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Author (s): Aalia Nazir¹, Hafeez Ullah¹, Ghulam Gilanie¹, Shabbir Ahmad¹, Zahida Batool¹, Asghar Gadhi²


Affiliation (s): ¹The Islamia University of Bahawalpur, Pakistan
²Bahawalpur Institute of Nuclear Medicine, Bahawalpur

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Exploring Breast Cancer Texture Analysis through Multilayer Neural Networks

Aalia Nazir^{1*}, Hafeez Ullah¹, Ghulam Gilanie¹, Shabbir Ahmad¹, Zahida Batool¹, and Asghar Gadhi²

¹ Institute of Physics, The Islamia University of Bahawalpur, Pakistan

²Bahawalpur Institute of Nuclear Medicine, Bahawalpur, Pakistan

ABSTRACT

Breast cancer is a significant health problem for women globally; however, timely detection can reduce female morbidity and mortality. Early breast screening has become imperative for all women, though, adequate screening facilities are necessarily required in developing countries like Pakistan, where breast cancer is a leading cause of death. To encounter this chronic disease, various image processing techniques have been introduced to automatically diagnose breast cancer from digital mammograms. The current study deployed data from a population of 35 participants. The mammograms used for screening were 5 normal, 15 benign, and 15 malignant patients. The breast images were marked by the radiologist and the system was trained with normal, benign, and malignant classes. Moreover, Multilayer Neural Networks (MNN) based texture analysis methodology was adopted to distinguish normal, benign, and malignant breast images. Reportedly, an automated approach was used to detect breast conditions after conducting the analysis of digital mammograms. Statistical parameters, namely sum, mean, variance, standard deviation, kurtosis, skewness, energy, and entropy were calculated, analyzed, and compared for the normal, malignant, and benign breast images. The results indicated a 100% accuracy after the analysis. The results of the extracted statistical parameters were promising and reliable in distinguishing between normal, malignant, and benign breast mammograms, again indicating the need for early detection of the disease to minimize the risk of breast cancer among women.

Keywords: breast cancer, benign and malignant cancer, mammography, MNN, neural network

* Corresponding Author: alia.nazir@iub.edu.pk

1. INTRODUCTION

Breast cancer is one of the most common cancers among women, which affects women's physical and mental health and is even life-threatening globally. The overall frequency is increasing, and the risk factors are well-documented [1].

There are several features, which are responsible for this disease like obesity, radiation exposure, family history, fat-enriched food, and pre-malignant injuries. Breast cancer once detected can become worse with a change in lifestyle [2, 3]. Breast cancer is the second major cause of mortality worldwide and in Pakistan every 1 woman out of 9 is suffering from this chronic disease. This can be due to the lack of medical facilities and unawareness, which are major causes of delayed diagnosis [4, 5]. It has been a challenging task to detect breast cancer at an earlier stage to lower the mortality rate. The risk of breast cancer among women aged less than 40 years is smaller, whereas an increased rate has been noticed in women between 45-55 years, resultantly causing an increase in mortality rate [6]. Mammography is an affordable, low-radiation test recommended for early detection of breast cancer [7, 8]. This test can be performed on both pre-symptomatic and symptomatic women; however, it is less efficient for women who are lower than 40 due to dense breasts [9]. Though, women at later stages can feel a lump, a hard loop within the breast or under the arm, swelling, changes in the mass of the breast, redness, and dimpling or creasing of skin. Countries with low-income and underdevelopment, such as Pakistan, face a scarcity of resources for essential diagnosis or detection. Delays in medical care may contribute to the spread of breast cancer's morbidity and mortality [10]. Michell *et al.* Identified that the addition of digital breast tomosynthesis (DBT) in conventional mammography increases the accuracy rate in cancer assessment [11].

