

**THERMOGRAPHY BASED DEEP LEARNING MODELS  
FOR EARLY BREAST CANCER DETECTION**

**BY**

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A thesis submitted in fulfillment of the requirement for the  
degree of Doctor of Philosophy in Engineering

**Kulliyyah of Engineering  
International Islamic University Malaysia**

**JULY 2022**

## ABSTRACT


Breast cancer is one of the most common causes of death in women around the world. Researchers are actively seeking to develop early detection methods for breast cancer. Several treatment technologies contributed to the reduction in mortality rate from this disease, but early detection contributes the most to preventing disease spread, breast amputation and death. The problem, however, lies in the accuracy of early detection methods. Thermography is a promising technology for early diagnosis where thermal cameras employed are of high resolution and sensitivity. The combination of Artificial Intelligence (AI) with thermal images is an effective tool to detect early-stage breast cancer and is foreseen to provide impressive predictability levels. This thesis reviewed systematically the state-of-the-art works employing thermography with AI, highlighted their contributions and drawbacks, and proposed open issues for research. Furthermore, the thesis has applied and investigated the behaviour of different recently introduced deep learning methods for identifying breast disorders and further proposed a modified method to suit the thesis goals. Inception MV4 achieved 7% faster classification response time compared to V4. The use of MV4 model is found to contribute to saving energy consumed and fluidity in arithmetic operations for the graphic processor. The results also indicate that increasing the number of layers may not necessarily be useful in improving the performance. Furthermore, the thesis develops a numerical simulation model to study the thermophysical properties of breast using COMSOL software. Topical Site-Cooling on breast surface area was found to contribute to increasing thermal contrast in the simulated thermal images. The highest variations in skin temperatures between breasts with cancer and without cancers can scope from 0.274 to 2.58 C. Finally, the thesis introduced an application design in a graphical user interface and linked it with the AirDroid application to send thermal images from the smartphone to the cloud and then retrieve back the diagnostic result from the cloud to the smartphone app. The suggested framework novelty lies in its design to generate high-quality input video of thermal imagery of the patients' breast region in real time, facilitating more accurate early breast cancer detection. The suggested structure was modelled in MATLAB 2019 and was compatible with majority of standard Desktop with thermal camera installed. It takes real time video stream of high-quality thermal imagery as input and produces defined video files with a binary classification characterizing normal or abnormal breasts with a recommended action for the patient. This is followed by a proposed thermal image acquisition procedure with set of recommendations for the development of a mobile app-based dataset. The thesis concludes that early breast cancer detection using smart apps is a valuable and reliable complementary tool for radiologists to aid the diagnosis process and reduce mortality rates.

