Lecture 8 - Applications of Image Processing in Machine Learning

January 31, 2021

1 Lecture 8 - Applications of Image Processing in Machine Learning

In this notebook, we will apply image processing in preparing our dataset for a machine learning algorthim.

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1.1 Leaf Classification

In the previous lectures, we discussed how to visualize, enhance, and extract information from images. We now apply the different algorithms that we have learned to create a leaf classification algorithm. Let's try it out. The file *leaves.zip* contains images of fives classes of leaves. We need to create a pipeline that would 1. Read and clean the images 1. Segment objects of interest 1. Extract features from the objects 1. Train an ML model

Take note that each of the steps can affect the accuracy of our model. Prioritizing which step to update will rely on heuristics. Let's practice:

Breakout Room Exercise: Create a machine learning pipeline and try to reach the highest accuracy possible. Make sure that you are able to answer the corresponding questions. 1. Did you apply any data cleaning methods to prepare the images? If yes, what are these methods? Upon inspection of the images, it was observed that there are some artifacts from the scanning process. To address this, we first convert the image to grayscale, then simply binarize the result using a threshold of 0.39.

2. What algorithms did you use to segment the different leaves? What worked best? As mentioned above, there were observed artifacts from scanning, and as well as some leaf samples are touching, which results in conjoined continuous elements. Therefore, morphological operations (i.e. erosion) was used to ensure that each leaf image segments neatly, as much as possible. To address any samples that re still conjoined, we simply filter the dataset to only include up to the 95^{th} percentile in terms of segment area.

3. What are the features that you have extracted from the leaves? What are the derived features that you have extracted? And what are the significant features in classifying each leaf? The following features were extracted using skimage's regionprops function:

- perimeter - approximation of the image contour length
- area - number of pixels in the region

- bbox_area - number of pixels contained by the bounding box
- convex_area - number of pixels in the convex hull image,
- eccentricity - ratio of the focal distance of the circumscribed elipse to the major axis length
- equivalent_diameter - diameter of the circle with the same area as the region
- extent - ratio of area to bounding box area
- filled_area - number of pixels in the area, plus pixels of all the holes
- major_axis_length - major exis of the circumscribed elipse
- minor_axis_length - minor exis of the circumscribed elipse
- local_centroid_y - bounding box centroid - y
- local_centroid_x - bounding box centroid - x
- euler_number - number of connected components subtracted by number of holes
- perimeter_crofton - perimeter from the Crofton formula
- solidity - ratio of area to convex hull area

In terms of derived features, we experimented with including the ratio of perimeter to area, and the ratio of the minor axis length to the major axis length.

4. How does the limited number of samples affect your training? On the one hand, it is reasonable to say that the limited number of samples makes it easier for the machine to learn this particular dataset. However, at the same time, it is hampered in its generalizability.

5. What machine learning algorithm did you use? What is your best performing algorithm? The chosen model for the experiment is the Random Forest Classifier. This is primarily due to its speed. While the best result is when we add the **ratio between the axis lengths (**90.6**)**, it appears that neither of the additional features improved the model significantly. The resultsing test accuracies are within two percent (2%) of each other. More research and experiments are needed.

[75]:
```
import os
import numpy as np
from skimage import data, io, filters
from skimage.measure import label, regionprops
from skimage.morphology import erosion, closing
from skimage.color import label2rgb, rgb2gray
import matplotlib.pyplot as plt
```

[76]:
```
kernel = np.array([[0,0,1,1,1],
                   [0,1,1,1,1],
                   [1,1,1,1,1]])
```

[104]:
```
leaves = {'A':[], 'B':[], 'C':[], 'D':[], 'E':[]}
for img in os.listdir(os.getcwd()):
    if img.startswith('plant'):
        leaves[img[5]].append(erosion(rgb2gray(io.imread(img)) < 0.39,
                                      kernel))
```

[105]:
```
plt.imshow(leaves['A'][0], 'gray')
```

[105]:
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<matplotlib.image.AxesImage at 0x7fe6898d9a30>
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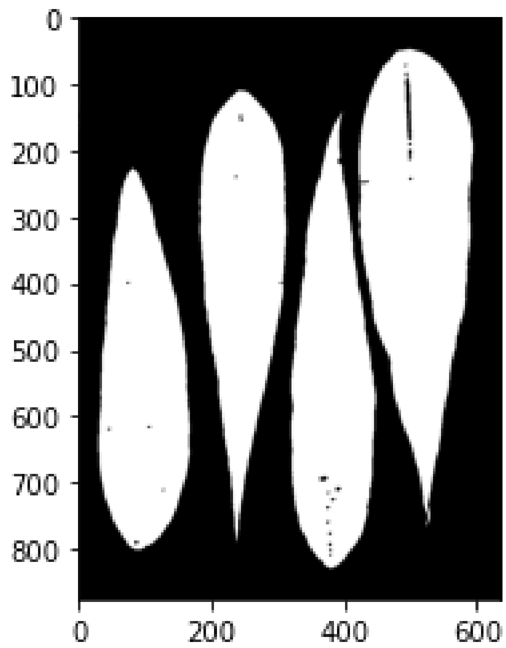

