Bhattacharjee, *et al. Kesmas: Jurnal Kesehatan Masyarakat Nasional (National Public Health Journal)*. 2022; 17 (Special Issue 1): 90-96
DOI: 10.21109/kesmas.v17i2.5970

Review of Different Methods of Abnormal Mass Detection in Digital Mammograms

Sangita Bhattacharjee[1*], Sandeep Poddar[2], Amiya Bhaumik[3], Indra Kanta Maitra[4], Dewi Susanna[5], Andrew Ware[6]

[1]Research Scholar, Lincoln University College, Selangor, Darul Ehsan, Malaysia, [2]Deputy Vice Chancellor (Research & Innovation) Lincoln University College, Selangor, Darul Ehsan, Malaysia, [3]President, Lincoln University College, Selangor, Darul Ehsan, Malaysia, [4]Controller of Examination, St. Xavier's University College, Kolkata, India, [5]Department of Environmental Health, Faculty of Public Health, Universitas Indonesia, Depok, Indonesia, [6]Director of Research, University of South Wales, Cardiff, Wales, United Kingdom

Abstract

Various images from massive image databases extract inherent, implanted information or different examples explicitly found in the images. These images may help the community in initial self-breast cancer screening, and primary health cares can introduce this method to the community. The present study objective is to review the different methods of abnormal mass detection in digital mammograms. One of best methods for the detection of breast malignancy and discovery at a nascent stage is digital mammography. Some of the mammograms with excellent images have a high intensity of resolution that enables preparing images with high computations. The fact that medical images are so common on computers is one of the main things that helps radiologists make diagnoses. Image preprocessing highlights the portion after extraction and arrangement in computerized mammograms. Moreover, the future scope of examination for paving could be the way for a top invention in computer-aided diagnosis (CAD) for mammograms in the coming years. This also distinguished CAD that helped identify strategies for mass that have been widely covered in our research work. However, the identification methods for structural deviation in mammograms are complicated in real-life scenarios. These methods will benefit the public health program if they can be introduced to primary health care's public health screening system. The decision should be made as to which type of technology fits the level of the primary health care system.

Keywords: breast cancer, computer-aided diagnosis, digital mammography, feature extraction

Introduction

One of most feared diseases in today's world is cancer. A widespread cause of cancer affects mortality, posing a problem relating to public health in the modern world, especially in elderly females. One of most rapidly emerging diseases in the world is breast cancer, the second most common type of cancer. Approximately one million females are examined and treated for breast cancer, but over 400,000 die.[1] Early identification and analysis and recognition detect cancer efficiently and minimize mortality. Numerous imaging methods exist that diagnostically and effectively map human anatomy in a non-invasive manner, like X-Ray, MRI, CT, USG, and so forth. Due to its accuracy and cost-effectiveness, computer-aided diagnosis (CAD), a reasonably developed interdisciplinary mechanism for cancer detection, helps detect abnormalities in analyzing medical images following a pattern of the robust segmentation algorithm.[2]

The grey shades are wide ranges in Computed Radiography (CR) mammogram DICOM images. So that, the intensity of the image is the primary feature to determine the abnormality. The primary characteristics derived from medical images are utilized to a greater degree by computerized images and decision-making algorithms to analyze medical images.

The fact that medical images are so familiar on computers is one of the main things that helps radiologists make diagnoses. Image preprocessing highlights the portion after extraction and arrangement in computerized mammograms. Moreover, the objective is to examine and pave the way as a top invention in the CAD for mammograms in the coming years. This also distinguished the CAD that helped identify strategies for mass that have been widely covered in our research. However, the identification methods for structural deviation in mammograms are complex in real-life scenarios.

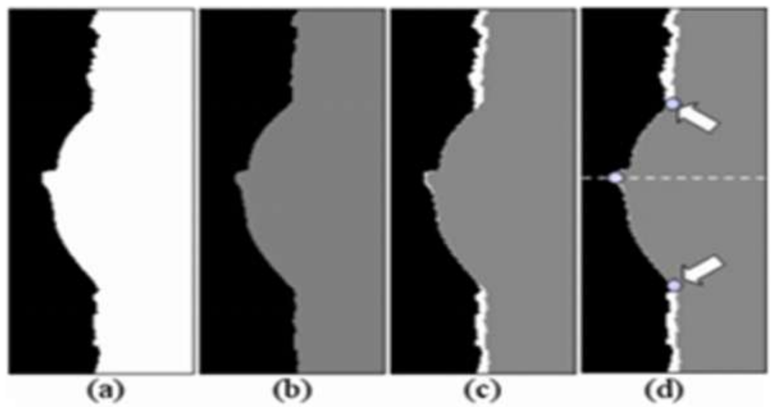
Literature Review

One of the leading efficient methods for breast cancer detection at a nascent stage is digital mammography, which requires high computational capabilities. There are several techniques for segmentation, feature extraction, and classification, and some of these procedures have been discussed in Figure 1.

