FUSION SCHEME OF SEGMENTATION AND CLASSIFICATION FOR BREAST CANCER STATIC ULTRASOUND IMAGES

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DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time. To my daughters Dohaa, Dunya, Ayat, my son Saleem, my wife, my brothers and sisters for their encouragement and support.

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ABSTRACT

Breast Cancer (BC) is defined as cancer that forms in the ducts of the breast (tubes that convey milk to the nipple) and lobules of the breast tissue. This study aims to develop a Computer-Aided Diagnosis (CAD) approach that provides a multi-disciplinary skill for breast ultrasound images that could aid specialists in improving accuracy in disease identification, thus reducing the rate of false-positive and false-negative results. To achieve this goal and build a fully automatic solution, the main limitations faced with the breast ultrasound image will be highlighted. First, ultrasound images suffer from speckle noise and artefacts. Second, the similarity between the textures inside the Region of Interest (ROI) and the background region, and that will end up with overlapping between the ROI and the backgrounds. Third, the similarity between the texture of the benign images and the malignant images, and this challenge will reduce the accuracy of the diagnosis by decreasing the sensitivity and the specificity of the proposed solution. Fourth, the borders of the ROI are not clear. Finally, applying a traditional segmentation method, i.e., the threshold method, will end up with a number of false-positive cases and false-negative cases, and both will affect the result of the automatic solution. In the segmentation stage, we have proposed a trainable schema based on multi-texture features to avoid problems related to the similarity between the texture of the ROI and the background. It also used to avoid the noise and the artifact by training the schema on good samples including regions with noise and artifacts. The trainable schema has solved the poor border problems by training the schema on blocks with poor borders. Forth, feature extraction stage (for the segmentation stage), an existing schema, a single feature that is Local Binary Pattern (LBP), was employed to describe the cancer region. This study has developed a hybrid model based on a multi descriptor (texture feature) to enable the effective extraction of the ROI. Furthermore, this thesis focuses on proposing a new describer that can help to identify the breast abnormality by enhancing the LBP texture features and the LBP descriptor using a new threshold that can help to identify the important information required for the identification of abnormal cases. Eventually, multi-level fusion for automatic classification of static ultrasound images of breast cancer is a method that makes it possible to diagnose breast diseases quickly and accurately compared to a manual approach. This study has used median and Wiener filters to reduce the speckle noise to enhance the ultra sound image texture. This process has helped to extract a powerful feature that can help to reduce the overlapping between the benign and malignant class. This process, followed by the fusion process, has helped to produce a significant decision based on different features produced from different filtered images. The experimental results show the proposed method can apply LBP based texture feature for categorizing ultrasound images, which registered a higher accuracy of 98.8%, the sensitivity of 98.01%, and specificity of 99.3%.