[106]:
```
sample = leaves['A'][0]
sample_labeled = label(sample)
plt.imshow(sample_labeled)
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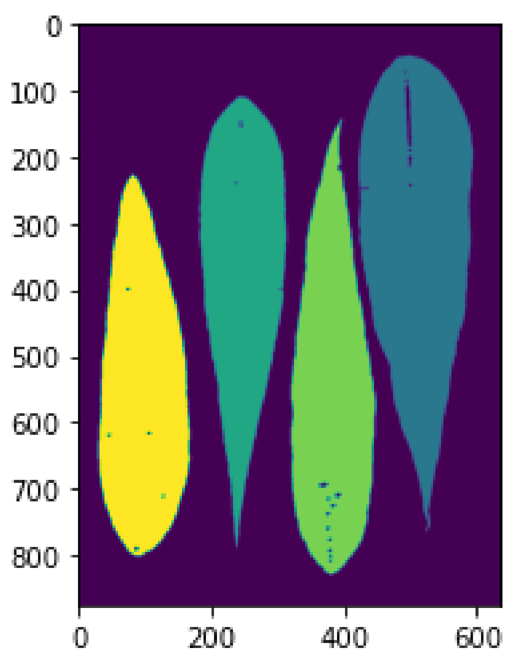
[106]: <matplotlib.image.AxesImage at 0x7fe68d2668b0>



[152]:

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for img in os.listdir(os.getcwd()):
    if img.startswith('plantA'):
        plt.imshow(rgb2gray(io.imread(img)) < 0.39)
        plt.show()
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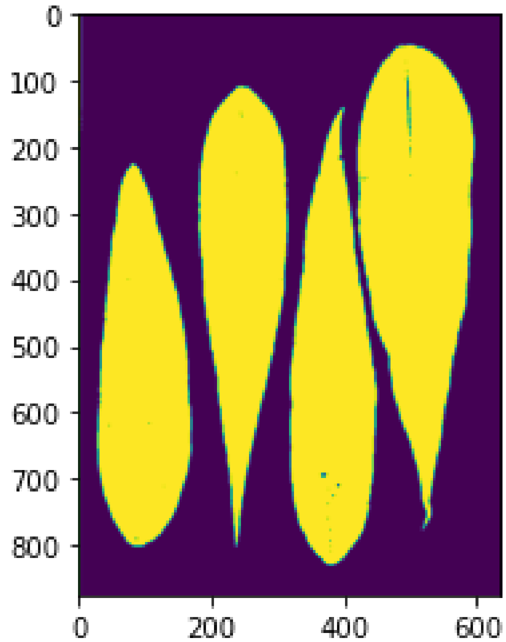

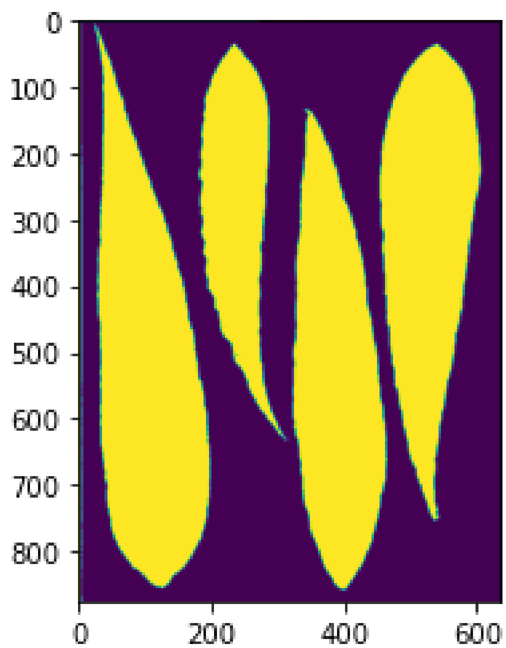

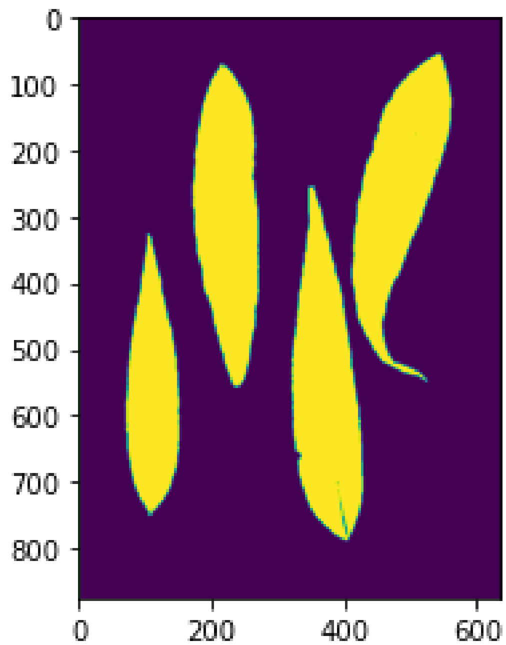

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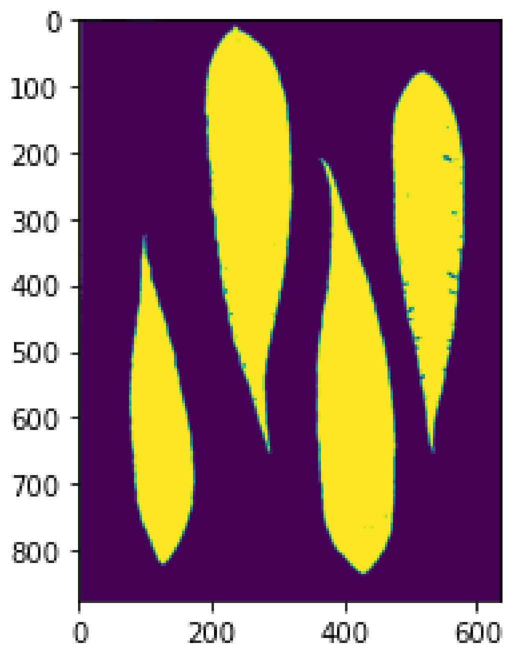

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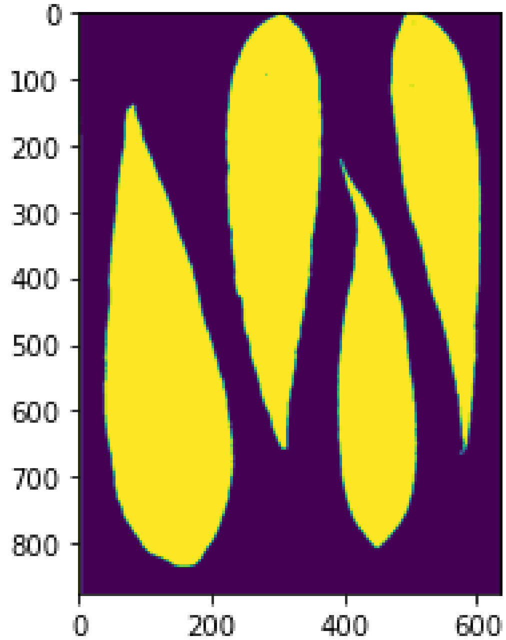
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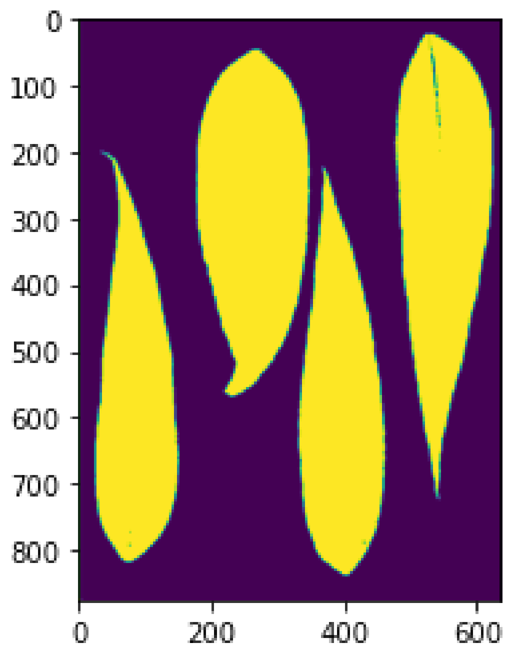
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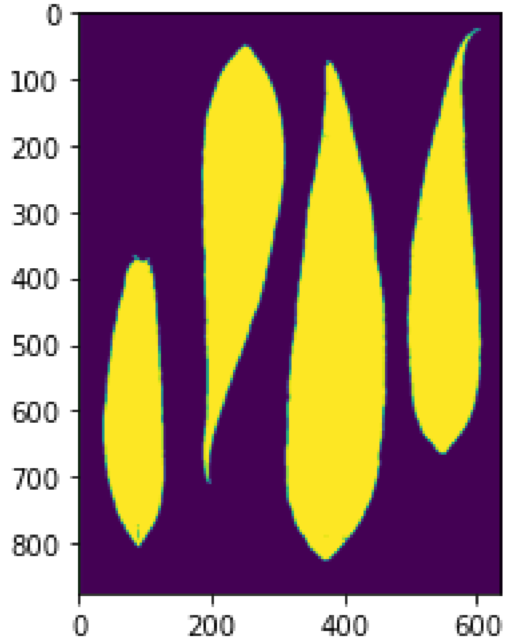

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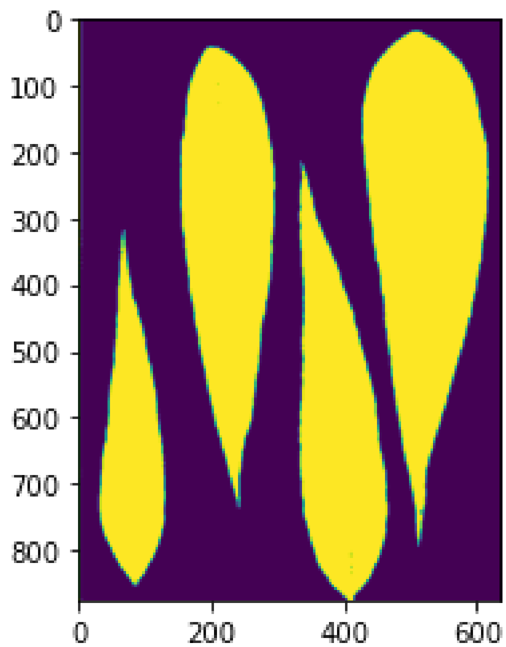

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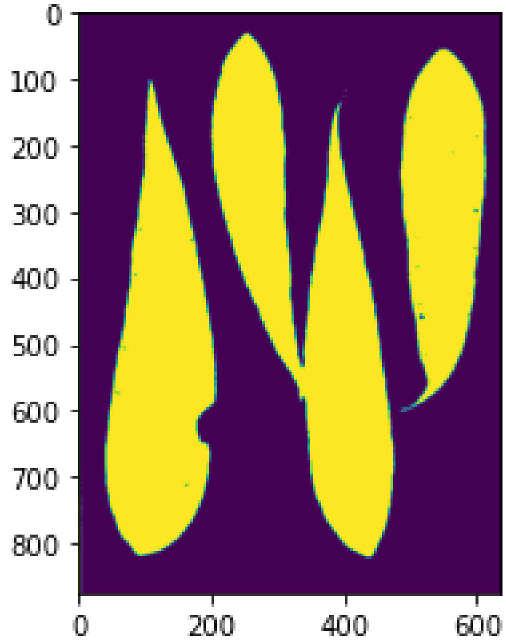
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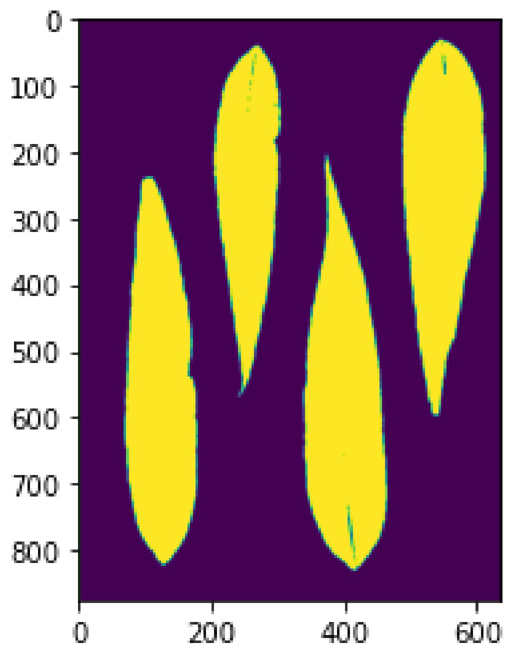
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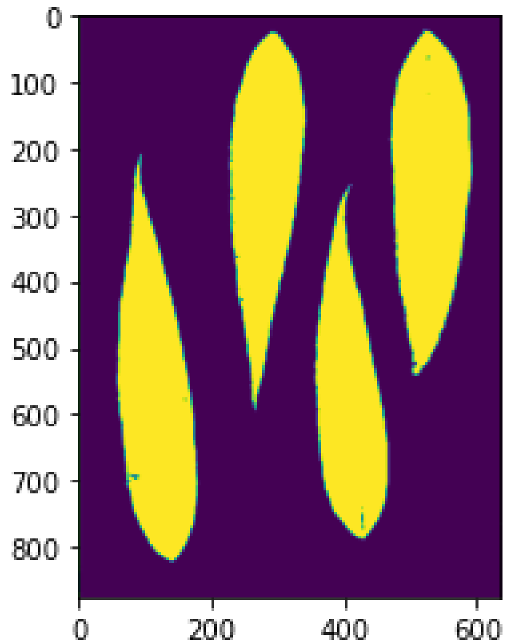
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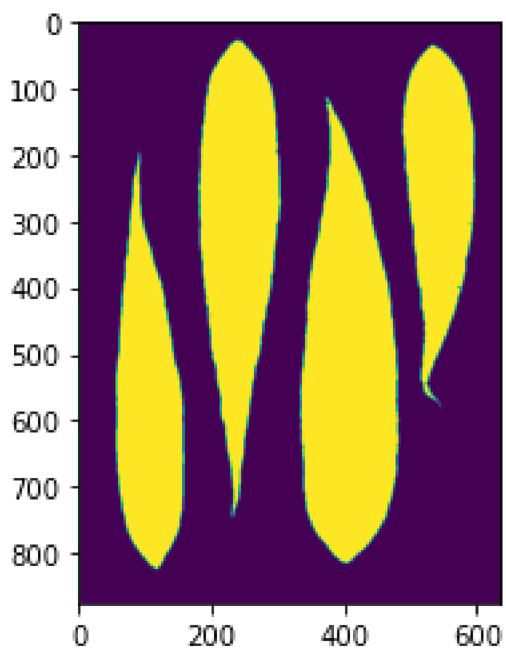
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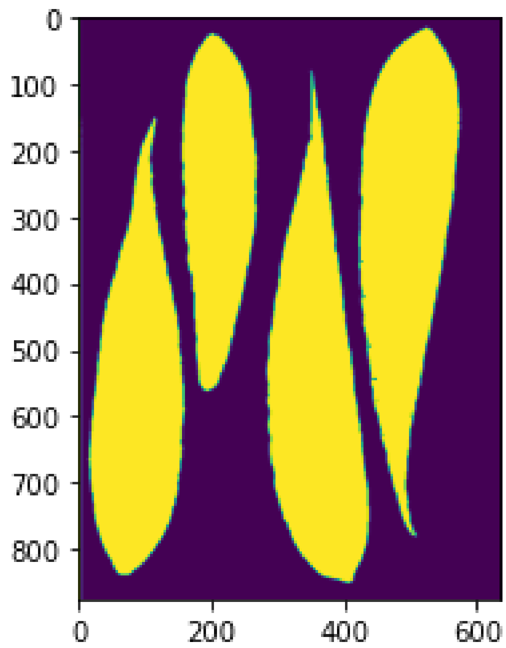
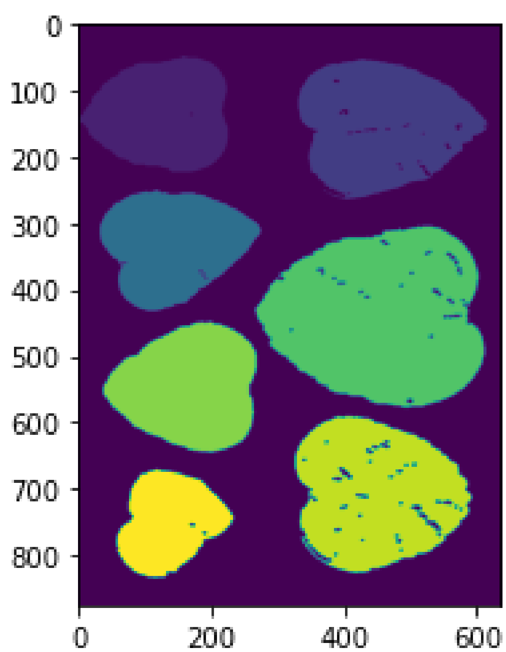


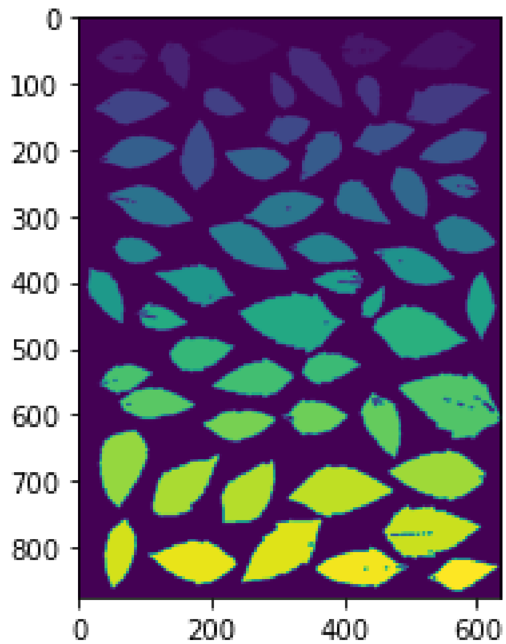
[109]:
```
sample2 = leaves['B'][0]
sample2_labeled = label(sample2)
plt.imshow(sample2_labeled)
```

[109]: <matplotlib.image.AxesImage at 0x7fe68a8784f0>



[110]:
```python
sample3 = leaves['C'][0]
sample3_labeled = label(sample3)
plt.imshow(sample3_labeled)
```

[110]: <matplotlib.image.AxesImage at 0x7fe68a5ef1f0>



[111]:
```python
sample3_props=regionprops(sample3_labeled)
sample3_props=sorted(sample3_props, key=lambda x: x.area, reverse=True)[1:]
print(sample3_props[-5].area, sample3_props[-4].area)
```

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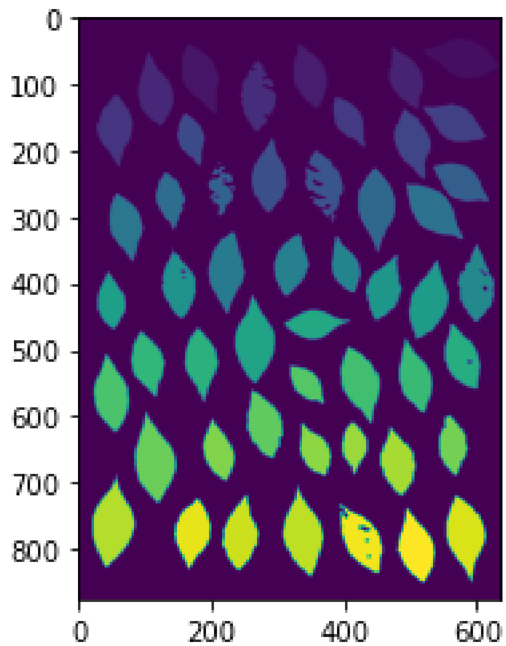
[84]:
```python
sample3 = leaves['D'][0]
sample3_labeled = label(sample3)
plt.imshow(sample3_labeled)
```

[84]: <matplotlib.image.AxesImage at 0x7fe68a544bb0>




