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Automated Malignancy detection using neural network

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Abstract — The present medical scenario though it is very trustworthy and reliable because of the latest medical imaging modalities like MRI and CT etc., manual segmentation is prominently used in early malignancy detection, which is time-consuming. So there is a need for the automated method in terms of both accuracy and time requirement, which will provide better insight to the medical expert. Nowadays the machine learning plays an important role in this aspect since it learns through experience. The purpose of this paper is to demonstrate and make comparison of neural network with a traditional approach. We have used computational phantom data set to be considered as medical images and compare the performance of neural network with traditional segmentation by using dice similarity coefficient. The result concludes that even noise increases in medical images, the neural network approach gives high dsc value than traditional techniques.

Keywords — Medical imaging, Sheep Logan phantom dataset, Fuzzy C-means, neural network

I. INTRODUCTION

We live into technological advancing era supported by high-end digitization in all aspects of life – including medical research and treatment. Unarguably, health wellness is the prime aspect of human life and has been always remained main concern for research and development [1]. Hence, a large amount of health-oriented issues and questions are answered continuously by the researchers. No need to mention, that disease diagnosis is one of the most crucial aspects of health wellness benefited by technological advancement.

Gigabits of a mammoth database from various sources including laboratory diagnostic tests, medical images, physical examinations, case studies etc are processed and analyzed by physicians/practitioners for one simple reason – to come out with a reliable prompt diagnosis. This becomes possible with the use of CAD – Computer-Aided Diagnosis. And obviously, medical image processing as a process which includes image capturing, processing, storing, analyzing etc has played a pivotal role in this whole process.

The sources of medical images are acquisition systems. Several new technologies are used for producing medical images such as X-ray, Computed Tomography (CT), Magnetic Resonance Tomography (MRT) and Magnetic Resonance Imaging (MRI). Out of these, many technologies use magnetic radio waves and crystal sensors to capture an identical structure of the human bodies as medical images [21, 22].

The outcomes of acquisition systems are 2D matrices, which are very complex. Image processing operations assist the radiologist for accurate diagnosis and accelerate the process for treatment. In medical image processing, segmentation is one of the early processing steps to be performed once we have data from image acquisition systems. Segmentation is partitioning a digital image into a set of classes or regions, which is used as a pre-processing step to represent different types of tissues or organs in medical images. It can be also useful to extract a region of interest (ROI), in directing the physician's attention regarding any abnormalities in the body tissues such as tumors[27].

Medical image segmentation is a challenging problem and it is the main foundation process for all medical imaging applications. Thresholding, clustering, region growing, and contour detection are a conventional segmentation algorithms. In comparison, the neural network approach takes advantage of the learning capability and training mechanism to classify medical images into homogeneous regions to complete the segmentation process.

The research work presented in this paper is concerned with the medical data generation and comparisons of traditional segmentation techniques like thresholding, clustering with an Artificial Neural network to detect tumor from that dataset.

This paper is organized as follow: Section I contain the introduction, Section II contains related work for medical image segmentation technique phantom dataset; especially in the medical domain. Section III discusses the methodology for traditional segmentation techniques, clustering techniques and Artificial Neural network Section IV describes the results. Finally, this work is concluded in Section V.

II. RELATED WORK

Due to their importance, many researchers (from both academia and industry) have proposed various CAD systems designed for various elements. These systems are based on image processing. Examples include bone fractures [2,3], osteoporosis[4], disc herniation [5,6], brain hemorrhage[7,8], brain tumor[9,10], breast cancer [11,12], lung cancer [13], liver cancer[14], colon cancer[15], myocardial infarction [16,17], diabetic retinopathy[18], etc. Effective and efficient processing of medical imaging processing is at the core of CAD systems [19, 20].

