Detection of Bacterial and Fungal Leaf Diseases Using Machine Learning Techniques

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***Abstract*—**: Leaf diseases have grownup to be a problem because it will cause vital reduction in each quality and amount of agricultural yields. Thus, automatic recognition of diseases on leaves plays a vital role in agriculture sector. This paper imparts a straightforward and computationally good technique used for plant disease identification and grading victimization digital image process and machine vision technology. during this paper we are focusing on major fungal and bacterial disease of leaves of plant and also focus given to various soft computing techniques used for detection of such diseases. Finally, we conclude the results of various SVM and decision tree based classifiers on the basis of their accuracies and ROC curve. We found highest accuracy for decision tree algorithm which was 96.8%.

***Keywords:-* Plant disease, Machine Learning Techniques, bacterial disease, fungal disease.**

I. INTRODUCTION

Fungi are the most common parasites causing plant disease. Most are microscopic (very small and can only be seen with the aid of a microscope) plants that feed on living green plants or on dead organic material. When they attack living plants, a disease results. Fungi usually produce spores which, when carried to a plant, can begin an infection. These spores may be carried from plant to plant by wind, water, insects and equipment. In order for fungus spores to begin new infections, adequate moisture and the right air temperature are required. A plant wound is sometimes also needed as an entry for the fungus. Fungus diseases are common during wet, humid seasons. Bacteria are single-celled microscopic organisms. Some attack living plants and cause plant disease. Bacteria can be carried from plant to plant by wind, rain splash, insects and machinery. These diseases occur primarily on leaves, but some may also occur on stems and/or fruit. Leaf diseases are the most common diseases of most plants. They are usually controlled with fungicides, bactericides and resistant varieties. Although leaf diseases are described under several different symptom types, keep in mind that differences are not always clear-cut and there are many names for leaf diseases other than those given, a situation which can be confusing[1].

A. Leaf Spots

Leaf spots are usually rather definite spots of varying sizes, shapes and colors. There is nearly always a distinctive margin. Sometimes the spot, which may be caused by bacteria or fungi, is surrounded by a yellow halo.

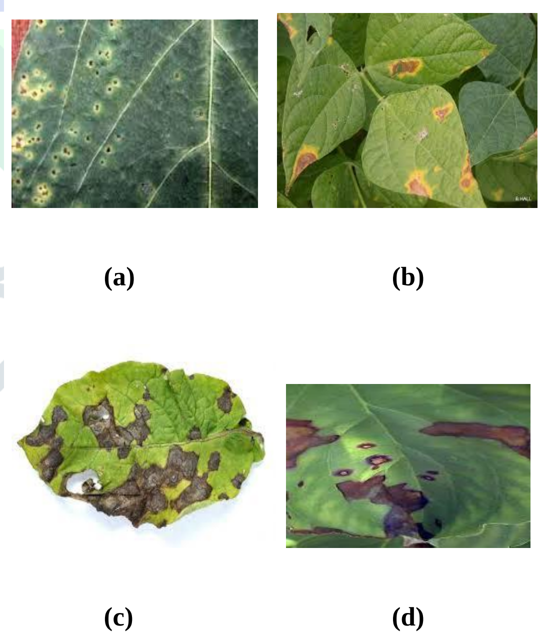


Figure 1: (a) Leaf Spot (b) Leaf Blights (c) Fungal Infection (d) Brown spot

1.4 Brown Spot

Infected plants have brown or black water-soaked spots on the foliage, sometimes with a yellow halo, usually uniform in size. The spots enlarge and will run together under wet conditions. Under dry conditions the spots have a speckled appearance. As spots become more numerous, entire leaves may yellow, wither and drop. Members of the Prunus family (stone fruits, including cherry, plum, almond, apricot and peach) are particularly susceptible to bacterial leaf spot. The fruit may appear spotted or have sunken brown areas. Bacterial leaf spot will also hit tomato and pepper crops in vegetable gardens[2,3].

B. Leaf Blights

Found on tomato and potato plants, late blight is caused by the fungus Phytophthora infestans and is common throughout the United States. True to its name, the disease occurs later in the growing season with symptoms often not appearing until after blossom. Late blight first appears on the lower, older leaves as water-soaked, gray-green spots. As the disease matures, these spots darken and a white fungal growth forms on the undersides. Eventually the entire plant will become infected. Crops can be severely damaged.

