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Automatic Plant Detection Using HOG and LBP Features With SVM

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Abstract

Plants play a vital role in the cycle of nature. Plants are the only organisms which produce food by converting light energy from the sun. They also help in maintaining oxygen balance on earth by emitting oxygen and taking carbon dioxide. They have plenty of use in medicine and industry. But plant species are vast in number. To identify this large number of existing plant species in the world is a tedious and time-consuming task for a human. Hence, an automatic plant identification tool is very useful even for experienced botanists to identify the vast number of plants. In this paper, we proposed a technique to identify the plant leaf images. For training and testing, we used a publicly available dataset called Flavia leaf dataset. Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) are used to extract features and multiclass Support Vector Machine (SVM) is applied to classify the leaf images. We observed that the accuracy of HOG+SVM with HOG feature extraction using cells size of 2 x 2, 4 x 4 and 8 x 8 are 77.5%, 81.25% and 85.31 respectively. The accuracy of LBP+ SVM is 40.6% and the combination of HOG and LBP based features with SVM achieved 91.25% accuracy. The experimental results indicate the effectiveness of HOG+LBP with SVM over HOG+SVM and LBP+SVM techniques.

Keywords: Plant Detection; HOG; LBP; SVM.

1. Introduction

Plants are the most precious part of the life of all the organisms living on the earth. We called earth a green planet because of the existence of plants. They provide us fresh oxygen to breathe and reduce pollution level by taking carbon dioxide. Plants produce food by converting light energy from the sun and we depend directly or indirectly on plants for their supply of food.

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They also provide shelter for many of the other organism. Fuel like coal, natural gas and gasoline also made from plants that lived millions of years ago. Plants also a major source of medicine. Hence, a good understanding of plants is necessary to explore the genetic relationship of the plant. Plants are vast in number. According to Maarten J. M. and his colleagues [1], all over the world, there are currently described and accepted the number of plant species is 374,000 of which approximately 308,312 are vascular plants, with 295,383 flowering plants. To identify the plant, people generally use leaf, flower, stem, and fruit and so on. Among them, plant leaves are of great importance to the botanists as they have discriminant feature. Therefore, it is very tedious and time-consuming task to identify and recognize this large number of plant species, which is generally done by a botanist. Therefore an automated plant identification system is necessary to identify the plant species from the leaf which may be useful for botanist as well as foodstuff and medicine [2] and for species identification and preservation [3].

A number of techniques have been proposed to identify plants from leaf images. Miao and his colleagues [4] classified rose based on evidence-theory-based method. Wang and his colleagues [5] and Du and his colleagues [6] proposed a moving median center hypershpere classifier to identify the leaf images. In another method, Du and his colleagues [7] proposed a dynamic programming algorithm for leaf shape matching. Im and his colleagues [8] proposed a method to identify the Maple leaves using the shapes of the leaves. Wang and his colleagues [9] presented a technique to recognize the plant leaf using shape features. To extract the shape characterization, they used centroid-contour distance curve and object eccentricity. The eccentricity is used to rank the leaf images. The problem of the above method is that they only focused on the contour of leaf and neglect other features such as leaf vein, leaf dent and so on. Zhang B. and Zhang H. [10] proposed a clustering method to retrieve tobacco leaf images from standard tobacco leaf database based on leaf shape, color, and texture. But they give lack of representation of domain features of leaves. Wu and his colleagues [11] used aspect ratio, leaf dent, leaf vein and invariant moment to identify 6 species of plants. In another paper Wu and his colleagues [12] classified 32 different kinds of plants based on aspect ratio, ratio or perimeter to the diameter of leaf, and vein features.

In this study, we propose a novel technique to classify the plant based on leaf images. Our main improvements are on feature extraction. In feature extraction, we used Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) features. After that, those features are inputted into multiclass Support Vector Machine (SVM) to classify the plant leaves. We tested our technique on Flavia leaf dataset [12]. Our experiment shows that HOG+LBP with SVM performed better than individual HOG+SVM or LBP+ SVM method.

We organized the rest of this paper as follows: Section 2 discusses the proposed method, section 3 presents the result and discussion and section 4 presents the conclusion and further work.

