

# Plant Leaf Recognition and Classification using Zernike Moments (ZM) and Histogram of Oriented Gradients (HOG)

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**ABSTRACT.** A method using Zernike Moments (ZM) and Histogram of Oriented Gradients (HOG) for classification and recognition of plant leaf images is proposed in this paper. After preprocessing, we compute the shape features of a leaf using Zernike Moments (ZM) and texture features using Histogram of Oriented Gradients (HOG) and then Support Vector Machine (SVM) classifier is used for plant leaf image classification and recognition. Experimental results show that using both Zernike Moments (ZM) and Histogram of Oriented Gradients (HOG) to classify and recognize plant leaf image is possible and the accuracy is comparable or better than other methods.

**Keywords:** Zernike Moments (ZM), Histogram of Oriented Gradients (HOG), Support Vector Machine (SVM).

## 1 Introduction

Plants play a vital role in the environment. However, recently, several species of plants are threatened with extinction. In order to protect plants and to catalogue various species of flora, a plant database becomes very essential. There is huge volume of plant species worldwide. In order to handle such volumes of information, development of a rapid and competent classification technique has become an active area of research [1]. Moreover, along with the conservation feature, recognition of plants has also become essential to exploit their medicinal properties and using them as sources of alternative energy sources like bio-fuel. There are various ways to recognize a plant, like flower, root, leaf, fruit etc. Recently, computer vision and pattern recognition techniques have been applied towards automated process of plant recognition [2].

The classification of plant leaves is a vital mechanism in botany and in tea, cotton and other industries [3], [4].

Additionally, the morphological features of leaves are employed for plant classification or in the early diagnosis of certain plant diseases [5]. Plant recognition is an essential and challenging task.

Leaf recognition plays an important role in plant classification and its key issue lies in whether the chosen features are constant and have good capability to discriminate various kinds of leaves. The recognition procedure is very time consuming. Computer aided plant recognition is still very challenging task in computer vision because of improper models and inefficient representation approaches.

In the past decade, research on contour-based shape recognition [18-19] is more active than that on region-based due to the following reasons [17]: Firstly, human beings are thought to discriminate shapes mainly by contour features. Secondly, in many shape applications only the shape contour is of interest, while the interior content is less important.

In this paper we have proposed a method for recognizing and identifying plant using Zernike Moments (ZM) up to order 20 and Histogram of Oriented Gradients (HOG). Support Vector Machine (SVM) has been used as a classifier. To train SVM first we separate the data into training data and testing data. Secondly, we have to find the best parameter  $C$  (penalize parameter) so that we have the best training model and use it for classification and recognition. We have used the Flavia dataset, the Swedish Leaves dataset, and a combination of Flavia and Swedish Leaves dataset.

For Flavia dataset, we used 40 samples from each species for training data and 10 samples for testing data. Also, for Swedish Leaves dataset we used 50 samples from each species for training data and 25 samples for testing data and we used a second separation for Swedish Leaves dataset which contains 25 samples from each species for training data and 50 for testing data.

Simulation results on Flavia dataset indicates that the proposed method yields an accuracy rate of 96.77%, on Swedish Leaves dataset 97.33% and on Flavia and Swedish Leaves combination dataset an accuracy rate of 96.46%.

## **2 Image pre-processing**

### **2.1 Convert RGB image to Binary image**

An RGB image is firstly converted into a grayscale image. After that, we first calculate a threshold using Otsu's method and using this threshold level we convert the grayscale image to binary, so that we can have the leaf image in white and background in black. All images are scaled in 512x512 resolution.

