iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 7 **Issue:** VII **Month of publication:** July 2019

DOI: http://doi.org/10.22214/ijraset.2019.7166

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.177
Volume 7 Issue VII, July 2019- Available at www.ijraset.com

Performance Analysis of MSVM Classifier based Botanical Leaf Disease Detection System

Samiksha Devi[1], Ritika[2], Bhanu Gupta[3]
[1, 2]Department of ECE, SSCET, IKGPTU,
[3]Department of R&D, FCSC, Jammu Tawi

Abstract: ***Agriculture is the backbone of the nation as it provides food and job opportunity to the humankinds and directly contributes to the economic growth of the nation. In agriculture, plant disease identification is more important one. If the diseases can be prevented early that would be more to helpful to farmers to save the crops. This paper presents as system for identification of disease of the plant by using symptoms on leaves. There are several methods reported in the literature to identify the disease. Moreover, many researchers paid their attention in identification of plant leaf disease and some of them used image processing and machine learning techniques to perform the disease prediction. This work presents a review on identification of plant disease using image processing and recognition. Disease detection involves the steps like image acquisition, image pre-processing, image segmentation, feature extraction and classification. Image processing is a method to covert an image into digital form and performs some operation on it. Feature extraction start from an initial set of measured data and builds derived values (features) intended to be informative and non–redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretation. The system applies GLCM, LBP and MSVM for plant disease feature extraction using MATLAB.***
Keywords: Botanical Leaf Disease, GLCM, LBP, MATLAB

I. INTRODUCTION

In an India 10% to 30 % of the total vegetable crop is destroyed yearly by diseases. To achieve good accuracy and efficiency of disease detection and classification is challenging task. Traditional method of human eyes observation of plant is unpredictable for proper drug treatments. Using different techniques of Image processing leaf diseases will be identify and classify accurately. Continue observation of leaf is crucial and effective for exact disease identification. It goes toward proper drug treatment to crop which is helpful for farmer. The most common plant diseases are Alternaria Alternata, Anthracnose, Bacterial Blight, Cercospora Leaf Spot, Powdery Mildew, Downy Mildew and Rust. The examples of some plant leaf diseases are shown in figure below.

Disease/Type	Cause/Identification	Prevention	Image
Cercospora Leaf Spot Fungal	Warm Wet Environment/ Small Dark Raised Spots	Destroy infected plants and use fungicides	
Bacterial Blight Bacterial	Cool Wet Weather/ Large Yellow Spots on leaves eventually turn brown	Remove infected plants and ensure proper spacing between plants	
Anthracnose Fungal	Seed and Plant Debris/ Leaf Tip turns yellow and then brown	Remove infected leaves and avoid over watering	
Alternaria Alternata Fungal	High humidity/ Leaf Stops, Blights	Remove infected parts and apply fungicides	

Fig. 1 Examples of Botanical Leaf Disease

The main part of plant to examine the plant diseases is leaf. The detection and classification of leaf diseases accurately is the key to prevent the agriculture loss. Different plant leaf bears different diseases. The major categories of plant leaf diseases are based on viral, fungal and bacteria. The naked eye observation of experts is the main approach used in practice for detection and identification of plant diseases. But, this needs continuous monitoring of experts. When there is a large farm, this approach might be prohibitively expensive. Further, in some developing countries, farmers may have to go long distances to contact experts, this makes consulting experts too expensive and time consuming and moreover farmers are unaware of non-native diseases. Automatic detection of plant diseases is an important research topic as it may prove benefits in monitoring large field of crops, and thus automatically detect diseases from symptoms that appear on plant leaves. Thus automatic detection of plant disease with the help of image processing technique provides more accurate and robot guidance for disease management. Comparatively, visual identification is less accurate and time consuming [1].

In the proposed work the automatic disease detection of leaf is done using image processing techniques. The automated plant leaf disease detection system is performed by five main steps:

A. Botanical Leaf Image Acquisition.
B. Botanical Leaf Image Pre-processing
C. Botanical Leaf Image Segmentation
D. Botanical Leaf Feature Extraction
E. Botanical Leaf Disease Classification

II. LITERATURE REVIEW

Kamlesh Golhani et. al. review advanced Neural Network (NN) techniques available to process hyper-spectral data, with a special emphasis on plant disease detection. Firstly, we provide a review on NN mechanism, types, models, and classifiers that use different algorithms to process hyper-spectral data. Then we highlight the current state of imaging and non-imaging hyper-spectral data for early disease detection. The hybridization of NN hyper-spectral approach has emerged as a powerful tool for disease detection and diagnosis. Spectral Disease Index (SDI) is the ratio of different spectral bands of pure disease spectra. Subsequently, we introduce NN techniques for rapid development of SDI. We also highlight current challenges and future trends of hyper-spectral data [2].

Aarju Dixit et. al. in this paper is highlighting the outliers about the wheat leaf disease detection. India is the second larger producer of wheat after china. The wheat diseases are harmful to wheat production, but there are algorithms that can effectively identify common diseases of wheat leaves. The wheat diseases are generally viral, bacterial, fungal, insects, rust etc. There are many types of disease which are presents in wheat leaf. Recently, wheat disease detection through leaf image and data processing techniques are used extensively and in expensive system especially for assisting farmers in monitoring the big plantation area. Machine learning techniques are described for wheat leaf disease detection and its classification also. The key issues and challenges in wheat leaf disease detection are also highlighted. A vast collection of papers, books and standards are listed in the reference list, which gives useful information to the researchers and farmers in agriculture [3].

T. Thamil Azhagi et. al. The main objective of this paper is detection of diseases at the early stage. In this paper, we mainly focus on image processing techniques. This includes a series of steps from capturing the image of leaves to identifying the disease through the implementation in Raspberry PI. Raspberry PI is used to interface the camera and the display device along which the data is stored in the cloud. Here the main feature is that the crops in the field are continuously monitored and the data is streamed lively. The captured images are analyzed by various steps like acquisition, preprocessing, segmentation, clustering. This in turn reduces the need for labor in large farm lands. Also the cost and efforts are reduced whereas the productivity is increased [4].

