Analyzing Breast Cancer Using Thermography and Convolutional Neural Networks

Student:
Hushang Jawzal

Master's Thesis
Department: Software Engineering
Supervisor: Prof. Dr. Sami EKICI
JUN-2019

REPUBLIC OF TURKEY

FIRAT UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCE

Analyzing Breast Cancer Using Thermography and Convolutional Neural Networks

MASTER'S THESIS

Hushang Jawzal

151137119

Submission Date to the Institude : 29.05.2019

Thesis Presentation Date : 28.06.2019

Department: Software Engineering

Superviser	:	**Prof. Dr. Sami EKICI (F.U.)**
Other Jury Members	:	**Prof. Dr. Asaf VAROL (F.U.)**
Other Jury Members	:	**Assoc. Prof. Dr. Muhammed Fatih Talu (I.U.)**

JUN-2019

ACKNOWLEDGEMENT

I would first like to thank my supervisor, Prof. Dr. Sami EKICI for their great help and guidance, and through the process of researching and writing this documentation, which it possible to accomplish this work.

I would also express a deep sense of gratitude to my parents and to my friends for providing me with continuous encouragement and their constant support throughout my years of study. This accomplishment would never have been happened without their support. Thank you.

Hushang Jawzal
ELAZIĞ - 2019

TABLE OF CONTENTS

ÖZET

Termografi ve Evrişimsel Sinir Ağları ile Meme Kanseri Analizi

Termografi, tıbbi alanda yaygın olarak kullanılan cerrahi işlem gerektirmeyen (non-invaziv) ve tamamen temassız bir görüntüleme tekniğidir. Kanserin erken teşhisi çok önemli olduğundan, bilgisayar destekli sistem etkilenen kişinin teşhis, tedavi ve hayatta kalma oranını artırabilir. Etkilenen kişilerin yaygınlığına ek olarak yüksek tedavi maliyeti de göz önüne alındığında, erken tanı bu hastalığın sağlık ve sosyal komplikasyonlarının azaltılmasında en önemli adımdır. Günümüzde meme kanseri taramasında kullanılan ana yöntem mamografidir. Ancak genç kadınlar için yoğun meme dokusundan kaynaklanan düşük çözünürlük nedeniyle mamografi önerilmemektedir ve bu amaçla alternatif teknikler göz önünde bulundurulmalıdır. Meme kanseri, kadınlar arasında kansere bağlı ölümlerin ana nedenidir. Kanserin erken teşhisi, özellikle meme kanseri tedavi sürecine yardımcı olacaktır. Bu tez çalışmasındaki amacımız, meme kanserinin erken teşhisine olanak tanıyan, görüntülerden hastalığın belirtilerini tespit ederek termal meme görüntülerini analiz etmek için görüntü işleme teknikleri ve algoritmalarını kullanan otomatik bir meme kanseri tespit yazılımı geliştirmektir. Biyo verilere, görüntü analizine ve görüntü istatistiklerine dayanarak meme karakteristik özelliklerinin çıkarılması için yeni bir algoritma önerilmiştir. Bu özellikler, bir termal kamera tarafından yakalanan termal görüntülerden elde edilmiştir ve Bayes optimizasyon algoritması ile optimize edilen evrişimsel sinir ağları (CNNs) kullanılarak meme görüntüleri normal veya şüpheli olarak sınıflandırılacaktır. Önerilen yöntem kullanılarak 140 kişiye ait termal görüntü içeren veri seti ile % 98.95'lik doğruluk oranı elde edilmiştir.

Anahtar Kelimeler: Meme kanseri, Göğüs termal görüntüsü, evrişimsel sinir ağı, görüntü analizi, termografi.

ABSTRACT

Analyzing Breast Cancer Using Thermography and convolutional neural network

Thermography is an entirely non-invasive and non-contact imaging technique that is widely used in the medicinal field. Since the early detection of cancer is very important, the computer-aided system can increase the rate of diagnosis, cure, and survival of the affected person. Considering the high cost of treatment in addition to the high prevalence of affected persons, early diagnosis is the most important step in reducing the health and social complications of this disease. Currently, mammography is the main method used for screening breast cancer. However, for young woman, mammography is not recommended due to the low contrast that results from the dense breast, and alternative techniques must be considered for this purpose. Breast cancer is the main cause of cancer-related mortality among women. Early detection of cancer-especially breast cancer-will aid the treatment process. Our goal is to develop software for detecting breast cancer automatically that uses image-processing techniques and algorithms to analyze thermal breast images to detect the signs of the disease in these images, allowing the early detection of breast cancer. A new algorithm is proposed for the extraction of the breast characteristic features based on bio-data, image analysis, and image statistics. These features have been extracted from the thermal images captured by a thermal camera, and will be used to classify the breast images as normal or suspected by using convolutional neural networks (CNNs) optimized by Bayes algorithm . By using our proposed algorithm, a 98.95% of accuracy rate was obtained for the thermal images in the data set belonging to 140 individuals.

Keywords Breast cancer, breast thermal image, convolutional neural network, image analysis, thermography

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBRIVATION

CT	Computer Tomography
MRI	Magnetic Resonance Imaging
CNN	Convolution Neural Network
GUI	Graphical User Interface
TP	True Positive
FP	False Positive
TN	True Negative
DBT	Digital Breast Tomosynthesis
IR	Infrared Radiation
DITI	Digital Infrared Thermal Imaging
RBNF	Radial Basis Function Network
ANN	Artificial Neural Network
LTI	Localized Temperature Increased
TLM	Transmission Line Matrix
SVM	Support Vector Machine
ICA	Independent Component Analysis
K-NN	K-Nearest Neighbor
PNN	Probability Neural Network
GA	Genetic Algorithm
ROI	Region of Interest
HPP	Horizontal Projection Profile
VPP	Vertical Projection Profile
RELU	Rectified Linear Activation System
DIRT	Dynamic Infrared Thermography

1. INTRODUCTION

Cancer is identified as one of the most challenging and fatal diseases worldwide. It is responsible for the loss of millions of lives every year. According to the World Health Organization (WHO), cancer accounts for the death of 8.8 million persons in 2015 alone [1]. Malignant neoplasm or cancer is considered as a genetic disorder due to somatic cells change resulting from epigenetic or genetic alteration [2]. In general, this genetic change can result from an error in cells division during the development process, and it may be inherited or caused a distortion of the DNA due to certain exposures. Scientists usually record three main types of genes that contribute to the cancer formation called cancer drivers, namely DNA repair genes, tumor suppressor genes, and proto-oncogenes [3]. These genes are responsible for permitting cells to grow and divide when they are not supposed to do so (proto-oncogenes), allowing cells go out of control in their division process (tumor suppressor), or leaving the damaged DNA without a proper fixing (DNA repair). Cancer may spread from an organ or tissue to another place in the body; in such cases, the cancer type is called metastatic cancer and keeps its type wherever it transfers in the body [4]. Cancer types vary in the location they are formed at and the degree of their severity. There are more than 100 recorded types of cancers, which are given names based on the organ or tissue they are formed at [3]. Essentially, understanding the process of cancer development, the organ it is developed in, and the causes of its development assist in treatment discovery. Despite the recent advances in medication and the drug industry, an optimal cure for cancer is yet to be discovered and evaluated. Perhaps one of the most effective discoveries relevant to cancerous types is regulating different cellular genetics, especially those responsible for their formation [5]. Nevertheless, this method is still far from being a successful treatment globally available for all societies [6].

Cancer affects all categories of people, males, and females, elderly and young, yet it is found more in elder people than their youth counterpart [7]. There are different statistics for the frequent types of cancers where both the geographic location, as well as the gender, play an important role for their existence. Among the most frequently reported cancer types in females is the breast cancer [8]. Thus, prompting the research in developing both diagnosis and treatment ways for it. Generally, breast cancer causes are not confirmed for sure. Up to now, doctors and specialists do not have an exact justification for the incidence of breast cancer in some women over others [9]. However, there are common facts and symptoms that

indicate the existence of breast cancer. Some of the common symptoms of breast cancer are pain in certain regions close to the breasts such as armpits, a change in the breast skin tone (redness or orange in color), an unusual reshape and sensitivity of the nipple, which is followed by discharges that may contain blood, and general change in size of the breast or its shape [10]. In most cases, any individual symptom may not necessarily mean the availability of breast cancer. Nevertheless, finding any of the symptoms should strongly motivate the woman to go for the standard breast cancer checking procedure. In early development stages, most, if not all, of these symptoms do not appear. Thus, diagnosing cancer at its early stage would be a challenging task.

One of the procedures, widely used in medicine, for combating cancer is to screen the patient for cancer prior to the development of tangible symptoms. The screening process is subject to an approved technology used for diagnosing individuals for early detection of cancer. Like other cancer types, discovering the tumor at its early stages assists in the treatment and lessens the burden taken by patients. Currently, Computerized Tomography (CT), Magnetic Resonance Imaging (MRI), mammography, thermography, and ultrasound are common breast cancer screening. These methods have their own distinguished approaches and tools; the expected outcomes of these methods rely on different types of factors, and it is recommended to use more than one methods for validating the results [11]. Despite the fact that mammography is considered as the golden standard procedure for breast cancer screening by many physicians and specialists, the demand for a more reliable method is on the rise. In recent years, thermography has been gaining a rapid interest, especially for breast cancer screening purposes [12]. This is due to the attractive facts relevant to its own low-risk technology, as well as possible improvements with the modern technological advancement. The ultimate goal of the contemporary studies in this field is to come up with a more accurate and validated diagnosis for the tumor, which can be accepted as a standard for breast cancer screening purposes. In addition, overcoming the previously recorded obstacles of the cumbersome screening process, especially when the image processing is relevant.

1.1 Problem Statement and Significance

The recent technological breakthroughs have revived the field of thermographic imaging and its applications. One of the most common applications of thermography is the breast cancer screening. However, thermographic has not yet been recognized as the standard procedure for this purpose. In addition, physicians tend to request mammography results over

thermography, even though it is not a fully risk-free methodology. Thus, thermographic breast cancer screening can be a replacement candidate if it is improved to the satisfactory point. For doing so, the main issue to be solved here is the image-processing task. This research proposes the use of Convolutional Neural Network (CNN) for thermographic breast cancer screening to overcome the abovementioned drawbacks.

1.2 Research Objectives

The main objective of this research is to develop a robust and high-performance analysis for breast cancer using thermograms. The used technique of this purpose is the CNN, which has a number of advantages, discussed in chapter 2, over other neural network applications. The main objective is divided into the following sub-objectives:

1. To investigate and review the literature related to both thermal imaging and thermographic breast cancer screening, in order to come up with the missing links in the research.
2. To develop a robust and high-performance thermographic breast cancer analyzer using CNN in MATLAB environment.
3. To test the development system using real images to prove the validity of the developed work.
4. To benchmark the performance of the developed system with previous systems that can be found in the literature.

1.3 Research Methodology

The methodology of this research is divided into a number of steps as follows:

- **Data Acquisition**: The data is collected from DMI database. The standard thermographic acquisition procedure was employed. A total of 3895 images were deployed for the analysis purpose.
- **Pre-processing**: All pre-processing and analysis tasks were applied using MATLAB 2019a environment. The pre-pre-processing step is used for removing the noise, and artifacts, and reducing any irregularities.
- **Segmentation**: This step is applied for extracting the Region of Interest (ROI), where both upper and lower as well as right and left borders are located. This step is extremely important as it allows the analyzer to be fully focused on ROI, which ultimately increases the success rate.

- **Feature Extraction**: In order to improve the outcomes of the developed analyzer, a number of distinctive features are extracted for the thermal images. This is followed by transferring the image to the feature space domain, where relevant statistical parameters are calculated and set to control the size of the dataset. These parameters are used as the inputs of the final stage.
- **Classifications**: In this step, a number of CNN algorithms are tested using the generated parameters from the features extraction step. The classifier here will be trained to screen the breast cancer with some part of the dataset, while the rest will be used for the performance analysis purpose.

1.4 Research Scope

This research is restricted to the following factors:

- Programming Environment: MATLAB 2019a which is installed on Lenovo laptop with Windows 8 Professional edition operating system. The processor of the laptop is 64-bit Intel(R) Core(TM) i7 with 2.6 GHz CPU.
- The used images are collected from a DMIR database, which has its own standard thermographic acquisition procedure, presented in chapter 3.
- The main classifier is based on CNN for breast cancer screening.
- All results are truly interpreted using a developed MATLAB GUI that allows the user to select and load different types of image formats.

1.5 Thesis Organization

Chapter I: Presents a general research introduction, the main problem and the significance of the research, the set research objectives, the main methodological steps, the scope of the research and the thesis organization.

Chapter II: The needed thorough background of the research where the basics of breast cancer screening, thermal imaging and main detection and classification methods are presented and explained in this chapter.

Chapter III: The most relevant methods presented in the recent trends in the background chapter are discussed in detail in this chapter, their pros and cons will be presented as well. Finally, a justification of the current research will be contemplated and presented.

Chapter IV: Presents the detailed methodology where each step elaborated with the needful explanation, illustration and justification are provided.

Chapter V: The developed system with the obtained results. In addition, it discusses the results and presents a sort of benchmark with similar systems available in the literature.

Chapter VI: The concluded remarks are presented in this chapter. In addition, possible ways for improvement, possible limitations, and suggested future research directions are provided.

2. BACKGROUND

Breast cancer is categorized among the most frequently reported cancer types worldwide [8]. This type of cancer has been reported in both males and females; however, its frequency with females is far beyond comparison. This is directly reflected by the essential difference between the breasts in both genders; where the frequent screening of cancerous cells are found in milk creating centers, lobules, and milk transferring canals, ducts [13]. Figure 2.1 presents an anatomical view of the female breast with the frequently common locations of breast cancer incidence. The development of breast cancer may occur due to unknown reasons. Nevertheless, one of the confirmed breast cancer initiatives is the abnormal development of the living cells. There are certain genes responsible for the division and multiplication of cells, but for some reasons, these genes fail in detecting the abnormalities. This leads to a rapid growth and spread of dead cells which are not supposed to divide and multiply; creating some sort of tumor. The created tumor is categorized cancerous if it spreads around and attacks its surrounding; when it remains contained in some tissues, like ducts and lobules, it is categorized as non-invasive tumor [15]. It is important to mention that cancerous cells may spread to other body parts; in the case of breast cancer, they transfer through the lymph or blood. In the latter scenario, the breast cancer is considered in its advanced stage and surgical intervention, called biopsy, is usually demanded.

It is highly recommended to contain breast cancer before it develops to advanced stages. For this specific reason, breast cancer screening methods and tools present the standard procedure for detection purpose. These methods vary in their technique, application, and outcome, yet there is no exact best method among them. Often, physicians require the screening of more than one method to confirm the obtained results. Nonetheless, a good point for comparison can be the side effect of the screening method. The recent advancements in the computerized process have stimulated researchers to re-look into screening methods for enhancement purposes. Nowadays, it is quite possible to find a re-evaluation of previously non-efficient breast screening techniques and adapting them to the available processing and classification technologies to produce considerable results.

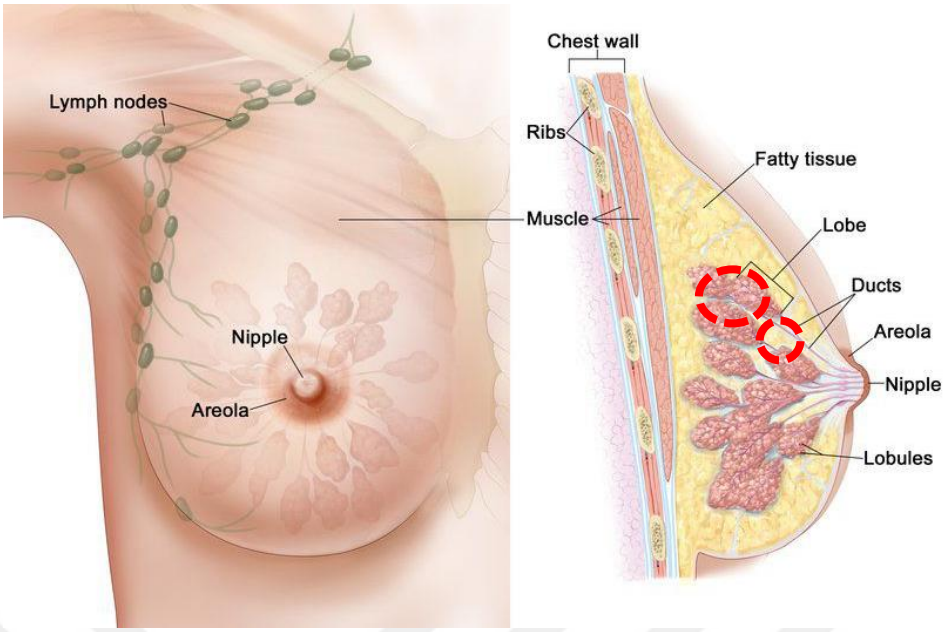

Figure 1 Common cancer incidence locations in the female breast [15]

2.1 Breast Cancer Screening Methods

As stated above, breast cancer screening is restricted to a particular method or technique; rather, there is a number of methods found in the clinical practical application. These methods have been continuously revised and improved over the past decades, and some of them are considered as a standard procedure for breast cancer detection. The proper use of breast cancer screening helps in detecting cancer at its early stages, which increases the chances of effective treatment and lowers the level of breast cancer mortality. Generally, breast cancer screening is categorized into two main streams: manual and device-based.

2.1.1. Manual Breast Cancer Screening

Manual breast cancer screening is referring to a thorough physical examination of the breast and its surrounding region. The examination here involves gentle rubbing of the breast tissue to detect the existence of any lumps, and visual inspection for any possible irritation or swelling. This type of screening can be self-conducted, called self-exam. This type of exam is recommended, at least, on a monthly basis to discover possible changes in the breast and its surrounding tissues. Essentially, the inspection here comprises of gentle pressing and centric movement around the breast and armpits, aiming to find any lumps, hard knots and thickening in the tissue. It is recommended for this self-exam to be taken in front of the mirror to observe the contour mismatching, dimpling or dripping in the nipple, redness or unusual change in the skin color. These symptoms are summarized and illustrated in Fig. 2.2.

