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Plant leaf recognition using shape features and colour histogram with k-nearest neighbour classifiers

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Abstract

Automated systems for plant recognition can be used to classify plants into appropriate taxonomies. Such information can be useful for botanists, industrialists, food engineers and physicians. In this work, a recognition system capable of identifying plants by using the images of their leaves has been developed. A mobile application was also developed to allow a user to take pictures of leaves and upload them to a server. The server runs pre-processing and feature extraction techniques on the image before a pattern matcher compares the information from this image with the ones in the database in order to get potential matches. The different features that are extracted are the length and width of the leaf, the area of the leaf, the perimeter of the leaf, the hull area, the hull perimeter, a distance map along the vertical and horizontal axes, a colour histogram and a centroid-based radial distance map. A k-Nearest Neighbour classifier was implemented and tested on 640 leaves belonging to 32 different species of plants. An accuracy of 83.5% was obtained. The system was further enhanced by using information obtained from a colour histogram which increased the recognition accuracy to 87.3%. Furthermore, our system is simple to use, fast and highly scalable.

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Keywords: Leaf; pattern recognition; shape features; colour histogram; k-nearest neighbour

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1. Introduction

Recognition of plants is a simple task for botanists. For machines however, the same speaks to an immense and complex computational exertion. Humans can undoubtedly recognize distinctive objects, determine their sizes, shapes, compositions and hues and comprehend the relationships between them using their senses. As for machines, achieving the same will include the use of sensors and cameras to emulate some of the senses that humans possess. It is also usually necessary to perform image-processing techniques to extract visual information and compare them to an existing set of data. This process requires the use of specialized programs or libraries. Computer vision[1] is the science of endowing computers or other machines with vision, or the ability to see. The rationale of recognition systems is that objects of the same kind will share some similar visual properties which can be captured and thereby allow for such systems to be feasible. This paper aims at studying existing leaf recognition systems and then implementing one based on shape descriptors. We also evaluate the effectiveness of the methods used while using a dataset with a fair amount of leaves per plant. The system allows the addition of new plants to the database without much effort.

This paper proceeds as follows. Section 2 gives an overview of existing leaf recognition systems. The methodology, dataset and pre-processing operations are explained in Section 3 while the results are presented and evaluated in Section 4. Section 5 concludes the paper with a description of some future works.

2. Related Works

Satti *et al.*[2] proposed a plant recognition system that used colour and shape information to produce an accuracy of 93.3% with an Artificial Neural Network (ANN) and 85.9% with the k-Nearest Neighbour classifier (kNN) on the Flavia[3] dataset. A more recent study by Chaki *et al.*[4] proposed a new method of characterizing and recognizing plant leaves using a combination of shape features and texture. A Gabor filter was used to model the texture of the leaves and the shape was captured using a set of curvelet transform coefficients together with invariant moments. The efficacy of the system was tested using two neural classifiers: a neuro-fuzzy controller and a feed-forward back-propagation multi-layered perceptron (MLP). The best accuracy obtained was 87.1% for 930 leaf images consisting of 31 different species. It is however not easy to compare these approaches because each one uses a different subset of the Flavia[3] dataset.

Vein patterns of scanned leaf images were used by Larese *et al.*[5] for the classification of three legume species. They obtained a relatively high accuracy of 84.1% using a penalized discriminant analysis (PDA) approach. They also performed the experiment using images of leaves that were cleared using a chemical process and this increased their accuracy to 88.4% at the expense of time and cost.

Wang *et al.*[6] used the concept of bag of words, borrowed from the field of text classification, and applied it to extract a bag of contours from the shape of leaves. They tested it on the Swedish leaf dataset[7] and achieved an accuracy of 96.6% using a nearest neighbour classifier. This is the first paper which actually introduced the idea of bag of contours together with local constrained linear coding (LLC) and spatial pyramid matching (SPM) for shape representation.

An automated system for the recognition of medicinal plant leaves was developed by Arun *et al.*[8]. They used grey tone spatial dependency matrices (GTSDM), grey textures and Local Binary Pattern (LBP) operators as features for recognition. This method uses six different classifiers to classify the plants based on the above features. Without using any pre-processing technique, an accuracy of 94.7% was obtained using a dataset of 250 different images from five plant species.