The basic step for medical image analysis or diagnose is the image segmentation. Image segmentation is defined as the process of classifying the pixel or voxels of an image into a set of distinct classes. A basic task in 3-D image (medical image) processing is the segmentation of an image which classifies voxels/pixels into objects or groups. The difficulty in medical image segmentation is the presence of high noise and low spatial resolution in CT/MRI/PET images. Regardless of the difficulties and known limitations, several image segmentation approaches have been proposed and used in the medical images including - thresholding, clustering, stochastic models, deformable models, and others.

In this research paper, Image segmentation approaches applied to three-dimensional data like CT/MRI/PET for diagnosing. We generate phantom dataset in three dimensions. Artefacts in medical slices are added using Gaussian noise and Speckle noise to present a realistic medical image that consists of multiple noises due to sensors' noise and the intensity inhomogeneity. Moreover, to generate a real medical dataset, tumors in the phantom dataset are inserted randomly. After successfully generating dataset both viz. traditional segmentation and artificial neural network methods are applied over it.

III.METHODOLOGY

In medical images (low resolution, high contrast), thresholding-based methods are very popular segmentation techniques. Due to the low resolution, inherent noise, large variability of pathologies, and high uncertainties in fuzzy object boundaries, there is no consensus on the automated selection of thresholding value. Therefore, an optimal threshold selection remains a challenging task. Apart from all these difficulties, thresholding methods are still under development for improving the result of segmentation. It also used both in pre-clinical and clinical studies. In this research paper, two popular thresholding techniques like OTSU (Global thresholding) and ISODATA (Iterative thresholding) for medical images are shown below.

A. OTSU

In this thresholding method [33], it analyzes the distribution of the gray value of an image histogram. It selects a value of Θ to choose the minimum value of two peaks of the histogram. Otsu defines this choice of Θ as the minimizing the value of the weighted sum of within-class variance and maximizing the interclass scatter. The result by using this method is stable and robust to noise and it holds for both bi-level and multi-level thresholding cases. For an image taking on discrete pixel (2 D image) values k, the optimal threshold value Θ is

$$\theta otsu = argmax\theta \{\sum_{k<\theta} p(k)(\mu 0-\mu)^2 + \sum_{k\gg\theta} p(k)\,(\mu 1-\mu)^2\} \quad (1)$$

Where p: normalized histogram
μ: Mean {f(x)}
μ1: Mean {f(x) | f(x) >= Θ}
μ0: Mean {f(x) | f(x) < Θ}

Threshold value T can be determined by calculating the no. of pixels for each gray value and selects the global minimum, while in the discrete case, it can be entirely evaluated from the histogram by summing over the appropriate value range. This method is useful in performing image segmentation as it requires less computational time compared to other technique.

B. ISODATA

It is the iterative isodata method [34] for the automated selection of thresholding value. It is actually an application of the more general isodata clustering algorithm to the gray values of an image. In this method, the threshold selection value is performed locally. Given an initial threshold $\Theta^{(0)}$, e.g., half of the maximum gray value, the isodata algorithm can be stated as follows:

1. Using initial threshold $\Theta^{(i)}$ for image f, generate binary image $g^{(i)}$ at iteration i.
2. Calculate the mean gray values $\mu_0^{(i)}$ and $\mu_1^{(i)}$ of current fore- and background voxels, respectively.
3. Compute new threshold t, $\Theta^{(i+1)} = (\mu_0^{(i)} + \mu_1^{(i)})/2$, until convergence.

In this method, the foreground and background can be characterized by different mean values. This method is commonly used in 2D image processing, mostly in medical applications.

C. Clustering techniques[35]

In this technique, pixels are grouped to form a cluster, which is closest among all clusters. Pixels having homogenous characteristics belong to the same cluster and pixels must follow the homogeneity criteria in the same cluster. It provides us with an exact and subtle analysis tool from the mathematics view. Clustering techniques provide better results for exact shapes, range, and area of tumors or any sort of abnormal growth. It is alike segmentation of an image. Among various clustering algorithms, fuzzy algorithms, FCM and non-fuzzy algorithms like k-means (KM), are most popular35,36. The segmentation techniques used in this paper are discussed below.

