RBFNN BASED DEEP LEARNING FOR QUANTIFICATION OF EPICARDIAL AND THORACIC ADIPOSE TISSUE FROM NON-CONTRAST CT

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Abstract--- Epicardial adipose tissue (EAT) is a unique fat depot around the heart which is related to coronary artery disease. Fully automated quantification of EAT volume in clinical practice could be a highly reliable and timesaving tool for cardiovascular risk assessment.This paper propose and evaluate a new multi-task framework based on deep Radial basis function neural networks instead of Convolutional neural network for advanced fully automated quantification of epicardial and thoracic adipose tissue volumes from non-contract CT datasets. The proposed method provides fast segmentation with strong agreement with expert manual volume measurements. The proposed approach may represent a tool for rapid measurement of EAT volume as an imaging biomarker for future clinical use, offering promise for improved prediction of adverse cardiac events. Radial Basis Function (RBF) Neural Network was used to distinguish between trained data and test data.We evaluate the performance of the method on CT datasetsfrom each asymptomaticindividuals.The automatic segmentation's accuracy was also validated by Artificial neural network(ANN).The amplitude values of the pixels are calculated using K-means clustering algorithm. RBF Neural Networks provides much more advantages compared with other neural network architectures which can be trained and possess the best approximation property.This paper is implemented using Mat lab simulation software tool.

Keywords: **EAT- Epicardial adipose tissue, TAT - Thoracic adipose tissue, RBF - Radial Basis Function neural network.**

I INTRODUCTION

Epicardial adipose tissue (EAT) is a fat depot contained entirely beneath the pericardium,thus surrounding the coronary artery tree and its branches.This metabolically active fat depot has been shown to promote the development of atherosclerosis, through its direct contact with the coronary arteries. Increased volume of EAT has been shown to be independently related to major adverse cardiovascular events (MACE), particularly in asymptomatic individuals, or to coronary artery diseases. EAT can be manually measured from coronary artery calcium (CAC) CT scans, which are widely used for performing cardiovascular risk assessment. However, it is a time-consuming process. To date, measurement of EAT is not implemented in clinical practice, due to the absence of highly reliable, efficient and fully-automated quantification techniques. Quantification of EAT is technically a challengingtaskasitrequiresidentificationofthepericardium; quantification of thoracic adipose tissue (TAT, union of epicardial and paracardial adipose tissue (PAT)) is easier as it does not have this requirement.However,even if TAT and EAT volumes are correlated,previous studies shown EAT has a higher prognosis capability due to its immediate proximity to the heart and coronary arteries.

The works on automatization can be divided into two parts, namely, segmentation and classification of image. Since there are a lot of fat deposits, we have to find a suitable way to detect and classify them. Numerous techniques have been introduced to achieve efficient and accurate medical image segmentation. However due to in-homogenous nature of medical images, segmentation is still an open and challenging research area. Neural networks are also widely used for classification of fat deposit problems.

We propose a fast and fully automated algorithm for Epicardial and thoracic adipose tissue volume quantification from non-contrast calcium scoring CT datasets, using a deep learning approach, based on Radial basis function neural network(RBFNN). Previous studies is on EAT quantification, and ConvNets applied to medical imaging. Our proposed approach, initially perform pre-processing for reducing high dimensional data.Segmentation of tissue along with the fat is also one of the main topics on analysis. Therefore, results are studied using K-mean clustering method and Fuzzy clustering method.Fuzzy clustering is used to assign higher weights to pixels having less local entropy and local variance results in terms of accuracy and efficiency.RBF neural networks with their structural simplicity and training efficiency are to perform a nonlinear mapping between the input and output vector spaces. RBFNN is a fully connected feedforward structure and consist of three layers namely, an input layer, a single layer of nonlinear processing units simply called hidden layer, and an output layer.Finally, we conclude this paper with potential involvements suggested by the results and provide some ideas for further analyses. To our knowledge,this is the first application of deep learning for more advanced and fully automated quantification of EAT and TAT from coronary calcium scoring CT scans.

II RELATED WORK

The previous works on EAT qualification was a bit semi automated which included a lot of manual labour to be a part of it. But with certain advancements in the process the

necessary changes were made in the upcoming models which were a bit developed than the existing models of that time but however these were limited to certain capabilities and needed a few changes which corresponds to the core objective of the proposed paper. Related works included automatic segmentation of the pericardium [11] They even considered thoracic cavity and combined region growing [8] with adaptive thresholds. However this alone wasn't sufficient and further models that addressed these issues were developed and this included the use of convolution neural network[16] which is a deep learning[15] method by which individual layers of the image was analyzed and mapped for better understanding of the image that was transmitted. This too was overcome with the proposal of a process referred to as segmentation[17] which was then combined with convolution neural network and was collectively referred to as ConvNets and segmentation[12] in which the network is provided as input with a patch in the centre and the process of analysis is done specifically to the pixies that lie next to the patches and in a similar way sever other patches are added for better analytical purposes. There was even an proposal on using fully convolutional networks (FCN) which was a variant of ConvNets but this too seemed inefficient against the system proposed. Though many such systems were proposed the need for development seemed to be on the rise with respect to the medical field and any further modification of the proposed system would benefit the society on the whole.

