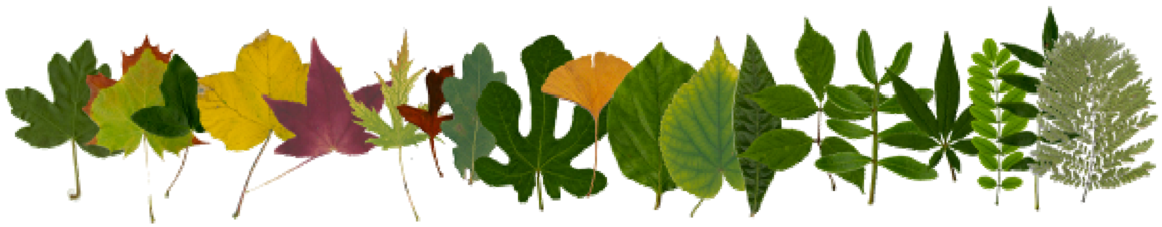

Sabanci-Okan System at ImageClef 2013 Plant Identication Competition

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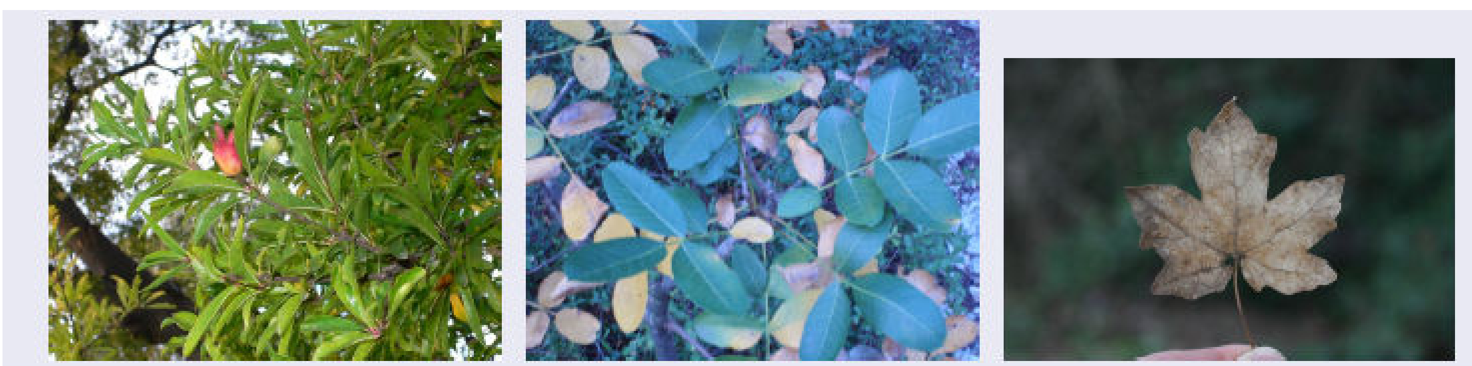
Problem & Motivation

- **Task:** Recognize the plant in agiven image
- **Motivation:**
  - An online content-based plant search engine
  - A tool for assisting botanists
  - A mobile application for recognizing edible plants or avoiding hazardous ones
  - ...



Challenges

A standard object recognition problem?

- **Lighting, pose, scale, color variations + …**
- Seasonal color variations
- Leaf shape variations due to plant age
- Leaf/Flower composition variations

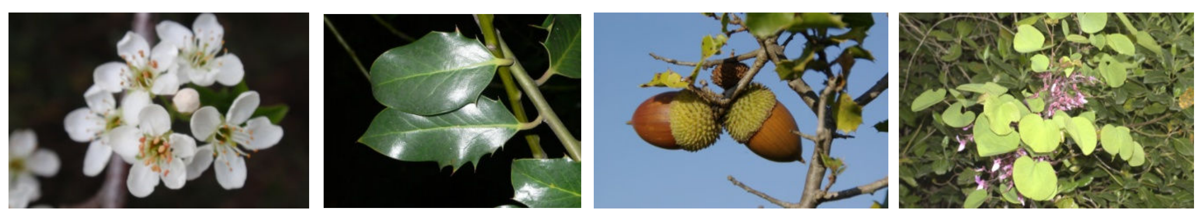
ImageCLEF Database: Image Types

Scanned & Simply Photographed Leaves
(Scan & Scan-like)

