Plant Leaf Recognition

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I. Introduction

Automatic plant species recognition with image processing has gained increasing interests recently. This is a fine-grained image recognition problem and generally considered a hard problem due to the subtle differences between different species in the same class. Sometime such fine differences can be even challenging to humans. Typically this requires large training data but it is not feasible due to the number of planets (over 220000 [2]).

The main application are weeds identification, species discovery, plant taxonomy, natural reserve park management and so on [3].

In this report, we describe our exploration with this problem, using traditional handcrafted features and features extracted from pretrained deep convolution neural network (ConvNets).

The rest of the report is organized as follows. In section IV, we describe the data set. Section.

II. Related Work

Research on automatic leaf classification from image has been active since 2000. Lots of hand-crafted features have since proposed, ranging from shape based, to statistical texture and margin [2] [3] [1]. Also generic computer vision object recognition/detection features, such SIFT and HOG are studied for this problem. [TODO] Most of such manually engineered features achieve excellent accuracy on clean images taken in controlled conditions, which consist of one single well aligned leave on contrasting background, such as those images in data set [TODO]. Recently, with the huge success of ConvNets, particularly in annual ImageNet Large Scale Visual Recognition Challenge [11], researchers start to apply ConvNets to this problem [TODO]. [TODO] have suggested that generic features can be extracted from large ConvNet and yield very good results on fine-grained classification problems even without fine-tuning the pretrained model.

III. Approach

A. Overview

Images captured in the field, such as those from ImageCLEF [17], are more challenging as there are much more intra class variations due to viewpoint, lighting condition and occlusion. We break down the problem into two pieces. Firstly, we want to locate the leaf in the image which is an single object localization problem. This step becomes necessary if the image have multiple objects and possibly leaf is not the most salient object. Then, we predict the specie of the leaf, which is a fine-grained classification problem. This is the main task and for most data set, we only need to perform this task. Here we explore both traditional method, such as Bag of Features, and ConvNets based method.

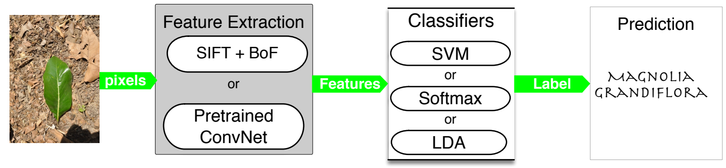

Fig. 1. Overview of the system

B. ConvNets

We use the transfer learning approach, in order to make use of the power of ConvNets with the constrains of time and computations. Specifically, we take a couple of ConvNets what are pretrained on ImageNet VGGNet/ResNet [TODO quote], remove the last fully connected layers and then treat the rest of the ConvNet as fixed feature extractor for the our data set.

Part of reason

[Explain the data set for our pretrained model and why this is this is applicable to our problem, i.e. same feature space.]

[Explains architecture of ResNet50]

The feature vector we get from ResNet50 is 2048 dimensions. We have two settings.

- [explain preprocessing] The feature vector is normalized with unit variance and we learn a linear SVM classifier [(or others)] from the features.
- We further augment the training set by adding rotated and shifted copies of samples.

[Explain if and how this method is suitable for our task] - The CNN codes are trained for the object image classification task of ILSVRC (2013 for VGGNet and 2015 for ResNet), which is aligned with our task except that ours are more fine-grained classification. -Some of our data set [ImageCLEF2013] is more challenging in term of clutter and occlusion.

IV. DataSet

We found these datasets.

1) ImageCLEF [17]: the most challenging dataset as images are collected through crowd sourced application. 250 species with 26077 images.
2) UCI leaf dataset [14]: 40 species with 5 to 16 samples per specie
3) Kaggle leaf dataset[3]: 99 species with 16 samples per specie
4) Swedish leaf dataset [15]: 15 species with 952 samples (roughly 60 samples per specie)
5) Flavia leaf dataset [16]: 33 species with roughly 60 samples per specie

V. OBJECT RECOGNITION

A. Bag of Features (BoF) + local feature descriptors

Due to the simplicity and performance, this well established approach was taken at first. Interest points are detected from the raw images and then local invariant feature descriptors are collected, which are clustered to form the visual vocabulary/codebook. Afterwards, each raw image can be represented with histograms of visual words, i.e. term vectors. We have prototyped a BoF system, based on the OpenCV package. Here is the illustration of the system 2.

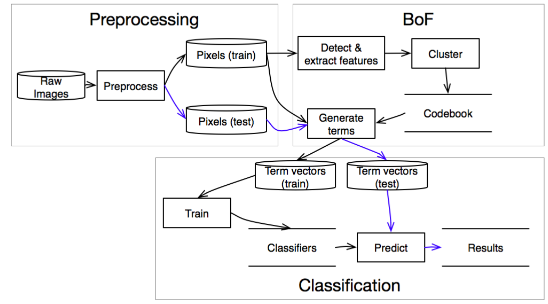

Fig. 2. System Design for BoF

During preprocessing, raw images are converted to gray-scaled images and resized to reduce computation complexity. We extract SIFT descriptors from the pixels after detecting the key points. Limiting the width of image to 128 pixels, we have roughly 200 SIFT descriptors per image. Then all the descriptors are clustered to build visual words via K-Means. Due to computation complexity, we pick randomly 100 training images to build the visual vocabulary for the initial run.

B. Background removal

[Discribe OpenCV GrapCut]

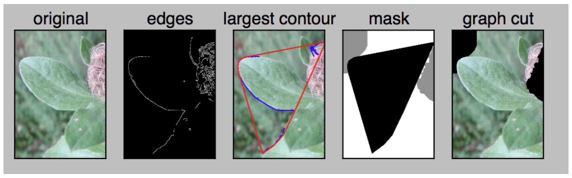

Fig. 3. Background Remove

C. ConvNets

VI. Object detection

[TODO describe why we need this] We use traditional exhaustive search method to scan through all window, scales.

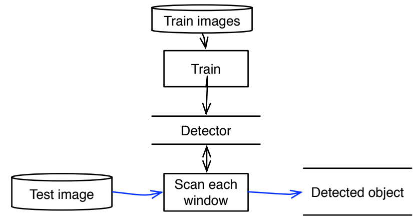

Fig. 4. Leaf Detection

VII. Experimental Results

[Explain cross validation approach we used]

We use prediction rank-1 identification (i.e. accuracy) as our performance metric, which is defined as $Accurary = \frac{N_c}{N_t} \times 100\%$, where N_c represents the number of correct match and N_t is the total number of test samples.

[Test results as table.] [Analysis of the results.]

VIII. Conclusion and Future work

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