

# An Old-Fashioned Way of Leaf Classification

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## Summary



# Introduction



# Background

- Know the name of the plant or flower
- Intelligent Agriculture: identify weed and crops
- Leaves are good indicators of different plants, including the shape, and texture etc.
- Not highly accurate Apps/Software on the market based on Deep Learning



**Goal:** Apply the Knowledge of CS 302, **extract good features of leaf** image and perform classification in an old-fashioned way



# Dataset

- Stephen Wu et. al.  
2007
- 32 classes and 1907  
images
- RGB Image on White  
Background
- Size 1600 by 1200  
(resize to 400 by 300)
- Split Train/Test by 70%  
and 30% for each class





# Method & Discussion



# Preprocessing- Image Augmentation

- Use Albumentations library
- Perform Vertical Flip and Horizontal Flip
- Training set size: 4002
- Test set size: 1719





# Baseline Model

- Flatten the image into 400x300x3 vector
- Train a Random Forest Classifier
- Apply Transfer Learning
- Train ResNet50 over images

Model	Random Forest Classifier	ResNet50
Train Accuracy	1.0	0.99
Test Accuracy	0.88	0.91





# Preprocessing – Background Removal

1. Convert to Gray image and apply Gaussian Filter
2. Otsu's Binarization
3. Apply Erosion Filter

Original



Binarized



Erosion



Without Background





# Preprocessing

pubescent bamboo



Chinese horse chestnut



Anhui Barberry



Chinese redbud



true indigo



Japanese maple



Nanmu



castor aralia



Chinese cinnamon



goldenrain tree



Big-fruited Holly



Japanese cheesewood



wintersweet



camphortree



Japan Arrowwood



sweet osmanthus



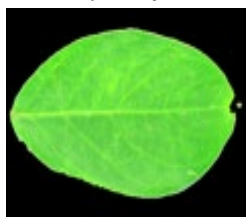
deodar



ginkgo



Crape myrtle



