Leaf classification project

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1 Introduction

In computer vision, image classification is a complex procedure which relies on different components.

Our task is to develop species classification system. The main steps of the project are feature extraction and machine learning model tuning.

2 Species Selection

In this project we used subset of around 10 species from leafsnap dataset. The species were chosen to have some differences and similarities between the classes. We are also provided with segmentation of each photo, but as most of them are invalid, I will not use them

Selected species were presented below

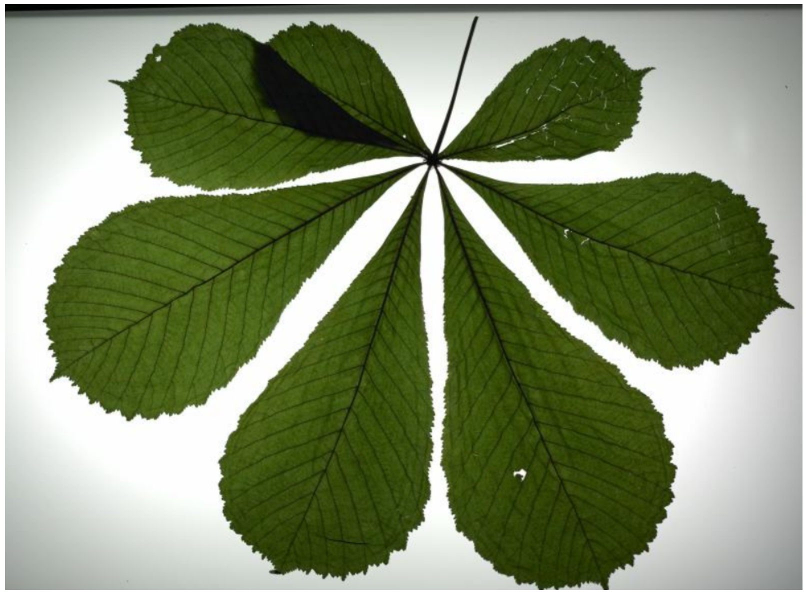

Fig. 1: Aesculus hippocastamon

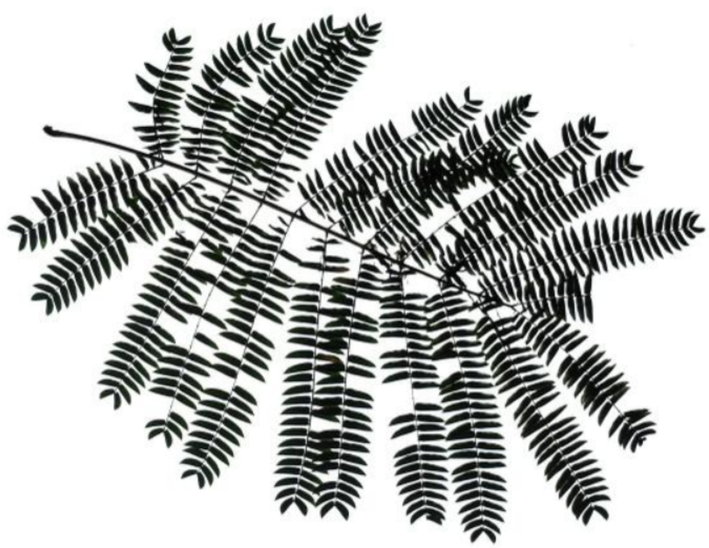

Fig. 2: Albizia julibrissin

Fig. 3: Celtis occidentalis

Fig. 4: Fagus grandifolia

Fig. 5: Magnolia stellata

Fig. 6: Malus baccata

Fig. 7: Malus pumila

Fig. 8: Taxodium distichum

Fig. 9: Tilia europaea

Fig. 10: Tilia americana

3 Feature extraction

3.1 Shape features

Shape description is key to species recognision as those descriptors are pretty much invariant to lighting conditions, are common across species. I have isolated such features:

- convex area
- area
- eccentricity
- extent
- inertia tensor
- major axis length
- minor axis length
- axis ratio
- number of labels

3.2 Texture features

Texture features can be used to pin down given texture features to given category. For example local binary patterns are pretty commonly used in this use scenario. However in this case there is too much variability in texture due to natural conditions and those data are as good as shape features.

3.3 Margin features

Margin features are key to plant recognition, for example Fagus grandifolia and Celtis accidentalis can have similar shape, but different margins. One way to measure margin is calculating curvature using integral measures, using formula: $curvature = \frac{numberofTruepixelsincircle}{totalnumberofpixelsincircle}$

4 model selection and evaluation

4.1 evaluation measures

$Precision = \frac{Truepositives}{TruePositives+TrueNegatives}$
$Accuracy = \frac{TruePositives+TrueNegatives}{all}$
$Recall = TruepositivesTruepositives + FalseNegative)$
$F1 - score = 2 * Recall * PrecisionRecall + Precision$

4.2 choosing ML models

As we have labels for each of a photo we can easily apply Supervised ML in this scenario. I have chosen to compare Gradient Boost Classifier and Random forest classifier

4.3 evaluation

	precision	recall	f1-score	support
Aesculus hippocastamon	0.92	1.00	0.96	22
Albizia julibrissin	0.96	0.92	0.94	24
Celtis occidentalis	0.78	1.00	0.88	18
Fagus grandifolia	1.00	0.96	0.98	24
Magnolia stellata	0.79	0.90	0.84	21
Malus baccata	1.00	1.00	1.00	24
Malus pumila	0.92	0.85	0.88	26
Taxodium distichum	1.00	0.96	0.98	24
Tilia americana	1.00	0.88	0.94	33
Tilia europaea	1.00	0.96	0.98	25
accuracy			0.94	241
macro avg	0.94	0.94	0.94	241
weighted avg	0.94	0.94	0.94	241

Fig. 12: Random forest classifier report table

	precision	recall	f1-score	support
Aesculus hippocastamon	0.96	1.00	0.98	23
Albizia julibrissin	0.96	0.92	0.94	24
Celtis occidentalis	0.78	0.86	0.82	21
Fagus grandifolia	1.00	0.96	0.98	24
Magnolia stellata	0.75	0.86	0.80	21
Malus baccata	1.00	0.92	0.96	26
Malus pumila	0.79	0.79	0.79	24
Taxodium distichum	1.00	1.00	1.00	23
Tilia americana	0.97	0.90	0.93	31
Tilia europaea	1.00	1.00	1.00	24
accuracy			0.92	241
macro avg	0.92	0.92	0.92	241
weighted avg	0.93	0.92	0.92	241

Fig. 13: Gradient boost classifier report table

In both cases the most of prediction falures happened between one-leaf, common-shape leaves, which makes sense, because their features look pretty the same. However 0.92 and 0.94 accuracies are very good scores.

4.4 room for improvement

It could be tested whether getting more features and feeding them to CNNs could yield better results. Furthermore we could get more features about the texture and margins.

5 References

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7.$https://blog.exsilio.com/all/accuracy - precision - recall - f1 - score - interpretation - of - performance - measures/$