Quality Improvement and Segmentation of Mammography Images Using Python

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Abstract. Mammography is an one of early examination to detect the presence of breast cancer. In this research, mammography image quality was improved by reducing the degree of gray and noise and segmenting the image to clarify the cancer area. A total of seven digital mammography images were used with different types of tissue classifications derived from the database on the Kaggle.com website and processing was carried out using the Python programming language. The first step is to improve the quality of mammography images with the Anisotropic Diffusion method. Then testing the results of image quality improvement will be carried out by calculating the value of Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). In addition to improving image quality, this research also carried out image segmentation, image segmentation process using 2 methods are Otsu and multilevel Otsu. Meanwhile, testing the results of image segmentation will be carried out by calculating the Miclassified Area Mutual Overlap (MMO) value from manual segmentation and automatic segmentation. The test results of image quality improvement obtained good values ​​where the MSE is getting closer to 0 and the PSNR value has reached 30 dB using a kappa value of 40 and a gamma of 0.005. The results of segmentation testing using the Otsu method, the images that pass the segmentation test are images with classifications of circumscribed, architectural, spiculated and ill-defined masses. The results of segmentation testing using Otsu's multilevel method on asymmetry, calcification and ill-defined masses of image classification in each class variant have passed the segmentation test.

# Introduction

To reduce the rate of death from breast cancer at this time can be done by means of early examination through mammography. Mammography is an examination using X-rays and then provides an overview of the breast tissue. The mammography results should be carried out laboratory testing to detect the introduction of the cancer area [1]. Decision making a diagnosis by a doctor based on the presence of breast tissue abnormalities by looking at the characteristics seen on mammography image. The presence of noise in the image and poor lighting will affect the doctor's diagnosis. The detection process is done manually also cause differences in the perception of the diagnosis. So that digital medical image processing can help improve the reading quality of mammography images [2]. One of the image processing operations is to improve image quality by denoising and segmenting mammography images.

Perona and Malik (PM) proposed a diffusion-reaction equation with anisotropic diffusion for image denoising. In this method, the isotropic diffusion expressed through the linear heat equation is replaced by anisotropic diffusion. The PM method manages to improve edges, but is very sensitive to noise [3]. Meanwhile, image segmentation is a technique for dividing an image into several regions according to the similarity of attributes. The simplest method for the segmentation process is image thresholding or image floating [4]. In this research, global thresholding is used using the automatic function of the Otsu method. The approach used by the Otsu method is discriminant analysis. Discriminant analysis will maximize these variables in order to divide the foreground and background objects. The purpose of the Otsu method is to divide the histogram of the gray level image into two different areas automatically without requiring user assistance to enter a threshold value [5]. Most mammography images still have a degree of gray [1] and there is still noise so that it can affect the doctor's diagnosis in seeing the cancer area [6]. So to help overcome this, it is necessary to improve the image quality without blurring the edges of the image. Therefore, a research was carried out with the title Improving the Quality and Segmentation of Python-Based Mammography Imagery. In this research using the Anisotropic Diffusion method or also called the Perona Malik (PM) method to reduce noise. Then perform image segmentation using Otsu and Multilevel Thresholding Otsu methods.

The research to improve image quality using the Anisotropic Diffusion method has been carried out by Nanda Ayu Lestari who has improved image quality in digital image radiography where the method has succeeded in reducing salt and pepper and gaussian noise [7]. Then Ganvir and Yadav extracted clustered micro calcifications from mammogram images using cellular automata segmentation with Anisotropic Diffusion filter. From this research, it was concluded that the Anisotropic Diffusion method can reduce quantum noise without eliminating and correcting low contrast[8]. Naglaa S, et al conducted research on the removal of automatic artifacts, noise from mammographic images and segmentation using the Otsu method. The Otsu method has succeeded in detecting cancer areas contained in mammographic images [9]. Meanwhile, Vicko and Nina have compared the Otsu method and multilevel thresholding for retinal blood vessel segmentation. The result is that the Otsu method is better but the multilevel thresholding method produces high performance if it has RMSE and PSNR values [10].

This research was conducted to produce digital mammography images with better image quality and can sharpen certain features of the image as well as a basic prefix for Artificial Intelligence (AI). To determine cancer is not only determined through mammography, but it is necessary to do some validation that cancer is present in patients such as biopsy tests, histopathology, sample calculations and others. In this research only quantitative mammography images were assessed because other steps were needed to determine cancer. The results of image quality improvement using the Anisotropic Diffusion method will be tested based on the Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) values. The results of image segmentation using Otsu and Multilevel Thresholding Otsu methods will be tested based on the Miclassified Area Mutual Overlap (MMO) value. The use of these two methods to be used as a comparison of the results of image segmentation. In this research, will programmatically improve image quality and segmentation using Python 3.8.

# methodology

## Research Material

The research material used is secondary data, namely image data obtained from the Mammographic Image Analysis Society (MIAS) database obtained from the website www.kaggel.com. The image used in the form of digital mammography images and used as many as seven samples to be used as research material. The seven samples included mammographic images with abnormal tissue classification calcification, circumscribed masses, spiculated masses, ill-defined masses, architectural distortion, asymmetry and normal tissues. The size of the mammography image used is 1024x1024 pixels. The following is a sample image used in this research shown in Figure 1.

      

1. (b) (c) (d) (e) (f) (g)

Figure 1. Mammography Images: (a) Asymmetry, (b) Circumscribed, (c) Architectural, (d) Normal, (e) Spiculated, (f) Calcification, (g) Ill-defined masses

## Mammography Image Quality Improvement

The process begins by inputting digital mammography image to be used and then adding noise. The addition of noise is done to determine the difference in the noise level in the image before and after the noise filtering process using the Anisotropic Diffusion method. The types of noise added are salt&pepper noise and quantum or poisson noise. The addition of this type of noise is used because the noise is often found in mammography images [11]. After adding noise to the input image, the next step is noise filtering using the Anisotropic Diffusion method. In this noise filtering process, inputting of kappa and gamma values is also carried out. Kappa and gamma are parameters that affect the size of the noise reduction in the image. Anisotropic Diffusion can be defined as :

|  |  |  |
| --- | --- | --- |
|  | $$\frac{∂x(i,t)}{∂t}= div(c\left(x\_{i, }t\right)∇x\left(i,t\right))$$ | (1) |

Where $x\_{i }$is image intensity at position i, $∇$ is gradient and $c$ is diffusion coefficient that controls the amount of diffusion [3]. After the application of the Anisotropic Diffusion method, the resulting image will be obtained which has less noise.

Before applying the Anisotropic method, the thing to do is add noise to the image. Adding salt and pepper noise and quantum noise can be done by importing 'random\_noise' in the scikit-image library. For salt and pepper noise, the 's&p' mode is used. Then to set the density of salt and pepper noise use default value from Python is 0.05. Meanwhile, to add quantum noise or also called Poisson noise the ‘poisson’mode is used and the density of quantum noise use default value from Python is ‘seed=None’. After adding noise to the input image, the next step is noise filtering using the Anisotropic Diffusion method. In this noise filtering process, inputting of kappa and gamma values is also carried out. Kappa and gamma are parameters that affect the size of the noise reduction in the image. After the application of the Anisotropic Diffusion method, the resulting image will be obtained which has less noise. For the program to adding noise and anisotropic diffusion method can be seen in attachment.

## Mammography Image Segmentation

From the process of improving the quality of the mammography image, it was found that the improved image with the appropriate test value was based on the MSE and PSNR values. Image of the improvements that have corresponding image is used as input to the segmentation process. Then the automatic segmentation process is carried out with the Otsu thresholding method and Otsu Multilevel thresholding method. In the segmentation process using the Otsu thresholding method, the histogram of the gray image is divided into two different areas automatically. To determine the threshold value, Otsu makes the variance between classes D0 and D1 [12] as shown in Equation 2.

|  |  |  |
| --- | --- | --- |
|  | $$σ\_{B}^{2}= P\_{0}\left(t\right) (μ\_{0}\left(t\right)-µ\_{T})^{2}+ P\_{1}\left(t\right) (μ\_{1}\left(t\right)-µ\_{T})^{2}$$ | (2) |

Where $P\_{0}\left(t\right)$ is cumulative probability of class D0, $P\_{1}\left(t\right)$ is cumulative probability of class D1 and $µ\_{T}$ is average of the degree of gray. Meanwhile, in the segmentation process using the Multilevel Otsu method, variations in the threshold value will be carried out. Based on Equation 2 can be use to calculate Multilevel Otsu [12] as shown in Equation 3 and 4.

|  |  |  |
| --- | --- | --- |
|  | $$σ\_{B}^{2}\left(t\_{1,}t\_{2, \cdots , }t\_{k}\right)=\sum\_{i=0}^{k}Pi(t)(μ\_{i}\left(t\right)-µ\_{T})^{2}$$ | (3) |

|  |  |  |
| --- | --- | --- |
|  | $$\left(T\_{0,}T\_{1, \cdots , }T\_{k}\right)=\begin{matrix}arg max\\0<T\_{1}<…<T\_{K}<L-1\end{matrix} \{σ\_{B}^{2}\left(t\_{1,}t\_{2, \cdots , }t\_{k}\right)\}$$ | (4) |

Threshold value variations are carried out to find out at what threshold value produces the best segmentation so that the results of segmentation between cancer objects and the background can be seen clearly. To apply segmentation method in this research use skimage.filters from scikit-image package which is provide otsu and multilevel otsu segmentation. In multilevel otsu segmentation, the variations of classes were carried out as much as 2, 3, 4, 5 and 6. The code program to apply this segmentation can be seen in attachment.

## Testing the Results of Image Quality Improvement

In testing this mammography image quality improvement program, kappa and gamma values ​​were inputted from previous research. In a previous research conducted by Nanda Ayu Lestari [7] the image with the best results was obtained, namely at the turning point of the kappa value of 30 and gamma of 0.25. This test was conducted to determine the effect of kappa and gamma values ​​from previous studies on mammography images based on the Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) values.

The test begins by entering the kappa and gamma values ​​in the resulting image that has been added with noise, then noise filtering is carried out. Furthermore, the calculation for the value of MSE and PSNR. Determination of the MSE and PSNR values ​​in this research using the input image that has added noise compared to the image resulting from the denoising process using the Anisotropic Diffusion method. The MSE value is calculated to determine the error value of the image added with noise and the image resulting from denoising. MSE can be calculate by Equation 5 [13].

|  |  |  |
| --- | --- | --- |
|  | $$MSE= \frac{1}{MN} \sum\_{x=0}^{M=1}\sum\_{y=0}^{N=1}\left(g\left(x,y\right)-g'(x,y))^{2}\right)$$ | (5) |

Where $g\left(x,y\right)$ is original image matrix and $g'\left(x,y\right)$ is processed image matrix. After the MSE value is known, the PSNR calculation will be carried out to determine the comparison of the noise image quality with the denoising image as shown in Equation 6 [13].

|  |  |  |
| --- | --- | --- |
|  | $$PSNR= 20log\_{10}\frac{2^{n}}{\sqrt{MSE}}$$ | (6) |

An image with a PSNR value of more than 30 dB is considered to be of good quality. However, if the PSNR value is less than 30 dB, the image quality has been significantly degraded [14]. The relationship between the PSNR value and the MSE value is that the greater the PSNR value, the smaller the MSE value [13]. In this research to calculate the PSNR and MSE value can be use skimage.metrics and then import peak\_signal\_noise\_ratio or mean\_squared\_error for complete program to test image quality can be seen in attachment.

## Testing the Results of Image Segmentation

To determine the success of an image segmentation method, it can be calculated using Miclassified Area Mutual Overlap (MMO) or Dice Evaluation is an overlapping approach based on field calculations between ground truth and segmented fields as shown in Figure 2 [15].



Figure 2. Mutual Overlap : segmented area with whole line algorithm and manually segmented area with dotted line

The test is carried out by comparing the results of manual segmentation with automatic segmentation for the Otsu thresholding method and Otsu multilevel thresholding. Manual segmentation is done using Adobe Photoshop software by manually segmenting the foreground. In this manual segmentation, the area where the cancer is located will be made black and the background section will be made white. The steps in making manual segmentation begin by selecting the area suspected of being cancer as shown in Figure 3.

  

1. (b) (c)

Figure 3. Manual Segmentation Process: (a) Original Image, (b) Giving color to the cancer area, (c) Giving color to the background

From the results of the two automatic segmentation methods (Otsu and Multilevel Otsu) a comparison will be made based on the MMO value. Comparison of these two automatic segmentation methods is carried out to determine which method is the best in segmenting mammographic images. MMO can be calculate by Equation 7, where $MO$ is mutual overlap, $A1$ is segmented area and $A2$ is ground truth area. The MMO value can be accepted if it gets a value of more than 50% [15].

|  |  |  |
| --- | --- | --- |
|  | $$M\_{MO} = \frac{2MO}{A1+A2} X100\%$$ | (7) |

The program to calculate MMO which is can be seen in attachment, the gold truth area is initialized with m while the segmented area is initialized with o. “common = np.sum(np.logical\_and(m, o))” used to calculate the area of overlap between the gold truth and the segmented area. Then the number of pixels is calculated in the gold truth area and the segmented area using the command cm = np.sum(m) dan co = np.sum(o). Furthermore, the MMO value can be calculated using the command “Dice = ((2 \* common) / (cm + co))”.

# Results and discussion

## Image Result of Added Noise

In the addition of salt and pepper noise, the size of the noise is influenced by the density (amount) value. Meanwhile, to adjust the size of the quantum noise can be done through the given seed value. Programming for adding noise is done using the scikit-image module, the module has provided default values for each type of noise addition. Since there is no definite limit regarding the density of salt and pepper noise and quantum noise for mammography images, the default value of python is used for the density noise to be added to the image. The default value available for salt and pepper noise is 0.05, so the program will enter the value = 0.05. Meanwhile, in quantum noise or also called Poisson noise, the default seed value entered in the program is None. The meaning of seed=None is that the generator value is a random number generator. The following is an image of the addition of salt and pepper noise and quantum noise which is shown in Table 1.

Table 1. Image Result of Added Noise

| **Tissue Classification** | **Result of Adding salt&pepper Noise** | **Result of Adding *Q*uantum Noise**  | **Tissue Classification** | **Result of Adding salt&pepper Noise** | **Result of Adding *Q*uantum Noise** |
| --- | --- | --- | --- | --- | --- |
| Asymmetry  |  |  | **Spiculated** |  |  |
| Circumscribed |  |  | **Calcification** |  |  |
| Architectural |  |  | **Ill-defined** **Masses** |  |  |
| Normal |  |  |  |  |  |

## Denoising Results with Anisotropic Diffusion

Previous research using digital radiographic images obtained turning point values of kappa 30 and gamma 0.25 [7]. Which meant the turning point of the value of kappa and gamma namely when the kappa values <30 impaired MSE and after a kappa value > 30, an increase in the value of MSE. When the kappa value <30 there is an increase in the PSNR value and after the kappa value > 30 there is a decrease in the PSNR value. Likewise, at the gamma value < 0.25 there was a decrease in the MSE value and an increase in the PSNR value. Meanwhile, when the gamma value > 0.25 there is an increase in the MSE value and a decrease in the PSNR value. The purpose of the trial is to find out how the influence of kappa and gamma values in previous studies when applied to mammographic images. Tested values of kappa 30 and gamma 0.25 using three images with tissue classification Asymmetry, Circumscribed and Architectural. The results of image testing with a kappa value of 30 and a gamma of 0.25 are shown in Table 2.

Table 2.Denoising Result with Kappa 30 and Gamma 0,25

|  |  |  |
| --- | --- | --- |
| Images | Denoising Results with Salt&Pepper Noise | Denoising Results with Quantum Noise |
| **MSE** | **PSNR (dB)** | **MSE** | **PSNR (dB)** |
| *Asymmetry* | 0.0223 | 16.5129 | 0.0020 | 26.8170 |
| *Circumscribed* | 0.0213 | 16.7120 | 0.0032 | 24.9070 |
| *Architectural* | 0.0204 | 16.8896 | 0.0017 | 27.5936 |
| *Normal* | 0.0221 | 16.5437 | 0.0038 | 24.1318 |
| *Spiculated* | 0.0241 | 16.1784 | 0.0038 | 24.1744 |
| *Calcification* | 0.0234 | 16.2914 | 0.0033 | 24.7214 |
| *Ill-defined masses* | 0.0241 | 16.1765 | 0.0058 | 22.3236 |

Based on the results of image testing with added salt and pepper noise and quantum noise, the MSE value is getting smaller but the PSNR value is smaller than 30 dB. Because the obtained PSNR value is less than 30 dB, it can be said that the image quality has been significantly degraded. In this research, if the results of the image quality test obtained a PSNR value of less than 30 dB, changes were made to the kappa and gamma values to obtain a PSNR value of 30 dB. Where the value of kappa and gamma are parameters that affect the size of the noise reduction. To find the appropriate kappa and gamma values, the author made a selection by trial and error. After trying several random kappa and gamma values on the image, kappa values of 40 and gamma of 0.005 were used. The use of kappa and gamma values is based on the results of image testing with the resulting MSE and PSNR values are shown in Table 3.

Table 3. Denoising Result with Kappa 40 and Gamma 0,005

|  |  |  |
| --- | --- | --- |
| Images | Denoising Results with Salt&Pepper Noise | Denoising Results with Quantum Noise |
| **MSE** | **PSNR (dB)** | **MSE** | **PSNR (dB)** |
| Asymmetry | 0.0008 | 30.8480 | 0.0005 | 32.6076 |
| Circumscribed | 0.0010 | 29.9157 | 0.0008 | 30.8052 |
| Architectural | 0.0009 | 30.3416 | 0.0006 | 31.7613 |
| Normal | 0.0010 | 29.9844 | 0.0006 | 31.7247 |
| Spiculated | 0.0008 | 30.5968 | 0.0006 | 31.6283 |
| Calcification | 0.0008 | 30.6573 | 0.0008 | 30.6638 |
| Ill-defined masses | 0.0009 | 30.2517 | 0.0012 | 29.1882 |

Based on the results of the image quality improvement tests that have been carried out, it can be seen that the anisotropic diffusion method can reduce salt and pepper and quantum noise better in images with asymmetry classification. This can be seen from the low MSE value and higher PSNR compared to other images.

## Segmentation Results with Otsu Method

In the segmentation process using the Otsu thresholding method, the histogram of the gray image is divided into two different areas automatically by obtaining the average threshold value of the gray level histogram. In this research, the first cropping process is carried out on the input image which will then be segmented using the Otsu method. The cropping process is carried out because when Otsu segmentation is applied to the input image, an over-segmented image is produced so that if there is an area suspected of cancer tissue, it becomes invisible as shown in Figure 4.



1. (b)

Figure 4. Segmentation Result with Otsu Method Without Crop: (a) Input Image, (b) Segmentation Result

In this research, the input image that will be segmented using the Otsu method with a crop process, determining the cropped area based on the location of the suspected cancer tissue seen in the image. The image of the segmentation result of the Otsu method is shown in Table 4.

Table 4. Otsu Segmentation Result with Croping Process

| **Tissue Classification** | **Original Images** | **Denoising Image Crop** | **The image of denoising salt&pepper is segmented** | **The image of denoising quantum is segmented** |
| --- | --- | --- | --- | --- |
| Circumscribed |  |  |  |  |
| Spiculated |  |  |  |  |

Based on the segmentation results of the Otsu method, only images are obtained on the classification of circumscribed tissue which can visually show the difference between cancer tissue and the background. While the results of other image segmentation are still over-segmented so that the location of the tissue suspected of being cancer is not clearly visible even though it has gone through the image crop process. This is because the image containing the cancer tissue has almost the same level of contrast between the cancer tissue and the background. So that when the segmentation process the Otsu method is applied it is not good at distinguishing between cancer tissue and the background.

## Otsu Method Segmentation Test Results

The following are the results of segmentation testing using the Otsu method which are shown in Table 5.

Table 5. Otsu Method Segmentation Test Results

| **Tissue Classification** | **MMO** |
| --- | --- |
| **The image of denoising salt&pepper is segmented** | **The image of denoising quantum is segmented** |
| Asymmetry | 40.89% | 42.06% |
| Circumscribed | 87.36% | 87.15% |
| Architectural | 52.87% | 53.60% |
| Spiculated | 71.73% | 70.68% |
| Calcification | 41.86% | 42.62% |
| Ill-defined masses | 52.96% | 52.73%  |

Based on the results of testing the MMO value on images with asymmetry and calcification tissue classifications, the values have not reached 50%, while images with other tissue classifications have reached 50%. So it can be said that of the 6 images segmented using the Otsu method, only 4 images successfully passed the test based on the level of similarity with the manual segmentation image. This happens because the Otsu segmentation image has an image that is over-segmented so that when the test is carried out, the level of similarity with the manual segmentation image is very different, resulting in a low percentage value.

## Segmentation Results with Multilevel Otsu Method

Otsu's multilevel segmentation process is done by dividing the histogram of the gray image into several different areas automatically based on the class variant used. In Python multilevel otsu thresholds have a default value of class 3 variant, Satapathy [16] conducted a research using multilevel Otsu variants of class 2, 3, 4 and 5. While in this research use variants of class 2, 3, 4, 5 and 6. The application of segmentation to class 6 variants is because when the author tries to carry out more class variants such as variants of class 7, 8 and so on, it takes a longer time to run the program. So that the class variant used is only up to the class 6 variant. The image segmentation results using the Otsu multilevel method are shown in Table 6.

Table 6. Segmentation Result with Multilevel Otsu Method

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Tissue Classification** | **Original Images** | **Class Variants** | **The image of denoising salt&pepper is segmented** | **The image of denoising quantum is segmented** | **Tissue Classification** | **Original Images** | **Class Variants** | **The image of denoising salt&pepper is segmented** |  | **The image of denoising quantum is segmented** |
| Circumscribed |  | 2 |  |  | Spiculated |  | 2 |  |  |  |
| 3 |  |  | 3 |  |  |  |
| 4 |  |  | 4 |  |  |  |
| 5 |  |  | 5 |  |  |  |
| 6 |  |  | 6 |  |  |  |

## Multilevel Otsu Method Segmentation Test Results

The following are the results of segmentation testing using the Multilevel Otsu method which are shown in Table 7.

Table 7. Multilevel Otsu Method Segmentation Test Results

| **Tissue Classification** | **Class Variants** | **MMO** | **Tissue Classification** | **Class Variants** | **MMO** |
| --- | --- | --- | --- | --- | --- |
| The image of denoising salt&pepper is segmented | The image of denoising quantum is segmented | The image of denoising salt&pepper is segmented | The image of denoising quantum is segmented |
| Asymmetry | 2 | 80.48% | 85.86% | Spiculated | 2 | 51.70% | 58.04% |
| 3 | 12.67% | 68.19% |  | 3 | 12.60% | 14.22% |
| 4 | 59.88% | 79.98% |  | 4 | 18.87% | 44.51% |
| 5 | 52.73% | 73.03% |  | 5 | 13.37% | 19.07% |
| 6 | 53.83% | 60.03% |  | 6 | 67.65% | 83.50% |
| Circumscribed | 2 | 83.23% | 84.74% | Calcification | 2 | 77.12% | 79.64% |
| 3 | 28.52% | 26.36% |  | 3 | 41.92% | 51.08% |
| 4 | 65.99% | 73.92% |  | 4 | 67.19% | 74.63% |
| 5 | 49.07% | 60,16% |  | 5 | 44.04% | 63.73% |
| 6 | 37.44% | 32.56% |  | 6 | 40.92% | 59.39% |
| Architectural | 2 | 56.53% | 54.55% | Ill-defined masses | 2 | 72.43% | 72.95% |
| 3 | 27.96% | 30.23% |  | 3 | 49.46% | 52.11% |
| 4 | 45.71% | 50.42% |  | 4 | 48.09% | 72.26% |
| 5 | 25.68% | 32.51% |  | 5 | 48.81% | 68.76% |
| 6 | 26.41% | 28.91% |  | 6 | 51.24% | 54.05% |

In the Otsu multilevel segmentation test results, it is known that the denoising salt and pepper images in 6 abnormal tissue classifications produce MMO values ​​that have not yet reached 50%. Meanwhile, in the image of quantum denoising results, only images with asymmetry, calcification and ill-defined masses in each class variant have reached a value of 50%.

Based on Table 7, the segmentation between the denoising noise salt and pepper image and the average quantum in class variants 3, 4 and 5 resulted in an MMO value of less than 50%. So it can be said that the image has a low level of similarity with the manual segmentation image. Visually, when viewed from the segmentation results, the class 6 variant on average produces segmentation that can sharpen the characteristics of the image, namely the clearer area suspected of being cancer. However, when viewed from the average MMO value, the class 2 variant has a higher MMO value, this is because by calculation the class variant has a higher level of similarity with the manual segmentation image created.

# CONCLUSION

Based on the results of the research that has been done, it can be concluded that:

1. Image quality improvement using Anisotropic Diffusion method and mammography image segmentation using Otsu and Multilevel Otsu methods based on Python 3.8 were successfully carried out.
2. Improved mammography image quality for good salt&pepper and quantum noise obtained with kappa 40 and gamma 0.005 seen from the average MSE and PSNR values for each denoising salt and pepper image, which are 0.0009 and 30.3708 dB. And the average MSE and PSNR in each quantum denoising image are 0.0007 and 31.1970 dB.
3. Based on the results of segmentation testing using the Otsu method, seen from the MMO value, the images that pass the segmentation test are images with tissue classifications of circumscribed, architectural, spiculated and ill-defined masses. Meanwhile, the results of segmentation testing using the multilevel Otsu method are seen from the MMO value in images with asymmetry, calcification and ill-defined masses in each class variant that has passed the segmentation test.

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# ATTACHMENT

## Add Noise Code Program

import cv2

from skimage.color import rgb2gray

import numpy as np

from skimage.util import random\_noise

img\_ori = cv2.imread('mdb025circ.jpg')

print (img\_ori.shape)

img = rgb2gray(img\_ori)

#add salt&pepper noise

sp = random\_noise(img, mode='s&p', amount=0.05) #nilai density default 0,05

sp = np.array(255\*sp, dtype = 'uint8')

cv2.imwrite('spCirc.jpg', sp)

#add quantum noise

quantum = random\_noise(img, mode='poisson', seed=None, clip=True)

quantum = np.array(255\*quantum, dtype = 'uint8')

cv2.imwrite('quantumCirc.jpg', quantum)

## Anisotropic Diffusion Method Code Program

import numpy as np

from skimage import io

from scipy import ndimage

import matplotlib.pyplot as plt

from skimage.color import rgb2gray

image\_file1 = ' spCirc.jpg'

iterations = 30

gamma = 0.25

kappa = 30

im = io.imread(image\_file, as\_gray=True)

im = im.astype('float64')

im = rgb2gray(im)

# PDE initial condition

u = im

dx = 1

dy = 1

dd = np.sqrt(2)

# 2D finite difference windows

windows = [

 np.array(

 [[0, 1, 0], [0, -1, 0], [0, 0, 0]], np.float64

 ),

 np.array(

 [[0, 0, 0], [0, -1, 0], [0, 1, 0]], np.float64

 ),

 np.array(

 [[0, 0, 0], [0, -1, 1], [0, 0, 0]], np.float64

 ),

 np.array(

 [[0, 0, 0], [1, -1, 0], [0, 0, 0]], np.float64

 ),

 np.array(

 [[0, 0, 1], [0, -1, 0], [0, 0, 0]], np.float64

 ),

 np.array(

 [[0, 0, 0], [0, -1, 0], [0, 0, 1]], np.float64

 ),

 np.array(

 [[0, 0, 0], [0, -1, 0], [1, 0, 0]], np.float64

 ),

 np.array(

 [[1, 0, 0], [0, -1, 0], [0, 0, 0]], np.float64

 ),

]

for r in range(iterations):

 nabla = [ ndimage.filters.convolve(u, w) for w in windows ]

 diff = [ 1./(1 + (n/kappa)\*\*2) for n in nabla]

 terms = [diff[i]\*nabla[i] for i in range(4)]

 terms += [(1/(dd\*\*2))\*diff[i]\*nabla[i] for i in range(4, 8)]

 u = u + gamma\*(sum(terms))

Kx = np.array(

 [[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]], np.int32

)

Ky = np.array(

 [[1, 2, 1], [0, 0, 0], [-1, -2, -1]], np.int32

)

Ix = ndimage.filters.convolve(u, Kx)

Iy = ndimage.filters.convolve(u, Ky)

# return norm of (Ix, Iy)

G = np.hypot(Ix, Iy)

# save image

plt.imsave("hasilaniso\_n028.jpg", u, cmap='gray')

## Image Segmentation Code Program

import cv2

from skimage.filters import threshold\_otsu

from skimage.filters import threshold\_multiotsu

# otsu thresholding

thresh1 = threshold\_otsu(img\_1)

binary\_otsu1 = img\_1 < thresh1

cv2.imwrite('Otsu SPcirc.jpg', binary\_otsu1\*255)

# multi-Otsu thresholding

multiotsu1 = threshold\_multiotsu(img\_1 , classes=3)

regions1 = np.digitize(img\_1 , bins=multiotsu1)

plt.imsave("multiotsu SPcirc.jpg", regions1)

## Image Quality Improvement Test Code Program

from skimage.metrics import peak\_signal\_noise\_ratio

from skimage.metrics import mean\_squared\_error

MSE = mean\_squared\_error(noise\_img, denoising\_img)

print(MSE)

PSNR = peak\_signal\_noise\_ratio(noise\_img, denoising\_img)

print(PSNR)

## Image Segmentation Test Code Program

#program to calculate mmo

import numpy as np

def mmo\_python(m, o):

 m = m[:]

 o = o[:]

 common = np.sum(np.logical\_and(m, o))

 cm = np.sum(m)

 co = np.sum(o)

 Dice = ((2 \* common) / (cm + co))

 return [Dice]

#program to process segmentation test

import cv2

import mmo\_rumus as mmo

manual = cv2.imread('manual.jpg')

manual\_gray = cv2.cvtColor(manual, cv2.COLOR\_BGR2GRAY)

manualbins = cv2.threshold(manual\_gray, 128, 1, cv2.THRESH\_BINARY)[1]

manualbinary = manualbins.flatten()

segmented= cv2.imread('otsu.jpg')

segmented\_gray = cv2.cvtColor(segmented, cv2.COLOR\_BGR2GRAY)

segmentedbins = cv2.threshold(segmented\_gray, 128, 1, cv2.THRESH\_BINARY)[1]

segmentedbinary = segmentedbins.flatten()

result = mmo.mmo\_python(manualbinary,segmentedbinary)

calculate = result[0]

print (calculate)