Moreover, the inspection should be conducted in the supine position with certain stretching maneuvers; for instance, to inspect the left breast, a pillow should be placed under the left shoulder and the left arm should be stretched behind the head. Then, the right hand should be used concentric movements around the left breast for examining any possible lumps. This kind of position will also help discover and possible charges from the nipple with gentle continuous pressing by hand [16]. It is interesting to mention that breast cancer screening using self-exam is responsible for the identification of breast cancer in around 70% of the recorded cases [16].

A similar exam can be conducted by physicians, called clinical-exam for breast cancer screening. In this case, the exact same symptoms are looked for during the exam. Further, the physician may ask a number of questions relevant to possible symptoms as well as the potential family history of breast cancer [17, 18].

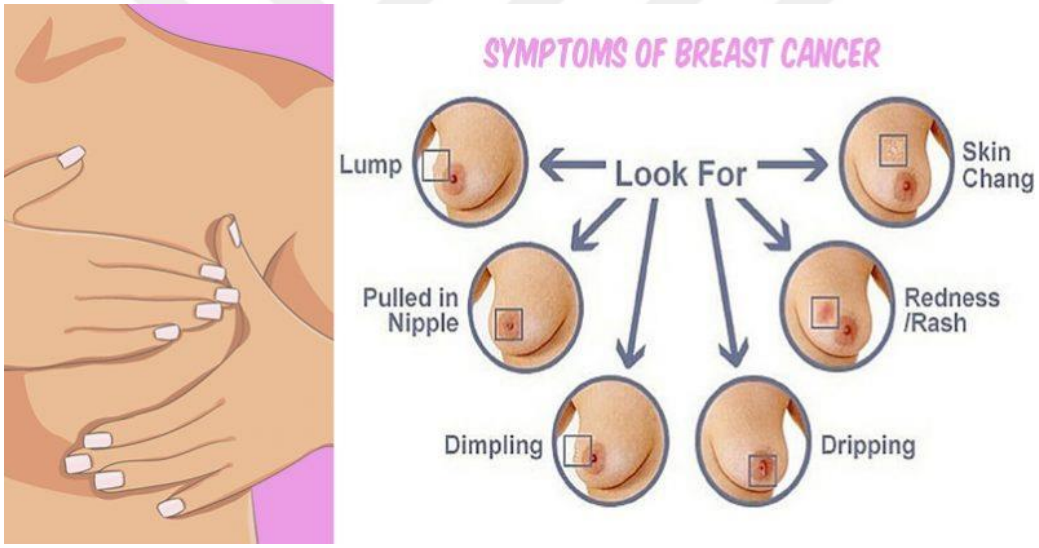

Figure 2.2 Self-exam screening symptoms [16]

2.1.2. Device-based Breast Cancer Screening

Apart from the clinical examination of breast cancer, the screening process can also be conducted using special devices, which operate with special technologies to image the breasts and their surroundings. Despite the fact that these methods coincide with the concept, the outcomes may vary from one method to another. Having in mind that the ultimate goal is the breast cancer screening, physicians may ask the patients to undergo more than one session with a different method when necessary. Common terminologies have always been reported

with device-based breast screening methods; some of which refer to the accuracy of the outcomes, while others govern different aspects. In fact, the coining of such terms has come from the practical application in real life. For instance, if a person, confirmed to have breast cancer, is identified negative with a breast cancer screening method, the result, in this case, is called False Negative (FN). Conversely, if a person, confirmed to have breast cancer, is identified positive with a breast cancer screening method, the result, in this case, is called True Positive (TP). On the other hand, if a person, confirmed not to have breast cancer, is identified as positive, the result, in this case, is called False Positive (FP). Similarly, if a person, confirmed not to have breast cancer, is identified negative, the result, in this case, is called True Negative (TN). Once FN, TP, FP, and TN are defined and set, common measures such as Positive Predictive Value (PPV) and Negative Predictive Value (NPV) can be formulated. Equations 2.1 and 2.2 present PPV and NPV respectively.

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \qquad 2.1$$

$$\mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN+FN}} \qquad 2.2$$

As indicated in Equations 2.1 and 2.2, PPV and NPV refer to the percentages of correctly screened positive and negative cases respectively.

Among the commonly used measures in breast cancer screening methods are both sensitivity and specificity. When characterizing a breast screening method by its sensitivity, the consideration will be guided towards the probability of obtaining a positive exam result knowing that the case is identified to have breast cancer. Likewise, the specificity is determined by the probability of obtaining a negative exam result knowing that the case is identified not to have breast cancer [19]. It is highly recommended for both sensitivity and specificity to have high levels. Any low sensitivity level indicates the possible misdetection of positive cases, which means losing the chance of early detection before cancer develops to advanced stages. Equally, any low specificity indicates the possible misdetection of negative cases, which means burdening the person with distress and unnecessary medical procedures [20].

2.1.2.1. Mammography

One of the oldest and most frequently used breast screening techniques is mammography. In this method, images of the breast are created by ionizing radiation in the form of X-ray [20]. Mammography or mammogram has a relatively long utilization history. Initially, this technique was using the standard X-ray imaging system, which is not the optimal choice for breast cancer screening. Here, the low-contrast nature of the breast's soft tissues does not allow the acquisition of satisfactory details for proper diagnosis. However, this is not the case anymore; currently, mammography is applied with an up-to-date equipment that provides high-level contrast and spatial resolutions needed for reliable outcomes. In addition, a continuous revision of its policy gets released almost on an annual basis. According to the recent recommendation of US Preventive Services Task Force (USPSTF), it is recommended for women aged between 50 and 74 to biennially undergo mammographic breast cancer screening. However, for women aged 40-49 years, the choice is an individual decision between routine annual or biennial based on the benefits and harms compromise [21]. This is because mammography is able to provide breast cancer screening speculation much before any clear symptoms [22]. Therefore, it is not a surprise that mammography is covered by medical insurance in many countries in the world [23].

The standard procedure of mammography dictates placing the breast inside a special unit attached to the mammogram. Once the breast is set in place, a gradual pressure will be applied on the breast to have a uniform thickness, which enhances the overall image quality and alleviates the overlapping of the breast structure in the final image [24]. Normally, there are two mammographic images taken to the breast; one is taken from top to bottom and the other is taken from side to side. These images are then inspected and evaluated by a specialist, usually radiologist, to conclude the screening result. In this regard, the judgment of the specialists here can be influenced by the quality of the image. Apart from that, both sensitivity and specificity play a vital role in the ultimate outcomes of mammography. There are a number of factors that affect these two measures; some of which controllable and the others are rather uncontrollable. Controllable factors are generally relevant to the image quality and accuracy, which are progressively improved with the advances in technology. On the contrary, uncontrollable factors are essentially relevant to the biological nature of the subject, which are very difficult to predict and manipulate [25]. The states of specificity and sensitivity of mammography are firmly found as a numerical number; rather, they vary based on a number of factors such as population, country, age, etc. [26-28]. Nevertheless, some

studies have proved that the sensitivity of mammography can reach 90% while the specificity to 95% [29].

It is commonly known that mammography is the golden standard of breast cancer screening. Apart from that mortality reduction, the prominent advantages of mammography are its noninvasiveness and improved treatment due to early detection, which improves the quality assurance of the diagnostic chain. Despite these advantages, there are some points that can be considered among the disadvantages of mammography. The risk imposed by radiation is usually considered a disadvantage of mammography, especially if taken biennial. In addition, the chance of false detection, false positive and false negative, has always been available in mammographic screening. It is possible due to these false alarms to have over diagnosis as well. Further, the chance of having interval cancer where the formation of cancer happens between two consecutive screenings. As stated earlier, in the US, the standard procedure is having annual and biennial based on the age. However, this is not the case in some other counties. For instance, there is a period of 3 years set in the UK for mammography. This kind of longer interval may lead to interval cancer [30].

2.1.2.2. Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI) technique is a widely used method for obtaining detailed images for the internal body organs or structures. The technique is based on the deployment of a strong magnetic field and radio signals to penetrate the skin and capture an image of the inside. The magnetic field and the radio signals restore hydrogen atoms that exist within the human body and produce an inside image of the body by the aid of a computing system [31]. MRI is widely used for many screening applications, ranging from pregnancy monitoring to breast cancer screening. This technique is relatively successful in detecting abnormalities, which are not detected by other screening methods. Therefore, physicians usually request it as a complementary for mammography to confirm any available doubts [32]. Unlike mammography, breast cancer screening with MRI is not recommended on a routine basis; rather, it is often recommended for women with genetic mutations, such as BRAC1, BRAC2 or PTEN, at high risk for breast cancer (20% and above) or with a serious family history. The main reason for not recommending MRI for routine breast cancer screening is its high false positive rate [33]. The main advantages of MRI are the non-ionizing or radiative nature, and its detection sensitivity. On the contrary, the method is not cost-effective and its availability is somehow restricted to certain facilities [34][35].

2.1.2.3. Tomosynthesis

Breast tomosynthesis is a branch of mammography. However, the main difference is that tomosynthesis is a developed version of mammography. Breast tomosynthesis is also referred to by Digital Breast Tomosynthesis (DBT) or 3-D mammography. Essentially, DBT deploys a low-dose X-ray to obtain a three-dimensional image of the breast, which enhances the possibility of early detection [36]. The key difference between the standard mammography and DBT is the 3-D imaging synthesis or reconstruction by the aid of a computing unit. Generally, what is offered by DBT is a more thorough view of the breast of a better diagnosis. However, there is a lack of the needed equipment compared to mammography.

2.1.2.4. Ultrasound

Ultrasound scanning or sonography for breast cancer screening deploys sound waves to penetrate the human body and outline breasts tissues. The main aim of ultrasound is to assist in making the proper diagnosis of the available lumps, as they may contain fluid or solid substances. The mechanism of ultrasound allows it to operate in real-time. Thus, enabling the visualization of internal movements as well as blood circulation. This allows the physician to have a better or more verified understanding of the breast's structure [37]. Sonography equipment is cost-efficient and widely available in most clinics and hospitals. In addition, the method is noninvasive and has no risk radiation effect. However, the method cannot replace the mammographic screening of breast cancer. The most suitable deployment of sonography for breast cancer screening is complementary of mammography for confirming the essence of detected abnormalities [38].

2.1.2.5. Thermography

Objects naturally emit thermal signals at certain temperatures. The type of emitted or radiated signals and the range of temperature level depend on the object's characteristics [39]. Like other objects, the human body, under normal circumstances, radiates Infrared (IR) signals [40]. The radiated IR signals here differ from one part to another based on its heat. This concept is generally applied for medical screenings, especially for the breast cancer. Any cancerous development in the breast is associated with the formation of inflammation and blood vessels, which are presented with a higher temperature profile. Thermography or thermal imaging is used in medicine as a non-invasive method for capturing the heat map of a certain limb. The method is non-contact and nondestructive, and it does not produce any radiation, which makes safer for frequent use. The method here takes advantage of the heat

map of the breasts and their surrounding environment, captured by a thermographic camera, to highlight any abnormalities. However, thermography breast cancer screening is criticized by having a high both FP and FN rates. FP implies requiring the standard mammography while the breasts are fine. On the other hand, FN may deviate the proper medical procedure to take place for unhealthy individuals. Apart from these two main issues, technically, thermography is not covered by insurance in most cases [41].

Thermography has been recently revived in medical applications. A number of studies have investigated and re-evaluated its use from different aspects [42,43]. This is induced by the technological breakthrough, which has established new directions for improvements of the available technique, one of which is thermography. In this regard, since this study is mainly focused on thermography breast cancer screening, thermography is discussed in more details in the following section.

2.2 Thermography in Medical Application

Thermography in medical application refers to mapping the heat or temperature variations emitted from the human body and converting them into images, which can be interpreted by specialists. This specific idea has a deep historical root; and goes back in time to ancient civilizations. For instance, the ancient Egyptians deployed their figures to detect the heat emitted by extremities in an effort to diagnose the disease. In addition, ancient Greeks were applying some sort of clay or mud to map the heat of the body parts, where the abnormality was found by observing the area that dried up first [44]. The elementary observed concept by ancient civilizations stimulated the improvement of the same idea. Heron of Alexandria invented an initiative of a thermoscope. This initiative was far from practical and its development halted for some time until Galileo redesigned it to the thermometer where the body temperature was recorded as levels. The astronomer Sir William Hirshel deployed some filters in a refracting telescope to investigate the components of the sunlight. The device Sir William created is considered as the first thermogram; with this thermogram, the term infrared was coined. The invention of Sir William along with other relevant developments had helped scientists to capture the reflection of IR signals in the 1920s. This was a turning point for the research in IR photography, which was later refined and used in World War II for developing night vision based on objects' heat. It is claimed that Dr. Leo Massopust took the lead in recording the first medical thermograms in 1948. He experimented with the thermographic of vascular in the body parts, including breasts. Up to the researchers' knowledge, the first known medical thermography for breast cancer

diagnosis was proposed by Ray Lawson in 1956. Within the next few years, tens of articles were written about the exact same application, and thus thermography entered the medical application as a standard [45].

2.2.1. Thermography's Physical Background

Heat is a form of energy that is emitted due to molecular movement inside the substance. One of the common characteristics of heat energy is its ability to be transferred in polymorphic ways. The most obvious example of heat transfer is the heat transferred to our globe from the sun. This typical example of heat transfer is done via IR radiation means. The relationship between the total radiant or emitted heat energy and its emitting surface was developed by Stefan-Boltzmann, which is named the Stefan-Boltzmann law. According to this law, the heat energy emitted from an object is proportional to its absolute temperature raised to the fourth power. The mathematical interpretation of this law is provided in Equation 2.3.

$$E = \sigma T^4 \tag{2.3}$$

Where E is the emitted heat energy ($W.M^{-2}$) of an object with temperature T (K) and the proportional constant in this law is σ given by $5.66x10^{-8}$ ($W.M^{-2}.K^{-4}$). Based on Boltzmann's law, any object with a temperature above 0 K or -273.15 ^{0}C shall be able to radiate electromagnetic waves in the form of energy [46].

Different types of electromagnetic waves represent the emitted energy referred to in Boltzmann's law. In fact, electromagnetic waves are distributed over a large frequency band or spectrum, as shown in Figure 2.3. As depicted in Figure 2.3, IR spreads over a band starts right after the red light (in the visible band) roughly from 0.75 μm to 10^3 μm. In energy emission studies, when the power is emitted at different frequencies or wavelengths, the term emissive power is used to describe the variations of power frequencies. The maximum emitted heat energy changes based on the temperature of the substance, and this in turn changes the wavelength at which the maximum radiation occurs. Wien's law for displacement, as given in Equation 2.4, provides the best mathematical description of the latter statement.

$$\lambda_1 T_1 = \lambda_2 T_2 \tag{2.4}$$

Where λ and T are denoting the wavelength and absolute temperature respectively. It can be noted from Equation 2.4 that the wavelength, which produces the maximum radiation energy, decreases as the temperature increases.

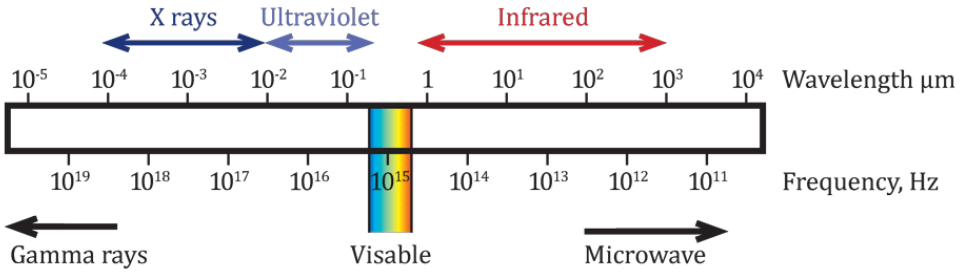

Figure 2.3 Electromagnetic Wave Spectrum [46]

Even though both Stefan-Boltzmann's law, as well as Wien's displacement law, are of extreme importance with respect to radiated energy emission, they are not adequate for mathematically representing an up-to-date model. Planck proposed one of the elementary mathematical models that cope with this lack of adequacy. Planck's law assumes the existence of blackbody that emits all of its energy in IR form at a certain temperature. Based on this assumption, the radiation's spectral distribution is presented, as given in Equation 2.5.

$$E_\lambda = \frac{2\pi hc^2}{\lambda^5\left(e^{\frac{A}{\lambda T}}-1\right)}, A = \frac{hc}{k} \qquad (2.5)$$

Where E_λ is the radiated energy per unit volume ($W.M^{-2}.Micron^{-1}$) at a single wavelength λ and with absolute temperature T (K). h represents Planck's constant ($6.624x10^{-24}$ J-Sec), c is the light velocity and k is Boltzmann's constant ($1.38x10\ J.K^{-1}$). Based on Equation 2.5 for Planck's law, the wavelength at which the emitted radiation takes place is inversely proportional to its frequency. The accurate definition of the blackbody in Planck's law is the object that absorbs any radiant energy that falls on it, and when it reaches to certain equilibrium, it radiates this energy with the same speed it absorbs it. This is of extreme importance in the study of thermography, as in the range of several hundred degrees, the blackbody radiates the majority of its energy in the IR region [48].