```
[112]: sample3 = leaves['E'][0]
       sample3_labeled = label(sample3)
       plt.imshow(sample3_labeled)
```

```
[112]: <matplotlib.image.AxesImage at 0x7fe689f0ffd0>
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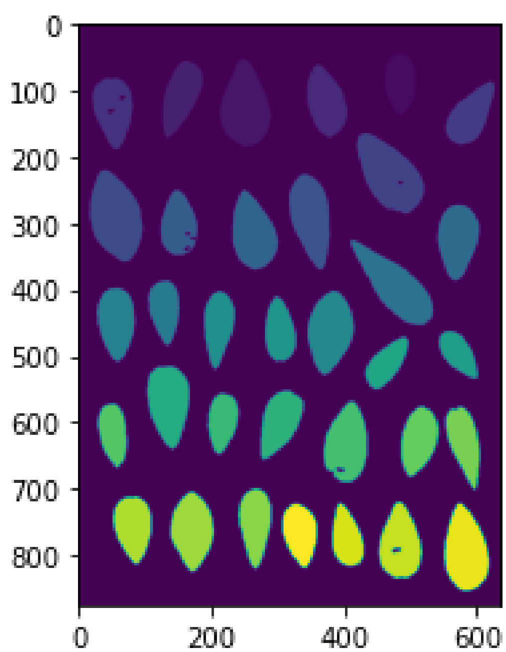
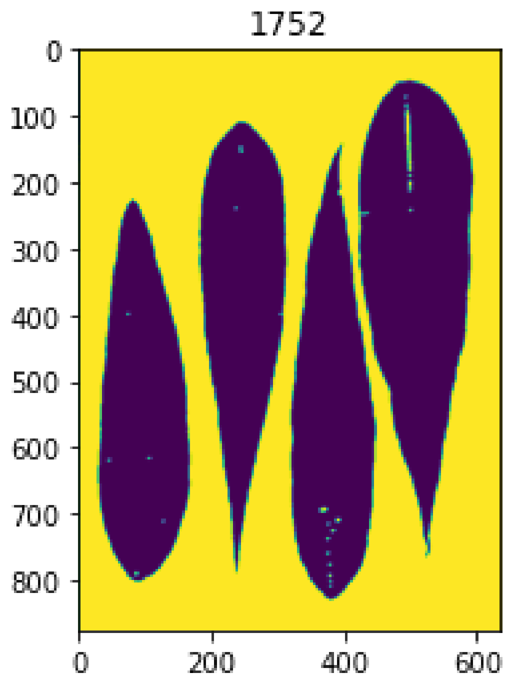
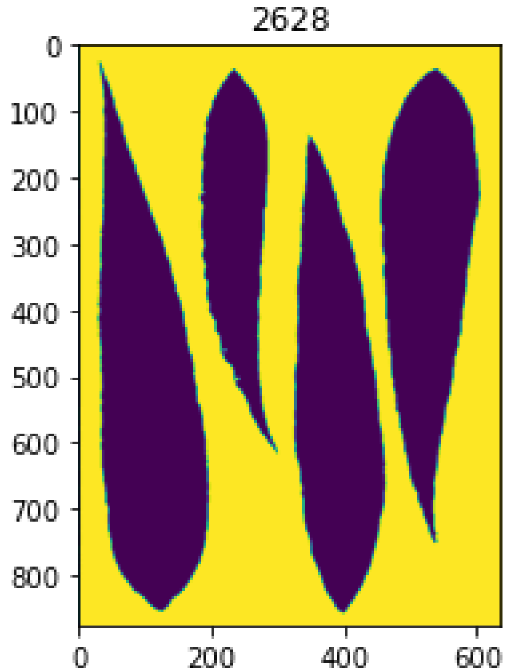


[120]:
```python
for leaf_class, images in leaves.items():
    for img in images:
        temp = label(img)
        temp_props = regionprops(temp)
        plt.imshow(temp==0)
        plt.title(f'{temp_props[0].bbox_area}')
        plt.show()
```

