



Cairo University

BREAST CANCER CLASSIFICATION IN ULTRASOUND IMAGES USING TRANSFER LEARNING

By

Ahmed Mostafa Salem Hijab

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

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Title of Thesis:

Breast Cancer Classification in Ultrasound Images using Transfer Learning

Key Words:

Breast lesion; ultrasound; convolutional neural networks; deep learning; transfer learning.

Summary:

We explored three versions of a deep learning solution to computer-aided detection of ultrasound images of cancerous tumor tissues. Experimentally, our work proved that the pre-trained VGG16 model has the best outputs in the fine-tuned version. In short, our test accuracy ranges from 79% to 97%. We employed data augmentation to enlarge the amount of training data, and avoid overfitting. We have also employed the VGG16 pre-trained model, and added practical fine tuning to improve precision. This work offers a path into developing realistic and versatile deep learning frameworks for detecting breast cancer. The findings suggest that the fine-tuned model with pre-training medical data has increased the classification accuracy. These frameworks should complement and provide assistance for approaches of clinical diagnosis and treatment.

Disclaimer

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute.

I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

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Dedication

This thesis is dedicated to my family, Mom, Dad and Eman who always encourage and support me as I try to get the best out of myself. Thank you for always being by my side.

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List of Abbreviations

AI: Artificial Intelligence	19
AUC: Area Under Curve	4
BCDR: Breast Cancer Digital Repository	27
BI-RADS: Breast Imaging Reporting and Database System score	23
BPANN: back-propagation artificial neural-network	29
BRCA1: Breast Cancer Gene type 1	8
BRCA2: Breast Cancer Gene type 2	8
CAD: Computer-Aided Diagnosis	5
CNN: Convolutional Neural Networks	5
CT: Computed Tomography	17
DBN: Deep Belief Networks	22
DCIS: Ductal Carcinoma in Situ	8
DICOM: Digital Imaging and Communications in Medicine	28
DL: Deep Learning.....	20
DM: Digital Mammography	5
DPN: deep polynomial network.....	30
GLCM: gray level co-occurrence matrix.....	30
GPU: Graphics Processing Unit.....	17
FCM: fuzzy c-means clustering	29
IDC: Invasive Ductal Carcinoma.....	8
ILC: Invasive Lobular Carcinoma.....	8
LCIS: Lobular Carcinoma in Situ	8
LR: Learning rate	48
MG: Mammogram.....	6
MHz: Mega Hertz.....	10
Mini-Mias: The Mammographic Image Analysis Society Digital Mammogram Database Exerpta Medica	27
ML: Machine Learning.....	20
MRI: Magnetic resonance imaging	5
NDE: Nondestructive Evaluation (ultrasound material evaluation)	16
NLP: Natural Language Processing	16
NN: Neural Networks.....	22
PCA: principal component analysis	31
PGBM: point-wise gated Boltzmann machine	31
PNG: Portable Network Graphics.....	28
QUS: Quantitative Ultrasound Parameters	22
RBM: restricted Boltzmann machine	31
ReLU: Rectified Linear Unit	23
RIW-BPNN: randomly initialized weight backward propagation NN	32
S-DPN: stacked deep polynomial network.....	30
SGD: Stochastic Gradient Descent	34
SVM: Support Vector Machine	29
SWE: shear-wave elastography	31
US: Ultrasound.....	5
VGG: Visual Geometry Group	6
WBCD: Wisconsin Breast Cancer Dataset.....	22

WHO: World Health Organization 7

Abstract

Computer-aided detection of malignant breast tumors in ultrasound images has been receiving growing attention. The lack of published data of ultrasound in breast cancer creates an obstacle for researchers and hinders them from achieving accurate conclusion. Proposed in this thesis is a deep learning methodology to tackle this problem. The training data, which contains several hundred images of benign and malignant cases, was used to train a deep convolutional neural network (CNN). Three training approaches are proposed: a baseline approach where the CNN architecture is trained from scratch, a transfer-learning approach where the pre-trained VGG16 CNN architecture is further trained with the ultrasound images, and a fine-tuned learning approach where the deep learning parameters are fine-tuned to overcome overfitting. The experimental results demonstrate that the fine-tuned model had the best performance (0.97 accuracy, 0.98 AUC), with pre-training on US images. Creating pre-trained models using medical imaging data would improve deep learning outcomes in biomedical applications.