***Correspondence*:** Sangita Bhattacharjee, Research Scholar, Lincoln University College, Wisma Lincoln, 12-18, Jalan SS 6/12, 47301 Petaling Jaya, Selangor, Malaysia, E-mail:sangs_555@yahoo.com, Phone: +91 98304 32134*

Received : June 08, 2022
Accepted : July 27, 2022
Published: July 31, 2022

Figure 1. The Major Preprocessing Steps Followed in Mammogram Image



Notes:
(a) The original greyscale image depicting the breast boundary
(b) The threshold images in two consecutive threshold levels
(c) Comparison of the two threshold images by overlapping
(d) The new breast boundary points are derived by analyzing the differences between the two threshold images.

Figure 2. An Example Illustrating the Breast Boundary Tracking Procedure

Image Segmentation

Medical image data from different sources are combined in the 3D volume due to its growing importance in modern times. Numerous algorithms are planned in the area of image segmentation.

Region Growing

By definition, the region-growing method assumes that the neighboring pixels within one region have similar features. The pixels can be grouped to form a cluster if a similarity exists. Senthilkumar, *et al.*,[3] proposed an automated seeded region growing algorithm (SRGA) based on Harri's detector method.

Statistical Methods

Different mathematical and statistical concepts, formulas, and models are used for medical image segmentation. Gouda et al. described how segmentation is based on statistical region merging (SRM) and linear discriminate analysis (LDA) for classification.[4]

Thresholding

Thresholding is one of the simplest methods for creating binary images in image segmentation (Figure 5). This proposed method by Maitra , *et al.*,[5] of Binary Homogeneity Enhancement Algorithm (BHEA) for digital mammography is followed by the technique of edge detection algorithm (EDA) and the Breast Border Boundary Enhancement Algorithm (BBEA).[5]

Fuzzy Method

Fuzzy logic is a multi-value function where the variable's truth value aids the segmentation procedure. Divyadarshini, *et al.,*[6] describes shape and margin characteristics obtained geometrically of maximum and minimum mass radius that can be utilized for classifying masses.

Information Difference

One valuable and usually-formatted data allowing straightforward human interpretation is preferably known as information difference. Cheng, *et al.*,[7] has shown how symptom of the abnormal region is essential.

Feature Extractions

The primary pair of estimated data feature extraction methods was calculated by modified resultant standards, proposed as carrying information and not redundant, facilitating the successive learning to improve interpretations.

Gabor

Different filtering models are used to improve the exterior of an image by compressing the intensity. Jangala, *et al.*,[8] portrayed mass detection as an edge detection technique that resides upon the segmentation for filtering in mammography.

Laplacian of Gaussian

This method has a filtering technique which is high pass to show faintly principal edges in an image for enhancement of the quality of the image. Cheng, *et al.*,[7] has showed that the CAD could offer similar assistance, and they are critical and indispensable for controlling breast cancer.

Gradient Vector Flow Snakes

This method used minimizing energy spline influenced by exterior constrain extraction of lines and edges. Malek, *et al.*,[9]'s study is based on active contour methods to locate and isolate the core portion extracted from the image.

Statistical Texture Features

The textural features of region of interests (ROIs) are extracted using gray level co-occurrence matrices (GLCM), constructed in four directions for each ROI (Figure 3).

Morphological

The device used to extract several parts is helpful in the demonstration, along with describing the different regions, sizes, shapes, and boundaries for implementation. Halkiotis, *et al.*,[10] considered every piece of a mammogram to represent the topography.

Image Classification

The classification process is performed on the ROI obtained from the image to classify the mass surrounding the suspected region. This classification improves efficiency to minimize the malignant count of false positives. The CAD assists the radiologist's interpretation of mammograms for performance evaluation.