Vinaya Mahajan et. al. publish that agricultural productivity is something on which economy highly depends. This is the one of the reasons that disease detection in plants plays an important role in agriculture field, as having disease in plants is quite natural. If proper care is not taken in this area then it causes serious effects on plants, due to which respective product quality, quantity and/or productivity is affected. For instance a disease named little leaf disease is a hazardous disease found in pine trees in United States. Detection of plant diseases through some automatic technique is beneficial as it reduces the tedious work of monitoring in big farms of crops, and at very early stage itself it detects the symptoms of diseases i.e. when they appear on plant leaves. This paper presents an algorithm for image segmentation technique which is used for automatic detection and classification of plant leaf diseases. Image segmentation, which is an important aspect for disease detection in plant leaf disease, is done using genetic algorithm. It uses fuzzy logic for detection of plant disease. The parameters are skewness, extract mean and extract deviation. A test image is taken and compared with database image and then dissimilarity is calculated with extracted parameters [5].

Sridhathan C et. al. publish that economy of a country depends on agricultural productivity. Identification of the plant diseases is the key for preventing the losses in the productivity and improving the quality of the agricultural product. Traditional methods are reliable but require a human resource for visually observing the plant leaf patterns and diagnose the disease. Traditional method consumes more time, tedious work for labors. In big farm lands, early stage detection of plant disease by using automated techniques will reduce the loss in productivity. In this paper, we propose a vision based automatic detection of plant disease detection using Image Processing Technique. Image processing algorithms are developed to detect the plant infection or disease by identifying the color feature of the leaf area. K mean algorithm is used for color segmentation and GLCM is used for diseases classification. Vision based plant infection showed efficient result and promising performance [6].
Ramya. R et. al. In this paper, it mainly focus on detection and analysis of plant infections which is present in crop fields and storage of information about the agricultural land and details about farmers in database and retrieving the information using Cloud computing. There are lot of plant diseases which occur due to the environmental conditions, mineral specifications, and insects in the farm land and many other miscellaneous factors. The detected information from the crop field is identified by image processing and stored in the database. It also aims to provide the farmer with required inputs for the fields at correct period of intervals by continuous sensing of plants [7].
S. Ramesh et. al. in this work, explain a framework for early detection of diseases in rice crops from visual symptoms. We target rice crops owing to their extensive use in the Indian subcontinent. Existing literature lists several algorithms that can be used in detection, classification, and quantification of crop diseases by analysis images. However, the evaluation process is tedious, time consuming and more over very much subjective. Infrastructure for image acquisition, communication, and processing is lacking in rural areas owing to lesser technological penetration. In this work, we develop a user-friendly IoT reference architecture to provide on-field disease detection and prediction using cloud analytics [8].

III.METHODOLOGY

The entire proposed framework is illustrated in Fig.2. The proposed automated botanical leaf disease detection system is performed by five main steps: image acquisition, image preprocessing, segmentation, feature extraction and classification. Diseased leaf images are captured and stored for experiment. Then images are applied for preprocessing for image enhancement. Captured leaf images are segmented using K-Means clustering method to form clusters. GLCM and LBP features are extracted after applying K-Means and MSVM has been used for classification and detection of plant leaves diseases namely Bacterial Blight, Cercospora Leaf Spot, Powdery Mildew and Rust.

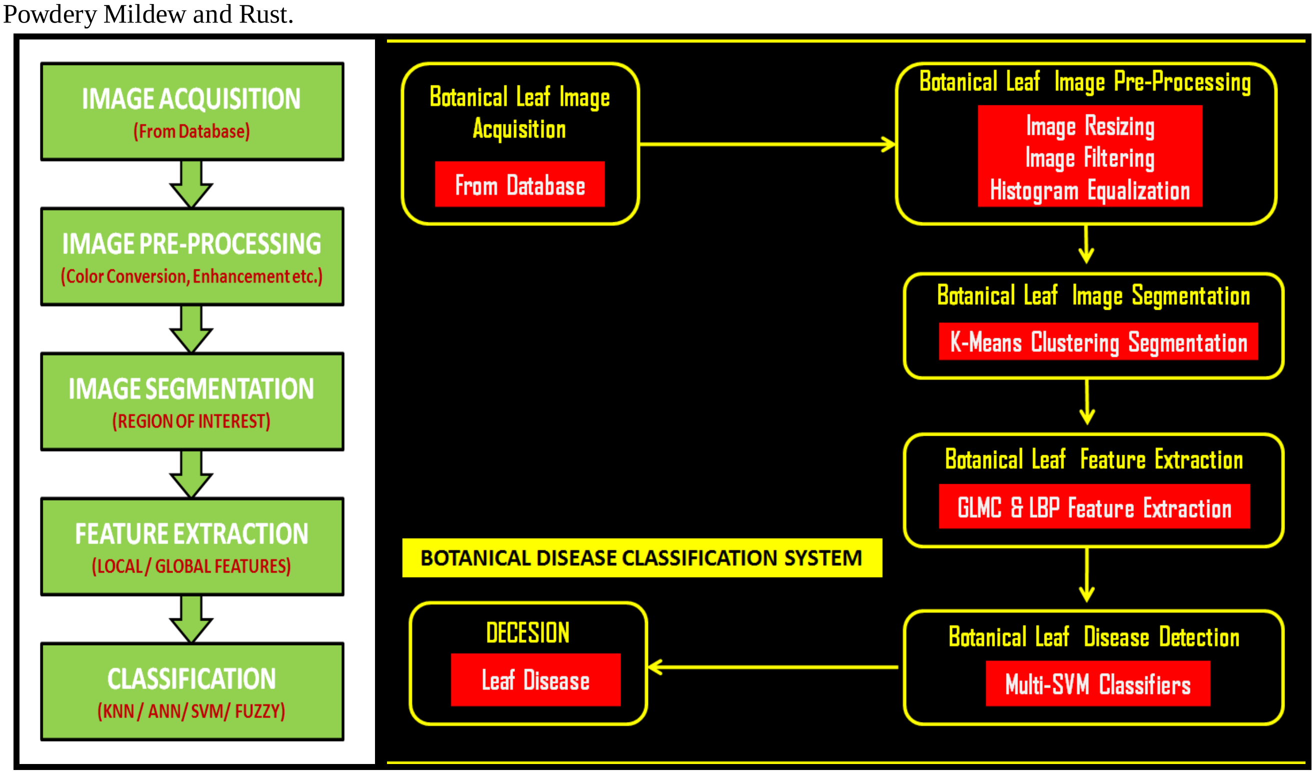


Fig. 2 Botanical Leaf Disease Detection System

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.177
Volume 7 Issue VII, July 2019- Available at www.ijraset.com