oleander



yew plum pine



Japanese Flowering Cherry



Glossy Privet



Chinese Toon



peach



Ford Woodlotus



trident maple



Beale barberry



southern magnolia



Canadian poplar



Chinese tulip tree



tangerine

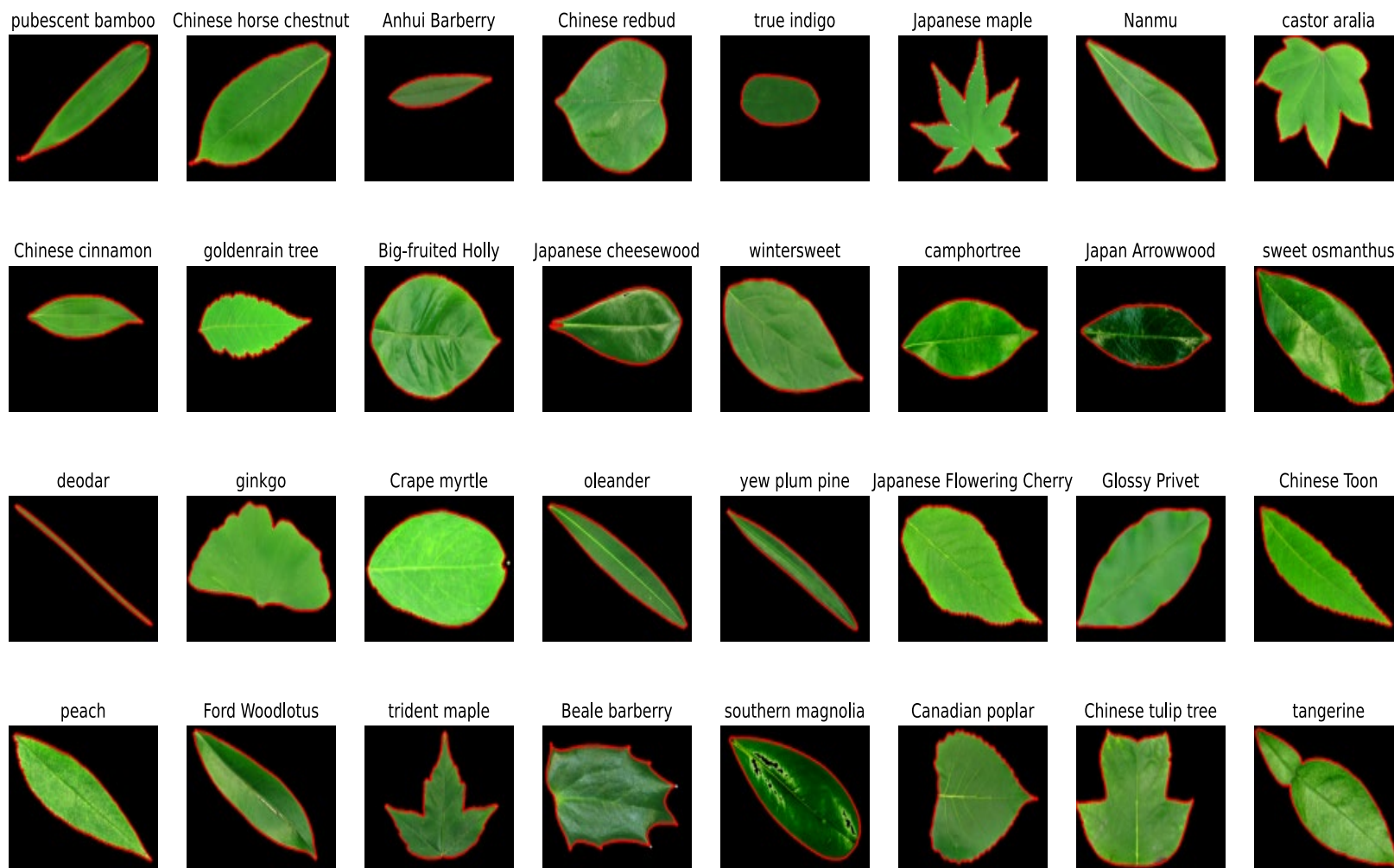




# Feature Extraction – Fourier Descriptor

0.75

- Fourier Descriptors are translational and rotational invariant
- Use opencv to get contours
- Compute complex contour representation
- Drop phase information
- Use scaled absolute amplitude
- Take value from 1 to 100





# Feature Extraction – Hu Moments

- Hu Moments have been proved to be invariant to translation, scale, and rotation, and reflection
- The 7th moment's sign changes for image reflection
- Use Opencv function



0.55



1.0e+00



2.3e-02

3.6e-04

3.2e-04

2.2e-08

2.4e-05

1.7e-08

$$\varphi_1 = \mu_{02} + \mu_{20}$$

$$\varphi_2 = (\mu_{02} - \mu_{20})^2 + 4\mu_{20}^2$$

$$\varphi_3 = (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2$$

$$\varphi_4 = (\mu_{30} - \mu_{12})^2 + (\mu_{21} - \mu_{03})^2$$

$$\varphi_5 = (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12}) [(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} - \mu_{03})^2] + (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03}) [3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2]$$

$$\varphi_6 = (\mu_{20} - \mu_{02}) [(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] + 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03})$$

$$\varphi_7 = (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12}) [(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2] + (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03}) [3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2]$$

(Alex and Eric)