2. Background Study

Most studies use shape, texture, color, venation or mixture of these features to identify the plants. Neto and his colleagues [33] used shape to identify young soybean, sunflower, redroot pigweed, and velvetleaf plants. They used Elliptic Fourier (EF) and discriminant analyses to extract the shape features. Du and his colleagues [6] proposed a leaf shape based plant species recognition system using Moving Median Center (MMC) hypershpere classifier to classify plants. In their technique, the shape is extracted using geometrical calculation and moment invariants. Aakif and Khan [13] proposed an algorithm by using geometrical calculation, Fourier descriptors, and SDF to identify the plants based on their leaves. Cope and Remagnino [14] classified plant leaves from their margins using Dynamic Time Warping (DTW).

Texture is a major feature to identify the plants. It describes the surface of the leaf. Backes and Bruno [15] used textural features to classify the plant leaf images. They modeled texture as a surface and multi-scale fractal dimension is applied over the surface. Cope and his colleagues [16] proposed a method for comparing and classifying plants based on leaf texture. He used Gabor co-occurrences to extract the textural feature. Rashed and his colleagues [17] proposed a technique to classify and recognize plants based on textural features. He used Learning Vector Quantization (LVQ) together with the Radial Basis Function (RBF). Olsen and his colleagues [18] used rotation and a scale variant Histograms of Oriented Gradients (HOGs) to extract textural features set to classify the leaf images.

Venation also an important feature to classify the leaf images. Charters and his colleagues [19] proposed a descriptor called EAGLE combining with SURF features to classify the leaf images. Larse and his colleagues [20] designed a legume varieties recognition system based on leaf venation. They used Hit or Miss Transform (UHMT) to segment the vein pattern and LEAF GUI to extract the set of features. Grinblat and his colleagues [21] used deep learning for plant identification using vein morphological patterns. They used UHMT to extract the vein patterns and Convolutional Neural Network (CNN) to train these features.

Chaki and his colleagues [22] proposed a technique to identify 31 classes of leaves by using a combination of texture and shape features. To extract texture features they used Gabor filter and gray level co-occurrence matrix (GLCM) while the shape of the leaf is extracted by using curvelet transform coefficients with invariant moments. Mouine and his colleagues [23] used advanced SC, hough, fourier, and edge oriented histogram to extract the shape and textural features to classify the leaf images. Beghin and his colleagues [24] proposed a method for plant leaf classification using shape and textural features. They extracted the shape based features using contour signature and calculated the dissimilarities using Jeffrey-divergence measure. The textural features are extracted from orientations of edge gradients.

3. Methodology

Our proposed technique is shown in Figure 1. It consists of three phases: preprocessing, feature extraction and classification. In preprocessing, we segmented the leaf from background then we normalized it. Feature extraction consists of extracting the different features from leaves using HOG and LBP method. These features become the input vector of the Support Vector Machine (SVM) in the classification stage. SVM classifies the leaf based on the extracted features. We now discuss all of the steps in detail below.

3.1 Image preprocessing

Image preprocessing is consists of Image Segmentation and Image Normalization.

3.1.1 Image Segmentation

In image segmentation, the input RGB leaf image is first converted into grayscale image using the Equation (1).

$$gray= 0.2989*R+0.5870*G+0.1140*B \quad (1)$$

Where, R, G, B correspond to the color of the pixel respectively. After that, we convert the grayscale image into a binary image by using the global thresholding technique [25]. We used the valley between two peaks as our threshold value.

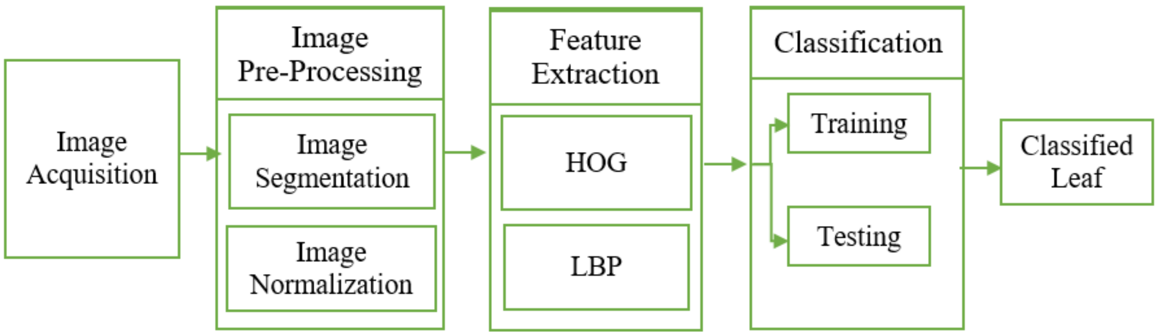


Figure 1: Block diagram of our proposed system.