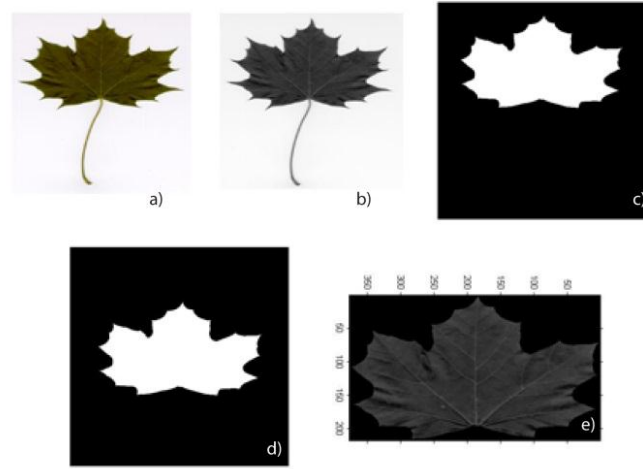
### **2.2 Eliminating the petiole**

Some leaves have petioles so we have to eliminate them. For that we use the Distance Transform operator which applies only to binary images. It computes the Euclidean distance transform of the binary image. For each pixel in binary image, the distance

transform assigns a number that is the distance between that pixel and the nearest nonzero pixel of binary image.

### 2.3 Center the image

After converting the image to binary we find the connected components of image and use the centroid property to find the center of mass of the region, so we can move the image to the center.



**Fig. 1.** a)RGB image, b)Grayscale image, c)Binary image and petiole elimination, d)Centered binary image, e)Cropped Grayscale image.

## 3 Feature extraction

In this paper we use Zernike Moments (ZM) on centered binary images and Histogram of Oriented Gradients (HOG) on cropped grayscale images to extract and calculate features of leaf image.

### 3.1 Zernike Moments (ZM)

We use Zernike Moments (ZM) to extract features using the shape of leaf. The computation of Zernike moments from an input image consists of three steps: computation of radial polynomials, computation of Zernike basis functions, and computation of Zernike moments by projecting the image on to the basis functions.

The procedure for obtaining Zernike moments from an input image begins with the computation of Zernike radial polynomials. The real-valued 1-D radial polynomial  $R_{nm}(\_)$

is defined as

$$(n - |m|)/2$$

$$R_{nm}(\rho) = \sum_{s=0}^{\lfloor (n-|m|)/2 \rfloor} c(n, m, s) \rho^{n-2s}, \quad (1)$$

where,

$$c(n, m, s) = (-1)^s \frac{(n-s)!}{s!((n+|m|)/2-s)!((n-|m|)/2-s)!}$$

In (1),  $n$  and  $m$  are generally called order and repetition, respectively. The order  $n$  is a non-negative integer, and the repetition  $m$  is an integer satisfying  $n - |m| = \text{even}$  and  $|m| \leq n$ .

The radial polynomials satisfy the orthogonal properties for the same repetition,

$$\int_0^{2\pi} \int_0^1 R_{nm}(\rho, \theta) R_{n'm'}(\rho, \theta) \rho \, d\rho \, d\theta = \begin{cases} \frac{1}{2(n+1)}, & n = n', \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Zernike polynomials  $V(\rho, \theta)$  in polar coordinates are formed by

$$V_{nm} = R_{nm}(\rho) \exp(jm\theta), \quad |\rho| \leq 1 \quad (3)$$

where  $(\rho, \theta)$  are defined over the unit disk,  $j = \sqrt{-1}$  and  $R_{nm}$  is the orthogonal radial polynomial defined in equation (1).

Finally, the two dimensional Complex Zernike Moments for a  $N \times N$  image are defined as,

$$Z_{nm} = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(\rho, \theta) V_{nm}^*(\rho, \theta) \rho \, d\rho \, d\theta \quad (4)$$

where  $f(x, y)$  is the image function being described and  $*$  denotes the complex conjugate [6].

