MULTI-FRACTAL DIMENSION FEATURES BY ENHANCING AND SEGMENTING MAMMOGRAM IMAGES OF BREAST CANCER

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A thesis submitted in partial fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

School of Computing
Faculty of Engineering
Universiti Teknologi Malaysia

JUNE 2020

DEDICATION

To my beloved parents who have so much faith in me.

To my brothers, sisters, sister-in-law, brother-in-law, my lovely nephews, and my lovely niece
To all of my relatives and friends
Who have stood by me through thin and thick.

To my virtuous supervisor whose taught me in a truthful, fair and honourable way.

To all who contributed to the success of this research.

Thanks for showering me with
love, care, encouragement, support and understanding in all my endeavours
Without all of you, this thesis would not have been made possible
Life has been wonderfully colored by you all

ACKNOWLEDGEMENT

First of all, gratefulness of thanks to our Creator, "**ALLAH**", who enabled us to complete this study.

I would like to express my gratitude to my supervisor, **Dr. Haza Nuzly Abdull Hamed and Prof. Dr. Habibollah Haron** for his guidance, encouragement and sharing his great knowledge and experience with me to complete this work, without his extensive support, valuable advice and suggestions; this thesis would not have reached a state of fruition.

I also indebted to Universiti Teknologi Malaysia (UTM), School of Computing for some fundings on my tuition fees. Also, I feel much grateful to wave my salutation to all UTM staff members for providing me timely help on various occasions.

I gratefully acknowledge for all I have received from my parents, by the way of inspiration, patience and encouragement at all times but most conspicuously during this period. I express my heart-felt thanks and profound gratitude for their assistance has made me feel motivated and supported in making this research successful.

Last but not least, special and countless thanks to my beloved siblings, sister-in-law, brother-in-law, all of my relatives, friends, and lab-mates, for their love, understanding, encouragement and moral support throughout the study.

ABSTRACT

The common malignancy which causes deaths in women is breast cancer. Early detection of breast cancer using mammographic image can help in reducing the mortality rate and the probability of recurrence. Through mammographic examination, breast lesions can be detected and classified. Breast lesions can be detected using many popular tools such as Magnetic Resonance Imaging (MRI), ultrasonography, and mammography. Although mammography is very useful in the diagnosis of breast cancer, the pattern similarities between normal and pathologic cases makes the process of diagnosis difficult. Therefore, in this thesis Computer Aided Diagnosing (CAD) systems have been developed to help doctors and technicians in detecting lesions. The thesis aims to increase the accuracy of diagnosing breast cancer for optimal classification of cancer. It is achieved using Machine Learning (ML) and image processing techniques on mammogram images. This thesis also proposes an improvement of an automated extraction of powerful texture sign for classification by enhancing and segmenting the breast cancer mammogram images. The proposed CAD system consists of five stages namely pre-processing, segmentation, feature extraction, feature selection, and classification. First stage is pre-processing that is used for noise reduction due to noises in mammogram image. Therefore, based on the frequency domain this thesis employed wavelet transform to enhance mammogram images in pre-processing stage for two purposes which is to highlight the border of mammogram images for segmentation stage, and to enhance the region of interest (ROI) using adaptive threshold in the mammogram images for feature extraction purpose. Second stage is segmentation process to identify ROI in mammogram images. It is a difficult task because of several landmarks such as breast boundary and artifacts as well as pectoral muscle in Medio-Lateral Oblique (MLO). Thus, this thesis presents an automatic segmentation algorithm based on new thresholding combined with image processing techniques. Experimental results demonstrate that the proposed model increases segmentation accuracy of the ROI from breast background, landmarks, and pectoral muscle. Third stage is feature extraction where enhancement model based on fractal dimension is proposed to derive significant mammogram image texture features. Based on the proposed, model a powerful texture sign for classification are extracted. Fourth stage is feature selection where Genetic Algorithm (GA) technique has been used as a feature selection technique to select the important features. In last classification stage, Artificial Neural Network (ANN) technique has been used to differentiate between Benign and Malignant classes of cancer using the most relevant texture feature. As a conclusion, classification accuracy, sensitivity, and specificity obtained by the proposed CAD system are improved in comparison to previous studies. This thesis has practical contribution in identification of breast cancer using mammogram images and better classification accuracy of benign and malign lesions using ML and image processing techniques.