SheetAsBackground

Partial or Full Plant Photographs on Natural BG.
(Photos)

NaturalBackground



Sabanci-Okan Collaboration

- Erchan Aptoula, Okan University
  - Expertise: Mathematical morphology
  - Main roles: Segmentation, Feature Extraction

- Berrin Yanikoglu, Sabanci University
  - Expertise: Object recognition (biometrics, handwriting recognition)
  - Main role: Feature Extraction, Classifiers

- Students: Caglar Tirkaz, Tolga Yildiran
  - Main role: System building
- We typically work for one month for ImageCLEF
  - Not full time of course!

Sabanci-Okan Results in ImageCLEF

Our collaboration has so far achieved:

- 4th place overall in 2011 (70 species, ~5,500 samples)
- **1st place overall in 2012** (126 species, ~12,000 samples) **in both automated and human assisted categories**
- **1st place in 2013** (250 species, ~26,000 samples) **with simple background images** (*SheetAsBackGround*)

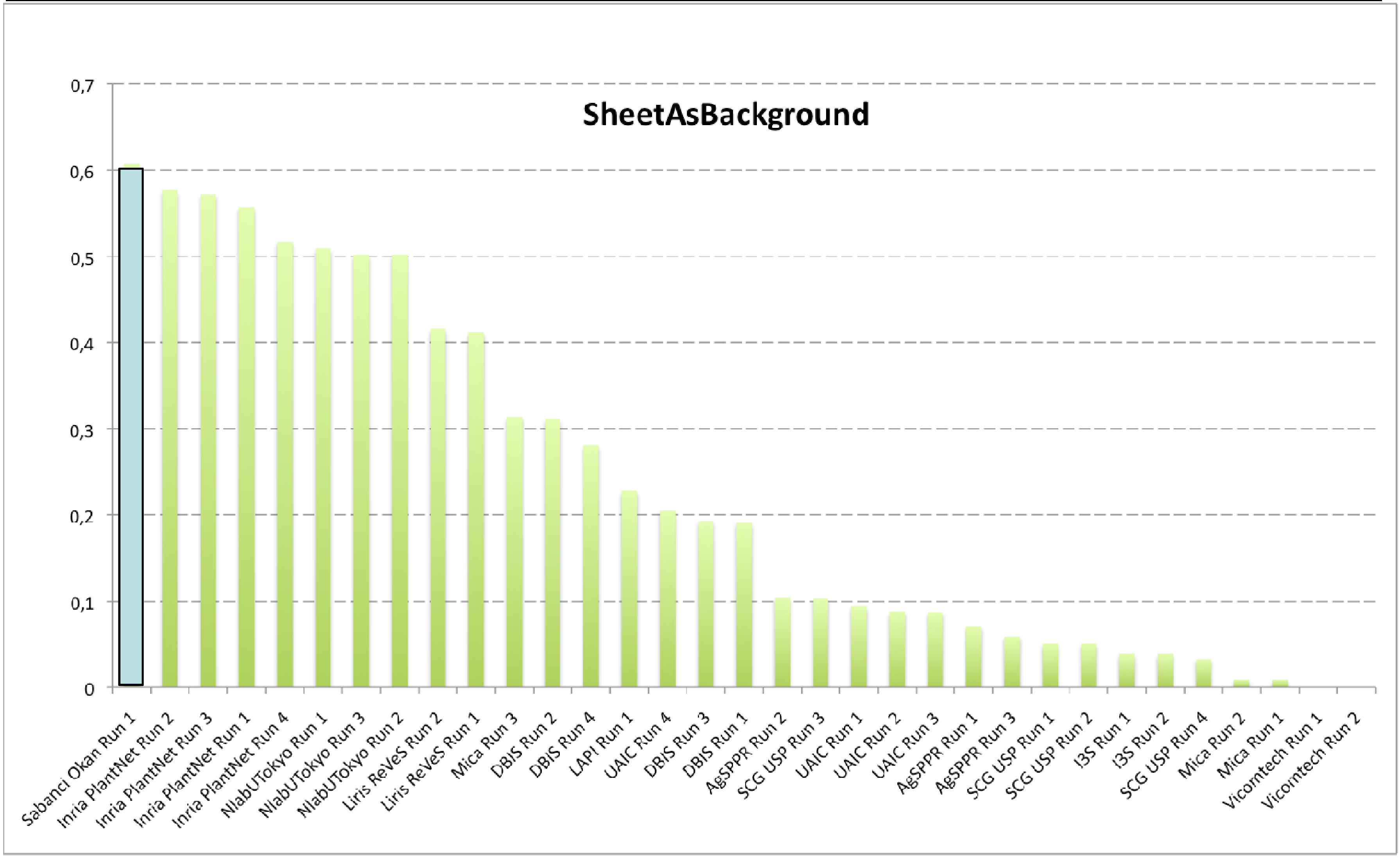
Our Results in ImageCLEF

ImageCLEF 2012 Plant Identification Competition Results

Group	Scan	Scan-Like	Photograph	Score
Sabancı-Okan run 1 [YANIKOGLU 2012]	**0.58 (1.)**	0.55	0.16	**0.43 (1.)**
INRIA-Imedia PlantNet run1 [BAKIC 2012]	0.49	0.54	0.22	0.42
