Evaluating and Optimizing Machine Learning Techniques for Automatic Nuclei Detection

1. Motivation

Many people die from cancer every year. This is terribly sad. :'(We would like to prevent this. One option is to identify the cancer early; treatment of nascent cancers tends to be more successful. Often, cells suffering from cancer display different biomarkers in their nuclei. These biomarkers can be seen in immunohistochemical (IHC) imaging. If there were a rapid and accurate way to screen images for cancerous cells, many cancer prognoses could be improved. We aim to develop an automated cell nuclei detection technique.

2. Challenges

Imaging conditions can vary tremendously - illumination, contrast, fluorescence and staining will all affect the appearance of the cell. We would also like our technique to be generalizable to many cell types because cancer is insidious and affects many cell types. Depending on the biological sample that was imaged, cells may also be aggregated; where a trained eye could distinguish individual nuclei, an algorithm might falter.

3. Pre-treatment and Initial Segmentation ("Detection")

Colour is usually either normalized or thresholded to remove noise and background [1]. A variety of pre-processing techniques can be used to find objects, from conventional blob detection, to morphological and/or contour resolution, to watershed segmentation [2-4]. We will use sensible discretion to pick a pre-treatment technique.

4. Segmentation and Identification

There are two primary approaches to cell segmentation:

Traditional methods segment nuclei from single or overlapping cells

Several traditional methods, often involving a-priori knowledge of cell shape and size [5]. First, cell clusters are segmented from the background by concavity [6-7]. Next, cell clusters can be separated into individual cells based on the concavity of the intensity distribution [7]. After individual cells have been identified, cell boundaries are often approximated using elliptical curve-fitting techniques [5,7]. Further segmentation can be applied to separate the cell nucleus from the cytoplasm. A gradient vector flow active contour model (GVF-ACM) has been shown to find boundaries between the nucleus and cytoplasm [8].

In this work, we can begin performing segmentation using the scikit-image package for python. This package includes methods for ellipse and boundary fitting, as well as edge detection and active contour modeling.

Machine learning methods identify nuclei via classification algorithms

Machine learning and pattern recognition have been successfully used to identify and segment cells in IHC images [9]. Whether using techniques such as cluster analysis [10], random forests [9], or deep neural networks [11-13], the workflow is similar. First, initial segmentation is performed (often in the pre-treatment step) to find cells and agglomerates. Then, training data is fed through a classifier to extract the most important features. Repeating this process while keeping only the most important feature vectors establishes a model, which is finally used to classify new test data.

We will start with cluster analysis and random forest classifiers (from the scikit-learn package), but likely will also employ traditional GVF or ellipse-fitting algorithms (which we will implement in python) to refine initial segmentation. If necessary, we also intend to look into convolutional neural networks implemented with the TensorFlow package.

References

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In [6]:
```
## change the following to where you have stored and/or extracted the files
path = './project/'
# path = '/Users/arrakis/Dropbox/Tool - Classes/ChBE 8803/Project'

n_samples = 3 #/665 total datasets in train1

####################################################################
```

UPDATED 3/28 ideas for future work

Updates (3/29 4 am)

- KMEANS clustering to separate into different cell/conditions type - will fix tomorrow (tired)
- Watershed performance metrics calculated (comparable to the random forest now)
- SVM classifier for detection (slow to train) - took 30 min and wasn't finished so I removed it(same Xtrain, Ytrain as random forest)
- Random forest classifier using HSV instead of RGB values
- Example of an active contour model, but so far it seems too slow to be practical
- Plan to add chan-vese level set segmentation

Detection

- try splitting three channels as HSV instead of RGB
- do dimensional reduction / PCA on all training set images to parse into different cell/conditions type, then threshold each one with best method for group

Segmentation

Package Requirements

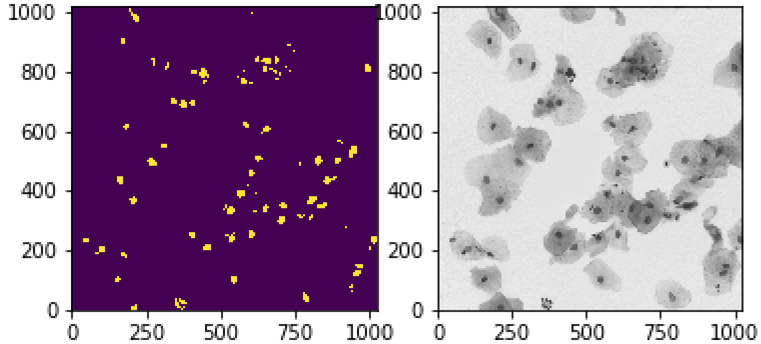
- numpy version 1.13.3
- pandas version 0.20.3
- matplotlib version
- sklearn version 0.19.1
- skimage version 0.13.0
- cv2 (used for image processing)
  - See lines 1-3 in the next block for installation on mac (version 3.2.0.6)
  - For PC, installation worked with pip install opencv-python from the anaconda prompt (version 3.4.0)

In [49]:
```
#import sys
#!{sys.executable} -m pip install opencv-python==3.2.0.6 # for mac
# >> https://stackoverflow.com/questions/47963386/image-not-found-error-afte
r-installing-opencv-python-wheel-on-mac

## load all packages used below
from skimage.color import rgb2gray
from skimage.filters import threshold_otsu
import zipfile, io
import numpy as np
import pandas as pd
import pylab as plt
import sklearn, cv2
import matplotlib.image as mpimg
from scipy import ndimage
from scipy.ndimage import label
from skimage import feature
from skimage.filters import sobel, laplace
from skimage.morphology import watershed
from sklearn import linear_model
from sklearn import svm
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
```

Loading Images and Masks from Training Set

- load_zipped_img takes an image and set of masks from the .zip
- A working example of extracting an individual image and associated masks is shown below

In [8]:
```
## STEP 1: Load an image (by index) and corresponding masks from ZIPPED stage1
_train as np array

def load_zipped_img(path, img_index): # Load an image and all its masks
    z = zipfile.ZipFile(path,'r') # access zip folder
    zlist = z.namelist() # list of files in zip folder

    img_name = zlist[img_index] # get selected image
    img_name = img_name[0:-1] # eliminate "/"

    # get image and return as np array
    img_raw = z.read('{}/images/{}.png'.format(img_name,img_name)) # get raw i
mage
    img = io.BytesIO(img_raw) # convert image
    img = mpimg.imread(img) # numpy array
    img = np.flip(img,0) # flip image

    # get all masks and return as np array
    mask_list = []
    for string in zlist:
        if string.startswith(img_name+'/mask'):
            mask_list.append(string)
    mask_list = mask_list[1:-1] # list of masks

    masks = []
    for m in mask_list:
        mask_raw = z.read(m) # get raw mask
        mask = io.BytesIO(mask_raw) # convert mask
        mask = mpimg.imread(mask) # numpy array
        mask = np.flip(mask,0) # flip mask
        masks.append(mask)

    return img, masks

# WORKING EXAMPLE OF load_zipped_img

(img, masks) = load_zipped_img(path+'/stage1_train.zip',177) # The one example
 that the model performs poorly for

fig, ax = plt.subplots(1,2)

ax[0].imshow(sum(masks), origin='lower')
ax[1].imshow(img, origin='lower')
plt.show()
```



Detection: Separating Object from Background

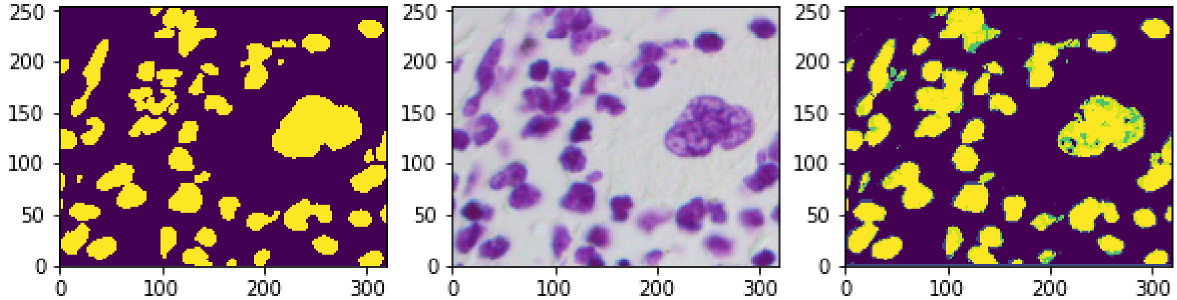
Before determining the positions of nuclei in an image, it is key to separate the image from the background using a process called image segmentation. Image segmentation is typically performed on grayscale images.

- The grayscale function converts images from rgb to grayscale
- The otsu function selects an optimal threshold for equal inter-/intra-class variance
- The function float2int8 converts the data type to int8, which is required for the cv2 package
- The function watershed applies watershed segmentation to a given image to determine objects and background with the following outputs
  - img_guess: masked objects identified by watershed segmentation
  - sure_bg: background pixels identifed with high confidence
  - sure_fg: object pixels identified with high confidence
  - uncertain: the region between sure_bg and sure_fg where pixels are identified with low confidence

In [9]:

```
# convert to grayscale
def grayscale(im):
    return rgb2gray(im)

# Otsu's Method, calculates optimal threshold for equal inter-/intra-class var
iance
def otsu(image_gray):
    threshold_val = threshold_otsu(image_gray) #Select threshold from Otsu's m
ethod
    img_masked = np.where(image_gray > threshold_val, 1, 0)

    if np.sum(img_masked==0) < np.sum(img_masked==1):
        img_masked = np.where(img_masked, 0, 1)
    return img_masked

# Function to convert float32 raw images to int8 single channel
def float2int8(img_float):
    img_int8 = (img_float * 255).round().astype(np.uint8)
    return img_int8
```

In [51]:
```
# Function to watershed segment images
def watershed(img_float32):
    img = img_float32[:, :, :3]

    # convert input image (float32) to 3-channel int8
    ch1 = float2int8(otsu(img[:,:,0:1][:,:,0]))
    ch2 = float2int8(otsu(img[:,:,1:2][:,:,0]))
    ch3 = float2int8(otsu(img[:,:,2:3][:,:,0]))
    img_guess = cv2.merge([ch1,ch2,ch3])

    # greyscale and otsu threshold original image
    img_grey = grayscale(img)
    int8_thresh = float2int8(otsu(img_grey))

    # noise removal
    kernel = np.ones((3,3),np.uint8)
    opening = cv2.morphologyEx(int8_thresh,cv2.MORPH_OPEN,kernel,iterations=2)

    # find sure background area
    sure_bg = cv2.dilate(opening,kernel,iterations=3)

    # find sure foreground area
    dist_transform = cv2.distanceTransform(opening,cv2.DIST_L2,5)
    ret, sure_fg = cv2.threshold(dist_transform,0.2*dist_transform.max(),255,0
)
    sure_fg = np.uint8(sure_fg)

    # finding uncertain region
    uncertain = cv2.subtract(sure_bg,sure_fg)

    # marker labelling
    ret, markers = cv2.connectedComponents(sure_fg)
    markers = markers+1 # add one to all labels so sure background is 1 (not
 0)
    markers[uncertain==255] = 0 # mark unknown region as 0

    # apply watershed and mark boundary as -1
    markers = cv2.watershed(img_guess, markers)
    img_guess[markers == -1] = [255,0,0]

    return img_guess, markers, sure_bg, sure_fg, uncertain


#### TESTING
(img, mask) = load_zipped_img(path+'/stage1_train.zip', 510)

img_guess, markers, sure_bg, sure_fg, uncertain = watershed(img)

fig, ax = plt.subplots(1,3, figsize = (10,10))

ax[0].imshow(sum(mask), origin='lower')
ax[1].imshow(img, origin='lower')
ax[2].imshow(grayscale(img_guess), origin='lower')
plt.show()
```