C. **Fungal Infection:**

Generally found in the eastern part of the United States, fungal infection is caused by fungi in the genus Colletotrichum, a common group of plant pathogens that are responsible for diseases on many plant species. Infected plants develop dark, water soaked lesions on stems, leaves or fruit. The centers of these lesions often become covered with pink, gelatinous masses of spores especially during moist, warm weather. Fungal infection can reduce a beautiful harvest into rotted waste in just a few days[3,4].

D. Brown spot:

Brown spot has been historically largely ignored as one of the most common and most damaging rice diseases. Brown spot is a fungal disease that infects the coleoptile, leaves, leaf sheath, panicle branches, glumes, and spikelets. Its most observable damage is the numerous big spots on the leaves which can kill the whole leaf. When infection occurs in the seed, unfilled grains or spotted or discolored seeds are formed[4].

II. LITERATURE SURVEY

Devi et.al in [1] for any automated image analysis process, the segmentation is an important task because all subsequent tasks in image processing heavily rely on the quality of image segmentation. It determines the eventual success or failure of the analysis. Chaudhary et.al in [2] in this research, an algorithm for disease spot segmentation using image processing techniques in plant leaf is implemented. This is the first and important phase for automatic detection and classification of plant diseases. Disease spots are different in color but not in intensity, in comparison with plant leaf color. So we color transform of RGB image can be used for better segmentation of disease spots. Bhattacharyya et.al in [3] multichannel information processing from a diverse range of channel information is highly time- and space-complex owing to the variety and enormity of underlying data. Most of the classical approaches rely on filtering and statistical techniques. Methods in this direction involve Markov random models, vector directional filters and statistical mixture models like Gaussian and Dirichlet mixtures.

Vijayakumar et.al in [4] the aim of this research paper is to identify the foot rot disease infected in the betelvine plants using digital imaging techniques. The digital images of the uninfected betelvine leaves and the digital images of the infected in foot rot diseased betelvine leaves at different stages are collected from different betelvine plants using a high resolution digital camera and collected betelvine images are stored with JPEG format. The digital image analyses of the betelvine leaves are done using the digital image processing toolbox in MATLAB. The median values for all betelvine leaves are computed and calculated median values are stored in the system. The median values of test betelvine leaves are computed and compared with the stored median values. As the consequence of this evaluation, it is identified whether test betelvine leaves are affected by foot rot disease or not. Finally this research work is helps to recognize the foot rot disease can be acknowledged before it spreads to complete crop. Singh et.al in [5] in India a majority of the population in rural areas is working in the agriculture field for their livelihood. They not only have to struggle for the better yield against the natural disasters but also have to tackle the losses of the net output because of land fertilization specifications and unskilled labour too. In the event of inadequate utilities and resources, in the face of unpredictable crises, their gain opportunities and livelihood are proportionally and adversely affected. However in this era of technology, the scenario may get changed as the Information and Communication and related fields of technology are providing a great for such type of crisis handling. Here in this paper, the method which may be used to compare the crop leaf color with the leaf color chart (LCC), has been proposed for getting a detail about the requirement of plant, before enough to get the yield affected. By making use of image processing technology a simple and robust method for the color prediction of paddy crop plant has been discussed along with the mathematical modelling which may provide a great platform to the advisory bodies in the agriculture field for the atomization of the crop health problems and solutions.