2.2.2. Thermal Radiation of the Human body

In medical applications, the focus of human thermal mapping is guided towards the core of the body and the outer shell or skin. In normal circumstances, the core of the human body of an average person maintains a roughly fixed temperature at 37 ^{0}C, which is needed for accomplishing the biological activities. On the other hand, the shell or surface temperature quickly changes according to the surrounding environment's temperature [49]. Maintaining the balancing of human body's temperature is the role of the thermoregulatory system. The thermoregulatory system here relies on thermoreceptors, which are located in different parts

of the body, but more than 30% of them are in the skin. Through thermoreceptors, temperature data can be continuously monitored. The human body reacts to different temperature levels based on the information provided by thermoreceptors. For instance, if the temperature drops down, different effects such as shivering appear in an effort to rebalance the temperature. Similarly, when the body temperature heats up, different effects take place such as radiation to rebalance the temperature. Essentially, heat is transferred between the human body (mostly through skin) and the environment via evaporation, conduction, convection and radiation [50]. Unlike the core, skin temperature changes rapidly depending on the surrounding or ambient heat. The transformation of heat from the human body to the environment is done via the skin, mostly in the IR range as long as there is a temperature difference. Thus, it is possible to monitor this exchange of energy, or more precisely the human body radiation. Considering the human body as a blackbody, defined by Planck's law, is not an accurate choice. Rather, scientists characterize the human body based on emissivity (ε), which is the ability of the human body to radiate heat energy. The clean human body emits IR energy in the range of 3 to 50 μm; the maximum emitted energy is found at 9.3 μm. For the perfect radiator in the IR range, the blackbody, the emissivity is given by 1. Other objects have relative emissivity values ranging from 0 to 1, depending on their characteristics. At wavelengths longer than 6 microns, the human body simulates the blackbody with a high-level of accuracy. Within this wavelength range, the emissivity of the human body is approximately equal to 0.98. Thus, in thermographic studies, this wavelength range is taken into account, while designing and developing its equipment [52].

It is important to mention that the above consideration of the human body is based on a clean skin surface. Meaning that, if any cream or lotion is applied to the skin, the emissivity will change. In addition, some medications or hormonal treatments do change the emissivity in a similar way. On the other hand, the environmental conditions, such as temperature, airflow, and humidity, present external factors that affect the emissivity. For this reason, thermography has its own protocols that dictate the use of controlled room environment and participants' health status [53].

2.2.3. Thermography Breast Cancer Screening

Thermography of breasts takes advantage of the difference in the heat map beneath the skin between healthy breasts and breasts with cancer. The existence of tumor in breasts increases the temperature of its surrounding tissues[51]. Specialists usually deploy some

symmetric analysis of healthy and unhealthy breasts. The procedure followed for breast cancer screening using thermography is very straightforward. It starts with a visual inspection of the breasts' surface. This allows the physician to correlate any unusual presence to the heat map. Then, the individual is required to remain at room temperature (18 ^{0}C to 25 ^{0}C) for 15 minutes for acclimation purpose. At the same time, the individual will have to disrobe the top part of the body, from waist to chin. This procedure is done in a room where both humidity and temperature are controlled. After the body temperature reaches to equilibrium, the individual will be asked to stand in front of the imaging system with hands up right, to image the surfaces of interest; these are upper chest, underarms, and breasts [54]. During the imaging period, the temperature should be maintained at 1 ^{0}C. In addition, any source of heat should be eliminated from the room to minimize the external thermal interference. Further, the air-conditioning air flow should be directed away from the individual to avoid any misleading results.

The imaging system is composed of an ultra-sensitive IR camera applicable for medical purposes and a computing unit. The captured images are digitalized and stored on the computing unit for diagnosis. The diagnosis here is made by thermologists with the aid of a computer, where the captured images are mainly categorized based on temperature and vascular analyses [55].

The standard protocol for categorizing is placing the image into one of five Thermological (TH) groups. These groups are:

TH 1: presents a normal uniform non-vascular subject.

TH 2: presents a normal uniform vascular subject.

TH 3: present an equivocal subject.

TH 4: presents an abnormal subject.

TH 5: presents a severely abnormal subject.

Upon the screening outcome, the step to be taken next is determined. The Thermologist decides whether mammography or any further test, such as biopsy, is needed.

2.2.4. Medical Thermography's Imaging Technology

Medical thermography or Digital Infrared Thermal Imaging (DITI) is generally used for screening purposes in clinical applications. In addition, DITI is deployed for treatment assessment in some cases. The early version of medical thermography was called evaporagaphy, which is no longer in use due to its limited applicability. Currently, DITI is

widely available in medical applications with two main versions: contact and non-contact systems.

In contact systems, recording or capturing the heat map is done using a special substance; commonly, the used substance is the liquid crystals. These crystals reserve a status between solid and liquid nature, and they have similar liquid mobility (up to a few degrees of freedom). Liquid crystals are stretched on a film with certain intensities and geometric properties. Once the film is applied to an extremity, it reacts to the reflected wavelengths and produces distinguished colors. Practically, when the film is heated, a color transition of red, yellow, green, blue and violet takes place. A popular application of the liquid crystal film is the cellulite liquid crystal, shown in Figure 2.4, which is used for the early detection of cellulite. Even though contact thermography has been available in medical applications, its use is highly limited by the essence of contact nature. Being in contact with the skin somehow affects the skin temperature and creates a wavelength overlapping in the outcomes. Thus, physicians restrict contact thermography to less sensitive applications where the high resolution is not demanded.

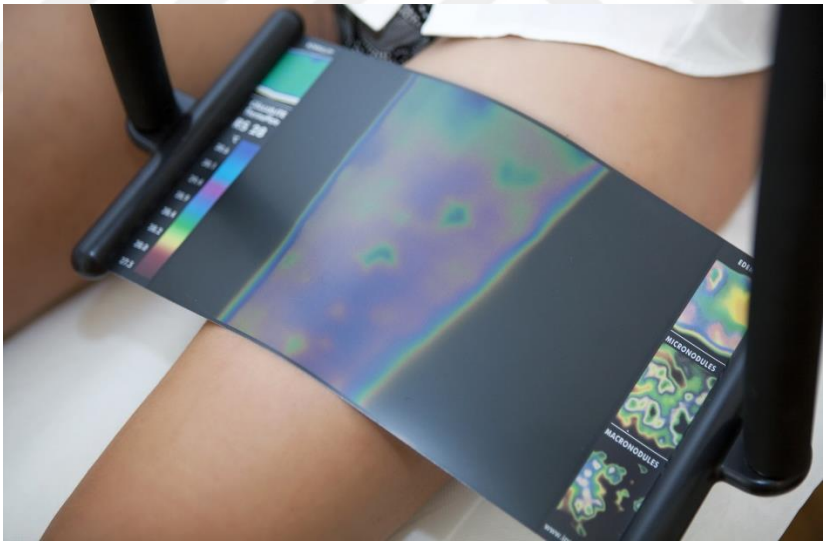

Figure 2.4 Cellulite liquid crystal film [56]

On the contrary, non-contact thermography systems are more popular in medical applications. These systems require sensitive IR cameras that are able to capture some of the radiated body energy and convert it into electrical signals. The deployed IR cameras use IR detectors to capture the incident flux. The initial version of IR camera detectors is the thermal type. These detectors operate based on thermal characteristics and it is not wavelength dependent. However, these detectors are relatively slow and insensitive. In current medical

thermography, IR cameras use photon detectors, which are much faster and more reliable; however, there are considered costly. Photon detectors capture the incident-radiated energy and then convert it into voltage. These detectors are wavelength dependent, as presented in Planck law (Equation 2.5); thus, they convert the detected flux into an electrical signal proportional to the incident wavelength [57]. In addition, modern medical thermographic technologies are usually attached to a computing unit for processing, classification and presentation purposes. In fact, the computing unit plays a vital role in the final image interpretation.

2.2.5. Thermographic Images Processing and Classification

During the early stage of thermography, images were diagnosed, classified and interpreted by the physician. However, the naked eye of the physician may not be able to discover the initial growth of the tumor in many cases. With the technological advancement, new image processing and classification methods have come to the application. These automated processing and classification methods can offer a great deal by confirming any doubt with validated tools. Within the past three decades, tens of images processing and classification research methods have been proposed and discussed. The ultimate aim of these works is to facilitate and enhance the outcome of the thermographic diagnosis. Chapter III of this thesis offers a thorough discussion of the proposed thermographic image processing and classification methods, especially for breast cancer screening purposes.

3. LITERATURE REVIEW

Thermography is considered a relatively old technique, the proper application of thermography for breast cancer screening goes back in time more than five decades. Nevertheless, the initiative attempts were not considered successful due to the lack of effective capturing, processing and analysis approaches. Thermography itself continued to develop to suit other applications, yet its implementation for breast cancer screening had paused for about three decades. Over the last two decades, progressive attention has been paid for this method again, as the technological advances have made it possible to obtain promising results using it. The progress in the literature, with respect to thermography breast cancer screening, can be categorized in a number of ways. However, the common ground for the available research is improving the outcome in one way or another.

Lawson conducted one of the pioneer studies presented in this specific field in 1956. In his work, a diagnosis for an abnormality in a subject's breast was given using a thermocouple. Essentially, the deployed thermocouple was based on recording the heat map in the breast to estimate any overheated parts [58]. The presented work was at a very early stage, and could not actually prove any promising applicability, but it encouraged other researchers to further investigate the same field. Vogler and Powell took the lead in 1959 and presented a work based on the observation of Lowsen. In their work, they used the thermocouple to investigate whether or not the malignant breast tumor has a higher temperature than its benign counterpart. In addition, they used heptyl aldehyde to observe the possibility of cooling down the area surrounding malignant breast tumor. In addition, heptyl aldehyde failed to change the temperature of the tumor, in both malignant and benign cases [59]. In 1964, Strax wrote a brief report on thermography for mass screening of breast cancer. Strax raised four important questions in his report, these are:

- Would it be possible for thermography to replace mammography as a standard breast cancer screening procedure?
- Is it possible for thermography to detect breast cancer at its early stages?
- Can thermography differentiate between benign and malignant tumors within the breast?
- Is it possible to correlate any temperature variations and use them as early evidence for cancer screening?

In his effort to answer these questions, Strax applied the needed procedure to 130 women whom they had undergone mammography procedure prior to thermography. The outcomes of the study indicated that there is strong evidence of the potential application of thermography for breast cancer screening. In addition, he recommended applying the same procedure for a bigger sample size to improve the obtained outcomes [60]. It turned out that Hoffman followed the recommendations of Strax where he applied the concept of thermography for detecting breast cancer malignancy. In his work, thermograms from only 25 percent of the volunteers, confirmed to have breast 1924 women were deployed. Most of these patients were actually referred by nine gynecologists, as their own long-term patients. According to the obtained results, FP rates of 3.3 percent in a normal woman and 16.6 percent in benign cases were recorded respectively. In addition, an FN of 8.4 percent was recorded out of all cases. A biopsy was used in this study, and only less than 2 percent of all sample mammographic images were available. The final recommendation of the author was directing practitioners to use thermography as a compliment for mammography, which coincides with the current view [61]. In a similar effort, Hitchcock et al. studied thermographic sample of 2523 volunteer women. In their work, they used a temperature-controlled environment for obtaining the needed thermograms. In addition, the volunteers were considered of women with 40 years or older, regardless of the clinical history of breast cancer. The extracted thermal images in this study were gray-scaled images. A special oscilloscope was used for recording the drifts from normal recorded temperature map. Based on the thermography outcomes as well as physical inspection, a request for mammography and/or biopsy was given to confirm whether there is a breast cancer. Based on the obtained outcomes, a considerably unacceptable FP rate was recorded. In addition, only 25 percent of the volunteers, confirmed to have breast cancer, were detected by thermography, which raises the double the reliability of the method [62]. This pessimistic had encouraged Karpman to come up with his comments on the reliability of thermography for breast cancer screening. In his article, Karpman provided a solid evidence based on a number of publications to prove the potential of the thermography breast cancer screening. According to his commentary on the topic, more than 80 percent of researchers agreed on the available potential of thermography for breast cancer [63]. The comments of Karpman were supported by the results obtained in the study of Lilienfeld et al. In their study, Lilienfeld and his colleagues compared the sensitivity and specificity of thermography with respect to both clinical examination as well as mammography. They deployed a sample of 3518 women, 862 of them had breast surgery or biopsy. According to their results, the sensitivity and specificity of thermography were

72.1 percent and 79.8 percent respectively. These rates resembled very close match with both physical examination (82.3 percent and 78.4 respectively) and mammography (70.3 and 80.7 respectively) [64].

Despite the optimistic view of Karpman, some studies presented during the same decade denoted that the recorded FP and FN rates might considerably hinder the applicability of thermography for breast cancer screening [65]. This had encouraged the researchers to conduct a thorough investigation of more solid conclusions. One such study was presented in the work of Feig et al. where the authors screened 16,000 volunteer women for breast cancer using clinical examination, thermography, and xeroradiography. In their study, they evaluated each screening examination independently, without referring to other examinations' results, in the first stage. Experienced thermographers or radiologists had interpreted the thermograms of the volunteers based on two blind readings. The inspection result could be one of two possibilities: positive where six-month follow-up was needed or negative where two-year follow-up was recommended. They also referred to the third reading of an expert to resolve any conflict that occurred. The outcomes presented a high potential for thermography in achieving an accurate early detection of breast cancer. Therefore, the authors recommended the use of thermography as a complimentary screening examination for breast cancer detection [66]. Moskowitz et al. approached the concept of thermography breast cancer screening from a different perspective. Their idea was based on how accurate the interpretation of thermograms can be. They used a sample of 42 breast cancer patients with stage Th I or smaller carcinomas, 44 confounding subjects and 64 randomly selected volunteers. Two groups of thermographers were requested to interpret the captured images, namely experienced and inexperienced groups. In their outcomes, the authors had concluded that the objective means of thermography must be improved for ensuring an efficient screening process. Moreover, they stated that the computerized interpretation process should be taken into account as a mandatory procedure [67]. In a more comprehensive study, Threatt and her colleagues examined the blind reading of breast cancer thermography. In their study, they attempted to answer seven main questions, which were all relevant to the applicability of thermography and its proper use. Essentially, the authors presented 576 thermograms for ten thermographers to interpret them blindly. The presented 576 thermograms belonged originally to 515 women. They discovered in their results that there was a strong tendency towards experts' readings, especially for abnormal cases. This variation also covered the sensitivity of readers; the interpretation of abnormalities existence varied from 65 to 327

cases. The authors indicated that a conducted computerized pattern recognition analysis provided lower FP and FN rates than obtained by experts' readings. Thus, they suggested the use of the computerized interpretation of more efficient outcomes [68].

The idea of mass breast cancer screening presented in the work of Feig et al. was also deployed for a more extensive work authored by Gautherie and Gros. The authors recruited patients with stage Th III (recorded as questionable) thermographic results in their investigation. The sample spanned over almost 12 years (from August 1965 until June 1977) and covered patients with breast complaints of 58,000 women in total. Out of the total size number, 1,245 patients were categorized by initial screening as benign or normal using the conventionally available methods (mammography, ultrasound, biopsy, etc.). These patients were diagnosed as questionable by thermography and within five years of following up, most of them recorded a progressive abnormality coinciding with cancer existence. Therefore, they recommended thermography for assessing the rapid growth of any abnormalities in the breast [69].

Although the interest in thermographic breast cancer screening had started in the late 1970s before regaining it back at the beginning of the current century. Throughout the 1980s, a number of studies had been presented aiming at one of the following main objectives:

- Distinguishing the best procedure for thermographic breast cancer screening.
- Estimating any risk that can be caused by thermography.
- Finding valid numerical values for both sensitivity and specificity thermographic applications for breast cancer detection.
- Improving the available methods of reading.
- Coming up with a computerized procedure to overcome the human confusion.
- Proving the reliability of thermographic breast cancer screening in order to make a standard screening procedure along with mammography.

As a practical explanation for the abovementioned points is represented in the work of Sterns et al., where the authors attempted to compare the results of two thermographic procedures. In their research, Sterns et al. tried to find out the best procedure for breast cancer thermography deploying two common methods of that time, i.e., IR Thermogram (IRT) and Plate Thermogram (PT). Over a two-year period, they deployed a sample of 502 women who were diagnosed by IRT, PT and clinical examination for breast cancer detection purpose. According to the findings of this study, the inconsistency of the outcomes compelled the

authors to conclude that thermography was insufficient, and precise diagnosing results could not be guaranteed using it [70]. Similarly, Gautherie conducted a thermobiological assessment for benign and malignant breast cancer. The author used liquid crystal thermal imaging for capturing the needed thermograms and used a computer for automated image analysis. Ultimately, the author could design a computer program to interpret thermograms in a more accurate way. However, it was recommended, based on the outcomes, that further research on the same field should be done [71]. Further, an extensive study conducted by Williams et al. for measuring the feasibility of breast cancer screening using thermography. The study was conducted over the period of five years and it involved 10,238 women aged between 40 and 65 years old. The study initially conducted both clinical examination and thermography for breast cancer screening. In case of any abnormalities, patients' mammograms were also obtained. According to the obtained results, the thermography sensitivity and specificity were found to be 61 percent and 74 percent respectively. In addition, a follow-up check after five years showed conflicting results with high FP and FN rates. Thus, the authors concluded that thermography cannot be considered sufficient for breast cancer screening due to insensitivity. Further, the study indicated that thermography cannot be used as a risk indicator for early detection of breast cancer [72].

The development of interest in thermography breast cancer screening started in the mid 1990s. The main reason for such regain of interest is due to the rapid development in both IR imaging system as well as advances in computerized pattern recognition. Some researchers paid attention to this observation and wrote their own views about it. One of the renowned works in this regard is presented by Foster in 1998. The author provides a review of the recent trends, at that time, relevant to the advances in thermography breast cancer screening. He also provided valuable information on specific publications on the field since the 1960s [73]. Within a few years, the concepts of computer simulation and pattern recognition for image processing have become very popular. Ng and Sudharsan deployed the very similar concepts where they used computer simulation in conjunction with thermography for the early detection of breast cancer. In their work, they developed a mathematical model for the breast relying on various parameters. They considered women with three main cases: normal breasts, a benign diagnosed lump with a pain in the right breast, and a removed benign lump from the right breast. The simulated model in this work can be used as a pilot or reference for further investigation. Nevertheless, the modeling effort was not completely mature [74]. Ng et al. further developed a computerized detection of breast cancer from thermograms using artificial intelligence. A new scenario was proposed in their work, where they used Artificial

Neural Networks (ANN) for classifying thermograms and detecting any abnormalities. Their developed ANN model used statistical inputs obtained from the acquired thermograms. Essentially, they developed elementary ANN models for testing purposes, which could achieve an accuracy of 61.54 percent [75]. Although this work is not considered sufficient for proving the reliability of the method, it could show the potential of the application itself which has been used ever after. For instance, Koay et al. deployed a similar idea of Ng et al. where they used ANN for analyzing thermograms to diagnose breast cancer [76].

