A Morphological and Gradient Based Approach to Classify Plant Leaves Using Support Vector Machines

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Introduction

A good understanding of plants is essential to improve agricultural productivity and sustainability to discover new pharmaceuticals to plan for and mitigate the worst effects of climate change, and to come to a better understanding of life as a whole. A leaf can be characterised by its colour, its texture, vain structure and its shape. The colour and texture of a leaf may differ with the seasons and climatic conditions. Living plant identification based on images of leaf is a challenging task in the field of pattern recognition and computer vision. In this work we focus on classifying plant leaves using basic, morphological and HOG features. A user just needs to input an image of a plant leaf, and the proposed system will predict the kind of plant leaf it is. The proposed system is evaluated on the Flavia dataset consisting of 32 classes.

Objective

- To develop an automated system for plant leaf classification of great significance.

Methodology

The following steps are used in our proposed system in classifying the plant leaves:

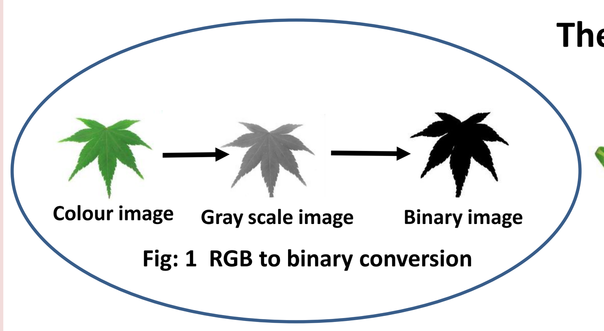

Fig: 1 RGB to binary conversion

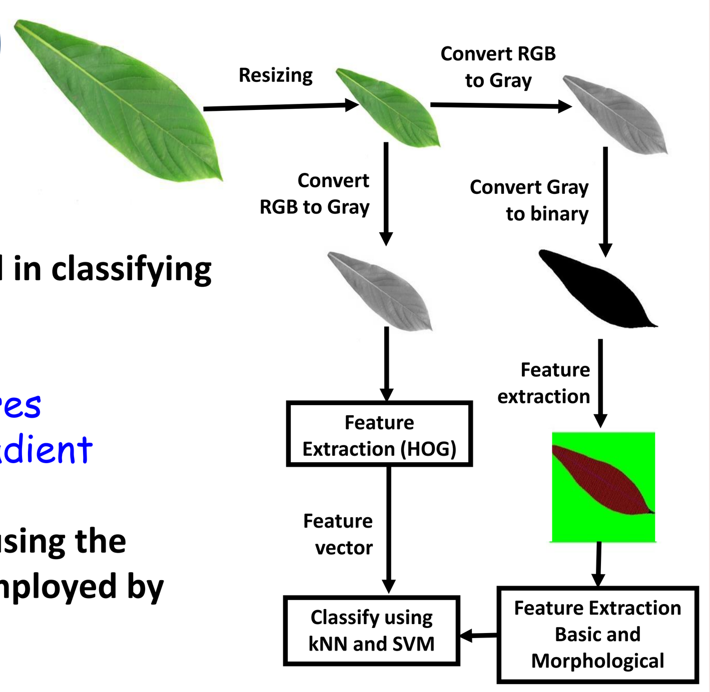

Fig: 2 Methodology

Following features have been used in classifying the plant leaves:

- Basic Geometric features
- Digital Morphological features
- Histograms of Oriented Gradient features (HOG)

The classification is compared by using the following multiclass techniques employed by SVM classifiers:

- One-versus-one (OVO)
- One-versus-all (OVA)