Asfarian et.al in [6] the efforts to increasing the quantity and quality of rice production are obstructed by the paddy disease. This research attempted to identify the four major paddy diseases in Indonesia (leaf blast, brown spot, bacterial leaf blight, and tungro) using fractal descriptors to analyze the texture of the lesions. The lesion images were extracted manually. The descriptors of `S' component of each lesion images then used in classification process using probabilistic neural networks. This techniques achieved at least 83.00% accuracy when identifying the diseases. This method has a potential to be used as one of the feature if it combined with other features, especially when two diseases with relatively same color involved. Paproki et.al in [7] the proposed method produces a smart partition of the initial mesh that allows to identify the main stem, branches, and leaves of the plant. Extracted regions are then processed through the next stage of the automated analysis, which retrieves accurate plant information such as stem length, leaf width, length or area. Results involved applying our top-down approach on a prototype population of 6 cotton-plant meshes studied at 3 or 4 time points. Using our partitioning pipeline, we obtained accurate meshes segmentations for 20 plants out of the initial 22. Results validate the feasibility of an automated analysis of plant data. Future work will involve extending our approach to multiple plant varieties and using an atlas-based iterative feedback scheme to improve the 3D plant reconstruction. Choong et.al in [8] segmentation on synthetic images and natural images are covered to study the performance and effect of different image complexity towards segmentation process. This study gives some research findings for effective image segmentation using graph partitioning method with computation cost reduced. Because of its cost expensive and it becomes un favourable in performing image segmentation on high resolution image especially in online image retrieval systems. Thus, a graph-based image segmentation method done in multistage approach is introduced here.

A.Meunkaewjinda et al. [9] represented disease detection in grapes using hybrid intelligent system in which the diseases in leaves of plants are graded by calculating the quotient of diseased area and the leaf area. Self-organizing maps back propagation neural networks was used by them for recognizing the colors of the grape leaves that were used to segment he pixels of the grape leaf within the entire image. After that disease segmentation is performed. Gabor wavelet is then used to filter the segmented image in order to analyze the color features of the leaf. After that support vector machines are applied in order to classify the different types of diseases in grape leaves. In this method the Segmentation was good enough as it suffered from the limitation of extraction of ambiguous color pixels from the background of the image. With the usage of back propagation neural network, there is an inability to know how to precisely and accurately generate an arbitrary mapping procedure. Stephen Gang Wu [10] put into practice a leaf recognition algorithm using easily extracted features and highly efficient algorithms for recognition purpose. A Probabilistic Neural Network (PNN) was used for recognition of plant leaves. In this, various features are mined and processed by which act as an input to PNN. The drawbacks of this technique were that accuracy of recognition observed was 90% and the features extracted were not up to the mark. Xu Pengyun et al. [11] presented a technique for monitoring plant diseases that were caused by spores. The colored images is firstly converted in to gray scale image so in order to analyze and process though histogram generation, the gray-level correction, image feature extraction, image sharpening and so on. Moreover in order to remove the components of the image having low frequency, the edges of the grayscale image is enhancing using Median Filter and canny edge algorithm. After thresholding, morphological features like dilation, erosion, opening etc are applied on the binary image obtained .The drawbacks for this technique were that processing time appears to be high and there also exists variations in the size of spores.

Rastogi, et.al. [21] proposed a model for detection of disease from leaf of plant , they first perform pre processing then, classification task have been done by using neural network. Finally, disease grading is provided according to severity of disease. Pujari J.D. et.al. [22] presented a study on different image processing techniques used for fungal disease detection and found fungi as a main source of disease in plants. Habib T. et.al. [23] present an online machine vision-based agro-medical expert system that processes an image captured through mobile or handheld device and determines the diseases in order to help distant farmers to address the problem.

III. METHODOLOGY

Flowchart of methodology used for detection of disease from affected leaf. Features Color, Shape, Texture.

A. DATABASE PREPRATION:

Database contain 1000 images collected from 3 different sources like Manually captured using high definition digital camera, Online available datasets.

Finally database is divided into 5 classes:

1. Fungal Infection
2. Bacterial Blight
3. Brown Spot
4. Leaf Spot
5. Healthy Leaf

B. FEATURE EXTRACTION

We have extracted 12 features from all input images, features are mainly based on:

1. Shape of Leaf.
2. Texture of Leaf
3. Color of Leaf
4. Intensity variation in Leaf

And Images used in reference papers.

