Texture Analysis of Breast Cancer via LBP, HOG, and GLCM techniques

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Abstract. Breast cancer is a prevailing reason for death, and it is a particular kind of tumor that is popular among ladies across the world. Till presently, there is no efficient method to stop the appearance of the breast tumor. Accordingly, early detection is the first stage in the diagnosis of breast tumors and reduces mortality. Screening Mammography is the most effective technique for early detection of breast tumors. Great experience and large practices of specialists are wanted when examining breast tissue in a mammogram. In this work, feature extraction techniques are offered as methods to decrease false-positive that occur in breast diagnosis. Mini-MIAS database used to evaluate these approaches. LBP, HOG, and GLCM are feature extraction techniques used for analyzing mass tissue and extract features from the ROI. Contrast, energy, correlation, and homogeneity are used as features properties. These features utilized as the input to the different classifiers which achieved the best results. To improve the diagnosis ability, “contrast limited adaptive histogram equalization” utilized as a pre-processing system. The best results gained in this work by LBP method and logistic regression classifier at ROI (30×30) where the accuracy 92.5%. The HOG method achieved the best results with the SVM classifier where accuracy 90% at ROI (30×30). GLCM provides the best results with the KNN classifier where the accuracy 89.3% at ROI (30×30). The greatest accuracy reached in the case of ROI (30×30) in all feature extraction methods that used in this work.

1. Introduction
Breast cancer is a common reason for death, and it is a particular kind of tumor that is popular among ladies across the world[1]. Breast cancer is an uncontrolled increase in irregular cells of breast tissue[2]. Till presently, there is no efficient method to stop the appearance of the breast tumor. Accordingly, early detection is the first stage in the diagnosis of breast tumors[3]. The detection for masses in breast tissue in the beginning stages is the most suitable instance to increase the possibilities of survival[4]. Many screening systems have been improved for early diagnosis of breast mass to decrease the mortality rate, and many assisted breast tumor analysis techniques have been utilized to raise the diagnostic accuracy[5]. Imaging examination systems are performed to recognize the appearance of breast tumors. These systems define the behavior of the tumor and also place the tumors in the breast. Images of the breast structure are practiced, and they are studied by the specialist to distinguish any irregularities inside the breast tissues[6]. Screening Mammography is the single system currently prepared for the safe detection of breast tumors in the early stage and has been presented to decrease the fatality rate[7]. Mammography more positive screening device than other screening modalities like MRI that utilize powerful magnetic fields and radio waves[8]. Great experience and large practices of radiologists are wanted when examining breast tissue in a mammogram[9]. There are many types of researches to analysis and identifying the tumors based on the feature extraction method:
S. Krishnaveni et al. (2014) [10] introduced a histogram of oriented gradients (HOG) as a feature extraction approach, and Naive Bayes classifier is employed to recognize microcalcification in the mammogram. The examination of the suggested method achieved 96.5% mass diagnosis mammograms. V. Pomponiu et al. (2014) [11] offered an uncomplicated method applied to filter the output of the automated tumor discovery systems. HOG is a method used for filtering the tumor and whole tissue areas. The sensitivity of this method is high. S. Beura et al. (2017) [12] suggested a mammogram classification system analyze the tissues of breast as normal, non-cancerous, or cancerous. The feature extraction is created utilizing GLCM to every coefficient from two dimension-DWT of (ROI). MIAS and DDSM used to the validation of the suggested system. The accuracy computed for normal and abnormal and benign and malignant—accuracy from the MIAS 98.0% and 94.2%, respectively.

In this work, we aim to implement and comparison feature extraction methods that provide important information about mammography images. These methods used to lessen the false-positive diagnosis and develop the performance of the detection systems.

2. Methodology

The levels of breast cancer diagnosis in the detection system are involved in preprocessing, feature extraction, and classification[13]. The following steps are used in this research to determine normal and abnormal tissue.