Jakubowska et al. thought of a relatively different idea for improving thermography breast cancer screening. In their study, they considered the use of statistical parameters to estimate the existence of any malignant tumor in the breast. For this purpose, they used a sample of 42 volunteers (32 healthy and 10 with malignant breast tumor). They captured four images for each volunteer with front and side view of the breasts. They used these images for calculating statistical parameters such as kurtosis, mean temperature, skewness, standard deviation, and variance. In order to predict abnormalities, they calculated the absolute difference between these parameters for left and right breasts. According to their analysis, the deployment of statistical parameters for image classification provided promising results. They also recommended the use of second-order statistical parameters for symmetric analysis to enhance the overall classification process [77].

Again, in 2008, Ng and Kee proposed an improved technique for breast cancer thermography. In their study, they integrated ANN and biostatistical methods for achieving a high accuracy rate. They specifically used Radial Basis Function Network (RBNF), linear regression, and Receiver Operating Characteristics (ROC) for the analysis purpose. Here, linear regression was used for creating the needful correlation between variables confirmed health status of the subjects, where the correct diagnosis in their study is based on mammography. The determined variables were then fed as inputs to the RBFN, which is trained to determine the final status of the screening. Their choice of RBFN over other ANN was made based on the superiority of the method in terms of speed, classification ability, and decision-making process. For the ultimate evaluation purpose, they considered accuracy, sensitivity, and specificity. For obtaining these measures, ROC was applied to the classified results of RBFN. The evaluation here was based on 90 breast thermography patients' images taken at Singapore General Hospital. Based on these images, the obtained accuracy rate of their study is 80.95 percent, while the sensitivity and the specificity are 100 percent and 70.6 percent respectively. Up to the date of Ng and Kee's study, the obtained results were positive compared to previous relevant studies. However, it is crucial in biomedical image processing

studies to test the method on a large-scale dataset in order to ensure its accuracy and applicability. Therefore, considering only 90 patients in a testing dataset makes the outcomes questionable [78].

Tang et al. investigated the possibility of improving breast cancer thermography screening using morphological measurement for Localized Temperature Increases (LTI). They mainly suggested an improved detection of breast cancer is possible if a morphological signal processing technique is used for measuring the LTI caused by the tumor. They applied dataset of 117 patients who are categorized as 47 malignant and 70 benign. Based on their study, they could screen 44 out of 47 cases. The obtained sensitivity is 93.6 percent. However, the use of a small dataset for breast cancer detection is always criticized. Further, the negative predictive value is 91.2 percent, which is considered very high. In addition, the recorded FP rate is 55.7 percent, which also indicates a very high false alarm that cannot be tolerated [79].

One of the important factors in thermography is the edge detection, where the proper identification of breasts reduce the unnecessary areas, thus increases the accuracy and lessens the overhead. Kapoor and Prasad had realized this aspect and suggested edge detection and Hough transform for asymmetric analysis of breast cancer thermography. The authors proposed that applying both image segmentation and asymmetric analysis for breast thermographic images could improve the efficiency of the detection results. In their work, they used edge detection for extracting breasts' boundaries. They further applied Hough transform for extracting the lower boundaries of the breasts. Based on the minimized image areas, which are the areas of interest, the authors classified the segments into pixels. These pixels were then used for breast cancer diagnosis using asymmetric analysis. Even though this study had addressed a very critical issue in breast cancer detection using thermography, it was extremely brief and had no proper actual application. In such scenarios, a suitable judgment for the improvement cannot be done. Yet, the study can be used as a pilot implementation for other studies [80].

As mentioned in chapter II, the interpretation of thermographic breast is generally conducted by thermologists. Here, the interpretation itself can be very tedious, confusing and time-consuming. Thinking about an alternative had sparked the notion of an interpreter, which does this task automatically. The main exact concept was presented in the work of Umadevi et al., where the author developed a possible thermal breast images interpreter for

mass screening. The authors had benefited from the work presented in [80] and similar studies, where the interpretation of the thermal images are based on segments' pixels. Using this methodology, the authors developed a thermographic breast screening interpreter called Infrared Thermography Based Image Construction (ITBIC). In this study, a total of 50 females were classified by ITBIC. Their procedure was based on taking the thermal image from in front, right side, and the left side. Thus, three sets of images were used for each individual. The study used a sort of boundary detection technique for extracting the Region of Interest (ROI), which was later used for getting needed pixels for classification. The classification process in this work was based on extracting the highest temperature area (color-related analysis). For evaluation purpose, the authors compared the results of their ITBIC assessment with the MRI assessment for the whole dataset. They could obtain 66.7 percent of sensitivity rate and 97.7 percent of specificity rate. In addition, the positive and negative predictive values were 80 percent and 95.6 percent respectively [81].

The same authors further developed their own idea for a complete framework for estimating tumor parameters from thermal images [82]. Apart from that, some studies had focused more on the assessment factors of breast cancer screening using thermography. Such a scenario is found in the work of Kontos et al. The ultimate aim of this study was focused on finding both sensitivity and specificity of Digital Infrared Thermal Imaging (DITI). For this purpose, the authors had deployed a dataset taken from 63 asymptomatic patients. Interestingly, the authors selected patients to compose 58 females and 5 males, which gives their study more confidence. Based on their analysis, they could obtain a sensitivity rate of 25 percent and specificity rate of 85%. Accordingly, they concluded that for the evaluation of asymptomatic patients DITI does not provide an adequate sensitivity to be used as a primary screening method [83].

Modeling methods for improving the thermal imaging for breast cancer screening have been addressed in the literature. One of the recent examples is the work of Amri et al. The authors had attempted to create a 3-D model for the breast and base their thermographic cancer detection on it. In their work, they used the Transmission Line Matrix (TLM) to create a 3-D model for the breast with an embedded tumor. This can be then used for analyzing the sensitivity parameters. Such studies are extremely useful, especially for future enhancements of the thermographic system [84].

One of the reviving reasons of thermographic breast cancer screening is the advances in image processing technologies. Boquete et al. had exactly considered this critical concept while developing their automated breast cancer detection method. The authors here had considered a relatively different technological concept for the analysis of thermographic images, namely the Independent Component Analysis (ICA). The authors used eight cases, six for cancer validation and two for control purpose; the dataset was extracted from an online resource. The study considered the analysis minimum defects, 4 x 4 pixels. It was possible for ICA to detect the cancer existence as independent components of YcrCb. The obtained sensitivity is very promising where a rate of 100 percent was obtained. Moreover, the obtained specificity is considered very high compared to other studies, where a rate of 94.7 percent was achieved [85]. The idea of using ICA was further developed later on by Etehadtavakol et al., where the authors used discrete wavelet transform and ICA for classifying breast thermograms [86]. Similarly, Rajendra Acharya et al. applied texture features and Support Vector Machine (SVM) for breast cancer thermographic automatic screening. Using 50 cases (25 cancerous and 25 normal) the authors could achieve an accuracy of 88.10 percent, while the sensitivity and specificity were 85.71 percent and 90.48 percent respectively [87].

Nicandro et al. preferred to try Naïve Bayesian classifiers for the analysis of thermographic breast cancer screening. In their study, they proposed the use of Naïve Bayesian classifier, Hill-Climber, and Repeated Hill-Climber. They deployed a dataset of 98 cases (77 are cancerous and 21 are healthy). Out of all their experiments, the best accuracy they could achieve was 76.12 percent obtained by Repeated Hill-Climber. Nevertheless, this accuracy is not adequate for reliable medical applications. Yet, the study itself is a very good reference for comparative investigations [88]. Apart from that, the use of wavelet for the screening of breast cancer using thermography is reported in [89]. In this study, the authors used wavelet-based multifractal analysis for thermographic images analysis. The recruited individuals composed of 33 females that underwent a surgical intervention for removing a breast tumor and 14 females with intact breasts. The authors had also developed an open source tool based on their investigation [90]. This tool can be used as a ready software application for thermographic images analysis.

Gogi et al. conducted a thorough investigation of the use of hybrid intelligent techniques for breast cancer detection using thermograms. The study presents a very rich resource for researchers interested in this particular [91]. Similarly, Lashkari et al. had employed the

concept of intelligent classification for the screening of breast cancer using thermography. The authors divided their approach into four main steps, namely pre-processing and segmentation, feature extraction, feature selection, and classification. As suggested by a number of previous studies, initially the authors extracted the ROI form the images. Then, right and left breasts were separated using edge detection and thresholding. Further, they considered 23 features based on the segmented images, and they deployed a number of feature selection algorithms for ensuring the best performance. In the classification stage, the authors had used AdaBoost, k-Nearest Neighbors (k-NN), Naïve Bayes (NB), Probability Neural Network (PNN) and SVM for comparative investigation. They applied their method to images captured from 67 patients. According to their findings, the best outcomes are determined by the combination of Genetic Algorithm (GA) and AdaBoost, where 87.42 percent with images taken with 0^0 [92].

Zadeh et al. proposed a thorough clustering-based development for automatic breast cancer screening using thermography. In their study, they used artificial intelligence, where the self-organizing neural network is applied for clustering purposes. Next, a multilayer perceptron neural network is used for the final screening. The authors considered double 200 cases and single 50 cases. Based on the used samples, they could achieve a sensitivity rate of 88 percent (for the double 200) and 100 percent (for single 50), while the accuracy was 98.5 percent for both cases [93]. Similarly, Santana et al. had used the concept of Extreme Learning Machine (EML) for breast cancer diagnosis using thermography. In their study, the authors deployed classifiers built by ANNs, Bayesian, decision trees and Haralick and Zernike attributes. The used sample is categorized into benign, cyst and malignant. According to their findings, ELM and Multilayer Perceptron (MLP) networks had shown the best performance for classification purpose. When the authors set 75 percent of the dataset (1052 images) for training, they could obtain an accuracy of 73.38 percent. In addition, the sensitivity and specificity rates were 78 percent and 88 percent respectively, while the efficiency of the system was recorded as 83 percent [94]. The main advantage of this study is a considerable number of used images in the dataset. This increases the credibility of the work and justifies the obtained accuracy drop compared to previously presented methods. In addition, the work presents a thorough comparison between a number of algorithms, which makes it particularly useful for survey studies.

It is essential to mention that the reviewed literature does not cover each work in this field, as there are thousands of articles that discuss the same topic on one side or another.

However, the reviewed literature was selected based on its relevance to the current research as well as its dominance in the realm of academia.

4. MATERIAL AND METHODOLOGY

4.1 Introduction

This section discusses the thermographic methodology/procedure used to detect breast lumps that are synonymous with breast cancer. Thermography employs thermal infrared images to identify lesions in breasts [95]. The process works by showcasing images that get warmer in the location with tumor or cancerous cells than those of the normal tissues [95]. Thus, the procedure works by distinguishing the cells through thermal infrared cameras that produce infrared images at preset time length in a sequential manner. This is an effective and more advanced way to screen cancerous cells through unusual temperature variation compared with the standard mammography that utilizes x-rays to detect tumors and abnormal breast cells [96]. As the methodology section will show, various stages are accomplished while undertaking the image processing using the thermography procedure. But the core of the procedure entails dividing the image into variant regions, identifying the region of interest (ROI), which is done by the thermal infrared camera and denoting the edges [97]. These core procedures can also be done after the segmentation of an image. The overall thermography methodology in Figure 4.1. outlines the key stages. An in-depth analysis of each of the stages discusses the processes and data collection techniques that occur through the extraction of the images. The images later undergo a pre-processing procedure for classification purposes.

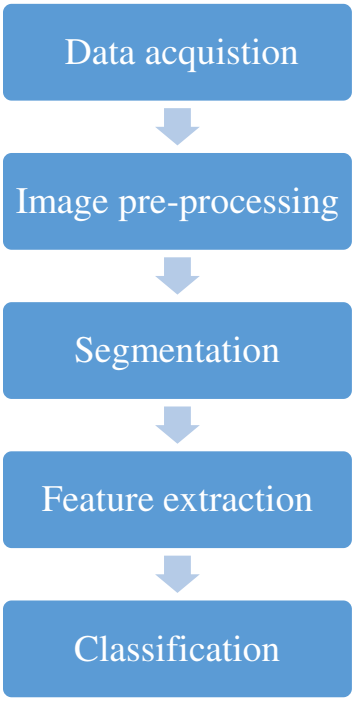

Figure 4.1 Breast cancer thermographic detection methodology

4.2 Data acquisition

Data acquisition is an essential step of the thermography procedure because it helps with further in-depth analysis and classification [97]. When undertaking the thermographic procedure for data acquisition, the environment using the infrared imaging procedure should be controlled. The purpose of a controlled environment is due to human physiology and environmental changes [98]. Thus, there is a given protocol and guidelines that patients should follow before entering the imaging room and there are stern guidelines under which the images are taken while in the laboratory. This should be done to avert artifacts on the final images. The laboratory conditions should be moderately cool at 65-75 degrees F with no luminescent lighting [99]. In addition, the laboratory should not have hot or cool that may affect the patient and the setting should be stable within 1° C throughout the duration of the imaging process. Only cool settings with thermal stability can produce more accurate results [100]. Moreover, the imaging equipment should meet the minimal standard specifications for medical application as well as be registered for the data to be accepted. Below is the outline of the various guidelines and protocols that were followed by the patient and technician when preparing the imaging laboratory.

Patient protocol

The patient was instructed to do the following:

- Refrain from sunlight;
- Not stimulate the breast or engage in any form of breast treatment pre-imaging procedure;
- Not apply cosmetic, lotion, antiperspirant or deodorant;
- Not exercise or do heavy physical activity;
- Not bath or clean up immediately before the imaging procedure;
- Remain nude from waist up for about 12 minutes to acclimatize the body with the setting's thermal condition.

The imaging laboratory setting

- The humidity of the infrared imaging room was controlled at all times;
- The temperature of the room was stable and maintained between 17° an 24 C
- The change of the room temperature was kept within 1° C during the scanning procedure. The stable temperature ensured that the patient did not undergo dramatic physiological change such as shivering or perspiring;

- The floor carpeted but the patient was encouraged to wear sandals or shoes to prevent stressing his or her physiology;
- The laboratory setting was clear of drafts and other light sources such as sunlight and luminous lighting.

When these protocols and guidelines were followed, the changes to the patient's body occurred gradually and uniformly and hence, did not impact the variations in homologous regions.

A FLIR SC-620 thermal camera was utilized to obtain thermal images of the breast [101]. The camera works by converting the infrared radiation discharged by the skin into electrical whims that are visualized and can be viewed on the screen. The view of temperature change is fundamental to the thermographic procedure where the thermal image captures the body temperature of the organ [102]. The basic theoretical driving process is that the use of the infrared thermal camera is that the metabolic activity and vascular circulation in the tumor cells and the surrounding area are higher than normal cells [101].This is because the tumor and cancerous cells sought for nutrients which inadvertently increase the blood circulation such as opening up inactive vessels and forming new ones. The increase in blood circulation and metabolic activities increases the temperature of the affected region that is captured by the infrared camera and computer [103]. Due to the extreme sensitive nature of the thermal infrared camera, the thermo vascular differences in the breast tissues may present the first signs of breast cancer [104].

The camera will produce visual images that illustrate the variations in body temperature through a range of colors that highlight a rise or fall in the amount of infrared radiation released from the surface of the breast. The detection of the unusual temperature symmetry is as a result of minimal high degree symmetry in the normal tissues. Figure 4.2 showcases the procedure and equipment used.

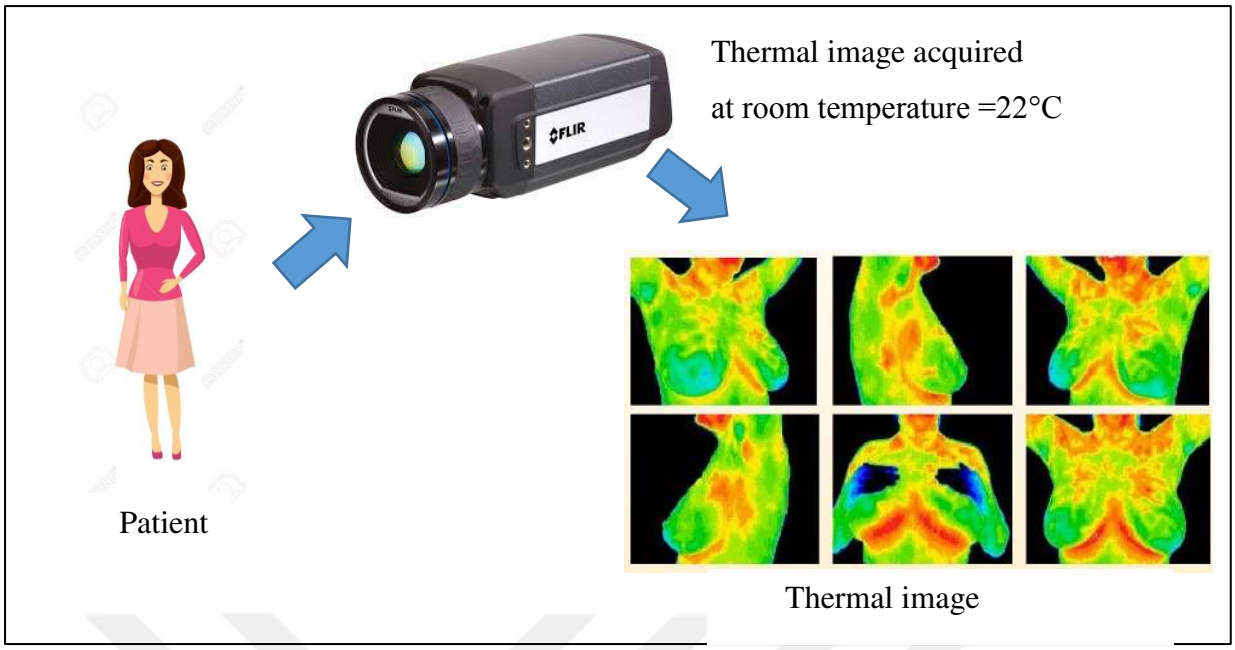

Figure 4.2 Thermographic breast cancer detection

Figure 4.3 below shows the breast thermal image that captures the body from the waist to the neckline. The visual image has a range of colors, primarily red, green and yellow that varies across the entire captured body.

