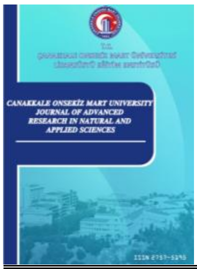
e-ISSN 2757-5195



Çanakkale Onsekiz Mart University

Journal of Advanced Research in Natural and Applied Sciences

Open Access

doi.org/10.28979/jarnas.1199343 2023, Vol. 9, Issue 2, Pages: 345-354 dergipark.org.tr/tr/pub/jarnas

Effect of Different Parameter Values for Pre-processing of Using Mammography Images

Hanife Avcı[1], Jale Karakaya[2,*]

[1,2]Department of Biostatistics, School of Medicine, Hacettepe University, Ankara, Türkiye

Article History
Received: 04.11.2022
Accepted: 26.12.2022
Published: 30.06.2023

Research Article

Abstract − Breast cancer is one of the most common types of cancer in women. To make a fast diagnosis, mammography images should have high contrast. Computer-assisted diagnosis (CAD) models are computer systems that help diagnose lesioned areas on medical images. The aim of this study is to examine the contribution of the changes in parameter values of various pre-processing methods used to increase the visibility of mammography images and reduce the noise in the images, to the classification performance. In this study, the mini-MIAS database were used. Gaussian filter, Contrast Limited Adaptive Histogram Equalization and Fast local Laplacian filtering methods were applied as pre-processing method. In this study, two different parameter values were applied for two different image processing methods (I. Parameter values are Gauss filter $\sigma = 3$, Laplacian filter σ=0.6 and α=0.6; II. Parameter values are Gauss filter $\sigma = 1$, Laplacian filter σ=2 and α=2). In the normal-abnormal tissue classification, higher accuracy and area under the curve were obtained in the 2nd parameter values in all classification methods. As a result, it has been acquired that different parameter values of the pre-processing methods used to improve mammography images can change the success of the classification methods.

Keywords *– Classification, computer-assisted, image enhancement, image processing, machine learning*

1. Introduction

In health care, determining the presence of a disease and developing various treatments involves the collection of complex multidimensional data for various purposes such as reducing the cost of drugs. Various biomedical imaging techniques such as magnetic resonance imaging (MRI), ultrasonography (US), computed tomography (CT), mammography, X-ray (X-ray) have been developed to increase the possibility of early and accurate diagnosis of diseases. In recent years, machine learning and deep learning algorithms are also frequently used as one of the areas of medical imaging, because it is one of the most important areas of radiology in the course of an investigation of the process of emergence of the disease in lighting and disease. Therefore, radiological images can be processed with machine learning and deep learning algorithms to assist health-care providers in making a diagnosis. Image processing is also used for a wide variety of scientific, artistic and commercial applications. In recent years, the image processing method has been used frequently, especially in the field of health. The use of various image processing methods for the processing of large-volume medical images in diagnosis, treatment planning and follow-up processes has increased especially in the last two decades (Scholl, Aach, Deserno, & Torsten, 2010). The purpose of medical image processing is to provide medical images used in diagnosis and treatment processes more understandable and informative. Cancer is one of the most common causes of death in the world. Breast cancer is one of the most common

[1] hanife.avci@hacettepe.edu.tr
[2] jalekarakaya@gmail.com
*Corresponding Author

types of cancer in women. Early diagnosis of cancer is very important because when cancer is diagnosed at an early stage, a more positive response to treatment methods can be obtained. Early and accurate diagnosis of the imaging as well as improving the statistical methods and various image processing algorithms can contribute importantly. Therefore, the use of mathematical and statistical methods in digital radiological images through Computer-Assisted Diagnosis (CAD) systems may be useful for radiologists to distinguish between benign and malignant masses (Mehdy, Ng, Shair, Saleh, & Gomes, 2017). Various algorithms have been proposed to increase the visibility of microcalcifications, one of the earliest signs of breast cancer, in mammography images (Besl & Jain, 1988). Among these algorithms, various methods such as mean filter, median filter, Gaussian filter, contrast-limited adaptive histogram equalization (CLAHE), un-sharp masking, Laplacian sharpening methods are used in the pre-processing step. In the literature, the success of various pre-processing methods on different images has been investigated in several studies (Ganvir & Yadav, 2019; Swathi, Anoop, Dhas, & Sanker, 2017; Al-Najdawi, Biltawi, & Tedmori, 2015). However, when we review at the literature, no study has been found in which the effect of the changes in the parameter values of the filtering methods used in the pre-processing step on the classification results. Due to the increasing amount of data, image processing and visualization algorithms need to be updated again.

In this study, different parameter values of Gaussian filtering, which is an image smoothing filter and Laplacian filtering methods used as sharpening filters, are discussed. The main motivation to examine the contribution of the changes in parameter values of various pre-processing methods used to increase the visibility of mammography images and reduce the noise in the images, to the classification performance. The plan of this study as follows. In Chapter 2, materials and methods were given. In Chapter 3, provides the experimental results and analysis. Finally, Chapter 4 discussion and concludes this work with future work.

2. Materials and Methods

In this study to show, the effect of the variability of parameter values of image pre-processing methods on classification performance, image processing algorithms was applied on mammography images. The image processing methods used in this study consist of 4 stages. The stages that are applied to images are image pre-processing, segmentation, feature selection after feature extraction and classification, respectively. The general flow diagram of the study is given in Figure 1.

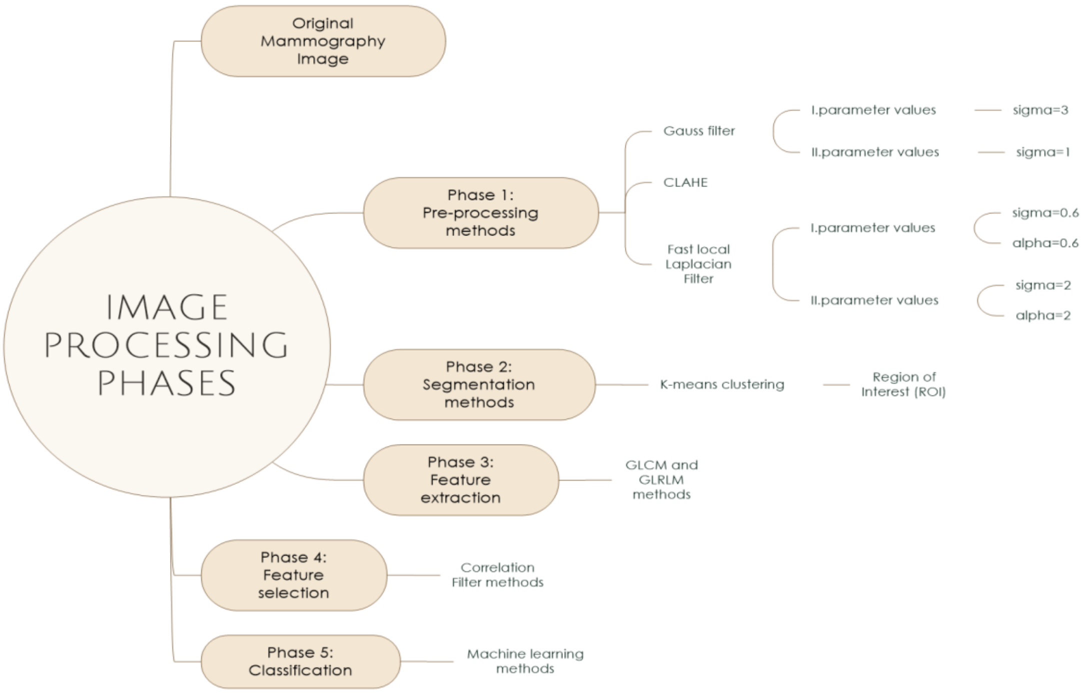


Figure 1. Flowchart of comparison of different parameter values of pre-processing methods for normal-abnormal lesion classification

2.1. Data collection

The open-access mini-MIAS database was used in the study (Suckling, 1994). It is an open-source database that is widely used in mammography image processing studies (Ganvir & Yadav, 2019; Bandyopadhyay, 2010; Ramani, Vanitha, & Valarmathy, 2013). This dataset consists of 322 digitized mammography images, including right and left breast images of 161 patients. Images are in “PGM” format. In the database all available mediolateral oblique (MLO) views of the left and right breast are included). The upper outer quadrant and axillary tail, which are the most common cancer locations in the breast, are better visualized with MLO imaging compared to other positions. All images in the database are 1024 x 1024 pixels in size, 200 microns in pixel thickness, and 8-bit (256 grey levels).

Ethics committee approval is not required because open access data was used in this study. Since it is public data, informed consent from patients is not required. This data set was collected from a single center and was preferred, because it provided us with the opportunity to compare with our own results according to image processing topic due to the application of standard measurement techniques and widespread use in the literature. In this study, 120 mammography images were randomly selected. Of these 120 images, 40 belong to individuals with normal, 40 benign and 40 malignant masses.

In this study, Fiji-ImageJ (Schindelin et al., 2012), MedPic (Demirci, 2020), MATLAB (The MathWorks, 2017) version R2017b for image processing methods and R Studio (RStudio Team, 2021) software were used to examine the performance of classification methods. We draw the plots in Figure 2A, B by using "ggplot2" package (Wickham, 2016) in RStudio.

2.2. Scenarios

For this study, the scenarios to be applied are given below.

i. Three different pre-processing methods were applied to mammography images (Gauss filter, CLAHE, Un-sharp masking).
ii. Two different parameter values were determined for Gaussian filter and Un-sharp masking filtering methods.
iii. I. Parameter values are Gauss filter $\sigma = 3$, Laplacian filter σ=0.6 and α=0.6.
II. Parameter values are Gauss filter $\sigma = 1$, Laplacian filter σ=2 and α=2.

2.3. Pre-processing

Pre-processing is an important step in medical image processing because some images contain unwanted information such as noise. Salt and pepper noise and Gaussian noise are the main types of noise in image processing (Swathi et al., 2017). Pre-processing methods remove noise in the analysed image and improve some image properties such as contrast. Pre-processing algorithms are usually done to prepare the data set to be used in the classification phase. The main purpose of pre-processing is to improve the image quality by removing irrelevant parts in the background of the images and make the images ready for segmentation. There are many pre-processing methods used in image processing (Bandyopadhyay, 2010).

Some mammography images in the mini-MIAS database contain label information. Since these labels originating from the mammography device have a high-density value, they may cause false results from the images. Therefore, thresholding and dilation morphological processes were applied to clear labels from mammography images. With processes, it is aimed to clean the labels, artificial lines and noisy areas in the images. Later, pre-processing methods were used in mammography images to improve image quality and improve segmentation results. In this study, mainly Gauss filter, CLAHE and Fast local Laplacian filtering methods were applied to mammography images.

The widely used smoothing filter in the image pre-processing stage is the Gaussian blur filter. This filter uses the Gaussian distribution function. Therefore, the effect of removing noise from the image depends on the standard deviation of the Gaussian distribution. The larger the standard deviation value in the Gaussian distribution, the larger the size of the Gaussian blur filter. The σ (sigma) parameter of the Gaussian filtering method varies in the range of $-3<\sigma<3$ (Dasgupta & Wahed, 2014).

Fast local Laplacian filtering is an image sharpening filtering method that measures the rate at which the first derivatives of images change. For the Laplacian filtering method, σ (sigma) and α (alpha) parameter values are determined. The σ value for binary images should be in the range of [0, 1] and for images with different intervals, the σ value should be in the range of [a, b]. The α value is in the range of [0.01, 10] (Paris, Hasinoff, & Kautz, 2011).

The CLAHE algorithm, on the other hand, balances the distribution of the grey values used, thus making the hidden areas of the image more visible.

In this study, two different parameter values were applied for two different image processing methods. First, the σ parameter value of the Gaussian filtering method was determined as 3 and the σ and α parameter values of the Laplacian filtering method were determined as 0.6. Then, the σ parameter value of the Gaussian filtering method was determined as 1, the σ and α parameter values of the Laplacian filtering method were determined as 2 and the performance results for classification according to the differences in parameter values were examined (Avcı & Karakaya, 2021). In other words, the performance of the classification methods was examined as the size of the Gaussian blur filter decreased and the size of the Fast local Laplacian filter increased.

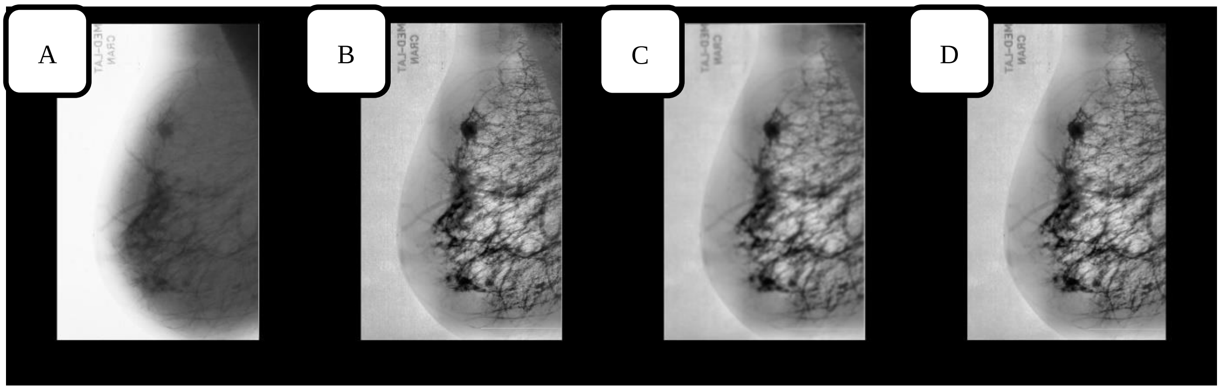


Figure 2. mdb023 malignant original left MLO mammography image in mini-MIAS database (A). Contrast-enhanced image with CLAHE algorithm (B). Image with Gaussian filter sigma=3 (C). Image with Gaussian filter sigma=1 (D).

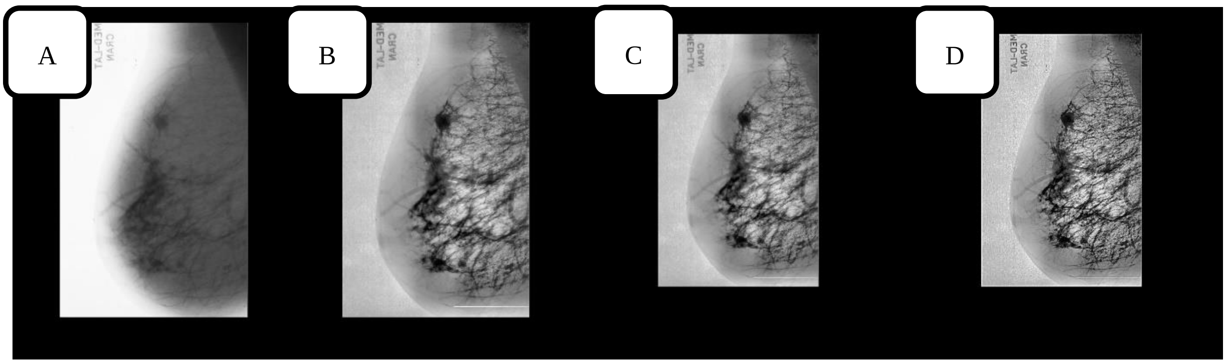


Figure 3. mdb023 malignant original left MLO mammography image in mini-MIAS database (A). Contrast-enhanced image with CLAHE algorithm (B). Image with Fast local Laplacian filter sigma=0.6, alpha=0.6 (C). Image with Fast local Laplacian filter sigma=2, alpha=2 (D).

2.4. Segmentation and ROI

It can be said that image segmentation is the most difficult step in image processing because the success of the segmentation process has a great effect on feature extraction and classification performance. Image segmentation is dividing an image into regions and objects with different features in each region. In other words, image segmentation is the process of dividing an image into meaningful parts. The pixels in the regions obtained at the end of the segmentation process have common features. In image processing, the region of interest (ROI) must be determined by the appropriate segmentation method before feature extraction.

The next important step for mammography images that are cleared of labels and artifacts by pre-processing methods is to extract ROIs by clearing pectoral muscle, etc., from images with the appropriate segmentation method. In this study, the k-means clustering algorithm was chosen as the segmentation method. This method has been preferred because it does not require any prior knowledge and is better than other region enlargement techniques. After the images obtained after the segmentation process are applied as a mask on the original images, ground truth images are obtained.

2.5. Feature Extraction and Selection

Another important step in image processing is to extract features from images. In the field of image processing, feature extraction methods are algorithms that calculate various features of ROIs in the image. In other words, feature extraction is a method of capturing the visual content of images. Correct classification of images depends on the selection of the most suitable features because these attributes characterize a particular region, they are used as input variables in the classification phase.

After the image pre-processing and segmentation processes were applied to the mammography images, feature extraction was performed. In this study, Grey-Level Co-Occurrence Matrix (GLCM) and Grey Level Run Length Matrix (GLRLM) methods were used as feature extraction techniques. 22 features were extracted with the GLCM method and 11 features were extracted with the GLRLM method. These features were extracted from ROI samples by GLCM and GLRLM methods in four different directions: 0°, 45°, 90° and 135°. The feature matrix was obtained by taking the average of these extracted features. Thus, with the help of this feature matrix, mammography images were converted into numerical data. The texture feature is used to identify the cancer area in the mammography image. Texture is a combination of patterns that are repeated with a regular frequency.

For feature selection, first of all, the correlation matrix was examined. Among the 33 features obtained, a selection was made by selecting only one of the features with a correlation of more than 0.90.

2.6. Classification

These numerical data obtained as a result of image processing were used as input variables in classification methods. Thus, in the application realized, the calculated features and ROI samples were classified as normal-abnormal tissue with 6 different classification methods according to different parameter values of the pre-processing methods. Methods used for classification:

(1) Support Vector Machine (SVM)
(2) Random Forest (RF)
(3) Artificial Neural Network (ANN)
(4) k-Nearest Neighbors (k-NN)
(5) Naive Bayes (NB)
(6) Decision Tree (DT)

The classification performances of each selected feature in detecting the presence of a lesion alone were examined with the area under the curve (AUC) values obtained as a result of the ROC Analysis. In this study, comments were made on the AUC values, as they combined the sensitivity and specificity values. The performances of these models established for classification methods were evaluated according to accuracy, sensitivity, specificity, AUC and F1 evaluation criteria. 95% confidence intervals (CI) for the accuracy and AUC values were also calculated. The accuracy of the triple classification was calculated with the help of confusion matrix. Accuracy values were calculated by the ratio of the correctly classified cells in the confusion matrix to the total sample number. The radiologist's evaluations in the mini-MIAS database were used as the gold standard for calculating sensitivity and specificity values. Details about the performance measures can be accessed from relevant source (Karakaya, 2021).

3. Results and Discussion

In this part, the results of the test performances of the scenarios of two different parameter values are given in this section. The results are presented below.

After applying Gaussian filter, CLAHE, Fast local Laplacian filtering and k-means clustering algorithms on the mammography images obtained from the mini-MIAS dataset, the classification success of the features obtained by GLCM and GLRLM methods was examined with the AUC. The AUC values of the selected features alone vary between 0.541-0.721 for the first parameter values and 0.550-0.826 for the second parameter values. In Table 1, the AUC values and confidence intervals of the 10 selected features are given according to the parameter values. It has been observed that most of the features obtained with the second parameter values have higher classification performances than the first parameter values.

Table 1
AUC values and confidence intervals for normal-abnormal classification of 10 features selected using the correlation coefficient

Feature name	**1. According to Parameter Values (95% CI)**	**2. According to Parameter Values (95% CI)**
Autocorrelation	0.721 (0.630-0.812)	0.732 (0.642-0.822)
Contrast	0.586 (0.480-0.692)	0.565 (0.458-0.672)
Correlation	0.541 (0.432-0.650)	0.623 (0.520-0.726)
Cluster prominence	0.552 (0.444-0.660)	0.550 (0.442-0.658)
Energy	0.661(0.562-0.760)	0.683 (0.586-0.780)
Short run emphasis	0.615 (0.511-0.719)	0.819 (0.745-0.893)
Long run emphasis	0.608 (0.504-0.712)	0.826 (0.754-0.898)
Low grey level run emphasis	0.619 (0.516-0.722)	0.678 (0.581-0.775)
Short run low grey-level emphasis	0.640 (0.539-0.741)	0.595 (0.490-0.700)
Long run low grey-level emphasis	0.614 (0.510-0.718)	0.694 (0.599-0.789)

1.Parameter values: Gauss filter $\sigma = 3$, Laplacian filter σ=0.6 and α=0.6
2. Parameter values: Gauss filter $\sigma = 1$, Laplacian filter σ=2 and α=2
CI: Confidence intervals

The accuracy values and its confidence intervals (95% CI) of classification methods as a three class (normal-benign-malignant tissue) according to the different parameter values of the mammography images in the MIAS database, where the 10 selected features are evaluated together, are given in Table 2. According to these results, as the parameter value of the Gaussian blur filter gets smaller and the Fast local Laplacian filtering parameter values get larger, higher accuracy values are obtained. According to the accuracy, in 2nd parameter values, SVM and Naive Bayes methods are more successful than other methods.

Table 2
Accuracy values and confidence intervals of classification methods according to different parameter values in normal, benign and malignant classification

Machine learning methods	1. According to Parameter Values (95% CI)	2. According to Parameter Values (95% CI)
SVM	0.556 (0.467-0.645)	0.833 (0.766-0.900)
RF	0.500 (0.411-0.589)	0.750 (0.673-0.827)
ANN	0.528 (0.439-0.617)	0.722 (0.642-0.802)
k-NN	0.417 (0.329-0.505)	0.444 (0.355-0.533)
NB	0.528 (0.439-0.617)	0.833 (0.766-0.900)
DT	0.389 (0.302-0.476)	0.722 (0.642- 0.802)

1.Parameter values: Gauss filter $\sigma = 3$, Laplacian filter σ=0.6 and α=0.6
2. Parameter values: Gauss filter $\sigma = 1$, Laplacian filter σ=2 and α=2
CI: Confidence intervals

According to these results, as the parameter value of the Gaussian blur filter gets smaller and the Fast local Laplacian filtering parameter values get larger, higher accuracy values are obtained. According to the accuracy, in 2nd parameter values, SVM and NB methods are more successful than other methods.

Then, to examine the classification performance of images with and without lesions as a two class, normal images were classified as normal-abnormal, considering normal images as a group and benign and malignant images as a group. The accuracy values of the classification methods according to the 1st and 2nd parameter values regarding the three (normal-benign-malignant) and two (normal-abnormal) classification results are given in Figure 4 and Figure 5.

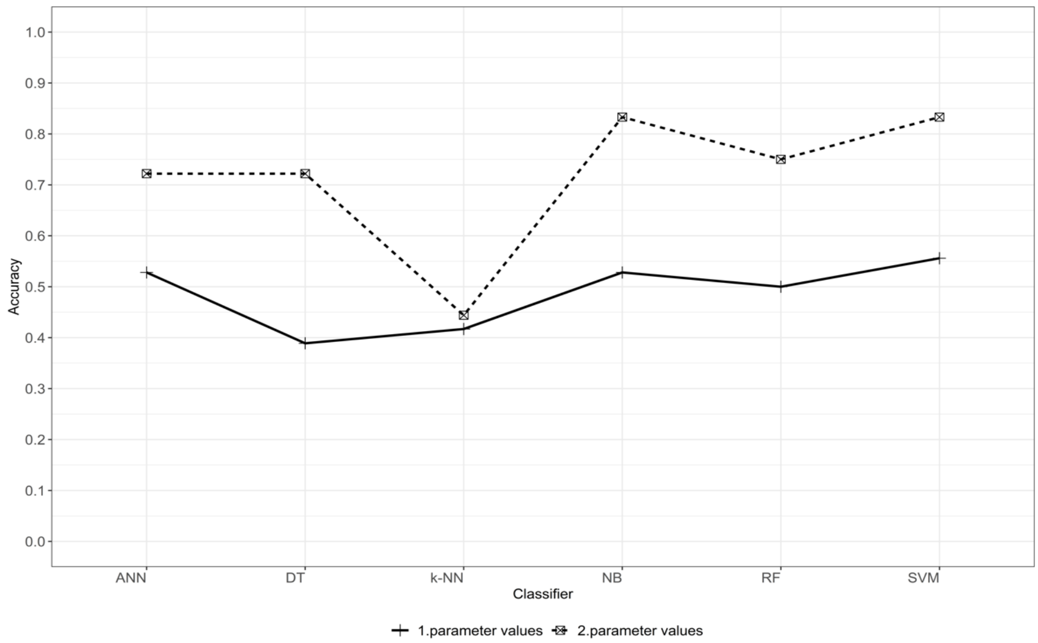


Figure 4. Comparison of accuracy values of classification methods according to different parameter values: 3 class (normal-benign-malignant classification).

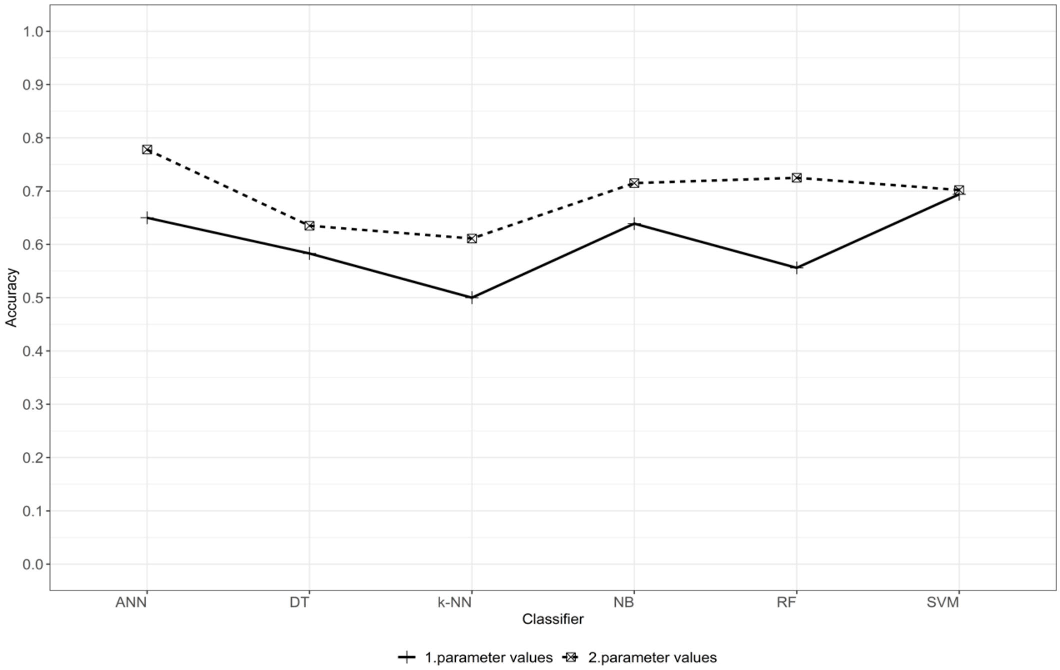


Figure 5. Comparison of accuracy values of classification methods according to different parameter values: 2 class (normal-abnormal classification).

The results of the normal-abnormal classification of the characteristics of the examined data set are given in Table 3. According to Table 3, the 2nd parameter values showed higher performance than the 1st parameter values in terms of both accuracy and AUC. When we look at measures such as Accuracy and AUC, according to the 2nd parameter values, the performances of the SVM, RF, ANN and NB classification methods are more successful than the k-NN and DT methods.

Table 3
Performance of classification methods according to different parameter values of pre-processing algorithms for normal-abnormal classification

	1. According to Parameter Values					**2. According to Parameter Values**				
Machine learning methods	**CA**	**Sensitivity**	**Specificity**	**AUC**	**F1**	**CA**	**Sensitivity**	**Specificity**	**AUC**	**F1**
SVM	0.694	0.683	0.214	0.566	0.800	0.702	0.823	0.571	0.795	0.711
RF	0.556	0.727	0.285	0.578	0.667	0.725	0.718	0.571	0.823	0.727
ANN	0.650	0.694	0.780	0.750	0.617	0.778	0.860	0.850	0.854	0.787
k-NN	0.500	0.530	0.480	0.500	0.555	0.611	0.583	0.455	0.550	0.601
NB	0.639	0.500	0.620	0.565	0.628	0.715	0.730	0.540	0.680	0.775
DT	0.583	0.525	0.513	0.520	0.634	0.635	0.615	0.475	0.550	0.640

CA: Classification accuracy
AUC: Area under the curve

It is emphasized that the pre-processing step is very important in the segmentation and feature extraction stages in determining the suspicious regions in mammography images by computer-assisted systems. In the literature, pre-processing algorithms have been used in single or double form in most of the studies (Al-Najdawi et al., 2015; Ramani et al., 2013). However, there is no study for examining the effect of parameter values on performance measures of classification methods, as in this study on filtering methods used as a pre-processing method.

Therefore, this study was planned to see the effects of the use of different parameter values for the blur and sharpen filtering dimensions on the performance of the classification methods.

The effects of mean, median, adaptive median, Wiener and Gaussian filtering methods on different noise types in mammography images were evaluated with measures such as Peak Signal-to-Noise Ratio (PSNR) and Signal-to-Noise Ratio (SNR) (George & Sankar, 2017). After using Transformer oil images mean, median, Wiener and non-local means (NLM) filtering methods as a pre-processing method, an evaluation was made according to image quality evaluation measures such as mean square error (MSE) and PSNR (Maheshan & Kumar, 2019). In our study, the effects of smoothing and sharpening filtering methods on the performance of classification methods according to different parameter values were investigated. It has been investigated that the applied filtering methods can change the performance of the classification methods when their size is changed.

Considering the results obtained in both three and binary classification, high classification results were obtained with SVM, RF, ANN and NB methods and low classification results were obtained with k-NN and DT methods. In this study, classical machine learning methods were used as a classification method.

We used sigma=3 and sigma=1 for Gaussian blur filtering method, sigma=0.6 alpha=0.6 and sigma=2 alpha=2 for Laplacian filter. However, instead of 2 different parameter values for filtering methods, an optimal value will be determined after trying all possible combinations after trying many parameter values. In future studies, an optimal value can be found by examining different parameter values of different filtering methods and the performance of deep learning methods can be examined.

4. Conclusion

In conclusion, it was seen that the changes in the parameters of the filtering methods used as the pre-processing method affected the performance results of the classification methods. In this study, two different filtering methods were analysed according to the parameter values. In other words, the performance of the classification methods increased as the parameter value of the Gaussian blur filter decreased and the Fast local Laplacian filtering parameter values increased.

Acknowledgement

Author would like to thank Prof. Dr. Recep DEMIRCI for the image processing software named MedPic used for the segmentation step in this study.

Author's Contributions

Hanife Avcı: Performed the data analysis, wrote the paper.

Jale Karakaya: Conceptualization, designing and coordinated the study, wrote the paper.

Conflicts of Interest

There is no conflict of interest declared by the authors.

References

Al-Najdawi, N., Biltawi, M., & Tedmori, S. (2015). Mammogram image visual enhancement, mass segmentation and classification. Applied Soft Computing, 35, 175-85. DOI: https://doi.org/10.1016/j.asoc.2015.06.029

Avcı, H., & Karakaya, J. (2021). Mamografi Görüntülerinde Ön işlemede Kullanılan Filtreleme Yöntemleri İçin Belirlenen Farklı Parametre Değerlerinin Sınıflama Başarısına Etkisi. 22.Ulusal ve 5. Uluslararası Biyoistatistik Online Kongresi.

Bandyopadhyay, S. (2010). Pre-processing of Mammograms Images. International Journal of Engineering

Science and Technology, 2(11), 6753-6758.

Besl, P.J., & Jain, R.C. (1988). Segmentation through variable-order surface fitting. IEEE Transactions on Pattern Analysis and Machine Intelligence, 10(2), 167-192. DOI: https://doi.org/ 10.1109/34.3881

Dasgupta, A., & Wahed, A. (2014). Clinical Chemistry, Immunology and Laboratory Quality Control. Chapter 4-Laboratory Statistics and Quality Control, 47-66.

Demirci R. MedPic interface software 2020.

Ganvir, N.N., & Yadav, D. M. (2019). Filtering Method for Pre-processing Mammogram Images for Breast Cancer Detection. International Journal of Engineering and Advanced Technology, 9(1), (2019), 4222-4229. DOI: https://doi.org/10.35940/ijeat.A1623.109119

George, M.J., & Sankar, S.P. (2017). Efficient pre-processing filters and mass segmentation techniques for mammogram images. IEEE International Conference on Circuits and Sytems, (2017). DOI: https://doi.org/ 10.1109/ICCS1.2017.8326032

Karakaya, J. (2021). Evaluation of binary diagnostic tests accuracy for medical researches. Turk J Biochem, 46(2), 103-113. DOI: https://doi.org/10.1515/tjb-2020-0337

MATLAB and Image Processing Toolbox Release 2017b, The MathWorks, Inc., Natick, Massachusetts, United States. Retrieved from https://www.mathworks.com/products/matlab.html.

Maheshan, C. M., & Kumar, H. P. (2019). Performance of image pre-processing filters for noise removal in transformer oil images at different temperatures. SN Applied Sciences, 2(1), 67-73. DOI: https://doi.org/10.1007/s42452-019-1800-x

Mehdy, M. M., Ng, P. Y., Shair, E. F., Saleh, N. I. Md., & C. Gomes. (2017). Artificial Neural Networks in Image Processing for Early Detection of Breast Cancer. Open Access Hindawi Computational and Mathematical Methods in Medicine, 1-15. DOI: https://doi.org/10.1155/2017/2610628

Paris, S., Hasinoff, S. W., & Kautz, J. (2011). Local Laplacian Filters: Edge-aware Image Processing with a Laplacian Pyramid. ACM Transactions on Graphics (TOG), 30(4), 1-12. DOI: https://doi.org/10.1145/2723694

Ramani, R., Vanitha, S., & Valarmathy, S. (2013). The Pre-Processing Techniques for Breast Cancer Detection in Mammography Images. International Journal of Image, Graphics and Signal Processing, 5(5), 47-54. DOI: https://doi.org/10.5815/ijigsp.2013.05.06

RStudio Team (2021). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA. Retrieved from http://www.rstudio.com.

Schindelin, J., Arganda-Carreras, I., Frise, E., Kaynig, V., Longair, M., Pietzsch, T., & Cardona, A. (2012). Fiji: an open-source platform for biological-image analysis. Nature Methods, 9(7), 676–682. DOI: https://doi.org/10.1038/nmeth.2019

Scholl, I., Aach, T., Deserno, T. M., & Torsten, K. (2010). Challenges of medical image processing. Comput Sci Res Dev, 26(1), 5-13. DOI: https://doi.org/10.1007/s00450-010-0146-9

Suckling, J. (1994). The Mammographic Image Analysis Society Digital Mammogram Database. In Exerpta Medica. International Congress Series 1069, York, England, 1069:375-378

Swathi, C., Anoop, B. K., Dhas, D.A.S., & Sanker, S. P. (2017). Comparison of different image preprocessing methods used for retinal fundus images. Conference on Emerging Devices and Smart Systems (ICEDSS, 2017). DOI: https://doi.org/ 10.1109/ICEDSS.2017.8073677

Turgut, A.T., Hasırcıoğlu, F., Koşar, U. (2000). Meme Hastalıklarının Tanısında Mamografi. Sted Sürekli Tıp Eğitimi Dergisi, 9 (12)

Wickham, H., (2016). ggplot2. Elegant Graphics for Data Analysis. New York, NY: Springer-Verlag New York.