# Feature Extraction – Local Binary Pattern

100	90	80
10	120	130
20	50	140

Run 3x3  
window

0 0	1 0	0
0	24	1
0	0	1

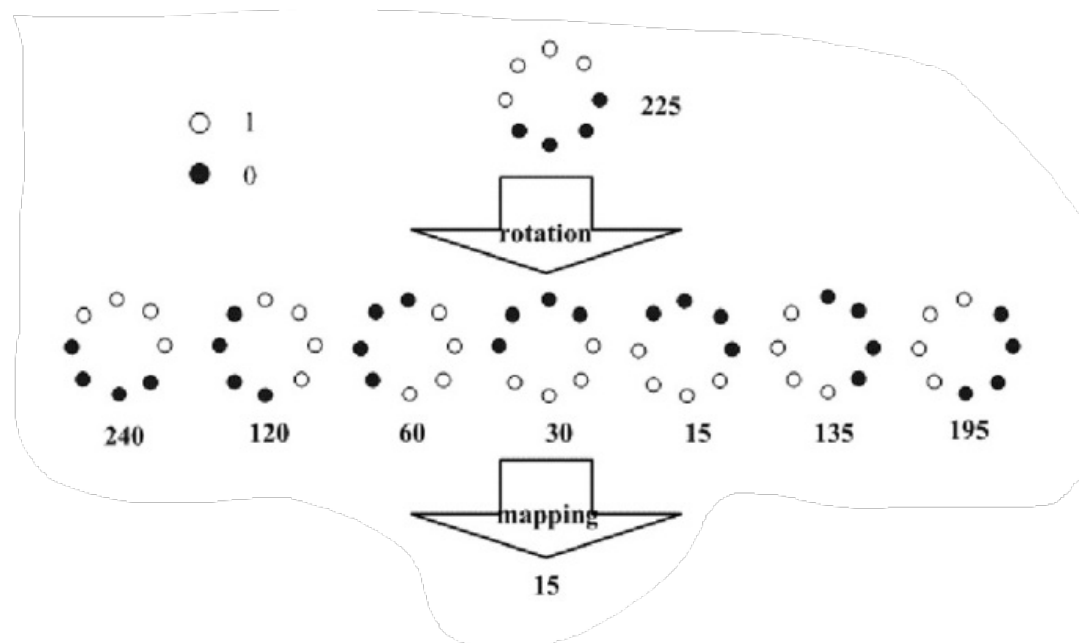
1 if larger  
than center

$$2^3 + 2^4$$

## Uniform Pattern



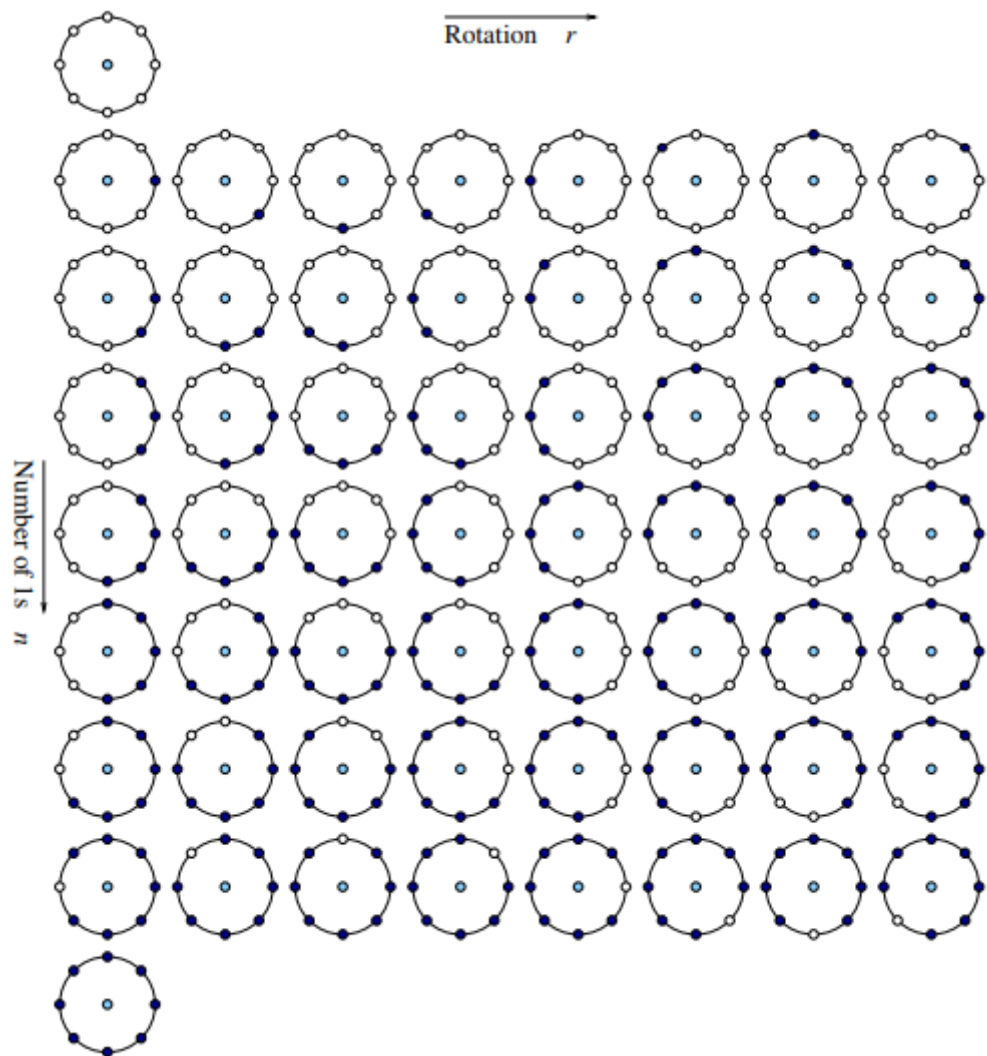
## Rotate circles and get lowest value



Ojala et. al.