The proposed work aims towards application of image processing techniques for detection of botanical leaf diseases. The proposed methodology that applied in this work follows the following steps:

A. Botanical Leaf Image Acquisition from available database.
B. Botanical Leaf Pre-processing: Resizing, Filtering and Histogram Equalization.
C. Botanical Leaf Segmentation: Leaf Segmentation into 3 regions using K-Means Clustering.
D. Botanical Leaf Feature extraction: Features extracted using GLCM and LBP methods
E. Botanical Leaf Disease Classification: Sample images were tested and classified by MSVM classifier for disease type and percentage of disease.

Preprocessing step is to improve image data by removing background, noise and also suppressing undesired distortions. It enhances image features for processing and analysis. The images stored in RGB format are resized to standard size. These resized RGB images are then converted to HSV format. The median filter is used for image smoothing, removal of noises and highlighting some information. Image enhancement is carried out for increasing the contrast. The histogram equalization which distributes the intensities of the images is applied on the image to enhance the plant disease images. Image segmentation is applied to simplify the illustration of image with segments so that it can be easily analyzed. Image segmentation is performed to segment the disease affected and unaffected portions of the leaf. K-Means clustering method is used for partitioning of images into clusters in which at least one part of cluster contain image with major area of diseased part. The k-Means clustering algorithm is applied to classify the objects into K number of classes according to set of features. Grey Level Co-occurrence Matrices is a statistical method. It is an old and used feature extraction method for texture classification. It has been an important feature extraction method in the domain of texture classification that computes the relationship between pixel pairs in the image. The textural features can be calculated from the generated GLCMs, e.g. contrast, correlation, energy, entropy and homogeneity. Extract the disease symptoms by calculating the GLCM texture feature values of Skewness, Standard Deviation, Homogeneity, Contrast, Smoothness, Correlation, Kurtosis, Energy, Entropy, Mean, Variance, RMS, and IDM. Local Binary Pattern (LBP) is also a type of texture feature used for classification in computer vision. LBP is the case of the Texture Spectrum model. A local binary pattern is called uniform if the binary pattern contains at most two 0-1 or 1-0 transitions. This gives the feature vector for the window. With the help of texture features, plant diseases are classified into different types. After extracting color and texture features, the classification is performed by using Multiclass Support Vector Machine (MSVM). The training and validation processes are among the important steps in developing an accurate process model using MSVM. The dataset for training and validation processes consists of two parts: the training feature set which are used to train the MSVM model and the testing features sets are used to verify the accuracy of the trained SVM model. Finally disease type with accuracy value is analyzed and percentage of disease affected region is evaluated by the ratio of disease data and leaf data. The details of Botanical Leaf Disease Dataset used for testing the application are shown in figure below.

Dataset	Leaf Disease	Infection Type	Image Samples per Dataset	Total Samples
Leaf Disease Dataset 1	Alternaria Alternata	Fungal	22	75
Leaf Disease Dataset 2	Anthracnose	Fungal	23	
Leaf Disease Dataset 3	Bacterial Blight	Bacterial	06	
Leaf Disease Dataset 4	Cercospora Leaf Spot	Fungal	09	
Leaf Disease Dataset 5	Healthy Leaf	Nil	15	

Fig. 3 Leaf Disease Datasets for Result Analysis and Performance Evaluation

IV. RESULTS

The snapshot of Application Graphical User Interface for Botanical Leaf Disease System which was developed using MATLAB GUIDE Tool is shown in figure below. It consists of 07 buttons which have been assigned different functions to be performed by the application. The display for images and results are provisioned in the same window in this GUI.

