# Project – Plant Classification using Leaves Recognition

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**Abstract.** Plant classification in recent times has proved very vital in conserving and taking care of the environment. Since the rise of climate change and global warming very sensitive plants have been affected in recent times since some of the plant species can grow in certain regions under certain climate conditions. Recognition plant system models that are created to differentiate plant species can be used by botanists and scientists to easily identify different plant species. Rather than using expensive electronic microscopes to perform the classification. We can use these recognition models to recognize plants in a much fast and a cost-effective way. For this specific study, we used Leafsnap for this study to create a plant recognition model system[12]. The goal, in this case, is to get a model that can identify different plant species at a rate of 85% and above.

**Keywords:** Plant classification · Machine learning · Gradient boosting classification

## 1 Introduction

Plants are a very important genus in the ecosystem, they are a food source for many animals particularly herbivores and omnivores. Most of the birds and animals use plants as a form of shelter, humans also use plants in our daily lives to build and for warmth, most of the developing countries particularly in Africa and Asia depended on a lot in these plants in medical practice, plants are readily available which is better than paying for health care because most of the families don't have monies for health care. Many of these plants carry significant information for human development. The urgent problem that we are facing is that plants are at risk of extinction, this is due to deforestation by us humans to build cities and farming to name a few. It is very vital to create a database that will be used to keep track of plants and classify them efficiently and effectively. The first step to achieve this is by constructing a recognition model that can be used to classify these plants. Pattern recognition is made up of four major constituents: data acquisition and collection, feature extraction and representation, similarity detection and pattern classifier design, and performance evaluation. These pattern recognition are very vital because they can continuously adapt and learn [7].

Leaf recognition is a pattern recognition task that is used to map a certain leaf belonging to a certain plant genus. Botanist uses different tools and techniques to identify different plants, but it is not easy to extract and transfer those features to a computer automatically [5, 3]. Storing these images to be used for pattern recognition makes it easy to transfer an image to a computer and a computer can be used to extract features automatically in image processing techniques. The are many algorithms that have been employed to perform leaf recognition, this research has focused on leaf classification with some texture feature extraction [3, 14].

The sections in this mini-project are organized as follows: Section 2 focuses on the work previously done by other researchers in the context of this mini-project. Section 3 focuses on the first step of image processing which is the acquisition of the dataset that is used for classification, and some preprocessing steps to remove noise in the images obtained. Section 4 focuses on extracting a feature vector on the images in our dataset, and getting the region of interest, in this case, separating leaves and the background. Section 5 gives a glimpse on how on the classification method that will be used and some architecture used in the programming of the solution.

## 2 Literature review and Related Works

Pattern recognition exists in both humans and animals, pattern recognition is used to interpret complex images, generalizing knowledge that is stored in our brain to infer decisions. Animals use pattern recognition to identify prey, predator, attract mates, and most importantly to navigate through their environment. This form of intelligent humans and animals need for daily survival needs to be incorporated in some way in robots for safe navigation and efficient manipulation, and bio-engineering involves reading and interpreting electrocardiograms. Pattern recognition is supplementary to computer vision, providing the abilities of interpretation and classification [7, 2].

They are two classifications that can be used for pattern classification [10]:
***Quantitative pattern***: are arranged in the form of pattern vectors.

***Structural pattern***: typically, are composed of symbols, arranged in the form of strings, trees, or, less frequently, as graphs.

In this study, we will be focusing more on quantitative patterns since vectors can be easily stored and processed by computing devices. We will then use these vectors for classification, using Gradient Boosting, we will compare the resulting model with some of the known feature vectors that have been used in leaf recognition.

## 2.1 Probabilistic Neural Network (PNN)

This type of leaf recognition technique focuses on reducing human dependence on creating the recognition models, using data acquisition from different plants, and then training a model to easily classifier different plants using leaves. Previous recognition models used skeleton segmentation by wavelet transform and Gaussian interpolation [16]. A moving media center hyper-sphere was used [16]. Many approaches also use the k-nearest neighbor classifier [6], while some papers adopted Artificial Neural Network. A more common feature is to use pattern elements to be featured, an early observation was conducted by Fisher [10] who, close to a century, reported the use of a new technique called discriminant analysis to recognize three types of iris flowers. The flower was described by Fisher using four features: the length and width of the petals, and similarly for the sepals [10]. These models that we created did not work well enough since most of the time human experts needed to improve the accuracy of these models [15, 11]. PNN predicted the mapping between the leaves and plants relative fine, the average accuracy was determined to be 90.312% [8].