### 3.2 Image Reconstruction using Zernike Moments (ZM)

Let  $f(x, y)$  be an image function with dimension  $N \times N$ , their moments of order  $n$  with repetition  $m$  are given by

$$\hat{f}(\rho, \theta) = \sum_{n=0}^{N_{\max}} \sum_{m=0}^{N_{\max}} Z_{nm} V_{nm}(\rho, \theta) \quad (5)$$

Expanding this using real-values functions, produces:

$$\hat{f}(\rho, \theta) = \sum_{n=0}^{N_{\max}} \sum_{m>0} (C_{nm} \cos(n\theta) + S_{nm} \sin(n\theta)) R_{nm}(\rho) + \frac{C_{n0}}{2} R_{n0}(\rho) \quad (6)$$

composed of their real (Re) and imaginary (Im) parts:

$$C_{nm} = 2\text{Re}[Z_{nm}] = \frac{2n+2}{\pi} \sum_x \sum_y f(\rho, \theta) R_{nm}(\rho) \cos(m\theta) \quad (7)$$

$$S_{nm} = -2\text{Im}[Z_{nm}] = \frac{-2n-2}{\pi} \sum_x \sum_y f(\rho, \theta) R_{nm}(\rho) \sin(m\theta) \quad (8)$$

bounded by  $x^2 + y^2 \leq 1$ .

### 3.3 Histogram of Oriented Gradients (HOG).

Histogram of Oriented Gradients (HOG) are feature descriptors used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

The essential thought behind the Histogram of Oriented Gradient descriptors is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The implementation of these descriptors can be achieved by dividing the image into small connected regions, called cells, and for each cell compiling a histogram of gradient directions or edge orientations for the pixels within the cell. The combination of these histograms then represents the descriptor. For improved accuracy, the local histograms can be contrast-normalized by calculating a measure of the intensity across a larger region of the image, called a block, and then using this value to normalize all cells within the block. This normalization results in better invariance to changes in illumination or shadowing [8].

#### Algorithm implementation.

- Gradient Computation: The gradient of an image has been simply obtained by filtering it with two one-dimensional filters:
  - Horizontal :  $(-1 \ 0 \ 1)$
  - Vertical :  $(-1 \ 0 \ 1)^T$
- Orientation Binning: The second step is orientation binning, which computes the histogram of orientation. One histogram is computed for each cell according to the number of bins. The numbers of bins we have used are 8.
- Descriptor Blocks: The purpose of this method is to split the image into a number of cells. A cell can be defined as a spatial region like a square with a predefined size in pixels. For each cell, we compute the histogram of gradients by accumulating votes into bins for each orientation. Votes can be weighted by the magnitude of

a gradient, so that the histogram takes into account the importance of gradient at a given point [8].

- **Block Normalization:** Due to the variability in the images, it is necessary to normalize cells histograms. Cells histograms are locally normalized, according to the values of the neighbored cells histograms. The normalization is done among a group of cells, which is called a block.

A normalization factor is computed over the block and all histograms within this block are normalized according to this normalization factor. Once this normalization step has been performed, all the histograms can be concatenated in a single feature vector.

Different normalization schemes are possible for a vector  $V$ , containing all histograms of a given block. The normalization factor  $Nf$  can be obtained along these schemes:

- None : no normalization applied on the cells,  $Nf = 1$
- L1-norm :  $Nf = V / (\|V\|_1 + e)$
- L2-norm :  $Nf = V / (\sqrt{\|V\|^2 + e^2})$

(9)

## 4 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a type of classifier that is a group of associated supervised learning technique utilized especially for the purpose of classification. SVM will generate a separating hyperplane in the space, one that increases the boundary between the two data sets. In order to establish the boundary, two parallel hyperplanes are produced, one on every side of the separating hyperplane between the two data sets. For SVM, a data point is denoted as a  $p$  dimensional vector, and it is needed to differentiate whether it can split such points with a  $p-1$ dimensional hyperplane. This is called a linear classifier.

As support vector machine are linear classifier that has the ability to discover the optimal hyper plane that increases the separation among patterns, this characteristic feature creates KSVMs as a potential significance for classification purposes. Initially, the whole data set is partitioned into training (F1) and testing (F2) data randomly. The features in F1 are trained using SVM classifier and features in F2 are predicted.