ABSTRAK

Kanser Payudara (BC) ditakrifkan sebagai kanser yang terbentuk dalam saluran payudara (tiub yang menyalurkan susu ke puting) dan lobul tisu payudara. Kajian ini bertujuan untuk membangunkan pendekatan Diagnostik Berbantukan Komputer (CAD) yang menyediakan kepakaran multi disiplin bagi imej gelombang ultra payudara yang dapat membantu pakar dalam memperbaiki ketepatan pengenalpastian penyakit, seterusnya mengurangkan kadar keputusan positif palsu dan negatif palsu. Untuk mencapai matlamat ini dan membina penyelesaian sepenuhnya secara automatik, batasan utama yang dihadapi dengan imej gelombang ultra payudara akan diserlahkan. Pertama, imej gelombang ultra mengalami hingar bintik dan artifak. Kedua, persamaan antara tekstur dalam kawasan terbabit (ROI) dan kawasan latarbelakang, dan itu akan berakhir dengan tindanan antara ROI dan latarbelakang. Ketiga, persamaan antara tekstur imej benigna dan imej malignan, dan cabaran ini akan mengurangkan ketepatan diagnosis dengan mengurangkan kepekaan dan kekhususan penyelesaian yang dicadangkan. Keempat, sempadan ROI tidak jelas. Akhirnya, menerapkan kaedah segmentasi tradisional, iaitu kaedah ambang, akan berakhir dengan sebilangan kes positif palsu dan kes negatif palsu, dan kedua-duanya akan mempengaruhi hasil penyelesaian secara automatik. Pada tahap segmentasi, penyelidik telah mengusulkan skema yang dapat dilatih berdasarkan ciri multi-tekstur untuk mengelakkan masalah yang berkaitan dengan persamaan antara tekstur ROI dan latarbelakang. Ini juga untuk mengelakkan hingar dan artifak dengan melatih skema pada sampel yang baik termasuk kawasan yang hingar dan artifak. Skema yang dapat dilatih telah menyelesaikan masalah sempadan yang rosak dengan melatih skema di blok dengan sempadan yang rosak. Untuk tahap pengekstrakan fitur (untuk tahap segmentasi), skema yang ada, satu ciri yang merupakan Pola Binari Tempatan (LBP), digunakan untuk menghuraikan kawasan kanser. Kajian ini telah membangunkan model hibrid berdasarkan multi penghurai (ciri tekstur) untuk membolehkan pengekstrakan ROI yang berkesan. Selanjutnya, tesis ini juga fokus kepada mencadangkan penghurai baru yang dapat membantu mengenalpasti ketidaknormalan payudara dengan meningkatkan fetur tekstur LBP dan penghurai LBP dengan menggunakan ambang baru yang dapat membantu mengenalpasti maklumat penting yang diperlukan bagi kes mengenalpasti ketidaknormalan. Akhirnya, cantuman multi aras untuk klasifikasi automatik bagi imej ultra bunyi statik kanser payudara adalah kaedah yang memungkinkan untuk mendiagnosis penyakit payudara dengan cepat dan tepat berbanding dengan kaedah manual. Kajian ini telah menggunakan penapis median dan Wiener untuk mengurangkan hingar bintik dalam meningkatkan tekstur imej ultra bunyi. Proses ini telah membantu mengekstrak fetur berkuasa yang boleh membantu mengurangkan tindanan antara kelas benigna dan malignan. Proses ini diikuti dengan proses fusion yang boleh membantu menghasilkan keputusan yang signifikan berdasarkan fetur yang berbeza terhasil dari imej tertapis yang berbeza. Hasil eksperimen menunjukkan kaedah yang dicadangkan boleh menggunakan ciri tekstur berasaskan LBP untuk mengkategorikan imej ultrabunyi, yang mencatat ketepatan yang lebih tinggi iaitu 98.8%, sensitiviti 98.01% dan spesifisiti 99.3%.

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LIST OF ABBREVIATIONS

ALN	-	Axillary Lymph Node
ANN	-	Artificial Neural Network
ASR	-	Age-Standardized Incidence Rate
BA	-	Bland-Altman
BC	-	Breast Cancer
BPNN	-	Back Propagation Neural Network
BUS	-	Breast Ultrasound
CAD	-	Computer-Aided Diagnostics
CAP	-	Computer-Aided Prediction
CAT	-	Computer-Aided-Theragnosis
CLBP	-	Completed Modeling of Local Binary Pattern
CNN	-	Convolutional Neural Network
CT	-	Computed Tomography
DSS	-	Decision Support Systems
FFDM	-	Full-Field Digital Mammography
FCM	-	Fuzzy C-means
FN	-	False Negative
FNA	-	Fine Needle Aspiration
FNA	-	Fine Needle Aspiration
FP	-	False Positives
GA	-	Genetic Algorithm
GCE	-	Global Consistency Error
GTR	-	Gross Total Resection
GVF	-	Gradient Vector Flow
KNN	-	K-Nearest Neighbor
LABC	-	Locally Advanced Breast Cancer
LBP	-	Local Binary Patterns
LMP	-	Local Multiple Pattern
LOG	-	Laplacian Gaussian
LVQP	-	Local Vector Quantization Pattern