## 2.2 Gray-Level Co-occurrence Matrix (GLCM)

A co-occurrence matrix, also referred to as a co-occurrence distribution, is defined over an image to be the distribution of co-occurring values at a given offset or represents the distance and angular spatial relationship over an image sub-region of a specific size. The GLCM is created from a gray-scale image, it calculates how often a pixel with gray-level (gray-scale intensity or tone) value occurs either horizontally, vertically, or diagonally to adjacent pixels with the value $i$ [4]. The following are directions for GLCM direction of analysis:

- **Horizontal** : $0°$
- **Vertical** : $90°$
- **Diagonal**
  - **Bottom left to top right** : $-45°$
  - **Top left to bottom right** : $-135°$

The following features are then typically computed from the image:

1. ***Autocorrelation***: also known as **serial correlation**, is the correlation of a signal with a delayed copy of itself as a function of delay.
2. ***Entropy***: is a statistical measure of randomness that can be used to characterize the texture of the input image
3. ***Contrast***: is the difference in luminance or colour that makes an object (or its representation in an **image** or display) distinguishable
4. ***Homogeneity***: expresses how similar certain elements (pixels) of the image are.
5. ***Correlation***: is the process of moving a filter mask often referred to as kernel over the image and computing the sum of products at each location

Some of the research studies focused on using GLCM to extract a feature vector, to map a leaf with a plant. The average recognition rate that was studied by [8] determined that the average recognition rate was similar for 0° and 90° which was 78.46% for 135° the recognition rate 70.76% with 45°, with lowest recognition [8, 13].

### 2.3 Feature extraction and classification using Machine Learning

The focus of this research paper is using machine learning for classification or mapping leaves to plants. Broadly speaking, we will be using supervised learning which is a computational task of learning correlations between variables in annotated data (the training set) [9]. The following features will be extracted from our dataset to create a feature vector for classification using gradient boosting, some of the features:

1. ***Inertia tensor***
2. ***Minor axis length***
3. ***Solidity***
4. ***25th percentile***
5. ***75th percentile***
6. ***Std intensity***
7. ***IQR***

## 3 Leaf Image Preprocessing and Enhancement

The dataset is obtained from *Leafsnap* and all the images are obtained in jpg format which is lossless compression. The leaves column sometimes varies between *600* and *597* pixels, but the row size of the columns is consistence which is *800* pixels.
An RGB image is converted into a gray-scale image before pre-processing, and the skimage.color with imported rgb2gray and used for conversion, and looking at the package the following formula is used to convert the RGB image into gray-scale:

$$Y = 0.2125R + 0.7154G + 0.0721B \tag{1}$$

Where $R$, $G$, and $B$ correspond to the colors red, green, and blue respectively.
After converting the color image dataset into grayscale images, we convert the image into a binary image using Otsu's method, the method is the mostly referenced thresholding methods, as it directly operates on the gray level histogram [1], the method Otsu's method for image thresholding:
if *g(x,y)* is a thresholder version of *f(x,y)* at some global the threshold T,

$$g(x, y) = \begin{cases} \text{1 if f(x, y)} \geq \text{T} \\ \text{0 Otherwise} \end{cases}$$

In the model that is used, we used Otsu's method used skimage.filter using threshold Otsus which is built-in in python, you just need to import it.
The closing morphology was then performed on the binary image that is formed after applying Otsu's method to the image. The closing process that applies dilation is followed by erosion on the input image, the closing is defined as follows:

$$Closing = IM \oplus SE \ominus SE \quad (2)$$

Where IM, and SE is an input image and structuring elements respectively [1]

## 4 Leaf Segmentation (detection of Region of Interest (RoI))

Features from the image we extracted using region properties, like all machine learning processes, we needed to construct a feature vector. For extracting features in the images, we used regionprops table located in skimage.measure, we then utilized a data frame to store all the features, after executing our model 50 features we obtained, the following we some of the features that we extracted in the model:

1. ***Convex area***: is greater than or equal to the area of the region
2. ***Area***: is the quantity that expresses the extent of a two-dimensional region, shape, or planar lamina, in the plane
3. ***Eccentricity*** : the eccentricity is the ratio of the focal distance (distance between focal points) over the major axis length.
4. ***Extent***: is defined as area of the image object divided by the area of its bounding rectangle
5. ***Inertia tensor***: this is a tuple representing the tensor of inertia. This relates on the segment's rotation around its mass
6. ***Major axis length***: line segment connecting the two vertices of the ellipse
7. ***Minor axis length***: this refers to the length of the minor axis or the shorter axis of the segment.
8. ***Perimeter***: distance around a two-dimensional shape
9. ***Solidity***: this is just the ratio of the area of the convex hull and the area of the binary image
10. ***Moments central***: an image moment is a certain particular weighted average (moment) of the image pixels' intensities
11. ***Euler number*** : is the total number of objects in the image minus the total number of holes in those objects
12. ***Mean intensity*** : is a data matrix, I , whose values represent intensities within some range
13. ***Bbox***: extracting the bound box

The following features we also derived from the properties from the grayscale raw image segment. All the features are just statistics of the grayscale values. IQR is just the difference between the 25th percentile and the 75th. Please note that all the features mentioned above are calculated by the regionprops table, on the data that is supplied for learning.