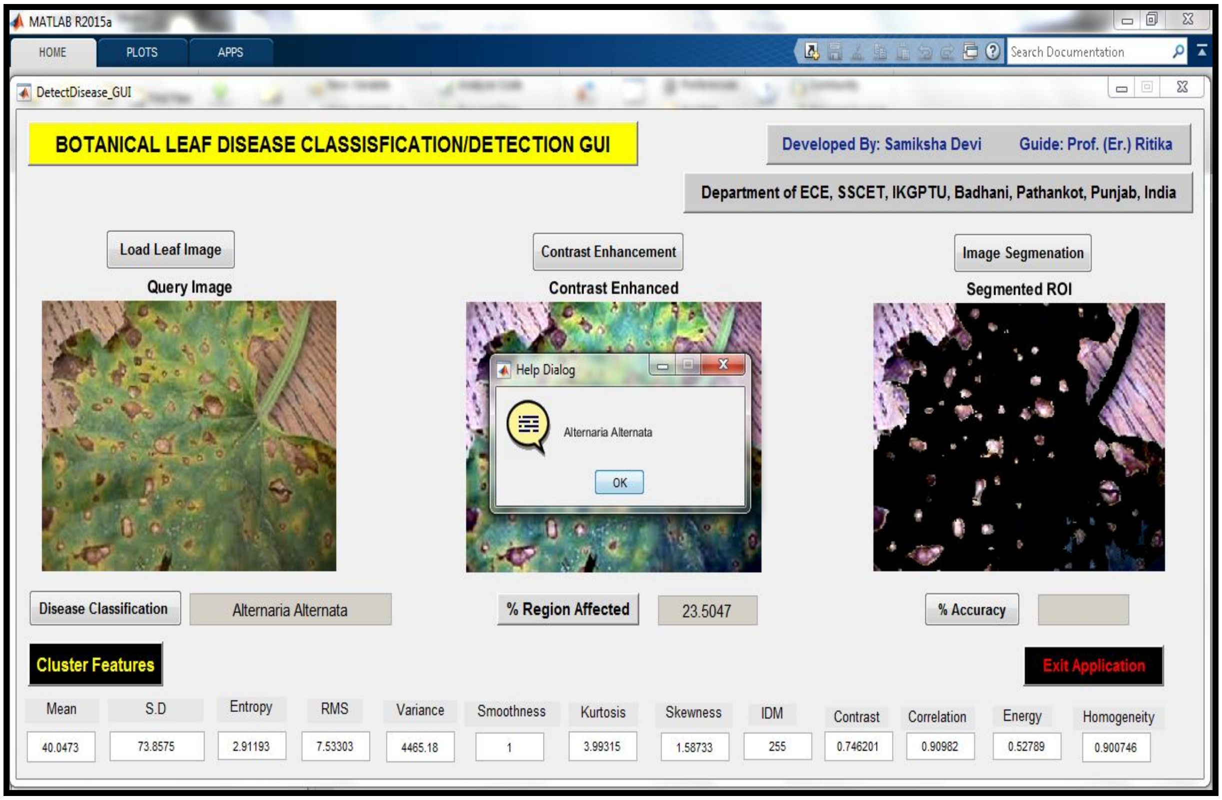


Fig. 4 Application Graphical User Interface for Botanical Leaf Disease System

The Analysis sheet snapshots for different Datasets are shown as under.

1	Sr. No.	Region Affected	Accuracy	Mean	SD	Entropy	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity	Match
2	1	15.0113	98.4	14.8439	47.8117	1.70988	5.57477	250.7	1	15.5978	3..63201	255	0.788756	0.978321	0.762589	0.974878	1
3	2	16.214	96.8	14.1501	48.1396	1.36585	4.31362	1632.22	1	15.7654	3.67443	255	0.466835	0.865708	0.796721	0.959196	1
4	3	15.314	98.4	16.2895	51.2167	1.65164	5.30216	2289.11	1	13.9662	3.42587	255	0.359513	0.911426	0.759202	0.962937	1
5	4	15.85	98.4	5.70641	29.9149	0.615448	2.5528	844.187	0.99	39.5829	5.92848	255	0.295895	0.732119	0.902138	0.978083	1
6	5	53.5633	96.8	17.137	35.5418	2.84528	10.4536	1163.81	1	27.5419	4.67615	255	0.513572	0.710152	0.894181	0.971536	1
7	6	15.9239	96.8	41.2491	71.5093	3.27917	8.19696	4609.22	1	3.8313	1.50194	255	0.666403	0.916991	0.480132	0.911685	1
8	7	59.9961	96.8	128.906	118.697	3.6237	12.5744	10666.3	1	1.09883	0.159212	255	0.41152	0.981417	0.350457	0.94482	1
9	8	12.4413	98.4	17.4376	52.4639	1.87888	5.7289	2052.45	1	12.8361	3.27632	255	0.430913	0.896565	0.765986	0.965598	1
10	9	15.2823	98.4	23.8136	60.7088	1.67343	5.43624	3220.87	1	6.95817	2.33486	255	0.576072	0.909153	0.710405	0.958389	1
11	10	23.5047	96.8	40.0473	73.8875	2.91193	7.53303	4465.18	1	3.99315	1.58733	255	0.746201	0.90982	0.52789	0.975127	1
12	11	15.3641	98.4	16.4181	55.6534	1.30024	4.3228	2841.54	1	12.3204	3.30101	255	0.88943	0.826304	0.818493	0.96507	1
13	12	14.1435	98.4	70.6184	97.9821	3.84392	9.36415	6332.29	1	1.51714	0.599022	255	0.413971	0.970172	0.410585	0.972992	1
14	13	20.2362	96.8	8.49443	35.2723	0.711676	2.47854	1098.04	0.99	18.8986	4.12406	255	0.816942	0.951204	0.886082	0.993719	1
15	14	15.85	98.4	5.70641	29.9149	0.615448	2.5528	844.187	0.99	39.5829	5.92848	255	0.295895	0.732119	0.902138	0.978083	1
16	15	16.1103	96.8	10.6032	41.1724	1.19449	3.82886	1594.45	1	22.3461	4.52079	255	0.413097	0.845948	0.842361	0.976562	1
17	16	15.0015	98.4	16.5251	54.6802	1.27996	4.55313	2763.69	1	12.4101	3.28896	255	1.01118	0.794138	0.796901	0.954354	1
18	17	59.9961	96.8	128.906	118.697	3.6237	12.5744	10666.3	1	1.09883	0.159212	255	0.41152	0.981417	0.350457	0.94482	1
19	18	15.0293	96.8	9.74195	38.4817	0.886391	3.51484	1388.82	0.99	19.3455	4.10935	255	0.27454	0.870993	0.859583	0.979117	1
20	19	15.2823	98.4	23.8136	60.7088	1.67343	5.43624	3220.87	1	6.95817	2.33486	255	0.576072	0.909153	0.710405	0.958389	1
21	20	15.665	96.8	13.2005	42.2956	1.26506	4.28869	1604.8	1	13.0418	3.29294	255	0.259298	0.87987	0.800012	0.976717	1
22	21	37.4182	96.8	17.9328	41.3004	3.79633	9.70887	1147.7	1	22.8364	4.3054	255	0.330285	0.865684	0.737989	0.957998	1
23	22	18.6898	96.8	18.7319	48.3585	3.36829	7.20135	2261.04	1	13.1763	3.21261	255	0.864721	0.76374	0.69854	0.934361	1
24																	

