

Classification of Leaf Disease Using Global and Local Features

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Abstract: Leaf disease of plants causes great loss in productivity of crops. So proper take care of plants is mandatory. Plants can be affected by various diseases. So Early diagnosis of leaf disease is a good practice. Computer vision-based classification of leaf disease can be a great way in diagnosing diseases early. Early detection of diseases can lead to better treatment. Vision based technology can identify disease quickly. Though deep learning is trending and using vastly for recognition task, but it needs very large dataset and also consumes much time. This paper introduced a method to classify leaf diseases using Gist and LBP (Local Binary Pattern) feature. These manual feature extraction process need less time. Combination of gist and LBP features shows significant result in classification of leaf diseases. Gist is used as global feature and LBP as local feature. Gist can describe an image very well as a scene. LBP is robust to illumination changes and occlusions and computationally simple. Various diseases of different plants are considered in this study. Gist and LBP features from images are extracted separately. Images are pre-processed before feature extraction. Then both feature matrix is combined using concatenation method. Training and testing is done on different plants separately. Different machine learning model is applied on the feature vector. Result from different machine learning algorithms is also compared. SVM performs better in classifying plant's leaf dataset.

Index Terms: Leaf disease, Gist, local binary pattern, machine learning.

1. Introduction

Bangladesh is a land of agriculture. Wide diversity of crops is produced in the land of Bangladesh every year. Besides a large number people are dependent on the agricultural work. Crops are very important for a country. It has a large impact on economy. Moreover, foods are come from plants. But plants can be infected in various ways. Disease symptoms are usually explored out through leaf. So, It is necessary to identify the disease and take steps to cure the disease as early as possible. Timely and accurate diagnosis of diseases can prevent losses of farmers in their production of crops. Farmers work hard in the field to produce crops. A lot of care is needed produce crops. Young farmers have less knowledge about disease and their treatment due to the lack of expertiseness. Though old farmers have idea about plants disease, but they may not be available all the time. Sometimes many of the old farmers do mistake in identifying disease. As a result, there cause a great loss in production. So, a disease classification system is necessary to mitigate this problem and also to provide corresponding treatment.

With the advancement of artificial intelligence, tasks are becoming easier day by day. Now it is possible to detect disease from leaf image using vision technology. Currently deep learning is in trending in classifying images. But deep learning requires huge data for training and training is also time-consuming. Global and local features are also useful in recognizing images. It needs less time. This study focused on the global and local feature based leaf image classification to identify diseases. These features can be extracted easily within very short time. Moreover, Gist feature provides low dimensional feature vector which is very helpful. Gist provides a well estimation of an image with lower feature size. LBP feature is beneficial in classifying images under different lighting and environmental changes like illusion, occlusion etc. This study takes into account ten different types of plant's dataset. Dataset are collected from kaggle [2] and mendeley data [3]. The plants and the disease considered in this study are- Apple (scab, black rot, Cedar apple rust),

Cherry (powdery mildew), Corn (Cercospora leaf spot, common rust, northern leaf blight), Grape (black rot, Esca, leaf blight), Peach (bacterial spot) , Pepper bell (bacterial spot), Potato (early blight, late blight), Strawberry (leaf scorch), Rice (bacterial blight, blast, brown spot, tungro) and Tomato (bacterial Spot early blight, late blight, leaf mold, septoria leaf spot, spider mites, target spot, mosaic virus, yellow leaf curl virus). Images from mendely data provides only the dataset of rice. Figure 1 shows disease of different plants leaf.

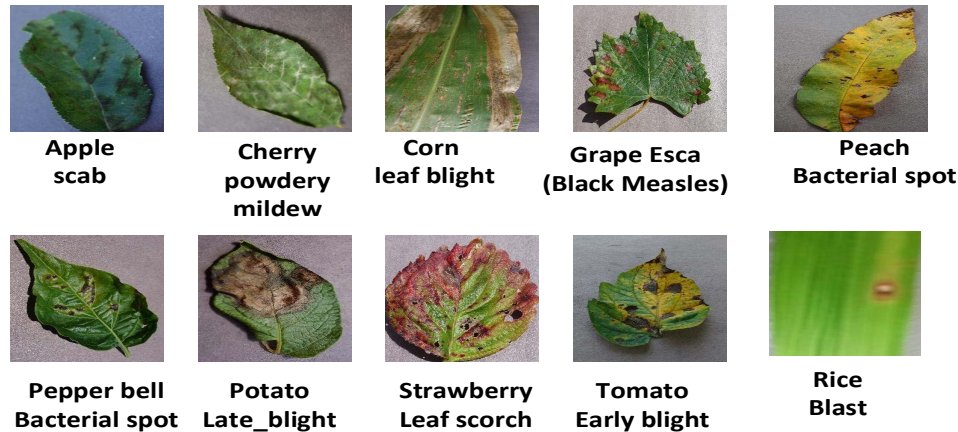


Fig.1. Sample images of leaf disease

Researchers have developed many features with reduced dimension to describe an image. Though CNN feature is very popular but it is time consuming. Leaf images are complex as there exists backgrounds. On the other hand, appropriate segmentation of leaf image may not possible. Various color or texture based feature extraction method have been used by many. In that case proper segmentation of image is a main issue. So, classifying the image as whole can be a better choice. For this purpose, Gist feature is used in this study along with LBP. Gist feature is very powerful as it is renowned in scene classification. LBP is also well against illumination. In this paper a combination of gist and LBP are used for classifying leaf disease. Among ten types of dataset, KNN results better in rice leaf disease (4 classes) classification and AdaBoost performs well for tomato leaf disease (10 classes) classification. SVM shows inspiring result for rest of the plant's leaf disease dataset.

2. Related Works

AI based application is increasing world-wide regularly. Researchers are trying to make the agricultural task quite easier for farmers. Several methods have been introduced to classify disease of leaf image. Detection and classification of grape leaf is proposed by Padol [1]. Segmentation of the image is carried out by k-means lustering method. Then color and texture features are extracted. Finally, SVM performs the classification tasks with an accuracy of 88.89%.

Color and texture featire are mostly used feature for leaf image classification [4-9,27-29]. Calculation of disease infected area was proposed by Islam [4]. Image processing techniques were used to calculate infected pixels from image. Segmentation was done by k means clustering method. Three cluster images were formed based on color property. Then pixels were calculated from infected and fresh region of those clustered images. Neural network is popular as classification of images. Back propagation Neural Network (BPNN) is used by many researchers.

Deshmukh proposed a method to extract feature from segmented leaf image [5]. At first infected regions are detected followed by k means clustering segmentation method. Features wee extracted using GLCM and discrete wavelet transform. Classification was made by back propagation neural network.

Wang proposed a method to classify grape and wheat leaf disease [6]. K means segmentation was used. PCA was employed to reduce feature dimensionality. Finally, neural network with back propagation was used for classifying leaf images.

A method proposed by Anthonys uses texture, color and texture features [7]. Input image is segmented with the help of morphological operation. Then membership function is used for classification of disease. Three types of diseases were considered by the method.

John proposed a system followed by image enhancement, segmentation feature extraction and classification [8]. Total 134 images were used in that system. Four types of features were extracted by the system. Fraction covered by the disease on the leaf, mean of R, G, and B, standard deviation of the R, G, and B, finally mean of H, S and V of the disease.

A feature matching method is used by Charlie paul to classify leaf disease image [9]. Color and shape features are extracted by the method. R, G and B color planes are considered for color features and DRSLE (Distance Regularized Level Set Evolution) algorithm used for identifying desired shape. Then feature matching method is used for predicting disease.

Phadikar presents a system consisting segmentation with otsu method and then feature extraction [10]. Hue value is considered for thresholding. Radial distribution of hue is used for feature. Bayes and SVM classifier are used for classification. SVM performs poor than Bayes.

Use of deep learning in classification tasks has increased since few years. A CNN based method represented by Brahimi that uses a number of 14, 828 images of tomato leaves [11]. Dataset consists of nine classes as diseases. For localizing disease region and understanding symptoms, visualization methods are used. Another method proposed by

Ramesh includes segmentation and then classification with deep learning [12]. RGB image is converted o HSV first. Then binary image of diseased and non-diseased parts is splitted based on the hue and saturation. Optimized Deep Neural Network with Jaya Optimization Algorithm (DNN_JOA) is used for classification.

Pre-trained cnn model is applied on a large leaves' dataset by Ferentinos [13]. Several pre-trained models were used on the dataset. System returns appreciable result, but time-consuming.

The automatic classification of leaf disease and corresponding steps to cure the disease of plant's leaf decreases the reliability on plants specialists [14,15]. Nowadays, various supervised and unsupervised machine learning algorithms are popular in classifying images. Few are- naïve bias classifier [16], k-nearest neighbor classifier [17], support vector machine [1], artificial neural network classifier [18] and convolution neural network [19]. Though many researches have been done but there is still a lot of space to improve diseased leaf classification in term of arrangement precision and computational expense [20-21].

3. Methodology

This paper presents global and local feature based classification of leaf disease. Steps are shown in fig 2. At first, some preprocessing of input images is necessary.

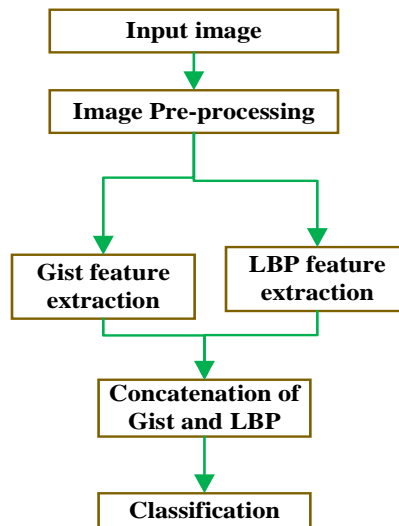


Fig.2. Flow of proposed system

3.1. Pre-processing

Pre-proessing makes image better for further processing. Pre-processing steps like- resize, noise filtering is used. These steps improve the quality of image.

A. Resize of image

Image resizing is a crucial step. It is time-worthy to process a large image. So, image should be resized into a standard size. This study resized image in 200x150 dimension. All the training and testing images are converted to that dimension.

B. Noise removal

An image may contain noise. Noise is unwanted information in an image. Noise makes feature selection and extraction quite difficult. Therefore, removal of noise is also necessary. For removing noise from image, median filter is used in this study. Median filter has edge preserving properties. Median filter removes noise without affecting the edges. It is robust to outliers. It eliminates outliers like- extreme brightness without blurring signal. Thus, the pre-processing steps enhances the quality of image. Then comes feature extraction phase.

3.2. Feature Extraction

Extraction of feature means representation of an image with reduced dimension. Feature extraction methods provides a compact feature vector of input image. Basically, feature vector contains most informative parts of an image. Low size feature vector helps to classify image in more short time. So powerful reduced feature is well suited for make the classification tasks faster. Gist and LBP are such that type of features.

A. Gist

Gist is a computational classic model for recognition of real world scenes. It is supported by very low dimensional feature representation of a scene, originally called by the authors as the Spatial Envelope [22]. Extraction process shown in fig 3. It needed to be stated that Gist is not an acronym; it provides a summary of a scene, so the name is Gist. Gist represents spatial structures, which are dominant in an image.

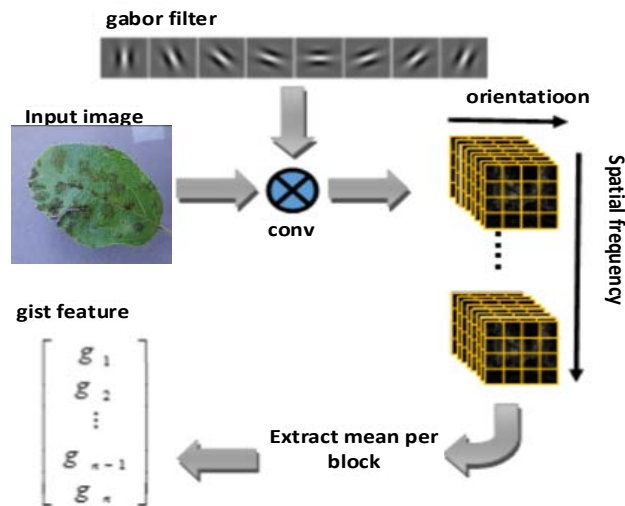


Fig.3. Gist feature extraction process

Gist provides the summarized information of gradient for different parts of an image. Gist descriptors work by employing a set of Gabor filters at several scale, location and orientations. In particular, the Gist descriptor uses a bank of 24 filters and computes the energy of the output of the filters. These are Gabor filter-like set to 4 orientations at 2 different scales. Scale and orientations can also be set at different values. The square output of each filter is then averaged on a 4x4 grid. Pre-processed image is splitted into grid, and a set of Gabor filters are applied to each cell. Finally, the average of these cells returns Gist feature vectors (vector of 128 values).

B. LBP

LBP is resistive to different lighting conditions. Computational complexity is also low. The original LBP operator works by labeling the pixel value of an image with decimal numbers. It's called Local Binary Patterns and it encodes the local structure around each pixel. Each center pixel is compared with its 3x3 neighborhood pixel values. If neighborhood value is less than the center value, then it becomes 0, otherwise 1. Then starting from the top-left and going in clockwise direction, a binary value is obtained. This derived binary number is known as local binary patterns. The corresponding decimal value works for labeling. Figure 4 represents basic operation of LBP operator.

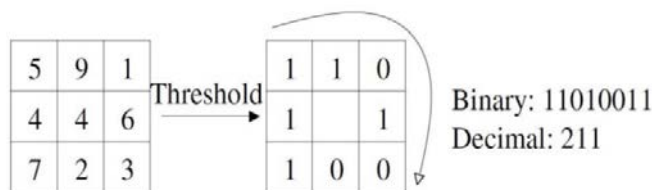


Fig.4. Basic LBP operation

The original LBP operator covers only a small area in a fixed radius. To mitigate this issue an extended LBP was proposed by Ojala [23]. Extended method is shown in fig 5. The 3x3 neighborhood can extend to any different neighborhoods and square neighborhood is replaced by circular neighborhood.

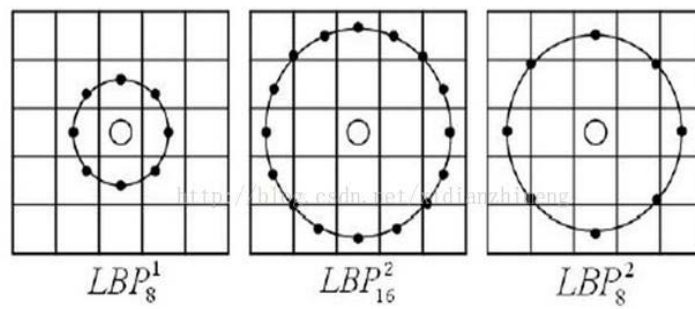


Fig.5. Extended LBP operator; the circular (8, 1), (16, 2) and (8,2) neighborhoods

3.3. Combination of Feature

Both gist and LBP features are combined with concatenation method. Gist provides a feature dimension of 128 and LBP operator extract 354 dimensional feature in this study. Combined feature vector contains 482 (128+354) dimensional feature size.

4. Classification Model

Classification is a process of predicting a given set of data into its own class from which it belongs. Classification can be implemented on both types of data-structured and unstructured. Classes are often denoted as labels or targets.

A. Support Vector Machine

Support Vector Machine which is in short known as SVM, is a machine learning model used for classification and regression problems. It works well in solving both linear and non-linear problems. SVM model proves good in different practical problems. The core principle of SVM is that SVM algorithm draws a line or a hyperplane which split up data into classes [24]. As shown in figure 6 [–] if one needs to separate red colors from blues then an ideal line needs to draw which separates both colors. SVM algorithm finds the points which are closest to the line from both the classes. These points are called support vectors. Then distance between the support vectors and the line is computed. This distance is known as margin and maximizing the margin is the goal of SVM. The optimal hyperplane is the one for which the margin is maximum. SVM tries to distinguish the classes as wide as possible

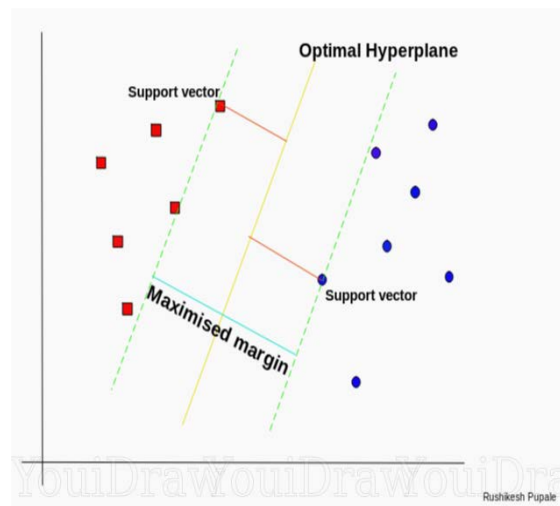


Fig.6. SVM algorithm's principal visualization

B. K Nearest Neighbor

KNN is a supervised classifier which is used for solving machine learning tasks. KNN works on a principle that the data point that falls near to each other, belongs to same class. New data point is classified by KNN on the basis of similarity [25].

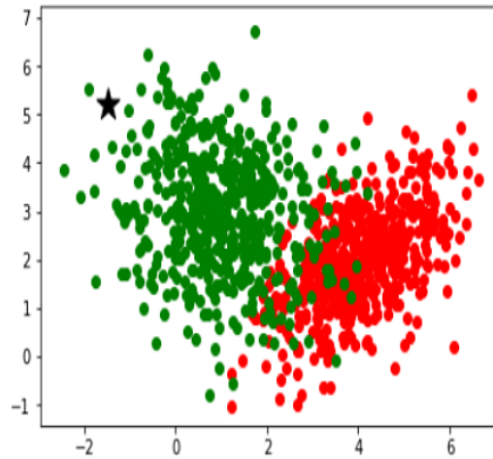


Fig.7. Understanding KNN classifier

KNN selects a value for K . K is the nearest neighbor for those data points which are to be classified. if $k=4$ then KNN looks for 4 the data points are which are near 4. Let consider fig 7 as an example. All the data points near black star data points belong to the green. That means black star belongs to green c class asper KNN principle. The black star is not considered in the red class because red class data points are not closer black star data point.

C. AdaBoost

Adaboost is an ensemble method used in machine learning. AdaBoost is the short form of Adaptive Boosting. This algorithm transforms weak learners to stronger [26]. It fits a sequence of weak learners on different weighted training data. It first predicts the original data set and provides same weight to each observation. If prediction is incorrect using the first learner, then it gives higher weight to observation which have been predicted incorrectly. Being an iterative process, it continues to add learner(s) until a limit is reached in the number of models or accuracy.

5. Performance Analysis

Proposed system is trained and tested on 10 different types of plants leaf dataset. Different machine learning model (SVM, KNN and AdaBoost) is used for classification purpose. 10-fold cross validation is applied. Table 1-10 shows classification accuracy of plant's leaf disease for different machine learning algorithm.

Table 1. Accuracy for apple leaf disease (4 classes) classification

Classifier	Accuracy
SVM	91.9%
KNN	82.1%
Adaboost	76.6%

Table 2. Accuracy for cherry leaf disease (2 classes) classification

Classifier	Accuracy
SVM	99.7%
KNN	99.4%
Adaboost	52.0%

Table 3. Accuracy for corn leaf disease (4 classes) classification

Classifier	Accuracy
SVM	92.6%
KNN	86.9%
Adaboost	83.4%

Table 4. Accuracy for grape leaf disease (4 classes) classification

Classifier	Accuracy
SVM	93.6%
KNN	86.1%
Adaboost	80.9%

Table 5. Accuracy for peach leaf disease (2 classes) classification

Classifier	Accuracy
SVM	98.2%
KNN	95.4%
Adaboost	91.6%

Table 6. Accuracy for paper bell leaf disease (2 classes) classification

Classifier	Accuracy
SVM	89.3%
KNN	88.6%
Adaboost	83.8%

Table 7. Accuracy for potato leaf disease (3 classes) classification

Classifier	Accuracy
SVM	90.4%
KNN	84.4%
Adaboost	81.2%

Table 8. Accuracy for rice leaf disease (4 classes) classification

Classifier	Accuracy
SVM	98.2%
KNN	99.6%
Adaboost	75.5%

Table 9. Accuracy for strawberry leaf disease (4 classes) classification

Classifier	Accuracy
SVM	96.9%
KNN	91.3%
Adaboost	92.7%

Table 10. Accuracy for tomato leaf disease (10 classes) classification

Classifier	Accuracy
SVM	80.0%
KNN	73.4%
Adaboost	80.9%

From table 1-7 and table 9, it is clear that SVM works better than other classifiers. In table 2 and table 6 for cherry and pepper bell leaf disease classification, KNN result is near to SVM. But for rice disease classification in table 8, KNN performs better slightly than SVM. Tomato leaf disease dataset contains 10 classes. According to table 10, AdaBoost performs well in tomato leaf disease classification. In this case SVM result is near to Adaboost.

Confusion matrix and receiver operating characteristics curve (ROC) helps to analyze the result of a classifier. Confusion matrix represents predicted class in column and actual class is in row. Table 11-19 depicts confusion matrix of leaf disease classification. ROC curve plots true positive rate (TPR) against false positive rate (FPR). AUC is a measure calculated from ROC. It is the ability of a classification model for distinguishing classes. Higher AUC indicates to better performance. The max AUC value is 1.

Table 11. Confusion matrix for apple leaf dataset using SVM

	Apple scab	Apple Black_rot	Apple Cedar apple rust	Apple healthy
Apple scab	425	43	19	17
Apple Black_rot	17	371	3	6
Apple Cedar apple rust	19	2	412	7
Apple healthy	9	8	8	477

Table 12. Confusion matrix for cherry leaf dataset using SVM

	Cherry healthy	Cherry_Powdery mildew
Cherry healthy	453	3
Cherry_Powdery mildew	0	421

Table 13. Confusion matrix for corn leaf dataset using SVM

	Corn Cercospora leaf spot	Corn Common rust	Corn healthy	Corn Northern Leaf Blight
Corn Cercospora leaf spot	337	3	11	59
Corn Common rust	2	470	3	2
Corn healthy	11	1	435	18
Corn Northern Leaf Blight	17	1	8	451

Table 14. Confusion matrix for grape leaf dataset using SVM

	Grape Black rot	Grape Esca	Grap Leaf blight	Grape healthy
Grape Black rot	425	46	1	0
Grape Esca	45	432	3	0
Grap Leaf blight	9	7	413	1
Grape healthy	1	1	1	420

Table 15. Confusion matrix for peach leaf dataset using SVM

	Peach Bacterial spot	Peach healthy
Peach Bacterial spot	449	10
Peach healthy	6	426

Table 16. Confusion matrix for pepper bell leaf dataset using SVM

	Pepper bell Bacterial spot	Pepper bell healthy
Pepper bell Bacterial spot	424	54
Pepper bell healthy	50	447

Table 17. Confusion matrix for potato leaf dataset using SVM

	Potato Early blight	Potato healthy	Potato Late blight
Potato Early blight	455	22	8
Potato healthy	35	418	32
Potato Late blight	6	34	416

Table 18. Confusion matrix for rice leaf dataset using KNN

	Rice Bacterial blight	Rice Blast	Rice Brown spot	Rice Tungro
Rice Bacterial blight	1581	2	1	0
Rice Blast	0	1429	5	6
Rice Brown spot	0	6	1594	0
Rice Tungro	0	1	0	1307

Table 19. Confusion matrix for strawberry leaf dataset using SVM

	Strawberry healthy	Strawberry Leaf scorch
Strawberry healthy	444	12
Strawberry Leaf scorch	16	428

Table 20. Confusion matrix for tomato leaf dataset using AdaBoost

	A	B	C	D	E	F	G	H	I	J
A	461	1	1	0	0	0	4	13	1	0
B	3	387	5	6	2	14	0	3	0	5
C	4	19	316	29	43	17	9	18	6	19
D	6	12	41	306	28	37	5	16	5	7
E	3	9	21	15	372	23	5	3	15	4
F	7	27	11	25	24	289	20	17	15	1
G	1	0	4	1	1	14	382	21	7	4
H	20	9	5	1	4	12	47	340	15	4
I	4	2	0	2	11	5	7	5	411	1
J	0	11	6	3	2	2	13	6	3	444

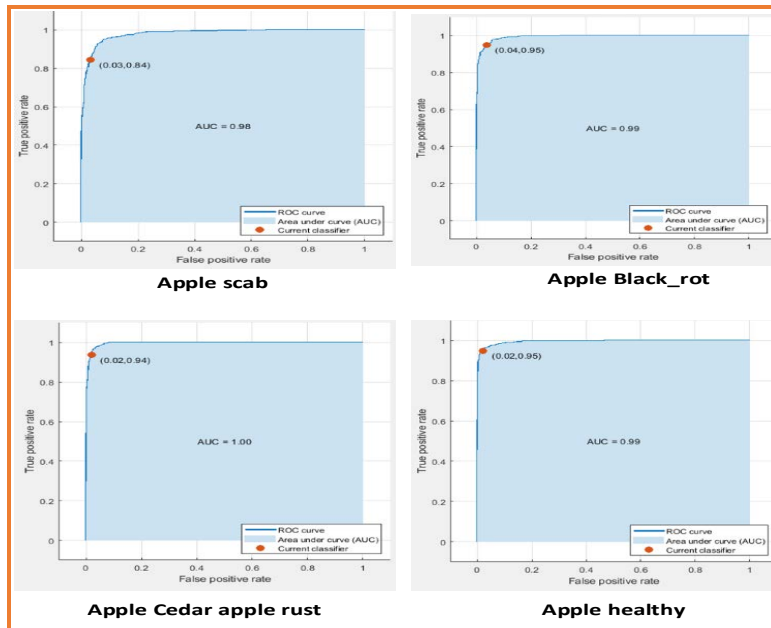


Fig.8. ROC curve for apple leaf disease classification using SVM

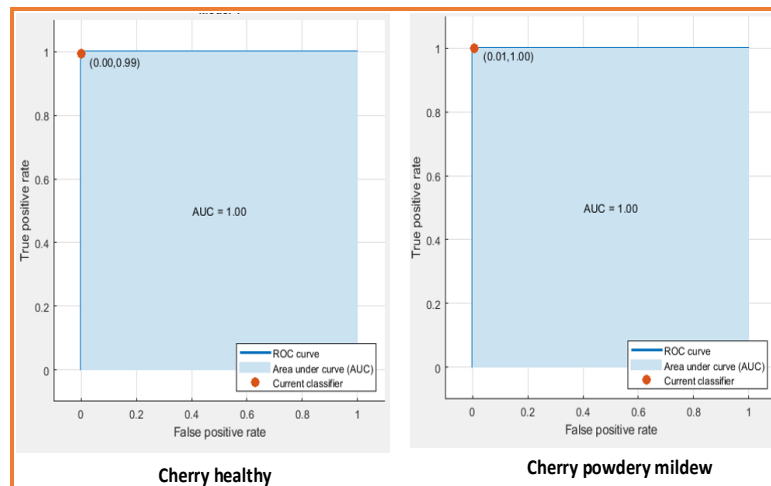


Fig.9. ROC curve for cherry leaf disease classification using SVM

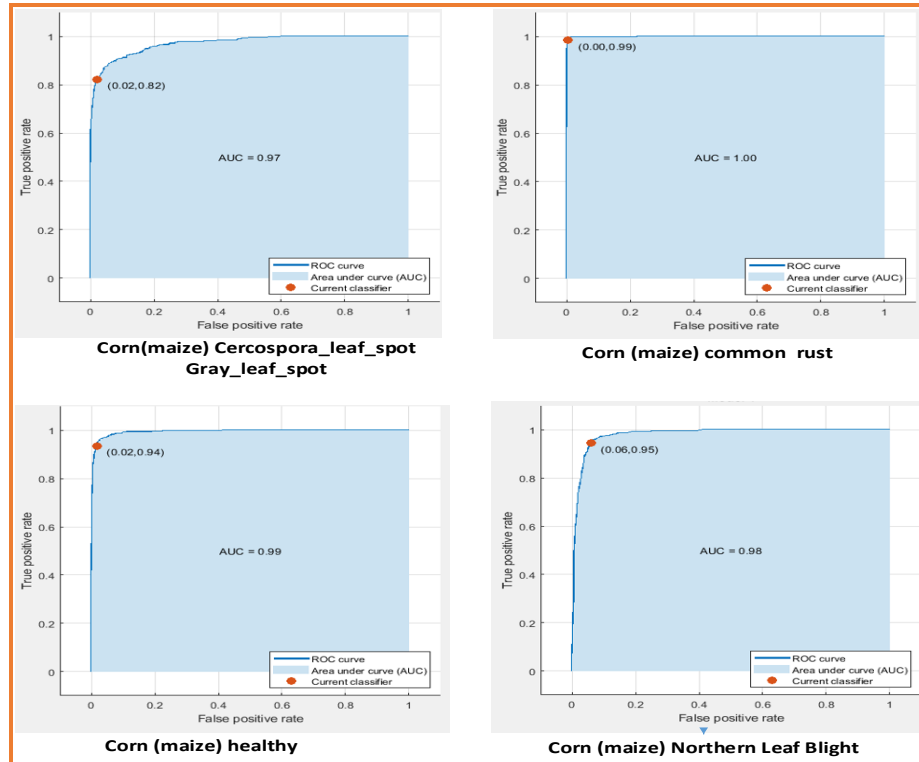


Fig.10. ROC curve for corn leaf disease classification using SVM

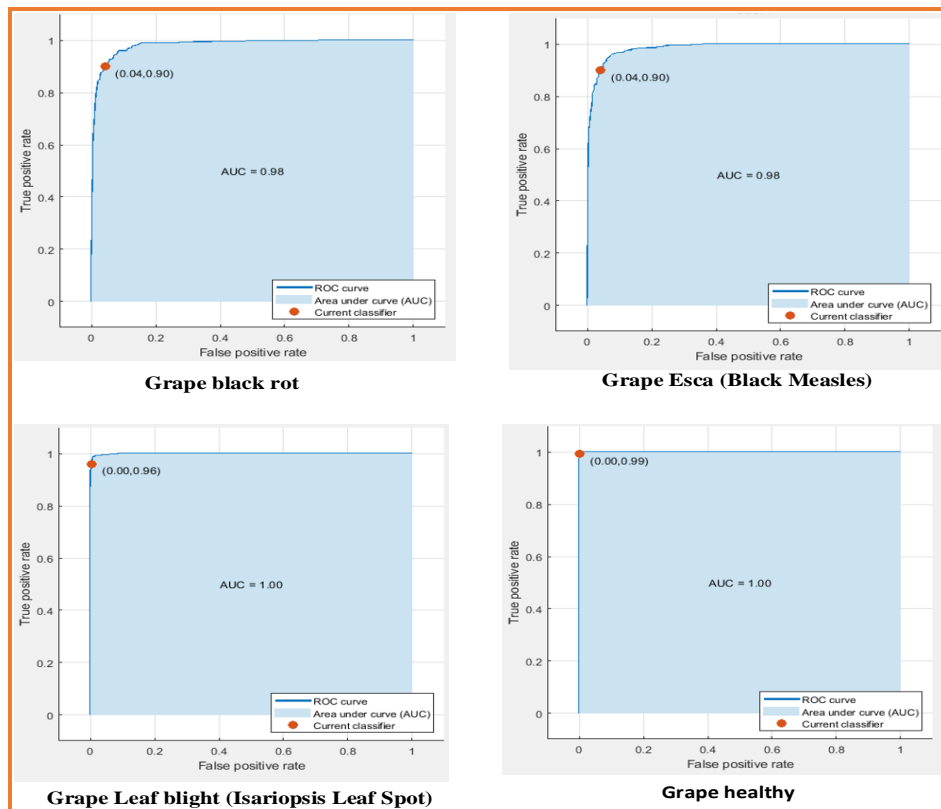


Fig.11. ROC curve for grape leaf disease classification using SVM

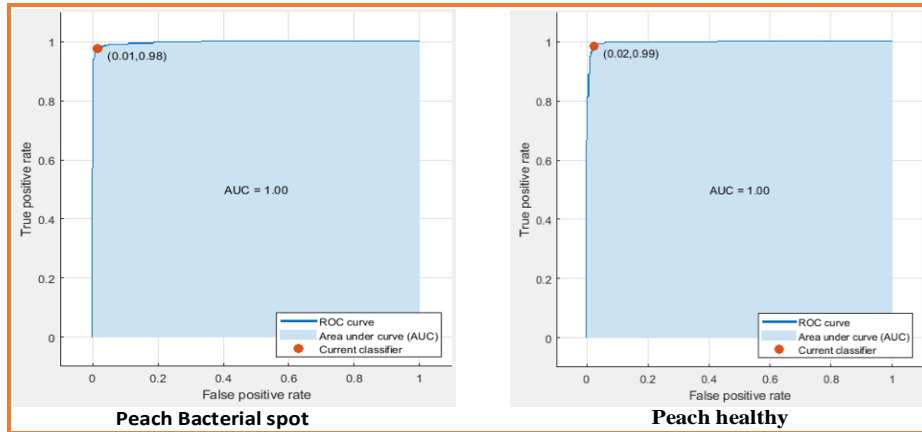


Fig.12. ROC curve for peach leaf disease classification using SVM

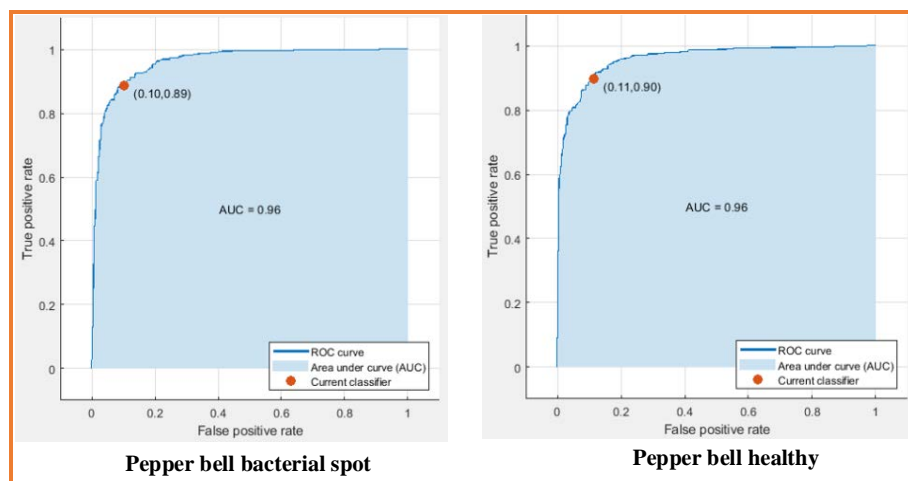


Fig.13. ROC curve for pepper bell leaf disease classification using SVM

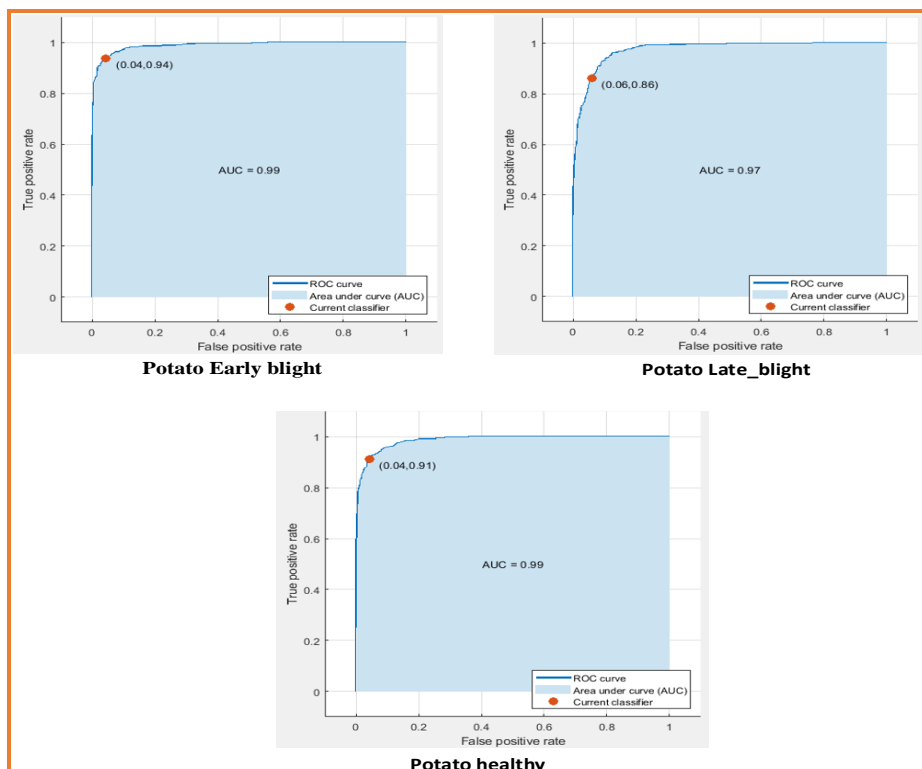


Fig.14. ROC curve for potato leaf disease classification using SVM

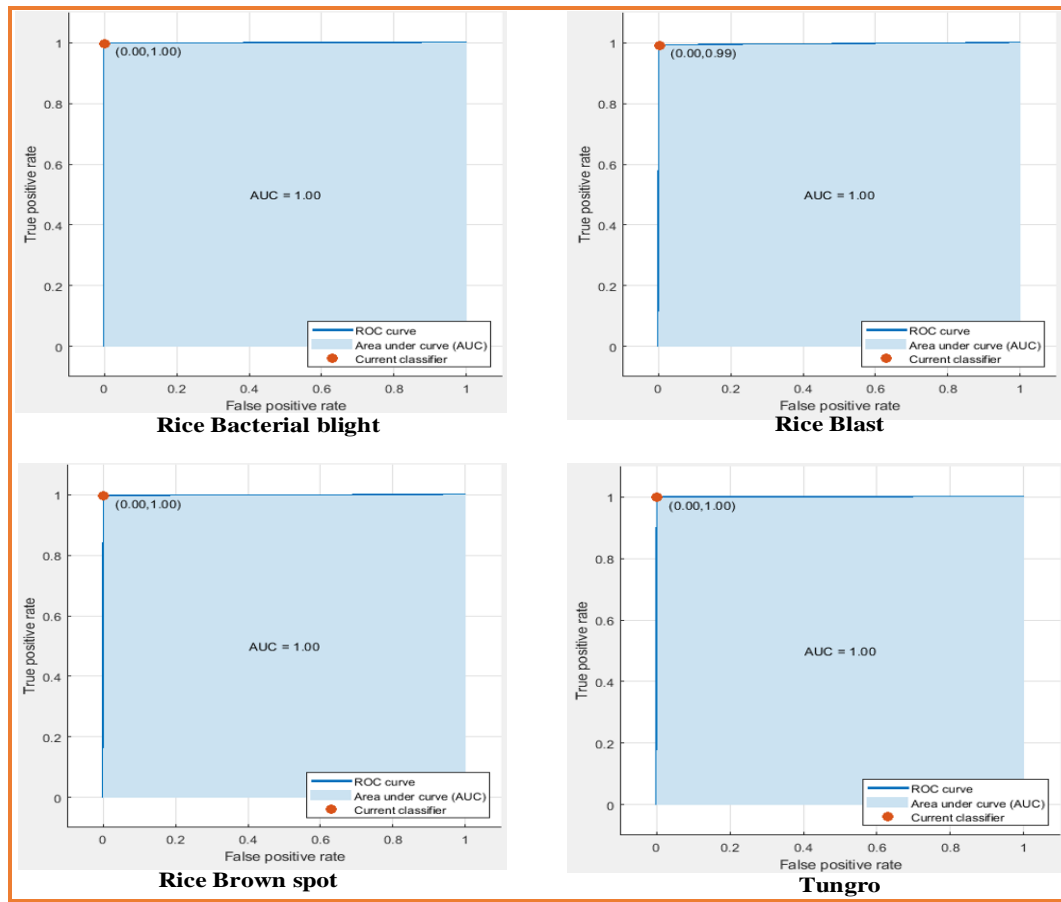


Fig.15. ROC curve for rice leaf disease classification using SVM

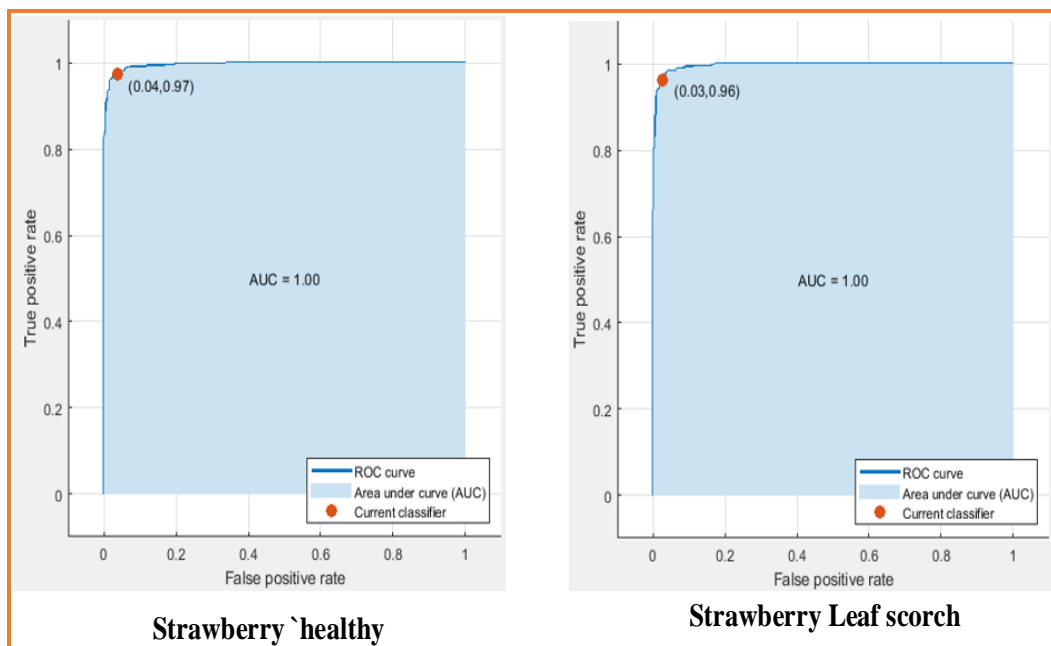


Fig.16. ROC curve for strawberry leaf disease classification using SVM

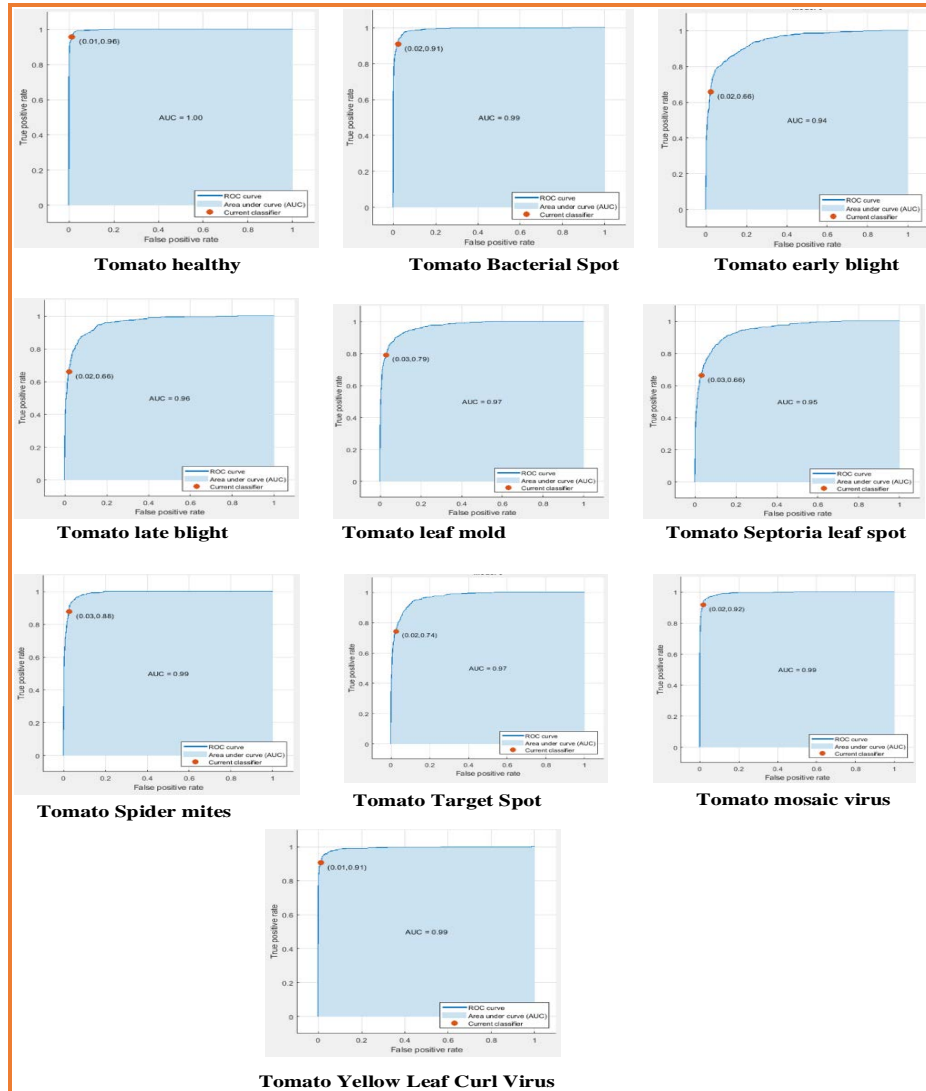


Fig.17. ROC curve for tomato leaf disease classification using SVM

6. Conclusion

In this paper, different plants leaf disease classification is presented using gist as global feature and LBP as local. This study aims to propose a improved classification system for leaf disease. The study shows that combination of gist and LBP are well suited in classifying the leaf disease. The combination shows inspiring results. Early detection of diseases can help farmers to reduce the losses. Vision based classification can be a great tool in the field of agriculture. Every year farmers need to face a great loss in the productivity of crops due to leaf disease. Total 21164 images of ten different plant's leaf is used in this study. Support vector machine, KNN and AdaBoost are tried out as classification model. Except rice and tomato, SVM works better than KNN and AdaBoost. KNN proves good for rice leaf disease classification and tomato leaf disease are classified well by AdaBoost. In future, different feature combination will be tried out to obtain better performance. Moreover, leaf sample of more plants will also be tried out to collect and classify.

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