The human nervous system is a compound neural system and our body collects external signals through dendrites. These signals are collected till a threshold level to make an action. A large number of neurons are interrelated to study input and optimize its output by means of computing and processing. Artificial Neural Network (ANN) is used in training a learned system by processing these signals in medical imaging so, that decisions can be automated. Computer-aided Detection Systems (CAD) trained using machine learning models, help radiologists, medical

practitioners, radiation oncologists or physicians in the accurate and more definite detection of breast cancer in the early stage [12]. CAD systems have been used in many medical institutes for clinical diagnosis as referred by doctors [13]. For the feature extraction process, curvelet moments are also very beneficial in giving reduced features and enhancing accuracy in the diagnosis of breast cancer [14]. An automated feature extraction process is utilized in diagnosing architecture distortion in the breast, which causes malignancy by applying texture models and vector machine classifiers on the region of interest [15]. A multivariate feature can also be used for extraction by applying a genetic algorithm and obtaining feature descriptive in two categories, which classify malignant and benign breasts and reduces the workload of radiologists [16]. Furthermore, the grey level co-occurrence matrix is used for feature extraction in different orientations to differentiate masses and non-masses, by combing the grey level with the wavelet approach through which the results are enhanced [17]. ANN-PSO (artificial neural network with particle swarm optimization) method has been used by Zhang *et al* to extract the intensity and shape features, which tested and then distinguished normal and abnormal breast mammograms [18]. The particle swarm optimized wavelet neural network (PSOWNN) technique was applied to breast mammograms by Sathyaa *et al* and the Receiver Operating Characteristic (ROC) curve indicated the sensitivity and specificity as indicated by Dheeba et al. [19, 20].

From the analysis of texture, an automated method was proposed to classify different breast tissues as normal, malignant, or benign. This method provided the radiographic details of breast lesions.

Breast tumors can be benign or malignant. Benign is not dangerous, it can grow but doesn't spread in surroundings. However, malignant is cancerous and can spread in the entire body and cause destruction [21, 22]. Therefore, in this study, an automated approach has been proposed to classify breast cancer as normal, benign, or malignant. This work explored ways to prevent this disease and provide a new taxonomy for breast cancer risk assessment.

2. MATERIALS AND METHODS

A dataset of mammograms, correspondingly collected from 35 subjects was obtained from the Bhawal Victoria Hospital. The women

who were considered for scanning ranged from age 45-55 years having either normal, benign, or malignant breast cancer stage. All patients were duly informed and the ethics review board signed for further process. Medial-lateral oblique and craniocaudal images were acquired and statistical mammographic data were analyzed. The following steps were taken to successfully classify breast conditions including normal, benign or malignant.

- i. The mammograms having high intensity and contrasts were input to the developed system. The developed system consisted of an architecture based upon 12-layered multi-layered neural networks (MNN).
- ii. Segmentation of Region of Interest (ROI), which had a suspicious area with distinguished surroundings was marked by the domain experts.
- iii. Texture features, namely, sum, mean, variance, standard deviation, kurtosis, skewness, energy, and entropy extracted from each of the segmented ROIs belonging to normal, benign, and malignant stages.
- iv. Training of the system using these extracted texture features through MNN using Matlab2020a was conducted on 70% of the total data.
- v. Evaluation of the proposed developed system was based on the standard evaluation measurement, such as accuracy.

3. RESULTS

In this research, statistical methods were used to extract texture features. Using image classification and segmentation methods was a more reliable approach, which ensured higher reliability in the obtained results. The feature extraction method underlying the statistical procedure consisted of the sum of the following parameters, namely mean (pixel value), variance (square root of deviation), energy (uniformity), standard deviation (pixel deviation from the mean), skewness (pixel asymmetry), kurtosis (flatness or peak), and entropy (random measurements). Normal, malignant, and benign breast mammograms and their bilateral statistical data were analyzed. There are usually two models for image projection, namely Craniocaudal (CC), a view from the apex, which allows for enhanced imaging of the central and internal breast regions, and Mediolateral Oblique (MLO) that provides an improved view of the gland from a specific side view.

