Plant Leaf Recognition

Albert Liu, albertliu@stanford.edu Yangming Huang, yangming@standford

I. Introduction

The number of plant species is estimated to be over 220000 in the world [2]. Automatic plant species recognition with image processing has gained increasing interests recently. The main application are crop/weeds identification, plan biology research and species tracking [3].

In this report, we explore the problem of identify leaf based on natural image. We describe our methods based on traditional handcrafted features and features extracted from pre-trained deep convolution neural network (ConvNets).

II. Related Work

Research on automatic leaf classification from image has been active since 2000. Many hand-crafted features have since proposed, ranging from shape based, to statistical texture and margin [2] [3] [1]. Also other computer vision image features, such SIFT and HOG are studied for this problem. [TODO] Most of such manually engineered features can achieve very good accuracy on clean images, which consist of one single well aligned object on contrasting background, such as data set [TODO]. Recently, with the huge success of ConvNets, particularly in annual ImageNet Large Scale Visual Recognition Challenge [11], researchers start to learn features using ConvNets on this problem [TODO].

III. Approach

A. Overview

Images captured in the field, such as those from ImageCLEF [17], are more challenging as there are much 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 category recognition 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.

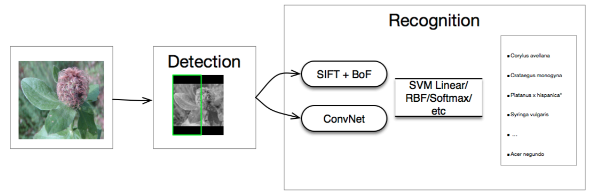

Fig. 1. Overview of the system

B. ConvNets

We use transfer learning method i.e., pre-trained model as feature extractor and then fine-tune the model to fit our data. [Explain the data set for our pre-trained model and why this is this is applicable to our problem, i.e. same feature space.]

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

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.

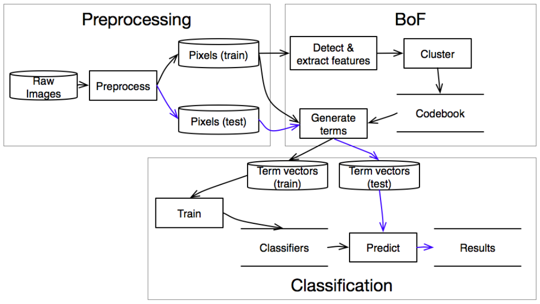

Fig. 2. System Design for BoF

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]

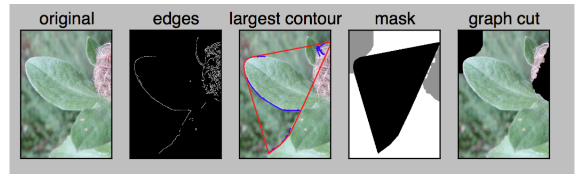

Fig. 3. Background Remove

C. *ConvNets*

VI. Object detection

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

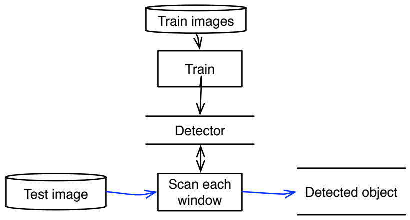

Fig. 4. Leaf Detection

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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