250
200
150
100
50
0
0
100
200
300

In [43]:
```
# Watershed Testing

for i in range(0,560):
    (img, masks) = load_zipped_img(path+'/stage1_train.zip', i)

    (img_guess, markers, sure_bg, sure_fg, unknown) = watershed(img)
    yp = np.round(grayscale(img_guess)).reshape(-1,1)
    y_real = sum(masks).reshape(-1,1)
    accuracy = sklearn.metrics.accuracy_score(y_real, yp)
    precision = sklearn.metrics.precision_score(y_real, yp)
    f1 = sklearn.metrics.f1_score(y_real, yp)
    print(i, accuracy, precision, f1)
    acc.append([accuracy, precision, f1])

    #output = yp.reshape(shap[0],shap[1])

precision = np.mean(np.array(acc)[:,1])
accuracy = np.mean(np.array(acc)[:,0])
f1 = np.mean(np.array(acc)[:,2])
print('The average precision of the model is {}%'.format(precision*100))
print('The average accuracy of the model is {}%'.format(accuracy*100))
print('The average f1-score of the model is {}%'.format(f1*100))
```

```
0 0.97004699707 0.941236068896 0.791059073976
1 0.99040222168 0.960157516794 0.929476398699
2 0.907202148438 0.934694875871 0.857800224467
3 0.917321777344 0.693524020546 0.802634262902
4 0.980444335938 0.877852348993 0.851087562744
5 0.993896484375 0.940975776186 0.932386747803
6 0.920379638672 0.951196898179 0.812221102634
7 0.960447530864 0.994979882618 0.913171624094
8 0.995407104492 0.922718808194 0.868155935173
9 0.962515432099 0.986386632938 0.924245259481
10 0.943564814815 0.90031102703 0.884764455648
11 0.946896475283 0.923741207605 0.847025767106
12 0.969436645508 0.954275952166 0.90459633246
13 0.986877441406 0.952051926298 0.91360257183
14 0.943410493827 0.952805361592 0.881022679342
15 0.993118286133 0.929990966576 0.901291311009
16 0.982620239258 0.935864978903 0.853843192609
17 0.944467592593 0.998547429582 0.897829389134
18 0.995651245117 0.814143245694 0.863046612206
19 0.997802734375 0.771889400922 0.823095823096
20 0.997329711914 0.856569709127 0.907063197026
21 0.857272325376 0.882874936519 0.718924801393
22 0.952530864198 0.939936651938 0.886548887987
23 0.813229560852 0.110506356741 0.198839021636
24 0.995269775391 0.767552182163 0.839211618257
25 0.868709564209 0.0867509248252 0.159494969229
26 0.982330322266 0.955830950111 0.838583774742
27 0.947402954102 0.929693961952 0.765302648601
28 0.996292114258 0.906022845275 0.934904902223
29 0.996438439434 0.714472537053 0.717757827896
30 0.996459960938 0.763440860215 0.859564164649
31 0.982604980469 0.904942965779 0.833625218914
32 0.96396484375 0.932766514061 0.828511676542
33 0.902526855469 0.966092047487 0.788126036484
34 0.932629394531 0.875267620108 0.881058597875
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36 0.95600308642 0.93775985107 0.913801965231
37 0.859802246094 0.880932095084 0.782658062563
38 0.904113769531 0.944340105856 0.637726276951
39 0.964123535156 0.950193593805 0.786052267598
40 0.930212402344 0.918021841766 0.870705837121
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42 0.839823717949 0.868505823078 0.717464092679
43 0.954282407407 0.990402811571 0.925184670749
44 0.993270874023 0.950012817226 0.94384311728
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46 0.994430541992 0.892811296534 0.884016523673
47 0.929061671088 0.686122188783 0.782858012788
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58 0.956018066406 0.924381119159 0.865705020687
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63 0.787580128205 0.316058892356 0.144315209528
64 0.929627577034 0.900619759388 0.795543103726
65 0.885168075562 0.0842899635606 0.155432419163
66 0.959320987654 0.95775295199 0.911326403606
67 0.995376586914 0.698232323232 0.784953867991
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106 0.948834876543 0.947447611752 0.912631592817
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112 0.973125 0.98916470536 0.927487352445
113 0.976028442383 0.901449275362 0.780862044916
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114 0.995512820513 0.918578972636 0.921765102611
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473 0.966766975309 0.997706572308 0.933952860714
474 0.994705200195 0.815927873779 0.862246923382
475 0.992691040039 0.873411764706 0.885707468385
476 0.950447530864 0.937975778547 0.910156687185
477 0.993240356445 0.910447761194 0.852579034942
478 0.953464854111 0.908938000029 0.880664909446
479 0.993148803711 0.910390324354 0.880616857219
480 0.969930555556 0.995197764778 0.921255228435
481 0.995193481445 0.933908045977 0.925266903915
482 0.941774691358 0.890048927072 0.859614525971
483 0.977428713528 0.978146787615 0.927418280038
484 0.995513916016 0.882838283828 0.879211175021
485 0.990798950195 0.957842675459 0.930983175003
486 0.985443115234 0.863761955367 0.894957057917
487 0.952868652344 0.705359729599 0.790946992257
488 0.995086669922 0.795112781955 0.840119165839
489 0.986892700195 0.964187831171 0.924734951371
490 0.972152709961 0.819234194123 0.858142246405
491 0.914770507813 0.910040099871 0.775049938785
492 0.972319849691 0.981241772707 0.92592866438
493 0.977229938272 0.982719186785 0.940208692128
494 0.99891688771 0.984681064792 0.952392518824
495 0.933279320988 0.953472939095 0.856768978483
496 0.969623121132 0.980029048656 0.915267822736
497 0.997772216797 0.902847571189 0.880718954248
498 0.985977172852 0.891130924449 0.805172779309
499 0.938732910156 0.851429584121 0.85170630817
500 0.96630859375 0.0584461867427 0.10621761658
501 0.970901489258 0.925568573398 0.738013463388
502 0.983703613281 0.956859035005 0.904489357897
503 0.885894775391 0.954576363389 0.652444692322
504 0.989105224609 0.891280947255 0.698734177215
505 0.984497070313 0.945125628141 0.902495201536
506 0.930529785156 0.813688747306 0.859234707759
507 0.992935180664 0.89790897909 0.863139225539
508 0.972503662109 0.948662925058 0.864470517449
509 0.988052368164 0.764091858038 0.737160120846
510 0.946398925781 0.873414781437 0.895439933325
511 0.9939627542 0.724106463878 0.813359528487
512 0.952523148148 0.995904501873 0.910684995137
```

```
513 0.919519042969 0.85142293951 0.86281445723
514 0.987152099609 0.939368421053 0.913782510752
515 0.909416445623 0.941000023074 0.832659561436
516 0.989791870117 0.923186344239 0.795099540582
517 0.984756469727 0.972948104527 0.913678389355
518 0.808378219604 0.112445661067 0.20197470848
519 0.851806640625 0.959200507614 0.756871776899
520 0.969153404067 0.947451555581 0.923284131827
521 0.929138183594 0.957390146471 0.553289726818
522 0.980941772461 0.981481481481 0.433045846573
523 0.991241455078 0.846225104215 0.864238410596
524 0.997665405273 0.97037037037 0.895420369105
525 0.973388671875 0.939904799683 0.844590982
526 0.894393920898 0.964545742324 0.725389834544
527 0.991119384766 0.9229390681 0.898464759246
528 0.962484567901 0.980613029381 0.923476454294
529 0.991409194192 0.930246700007 0.934681042701
530 0.944043209877 0.925970042584 0.895567523977
531 0.951203703704 0.921760633037 0.898390051094
532 0.996612548828 0.940561724363 0.928433268859
533 0.908983645713 0.293551315132 0.451934022626
534 0.85126953125 0.918309002433 0.712492330926
535 0.917407226562 0.880326530612 0.761205618691
536 0.970620579134 0.978473534119 0.93863299263
537 0.965709876543 0.983576754791 0.93492077439
538 0.993148803711 0.867386276022 0.833642089663
539 0.986709594727 0.914888735949 0.90154854753
540 0.986846923828 0.937446928956 0.884851723217
541 0.985748291016 0.950241122315 0.902748854644
542 0.953680555556 0.945542521994 0.914837776107
543 0.95112654321 0.998953294294 0.917695366304
544 0.99577331543 0.886327503975 0.889509373753
545 0.989761352539 0.807311500381 0.759584378359
546 0.993087768555 0.852567642187 0.872070036713
547 0.9392578125 0.907197862643 0.822703627165
548 0.986679077148 0.749255706252 0.838423098279
549 0.994567871094 0.889105058366 0.885087153002
550 0.995162963867 0.841616964877 0.889044452223
551 0.989959716797 0.96718050721 0.922019435885
552 0.994232177734 0.771599657827 0.826764436297
553 0.996139526367 0.902649006623 0.91507217187
554 0.957484567901 0.950760230354 0.91887036928
555 0.978868258179 0.977553531229 0.951294690051
556 0.917556762695 0.988331495774 0.799271835643
557 0.95861882716 0.916947636414 0.908585746672
558 0.956080246914 0.934598378777 0.899117365567
559 0.942908950617 0.947619047619 0.892285743402
The average precision of the model is 78.3639440129741%
The average accuracy of the model is 95.20080933923725%
The average f1-score of the model is 78.23251191371496%
```

Classify Images for Future Segmentation

- Imaging conditions can vary from image to image. It can be difficult to determine a general method for nucleus segmentation under the variety of conditions. This section provides a method for separating images by type using a KMeans clustering algorithm.
- The function img_info determines a

In [35]:
```
# one-indexes a 2d array into 1d, top down then left right, output is np 1d ar
ray
def one_index(arr2d):
    h, w = arr2d.shape[0:2]

    arr1d = []
    for col in range(0, w):
        for row in range(0, h):
            arr1d.append(arr2d[row][col])
    return np.array(arr1d)

# pads all vectors in array to have max_len, returns np array
def pad_normalize(array, max_len):
    for i in range(0, len(array)):
        vec = array[i]
        print(len(vec))
        if len(vec) < max_len:
            array[i] = np.concatenate(( np.array(vec).reshape(1,-1), np.zeros
((1, (max_len-len(vec)))) ), axis=1)
        else:
            array[i] = np.array(vec).reshape(1,-1)
    return np.array(array)
```