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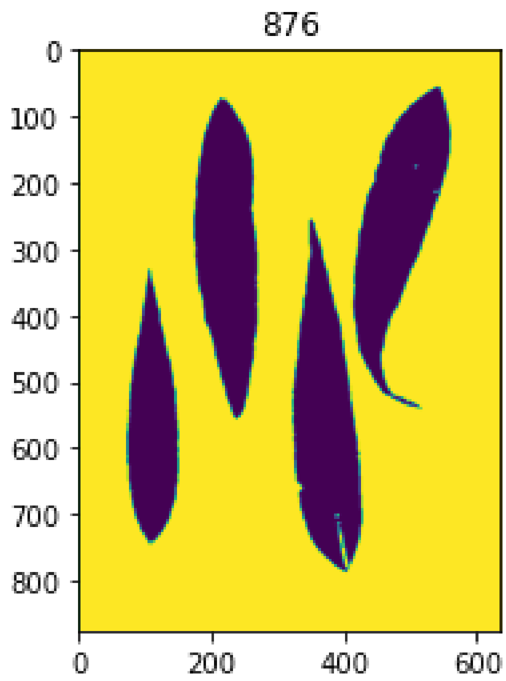
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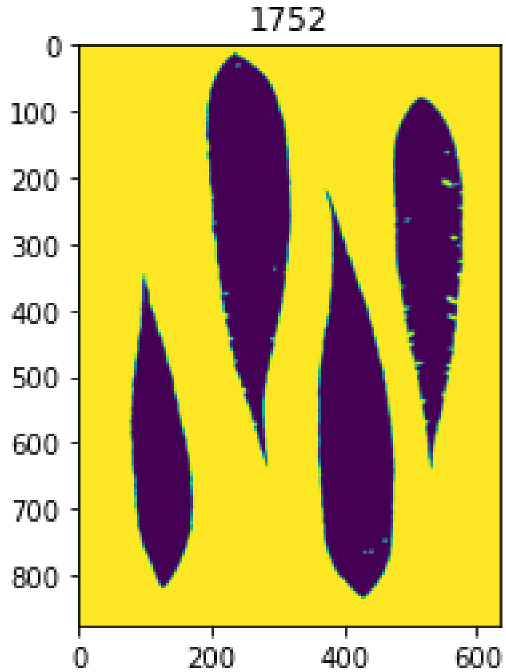
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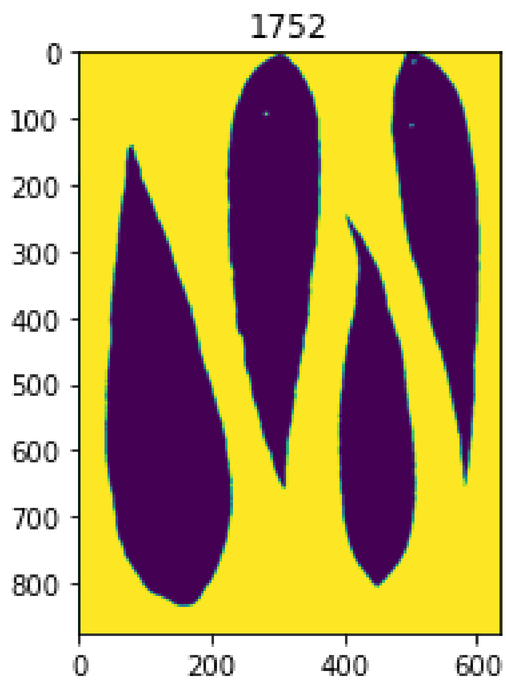
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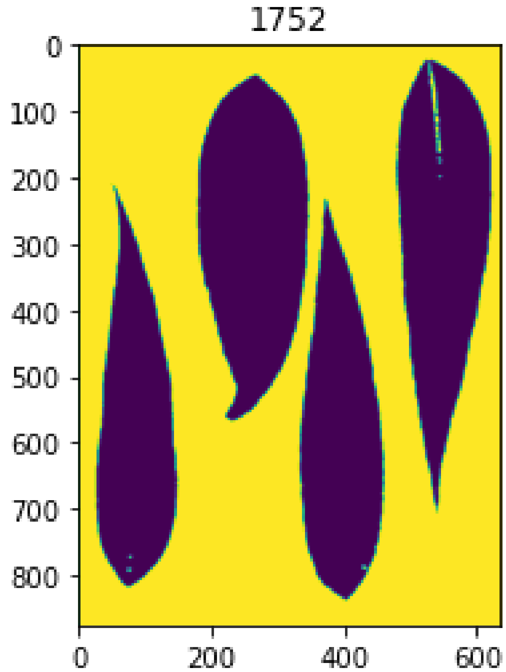
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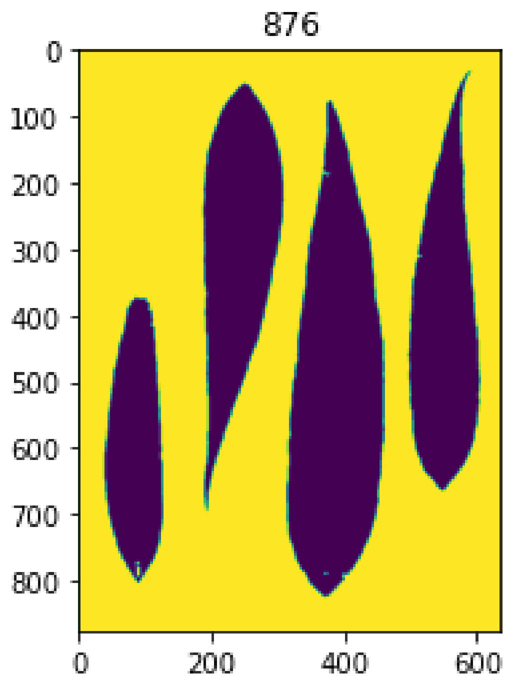
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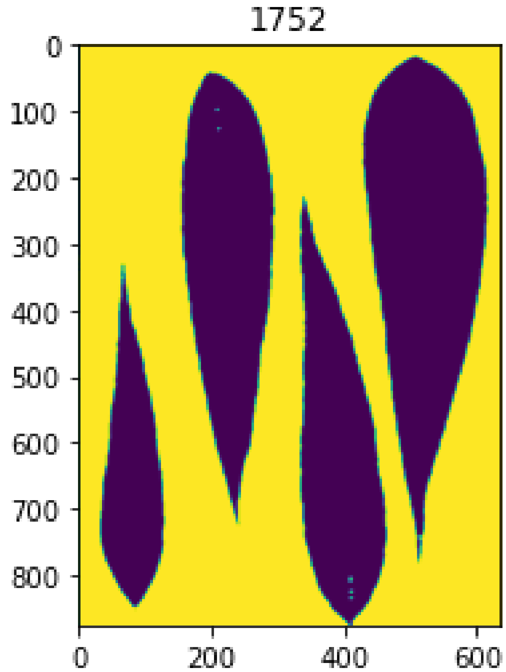
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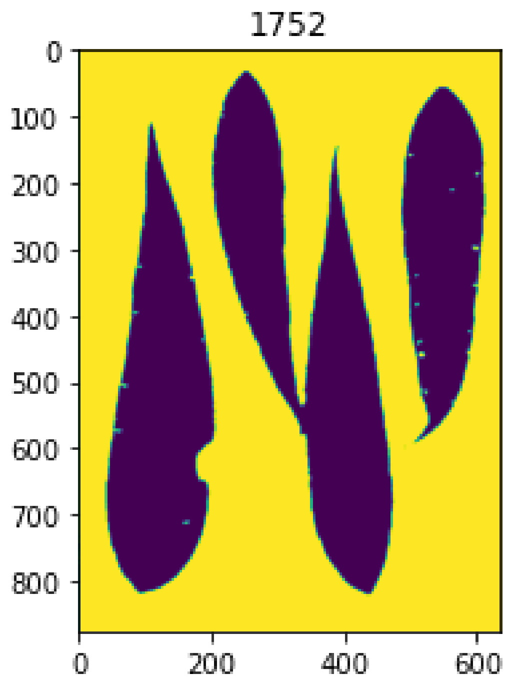
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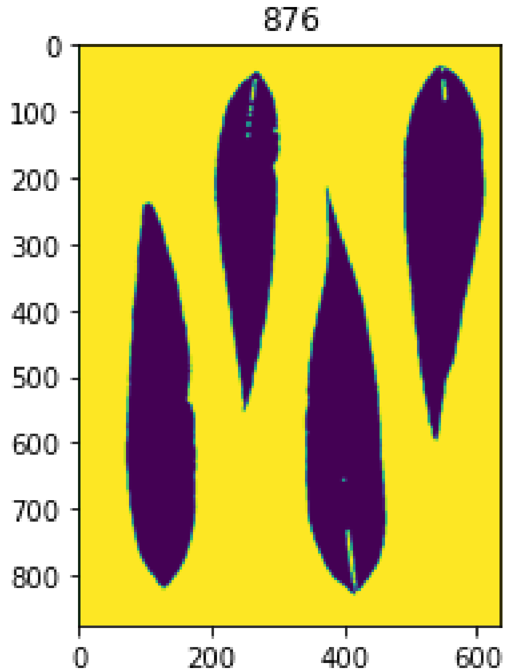