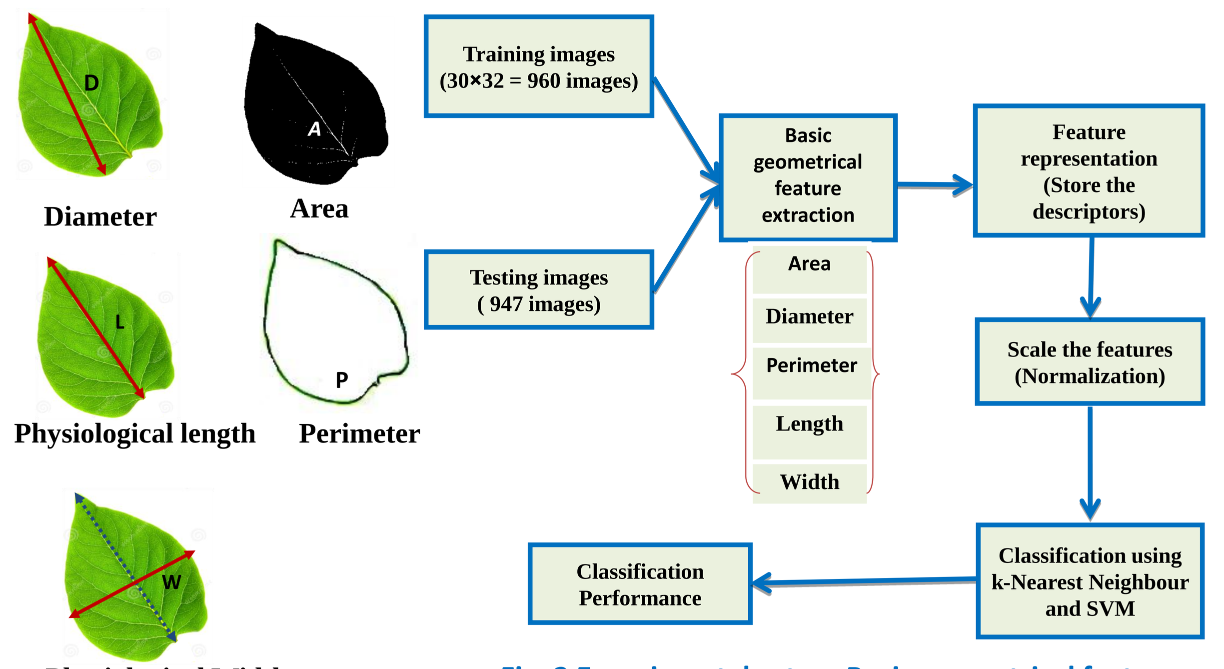

Fig: 3 Experimental setup: Basic geometrical features

Methodology…

1. **Smooth factor**: The ratio between area of leaf image smoothed by a 5×5 and 2×2 rectangular averaging filters, respectively.
2. **Aspect ratio (slimness):** L/W
3. **Form factor (roundness):** $4\pi A/P^2$
4. **Rectangularity:** L x W/A
5. **Narrow factor:** D/L
6. **Perimeter ratio to diameter:** P/D
7. **Perimeter ratio to physiological length and physiological width** P/(L +W)
8. **Vein features:** $\frac{V_1}{A}, \frac{V_2}{A}, \frac{V_3}{A}, \frac{V_4}{A}, \frac{V_4}{V_1}$