In [71]:
```
# Get image information, apply clustering
def get_image_info(samples):
    # complete img ,rgb mode
    full_img_list = []
    # just grey mode
    img_list = []

    # average value of gray pixels per image
    average_list = []

    # max Contour area value per image
    max_cnt_area = []

    # mean Contour area value per image
    average_cnt_area = []

    # how many Contour areas per image
    num_cnt = []

    #  width per image
```

```
    wid_list = []

    #  length per image
    len_list = []

    #  red per image
    r=[]

    #  green
    g=[]

    #  blue
    b=[]
    for i in samples:
        (img, masks) = load_zipped_img(path+'/stage1_train.zip', i)
        full_img_list.append(i)
        r.append(np.average(img[:,:,0]))
        g.append(np.average(img[:,:,1]))
        b.append(np.average(img[:,:,2]))

        img = grayscale(img)
        img = float2int8(img)
        #img = cv2.imread(img,cv2.IMREAD_GRAYSCALE)
        print(i)
        # in some cases, image background is bright and cell darker, there nee
ds a inverse of pixel value
        if np.average(img) > 125:
            img = 255 - img
        img_list.append(img)

        lenth = img.shape[0]
        len_list.append(lenth)
        width = img.shape[1]
        wid_list.append(width)
        average_list.append(np.average(img))

        # use opencv to find contour and get some stactistic data
        img = cv2.GaussianBlur(img, (3, 3), 1)
        ret, thresh = cv2.threshold(img, 0, 255, cv2.THRESH_OTSU)

        _, cnts, _ = cv2.findContours(thresh, cv2.RETR_TREE, cv2.CHAIN_APPROX_
SIMPLE)
        cnts = sorted(cnts, key=cv2.contourArea, reverse=True)
        max_cnt_area.append(cv2.contourArea(cnts[0])/lenth/width)

        av = 0
        for i in cnts:
            av = av + cv2.contourArea(i)
        av = av/len(cnts)

        # since different pic has different size, we'd better normalise it
        average_cnt_area.append(av/lenth/width)
        num_cnt.append(len(cnts))

    df = pd.DataFrame({'img':full_img_list,'max_area':max_cnt_area,'average_ar
ea':average_cnt_area,
                       'num_cnt':num_cnt,'average':average_list,'wid':wid_list
```

```
,'len':len_list,
                        'r':r,'g':g,'b':b
                       })
    return df

df = get_image_info(range(0,560))
```

```
0
1
2
3
4
5
6
7
8
9
10
11
12
13
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17
18
19
20
21
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```

In [87]:
```
df.to_csv('KMEANS_summary.csv')
df
```

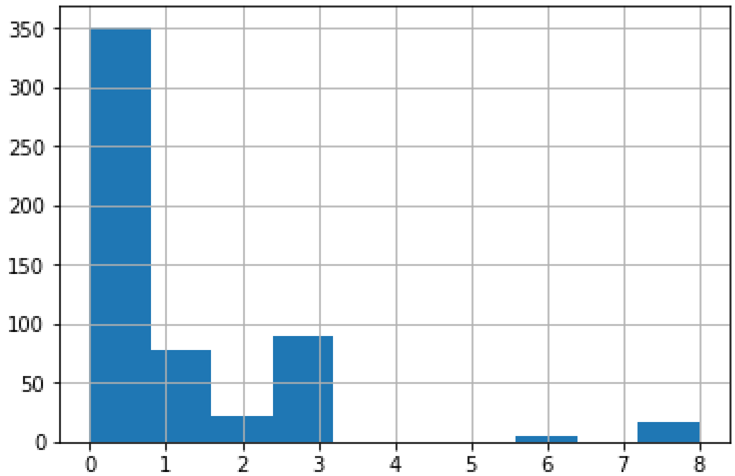
Out[87]:

	average	average_area	b	g	img	len	max_area	num_cnt	
0	6.142227	0.002843	0.024087	0.024087	0	256	0.008263	20	0.024
1	9.018600	0.001648	0.035367	0.035367	1	256	0.004219	36	0.035
2	93.074377	0.006824	0.756961	0.604796	2	256	0.031854	45	0.695
3	81.215198	0.004652	0.802636	0.662910	3	256	0.033124	53	0.702
4	92.987366	0.008269	0.786623	0.604949	4	256	0.021552	8	0.686
5	15.242493	0.002391	0.059774	0.059774	5	256	0.006172	17	0.059
6	16.667801	0.004530	0.065364	0.065364	6	256	0.022232	39	0.065
7	10.765440	0.011759	0.042217	0.042217	7	360	0.026779	18	0.042
8	16.871002	0.001431	0.066161	0.066161	8	256	0.003487	11	0.066
9	11.848765	0.013118	0.046466	0.046466	9	360	0.030363	18	0.046
10	10.967122	0.011311	0.043008	0.043008	10	360	0.028152	22	0.043
11	41.003713	0.001948	0.160799	0.160799	11	260	0.014038	78	0.160
12	17.424622	0.002013	0.068332	0.068332	12	256	0.006447	69	0.068
13	17.616776	0.002971	0.069085	0.069085	13	256	0.006477	24	0.069
14	8.932731	0.011968	0.035030	0.035030	14	360	0.036238	19	0.035
15	19.130478	0.001559	0.075021	0.075021	15	256	0.006889	20	0.075
16	6.385361	0.003363	0.025041	0.025041	16	256	0.008949	15	0.025
17	13.160849	0.009568	0.051611	0.051611	17	360	0.034024	26	0.051
18	4.869278	0.001752	0.019095	0.019095	18	256	0.004295	9	0.019
19	13.656174	0.001205	0.053554	0.053554	19	256	0.001526	5	0.053
20	4.103210	0.001934	0.016091	0.016091	20	256	0.002579	7	0.016
21	44.637525	0.001336	0.175049	0.175049	21	520	0.017916	158	0.175
22	11.913171	0.007606	0.046718	0.046718	22	360	0.023819	27	0.046
23	49.972590	0.000765	0.804029	0.804029	23	1024	0.042792	285	0.804
24	13.539978	0.002114	0.053098	0.053098	24	256	0.003540	7	0.053
25	39.509685	0.000499	0.845060	0.845060	25	1024	0.031569	313	0.845
26	19.444366	0.000888	0.076252	0.076252	26	256	0.003250	48	0.076
27	8.581192	0.003105	0.033652	0.033652	27	256	0.011017	29	0.033
28	15.459991	0.002969	0.060627	0.060627	28	256	0.005096	9	0.060
29	10.707253	0.000910	0.041989	0.041989	29	520	0.001405	7	0.041
...	...	...	...	...	...	...	...	...	...
530	14.649954	0.013698	0.057451	0.057451	530	360	0.051968	19	0.057

	average	average_area	b	g	img	len	max_area	num_cnt	
531	11.667593	0.011300	0.045755	0.045755	531	360	0.042519	21	0.045
532	5.318527	0.001477	0.020857	0.020857	532	256	0.003426	14	0.020
533	4.768578	0.000778	0.018700	0.018700	533	603	0.141384	198	0.018
534	109.992847	0.001993	0.804628	0.525771	534	256	0.052612	111	0.633
535	105.444226	0.002133	0.802869	0.547219	535	256	0.015259	73	0.645
536	10.283626	0.001660	0.040328	0.040328	536	520	0.005555	134	0.040
537	12.737670	0.012654	0.049952	0.049952	537	360	0.024618	20	0.049
538	3.725769	0.002308	0.014611	0.014611	538	256	0.004410	8	0.014
539	18.685562	0.001206	0.073277	0.073277	539	256	0.003036	50	0.073
540	16.692749	0.002115	0.065462	0.065462	540	256	0.007034	24	0.065
541	9.459320	0.001871	0.037095	0.037095	541	256	0.008713	35	0.037
542	11.870787	0.012394	0.046552	0.046552	542	360	0.045467	22	0.046
543	12.611875	0.011758	0.049458	0.049458	543	360	0.030096	24	0.049
544	16.025085	0.002214	0.062843	0.062843	544	256	0.003166	8	0.062
545	18.036499	0.001205	0.070731	0.070731	545	256	0.003441	16	0.070
546	13.798157	0.001833	0.054110	0.054110	546	256	0.005379	14	0.054
547	20.384412	0.006652	0.079939	0.079939	547	256	0.113544	24	0.079
548	18.372604	0.002701	0.072049	0.072049	548	256	0.004974	16	0.072
549	5.101028	0.001887	0.020004	0.020004	549	256	0.003365	11	0.020
550	5.940491	0.002115	0.023296	0.023296	550	256	0.004662	10	0.023
551	10.402206	0.001809	0.040793	0.040793	551	256	0.005920	31	0.040
552	4.996063	0.002335	0.019592	0.019592	552	256	0.003830	7	0.019
553	4.743835	0.002055	0.018603	0.018603	553	256	0.003914	10	0.018
554	10.327932	0.013414	0.040502	0.040502	554	360	0.048264	19	0.040
555	8.276042	0.001775	0.032455	0.032455	555	520	0.004642	113	0.032
556	13.301880	0.002986	0.052164	0.052164	556	256	0.008171	52	0.052
557	11.551404	0.011880	0.045300	0.045300	557	360	0.025058	19	0.045
558	8.408935	0.011111	0.032976	0.032976	558	360	0.023954	19	0.032
559	9.683364	0.011822	0.037974	0.037974	559	360	0.042052	22	0.037

560 rows × 13 columns

In [83]:
```
from sklearn.cluster import KMeans

# train seperately
input_x = np.array(df[['max_area','average_area','num_cnt','average','wid',
'len']])

fkmeans = KMeans(n_clusters = 3).fit(input_x)

df['flabel'] = fkmeans.labels_

input_c = np.array(df[['r','g','b']])

ckmeans = KMeans(n_clusters = 3).fit(input_c)

df['clabel'] = ckmeans.labels_

# and then make an combination
df['cflabel'] = 3 *df['flabel']

df['cflabel'] = df['cflabel'] + df['clabel']

df['cflabel'].hist()
plt.show()
df['cflabel'].values
```




```
Out[83]: array([0, 0, 1, 2, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0,
                8, 0, 8, 0, 0, 0, 3, 0, 0, 1, 0, 2, 0, 0, 1, 0, 1, 1, 0, 3, 0, 0, 3,
                0, 3, 0, 1, 0, 0, 1, 3, 0, 2, 3, 0, 2, 0, 0, 3, 0, 3, 0, 8, 0, 0, 0,
                8, 3, 0, 0, 0, 0, 3, 2, 0, 0, 0, 1, 0, 0, 2, 0, 0, 3, 0, 0, 6, 3, 3,
                3, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 3, 8, 0, 0, 3,
                0, 0, 0, 2, 3, 0, 3, 0, 3, 1, 0, 3, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                2, 1, 0, 0, 3, 0, 3, 2, 0, 0, 0, 8, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1,
                0, 0, 0, 0, 1, 0, 0, 0, 3, 3, 1, 3, 0, 0, 1, 2, 8, 0, 0, 3, 1, 3, 3,
                0, 0, 1, 3, 3, 0, 1, 0, 0, 0, 3, 0, 1, 0, 0, 0, 0, 1, 1, 3, 1, 3, 0,
                0, 1, 3, 8, 3, 1, 2, 3, 0, 0, 0, 0, 0, 1, 6, 3, 0, 8, 3, 0, 0, 0, 2,
                0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 3, 0, 0,
                1, 0, 3, 0, 8, 1, 0, 8, 1, 3, 3, 0, 0, 0, 1, 0, 0, 0, 3, 3, 0, 0, 0,
                0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 3, 3, 3, 0, 0, 0, 1, 0, 1, 0,
                3, 0, 0, 3, 3, 0, 1, 1, 2, 3, 0, 0, 1, 0, 0, 8, 0, 0, 3, 2, 0, 1, 0,
                0, 0, 0, 3, 1, 0, 0, 0, 0, 0, 0, 0, 0, 3, 2, 8, 0, 1, 3, 3, 0, 1,
                0, 0, 0, 0, 1, 3, 0, 3, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 3, 8, 3, 0,
                0, 1, 0, 0, 3, 1, 0, 0, 8, 0, 0, 0, 2, 0, 0, 1, 2, 0, 3, 1, 3, 0, 3,
                0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 3, 2, 1, 0,
                0, 0, 6, 0, 0, 0, 0, 1, 0, 0, 3, 2, 0, 3, 1, 0, 0, 0, 3, 0, 3, 1, 1,
                0, 3, 1, 3, 0, 0, 0, 1, 0, 3, 0, 0, 1, 0, 0, 1, 3, 0, 1, 0, 1, 2, 0,
                3, 0, 0, 1, 0, 0, 0, 3, 1, 3, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0,
                3, 0, 0, 0, 1, 0, 0, 0, 2, 3, 0, 3, 0, 3, 0, 0, 1, 1, 0, 0, 0, 0, 0,
                1, 0, 0, 0, 1, 3, 0, 1, 0, 3, 0, 0, 8, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0,
                6, 0, 0, 0, 6, 1, 1, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 3, 0, 0, 0, 0])
```

Segmentation: Separating Individual Objects

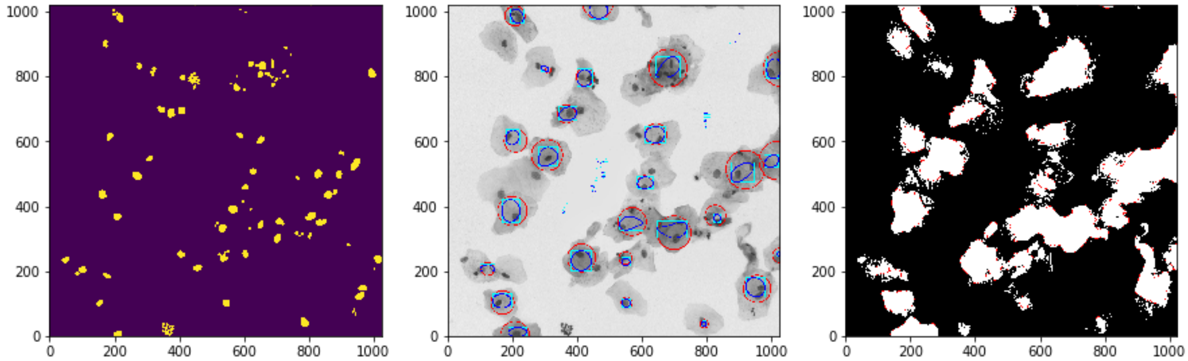
- The function separate_obj separates the objects in an image after a thresholding method has been applied
- The function convert2runlength finds the objects in an image (1 corresponds to object, 0 to background) and finds runs of continuous object pixels
- The function rle generates a dataframe of images in run-length format. This is the output format required by the Kaggle competition

In [38]:
```
## STEP 3: Separate individual objects and encode in run-length format

