# Vision System for Medicinal Plant Leaf Acquisition and Analysis

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## 1 Introduction

In nature, plant plays major role in life cycle on earth and balance the environment. In addition, few plants are medicinal herbs that are used in healing pains and curing several diseases. For example, for rheumatoid arthritis several chemical drugs and allopathic medicines are available but compromises therapeutic treatment and therefore, ayurvedic treatments are very effective in such cases. Unfortunately, there is no much care given to such herbs that are used in several treatments. They are knowingly or unknowingly being destroyed from this vast nature's biodiversity. As a major objective of this paper, we are trying to prevent the medicinal herbs from destruction using awareness and information technology.

There are many efforts taken in this direction starting from past two decades [1–3]. Nearly one third of population in developed countries and more than 80% in other developing countries use herbal products directly in the hope of good health and manage common maladies likes colds, heart disease, diabetes, inflammation, and central nervous system diseases [4]. As researchers study, roughly 11,146 herbs are known and out of them 500 are majorly used in India as daily [1, 4]. Therefore, efficient and accurate identification of medicinal plants and their products are difficult. For same, in 2003, Hebert coined "DNA barcode" for globally species identification [5].

In recent decade, automatic species identification has become an interesting area of computer vision [2]. For this, various different parts of plants were used to identify like flower [6] and leaf [2, 7]. Features like GIST [2], Inner Distance Shape

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Context (IDSC) [8], Curvelet [7], leaf skeleton [9], fuzzy inference neural network [10], genetic algorithm [11], and others [12, 13] are used to extract features from plant leaves. Recent proposed methods for plant identification are summarized in [12].

These plants can be further classified as medicinal herds by expert botanists. The different parts of a medicinal plant like leaf, seed, flower, bark and root are used in different disease diagnosis. Wendel et al. proposed method to identify species using plant bark, leaves and needles with an accuracy rate for bark classification 69.7% and 93.6% for leaf. But the major problem with this is the cost involved in computing the SIFT features and the bag of word model for online learning which is not possible. Similarly, the other above proposed approaches extracts information either globally or locally from the plant leaf but very few are having both information. Addition to this, since the leaf texture information mainly contributes in automated plant species identification and so proper image acquisition is important to define the algorithm(s).

In this paper, first we present a novel way to acquire the leaf shape and texture information using a simple setup to create plant leaf dataset. Second, a novel approach to extract local and global texture information of medicinal leaves that uses Convolutional Neural Network (CNN) for identification. As CNN is an artificial feed forward NN and used in several research for object recognition [14]. Before the image passed through the the multiple-NN of CNN image is transformed to $l\alpha\beta$ color space from RGB space. The feature vector is then re-projected to a Principal Component Analysis (PCA) which is classified using Support Vector Machine (SVM) with Radial Basis Function (RBF).

The work is organized in this paper as following sections. In Sect. 2, the proposed methodology used in paper is presented followed by the experiments and results in Sect. 3. In Sect. 4, finally a brief discussion and conclusion is given.

## 2 Proposed Methodology

Our approach uses the CNN feature in PCA sub-space to represent medicinal plants uniquely for classification. The feature vector for every leaf sample is allowed to compare with the pre-computed leaf dataset to identify the species or to search for the most relevant medicinal plants. Since the input to CNN is a fixed size, thus needs pre-processing. Along with this, we have come up with a new approach to capture leaf samples efficiently and clear. The image then transformed to $l\alpha\beta$ color space and passed over fully connected CNN to extract feature vector for classification using SVM, discussed next.

**Fig. 1** Plant leaf samples captured using mobile devices

### 2.1 Image Acquisition and Pre-processing

As we know, leaves are 2+ dimensional real object and image is a colored 2D representation. The folds in leaf creates issues while capturing using simple camera devices which changes the shape information. Also while real-time capturing sometimes shadowing effect is seen on the image or flash spots, as shown in Fig. 1. This can be overcome by using some pre-processing prior to feature extraction and classification but may or may not give accurate results for every cases. Therefore, a small setup to capture real leaf images without any artificial shapes.