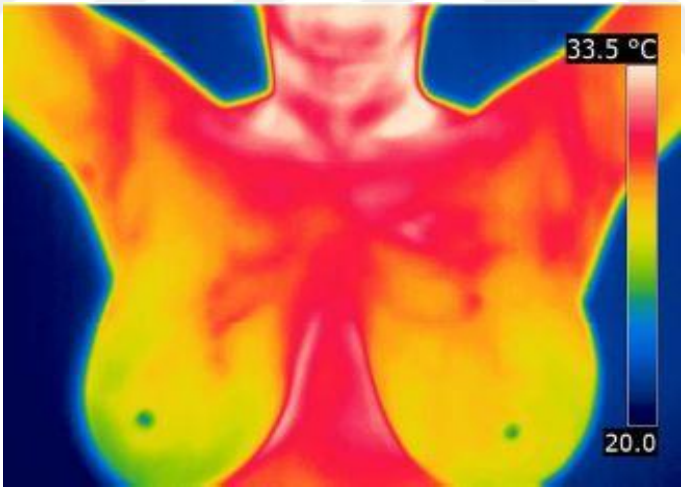

Figure 4.3 The breast scan captured by the thermal image camera [6]

4.3 Image pre-processing

The pre-processing stage of the infrared image was essential because it was used to find the point of reference/orientation of the thermal image and enhance the image quality by eliminating any unwanted element [96]. The images need to be accounted for as they appear and the pre-processing stage improves the image without undue influence or alterations to the background. In addition, the pre-processing stage is also necessary for removing the noise that usually accompanies the thermal images [96]. There are several types of noise, namely

the Gaussian, impulse and speckle noises [95]. The noise is eliminated or reduced since the pre-processing stage works with a consistent theme meaning that anything else outside the theme is detected and removed. The characteristics of the image rely on the noise distribution and it is typically defined as the characteristic of the demographic law. Figure 4.4 shows the pre-processing stage of image filtering.

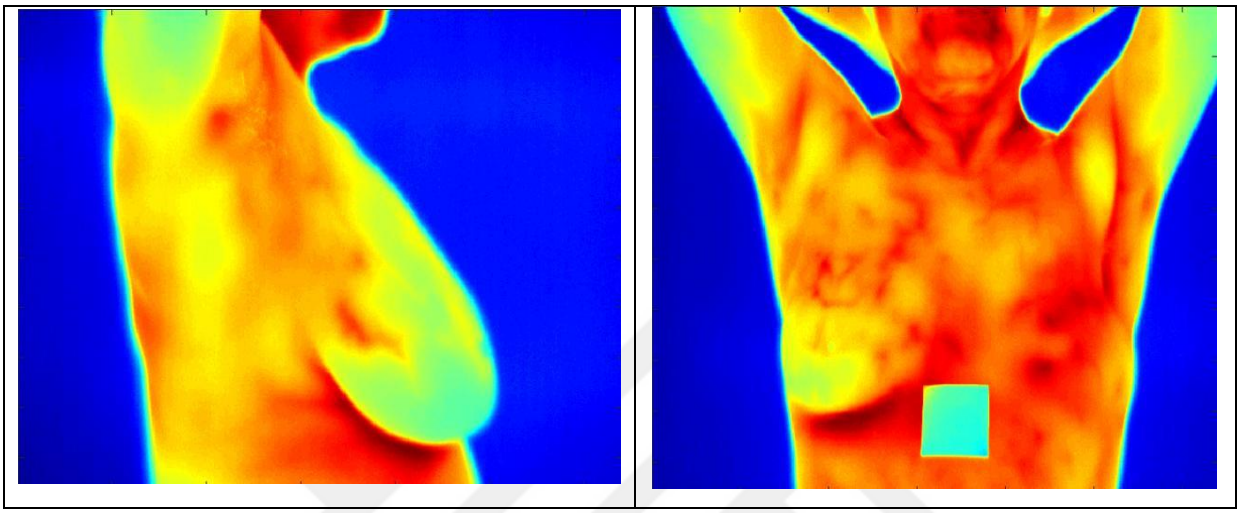

Figure 4.4 The pre-processing stage where images are filtered

The pre-processing stage undergoes different types of filters, namely the wiener, median, adaptive, and average filters [105]. The enhanced image typically undergoes the average filtering process and later the quality process that is used for the final visual image. The filtering process adjusts the average value and intensifies the adjacent regions by adjusting the pixel [97]. This filtering process also diminishes the noise and reduces the variance. However, the average filter contains the following limitations:

- Blurring of images where the features are localized and accuracy is not guaranteed.
- The averaging operation done to a corrupted image it attenuates the impulse noise and diffuses it but is unable to remove the noise completely.

The non-linear filter process also known as average filter is more efficient in eliminating noise as it tends to keep the edges of the image sharp while removing the noise simultaneously.

4.4 Segmentation

The projection profile analysis is used for segmenting either the left or right breast. The profile analysis is used for assessing the upper, lower, left and right borders of the breast undergoing the breast thermogram. The camera contains a histogram, which is a horizontal or vertical projection profile that is one dimensional with several entries to the number of rows

or columns [110]. The black and white pixels are contained in a row or column that is amassed in the corresponding entry. The Horizontal Projection Profile (HPP) routine is employed to locate the upper and lower edges, while the Vertical Projection Profile (VPP) routine is used to locate the left and right edges of the breast [110]. Initially, the breast pseudo color image is converted into a grayscale image. Figure 4.5 shows the block diagram of the segmentation. The image will then undergo the following sequence of operations:

1) Image filtering
2) Detection of the edges
3) Detection of the lower border
4) Detection of the upper border
5) Image threshold
6) Detection of the left and right border
7) Locating the central axis
8) Segmentation of the left and right breast

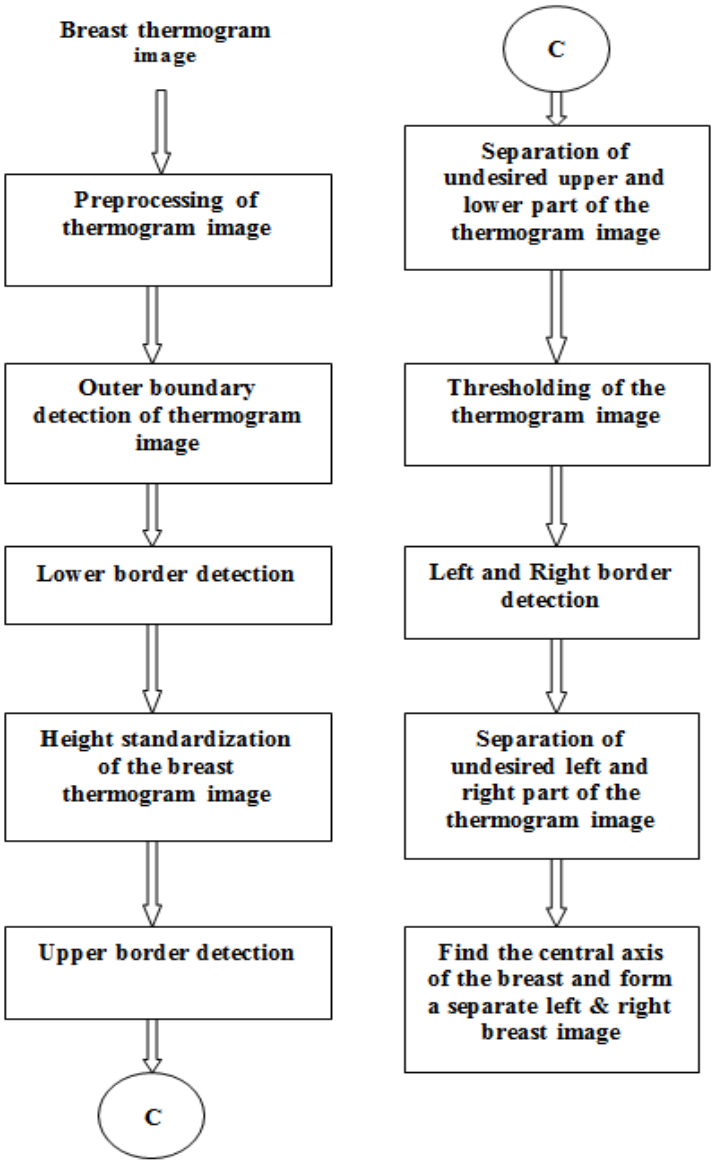

Figure 4.5 The block diagram of the segmentation [110]

The image literature analysis contains various estimations such as the line segmentation text, layout segmentation and other different segmentations. In the equation (1, 2) 'm' rows and the 'n' columns of the literature image analysis of the uncompressed document of the vertical projection profile contained mathematical representation [101]. An example of the mathematical representation for the vertical projection profile (VPP) and horizontal projection profile (HPP) is given below.

$$\mathrm{VPP}(y) = \sum_{1 \le x \le m} f(x, y) \quad (1)$$

$$\mathrm{HPP}(x) = \sum_{1 \le x \le n} f(x, y) \quad (2)$$

Yet, in order to work with the compressed data already found, the above formulas or mathematical representations may not be applicable. Obtaining the VPP from the compressed data directly is simpler and the recommended procedure [102]. In addition, the intricate task in all these is getting the HPP curve. This is because the compressed data of the VPP may not be directly available [101]. When the image is projected in the data structure over the normal x-y axis, the number indicated at the background of the pixel will assist the projection profile. It is worth noting that the numbers of pixels are a predefined threshold of each cell of the projection vector that is linked to it [102].

The localized temperature increase (LTL) located in the infrared thermogram helps to measure the amplitude [103]. When the patient is experiencing a high localized temperature increase during the thermography procedure, the patient's amplitude will also be considered as it also marks a high likelihood of breast cancer. $1^{\circ}C$ is calculated by optimal localized temperature increase threshold during the breast cancer detection [103]. However, due to the likelihood of a false positive occurring, it may not yield accurate results. A set method will typically be used for the image segmentation [103].

4.5 Feature extraction

During the feature extraction stage, the thermal image processing technique is applied in order to detect and assess the abnormal regions so that the visual images can have improved results [105]. To be more specific about the stage of the feature extraction, the convolution neural network (CNN) method is used and discussed. It is worth noting at this point that CNN and the texture feature extraction are the two steps of medical image classification process [106]. However, in the breast cancer detection process, the feature extraction is the most important step.

4.5.1 Convolution neural network (CNN)

The CNN are a specialized type of neural network meant for processing data. Four stages exist for the CNN layers as outlined below [114]:

1) Generating a set of linear activation in parallel numerous convolution operations;
2) Computing a set of filter feature maps of the previous layer;
3) The computation of non-linear function through linear activation such as the computation of rectified linear activation system (RELU). This typically occurs in

deep nets that lead to a quick training stage of the RELU. This stage is commonly referred to as the detector stage.

4) Modifying the output for further layer pooling function as well as reducing the size of the feature maps. The size of the pooling layer is used to reduce the patch of 2x2 pixels to one pixel. This result into better generalization of the visual image and a faster convergence of the results generated.

Figure 4.6 shows an image depicting the stages of CNN. As shown, the convolution net comprising of a small number of complex layers is seen engaging multiple stages with each layer. The feed forward neural network is similar to the CNN training. Each image is forwarded through the layers until it is computed and no function remains. But based on the gradient descent technique, changing the weight propagates the loss of the function. It is worth noting that the procedure can become ineffective if a pre-defined number of iteration is not made.

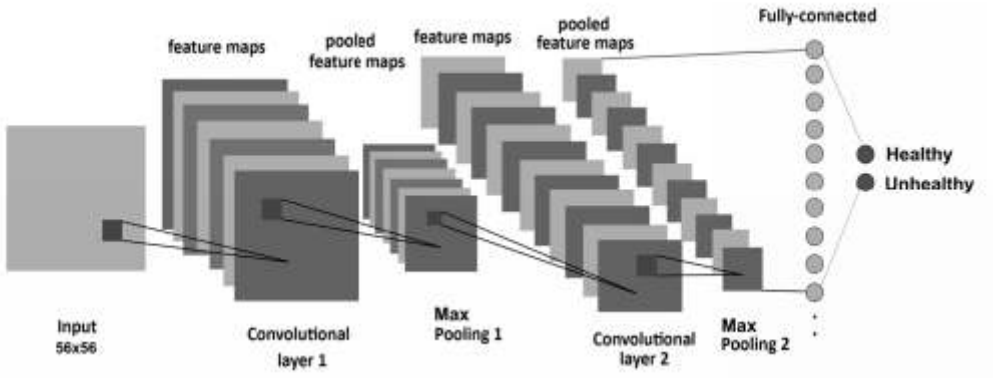

Figure 4.6 The architectural structure of the CNN process

Typically, the static dataset of DMI will create images of healthy patients as well as those patients with cancerous cells [107]. In this study, 98 healthy patients as well as 42 patients with cancer were generated. It becomes important to apply the CNN architectural balance of the images until the classes have similar amounts of images and the images showing cancerous cells are enhanced and enlarged further. The CNN feature is also significant because it selects the abnormal set of images randomly meaning that it is easier to distinguish the images [104].

One strategy was proposed for the dynamic protocol of the verification process of the CNN classification of the breast thermal images. The strategy assigned all data in a single

array but the data are associated with a single image at a time. Figure 7 depicts the array of images produced based on the first strategy.

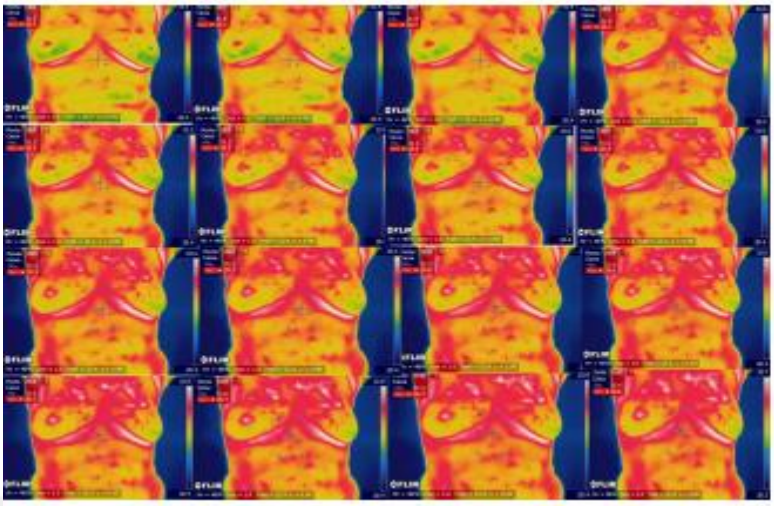

Figure 4.7 The strategy for the verification process of the CNN classification

Based on Figure 4.4, multiple layers of the convolution are created. Each layer is followed by the attached layer as well as the multilayer neural network. The CNN architecture is designed to make the 2D insight image and these images can be generated by different processes [98]. For instance, the pooling process is responsible for suitable local connections as well as tying the weights in diverse types of layers. Another significant feature is translation that generates invariant results. Following an accurate detection of breast cancer, specific treatments are recommended that can be used to eradicate the cancerous cell depending on the stage of the cancer [98].

4.6 Classification

In the classification stage, a vector is depicted on the image to represent the characteristics of the breast mass [108].

The CNN in this case is employed as the classifier. Different levels of abstraction change depending on the number of layers as well as with the composition and style of coating. The attributes obtained can be classified further into four types in order to make the final decision.

So far, the medical advancement and technology associated with them are increasing to discover the cancer at various stages and cure the disease. The machine learning, which is gaining momentum, provides in-depth analysis and attaining the objectives are leaning towards artificial intelligence[109].

5. Results and Discussion

This section discusses the outcomes of the study in detail. The highlights of the research, the limitations and a thorough benchmarking of other relevant study attempts are presented. Together with this, the outcomes of the correlation analysis and the derivation of the statistical input parameters of the CNN are presented and explained. The Edge detection analysis is also discussed and their capacity to classify the images based on thermal vascularity is discussed. Finally, the results obtained in the CNN analysis with other various network configurations and input parameters are discussed. The chapter concludes with the overall discussion of the results.

5.1 Convolutional Neural Network (CNN) Classification

In a convolution neural network (CNN), each neuron is connected with a few local neurons in the previous layer, and the weight is shared for every neuron in that layer. Convolution neural networks are effective for image classification problems because the convolution operation produces information on spatially correlated features of the image. For example, convolution may result in edges becoming more prominent.

The constructed convolutional neural network has three convolutional layers, and each of them is generated by convolving through a 5x5 filter/kernel with the previous layer image. By feeding the output of one convolutional layer to another, higher-order features can be extracted. After convolution, these features can be readily learned by a fully connected neural network. The convolutional layers can be thought of as preparing the data so that the fully connected layers can take advantage of the spatial structure of the input image. The idea is that after the image has been passed through multiple convolutional layers, the neurons will be encoded with all the relevant spatial features. Following the convolutional layers, there are two fully connected layers with 512 and 256 nodes, respectively. This CNN architecture was inspired by the first few layer [4]. The detailed diagram of CNN architecture is shown in Figure 5.1.