# Feature Extraction – Local Binary Pattern



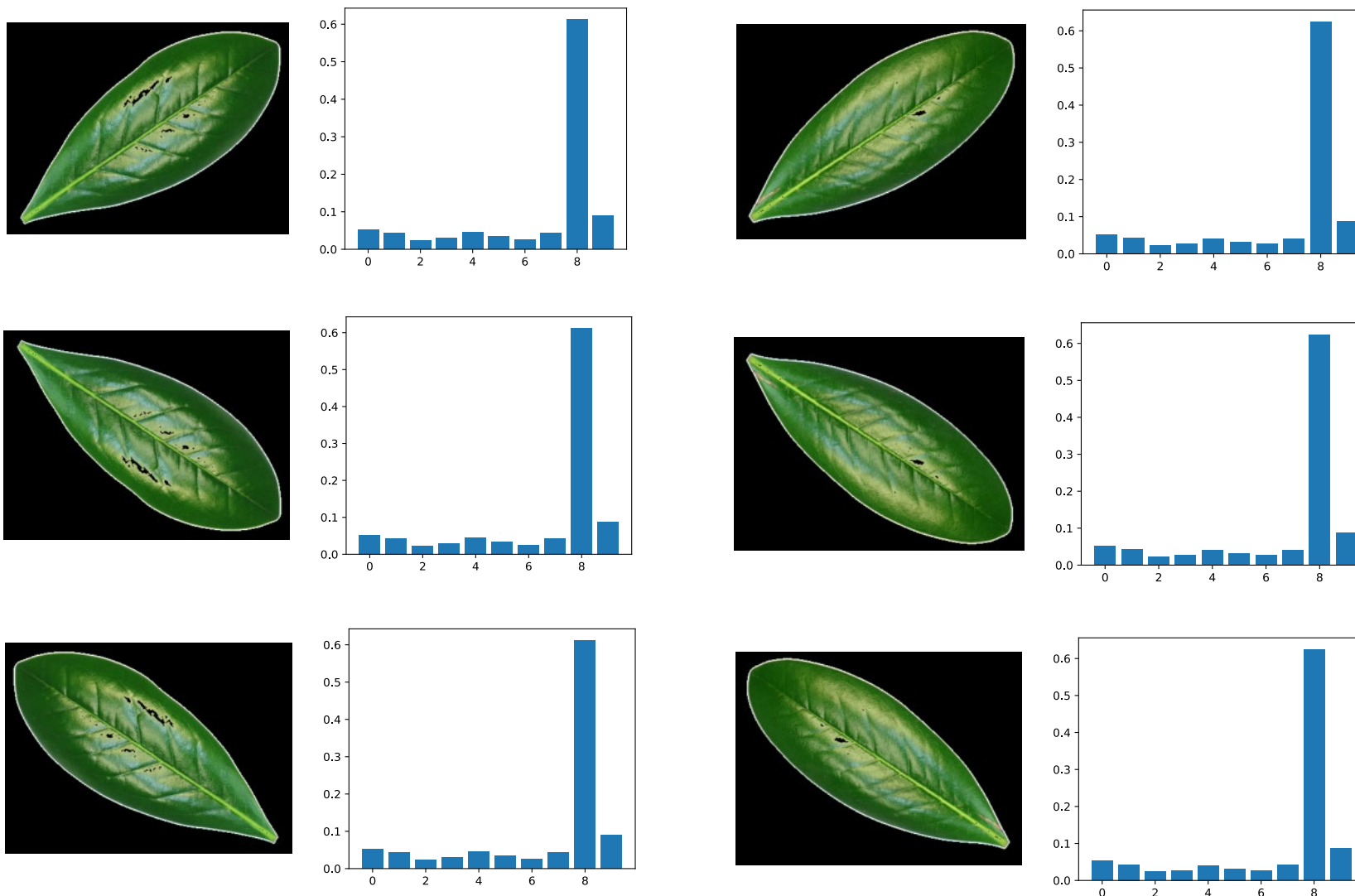
- Texture Identification
- Scale Invariant and Rotation Invariant
- Select radius 1 and sampling 8 neighbors
- Compute Histogram of LBP values including uniform and nonuniform
- 10 features in total



