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Exercise 1)

a)

The GLCM paramaters are d (distanse) and θ (angle). Or as i will use Δx and Δy. Corresponding to distance in x and y direction respectivly.

The circle region looks like a grid going from light to dark values (especially in the x direction).
The outside region texture is more homogenious but stil has a distinct line pattern at $\sim 45^0$.
I would chose a offset of $\Delta x = 1$ and $\Delta y = 0$.
This will make the outside region more consentrated on the diagonal. While the circle texture gets more nondiagonal ellements.

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Exercise 1b)

We will need a possision based GLCM feature that diferenciates diagonal from non-diagonal GLCMs.

We could use Inertia (also called contrast) This will give 0 wheighting for elements on the diagonal and weihgting with the sqare of the distance from the diagonal for other ellements. Making it good at differenciating between the two types.

$$\text{Inertia} = \sum_{i=1}^{G} \sum_{j=1}^{G} (i-j)^2 P(i,j)$$

(could have used homogeneity as well)

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Exercise 1c)
Firs I would quantize the image, reducing the number of gray levels to G. Typicaly $G=16$ or $G=32$.
Then we chose a size of the sliding window. Smaler windows give higher distincton on where texture boundries are but also lower certainty of which texture it discribes.
We usualy chose a rectangular window with odd numer of ellements e.g. 21x21 to ensure we have a center square/pixel.
We also usaly pad the image, either with zeros or some othe technique based on the edge pixels.
Then we slide the window across the image. Calculatin the GLCM in that window (using our chosen Δx and Δy). This GLCM is used as input for the chosen GLCM-feature function. The output is used as the pixel vale of the feature image at the position of the center pixel of the window.

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Exercise 1d)

We could do morphological edge detection since the only edge is the circle to background edge.
This is done by subtracting the erosion from the image. $f-(f \ominus S)$.
(f is the binary image and S is the structuring ellement).

Can also use morphological gradient which is dilation - erosion, $(f \oplus S)-(f \ominus S)$.

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Exercise 1e)

We would still need a binary gradient image to use the hough transform. So either go the GLCM route, or try something like the Sobel gradient magnitude with thresholding.

We then use the Hough transform for circles using. $(x-x_c)^2+(y-y_c)^2=r^2$ resulting in a 3D parameter space where we hopefully have one peak describing the circle.

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Exercise 1f)

The 5 parameters are
Center - x_c and y_c
Semi-axes - a and b
Orientaton - θ

We can pick pixel pairs with opsite gradient directons. Take the mid-point of all these pairs and sum them in an 2D accumulation histogram. Peaks in this histogram are candidats for the center (x_c, y_c) reduing us to 3 parameters.

Could also chose pixel pairs with non-paralled tangents. These tangents will itersect at sum point T. If M is the mid-point of the pixels, the line TM passes through (x_c, y_c). Accumulate inter-sections of such lines to get (x_c, y_c). Also reducing to 3 parameters.

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Exercise 2a)

I would like to do thresholdin to get an binary image with just the triangles in the forground. But the noise and dark background region wil make this dificult.
I would use a top-hat transform.
Creating the opening with a large structuring ellement (~41x41) giving an estimate for the background. Then do top-hat by taking the original-opening. Hopefully making the background less noisy and even.
I could then use otsus method or something similar to threshold the image.

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Exercise 2b)
As I said in part a. I would use Otsus method or something similar to threshold to a binary image with the triangles in the forground.

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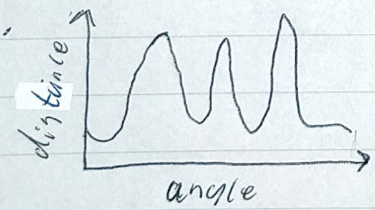
Exercise 2c)

Could do gradien or edge detection s.t. we only have the edge of the object. Then do a hough transform in the area of the object (like the blue and red squares). In hough space equiangular triangles will have three peaks. And if we put the origin inside the object. triangles will have three peaks $\frac{\pi}{3}$ apart in the θ-direction. And if we further put the origin in the center of mass of the object. the $|\rho|$ values will all be equal.

Could also do gradient/edge detection and then do the signature representation of the object. Triangles will then have three peaks.

e.g.



A third method is to find the area and circumference of the object an look at the ratio of these $\left(\frac{\text{Area}}{\text{circumference}}\right)$.

Of these using the hough transform with origin inside the object is probably the most robust.

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Exercise 2d)

We can do an morphological opening.

$f \circ S = (f \ominus \hat{S}) \oplus S$

This will split objects conected by a thin bridge (barly connected) without shrincing the original objects to math.

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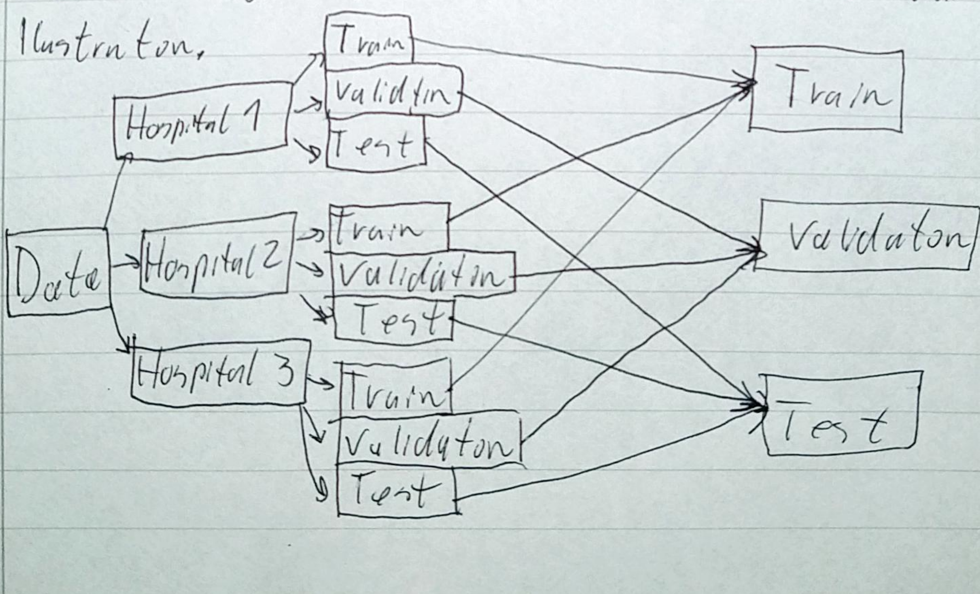
Exercise 3a)
I would do histogram equlization on the images. This will minimize the diffarance in contrast and brightness between the pictures. Hopefully making it sut. contrast/brightness does not have an unwanted effect on the classificaton.

Exercise 3b)
I would like to have even representaton off all the hospitals in train, validaton and test sets. As not to have quircs from one hospital effect the classifier.
I would firs spit into groups by hospital origin. then suffle the images. splitt into validation, train an test each being eg. 40%, 40%, 20% of the data respectivly. then combine the validaton from the different hospitals into one validatin sett. and the same for test and train.
Illustraton.



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Exercise 4a)

By using the scale-invariant central moments $\eta = \frac{\mu_{pq}}{(\mu_{00})^{\gamma}}$, $\gamma = \frac{p+q}{2}+1$, $p+q \geq 2$

We can construct the Hu moments

$$\phi_1 = \eta_{20} + \eta_{02} \qquad \phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

Which are rotation invariant.

We could also use that

$$\theta = \frac{1}{2}\tan^{-1}\left[\frac{2\mu_{11}}{(\mu_{20} - \mu_{02})}\right]$$

given the objects orientation.
If we rotate the object or axis-grid by θ we establish rotation invariance.
(objects like circles has no distinct θ, but those are rotation invariant anyway).

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Exercise 4b)

The object-oriented bounding box is the smallest rectangle having one side parallel to the orientation of the object. (θ)

We do the transform:

$\alpha = x \cos\theta + y \sin(\theta)$

$\beta = y \cos\theta + x \sin(\theta)$

to all object pixels or boundary pixels.

Then search for $\min(\alpha)$, $\min(\beta)$, $\max(\alpha)$, $\max(\beta)$.

Which describe the object-oriented bounding box.

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Exersice 4c)
We can look at the data in scatter plots. Ofcorse we cant look at all 10 dimentons at the same time. But we an study a set of 2D or 3D scatter plots with different combinations of features.
We then look for fatures / fature-combinatons giving high within-class homogeneity and large between class seperation.
We can also look at corrolaton between features, where fatures with high correlaton are redundant, and we should only use one of them.

PCA is also a good algorithm to use as it finds feature combinations that maximize the variance in the data.

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Exercise 5 a)

It tries to keep the margin as large as possible while also keeping the number of points inside the margin as small as possible.
Can also say we have inverse ~~of~~ the margin (large margin gives small number) pluss ~~a~~ wheighted sum of values for points inside the margin and points that are missclassified (Having higher values the closer it is to the wrong class). The criterium funktion is minimizing this sum.

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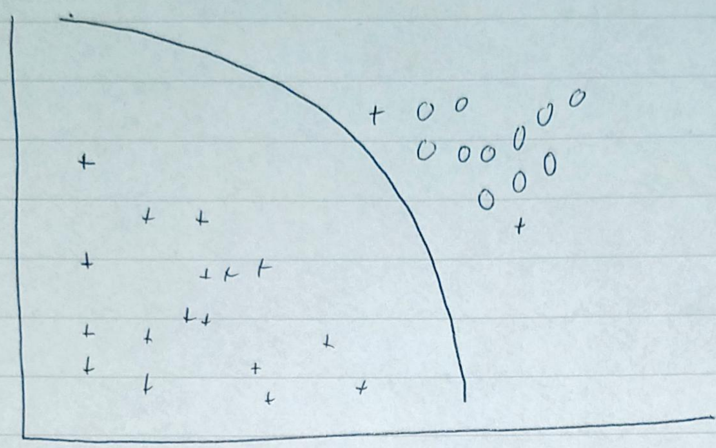
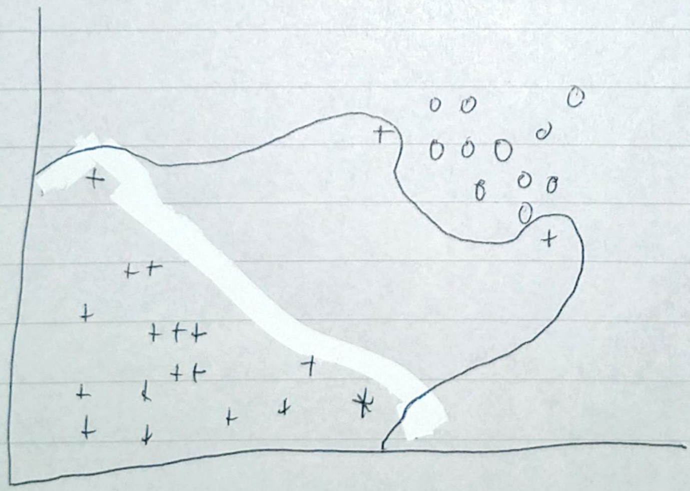
Exercise 5b)

Large σ gives low γ (gamma)



Exercise 5c)

Low σ gives high γ (gamma)



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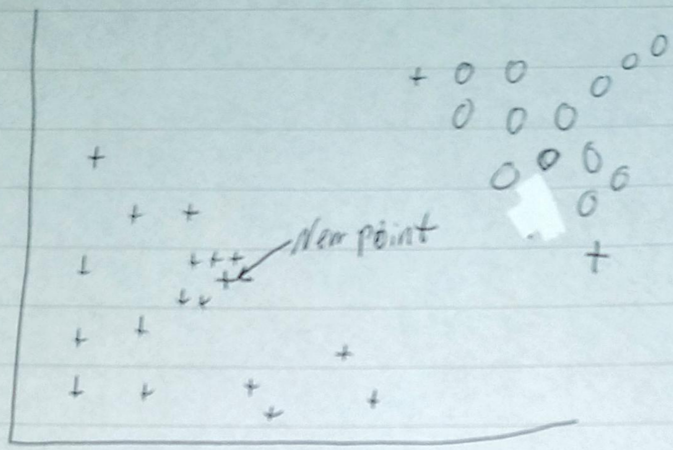
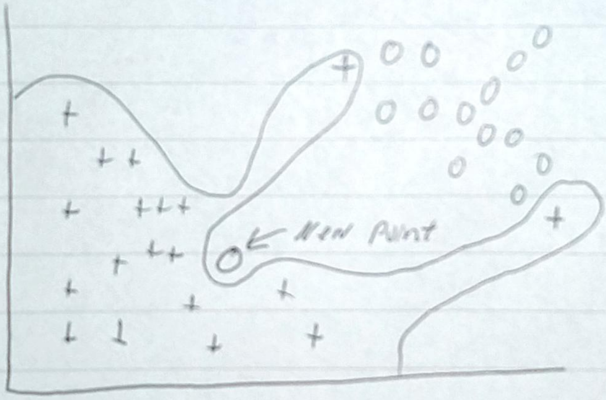
Exercise 5d)



Exercise 5e)



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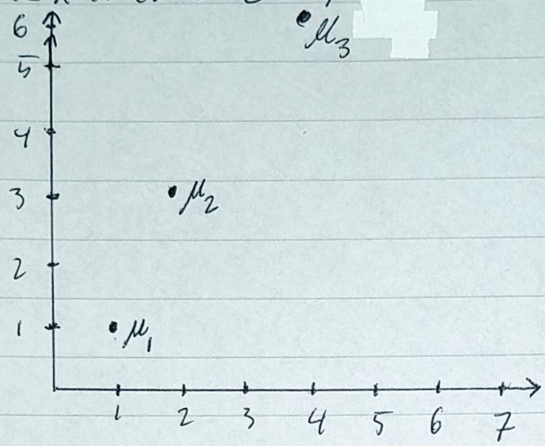
Exercise 6a)



I would chose the distance between the class means. As since they hve equal diagonal covariance matices the data clusters have the same shape.
Since we have more than 2 classes we need to chose how we represent this. I will chose smalest distance between a pair of classes.

Exercise 6b)
Using smallest distance between class means.

Class 1: $\min(|\mu_2-\mu_1|, |\mu_3-\mu_1|) = \min(\sqrt{3}, \sqrt{34}) = \underline{\underline{\sqrt{3}}}$
Class 2: $\min(|\mu_1-\mu_2|, |\mu_3-\mu_2|) = \min(\sqrt{3}, \sqrt{13}) = \underline{\underline{\sqrt{3}}}$
Class 3: $\min(|\mu_1-\mu_3|, |\mu_2-\mu_3|) = \min(\sqrt{34}, \sqrt{13}) = \underline{\underline{\sqrt{13}}}$