INRIA-Imedia PlantNet run2 [BAKIC 2012]	0.39	**0.59 (1.)**	0.21	0.40
LSIS-DYNI run 3 [PARIS 2012]	0.41	0.42	**0.32 (1.)**	0.38
ARTELAB run 1 [GALLO, 2012]	0.40	0.37	0.14	0.30
Zhao/HFUT run 3 [ZENG, 2012]	0.32	0.26	0.11	0.23
BTU DBIS run 2 [BÖTTCHER, 2012].	0.27	0.17	0.17	0.21
IFSC/USP run 3 [CASANOVA 2012]	0.20	0.14	0.12	0.16

ImageCLEF 2013 Plant Identification Competition Results

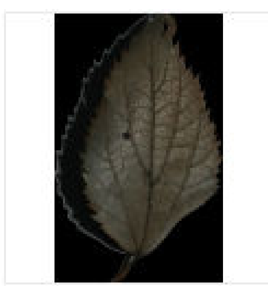
Group	Scan and Scan-Like	Natural Background
Sabancı-Okan Run 1	**0.607 (1.)**	0.181 (3.)
Inria PlantNet Run 1	0.577 (2.)	0.385 (2.)
Nlab Univ. Of Tokyo Run 3	0.502 (3.)	**0.393 (1.)**
Mica Run 3	0.314 (3.)	0.042 (9.)
DBIS Run 2	0.311 (4.)	0.159 (4.)
...	...	...


SheetAsBackground
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
Sabanci Okan Run 1
Inria PlantNet Run 2
Inria PlantNet Run 3
Inria PlantNet Run 1
Inria PlantNet Run 4
NlabUTokyo Run 1
NlabUTokyo Run 3
NlabUTokyo Run 2
Liris ReVeS Run 2
Liris ReVeS Run 1
Mica Run 3
DBIS Run 2
DBIS Run 4
LAPI Run 1
UAIC Run 4
DBIS Run 3
DBIS Run 1
AgSPPR Run 2
SCG USP Run 3
UAIC Run 1
UAIC Run 2
UAIC Run 3
AgSPPR Run 1
AgSPPR Run 3
SCG USP Run 1
SCG USP Run 2
I3S Run 1
I3S Run 2
SCG USP Run 4
Mica Run 2
Mica Run 1
Vicomtech Run 1
Vicomtech Run 2