Markov

This technique involves random transitions in state space from one state to another. The MRF-based classification by Li, *et al.*,[11] uses a binary decision tree that is fuzzy based and possesses radiography features interlinked with density.

K-nearest Neighbour

The nearest neighborhood method implements every intensity of nearest neighbor pixels found inside the unique image. The K-nearest neighbor is a non-parametric in classifying and finding regression (Figure 4). Akila, *et al.*,[12] showed the K-means used classification of the tumor degree and number of mammogram pixels.

Linear Discriminant Analysis

The linear discriminate algorithm (LDA) is primarily a traditional classification method. Cheng, *et al.*,[7] have proposed that these boundaries set by the decision are built straight by maximizing the error condition to detach the object class.

Discussion

According to Sung, *et al.*,[1] the extraordinary diversity of cancer continues to offer clues to the underlying caus-

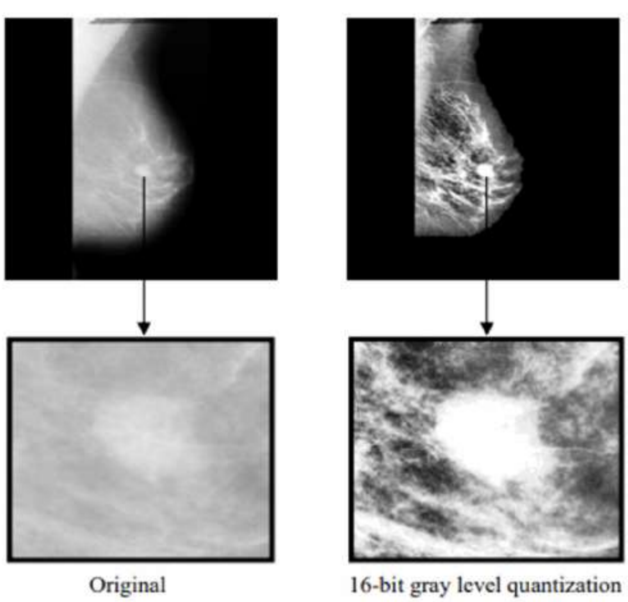


Figure 3. The 16-Bit Gray Level Quantization Produces Better Information than the Original

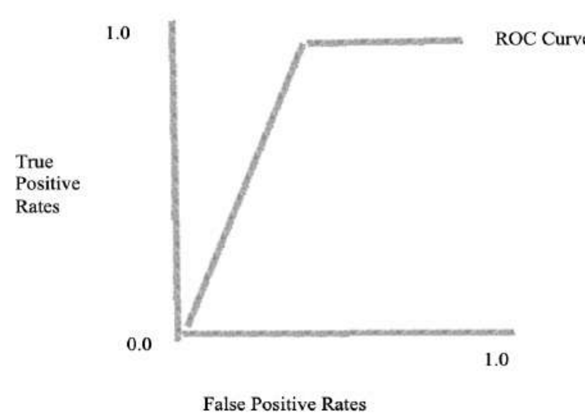


Figure 4. The Empirical Receiver Operating Characteristics Curve for Tumour Identification

es, but also reinforces the need for a global escalation of efforts to control the disease. The packages of effective and resource-sensitive preventative and curative interventions available for cancer and their tailored integration into health planning nationally can only serve to reduce and curb the future burden of cancer. The outcome was also accompanied by low referral rates for additional assessments, resulting in significant reductions in false-positive tests and unnecessary workup procedures.

Jangala, *et al.*,[9] showed that in the frequency components or the smoothing introduced by most sensing devices, sharp discontinuities had been found to exist in real signals scarcely, which is a unique achievement rarely found in other works. This method also showed the K-means clustered image segmentation for detecting masses, that the method would only find masses when they are still harmless. The results achieved by this methodology will give better results in terms of accuracy using statistical values.

Divyadarshini, *et al.*,[6] showed that the advantage of this method lies in its simplicity and cost-effectiveness. These geometric features are good at discriminating regular shapes from irregular ones. It is found that the masses, represented using shape and margin properties, possess a certain amount of imprecision. The disadvantage is that it can be deceptive at times. The classification accuracy for different shapes and severeness yields comparatively better results.