III METHODS

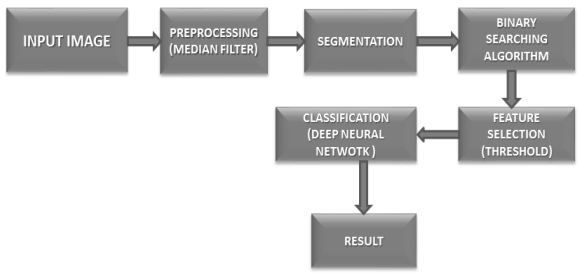

Fig 3.1: Workflow of the proposed system

A. Preprocessing

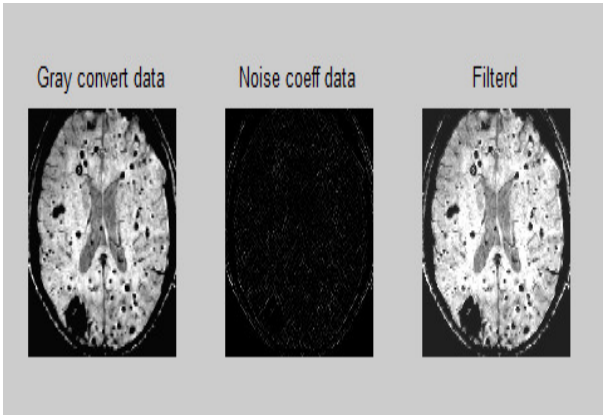

Fig 3.2:Pre-processing

The image pre-processing procedure is a very important step in the image processing. Colour processing is performed if the given input image is in colour. It is then converted into grey scale image. If the given input CT image is in grey scale, then pre-processing is performed without colour processing. The aim of the pre-processing phase is to obtain images which have normalized intensity, uniform size and shape. Finally, the images were scaled to the same size of 256 × 256 pixels.

B. Segmentation

The segmentation is carried out in multi-frame MRI in which the image is converted into discrete signals called samples where the number of samples are obtained by using the resolution formula 2^8(256 samples).The segmented 256 samples are analyzed and processed them further with feature extraction where the maximum pixel size and the minimum pixel size is identified along with the average pixel size. The individual samples are analyzed based on the abnormalities on the pixel size. K-means clustering is used to cluster the pixels into groups based on their intensities in order to separate the foreground pixels from the background pixels. Fuzzy C mean clustering is used to store the amplitude of the samples in an external fuzzy cluster memory which provides higher efficiency.

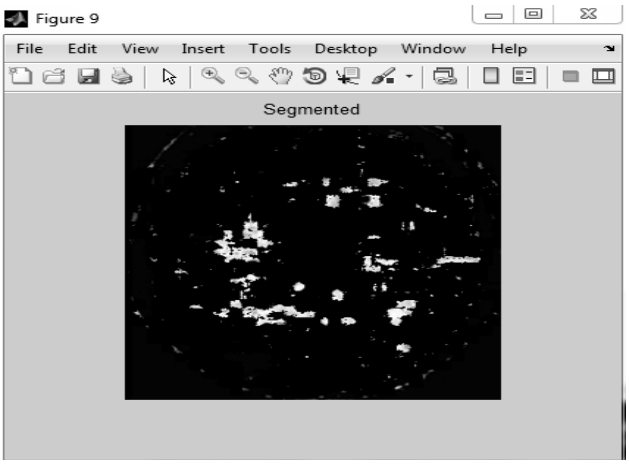

Fig:3.3: Segmentation

C. Feature extraction

The data given as input to an algorithm is too large to be processed so that the input data will be transformed into a reduced representation set of features (features vector). Feature Extraction is helpful in identifying brain tumour where is exactly located and helps in predicting next stage. It is a dimensionality reduction process, where an initial set of data is reduced to more manageable groups for processing, while still accurately and completely describing the original data set.The feature Extraction is achieved using Grey level co-occurrence matrix(GLCM) extraction.The features which are extracted from the CT image are Contrast,Correlation,Homogeneity,Entropy,Energy,Shape,Color,Texture and Intensity. The extracted features of the 256 samples are stored in Fuzzy cluster memory.

