

Dedication

I dedicate this thesis to:

My parents

My precious daughter

My family

My friends

My colleges

Acknowledgement

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Abstract

Breast cancer is the most common type of cancer among women in the world. Mammography is regarded as an effective tool for early detection and diagnosis of breast cancer. In this study an approach is proposed to develop a computer-aided classification system to characterize breast mass from digital mammograms using IDL programming language by feature extraction for 9 features. The sample is 155 mammogram images and the data collected randomly from X-ray department at cancer diagnostic medical center. The study was conducted from April 2016 to March 2020. The proposed system consists of two steps. The first step is the feature extraction by using first order statistics using 3 features (mean-energy-standard deviation) and the classification accuracy of breast tissues and tumors is for Tumor 96.8%, gland 57.9%, fat 98.9, While the connective tissue showed a classification accuracy 98.5%. The overall classification accuracy of breast area by using first order

The second step is feature extraction by using higher order statistics (long run emphasis (LRE) , grey level non uniformity (GLN), run length non uniformity (RLN), Run percentage (RP), High Gray Level Run Emphasis (HGLRE) and Low Gray Level Run Emphasis (LRHGLE)) and the classification accuracy of breast tissue and tumor showed a classification accuracy for tumor 88.9%, gland 98.9%, fat 86.3%, connective tissue 91.9%.The overall classification accuracy of breast area by using second order statistics 91.5%.

Mammographic texture analysis is a reliable technique for differential diagnosis of breast tumors and breast tissue. Furthermore, the combination of imaging-based diagnosis and texture analysis can significantly improve diagnostic performance.

الخلاصة:

يعتبر سرطان الثدي أكثر أنواع السرطان شيوعًا بين النساء في العالم. يعتبر التصوير الإشعاعي للثدي أداة فعالة للكشف المبكر عن سرطان الثدي وتشخيصه. في هذه الدراسة ، تم اقتراح نهج لتطوير نظام تصنيف بمساعدة الكمبيوتر لتمييز أورام الثدي من التصوير الإشعاعي للثدي باستخدام لغة البرمجة **IDL** عن طريق استخلاص مزايا الصورة لـ **9** مزايا لصورة الماموقرام. تكونت العينة من **155** صورة ماموجرام التي تم جمعها عشوائيًا من أقسام الأشعة السينية في المراكز الطبية التشخيصية . أجريت الدراسة في الفترة من أبريل **2016** إلى مارس **2020**. يتكون النظام المقترح من خطوتين. الخطوة الأولى هي استخلاص المزايا باستخدام الإحصائيات من الدرجة الأولى باستخدام **3** مزايا (الوسيط - الانحراف المعياري - الطاقة) ونتيجة دقة تصنيف أنسجة أورام الثدي : للورم **96.8%** ، الغدة **57.9%** ، الدهون **98.9%** ، بينما أظهرت الأنسجة الضامة دقة التصنيف **98.5%**. ودقة التصنيف الإجمالية لمنطقة الثدي باستخدام إحصائيات الدرجة الأولى هي **94.0%**. الخطوة الثانية هي استخلاص المزايا باستخدام إحصائيات الدرجة العليا (**IRE** ، **GIN** ، **RIN** ، **RP** ، **HGRE** و **IRHGLE**) وأظهرت دقة تصنيف لأنسجة الثدي والأورام : للورم **88.9%** ، الغدة **98.9%** ، الدهون **86.3%** ، النسيج الضام **91.9%** و دقة التصنيف الإجمالية لمنطقة الثدي باستخدام إحصائيات الدرجة العليا **91.5%** .

يعد تحليل النسيج الماموقرام تقنية موثوقة للتشخيص التفريقي لأورام الثدي وأنسجة الثدي. علاوة على ذلك ، يمكن أن يؤدي الجمع بين التشخيص المستند إلى التصوير وتحليل النسيج إلى تحسين الأداء التشخيصي بشكل كبير

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Abbreviation:

WHO: World health organization.

NCI: National cancer institute

kV_P: kilo voltage peak

keV: kilo electron volt

PEM: Positron emission mammography

MRI: Magnetic resonance imaging

CTV: Clinical target volume

ROI: Region of interest

IDL: Interactive Data Language

FCC: False Colour Composite

DCIS: ductal carcinoma

LCIS: Lobular Carcinoma

IBC: Inflammatory breast cancer

CC: Cranial-Caudal

MLO: mediolateral-oblique

AEC: Automatic exposure control

Pb:lead

FSM: finite-state machine

FFDM: full-field digital mammography

CAD: computer-aided diagnosis

DICOM: Digital Imaging and Communications in Medicine

GLCM: Gray level Dependency Matrix

SGLD: Spatial gray-level dependence

DSGLD: diagonal Spatial gray-level dependence

LBP: Local Binary Pattern

LBPV: local binary pattern variance

CLBP: Completed Local Binary Pattern

DDSM: Digital Database for Screening Mammography

FLDA: Fisher linear discriminant analysis

MIAS: Mammographic Image Analysis Society

RBST: Rubber band straightening transform

ROC: A receiver operating characteristic curve

LDA: Linear discriminant analysis

SVM : Support Vector Machine

UK: United Kingdom

FNAC: fine needle aspiration cytology

SPSS: Statistical Package for the Social Sciences

GLRLM: Grey-level run-length matrix

LRE: long run emphasis

GLN: grey level non uniformity

RLN: run length non uniformity

RP: Run percentage

HGLRE: High Gray Level Run Emphasis

LRHGLE: Low Gray Level Run Emphasis