Maitra, *et al.*,[5] showed a fully-automated detection technique of abnormal masses by anatomical segmentation of the breast ROI in a mediolateral oblique (MLO) view of mammograms using different algorithms like binary homogeneity (BHEA), breast boundary detection algorithm (BBDA), and pectoral muscle detection (PMDA) to suppress the breast ROI. Also, the anatomical segmentation of breast (ASB) ROI in various regions within the breast and the SRGA to isolate abnormal regions in a simple and faster method compared to others. The limitation is that these results had been tested only in the mini-MIAS database and detected abnormalities in only those mammograms that contain abnormal masses according to the MIAS database. The percentage of accuracy agreement achieved is approximately 0.9987.

Malek, *et al.*,[8] obtained a higher classification performance that diagnoses the presented cases accurately and categorizes them as benign or malignant. This system provided a binary diagnosis and an output as a numeric value representing the degree to which the system could confidently respond in achieving placement and routing. This diagnostic system performs similarly to a software solution as a hardware solution, which is sometimes confusing. The malignant textures are distinguished from the benign ones solely based on assumption. This method attained a 97% correct classification over the benign cases, a 93% correct classification over the malignant cases, and an overall classification rate of 95% of the testing data. At the end of this process, the images in the database were categorized more accurately.8

Dong, *et al.*,[13] showed that the performance of the bilateral image feature subtraction method is better than the single image processing technique. This technique did not reduce false positives and further tested the bilateral image subtraction method on a smaller rather than more extensive data set. The classification accuracy on bilateral image feature extraction is 71.15%, and single image processing is 51.92%.

Eddaoudi, *et al.*,[14] cited normal mammogram images based on statistical feature calculations used to define decision criteria that would allow distinguishing between normal and pathological tissue types. Each value represented the average of the parameters computed over the entire dataset. These preliminary results showed that the statistical features of the mammary gland tissue are insignificant and proved to be different from the statistical features of the fat one. A new method has been described to characterize normal mammograms with a set of parameters calculated to find the variance, the contrast, and the correlation representing the most significant features in characterizing the fat tissue and the mammary gland. The results are in the formation of the tissue for a normal breast. The effectiveness of these features and the computational results shown by processing 30 normal mammograms showed the contrast and the correlation in the directions $dx = 1$ $dy = 1$ and $dx = 1$ $dy = 2$ are found to be more significant in terms of discriminating a normal mammogram.

Hassan, *et al.*,[16] provided a dataset-based quantitative comparison of the most recent techniques and the most commonly-used evaluation metrics for the breast cancer CAD systems. The survey also highlighted challenges and limitations of the current breast cancer detection and classification techniques. The results showed that the segmentation accuracy increased to 73.6% when using samples from the Curated Breast Imaging Subset of the Digital Database for Screening Mammography (CBIS-DDSM) dataset. Furthermore, the classification accuracy improved to 87.2%, with an area under the curve (AUC) of 94%. Due to the insufficient number of mammographic images in the publicly available datasets, data augmentation techniques are required to create synthetic mammographic images. This method has been demonstrated to have promising performance and contribute significantly to the development of CAD systems.

Gouda, *et al.*,[4] showed that using Patient-controlled analgesia (PCA) in selecting features gave good results. This selection could be made by developing a CAD system capable of assisting health professionals in the painstaking task of tracing mammograms and abnormalities. There is a need for methodologies that support the automatic detection of lesions in mammogram images with little or no specialist participation. Such an objective is still a great challenge for the segmentation methods because of the dependability of the characteristics of objects. The testing accuracy of this method is 98.00995025, and its sensitivity is 94.87%.

Suliga, *et al.*,[15] showed a new pixel clustering model for analyzing digital mammograms. The clustering represents the first step in a more general method aimed at creating a concise clustered dataset for automatic detection and classification of masses, typically among the first symptoms analyzed in early diagnosis. A probabilistic description of the model, which can be written in any high-level or low-level programming language, makes it possible to run on almost any platform. The MRF-based technique is suitable for clustering in an environment that is limited and described by poor or limited data. Evaluation of the algorithm against the classical K-means clustering routine yielded comparatively superior results to the MRF scheme.

Halkiatos, *et al.*,[10] showed a new algorithm for detecting clustered microcalcifications using mathematical morphology and efficiently combining an artificial neural network approach. The morphological filters are applied in order to only remove (a) noise from the image and (b) regional maxima that do not even correspond to calcifications. The MLP with 10 hidden nodes achieved the best classification score with a true positive detection rate of 94.7% and 0.27 false positives per image.

