Identification of the Plants Based on Leaf Shape Descriptors

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Abstract Plants are living organisms belonging to the vegetal kingdom that can live on land and in water. Plants form the critical base of food chains in nearly all ecosystems. Plants are vitally important for environmental protection and contribute to maintain biodiversity. Plant taxonomy has attracted many researchers to study the bio-diversities based on plants. Automated identification of plant species using leaf shape descriptor addresses the automatic classification of plants and simplifies taxonomic classification process. In this research work, we used Zernike moments (ZM) and Histogram of Oriented Gradient (HOG) method as a shape descriptor resulting 84.66 and 92.67 % accuracy for ZM and HOG, respectively, on '*VISLeaf*' database.

Keywords Plant recognition · Zernike moments · Histogram of oriented gradients · Leaf shape

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1 Introduction

Most of the plants carry significant information and are considered as an essential resource for the well-being of humans. Scientifically, the discrimination among entities are based on their unique characteristics. In plants, leaves retain such unique and discriminative characteristics by means of venation architecture, geometric representation (size and shape). This complexity has generated curiosity in the minds of researchers from *Plant Sciences*, *Computer Sciences, Medicine*, *Pharmaceutical sciences*, *Mathematician* etc. Leaf patterns of different species exhibit a large variety of structures. Leaf shape has been investigated for its possible use in the systematic determination of species, by extracting its shape and size features, more precisely morphological and geometric features. This approach helped in characterizing the shape of leaf using machines.

Several attempts were made in order to classify these patterns; it was initiated by Von Ettinghausen [1]; his classification was refined and completed by Hickey [2]. However, the only color and margin of the leaf have not been considered as the safe criteria for the systematic classification and identification of plants because of its observed variability [3]. Plant identification can be performed using many organs namely *flowers*, *seeds*, *fruits*, *leaves*, and *woody* parts. Among these, leaves are the most appropriate for our experimental work targeted under this research work. Unlike other organs, leaves are easily available and they are generally observed throughout the year. Moreover, they contain a lot of information that are generally used for plant metadata formation and it becomes first possible method for plant identity and description.

Leaf images can be recognized either by color, texture, shape, or by an appropriate combination of these characteristics. Particularly for the plant recognition task, shape descriptors are mostly preserved. There are many methods reported by researchers in the literature for shape representation like *Chain code*, *Fourier descriptors*, *moments*, and *curvature scale space* which are just few of them. Two-dimensional shapes can be described either by encapsulating the information provided or by object's boundary, its features by description of the region occupied by the object on the image plane. An appropriate shape descriptor should be invariant to several geometrical transformations such as, *rotation, reflection, scaling,* and *translation*. Shape descriptor is a highly informative characteristic, since it is utilized in this research work for automatic recognition of plants based on leaf descriptor. This paper is organized in five section: Sect. 1 deals introduction; Sect. 2 deals with related work; the methodology adapted in this research work was discussed in Sect. 3; the obtained results were presented in Sect. 4 and conclusion in Sect. 5.

