

شبكة المعلومات الجامعية التوثيق الإلكتروني والميكروفيلو

بسم الله الرحمن الرحيم





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شبكة المعلومات الجامعية التوثيق الإلكتروني والميكرونيله



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جامعة عين شمس التوثيق الإلكتروني والميكروفيلم قسم

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Real Time Implementation of Medical Data Analysis Approaches

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Dedicated to

my beloved mother

and the memory of my father who lost his life fighting Alzheimer's

May this work help others in their battle...

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First and foremost, all praise is due to Allah, we worship Him, we seek His help and His forgiveness. The Prophet Muhammad (pbuh) said: "He who does not thank the people is not thankful to Allah." [Sunan Abi Dawud, graded Sahih by Shaikh al-Albani.]

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Abstract

With the increasing size of medical datasets and their high dimensionality nature there arises a significant need for methods to accelerate the processing and analysis. High dimensional medical images may consume several hours and even days executing exhaustive analysis processes, such as those employed in the classification of Alzheimer's disease.

Alzheimer's disease is a serious form of dementia. In 2018, fifty million people worldwide has been reported living with dementia. This number will reach 152 million people by 2050 [95]. This vastly expanding disease causes a progressive decline in the mental abilities that usually starts with memory loss and ends with cognitive and behavioral disorders. With no current cure, treatments focus on slowing the progression of the disease and controlling its symptoms. Early diagnosis by studying structural MRI (sMRI) is the key.

Image registration of sMRI is a serious challenge in the field of medical image analysis generally and for Alzheimer's disease analysis specifically. The correct localization of brain tissue deformation and determination of the tumor growth rely majorly on the accuracy of the image registration process. Image registration techniques are computationally intensive time-consuming tasks. Field Programmable Gate Arrays (FPGAs) have fast-evolving and customizable hardware acceleration capabilities that promise to help speed up these tasks.

The work in this thesis presents analytical predictive solutions for the classification of Alzheimer's disease problem using unsupervised and supervised learning techniques. The supervised learning solution run in an accelerated framework of a software/hardware co-design model using FPGA hardware chips.

The proposed image analysis uses texture features extracted from the gray level cooccurrence matrix and voxel-based morphometry (VBM) neuroimaging analysis to classify
Alzheimer's disease patients. VBM initially explores the differences in brain anatomy using
statistical parametric mapping. Unsupervised clustering techniques are investigated for an
early diagnosis of Alzheimer's disease. Different supervised classification techniques are
studied as well to come up with the best classification accuracy. The studied techniques are
support vector machine, k-nearest neighbor, and decision tree. Moreover, feature selection
using entropy and feature reduction using principle component analysis are employed with
supervised learning techniques to overcome the curse of dimensionality hence contributing
to faster response. The thesis explores as well the discriminative power of certain anatomical
regions of interest (ROI) for classifying Alzheimer's disease.

The proposed classification technique is accelerated using an optimized software/hardware co-design model where a part of the VBM analysis runs on CPU, while the rest runs on FPGA. FPGA's acceleration power is used in the implementation of the diffeomorphic image registration algorithm DARTEL as a part of the registration process in the VBM analysis. An optimized and pipelined hardware architecture is proposed.

The proposed clustering technique provided a preliminary insight with an accuracy 76%, while the proposed classification technique managed successfully to differentiate between Alzheimer's disease patients and normal controls with an accuracy of 93%. The proposed classification technique proved as well that analyzing brain regions that include Hippocampus, Cerebelum Left, Cerebelum Right, and Calcarine would lead to better time performance results than analyzing the whole brain regions. This set of ROI discriminators recorded 4% increase in the accuracy compared to whole brain method with only 7% of the whole brain feature vector and a 16x speedup in the run time. The hardware acceleration of the DARTEL registration algorithm resulted in a maximum speed up factor of 114x on function-level, compared to the CPU, with a contribution of 8x faster for the overall performance in the registration process of the software tool.

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