MMD	-	Maximum Mean Discrepancy
ML	-	Machine Learning
MLPs	-	Multilayer Perceptron Networks
MRI	-	Magnetic Resonance Imaging
MSSIM	-	Multiscale Structural Similarity index
PC	-	Phase Congruency
PCBP	-	Phased Congruency-Based Binary Pattern
PRI	-	Probabilistic Rand Index
RCNN	-	Regine Convolutional Neural Network
ROC	-	Receiver Operating Characteristics
ROI	-	Region of Interest
SFM	-	Screen-Film Mammography
SRAD	-	Speckle Reducing Anisotropic Diffusion
SRG	-	Seeded Region Growing
SSIM	-	Structural Similarity Index
SVM	-	Support Vector Machine
TN	-	True Negative
TP	-	True Positives
URG	-	Unseeded Region Growing
URG	-	Unseeded Region Growing
US	-	Ultrasound
VIP	-	Vertical Intensity Profiles
VOL	-	Variation of Information

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter rationalizes this research, which aims at segmenting and identifying Breast Cancer (BC) diagnosis tumour in ultrasound images using a proposed model of machine learning techniques. The U.S. National Cancer Institute defines breast cancer as cancer that forms in the ducts of the breast (tubes that convey milk to the nipple) and lobules of the breast tissue. In 2009, the estimated incidence of breast cancer was 192,370 for females and 1,910 for males, while a total of 40,170 females and 440 males were estimated to have died as a result of cancer in the same year (Huang et al., 2015; Siegel et al., 2017). Correspondingly, in Peninsular Malaysia, the National Cancer Registry (NCR) registered 3,525 female cases in 2006, making up for 16.5% of all registered cancer cases (AbM et al., 2016). The report stated that 39.3 per 100,000 population was the total Age-Standardized Incidence Rate (ASR), with age group 50-59 years displaying a peak ASR in age pattern for the year 2006. The Chinese recorded the highest incidence in breast cancer, with 46.4 per 100,000 population ASR, the Indian race had an ASR of 38.1 per 100,000 population then lastly, the Malays with ASR of 30.4 per 100,000 population. These reported figures generated a deep sense of concern for the Government of Malaysia and it is citizens.

Cancer of the breast results from mutations or unusual transformation of genes that control cell growth and promote healthy function in the breast. However, the mutation, which is abnormal, prompts excessive and unorderly cell division, thereby replicating more cells which later form a tumor. Tumors are classified into benign or non-cancerous and malignant or cancerous tumors. A benign tumor, which is reported to be less detrimental to the health, bears a close-to-normal appearance, has a fairly slow progression and metastasizing rate. Contrarily, malignant tumors are detrimental to health, and without a prompt and accurate diagnosis, malignancy can result from increases in tumor size and metastasis to surrounding tissues. Fortunately, cancer of the breast can be cured at the early stages (Mohammed et al., 2018). Present-day diagnosis initially includes screening testing, at that point pursued by treatment and breast biopsy. The screening test process is done to recognize the nearness of substantial masses inside the breast tissues. The purpose of the screening tests, the nearness of the cancer lesion, is resolved, and the lesion location in the BC is found (Obaid et al., 2018). Photos of BC interior structure are captured, and the pictures are considered by oncologists to distinguish any variations from the norm inside BC tissues.

Ultrasound images (US) is probably the most normally sent therapeutic image methodology and has been utilized for over 50 years. Because of its non-intrusive nature and safe, this imaging methodology is regularly utilized in breast disease studies, especially amid the time of breast for identifying tumor development (Cheng et al., 2010). A significant part of the current studies has demonstrated that ultrasound images have practically no conspicuous negative impacts on the patients. The medical imaging modalities furnish oncologists with an extraordinary measure of data, for example, the shape, size, and state of the tumor in the region of multiplication, including the tumor location. Previously, the mammography technique (which utilizes X-beams for catching BC cases) was the most utilized technique for the screening process. This strategy is unsafe because of the measure of radiation, which the patient is presented amid every screening process. Working with these radiations adds to leukemia and other long haul sicknesses (Chen et al., 2005).