Fig. 5 Data Analysis Sheet for Leaf Disease Dataset 1

Sr. No.	Region Affected	Accuracy	Mean	SD	Entropy	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity	Match
1	17.8756	96.8	30.5324	59.6242	3.06109	8.22711	3344.44	1	6.3781	2.0451	255	0.930867	0.832831	0.507407	0.888494	1
2	15.0015	96.8	40.9801	63.318	3.80912	9.33332	3320.66	1	4.27764	1.47828	255	0.98102	0.838466	0.388415	0.881297	1
3	16.87	96.8	42.1225	73.5128	3.52031	8.5236	4324.13	1	4.13493	1.58809	255	0.505515	0.943253	0.480298	0.927162	1
4	15.7917	96.8	17.9717	37.6635	2.58288	7.4037	1306.81	1	10.4951	2.58834	255	0.541288	0.751034	0.538239	0.922202	1
5	15.7728	96.8	14.9825	48.7526	1.31056	4.93734	2262.46	1	13.7375	3.40321	255	1.33877	0.626291	0.760319	0.934336	1
6	15.162	96.8	31.5604	56.4596	2.98298	8.11404	2844.33	1	4.40084	1.61293	255	0.697626	0.873892	0.487259	0.910412	1
7	15.0233	98.4	12.521	40.3782	1.2719	4.31644	1490.06	1	13.5047	3.33848	255	0.762408	0.701967	0.776902	0.949099	1
8	23.6869	96.8	13.6528	42.1577	1.53765	4.83814	1633.13	1	13.7142	3.34001	255	0.599786	0.801693	0.727155	0.953956	1
9	15.0016	96.8	13.9399	40.5348	1.52332	5.272	1561.76	1	11.3375	3.01159	255	0.681832	0.766913	0.724251	0.943182	1
10	15.0139	96.8	34.5562	61.3363	2.79048	7.89417	3343.26	1	3.58324	1.44686	255	0.738695	0.873205	0.508231	0.893922	1
11	11.9856	98.4	19.741	49.3344	1.95386	5.62567	2162.61	1	9.92354	2.69714	255	1.0907	0.748981	0.644755	0.919102	1
12	15.4004	96.8	30.1403	52.7286	3.57894	8.75799	2419.03	1	6.57678	1.92621	255	0.945175	0.748976	0.439598	0.886094	1
13	15.0015	96.8	13.0068	38.7839	1.44955	5.06633	1340.22	1	12.6418	3.17204	255	0.347335	0.742377	0.751383	0.965933	1
14	15.1794	96.8	26.9492	60.874	2.4818	6.95597	3471.25	1	6.62879	2.20753	255	1.04505	0.816676	0.619172	0.920878	1
15	15.729	96.8	24.3821	47.9186	2.81933	7.94094	2035.95	1	6.48709	2.03542	255	0.417647	0.858035	0.565384	0.938983	1
16	18.3285	96.8	16.5903	45.5681	2.14534	6.81802	1967.24	1	13.2184	3.27004	255	0.611872	0.791485	0.734522	0.959021	1
17	18.4905	96.8	18.6408	46.7285	1.94559	6.41862	2044.08	1	9.8307	2.69374	255	0.360815	0.860382	0.681831	0.964405	1
18	15.0187	98.4	25.556	53.085	2.70907	7.2309	2274.23	1	6.82861	2.15483	255	0.831449	0.83651	0.511313	0.908326	1
19	15.074	96.8	28.9204	61.2697	2.65612	7.51614	3571.18	1	6.64785	2.15394	255	1.3815	0.770603	0.561566	0.896044	1
20	18.2583	96.8	33.2793	61.8516	2.90342	8.02248	3513.44	1	4.72722	1.71194	255	0.68894	0.848003	0.523571	0.90232	1
21	16.1374	96.8	27.1278	58.1769	2.28255	7.08555	3267.62	1	5.52667	1.97227	255	1.1523	0.087736	0.588948	0.910852	1
22	15.0324	98.4	20.0995	44.7045	2.30554	6.40375	1703.09	1	8.01679	2.35098	255	0.417264	0.84978	0.612307	0.934665	1
23	15.1108	96.8	23.3472	59.2528	2.56518	6.53031	3385.81	1	8.20263	2.54593	255	1.39372	0.753213	0.695443	0.925706	1

Fig. 6 Data Analysis Sheet for Leaf Disease Dataset 2

Sr. No.	Region Affected	Accuracy	Mean	SD	Entropy	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity	Match
1	15.0077	96.8	32.046	66.6028	2.29203	7.414	4217.12	1	5.17922	1.88061	255	1.48286	0.785504	0.584137	0.927109	1
2	15.0062	98.4	41.6235	63.6705	4.10045	9.52182	3237.63	1	3.77506	1.39154	255	1.1544	0.77305	0.408599	0.893283	1
3	15.0093	96.8	33.7005	70.1319	2.21451	6.6518	4381.99	1	4.31683	1.73957	255	1.97687	0.770042	0.585182	0.897547	1
4	15.0139	96.8	32.2259	59.7001	2.74907	7.37212	3191.71	1	3.99857	1.57482	255	3.25682	0.486782	0.42061	0.809577	1
5	15.0142	96.8	22.7644	57.3393	1.98148	6.2139	3126.68	1	8.14521	2.5054	255	2.18199	0.580498	0.639253	0.900043	1
6	15.0015	96.8	27.4955	59.0481	2.20094	5.52611	2362.59	1	5.70507	1.99746	255	0.61682	0.861205	0.62476	0.95137	1