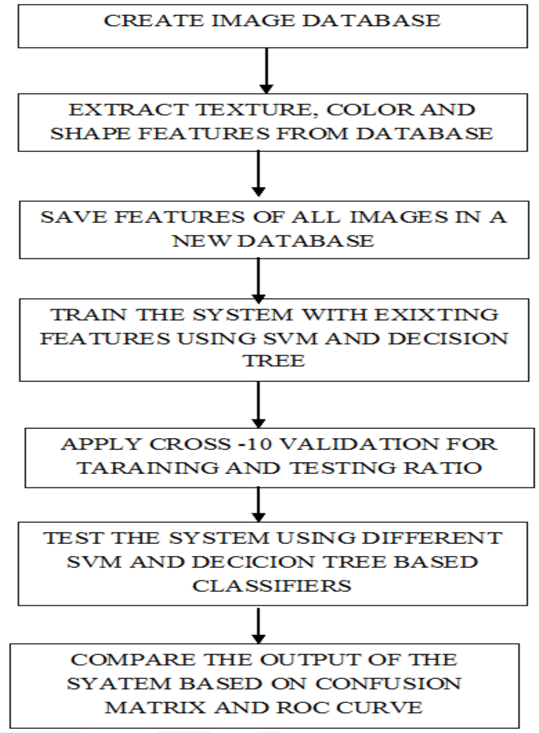


Figure 2: flow chart of methodology

A brief description of extracted features are as follows:

Contrast

$$CONTRAST = \sum_{n=0}^{G-1} n^2 \{\sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)\}, \quad |i-j| = n \tag{1}$$

This measure of contrast or local intensity variation will favour contributions from P(i, j) away from the diagonal, i.e. i != j.

Mean:

$$AVER = \sum_{i=0}^{2G-2} i P_{x+y}(i) \tag{2}$$

It calculates the average of all pixels

Inverse Difference Moment (IDM)

$$IDM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \tag{3}$$

IDM is also influenced by the homogeneity of the image. Because of the weighting factor (1+(i−j)2)−1 IDM will get small contributions from inhomogeneous areas (i != j). The result is a low IDM value for inhomogeneous images, and a relatively higher value for homogeneous images.

Entropy:

Inhomogeneous scenes have low first order entropy, while a homogeneous scene has a high entropy.

$$ENTROPY = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) \times log(P(i,j)) \quad (4)$$

Correlation :

$$CORRELATION = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \quad (5)$$

Correlation is a measure of gray level linear dependence between the pixels at the specified positions relative to each other.

Variance:

$$VARIANCE = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-\mu)^2 P(i,j) \quad (6)$$

This feature puts relatively high weights on the elements that differ from the average value of P(i, j).

Sum Entropy

$$SENT = -\sum_{i=0}^{2G-2} P_{x+y}(i) log(P_{x+y}(i)) \quad (7)$$

C. CLASSIIFICATION ALGORITHMS:

Support Vector Machine:

Input: initialize subset S = { 1,2,3.....}

Output: Rank list according to smallest weight R

Step1: Initially defined R = { }.

Step2: Repeat step 3 to 8 until G is not empty.

Step3: Train support vector machine model using G.

Step4:Compute weight W vector for SVM

Step5: Compute Rank R= W*W

Step6: Rank features and sort accordingly

Rank $_{new}$ = Sort (Rank);

Step7: Update feature rank list

Update R = R + G (Rank $_{new)}$

Step8: Eliminate feature with smallest rank

Update G = G- G(Rank $_{new}$)

Step9: End

Algorithm used for Decision Tree classification:

A decision tree may be a tree within which every branch node represents an alternative between variety of alternatives and every leaf node represents a choice. It is a sort of supervised learning classifier that's largely utilized in classification issues and works for each categorical and continuous input and output variables. It's one in all the foremost wide used and sensible ways for inductive illation.

Step1: Place the best attribute of the dataset at the root of the tree

Step2: Split the training set into subsets.

Step3: Repeat step1 and step2 on each subset until you find the leaf nodes in all the branches of the tree