Therefore, the radiologists and patients favor ultrasound examine as a less destructive substitute for the screening process. The use of ultrasound exposes parts of the body to sound waves of high frequency, thereby generating images containing the internal structures of the body. Unlike the mammogram, ultrasound fails to employ the use of ionizing radiation, thus corroborating it is safe. In addition, images of fairly high resolution are produced (Mohammed et al., 2018). The subsequent stage in BC was finding as diagnosis procedure is the breast biopsy process whereby an example of BC tissue is removed in order to establish whether the presence of malignancy (cancerous) in the tumor exists, or if it is just benign (non-cancerous). Although other methods of imaging, as well as ultrasound, are used to detect abnormalities of the breast, biopsy accompanied by pathological analysis remains the most reliable method of detecting cancer. There are so many methods of biopsies; this varies with magnitude, appearance, site, and features that the anomalies possess. These include core needle biopsy, Fine Needle Aspiration (FNA), vacuum-assisted biopsy, and then open surgical biopsy (Akay, 2009; Polat & Güneş, 2007).

Certainly, accurate identification of the breast cancer abnormality type is crucially needed to reduce errors associated with diagnosis and also to recommend the appropriate management regimen. Therefore, the use of Computer Aided Diagnostics (CAD) as a diagnostic tool has remarkably improved the identification precision. The CAD system not only offers an alternative opinion to bear the interpretation of images by the radiologist. Nevertheless, it drastically lessens the time spent in reading the image. Segmentation of the breast to detect any anomalies present in images viewed ultrasound is extremely wearisome due to the complexity of the human anatomy, including attributing issues characterized by the image (Liu et al., 2009). The diverse and diffused evidence of pathology found in medical imageries frequently rules out the use of computational approaches. Primarily, several classes of tumour types possess a variety of sizes and shapes (Ayres & Rangayyan, 2007). The appearance of tumour at different locations in the breast with varying image intensities is another factor that renders automated breast tumour image detection and segmentation challenging (Ayres & Rangayyan, 2007). The diffusive growth of tumours frequently adds to the inherent difficulty of resection. Typically, the implementation of surgery is to achieve a Gross Total Resection (GTR) as the extent of surgical resection, in turn, determines the patient's longevity.

Numerous endeavors have been made to develop an effective elective approach to breast cancer classification, which could outride the necessity of performing biopsies. Sadly, none of such options have been found to date. In any case, huge endeavors have been made to think of proficient strategies for decreasing the number of biopsies in which the elective techniques can yield results that are indistinguishable from biopsy results (Polakowski et al., 1997). At present, the widely used technique which is also being improved is the image analysis method. In this technique, the tumors are classified through counts utilizing just the images acquired from screening tests. The advantage of this method is that it requires no physical medical procedure, therefore, causing any damage or hazard to patients, in opposition to biopsies. Unfortunately, this technique is far from perfect as it influences the precision of the outcomes (Jalalian et al., 2013). This drawback is the principal reason for the hesitance of oncologists to depend on the outcomes given by image analysis and examination techniques. In spite of all chances, studies far and wide are endeavoring to make this innovation to be progressively precise and reliable.

Popular Machine Learning (ML) approaches such as clustering analysis, Genetic Algorithm (GA), Support Vector Machines (SVM), Fuzzy Logic, and Artificial Neural Networks (ANN) among many, are some of the well-known techniques (Cireşan et al., 2013; Patel & Sinha, 2010; Pena-Reyes & Sipper, 1999; Rejani & Selvi, 2009). These techniques use different strategies used to assimilate the data previously existing together with detection or automatic segmentation. The automatic computation scheme and an interaction plan decide the implementation of this kind of technique. Furthermore, evaluation of performance differs across applications since exclusively different intricate anatomical structures are involved in several medical images. As such, the techniques encounter setbacks in the management of fragile edges, peripheral concavities, and medical image noises.