Akila, *et al.*,[12] showed that the primary step is preprocessing, which removes noise in the images. Then canny edge detection is used to detect the edges of images. After finding the edges, morphological operations are done to get the clearest mass. Then the original image overlapped with the eroded image to get an even more detailed view of the tumor. The K-means algorithm is used as an effective method to classify the tumor level. Thresholding segmentation is performed after edge detection is applied to get a vague or clear border of the mass. The mass morphological filtering is done, including grayscale dilation, hole-filling, and erosion, to obtain a clearer image. Then the original image overlapped with the eroded image to get an even more detailed view of the tumor since it failed to obtain a better view at the first attempt. This method shows that mammography detects about 80–90% of breast cancers in women without symptoms.

Ozha, *et al.*,[17] surveyed the different scientific methodologies and techniques to detect suspicious regions in mammograms, spanning from methods based on low-level image features to the most recent novelties in artificial intelligence (AI)-based approaches. This method proved a considerable success with mammography in biomedical imaging. Detecting suspicious areas remains challenging due to the manual examination and variations in shape, size, and other mass morphological features. Mammography accuracy changed with the density of the breast. This model was tested on the MIAS dataset and achieved an accuracy rate of 98.5%.

Shen, *et al.*,[18] obtained the AI system achieving radiologist-level accuracy in identifying breast cancer in ultrasound images The hybrid models of the AI system and the predictions of each of these were computed as an equally weighted average between the AI system and each value reader. This analysis revealed that the performance of all reader values was improved to some extent by incorporating the predictions of the AI system, which was otherwise not possible. The result achieved by the AI was an area under the receiver operating characteristic curve (AUROC) of 0.976 on a test set consisting of 44,755 exams.

Senthilkumar, *et al.*,[3] included a new uncertainty theory, namely the Cloud Model, to realize automatic and adaptive threshold selection, which considers the uncertainty of an image and extracts concepts from characteristics of the region to be segmented as efficiently as a human being. Segmentation of medical images using a seeded region growing technique is increasingly becoming popular because of its ability to involve anatomical structures in the seed selection process. In this paper, only the part showing improvements in region-growing image segmentation has been shown. Furthermore, the method had been tested for over 40 sample images, and the results were comparatively better.

Li, *et al.*,[11] show that general mammographic parenchymal and ductal patterns could be well modeled by a set of parameters of affine transformations. The present study results are compared with those of the partial wavelet reconstruction and morphological operation approaches, which yield not the best but comparatively better results. The results demonstrated that the fractal modeling method is an even more effective way to yield better results for enhancing microcalcifications.

Lee, *et al.*,[2] reviewed computer vision techniques adopted in medical image analysis, particularly for cancer detection. This work focused on detecting the most common types of cancer forms. A cloud computing framework in modern days inspired the study to utilize the existing work on image-based cancer study and develop an even more versatile CAD detection technique. The results only gave a general idea of how segmentation was used in these common medical image modalities to find the most common types of cancer, and the results were good.

Cheng, *et al.*,[7] have shown a significant advantage of the proposed method in detecting microcalcifications at every point in dense breast mammograms. Mostly, the clusters in the mammogram detected are almost invisible,

Table 1. An Example of a Table Showing the Different Methods of Segmentation and Feature Extraction

Category	Rational	Method	Reference
Region growing	Homogenous gray level information for detection of the region found as potential.	Region-growing-based algorithm multi-tolerance region-growing.	[3], [4]
Statistical methods	Global and local thresholding. Estimation of model spatial relation by maximizing estimation.	Histogram threshold-holding. Markov random field model estimation.	[5] [6]
	The area under Receive Operating Characteristics curve.	This curve and this method determine the sensitivity and specificity.	[16]
Thresholding	Used to create binary images.	Binary Homogeneity Enhancement Algorithm.	[5]
Fuzzy method	Using fuzzy rules and properties to separate	Fuzzy logic	[7]
Information difference	The difference between a pair of mammograms to detect the ROI.	Bilateral image subtraction.	[13]
LOG	Filtering technique which is high pass to show faintly principal edges which is critical and indispensable.	Transformation of an image to different scale space, Laplacian of Gaussian.	[7]
GVF Snakes	Active contour and Snakes.	Energy minimizing spline, which is guided by external constraint forces to extract features like lines and edges.	[8]
Statistical Texture	Gray level histogram moments and gray level co-occurrence (matrix).	4 features: energy measure, correlation, skewness, kurtosis, 1 inertia, entropy, inverse difference moment, sum average, sum, variance, correlation.	[14]
	Texture Descriptor Analysis.	This method helps indicate visual patterns in medical images and feed into the classification system that enables decision-making.	[17]
Morphological	Morphological operations: dilation and erosion.	Measurement by mathematical morphology in case suspicious such as shape	[10]

Notes: LOG = Laplacian of Gaussian; ROI = Region of Interests; GVF = Gradient Vector Flow.