ABSTRAK

Malignan biasa yang menyebabkan kematian kepada wanita ialah kanser payudara. Lesion payudara boleh dikesan dan diklasifikasikan secara pemeriksaan mammografi. Pengesanan awal kanser payudara menggunakan imej mammografi boleh membantu mengurangkan kadar mortaliti dan kebarangkalian berulang. Lesion payudara boleh dikesan menggunakan peralatan terkenal seperti Pengimejan Resonan Magnetik (MRI), ultrasonografi, dan mammografi. Walaupun mammografi sangat berguna untuk diagnosis kanser payudara, persamaan corak antara kes normal dan patologik menyebabkan proses diagnosis menjadi sukar. Oleh itu, dalam tesis ini sistem Diagnosis Berbantukan Komputer (CAD) telah dibangunkan untuk membantu doktor dan juruteknik mengesan lesion. Matlamat tesis ialah meningkatkan ketepatan mendiagnosis kanser payudara bagi pengkelasan kanser yang optimum. Ia dicapai menggunakan Pembelajaran Mesin (ML) dan teknik pemprosesan imej ke atas imej mammogram. Kajian ini juga mencadangkan penambahbaikan bagi pengekstrakan automatik isyarat tekstur berkuasa. Sistem CAD yang dicadangkan mengandungi lima peringkat iaitu pra-pemprosesan, segmentasi, pengekstrakan ciri, pemilihan ciri, dan pengkelasan. Peringkat pertama ialah pra-pemprosesan yang digunakan untuk mengurangkan hingar dalam imej mammogram. Oleh itu, berdasarkan domain frekuensi, kajian ini menggunakan penukaran wavelet untuk meningkatkan imej mammogram dengan dua tujuan iaitu untuk mendapatkan sempadan imej mammogram bagi peringkat segmentasi, dan untuk meningkatkan kawasan terpilih (ROI) menggunakan aras kabur adaptif dalam imej mammogram bagi tujuan pengekstrakan ciri. Tahap kedua adalah menggunakan proses segmentasi untuk mengenalpasti ROI imej mammogram. Proses segmentasi ini ialah tugas yang sukar disebabkan oleh isu tanda aras sempadan payudara dan artifak, begitu juga aspek otot pektoral dalam Oblik Medio-Lateral (MLO). Oleh itu, algoritma segmentasi automatik berdasarkan aras kabur baru digabungkan dengan teknik pemprosesan imej. Keputusan eksperimen menunjukkan bahawa teknik yang dicadang meningkatkan ketepatan bagi ROI daripada latarbelakang payudara, tanda aras, dan otot pektoral. Peringkat ketiga adalah pengekstrakan ciri yakni algoritma peningkatan berdasarkan dimensi fraktal dicadangkan untuk mendapatkan ciri tekstur imej mammogram. Berdasarkan model yang dicadangkan, isyarat tekstur berkuasa bagi tujuan pengkelasan telah diekstrakkan. Peringkat keempat ialah pemilihan ciri yakni algoritma genetik (GA) telah digunakan sebagai teknik pemilihan ciri untuk memilih ciri yang penting. Dalam peringkat terakhir, teknik rangkaian neural buatan (ANN) telah digunakan untuk membezakan antara kelas kanser benigna dengan malignan berasaskan ciri tekstur yang berkaitan. Sebagai kesimpulan, ketepatan, sensitiviti, dan spesifisiti pengkelasan yang diperolehi oleh sistem CAD yang dicadangkan telah diperbaiki setelah dibandingkan dengan kajian terdahulu. Dengan itu, kajian ini memberi sumbangan kepada pengenalpastian kanser payudara bagi imej mammogram dengan ketepatan lebih baik pengkelasan kanser benigna dan malignan menggunakan ML dan teknik pemprosesan imej.

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LIST OF ABBREVIATIONS

AC	-	Active Counter
AFBHE	-	Adaptive Fuzzy Logic Based Bi-Histogram Equalization
ANFIS	-	Neuro-Fuzzy System
ANN	-	Artificial Neural Network
ARL	-	Angle of Regression Line
ASR	-	Age Standardised Ratio
BA	-	The Bland-Altman
BIRADS	-	Breast Imaging Reporting and Data Systems
CAD	-	Computer-Aided Diagnosis
CC	-	Craniocaudal
CLAHE	-	Contrast limited adaptive histogram equalisation
CM	-	Coincidence Measure
CNN	-	Convolutional Neural Networks
CeNN	-	Cellular Neural Network
CT	-	Computer Tomography
DBC	-	Differential Box Counting
DBT	-	Digital Breast Tomosynthesis
DCT	-	Discreet Cosine Transform
DDSM	-	Digital Database for Screening Mammography
DL	-	Deep Learning
DM	-	Digital Mammogram
ECE	-	Exponential contrast enhancement
ELM	-	Extreme Learning Machine
ELO	-	Electromagnetism-Like Optimization
EWBFEM	-	Enhance Wavelet-Based Feature Extraction Model
EWBSM	-	Enhance Wavelet-Based Segmentation Model
FCM	-	Fuzzy C Means Clustering
FC-NNs	-	Fully Connected Neural Networks
FD	-	Fractal Dimension
FFDM	-	Full-Field Digital Mammography