## خلاصة البحث

يعد سرطان الثدي أحد أكثر مسببات الوفاة شيوعاً بين النساء حول العالم. يسعى الباحثون بنشاط لتطوير طرق الكشف المبكر عن سرطان الثدي. ولقد ساهمت العديد من تقنيات العلاج في خفض معدل الوفيات من هذا المرض لكن الاكتشاف المبكر يساهم بشكل أكبر في منع انتشار المرض الذي يؤدي الى بتر الثدي والوفاة. لكن المشكلة تكمن في دقة طرق الكشف المبكر. يعد التصوير الحراري تقنية واعدة للتشخيص المبكر حيث تكون الكاميرات الحرارية المستخدمة عالية الدقة والحساسية. بالإضافة الى ان الجمع بين الذكاء الاصطناعي (AI) والصور الحرارية أداة فعالة للكشف عن سرطان الثدي في مراحله المبكرة ومن المتوقع أن يوفر مستويات رائعة من القدرة على التنبؤ. استعرضت هذه الأطروحة بشكل منهجي أحدث الأعمال التي تستخدم التصوير الحراري مع الذكاء الاصطناعي وسلطت الضوء على مساهماتها وعيوبها واقترحت قضايا مفتوحة للبحث. علاوة على ذلك قامت الأطروحة بتطبيق واستقصاء سلوك طرق التعلم العميق المختلفة التي تم تقديمها مؤخراً لتحديد اضطرابات الثدي واقترحت أيضاً طريقة معدلة لتناسب أهداف الرسالة. حقق Inception MV4 استجابة عالية وسرعة في التصنيف بنسبة 7٪ مقارنةً بـ Inception V4. تشير النتائج الى ان MV4 تساهم بشكل كبير في توفير الطاقة المستهلكة وانسيابية في العمليات الحسابية لدى وحدة معالج الرسوم. تشير النتائج أيضاً إلى أن زيادة عدد الطبقات قد لا يكون بالضرورة مفيداً في تحسين الأداء. علاوة على ذلك تقوم الأطروحة بتطوير نموذج محاكاة عددي لدراسة الخصائص الفيزيائية الحرارية للثدي باستخدام برنامج COMSOL. تشير النتائج الى ان استخدام جل التبريد على سطح الثدي يساهم في زيادة التباين الحراري في الصور الحرارية. كما ان الفارق في درجات الحرارة بين الثدي السليم والمصاب قد تصل من 0.274 إلى 2.58 درجة مئوية. وفي الختام فان هذه الأطروحة قدمت تصميم واجهة مستخدم رسومية وربطته بتطبيق AirDroid لإرسال الصور الحرارية من الهاتف الذكي إلى الحوسبة السحابية ثم إرجاع نتيجة التشخيص من السحابة إلى تطبيق الهاتف الذكي. بالإضافة الى انه تم تطوير التطبيق للكشف عن سرطان الثدي في الوقت الفعلي و تم تصميم الهيكل المقترح في MATLAB 2019 وكان متوافقاً مع غالبية أجهزة سطح المكتب القياسية المزودة بكاميرا حرارية مثبتة. أخذ مقاطع الفيديو في الوقت الحقيقي للصور الحرارية عالية الجودة كمدخلات و ينتج ملفات فيديو محددة بتصنيف ثنائي يميز الثدي الطبيعي أو غير الطبيعي مع الإجراء الموصى به للمريض. وبلي ذلك إجراء مقترح للحصول على الصور الحرارية مع مجموعة من التوصيات لتطوير مجموعة قاعدة بيانات قائمة على تطبيقات الهاتف المحمول. تخلص الأطروحة إلى أن الاكتشاف المبكر لسرطان الثدي باستخدام التطبيقات الذكية هو أداة تكميلية قيمة وموثوقة لأخصائي الأشعة للمساعدة في عملية التشخيص وتقليل معدلات الوفيات.

## APPROVAL PAGE

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## DECLARATION

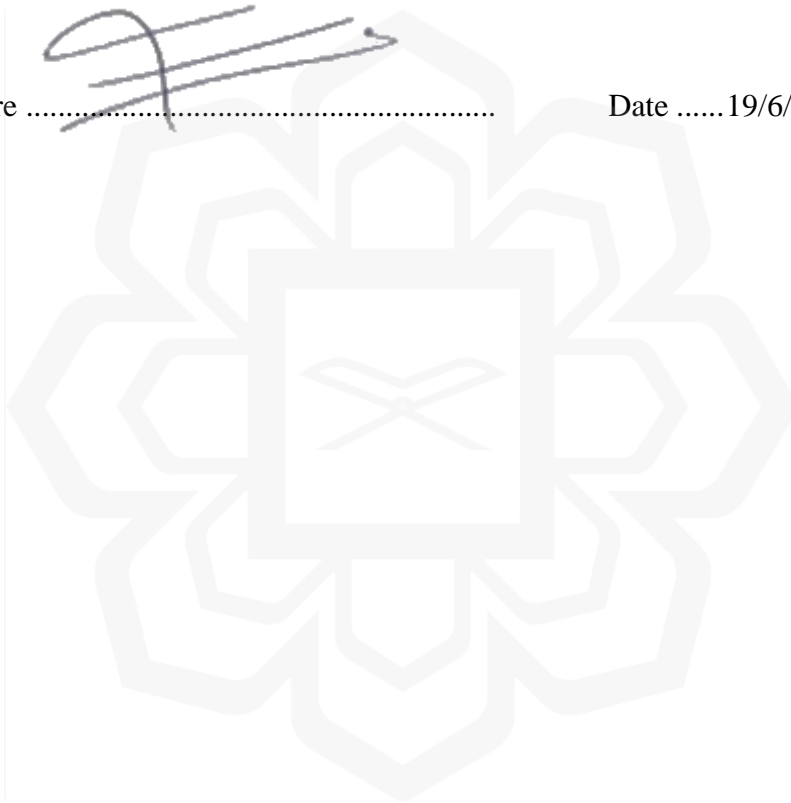
I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole or any part of for any other degrees at IIUM or other institutions.