# separate objects in image into individual masks
def separate_obj(img_masked):
    labels, nlabels = ndimage.label(img_masked)

    label_arrays = []
    for label_num in range(1, nlabels+1):
        label_mask = np.where(labels == label_num, 1, 0)
        label_arrays.append(label_mask)
    return labels, nlabels, label_mask

# convert path to run-length encoding (RLE) output format
def convert2runlength(x):
    obj = np.where(x.T.flatten()==1)[0] #1 corresponds to object, 0 to backgro
und
    run_lengths = []
    prev = -2
    for b in obj: # find continuous set of object pixels
        if (b>prev+1): run_lengths.extend((b+1, 0))
        run_lengths[-1] += 1
        prev = b
    return " ".join([str(i) for i in run_lengths])

def rle(img_masked, im_id):
    (labels, nlabels, label_mask) = separate_obj(img_masked)
    im_df = pd.DataFrame()
    for label_num in range(1, nlabels+1):
        label_mask = np.where(labels == label_num, 1, 0)
        if label_mask.flatten().sum() > 10:
            rle = convert2runlength(label_mask)
            s = pd.Series({'ImageId': im_id, 'EncodedPixels': rle})
            im_df = im_df.append(s, ignore_index=True)
    return im_df
```

In [39]:
```
# Function to contour segment images
def contouring(img_float32, borderSize, gap, draw='off'):
    img = float2int8(img_float32[:, :, :3])

    # perform a BGR->HSV conversion and use the V channel for processing
    hsv = cv2.cvtColor(img, cv2.COLOR_BGR2HSV)

    # threshold, apply morphological closing, then take the distance transfo
rm (dist)
    th, bw = cv2.threshold(float2int8( hsv[:, :, 2] ), 0, 255, cv2.THRESH_BI
NARY | cv2.THRESH_OTSU)
    kernel = cv2.getStructuringElement(cv2.MORPH_ELLIPSE, (3, 3))
    morph = cv2.morphologyEx(bw, cv2.MORPH_CLOSE, kernel)
    dist = cv2.distanceTransform(morph, cv2.DIST_L2, cv2.DIST_MASK_PRECISE)
    distborder = cv2.copyMakeBorder(dist, borderSize, borderSize, borderSize
, borderSize, cv2.BORDER_CONSTANT | cv2.BORDER_ISOLATED, 0)

    # create a template, take its distance transform and use it as the templ
ate (temp)
    kernel2 = cv2.getStructuringElement(cv2.MORPH_ELLIPSE, (2*(borderSize-ga
```

```
p)+1, 2*(borderSize-gap)+1))
    kernel2 = cv2.copyMakeBorder(kernel2, gap, gap, gap, gap, cv2.BORDER_CON
STANT | cv2.BORDER_ISOLATED, 0)
    distTempl = cv2.distanceTransform(kernel2, cv2.DIST_L2, cv2.DIST_MASK_PR
ECISE)

    # template matching (dist*temp)
    nxcor = cv2.matchTemplate(distborder, distTempl, cv2.TM_CCOEFF_NORMED)

    # find local maxima of the resulting image, positions correspond to circ
le centers and values correspond to radii
    mn, mx, _, _ = cv2.minMaxLoc(nxcor)

    # thresholdig template matched image
    th, peaks = cv2.threshold(nxcor, mx*0.5, 255, cv2.THRESH_BINARY)
    peaks8u = cv2.convertScaleAbs(peaks)
    _, contours, _ = cv2.findContours(peaks8u, cv2.RETR_CCOMP, cv2.CHAIN_APP
ROX_SIMPLE)
    # peaks8u = cv2.convertScaleAbs(peaks)    # to use as mask

    # detecting circles as local maxima
#     if draw == 'on':
    for i in range(len(contours)):
        x, y, w, h = cv2.boundingRect(contours[i])
        _, mx, _, mxloc = cv2.minMaxLoc(dist[y:y+h, x:x+w], peaks8u[y:y+h, x
:x+w])
        cv2.circle(img, (int(mxloc[0]+x), int(mxloc[1]+y)), int(mx), (255, 0
, 0), 2)
        cv2.rectangle(img, (x, y), (x+w, y+h), (0, 255, 255), 2)
        cv2.drawContours(img, contours, i, (0, 0, 255), 2)

    img_contoured = img

    return img_contoured

#### TESTING
(img, mask) = load_zipped_img(path+'/stage1_train.zip', 177)
#177
img_guess, markers, sure_bg, sure_fg, uncertain = watershed(img)

# one way of determining borderSize and gap
num_markers = np.max(markers)
obj_size = []
for i in range(1, num_markers):
    obj_size.append(len(markers[markers==i]))

min_size = min(a for a in obj_size)
max_size = max(a for a in obj_size)
avg_size = np.sum(obj_size)/num_markers

borderSize = int(np.sqrt(5000))
gap = int(borderSize/10)

img_contoured = contouring(img, borderSize, gap, draw='off')

fig, ax = plt.subplots(1,3, figsize = (15,15))
```

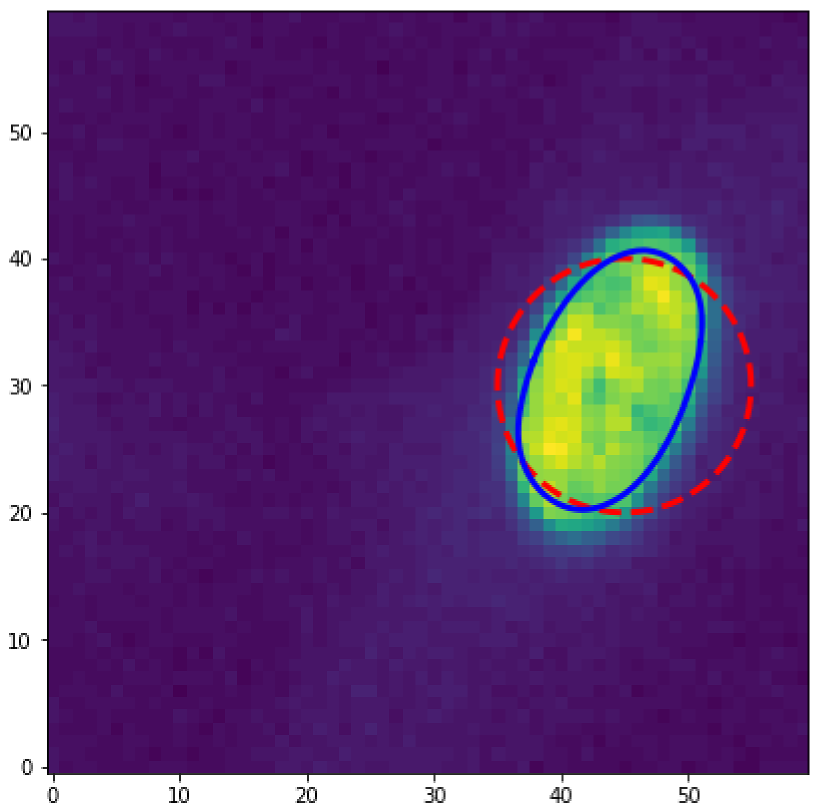
```
ax[0].imshow(sum(mask), origin='lower')
ax[1].imshow(img_contoured, origin='lower')
ax[2].imshow(img_guess, origin='lower')
plt.show()
```



Active Contour Modeling

- This method applies level set methods for nucleus segmentation

In [24]:
```
from skimage.segmentation import active_contour
from skimage.filters import gaussian

(img, mask) = load_zipped_img(path+'/stage1_train.zip', 1)
img = grayscale(img)[100:160,100:160]

s = np.linspace(0, 2*np.pi, 400)
x = 45 + 10*np.cos(s)
y = 30 + 10*np.sin(s)
init = np.array([x, y]).T

snake = active_contour(gaussian(img, 3), init, alpha=0.015, beta=10, gamma=
0.001)
fig, ax = plt.subplots(figsize=(7, 7))
ax.imshow(img, origin = 'lower')
ax.plot(init[:, 0], init[:, 1], '--r', lw=3)
ax.plot(snake[:, 0], snake[:, 1], '-b', lw=3)
#ax.set_xticks([]), ax.set_yticks([])
#ax.axis([0, img.shape[1], img.shape[0], 0])
plt.show()
```



Data Shape Manipulation

- The function one_index takes an image (2d array) and converts it to a 1d array. They are indexed from top to bottom then left to right
- The function pad_normalize helps account for variation in image sizes. It determines the maximum length in a set of one-indexed images and "pads" all other one-indexed images with zeros so that all images have the same length.

In [40]:
```
# one-indexes a 2d array into 1d, top down then left right, output is np 1d ar
ray
def one_index(arr2d):
    h, w = arr2d.shape[0:2]

    arr1d = []
    for col in range(0, w):
        for row in range(0, h):
            arr1d.append(arr2d[row][col])
    return np.array(arr1d)