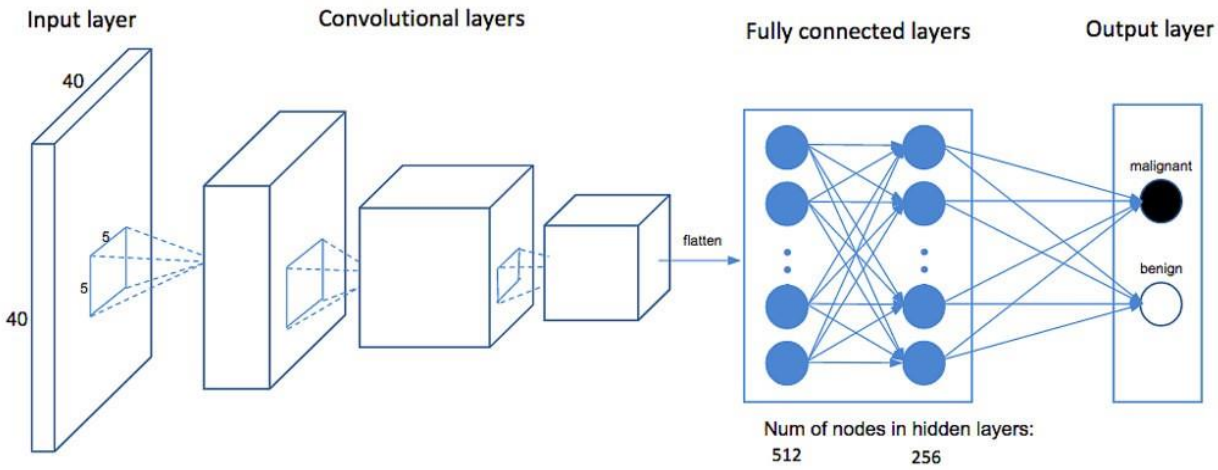

Figure 5.1 The proposed CNN architecture

5.2 Dataset

The raw dataset contains 3895 thermal breast images in JPEG format and the size of each thermal image is 640 x 480 pixels.

Table 5.1. Thermal image samples of DMI dataset

Cases	Number of Thermal Images	Patient Number
Benign	3,098	98
Malignant	797	42

5.3 The GUI of Application

The Graphical User Interface (GUI) generates visual elements as well as making possible the transfer of data from separate applications. In this case, the formats were distinct and contained dissimilar programs that perform under the GUI. This enabled data sharing. Thus, the copying of graphs and formation of spreadsheets in the document was doable. Hence, we were able to gain instant visual feedbacks concerning the upshot of each action. The GUI allowed for multitasking where several programs functioned concurrently as well as be displayed. All these improved the flexibility and the results. In Figure 5.2, the GUI of application which is prepared in Matlab software is illustrated. As can be seen from the figure, there are some arbitrary steps that should be followed by the users when they try to classify the thermal breast images. These steps are explained below.

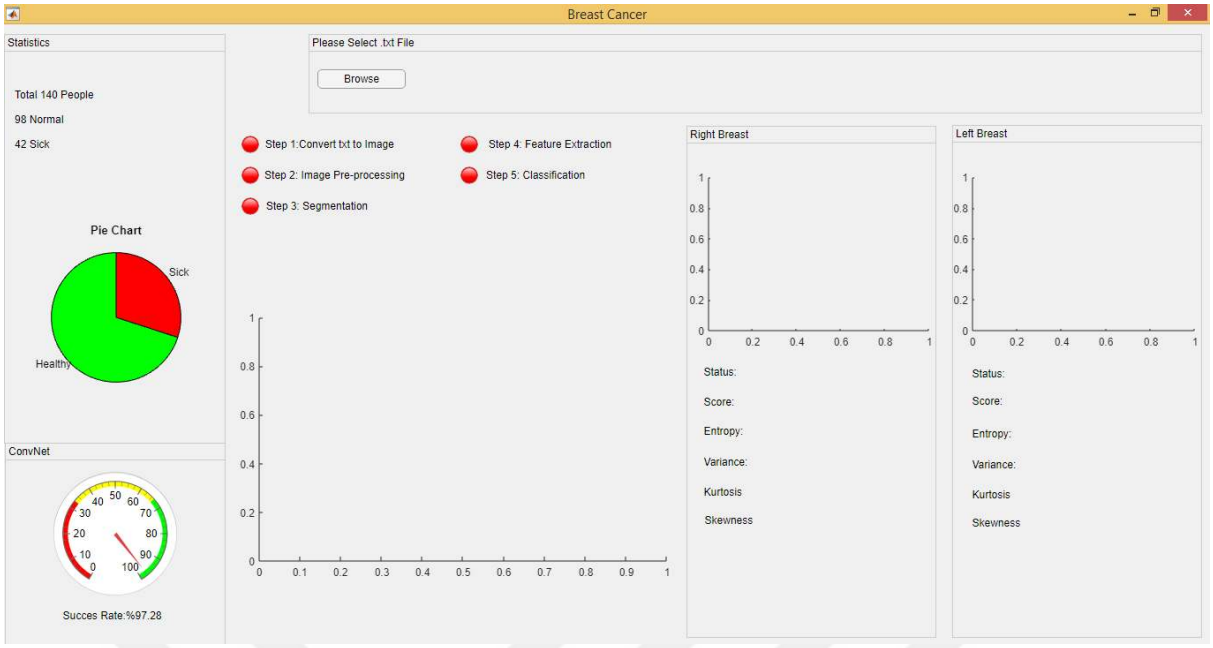

Figure 5.2 GUI of application

Step 1: Convert TXT file to Image

The text files were converted into images for visual effects. This was accomplished by saving the saved text file that would be used. The reason for saving the text is to maintain the quality and resolution of the data. This was done by selecting the text and copying it on the clipboard.

Step 2: Image Pre-Processing

The image pre-processing step is crucial for attaining clear and distinguishable images. The image pre-processing step enables the classifying step. Firstly, the data augmentation process was employed. This process helps to increase the volume of the dataset by employing numerous conversions to the initial input. The input was replicated by doing different types of conversions such as the translation, symmetries and rotations. The pre-processing augmentation steps performed are listed below;

1) Translation – the images were translated to a given number of pixels and towards a given direction.
2) Centering – the rows and columns were removed from the edges of each images. Thus, it was possible to obtain images of varying sizes. Later, the full amount of rows and columns are cropped and the number of images counted. Then the images are resized by leveling them into a single size as shown in Figure 5.3.

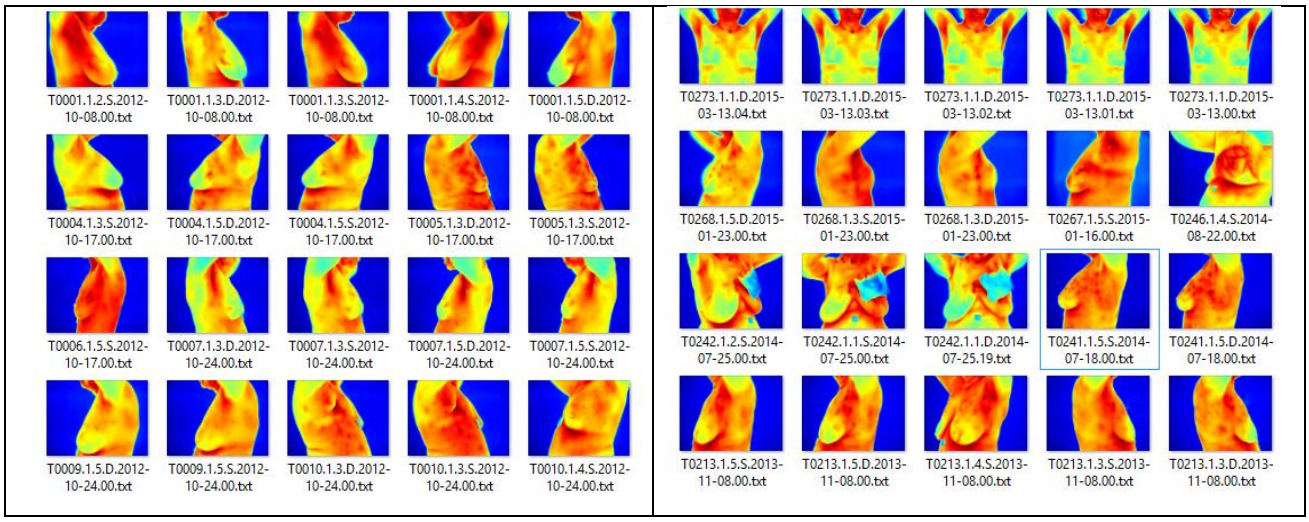

Figure 5.3 Thermal breast images after pre-processing

After the pre-processing process, the randomized images are selected based on clarity for normal and sick patients. The cases, number of thermal images and patients are highlighted in Table 5.2.

Table 5.3. Number of patients and their thermal images of training dataset

Cases	Thermal image	Patient number
Benign	558	98
Malignant	558	42

Step 3: Segmentation

The segmentation process was necessary for the extraction and target classification of high resolution images. While segmenting the high resolution images, spectral confusion occurred, delineation was decreased and the precision of the images reduced. However, to improve on this, the object-oriented image segmentation method was applied by eliminating the salt and noise as well as enhancing the preciseness of the image through the application of object structure as well as spectral signature. In Figure 5.4 and 5.5, the segmentation steps and a segmented image in GUI application are illustrated respectively.

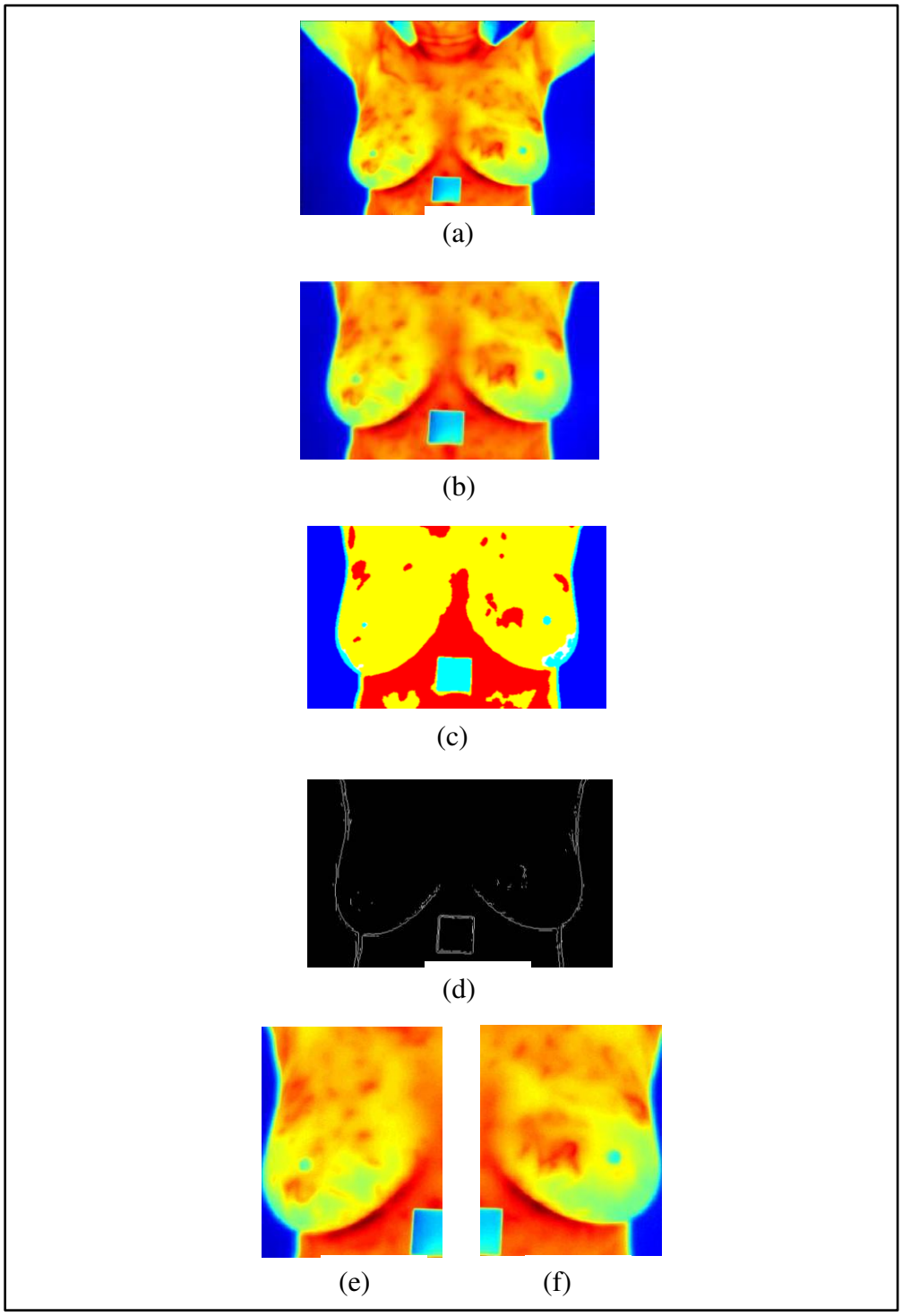

Figure 5.4 Segmentation steps (a) original thermal image, (b) profile projection, (c) region of interest, (d) image segmentation, (e) left breast vertical profile projection, (f) right breast vertical profile projection

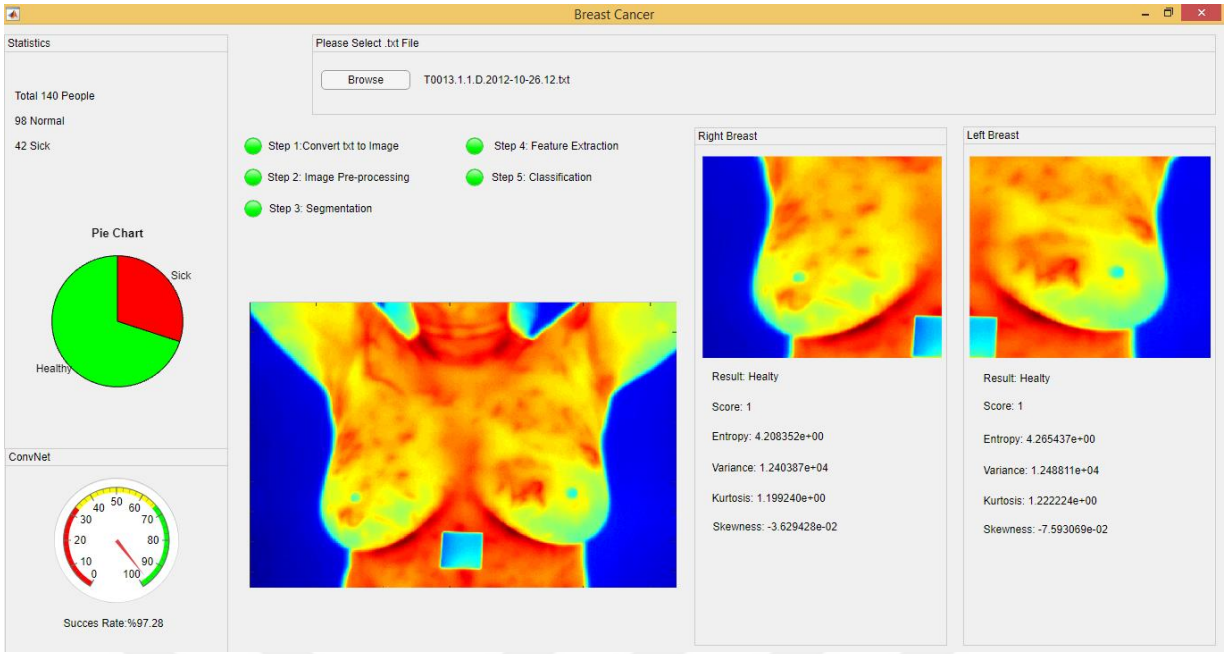

Figure 5.5 GUI of application after applying sample

Step 4: Feature extraction

The feature extraction helps to scale up the process and to create more sensible datasets that have bigger and superior images. Unlike other feature extraction methods, the CNN can directly extract the properties of the images in the input data set. This form of feature extraction allows for the extraction of features on various parts of the image using convolution. This is doable because natural images typically have the feature of being motionless suggesting that the quantification and features of one side of the image are similar to any other side.

Step 5: Classification

The classification step employed the confusion matrix to provide a general overview of how the classifier has managed to undertake the classification process. The overview is typically on how single classes have performed. The matrix was filled with test set of pre-determined tags that were considered accurate. The data was passed through the CNN classifier and predictions were noted in Table 5.2. The training progress of CNN classifier is shown in Figure 5.6.

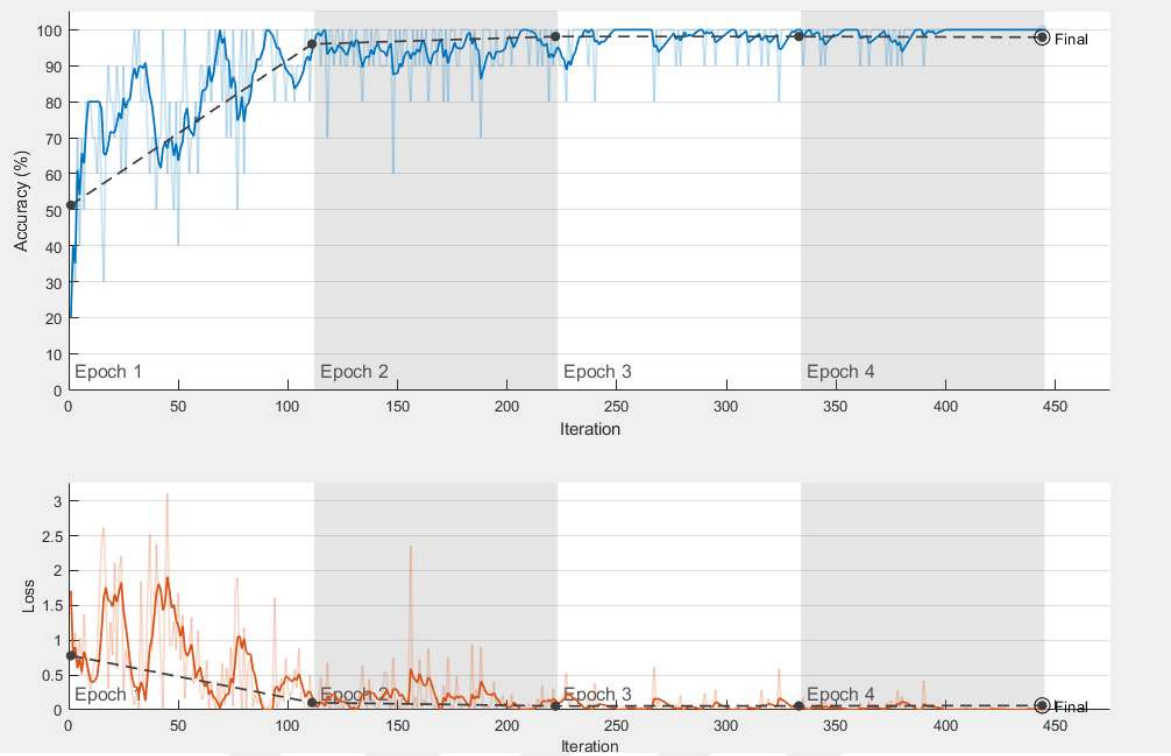

Figure 5.6 Training progress of CNN classifier

5.4 Discussion

The existence of several feature sets and classifier models makes it problematic to envisage a breast abnormality. Thus, selecting the most proficient model to handle breast thermograms is tricky. This knowledge informed the decision to select the CNN to handle the feature selection challenge as well as the classification. For example, the Support Vector Machine (SVM) classifier together with a combination of statistical measures did much of the work. The method required a manual feature extraction, which needed the dedication of the system developer. In contrast, the CNN handles automatic feature selection in a vigorous manner. It became important to compare the obtained results in this study with the other studies that were used in a similar breast database. The comparison was also done because our work was the first one that applied the CNN to automatic classification of breast thermograms [112] – [117]. Table 5.3 summarizes both our study and some other studies performed in the literature. Based on this table, our work overperforms and more images than the rest of the studies compared.