2.1. Dataset Collection

The digitized mammogram was used from the mini-MIAS [14]. It has 322 images, including 209 normal, 62 benign, and 51 malignant. The size of all images in the database is 1024×1024 pixels. Mammograms in mini-MIAS are classified by the kind of exact mass (ill-defined(MI), asymmetry(AS), architectural distortion(AR), speculated(SP), circumscribed(CI), and calcification(CA))[15].

2.2. Pre-processing of Mammography Images, CLAHE method

The raw mammograms obtained from the database are not suitable for immediate processing since the mammogram include various types of noise and undesired data that affect to the result of classification. Accordingly, it is important to apply the preprocessing techniques before examining it. Pre-processing is a useful step in all machine learning techniques to develop its performance and progress the image data by overcome undesired deformation or enhances some necessary characteristics for more processing [16]. Accordingly, we enhance all mammograms collected from the mini-MIAS database that used in this work by applying the “contrast limited adaptive histogram equalization” (CLAHE) method.

CLAHE is an enhancing method applied to develop the contrast of the image. It dividing the image into small and equal parts named tiles, and works on each part instead of the entire image. Every tile's contrast is improved by applying histogram equalization on each of them, then each histogram cropped by a clipping border that depends on the wanted contrast development and the extension of the adjacent region. The adjacent regions are then joined utilizing bilinear interpolation to lessen artificially produced boundaries and limiting The contrast in the homogeneous regions, thereby eliminating the difficulty of noise amplification [17]. Figure 1 samples of six types of abnormality mammograms collected from the mini-MIAS database before and after applying CLAHE method.
Figure 1: samples of mammograms when applying the CLAHE method: first row original mammograms, second row enhanced mammograms.

2.3. Feature Extraction Methods

Feature extraction is a particular kind of dimensionality modification. The chief purpose of this technique to capture the important characteristics of the raw data and interpret this character in a less dimensionality space [18]. In this work, we used three methods for feature extraction, which involve local binary pattern, the histogram of oriented gradient, and gray level co-occurrence matrix. The following parts introduce a description of each technique.

LBP is an effective descriptor in tasks of face recognition and computer vision. The LBP coding the gray levels of an image by comparing the central pixel with its neighbors and the result counted as a binary number converted to decimal number substitutes the central pixel value [19]. The calculating LBP with a neighborhood can be defined:

\[
LBP_{P,R} = \sum_{P=0}^{P-1} s(g_p - g_c)2^P, \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1)
\]

Where \(g_p\) is the neighbor value, \(g_c\) is the current pixel value, \(R\) is the radius of the circular neighborhood, and \(P\) is the number of neighbors.

HOG is an object descriptor introduced by Dalal and Triggs [20] focalize on the structure or appearance of an object in an image. Histogram of Oriented gradients provides distinguishing features when lighting variation and background noise, so it is an effective descriptor. HOG technique calculated the occurrence of gradient directions in ROI [21]. This technique describes the structural shape within ROI by capturing the local grey levels gradient. In the HOG descriptor, histograms do not create for entire ROI, ROI is divided into small related regions called a cell and the histogram of gradients is calculated for every cell [22]. The grayscale value is computed for larger overlapping regions denominated blocks. These blocks are produced by accumulated cells in ROI. The cells inside the blocks are normalized by computed the grayscale value for each block and applying the contrast normalization process. Next, the HOG features derived from the normalized ROI [23].

GLCM is one of the several popular texture examination techniques that calculate the occurrence of specific gray levels about other grey levels [24]. GLCM counts the frequency of various sequences of gray level values that appear in ROI [25]. This technique examines the association among adjacent pixels, the original pixel is identified as a reference, and the other is a neighbor pixel. In the GLCM matrix, the dimension of matrix similar to the dimension of the ROI. The GLCM factor \(P (i, j|\Delta x, \Delta y)\)
is the relativistic recurrence through which pair of pixels are distributed with a gray level range ($\Delta x$, $\Delta y$) happens in a provided region, one by gray level (i) and another by a gray level (j). The GLCM factor $P(i, j|d, \Theta)$ includes the second-order analytical expectation values of variations among the pixel (i) and (j) in a special range (d) and a special direction ($\Theta$). Utilizing a high dimension of the image means collecting large passing data [26]. Therefore, GLCM utilizes scaling to decrease the dimension of images. The dimension of the image defines the dimension of the GLCM [27]. For example, consider the ROI (I) shown in figure 2, in the GLCM matrix of the mentioned ROI (I), 3 is the element value of the position (1, 3) since three cases in the ROI when a joining of neighboring gray level values (1, 3). Furthermore, 1 is the element value of the position (8, 3) because of one case of the sequence of values 8 and 3. GLCM maintains this operation to supply in every pixel in the matrix.