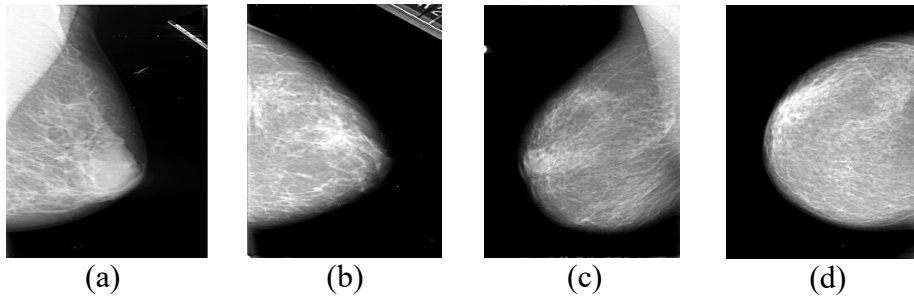


Figure 1. (a) Case 1 (L-MLO), (b) Case 2 (R-CC), (c) Case 35 (R-MLO), and (d) Case 35 (R-CC)

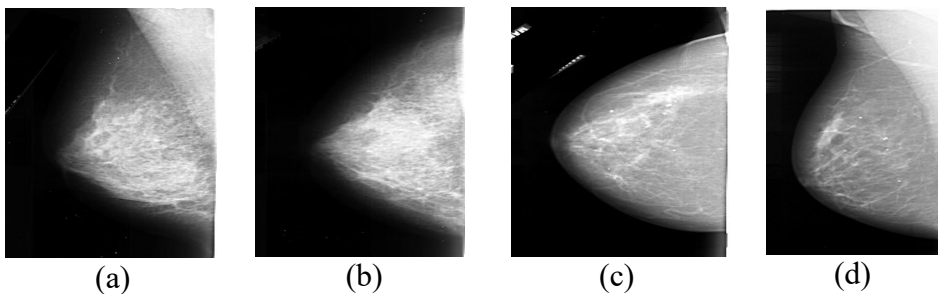


Figure 2. (a) Case 7 (R-MLO), (b) Case 7 (L-CC), (c) Case 19 (L-MLO), and (d) Case 19 (R-CC)

Figures 1 and 2 show a normal case in which no tumor was detected on mammography screening of the two selected subjects.

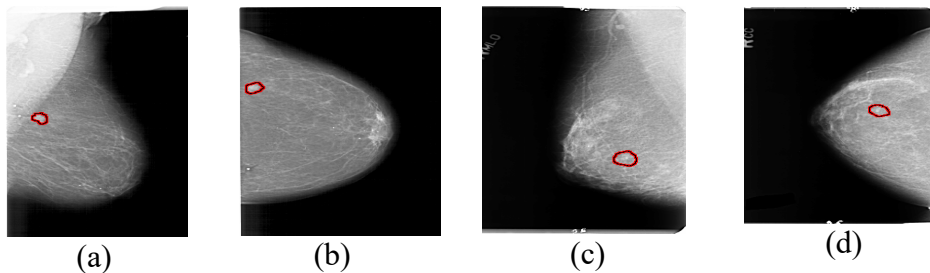


Figure 3. (a) Case 1 (L-MLO), (b) Case 1 (L-CC), (c) Case 2 (L-MLO), and (d) Case 2 (L-CC)

Figure 3 contains randomly selected left mammograms from two different subjects. The regions highlighted in these MLO and CC images are malignant breast lesions. Benign areas are brighter due to their higher intensity. Figure 4, shows right mammograms of two cases containing malignant areas in MLO and CC image projections. In Figure 4, Case 3 R

(MLO and CC) shows abnormalities, lesion-like masses, foci, asymmetric dense margins, and unclear partially malignant pathology (a, b). Case 4 R (MLO and CC) showed abnormalities, with lesion-like mass morphology and suspiciously malignant irregular margins in parts (c, d). The selected area is the tumor-containing lesion.