Amin and Khan[9] obtained an accuracy of 71.5% by using 64 features derived from shape only. They proposed a new scheme called the Distributed Hierarchical Graph Neuron (DHNG) for pattern recognition and a k-Nearest Neighbour for pattern classification. They used a database consisting of 1600 images from 100 plant species. 70% of the database was used as training set and the rest as testing set.

Uluturk *et al.*[10] suggested a method of classification based on the bisection of leaves. Pre-processing techniques were initially applied on the leaves, then 7 low cost morphological features alongside 3 extra features using half leaf images were extracted. For leaves which had similar morphological structures, the image was split into two regions. All these features were then used as input in a Probabilistic Neural Network and an accuracy of 92.5% was obtained.

Zhang and Lei[11] used a locally modified linear discriminant embedding algorithm (MLLDE) on the ICL[12] plant leaf database. The system was tested on 750 leaf images consisting of 50 different species and obtained an accuracy of 93.5% which showed that the MLLDE is an effective technique for plant leaf recognition. Kadir *et al*[13] suggested a method that uses the vein, shape, colour and texture features of the leaf. Fifty-four different features were extracted and a Probabilistic Neural Network was used to classify the leaves. Testing was performed on the Flavia[3] and Foliage[14] datasets. The accuracy in both cases was around 95%. Using the Principal Component Analysis (PCA) as a feature selection method only improved the accuracy by about 2%.

A recognition technique for broad flat leaves proposed by Hossain *et al.*[15] uses a Probabilistic Neural Network and the shape is extracted after the user selects a base point and a few reference points on the leaf blades, to produce a binary image. From this image, several features are extracted such as area, perimeter, and eccentricity. The proposed framework uses a ten-fold cross validation technique and a 91.4% accuracy was obtained.

Table 1. Summary of Related Works

Authors	Features	Classifiers	Accuracy	Dataset	Training	Testing	Species	Samples
Satti *et al.*	Shape, Colour	ANN	93.3%	1907	1742	165	33	40-60
Chaki *et al.*	Shape, Texture	ANN	87.1%	930	620	310	31	30
Larese *et al.*	Shape, Colour	PDA	88.4% 84.1%	150 866	10-fold cross validation			3
Wang *et al.*	Shape Contours	kNN	96.6%	1125	750	375	15	75
Arun *et al.*	Texture	SGD, kNN, SVM, DT, RF	94.7%	250	175	75	5	50
Amin and Khan	Shape	kNN	71.5%	1600	1120	480	100	16
Uluturk and Ugur	Shape	PNN	92.5%	1280	1120	160	32	40
Zhang and Lei	Shape	MLLDR	93.5%	750	500	250	50	15
Kadir *et al.*	Shape, Veins Texture	PNN	95.8% 95.0%	6900 1600	5700 1280	1200 320	60 32	95 50
Hossain and Amin	Shape	PNN	91.4%	1330	1200	130	30	40

3. Methodology

The proposed system is essentially divided into two separate phases: the client and the server phases. The client side is a software that allows a user to upload the picture of a leaf to the server. An overview of the system is shown below.

Fig. 1. Overview of classification system

The server uses shape descriptors and colour information to compare the information extracted from the database of the leaf images with a newly acquired one and uses a k-Nearest Neighbour algorithm to find the best matches.

3.1 Dataset

We have created our own dataset and named it ***Folio***. Pictures of leaves were taken from the farm of the University of Mauritius and nearby locations. The database consists of 20 different pictures for each species, for 32 different plants species. The pictures have been taken in broad daylight with a Smartphone camera having a resolution of 1980*1024. ***Folio*** is available on the UCI Machine Learning Repository website.

3.2 Pre-processing Steps

A series of digital image processing techniques are used to prepare the image for further processing and these are described below:

3.2.1. Rotation: The image is rotated to the proper orientation if required (the tip of the leaf must point upwards) by rotating the image clockwise if its width is greater than its height.

3.2.2. Greyscaling: The image is converted to greyscale since this part of the system needs shape information and not colour information.

3.2.3. Thresholding: A thresholding operation is performed using OTSU's[16] thresholding method to obtain a binary image.

3.2.4. Opening operations: Three successive sets of opening operations are applied (erosion followed by dilation) to remove the small unwanted 'holes' appearing in the processed images due to noise.