3.1.2 Image Normalization

Image normalization involves rotating a leaf so that its tip at the top, maintaining the angle between the major axis of the leaf and frame is zero, keeping the centroid of the leaf and frame is same, and maintaining the fixed frame size of all the sample images regardless of the size of the leaf and resolution of the image [13]. In our proposed method, we have fixed the frame size of the image to 134*100 pixels and we used the Equation (2) to rotate the leaf around its centroid.

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix} \quad (2)$$

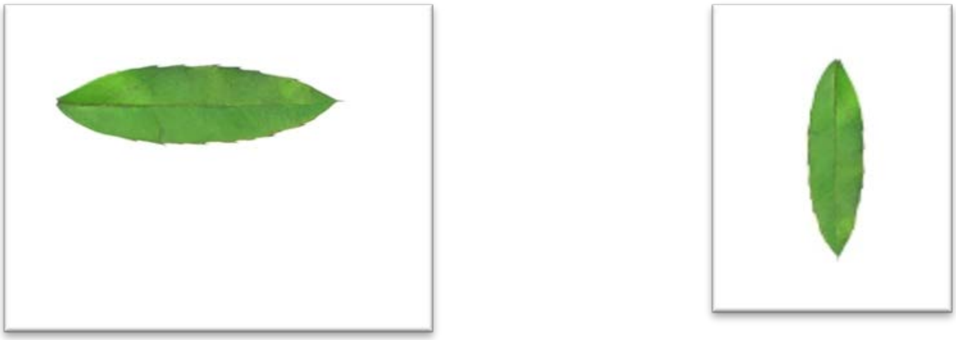
Where X, Y represents the original coordinates of the images, θ is the angle between the leaf and frame, tx and ty are the displacements along the x-axis and y-axis. An example is shown in Figure 2. Figure 2(a) shows the original image with a size of 1600x1200 pixels and Figure 2(b) shows the normalized image with the size of 100*134 pixels.

3.2 Feature Extraction

In our proposed technique, we used Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) features.

3.2.1 Histogram of Oriented Gradients (HOG)

One of the popular method of feature extraction is Histogram of Oriented Gradients (HOG) [26]. In this method, an image is described by a set of local histograms. Then, the occurrences of gradient orientation is accumulated



(a) Originial Image (1600*1200 pixels) (b) Normalized Image (100*134 pixels)

Figure 2: Image Normalization Example.

in a small spatial localized portions of the image referred as cell. The subsequent concatenation of 1-D histograms produces the features vector. Let the intensity value of the image to be analyzed is L. If the image is divided into N x N cells of size then the orientation ϴx, y of the gradient in each pixel is calculated by using the Equation (3) [27].

$$\theta_{x,y} = \tan^{-1}\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)} \tag{3}$$

The successive orientation $\theta_i{}^j$, i=1……..N2 belonging to the same cell j are quantized and accumulated into an M-bins histogram. Then, we ordered all the histograms and accumulated into a unique HOG histograms which is our HOG features.

3.2.2 Local Binary Pattern (LBP)

One of the simple and efficient method of texture feature extraction is Local Binary Pattern (LBP) introduced by Ojala and his colleagues [28]. LBP used each pixel as a threshold, then transferred its 3 x 3 neighborhood into an 8-bit binary code (Figure 3).

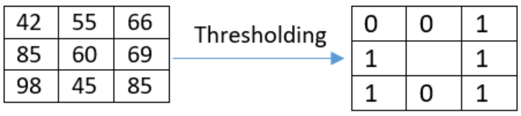


Figure 3: LBP Operator

The fixed order of this binary code reserves the texture direction information around pixels. The number of variations in this way is 2P. When in variation, there exist at most 2 times of 0 to 1 or 1 to 0, the binary pattern is called uniform LBP and is denoted by $LBP_{(P,R)}^{u2}$. The number of uniform pattern in a sampling density P is P2 – P + 2. In our proposed system, we used uniform LBP to extract the feature of leaves.

