimized using PSO and then multiclass SVM is used for classification process. The amount of cataloguing is done through high scale percentage of classification gain, Equation (8).

Classification Gain (%) =

$$\frac{\text{Number of correct classification}}{\text{Total no of test images}} \times 100\% \qquad (8)$$

VI. RESULTS

All the experiments are demonstrated by means of MATLAB. The various type of diseased rice leaf samples is taken as input. In this paper four type of rice leaf disease are considered i.e. Brown Spot, Bacterial Blight, Leaf Blast and Leaf Scald. Figure 7 shows the original images followed by its enhanced image and HIS colour space images. Figure 8 shows the input image and output segmented images followed by classification results and classified as Brown Spots disease. Figure 9 shows the input image and output segmented images followed by classification results and classified as Bacterial Blight disease. Figure 10 shows the input image and output segmented images followed by classification results and classified as Leaf Blast disease. Figure 11 shows the input image and output segmented images followed by classification results and classified is Leaf Scald disease.

By the help of this proposed method the total 12 sets of rice crop leaf disease specimens are taken and categorized into four broad categories of diseases which has displayed in Table 4 and Fig. 12. As a result, it has been observed that out of the total sets very few specimens are improper and mismatched between Bacterial Blight and Brown Spot disease leaves. Among 12 number of test samples of Bacterial Blight diseased leaf only one is erroneously classified as Brown Spots diseased leaf, which imply 91.66% of accuracy for Bacterial Blight diseased category. And the other three categories of diseased leaf i.e. Brown Spots, Leaf Blast and Leaf Scald are successfully classified with 100% of accuracy. The average accuracy of classification of proposed method is 97.91%. Table 4 illustrate the classification results per class/ category for proposed methodology.

In this paper, classification is first done using the K-Nearest Neighborhood (KNN) using K-Mean's grouping with a productivity accuracy of 77.90%. The finding precision is enhanced by 85.64% using Feed Forward neural network (FFNN). For the next stage, cataloguing is done through using SVM ordering process and whose productivity accuracy of 90.50%. Hence the exposure exactness is now enhanced by a factor of 97.91% by PSO data optimization and classified by SVM. The same extracted feature dataset is used in this paper for the classification accuracy estimation. Here also we compare with other classification techniques with our proposed method and examine the performance analysis with respect to each four type of diseases which is illustrated in Table 5 and Fig.13. After all, among all classification techniques, the proposed methodology result is outperforming i.e. accuracy of 97.91%, illustrated in Fig. 14.

Table 4: Classification results for different diseases for Proposed Method

Leaf Disease	Brown Spots	Bacterial Blight	Leaf Blast	Leaf Scald	Accuracy
Brown Spots	12	0	0	0	100
Bacterial Blight	1	11	0	0	91.66
Leaf Blast	0	0	12	0	100
Leaf Scald	0	0	0	12	100
Average Accuracy					97.91

Table 5: Comparison of different classification techniques for different diseases.

Leaf Disease	GLCM + KNN	GLCM + NN	GLCM + SVM	GLCM+ PSO+SVM
Brown Spots	78.02	84	91.11	100
Bacterial Blight	80.00	85.5	90.02	91.66
Leaf Blast	75.2	88.08	90	100
Leaf Scald	78.4	85	91.01	100
Average Accuracy	77.90	85.64	90.50	97.91

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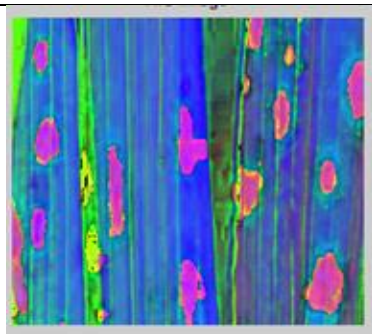
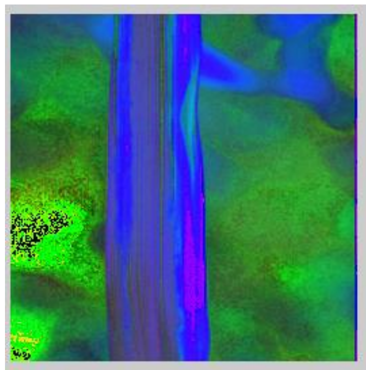
		