FGMM	-	Fuzzy Gaussian Mixture Model
FN	-	False Negative
FOS	-	First-Order Statistics
FP	-	False Positive
FRCN	-	Full Resolution Convolutional Network
GA	-	Genetic Algorithm
GGD	-	Generalized Gaussian Density
GLCM	-	Gray-Level Co-occurrence Matrices
GLDM	-	Gray-Level Difference Matrices
GLRLM	-	Gray-Level Run- Length Matrices
HB	-	Hausdorff-Besicovitch
HE	-	Histogram Equalization
HH	-	High-High
HL	-	High-Low
HOG	-	Histogram of Oriented Gradients
HOT	-	Histogram of Oriented Texture
HVS	-	Human Visual System
IARC	-	International Agency for Research on Cancer
IRMA	-	Image Retrieval in Medical Applications
IMEM	-	Intelligibility Mammogram Enhancement Method
IRT	-	Infrared Thermography
KNN	-	K-Nearest Neighbour
LBP	-	Local Binary Pattern
LCE	-	Logarithmic contrast enhancement
LDA	-	Linear Discriminant Analysis
LH	-	Low-High
LL	-	Low-Low
LPQ	-	Local Phase Quantization
MCs	-	Microcalcifications
M-FD	-	Multi- Fractal Dimension
Mini-MIAS	-	Mini Mammographic Image Analysis Society
MI-RF	-	Multiple-Instance Random Forests
ML	-	Machine Learning

MLO	-	Medio-Lateral Oblique
MLP	-	Multilayer Perceptron
MRI	-	Magnetic Resonance Imaging
MSE	-	Mean Square Error
NB	-	Naïve Bayes
NCDs	-	Noncommunicable Diseases
NN	-	Neural Network
PB-DCT	-	Pass Band - Discrete Cosine Transform
PCA	-	Principal Component Analysis
PET	-	Positron Emission Tomography
PM	-	Pectoral Muscle
PNN	-	Probabilistic Neural Network
PSNR	-	Peak Signal to Noise Ratio
RAM	-	Installed Physical Memory
RG	-	Region Growing
ROC	-	Receiver Operating Characteristics
ROI	-	Region-of-Interest
SAR	-	Synthetic Aperture Radar
SFM	-	Screen-Film Mammography
SNR	-	Signal to Noise Ratio
SOM	-	Self-Organizing Map
SVM	-	Support Vector Machine
SWA	-	Sliding Window Algorithm
TN	-	True Negative
TP	-	True Positive
US	-	Ultrasound
WHO	-	World Health Organization
WT	-	Wavelet Transform
YOLO	-	You Only Look Once

CHAPTER 1

INTRODUCTION

1.1 Introduction

Causes of global deaths are recognised to have been largely contributed by Noncommunicable Diseases (NCDs). Among the NCDs, cancer is identified as a primary contributor to an increase in mortality rate and a main impediment to improving the life span of humans across the globe in the 21st century. In 2015, the World Health Organization (WHO) reported that cancer is the leading or the second largest contributor of global deaths. In addition, the prevalence of cancer cases and cancer related deaths around the globe have witnessed a staggering growth. Root causes of cancer are difficult to be dissected but highlight the effect of population growth and aging, in addition to increment of incidences and widespread of primary risk factors of cancer, some of which are related to socioeconomic development (Bray *et al.*, 2018). Uncontrollable cell growths trigger the occurrence of cancer diseases. Predominantly, masses or lumps are formed in cancerous cells, known as tumours, and are identified based on the region in the body in which they are detected. Various external factors could also lead to the formation of cancer cells including poor diet, infectious organisms, and tobacco, besides internal factors which include immune conditions, hormones, and hereditary genetic mutations.