a) K-Means Clustering

K-Means clustering is a type of hard clustering algorithm. It belongs to the unsupervised cluster analysis algorithm and achieves partitioned clustering method. It is a key technique in pixel-based methods. By using pixel-based K-means clustering, an approach is simple and also the computational complexity is relatively low compared with other segmentation methods like region-based or edge-based Algorithm with mathematical equation is described as follows:

1. Initialization of k no. of clusters.
2. Select k cluster center randomly
3. Compute mean M or center of the cluster by eq(2)

$$M = \frac{\sum_{i.c(i)=k} x_i}{N_k} \quad k= 1,2,\ldots\ldots, k \tag{2}$$

4. Compute the distance between each pixel to each cluster center

$$D(i) = \arg\min ||x_i - M_k||^2 \quad , i= 1,2,\ldots\ldots, k\ 1,2..N \tag{3}$$

5. If the distance is closest to the center then move to that cluster else move to another cluster.
6. Calculate the center.
7. Repeat the steps until the center doesn't move.

In this algorithm, data points belong to the cluster has a minimum distance to the center of an assigned cluster. This technique is easy to implement and also faster, but the no. of clusters need to be predefined. The quality of the final clustering results depends on the random selection of the initial center. Because of a random selection of center it may give unexpected results. In this technique, if we carefully chose the initial center, value, then we shall achieve our desire segmentation results.

b) Fuzzy C-Means Clustering

Fuzzy C-Means [35, 36] is a method of clustering which allows one pixel to belong to two or more clusters. It is a soft clustering technique and unsupervised clustering algorithm that has been applied to a wide range of problems involving feature analysis, clustering and classifier design. Fuzzy logic is a form of probabilistic logic which contains only approximate values. The fuzzy logic is a way to process the data by giving a partial membership value to each pixel in the image. A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) and it lies between 0 and 1 for fuzzy sets. The addition of all membership degrees for any given data point is equal to 1. The membership function describes the fuzziness of an image and also to define the information contained in the image. There are three main basic features involved in this concept characterized by a membership function. They are core, support, and boundary. The core consists of a full member of the fuzzy set. The support is a non-membership value of the set and boundary is the intermediate or partial membership with a value between 0 and 1. Mathematical step along with algorithm is described as follows:

1. Initialize U = $[u_{ij}]$ matrix, $U^{(0)}$
2. At iteration, calculate center vectors $C^{(k)} = [c_j]$ with $U^{(k)}$

$$C_j = \frac{\sum_{i=1}^{N} uij.^{m}\ .\ xi}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{4}$$

3. Update the membership matrix u for the k^{th} step and.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{||x_i - c_j||}{||x_i - c_k||}\right)^{\frac{2}{m-1}}} \tag{5}$$

4. If $\|U^{k+1} - U^{k}\| < \delta$ then END, otherwise return to step 2.

Here, δ is a termination criterion between 0 and 1.

Fuzzy C-means (FCM) algorithm is proved to be superior over the other clustering approaches in terms of segmentation efficiency. The major problem of the FCM algorithm is the huge computational time required for convergence.

D. Artificial Neural Network

Artificial Neural networks popularly known in the field of medical imaging due to their functionalities like adaptive learning from input information, usage of a suitable learning algorithm and have the capability of optimizing the relationship between the inputs and outputs via training, processing and leading to a reliable solution desired by specifications. The motivation behind the neural network is to form a structure like the human brain using biological neurons that are highly reluctant to noise, robust etc. The basic structure of a neural network as shown in Figure 3, where X $\{x_i,\ i = 1, 2, \ldots, n\}$ represent the inputs to the neuron and Y represents the output. In this model each input is multiplied by its weight w_i, a bias b is associated with each neuron and their sum goes through a transfer function f. The basic relationship of neurons in terms of input and output can be described as follows.

$$y = f\left(\sum_{i=1}^{n} w_i\, x_i + b\right) \tag{6}$$

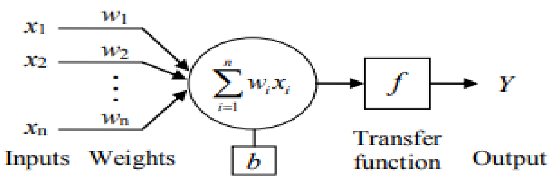


Figure 1. The model of a neuron

In Neural network, a range of transfer functions available to process the weighted and biased inputs, four basic transfer functions widely adopted for medical image processing are illustrated in Figure 4.