Isolated Leaf Recognition

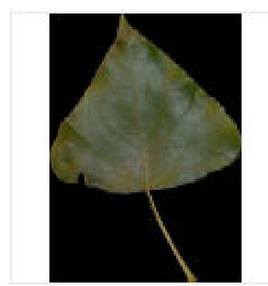
- **Segmentation:**
  - Morphological top-hat by reconstruction with a very large structuring element (edge preserving filter for uneven illumination correction)
  - Area based attribute filter (for noise and artifact removal)
  - Quasi-flat zone based simplification (basic level aggregation of spectrally similar pixels)
  - Adaptive threshold for binarization
  - Post-processing: preserve the largest CC, make sure the foreground contains the object of interest, fill holes.
- **Preprocessing:**
  - Image height normalized to 600 pix, preserving aspect ratio

8408.png

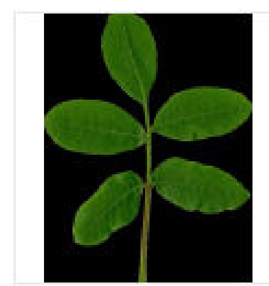


21333.png

29318.png



2277.png

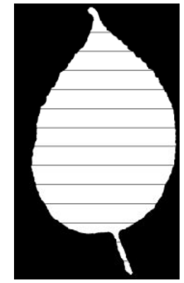


6075.png

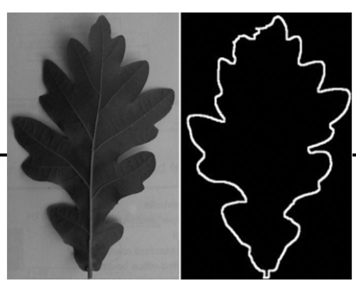
Feature Descriptors

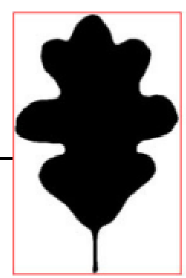
Feature Group	Feature	Comment
Shape	Fourier Descriptors; Basic Geometrical Features (area, convexity,…); Moment invariants	Rich set including both contour and area-based descriptors
Texture	Gabor filters; Local Binary Patterns; Color morphological covariance	Rich set containing complementary and/or alternative descriptors
Color	Color auto-correlogram; Saturation-weighted hue histogram	Two basic features only. Needs more work.
Local Invariants	Dense SIFT	Not used in the final system, due to shortage of time

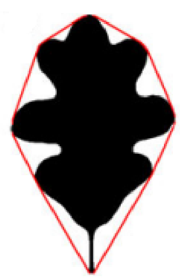
Shape Features

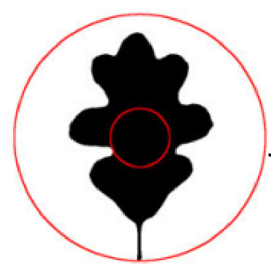


- Fourier Descriptors (50-dim.)
- Area Width Factor (10-dim.)
  - The normalized area of the horizontal strips of the leaf
- Regional Moments (7-dim.)
- Basic Shape Statistics (4-dim.)
  - {mean,min,max, stdev,…} of contour points' distance to the centroid
- Angle Code Histogram (10-dim.)
  - Normalized histogram of the angles between 3 successive points on the contour.
- Perimeter Convexity (1-dim.)
  - Ratio of the perimeter of the convex hull, to contour length
- …









Feature Effectiveness

- Measured using 10-fold cross-validation experiments & separate validation data using ImageCLEF'2012 data

Name	Length	Cross-Val. Acc.(%)	Val Acc.(%)	Top-10 Val. Acc.
FFT	50	49.95	46.26	86.17
Area Width Factor	13	49.89	38.79	81.78
Lobe Descriptor	7	48.65	43.97	86.56
Regional Moments	7	48.58	41.74	83.03
B. Shape Statistics	4	39.66	34.34	81.32
Angle Code Hist.	10	33.76	26.61	76.21
Contour Pnt. Dist. Hist.	7	33.16	30.14	77.13
Perimeter Convexity	1	12.36	11.14	54.13
Area Convexity	1	11.50	11.60	54.59
Compactness	1	11.47	9.24	53.47
Elongation	1	9.93	11.66	51.77
Region based features (2,3,4,5,9,10,11)	35	77.57	62.52	-
Contour based features (1,6,7,8	71	67.46	60.16	-
All shape features	102	77.44	67.89	94.23

