

Classification of Microscopic Images of Normal Breast Tissue Using Texture Features

Mihad M. B.Abdalrahman¹, M. E. M.Garelnabi², Eltahir Mohamed Hussein³,
Fatima Majzoub Ibrahim⁴ and Jihan Ahmed Ibrahim Abdrahman⁵

¹Faculty of Engineering and Technology, University of Gezira, Sudan

²College of Medical Radiologic Science, Sudan University for science and technology, Sudan

³College of Engineering, Sudan University for science and technology, Sudan

⁴College of Medical Laboratory Science, Sudan University for science and technology, Sudan

⁵Faculty of Medicine, University of Al-Neelain, Sudan

*Corresponding Author: Mihad M. B.Abdalrahman¹

ABSTRACT: Image analysis depends on the study of the image data for a specific application to extract significant information from the image; normally the input data of the image is too large to be processed and it might lead to oversight; such as microscopic samples contain large numbers of cells and other structures and surrounded by different types of tissue. Hence, the manual interpretation of histological images is time-consuming and requires a considerable skill and experience. This study, was demarcate the main types of breast tissue (fat, glandular tissue and connective tissue) on images microscopic using various sizes of windows for extracting data from a defined region of interest (ROI) on an image and the elect window was determined in respect to the best accuracy, similarly textural feature revolutionized (stepwise) in order to choose the most discriminant feature to identify the (ROI). was found that the window size (20×20 pixel) gives high accuracy in demarcating normal tissues of breast; also the features: Median, mode, variance and stander deviation were the most discriminant textural feature, where the overall and higher classification was **99.4%**.

Keywords: breast tissue, microscopic samples, histological images, textural feature

I. INTRODUCTION

Histology is the study of the microscopic anatomy of cells and tissues of the living organism. It is an important tool for pathologists to identify the morphological characteristics of tissues which indicate the presence of disease like cancer and hence determine the grade of disease according to the transformation and spreading of transformed cells of the tissues, which lead to appropriate management [1].

Normal tissues must be recognize first in order to get attention to any changes in tissue and hence detection of cancerous tissue, In this study, the main types of breast tissues were identified i.e. fat, glandular tissue and connective tissue on microscopic images using various sizes of windows for determining the region of interest (ROI) on an image and to choose the best window (in respect to accuracy), as well as integrated several textural features, where the most discriminant and well correlated (ROI) were adopted.

The breast is a complex organ consisted of different types of tissue Fig1 [2]. It is primarily made up of fat and breast tissue, along with connective tissue, nerves, lymphatic vessels and blood vessels [3]. The fat tissue (adipose tissue) increases as women aged [4]. Fibrous tissue and fat gives breast their size and shape and hold the other tissues in place [5]. Breast tissue is a complex network of lobules and ducts. Lobules produce milk during pregnancy and lactation. The ducts carry milk from the lobules to the nipple openings. Breast tissue may also be called glandular tissue [3]. The connective tissue (stroma), it supports the breast elements including the ducts and lobules. There are ligaments that stretch from the chest wall muscle to the skin which hold the breast in place (Cooper's ligaments). The lymphatic and blood vessels are located within the stroma [4].

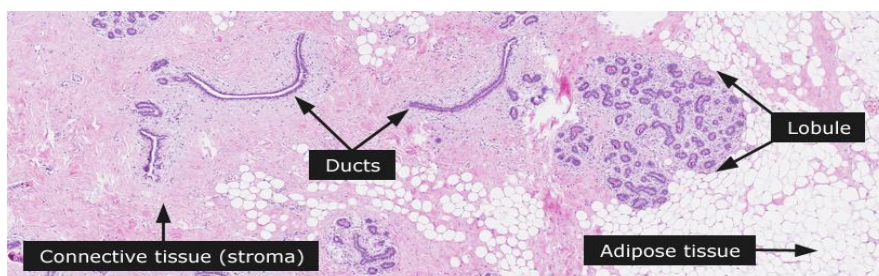


Fig 1. Microscopic sample of normal breast (arrows)

Angel et al., (2014) introduced a deep learning approach for automatic detection and visual analysis of invasive ductal carcinoma (IDC) tissue regions in whole slide images (WSI) of breast cancer (BCA). The method was carried out over a WSI dataset for 162 patients diagnosed with IDC. Three hundred and thirteen slides were selected for training and 49 slides were held out for independent testing. This method produced a results for automatic detection of IDC regions on WSI in terms of F-measure and their accuracy was 71.80%, 84.23% respectively [6]. Teresa et al. (2017) presented method for the classification of Hematoxylin and eosin stained breast biopsy images using Convolutional Neural Networks (CNNs). Images were classified into four classes, normal tissue, benign lesion, carcinoma in situ and invasive carcinoma, as well as into two classes; carcinoma and non-carcinoma, for four classes; the accuracy of the obtained results was 77.8% and 83.3% for two classes [7]. Amirreza et al. (2018) proposed fully automatic method to classify breast cancer in histological images into four classes: normal, benign, carcinoma in situ and invasive carcinoma. The proposed method takes normalized Hematoxylin and eosin stained images as input and gives the final prediction by fusing the out- put of two residual neural networks (ResNet) of different depth. The accuracy of the obtained results was 97.22% when applied on the BioImaging 2015 challenge dataset, the accuracy was 88.50% when applied on the ICIAR 2018 grand challenge dataset[8]. Kamyar et al. (2014) introduced Two-Stage Convolutional Neural Network for Breast Cancer Histology Image Classification the first network is aimed at extracting local information while the second network obtains global information of an input image. This proposed method yields 95% accuracy on the four-class: normal, benign, carcinoma in situ, and invasive carcinoma [9].

II. MATERIAL AND METHODS

The proposed method is fundamentally based on several stages the most important one was: preprocessing, feature extraction and classification .shown in Fig 2.

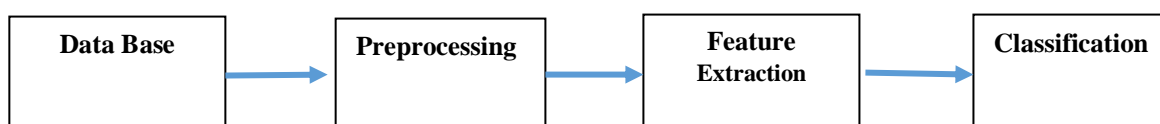


Fig 2. The proposed method

Pre-processing: Since the microscopic images of breast contain added color information to enhance certain anatomical features of it, thus preprocessing is employed to transform color (RGB) image into grayscale image. This transformation results in a significant reduction of computational time in the feature extraction process. The microscopic images of the breast have a large size, can be subdivided into the required size using windows.

Feature extraction First-order statistical (FOS) features are extracted from the grey scale image, they represent, the general quality of the image [10]. Now will describe some of the textural features: Mean (signal) is the measure of the average intensity of all pixels in inside the window, similarly the Median is a measure of the intensity level of a pixel which is separating the pixels in respect to their density, the mode vote the highly populated pixel type. The standard deviation and variance refers to the measure of the variability in an image. The skewness (3rd moment) is a measure of symmetry; which deals with the degree of histogram asymmetry around the mean. The kurtosis (4th moment) is a measure of relative flatness also known as the fourth moment, a descriptor of the shape of a probability distribution. The mathematical expressions of the above descriptors are available [11].

III. RESULTS AND DISCUSSION

In this study 900 sub-images of normal tissues (300 Fat tissues, 300 Connective tissue and 300 glandular tissues) from Pathpedia [12]. The data in this study extracted using 3 sizes of window based on three features (mean, skewness and Kurtosis) the result as shown in Table.1

Table 1. Classification accuracy versus window size

Window	Accuracy%
Window one (5×5)pixels	82,1
Window two(10×10) pixels	82.9
Window three(20×20) pixels	92.9

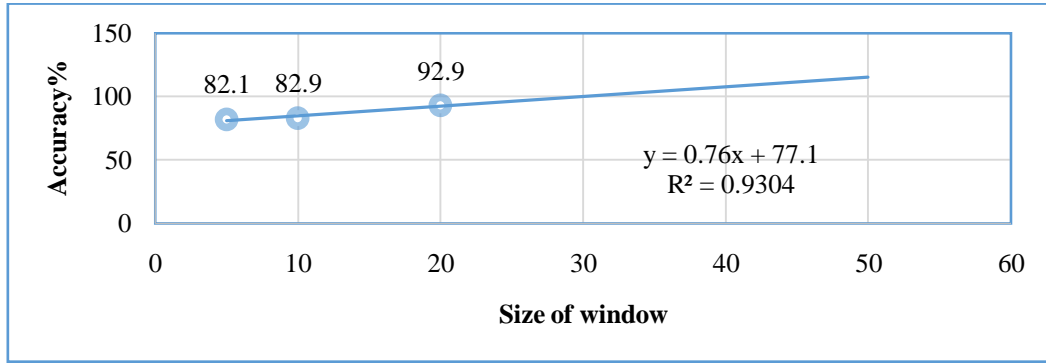


Fig 3. Liner regression of results based on size of window When use the window

The classification accuracy increases by 0.76 percent/cm of window side starting at 86.7% i.e. the accuracy significantly and directly correlated with window size where the correlation coefficient (r) equal to 0.9645 (Fig.3,4 &5 and Table 2 & 3)

Actual	Predicted			
	Tissues	Fat	Connective	Glandular
Fat	292	4	4	
Connective	0	239	61	
Glandular	51	41	208	

Table 2. Confusion matrix for window (5×5) pixels

Actual	Predicted			
	Tissues	Fat	Connective	Glandular
Fat	300	0	0	
Connective	0	260	40	
Glandular	28	4	268	

Table 3. Confusion matrix for window (20×20) pixels

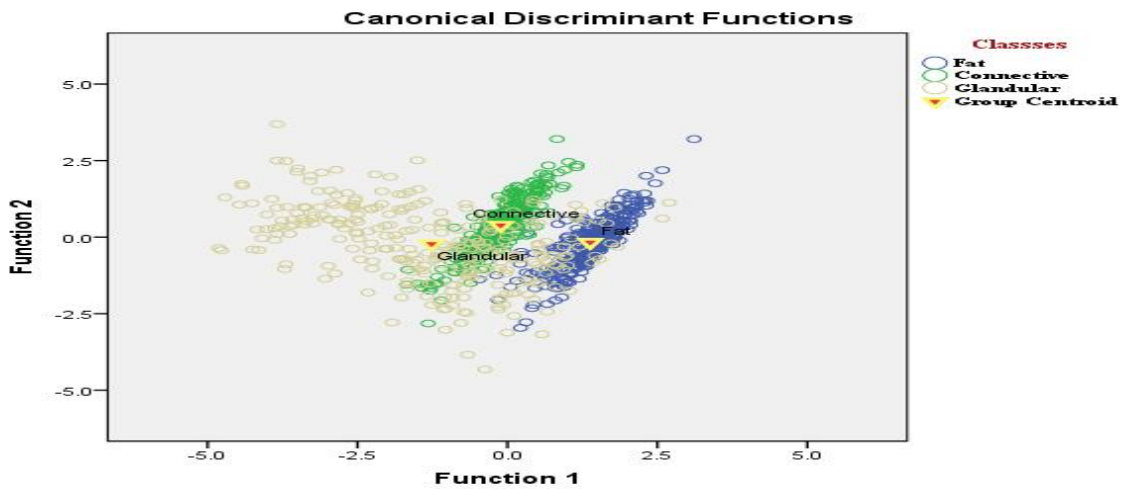


Fig 4. Classification of normal tissues window (5*5) pixels

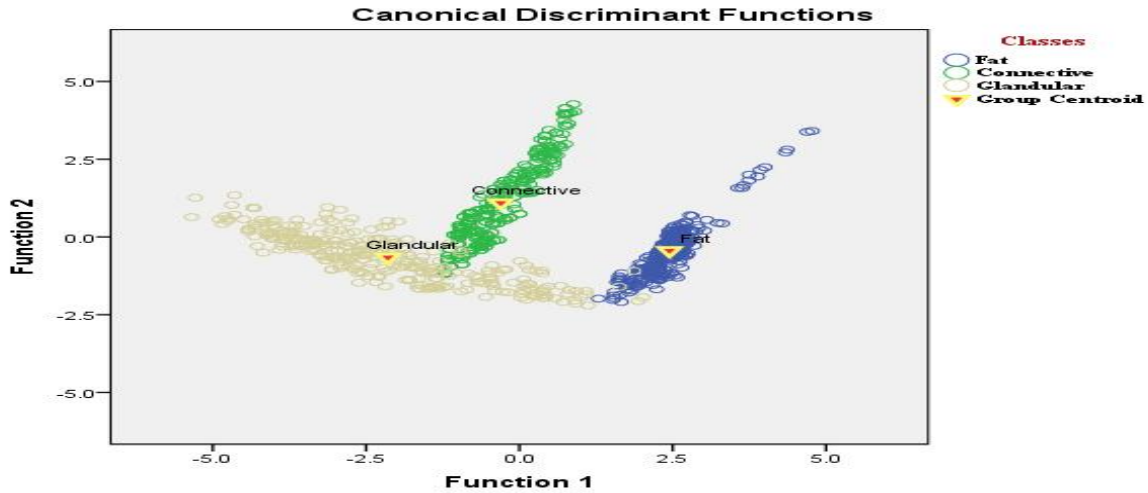


Fig 5. Scatter plot for fat, glandular and connective tissues their textural features were classified using linear discriminant which minimize the within group variation and maximize the between group using window 20×20 pixels

Features	Accuracy
Contrast	71.9 %
Mean , skewness and kurtosis	92 %
Median, mode , variance and stander deviation	99.4 %

Table 4. Comparison of Classification Results based features

In this study different combination features were used to find the most discriminant one and hence the better accuracy this result shown in Table 4. Where the results compares the performance of First-order statistical features with window 20×20 pixel which gives best classification result concerning three main types of normal breast tissue on microscopic images. The following combination (Median, Mode, Variance and Standard Deviation) gives an optimum result using LDA algorithm Fig 6.

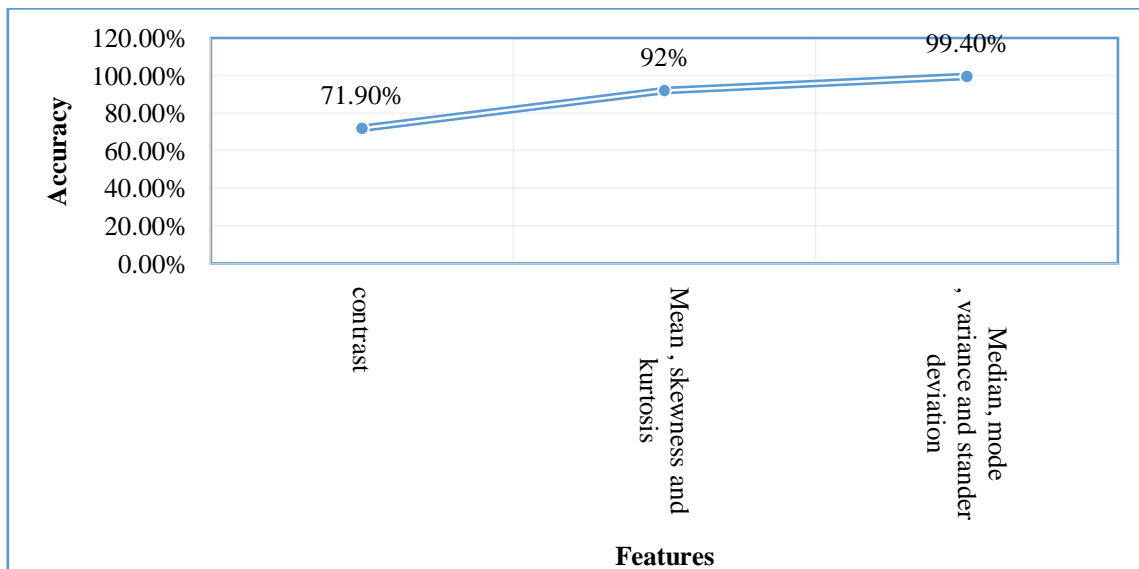


Fig 6. Line graph compare the classification accuracy for the three groups of textural features

IV. CONCLUSION

This study explore the efficiency of window size and textural features combination in classification of normal breast tissues in microscopic. Grey scale images (that converted from RGB format) gives satisfactory result in respect to single channel signal in conclusion LDA classifier is and effective method for classification

might be due to linear combination and relation of texture, as the result the classification accuracy of 99.4% has been achieved by window 20×20 pixels based on textural features include: Median, Mode, Variance and Standard deviation.

REFERENCES

- [1]. C. Denise Miller. *Image analysis techniques for classification of pulmonary disease in cattle*. master, thesis . University of Saskatchewan .Saskatoon.2007.
- [2]. <https://www.nationalbreastcancer.org/breast-anatomy>. January .2019
- [3]. <https://www5.komen.org/BreastCancer/TheBreast.html>. September .2018
- [4]. http://www.bccmiami.com/articles/anatomy_of_breast.cfm. September .2018
- [5]. <https://www.cancer.org/cancer/breast-cancer/screening-tests-and-early-detection/mammograms/breast-density-and-your-mammogram-report.html>. September .2018
- [6]. Angel Cruz-Roa, Ajay Basavanahally, Fabio Gonzalez, Hannah Gilmore, Michael Feldman, Shridhar Ganesan, Natalie Shih, John Tomaszewski and Anant Madabhush. *Automatic detection of invasive ductal carcinoma in whole slide images with Convolutional Neural Networks*. The International Society for Optical Engineering. 2014
- [7]. Teresa Arau, Guilherme Aresta, Eduardo Castro, Jose Rouco, Paulo Aguiar, Catarina Eloy, António Polo, Aurelio Campilho. *Classification of breast cancer histology images using Convolutional Neural Networks*. PloS one 12(6) (2017).
- [8]. Amirreza Mahbod, Isabella Ellinger, Rupert Ecker, Orjan Smedby, Chunliang Wang. *Breast Cancer Histological Image Classification Using Fine-Tuned Deep Network Fusion*. Springer. 2018
- [9]. Kamyar Nazeri, Azad Aminpour, and Mehran Ebrahimi. *Two-Stage Convolutional Neural Network for Breast Cancer Histology Image Classification*. <https://www.researchgate.net/publication/323722834>. 2018
- [10]. Karolina Nurzyńska, Mamoru Kubo, & Ken-Ichiro Muramoto. *Grey scale texture classification method comparison considering object and lighting rotation*. International Journal of Computer Theory and Engineering. 2013
- [11]. Vijay Kumar, Priyanka Gupta. *Importance of statistical measures in digital image processing*. International Journal of Emerging Technology and Advanced Engineering. Volume 2, Issue 8, August 2012
- [12]. <https://www.pathpedia.com/education/eatlas/histology/breast/Images.aspx?1>. September .2018

***Corresponding Author: Mihad M. B. Abdalrahman¹**

¹Faculty of Engineering and Technology, University of Gezira, Sudan