3.2.5. Inverse threshold: The binary image is inverted to represent the background as black.

3.2.6. Edge extraction: The contours in the image were extracted using the Suzuki's algorithm[17].

3.2.7. Edge filtering: The contours with small lengths (relative to the largest contour) are eliminated.

3.3 Feature Extraction

The following information are then extracted from the processed image:

3.3.1. Convex hull information

A convex-hull is formed using the boundary points of the leaf. The convex-hull is approximated and the number of vertices is extracted. The area and perimeter of the hull are also calculated.

3.3.2. Morphological information

The length and width of the leaf is calculated by finding the minimum and maximum x and y coordinates. The perimeter and area of the leaf are also calculated using the boundary points.

3.3.3. Distance maps

i. Vertical and horizontal maps: lines are drawn on the segmented image and each line consists of the minimum and maximum coordinate which intersects with the leaf on the respective axes. The distance of each line is estimated and stored. This is shown below in Figure 2.

ii. Centroid radial map: The centroid of the leaf is found by intersecting the diagonal axes through the bounding box around the leaf. Sixteen points radiating from the centroid are taken on the boundary box. The Euclidean distances between these points and the centroid are calculated as well as that between the centroid and the points which intersect with the leaf's boundary. This is shown below in Figure 3.

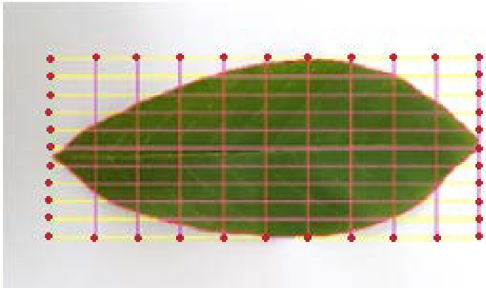

Fig. 2. Distance map X and Y

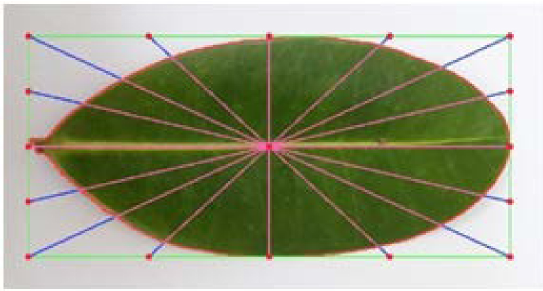

Fig. 3. Centroid radial distance map

The information extracted are then used to create ratios which will be used for the pattern matcher. Table 2 shows the ratios that have been calculated from the previous measurements.

Table 2. Ratios

Aspect ratio	**White area ratio**	**Perimeter to area**	**Perimeter to hull**	**Hull area ratio**	**Distance map x**	**Distance map y**	**Centroid radial distance**
Width/ Length	Area of leaf /(Length * Width)	Perimeter of leaf / Area of leaf	Perimeter of hull / Perimeter of leaf	Area of leaf / Area of hull	Distance of the lines parallel to x-axis / Length	Distance of the lines parallel to y-axis / Width	Distance from centroid to intersecting points / Distance from centroid to boundary box

3.3.4. Colour histogram

A colour histogram is computed for a cropped part of the image since if the whole image is used, white spaces surrounding the leaf would affect the histogram. To crop the image, the length and width of the bounding box are used as markers to crop the central part of the leaf image.

3.4 Matcher

The matcher algorithm consists of 2 stages of kNN. All the ratios are normalised to a value between 0 and 1 before any comparison is made.

Stage 1: The leaf to be recognised undergoes the same processing as the ones in the database. The new values for the ratios are also normalised. The new leaf is then compared to each leaf in the training set one by one. The sum of the Euclidean distances between the new leaf and those in the database are calculated. The 3 closest results are then returned. Each ratio is used as a feature in the kNN classifier. For the distance and centroid maps, all the distances in the sets are considered as individual features.

Stage 2: For instances where the result set from stage 1 consists of different plants, the colour histogram[18,19] of the new leaf is compared to those from that result set. The correlation coefficient is then calculated. This value lies between 1 and -1. A value close to 1 indicates a very high positive correlation, which means that the two images are very similar. The closest matches are calculated using a kNN algorithm.

4. Results

The method of testing used was to use every photo of the leaves in the database as input image to the system, compare it to all the other leaves and calculate the percentage accuracy of the system. This technique has the advantage of testing all the leaves in the database rather than just a small percentage of it. Every time the system applies the matcher to a leaf, it will create a record in a CSV file with the actual plant name and the predicted plant name.