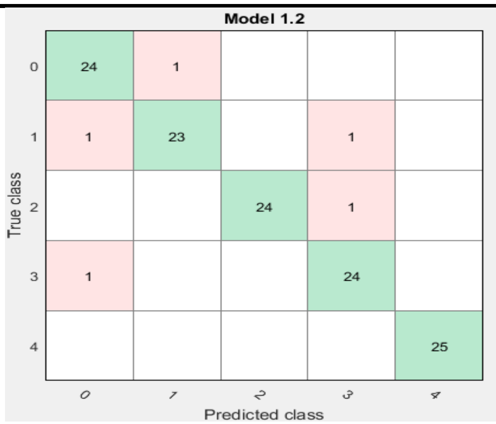
IV. RESULT ANALYSIS

Extracted features from different methods

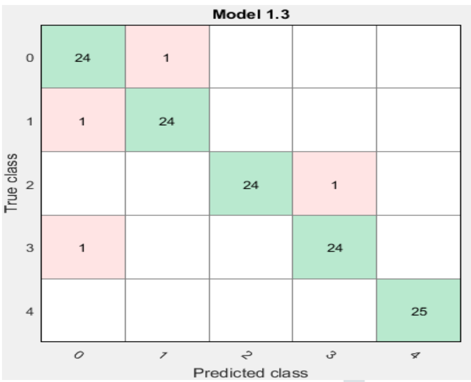
Table 1 Results after applying proposed method with previous method

Contrast	Corelation	Energy	Homegeniety	Mean	S.D.	Entropy	RMS	Variance	Smoothness	ASM	IDM	Class
0.078876	0.9783213	0.762589	0.974878217	14.84385	47.81168	1.709878	5.574773	2150.696	0.999999657	15.59777	255	0
0.466835	0.8657081	0.796721	0.959196082	14.15012	48.13958	1.365848	4.313618	1632.216	0.999999641	15.7654	255	0
0.367586	0.910197	0.757318	0.96254705	16.44411	51.41943	1.667891	5.340374	2305.041	0.999999691	13.79264	255	0
0.541238	0.7510341	0.538239	0.922201579	17.97166	37.66352	2.582884	7.403698	1306.813	0.999999717	10.4951	255	0
0.512776	0.7103205	0.894702	0.971681238	17.1185	35.52045	2.843172	10.45046	1162.225	0.999999703	27.60328	255	0
0.697626	0.8738924	0.487259	0.910412089	31.56037	56.45961	2.982981	8.114045	2844.325	0.999999839	4.400836	255	0
0.488618	0.9580138	0.268706	0.940313539	71.85277	83.07288	5.120415	11.46161	5682.676	0.999999929	1.826999	255	0
0.430913	0.896565	0.765986	0.965597736	17.43762	52.46393	1.878881	5.728899	2052.447	0.999999708	12.8361	255	0
0.576072	0.9091526	0.710405	0.958389301	23.81361	60.20883	1.673428	5.436237	3230.313	0.999999786	6.958173	255	0
0.746201	0.9098204	0.52789	0.900746163	40.04733	73.85749	2.911928	7.533026	4465.177	0.999999873	3.993152	255	0
0.88943	0.8263042	0.818493	0.965069791	16.41812	55.65341	1.300243	4.322796	2841.536	0.99999969	12.32038	255	0
0.413971	0.9701724	0.410585	0.972991582	76.61838	97.98215	3.843924	9.364152	6332.289	0.999999934	1.517145	255	0
0.08629	0.9490796	0.884848	0.993442132	8.575495	35.45269	0.717587	2.515133	1110.396	0.999999407	18.75243	255	0
1.045052	0.8166756	0.619172	0.920878377	26.94916	60.87399	2.481799	6.955969	3471.252	0.999999811	6.628791	255	0
0.413097	0.8459476	0.842361	0.976561679	10.60321	41.47241	1.194491	3.828865	1594.445	0.99999952	22.34609	255	0
1.006648	0.7952485	0.796001	0.95426456	16.59695	54.72505	1.297603	4.600875	2771.884	0.999999694	12.37107	255	0
1.319761	0.8648023	0.480227	0.919423217	44.17804	76.84772	3.321984	8.689485	5494.231	0.999999885	3.411599	255	0
0.27454	0.8709934	0.859583	0.979117246	9.741954	38.48165	0.886391	3.514845	1388.821	0.999999478	19.34547	235	0
0.565518	0.8692294	0.673009	0.954929005	21.60405	53.86949	2.322427	6.205505	2484.706	0.999999765	9.931365	234	0
0.262546	0.8792221	0.798925	0.976501262	13.27572	42.41368	1.271065	4.301087	1614.019	0.999999617	12.9619	233	0
0.331847	0.8661782	0.734424	0.95745191	18.0845	41.43077	3.817042	9.743996	1158.825	0.999999719	22.60748	232	0
0.841958	0.7638812	0.704448	0.93560877	18.29885	47.74902	3.338588	7.146066	2201.596	0.999999722	13.60903	231	0
0.41152	0.9814167	0.350451	0.944820316	128.9061	118.6973	3.6237	12.57438	10666.31	0.999999961	1.098829	230	0
0.667126	0.9168987	0.480335	0.911658187	41.22886	71.50431	3.270195	8.194657	4609.107	0.999999877	3.833673	255	0