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## ACKNOWLEDGEMENTS

In the name of God, the Most Gracious, the Most Merciful. All thanks and credit to God for His blessings and help me complete this thesis, which is the path of wellness for humanity. Therefore, I would like to express my sincere thanks, appreciation, and gratitude to International Islamic University of Malaysia for giving me opportunity and providing all means of support for my doctoral study, indicating their keenness to advance scientific and research level.

It is an honor for me to extend my heartfelt thanks to my supervisor, Professor Dr. Mohamed Hadi Habaebi, who devoted all his time to guiding and directing me tirelessly. I wish him all happiness, success, and luck. In addition to two Professors, Dr. Teddy Surya Gunawan and Dr. Md Rafiqul Islam, whom I paid attention to and were of help to me in this academic stage. May God bless them all for their giving and inspire them happiness and success.

I would also like to extend my thanks and gratitude to my dear wife, who supported me from the first moment in the study until the completion of this thesis. May God make her an asset and a source of pride for me and grant her happiness, luck, and success always.

I wish my parents, my children, and my family all health and happiness, and they did not hesitate for a moment to encourage and support me to successfully complete my work in the thesis. I would also like to thank all my friends in the Sultanate of Oman and at Sultan Qaboos University. They were the best example of giving.

Finally, I dedicate this thesis to all mankind who seek knowledge and health, wishing God to raise Islam and all Muslims.

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## LIST OF ABBREVIATIONS

CT	Computerized Tomography
ANN	Artificial Neural Network
MRI	Magnetic Resonance Imaging
GPU	Graphics Processing Units
DMR-IR	Mastology Research with Infrared Image
CNN	Convolutional Neural Network
DL	Deep Learning
IFOV	Instantaneous Field of View
IR	Infrared Radiation
PEs	Processing Elements
MAC	Multiply-Accumulate
DCNN	Deep Convolutional Neural Network
AI	Artificial Intelligence
RBFN	Radial Basis Function Network
KNN	K-Nearest Neighbors
PNN	Probability Neural Network
SVM	Support Vector Machine
C-DCNN	Convolutional and DeConvolutional Neural Networks
BPN	Backpropagation Network
RBFN	Radial Basis Function Network
DT	Decision Tree
ELM	Extreme Learning Machines
MLP	Multi-layer Perceptron

IFI	Initial Feature point Image
DWT	Discrete Wavelet Transform
MLP	Multilayer Perceptron network
BV	Block Variance
FANN	Feed-Forward Neural Network
CASH	Combined Algorithm Selection and Hyperparameter Optimization
AUC	Area Under Curve
ROC	Receiver Operating Characteristic
SSigFS	Statistically Significant Feature Set
ROI	Region Of Interest
FV	Feature Vector
GLCM	Grey Level Co-Occurrence Matrix
RLM	Run-Length Matrix
TRF	Tree Random Forest
RGB	Red Green Blue
SRs	Suspicious Regions
TBIs	Thermal Breast Images
SCH-CS	Smaller-Peaks Corresponding to High-Intensity-Pixels and Centroid-Knowledge of SRs
LSM	Level Set Method
DLPE	Different Local Priorities Embedded
rms	root mean-squared
HOS	Higher-Order Spectra
PFE	Proposed Three- Stage Feature Extraction
SFE	Statistical Feature Extraction

TFE	Texture Feature Extraction
IM	Information Measure
ID	Inverse Difference
BoF	Best Of Five
SD	Standard Deviation
ADAM	Adaptive Moment
RMSPROP	Root Mean Square Prop
SGD	Stochastic Gradient Descent
RLM	Run-Length Matrix
FPGA	Field-Programmable Gate Array
SGDM	Stochastic Gradient Descent Momentum
WSP	WeChat-based Support Program
BC	Breast Cancer
DT	Distress Thermometer
ML	Machine Learning
FCR	Fear of Cancer Recurrence
MOCHA	Methodist Hospital Cancer Health Application
BR	Breast Region
GUIDE	Graphical User Interface Development Environment
BCD	Breast Cancer Detection