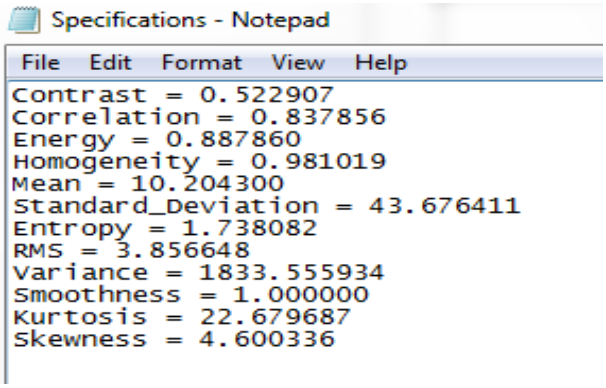

Fig 3.4: Specifications

D. Classification

RBFNN classifier is used for classification which is a combination of Fuzzy cluster, Artificial neural network (ANN) and Radial basis function (RBF). The mapping properties of the RBFNN can be modified through the weights in the output layer, the centres of the RBFs, and spread parameter of the Gaussian function. The number of centres of RBF is fixed. If the number of centres is made equal to the number of input vectors of the exact RBF, then the error between the intended and actual network outputs for the training data set will be equal to zero. In this work, exact RBFNN was used due to its infinite range. The number of RBF centres was made equal to the number of input vectors. The feature set is classified using RBFNN classifier.Similarity matching was also performed by measuring the distance between vectors calculated for database images and query images.

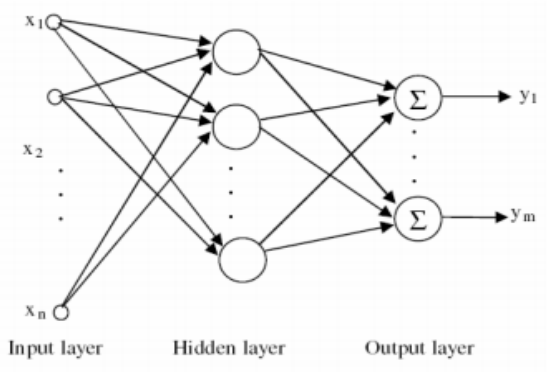

Fig: 3.5:Structure of Neural Network

IV EXECUTION AND RESULT

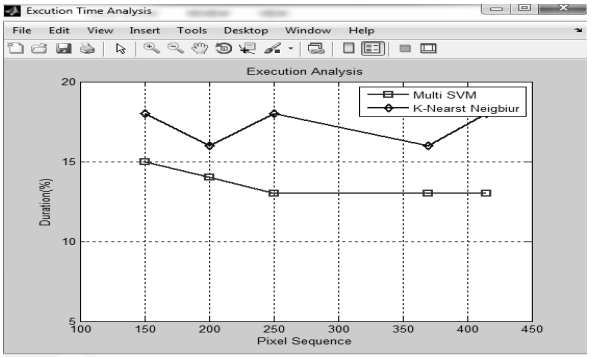

Fig 4.1: Execution Time

With the rise in the need for medical services around the globe the need for an mechanism that deals with the issues of a patient rather faster that the existing system was necessary which was the basic idea behind the development of such a beneficial outcome. And thus the result obtained was Highly accurate due to ANN.Highsensitivity. And this process required Less amount of memory when compared to any of the previous models that are in existence today. Region based algorithm extracts the problematic area sharply thereby

enabling better understanding of the problem in hand.The epicardial and thoracic adipose tissue volumes from non-contract CT datasets were focused which weren't so in the previous models and lacked the clear sense of understanding. The accuracy of proposed work using RBFNN based deep learning classifier increased the accuracy of the results with the help of RBFNN and CNN classifiers.

V CONCLUSION

A fuzzy logic based image segmentation approach is proposed for medical images comprising active contours and level set segmentation, to improve segmentation results. The pixels of level set segmentation are assigned weights, based on local entropy and local variance, evaluated by Fuzzy inference engine. Higher weights are assigned to pixels having less local entropy and less local variance, and vice versa.Simulation results of our proposed scheme have shown improvement in segmentation efficiency as compared with existing Convolution model.We propose and evaluate a new multi-task framework based on deep convolutional neural networks for fully automated quantificationofepicardialandthoracicadiposetissuevolumes from non-contract CT datasets. The proposed method provided fast segmentation with strong agreement with expert manual volume measurements.The proposed approach may represent a tool for rapid measurement of EAT volume as an imaging biomarker for future clinical use, offering promise for improved prediction of adverse cardiac events. As a result, large reduction of the processing units and great improvement of the algorithm anti-interference make the algorithm improve not merely convergence speed but also segmentation accuracy. Besides, the practical application of K-means clustering segmentation algorithm is greatly improved in 3D medical data field segmentation.

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