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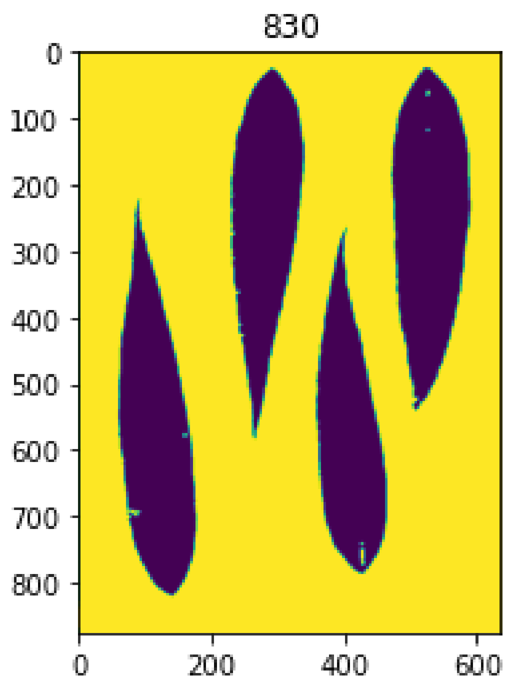
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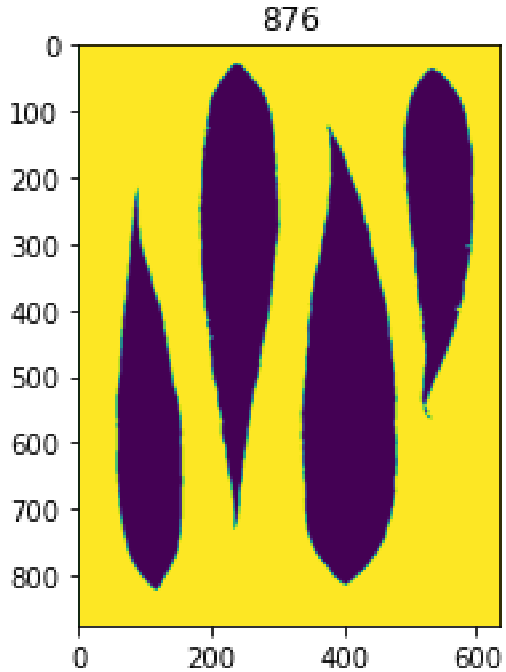
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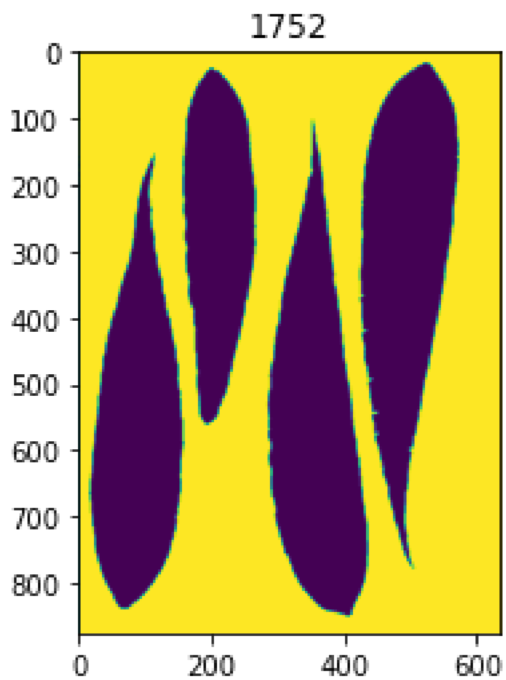
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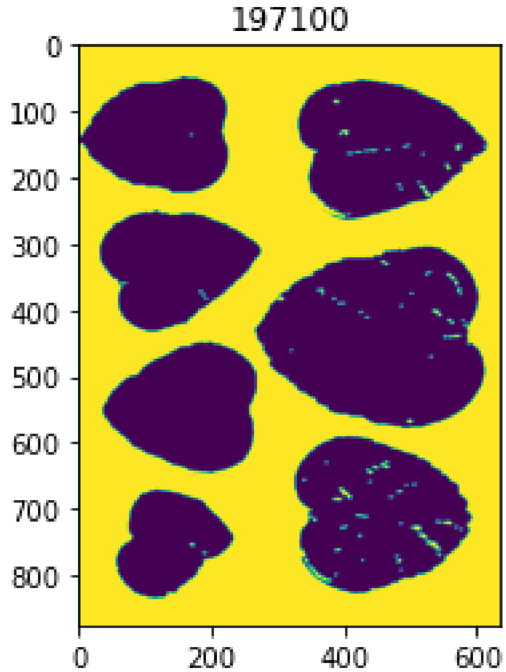
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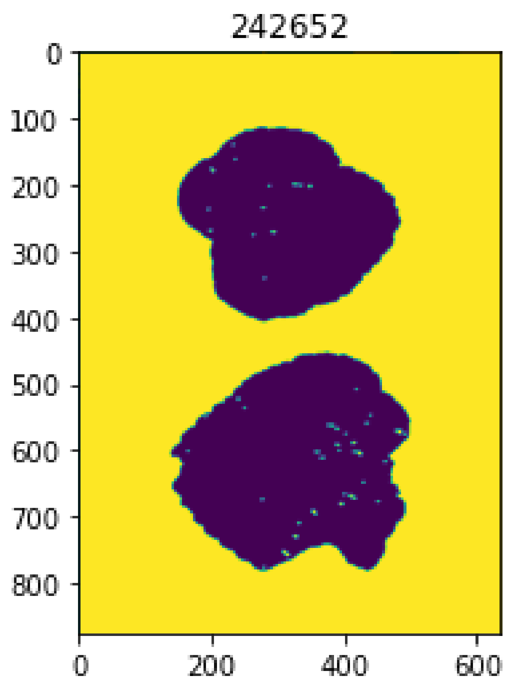
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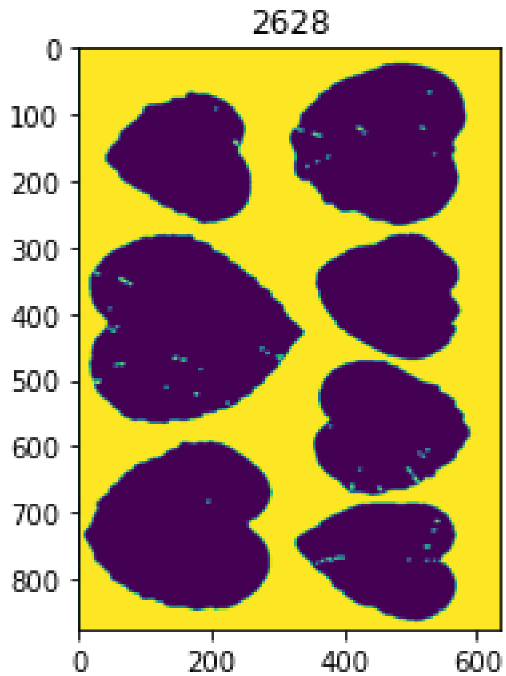
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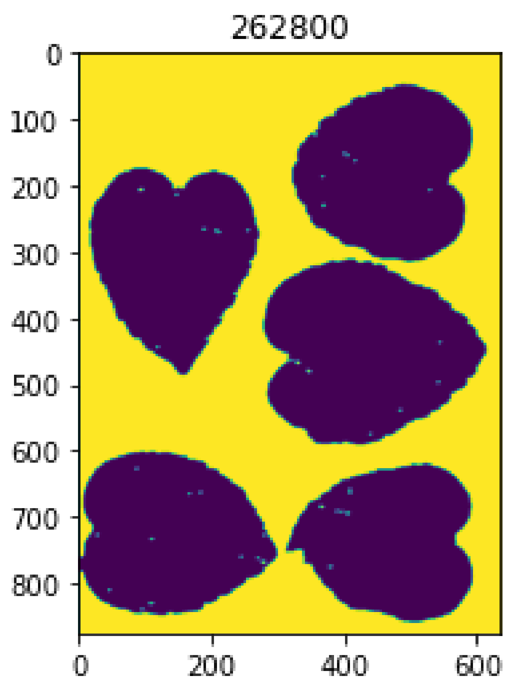
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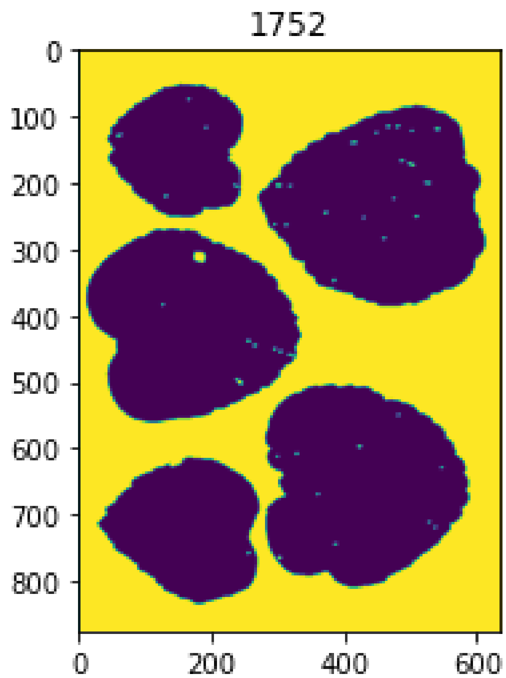
