Optic Disc Segmentation Based on K-means for Glaucoma Detection

Yufan Wang #1

#International School, Beijing University of Posts and Telecommunications, China

1wyffancy@bupt.edu.cn

Abstract— **Glaucoma is the second leading cause of blindness all over the world, with approximately 60 million cases reported worldwide in 2010. If undiagnosed in time, glaucoma causes irreversible damage to the optic nerve leading to blindness. The optic nerve head examination, which involves measurement of cup-to-disc ratio (CDR), is considered one of the most valuable methods of structural diagnosis of the disease. Estimation of cup-to-disc ratio requires segmentation of optic disc and optic cup on eye fundus images and can be performed by modern computer vision algorithms.**

In this paper, I present a model of K-means to segment optic fundus image. K-means is one of the methods of clustering , the main idea of it is to find a partition of k clusters that optimizes the chosen partitioning criterion. Through the K-means clustering algorithm, the position and contour of the disc region can be obtained. By comparing with the correct segmentation of the image, we can derive the accuracy of the K-means algorithm in image segmentation.

Keywords—**K-means, optic disc segmentation, computer vision, glaucoma**

I. INTRODUCTION

Glaucoma is the second leading cause of blindness all over the world, with approximately 60 million cases reported worldwide in 2010, and an increase by 20 million is expected in 2020. If left unnoticed, glaucoma can cause irreversible damage to the optic nerve leading to blindness. Therefore, diagnosing glaucoma at early stages is very important. [1]

The most important diagnostic factor for glaucoma is the cup-to-disk ratio (CDR), so it is important to determine the optic disc, optic cup and the boundaries between them. Solutions for automated analysis and assessment of glaucoma can be very valuable in various situations, such as mass screening and medical care in countries with significant lack of qualified specialists [2]. And the cup and plate segmentation is very time consuming, and the results obtained by different people may not be the same.

There are two ways to diagnose glaucoma in general. The first is to use the global fundus images to consider the diagnosis of glaucoma with information such as blood vessels and cups. The second one is based on the optic disc and optic cup, using its cup-to-disk ratio and contour features for diagnosis.

Identifying quality and forecasting time are the most critical factors in measuring the quality of a glaucoma diagnosis algorithm. Therefore, in order to obtain the best method of splitting the cup, the divided area should be basically the same as the manually segmented area, and the running time of the program should be reduced as much as possible.

This paper plans to use the K-means algorithm to segment the optic disc from the glaucoma global image, and use the accuracy to evaluate the rationality of the algorithm.

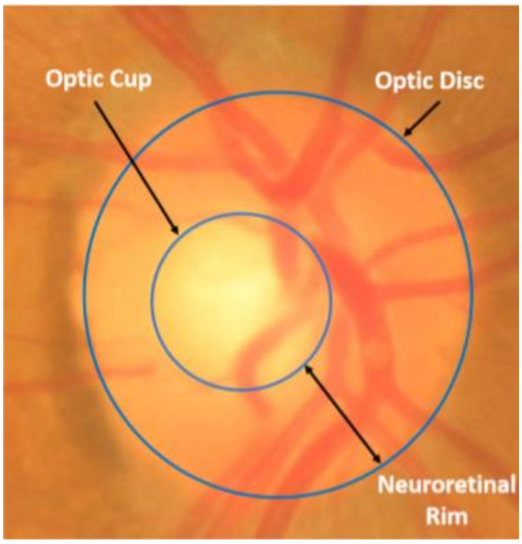


Figure 1 An example fundus image showing the optic disc and cup [2]

II. LITERATURE REVIEW

In this section, I will give several ways of segmentation and may be most of them are more advanced than K-means in the field of optic disc segmentation.

Current state-of-art methods for disc segmentation use morphological features [3] and active contours [4]. In recently years, there is an increasing trend in adopting deep learning-based methods for the optic disc segmentation. Shankaranarayana et al. utilized fully convolutional networks with adversarial training to jointly segment the optic cup and disc. The model achieved intersection over union (IOU) score of 0.961 for disc segmentation on RIM-ONE dataset. [5] K. Maninis and his colleagues used a Fully Convolution Network based on VGG-16 and transfer learning techniques. [6] Ful et al. proposed an architecture named M-Net combined with polar transformation to segment optic disc and cup simultaneously. The disc centred region is first passed through a polar transformation before training and prediction with M-Net. The method achieved a balanced accuracy of 0.983 for disc segmentation. [7]

III. THE PRESENTED APPROACH

A. Method

Image segmentation is the division of images into a set of non-overlapping regions. It is one of the basic problems of image processing and machine vision learning. Image segmentation is widely used in real life: for example, different cloud systems and backgrounds in segmented remote sensing clouds In the medical field, the application of image segmentation technology distinguishes brain tissue in brain MR images, such as gray matter, white matter, cerebrospinal and other non-brain tissues; in the field of transportation, vehicle targets can be segmented from the background region, which is It is equivalent to the map that everyone is familiar with.

K-means algorithm is implemented in four steps, that is partitioning objects into k nonempty subsets, computing seed points as the centroids of the clusters of the current partitioning, then assigning each object to the cluster with the nearest point and at last going back to step 2 until there is no change in the assignment. In this example, I want to use the RGB information to cluster the region.

K-means algorithm is widely used into the fields like text analysis, client classification, identifying the crime spot and image segmentation and compression. So, in this paper, I use this method to generate a binary figure to identify the optic disc and compare it to our standard image although it may generally be used for clustering by setting the k to 2 to identify the background and optic disc.

B. Dataset

I used 74 fundus images with glaucoma for segmentation. Since the given dataset consists of stereoscopic fundus images, so I first need to crop them into two separate parts.

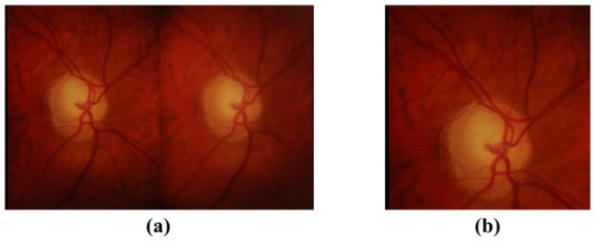


Figure 2 (a) is the original stereoscopic fundus image and (b) is pre-processed by cropping the left part of the original image then cropping into the size of (1000,1000)

The standard optic disc images are generated by averaging 2 professional ophthalmologists' division results. Since the result was marked in the left part of the stereoscopic fundus images, so in this experiment I only used the left part of the images.

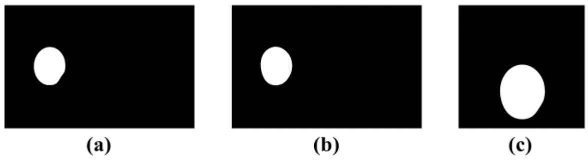


Figure 3 (a), (b) were the results of the optic sic segmentation of two experts and (c) was their average

C. Evaluation

Although the K-means method is an unsupervised algorithm, in order to evaluate the result of K-means, I can compare it to the standard. I use the following formula to get the accuracy:

$$\text{Acc} = \frac{N}{T}$$

where N represents the value of the pixel in the standard image equals to the value of the experimental result, and T represents the total number of pixels in the picture. And the accuracy is often called Intersection-over Union (IOU) score.

IV. EXPERIMENTS

This section of the paper contains comparison between my solution and the correct segmented image. Results are reported for the dataset RIM.

First, I preprocessed the image and cut the original 1424*2144 image into 1000*1000. At the same time, the same processing is done for the correct segmentation picture. Then we use the K-means algorithm to train the segmented images.

In the K-means algorithm we first need to average the RGB image, then we call kmeans in *scipy.cluster.vq* to implement the K-means algorithm. Since we want the last generated image to be a segmented optic disc and background, we have to set the parameter to 2.

Finally, the generated array is converted into a picture, and a corresponding binarized picture is generated, and the pixel value is compared with the correctly divided picture. The specific method is: traverse all the pixels, if the two results are the same, the parameters of the correct segmentation are increased by one, and the total number of points is increased by one. Otherwise, only the total number of points is increased by one.

```
for i in range(rows):
  for j in range(cols):
    if(correct image pixel [i,j] == generated image pixel [i,j]):
      acc=acc+1
      count=count+1
    else:
      count=count+1
```

Figure 4 The evaluation method

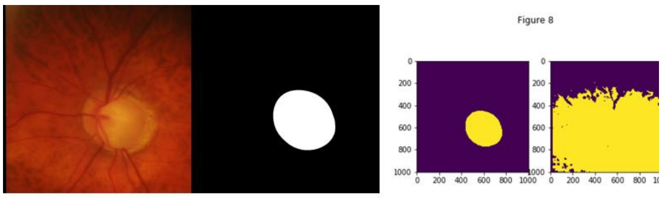
Through the calculated accuracy information and calculation time, we can analyze the influence of different pictures on the final segmentation result, and then derive the advantages and disadvantages and improvement methods of this algorithm.

V. RESULTS

The results of each picture can be seen in the appendix. The left side is the correct segmentation picture, and the right side is the K-means segmentation result. Accuracy information is also displayed at the top of the image, and the title of each image is the number of the image.

The total accuracy is 62.7654% which is far from enough. This shows that the simple K-means for the segmentation of glaucoma disc is not feasible. So, I started looking at what the pictures with the highest correct rate and the lowest correct rate.

The image with worst accuracy is (33.89%):

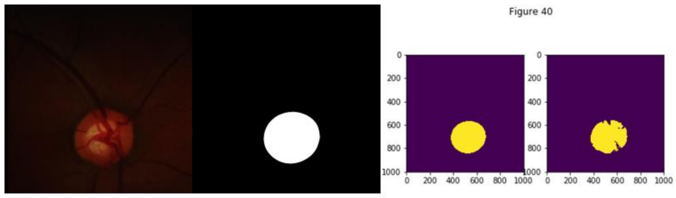


(a) (b) (c)

Figure 5 (a) is the original fundus image, (b) is the correct standard disc image and (c) is my result of correct disc image and the K-means segmentation fundus image

We can see that the non-disc area in the picture is very bright, and the result of K-means incorrectly classifies these bright areas as disc areas. At the same time, the results of K-means are also affected by the surrounding blood vessels, resulting in the K-means area boundary is not obvious, the surrounding contour is not as smooth as the correct picture.

The image with best accuracy is (93.08%):



(a) (b) (c)

Figure 6 (a) is the original fundus image, (b) is the correct standard disc image and (c) is my result of correct disc image and the K-means segmentation fundus image

On the contrary, the result of the division of the highest correct rate is darker, so the contrast between the disc region and the background is high, and the recognition result is more accurate. Although this picture is also affected by the surrounding blood vessels, the outline is clearer, it can be seen that the divided area is more like an oval.

Accuracy	Number
above 90%	9
80% - 90%	5
70% - 80%	5
60% - 70%	21
50% - 60%	17
40% - 50%	12
30% - 40%	5

Table 1 Accuracy rate distribution

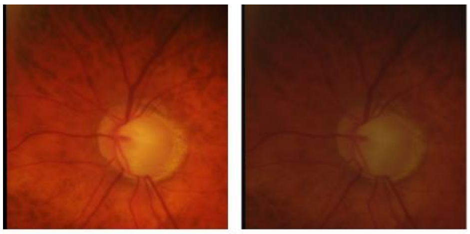
From Table1 we can see that the accuracy rate is basically stable at 60%-70%, which shows that the K-means algorithm is very weak compared to algorithms such as deep learning. However, due to the algorithm's simplicity, the average operation time of a picture in a personal notebook (model: ThinkPad X1 carbon, CPU @2.90GHz) is only 36 seconds. Therefore, the K-means algorithm is generally used for image pre-processing, not for areas such as segmentation and detection.

In order to improve the accuracy of the experiment, and to determine whether the brightness and contrast information affects the accuracy of the K-means algorithm. In my next step, I did the brightness and contrast processing of the image with the worst accuracy. The brightness adjustment is to increase or decrease the intensity of the image pixels as a whole. Contrast adjustment means that the pixel intensity in the dark portion of the image becomes lower and the brightness is higher, thereby widening the display accuracy in a certain area. So, in the OpenCV, we use the following formula to adjust the brightness and contrast:

$$g(x) = \alpha f(x) + \beta$$

So, we just need to set the value of α and β to different numbers.

In order to adjust the brightness of the picture, we set α to 0.5 and β to 0:



Original image **Darker image**

Figure 6 Adjusting the brightness

The accuracy and comparison pictures after adjustment are:

```
Acc: 0.336748
```

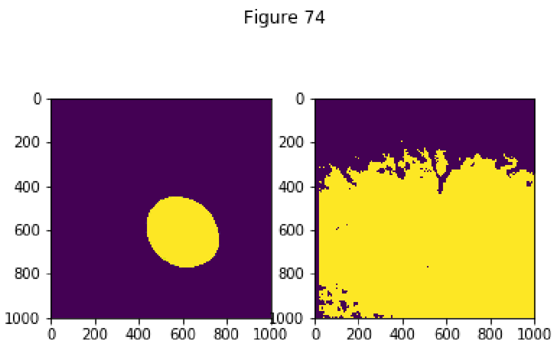
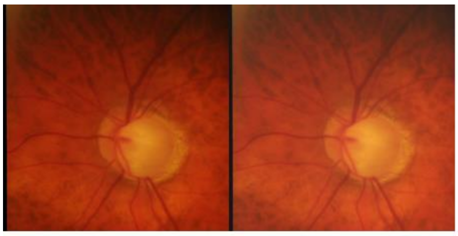


Figure 7 The result after adjusting the brightness

We found that the accuracy rate did not increase significantly, and the identified disc contours were not very clear. As the overall picture brightness becomes lower, the brightness of the disc area is also reduced. It can be found that the brightness is not a factor affecting the accuracy of the graph.

Next, we adjust the contrast of the image, let α be 1, β be 20:



Original image **Higher contrast**

Figure 8 Adjusting the contrast

The K-means result is:

```
Acc: 0.339152
```

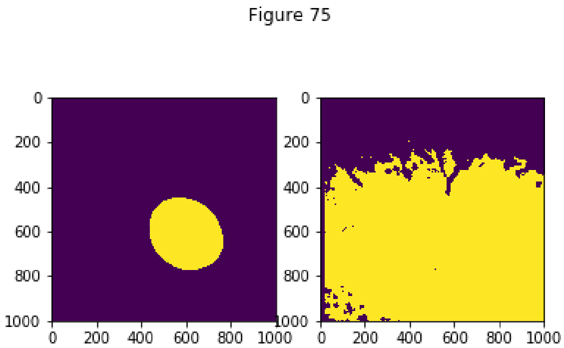


Figure 9 The result after adjusting the contrast

We found that as the contrast increased, the accuracy did not improve significantly. Even in a few trainings, the accuracy rate has dropped. So, it can be concluded that contrast does not significantly improve its accuracy.

VI. CONCLUSIONS

In this paper we show that our method based on modified K-means can provide results weaker than existing methods for the tasks of optic disc segmentation on eye fundus images. The reason is not because of the quality of the picture. No matter how I adjust the brightness and contrast, the accuracy has not been greatly improved. Therefore, the flaws of the K-means algorithm are very obvious in this experiment.

The weaknesses of K-means are:

1) Very sensitive to noise, unable to correctly identify the disc contour. Therefore, this algorithm cannot correctly identify the disc area and is easily interfered by background information such as surrounding blood vessels.

2) It is easy to fall into the local optimal solution. Unable to expand and compare regions, resulting in very low accuracy.

We can conclude that K-means has a certain effect on the segmentation of disc, but the accuracy is not high. The accuracy is not enough compared to today's algorithms. But through K-means' analysis of the image, we can determine the rough location of the disc. Therefore, K-means can be used for positioning and pre-processing, and then by using other deep learning algorithms, such as U-Net, we can continue the process of further segmentation and diagnosis.

The code of this experiment is uploaded to:

https://github.com/yukikikikiki/Optic-Disc-Segmentation-Based-on-K-means-for-Glaucoma-Detection.git

But there are no images in this respository, since the ownership is not mine and if anyone want the access, please contact me at my email: yeahyuki@163.com

REFERENCES

[1] A. Almazroa, R. Burman, K. Raahemifar, and V.Lakshminarayanan, *"Optic disc and optic cup segmentation methodologies for glaucoma image detection: a survey,"* J. Ophthalmology. 2015, (2015).

[2] A. Bastawrous, H. K. Rono, I. A. Livingstone, H.A.Weiss, S. Jordan, H. Kuper, and M. J. Burton, *"Development and validation of a smartphone-based visual acuity test (peek acuity) for clinical practice and community-based fieldwork,"* JAMA Ophthalmology. 133 (8), 930–937 (2015).

[3] A. Aquino, M. E. Gegundez-Arias and D. Marin, "Detecting the Optic Disc Boundary in Digital Fundus Images Using Morphological, Edge Detection, and Feature Extraction Techniques," in *IEEE Transactions on Medical Imaging*, vol. 29, no. 11, pp. 1860-1869, Nov. 2010. doi: 10.1109/TMI.2010.2053042

[4] G. D. Joshi, J. Sivaswamy and S. R. Krishnadas, "Optic Disk and Cup Segmentation From Monocular Color Retinal Images for Glaucoma Assessment," in *IEEE Transactions on Medical Imaging*, vol. 30, no. 6, pp. 1192-1205, June 2011. doi: 10.1109/TMI.2011.2106509

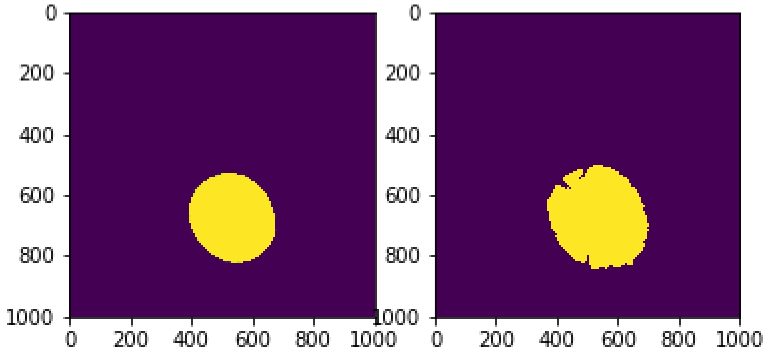
[5] M. Shankaranarayana, S.M. Ram, K. Mitra, K. Sivaprakasam Joint optic disc and cup segmentation using fully convolutional and adversarial networks Fetal, Infant and Ophthalmic Medical Image Analysis, vol. 10554, Springer, Cham (2017), pp. 168-176

[6] K.-K. Maninis, J. Pont-Tuset, P. Arbeláez, and L. Van Gool, "Deep retinal image understanding," in Proc. Int. Conf. on Medical Image Computing and ComputerAssisted Intervention (Springer, 2016), pp. 140–148.

[7] H. Fu, J. Cheng, Y. Xu, D.W.K. Wong, J. Liu, X. Cao.Joint optic disc and cup segmentation based on multi-label deep network and polar transformation, IEEE Trans. Med. Imaging (2018), pp. 1-9

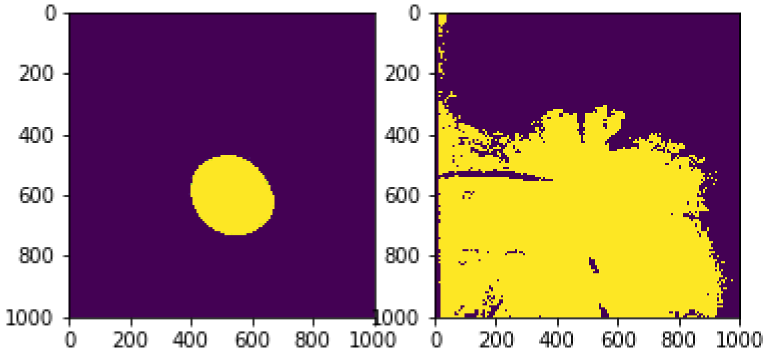
Acc: 0.916465

Figure 0



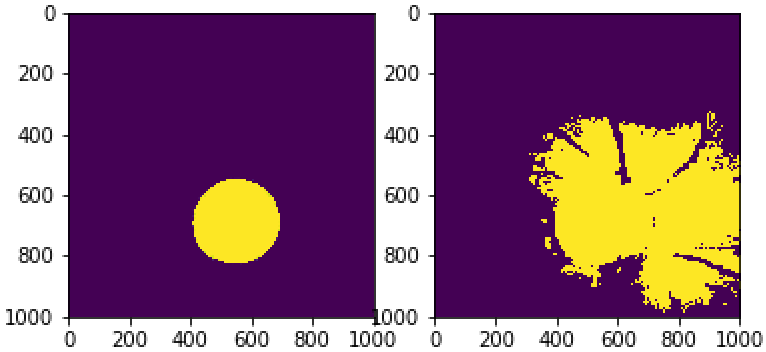
Acc: 0.485697

Figure 1



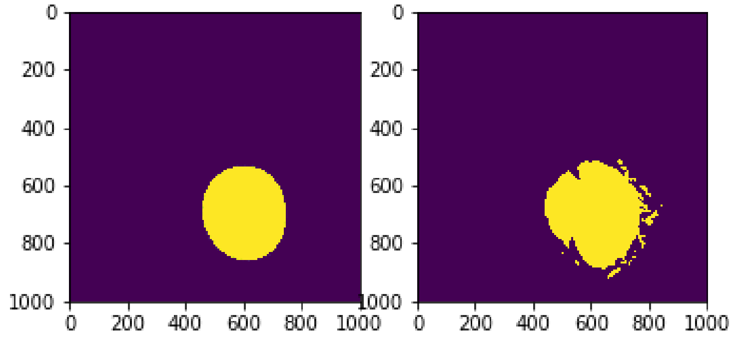
Acc: 0.710087

Figure 2



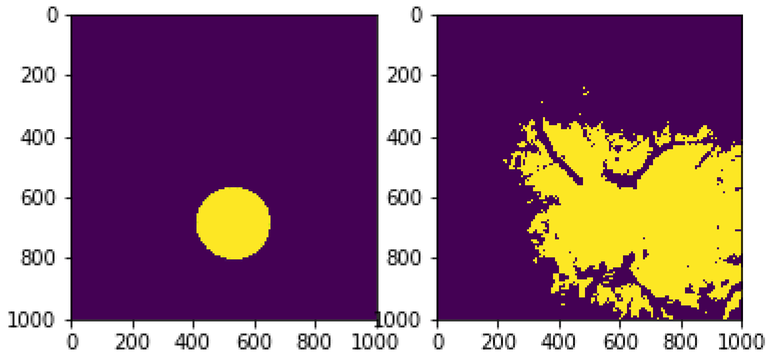
Acc: 0.905640

Figure 3



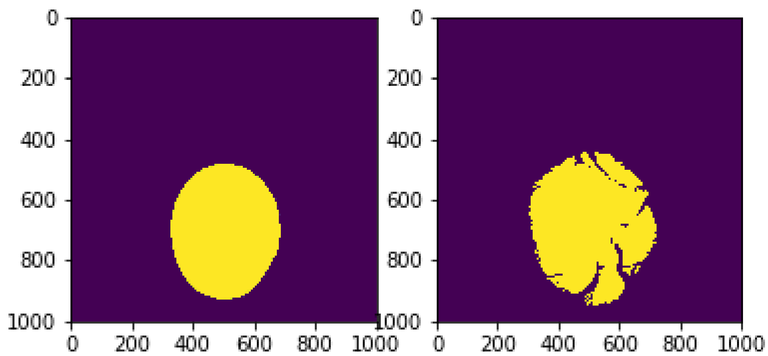
Acc: 0.677499

Figure 4



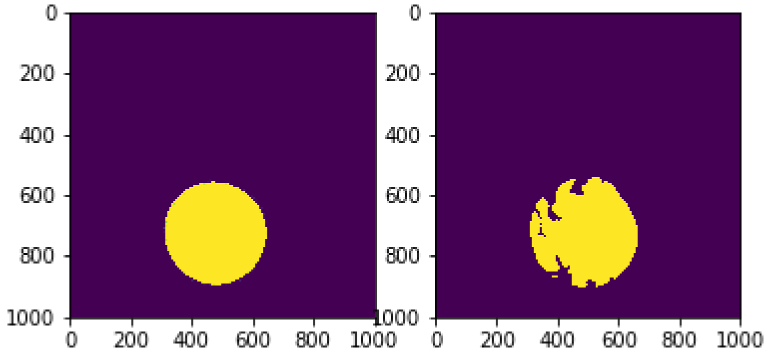
Acc: 0.849365

Figure 5



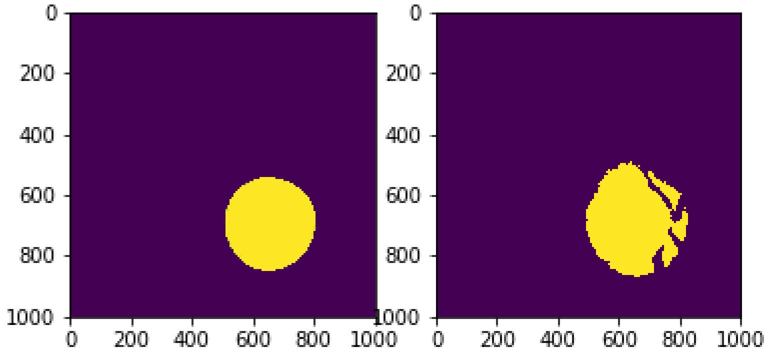
Acc: 0.902995

Figure 6



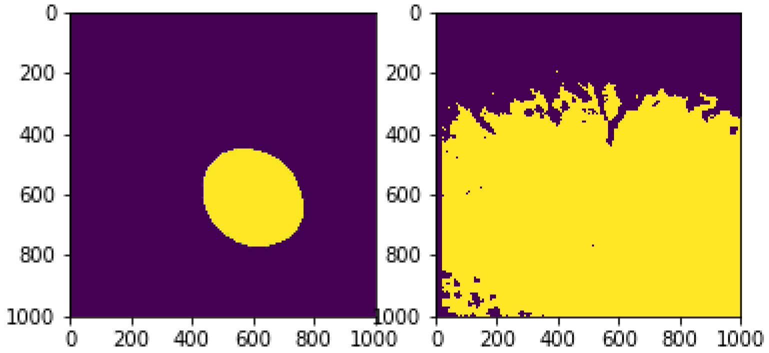
Acc: 0.910766

Figure 7



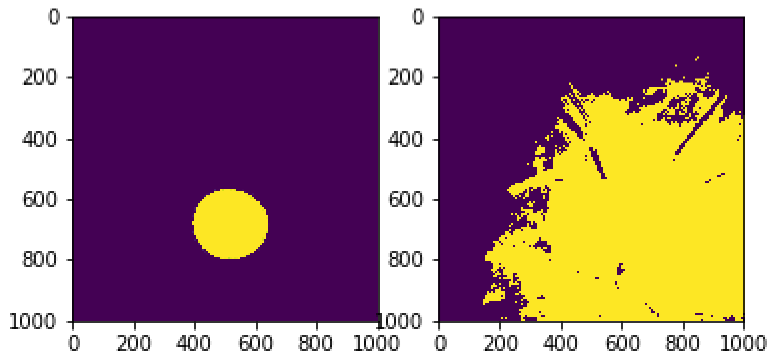
Acc: 0.338923

Figure 8



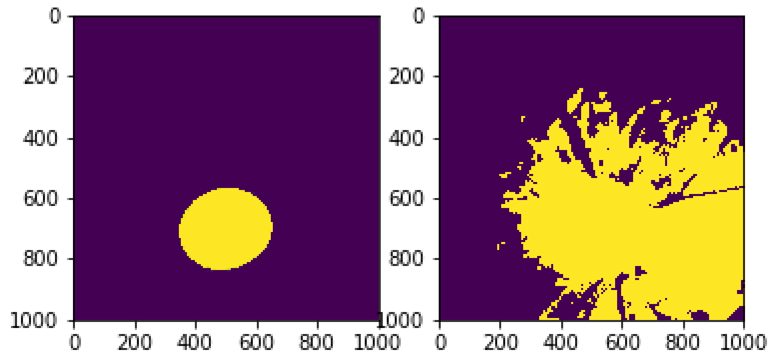
Acc: 0.505205

Figure 9



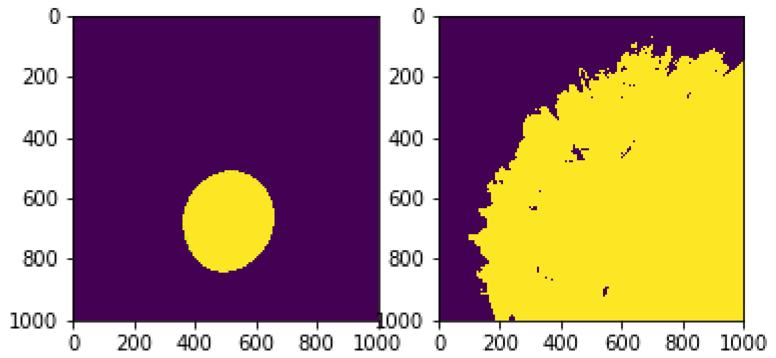
Acc: 0.606332

Figure 10



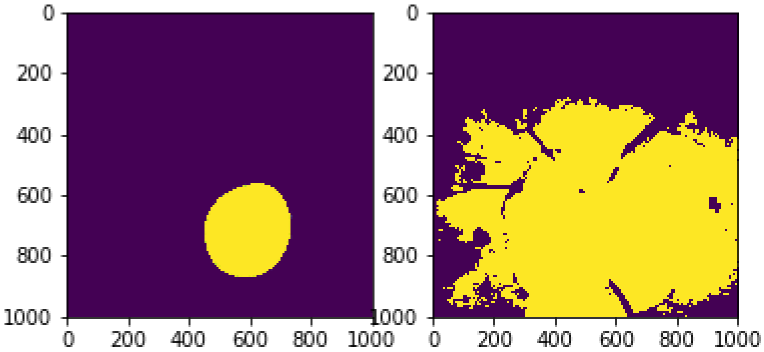
Acc: 0.354536

Figure 11



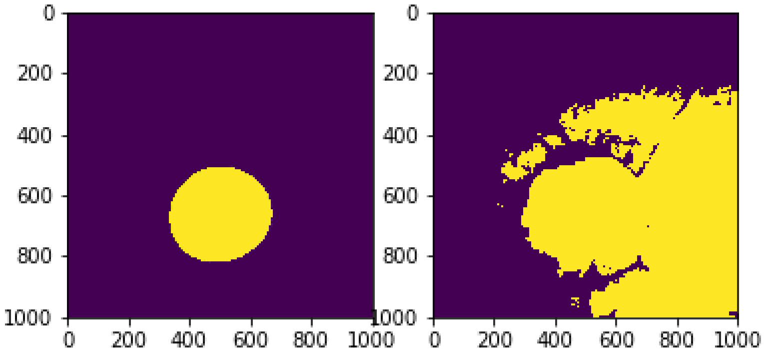
Acc: 0.474552

Figure 12



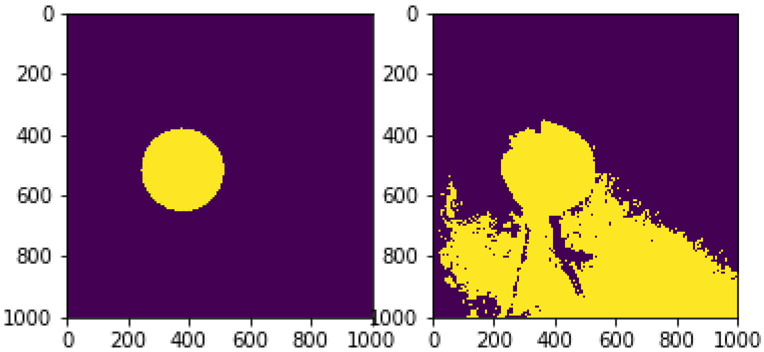
Acc: 0.585511

Figure 13



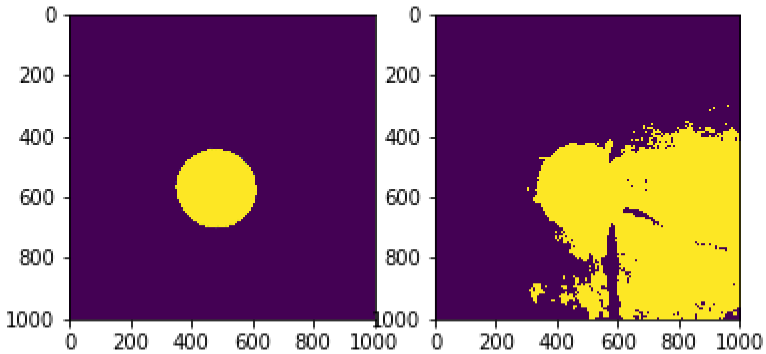
Acc: 0.660049

Figure 14



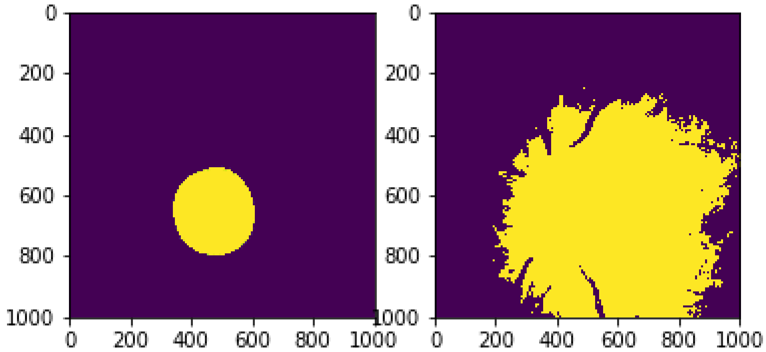
```
Acc: 0.673300
```

Figure 15



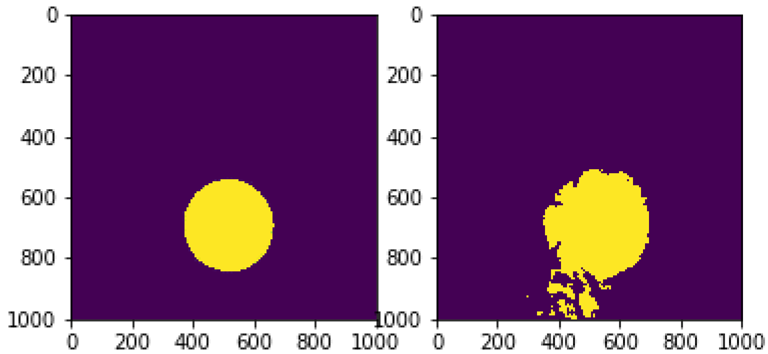
```
Acc: 0.583464
```

Figure 16



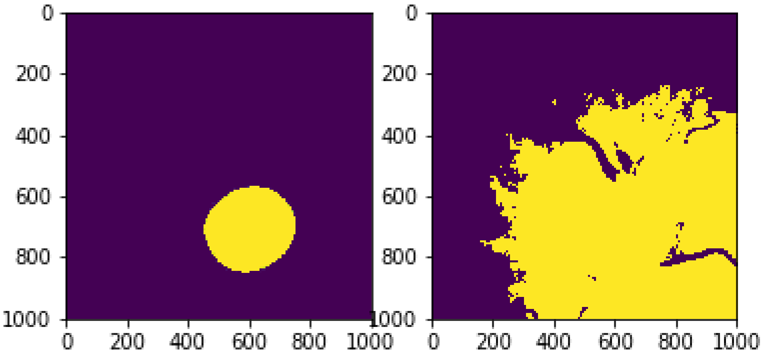
```
Acc: 0.895026
```

Figure 17



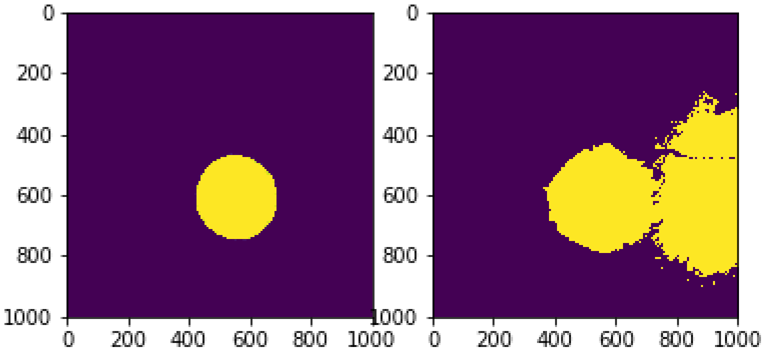
Acc: 0.528475

Figure 18



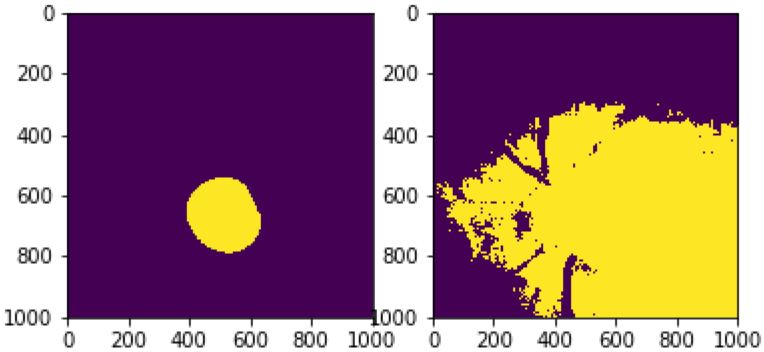
Acc: 0.777532

Figure 19



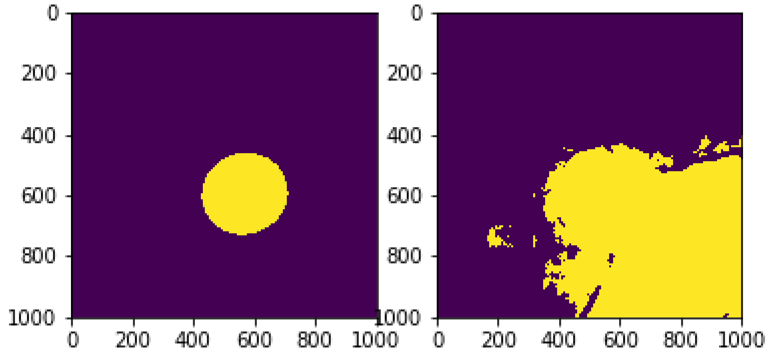
Acc: 0.508025

Figure 20



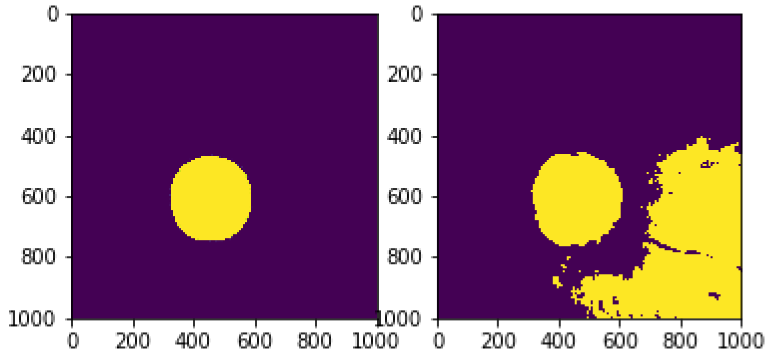
Acc: 0.676471

Figure 21



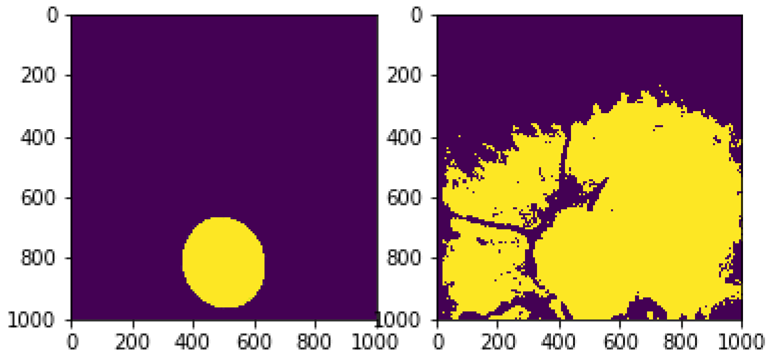
Acc: 0.736748

Figure 22



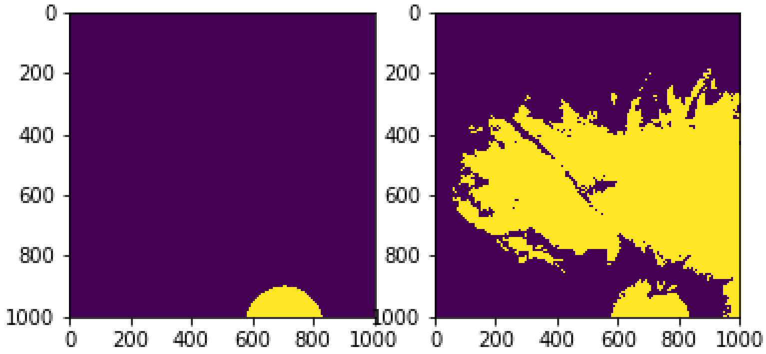
Acc: 0.478219

Figure 23



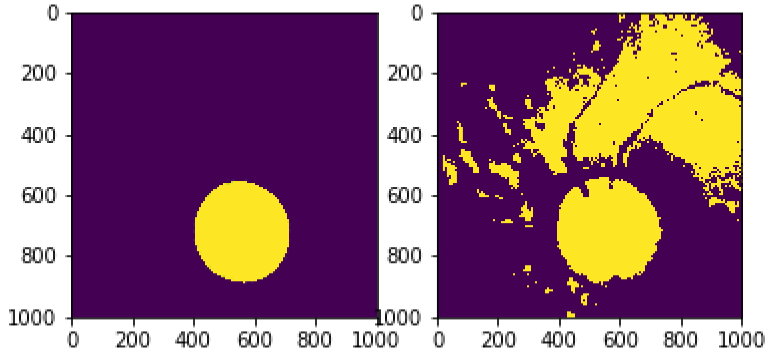
Acc: 0.581761

Figure 24



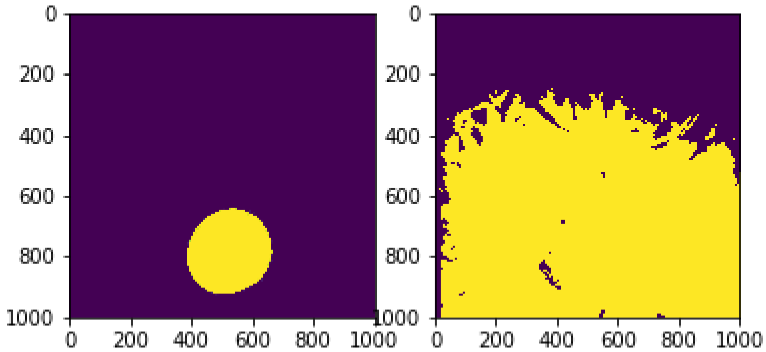
Acc: 0.655082

Figure 25



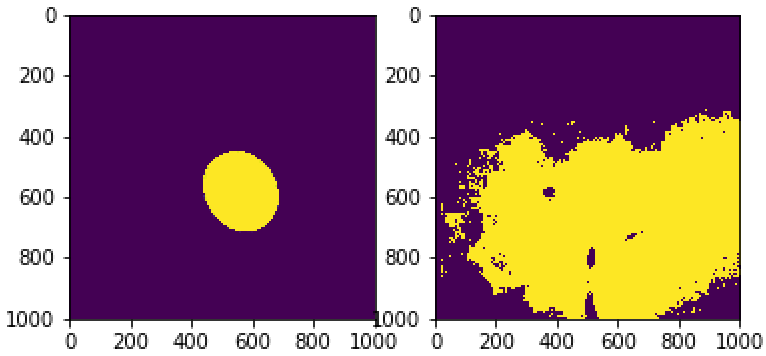
Acc: 0.376196

Figure 26



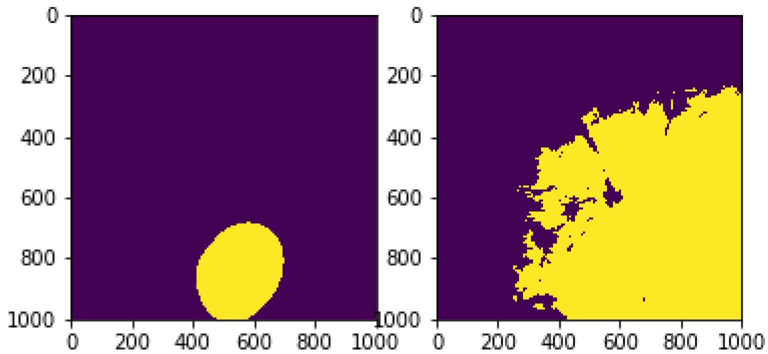
Acc: 0.538049

Figure 27



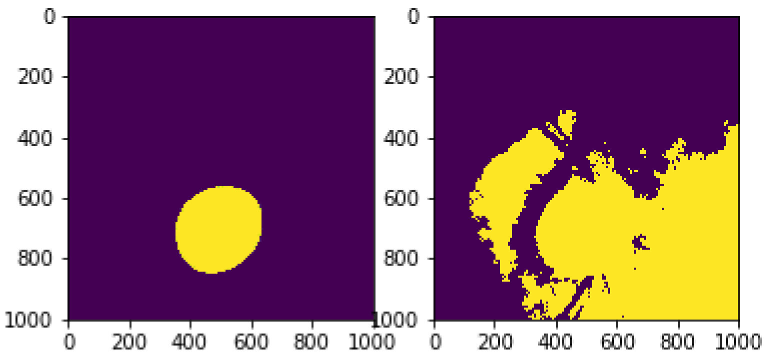
Acc: 0.560003

Figure 28



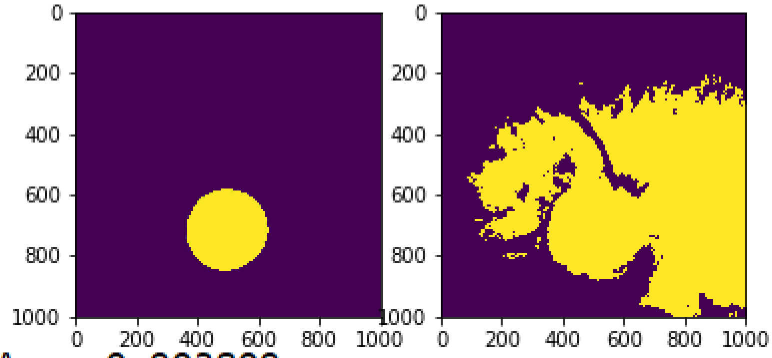
Acc: 0.618214

Figure 29



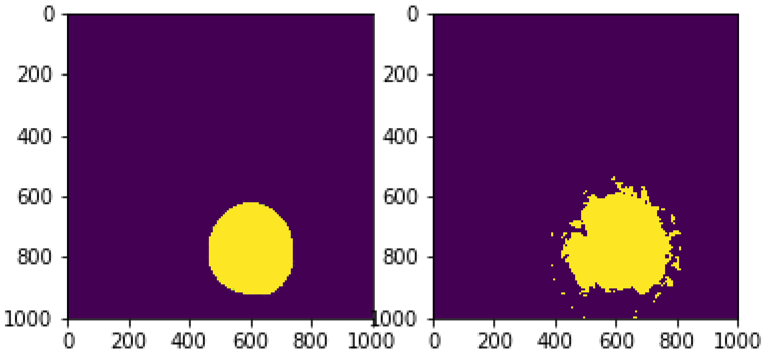
Acc: 0.557630

Figure 30



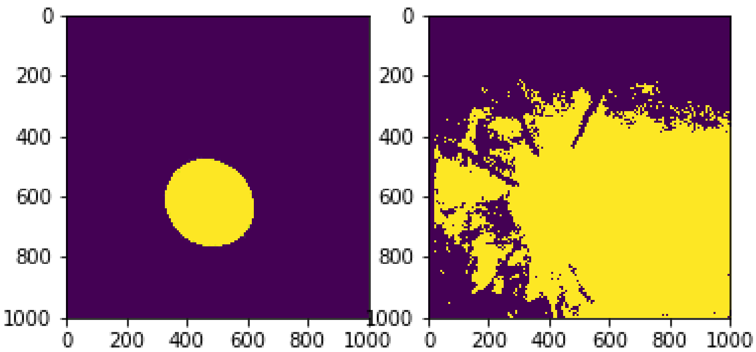
Acc: 0.903809

Figure 31



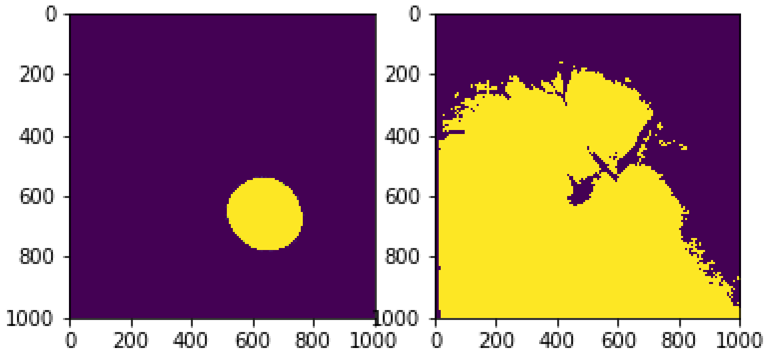
Acc: 0.462702

Figure 32



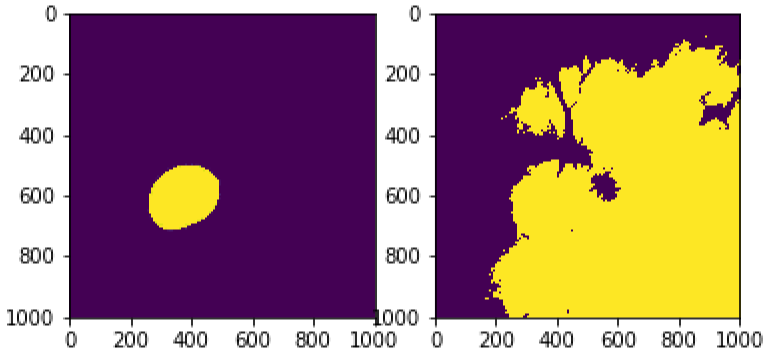
Acc: 0.426041

Figure 33



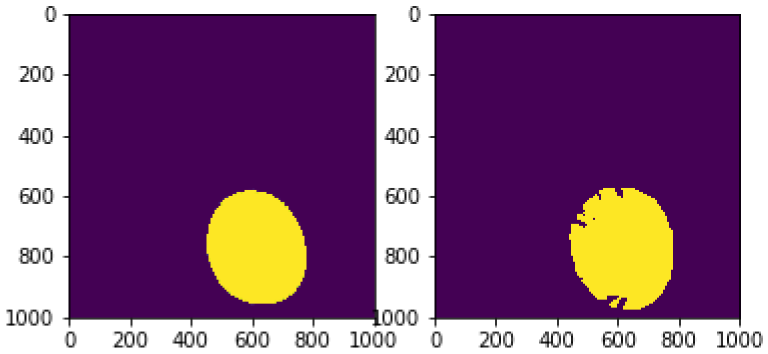
Acc: 0.426359

Figure 34



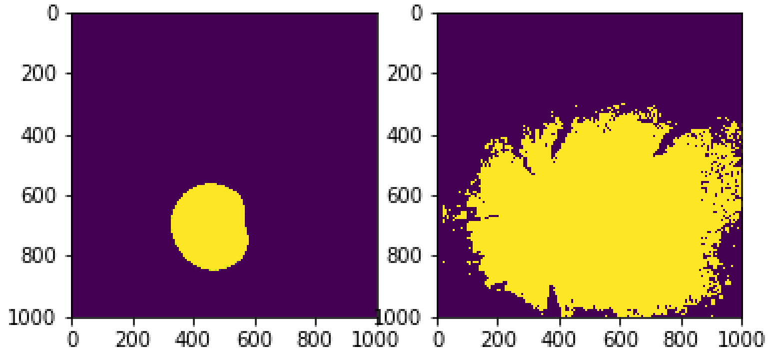
Acc: 0.892966

Figure 35



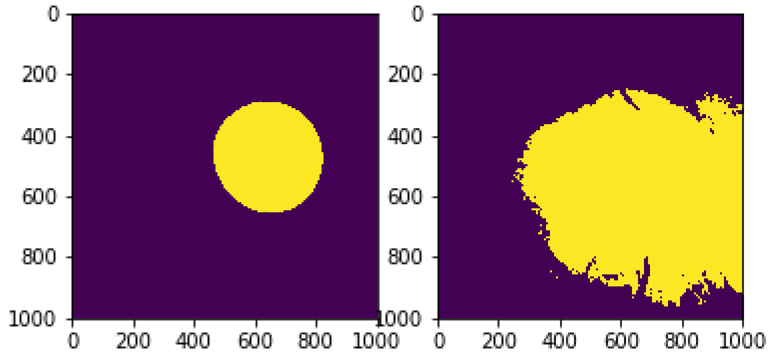
Acc: 0.541656

Figure 36



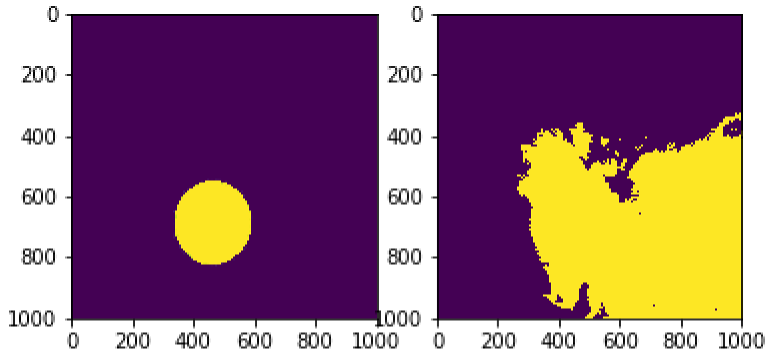
Acc: 0.605982

Figure 37



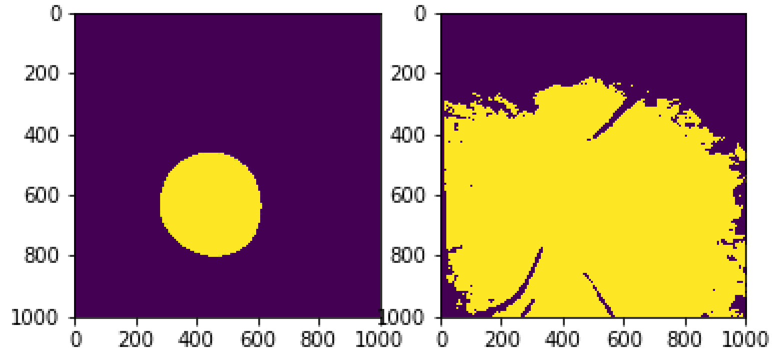
Acc: 0.628381

Figure 38



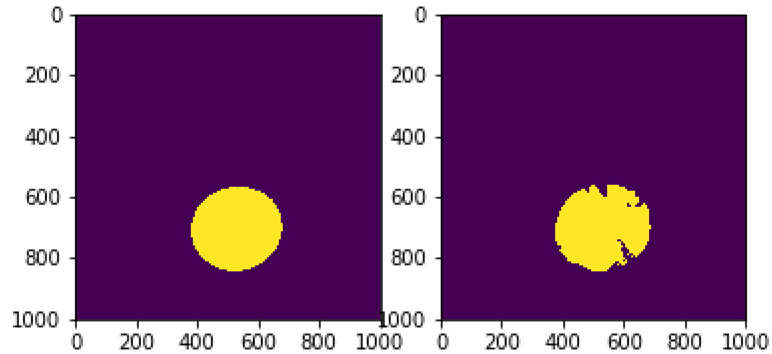
Acc: 0.362350

Figure 39



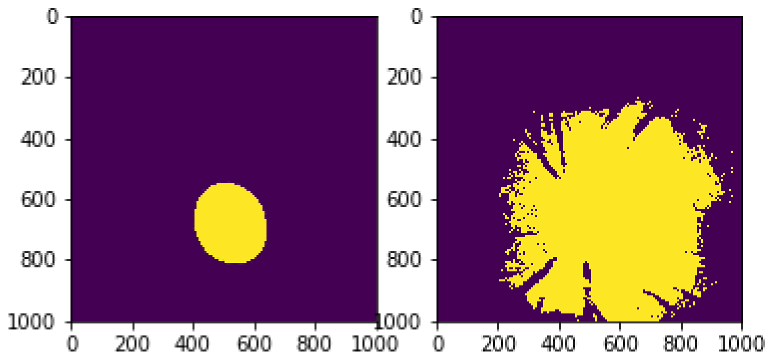
Acc: 0.930830

Figure 40



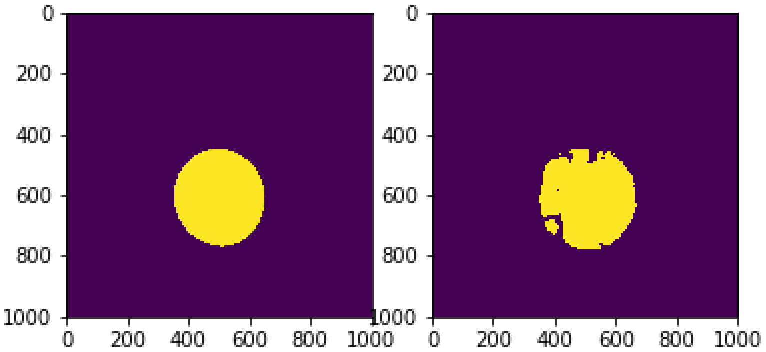
Acc: 0.640269

Figure 41



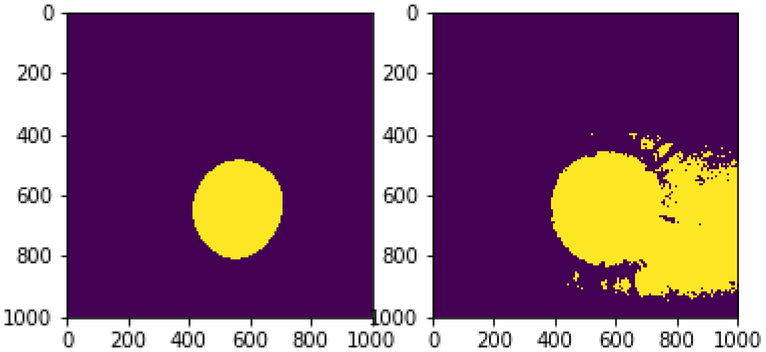
Acc: 0.917267

Figure 42



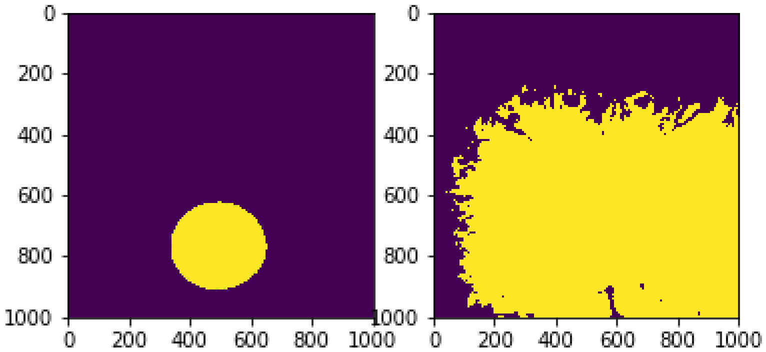
Acc: 0.769359

Figure 43



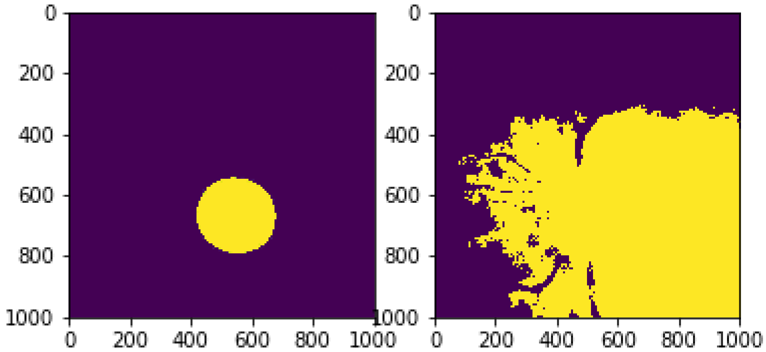
Acc: 0.406113

Figure 44



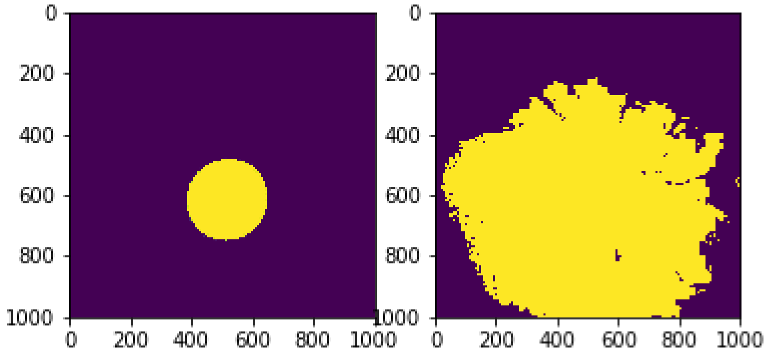
Acc: 0.509111

Figure 45



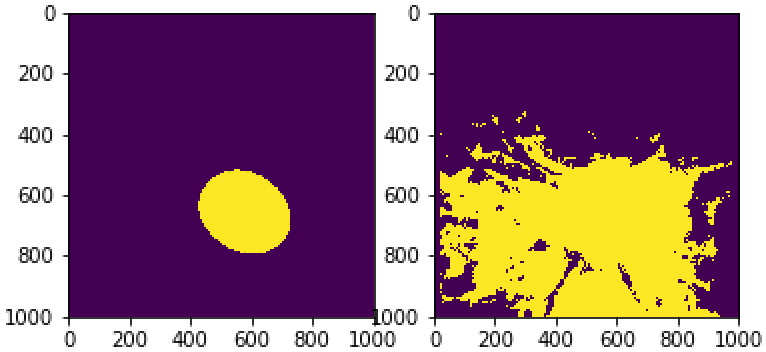
Acc: 0.477449

Figure 46



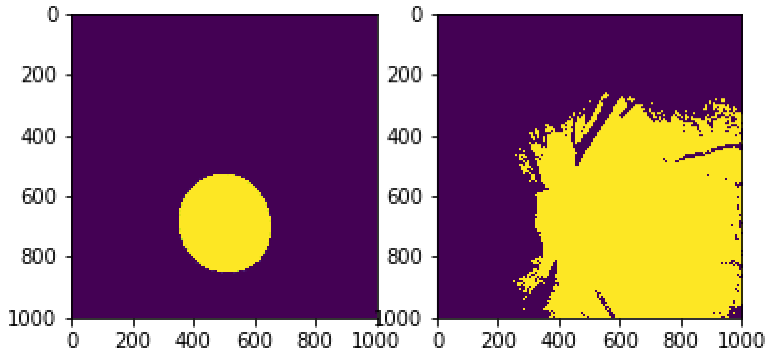
Acc: 0.620556

Figure 47



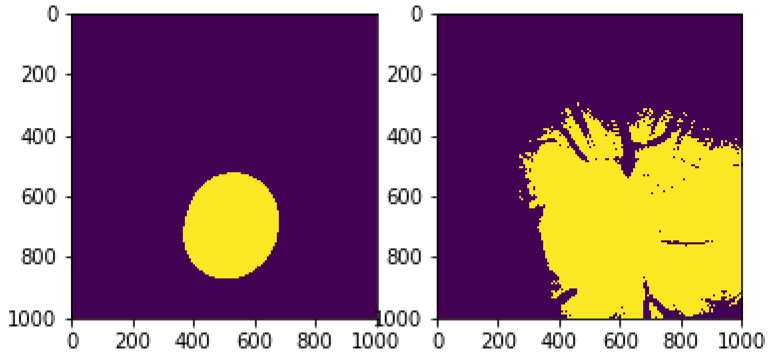
Acc: 0.577560

Figure 48



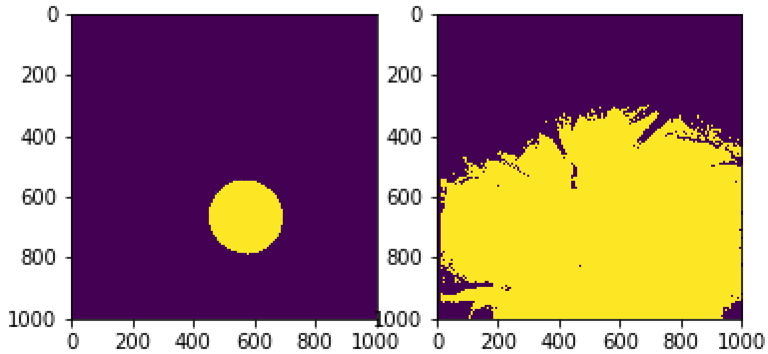
Acc: 0.629332

Figure 49



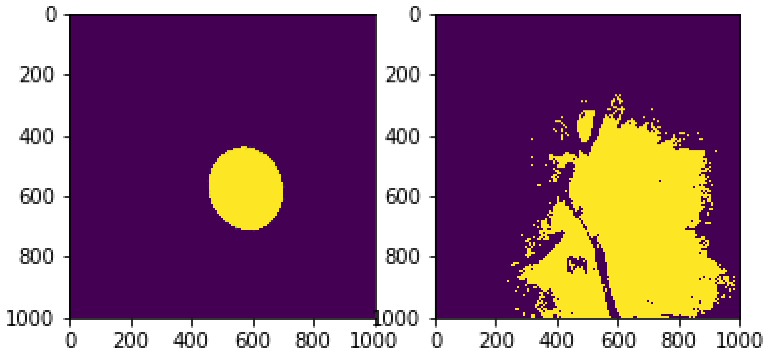
Acc: 0.442844

Figure 50



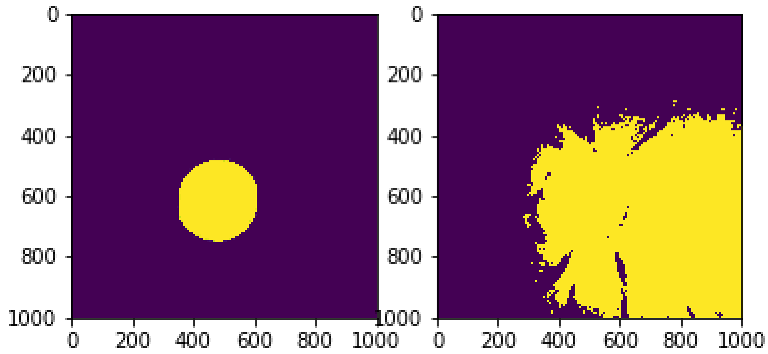
Acc: 0.701506

Figure 51



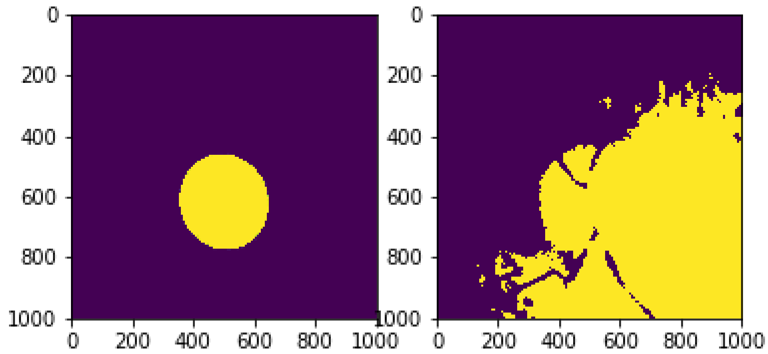
Acc: 0.606736

Figure 52



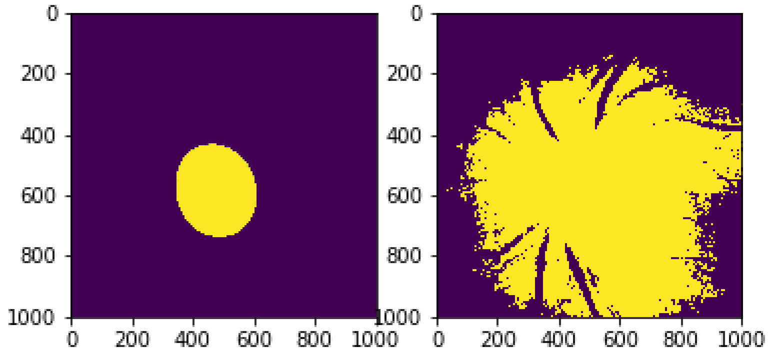
Acc: 0.573346

Figure 53



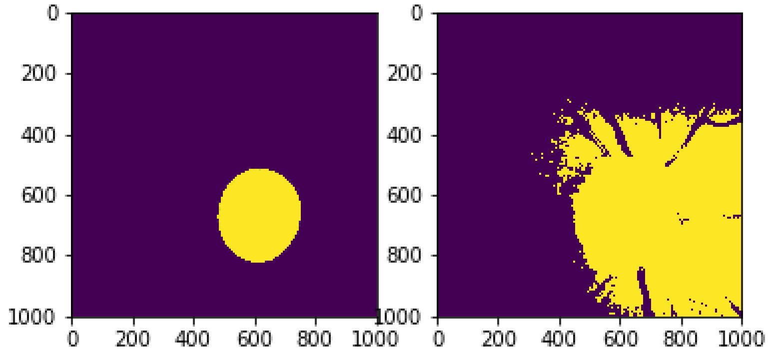
Acc: 0.482424

Figure 54



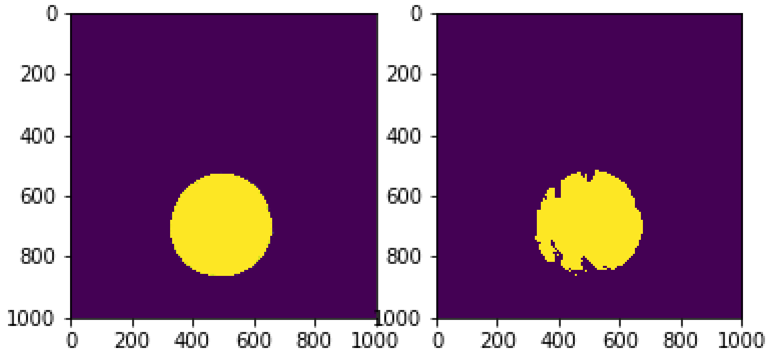
Acc: 0.671669

Figure 55



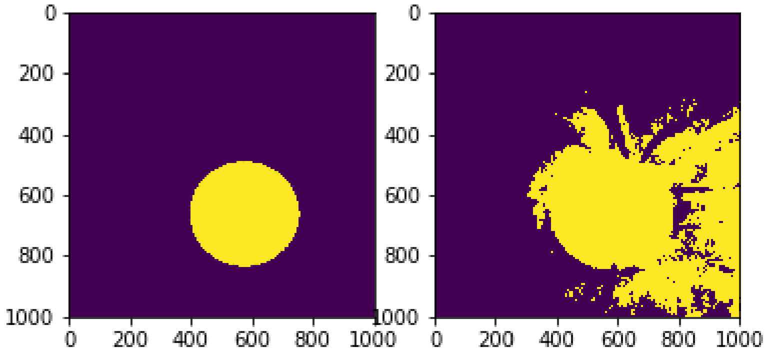
Acc: 0.905763

Figure 56



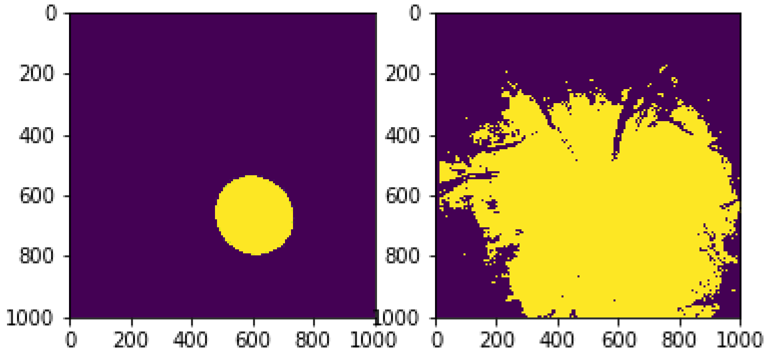
Acc: 0.695860

Figure 57



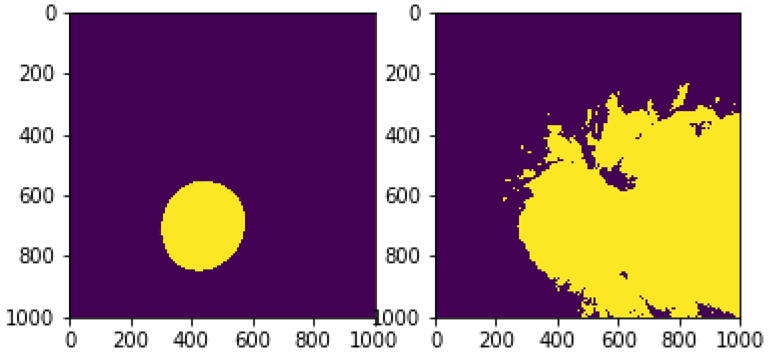
Acc: 0.484296

Figure 58



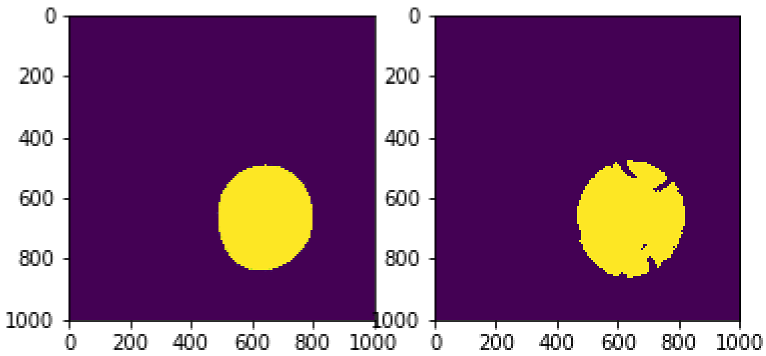
Acc: 0.592241

Figure 59



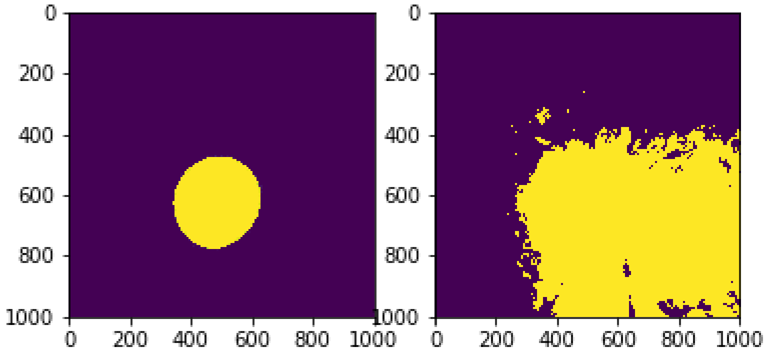
Acc: 0.896924

Figure 60



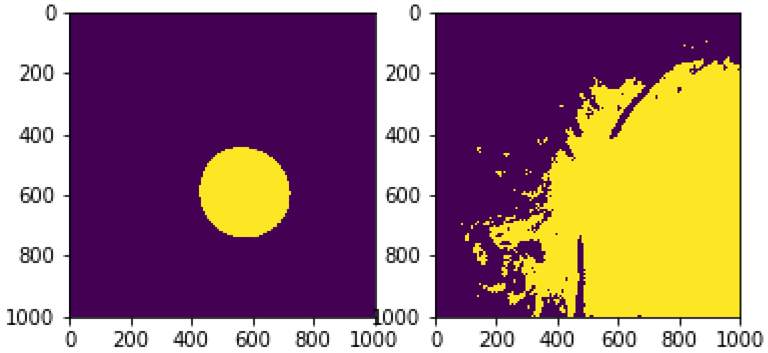
Acc: 0.615717

Figure 61



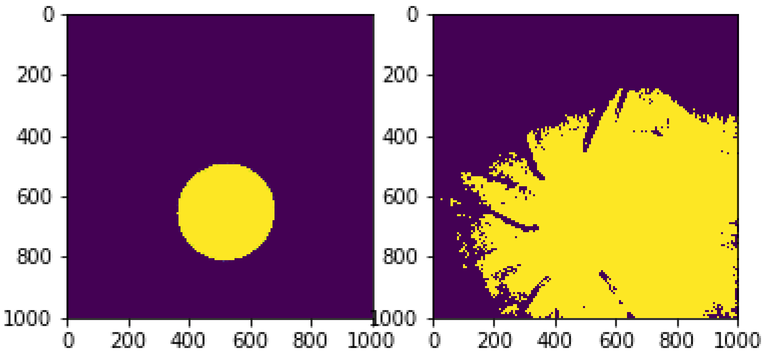
Acc: 0.509065

Figure 62



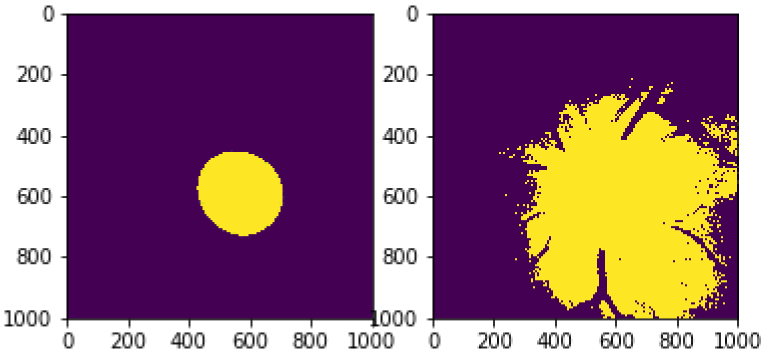
Acc: 0.492412

Figure 63



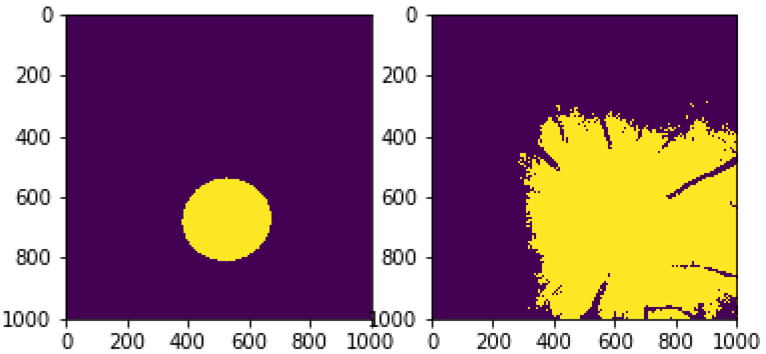
Acc: 0.636646

Figure 64



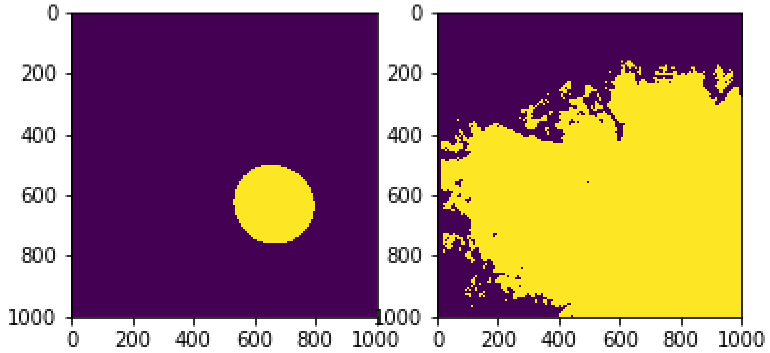
Acc: 0.606165

Figure 65



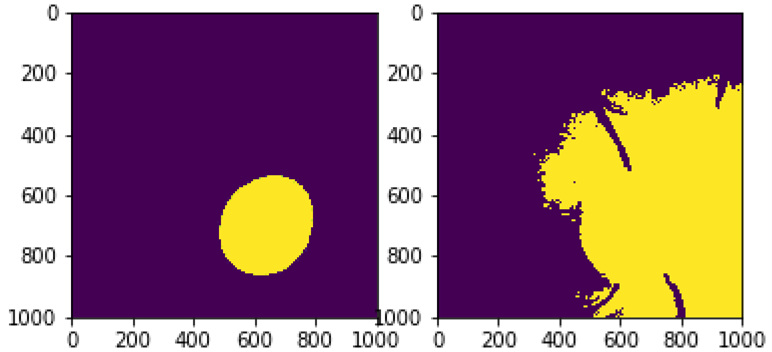
Acc: 0.381076

Figure 66



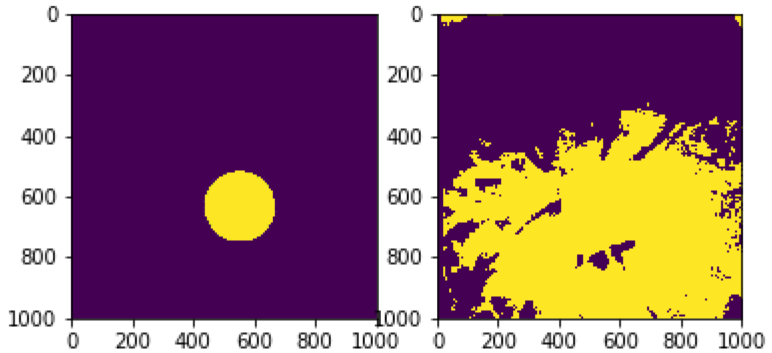
Acc: 0.609892

Figure 67



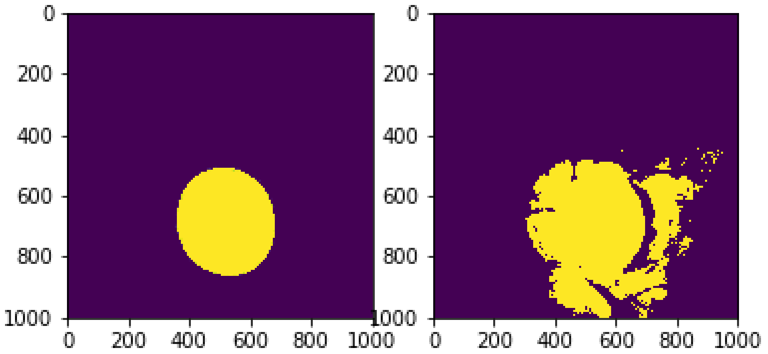
Acc: 0.523571

Figure 68



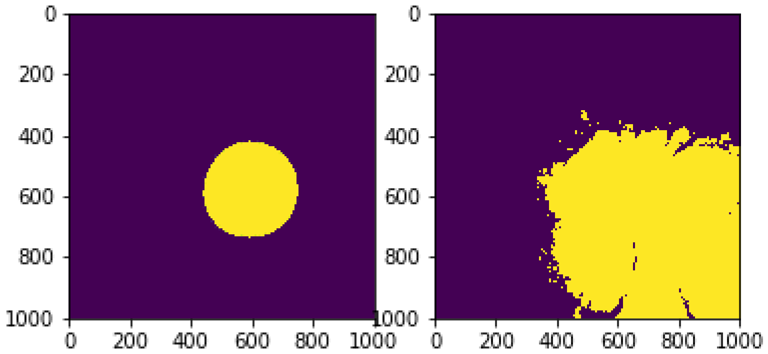
```
Acc: 0.818476
```

Figure 69



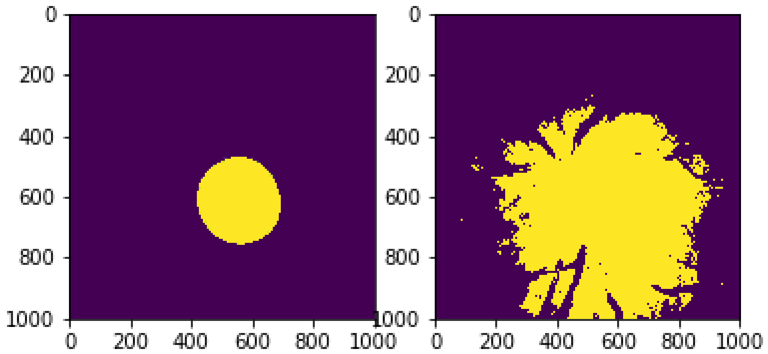

```
Acc: 0.652834
```

Figure 70



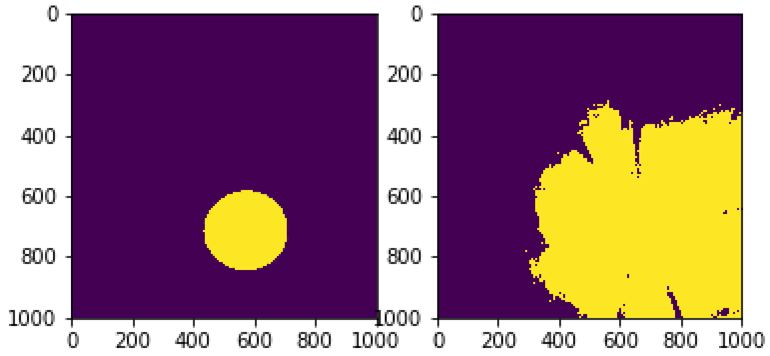

```
Acc: 0.664390
```

Figure 71



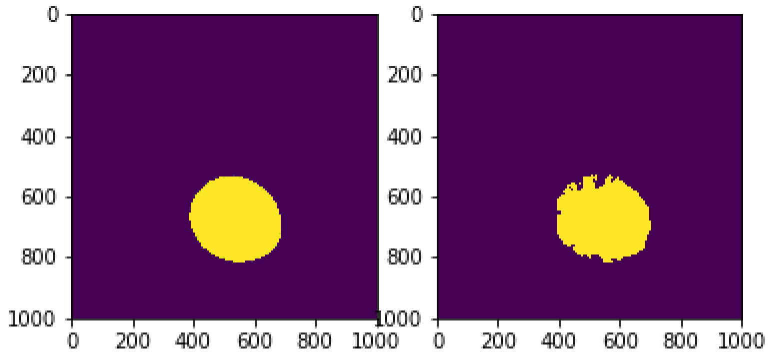
Acc: 0.597999

Figure 72



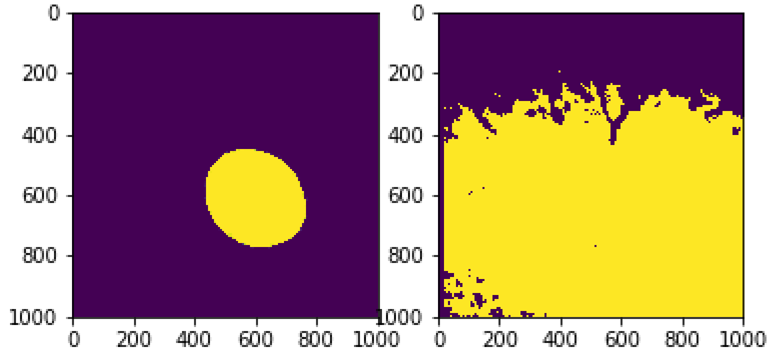
Acc: 0.929653

Figure 73



Acc: 0.336748

Figure 74



```
Acc: 0.339152
```

Figure 75