Figure 4: Samples of Flavia leaf dataset.

3.3 Classification

In our proposed method, we used multiclass Support Vector Machine for classification.

3.3.1 Support Vector Machine (SVM)

SVM is a popular classification tool used for pattern recognition and other classification problems [29]. SVM uses a hyperplane to separate a training sample using the decision function of Equation (4) [30].

$$f(x) = sign\ (w.x) + b \tag{4}$$

Where w is a weight vector and b is the threshold value. Using the Equation (5), b is minimized to maximize the margin w ϵ f, which can be expressed as a quadratic optimization problem shown in Equation (6).

$$y_i(w.x_i) + b \geq 1 \tag{5}$$

$$\min_{w,b} \frac{1}{2} \|w\|^2 \tag{6}$$

In nonlinearly separable cases an additional stack variable is added with the risk of overfitting (Equation 7).

$$y_i(w.x_i) + b \geq 1 - \xi_i \tag{7}$$

SVM solves this over fitting problem by optimizing it using Equation (8)

$$\min_{w,b,\xi} \frac{1}{2} [\![w]\!]^2 w + C \sum_{i=1}^{1} \xi_i \tag{8}$$

Where C is a constant which determines the trade-off between training error and the complexity term.

A SVM maps a set of training vector into a high dimensional space f via a nonlinear map $\Phi: R^n \to f$ and the condition for perfect classification is shown in Equation (9).

$$y_i(w.\Phi(x_i)) + b \geq 1 - \xi_i \tag{9}$$

For each training sample xi, $\Phi(x_i)$is only substituted.

SVM is a binary classifier which classifies data into two different classes. When the problem of classification involves more than two classes, as it is in our study of plant identification, multiclass SVM is used. There are several techniques to deal with multiclass classification. In our method, we used one-vs-one technique [31,32]. In this technique k (k-1) / s classifier is constructed where each classifier is trained on data from two classes. For training data from the jth classes, we used the Equation (10).

$$\min_{w,b,\xi} \frac{1}{2} [\![w^{ij}]\!]^T w^{ij} + C \sum_{t} \xi_t^{ij} \, (Wi^j)^T \tag{10}$$

4. Result and Discussion

To implement our proposed system we used Flavia leaf dataset. This dataset contains 1907 scans of leaves of 32 species. We used 40 images per species as our training set and 10 images per species as our testing set. Detail description of Flavia leaf dataset is shown in Table 1 and some leaf images of this flavia dataset is shown in Figure 4.

The size of our dataset leaf images is 1600 x 1200 pixels. To extract feature using the HOG descriptor we first resize the images into 134*100 pixels by preserving its aspect ratio. We randomly split the dataset into two sets, one set is used for training and one set is used for testing. For training and testing, we used 40 and 10 leaf images for each species respectively.

In our experiment, we used three different cell size: 2x2, 4x4 and 8x8, to extract the HOG descriptors from leaf images. Table 2 lists the detail classification result of different HOG descriptor with SVM and the overall accuracy of this descriptor is shown in Table 3. We observed that for plant detection HOG descriptor with cell size 8 x 8 performs better than other HOG descriptors.