# Feature Extraction – Local Binary Pattern

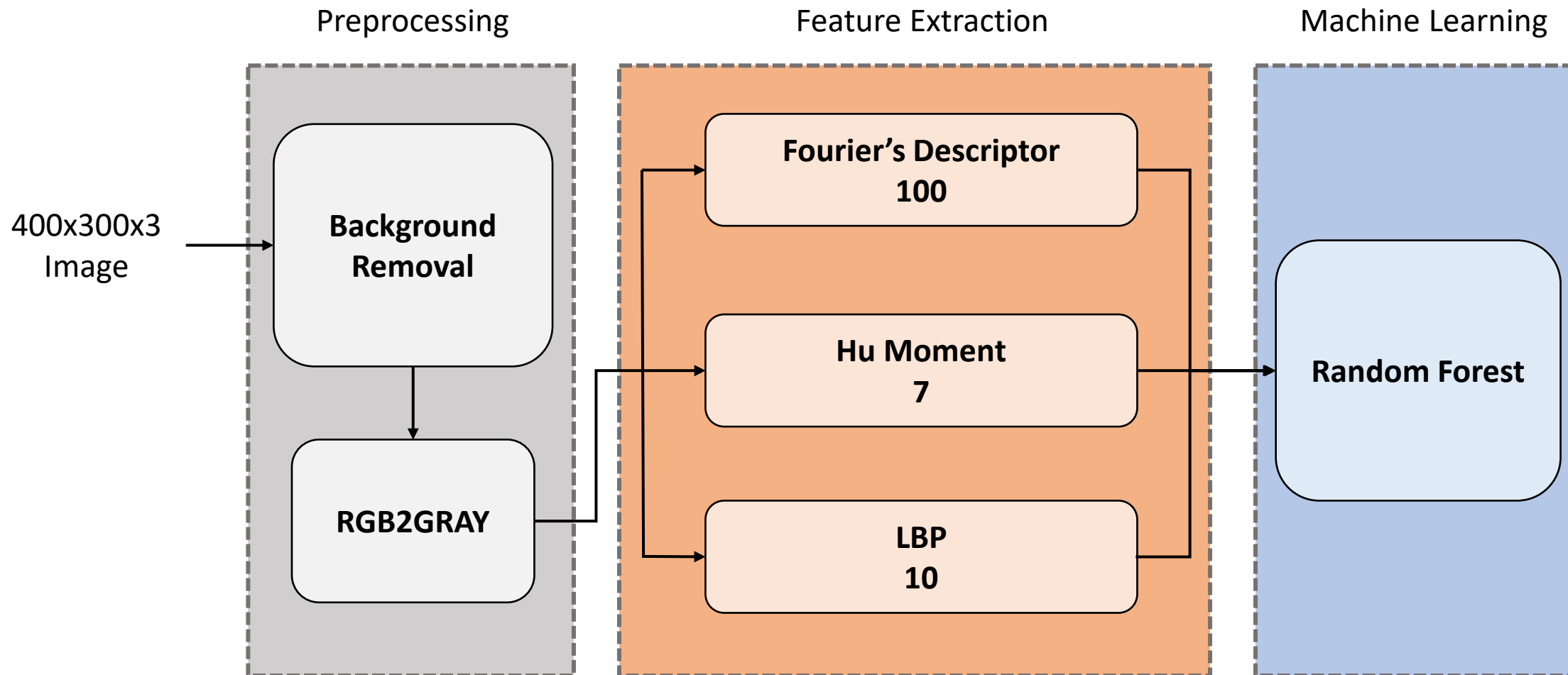
0.65

- Two cols are not identical
- Within the col, the value are same





# Model & Comparison

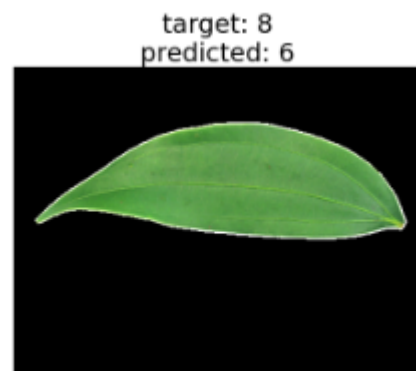
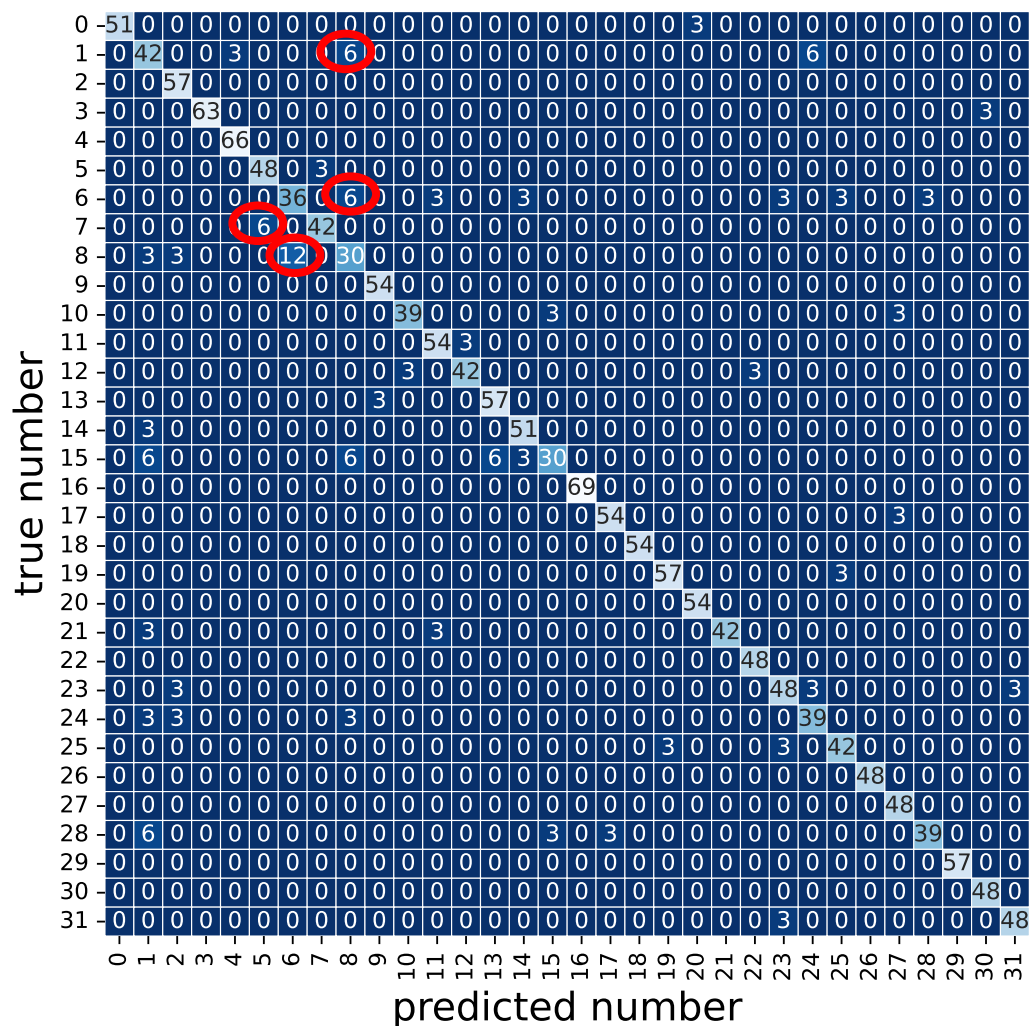






# Model & Comparison

91% Accuracy with 162 errors





# Model & Comparison

Model	Random Forest Classifier	ResNet50	Model X
Train Accuracy	1.0	0.99	1.0
Test Accuracy	0.88	0.91	0.91
Time (s)	2.85	6.22	119.46 (0.23)

- The final accuracy is 0.91
- Feature Extraction is time consuming



# Limitation & Improvement

- Optimize feature extraction section and reduce time
  - Tune hyperparameters or try more advanced models
  - Explore more classical features
- 
- The model is based on ideal situation
  - Influenced by lighting and shooting angles
  - Require Object (leaves) segmentation



<https://www.saferbrand.com/articles/plants-turning-yellow>



# Summary



# Summary

- Leaves Classification over 32 classes
- Apply Background Removal, Fourier Descriptors, Hu's moments, and Local Binary Pattern
- Train Random Forest over 117 features
- Accuracy over 90%
- The model is ideal and needs further improvement

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2. <https://pixabay.com/zh/photos/flowers-plum-blossom-spring-petals-7144467/>
3. Ojala, Timo, Matti Pietikainen, and Topi Maenpaa. "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns." *IEEE Transactions on pattern analysis and machine intelligence* 24.7 (2002): 971-987.
4. Ahonen, Timo, et al. "Rotation invariant image description with local binary pattern histogram fourier features." *Scandinavian conference on image analysis*. Springer, Berlin, Heidelberg, 2009.
5. <https://www.saferbrand.com/articles/plants-turning-yellow>

Thank You





# Q&A