Input Image	Enhanced Image	HIS Colour Space Image
		
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		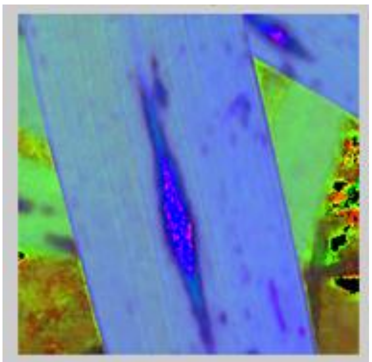
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	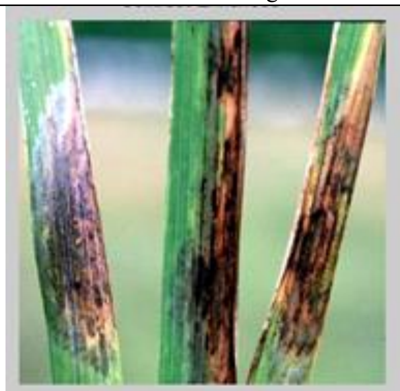	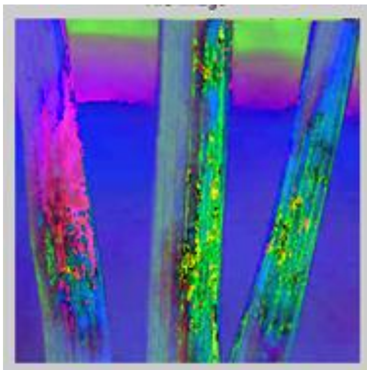
Input Image	Enhanced Image	HIS Colour Space Image

Fig. 7: Input Image, Enhanced Image, & HIS Images of Different Disease Infected Rice Crop Leaves

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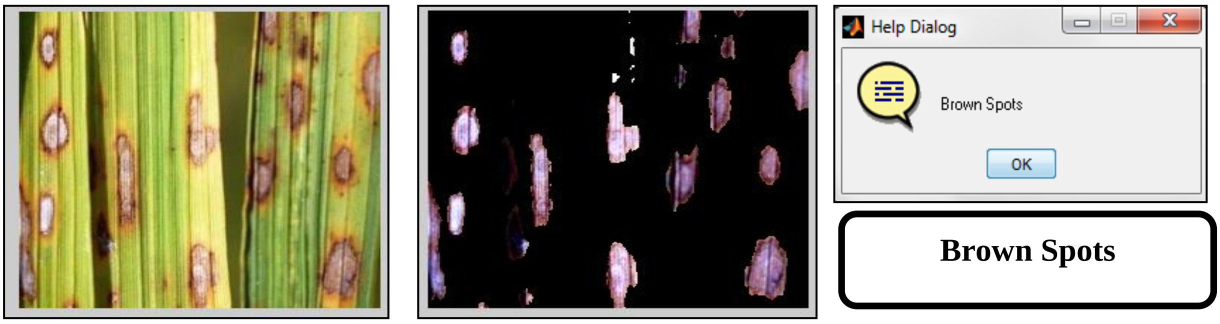

Input Image Disease Contain Cluster Image Classification Results

Fig. 8: Input Image, Disease Contain Cluster & Classification Results of Brown Spots Disease Infected Rice Crop Leaves.

Input Image Disease Contain Cluster Image Classification Results

Fig. 9 Input Image, Disease Contain Cluster & Classification Results of Bacterial Blight Disease Infected Rice Crop Leaves.

Input Image Disease Contain Cluster Image Classification Results

Fig. 10 Input Image, Disease Contain Cluster & Classification Results of Leaf Blast Disease Infected Rice Crop Leaves.