Cancer type that is commonly suffered by the female population globally is breast cancer. Different cancers affect the female population as well, however, breast cancer is the primary cause of cancer-related deaths among women, trailed by colorectal and lung cancers. Globally, in 2018, there are approximately 2.1 million women that have been diagnosed with breast cancer. This type of cancer is recognised as a deadly cancer disease. Among all cancers, breast cancer is the second most frequently diagnosed cancer and stands as the fifth deadly cancer that could lead to death. Incidences of breast cancer are rampant in developing nations. One way to curb this worrying trend is to perform an early diagnosis, as this could potentially cure the sufferers (Diniz *et al.*, 2018 and Bray *et al.*, 2018). Occurrences of breast cancer seem unbiased on a specific ethnic group in Malaysia. Statistics of breast cancer incidences in Malaysia, as reported by the International Agency for Research on Cancer (IARC) in 2012 estimated that new breast cancer cases would reach 5400 incidences while cancer-related mortality would peak at 2500 incidences. The most commonly diagnosed cancers among women include breast, cervix uteri, and colorectum cancers. Mortality associated with breast cancer has caused 2500 deaths, while lung cancer has caused 1300 deaths, meanwhile, colorectum cancer resulted in 1000 deaths. In terms of incidences and death rates associated with breast cancer, by country, Malaysia is among the leading country in the Southeast Asia region with the highest reported incidences and death rates. Specifically, the Age Standardised Ratio (ASR) of death rates associated with breast cancer stands at 38.7 incidences for every 100,000 persons in Malaysia, which is palpably higher than Thailand (29.3), Myanmar (22.1), Cambodia (19.3), and Laos (19). Malaysia's breast cancer-related deaths are estimated to reach 4546 incidences from 9248 newly reported breast cancer cases in 2030. In terms of percentages, the increment of new breast cancer incidences translates to a 28% increment in 2020, while a staggering 76% increment in 2030 (Refer to Table 1.1) (Sajahan and Omer, 2018).

Table 1.1 Prediction of Number of New Cases and Breast Cancer Deaths in the Years 2012, 2020 and 2030 in Malaysia

Year	Incidence (Number)	Increase (%)	Mortality (Number)	Increase (%)
2012	5410	-	2572	-
2020	6977	28	3386	31
2030	9248	70	4546	76

Breast cancer could be effectively diagnosed through employing a medical image examination. Various techniques of medical imaging may be used to perform the examination including Infrared Thermography (IRT), microscopic (histological) images, Magnetic Resonance Imaging (MRI), Ultrasound (US), and Digital Mammogram (DM). Among the techniques, breast cancer could be detected by using a non-sophisticated DM technique. In medical imaging, fatty tissue is manifested in a dark coloration (black) while dense breast tissues appear in lighter colouration (white), which can be mistaken as tumours or masses in breast due to their similar colouration (Zhang *et al.*, 2018). State-of-the-art development into the medical imaging field saw the emergence of DM as a highly favoured technique, in contrast to screen film or analogue mammography, attributed to various cost-related and practical motives. Primary motivation for the adoption of DM is concerning the relative ease in acquiring and storing the data of medical images which eventually lead to a substantial reduction of associated costs. In addition, digitisation of image acquisition and storage allow healthcare providers to keep a digital record of patients, which is useful as patients' files may be re-visited in years to come by radiologists, thus, highlighting the robustness and cost-effectiveness of digital mammography in practice.

Long term survival chances and cancer diagnosis may be improved through employing early detection techniques. Such techniques employed in medical imaging is key to detecting and diagnosing cancer earlier. Interpreting medical images in large volumes manually consumes a significant amount of time, is a monotonous process, and is vulnerable to mistakes and biases due to the nature of human judgments. This was the motivation towards the development of Computer-Aided Diagnosis (CAD) systems in the 1980s, which was designed to aid medical practitioners to efficiently interpret medical images to a certain extent of accuracy and speed (Hu *et al.*, 2018). The primary role of a CAD system is to resolve the challenge of interpreting mammogram images. The goals of the system include to effectively diagnose cancer and to correctly interpret mammogram images. CAD systems come in quasi-automatic and fully automatic versions, which assist medical practitioners; not only in mammography but also in different application areas that are often utilised by medical practitioners. In general, five processes are involved in a standard CAD system: 1) Pre-processing for de-noising, 2) Segmenting image into several Region-of-Interest (ROI) segments, 3) Extracting features from Region of Interest (ROI), 4) Feature selection, and finally, 5) Classifying features. *Therefore, in this thesis attempts have been done to enhance a CAD framework. Based on the literature review it has been investigated CAD stages been an improvement. Thus, this thesis adopted the development of the pre-processing stage to enhance mammograms for segmentation and feature extraction. Wavelet transform will be exploited to propose two models for these two purposes. In the next stage, a segmentation technique will be improved based on the proposed new threshold value as well as building a machine learning model. Fractal*

Dimension (FD) technique will be enhanced based on blocking and threshold value to extract powerful features. Finally, the developed technique is able to increase the classification accuracy to discover the cancer subtype.