It is clear that cancer is considered as the sickness of the century. In this work, a trainable method that can help to segment the breast cancer ultrasound images is proposed. The proposed segmentation method is based on machine learning and local pixels information. Here, different features have been extracted from each pixel. Fusion has been used to benefit from all features and feed it to the ANN. Also, to propose a new describer that can help to identify the abnormality of the breast by enhancing the Local Binary Patterns (LBP) texture features and enhance the LBP descriptor by using a new threshold that can help to identify the important information required for the identification of abnormal cases. In the next stage, the most significant features are extracted from the breast tumour images. The features could fall under the frequency or spatial domain. The extracted features for automatic tumour diagnosis are additional and different from those that a radiologist extracted manually. Based on the discussion above, the next section focuses on the problem statement.

1.2 Problem Statement

The breast cancer diagnostic procedure relies wholly on the physician's expertise and different subjective judgments. Inter-observer and intra-observer variations can result from these subjective judgments. The sum of variances in the results attained from the examination of comparable materials by two or more observers is known as inter-observer variation, while intra-observer variation refers to the sum of variances experienced by one observer after examining comparable materials many times (Kobayashi, 1979). The traditional method of a breast cancer diagnosis is not without limitations. For instance, the long period of time used by doctors to identify the tumor region (Kuhl et al., 2005). Another challenge is human errors, which involve the use of human eyes by doctors to observe BC cases, thus leaving out some important details. The use of human visual system as a diagnostic technique largely depends on the experience the doctor has, which physically computes the percentages of BC that was successfully separated.

With the help of mammography and ultrasound, early diagnosis and treatment of BC are achieved, and this is the most efficacious way of enhancing mortality decline. While it is true that mammography has the capability of visualizing non-palpable and tiny tumors, ultrasound is considered to have more advantages in daily clinical practice, especially as regards mass breast evaluation (Bonnema et al., 1997). CAD introduced, which provides extra information to improve the accuracy of diagnosis, this is to avoid needless biopsies. Ultrasound, which is a useful variation for their differentiation, is viewed as a textural variation between benign and malignant tumors.

In the context of image analysis, segmentation is the process of separating the distinguished or interesting image objects from the image background, i.e., partitioning the image into meaningful regions and then selecting the wanted region known as Region of interest (ROI) (Chang et al.,2005). Image segmentation is an important step that can make the image analysis easier. In medical imaging applications, ROIs are often extracted either manually by experts or automatically using image segmentation methods before analysing the image for the purposes that they were captured for (Huang et al., 2015).

Generally, methods planning to isolate structures or regions from different locations, such as the background, use particular and quantifiable features. Helpful features incorporate picture power appropriation in the spatial just as gradient magnitude, recurrence spaces, entropy, and entropy (Chang et al.,2005). The breast segmentation process helps in searching for the pixels with qualities inside the characterized extents that are set up in the pre-decided edges. Automatic or manual determination is a viable method to select edges that utilized in the techniques. In manual determination, hypothetical information and preliminary tests that are required to decide the fitting threshold esteems. Preliminary analyses are expected to join data from the pictures and to consequently locate the versatile edge esteems (Kobayashi, 1979). The Otsu's strategy (Otsu, 1979) is one of the cases ordinarily utilized in acquiring the threshold value with picture histogram. In view of the data that characterizes threshold esteems, it has been affirmed that methods have distinctive characterization, in particular, the hybrid methods, edge-based techniques, and region-based methods (Jeong et al., 2005).