Table 2. An Example of a Table above Showing the Different Methods of Classification

Category	Detail	Reference
Markov	Statistical classification model by the use of statistical and contextual information for masses, based on K-means cluster scheme.	[15]
KNN	Co-occurrence features, wavelet features, and shape features Convolution Neural Network (CNN) showed an improved technique over CAD.	[12]
LDA	Texture features and morphological features.	[7]

Notes: KNN = K-Nearest Neighbor; LDA = Linear Discriminant Analysis, CAD = Computer Aided Diagnosis.

making it exceedingly difficult to distinguish them for the radiologist. This kind of error is because microcalcifications are superimposed on curve-like tissues and are removed when the curve detector for removing irrelevant breast structures is applied. The Free-response Receiver Operating Characteristics (FROC) curve proved that the proposed method achieved a greater than 96% TP rate with an FP rate of four clusters per image.

Conclusion

The present study on the CAD mammography is a key point for detecting breast abnormalities as benign, malignant, or normal. Several techniques of segmentation, feature extraction, and classification have been developed, as different scholars propose. Numerous research have been carried out, but selecting an accurate segmentation, detection, and classification method to detect the abnormality in the breast ROI remains a major challenge.

The objective is to examine and pave the way as a top invention in the CAD for mammograms in the coming years. This also distinguishes the CAD that helped identify strategies for mass widely covered in this research work. However, the identification methods for structural deviation in mammograms are complex in real-life scenarios and remain a significant challenge.

Further discussion should be made among Information Technology personnel and statisticians and the primary health care team management in the Ministry of Health to decide which method suits the primary health care system. The mechanism can help the decision process to refer the suspect directly to the higher-level health institution to be treated accordingly and at the very early stage.

Abbreviations

CAD: Computer Aided Diagnosis; CR: Computed Radiography; DICOM: Digital Imaging and Communications in medicine; 3D: Three-Dimensional; SRGA: Seeded Region Growing Algorithm; SRM:

Statistical Region Merging; LDA: Linear Discriminate Analysis; BHEA: Binary Homogeneity Enhancement Algorithm; EDA: Edge Detection Alrgotithm; BBEA: Breast Border Boundary Enhancement Algorithm; ROIs: Region of Interest; GLCM: Gray Level Co-occurrence Matrices; MLO: Mediolateral oblique (MLO); PMDA: Pectoral Muscle Detection; ASB: Anatomical Segmentation of b\Breast; MIAS: Malnutrition, Inflammation, Atherosclerosis Syndrome; CBIS-DDSM: Curated Breast Imaging Subset of the Digital Database for Screening Mammography; AUC: Area Under the Curve; PCA: Patient-Controlled Analgesia; MRF: Markov Random field; AI: Artificial Intelligence; AUROC: Area Under the Receiver Operating Characteristic Curve; FROC: Free-response Receiver Operating Characteristics; LOG: Laplacian of Gaussian; GVF: Gradient Vector Flow; KNN: K-Nearest Neighbor; LDA: Linear Discriminant Analysis.

Ethics Approval and Consent to Participate
Not Applicable.

Competing Interest
The authors declare that there are no significant competing financial, professional, or personal interests that might have affected the performance or presentation of the work described in this manuscript.

Availability of Data and Materials
The dataset used and analyzed are available in published documents and on the internet.

Authors' Contribution
SB and IKM have contributed to developing the algorithms, detailed investigation and analysis of the methods, implementation of the methods, and writing the manuscript. SP helped verify, guide, and supervise this work's findings. AB has also helped in guiding and supervising this work. DS and AW both helped review and edit and provided valuable feedback that helped shape the research work.

Acknowledgment
The author would like to thank Lincoln University College Malaysia for supporting the Development of Computer Aided Diagnosis System for the Detection of Breast Abnormalities Using Digital Mammograms.

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