1.2 Research Background

Lately, there is an extremely widespread image recognition applications, because of the crucial roles they play in many life sectors including engineering, medicine, and science. The most advanced sense of a human being is vision, but sometimes, the human vision is limited in it is the capacity to process images. Therefore, through the concept of image processing and machine learning, computerized systems are able to acquire information about a problem that the human vision cannot acquire. This means that sometimes computerized systems are required in cases whereby the human vision is limited and cannot distinguish a problem. Machine learning techniques and image processing have made great contributions to the area of medicine through the digitalization of medical images, which allows the analysis and investigation of phenomena using a computer. There has been a significant contribution to the field of medicine through the continuous progress in the research and development in the area of image analysis. Medical images are crucial to the process of disease diagnosis and analysis like chest and breast-related ailments, blood disorder and abdominal illness and more. A disease can be further analysed using the digital format of the medical images, thereby enhancing the accuracy of diagnosis as well as optimal patient treatment and management. The use of such images can also be employed in teaching and research. More specifically, the kind of digital medical images which this study focuses on, are mammographic images. Regularly, the components of the breast and the changes that occur in them are analysed through clinical tests and diagnosis (Obaid *et al.*, 2018).

The leading reason for cancer deaths between women is breast cancer which ranked as second leading. Thus, it is considered as one of the most popular malignancy in women. Presently, there are no efficient ways through which breast cancer can be prevented since it causes is yet unknown. However, the only effective way of diagnosing and managing breast cancer is early detection which consider as a higher chance of full recovery from breast cancer. Thus, the mortality and morbidity rates can be reduced through early detection (Otsu, 1979). Medical imaging techniques encompass different modalities like Computer Tomography (CT scan), US, conventional X-Ray, MRI, and more. With the use of these techniques, tissues, organs, and bones can be scanned through, the waves of ultrasound, X-ray radiation, as well as both waves magnetic and radio, respectively. These waves are made to pass over the parts of the human body for medical examination. These medical examinations produce results that can be used by radiologists and clinicians for the assessment and diagnosis of abnormalities, to be able to decide the most appropriate treatment for the patient. Over the years, mammography has assured to be the tool that is most efficient for detecting early and treatment of breast cancer. Therefore, it remains the main imaging modality for screening and breast cancer diagnosis. More so, with mammography, other pathologies can be detected, and nature (malignant, normal or benign) can be determined. One of the most ground-breaking advancements in the area of breast imaging is the introduction of digital mammography (Nagi *et al.*, 2010).

The life span of a person with malignant growth can be longer if the detection is done at an early stage (Filipczuk *et al.*, 2011 and Tang *et al.*, 2009). The 5-year life span approximate for females with bosom malignant growth has increased from 63% in the mid-1960s to 89% presently. The life span estimate for ladies with restricted breast malignant (harmful malignancy that has spread to lymph hubs or different areas outside the breast) is 98% (Székely *et al.*, 2006). Mammography is the most popular and powerful technique used by clinicians to detect breast cancer. Even though the use of x-ray has been employed in the examination of breast cancer, most researchers have noted that mammogram is the most reliable technique which can be utilized in the early cancer detection, which in turn reduces death rates in females with the disease (Ganesan *et al.*, 2012). More so, mammogram is considered as a cheaper and more accessible option. Breast cancer can be efficiently remedying if at an early stage it is detected using a mammogram (Ganesan *et al.*, 2013). After the detection of breast malignancy in a female, further testing is required, and this may involve breast scanning using a mammogram, fine center needle goal. In the fine center needle goal, the use of analgesic is involved, and a needle is used to assemble cells which are embedded in the breast for biopsy. To extract the cell from the suspected region of the breast, a sedative is used on the patient. The needle is used within a restricted area when the malignancy is confirmed. Breast cancer is treated using lumpectomy or mastectomy. Fundamental treatment of breast cancer involves the use of either chemotherapy or tamoxifen, which is a medication for the treatment of malignant growth.

One of the tools that has been very helpful in the breast cancer detection early, is the CAD, which marks suspicious regions on a screening mammogram, thereby facilitating the reduction of the rate of death among women with breast cancer. Here, abnormalities in mammograms are detected using computer technologies. With the results of the CAD, a radiologist is able to characterize lesions by analysing the image automatically. Due to the fact that the detection of some lesions is more difficult than some, there may be variation in the performance of the CAD; the difficulty in the detection is due to the similarity between the characteristics of malignant and normal tissue. However, continuous research is needed so as to reduce the number of incorrect diagnosis. A high level of accuracy is required during the detection and classification of different medical images because the lives of humans are involved. As a result, most medical institutions resort to using computerized techniques of detection because they are able to reduce the rate of false negatives. It has been proven that the detection of tumor can be enhanced by double reading of medical images. However, the cost of double reading is high, and as such, medical institutions are more inclined towards using good software for such a task.