Texture Features

- **Orientation Histograms:**
  - Distribution histogram of subquantized gradient orientations.
- **Circular Covariance Histogram***
  - A rotation and illumination invariant morphological texture descriptor describing periodicity.
- **Rotation Invariant Point Triplets***
  - A rotation invariant morphological texture descriptor, describing roughness and granularity.
- **Gabor Filters**
  - Average response to Gabor filters in each of the 8 directions

**) E. Aptoula, Extending Morphological Covariance, Pattern Recognition, 45(12), 2012.*

Feature Effectiveness

Feature Name	Length	Cross-Val. Acc. %	Val. Acc. %
Orientation Histogram	6	38.81	34.64
Circular Covariance Histogram	24	-	28.26
Rotation Invariant Point Triplets	24	-	17.50
Gabor features	8	26.26	15.60

Color Features

- **Color auto-correlogram** (252-dim.) describes the spatial correlation of colors.
  - It is computed in the LSH color space after a non-uniform quantization to 63 colors (7 levels for hue, 3 for saturation and 3 for luminance).
  - It consists of a 63x4 table where the entry (i; j) denotes the probability of encountering two pixels of color i at a distance of j pixels for (1,3,5, or 7 pixels) .

- **Saturation-weighted hue histogram**
  - W_θ for $\theta \in [0; 360]$ is calculated as:

$$W_\theta = \sum_x S_x \delta_{\theta H_x}$$

where H_x and S_x are the hue and saturation valu

δ_{ij} is the Kronecker delta function.

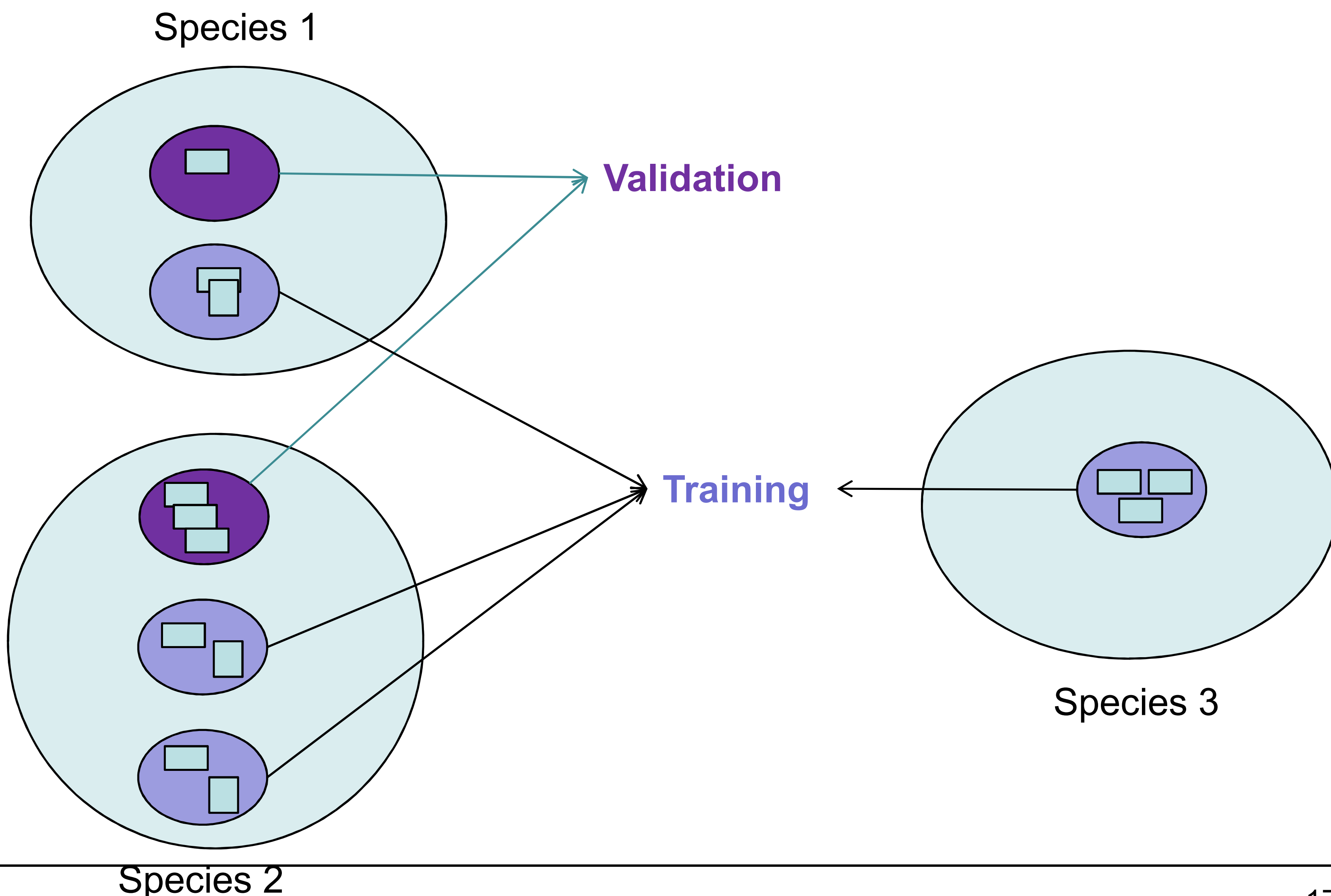
Used in NaturalBackground photos only.