For this, simple triangular glass setup kept over a black background with lights (LED, so that scattering is minimized) at all the pillars and a camera with a fixed distance on top is used to capture the leaf placed in between the glasses. Figure 2 shows the clear picture of the setup. In this paper, a fixed distance $L$ and angle $\lambda$ are used to digitize all the specimens of plants. $L$ is the distance of camera from the object leaf and $\lambda$ is the angle by which the object is captured. To make is standard the $\lambda = 90°$ and $L = 1$ m. They are variable and needs to be optimized such that no biasing is done for varying leaf size of the same species. The real leaf image acquisition setup is shown in Fig. 3.

The black background enhances the texture making CNN feature more effective. Also logically black = 0, reduces the computational cost of the processing unit.

The captured image $I$ is in RGB color space which is device dependent space. Therefore, it is transformed to device independent CIE $l\alpha\beta$ color space [15] using Eq. 1. Note that there is no direct transform between RGB and $l\alpha\beta$ so it is first transformed to XYZ color space

$$I \xrightarrow{XYZ} I_{XYZ} \xrightarrow{l\alpha\beta} I_{l\alpha\beta}. \tag{1}$$

$I_{l\alpha\beta}$ is then re-scaled to a standard size $(x, y)$ that is suitable with fully-connected CNN, discussed next. Such transform effects the learning rate of CNN. But before this the leaf portion is cropped from $I_{l\alpha\beta}$ such that the majority area of image is

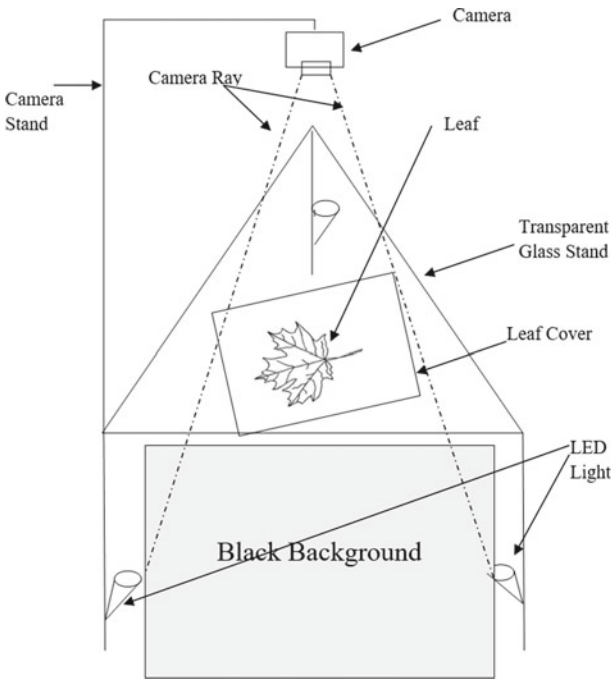


**Fig. 2** A block diagram of leaf capture setup proposed

occupied by leaf so that in feature vector the maximum weight is of leaf and not of the background (translation invariant).

## 2.2 *Feature Extraction*

Before $I_{l\alpha\beta}$ under go feature extraction a brief intro of convolutional deep NN, that is, ConvNet is presented to understand the functionality of CNN and how it is actually useful in case of medicinal plant recognition. A deep ConvNet comprises number of convolutional and pooling layers which is then followed by fully-connected layers Fig. 4 [16, 17].

In this paper, instead of designing and training new fully-connected deep CNN from the scratch, we used ConvNet architecture trained for classification of large collection of images from ImageNet [18]. The top layer in pre-trained model is modified to satisfy our medicinal plant species classification problem.

