IDENTIFICATION OF HERBAL PLANT SPECIES USING MACHINE LEARNING TECHNIQUES

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Abstract
Plants are the key factor for the survival of life on earth and it essential for natural security, it is more vital to distinguish and characterize them precisely. The identification of plants by conventional keys is complex, time consuming, and due to the use of specific botanical terms frustrating for non-experts. This creates a hard to overcome hurdle for novices interested in acquiring species knowledge. Today, there is an increasing interest in automating the process of species identification. The existing plant species identification approaches are almost impossible for the general public and challenging even for professionals that deal with botanical problems daily, such as, conservationists, farmers, foresters, and landscape architects. Even for botanists themselves species identification is often a difficult task.

Index Terms: Optimization Technique, Spiking Neural Network, Hough Transform

I. INTRODUCTION

Categorization of plants has a wide usage forthcoming in horticulture and medication, and is particularly critical to the science assorted qualities explore [1]. Leaf image Classification method is the most preferred choice for plant classification. Earlier researchers have attempted to identify the plant based on image color histogram, edge features and its texture information. Research has been already done to classify the plants as trees, shrubs and herbs using neural networks [2]. A maiden attempt has been put forth by just considering the leaf details. Plants can be regularly grouped based on different parts of plants. There are three dimensional objects that expand intricacy. The plant classification, recognizing its respective leaf image is a simple and easier way. Each leaf image is classified through a number of related processes. A data base is created using sample images of all kinds of leaves. Each leaf image is linked to the corresponding plant details [3]. When the leaf image is uploaded to system and then it’s essential features are identified and recorded using image processing methods. The different steps to be followed in plant classification [4],

- Image acquisition
- Image pre-processing (noise removal, resize)
- Feature extractions
- Identification/recognition

Several classification and detection techniques have been proposed recently. The distributed hierarchical graph neuron (DHGN) is combined with k-nearest neighbor (k-NN) algorithm [5] for classifying plant leaves using the 2-dimensional shape feature. The Euclidean Distance (ED) and the Matching Measures (MM) classifier [6] are used for leaf identification. A multi-class SVM (K-SVM) [7] provides a way to take better account of the variability of the classes. The classifier actually consists of a set of 1vs1 SVMs making a decision for any pair of classes, and the final classification is based on a number of such binary votes received by each class. An automatic procedure aimed at recognizing legume species is used to discards any leaf shape, size, color or texture information, since the interest is focused exclusively in detecting differences in the leaf vein morphology [8]. A phenotypic classification system [9] of mulberry in Taiwan based on vegetative traits and chilling requirements using numerical taxonomic analysis. Leaf thickness [10] had a significant positive correlation with leaf length and a positive correlation with leaf width, indicated that thicker leaf was beneficial to increasing the single leaf area.

II. RLETAED WORK

Fan et al. [11] have proposed a hierarchical multi-task structural learning algorithm to support large-scale plant species identification. A visual tree is constructed for organizing large numbers of plant species in a coarse-to-fine fashion and determining the inter-related learning tasks automatically. The visual tree contains a set of sibling coarse-grained categories of plant species or sibling fine-grained plant species, and a multi-task structural learning algorithm is developed to train their inter-related classifiers jointly for enhancing their discrimination power. The inter-level relationship constraint, e.g., a plant image must first be assigned to a parent node correctly if it can further be assigned to the most relevant child node on the visual tree, is formally defined and leveraged to learn more discriminative tree classifiers over the visual tree.

Lopez et al. [12] have introduced a method to detect compound leaves using concentric circles to explore the surface of the leaf to count the changes of color in binary images, then, the changes are analyzed to detect compound leaves. The efficiency of the Radial Basis Function neural network is further enhanced for region growing method used seed points and grouping them having similar attributes that help in feature extraction process. The method predicts correctly more than 96% of the leaves in the Flavia data set. Then, it is tested with some images of leaves available on the Internet, with 100% of correctness.