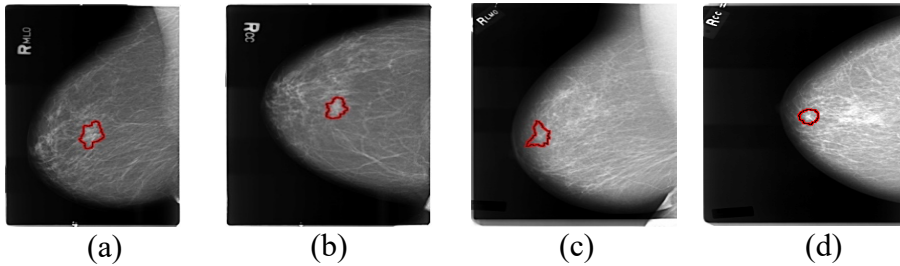


Figure 4 (a) Case 3 (R-MLO), (b) Case 3 (R-CC), (c) Case 4 (R-MLO), and (d) Case 4 (R-CC)

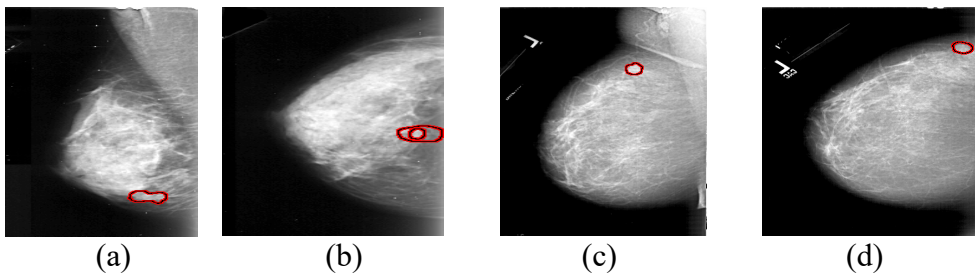


Figure 5. (a) Case 1 (L-MLO), (b) Case 1 (L-CC), (c) Case 2 (L-MLO), and (d) Case 2 (L-CC)

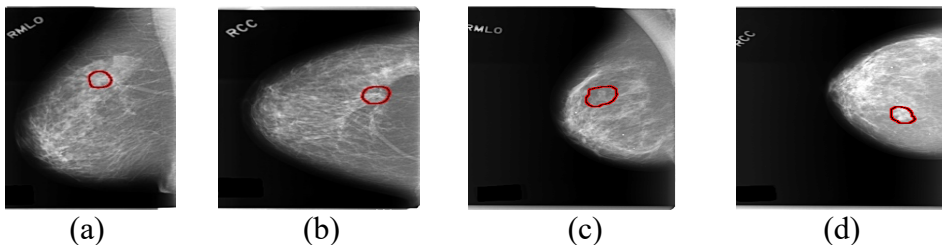


Figure 6. (a) Case 3 (R-MLO), (b) Case 3 (R-CC), (c) Case 4 (R-MLO), and (d) Case 4 (R-CC).

Mammograms of the left breast for case 1 and case 2 are shown in Figure 5, with the mediolateral and craniocaudally view with affected highlighted areas. This study has dealt with images of benign breasts having calcification, pleomorphic distribution, and architectural distortions

as shown in Figure 6. Case 3 R (MLO) is abnormal. Lesion-type classification, pleomorphic distribution, and clustered benign mammogram are shown in Figure 6 (a). Case 3 R (CC) is abnormal lesion-type calcification, pleomorphic distribution clustered, and architectural distortion margins speculated benign as shown in Figure 6 (b). Case 4 R (MLO and CC) shows abnormality lesion-type mass and shape round margins obscured benign as shown in Figure 6 (c, d). Red enclosed areas in the normal and benign breasts are the regions of interest, which are segmented and processed for statistical feature extraction of mammograms.

Texture parameters extracted from normal ROIs of the selected 35 patients age ranging from 45-55 are shown in Table I. Texture analysis was performed on 35 women with bilaterally normal breasts. Data from all the patients were collected and summarized below, showing medial-lateral oblique and craniocaudal views.

Table 1. Statistical Parameters in Medirolateral Oblique and Craniocaudal view of Normal Right and Left Breast

Statistical Parameters	Normal (MLO)		Normal (CC)	
	(Average values)		(Average values)	
	Right Breast	Left Breast	Right Breast	Left Breast
Sum	53.0	50.00	43.0	42.00
Mean	81.3	81.67647	66.4	65.470588
Variance	68.0	6768.161	63.0	6470.7764
Standard deviation	82.0	82.04567	79.0	80.050905
Skewness	0.49	0.455200	0.86	0.8279944
Kurtosis	-1.20	-1.272985	-0.60	-0.7750828
Entropy	26.0	2651414	21.0	21112641.1
Flatness	0.46	0.475726	0.52	0.53155200
Energy	3.2 E-05	3.268E-05	4.0 E-05	4.16294E-05

Table 1 provides textural parameters, such as, sum, mean, variance, standard deviation, skewness, kurtosis, entropy, flatness, and energy, along with maximum, minimum, and mean ranges for all normal mammograms.