2 Related Work

Many researchers have contributed in this area; some of most promising works were discussed here; Singh et al. [4] proposed three techniques of plants classification based on leaf shape; they are as Probabilistic Neural Network with Principal Component Analysis (PCA), Support Vector Machine (SVM) utilizing Binary Decision Tree and Fourier Moment. These methods were helped in solving multiclass classification problems. The SVM-based Binary Decision Tree architecture has improved in both, that is the stable and efficient decision tree architecture resulting high classification accuracy of Support Vector Machine. Krishna Singh et al. observed that SVM-BDT is efficient than Fourier Moment and PNN techniques [4]. Bama et al. [5] used shape, color, and texture features. These features were used in HSV color space to extract the features. Texture feature extraction was carried out using Log-Gabor wavelet on the input image. All feature points were extracted using the Scale Invariant Feature Transform (SIFT). B. Sathya Bama et al. extended their work by incorporating HU's moments for shape feature extraction, and these computed features were matched using Euclidean distance classifier [5]. Jyotismita et al. [6] proposed Moments-Invariant (M-I) and the Centroid-Radii (C-R) modeling techniques. Jyotismita et al utilized M-I model and normalized central moments, and its combinations were considered for generation of optimal result. The C-R model was used as an edge detector for identification of leaf boundary generating its shape. The feature vector for all samples with criteria of 36 radii at 10° angular separation for marking leaf boundary was applied and passed to Neural Networks for recognition purpose [6]. Kadir et al. [7] incorporated *shape*, *vein*, *color*, and *texture features* to classify a leaf using Probabilistic Neural Network (PNN). Fourier Descriptors, Slimness Ratio, Roundness Ratio, and dispersion were also used for representing shape features [7]. Wang et al. [8] proposed the method to improve leaf image classification by using global features and local features of the leaves. Shape context was used as global feature, and SIFT (Scale Invariant Feature Transform) descriptors were also utilized for local features. Weighted K-NN algorithm was utilized for classification purpose [8]. Wijesingha et al. [9] used leaf length, width, area and perimeter and other morphological features to achieve automatic leaves image identification. Extracted features were fed to Probabilistic Neural Network (PNN) for classification [9]. Kadir et al. [10] used the combination of three geometric features that are Zernike Moments (ZM), Color Moments (CM), and Gray-Level Co-Occurrence Matrix (GLCM) for preparation of feature vector. For implementation purpose, two approaches have been investigated. In first approach, distance measures were used and in second Probabilistic Neural Networks (PNN) was implemented. The results show that the Zernike Moments have more clear features supporting for leaf identification [10].

Aptoula et al. [11] investigated performance of descriptors based on mathematical morphology. The first descriptor consists of the computation of morphological covariance on the leaf contour profile and the second descriptor was Circular Covariance Histogram for capturing leaf venation characteristics. These descriptors were compared with *Contour Morphological Covariance* (CC) and *Extended Circular Covariance Histogram* (ECCH) against standard *Morphological Covariance* (MCOV), *Angle Code Histogram* (ACH), *Contour Point Distribution Histogram* (CPDH), *Rotation Invariant LBP*, and the standard *Circular Covariance Histogram* (CCH) descriptors. Classification was done with the help of nearest neighbor classifier [11]. Bhardwaj et al. [12] used the Nearest Neighborhood Classifier in their study. Work presented the use of Hu's moment, that gives seven features descriptor of different plant leaves and different morphological feature extraction and parametric calculations such as smooth factor, aspect ratio, leaf area, rectangularity, circularity, eccentricity, etc., and area convexity was computed for recognition purpose [12]. Bong et al. [13] suggested the Centroid Contour Gradient (CCG) feature extraction method calculates the gradient between pairs of boundary points corresponding to interval angle. It was observed that the CCG had better efficiency compared to Centroid Contours Distance (CCD), because it captures the curvature of the tip and base of leaf. Mei Fern Bong et al. used the Feed-forward Back-Propagation Neural Network as a classifier [13]. Satti et al. [14] adopted a combination of color, shape, tooth features as well as morphological features of the leaves. The classification was performed using Neural Networks and Euclidean classifier [14]. Mouin et al. [15] classify the plants based on the visual information provided by the plant leaves. They considered two sources of information which are leaf margin and the leaf salient points. Sofiene Mouin et al. have introduced two shape context-based descriptors: first one represents the leaf boundary while the second represents the spatial correlation between salient points of the leaf and its margin. Sofiene Mouin et al. also studied the performance of the fusion of descriptors [15].