One of the limitations of the prior CAD systems utilizing textural analysis is its need for a particular ultrasound system for it to function effectively (Cheng et al., 2010). Physicians take note of information concerning the shape of the tumor and the contour while making decisions in diagnosis. The difference between benign lesions and malignant lesions has been well presented by many projected CAD algorithms through analysis of a tumor’s shape (Kelly et al., 2010). The look of the morphological characteristics is virtually not dependent on ultrasound gain setting, which can allow practical disparity in contour segmentation coupled with several machines utilized. The main step in the analysis of the images is to extract relevant features that will form the basis for the analysis and diagnosis. In image-based automatic pattern recognition applications, the main goal of feature extraction is to obtain the most discriminating information from an image. Such features are either encapsulated in the image spatial domain and/or after transforming it into another domain such as frequency or wavelet domain. The extracted features are then represented as feature vectors to be fed into a classifier to the next stage in the identification process. The main investigations in this chapter are concerned with complementing existing features, currently determined manually in clinics for diagnosis, by innovative sets of spatial/frequency domain features that can be used in the analysis of gynecological ultrasound images for investigated abnormalities (i.e., breast cancer).

Speckle noise” is a rare type of noise that has been known to influence images of ultrasounds. It occurs as a result of energy interference from randomly distributed scattering, which is made up of artifacts (Jesneck et al., 2006). The noise belongs to the multiplicative noise type. The quality of an image can be affected negatively by speckle noise, which hides and blurs the vital details of the image. This, in turn, affects the post-processing operations and extraction of features in the future, thereby reducing the diagnostic value of the image. Speckle noise reduction remains an essential aspect of the analysis and automatic processing of ultrasound images. Automatic biomedical image processing and analysis, it is very important to eliminate or at least reduce the effect of noise to minimise its negative impact on the later stages, i.e., the features extraction stages and to increase diagnosis (classification) accuracy manually or automatically. Also, Decision Support Systems (DSS) seeks to create a model that yields accurate decisions with little input of data/information. Very often, the accuracy of the decisions taken is of importance, particularly in safety-critical systems. Where this occurs, deriving the final decision in good time is more important than the limitation resulting from the minimum information. According to an approach, developing already found methods and establishing new ones should be the basis for DSS to progress (Cheriguene et al., 2016; Itoh et al., 2006). However, another approach proposed that it may be difficult to create another model, and so the existing method should be further developed by using other methods that have been known to function effectively in terms of achieving better results. To reduce uncertainty, it seems best to combine information, although, each certain errors such as may accompany some methods and incomplete or corrupt input of information. Nevertheless, it is expected that different methods operating with different data will produce different errors. In the event that all the individual methods function effectively, the benefits of the various methods should be used jointly in order to reduce the general classification errors, thus resulting in an emphasis on the correct output.

1.3 Research Questions

The following research questions have been framed to set the direction for this research:

1. Is it possible to use the existing machine learning methods to segment and classify breast cancer as benign and malignant?
2. Can a new method of overcoming the earlier limitations associated with ultrasound images of breast cancer segmentation, feature extraction, and classification be developed? Is the trainable segmentation model able to precisely segment the Breast tumour, and capable of first, extracting a good texture features, second, training a good classifier to detect the breast ROI?
3. Is the proposed method capable of extracting suitable features from the abnormal tissues which can be used to represent the breast cancer in the ultrasound images?
4. Is it possible to combine the expert measurements or the existing features with the new user that produced by a mathematical transformation to predict a confident decision?

1.4 Research Aim

This study aims at developing a new trainable segmentation model based on backpropagation and region growing algorithms to segment the breast static ultrasound image and extract the ROI from the rest. Then, enhance the uniform local binary pattern feature algorithm to extract a powerful feature that can help to identify the risk of the malignant from the benign. Finally, develop a feature-based fusion scheme using eU-LBP and filtered noise reduction to get a more effective model to diagnose the malignant in the early stage.