![GLCM Matrix](image)

**Figure 2:** GLCM operation (a) image. (b) GLCM

### 2.4. Classification Techniques

Classification methods represent an important part of image processing. It is applied to classify the features derived from the image to various types according to various properties[28]. The following parts explain classifiers utilize in this work.

**Logistic Regression** is a Statistical Learning method characterized in the supervised techniques applied to classification assignments. It has achieved a huge reputation in the latest two decades because of its ability to recognize defaulters. Logistic regression aims to practice a classifier that can create a binary decision of the type of different input detection[29].

**SVM** is an assortment of relevant supervised learning techniques employed for classification and regression. However, it is chiefly utilized in classification difficulties[30]. SVM is an analytical learning algorithm that divides the input data into classes utilizing a subset of training data [31].

**KNN algorithm** is a class of supervised learning algorithms that employed for both classifications and regression predictive difficulties[32]. In two states, the input includes the k nearest training samples in the feature space. The output based on KNN is utilized for classification or regression. While its largest use is classification[33].

### 3. Results and Discussion

Since the mammograms include various types of noise and unclear data that affect to the result of classification. Accordingly, we enhance all mammograms collected from the mini-MIAS database by applying the CLAHE method to increase the accuracy of the diagnosis of a breast tumor. After that, ROI cropped manually inside ground truth GT from enhancing mammograms in three sizes (10×10, 20×20, and 30×30) pixels according to the dimensions of masses in mammograms. LBP, HOG, and GLCM are feature extraction methods used in this research to extract features from all ROIs at (10×10), (20×20) and (30×30). Contrast, correlation, energy, and homogeneity are features derived from all ROIs. In LBP, the histogram displays the number of features extracted from each ROI and the value of each feature. By the histograms, we noted when increasing the size of ROI, the number of features increases, and the feature values for some images decrease. As when increasing the size of
ROI, we encoded greater information around each pixel however some local details may be lost. See figure 3.

Figure 3: histogram of features extracted from ROI at (10 ×10), (20 ×20) and (30 ×30)

In HOG method, features representations for all abnormalities are illustrated in figure 4; the direction of all cells is reached. This viewing to edge directions can be better to understand the contours and shape encoding.

Figure 4: Samples HOG representation for ROI at (10 ×10), (20 ×20) and (30 ×30)

The third method utilizing in this work is the GLCM. For each ROI we counted GLCM in one orientation (0°) and three distances (10, 20 and 30 pixels). GLCM extracted features by joining orientation (0°) and the pixels distance. We evaluated the suggested methods by using 5-fold cross-validation and compute accuracy, sensitivity, and specificity.

LBP produced the best mass classification for normal and abnormal by logistic regression classifier. Table 1 indicates the LBP method present the best description of breast tissues in the case of AS abnormalities mammograms at ROI (30×30), where the accuracy, sensitivity 92.5%, 88.0% respectively. CI abnormalities mammograms at ROI (10×10) achieved the lowest accuracy and sensitivity of 71.7%, 20.0% respectively. 97.0% is the best Specificity reached in the case of AS abnormalities mammograms at ROI (10×10), while the lowest Specificity 85.0% in the case of AR abnormalities mammograms at ROI (20×20).