Kulkarni et al. [16] used the shape, vein, color, and texture features with the combination of pseudo Zernike movements. Classification was done by Radial Basis Probabilistic Neural Network (RBFNN) [16]. Larese et al. [17] used leaf shape, size, texture, and color features for plant recognition. The segmentations were completed by the means of the unconstrained hit-or-miss transform and adaptive thresholding. Classification was done by the Support Vector Machines (SVM), Penalized Discriminant Analysis (PDA), and Random Forests Methods (RF) [17]. Mythili et al. [18] classified the medical plant leaves using the geometric features such as diameter, leaf length, leaf width, and tooth features. Leaves were segmented using Effective Robust Kernelized Fuzzy C-Means (ERKFCM). Classification has been performed using Support Vector Machine Classifier (SVM), and finally Artificial Neural Network (ANN) was used to recognize leaf [18]. Pradhan et al. [19] proposed physiological features for recognition of plant leaves. The features were classified using Probabilistic Neural Network (PNN) [19]. Amlekar et al. [20] extracted leaf venation morphological feature to classify them. Multi-layer perceptron based Artificial Neural Network method [20]. These trends in the design of automatic plant recognition that based on leaf shape have been tested on various databases as well as variety of feature extraction schemes.

3 Methodology

This piece of work primarily focused on Zernike Moments (ZM) and HOG Descriptor applied over Centered binary leaf images and cropped grayscale leaf images from '*VISLeaf*' dataset, respectively. The dataset was constituted with 180 plant species collected from the Botanical garden of Dr. Babasaheb Ambedkar Marathwada University campus, Aurangabad (MS) India. Total volume of '*VISLeaf*' contains 1800(180*10) leaf samples. In this research work we used subset of '*VISLeaf*' containing 50 kinds of plant species and each species includes 10 sample images. Hence there are totally 500(50*10) images in the proposed dataset (Fig. 1).

Automatic plant identification process begins with the input leaf image. At the time of data collection, fresh leaf samples were plucked from Botanical Garden and were scanned with the resolution of 300 dpi. Metadata related to the sample was also recorded with taxonomical classification. These scanned samples were enhanced and passed for feature extraction. All extracted features of training set were saved on the disk and later used for testing and classification purpose.

3.1 Feature Extraction

3.1.1 Zernike Moments (ZM)

We use Zernike Moments (ZM) to extract features using the shape of leaf. We compute the Zernike moments from an input leaf image sample following these three steps: computation of radial polynomials, computation of Zernike basis functions, and computation of Zernike moments by casting the image on to the Zernike basis functions. The procedure for obtaining Zernike moments from an input image begins with the computation of Zernike radial polynomials [21].

$$Z_{mn} = \frac{m+1}{\pi} \int_x \int_y I(x,y)[V_{mn}(x,y)]\mathrm{d}x\mathrm{d}y, \tag{1}$$

where 'm' defines the order of Zernike polynomial of degree 'm', 'n' defines the angular dependency, and $I(x,y)$ be the gray level of a pixel of image on which the moment is calculated.

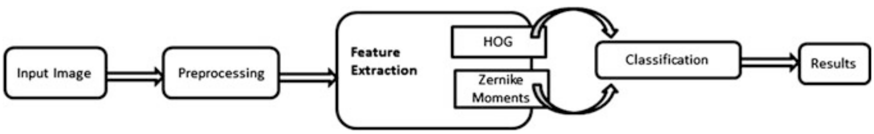

Fig. 1 Overall process for plant recognition

The Zernike polynomials $V_{mn}(x, y)$ are expected in polar coordinates using radial polynomial (R_{mn}) as per Eqs. (2) and (3).

$$V_{mn}(r, \theta) = R_{mn}(r)e^{-jn\theta} \tag{2}$$

$$R_{mn}(r) = \sum_{s=0}^{\frac{m-|n|}{2}} (-1)^s \frac{(m-s)!}{s!\left[\frac{m+|n|}{2} - s\right]!\left[\frac{m-|n|}{2} - s\right]!} r^{m-2s}. \tag{3}$$

The resultant Zernike moments Z_{mn} are invariant under rotation, scale and translational changes. Zernike Moments are the pure statistical measure of pixel distribution around center of gravity of shape and allows capturing information just at single boundary point. They can capture some of the global properties missing from the pure boundary-based representations. Zernike moments have mathematical properties that make them the ideal image features to be used as shape descriptors in shape classification problems. Michael V. et al. [22] presented the technique which explored the optimal use of Zernike Moments as a descriptor and some experiments have been done by Borde et al. [23] on 'vVISWa' dataset. We have calculated Zernike Moments up to order n = 12 and formulated Zernike feature vector containing 49 features for each sample. These features were calculated for all the samples of 'Training set' and 'Test set.' The 'Zernike Feature Matrix' for the samples of 'Training set' is shown in Table 1 and 'Test set' is shown in Table 2.