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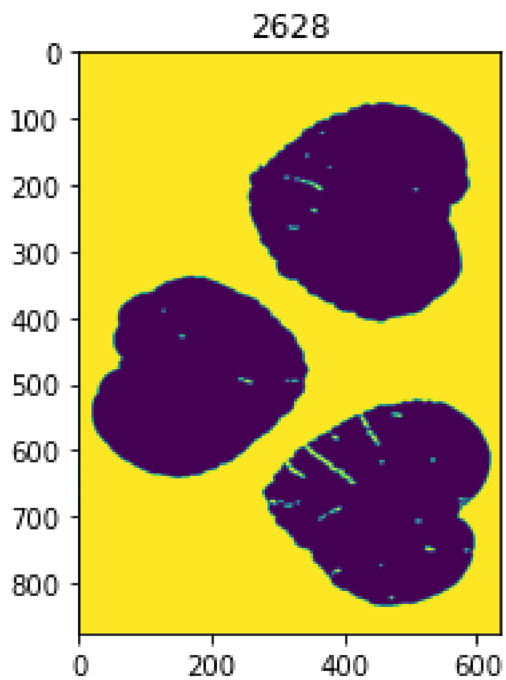
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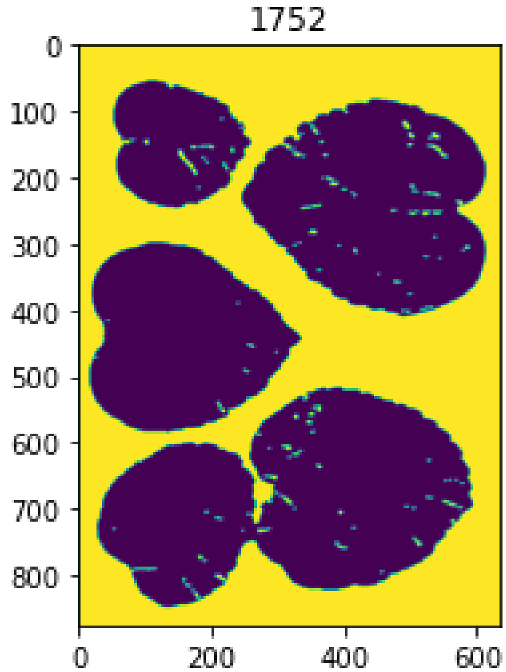
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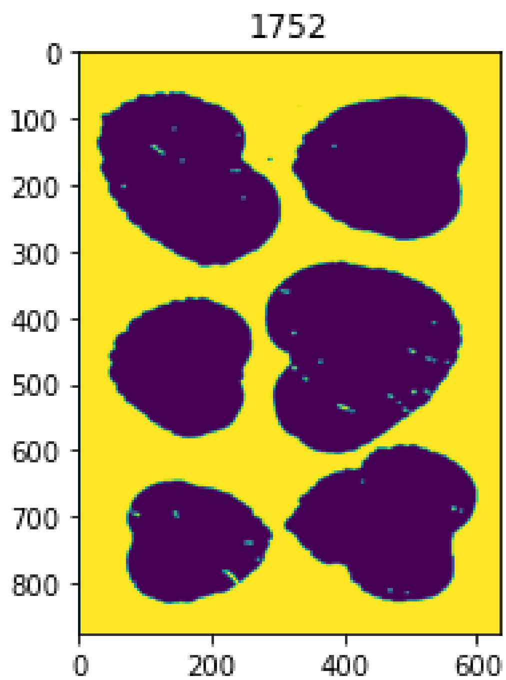
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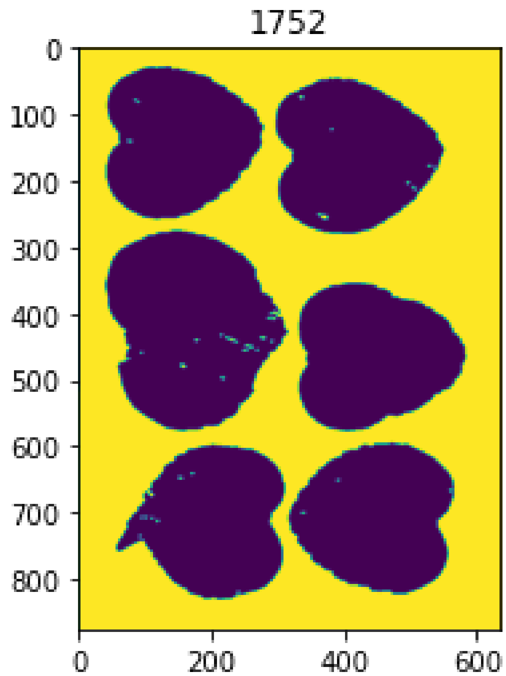
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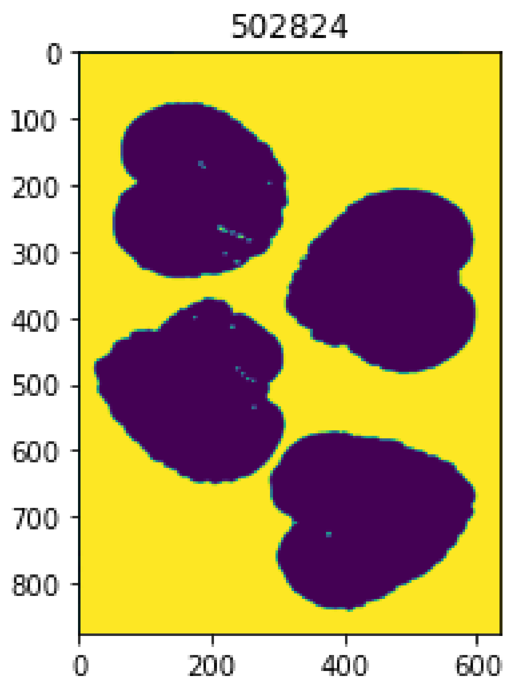
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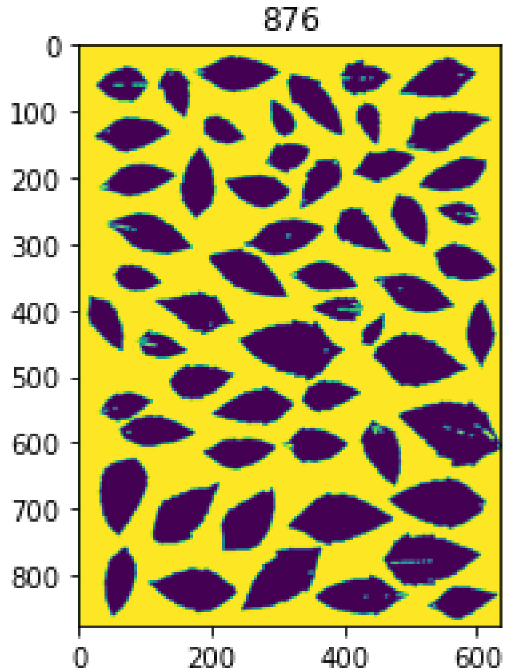
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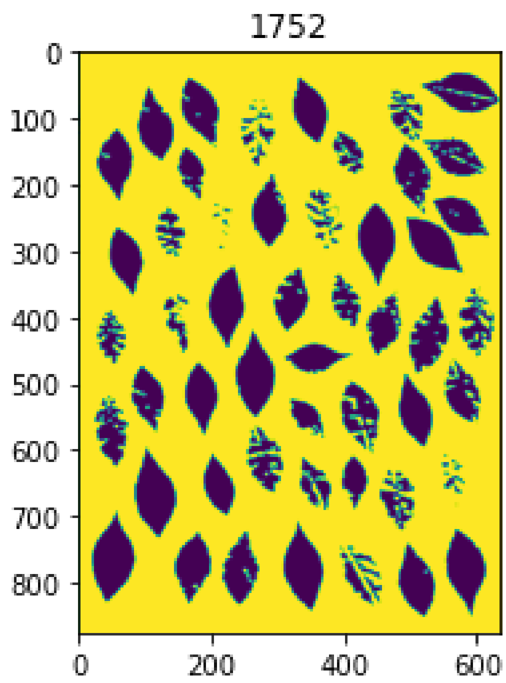
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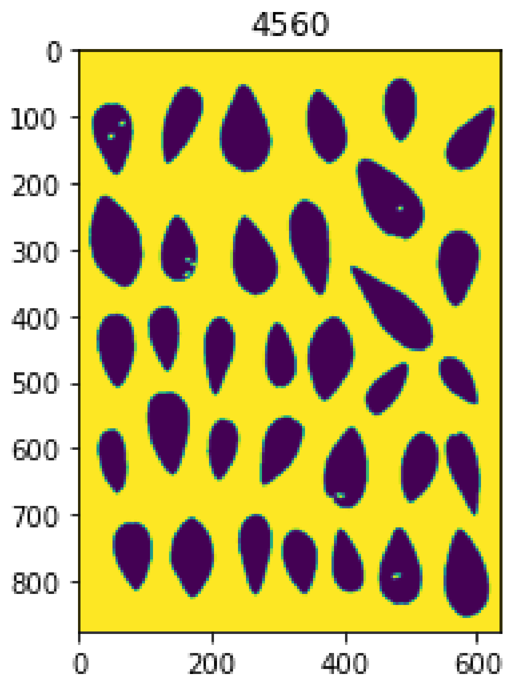
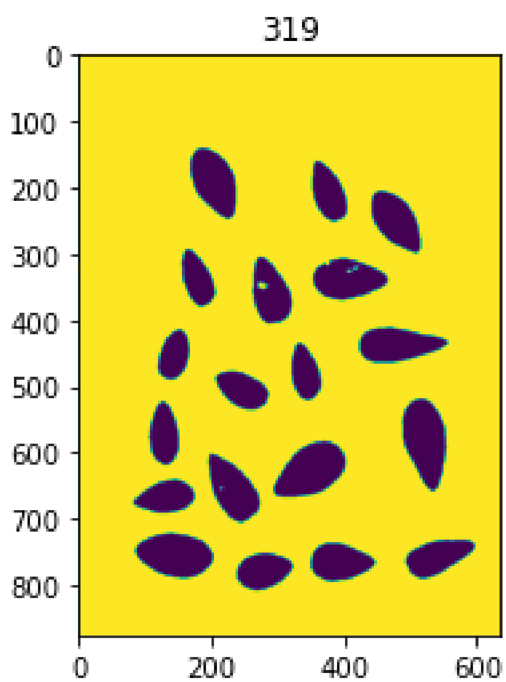