# pads all vectors in array to have max_len, returns np array
def pad_normalize(array, max_len):
    for i in range(0, len(array)):
        vec = array[i]
        if len(vec) < max_len:
            array[i] = np.concatenate(( np.array(vec).reshape(1,-1), np.zeros
((1, (max_len-len(vec)))) ), axis=1)
        else:
            array[i] = np.array(vec).reshape(1,-1)
    return np.array(array)
```

In [35]:
```
#Separate the cells
```

Training a Model

- X = a vector of the one-indexed images in the training set
- Y = a vector containing the sum of the one-indexed masks for each image (The correct nuclei)
- Currently fits a Random Forest Classifier with a maximum depth of 4. The feature vector contains the following information:
    1. The grayscale pixel intensity (continuous)
    2. The watershed prediction for a pixel (discrete)
    3. The magnitude of the gradient of pixel intensity (calculated using the Sobel operator) 4-6. The intensity for the rgb color channels respectively (continuous)

Model Validation

- Tests the performance of the model
- Uses cross-validation for tuning of hyperparameters?
- Uses confusion matrix to quantify types of errors (fp, fn, tp, tn)

In [53]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier

# Not rigorous but I picked a few images to train on - it went pretty well

n_samples = [0, 19, 50, 100, 149, 150, 175, 177, 200, 250, 300, 350, 400, 51
0, 560, 650]
#n_samples = range(0,560)
x_train = np.zeros(7).reshape(1,7) # predicted segmentation using Otsu's thr
esholding

y_train = np.zeros(1) # "correct" segmentation from sum of masks

max_len = 0
conm = []
acc = []
for i in n_samples:
    (img, masks) = load_zipped_img(path+'/stage1_train.zip', i) # Loads imag
e and associated masks

    print(i)
    (img_guess, markers, sure_bg, sure_fg, uncertain) = watershed(img)

    intensity=grayscale(img)
    #img_guess = otsu(intensity)
    img_guess=grayscale(img_guess)
    #img_guess = np.dot(0,intensity)
    laplac = laplace(grayscale(img))[uncertain==255].reshape(-1,1)
    fil = sobel(grayscale(img))[uncertain==255].reshape(-1,1)
    #fil = sobel(grayscale(img)).reshape(-1,1)
    intensity_raw = intensity[uncertain==255].reshape(-1,1)
    #intensity_raw = intensity.reshape(-1,1)
    watershed_raw = img_guess[uncertain==255].reshape(-1,1)
    #watershed_raw = img_guess.reshape(-1,1)

    img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    ch1,ch2,ch3 = cv2.split(img3)
    #ch1 = ch1.reshape(-1,1)
    #ch2 = ch2.reshape(-1,1)
    #ch3 = ch3.reshape(-1,1)

    ch1 = ch1[uncertain==255].reshape(-1,1)
    ch2 = ch2[uncertain==255].reshape(-1,1)
    ch3 = ch3[uncertain==255].reshape(-1,1)

    feature = np.concatenate((intensity_raw,watershed_raw, fil, laplac, ch1,
 ch2, ch3), axis = 1) # Features include grayscale intensity, watershed, sob
```

```
el, rgb channels


    y_raw = sum(masks)
    y_raw = y_raw[uncertain==255].reshape(-1,1)


    x_train = np.append(x_train,feature).reshape(-1,7)
    y_train = np.append(y_train,y_raw).reshape(-1,1)


Xtrain, Xtest, ytrain, ytest = train_test_split(x_train,y_train)
# Kept a split training set around but not needed

#clf = svm.SVC(C = 1.0)
clf = RandomForestClassifier(max_depth=5, random_state=0)
%time clf.fit(Xtrain, ytrain[:,0]) #599 ms for a training set of this size!


    #y_pred = clf.predict(Xtest)
    #cm = confusion_matrix(ytest, y_pred)
    #print(cm)
    #conm.append(cm)
    #accuracy = sklearn.metrics.accuracy_score(ytest, y_pred)
    #print(accuracy)
    #acc.append(accuracy)

    #(img_guess, markers, sure_bg, sure_fg, unknown, reduced_area) = watersh
ed(img)

    #fig, ax = plt.subplots(1,4, figsize = (10,10))

    #ax[0].imshow(sum(masks), origin='lower')
    #ax[1].imshow(grayscale(img), origin='lower')
    #ax[2].imshow(output, origin='lower')
    #ax[3].imshow(img_guess, origin='lower')
    #plt.show()

#A = np.array(acc)
#Avg_acc = np.mean(A)
#print(Avg_acc)
```

```
0
19
50
100
149
150
175
177
200
250
300
350
400
510
560
650
Wall time: 4.87 s
```

```
Out[53]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=5, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                     oob_score=False, random_state=0, verbose=0, warm_start=False)
```

In [28]:
```
# Random Forest Except using HSV instead of RGB

# Not rigorous but I picked a few images to train on - it went pretty well
from sklearn.ensemble import RandomForestClassifier
n_samples = [0, 19, 50, 100, 149, 150, 175, 177, 200, 250, 300, 350, 400, 51
0, 560, 650]
#n_samples = range(0,560)
x_train = np.zeros(6).reshape(1,6)

y_train = np.zeros(1) # "correct" segmentation from sum of masks

max_len = 0
conm = []
acc = []
for i in n_samples:
    (img, masks) = load_zipped_img(path+'/stage1_train.zip', i) # loads imag
e and associated masks

    print(i)
    (img_guess, markers, sure_bg, sure_fg, uncertain) = watershed(img)

    intensity=grayscale(img)
    #img_guess = otsu(intensity)
    img_guess=grayscale(img_guess)
    #img_guess = np.dot(0,intensity)
    fil = sobel(grayscale(img))[uncertain==255].reshape(-1,1)
    #fil = sobel(grayscale(img)).reshape(-1,1)
    intensity_raw = intensity[uncertain==255].reshape(-1,1)
    #intensity_raw = intensity.reshape(-1,1)
    watershed_raw = img_guess[uncertain==255].reshape(-1,1)
    #watershed_raw = img_guess.reshape(-1,1)
```

```
    img_cv = float2int8(img[:, :, :3])

    # perform a BGR->HSV conversion and use the V channel for processing
    hsv = cv2.cvtColor(img_cv, cv2.COLOR_BGR2HSV)

    #img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    ch1,ch2,ch3 = cv2.split(hsv)
    #ch1 = ch1.reshape(-1,1)
    #ch2 = ch2.reshape(-1,1)
    #ch3 = ch3.reshape(-1,1)

    print(ch1.shape)

    ch1 = ch1[uncertain==255].reshape(-1,1)
    ch2 = ch2[uncertain==255].reshape(-1,1)
    ch3 = ch3[uncertain==255].reshape(-1,1)

    feature = np.concatenate((intensity_raw,watershed_raw, fil, ch1, ch2, ch
3), axis = 1) # Features include grayscale intensity, watershed, sobel, rgb
 channels


    y_raw = sum(masks)
    y_raw = y_raw[uncertain==255].reshape(-1,1)


    x_train = np.append(x_train,feature).reshape(-1,6)
    y_train = np.append(y_train,y_raw).reshape(-1,1)


Xtrain, Xtest, ytrain, ytest = train_test_split(x_train,y_train)
# Kept a split training set around but not needed

#s_v = svm.SVC(C = 1.0)
clf = RandomForestClassifier(max_depth=5, random_state=0)
%time clf.fit(Xtrain, ytrain[:,0]) #599 ms for a training set of this size!


    #y_pred = clf.predict(Xtest)
    #cm = confusion_matrix(ytest, y_pred)
    #print(cm)
    #conm.append(cm)
    #accuracy = sklearn.metrics.accuracy_score(ytest, y_pred)
    #print(accuracy)
    #acc.append(accuracy)

    #(img_guess, markers, sure_bg, sure_fg, unknown, reduced_area) = watersh
ed(img)

    #fig, ax = plt.subplots(1,4, figsize = (10,10))

    #ax[0].imshow(sum(masks), origin='lower')
    #ax[1].imshow(grayscale(img), origin='lower')
    #ax[2].imshow(output, origin='lower')
    #ax[3].imshow(img_guess, origin='lower')
    #plt.show()
```

```
#A = np.array(acc)
#Avg_acc = np.mean(A)
#print(Avg_acc)
```

```
0
(256, 256)
19
(256, 256)
50
(256, 256)
100
(256, 256)
149
(1024, 1024)
150
(256, 256)
175
(256, 320)
177
(1024, 1024)
200
(256, 256)
250
(520, 696)
300
(256, 256)
350
(520, 696)
400
(256, 256)
510
(256, 320)
560
(256, 256)
650
(256, 256)
Wall time: 8.93 s
```

Out[28]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=5, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
```

In [55]:
```
# Testing the classifier on the remaining images
acc = []
for i in range(0,560):
    (img, masks) = load_zipped_img(path+'/stage1_train.zip', i)

    (img_guess, markers, sure_bg, sure_fg, unknown) = watershed(img)
    intensity = grayscale(img)
    shap = intensity.shape
    intensity_raw = intensity.reshape(-1,1)
    #watershed_raw = img_guess[unknown==255].reshape(-1,1)
    watershed_raw = grayscale(img_guess).reshape(-1,1)
    fil = sobel(grayscale(img)).reshape(-1,1)
    laplac = laplace(grayscale(img)).reshape(-1,1)
    #img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    hsv = cv2.cvtColor(img, cv2.COLOR_BGR2HSV)

    #img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    ch1,ch2,ch3 = cv2.split(hsv)


    #ch1,ch2,ch3 = cv2.split(img3)
    ch1 = ch1.reshape(-1,1)
    ch2 = ch2.reshape(-1,1)
    ch3 = ch3.reshape(-1,1)
    #print(ch1.shape)
    #print(intensity_raw.shape)
    feature = np.concatenate((intensity_raw,watershed_raw, fil, laplac, ch1,
 ch2, ch3), axis = 1)

    yp = clf.predict(feature)
    y_real = sum(masks).reshape(-1,1)
    accuracy = sklearn.metrics.accuracy_score(y_real, yp)
    precision = sklearn.metrics.precision_score(y_real, yp)
    f1 = sklearn.metrics.f1_score(y_real, yp)
    print(i, accuracy, precision, f1)
    acc.append([accuracy, precision, f1])

    #output = yp.reshape(shap[0],shap[1])

precision = np.mean(np.array(acc)[:,1])
accuracy = np.mean(np.array(acc)[:,0])
f1 = np.mean(np.array(acc)[:,2])
print('The average precision of the model is {}%'.format(precision*100))
print('The average accuracy of the model is {}%'.format(accuracy*100))
print('The average f1-score of the model is {}%'.format(f1*100))
```