Fig. 7 Data Analysis Sheet for Leaf Disease Dataset 3

Sr. No.	Region Affected	Accuracy	Mean	SD	Entropy	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity	Match
1	15.0191	96.8	33.0064	61.7117	3.21576	8.5239	3371.13	1	5.24589	1.83395	255	1.15518	0.816261	0.479883	0.897515	1
2	15.6087	96.8	28.3379	52.1931	3.81636	9.19912	2421.76	1	8.95197	2.41677	255	0.498667	0.876104	0.459063	0.927747	1
3	18.2951	96.8	35.4631	63.6863	3.13484	8.20571	3327.35	1	4.66504	1.66461	255	1.11792	0.830673	0.482412	0.896201	1
4	15.241	96.8	49.6179	81.2699	3.76222	8.57418	5644.68	1	2.90894	1.25886	255	2.06046	0.813369	0.441216	0.880521	1
5	23.0239	96.8	51.6916	70.9386	4.98209	11.1231	4409.05	1	3.71987	1.37981	255	0.831679	0.899591	0.300285	0.915275	1
6	12.4198	98.2	39.8919	65.6084	3.42414	8.78958	3941.74	1	3.78317	1.43343	255	1.20406	0.831454	0.419351	0.891277	1
7	52.8251	98.4	71.9126	83.0717	5.1251	11.4688	5683.78	1	1.82568	0.648438	255	0.48724	0.958136	0.268256	0.940192	1
8	15.0016	96.8	33.2005	66.7847	2.59338	7.33983	4119.71	1	4.69272	1.78592	255	1.68387	0.78904	0.529931	0.889358	1
9	15.6737	98.4	44.178	76.8477	3.32198	8.68948	5494.23	1	3.4116	1.43086	255	1.31976	0.864802	0.480227	0.919423	1

Fig. 8 Data Analysis Sheet for Leaf Disease Dataset 4

Sr. No.	Region Affected	Accuracy	Mean	SD	Entropy	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity	Match
1	0	98.4	35.9274	64.0484	3.24063	8.36129	3443.43	1	3.70728	1.50846	255	0.757261	0.898844	0.442433	0.928486	1
2	0	95.2	51.2564	68.8971	4.43763	10.1617	3726.16	1	2.50139	0.969182	255	1.01828	0.878389	0.280931	0.884878	1
3	0	98.2	54.0321	63.2741	4.71942	11.2881	3330.79	1	2.00616	0.700139	255	0.307276	0.955854	0.289368	0.947208	1
4	0	96.8	44.5924	60.2637	4.38159	10.0989	2838.32	1	2.97738	1.09995	255	0.438986	0.93194	0.315136	0.932463	1
5	0	98.4	51.2905	70.0072	5.0792	10.4595	2936.17	1	3.1091	1.17011	255	0.38796	0.950036	0.227298	0.929342	1
6	0	98.4	38.1777	66.0844	3.24815	8.31329	3250.38	1	3.91934	1.53022	255	0.814154	0.902935	0.446787	0.910593	1
7	0	91.4	47.9386	58.5852	4.84793	11.193	3011.54	1	2.84602	0.958266	255	1.14199	0.802741	0.233953	0.867061	1
8	0	96.8	34.4732	62.1049	3.00311	7.39567	2879.83	1	4.14167	1.58164	255	0.759176	0.895552	0.494798	0.928861	1
9	0	96.8	17.4601	34.4339	2.78856	7.39482	913.373	1	5.84628	1.97717	255	0.162944	0.916674	0.519516	0.962232	1
10	0	96.8	35.3337	54.4009	4.1146	9.72723	2463.72	1	3.89547	1.42006	255	0.495267	0.900394	0.322721	0.92598	1
11	0	96.8	45.5123	65.7257	4.14309	9.77601	3357.7	1	3.22255	1.20674	255	0.626271	0.91891	0.328937	0.933606	1
12	0	95.2	37.2514	68.1294	3.95505	9.33873	3020.85	1	3.18223	1.18559	255	0.528416	0.940247	0.368332	0.946514	1
13	0	98.4	17.515	40.7595	2.05378	6.10987	1158.47	1	6.5288	2.22604	255	0.207047	0.928402	0.640989	0.96728	1
14	0	96.8	36.5711	50.5389	4.62332	10.5994	2253.88	1	4.66154	1.44413	255	0.75579	0.8265	0.266591	0.883938	1
15	0	96.8	30.3694	46.5165	3.83325	9.15991	1790.8	1	3.84979	1.38263	255	0.338695	0.902539	0.379189	9.943382	1

Fig. 9 Data Analysis Sheet for Leaf Disease Dataset 5

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.177
Volume 7 Issue VII, July 2019- Available at www.ijraset.com

The graphical comparative parameter analysis for different Leaf Disease Datasets is shown as under.