Against this backdrop, it is important to study the different approaches used in the production of medical images. It is also important to have a knowledge of the most appropriate technique to use for a specific kind of medical image to obtain better results. It has been found in the literature, that many techniques have been introduced for computed tomography like different kinds of MRI images, X-rays and other radiological techniques. Despite the fact that much efforts have been made in this area of research; more improvements need to be made as the area of medical image processing requires continuous expansion (Ganesan *et al.*, 2013). The main goal of using computerized methods of detection is to reduce possible human errors to the barest minimum so that better results can be obtained, this is crucial to reducing mortality rates.

1.3 **Problem Statement**

Due to the fact that breast cancer's cause is still unknown, disease prevention remains a major challenge in the medical field. However, effectively diagnosing breast cancer can increase the possibility of total recovery at an early stage. This means that the rates of morbidity and mortality associated with breast cancer can be decreased if it is identified early. Depending on radiographic breast imaging and screening the breast cancer diagnosis advances have been done an earlier stage. Nevertheless, statistics have shown that missed 10% to 30% of malignant biopsy proven as a result of different factors like technical problems that arise in imaging procedure, misinterpreted abnormalities and abnormalities that are not obvious (Raba *et al.*, 2005). It has been mentioned earlier that when traditional screening mammography is used, the rates of missed cases will be high (Mudigonda *et al.*, 2000). Producing a big set of images by mammogram screening, a huge workload for tests by a few radiologists is responsible for interpreting the images. However, the workload of these radiologists can be reduced through the use of computerized mammographic analysis that can help the radiologist detect breast cancer. The structure and characteristics of breast abnormalities make the detection of abnormality challenging. One of the most reliable ways through breast cancer can be screened is through the use of a mammogram. However, just like any other screening technique, the mammogram is not a perfect technique, as it has it is shortcomings. Some of the concerns associated with mammograms include such as the occurrence of false-negative test results (screening test results may show that the breast is normal in spite of the presence of breast cancer). Moreover, the occurrence of false-positive test results (screening test results may show that the breast is abnormal despite the absence of breast cancer) (American Cancer Society, 2015; Hong and Sohn, 2009).

Thus, this research is motivated by the need to design and create a CAD system, which is able to detect abnormalities through advanced image analysis techniques. The goal of this study is to improve the accuracy, sensitivity, and specificity of CAD. The success rate of the CAD system is depending on the entire stages of CAD. Typically, a CAD system comprises of some steps including, pre-processing, segmentation, extraction of feature, feature selection, and classification. Some challenges accompany each of the steps, and the result of each step is affected by the outcome of a previous step. This study only concentrates on the pre-processing, segmentation, and feature extraction stages. For the classification stage, previous Machine Learning (ML) techniques were employed to continue the process and classify breast cancer into its subtype. Therefore, there are three subjects considered to drive this thesis in relation to improve the performance of CAD which are pre-processing, segmentation, and feature extraction.

It has been investigating this research faces three main problems that made the work of the CAD not affective. Three main limitations have been listed below that are this research faced by.

1. The noise and artifacts are one of the major problems that faces with the medical images, especially in mammogram. Those two factors have side effect on the stages that used to build the CAD (i.e segmentation and features extraction). The noise has made the edge of the ROI not clear as well as cannot capture a good texture features that can help to identify the risk in early stage. In addition, the artifact has made the segmentation very hard due to that the artifacts will appear as a false positive object. Therefore, this research should propose different filters to prepare the images for the segmentation task and feature extraction task.

2. Using the traditional methods such as threshold, region growing, and watershed will not produce a good quality of segmentation with the medical image specially with mammogram. With this type of images, the border or the edge of the ROI is not clear and that will end up with over-segmentation problem. Moreover, the artifacts that mentioned before has made the problem more complicated. Therefore, this research should find a powerful solution that can help to identify the ROI from the non-ROI.

3. Based on the existing papers that have reviewed in the literature, it has been found that one of the difficult issues that the researchers faces is find a new sign (features) and classification to identify the risk of the malignant in early stage. Thus, this research attempts to develop a feature extraction technique to extract significant features from mammogram images.