3.1.2 Histogram of Oriented Gradients (HOG)

The HOG descriptors are local statistic of the orientations of the image gradients around key points [24, 25]. A HOG descriptor is extracted from image local region, and we considered each leaf sample as a one single local region in this research work. The image sample was divided into $M*M$ cells after preprocessing; each cell has a pixel size of $N*N$. The gradient magnitude g and the gradient orientation θ were computed for all the pixels in the block using Eqs. (4) and (5); the derivatives (g_x) and (g_y) of the image I were computed with pixel differences using Eqs. (6) and (7).

$$g(\emptyset, \omega) = \sqrt{g_x(\emptyset, \omega)^2 + g_y(\emptyset, \omega)^2} \tag{4}$$

$$\theta(\emptyset, \omega) = \arctan \frac{g_y(\emptyset, \omega)}{g_x(\emptyset, \omega)} \tag{5}$$

$$g_x(\emptyset, \omega) = I(\emptyset + 1, \omega) - I(\emptyset - 1, \omega), \tag{6}$$

$$g_x(\emptyset, \omega) = I(\emptyset, \omega + 1) - I(\emptyset, \omega - 1). \tag{7}$$

Table 1 Zernike moment features for training set

Known leaf samples	Moment 1	Moment 2	Moment 3	Moment 4	Moment 5	…	Moment 47	Moment 48	Moment 49
1	77.75856	0.421456	−181.26	−6.85063	−0.89602	…	4.339012	0.668848	0.029231
2	110.5445	−3.38274	−234.741	−12.704	8.903311	…	3.743267	0.685658	0.039514
3	64.70785	−0.61887	−143.405	−6.02157	0.27391	…	−1.71328	0.001795	0.010238
4	78.66801	−6.33958	−184.329	−4.99839	17.85077	…	4.484767	0.656743	0.03365
5	97.99397	−4.12805	−216.46	−14.9965	11.56273	…	5.5169	0.738296	0.037488
6	56.84105	−2.98124	−117.703	−8.62756	5.070737	…	−0.29347	−0.47975	−0.01262
7	126.2326	−10.0928	−234.874	−23.1098	28.07237	…	−3.0651	1.289855	0.174406
8	109.3622	−3.45815	−237.331	−10.92	8.982125	…	3.105148	0.472418	0.026597
9	91.76419	1.091348	−193.86	−18.8074	−5.70007	…	−0.77591	−1.02049	−0.15835
:	:	:	:	:	:	…	:	:	:
:	:	:	:	:	:	…	:	:	:

Table 2 Zernike movement features for test set

Known leaf samples	Moment 1	Moment 2	Moment 3	Moment 4	Moment 5	…	Moment 47	Moment 48	Moment 49
1	65.57184	−0.86953	−157.864	−7.19407	3.224065	…	5.893298	0.956701	0.052449
2	74.80282	8.151839	−176.22	−6.86686	−24.9254	…	5.294342	0.517398	0.000907
3	97.72114	−1.25771	−215.353	−7.0441	3.617263	…	3.566638	0.900063	0.061227
4	83.7155	−0.10869	−194.423	−7.56672	2.266452	…	−1.30561	−0.57115	−0.04454
5	89.44508	−2.28251	−203.655	−4.01741	6.650382	…	5.368352	0.782443	0.008044
6	64.93522	3.260735	−156.295	−9.23458	−9.95418	…	6.996193	1.464478	0.103416
7	68.11832	−3.94394	−165.013	−6.03066	12.84926	…	4.559873	0.632003	0.023117
8	114.9099	−0.76084	−237.057	−15.6788	1.92062	…	3.01589	1.157132	0.078043
9	65.57184	−0.86953	−157.864	−7.19407	3.224065	…	4.335175	1.217952	0.096438
:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	…	:	:	:	:

After gradient computation, each pixel within a cell casts a weighted vote for an orientation-based histogram based on the gradient magnitude and orientation. This histogram divides the gradient angle range into K bins. The cells were normalized by histogram so that the effect of noise and overlapping cells was reduced. We consider the histogram in the same cell as a feature. Let F be the feature, and for getting feature vector we used the function as follows:

$$F = \frac{F}{\sqrt{\|F\|_2^2 + \varepsilon}}. \tag{8}$$

The histograms of all the blocks combined into a whole HOG descriptor were processed. For example, in this work of feature extraction using HOG, the block size of 3 × 3 cells was considered and the number of bins i.e. K is set to 9. As a result, algorithm calculates 81(3 * 3 * 9) blocks, so the dimension of overall HOG feature is 81 for each image. This was used further for classification purpose. Dataset was divided into 70 % known samples and 30 % unknown samples. The System was trained over 70 % known set and 30 % unknown samples were tested on the known set and success recognition of plant species was evaluated. Table 3 shows the training set and Table 4 shows the testing set.

4 Experimental Results

The recognition of plant species was carried out by Zernike moment and HOG-based features. These features were calculated for all samples of training set and stored for recognition purpose as a feature vector. The recognition of leaf samples was divided into two parts: first recognition by Zernike features and second recognition by HOG features.

4.1 Zernike Features-Based Recognition

For plant species, recognition using Zernike features was computed for all leaf samples and considered it as training and test set. The calculated training and test set were loaded into the machine for further process of plant species recognition. These feature vectors of training samples and test samples were tested for getting the minimum distance index using *minimum* distance classifier. We considered the 'index' provided by classifier as the correctly classified plant species class from the information obtained between each pair (one vector from test set and other vector from training set) of observations. The resultant confusion matrix of training samples and test samples using Zernike moment is shown in Table 5.

Table 3 HOG-based features for train set

Known leaf samples	F1	F2	F3	F4	F5	…	F79	F80	F81
1	0.208353	0.234566	0.442596	0.26377	0.507841	…	0.282264	0.260643	0.217594
2	0.213664	0.233403	0.415034	0.269162	0.521817	…	0.300757	0.311725	0.275429
3	0.264304	0.279324	0.416075	0.225411	0.493739	…	0.291849	0.245247	0.254807
4	0.233169	0.277899	0.442072	0.265329	0.435073	…	0.357607	0.311253	0.270283
5	0.271641	0.228432	0.369083	0.251361	0.522816	…	0.264287	0.241343	0.293376
6	0.24964	0.28438	0.439906	0.250599	0.436839	…	0.441629	0.259656	0.223369
7	0.287118	0.169654	0.577579	0.194941	0.526851	…	0.367056	0.315031	0.253209
8	0.226611	0.153502	0.592977	0.193349	0.535891	…	0.332522	0.326393	0.285111
9	0.268931	0.198983	0.505586	0.212044	0.491421	…	0.316813	0.28886	0.287233
:	:	:	:	:	:	…	:	:	:
:	:	:	:	:	:	…	:	:	:

Table 4 HOG-based features for test set

Known leaf samples	F1	F2	F3	F4	F5	…	F79	F80	F81
1	0.212627	0.23506	0.441837	0.217808	0.556511	…	0.280534	0.259609	0.260309
2	0.21471	0.23796	0.427174	0.26698	0.507448	…	0.41566	0.238652	0.204317
3	0.236453	0.235787	0.397133	0.265942	0.523465	…	0.385834	0.307147	0.251926
4	0.252054	0.256935	0.434326	0.215459	0.498048	…	0.290687	0.252896	0.245929
5	0.227718	0.251636	0.424993	0.256594	0.499526	…	0.297719	0.291904	0.266785
6	0.220281	0.22336	0.460269	0.236036	0.522398	…	0.427789	0.257082	0.237993
7	0.220226	0.249701	0.43528	0.219691	0.537259	…	0.405236	0.244232	0.257477
8	0.232914	0.279924	0.440937	0.240242	0.457245	…	0.372766	0.285954	0.237928
9	0.223486	0.273273	0.445324	0.265882	0.441633	…	0.345817	0.302861	0.241916
:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	…	:	:	:

Table 5 Confusion matrix produced on 50 plant datasets using ZM method

Class no.	Class name—species	No. of test samples/class	Recognized	Missed	Accuracy (%)
1	*Alstonia scholaris*	3	3	0	100
2	*Crescentia alata*	3	2	1	66.66
3	*Syzygium cumini*	3	3	0	100
4	*Tridax procumbens*	3	3	0	100
5	*Eriogloss amedule*	3	2	1	66.665
6	*Lantana camara*	3	3	0	100
7	*Holoptelia integrifolia*	3	2	1	66.66
8	*Milletia peguensis*	3	3	0	100
9	*Annona reticulata*	3	3	0	100
10	*Ficus benghalensis*	3	3	0	100
11	*Citrus limon*	3	2	1	66.66
12	*Catharanthus roseus*	3	1	2	33.33
13	*Dregea volubilis*	3	3	0	100
14	*Santalum album*	3	2	1	66.665
15	Cocculus *hirsutus*	3	3	0	100
16	*Acalypha indica*	3	2	1	66.66
17	*Barleria prionitis*	3	3	0	100
18	*Rauvolfia serpentina*	3	3	0	100
19	*Carissa carandas*	3	3	0	100
20	*Oxalis corniculata*	3	3	0	100
21	*Ficus racemosa*	3	2	1	66.66
22	*Sterculiaceae abroma*	3	0	3	0
23	*Pisum sativum*	3	3	0	100
24	*Senna occidentalis*	3	3	0	100
25	*Hibiscus syriacus*	3	3	0	100
26	*Jatropha curcas*	3	2	1	66.66
27	*Adansonia digitata*	3	3	0	100
28	*Pithecellobium dulce*	3	2	1	66.66
29	*Sphagneticola trilobata*	3	3	0	100
30	*Euphorbia grantii*	3	3	0	100
31	*Murraya paniculata*	3	3	0	100
32	*Bryophyllum pinnatum*	3	2	1	66.66
33	*Passiflora edulis*	3	3	0	100
34	*Combretum indicum*	3	3	0	100
35	*Turnera ulmifolia*	3	2	1	66.66

(continued)

Table 5 (continued)

Class no.	Class name—species	No. of test samples/class	Recognized	Missed	Accuracy (%)
36	*Hamelia patens*	3	3	0	100
37	*Jasminum multiflorum*	3	3	0	100
38	*Helianthus cucumerifolius*	3	2	1	66.66
39	*Nerium oleander*	3	3	0	100
40	*Tabernaemontana divaricata*	3	3	0	100
41	*Ipomoea purpurea*	3	2	1	66.66
42	*Ipomoea cairica*	3	3	0	100
43	*Cestrum nocturnum*	3	2	1	66.66
44	*Tecoma stans*	3	3	0	100
45	*Acalypha wilkesiana*	3	2	1	66.66
46	*Euphorbia heterophylla*	3	2	1	66.66
47	*Lythraceae lagerstroemia*	3	3	0	100
48	*Rhamnaceae ventilago*	3	2	1	66.66
49	*Gmelina arborea*	3	3	0	100
50	*Jasminum azoricum*	3	2	1	66.66
Total			127	23	84.66

4.2 HOG Features-Based Recognition

HOG feature samples from training set and test set were computed. The minimum distance classifier was used for measuring the similarity between test samples and training sample. Table 6 shows confusion matrix for HOG features-based recognition. It was seen that 139 samples were recognized correctly out of 150 samples, and over all recognition rate was measured to be 92.67 %. The resultant confusion matrix of training samples and test samples using HOG features is shown in Table 6.