Testing was done on 640 leaves coming from 32 different species of plants. In particular, we noted a 100% accuracy for seven different types of leaves. Only one plant species had a recognition accuracy of less than 75%. The overall accuracy at the first stage was 83.5%. The colour histogram matching operation was then applied on the results from the first stage and the accuracy rose to 87.2%. Moreover, the same test was carried out on the entire Flavia[3] dataset and a high accuracy of 86.0% and 91.1% were obtained after the first and second stages respectively. Thus, we can see that this approach is very effective in the classification of plant leaves.

Further experiments were conducted in order to assess the effect of increasing the number of plant species and the number of leaves on the classification accuracy.

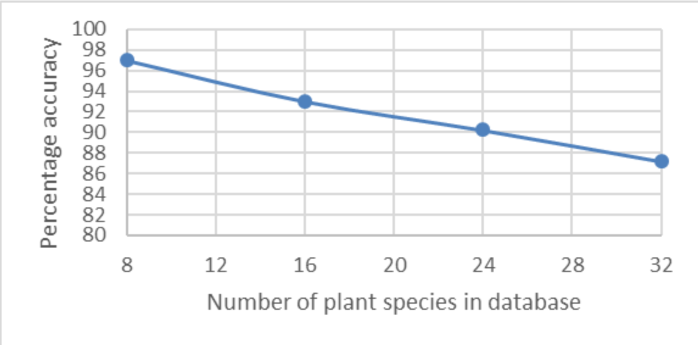

Fig. 4. Effect of increasing number of plant species on accuracy

From Figure 4, it can be noted that with only eight species, we have a very high classification accuracy of 97.0% but this slowly drops to 87.2% with 32 species. We usually expect the recognition accuracy to go down when there are more variety in the dataset. However, in this case, the accuracy is going down very slowly and it is still very high with 32 different species.

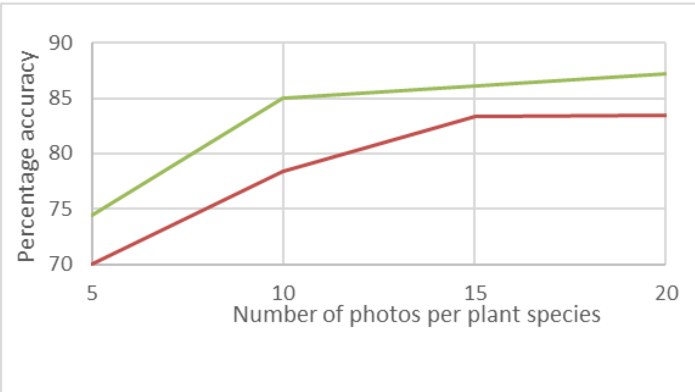

Fig. 5. Effect of increasing number of leaves on accuracy

From Figure 5, it can be noted that as the number of leaves increases from 5 to 20, the accuracy of the kNN classifier rises from 70.0% to 83.5%. However, there is no significant increase in accuracy if more than 15 leaves per plant species are used. The overall accuracy (kNN + information from colour histogram) follows a similar trend but there is an increase of approximately 1% for each additional set of 5 leaves that is added to the database after the first 10 leaves.

Thus, we observe that it is possible to obtain a high value for classification accuracy by using a relatively large number of plant species but with only a small number of sample leaves per species. We also demonstrated how the accuracy varies on the number of plant species and the number of leaves. The accuracies obtained are comparable with existing works. However, since our approach is based entirely on the k-Nearest Neighbour classifier, it is expected to run faster than comparable approaches using probabilistic neural networks or support vector machines. The effect of varying the number of species and varying the number of leaves had not been sufficiently tackled in the literature.

5. Conclusion

In this paper, we demonstrate an approach to classify plants into their appropriate species using images of their leaves. A high-resolution camera was used to take pictures of 32 different species of plant. For each plant species, 20 different leaf images were captured. The images were pre-processed and a number of features were extracted from them. We implemented our own k-Nearest Neighbour classifier. Each leaf image was then compared with every other leaf image in the database. We obtained an accuracy of 83.5% at the first stage. The next stage consisted of using information obtained from colour histograms in order to further differentiate between more difficult cases. This technique had a positive impact of about 4% on the recognition accuracy. We also discovered that increasing the number of species leads to a small decrease in the accuracy but increasing the number of leaves beyond a threshold of ten had no significant impact on the overall accuracy. Compared to earlier approaches, our system provides comparable accuracies and is expected to produce results much faster. The main difficulty in this work was the need to take all the photos in broad daylight failing which the accuracy could be adversely affected. In our future work, we intend to create a system which is more robust to light variation and to include vein patterns as a feature. We will also create a more elaborate dataset.