### 4.1 Linear SVM

The linear classifier  $f(X) = \text{sign}\langle w, X \rangle$  is parameterized by a weight vector which is normal (i.e. perpendicular) to the decision boundary which is a subspace or a linear hyperplane passing through the origin (note that as described above this does not preclude having a bias term). Any  $X$  can be represented as a sum of its projection onto

the subspace and its perpendicular component  $X = X_{\perp} + X_{\parallel} = X_{\parallel} + r \frac{w}{\|w\|}$ . Since

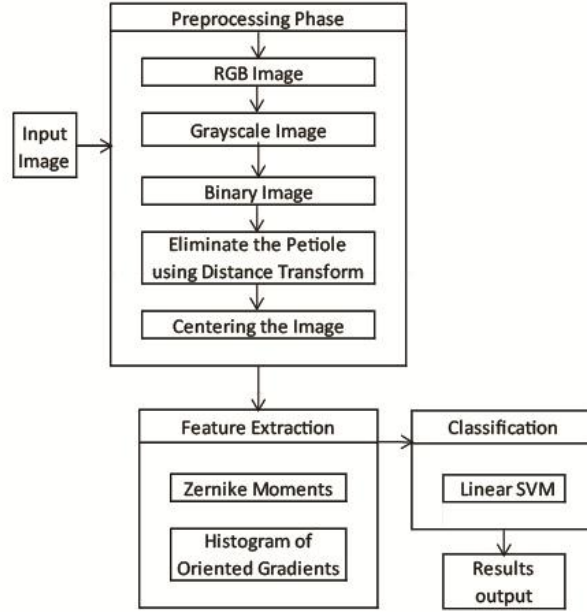
$$\langle w, X \rangle = \langle w, X_{\parallel} \rangle + \langle w, r w / \|w\| \rangle = 0 + r \|w\| \Rightarrow r = \langle w, X \rangle / \|w\|, \quad (10)$$

we have that for correctly classified points  $X(i), Y(i)$  the distance to the hyperplane is  $|r_i| = Y(i) \langle w, X(i) \rangle / \|w\|$  (11).

The idea of support vector machines in the context of linearly separable data is to choose  $w$  that leads to the largest margin – defined as the distance of the closest data point to the hyperplane

$$w = \arg \max(\|w\| - 1 \min Y(i) \langle w, X(i) \rangle), \quad w \in \mathbb{R}, \quad 1 \leq i \leq n \quad (12)$$

In this paper we use linear SVM as classifier. Before we start the classification we concatenate Zernike Moments (ZM) and Histogram of Oriented Gradients (HOG) arrays and then we normalize our data into range [0, 1]. After that we choose 80% to be the training data and 20% to be the testing data.



**Fig. 2.** Proposed method for leaf classification.

## 5 Experimental Results

To experiment the proposed method we first use both Flavia and Swedish Leaves dataset, secondly we use only the Flavia dataset and at last we use only the Swedish Leaves dataset. We have 47 species from both datasets, 32 species from Flavia dataset and 15 species from Swedish Leaves dataset. We separate the data into training data and testing data. After obtaining the best C parameter for our training model we cal-

culate the overall accuracy of our system. Using Zernike Moments (ZM) up to order 20 and Histogram of Oriented Gradients (HOG) as features, resulted in a highest accuracy of 96.77% for using only Flavia dataset, 97.33% for using only Swedish Leaves dataset and 96.46% for using both datasets, which are listed in Table 1.