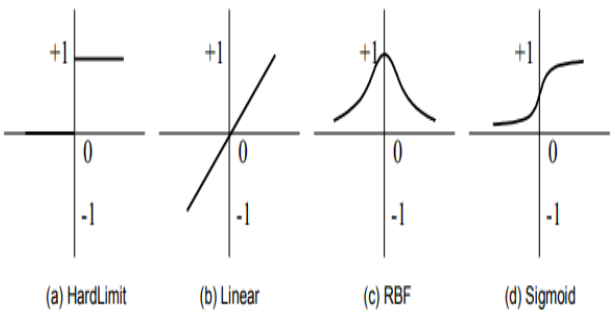


Figure 2: Basic transfer function

In medical image processing, most commonly used types of neural network are feed-forward, feedback networks and self-organizing maps. With the selection of suitable transfer functions and connection of neurons, various neural networks can be constructed to be trained for producing the specified outputs. The main goal of selection of all above mentioned parameter is to minimize the network's overall output error by iteratively adjusting the weights and bias for specific training function. In this research paper Feed-forward, neural network type is used for phantom data set.

a) Feed-forward Network

It is most commonly used neural network architecture among several available types in medical imaging applications. In this type, it consists of multiple layers, including one input layer, a no. of hidden layers and an output layer. In this, the neurons in each layer are connected only with the neurons in the next layer. These connections are unidirectional. The structure of a feed-forward network is shown in Figure 5.

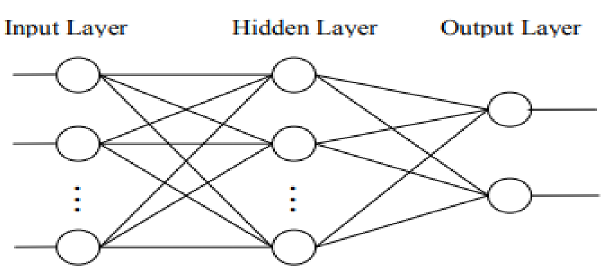


Figure 5 An example feed-forward network with a single hidden layer and two outputs

The Feed-forward type of networks generally uses the Backpropagation (supervised) learning algorithm. In this algorithm, it dynamically alters the weight and bias values for each neuron in the network. Based on the weight value, it compares the network's actual output with target output value. The output error is first used to alter the weights between the final hidden layer and the output layer neurons by calculating the change in weight values needed to correct the output error. The weights between the final hidden layer and the previous layer are then updated, and in this pattern, the error is propagated backward through the network to try and improve the output accuracy. The actual alteration of weights is carried out using a (normally stochastic) gradient descent algorithm, where the weights are modified after each training example is present to the network. Alternatively, the weights can be altered after all of the training cases have been processed in a batch fashion. The Multiplayer Perceptron is a special type of feed-forward network using three or more layers with nonlinear transfer functions in the hidden layer. It is suitable to associate training patterns with outputs for nonlinearly separable data. This type of network is mainly suitable for applications in medical imaging where the inputs and outputs are numerical and pairs of input/output vectors provide a clear basis for training in a supervised manner.