## 5 Leaf Classification

As previously stipulated in this research paper, we utilized machine learning using supervised learning for creating a model that can be used to predict a plant name given a dataset, but for this study, we used Leafsnap for our dataset and used 5 different plant type because if we are using a large dataset the model takes a lot of time.

### 5.1 Gradient Boosting Classfier

The gradient boosting classifier was determined to be the most efficient when classifying and mapping leaves into correct plant labels. GB builds an additive model in a forward stage-wise fashion; it allows for the optimization of arbitrary differentiable loss functions. In each stage, nth classes regression trees are fit on the negative gradient of the binomial or multinomial deviance loss function. Binary classification is a special case where only a single regression tree is induced.

### 5.2 Supervised Machine Learning

The idea behind supervised learning is to build a model that can be used to map class labels into predictor features. When the values of the predictor characteristics are known, but the value of the class label is unknown, the resulting classifier is used to assign class labels to the testing cases.

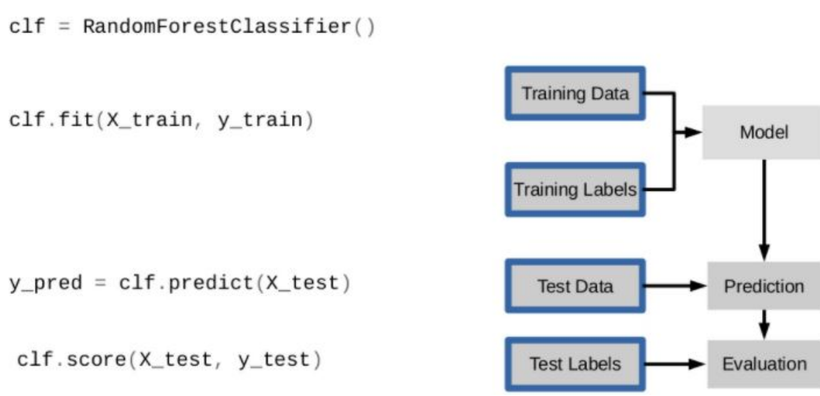


**Fig. 1.** Supervised machine learning using python model

The following is a detailed figure on this supervised learning model:

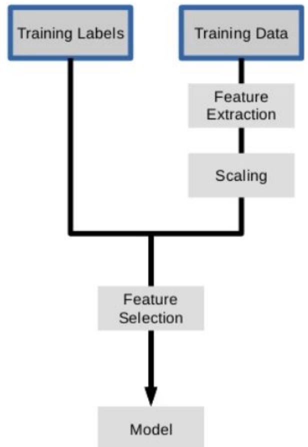


**Fig. 2.** Detailed supervised learning on creating a model for classification

## 6 Software specification

The model was coded using a high-level programming language which is Python and opens source libraries from the machine learning written in scikit-learn. scikit learn can be used in a lot of things such as classification, regression, semi-supervised learning, feature selection feature extraction, manifold learning, dimensionality reduction, kernel approximation, hyperparameter optimization, etc.

- **OS Name** : Microsoft Windows 10 Home Single Language
- **Version** : 10.0.19043 Build 19043
- **System Name**: SANELE
- **System Model**: Predator PT315-52
- **System Type**:x64-based PC
- **Processor**:Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz, 2592 Mhz, 6 Core(s), 12 Logical Processor(s)
- **Installed Physical Memory(RAM)**: 16.00 GB

## 7 Results and Discussion

To each kind of leaves supplied, 31 leaves we processed for each plant species which are abies concolor, abies nordmanniana, acer campestre, acer ginnala, and

acer griseum respectively, and the average test accuracy is 91.48% for the dataset tested.
Some of the plant species obtained a much lower accuracy due, to the similarity of some plant species specifically abies concolor and abies nordmanniana.
We compared this algorithm with the GLCM if it's used as a feature extract and was noted that using machine learning was much more efficient. The source code and the dataset used can be obtained in the zip document accompanying this research paper

## 8 Conclusion

This research paper introduces a machine learning approach for plant leaf recognition. The program can automatically classifier 5 plant species via images that have been obtained from the Leafsnap dataset. Gradient boosting was used for the classification of the different images using 0.25 or 25% of the original data supplied. Experiment shows that using this algorithm we can predict the correct mapping from leaf to a plant label with an accuracy of 91.48%. Compared with some of the methods this algorithm or approach is better in obtaining results in a much small-time and high level of accuracy.

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