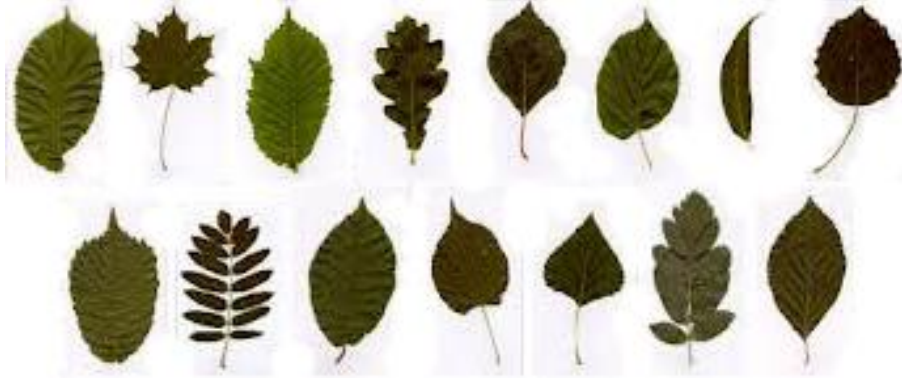


**Fig. 3.** Overview of the Flavia Leaf Dataset

**Table 1.**

Dataset	Features	Classifier	Accuracy
Flavia	ZM + HOG	Linear SVM	96.77%
Flavia + Swedish Leaves	ZM + HOG	Linear SVM	96.46%
Swedish Leaves	ZM + HOG	Linear SVM	97.33%





**Fig. 4.** Overview of the Swedish Leaf Dataset

## 6 Comparison with other Systems

To compare our proposed method with other researches who have used only Flavia dataset and only Swedish Leaves dataset, we have listed their proposed technique and their results as given in Table 2 and 3.

**Table 2.**

Dataset	Features	Training Data	Testing Data	Classifier	Accuracy
Swedish Leaves	MDM-CD-C	25 samples	50 samples	1-NN [16]	91.07%
Swedish Leaves	MDM-CD-A	25 samples	50 samples	1-NN [16]	91.33%
Swedish Leaves	MDM-CD-M	25 samples	50 samples	1-NN [16]	91.20%
Swedish Leaves	MDM-RA	25 samples	50 samples	1-NN [16]	91.60%
Swedish Leaves	TSLA	25 samples	50 samples	1-NN [15]	96.53%
Swedish Leaves	TSL	25 samples	50 samples	1-NN [15]	95.73%
Swedish Leaves	SPTC + DP	25 samples	50 samples	1-NN [15]	95.33%
Swedish Leaves	TAR	25 samples	50 samples	1-NN [15]	90.40%
Swedish Leaves	ZM + HOG	25 samples	50 samples	Our method SVM	95.57%
Swedish Leaves	ZM + HOG	50 samples	25 samples	Our method SVM	97.33%

**Table 3.**

Dataset	Features	Training Data	Testing Data	Classifier	Accuracy
Flavia	Shape Features	40 samples	10 samples	RBRNN [11]	95.12%
	Vein Features				
	Color Features				
	Texture Features				
	Pseudo-Zernike Moments				
Flavia	Shape Features	40 samples	10 samples	RBPNN [12]	93.82%
	Vein Features				
	Color Features				
	Texture Features				
	Zernike Moments				
Flavia	Geometrical Features	40 samples	10 samples	PNN [10]	90.30%
	Morphological Features				
Flavia	Geometrical Features	40 samples	10 samples	K-SVM [14]	96.20%
	Morphological Features				
Flavia	Geometrical Features	40 samples	10 samples	SVM [14]	94.50%
	Morphological Features				
Flavia	ZM + HOG	40 samples	10 samples	Our Method - SVM	96.77%

## 7 Conclusion

A new approach of plant classification based on leaves recognition is proposed in this paper. An efficient machine learning approach for plant leaf classification is presented in this research. The approach consisted of three phases namely the preprocessing phase, feature extraction phase and the classification phase. The computer can automatically classify plants via the leaf images loaded from digital cameras or scanners.

Zernike Moments (ZM) and Histogram of Oriented Gradient have been used for features extraction and Linear SVM has been adopted for classification. Compared with other methods, this approach produces better accuracy than the others. For further research by incorporating efficient kernel functions the performance of the classifier can be improved.

## 8 References

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