Table 1: Details Description of Flavia Leaf Dataset

Scientific Name	Common Name	No. of Sample Images
Phyllostachys edulis (Carr.) Houz.	Pubescent bamboo	58
Aesculus chinensis	Chinese horse chestnut	63
Berberis anhweiensis Ahrendt	Anhui Barberry	58
Cercis chinensis	Chinese redbud	72
Indigofera tinctoria L.	true indigo	72
Acer Palmatum	Japanese maple	53
Phoebe nanmu (Oliv.) Gamble	Nanmu	60
Kalopanax septemlobus (Thunb. Ex A.Murr.) Koidz.	Castor aralia	51
Cinnamomum japonicum Sieb.	Chinese cinnamon	51
Koelreuteria paniculata Laxm.	Goldenrain tree	57
Ilex macrocarpa Oliv.	Big-fruited Holly	50
Pittosporum tobira (Thunb.) Ait. F.	Japanese cheesewood	61
Chimonanthus praecox L.	wintersweet	51
Cinnamomum camphora (L.) J. Presl	camphortree	61
Viburnum awabuki K.Koch	Japan Arrowwood	58
Osmanthus fragrans Lour.	Sweet osmanthus	55
Cedrus deodara (Roxb.) G. Don	deodar	65
Ginkgo biloba L.	ginkgo, maidenhair tree	57
Lagerstroemia indica (L.) Pers.	Crape myrtle, Crepe myrtle	57
Nerium oleander L.	oleander	61
Podocarpus macrophyllus (Thunb.) Sweet	yew plum pine	60
Prunus serrulata Lindl. Var. lannesiana auct.	Japanese Flowering Cherry	50
Ligustrum lucidum Ait. F.	Glossy Privet	52
Tonna sinensis M. Roem.	Chinese Toon	58
Prunus persica (L.) Batsch	peach	50
Manglietia fordiana Oliv.	Ford Woodlotus	50
Acer buergerianum Miq.	Trident maple	50
Mahonia bealei (Fortune) Carr.	Beale’s barberry	50
Magnolia grandiflora L.	southern magnolia	50
Populus ×canadensis Moench	Canadian poplar	58
Liriodendron chinense (Hemsl.) Sarg.	Chinese tulip tree	50

Table 2: Classification result of different HOG descriptor with SVM

Species	Hog cell size 2 x 2 with SVM		Hog cell size 4 x 4 with SVM		Hog cell size 8 x 8 with SVM	
	TP	FN	TP	FN	TP	FN
Anhui Barberry	8	2	8	2	8	2
Beales barberry	8	2	8	2	9	1
Big-fruited Holly	10	0	9	1	9	1
Canadian poplar	7	3	10	0	10	0
Chinese Toon	10	0	8	2	7	3
Chinese cinnamon	5	5	7	3	6	4
Chinese horse chestnut	8	2	7	3	8	2
Chinese redbud	9	1	7	3	10	0
Chinese tulip tree	7	3	9	1	10	0
Crape myrtle	8	2	10	0	9	1
Ford Woodlotus	5	5	8	2	8	2
Glossy Privet	6	4	7	3	8	2
Japan Arrowwood	9	1	7	3	9	1
Japanese Flowering Cherry	6	4	6	4	8	2
Japanese cheesewood	9	1	10	0	10	0
Japanese maple	8	2	9	1	10	0
Nanmu	9	1	9	1	7	3
camphortree	8	2	10	0	7	3
castor aralia	10	0	10	0	10	0
deodar	10	0	10	0	10	0
goldenrain tree	9	1	10	0	10	0
maidenhair tree	6	4	8	2	10	0
oleander	6	4	10	0	9	1
peach	5	5	10	0	6	4
pubescent bamboo	7	3	9	1	8	2
southern magnolia	7	3	6	4	4	6
sweet osmanthus	8	2	7	3	9	1
tangerine	7	3	8	2	10	0
Trident maple	9	1	10	0	9	1
True indigo	9	1	8	2	10	0
Wintersweet	6	3	4	6	5	5
Yew plum pine	9	1	8	2	10	0

*TP= True Positive , *FN= False Negative

Table 2: Classification Accuracy of different HOG descriptor

HOG cell Size	Accuracy (%)
2 x 2	77.5%
4 x 4	81.5%
8 x 8	85.3%

We also extracted LBP features from the leaf images than feed into SVM. Figure 5 shows the result of LBP with SVM and the accuracy result is 40.6%. Which means LBP features can also contribute to plant leaf contribution. After that, we combined HOG 8 x 8 cell size descriptor with LBP Features and classify by Multiclass SVM

Classifier. The classification result is shown in Figure 6. We observed that the overall accuracy of plant leaf detection increase significantly and the accuracy is 91.25%. The experimental result shows the effectiveness of plant leaf image detection by combining the feature of HOG and LBP with multiclass SVM.