Classifier Training

- **Development-Validation Sets Partition:**
  - **Try to reduce overfitting:** For all species, if there are more than one individual plant in its images, then all of the images of that individual plant is used for validation and all other are used for training.

Category	Development	Validation
SheetAsBackground (Isolated leaves)	7,867	1914
NaturalBackground (Unconstrained photos)	7,865	2,562
Flower	2,325	1197
Entire	1,455	594
Fruit	960	495
Stem	1,045	276
All	15,732	4,476

- **Dataset**:
  - Used only the development images of a class for the recognizer trained for that class.


Species 1
Validation
Training
Species 3
Species 2

Classifier Training

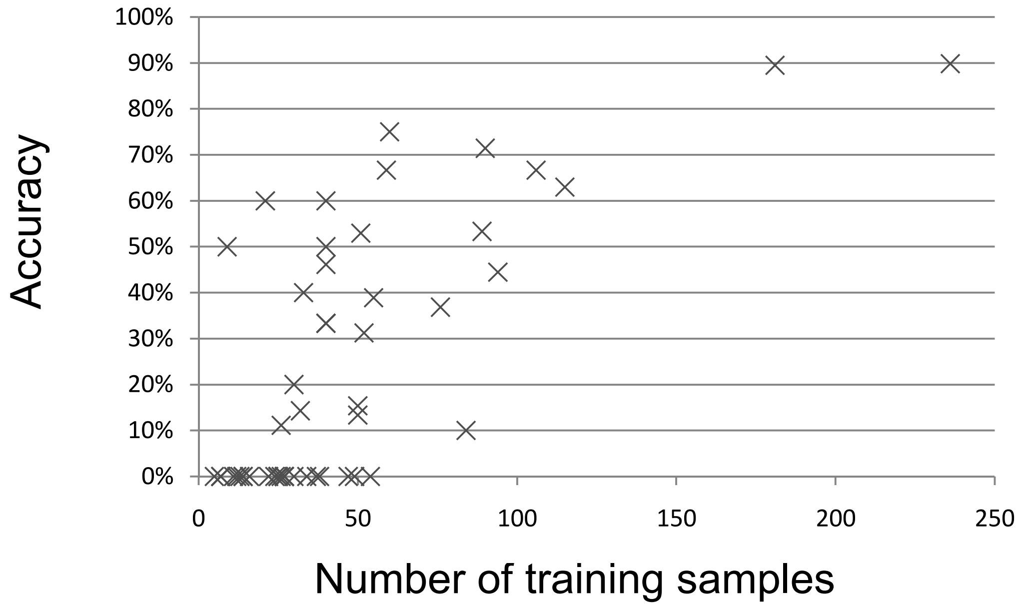
- **Base Classifier:**
  - Support Vector Machines:
    - SMO optimization on Weka, with 2nd degree polynomial kernel.
    - Low soft penalty (C) value to reduce overfitting