Table 6 Confusion matrix produced on 50 plant datasets using HOG method

Class no.	Class name—species	No. of test samples/class	Recognized	Missed	Accuracy (%)
1	*Alstonia scholaris*	3	3	0	100
2	*Crescentia alata*	3	3	0	100
3	*Syzygium cumini*	3	3	0	100
4	*Tridax procumbens*	3	3	0	100
5	*Eriogloss amedule*	3	3	0	100
6	*Lantana camara*	3	3	0	100
7	*Holoptelia integrifolia*	3	1	2	33.33
8	*Milletia peguensis*	3	3	0	100
9	*Annona reticulata*	3	2	1	66.66
10	*Ficus benghalensis*	3	3	0	100
11	*Citrus limon*	3	3	0	100
12	*Catharanthus roseus*	3	3	0	100
13	*Dregea volubilis*	3	3	0	100
14	*Santalum album*	3	3	0	100
15	*Cocculus hirsutus*	3	3	0	100
16	*Acalypha indica*	3	3	0	100
17	*Barleria prionitis*	3	3	0	100
18	*Rauvolfia serpentina*	3	2	1	66.66
19	*Carissa carandas*	3	2	1	66.66
20	*Oxalis corniculata*	3	2	1	66.66
21	*Ficus racemosa*	3	2	1	66.66
22	*Sterculiaceae abroma*	3	3	0	100
23	*Pisum sativum*	3	3	0	100
24	*Senna occidentalis*	3	3	0	100
25	*Hibiscus syriacus*	3	3	0	100
26	*Jatropha curcas*	3	3	0	100
27	*Adansonia digitata*	3	3	0	100
28	*Pithecellobium dulce*	3	3	0	100
29	*Sphagneticola trilobata*	3	3	0	100
30	*Euphorbia grantii*	3	3	0	100
31	*Murraya paniculata*	3	3	0	100
32	*Bryophyllum pinnatum*	3	3	0	100
33	*Passiflora edulis*	3	3	0	100
34	*Combretum indicum*	3	2	1	66.66
35	*Turnera ulmifolia*	3	3	0	100

(continued)

Table 6 (continued)

Class no.	Class name—species	No. of test samples/class	Recognized	Missed	Accuracy (%)
36	*Hamelia patens*	3	3	0	100
37	*Jasminum multiflorum*	3	3	0	100
38	Helianthus cucumerifolius	3	3	0	100
39	*Nerium oleander*	3	3	0	100
40	*Tabernaemontana divaricata*	3	3	0	100
41	*Ipomoea purpurea*	3	3	0	100
42	Ipomoea cairica	3	3	0	100
43	*Cestrum nocturnum*	3	3	0	100
44	*Tecoma stans*	3	3	0	100
45	*Acalypha wilkesiana*	3	2	1	66.66
46	*Euphorbia heterophylla*	3	2	1	66.66
47	*Lythraceae lagerstroemia*	3	2	1	66.66
48	*Rhamnaceae ventilago*	3	3	0	100
49	*Gmelina arborea*	3	3	0	100
50	*Jasminum azoricum*	3	3	0	100
Total			139	11	92.67

Table 7 Comparison of recognition rate of proposed methods

Method	Recognition rate (%)
Zernike moments	84.66
HOG	92.67

Table 7 shows the overall performance of recognition system among fifty plant species. By using Zernike Moments as a features we achieved 84.66 % of recognition rate. And it indicates that ZM has low accuracy as compared with HOG based features. In recognizing 50 types of leaves using two different feature extraction techniques, i.e., Zernike Moments and Histogram of Oriented Gradients, the accuracy was 84.66 and 92.67 %, respectively, using 'Euclidean' minimum distance classifier.

5 Conclusion

In this research work, the results show that Zernike moments (ZM) and Histogram of Oriented Gradients (HOG) approach have contributed in the design of automatic plant recognition system based on the leaf shapes descriptors. The performance of HOG features was found to be excellent over Zernike moments. Increase in the HOG performance ratio was majorly due to its robustness and feature persistance capability. HOG generates more robust shape descriptor features compared to Zernike Moments. These features may be combined together with Neural network or other classifiers. And this may lead for design of more robust automatic plant identification system based on leaf shapes.

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