As a general aim of this workis developing an automatic solution that provides a multi-disciplinary skill for breast ultrasound images, which could aid specialists in developing accuracy in disease identification, thus reducing the rate of false-positive and false-negative results. This, in turn, improves specificity and sensitivity. There is an urgent call for improvement in breast cancer detection methods, and also new methods of analysis, as well as integrating identification of anomalies in ultrasound images, breast tumor detection, segmentation, and breast classification, with a higher degree of accuracy than the existing ones are offering. Also, it is essential to find a new sign (texture feature) to diagnose the breast ultrasound images.

1.5 Research Objectives

This study proposes to achieve this through the following objectives:

1. To investigate the machine learning techniques based on ultrasound Images segmentation and proposed Multi-Level segmentation method based on the Backpropagation classifier and Region Growing Algorithm.
2. To propose Enhancement Uniform-Local Binary Pattern (eU-LBP) Features Extraction Algorithm.
3. To Integrate Features-Based Fusion Scheme Using eU-LBP and Filtered Noise Reduction.

Having determined the objectives of this research, the next section states the scope of the study, what will be researched and done, as well as what will be excluded in line with the stated objectives of this study.

1.6 Research Scopes

Fundamentally, this research focuses on designing a new model and evaluating solutions for breast cancer identification for intelligent diagnosis using ML techniques. In this work, a dataset containing 250 of breast ultrasound images was used, 100 benign and 150 malignant. Breast ultrasound images is a database already widely used in the literature (https://data.mendeley.com/datasets/wmy84gzngw/1). This data set includes the most challenges that can affect the solutions. Based on the investigations, the researcher strongly believes that proposed solutions to cover the limitations and challenges with this dataset can be used for different images extracted from different hospitals and different countries.

In addition, the application of machine learning techniques is restricted to compound issues having an enormous solution space. Investigating the solution space and reducing the size is the research goal. The testing and implementation of the model are carried out in the MATLAB programming language. It is hoped that the results of this effort will facilitate the investigation of automatic methods for distinguishing between different types of tumours (benign or malignant); a similar approach may interpret the same case differently in various situations. This may lead to having a similar specialized approach to understanding the same case differently. This, in turn, makes the proposed system capable of supporting the decision and producing more reliable outcomes.

1.7 Significance of the Research

The imperative need for the aforementioned diagnosis is the driving force behind this study. There is an effective belief that ample CAD would offer a multi-disciplinary ability for breast images, thus enabling specialists to improve the accuracy of identifying the disease leading to a decline in the rate of false negative and false positive and false results and improving the specificity and sensitivity results. This research was prompted by the need to improve the methods of breast cancer identification. The significance of the present study is to develop a new method of image analysis for producing precise and reliable results that can be similar to results produced by biopsies. With that in mind, oncologists and physicians can assertively trust the results of the analysis; the results could, therefore, back the physician's resolution in continuing with the management of breast cancer. Accordingly, there would be little or no need for patients to undertake countless biopsies as previously done for corroborating the manifestation of cancer. This would, in turn, prevent the many side effects of biopsies and also reduce the financial burden on the part of the patients.

To provide a quick overview of the total research project and offer a holistic picture of this current study, the next section provides brief descriptions of the various chapters in this thesis.

1.8 Thesis Organization

This thesis is organized as follows:

Chapter 1: Which provides a comprehensive overview of the Research Background and the various structural components of the study present including the Scope of the Study, Research Questions, Problem Statement, Research Objectives, and Significance of the Study, the remaining chapters deal with various aspects of this research systematically and in detail.

Chapter 2: Provides an in-depth overview of relevant literature on Breast cancer including Breast cancer components, Initial Symptoms of Breast cancer, Stages of Breast cancer, Diagnosis of Breast cancer, Breast cancer and Existing Methods of Diagnosis, Treatment Options of Breast cancer, Breast cancer Prognosis, and Prevalence of Breast cancer. The chapter also provides an in-depth overview of relevant literature on Medical images of Breast cancer tumour detection, segmentation, and classification. The limitations of the existing methods and the need to develop a new method for detecting abnormal Breast cancer cases,

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