Three studies that were compared used different features and classifiers. Five of the studies used statistical features, but employed different classifiers namely SVM, RBF, artificial neural network, genetic algorithm and linear SVM. One of the studies applied the

Gabor coefficient as feature while the SVM and RBF were used as classifiers. On the other hand another study used several features with feature selection and the Bayes Nets classifier. In our case, we used the CNN features and CNN classifiers. Another point that should be considered is that some of the studies given in Table 5.3.

Table 5.4 Comparison of different breast cancer detection methods

Researcher	Features / Classifiers	Number of Images	Accuracy
SILVA ET AL [112]	Several using Feature Selection / Bayes Nets	80 patients with 20 images each (40 healthy and 40 non-healthy)	100%
MATHEUS[117]	CNN Features / Convolutional Neural Networks	137 patients with 20 images each (95 healthy and 95 non-healthy)	95%
Our Work	CNN Features / Convolutional Neural Networks optimized by Bayes algorithm	140 patients (98 healthy and 32 non-healthy)	%98.95

The accuracy of non-optimized CNN was 97.91%. After we optimized CNN parameters by using Bayes optimization algorithm, we obtained much better results with 98.95% testing accuracy. The confusion matrix of the testing of the optimized CNN is illustrated in figure 5.7

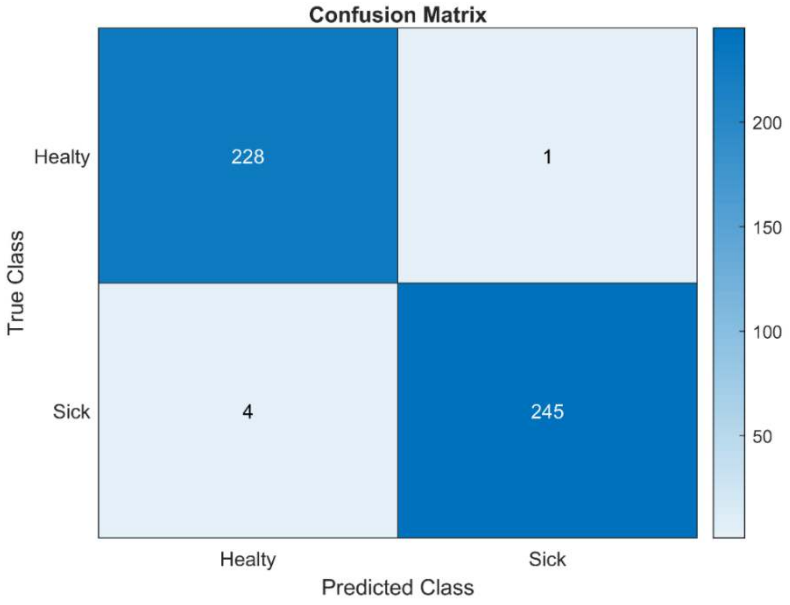

Figure 5.7 Confusion matrix for optimized CNN.

The final CNN parameters which are obtained from Bayes optimization algorithm are shown in Table 5.4 . The minimum objective function and the number of function evaluation curve is given in figure 5.8

Table 5.4. The best CNN parameters obtained from Bayes optimization

Parameters	**Best values**
Mini-batch size	116
Network depth	2
Initial learning rate	0.029128
Momentum	0.89495
L2-regularization	7.6412e-07

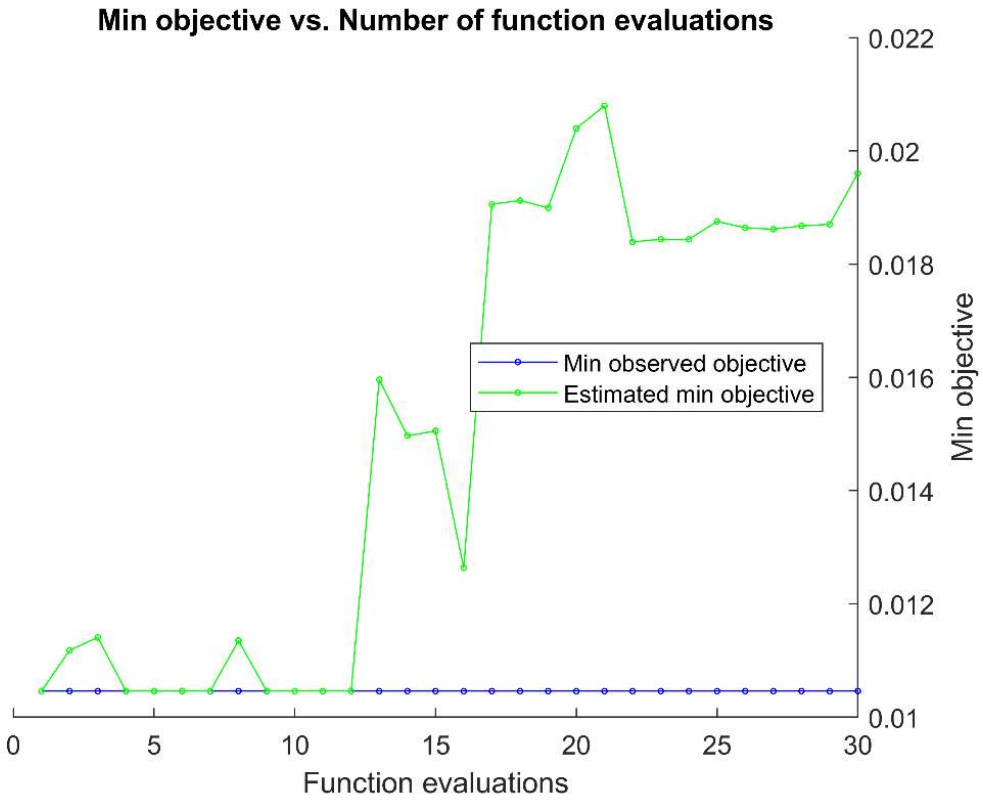

Figure 5.8 Minimum objective function vs. number of function evaluation.

Table 5.4. Performance parameters of CNN

Validation error, E_{val}	0.0105
Standard test error, E_{std}	0.0105
95% confidence interval, E_{95CI}	[0.0013 0.01960]
Observed objective function value	0.01046
Estimated objective function value	0.019604
Function evaluation time (sec)	229.9511

In figure 5.9 randomly selected and tested breast images are illustrated.

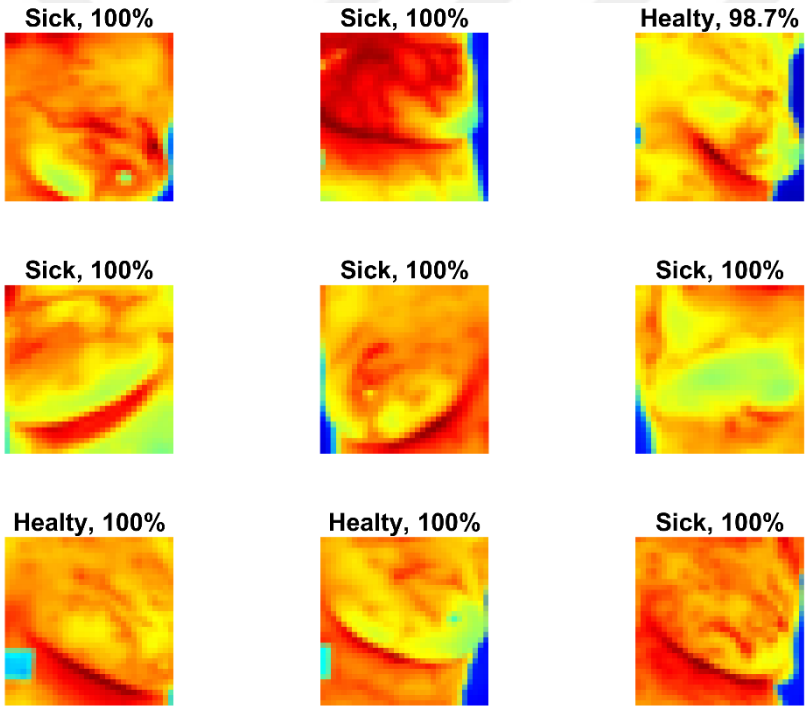

Figure 5.8 Randomly selected and tested breast images.

6. CONCLUSION

The early detection of breast cancer can help avert the spread of the disease, which can turn fatal. Most women overlook the need for frequent breast cancer screening due to financial reasons, lack of convenience and discomfort with traditional exams such as the mammograms. Thermography offers solutions to some of these challenges because it is affordable, easy to apply and causes minimal distress to the patient because it is non-invasive and painless. Thermography is an advanced alternative to mammography, which is known to cause pain to some degree and an ineffective means of detection. If thermographic application can reach a point where it can identify cells without tumors, then the need for a mammogram test would be eliminated. Additionally, if the thermogram can indicate a possible tumor, then a mammogram can be conducted as the next step to confirm or reject the claim. Such an option may induce more women to get examined.

The thesis study employed a methodology containing 5 processes, namely data acquisition, image processing, segmentation, feature extraction and classification. All these processes basically entailed obtaining the images through an infrared camera used to convert the infrared radiation; finding the orientation regarding the thermal image, increasing the quality of the image and eliminating the sound; and the use of thousands of neurons to extract features of the image to be used for classification. These processes consist of the Convolution Neural Network (CNN) for thermographic breast cancer screening.

According to our results, thermography is a good alternative to other breast cancer detection procedures because it provides better localization of the cancer/tumor cells through differences in temperature given that such cells undergo angiogenesis. The blood perfusion rate in the subcutaneous tissue can vary as much as one degree depending on the size and location of the tumor. This difference is enough to create a false positive upon analysis or miss a tumor all together—an obvious problem in the procedure. The validation accuracy of training was 97.91% .After we optimized the CNN parameters by Bayes optimization algorithm, we obtained better results with 98.95% testing accuracy.

Future research can be undertaken to analyze the thermography approach ability to detect cancer level. Currently, the thermography approach is known to rely on the metabolic activities of the cancerous cells that generate heat in the affected breast mass regions. But questions abound what other capabilities can the deep-learning application that relies on infrared thermal imaging yield. Another area of thermography that needs further research is

the application of the Dynamic Infrared Thermography (DIRT) that is quite advanced which provides a non-invasive, painless assessment without radiation risk. The application of various models such as the CNN, statistical texture features and Gabor coefficients classifiers together with the DIRT can be evaluated to see their breast cancer detection performance.

Thus, further research can explore the methodologies of various models and the type of data used to establish a more linear and balanced data collection and application technique. This is important for reproducing the same results and ensuring the study is reliable, valid and replicable.

Thermography and models such as the CNN can only provide as much information based on their capacity. Typically, doctors will consider more data and information. Hence, future research can explore areas where knowledge can be obtained and a framework that guides deep-learning applications drawn from this knowledge.

REFERENCES

[1] **WHO** "Media Center, Cancer," http://www.who.int/mediacentre/factsheets/fs297/en/ (Accessed on March 1, 2018)

[2] **Chakraborty, S., & Rahman, T.** (2012). The difficulties in cancer treatment. ecancermedicalscience, 6.

[3] **National Cancer Institute,** "What is cancer?", 2015. https://www.cancer.gov/about-cancer/understanding/what-is-cancer (Accessed on March 1, 2018)

[4] **Grisham J**, "What Is Metastatic Cancer? Answers to Six Common Questions. Memorial Sloan Kettering Cancer Center. 2017. https://www.mskcc.org/blog/what-metastatic-cancer-answers-six-common-questions (Accessed on March 2, 2018)

[5] **Roake, C. M., & Artandi, S. E**. (2017). Control of cellular aging, tissue function, and cancer by p53 downstream of telomeres. Cold Spring Harbor perspectives in medicine, 7(5).

[6] **Nixon, N. A., Khan, O. F., Imam, H., Tang, P. A., Monzon, J., Li, H., ... & Tam, V. C**. (2017). Drug development for breast, colorectal, and non–small cell lung cancers from 1979 to 2014. Cancer, 123(23), 4672-4679.

[7] **Cancer Research UK,** "Cancer and Age," http://www.cancerresearchuk.org/about-cancer/causes-of-cancer/age-and-cancer (Accessed on March 4, 2018)

[8] **American Cancer Society,** "About breast Cancer," https://www.cancer.org/cancer/breast-cancer/about/how-common-is-breast-cancer.html (Accessed on March 5, 2018)

[9] **National Breast Cancer Foundation. Causes of Breast Cancer.** http://www.nationalbreastcancer.org/causes-of-breast-cancer (Accessed on March 5, 2018)

[10] **Christian Nordqvist, Medical News Today.** What you need to know about breast cancer. https://www.medicalnewstoday.com/articles/37136.php, 2017. (Accessed on March 5, 2018)

[11] **National Breast Cancer Foundation,** "About breast cancer: stages 0 & 1," http://www.nationalbreastcancer.org/breast-cancer-stage-0-and-stage-1 (Accessed on March 5, 2018)

[12] **Kandlikar S. G., Perez-Raya, I. Raghupathi P. A.,,** et al. (2017) "Infrared imaging technology for breast cancer detection–Current status, protocols and new directions," International Journal of Heat and Mass Transfer, vol. 108, pp. 2303-2320.

[13] **Borchartt, T. B., Conci, A., Lima, R. C., Resmini, R., & Sanchez, A.** (2013). Breast thermography from an image processing viewpoint: A survey. Signal Processing, 93(10), 2785-2803.

[14] **Agide, F. D., Sadeghi, R., Garmaroudi, G., & Tigabu, B. M**. (2018). A systematic review of health promotion interventions to increase breast cancer screening uptake: from the last 12 years. European journal of public health.

[15] **National Breast Cancer Foundation.** Breast anatomy and how breast cancer starts. [Online]. Available at https://nbcf.org.au/about-national-breast-cancer-foundation/about-breast-cancer/what-you-need-to-know/breast-anatomy-cancer-starts/ (Accessed on March 13, 2018)

[16] The hearty soul. How to Do a Self Breast Exam At Home: Signs of Breast Cancer. [Online]. Available at https://theheartysoul.com/breast-cancer-self-exam/ (Accessed on March 13, 2018)

[17] **Breast Cancer.** Breast Physical Exam. [Online]. Available at http://www.breastcancer.org/symptoms/testing/types/physical_exam (Accessed on March 13, 2018)

[18] **National Breast Cancer Foundation.** Clinical Breast Exam. [Online]. Available at http://www.nationalbreastcancer.org/clinical-breast-exam (Accessed on March 13, 2018)

[19] **Koay, J, Phaik S**. Quantitative analysis of infrared images for early breast cancer detection. Carleton University, 2004.

[20] **U.S. National Library of Medicine and National Institute of Health**, MedlinePlus Medical Encyclopedia. [Online]. Available at https://medlineplus.gov/ency/article/003380.htm (Accessed on March 14, 2018)

[21] **U.S. Preventive Task Force.** Final Recommendation Statement. Breast Cancer: Screening. [Online]. Available at https://www.uspreventiveservicestaskforce.org/Page/Document/RecommendationStatementFinal/breast-cancer-screening1 (Accessed on March 15, 2018)

[22] **Hirsch, B. R., & Lyman, G. H.** (2011). Breast cancer screening with mammography. Current oncology reports, 13(1), 63-70.

[23] **Bitler, M. P., & Carpenter, C. S.** (2016). Health insurance mandates, mammography, and breast cancer diagnoses. American Economic Journal: Economic Policy, 8(3), 39-68.

[24] **Radiology Information For Patients.** Breast Cancert Screening. [Online] Available at https://www.radiologyinfo.org/en/info.cfm?pg=screening-breast (Accessed on March 14, 2018)

[25] **Schueler, K. M., Chu, P. W., & Smith-Bindman, R**. (2008). Factors associated with mammography utilization: a systematic quantitative review of the literature. Journal of women's health, 17(9), 1477-1498.

[26] **Ohuchi, N,** (2016) "Sensitivity and specificity of mammography and adjunctive ultrasonography to screen for breast cancer in the Japan Strategic Anti-cancer Randomized Trial (J-START): a randomised controlled trial." The Lancet 387.10016: 341-348.

[27] **Banks, E., et al** (2004). "Influence of personal characteristics of individual women on sensitivity and specificity of mammography in the Million Women Study: cohort study." Bmj 329.7464: 477.

[28] **Kemp J, K, et al.** (2015) "Comparing sensitivity and specificity of screening mammography in the U nited S tates and D enmark." International journal of cancer 137.9: 2198-2207.

[29] **Siu, A.L.** (2016) "Screening for breast cancer: US Preventive Services Task Force recommendation statement." Annals of internal medicine 164.4: 279-296.

[30] **Heywang-K, Sylvia H., Astrid H, and Stefan S**. (2011) "Advantages and disadvantages of mammography screening." Breast care 6.3: 199-207.