[185]:
```
# major_axis_length, local_centroid, filled_area, extent, equivalent_diameter,
# eccentricity, convex_area, bbox_area, area, perimeter, minor_axis_length
```

```
import pandas as pd

data = pd.DataFrame()

for leaf_class, images in leaves.items():
    for img in images:
        temp = label(img)
        temp_props = regionprops(temp)
        temp_props = [x for x in temp_props if x.area > 100]
        temp_props = [[x.perimeter, x.area, x.bbox_area, x.convex_area,
                       x.eccentricity, x.equivalent_diameter, x.extent,
                       x.filled_area, x.major_axis_length,
                       x.minor_axis_length, x.local_centroid[0],
                       x.local_centroid[1], x.euler_number, x.solidity,
                       leaf_class]
                      for x in temp_props]
        data = pd.concat([data, pd.DataFrame(np.array(temp_props))])
```

[186]:
```
data.columns = ['perimeter', 'area', 'bbox_area', 'convex_area',
                'eccentricity', 'equivalent_diameter', 'extent',
                'filled_area', 'major_axis_length', 'minor_axis_length',
                'local_centroid_y', 'local_centroid_x', 'euler', 'solidity',
                'class']
```

[187]:
```
data = data[data.area.astype(float) < data.area.astype(float).quantile(0.95)]

X = data.iloc[:,:-1].astype(float)
Y = data['class']

X.describe()
```