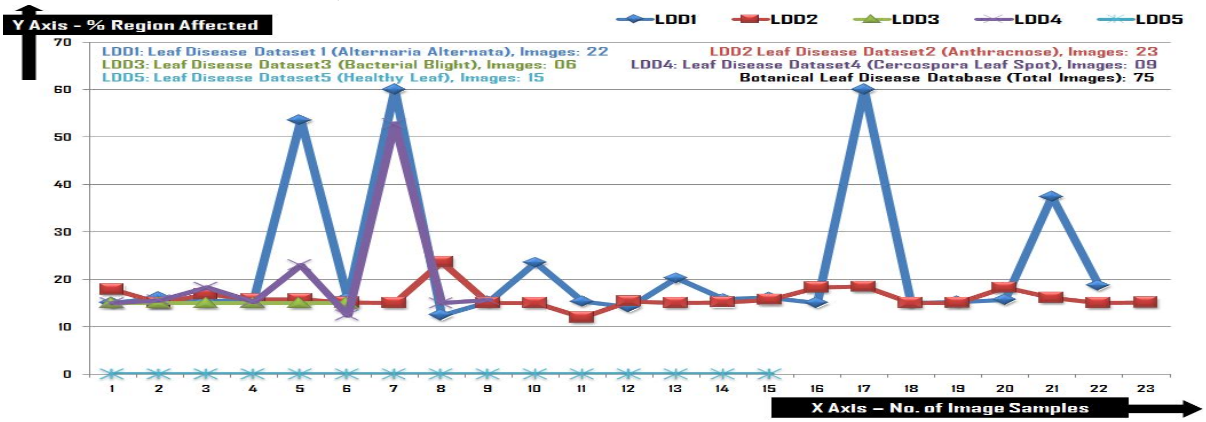


Fig. 10 Data Analysis Graph: % Region affected in each Dataset

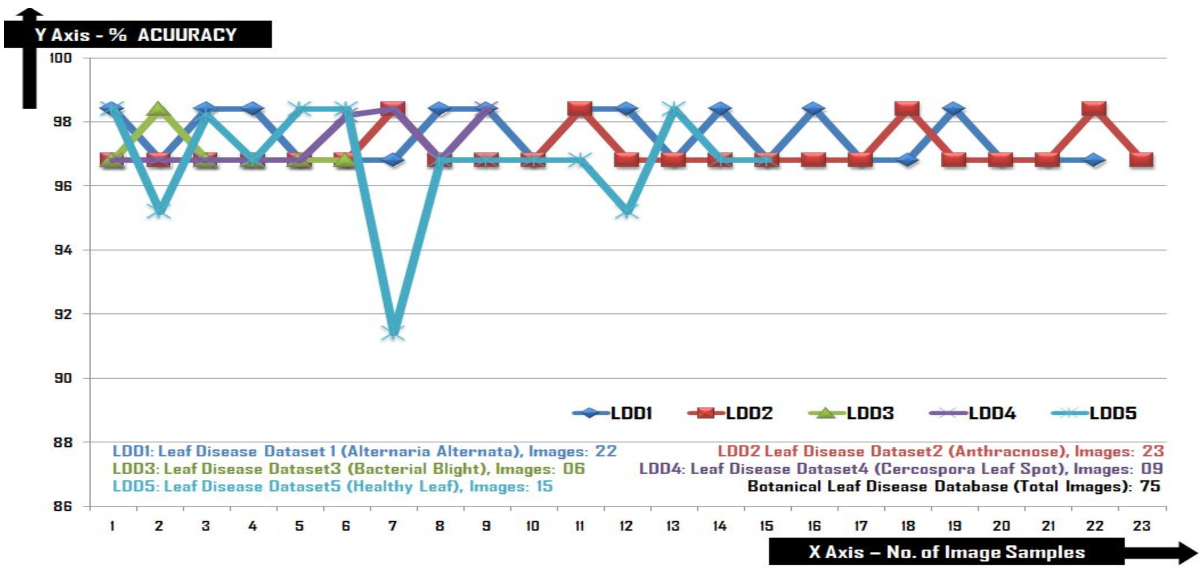


Fig. 11 Data Analysis Graph: % Region affected in each Dataset

Previous Work		
Sr. No.	**Technique**	**Accuracy (%)**
1.	Logistic Regression (LR)	65.33%
2.	Support Vector Machine (SVM)	40.33%
3.	K-nearest Neighbor (KNN)	66.76%
4.	CART	64.66%
5.	Random Forests (RF)	70.14%
6.	Naïve Bayes (NB)	57.61%
Present Work		
Sr. No.	**Technique**	**Accuracy (%)**
1.	K-means Clustering	97.31%
2.	GLCM and LBP	96.74%
3.	Multi-class SVM (MSVM)	97.50%

Fig. 12 Comparison of Techniques in terms of %Accuracy

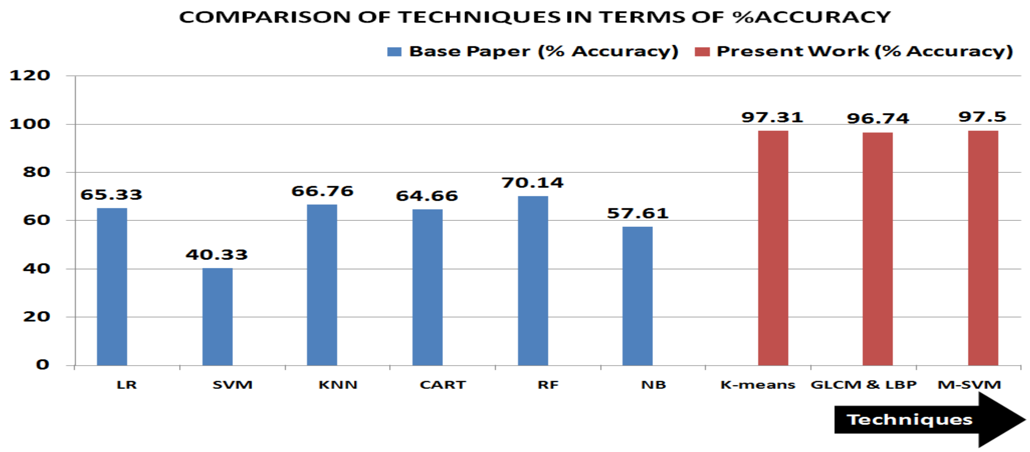


Fig. 13 Analysis Graph: Comparison of Techniques in terms of %Accuracy (Previous Work versus Present Work)

V. CONCLUSIONS

The classification of diseased plant leaves performance of various classification techniques which have been analyzed for the 75 input leaf images. The performance evaluated for the classification techniques which have been used in this paper from the confusion matrix of their respective classifier. In SVM classification, 22 images are of Alternaria Alternata disease are correctly classified. The correct classification rate for Alternaria Alternata disease is 100%. For Anthracnose disease, 23 samples are correctly classified. For Bacterial Blight disease, 06 samples are correctly classified. The correct classification for Bacterial Blight disease is 100%. For Cercospora Leaf Spot disease, 09 samples are correctly classified. The correct classification for Cercospora Leaf Spot disease is 100%. For Healthy Leaf, all 15 samples are correctly classified. So the correct classification for Healthy Leaf is 100%. In case of SVM, the best accuracy is obtained under cubic kernel. From the experimental result it can be observed that best accuracy is achieved for SVM classifier. For all classifiers 10-folds cross validation is considered. From the above results, the proposed system is efficient enough for detection and classification of botanical leaf diseases.

REFERENCES

[1] K. Mohanapriya, M. Balasubramani, “A Study on Identification of Unhealthy Plant Leaves using Image Processing with PCA, LDA Techniques”, Indo-Iranian Journal of Scientific Research (IIJSR) ISSN: 2581-4362,Volume 2, Issue 4, pp. 37-42, 2018.