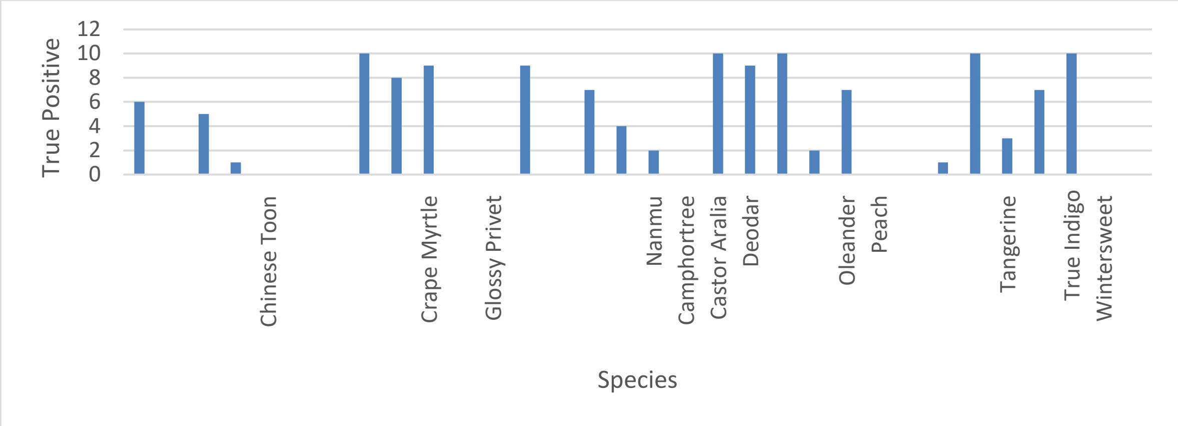


Figure 5: Result of LBP+SVM for plant detection.

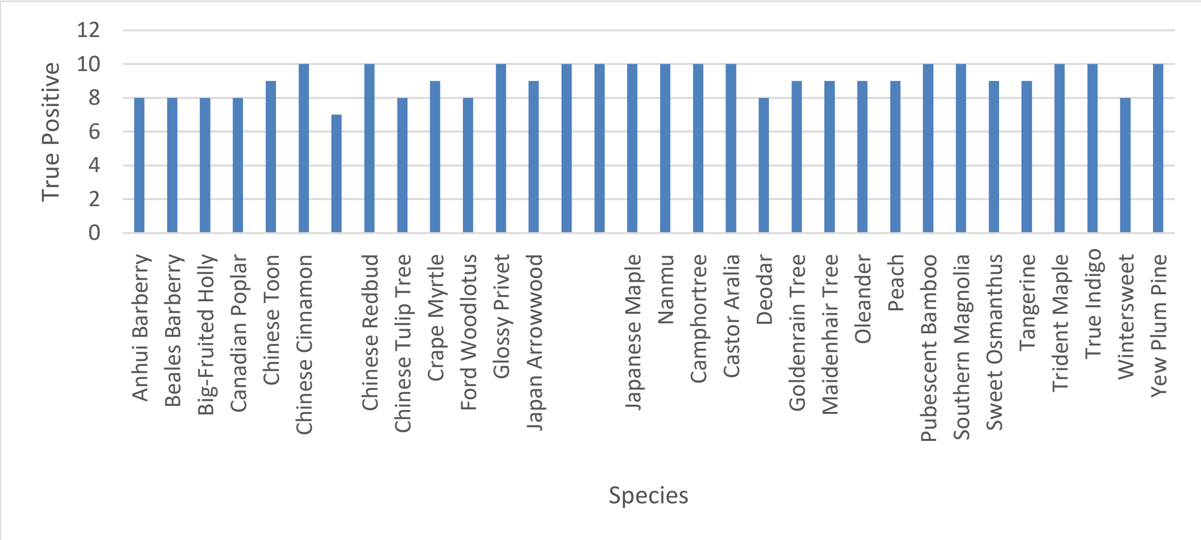


Figure 6: Result of HOG+LBP feature with SVM

5. Conclusion

In this paper, we present a novel technique to detect plant leaf images by combining HOG and LBP features and then classify the leaves using Multiclass Support Vector Machine (SVM). We carried out our experiment on a publicly available dataset called Flavia Leaf Dataset. We applied different HOG descriptor and found that HOG descriptor with cell size 8 x 8 performed better than HOG descriptor with cell size 2 x 2 and 4 x 4. Besides we can see that LBP features with SVM accuracy is 40.6%. Then we combined HOG 8 x 8 cell size descriptor with LBP features and feed into SVM and the overall detection accuracy is 91.25%. The experimental shows the effectiveness of HOG and LBP for plant leaves detection. In the future, it will be interesting to apply this method to the different publicly available dataset and also in various domain.

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