[187]:
```
        perimeter          area      bbox_area    convex_area  eccentricity  \
count  283.000000    283.000000     283.000000     283.000000    283.000000
mean   663.834682  15967.310954   27985.696113   18772.547703      0.829478
std    544.688045  20940.770619   47416.278346   28204.562513      0.177992
min     45.627417    103.000000     103.000000     103.000000      0.160207
25%    262.814755   2489.000000    4183.000000    2755.000000      0.825015
50%    343.806133   3994.000000    6540.000000    4266.000000      0.865297
75%   1083.043289  31798.000000   49086.500000   35133.500000      0.972688
max   2873.572727  68600.000000  502824.000000  252726.000000      1.000000

       equivalent_diameter      extent   filled_area  major_axis_length  \
count           283.000000  283.000000    283.000000         283.000000
mean            113.265694    0.629944  16019.257951         265.246759
std              86.762285    0.147923  20992.497875         280.881065
min              11.451798    0.004938    103.000000          13.565450
```

```
25%              56.294659    0.574495    2528.500000          88.501715
50%              71.311421    0.629047    3997.000000         113.795177
75%             201.205981    0.712019   32007.000000         370.029779
max             295.540577    1.000000   68686.000000        1222.345030

       minor_axis_length  local_centroid_y  local_centroid_x       euler  \
count         283.000000        283.000000        283.000000  283.000000
mean           80.548936        126.042499         48.882566   -0.667845
std            74.449697        138.949066         38.568380    3.493041
min             0.000000          0.000000          0.000000  -31.000000
25%            41.046784         33.224947         24.134395   -1.000000
50%            51.738385         52.634532         37.659745    1.000000
75%           103.064860        156.291373         62.515708    1.000000
max           471.031488        717.234813        162.353358    1.000000

         solidity
count  283.000000
mean     0.900393
std      0.142308
min      0.009825
25%      0.912838
50%      0.952869
75%      0.971785
max      1.000000
```

[ ]:
```python
import seaborn as sns

sns.pairplot(X)
```

1.2 The Models

[ ]:
```python
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
```

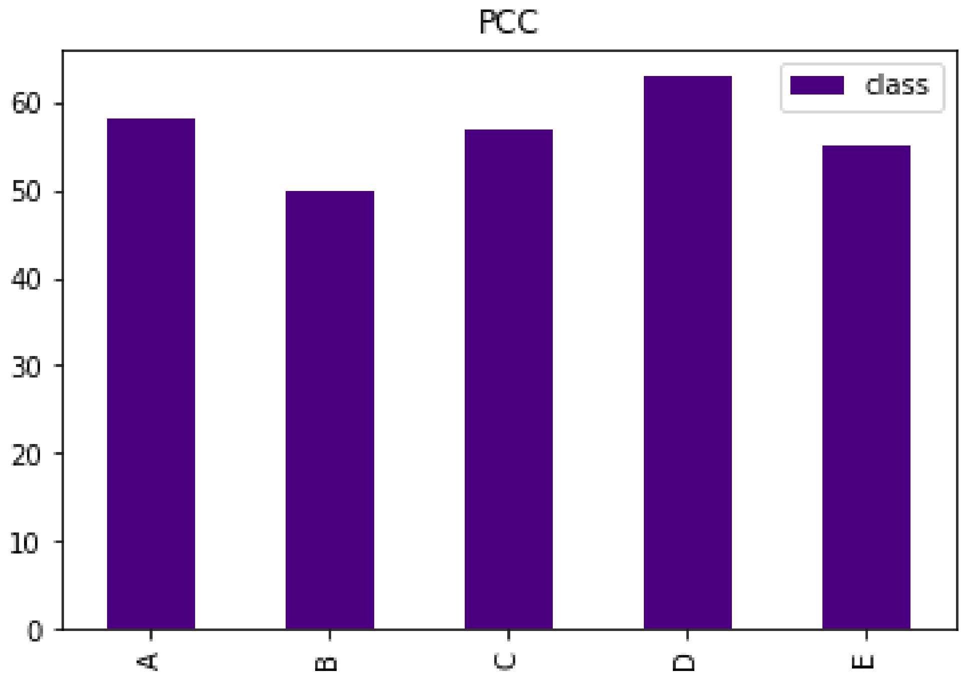
[158]:
```python
# PCC

from collections import Counter
state_counts = Counter(Y)
df_state = pd.DataFrame.from_dict(state_counts, orient='index',
                                  columns=['class'])
df_state.plot(kind='bar', color='indigo', title='PCC')

num=(df_state['class']/df_state['class'].sum())**2
print("Population per class: {}\n".format(df_state))
print("1.25 * Proportion Chance Criterion: {}%".format(1.25*100*num.sum()))
```

```
Population per class:    class
A     58
B     50
C     57
D     63
E     55

1.25 * Proportion Chance Criterion: 25.13922011761915%
```




```
[159]: def train_leaves(X, Y):
    """Run Grid Search to train the RF Classifier on different parameters."""
    xtrain, xtest, ytrain, ytest = train_test_split(X, Y, test_size=0.25)

    # Hyperparameters for tuning
    params = {'n_estimators': [50, 100, 150, 200],
              'max_depth': range(2,5),
              'max_features': ['auto', 'sqrt', 'log2', 0.2, 0.3, 0.4]}

    # Model training and evaluation
    model = RandomForestClassifier()
    model_cv = GridSearchCV(model, params)

    model_cv.fit(xtrain, ytrain)

    train_pred = model_cv.predict(xtrain)
```

```
    test_pred = model_cv.predict(xtest)

    test_score = model_cv.score(xtest, ytest)

#     print(model_cv.best_score_)
#     display(confusion_matrix(train_pred, ytrain))
#     display(confusion_matrix(test_pred, ytest))
    return (model_cv.best_score_, test_score,
            confusion_matrix(train_pred, ytrain),
            confusion_matrix(test_pred, ytest))
```

1.2.1 Baseline

[173]:
```
from tqdm import tqdm
cv_accuracy = []
test_accuracy = []
conf_train = []
conf_test = []

for i in tqdm(range(20)):
    score, tscore, ctrain, ctest = train_leaves(X, Y)
#     print(f'Run {i}: {score}')
    cv_accuracy.append(score)
    test_accuracy.append(tscore)
    conf_train.append(ctrain)
    conf_test.append(ctest)
```

```
100%|      | 20/20 [19:23<00:00, 58.17s/it]
```

[174]:
```
print('Cross Validation Accuracy: ', np.mean(cv_accuracy))
print('Test Accuracy: ', np.mean(test_accuracy))
```

```
Cross Validation Accuracy:  0.8974584717607973
Test Accuracy:  0.8992957746478872
```

1.2.2 Perimeter-to-Area Ratio

[188]:
```
X_pta = X.copy()

X_pta['pta_ratio'] = X['perimeter'] / X['area']
```

[189]:
```
from tqdm import tqdm
cv_accuracy = []
test_accuracy = []
conf_train = []
conf_test = []
```

```python
for i in tqdm(range(20)):
    score, tscore, ctrain, ctest = train_leaves(X_pta, Y)
#     print(f'Run {i}: {score}')
    cv_accuracy.append(score)
    test_accuracy.append(tscore)
    conf_train.append(ctrain)
    conf_test.append(ctest)
```

```
100%|      | 20/20 [19:50<00:00, 59.52s/it]
```

[190]:
```python
print('Cross Validation Accuracy: ', np.mean(cv_accuracy))
print('Test Accuracy: ', np.mean(test_accuracy))
```

```
Cross Validation Accuracy:  0.8932668881506091
Test Accuracy:  0.8845070422535212
```

1.2.3 Major-Minor Axes Ratios

[191]:
```python
X_mma = X.copy()

X_mma['mma_ratio'] = X['minor_axis_length'] / X['major_axis_length']
```

[192]:
```python
from tqdm import tqdm
cv_accuracy = []
test_accuracy = []
conf_train = []
conf_test = []

for i in tqdm(range(20)):
    score, tscore, ctrain, ctest = train_leaves(X_mma, Y)
#     print(f'Run {i}: {score}')
    cv_accuracy.append(score)
    test_accuracy.append(tscore)
    conf_train.append(ctrain)
    conf_test.append(ctest)
```

```
100%|      | 20/20 [19:58<00:00, 59.91s/it]
```

[193]:
```python
print('Cross Validation Accuracy: ', np.mean(cv_accuracy))
print('Test Accuracy: ', np.mean(test_accuracy))
```

```
Cross Validation Accuracy:  0.8975581395348838
Test Accuracy:  0.9056338028169014
```

[ ]:
```python
```