```
0 0.975708007813 0.894091187896 0.846005029986
1 0.988327026367 0.898442367601 0.91876393756
2 0.714721679688 0.89941083489 0.348807400802
3 0.835083007813 0.676328502415 0.212244897959
4 0.934167480469 0.728658536585 0.0814171350707
5 0.979019165039 0.692124105012 0.808362369338
6 0.93537902832 0.905896242795 0.860337037892
7 0.97013117284 0.979405737705 0.936774193548
8 0.97004699707 0.229555236729 0.245870149827
9 0.97112654321 0.971032041729 0.943552766548
10 0.952330246914 0.891814006544 0.905817427892
11 0.911483041454 0.823177758571 0.741084165478
12 0.961273193359 0.831437032419 0.893700787402
13 0.974761962891 0.786783854167 0.853912736266
14 0.954444444444 0.947524069267 0.907134767837
15 0.959701538086 0.432483474976 0.409568522245
16 0.985092163086 0.8735395189 0.886434964547
17 0.961404320988 0.989761290135 0.93171331058
18 0.991958618164 0.655839668279 0.782680412371
19 0.980895996094 0.153968253968 0.236585365854
20 0.994262695313 0.702702702703 0.824626865672
21 0.844473916888 0.826363929306 0.703184982071
22 0.963163580247 0.928815142046 0.915498442368
23 0.945902824402 0.297616653258 0.454970838898
24 0.980590820313 0.406043437205 0.57486631016
25 0.976623535156 0.328990820129 0.469781527147
26 0.9609375 0.685367702805 0.679358717435
27 0.953964233398 0.875250166778 0.813038359051
28 0.980194091797 0.5842994369 0.731040198923
29 0.989680039788 0.356158992523 0.492182188987
30 0.980484008789 0.359129994942 0.526120785476
31 0.96662902832 0.678074109039 0.724316147737
32 0.88740234375 0.936708860759 0.074267362505
33 0.925079345703 0.933016595289 0.85028662032
34 0.766613769531 0.86209439528 0.328474588177
35 0.973449707031 0.763193302437 0.854393305439
36 0.963047839506 0.927003019554 0.929605620967
37 0.642309570313 0.589333333333 0.0148601398601
38 0.919174194336 0.922604422604 0.718469306404
39 0.903967285156 0.979591836735 0.046539813356
40 0.786584472656 0.873429200674 0.435431265541
41 0.972396850586 0.822108626198 0.876729131175
42 0.799718169761 0.791876689313 0.642161073428
43 0.967662037037 0.978982914168 0.948819714973
44 0.978118896484 0.749801587302 0.840524911032
45 0.987792882405 0.960583574393 0.945317721613
46 0.991485595703 0.760485093482 0.843609865471
47 0.912350795756 0.623476064002 0.752109902476
48 0.933013916016 0.677920324105 0.578452083733
49 0.888146972656 0.954751131222 0.0440271257173
50 0.99267578125 0.722747321991 0.826964671954
51 0.976058959961 0.584280012281 0.708093023256
52 0.4291015625 0.387334315169 0.0219991635299
53 0.962051391602 0.874840829739 0.774036452181
54 0.956913580247 0.931550646708 0.919866827392
55 0.913537597656 0.803687265278 0.399287592231
56 0.91962035809 0.817164754333 0.836117198371
```

```
57 0.974845679012 0.940385260256 0.939335293461
58 0.867932128906 0.954150197628 0.400974475389
59 0.986190795898 0.898560209424 0.752122706108
60 0.993850708008 0.8059785674 0.876418276602
61 0.960734416446 0.909725721054 0.935419516385
62 0.996688842773 0.848167539267 0.8818726184
63 0.792561892131 0.353397661714 0.155690508322
64 0.883928175571 0.788875799394 0.641639860379
65 0.972061157227 0.26646452707 0.414501558878
66 0.968310185185 0.948757918477 0.933022391102
67 0.980072021484 0.317435082141 0.478434504792
68 0.97477722168 0.480572597137 0.630449362844
69 0.966395378113 0.429607314254 0.581970033099
70 0.978395778073 0.953760527819 0.929762942069
71 0.983703613281 0.867280334728 0.906578026592
72 0.944737654321 0.886381187256 0.90856165258
73 0.972946166992 0.546119235096 0.68658299452
74 0.931533813477 0.639653035936 0.534977717898
75 0.96844882847 0.933527202784 0.934559729505
76 0.926232910156 1.0 0.0360504067634
77 0.991027832031 0.927508705286 0.908808933002
78 0.997512817383 0.894383906119 0.92903787549
79 0.981369018555 0.520582120582 0.672214765101
80 0.844799804688 0.379381443299 0.0281302553126
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409 0.98469543457 0.897172236504 0.900466408653
410 0.985820070734 0.90490625 0.918599118104
411 0.830810546875 0.989949748744 0.0537957400328
412 0.960974121094 0.984 0.0714493174557
413 0.957461419753 0.903997727757 0.902315856619
414 0.94091796875 0.70079787234 0.655822222222
415 0.974655151367 0.446343779677 0.530923467947
416 0.757319273653 0.162502702898 0.279326018445
417 0.954212962963 0.98658156993 0.927073860145
418 0.990875244141 0.621827411168 0.766223612197
419 0.953460693359 0.877898444379 0.796856267484
420 0.913513183594 0.964830412019 0.749447440545
421 0.563427734375 0.660377358491 0.0019534520288
422 0.988372802734 0.775072224515 0.831341301461
423 0.975402832031 0.3870789619 0.465162574652
424 0.977641467728 0.926112288136 0.912062595088
425 0.87060546875 0.860032804811 0.372484016102
426 0.992431640625 0.697836706211 0.801282051282
427 0.949990844727 0.870593069443 0.795031832793
428 0.704418945313 0.869932432432 0.0408017746791
429 0.993057250977 0.855797819623 0.883601944231
430 0.963146972656 0.666077217801 0.599549011805
431 0.981536865234 0.55335661622 0.702117183653
432 0.971562776304 0.940893852111 0.939352512051
433 0.960779320988 0.930239601561 0.915801156223
434 0.974300950486 0.955430821991 0.938786255372
435 0.589453125 0.82 0.0024322240019
436 0.700109863281 0.846153846154 0.0044575920898
437 0.974319458008 0.522310756972 0.609059233449
438 0.968893678161 0.955237952388 0.940615472259
439 0.792700195313 0.532110091743 0.0134774021146
440 0.962276193634 0.853292769122 0.89053166668
441 0.945205688477 0.859563846558 0.879346840036
442 0.976501464844 0.942809083263 0.879215686275
443 0.9931640625 0.715249662618 0.82554517134
444 0.831225585937 0.680888114933 0.404308487721
445 0.991790771484 0.648838845883 0.774139378673
446 0.963168656057 0.899867294004 0.924870933562
447 0.970260620117 0.886743371686 0.900940279543
448 0.996185302734 0.911869587366 0.934725848564
449 0.880554199219 0.739583333333 0.0282053828583
450 0.970038580247 0.971872227152 0.944210571687
451 0.934182098765 0.942658175417 0.895152170707
452 0.865197753906 0.292307692308 0.00342929338507
453 0.949017333984 0.877311503206 0.798567570175
454 0.833009259259 0.253531813419 0.393373696603
455 0.84462890625 0.513513513514 0.00297665674448
```

```
456 0.962265014648 0.740278796772 0.765481270744
457 0.9966796875 0.135135135135 0.0354609929078
458 0.919372558594 0.772087451333 0.4383980954
459 0.976776123047 0.787641705253 0.866350544433
460 0.982070623342 0.765653623937 0.833994218322
461 0.994201660156 0.901371894698 0.92750858451
462 0.963333333333 0.91401025641 0.903630095315
463 0.814575195313 0.70985915493 0.0321141837645
464 0.943788580247 0.903557235631 0.911007683757
465 0.988815307617 0.871180842279 0.852008883505
466 0.938981481481 0.740318017754 0.793330545683
467 0.971181476569 0.90449168279 0.930345002605
468 0.755456542969 0.875130981488 0.333455331892
469 0.934449602122 0.913120084803 0.843107689866
470 0.992279052734 0.752234359484 0.856900452489
471 0.987533569336 0.827246827247 0.886606523248
472 0.994232177734 0.668711656442 0.801470588235
473 0.97787037037 0.986455498823 0.95744554573
474 0.992263793945 0.711622125544 0.818734358241
475 0.976608276367 0.585389298302 0.704453441296
476 0.959645061728 0.925379971974 0.929236347892
477 0.970565795898 0.418832761157 0.469617816882
478 0.945932802829 0.837917847205 0.870810996382
479 0.976104736328 0.567723342939 0.668079694786
480 0.978834876543 0.982708350207 0.946506230864
481 0.993637084961 0.875659050967 0.905291846468
482 0.951242283951 0.879327398615 0.887367876941
483 0.97858642794 0.924342159531 0.935313167735
484 0.99528503418 0.812457221081 0.884830413716
485 0.990203857422 0.907992368031 0.930278019114
486 0.972030639648 0.714285714286 0.822263162998
487 0.900646972656 0.341772151899 0.00659099231051
488 0.993774414063 0.708782742681 0.818505338078
489 0.981994628906 0.870024875622 0.904623343033
490 0.96369934082 0.730390951561 0.833181403829
491 0.811108398438 0.869141239383 0.263142857143
492 0.979313107869 0.941899194273 0.947932096834
493 0.98550154321 0.968732814832 0.963302931469
494 0.998903072502 0.961676646707 0.952889521775
495 0.944212962963 0.949732065687 0.88370970855
496 0.972897325376 0.931175265521 0.928914623629
497 0.977981567383 0.203056768559 0.278860569715
498 0.960067749023 0.493686354379 0.480856972823
499 0.793774414063 0.528535980149 0.0245958429561
500 0.995642089844 0.190082644628 0.114143920596
501 0.939666748047 0.570523507836 0.463937093275
502 0.952590942383 0.76380484115 0.722217255253
503 0.90837097168 0.950220750552 0.741420143823
504 0.969039916992 0.302684563758 0.307744796998
505 0.984237670898 0.862114248194 0.910461991852
506 0.76748046875 0.561403508772 0.0165220983065
507 0.992721557617 0.84632034632 0.867683772538
508 0.955612182617 0.809523809524 0.795587098588
509 0.970840454102 0.4186866461 0.498556809236
510 0.796362304688 0.802783109405 0.375673652695
511 0.98721540672 0.527100998175 0.679770226313
512 0.96612654321 0.991833328366 0.938120207488
```

```
513 0.710485839844 0.430769230769 0.00235561351113
514 0.953674316406 0.699757869249 0.695547533093
515 0.89932581786 0.890003214401 0.820125984874
516 0.990341186523 0.845546786922 0.825763831544
517 0.974258422852 0.82382892057 0.870360408822
518 0.940093994141 0.28285083157 0.435199338237
519 0.881393432617 0.927310596199 0.820861468968
520 0.967028625111 0.890575348611 0.922945791496
521 0.894607543945 0.584642233857 0.326606220142
522 0.979217529297 0.917647058824 0.364145658263
523 0.968170166016 0.497063903282 0.579774375504
524 0.996994018555 0.833898305085 0.882247459653
525 0.939590454102 0.714589371981 0.651343020696
526 0.918731689453 0.948353164339 0.805079783341
527 0.971572875977 0.648418156809 0.716740155086
528 0.97388117284 0.96717967736 0.948694241933
529 0.962735535358 0.895477699576 0.631329330811
530 0.952183641975 0.909995577178 0.913974762969
531 0.961041666667 0.912897770945 0.921639532538
532 0.996810913086 0.909254807692 0.935394126739
533 0.903479197305 0.283200946589 0.440977701932
534 0.689599609375 0.877218934911 0.0445630119486
535 0.807629394531 0.845010615711 0.0480821504077
536 0.974021883289 0.929026774331 0.948980367046
537 0.978279320988 0.970341035357 0.960313544149
538 0.993621826172 0.79854368932 0.862950819672
539 0.9716796875 0.736435501258 0.815396856972
540 0.974990844727 0.740240863787 0.813091572585
541 0.981842041016 0.841610500177 0.888576779026
542 0.965601851852 0.937087633805 0.938861155302
543 0.964359567901 0.986428909579 0.941994951715
544 0.980529785156 0.493899683687 0.631426920855
545 0.973007202148 0.423702149974 0.477400295421
546 0.976608276367 0.533198517021 0.673621460507
547 0.936413574219 0.878502577897 0.818647077255
548 0.970611572266 0.555474095797 0.702410383189
549 0.994216918945 0.828220858896 0.886831890116
550 0.992645263672 0.742441209406 0.846202935546
551 0.990676879883 0.931308093403 0.930780559647
552 0.991882324219 0.661301140174 0.787539936102
553 0.993133544922 0.774959525094 0.864539434076
554 0.96475308642 0.937917778352 0.934699945679
555 0.9752127542 0.914383205136 0.94630619415
556 0.937835693359 0.941780568895 0.862215909091
557 0.965470679012 0.902324985589 0.926430696894
558 0.963194444444 0.923262881613 0.918094714791
559 0.953302469136 0.941174757564 0.914386759089
The average precision of the model is 76.34429243351293%
The average accuracy of the model is 93.71913791606703%
The average f1-score of the model is 67.14543699222496%
```

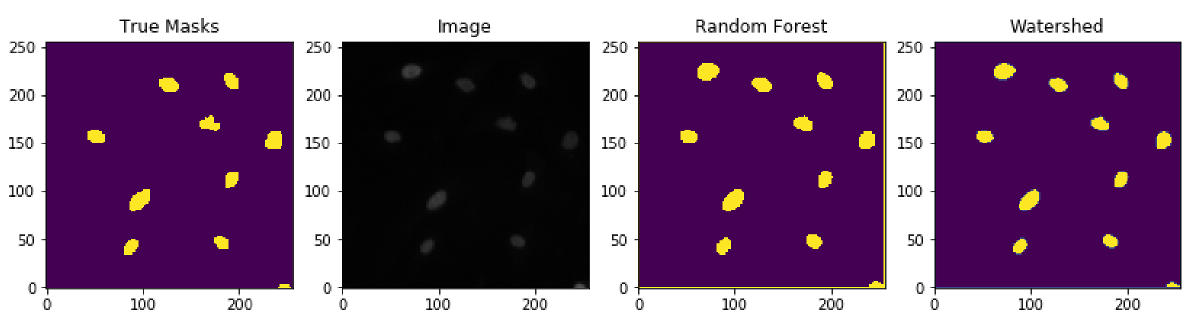
Working Example of the Code

- Demonstrates the methods involved using a smaller set of 30 training images
- Evaluates performance based on a confusion matrix and accuracy (compared to the true masks)

In [53]:
```
precision = np.mean(np.array(acc)[:,1])
accuracy = np.mean(np.array(acc)[:,0])
f1 = np.mean(np.array(acc)[:,2])
print('The average precision of the model is {}%'.format(precision*100))
print('The average accuracy of the model is {}%'.format(accuracy*100))
print('The average f1-score of the model is {}%'.format(f1*100))
```