## LIST OF SYMBOLS

V	Voltage
$\eta$	Efficiency
I	Current
P	Power
$t_c$	cooling time
D(t)	cooling penetration depth
T <sub>ss</sub>	temperature distribution along a surface normal across tissue in steady state
T <sub>cp</sub>	temperature distribution along the same line at time t during the cooling phase
T <sub>c</sub>	cooling temperature
W	input size of image
F	filter size
P	padding sitting
S	strid setting
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
Accu	Accuracy
Sen	Sensitivity
Spe	Specificity
P	Precision

NPV	Negative Predictive Value
FPR	False Positive Rate
FNR	False Negative Rate
LRP	Likelihood Ratio Positive
LRN	Likelihood Ratio Negative
AUC	Area Under Curve
EER	Equal Error Rate
F1	Harmonic mean of precision & recall
$\rho_t$	density of the tissue
$c_t$	specific heat of the tissue
$\nabla$	Laplace operator
$k_t$	thermal conductivity of the tissue
$T_t$	local temperature of the tissue
$\omega_b$	blood perfusion rate
$c_b$	specific heat of blood
$T_a$	temperatures of the arterial blood entering the tissue
$t$	time variable
$q_m$	metabolic heat generation

# CHAPTER ONE

## INTRODUCTION

### 1.1 BACKGROUND OF THE STUDY

#### 1.1.1 History Of Breast Cancer Detection

Egyptians identified breast cancer 3,000 BC (Lakhtakia, 2014). Then the Greeks, when a woman brought to Hippocrates, had a bloody discharge from the nipple and died. Hippocrates linked breast cancer due to menopause and called it hidden cancer because it did not appear on the skin. In 450 BC, Hippocrates diagnosed the hidden diseases of the patient by placing the mud on the entire body of the patient and the area that first dries out is the disease. It is the primitive process of thermal detection in the medical field (Amalu, n.d.). Signs of breast cancer appear in a bitter taste in the mouth, loss of appetite, disturbed intelligence, dry eyes and nostrils, and loss of smell (Hartman, 1989). In the first century AD, the surgeon from the school of Alexandria pointed out that breast cancer is a huge swelling of harsh texture and uneven and grey to red. In 1913, radiography of breast cancer patients began in Germany. The study was carried out on 3,000 patients by surgeon Salmon (H. Koch, 2016). In 1951 ultrasound was used as a research tool to detect breast cancer tumour and identify it benign or malignant. The other research supported in 1952, when 21 cases of breast cancer successfully identified. Through the results of this research, ultrasound tested in the hospital as a diagnostic tool for breast cancer in 1954. In the 1960s, improvements made to the internal structure of the ultrasound system and improvements in detection methods, including placing breasts on controlled temperature water for early

detection of the tumour. Technological revolution after 1980 contributed to changes in the detection of the tumour and the flow of blood to the tumour. In the late 20th century, it was developed to use ultrasound to guide the needle biopsy in the breast area (Dempsey, 2004). In 1957 Lawson used the thermal camera for the first time to diagnose breast cancer when he found the temperature difference of the tumour and the surrounding healthy area. When doctors and surgeons found Lausanne and Ghatmati in 1963 when they published research that the increase in skin temperature associated with breast cancer was associated with venous convection. In 1982, the Food and Drug Administration approved the use of a thermal camera as a diagnostic aid to detect breast cancer. In 1996, a comparison between thermal images and X-rays for the diagnosis of a patient was conducted where the disease was detected by the thermal images disease, while it was not detected by X-rays (Amalu, n.d.).

## **1.1.2 Types Of Breast Cancer Imaging**

### ***1.1.2.1 Mammogram***

Mammograms are the gold standard for breast cancer screening since 1960. However, there are many challenges affecting diagnosis using mammograms such as age, breast tissue density and family history (Kennedy et al., 2009). Mammograms can detect breast cancer in early stage, reducing mortality by 25%. The doses of mammograms used in diagnosis affect patients over 70 years of age and cause rupture of weak tissue in the breast. They may also cause the formation of cancer in these vessels. Also, it is unable to detect cancer in younger women because of the density of breast tissue (Yao et al., 2014).