Basically, in the pre-processing stage the resolution and the quality of the information of images are significant elements that influence the segmentation and classification precision of automated images characterization frameworks, including mammogram classification. Noise often has a negative impact on contrast of image and blurring edges which affects the image segmentation and other post-processing operations. One of the major activities of the pre-processing stage involves segmenting the breast region in mammograms precisely. Even though there are many reasons why this is important, it is mainly done because it enables the reduction of the search area for abnormalities without too much influence from the mammogram's background. Thus, pre-processing is important to highlight and contrast the ROI and make difference with its background. More so, the noise often has a negative impact on image quality by, in particular, hiding important details and may eventually reduce the overall diagnostic value of the image. Thus, one more activity of this stage is to eliminate existing noise which can be affected by the image features. In order to extract the powerful features which, lead to better classification pre-processing stage is a crucial task. Therefore, the wavelet transform has been exploited to enhance mammogram images for segmentation and feature extraction stages.

Furthermore, in the segmentation stage the image must segment to extract features automatically. Nevertheless, the most important determinant of accurate segmentation is the quality of the image because the task can be made more challenging because of the presence of artifacts like signal dropout, noise, and shadows. The implication of these quality impacts can be missed boundaries as a result of the existing of these low contrasts of both artifacts and acquisition orientation between the ROI. Tape artifacts, high-intensity rectangular labels, and low-intensity labels are information included in mammograms background which must be segmented and excluded from the region of mammogram. Mammogram screening in

Medio-Lateral Oblique (MLO) view in the upper posterior margin of mammogram a triangular region with high intensity is always appear which is called pectoral muscle. This kind of challenge is dealt with in the fifth chapter of this thesis by proposing the extraction of breast border and suppression of pectoral muscle. In this thesis, a new approach is presented for the automatic segmentation of breast images from static images, which is strongly indicative of the kind of cancer.

Essentially, the feature extraction purpose is to obtain numerous image characteristics. That could use in differentiating the labels of the images by the label another image than in finding the subsets of feature which affects CAD performance. Thus, another challenge that accompanies the detection of breast cancer, is obtaining accurate results of the automatic extraction of the best features of breast abnormality. The Fractal Dimension (FD) technique has been exploited in this thesis to extract significant features. based on blocking and thresholding values the FD technique enhanced to extract multi features which is called Multi- Fractal Dimension (M-FD). Additionally, the final result of abnormality detection can be influenced by the kind of classifier used. Artificial Neural Network (ANN) classification model is used to classify the breast cancer subtype into benign and malignant. The ANN classification performance of breast cancer is depended on the extracted features representing the mammogram images as provide data input for the classification. Thus, not powerful features as an input for the ANN classifier will result in low classification performance. Therefore, in this thesis fractal dimension technique is exploited with the feature extraction process in generating powerful features. Besides, the performance of the breast cancer diagnosis can be enhanced by feeding powerful features to the ANN classifier. As a result, it will improve the performance of the CAD. All these challenges are dealt with in this thesis through the investigation of different techniques of pre-processing, segmentation, feature extraction, feature fusion, and classification in the fourth, fifth, and sixth chapters of this thesis. The task of breast cancer detection is challenging because masses are different in shape, size and density, they are poor in image contrast, usually identical from adjacent tissues, highly connected to the surrounding tissue, and surrounded by inconsistent tissue background with similar characteristics.

1.4 Research Questions

In literature, many CAD has been proposed for mammogram images to achieve good performance. However, there remain several challenges that should be considered when any researcher tries to propose CAD with high accuracy. These challenges can be discussed as follows:

1. How to enhance the mammogram images for the segmentation stage.
2. How to enhance the mammogram images for the feature extraction stage.
3. How to use the most effective filter for both stages.
4. How to extract the ROI from the mammogram.
5. How to enhance texture features for mammogram images.

In order to achieve good answers to the above questions, other secondary questions will address the problem with more accuracy, and are formed as follows:

1. How to propose a model to reduce the noise and highlight the ROI from the background based on the wavelet transform?
2. How to propose a model to reduce the noise and enhance texture feature for classification based on wavelet transform?
3. How to evaluate the proposed models and see the limitations? Based on this investigation, enhance the most effective model and use it for both segmentation and feature extraction tasks?
4. How to propose a multi-level segmentation model to extract ROI from the mammogram?
5. How to propose a new model for texture feature extraction and to make them suitable for the mammogram images?

1.5 Research Objectives

The main aim of this study is to develop a diagnostic methodology for breast cancer through the use of ML and image processing techniques on mammogram images. Firstly, in this thesis, a discussion on the relevant ML and image processing techniques is given, to facilitate the identification of the most appropriate approach for the diagnosis of breast cancer. The research aims at increasing the accuracy of diagnosing breast cancer for the optimal classification of the disease; this is done using ML and image processing techniques. To this end, the following specific objectives have been formulated to achieve the purpose of the study:

(a) To design an efficient wavelet-based image enhancement model for segmentation and feature extraction purposes.

(b) To improve threshold-based and trainable segmentation model for Region of Interest (ROI) derivation.