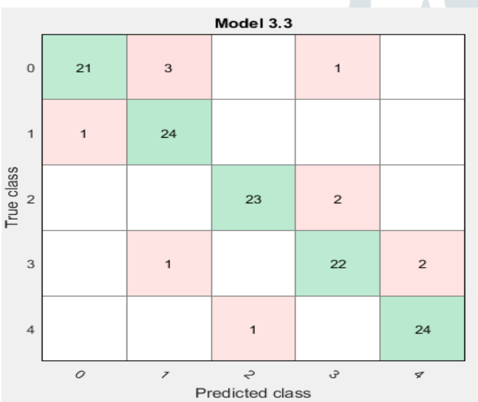
Above table 5.1 shows the features extracted from different leaves, the feature mainly contains texture, shape and color features of leaf.



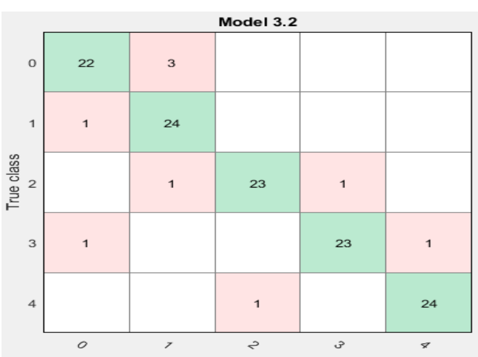
(a)



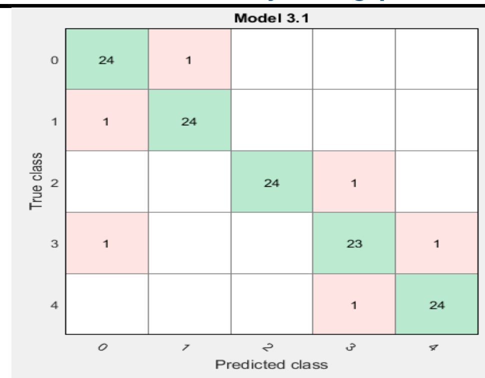
(b)



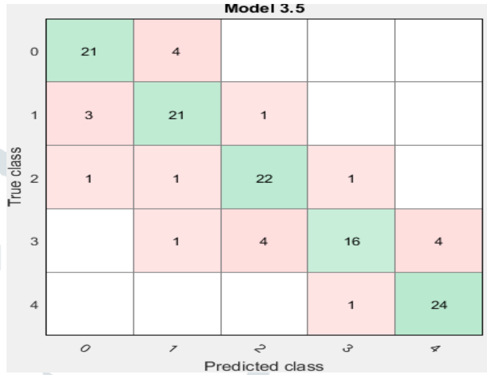
(c)



(d)



(e)



(f)

Figure3: confusion matrix of (a) Complex Tree (b) Medium Tree (c) Simple Tree (d) Linear SVM (e) Quadratic SVM (f) Cubic SVM

Table 2 Results after applying proposed method with previous method

Classifier	**Accuracy**
Complex Tree	96%
Medium Tree	96%
Simple Tree	96.8%
Linear SVM	95.2%
Quadratic SVM	92.8%
Cubic SVM	91.2%
Medium Guassian SVM	83.2%
[12] Tasneem	94.1%
[13] B. Klatt et al	96.6%
[14] Shovon Paulinus Rozario	Not Available
[17] Shitala Prasad et al	93%
[18] Rahat Yasir et al	85%
[19] Alham F	87.75%

From figure 5.5 and table 5.1 we cam easily obseve accuracy of our method

VI. CONCLUSION

From figure 5.5 and table 5.1 we can conclude that Highest Accuracy we can get using Simple Decision Tree Method i. e. 97% After applying all SVM classifiers we can see that highest accuracy is 95.2% for Linear SVM.In previous methods range of accuracy was 82% to 97% which is less than our method here range of accuracy for different classifiers is 83.2% to 97% which is better than previous method.

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