```
The average precision of the model is 81.38706474131074%
The average accuracy of the model is 94.68844817046038%
The average f1-score of the model is 74.83144803204694%
```

In [42]:
```
for i in range(173,174):
    (img, masks) = load_zipped_img(path+'/stage1_train.zip', i)

    (img_guess, markers, sure_bg, sure_fg, uncertain) = watershed(img)

    intensity = grayscale(img)
    shap = intensity.shape
    intensity_raw = intensity.reshape(-1,1)
    #watershed_raw = img_guess[unknown==255].reshape(-1,1)
    watershed_raw = grayscale(img_guess).reshape(-1,1)
    fil = sobel(grayscale(img)).reshape(-1,1)

    img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    ch1,ch2,ch3 = cv2.split(img3)
    ch1 = ch1.reshape(-1,1)
    ch2 = ch2.reshape(-1,1)
    ch3 = ch3.reshape(-1,1)
    feature = np.concatenate((intensity_raw,watershed_raw, fil, ch1, ch2, ch3
), axis = 1)

    yp = clf.predict(feature)
    y_real = sum(masks).reshape(-1,1)

    labels, nlabels, label_mask = separate_obj(grayscale(yp.reshape(shap[0], s
hap[1])))

    #print(labels, nlabels, label_mask)
    #print(len(masks))

fig, ax = plt.subplots(1,4, figsize = (14,14))

ax[0].imshow(sum(masks), origin='lower')
ax[0].set_title('True Masks')
ax[1].imshow(img, origin='lower')
ax[1].set_title('Image')
ax[2].imshow(grayscale(yp.reshape(shap[0], shap[1])), origin='lower')
ax[2].set_title('Random Forest')
ax[3].imshow(grayscale(img_guess), origin='lower')
ax[3].set_title('Watershed')
plt.show()
```



In [46]:
```
# Compare mask by mask

def mask_by_mask_score(img, masks):
    mask_scores = []
    mask_num = len(masks)
    for i in range(0,mask_num):
        individual_mask = img[masks[i] == 1]
        score = np.sum(individual_mask)/individual_mask.size
        mask_scores.append(score)



    return mask_scores

print(mask_by_mask_score(grayscale(yp.reshape(shap[0], shap[1])),masks))
```

```
[0.89323843416370108, 0.97409326424870468, 0.9543568464730291, 0.919540229885
05746, 1.0, 0.98469387755102045, 0.96385542168674698, 0.95580110497237569, 0.
99521531100478466, 0.9285714285714286, 0.94545454545454544]
```

In [40]:
```
import numpy as np
from scipy.ndimage.morphology import distance_transform_edt as dtx
import scipy.ndimage.filters as filters

def ConvertMask(Mask):
    # convert binary mask to signed distance function
    Phi0 = dtx(1-Mask) - dtx(Mask) + Mask - 1/2
    return Phi0

def Kappa(Phi):
    dPhi = np.gradient(Phi)  # calculate gradient of level set image
    xdPhi = np.gradient(dPhi[1])
    ydPhi = np.gradient(dPhi[0])
    K = (xdPhi[1]*(dPhi[0]**2) - 2*xdPhi[0]*dPhi[0]*dPhi[1] +
         ydPhi[0]*(dPhi[1]**2)) / ((dPhi[0]**2 + dPhi[1]**2 + 1e-10)**(3/2))
    K *= (xdPhi[1]**2 + ydPhi[0]**2)**(1/2)
    return K

def Impulse(X, Epsilon):
    # Smooth dirac delta function.

    # calculate smoothed impulse everywhere
    Xout = (1 + np.cos(np.pi * X / Epsilon)) / (2 * Epsilon)

    # zero out values |x| > Epsilon
    Xout[np.absolute(X) > Epsilon] = 0

    return Xout

def ChanVese(I, Mask, Sigma, dt=1.0, Mu=0.2, Lambda1=1, Lambda2=1, It=100):

    # smoothed gradient of input image
    I = filters.gaussian_filter(I, Sigma, mode='constant', cval=0)
#    dsI = np.gradient(sI)
#    I = 1/(1 + dsI[0]**2 + dsI[1]**2)
```

```
    # generate signed distance map
    Phi = ConvertMask(Mask)

    # evolve level set function
    for i in range(0, It):

        # calculate interior and exterior averages
        C1 = np.sum(I[Phi > 0]) / (np.sum(Phi > 0) + 1e-10)
        C2 = np.sum(I[Phi <= 0]) / (np.sum(Phi <= 0) + 1e-10)
        Force = Lambda2 * (I - C2)**2 - Lambda1 * (I - C1)**2

        # curvature of image
        Curvature = Kappa(Phi)

        # evolve
        Phi += dt * Force / np.max(np.abs(Force)) + Mu*Curvature

    return Phi



print(ChanVese(grayscale(img),sum(masks),3))
```

```
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: RuntimeWa
rning: overflow encountered in square

C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:15: RuntimeWa
rning: overflow encountered in square
  from ipykernel import kernelapp as app
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:15: RuntimeWa
rning: overflow encountered in power
  from ipykernel import kernelapp as app
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:15: RuntimeWa
rning: invalid value encountered in true_divide
  from ipykernel import kernelapp as app
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:16: RuntimeWa
rning: overflow encountered in square
  app.launch_new_instance()
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:44: RuntimeWa
rning: invalid value encountered in greater
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:45: RuntimeWa
rning: invalid value encountered in less_equal
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: RuntimeWa
rning: overflow encountered in multiply

C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:14: RuntimeWa
rning: invalid value encountered in subtract

C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:15: RuntimeWa
rning: invalid value encountered in add
  from ipykernel import kernelapp as app
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:16: RuntimeWa
rning: overflow encountered in multiply
  app.launch_new_instance()
C:\Users\John\Anaconda3\lib\site-packages\numpy\lib\function_base.py:1768: Ru
ntimeWarning: invalid value encountered in subtract
  out[slice1] = (f[slice4] - f[slice2]) / (2. * dx[i])
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:15: RuntimeWa
rning: overflow encountered in multiply
  from ipykernel import kernelapp as app
```

```
[[ nan  nan  nan ...,  nan  nan  nan]
 [ nan  nan  nan ...,  nan  nan  nan]
 [ nan  nan  nan ...,  nan  nan  nan]
 ...,
 [ nan  nan  nan ...,  nan  nan  nan]
 [ nan  nan  nan ...,  nan  nan  nan]
 [ nan  nan  nan ...,  nan  nan  nan]]
```

```
C:\Users\John\Anaconda3\lib\site-packages\ipykernel_launcher.py:52: RuntimeWa
rning: invalid value encountered in true_divide
```

In [94]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier

# Not rigorous but I picked a few images to train on - it went pretty well

n_samples = [0, 19, 50, 100, 149, 150, 175, 177, 200, 250, 300, 350, 400, 51
0, 559]
#n_samples = range(0,560)
```

```
x_train = np.zeros(8).reshape(1,8) # predicted segmentation using Otsu's thr
esholding

y_train = np.zeros(1) # "correct" segmentation from sum of masks

max_len = 0
conm = []
acc = []
for i in n_samples:
    (img, masks) = load_zipped_img(path+'/stage1_train.zip', i) # Loads imag
e and associated masks

    print(i)
    (img_guess, markers, sure_bg, sure_fg, uncertain) = watershed(img)

    intensity=grayscale(img)
    #img_guess = otsu(intensity)
    img_guess=grayscale(img_guess)
    #img_guess = np.dot(0,intensity)
    laplac = laplace(grayscale(img))[uncertain==255].reshape(-1,1)
    fil = sobel(grayscale(img))[uncertain==255].reshape(-1,1)
    #fil = sobel(grayscale(img)).reshape(-1,1)
    intensity_raw = intensity[uncertain==255].reshape(-1,1)
    #intensity_raw = intensity.reshape(-1,1)
    watershed_raw = img_guess[uncertain==255].reshape(-1,1)
    #watershed_raw = img_guess.reshape(-1,1)
    #print(np.ones(len(watershed_raw)).shape)
    img_type = df['cflabel'][i]*np.ones(len(watershed_raw)).reshape(-1,1)
    img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    ch1,ch2,ch3 = cv2.split(img3)
    #ch1 = ch1.reshape(-1,1)
    #ch2 = ch2.reshape(-1,1)
    #ch3 = ch3.reshape(-1,1)

    ch1 = ch1[uncertain==255].reshape(-1,1)
    ch2 = ch2[uncertain==255].reshape(-1,1)
    ch3 = ch3[uncertain==255].reshape(-1,1)

    feature = np.concatenate((intensity_raw,watershed_raw, fil, laplac, ch1,
 ch2, ch3, img_type), axis = 1) # Features include grayscale intensity, wate
rshed, sobel, rgb channels


    y_raw = sum(masks)
    y_raw = y_raw[uncertain==255].reshape(-1,1)


    x_train = np.append(x_train,feature).reshape(-1,8)
    y_train = np.append(y_train,y_raw).reshape(-1,1)


Xtrain, Xtest, ytrain, ytest = train_test_split(x_train,y_train)
# Kept a split training set around but not needed

#clf = svm.SVC(C = 1.0)
clf = RandomForestClassifier(max_depth=6, random_state=0)
%time clf.fit(Xtrain, ytrain[:,0]) #599 ms for a training set of this size!
```

```
    #y_pred = clf.predict(Xtest)
    #cm = confusion_matrix(ytest, y_pred)
    #print(cm)
    #conm.append(cm)
    #accuracy = sklearn.metrics.accuracy_score(ytest, y_pred)
    #print(accuracy)
    #acc.append(accuracy)

    #(img_guess, markers, sure_bg, sure_fg, unknown, reduced_area) = watersh
ed(img)

    #fig, ax = plt.subplots(1,4, figsize = (10,10))

    #ax[0].imshow(sum(masks), origin='lower')
    #ax[1].imshow(grayscale(img), origin='lower')
    #ax[2].imshow(output, origin='lower')
    #ax[3].imshow(img_guess, origin='lower')
    #plt.show()

#A = np.array(acc)
#Avg_acc = np.mean(A)
#print(Avg_acc)
```

```
0
19
50
100
149
150
175
177
200
250
300
350
400
510
559
Wall time: 12.7 s
```

Out[94]:

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=6, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
```

In [95]:
```
# Testing the classifier on the remaining images
acc = []
for i in range(0,560):
    (img, masks) = load_zipped_img(path+'/stage1_train.zip', i)

    (img_guess, markers, sure_bg, sure_fg, unknown) = watershed(img)
    intensity = grayscale(img)
    shap = intensity.shape
    intensity_raw = intensity.reshape(-1,1)
    #watershed_raw = img_guess[unknown==255].reshape(-1,1)
    watershed_raw = grayscale(img_guess).reshape(-1,1)
    fil = sobel(grayscale(img)).reshape(-1,1)
    laplac = laplace(grayscale(img)).reshape(-1,1)
    img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    #hsv = cv2.cvtColor(img, cv2.COLOR_BGR2HSV)
    img_type = df['cflabel'][i]*np.ones(len(watershed_raw)).reshape(-1,1)
    img3 = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
    #ch1,ch2,ch3 = cv2.split(hsv)


    ch1,ch2,ch3 = cv2.split(img3)
    ch1 = ch1.reshape(-1,1)
    ch2 = ch2.reshape(-1,1)
    ch3 = ch3.reshape(-1,1)
    #print(ch1.shape)
    #print(intensity_raw.shape)
    feature = np.concatenate((intensity_raw,watershed_raw, fil, laplac, ch1, c
h2, ch3, img_type), axis = 1)

    yp = clf.predict(feature)
    y_real = sum(masks).reshape(-1,1)
    accuracy = sklearn.metrics.accuracy_score(y_real, yp)
    precision = sklearn.metrics.precision_score(y_real, yp)
    f1 = sklearn.metrics.f1_score(y_real, yp)
    print(i, accuracy, precision, f1)
    acc.append([accuracy, precision, f1])

    #output = yp.reshape(shap[0],shap[1])

precision = np.mean(np.array(acc)[:,1])
accuracy = np.mean(np.array(acc)[:,0])
f1 = np.mean(np.array(acc)[:,2])
print('The average precision of the model is {}%'.format(precision*100))
print('The average accuracy of the model is {}%'.format(accuracy*100))
print('The average f1-score of the model is {}%'.format(f1*100))
```

```
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The average precision of the model is 64.76129213178552%
The average accuracy of the model is 85.67608686011847%
The average f1-score of the model is 68.71381375457058%
```
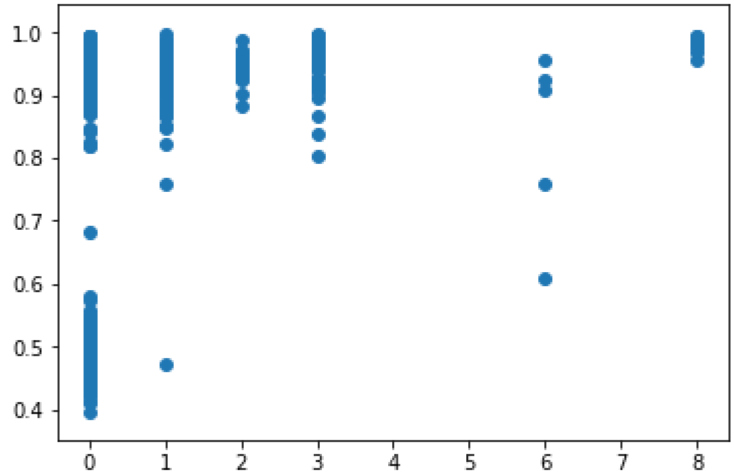

In [114]:
```
fig, ax = plt.subplots()
zz = df['cflabel'].values
acc_vec = np.array(acc)

ax.scatter(zz, acc_vec[:,0])
plt.show()

FDIV = 3
CDIV = 3
for t in range(FDIV*CDIV):
    print('for type=>'+str(t))
    fig,ax= plt.subplots(2,10,figsize=(32,5))

    n=0
    for i in range(2):
        for j in range(10):
            if n < len(df[df['cflabel']==t].index):
                sn = df[df['cflabel']==t].index[n]
                (img, masks) = load_zipped_img(path+'/stage1_train.zip', sn)
                ax[i,j].imshow(img)
                n = n+1
    plt.show()
```



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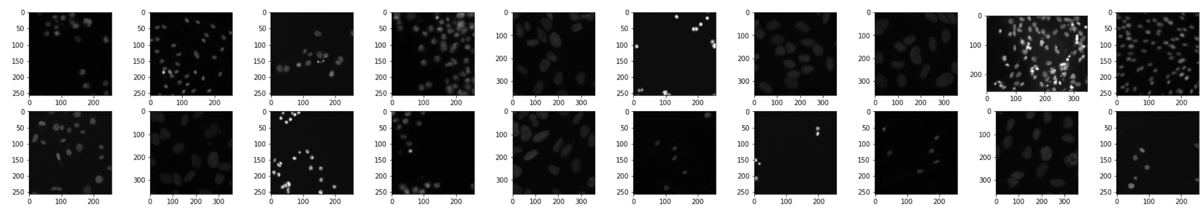

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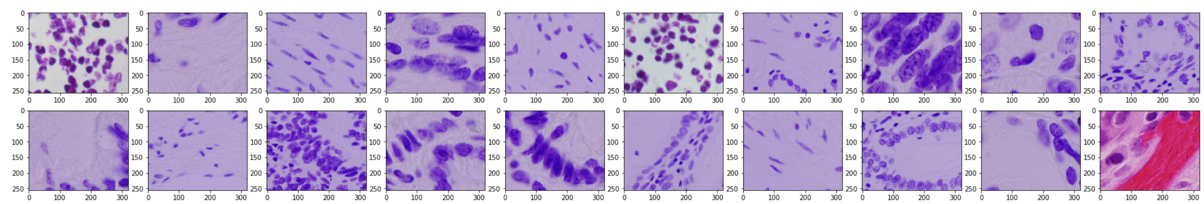

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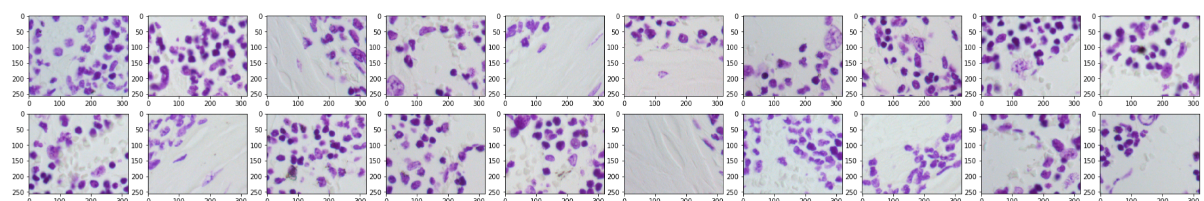

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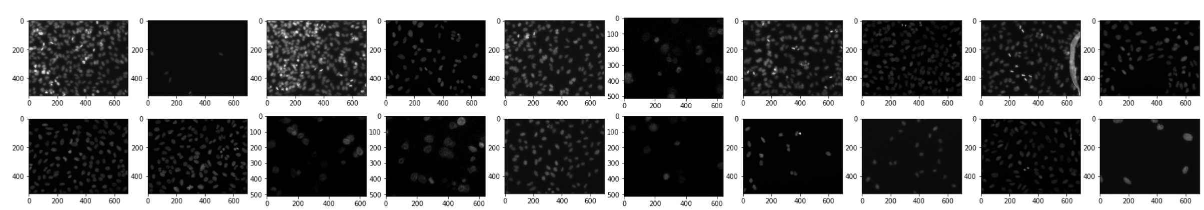

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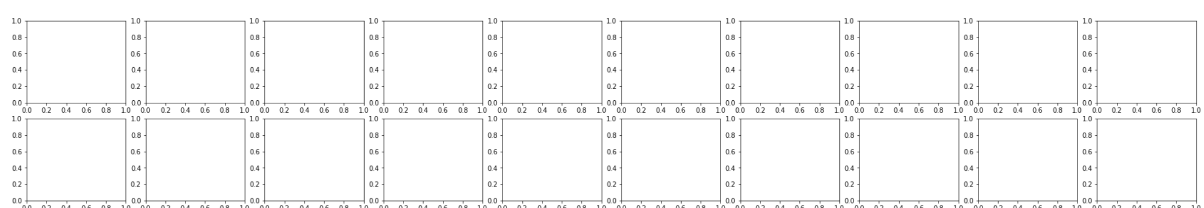

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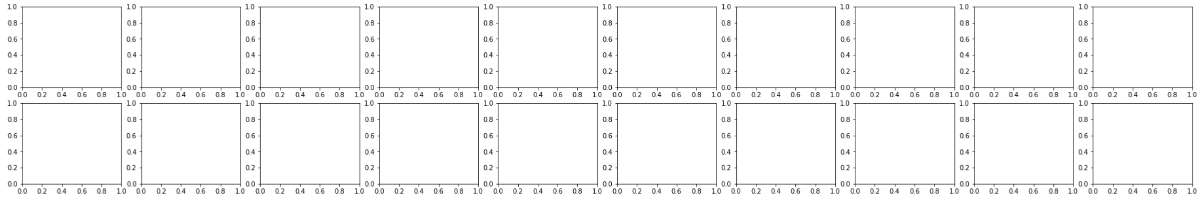

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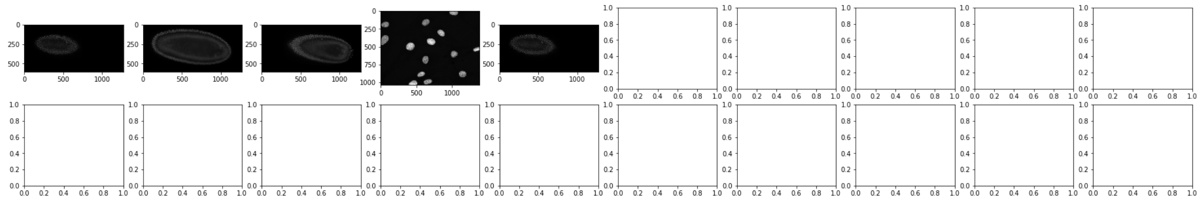

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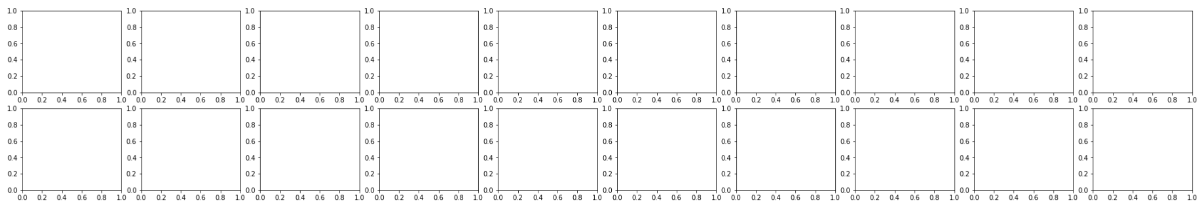

for type=>8