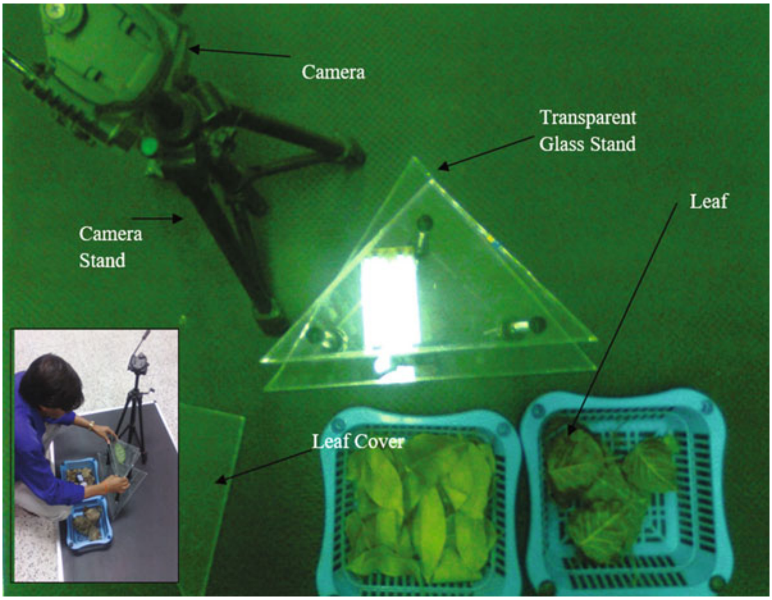


**Fig. 3** The real-time setup for plant leaf capturing

The mapping function of the ConvNet is $f_m$ such that $f_m : I_{l\alpha\beta} \rightarrow \mathscr{P}(P_{I_{l\alpha\beta}} = \mathscr{C}|I_{l\alpha\beta})$, where $\mathscr{P}$ is the posterior probability for input image with class label $\mathscr{C}$. The output of fully-connected CNN, say $f_{CL}(I_{l\alpha\beta})$, defines:

$$\mathscr{P}(P_{I_{l\alpha\beta}} = \mathscr{C}|I_{l\alpha\beta}) = \frac{1}{1 + e^{-f_{CL}(I_{l\alpha\beta})}}. \tag{2}$$

The fully-connected deep convolutional NN for medicinal plant species classification in shown in Fig. 4. As shown, the first part involves convolutional and pooling layers and the second part has all fully-connected neural layers which refines the feature information. The pooling layer sizes used in this paper are $12 \times 12$, $9 \times 9$, $6 \times 6$, $4 \times 4$, and $2 \times 2$.

The output of the fully-connected CNN is a feature vector of dimension 4096. This is a very high feature dimension which increases the classification cost. Therefore, the feature vector $f_{CL}$ is re-projected on PCA space and the PCA sub-space is used by SVM for classification. This not only reduces the classification cost but also improves the performance of computing device.

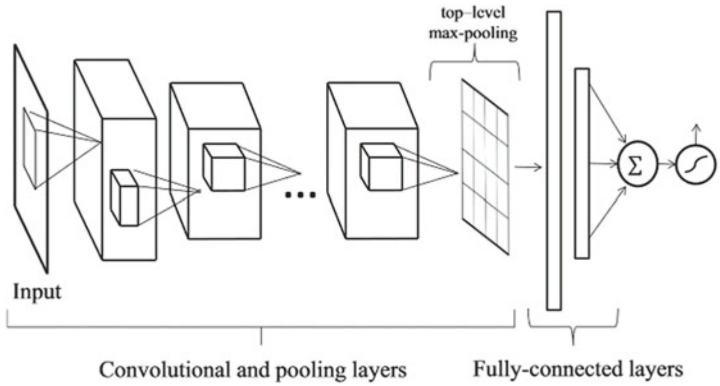


**Fig. 4** ConvNet flow graph for medicinal plant species recognition. The architecture is divided into two parts as shown: convolutional and pooling layers, and fully-connected layers

# 3 Experiments and Results

The experiments were carried out on two different types of plant leaf datasets: first is the publicly available ICL leaf benchmark dataset [19] and secondly our own datasets of medicinal plant leaves. ICL leaf dataset is a collection of plants from Botanical Garden of Hefei, Anhui by Intelligent Computing Laboratory in Institute of Intelligent Machines. ICL contains 17k plant leaf samples from 220 species, minimum 30 each [20]. The second database is a set of 1.5k leaf images of 30 species collected from Forest Research Institute.