### ***1.1.2.2 Computerized Tomography (CT)***

Computerized tomography takes X-rays of the breast from different angles as the patient enters in a closed machine, and a computer collects the image of the breast. The patient is injected into the vein of his hand with a substance to increase the contrast of the image (Hossam et al., 2018). Modern image reconstruction techniques have reduced 70% of the radiation and reduced the time it takes to take pictures (Power et al., 2016). However, there are disadvantages to this technique, including that some patients cannot hold breathing. This is in addition to the risk of radiation to the patient and its effect on pregnant women.

### ***1.1.2.3 Magnetic Resonance Imaging (MRI)***

MRI is a medical examination tool that uses radio waves and a field Magnetic. To show the tumour and calcifications clearly, the patient is injected with a substance into the bloodstream. MRI is often used to follow the response to chemotherapy for breast cancer patients before resorting to breast amputation (Bhide et al., 2019). Furthermore, when using MRI, the patient must be injected with gadolinium to show the details of the blood vessels in the breast. The syringe Gadolinium has the least effect on the sensitivity of iodine used in X-ray. However, the Gadolinium affects allergic patients, so a supervision doctor is needed. MRI imaging has many disadvantages such as its inability to detect breast cancer at an early stage and it is expensive too. Furthermore, women are not allowed to breast-feed for 48 hours. The device is also a closed space that causes anxiety in claustrophobic patients who are afraid of confined places.

#### ***1.1.2.4 Ultrasound***

Ultrasound imaging based on echo or reflection of sound waves is considered safer and more effective than X-rays. Ultrasound was first used in 1940 by France and Germany in the medical field. Ultrasound can detect breast cancer successfully in women with dense tissue and it has no impact on health and is quick and comfortable. However, the disadvantage of this technique is its inability to detect breast cancer at an early stage and it has a higher rate of false positive results (Bhide et al., 2019).

#### ***1.1.2.5 Histology Imaging***

Histological images are generated using a microscope and they allow for the study of the microanatomy of cells, tissues, and organs by examining the correlation between structure and function. To detect cancer, breast tissue is stained with hematoxylin and eosin. The diagnosis of breast cancer histology images with hematoxylin and eosin stained, however, is non-trivial, labor-intensive and often leads to a disagreement between pathologists (Aghdam & Heravi, 2017). Furthermore, the process of generating the images themselves require a microscope that is expensive to acquire and maintain.

#### ***1.1.2.6 Thermography***

Greeks used wet clay to apply on the area of the disease; if the particular area dries faster than other areas, it means that it has higher heat (Williams, 2013). Later, the same idea evolved slowly on the use of specific measurements that indicates the existence of heat from 16th to 18 centuries. In 1800, Williams Herschel discovered the infrared radiation and in 1956 infrared imaging was adopted in medicine. Hence from the recent past, the thermal camera was used to diagnose the disease and detect recovery (Hairong Qi & Diakides,

2009). A thermal camera is a device used to detect infrared radiation from any objects having a temperature higher than absolute zero. The body which emits temperature more than absolute zero radiates electromagnetic waves. Plank equation shows the relationship between the wavelength, temperature, and radiation of body surface (Gade & Moeslund, 2014). As the range of wavelength for infrared radiation is unseen by human eyes, hence a device is required to detect this wavelength. One of the best ways to detect the range of wavelength is by using a thermal camera. Usually, Infrared radiation contains different wavelengths between the visible range and microwave spectrum. This wavelength range of infrared radiation is between  $0.75\mu\text{m}$  to  $1000\mu\text{m}$  (Hairong Qi & Diakides, 2009). However, the wavelength range of radiation of the human body is between  $8\mu\text{m}$  to  $12\mu\text{m}$ . The medical infrared thermography is utilized in breast abnormality detection because its advantages such as radiation-free, non-invasive and painless nature. Infrared breast thermography is an alternative breast imaging modality that can detect early changes or tumours which cannot be detected by X-ray mammography. Breast cancer is a highly treatable disease, with 97% chances of survival if getting detected earlier (Madhavi & Thomas, 2019). Thus, early detection of breast cancer using infrared breast thermography may improve the survival rate of breast cancer patients. The temperature pattern in both breasts of a healthy breast thermogram is closely symmetrical. Hence, a small asymmetry in the temperature pattern of the left and right breast may signify a breast abnormality shows in figure 1.1. There are a series of texture features that play a vital role in asymmetry analysis of breast thermograms. The use of ANN tools to classify these images as benign or malignant tumours is strongly motivated once features are selected and extracted.