The statistical characteristics of all the patients with malignancies were determined and presented in Table 2.

Table 2. Numerical Analysis of Right and Left Malignant Breast in MLO and CC view

Statistical Parameters	Malignant (MLO) (Average values)		Malignant (CC) (Average values)	
	Right Breast	Left Breast	Right Breast	Left Breast
Sum	5754958.9	5665979.1	4779375.86	4332792.4
Mean	78.371429	77.400000	62.6571429	59.828571
Variance	6171.9399	6381.0684	5749.74924	5489.5443
Standard deviation	78.195735	79.510718	75.2393183	73.539115
Skewness	0.5173302	0.5314520	0.89566069	0.9520324
Kurtosis	-1.0368810	-1.0458932	-0.48604212	-0.2584942
Entropy	30025540	28286342	23421773.6	21287130
Flatness	0.4867556	0.4924317	0.55017747	0.5496571
Energy	2.727E-05	2.9818E-05	3.49926E-05	3.8034E-05

Table 3 summarizes the texture parameters of the image window pixels, including the maximum, minimum, and mean values of the left and right benign breasts, with promising results. Reportedly, maximum and minimum values are now equal to absolute values.

Table 3. Pixel Parameters of Right and Left Benign Breast Images

Statistical Parameters	Benign (MLO) (Average values)		Benign (CC) (Average values)	
	Right Breast	Left Breast	Right Breast	Left Breast
Sum	5798909.86	5172456	4832506.3	5066756.51
Mean	73.2285714	66.485714	62.200000	65.2857143
Variance	5685.44068	5397.0492	5488.9733	5285.80702
Standard deviation	74.9817381	73.053862	73.571646	72.37847995

Statistical Parameters	Benign (MLO) (Average values)		Benign (CC) (Average values)	
	Right Breast	Left Breast	Right Breast	Left Breast
Skewness	0.68503344	0.7359084	0.9761847	0.80500920
Kurtosis	-0.7213016	-0.604295	-0.1948880	-0.41404877
Entropy	28338321.9	25325634	214942223	24647141.59
Flatness	0.51946173	0.5318824	0.5694440	0.536184773
Energy	2.727E-05	2.9818E-05	3.49926E-05	3.8034E-05

The results for the left and right benign breasts are shown in Table 3. To obtain reliable results and conclusions about the texture parameters of all normal, malignant, and benign breast images, comparisons were made numerically, to classify the results of normal and benign breast data by using MNN. The proposed approach was analyzed and found to be a reliable approach for the assessment. Digital data from previous mammograms of benign and healthy breasts were used for differentiation. Texture parameters are compared in Table 4 for maximum and minimum values for both of the selected cases.

Table 4. Comparison of Right MLO view Texture Parameters of Normal and Benign Breast Mammograms

Statistical Parameters	Right normal (MLO) (Average Values)	Right benign (MLO) (Average values)	% Differences
Sum	5383731.714	5798909.86	-7.1595896
Mean	81.34285714	73.2285714	11.0807648
Variance	6807.459804	5685.44068	19.7349544
Standard deviation	82.28868257	74.9817381	9.74496545
Skewness	0.491937579	0.68503344	-28.187801
Kurtosis	-1.20984084	-0.7213016	67.730231
Entropy	26957357.8	28338321.9	-4.8731329
Flatness	0.468915193	0.51946173	-9.730559
Energy	3.23365E-05	2.75458E-05	17.3917621

4. DISCUSSION

Normal, benign, and malignant mammograms were analyzed and the extracted textural features were presented in medial-lateral and

craniocaudal (CC) views. Subtle and obscure areas are enhanced using algorithms to make areas of interest easier to see and texture extraction methods are more useful in these areas. In this research, mammograms were used to train and test the proposed model to automatically classify normal, benign, and malignant breast images based on their texture. Each mammogram contains 20 slices of both views (MLO and CC) along the left and right breast. Therefore, $35 \times 2 \times 20 \times 2$ slices were used for training and testing the reported system. Of these total 2800 slices, 1848 slices were used for training the reported system and the remaining 952 slices were used for testing the reported system. Reportedly, two clues to malignant tumors are identified, namely microcalcifications and masses. These texture features were used to train the proposed method using MNNs and then compared to the literature [23, 24], both types yielded up to 90% of accuracy in discriminating benign or malignant abnormalities.

The statistical analysis examined each category's sum, mean, variance, entropy, skewness, and other pixel features of left and right breasts. Variations in these parameters, such as maximum, minimum, and mean values, were used to classify normal and benign tumor, including breast and the areas of microcalcification. In this work, MLO-mapped parameters of mammograms of healthy and malignant breasts were used in which clear differences in all values were noticed.

Differences between all parameters and maximum, minimum, and mean values demonstrated the intelligent classification of normal and benign breasts. This study's results were promising for various statistical approaches to describe and analyze image textures. By analyzing the variance of all outcomes, it was concluded that a distinction is required between the normal and benign cases with 100% accuracy. Different values are also agreed upon for normal and abnormal benign images. The observed variance for normal cases ranges from 8831.9-3896.8 and all findings for abnormal benign cases are above the maximum for normal images. Therefore, the variance parameter gave 100% results from benign to normal images. Furthermore, it was observed that normal and abnormal benign cases could achieve different ranges of kurtosis 88% of the time, with 89% of perfect results. For the rest of the parameters, a clear result was also noticed. This demonstrated good results obtained in a large number of breast cancer cases and benign cases. These were further compared on various parameters of normal, benign, and malignant breasts

by plotting kurtosis, energy, flatness and distortion on the x-axis and their intensity on the y-axis. Data were obtained from random patients and parameters were plotted with intensity. The variation in values of normal, malignant, and benign breast mammograms can be clearly observed graphically.

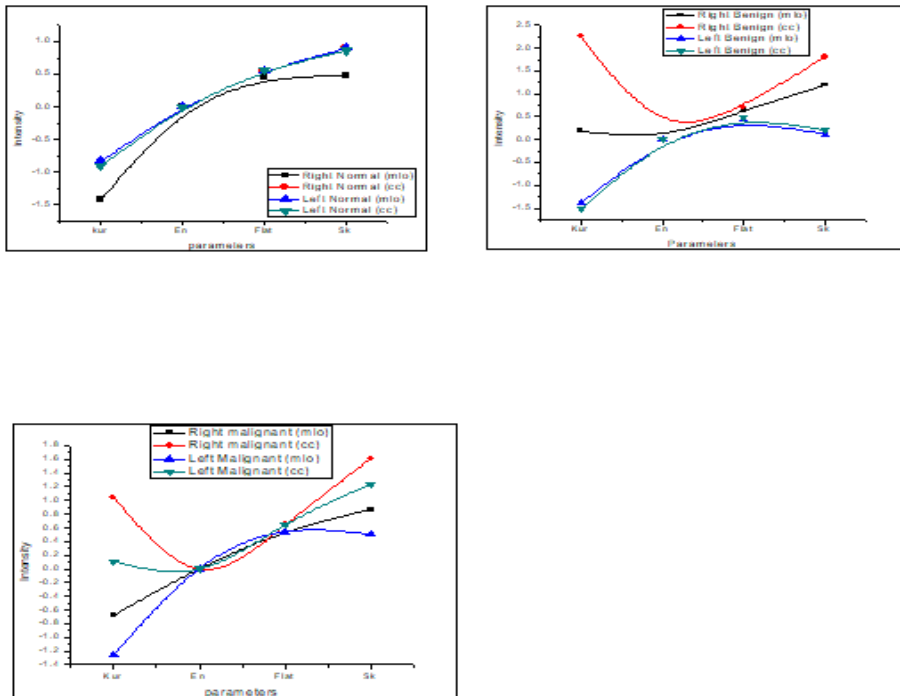


Figure 7. (a) The normal breast parameters of right and left mammogram in MLO and CC view, (b) Parameters of benign breast images along with intensities, and (c) Malignant breast mammogram parameters along with intensities.

Figure 7(a) shows the changes in kurtosis, energy, flatness, and skewness of left and right mammograms of a normal breast in craniocaudal and medial-lateral views. The parameters compared with the benign mammography parameters are shown in Fig. 7(b). In Fig. 7(b), the hyperintensities of the right benign image in CC view and MLO show the variation of values in normal parameters. The kurtosis parameter has a high intensity, which decreased at the energy point and increased again with flatness and strain but increase in the value at cc and then decreases

gradually. Comparing these two charts with the malignant breast image, the deviations from normal values are larger than the benign image parameters, as shown in Fig. 7(c). Intensity fluctuations in right malignant CC views are rather instantaneous and different from benign and normal breast parameters. The left malignant tumor (MLO, CC) and right malignant MLO also showed strange curves, which were different from the normal breast curve. This artificial texture analysis approach would play an important role in the future. Furthermore, the research aims to test these methods with other classifiers or segmentation schemes and in more realistic texture interpretation situations. These results showed that there is considerable performance variability between different texturing methods. These results are supported by previous comparative studies in this field. Hence, the feature extraction results may assist radiologists in the early screening of breast mammograms and discrimination between healthy and unhealthy breasts by analyzing the numerical data.

4.1. Conclusion

The current study, aimed to propose a multi-layered neural network (MNN) approach to demonstrate the potential to distinguish between healthy, benign, and malignant breast mammograms in breast region analysis and segmentation. Texture analysis and comparison parameters of statistical data such as mammogram sum, variance, mean, kurtosis, standard deviation, skewness, energy, entropy, and flatness were used to obtain the results. It was obvious from the results that this feature extraction modality was reliable for diagnosing cancerous or malignant breasts. Therefore, it was recommended that early detection could increase the survival rates among women possessing breast cancer. Moreover, screening tests are mandatory for all women, especially in developing countries like Pakistan, where cancer mortality is relatively higher than in other developed countries.

REFERENCES

1. Li H, Zhuang S, Li D, Zhao J, Ma Y. Benign and malignant classification of mammogram images based on deep learning. *Biomed Signal Proc Control*. 2019;51:347–354. <https://doi.org/10.1016/j.bspc.2019.02.017>
2. Morman NA, Byrne L, Collins C, Reynolds K, Bell JG. Breast cancer risk assessment at the time of screening mammography: Perceptions

- and clinical management outcomes for women at high risk. *J Gen Counsel.* 2017;26(4):776–784. <https://doi.org/10.1007/s10897-016-0050-y>
3. Puliti D, Bucchi L, Mancini S, et al. Advanced breast cancer rates in the epoch of service screening: The 400,000 women cohort study from Italy. *Eur J Cancer.* 2017;75:109–116. <https://doi.org/10.1016/j.ejca.2016.12.030>
 4. Khan NH, Duan SF, Wu DD, Ji XY. Better reporting and awareness campaigns needed for breast cancer in Pakistani women. *Cancer Manag Res.* 2021;13:212–2129. <https://doi.org/10.2147/cmar.s270671>
 5. Menhas R, Umer S. Breast cancer among Pakistani women. *Iran J Public Health.* 2015;44(4):586–587.
 6. Pisano ED, Gatsonis C, Hendrick E, et al. Diagnostic performance of digital versus film mammography for breast-cancer screening. *New Eng J Med.* 2005;353(17):1773–1783. <https://doi.org/10.1056/nejmoa052911>
 7. Sung H, Ferlay J, Siegel RL, et al. Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *Cancer J Clinic.* 2021;71(3):209–249.
 8. Zahoor S, Lali IU, Khan MA, Javed K, Mehmood W. Breast cancer detection and classification using traditional computer vision techniques: A comprehensive review. *Curr Med Imag Form Curr Med Imag Rev.* 2021;16(10):1187–1200. <https://doi.org/10.2174/1573405616666200406110547>
 9. Elizalde A, Pina L, Etxano J, Slon P, Zalazar R, Caballeros M. Additional US or DBT after digital mammography: Which one is the best combination? *Acta Radiol.* 2016;57(1):13–18.
 10. Selove R, Kilbourne B, Fadden MK, et al. Time from screening mammography to biopsy and from biopsy to breast cancer treatment among Black and White, non-HMO Medicare women beneficiaries not participating in a health maintenance organization. *Women Health Issue.* 2016;26(6):642–647. <https://doi.org/10.1016/j.whi.2016.09.003>
 11. Galván-Tejada C, Zanella-Calzada L, Galván-Tejada J, et al. Multivariate feature selection of image descriptors data for breast

- cancer with computer-assisted diagnosis. *Diagnostics*. 2017;7(1):e9. <https://doi.org/10.3390/diagnostics7010009>
12. Jiang J, Trundle P, Ren J. Medical image analysis with artificial neural networks. *Comput Med Imag Graph*. 2010;34(8):617–631. <https://doi.org/10.1016/j.compmedimag.2010.07.003>
13. Fujita H. AI-based computer-aided diagnosis (AI-CAD): The latest review to read first. *Radiol Phy Technol*. 2020;13(1):6–19. <https://doi.org/10.1007/s12194-019-00552-4>
14. Michell MJ, Iqbal A, Wasan RK, et al. A comparison of the accuracy of film-screen mammography, full-field digital mammography, and digital breast tomosynthesis. *Clin Radiol*. 2012;67(10):976–981. <https://doi.org/10.1016/j.crad.2012.03.009>
15. Dhahbi S, Barhoumi W, Zagrouba E. Breast cancer diagnosis in digitized mammograms using curvelet moments. *Compute Biol Med*. 2015;64:79–90. <https://doi.org/10.1016/j.compbiomed.2015.06.012>
16. Kamra A, Jain V, Singh S, Mittal S. Characterization of architectural distortion in mammograms based on texture analysis using support vector machine classifier with clinical evaluation. *J Digit Imaging*. 2016;29(1):104–114. <https://doi.org/10.1007/s10278-015-9807-3>
17. Kulkarni DA, Bhagyashree. SM, Udipi GR. Texture analysis of mammographic images. *Int J Comput Appl*. 2010;5(6):12–17. <https://doi.org/10.5120/919-1297>
18. Zhang C, Shao H, Li Y. Particle swarm optimisation for evolving artificial neural network. Paper presented at: SMC 2000 conference proceedings. 2000 IEEE International Conference on Systems, man and Cybernetics; October 8–11, 2000; Nashville, TN, USA. <https://doi.org/10.1109/ICSMC.2000.884366>
19. Sathya DJ, Geetha K. Mass classification in breast DCE-MR images using an artificial neural network trained via a bee colony optimization algorithm. *ScienceAsia*. 2013;39(3):294–305. <https://doi.org/10.2306/scienceasia1513-1874.2013.39.294>
20. Dheeba J, Singh NA, Selvi ST. Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet

- neural network approach. *J Biomed Info.* 2014;49:45–52. <https://doi.org/10.1016/j.jbi.2014.01.010>
21. Sharma M, Dubey RB, Gupta S. Feature extraction of mammograms. *Int J Adv Comput Res.* 2012;2(3):201–209.
22. Ranjbarzadeh R, Sarshar NT, Ghouschi SJ, et al. MRFE-CNN: Multi-route feature extraction model for breast tumor segmentation in Mammograms using a convolutional neural network. *Ann Oper Res.* <https://doi.org/10.1007/s10479-022-04755-8>
23. Kayode AA, Afolabi BS, Ibitoye BO. Preparing mammograms for classification task: Processing and analysis of mammograms. *Int J Info Eng Elect Bus.* 2016;8(3):57–66. <https://doi.org/10.5815/ijieeb.2016.03.07>
24. Chan HP, Sahiner B, Petrick N, et al. Computerized classification of malignant and benign microcalcifications on mammograms: Texture analysis using an artificial neural network. *Phy Med Biol.* 1997;42(3):549–567. <https://doi.org/10.1088/0031-9155/42/3/008>