## *3.1 Implementation*

All the CNN training and testing are done using Matlab 2015b in Windows environment. The learning rate set to 0.05. A pre-trained VGG-Net [21] of ImageNet dataset is used. It is the state of the art network in object recognition adopted by several computer vision researchers. Our experiments shows that the VGG-Net in PCA sub-space for $l\alpha\beta$ images results best for plant/medicinal species classification.

## *3.2 Comparison with State of the art*

We compare our approach with state of the art methods [8, 20, 22–24]. The classification results are obtained from their papers and are compared with our methods as shown in Table 1. Comparing our method with [20, 24], shows that CNN in $l\alpha\beta$ most likely improves the plant species classification.

**Table 1** ICL classification accuracy comparison with state of the art

| Methods | Feature length | Accuracy (%) |
|---|---|---|
| MCC [22] | 1280 | 73.17 |
| TAR [23] | 8067 | 78.25 |
| IDSC [8] | 12,288 | 81.39 |
| MARCH [24] | 101 | 86.03 |
| $l\alpha\beta$-CNN (Proposed) | 4096 | 91.6 |
| $l\alpha\beta$-CNN + PCA (Proposed) | 29 | 90.1 |

**Table 2** Medicinal plant dataset accuracy comparison with other methods

| Methods | Feature length | Accuracy (%) |
|---|---|---|
| MCC | 1280 | 75.0 |
| Fourier descriptor | 8067 | 67.9 |
| IDSC | 12,288 | 79.0 |
| $l\alpha\beta$-CNN (Proposed) | 4096 | 92.9 |
| $l\alpha\beta$-CNN + PCA (Proposed) | 29 | 90.7 |

Similarly, Table 2 shows the performance of medicinal plant leaf dataset collected using our proposed approach (discussed in Sect. 2.1). This dataset is compared with other methods like Fourier descriptor, MCC, and IDSC. Our $l\alpha\beta$-CNN architecture trains the networks for each scale and then combine them together and thus results high accuracy.

## 4 Discussions and Conclusions

The paper presents a $l\alpha\beta$-CNN in PCA sub-space for plant species identification. $l\alpha\beta$-CNN is trained and tested with the original image transformed to $l\alpha\beta$ color space. A new capturing setup for 2+D leaf object is proposed that helps in capturing 2D images without extra folds. Similarly, Fig. 5 show the setup to capture 3D objects like plant fruits, stems, and roots without any shadow effect. The leaf information is extracted from multi-scales and therefore, is a rich feature vector. Finally, the vector is reduced to optimize the classification cost using PCA. Our experiments on two different datasets proves the robustness and accuracy of our algorithm in improving the state of the art of medicinal plant species identification.

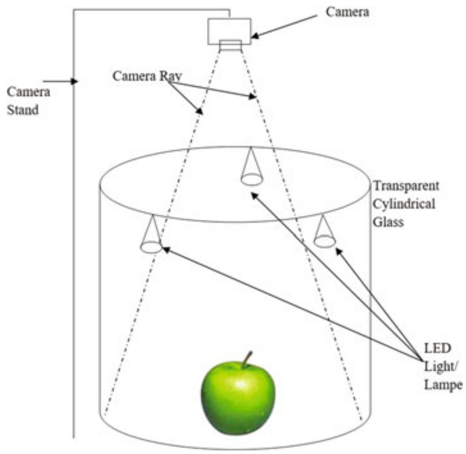


**Fig. 5** Block diagram for 3D object capturing setup

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