Pattern Recognition 71 (2017) 1–13

Contents lists available at ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/patcog

How deep learning extracts and learns leaf features for plant classification

Sue Han Lee[a], Chee Seng Chan[a,*], Simon Joseph Mayo[b], Paolo Remagnino[c]

[a] Centre of Image & Signal Processing, Faculty of Computer Science and Information Technology, University of Malaya, Malaysia
[b] Herbarium, Royal Botanic Gardens, TW9 3AE, United Kingdom
[c] Faculty of Science, Engineering and Computing, Kingston University, KT1 2EE, United Kingdom

ARTICLE INFO

Article history:
Received 11 November 2016
Revised 23 April 2017
Accepted 13 May 2017
Available online 18 May 2017

Keywords:
Plant recognition
Deep learning
Feature visualisation

ABSTRACT

Plant identification systems developed by computer vision researchers have helped botanists to recognize and identify unknown plant species more rapidly. Hitherto, numerous studies have focused on procedures or algorithms that maximize the use of leaf databases for plant predictive modeling, but this results in leaf features which are liable to change with different leaf data and feature extraction techniques. In this paper, we learn useful leaf features directly from the raw representations of input data using Convolutional Neural Networks (CNN), and gain intuition of the chosen features based on a Deconvolutional Network (DN) approach. We report somewhat unexpected results: (1) different orders of venation are the best representative features compared to those of outline shape, and (2) we observe multi-level representation in leaf data, demonstrating the hierarchical transformation of features from lower-level to higher-level abstraction, corresponding to species classes. We show that these findings fit with the hierarchical botanical definitions of leaf characters. Through these findings, we gained insights into the design of new hybrid feature extraction models which are able to further improve the discriminative power of plant classification systems. The source code and models are available at: https://github.com/cs-chan/Deep-Plant.

1. Introduction

Computational botany consists of applying innovative computational methods to help progress on an age-old problem, i.e. the identification of the estimated 400,000 species of plants on Earth [1]. This interdisciplinary approach combines botanical data and species concepts with computational solutions for classification of plants or parts thereof and focuses on the design of novel recognition methods. These are modelled using botanical data, but are extendable to other large repositories and application domains. Plant species identification is a subject of great importance in many fields of human endeavour, including such areas as agronomy, conservation, environmental impact, natural product and drug discovery and other applied areas [2,3].

Advances in science and technology now make it possible for computer vision approaches to assist botanists in plant identification tasks. A number of approaches have been proposed in the literature for automatic analysis of botanical organs, such as leaves and flowers [4–6]. In botany, leaves are almost always used to supply important diagnostic characters for plant classification and in some groups exclusively so. Since the early days of botanical science, plant identification has been carried out with traditional text-based taxonomic keys that use leaf characters, among others. For this reason, researchers in computer vision have used leaves as a comparative tool to classify plants [7–10]. Characters such as shape [11–13], texture [14–16] and venation [17,18] are the features most generally used to distinguish the leaves of different species. The history of plant identification methods, however shows that existing plant identification solutions are highly dependent on the ability of experts to encode domain knowledge. For many morphological features pre-defined by botanists, researchers use hand-engineering approaches for their characterization. They look for procedures or algorithms that can get the most out of the data for predictive modeling. Then, based on their performance, they justify the subset of features that are most important to describe leaf data. However, these features are liable to change with different leaf data or feature extraction techniques. This observation therefore raises a few questions: (1) *In general, what is the best subset of features to represent leaf samples for species identification?* (2) *Can*

* Corresponding author.
E-mail addresses: leesuehan@siswa.um.edu.my (S.H. Lee), cs.chan@um.edu.my (C.S. Chan), s.mayo@kew.org (S.J. Mayo), p.remagnino@kingston.ac.uk (P. Remagnino).

http://dx.doi.org/10.1016/j.patcog.2017.05.015
0031-3203/

we quantify the features needed to represent leaf data? We want to answer these questions in order to solve the ambiguity surrounding the subset of features that best represent leaf data.

In the present study, we propose the use of deep learning (DL) for reverse engineering of leaf features. We first employ one of the DL techniques – Convolutional Neural Networks (CNN) to learn a robust representation for images of leaves. Then, we go deeper into exploring, analyzing, and understanding the most important subset of features through feature visualization techniques. We show that our findings convey an important message about the extent and variety of the features that are particularly useful and important in modeling leaf data.

In this paper, we present several major contributions:

1. We define a way to quantify the features necessary to represent leaf data (Section 4). We first train a CNN based on raw leaf data, then use a Deconvolutional Network (DN) approach to find out how the CNN characterizes the leaf data.
2. We experimentally show that shape is not a dominant feature for leaf representation but rather the different orders of venation (Section 4.3).
3. We quantify the characteristics of features in each CNN layer and find that the network exhibits layer-by-layer transition from general to specific types of leaf feature. We find that this effect emulates the botanists' character definitions used for plant species classification (Section 5).
4. We show that CNNs trained on whole leaves and leaf patches exhibit different contextual information of leaf features. We categorise them into global features that describe the whole leaf structure and local features that focus on venation (Sections 4.3 and 5).
5. We propose new hybrid global-local feature extraction models for leaf data, which integrate information from two CNNs trained using different data formats extracted from the same species (Section 6).
6. We demonstrate that our proposed hybrid global-local feature extraction models can further boost the discriminative power of plant classification systems (Section 6.2.1).