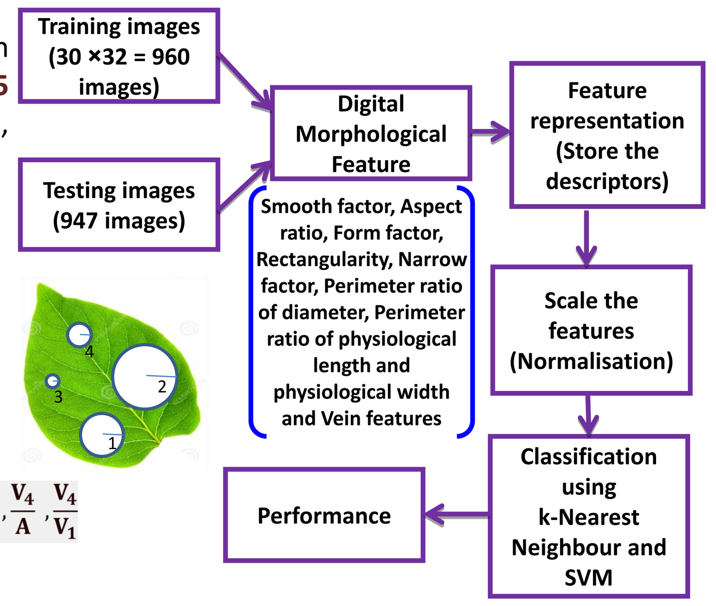

Fig: 4 Experimental setup: Morphological features

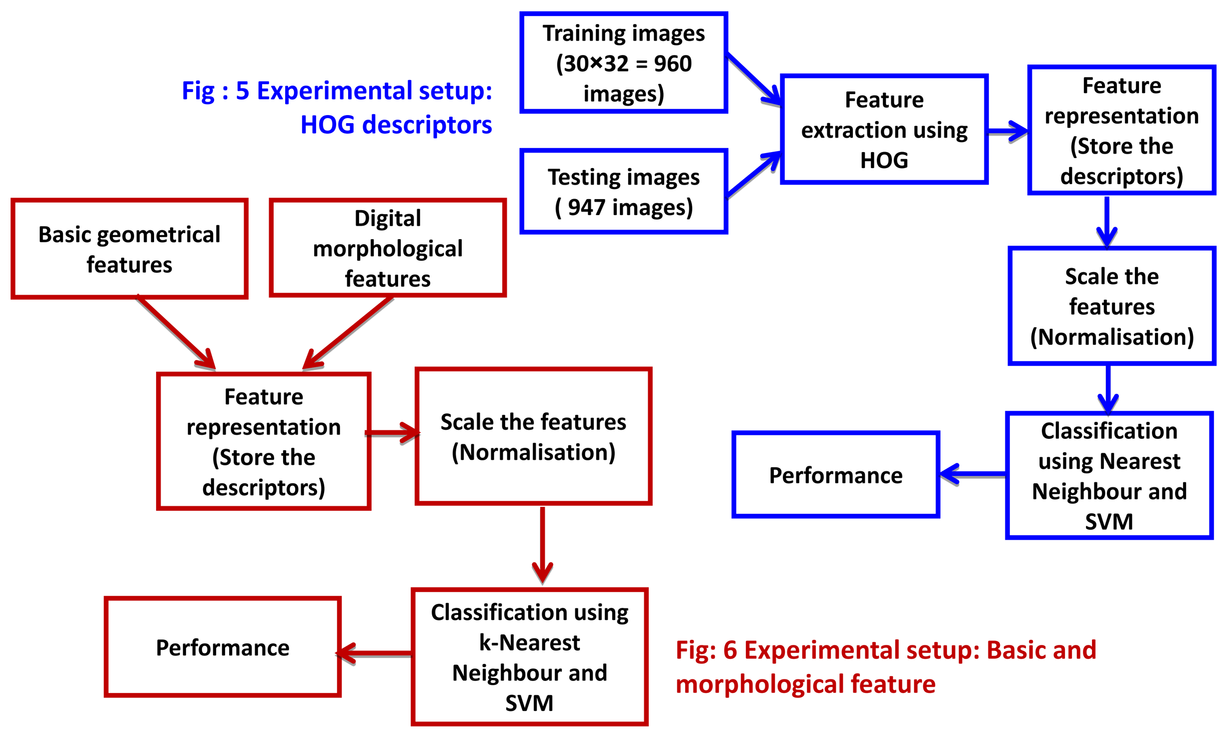

Fig : 5 Experimental setup: HOG descriptors

Fig: 6 Experimental setup: Basic and morphological feature

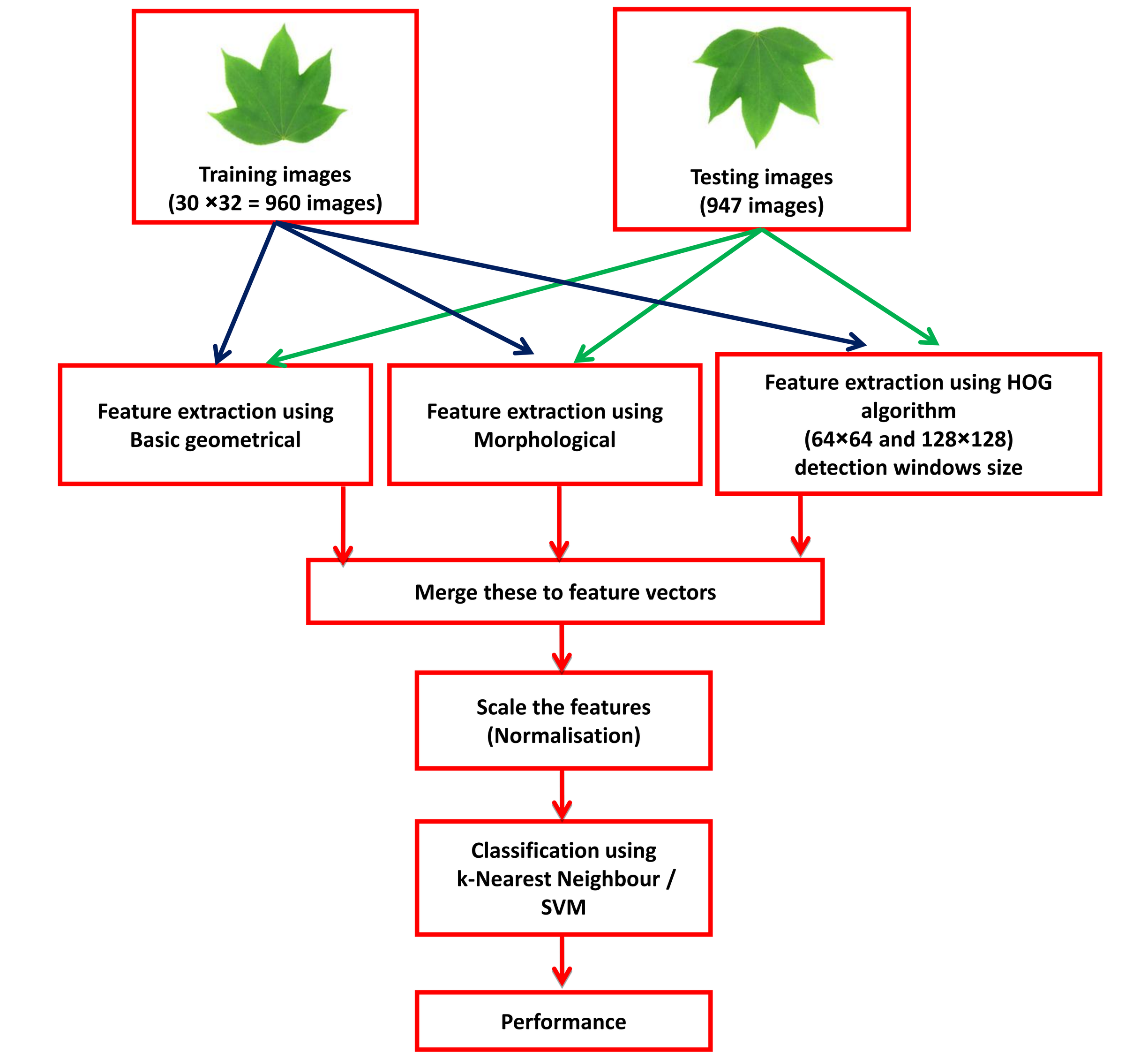

Fig: 7 Experimental setup: Concatenation of basic, morphological and HOG features

Dataset

This study uses the Flavia dataset. It consists of 32 classes of different plants. Each class includes 50–70 sample images, thus resulting in a total of 1900 images. Each image consists exactly one image with a clear background

Testing Results

Table 1: The classification accuracy using basic and morphological features with k-Nearest Neighbour.

Feature / k-NN Classifier	Classification rate: Basic Geometrical	Digital Morphological
1-NN	65.00	82.19
3-NN	58.96	78.44
5-NN	55.83	76.35
7-NN	55.94	75.52
9-NN	54.90	73.65

Table 2: The classification accuracy using both basic and morphological features with k-Nearest Neighbour and SVM classifiers

Feature / Classifier	Basic Geometrical and Digital Morphological (Classification rate)
1-NN	88.60
3-NN	84.58
5-NN	82.79
7-NN	82.05
9-NN	80.25
OVO SVM	89.23
OVA SVM	83.10

Table 3: The classification accuracy using basic and morphological features with linear SVM

Feature / SVM Classifier	Classification rate: Basic Geometrical	Digital Morphological
OVO	68.23	86.56
OVA	34.48	73.96