Table 3: Cross-validation and validation set accuracies, along with the official test scores obtained by our system.

Category	Features	Cross-Val.	Validation	Inverse Rank
UniformBackground	Shape, texture	93.77%	70.64%	0.607
NaturalBackground				0.181
Flower	Texture, color, month	40.20%	34.50%	0.223
Fruit	Texture, color, month	51.33%	43.64%	0.194
Entire	Texture, color, month	34.23%	29.50%	0.174
Stem	Texture	-	9.30%	0.106
Leaf	Shape, texture	-	-	0.049

Errors

- Accuracy increases with number of training samples



- Accuracy is lower for multi-leaflet plants
  - Often, the confused class is also a multi-leaflet plant

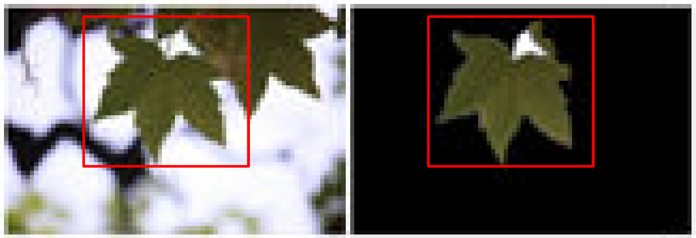
- Overfitting is a problem
  - Classifier combination techniques may help

