



Cairo University

# **COMPUTER AIDED DIAGNOSTIC SYSTEM FOR DIGITAL MAMMOGRAPHY**

By

**Hani Mahmoud Mohammed Bu-Omer**

A Thesis Submitted to the  
Faculty of Engineering at Cairo University  
in Partial Fulfillment of the  
Requirements for the Degree of  
**MASTER OF SCIENCE**  
in  
Biomedical Engineering and Systems

FACULTY OF ENGINEERING, CAIRO UNIVERSITY  
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Under the Supervision of

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FACULTY OF ENGINEERING, CAIRO UNIVERSITY  
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**Title of Thesis:**

Computer Aided Diagnostic System for Digital Mammography

**Key Words:**

Digital Mammography; Breast Cancer; Computer-Aided Diagnosis; Machine Learning; Medical Image Processing.

**Summary:**

Digital mammography has emerged as the most popular screening technique for early detection of breast cancer and other abnormalities in human breast tissue and it continues to be the standard screening tool for breast cancer detection. In this study, we developed Computer-Aided Detection (CADE) and Computer-Aided Diagnosis (CADx) systems and we tested and experimentally verified these systems using the publicly available MIAS and DDSM mammographic databases, respectively. We first applied preprocessing technique to enhance the breast peripheral regions, then we extracted a set of 543 different textural features from the regions of interest, and after that the most relevant features were selected using four selection methods. The selected features are then used as input to different classifiers to differentiate between normal and abnormal breast masses in CADE system, and to distinguish between normal, benign and malignant breast tissues in CADx system. All cases were correctly detected in the proposed CADE system, while CADx system achieved 98.67% overall accuracy.

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## Dedication

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# Nomenclature

ADEWNN / Ada-DEWNN	Adaptive Differential Evolution Wavelet Neural Network
ACR	American College of Radiology
ANN	Artificial Neural Networks
ARCH	Architectural distortion
ASYM	Asymmetry
AUC	Area Under Curve
BI-RADS	Breast Imaging-Reporting and Data System
BI	Blurred Image
BBS	Branch and Bound Selection
CAD	Computer Aided Diagnosis
CADe	Computer Aided Detection
CADx	Computer Aided Diagnosis
CBIR	Content-Based Image Retrieval
CC	Cranio-Caudal
CIRC	Well-defined/circumscribed masses
DBN	Deep Belief Network
DCT	Discrete Cosine Transform
DDSM	The Digital Database For Screening Mammography
DF-BrCanD	diverse features based breast cancer detection
DWT	Discrete Wavelet Transform
ELM	Extreme Learning Machine
FCM	Fuzzy C-Mean
FFDM	Full Field Digital Mammography
FDA	Food and Drug Administration
F-GA	Frequency-Genetic Algorithm
FN	False Negative
FNR	False Negative Rate
FP	False Positive
FPR	False Positive Rate
FSLR	Forward stepwise linear regression
GLCM	Gray Level Co-Occurrence Matrix
GLPF	Gaussian Low Pass Filter

IRMA	Image Retrieval in Medical Applications
K-NN	K-voting Nearest Neighbor
LCP	Local Configuration Pattern
LDA	Linear Discriminant Analysis
MIAS	The Mammographic Image Analysis Society
MLO	Mediolateral-Oblique
MLP	Multi-Layer Perceptron
MISC	Ill-defined Masses
NLM	Non-Local Means
NPV	Negative Predictive Value
NTP	Normalized Thickness Profile
OWBPE	Opposite Weight Back Propagation per Epoch
OWBPI	Opposite Weight Back Propagation per Pattern in Initialization
OWBPP	Opposite Weight Back Propagation per Pattern
pAUC	Partial Area Under the Curve
PCA	Principal Component Analysis
PCET	Polar Complex Exponential Transform
PNN	Probabilistic Neural Network
PPV	Positive Predictive Value
QDA	Quadratic Discriminant Analysis
ROC	Receiver Operating Characteristic
RBF	Radial Basis Function
ROI	Region of Interest
S3VM	Semi Supervised Support Vector Machine
SBS	Sequential Backward Selection
SFFS	Sequential Floating Forward Selection
SFS	Sequential Forward Selection
SI	Segmented Image
SPIC	Spiculated masses
SSL	Semi-Supervised Learning
SVM	Support Vector Machines
TN	True Negative
TP	True Positive
WBCD	Wisconsin Breast Cancer Dataset
WPD	Wavelet Packet Decomposition

# Abstract

Breast cancer is the most common cause of death in women and the second leading cause of cancer deaths worldwide. Digital mammography has emerged as the most popular screening technique for early detection of breast cancer and other abnormalities in human breast tissue and it continues to be the gold standard screening tool for breast cancer detection.