IV. RESULTS AND DISCUSSION

In this research paper, traditional segmentation techniques and artificial neural network approach applied on the phantom dataset. The generation of phantom dataset for medical images are mentioned below:

A. Phantom Dataset

The Phantom is a specially designed object that is scanned or imaged in the field of medical imaging to evaluate, analyze, and tune the performance of various imaging devices. A phantom is more readily available and provides more consistent results than the use of a living subject or cadaver, and likewise avoids a living subject to direct risk. Originally, Phantoms were employed for use in 2D X-Ray based imaging techniques such as radiography or fluoroscopy, though more recently phantoms with desired imaging characteristics have been developed for 3D techniques such as MRI, CT, Ultrasound, PET, and other imaging methods or modalities.

The two-dimensional (2D) Sheep-Logan phantom was developed in 1974 as a tool for simulating image reconstruction in the head and brain for 2D computerized tomography (CT) and projection reconstruction (PR) [9]. The phantom developed is made up of an ellipse shape, which allows the user to obtain the projection values for all point of interest on the screen for any projection angle. The topology of the mathematical model is shown in figure 6.

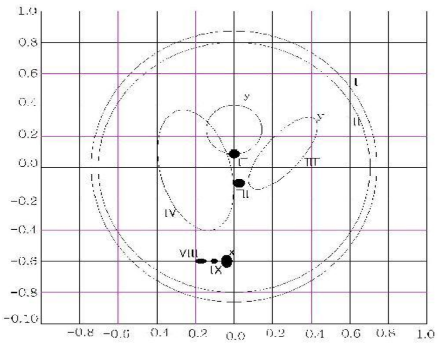


Figure 6 Topology of User-defined Phantom

As seen from figure 6, the model consists of ten ellipses of varying size, signal intensity (i.e., grey levels), and material density to mimic the geometric and x-ray attenuation properties of the head. The mathematical equation describing the individual three categories of ellipses are given below:

a) For ellipse centerd at origin:

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} \leq 1 \quad (7)$$

b) An ellipse with its center displayed to the point $(x_0,\ y_0)$.

$$\frac{(x - x_0)^2}{a^2} + \frac{(y - y_0)^2}{b^2} \leq 1 \quad (8)$$

c) Ellipse displayed to point $(x_0,\ y_0)$ and rotated at angle $\propto_0$:

$$\frac{((x - x_0)cos\propto_0 + (y - y_0)sin\propto_0)^2}{a^2} + \frac{(-(x - x_0)cos\propto_0 + (y - y_0)sin\propto_0)^2}{b^2} \leq 1 \quad (9)$$

The user-defined phantom is developed by superimposing successive elements of the phantom using the equation of ellipse defined below:

a) An ellipse centerd at origin:

$$\mu_i(x,y) = \begin{cases} \mu_i^{const} for\ \frac{x^2}{a^2} + \frac{y^2}{b^2} \leq 1 \\ 0\ for\ \frac{x^2}{a^2} + \frac{y^2}{b^2} > 1 \end{cases} \quad (10)$$

b) An ellipse with its center displayed to the point $(x_0,\ y_0)$.

$$\mu_i(x,y) = \begin{cases} \mu_i^{const} for\ \frac{(x - x_0)^2}{a^2} + \frac{(y - y_0)^2}{b^2} \leq 1 \\ 0\ for\ \frac{(x - x_0)^2}{a^2} + \frac{(y - y_0)^2}{b^2} > 1 \end{cases} \quad (11)$$

d) Ellipse displayed to point $(x_0,\ y_0)$ and rotated at angle $\propto_0$:

$$\mu_i(x,y) = \begin{cases} \mu_i^{const} for\ \frac{((x - x_0)cos\propto_0 + (y - y_0)sin\propto_0)^2}{a^2} + \frac{(-(x - x_0)cos\propto_0 + (y - y_0)sin\propto_0)^2}{b^2} \leq \\ 0\ for\ \frac{((x - x_0)cos\propto_0 + (y - y_0)sin\propto_0)^2}{a^2} + \frac{(-(x - x_0)cos\propto_0 + (y - y_0)sin\propto_0)^2}{b^2} > \end{cases}$$

The user-defined phantom is created in MATLAB® giving users, the flexibility to decide regarding the resolution of the image. The original number of projections was 180x160, while 256x256 or 512x512 images are common today.