[31] **Elmore, Joann G., et al.** (2005)"Screening for breast cancer." Jama 293.10: 1245-1256.

[32] McLaughlin, Sarah A. "Current Controversies Surrounding MRI Screening for Breast Cancer." American Journal of Hematology/Oncology® 11.8 (2015).

[33] **Breast Cancer.** Breast MRI for Screening. [Online]. Available at http://www.breastcancer.org/symptoms/testing/types/mri/screening (Accessed on March 17, 2018)

[34] **Heller, SL., and Linda M.** (2016) "Breast MRI Screening: Benefits and Limitations." Current Breast Cancer Reports 8, no. 4: 248-257.

[35] **Shah, TA, and Shaista SG.** (2017) "Breast cancer screening programs: Review of merits, demerits, and recent recommendations practiced across the world." Journal of Microscopy and Ultrastructure 5, no. 2: 59-69.

[36] **Geisel, JL., and Liane E. P.** (2014) "Breast Tomosynthesis: a Replacement or an Adjunct to Conventional Diagnostic Mammography?." Current Breast Cancer Reports 6, no. 2: 132-137.

[37] **Brem, RF., Megan J. L, Jennifer L, and Jessica T.** (2015) "Screening breast ultrasound: past, present, and future." American Journal of Roentgenology 204, no. 2: 234-240.

[38] **Chang, JM, Hye RK, and Woo KM.** (2015) "Radiologist-performed hand-held ultrasound screening at average risk of breast cancer: results from a single health screening center." Acta Radiologica 56, no. 6: 652-658.

[39] **Usamentiaga R., Venegas, P. Gueredíaga, J., et al.,** (2014) "Infrared thermography for temperature measurement and non-destructive testing," Sensors, vol. 14, pp. 12305-12348

[40] **Tan J. H., Ng E. Y. K., Acharya U. R., and Chee C.,** (2009) "Infrared thermography on ocular surface temperature: a review," Infrared physics & technology, vol. 52, pp. 97-108, 2009.

[41] **Cowley, G**. "Comparing mammography and thermography," Medical News Today. Available at https://www.medicalnewstoday.com/articles/316632.php (Accessed on March 22, 2018)

[42] **Renkielska, A, Antoni N, Mariusz Ka, Marek K.. et al** (2005 "Static thermography revisited—an adjunct method for determining the depth of the burn injury." Burns 31, no. 6: 768-775.

[43] **Veterinary Thermal Image LTD.** History of Animal Thermography. [Online]. Available at: http://www.veterinary-thermal-imaging.com/thermography/history-of-animal-thermography (Accessed on March 23, 2018)

[44] **Clinical Thermography Associates.** Historical Overview of Clinical Thermology. [Online]. Available at: http://clinicalthermography.com/history/ (Accessed on March 23, 2018)

[45] **Ceramic**. Fundamentals of IR. [Online]. Available at: https://www.ceramicx.com/infrared-heat/ (Accessed on Mach 25, 2018)

[46] **Encyclopedia Britannica.** Stefan-Boltzmann law. [Online]. Available at: https://www.britannica.com/science/Stefan-Boltzmann-law (Accessed on March 23, 2018)

[47] **Riedl, MJ.** 2001. Optical design fundamentals for infrared systems. Vol. 48. SPIE press.

[48] **Optotherm Thermal Imaging.** Emissivity in the Infrared: Planck's Blackbody Distribution Law. [Online]. Available at: https://www.optotherm.com/infrared-planck.htm (Accessed on March 24, 2018)

[49] **Medline Plus**. Body temperature norms. [Online]. https://medlineplus.gov/ency/article/001982.htm (Accessed on March 24, 2018)

[50] **Díaz, M, and Daniel E. B.** (2010) "Thermoregulation: physiological and clinical considerations during sedation and general anesthesia." Anesthesia progress 57, no. 1: 25-33.

[51] **Abdelhameed , Shaimaa, and Hesham** (2018) "reast Cancer Detection and ClassificationUsing Thermography: A Review." The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2018)

[52] **Bernard, V, Erik S, V. M, and A. Bourek.** "Infrared camera assessment of skin surface temperature–effect of emissivity." Physica Medica: European Journal of Medical Physics 29, no. 6 (2013): 583-591.

[53] **Ng E. Y. K.,** (2009) "A review of thermography as promising non-invasive detection modality for breast tumor," Int. J. Therm. Sci., vol. 48, no. 5, pp. 849–859.

[54] **Breast Thermography,** "How is breast thermography is performed?". [Online]. http://www.breastthermography.com/breast_thermography_proc.htm (Accessed on March 28, 2018)

[55] **Euhus D., Di Carlo P. A. and Khouri, N. F**. (2015) "Breast cancer screening," Surgical Clinics, vol. 95, pp. 991-1011, 2015.

[56] **International Products & Services srl.** Cellulite Contact Thermography. [Online]. Available at: https://ips-aesthetics.it/cellulite-contact-thermography/?lang=en (Accessed on March 28, 2018)

[57] **Dam, JS, Peter TL, and Christian P.** (2012) "Room-temperature mid-infrared single-photon spectral imaging." Nature photonics 6, no. 11: 788.

[58] **Lawson, R.** (1956) "Implications of surface temperatures in the diagnosis of breast cancer." Canadian Medical Association Journal 75, no. 4: 309.

[59] **Vogler, William R., and Ralph Waldo Powell**. (1959) "A clinical evaluation of thermography and heptyl aldehyde in breast cancer detection." Cancer research 19, no. 2: 207-209.

[60] **Strax, P.** (1969) "Thermography in mass screening for breast cancer." Annals of the New York Academy of Sciences 121, no. 1: 282-282.

[61] **Hoffman, RL.** "Thermography in the detection of breast malignancy." American Journal of Obstetrics & Gynecology 98, no. 5 (1967): 681-686.

[62] **Hitchcock, CR., David F. Hickok, John S, Tracy M, and Richard C. B.** 1968 "Thermography in mass screening for occult breast cancer." JAMA 204, no. 6 (1968): 419-422.

[63] **Karpman, HL**. (1968) "Screening breast cancer by thermography." JAMA 206, no. 1 (1968): 136-136.

[64] **Lilienfeld, A.M., Barnes, J. M. Barnes, R. B. Brasfield, R., et al.** (1969) "An evaluation of thermography in the detection of breast cancer. A cooperative pilot study." Cancer 24, no. 6 (1969): 1206-1211.

[65] **Nathan, B. E., Galasko C. S. B., and Pallett. J. E.** (1970) "Thermography in breast cancer." BJS 57, no. 7: 518-520.

[66] **Feig, SA., Gary S. Shaber, Gordon F. et al**. (1977)"Thermography, mammography, and clinical examination in breast cancer screening: review of 16,000 studies." Radiology 122, no. 1 (1977): 123-127.

[67] Moskowitz, M, John M, Peter G, Alfonso Z, and David M. (1976) "Lack of efficacy of thermography as a screening tool for minimal and stage I breast cancer." New England Journal of Medicine 295, no. 5: 249-252.

[68] Threatt, B, Joseph M. Norbeck, NS. et al. (1980) Annals of the New York Academy of Sciences 335, no. 1: 501-519.

[69] **Gautherie, M, Charles M G.** (1980) "Breast thermography and cancer risk prediction." Cancer 45, no. 1 (1980): 51-56.

[70] **Sterns, EE., Arthur C. Curtis, SM, and John R H.** (1982) "Thermography in breast diagnosis." Cancer 50, no. 2: 323-325.

[71] **Gautherie, M.** (1983) "Thermobiological assessment of benign and malignant breast diseases." American journal of obstetrics and gynecology 147, no. 8 (1983): 861-869.

[72] **Williams, KL, Barbara HP, Pamela AJ, et al.** (1990) "Thermography in screening for breast cancer." Journal of Epidemiology & Community Health 44, no. 2 (1990): 112-113.

[73] **Foster, KR.** "Thermographic detection of breast cancer." IEEE Engineering in medicine and biology Magazine 17, no. 6 (1998): 10-14.

[74] **Ng, Eddie YK, and N. M. Sudharsan**. (2007)"Computer simulation in conjunction with medical thermography as an adjunct tool for early detection of breast cancer." BMC cancer 4, no. 1 (2004): 17.

[75] **Ng, EY-K., S. C. Fok, Y. C. Peh, F. C. Ng, and L. S. J. Sim.** (2002) "Computerized detection of breast cancer with artificial intelligence and thermograms." Journal of medical engineering & technology 26, no. 4: 152-157.

[76] **Koay, J., Herry C., and Frize. M.** (2004) "Analysis of breast thermography with an artificial neural network." In Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE, vol. 1, pp. 1159-1162. IEEE,

[77] **Jakubowska, T., Wiecek, B. Wysocki, M. and Drews-Peszynski. C.** (2003) "Thermal signatures for breast cancer screening comparative study." In Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE, vol. 2, pp. 1117-1120. IEEE.

[78] **Ng, E. Y. K., and E. C. Kee.** (2008) "Advanced integrated technique in breast cancer thermography." Journal of Medical Engineering & Technology 32, no. 2: 103-114.

[79] **Tang, X, Haishu D, Yun-E. Y, and Qing W.** (2008) "Morphological measurement of localized temperature increase amplitudes in breast infrared thermograms and its clinical application." Biomedical Signal Processing and Control 3, no. 4 (2008): 312-318.

[80] **Kapoor, P, and Prasad. S. V..** (2010) "Image processing for early diagnosis of breast cancer using infrared images." In Computer and Automation Engineering (ICCAE), 2010 The 2nd International Conference on, vol. 3, pp. 564-566. IEEE.

[81] **Umadevi, V., Raghavan, S. V. and Sandeep J** (2010). "Interpreter for breast thermogram characterization." In Biomedical Engineering and Sciences (IECBES), 2010 IEEE EMBS Conference on, pp. 150-154. IEEE.

[82] **Umadevi, V., Raghavan, S. V. and Jaipurkar. S** (2011) "Framework for estimating tumour parameters using thermal imaging." The Indian journal of medical research 134, no. 5: 725.

[83] **Kontos, M., Wilson R., and Fentiman. I.** (2011) "Digital infrared thermal imaging (DITI) of breast lesions: sensitivity and specificity of detection of primary breast cancers." Clinical radiology 66, no. 6: 536-539.

[84] **Amri, A, Ayda S, and Pulko. S.** (2011) "Thermal analysis of a three-dimensional breast model with embedded tumour using the transmission line matrix (TLM) method." Computers in Biology and Medicine 41, no. 2: 76-86.

[85] **Ann Arbor Thermography,** http://aathermography.com/ (Accessed on 13 May)

[86] **Etehadtavakol, Mahnaz, E. Y. K. Ng, Vinod C, and Hossien R.** (2013) "Separable and non-separable discrete wavelet transform based texture features and image classification of breast thermograms." Infrared Physics & Technology 61: 274-286.

[87] **Acharya, U. Rajendra, Eddie Yin-Kwee Ng,** et al (2012) "Thermography based breast cancer detection using texture features and support vector machine." Journal of medical systems 36, no. 3: 1503-1510.

[88] **Nicandro, Cruz-Ramírez, Mezura-Montes Efrén, et al** (2013) "Evaluation of the diagnostic power of thermography in breast cancer using bayesian network classifiers." Computational and mathematical methods in medicine 2013.

[89] **Gerasimova, E, Benjamin A, Stephane G.R,** et al. (2014)"Wavelet-based multifractal analysis of dynamic infrared thermograms to assist in early breast cancer diagnosis." Frontiers in physiology 5: 176.

[90] http://perso.ens-lyon.fr/benjamin.audit/LastWave/ (Accessed on 15 May)

[91] **Gogoi, UR, Mrinal KB, Debotosh B, et al**. (2016) "A study and analysis of hybrid intelligent techniques for breast cancer detection using breast thermograms." In Hybrid Soft Computing Approaches, pp. 329-359. Springer India.

[92] **Lashkari, AE, Fatemeh P, and Mohammad F.** (2016) "Full intelligent cancer classification of thermal breast images to assist physician in clinical diagnostic applications." Journal of medical signals and sensors 6, no. 1: 12.

[93] Ghayoumi Z, Hossein, AM, Iman AK, and Javad H. (2017) "Clustering and screening for breast cancer on thermal images using a combination of SOM and MLP." Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization 5, no. 1: 68-76.

[94] Santana, M. A, Jessiane MS, Pereira, F. et al. (2018) "Breast cancer diagnosis based on mammary thermography and extreme learning machines." Research on Biomedical Engineering AHEAD: 0-0.

[95] Silva, L. F., Saade, DC. M., Sequeiros-Olivera, G. O., Silva, et al. (2017) "A New Database for Breast Research with Infrared Image", Journal of Medical Imaging and Health Informatics, Volume 4, Number 1, March, pp. 92-100.

[96] **Watmough DJ.** (1976) The role of thermographic imaging in breast screening, discussion by CR Hill. In Medical Images: Formation, Perception and Measurement, 7th LH Gray Conference: Medical Images, pp. 142-58, 1976.

[97] Keyserlingk JR, Ahlgren PD, Yu E, Belliveau N and Yassa M. (2000) "Functional infrared imaging of the breast", IEEE Engineering in Medicine and Biology, 19(3), pp. 30-41.

[98] **Gautherie M.,** Atlas of breast thermography with specific guidelines for examination and interpretation. Milan, Italy: PAPUSA. 1989.

[99] **Gonzalez R. C. and Woods, R. E.** (2002) Digital Image Processing.Second Edition, Prentice Hall, New Jersy, 2002.

[100] Transactions on Geoscience and Remote Sensing, (1995) Vol. 33, No. 2, pp. 293- 304,.

[101] **Sutton and Bezdek (**2013) "Breast Cancer Detection Using Image Processing Techniques" International Journal of Computer Science 2013.

[102] **Berndt M, Joachim R, Michael T. S,** (1995) Neural Networks: An Introduction (Physics of Neural Networks) 2nd Edition, Springer-Verlag.

[103] **Jemal, A. Siegel, R.. Ward, E Hao, Y. et al.** (2009), Cancer statistics, CA Cancer J Clin., Vol.59, pp. 225-249, 2009.

[104] **Madjar H..** (2010) Role of Breast Ultrasound for the Detection and Differentiation of Breast Lesions.Breast Care 2010;5:109-114

[105] **Chang R. F. Chen C. J. Ho M. F. Chen D. R. et al.** (2004) Breast ultrasound image classification using fractal analysis. Proceedings of the Fourth IEEE Symposium on Bioinformatics and Bioengineering, 2004.

[106] **Guo Y., Cheng H., Huang J., Tian J., Zhao W.,** et al. Breast ultrasound image enhancement using fuzzy logic, Ultrasoundin Medicine & Biology, Volume 32, Issue 2, Pages 237-247, Feb 2006.

[107] **Chen D., Chang R., Kuo W., Chen M. et al.** (2002) Diagnosis of breast tumors with sonographic texture analysis using wavelet transform and neural networks, Ultrasound in Medicine & Biology Volume 28, Issue 10, October 2002, Pages 1301-1310.

[108] **Monica J** (2014) "An Efficient Image Processing Methods for Mammogram Breast Cancer Detection" Journal of Theoretical and Applied Information Technology Vol. 69, November 2014.

[109] **Mohamed, N.A.E.** (2015) "Breast Cancer Risk Detection Using Digital Infrared Thermal Images," vol. 1, no. 2, pp. 185–194.

[110] **Kamath, S**. (2015) "Segmentation of Breast Thermogram Images for the Detection of Breast Cancer – A Projection Profile Approach," vol. 3, no. 1, pp. 47–51, 2015.

[111] **Lessa V. Marengoni, M.** (2016) "Applying artificial neural network for the classification of breast cancer using infrared thermographic images," Computer Vision and Graphics, vol. 9972, pp. 429–438, 09 2016.

[112] **Silva, L. F. Santos AAS., Bravo RS., Silva A.C.,** et al. Hybrid analysis for indicating patients with breast cancer using temperature time series," Computer Methods and Programs in Biomedicine, vol. 130, pp. 142 – 153, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0169260715300249

[113] **Gaber T, Ismail G, Anter A, Soliman M.,et al**. (2013)"Thermogram Breast Cancer Prediction Approach based on Neutrosophic Sets and Fuzzy C-Means Algorithm," Dec. 2013. [Online]. Available: https://doi.org/10.5281/zenodo.34913

[114] **Sathish D., Kamath S., Prasad K., Kadavigere R., and Martis, R.** (2017) "Asymmetry analysis of breast thermograms using automated segmentation and texture features," Signal, Image and Video Processing, vol. 11, no. 4, pp. 745–752, 5

[115] **Borchartt T. B. Resmini R. Motta, L.S. et al.** (2012) "Combining approaches for early diagnosis of breast diseases using thermal imaging," Int. J. Innov. Comput. Appl., vol. 4, no. 3/4, pp. 163–183, Oct. 2012. [Online]. Available: http://dx.doi.org/10.1504/IJICA.2012.050054

[116] **Gogoi U.R., Bhowmik M. K., Ghosh, A. K. et al.** (2017) "Discriminative feature selection for breast abnormality detection and accurate classification of thermograms," pp. 39–44.

[117] **Baffa M. F. O. and Lattari, L. G.** (2018) "Convolutional Neural Networks for Static and Dynamic Breast Infrared Imaging Classification. "October 2018

CURRICULUM VITAE

Hushang Jawzal

Email: Hoshankseny@yahoo.com

phone: +90 539 896 6078

+964 750 425 0683

Education: Bachelor of Science, University of Duhok/Faculty of Science, Duhok /Kurdistan Region-Iraq, 2009-2013.

Work experiences:

- Assistant Programmer at Duhok Polytechnic University/Zakho Technical Institute, department of Information Technology, September 2013 - present.
- Assistant Programmer at University of Zakho, department of computer science , September 2018 - present.

Awards:

- Certificate of participating in the **International Cyber Security Workshop Certificate Program**, Gelişim University/Istanbul-Turkey, on May 23-27, 2016.

Membership:

- Member in Kurdistan Computerist Syndicate
- Kurdistan Photographs Society Duhok Branch

Languages:

- **Kurdish, Persian**, **English**, **Arabic, and Turkish.**