Input Image Disease Contain Cluster Image Classification Results

Fig. 11 Input Image, Disease Contain Cluster & Classification Results of Leaf Scald Disease Infected Rice Crop Leaves.

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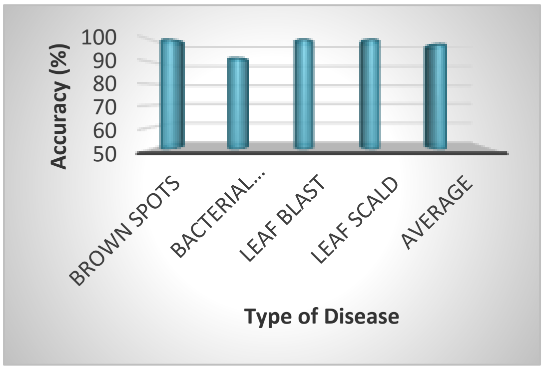

Fig. 12: Graphical representation of Classification of different diseases for Proposed Method.

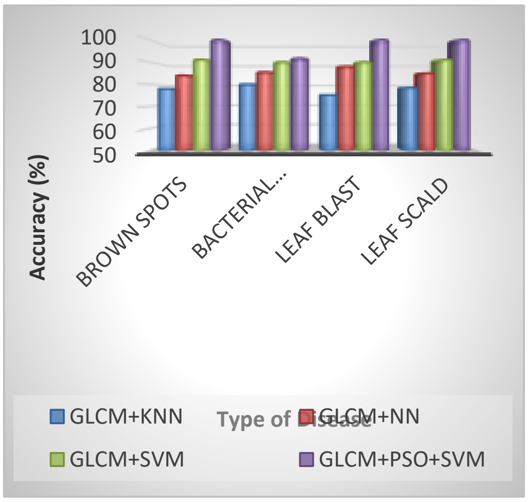

Fig. 13: Graphical representation for Comparison of different classification techniques for different Diseases.

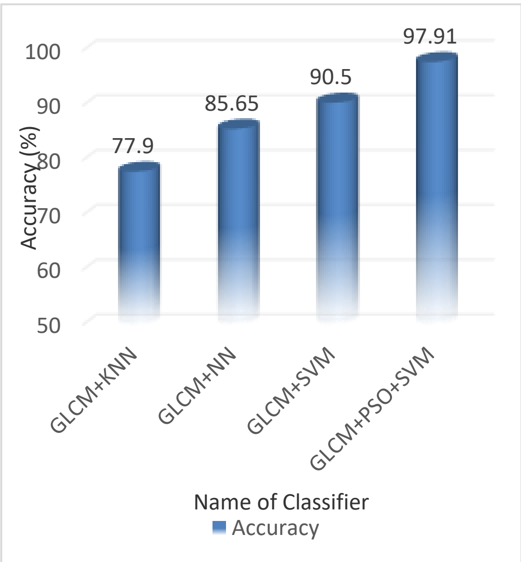

Fig. 14: Average accuracy comparison of different classification techniques.

VII. CONCLUSION

Here, in this paper it suggests a method of dissimilar disease cataloguing for the green foliage identification of the infected plants. It also recommends and assesses an instinctive image dissection and cataloguing techniques by framing a layered set of rules for the infected plants. From the execution point of view, the proposed methodology was tried and verified on various kind of rice leaf diseases like bacterial blight, brown spot, leaf scald and leaf blast successfully. Over and above it has been seen that, by means of least methodical pains the finest outcome can be gained resourcefully to verify the productivity of planned methods. Another perspective of employing this method is that, the plant disease can be documented at the beginning or primary stage only. Therefore, by using PSO technique to optimize the feature dataset, SVM proved to be the promising technique for the differentiation and categorization of the rice leaf diseases with normal precision of 97.91%. The research may be extended by collection of a greater number of samples with more variety of diseased rice leaf.

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