Table 2 displays the evaluation of the performance of HOG method. The HOG method achieved the best results with the SVM classifier. HOG method given high results in accuracy and specificity 90%, 100% respectively in the case of (CA) abnormalities mammograms at ROI (30×30). 70% is the lowest value of accuracy reached in ROI (10×10) for (CI) abnormalities mammograms. The highest sensitivity value is observed 79% for architectural (AR) tumors at ROI (30×30) while the less value of sensitivity in the case of (AS) abnormalities mammograms at ROI (10×10). The lowest value of specificity 73% achieved by (SP) abnormalities mammograms at ROI (20×20).
Table 3 explains that utilizing the GLCM is the only method that provides the best accuracy, sensitivity, and specificity results with the KNN classifier. The (GLCM) method given high results in accuracy 89.3% in the case of (MI) abnormalities mammograms at ROI (30x30), while 73.1% is the lowest value of accuracy reached in ROI (10x10) for (CI) abnormalities mammograms. The highest sensitivity value is observed 78% for architectural (AR) tumors at ROI (10x10) while the less value of sensitivity 32% reached in the case of (CA) abnormalities mammograms at ROI (30x30). The highest value of specificity 99% achieved by (CA) abnormalities mammograms at ROI (30x30). 65% is less value of specificity in the case of (AR) abnormalities mammograms at ROI (10x10).

Table 1: accuracy, sensitivity, and specificity of breast mass detection with LBP and logistic regression classifier

| Accuracy % | type | ROI  | AR  | AS  | CA  | CI  | MI  | SP  |
|------------|------|------|-----|-----|-----|-----|-----|-----|
|            |      | 10x10| 77.7| 77.4| 85.2| 71.7| 82.0| 72.5|
|            |      | 20x20| 85.0| 82.0| 79.0| 72.0| 84.3| 75.0|
|            |      | 30x30| 90.1| 92.5| 89.1| 82.0| 86.2| 85.0|

| Sensitivity % | type | ROI  | AR  | AS  | CA  | CI  | MI  | SP  |
|---------------|------|------|-----|-----|-----|-----|-----|-----|
|               |      | 10x10| 36.0| 30.0| 59.0| 20.0| 30.0| 31.0|
|               |      | 20x20| 78.0| 46.0| 34.0| 25.0| 32.0| 33.0|
|               |      | 30x30| 83.0| 88.0| 71.0| 65.0| 46.0| 73.0|

| Specificity % | type | ROI  | AR  | AS  | CA  | CI  | MI  | SP  |
|---------------|------|------|-----|-----|-----|-----|-----|-----|
|               |      | 10x10| 95.0| 97.0| 92.0| 92.0| 95.0| 90.0|
|               |      | 20x20| 85.0| 95.0| 93.0| 93.0| 96.0| 88.0|
|               |      | 30x30| 90.0| 90.0| 93.0| 88.0| 95.0| 89.0|

Table 2: Accuracy, sensitivity, and specificity of breast mass detection with HOG and SVM classifier

| Accuracy % | type | ROI  | AR  | AS  | CA  | CI  | MI  | SP  |
|------------|------|------|-----|-----|-----|-----|-----|-----|
|            |      | 10x10| 70.6| 71.4| 72.9| 70.0| 76.6| 71.4|
|            |      | 20x20| 78.0| 78.0| 80.4| 71.4| 79.6| 71.7|
|            |      | 30x30| 81.1| 80.0| 90.0| 75.5| 83.3| 78.0|

| Sensitivity % | type | ROI  | AR  | AS  | CA  | CI  | MI  | SP  |
|---------------|------|------|-----|-----|-----|-----|-----|-----|
|               |      | 10x10| 39.0| 23.0| 31.0| 35.0| 56.0| 63.0|
|               |      | 20x20| 69.0| 43.0| 72.0| 60.0| 54.0| 48.0|
|               |      | 30x30| 79.0| 41.0| 72.0| 57.0| 35.0| 41.0|

| Specificity % | type | ROI  | AR  | AS  | CA  | CI  | MI  | SP  |
|---------------|------|------|-----|-----|-----|-----|-----|-----|
|               |      | 10x10| 91.0| 97.0| 94.0| 91.0| 88.0| 82.0|
|               |      | 20x20| 88.0| 97.0| 88.0| 88.0| 94.0| 73.0|
|               |      | 30x30| 84.0| 95.0| 100 | 84.0| 97.0| 95.0|