[2] Gaganpreet Kaur, Sarvjeet Kaur, Amandeep Kaur, “Plant Disease Detection: a Review of Current Trends”, International Journal of Engineering & Technology, 7, (2018), pp. 874-881.

[3] Yin Min Oo, Nay Chi Htun, “Plant Leaf Disease Detection and Classification using Image Processing”, International Journal of Research and Engineering ISSN: 2348-7860 (O), 2348-7852 (P), Vol. 5, No. 9, September-October 2018, pp. 516-523.

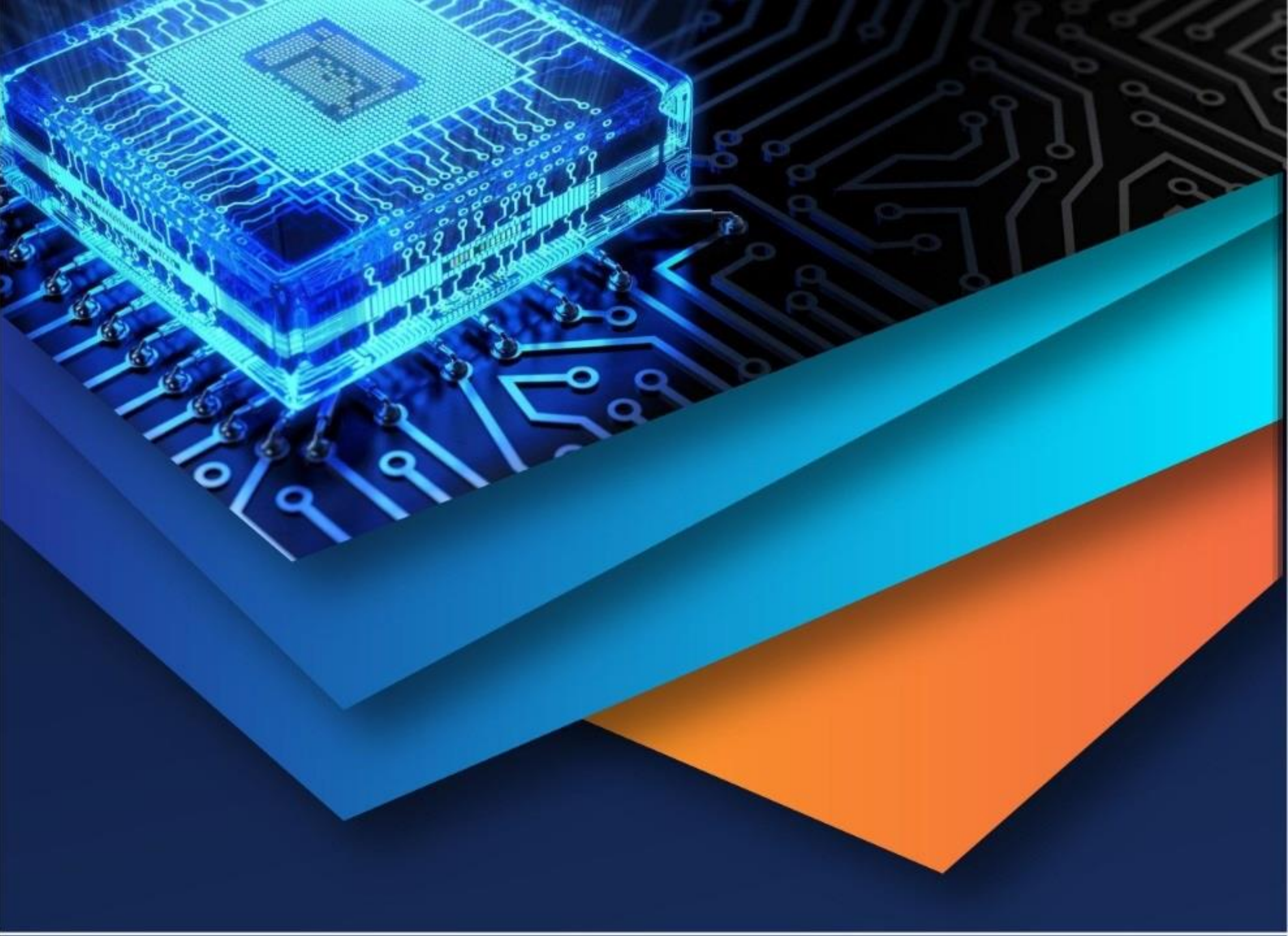
[4] Kamlesh Golhani, Siva K. Balasundram, Ganesan Vadamalai, Biswajeet Pradhan, “A review of neural networks in plant disease detection using hyper-spectral data”, Information Processing in Agriculture ISSN 2214-3173, Volume 5, Issue 3, pp. 354-371, 2018.

[5] Aarju Dixit, Sumit Nema, “Wheat Leaf Disease Detection Using Machine Learning Method- A Review”, International Journal of Computer Science and Mobile Computing ISSN 2320–088X, Vol.7 Issue.5, pp. 124-129, May- 2018.

[6] T. Thamil Azhagi, K. Swetha, M. Shravani, A.T. Madhavi, “Plant Pathology Detection and Control using Raspberry Pi”, International Journal of Engineering Sciences & Research Technology (IJESRT) ISSN: 2277-9655, pp. 519-525, 2018.

[7] Vinaya Mahajan, N.R. Dhumale, “Leaf Disease Detection Using Fuzzy Logic”, International Journal of Innovative Research in Science, Engineering and Technology ISSN (Online): 2319-8753, Vol. 7, Issue 6, pp. 6801-6807, June 2018.

[8] Dr. Sridhathan C, Dr. M. Senthil Kumar, “Plant Infection Detection Using Image Processing”, International OPEN ACCESS Journal of Modern Engineering Research (IJMER) ISSN: 2249–6645, Vol. 8, Issue. 7, pp. 13-16, July 2018.



10.22214/IJRASET

INDEX COPERNICUS 45.98

ISRA JIF IMPACT FACTOR: 7.129

SJIFactor TOGETHER WE REACH THE GOAL IMPACT FACTOR: 7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY