Leaf Classification using Local Binary Pattern and Histogram of Oriented Gradients

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***Abstract*—Categorization of plant species is a significant process in studying the diversity of different plant species in order to utilize it as medical treatment and to keep track of invasive plant species to maintain the balance of the environment. However, plants have extremely complex structure and diverse with millions of species around the world which makes the classification process extremely tedious. This paper introduces a method which utilizes the combination of Local Binary Pattern and Histogram Oriented Gradient as feature extractor for leaf classification which increases the accuracy during classification. Support Vector Machine was used as classifier of the leaf features. Two well-known datasets, Swedish Leaf Dataset and Flavia Dataset, were used to carry out the experimental studies. Our proposed method performed the best when compared to three other methods.**

Keywords—Leaf Classification, Local Binary Pattern, Histogram Oriented Gradient, Computer Vision, Machine Learning.

I. INTRODUCTION

The agriculture industry has been constantly expanding around the world. Especially in recent years where various species of herbal plants have been formulated to serve as a substitution for conventional medication. Plants and agricultural management of crops are also vital for keeping track on invasive plant species to maintain the balance of the environment. This resulted in the necessity to categorize these plant species which often require the knowledge of experts in this field. Therefore, a simpler method to aid the complexity in classifying plant species has been developed. In this modern era, image processing and machine learning has become a commonly used technique in object detection and face recognition. The use of image processing and machine learning can serve as a vast aid in simplifying and speeding up the process of plant species classification and reduce the number of human resources required in accomplishing the classification task. The leaf is the part of a plant which contains the richest information and trait of a plant species. Several researches have proposed different feature extraction methods either concentrating on features such as the biological shape, leaf structure, leaf colour, leaf venation or the leaf texture. In recent researches, different combinations of feature extraction methods have been combined to increase the accuracy in classification. This paper combines LBP with HOG feature extraction using a SVM for classification.

II. RELATED WORKS

The classification of plant species is an important process to help keep track on biological diversity which is important in maintaining the balance of nature. It also serves a broad application prospective in agriculture and medicine. Several researches have been done in attempt to make a more robust leaf classification system and different parts of the plant have been tested as a trait recognition for example, the flower, pollen grains, leaves, bark and the fruits. Among them, the leaves have been used the most to help differentiate between plant species.

There are many different leaf classification methods where improvements can be done at different phases throughout the classification process. In a research done by Aidil et al [1], image pre-processing was done where the edges of the leaf image will be thinned to only one pixel wide for detection. A graph based approach was used by converting the complex shape of the leaf images into graph structures using Medial Axis Transformation (MAT) for feature extraction was introduced by Andrew et al [2]. The graph structure describes the topological skeletons each leaf images which will then be used for classification. Phuchitsan et al [3] proposed a new reference axis called Mid-Leaf axis where the leaf shape feature was extracted based on partitioning the morphological features and the tangent's direction angle of the leaf contour.

Stephen et al [4] used Probabilistic Neural Network (PNN), classifier, which consists of three layers where each layer will evaluate vector distances and find training pattern closest to the input pattern. A multiple classifier system (MCS) was proposed by Voncarlos et al [5], where a diverse pool of eight different classifiers were trained on four feature sets. Modifications made to the feature extraction phase is the most common approach. Some researches concentrate on the texture features of the leaves for example in [6], distribution of joints using Gabor filters was used for texture analysis for leaf classification. Xiang et al [7] proposed a method to extract the shape and venation features using fractal dimensions of the boundary and veins of the leaf. The shape and edge feature were extracted and combined in classification for method proposed by Pullela et al [8] where the slimness, roundness, and dispersion were extracted for the shape feature and canny edge detection was used for extraction of the edge feature. Texture based feature extraction methods includes SIFT descriptor which was used in Zhiyong et al [9] research work, where it is partially robust to a changing of viewpoints.

The most common feature extraction methods used for classification either for leaf classification, object detection, or

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facial recognition is Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG). A modified LBP was proposed by Naresh et al [10], where mean and standard deviation is added to consideration during LBP thresholding. A fusion of colour histogram with LBP was proposed in Peizhong et al [11], where both colour feature and texture feature were taken into consideration during feature extraction. Anilkumar et al [12] used Completed Local Binary Pattern (CLBP), which combined signed component, centre pixel and the magnitude component of LBP during feature extraction. Xianbiao et al [13] introduced a modified LBP which can capture spatial context co-occurrence and possess rotation invariance. A study conducted by Alex et al [14], which uses HOG in classification, demonstrates its ability to be used for real-time application. Classification accuracy can be further increased by combining two types of feature extraction methods. Method proposed by Amala et al [15] proved the ability of HOG and SURF to extract prominent features which increases the classification accuracy in Ayurvedic medical plant dataset.

In other applications such as signature verification [16], results in classification accuracy have shown to increase fairly by combining HOG with LBP feature extraction. Different combinations of feature extraction methods have been experimented on detection of people in beaches and combination of LBP and HOG have shown to have the best accuracy in classification [17]. Therefore, combination of LBP and HOG based feature extraction methods were proposed in this paper to classify leaves at higher accuracy.

III. METHODOLOGY

The proposed system contains three phases, namely, Feature Extraction, Feature Combination and Classification. The leaf datasets will first be distributed into training and testing sets with all images converted to grayscale for feature extraction. LBP and HOG feature vectors were then extracted from each image in the leaf datasets. Next, the LBP and HOG feature vectors were combined to form the final feature vector which will then be fed to a classifier machine for classification. Fig. 1 shows the full process of the proposed system for training and testing.

A. *Feature Extraction*

LBP and HOG feature descriptors functions in two dimensions, therefore, all the leaf images were converted to grayscale before the feature extraction stage. Yasser et al [18] reported that higher classification results were obtained when the images were resized to 150x200 pixels resolution. Therefore, all images were also resized prior to feature extraction phase. After extracting the LBP and HOG features, feature vectors were normalized individually before combining them.

i. *Local Binary Pattern*

Local Binary Pattern (LBP) is a feature extraction method proposed by Ojala et. al. [19] for texture analysis and has drawn the attention of many researchers due to its simplicity in computation and its impressive texture classification. Before LBP feature extraction, images will have to be converted to grayscale. Labelling of each pixel will be done by thresholding the neighbourhood pixels, *Gi*, with centre pixel, *Gc*. The pixel, *Gi*, will one of the neighbourhood pixel confined within neighbourhood pixel P which corresponds to radius, R. Fig. 2 shows the different sizes of LBP resolutions with corresponding P and R. Once the radius and neighbourhood pixels are set, the resultant binary number 0 and 1 will be assigned to binary coefficient, *S*, according to equation 1.

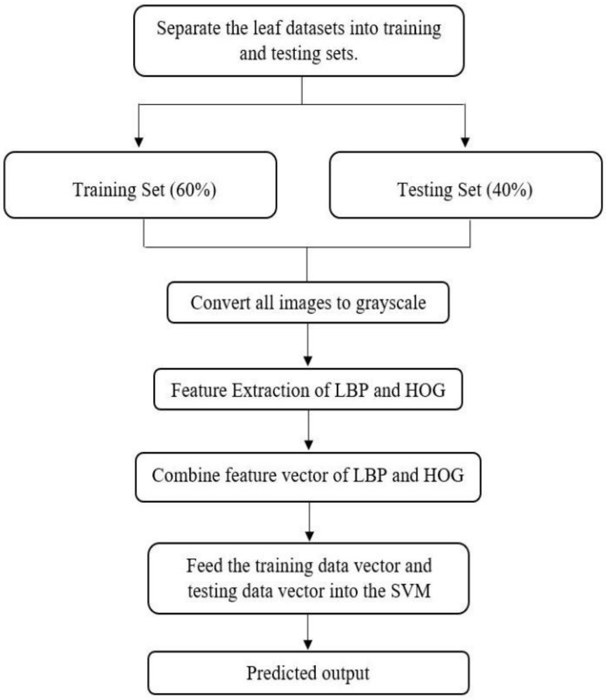

Fig.1. Proposed system architecture.

$$S = \begin{cases} 1, & (Gi - Gc) \geq 0 \\ 0, & otherwise \end{cases} \quad (1)$$

Each neighbourhood pixels with the binary number assigned is then arranged into a sequence either clockwise or counter clockwise to form an *n*-bit binary number. Each bit is then sum up to get the LBP code using equation 2.

$$LBP_{P,R} = \sum_{i=1}^{P} S * 2^{i-1} \quad (2)$$

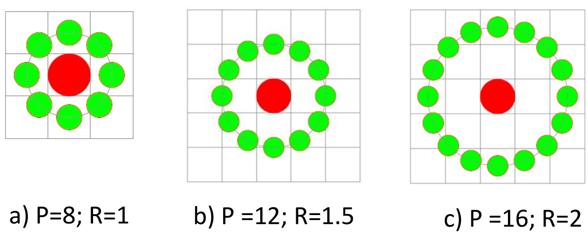

Fig. 2. Radius R with corresponding neighbourhood pixels P.

TABLE I. NUMBER OF UNIFORM LBP VECTOR FOR EACH RADIUS VALUE WITH CORRESPONDING NEIGHBOURHOOD PIXELS

LBP (P, R)	No. of uniform feature vector
LBP (8, 1)	59
LBP (12, 1.5)	135
LBP (16, 2)	243

Uniform LBP was considered in this study where U represents a certain set of patterns which corresponds to the number of spatial transitions in the pattern. For example, if we have a value set of 00001111_2, the U value of this pattern set will be 1 where only one transition from 1 to 0 occurred. Table I shows the number of uniform LBP vector for each radius value with corresponding neighbourhood pixels.

ii. Histogram of Oriented Gradients

Histogram of Oriented Gradients (HOG), was first introduced in the year 2005 by Dalal and Triggs [20], with the objective for human detection in cluttered backgrounds. HOG describes the local appearance and shape of an object by distribution intensity gradients and edge directions. It is a commonly used feature descriptor for real-time pedestrian detection. HOG is computed over cells which are uniformly spaced which uses overlapping local contrast normalization procedure for increased accuracy [15]. The image will first go through a normalizing process to correct the light intensity of the image. This process can often be omitted as it only shows considerable effect on the overall results. Gradient computation will be computed in both x and y direction with magnitude and orientation of gradients calculated with the following equations.

$$Gx = P * Dx; \quad Gy = P * Dy \tag{3}$$

$$|G| = \sqrt{Gx^2 + Gy^2} \tag{4}$$

$$\theta = arctan2(Gy, Gx) \tag{5}$$

The following step is to weight votes for each edge orientation channel based on the orientation of the gradient element centred on it. The votes are accumulated into orientation bins over a local spatial region which is known as cells. The orientation bins can either be "signed" or "unsigned" gradient with even space over 0 to 180 degrees for signed orientation bins and 0 to 360 degrees for unsigned orientation bins. The number of bins can vary over 9 to 12 bins. For example, if we have 9 bins unsigned orientations, the first bin will vary from 0 to 20 degrees with every consecutive 20 degrees in each bin until the 9th bin. The last step is to compute block normalization where blocks of cells are overlapped in order to make the descriptor more robust to illumination and shadowing. The original paper of HOG uses 9 bins unsigned gradient orientation with 3x3 block cells per image and have shown to obtain the best results. Therefore, this experiment will utilize the same parameters as in [20].

B. Feature Combination

Once the LBP and HOG feature vectors were extracted from training and testing images, both feature vectors of each image were concatenated to form a new feature vector. The new formed feature vector will be treated as the final feature vector in the classification stage. HOG contains a feature vector length of 1x81 vectors and it will be combined with the LBP vector to obtain the final feature vector of 1x140. Thus each image is represented by a feature vector with length of 140 elements. Table II shows the combined vector length with different LBP parameters.

C. Classification

Support Vector Machine (SVM) classifier is used for the classification of leaves in this experiment. A total of 60% of the leaf sample images were used for training and the remaining 40% of the images were used for testing. The combined feature vector was fed to the SVM classifier to classify each test images to their respective predicted class. SVM classifier is a well-known classifier machine normally used with HOG descriptors [18][21].

TABLE II. COMBINED VECTOR LENGTH WITH DIFFERENT LBP PARAMETERS

Feature Extraction	Original vector length (1 x L)	Combined vector length (1 x L)
LBP (8, 1) + HOG (unsigned, 9 bins)	(1x59) + (1x81)	1x140
LBP (12, 1.5) + HOG (unsigned, 9 bins)	(1x135) + (1x81)	1x216
LBP (16, 2) + HOG (unsigned, 9 bins)	(1x243) + (1x81)	1x324

SVM is a supervised model associated with respect to learning algorithm and mainly used for analysing the data for regression and classification [22]. In [14], different classifiers were tested with HOG descriptor to evaluate performances of classifier. SVM have shown to obtain the best accuracy with HOG. SVM have shown to perform well with combined feature vectors of LBP and HOG [16] [17].

SVM classifier differentiate classes by finding the hyper-plane that differentiates different classes. There can be several hyper-planes in a set of data where the hyper-plane selected is the one that best segregates the two set of data. Support vectors are the position of the individual observations and SVM is a frontier which best segregates data into different classes.

IV. Results and Analysis

A. Experimental Setup

There are several open source leaf datasets provided online which contains various plant species and each with multiple samples of leaf images. Experiments were carried out on two types of leaf datasets, which are Flavia dataset and Swedish Leaf dataset. The Flavia dataset consists of 32 leaf classes with over 50 sample images for each class. All 1907 leaf images in the Flavia dataset is being used in the experiment [4]. By having 60% of the images for training the remaining for testing, 1144 of the images are for training and the remaining 763 images are for testing. For the Swedish Leaf dataset, each class has 75 sample images with a total of 15 classes [23]. A total of 675 images were distributed for training and the remaining 450 images were for testing. Fig. 3 and 4 shows several sample images from Flavia and Swedish Leaf datasets, respectively. The name of the species and its corresponding file name are stated in the title of each picture.

B. Experimental Results

For LBP, there were three sets of input parameters tested and compared to choose the one with the highest accuracy in order to be combined with the HOG feature vector. To select the best parameters, these values were tested on both Flavia and Swedish Leaf datasets. Table III tabulates the classification accuracy in percentage for the three types of parameters on both datasets. Results have shown that LBP with radius of 2 and corresponding neighbourhood pixels of 16 performed the best. Thus, it is chosen, in order to be combined with HOG feature vector in the feature combination stage. Table IV shows the predicted output obtained in classification for Flavia dataset and Table V shows the predicted output obtained for Swedish Leaf dataset.

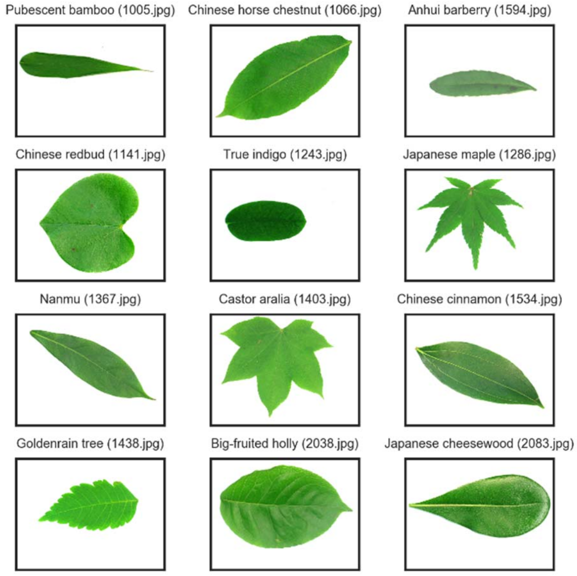

Fig. 3. Flavia Leaf Dataset

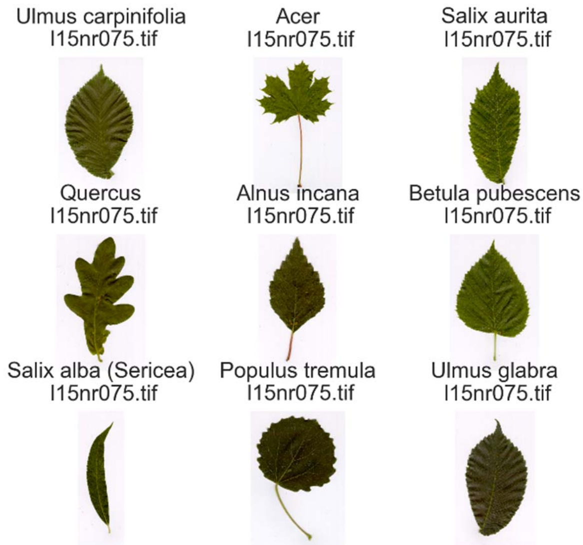

Fig. 4. Swedish Leaf Dataset

C. Comparison of results

In order to show the classification accuracy of the proposed method is comparatively better, the result of the proposed method is compared with three other feature extraction methods which is LBP, HOG and CLBP. Experiments were done using the prepared training and testing datasets. Results have shown that the proposed method obtained the highest classification accuracy for both Flavia and Swedish Leaf datasets. Table VI is the classification accuracy in percentage for the four comparative methods.

TABLE III. CLASSIFICATION ACCURACY FOR THREE LBP INPUT PARAMETERS ON FLAVIA AND SWEDISH LEAF DATASET

LBP (P, R)	Accuracy of Flavia dataset (%)	Accuracy of Swedish Leaf dataset (%)
LBP (8, 1)	64.22	78.44
LBP (12, 1.5)	72.48	81.56
LBP (16, 2)	75.49	85.56

The proposed method had shown to have an accuracy of 77.33% on the Flavia dataset and 90.22% accuracy on the Swedish Leaf dataset which is the highest classification accuracy among all the four feature extraction methods. By combining the feature vectors of LBP and HOG, the ability of recognition and classification of both feature descriptors will compensate each other, thus resulting in a better classification accuracy.

TABLE IV. PREDICTED OUTPUT FOR COMBINATION FEATURE VECTOR ON FLAVIA DATASET

Class Label	True Positive	True Negative	False Positive	False Negative
1	8	741	1	13
2	18	740	1	4
3	18	730	8	7
4	21	735	2	5
5	31	731	1	0
6	28	734	0	1
7	12	740	2	9
8	19	740	1	3
9	10	737	0	16
10	15	735	6	7
11	22	738	0	3
12	7	743	0	13
13	25	734	0	4
14	19	742	0	2
15	23	739	0	1
16	24	735	4	0
17	21	740	1	1
18	15	739	3	6
19	16	740	0	7
20	18	741	0	4
21	17	742	0	4
22	26	737	0	0
23	19	739	2	3
24	25	737	1	0
25	19	739	0	5
26	20	738	0	5
27	13	737	2	11
28	23	735	2	3
29	3	740	1	19
30	11	741	0	11
31	21	736	1	5
32	23	605	134	1

TABLE V. PREDICTED OUTPUT FOR COMBINATION FEATURE VECTOR ON SWEDISH LEAF DATASET

Class Label	True Positive	True Negative	False Positive	False Negative
1	29	420	0	1
2	28	420	0	2
3	25	420	0	5
4	30	417	3	0
5	29	420	0	1
6	29	420	0	1
7	26	419	1	4
8	29	420	0	1
9	24	420	0	6
10	30	420	0	0
11	19	420	0	11
12	27	419	1	3
13	29	420	0	1
14	23	420	0	7
15	29	381	39	1

TABLE VI. COMPARISON RESULTS OF FOUR FEATURE EXTRACTION METHODS

Leaf Dataset	Feature Extraction Method			
	LBP (%)	HOG (%)	CLBP (%)	Combined Method (LBP+HOG) (%)
Flavia	75.49	72.21	74.97	77.33
Swedish Leaf	85.56	85.56	85.78	90.22

V. CONCLUSION

This paper proposed and implemented an automated classification system to identify and classify different leaf classes with considerable classification accuracy. The aim is to make use of image processing and machine learning techniques to ease the classification process of leaves with a relatively high accuracy and simple computation. The proposed method has suggested to combine LBP with HOG feature vector and use SVM classifier to classify the testing images to obtain the predicted results. By combining the feature vectors of LBP and HOG, the classification results can be improved significantly by obtaining highest accuracy among the four compared methods. The combination method obtained 77.33% in classification accuracy for the Flavia dataset and 90.22% of accuracy for the Swedish Leaf dataset. Scope of future work includes modifying the system to be viable for real-time classification.

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