Table 3: Accuracy, sensitivity, and specificity of breast mass detection with GLCM and KNN classifier
Accuracy %

| type ROI | AR   | AS   | CA   | CI   | MI   | SP   |
|----------|------|------|------|------|------|------|
| 10 × 10  | 76.8 | 79.4 | 76.5 | 73.1 | 77.0 | 81.9 |
| 20 × 20  | 80.3 | 87.1 | 77.8 | 80.2 | 84.1 | 79.6 |
| 30 × 30  | 76.2 | 88.2 | 84.4 | 79.6 | 89.3 | 77.2 |

Sensitivity %

| type ROI | AR   | AS   | CA   | CI   | MI   | SP   |
|----------|------|------|------|------|------|------|
| 10 × 10  | 78.0 | 52.0 | 68.0 | 57.0 | 67.0 | 51.0 |
| 20 × 20  | 67.0 | 70.0 | 49.0 | 63.0 | 73.0 | 67.0 |
| 30 × 30  | 61.0 | 67.0 | 32.0 | 59.0 | 51.0 | 33.0 |

Specificity %

| type ROI | AR   | AS   | CA   | CI   | MI   | SP   |
|----------|------|------|------|------|------|------|
| 10 × 10  | 65.0 | 92.0 | 82.0 | 82.0 | 81.0 | 93.0 |
| 20 × 20  | 87.0 | 93.0 | 91.0 | 88.0 | 94.0 | 85.0 |
| 30 × 30  | 84.0 | 86.0 | 99.0 | 88.0 | 92.0 | 95.0 |

The accuracy of all proposed methods ranged between growing up and growing down around ±20 for different breast tumors. This extension is due to the different types of masses. The best results obtained in this work using the three texture extraction methods (LBP, HOG, and GLCM) were in case of ROI (30×30) because increasing the size of ROI gives more excellent details around each pixel in the mammogram.

4. Comparison with Previous Works

The result of classification performance for the mini-MIAS database explains that the proposed feature extraction methods used in this work provide good results in terms of accuracy, sensitivity, and specificity. The results achieved in this work are comparable with similar works offered by different researchers. Table 4 shows the comparative examination of this work with other researchers. The detailed comparative examination is difficult because of the variability of size and kind of databases utilized in the different similar works.

**Table 4**: comparison approach work with previous works

| Title                  | Year | Feature extraction methods | Data classifier | Accuracy % | Sensitivity % | Specificity % |
|------------------------|------|----------------------------|----------------|------------|---------------|---------------|
| A. Unni et al. [34]    | 2018 | GLCM                       | MIAS            | SVM        | 74.59         | -             |
| T. T. Htay et al. [35] | 2018 | GLCM                       | MIAS            | KNN        | 92.0          | -             |
| N. Ponraj and M. Mercy [36] | 2017 | LBP                        | MIAS            | SVM        | 91.0          | 90.0          | 92.0          |
| M. M. Pawar et al.[37] | 2018 | LBP                        | MIAS            | ANN        | 98.57         | -             | -             |
| M. Abdel-Nasser et al.[38] | 2016 | HOG                        | MIAS            | SVM        | -             | 72.0          | 95.0          |
| K. C. Tatikonda et al.[39] | 2018 | HOG                        | MIAS            | SVM        | 90.0          | 76.66         | 98.89         |
4. Conclusion

In this work, feature extraction methods used to improve the accuracy in the detection of masses since the features derived from ROI explain the changes in the mammogram. Using the CLAHE method to enhance mammograms gives better results than using mammograms without enhancement. After enhancing mammograms, ROI selecting inside the mass region where all crop region is infected, that increasing classification accuracy. Increasing the size of ROI improves the accuracy of discriminating between normal and abnormal breast tissue due to encoding more fine details around each pixel in the mammogram where the best size of ROI is (30x30) in all feature extraction methods. The best classification of features derived from the LBP method achieved with a logistic regression classifier. SVM is the best classifier for features derived by the HOG method. While the best classification of features derived from the GLCM method achieved with the KNN classifier.

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