Zhang et al. [13] have proposed a segmentation algorithm based on similar tangential direction (TD) to retrieve skeletons, and use the relative moment and the number of pixels for directions to compute the leaf distribution. They used the luminance and linear characteristics to detect the leaf skeletons. These two characteristics are common features of the leaf skeletons, so similar TD scheme based on these features can be applied to numerous types of horticultural crops as well as in complex scenarios that include overlapping, weeds, and bad leaves. This system computes the leaf distribution using the relative moment and the number of pixels in specific directions. The system has the potential to provide accurate information for use in many novel applications

Anjomshoae et al. [14] have proposed a template-based method for overlapping rubber tree leaf identification. The key point based feature extraction method is adopted. The key features of overlapping and non-overlapping leaf assist in identifying similar shapes through comparison, using the nearest neighbor algorithm. This process is implemented by constructing a directory which consists of various rubber leaf images with different positions. The key points in the input leaf image are compared with the key points of the template image to identify the position of leaflets.

Benhajrhouma et al. [15] have introduced seven new invariants for multi-component shapes, and apply them to the leaf classification problem. One of the new invariants is an area based analogue of the already known boundary based anisotropy measure, defined for the multi-component shapes. The other six invariants are completely new. They are derived following the concept of the geometric interpretation. All the invariants introduced are computable from geometric moments corresponding to the shape components. This enables easy straightforward computation of translation, rotation, and scaling invariants. Also, being area based, the new invariants are robust to noise and mild deformations. All derivations are made in a continuous space. This makes the methods applicable in all discretization schemes directly.

Chaki et al. [16] have proposed path for classification of plant species from digital leaf images. Plant leaves can have an assortment of unmistakable elements like green and non-green hue, simple and compound shape and distinctive vein designed surfaces. A solitary arrangement of elements may not be sufficiently adequate for a viable classification of heterogeneous plant sorts. A hierarchical architectural design is used numerous components are joined together for a more powerful and strong classification of the visual data. The database itself is sectioned in light of conspicuous components by visual discriminators, as this enhances proficiency. Feature based shape selection template (FSST) is used for the choice of shape features for various sorts of leaves.

Mzoughi et al. [17] have presented a novel, simple and fully-automatic leaf identification approach based on the idea of subsequent structuring of the search space using botanical concepts, particularly, the leaf arrangement, location and partition. The latter depends on the leaf category, namely apical, basal and middle parts for simple leaves and leaflets for compound leaves. They perform this structuring process automatically using some geometric parameters that were defined using some botanical assumptions. They describe spatial relationships between some interest points that are selected from the leaf contour in a way that they are correspond to the base, apex, lobe and leaflet apice and terminal locations. This task was achieved with considerable accuracy and without resorting to computationally expensive machine learning methods.

III. PROBLEM METHODOLOGY

Vijayalakshmi et al. [18] have proposed leaf classification approach based on characterization of texture, shape, and color properties. An original plant leaf is preprocessed initially using the cellular automata (CA) filter to minimize the noise. For enhancing the contrast and quality of the image, the histogram equalization and ROI segmentation are applied respectively. It has the issues of lower accuracy and recognition rate. The feature extraction techniques overcome the difficulties faced by the existing method. The feature comprises of texture based features, Gabor features, shape features, and color features. The features are extracted from each leaf image, which increases the time complexity. Subsequently, the kernel-based PSO is used to overwhelm the above issue of selecting the optimum features. Then, fuzzy relevance vector machine (FRVM) is used to characterize the type of leaves.

IV. CONCLUSION

In this paper, a leaf classifier is proposed using optimization technique for herbal plant species identification using multiple leaf features. In this technique, image corners are detected first, and the abnormal image corner is removed by the Spiking neural networks (SNN) using the Hough transform. Next, top and bottom leaf edges are compute by the modified edge detection algorithm and perform the feature extractions. The feature comprises of shape features, color features, tooth features and Gabor features for classification that are extracted from each leaf image. The main objective of the proposed approach is to accurately predict the type of leaf from the given input leaf images. The MATLAB experimental analysis showed better results such as accuracy, sensitivity and specificity.

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