Table 4: The classification accuracy of the HOG

Classifier / Feature	k-Nearest Neighbour	OVO–SVM
64×64	78.46	83.42
128×128	84.48	87.86

Table 5: The classification accuracy using basic, morphological and HOG features and their concatenation with linear SVM classifiers. Basic Geometrical (BG), Digital Morphological (DM), Histograms of Oriented Gradient (HOG)

Feature / SVM Classifier	Classification rate: BG	DM	HOG	BG+DM	BG+DM+HOG
OVO	68.23	86.56	87.86	89.23	89.86
OVA	34.48	73.96	86.59	83.10	84.48

Table 6: A performance comparison of the proposed method with state-of-the-art approaches applied on the Flavia dataset

Author	#training images	#testing images	Features	Classifier	Performance
Wu *et al.*,	40-60	10	Morphological	PNN	90.31
Abdul *et al.*,	40	10	Shape, vein, colour and texture	PNN	93.75
Vijay et *al.*,	45-65	5	Colour and shape	ANN	93.30
Ours	30	20–47	Basic, Morphological, and HOG	SVM	89.86

In order to compare our proposed method with other works listed in Table 6, we increase our training set and reduce the testing set as shown in Table 7 so that the comparison becomes same as of others experimental setup.

Table 7: A performance comparison of the proposed method when using large number of training images and testing on small number of images

#training images	#testing images	Features	Performance
40	10	Basic and Morphological	94.60
40	5		95.01

Discussion

- ☹ Majority researchers have used a large number of training images (40–65 images/class) to train their proposed systems.
- ☹ Only a very small number of testing sets (5–10 images/class) are used.
- ☹ The selection of testing images made by those researchers mentioned as indicated in Table 6 is questionable due the reason of selecting just five images though at least 20 images are available from each of the classes of the Flavia dataset.
- ☹ The selection of less number of testing images may favour the classification rate for slightly outperforming our technique.
- ☺ We have used linear SVMs which is quite naturally designed to perform classification in high dimensional spaces.
- ☺ Our approach shows a classification rate of 94.6% which outperforms the Abdul *et al*'s method [1] with basic and morphological features amounting to 17 dimensions. It also outperforms the method proposed by Wu *et al.*, [5] by a performance increase of 4%.
- ☺ Our approach shows a classification rate of 95% which outperforms the method proposed by Vijay *et al.*, by a performance increase of 1.7%.
- ☺ Our main argument in this work is not just to show an increased performance but to propose the selection of discriminative features that could be applied on the classification of Flavia leaves.
- ☺ We have used less number of training images (30 images/class) and have tested on the rest of the images from each of the 32 classes.
- ☺ Out testing results are very similar to what others have achieved and it involves no manual process in extracting features and classifying them.

Conclusion

- This study confirms the importance of leaf basic and morphological features since the results obtained by the feature selection method selected these features as the most discriminate.
- The five basic and twelve morphological features and HOG features are used to classify 32 types of plant leaves.
- The experimental result demonstrates that the proposed method is effective and efficient.
- The testing result is around 90%. The accuracy of the current proposed approach is comparable to those results reported on Flavia dataset.

References

1. Abdul Kadir, Lukito Edi Nugroho, Adhi Susanto and Paulus Insap Santosa, *Leaf classification using shape, color, and texture features*,**2011**, 225-230.
2. Dalal N. and Triggs B., *Histograms of Oriented Gradients for Human Detection*, In proceedings of IEEE Conference on Computer Vision and Pattern Recognition, **2005**, 55-79.
3. Rifkin R. and Klautau A., *In Defense of One-vs-All Classification,* Journal of Machine Learning Research, **2004**, 5, 101–141.
4. Vijay satti, Anshul satya, and Shanu sharma, *An automatic leaf recognition system for plant identification using machine vision technology*, International Journal of Engineering Science & Technology, **2013**, 874-879.
5. Wu S G., Bao F S, Xu E Y., Wang Yu-Xuan., Chang Yi-Fan. and Xiang Qiao-Liang., *A Leaf Recognition Algorithm for Plant Classification using Probabilistic Neural Network*, Signal Processing and Information Technology, **2007**, 11-16.