6. References

[1] E.G. Learned-Miller. Introduction to computer vision. University of Massachusetts, Amherst, (2011).

[2] V. Satti, A. Satya, S. Sharma. An automatic leaf recognition system for plant identification using machine vision technology. International Journal of Engineering Science and Technology (IJEST), Vol. 5.4, (2013): 874-879.

[3] Flavia Plant Leaf Recognition System, (http://flavia.sourceforge.net/).

[4] J. Chaki, R. Parekh, S. Bhattacharya. Plant leaf recognition using texture and shape features with neural classifiers. *In:* Elsevier: Pattern Recognition Letters, Vol. 58, (2015): 61-68.

[5] M.G. Larese, R. Namias, R.M. Craviotto, M.R. Arango, C. Gallo, P.M. Granitto. Automatic classification of legumes using leaf vein image features. *In:* Elsevier: Pattern Recognition, Vol. 47.6, (2014): 158-168.

[6] X. Wang, B. Feng, X. Bai, W. Liu, L.J. Latecki. Bag of contour fragments for robust shape classification. *In:* Elsevier: Pattern Recognition, Vol. 47.6, (2014): 2116-2125.

[7] O. S. Oderkvist. Computer vision classification of leaves from Swedish trees. Master's Thesis, Linkoping University, (2001).

[8] C.H. Arun, W.R. Sam Emmanuel, D.C. Durairaj. Texture feature extraction for identification of medicinal plants and comparison of different classifiers. International Journal of Computer Applications, Vol. 62.12, (2012): 1-9.

[9] A.H.M. Amin, A.I. Khan. One-shot classification of 2-D leaf shapes using distributed hierarchical graph neuron scheme with k-NN classifier. *In:* Elsevier: 17th Asia Pacific Symposium on Intelligent and Evolutionary Systems, (2013): 84-96.

[10] C. Uluturk, A. Ugur. Recognition of leaves based on morphological features derived from two half-regions. *In:* Institute of Electrical and Electronics Engineering (IEEE), International Symposium on Innovations in Intelligent Systems and Applications, (2012): 1-4.

[11] S. Zhang, Y.K. Lei. Modified locally linear discriminant embedding for plant leaf recognition. *In:* Elsevier: Neurocomputing, Vol. 74.14, (2011): 2284-2290.

[12] X.M. Ren, X.F. Wang, Y. Zhao. An efficient multi-scale overlapped block LBP approach for leaf image recognition. *In:* Springer, International Conference on Intelligent Computing (ICIC), Vol 8, (2012): 237-243.

[13] A. Kadir, L.E. Nugroho, A. Susanto, P.I. Santosa. Performance improvement of leaf identification system using Principal Component Analysis. International Journal of Advanced Science and Technology, Vol. 44, (2012): 113-124.

[14] A. Kadir, L.E. Nugroho, A. Susanto, P.I. Santosa. Experiments of zernike moments for leaf identification. Journal of Theoretical and Applied Information Technology (JATIT), Vol. 41.1, (2012): 82-93.

[15] J. Hossain, M.A. Amin. Leaf shape identification based plant biometrics. *In:* Institute of Electrical and Electronics Engineering (IEEE), Proceedings of 13th International Conference on Computer and Information Technology (2010): 458-463.

[16] S.U. Lee, S.Y. Chung. A comparative performance study of several global thresholding techniques for segmentation. Computer Vision, Graphics, and Image Processing, Vol. 52, (1990); 171-190.

[17] S. Suzuki, K. Abe. Topological structural analysis of digitized binary images by border following. Computer Vision, Graphics, and Image Processing, Vol. 30.1, (1985): 32-46.

[18] N. Petkov, X. Jiang. CAIP - computer analysis of images and patterns. *In:* Elsevier: Pattern Recognition, Vol. 44.9, (2011): 1841.

[19] G. Ramella, G.S.D. Baja. Color histogram-based image segmentation. *In:* Springer Berlin Heidelberg, Proceedings of 14th International Conference (CAIP), (2011): 76-83.