Unconstrained Photographs

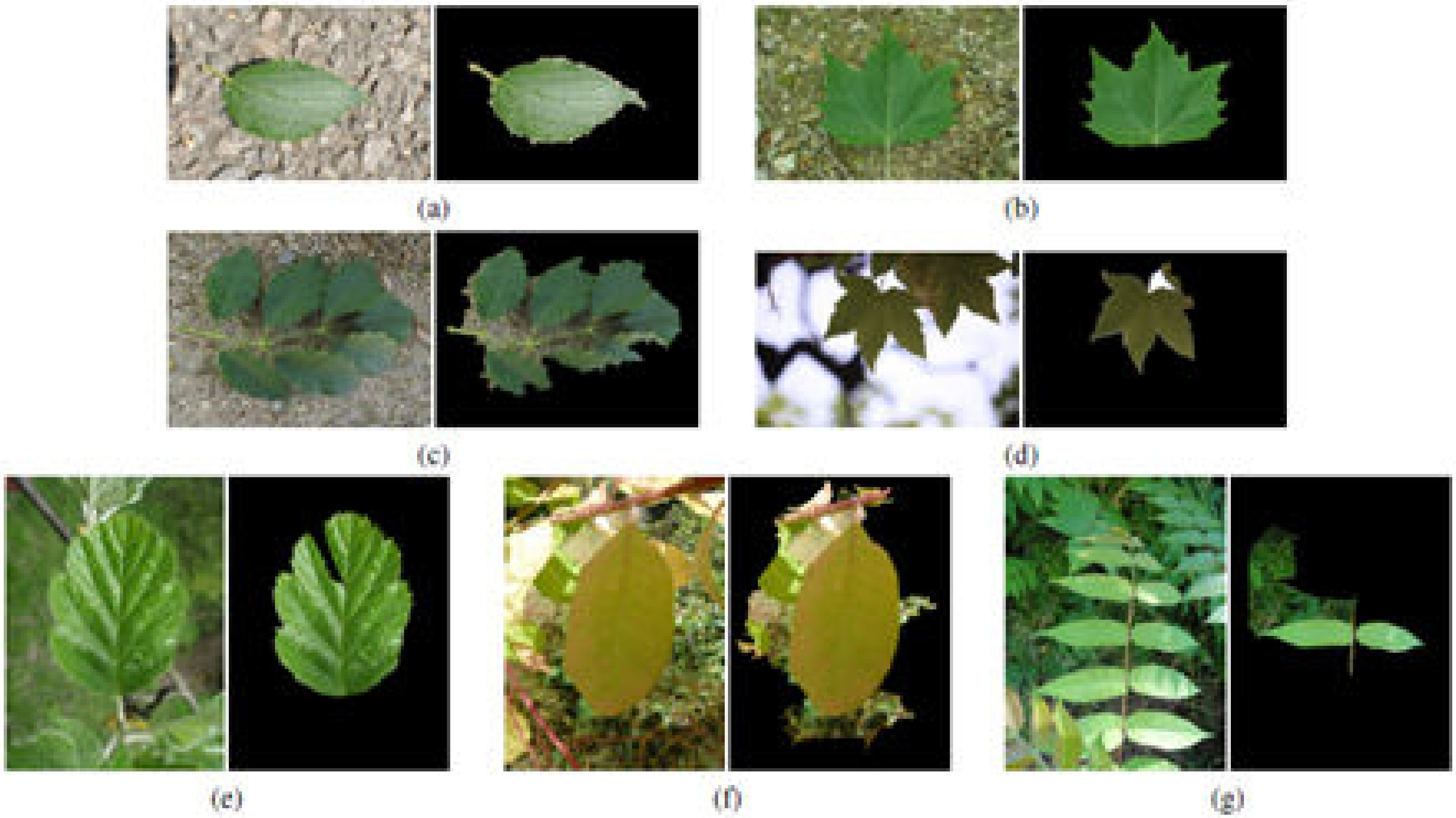
To recognize photographs, we adopt these three approaches that we believe are complementary:

1. **Single leaf segmentation and recognition (2012)**
   - to leverage our expertise in isolated leaf recognition and as a complementary method to local invariants.
2. **Globally extracted features (2013)**

   (color, texture and month)
   - Surprisingly good despite using little information
3. **Local invariants** (2013, but unfinished)
   - Avoids segmentation and is found successful promising (as others have successfully used)



Recognizing Photographs from a Single Leaf



Segmentation

- Based on Otsu's algorithm (2011)
- Based on quasi-flat regions and watershed transform (2012)
  - We also used a separate marker-based approach in the human assisted category

Overall Challenges

- System building
  - Separate classifiers (e.g. For flower, stem etc) are often beneficial but increase the effort
- Collaboration is very useful, but requires effort
  - Until this year, anytime something changed (e.g. segmentation algorithm), we changed the whole set of processed images, now we share codes that are simply re-run wherever needed.
- Fully general features and approaches are good, but the extra mile is gained through special focus.
  - This is a fun problem.

Future Work

- **Local invariants** for NaturalBackground photographs
  - SIFT, SURF,…
- Exploit **color** information for leaf recognition
- Combine classifiers to reduce **overfitting**
- Use a **classifier hierarchy** according to image content
  - E.g. For multi-lobe leaves (98.8% success on identifying them)
- …

- Thank you for listening!

- Thanks to the ImageCLEF organizers for a well-run lab!
  - Keeping the data and results on the web is great for future comparative work.

- For any further questions or comments, please email yanikoglu@gmail.com

- Erhan 106: + FFT:50 is the shape features
  - Area width factor 15
  - Regional moments of inertia 13
  - Basic shape statistics 4
  - Angle code histogram 10;0.1 10
  - Orientation Histogram 6;11 6
  - CCH ED 12;1 24
  - RIP median 12;1 24
  - EdgeForegroundRatio 10;3 10