Our paper begins with an introduction to deep learning. Next, we proceed to a critical and comprehensive review of existing methods and a description of the context of plant identification - i.e. how species are delimited by botanists using morphology. Then, we introduce the idea of deep learning for automatic processing and classification in order to learn and discover useful features for leaf data. We describe how computational methods can be adapted and learnt using visual attention. The universal occurrence of variability in natural object kinds, including species, will be described, showing first how it can confound the classification task, but also how it can be exploited to provide better solutions by using deep learning.

2. Deep learning

Deep learning is a class of techniques in machine learning technology, consisting of multiple processing layers that allow representation learning of multiple level data abstraction. The gist of DL is its capacity to create and extrapolate new features from raw representations of input data without having to be told explicitly which features to use and how to extract them.

In the plant identification domain, numerous studies have focused on procedures or algorithms that maximize the use of leaf databases, and this always leads to a norm that leaf features are liable to change with different leaf data and feature extraction techniques. Heretofore, we have been engaged with ambiguity surrounding the subset of features that best represent the leaf data. Hence, in the present study, instead of delving into the creation of feature representation as in previous approaches, we reverse engineer the process by asking DL to interpret and elicit the particular features that best represent the leaf data. By means of these interpretation results, we are able to perceive the cognitive complexities of vision for leaves as such, reflecting the trivial knowledge researchers intuitively deploy in their imaginative vision from the outset.

3. Related studies

In this section, we describe various feature extraction methods that have been proposed to classify species based on different leaf features.

Shape. Most studies use shape recognition techniques to model and represent the contour shape of the leaf. In one of the earliest papers, Neto et al. [11] introduced Elliptic Fourier and discriminant analyses to distinguish different plant species based on their leaf shape. Next, two shape modeling approaches based on the invariant-moments and centroid-radii models were proposed [19]. Du et al. [20] proposed combining geometrical and invariant moments features to extract morphological structures of leaves. Shape Context (SC) and Histogram of Oriented Gradients (HOG) have also been used to attempt to create a leaf shape descriptor [12,13]. Recently, Aakif and Khan [21] proposed using different shape-based features such as morphological characters, Fourier descriptors and a newly designed Shape-Defining Feature (SDF). Although the algorithm showed its effectiveness in baseline dataset like Flavia [5], the SDF is highly dependent on the segmented result of leaf images. Hall et al. [8] proposed using Hand-Crafted Shape (HCS) and Histogram of Curvature over Scale (HoCS) [7] to analyse leaves. Zhao et al. [22] proposed a new counting-based shape descriptor, namely independent-IDSC(I-IDSC) features, to recognize simple and compound leaves. Apart from studying the whole shape contour of the leaf, some studies [9,23] analysed leaf margins for species classification. There are also some groups of researchers who are incorporating plant identification into mobile computing technology such as *Leafsnap* [7] and *Apleafis* [24].

Texture. Texture is another major field of study in plant identification. It is used to describe the surface of the leaf based on the pixel distribution over a region. One of the earliest studies [25] applied multi-scale fractal dimension to plant classification. Next, Cope et al. [16] proposed using Gabor co-occurrences in plant texture classification. Rashad et al. [26] employed a combined classifier – Learning Vector Quantization (LVQ) together with the Radial Basis Function (RBF) – to classify and recognize plants based on textural features. Olsen et al. [27] proposed using rotation and a scale invariant HOG feature set to represent regions of texture within leaf images. Naresh and Nagendraswamy [14] modified the conventional Local Binary Patterns (LBP) approach to consider the structural relationship between neighboring pixels, replacing the hard threshold approach of basic LBP. Tang et al. [15] introduced a new texture extraction method, based on the combination of Gray Level Co-Occurrence Matrix (GLCM) and LBP, to classify tea leaves.

Venation. Identification of leaf species from their venation structure is widely used by botanists. In computer vision, Charters et al. [17] designed a novel descriptor called EAGLE. It comprises five sample patches that are arranged to capture and extract the spatial relationships between local areas of venation. They showed that a combination of EAGLE and SURF was able to boost the discriminative ability of feature representation. Larese et al. [18] recognised legume varieties based on leaf venation. They first segmented the vein pattern using Hit or Miss Transform (UHMT), then used LEAF GUI measures to extract a set of features for veins and areoles. The latest study [30] attempted deep learning in plant identification using vein morphological patterns. They first extracted the vein patterns using UHMT, and then trained a CNN