In this work, Computer-Aided Detection (CAdE) and Computer-Aided Diagnosis (CAdx) systems are developed and tested using the public and freely available mammographic databases named MIAS and DDSM databases, respectively. CAdE system is used to differentiate between normal and abnormal tissues and it assists radiologists avoid missing a breast abnormality, while CAdx is developed to distinguish between normal, benign and malignant breast tissues and it helps radiologists to decide whether a biopsy is needed when reading a diagnostic mammogram or not.

Any CAD system is constituted of common stages including: preprocessing and segmentation of mammogram images, extraction of regions of interest (ROI), features extraction, features selection and classification. In both proposed CAD systems, ROIs are selected using window size of  $32 \times 32$  pixels then a total of 543 features from four different feature categories are extracted from each ROI and then normalized. After that the selection of the most relevant features is performed using four different selection methods from MATLAB Pattern Recognition Toolbox v.5 (PRtool5) named Sequential Backward Selection (SBS), Sequential Forward Selection (SFS), Sequential Floating Forward Selection (SFFS) and Branch and Bound Selection (BBS) methods. We also utilized Principal Component Analysis (PCA) as the fifth method to reduce the dimensions of the features set. After that we used different classifiers such as Support Vector Machines (SVM), K-voting Nearest Neighbor (K-NN), Quadratic Discriminant Analysis (QDA) and Artificial Neural Networks (ANN) for the classification. Both CAD systems have the same implementation stages but different output. CAdE systems is designed to detect breast abnormalities while CAdx system indicates the likelihood of malignancy of lesions. Finally, we independently compared between performance of all classifiers with each selection method in both systems.

The evaluation of the proposed CAD systems is done using performance indices such as sensitivity, specificity, the area under curve (AUC) of the Receiver Operating Characteristic (ROC) curves, the overall accuracy and Cohen-k factor.

Both CAD systems provided encouraging results. These results were different corresponding to selection method and classifier.

# **Chapter 1 : Introduction**

## **1.1. Overview and Problem Definition**

Before the twentieth century breast cancer was considered as shameful disease and women felt shy to complain from health problems related to their breast regions and tended to silently suffer rather than talking to their doctors. After surgery has been advanced, and long-term rates of survival are improved, the awareness of this disease started to raise among women around the world and the successful treatment possibility has been improved [1].

Breast cancer is the abnormal growth of breast cells, which usually starts in the lobules of the inner lining of the milk ducts. Different types of breast cancer exist with different stages, truculence and genetic makeup. 10-years disease-free survival rates vary from 98% to 10% with best treatment plan. Breast cancer treatment includes various strategies such as surgery, chemotherapy, hormone therapy and radiation. Breast cancer is still being a significant public healthcare problem among women and it is the most common cancer around the world. The cause of this disease still remain undetermined and this make primary prevention to be impossible. It is believed that early detection of breast cancer is the most promising way to lower the number of women suffering from it and this improves the chances to provide proper treatment options so that treatment will work with better results [2].

Among women in U.S., breast cancer is the most commonly diagnosed cancer besides skin cancer and its death rates are the highest among other cancers besides lung cancer. In 2016, it is expected to diagnose an approximately 246,660 new cases of invasive breast cancer in women, and the expected diagnosed cases of non-invasive breast cancer are 61,000 women in the U.S. Also About 2,600 new patients of invasive breast cancer in men are expected to be discovered [3].

Mammography is a special type of radiography, using low radiation levels to acquire images for breast to diagnose a consequent exist of abnormal structures that implies a disease like cancer. The early detection of strange mammary pathologies like non-palpable breast masses and calcifications is extremely important for successful cure of breast cancer patients. Mammography is the standard screening tool that is used to perform the task of breast cancer detection and it results to reduce at least 30% in breast cancer deaths in the world [4], [5].

The benefit of mammography screening has undergone some recent contention since definite evidence relating mammography with mortality may not be proven. In contrast, an Institute of Medicine Report on Mammography suggests that using mammography screening for earlier detection of breast cancer may be an important factor in decreasing mortality from breast cancer in recent years [6].

The computer-based systems may provide a second supportive alternative in detecting breast abnormalities by completing the expert knowledge of radiologists, and