(c) To develop Multi-Fractal Dimension (M-FD) feature extraction model for to extract significant texture features for breast cancer identification.

1.6 Research Scope

In order to achieve the desired goals and objectives of this research, it is very important to define the research scope, which can be stated as below:

1. The domain choice for this research is breast cancer detection using mammogram images.

2. The frequency domain is used in this research to enhance the mammogram images.

3. Mini Mammographic Image Analysis Society (Mini-MIAS) and Digital Database for Screening Mammography (DDSM) are the datasets used to test the proposed framework. All images in the MIAS database are used whereas some samples from the DDSM database are used for testing.

5. The proposed framework is implemented and tested using the MATLAB programming language.

    6. Mammogram enhancement test done by implementing different performance analysis methods which are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), and Signal to Noise Ratio (SNR) whereas the evaluation performance for the classification of breast cancer detection is performed based on sensitivity, specificity, and accuracy.

1.7 Research Significance

The most common malignancy which causes deaths in women is breast cancer. One of the best ways through which mastectomy can be avoided is through early detection of the cancer. More so, early detection can help in reducing the mortality rate and the probability of reoccurrence. Through the mammographic examination, breast lesions can be detected and characterized. Therefore, it is crucial for women to be aware of this disease and have themselves checked frequently using automatic methods. After the females must have acquired a certain age, regular mammography x-rays are required. The lesions on the breast can be detected using many techniques such as magnetic resonance imaging, ultrasonography, and mammography is the most popular choice. Although mammography is very useful in breast cancer diagnosis, the similarities between normal and pathologic patterns make the process of diagnosis difficult. Therefore, CAD systems have been developed to help doctors and other technicians in detecting mammary lesions, thus, providing an alternative.

This study is motivated by the urgent need for the aforementioned diagnosis. It is strongly believed that a multi-disciplinary ability for breast images can be provided by ample computer-aided diagnostics, thereby helping specialists identify the disease with a high level of accuracy, which in turn reduces the reduction in the rates of false positive and false negative results. This can also ameliorate sensitivity and specificity results. This research was prompted by the need to improve the methods of breast cancer identification. The major contribution of this research is to develop a new method of image analysis that can facilitate the production of accurate and credible results. This way, the mammography can be screened to identify patients with a high risk of developing breast cancer. With such identification, screening resources can better be allocated, cancer can be detected at an early stage, and mortality results can be minimized. It is expected that with the proposed system, doctors will be able to efficiently detect cancer and make better decisions. Consequently, the proposed system will help reduce the total cost which patient have to bear for diagnosis.

1.8 Thesis Organization

The proposed research is presented through this thesis and organized into seven chapters, which can be outlined as follows:

Chapter 1: Apart from this introductory chapter 1, an introduction to the proposed research was done including problem formulation and the various structural components of the study present including a description of research the research questions, research objectives, scope, and significance of the study.

Chapter 2: This chapter previous studies and related issues are discussed in detail. This chapter covers several fields: cancer, breast cancer, stages of breast cancer, medical imaging. More so, an in-depth review of relevant literature on breast cancer based on mammograms is presented. A detailed review of the relevant literature of mammogram pre-processing, segmentation, feature extraction, feature reduction, and classification. The limitations of the existing methods in each stage and the need for the development of the existing methods are highlighted as well.

Chapter 3: In this chapter, the roadmap of the study is presented so that the reader can have a quick grasp of the detailed research framework. Emphasis is placed on the benefits associated with the use of the newly developed methods. More so, the layout of the whole research framework, procedures, and strategies, is given.

Chapter 4: This chapter proposed two pre-processing models using wavelet transform in terms of mammogram enhancement for segmentation and feature extraction. The method is applied to MIAS datasets to highlight the breast border as well as to reduce the noise. The evaluation has been done on both models based on different criteria. Evaluate the model used for segmentation enhancement with the classification accuracy whereas the model used for feature extraction with the PSNR, MSE, and SNR.

Chapter 5: This chapter proposed a multi-level segmentation method for MIAS datasets to extract ROI from background and pectoral muscle. The performance of the proposed models is rectified by it is classification accuracy.

Chapter 6: This chapter proposed a method to extract powerful features. In this chapter Fractal Dimension (FD) technique has been exploited. The technique is developed to extract more than one feature based on different thresholds. This method is applied to MIAS and DDSM datasets to extract powerful features and feed them to a suitable classifier. The proposed models are evaluated by classification accuracy, sensitivity, and specificity.

Chapter 7: The conclusion of the thesis is given in this chapter by emphasizing the major contributions, significant findings, while areas for future research are recommended for the expansion of the contributions of the present study.

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