B. *Implementation*

In this research, the Sheep Logan Phantom dataset with three-dimensional data of size 128X 128 X 128 is considered for the experiment.

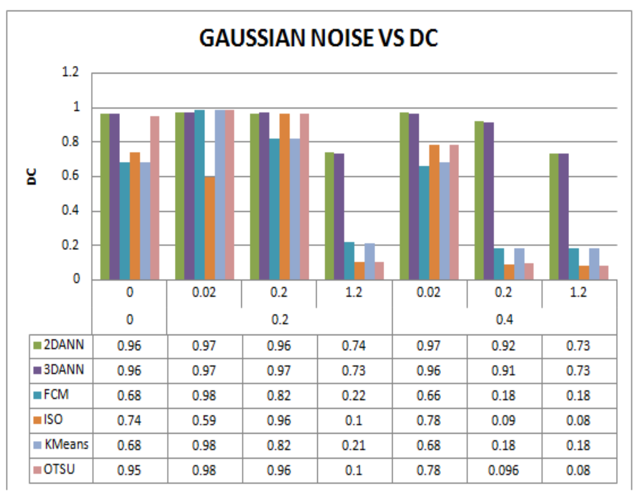
Artefacts in medical slices are added using Gaussian noise and Speckle noise to present a realistic medical image, which consists of multiple noises due to sensors' noise and the intensity inhomogeneity. Moreover, to detect malignancy from medical dataset, tumors in the phantom dataset are inserted randomly. After successfully generating dataset both viz. traditional segmentation and soft computing methods are applied over it. The research has an objective to detect malignancy from medical images which helps an expert in his accurate diagnosis.

After successful generation of medical dataset, traditional and neural network techniques are applied on it. To see the performance of above mentioned segmentation technique, dice co-efficient measure is used.

C. Dice Co-efficient

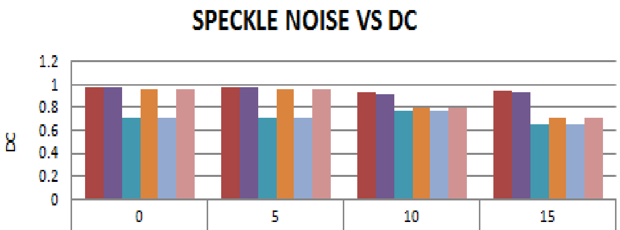
It is a widely used similarity measure in the field of medical imaging to evaluate the performance of the segmentation algorithm. This measure requires ground truth information for the evaluation. It is calculated using the formula,

$$DC = \frac{2|\ M \cap N\ |}{|M| + |N|} \quad (13)$$



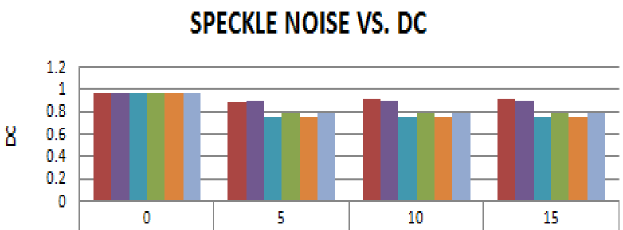
	0	0.02	0.2	1.2	0.02	0.2	1.2
	0	0.2			0.4		
2DANN	0.96	0.97	0.96	0.74	0.97	0.92	0.73
3DANN	0.96	0.97	0.97	0.73	0.96	0.91	0.73
FCM	0.68	0.98	0.82	0.22	0.66	0.18	0.18
ISO	0.74	0.59	0.96	0.1	0.78	0.09	0.08
KMeans	0.68	0.98	0.82	0.21	0.68	0.18	0.18
OTSU	0.95	0.98	0.96	0.1	0.78	0.096	0.08

Figure 1: Gaussian Noise Vs. DC



	0	5	10	15
2 D ANN	0.98	0.98	0.94	0.95
3DANN	0.98	0.98	0.92	0.94
FCM	0.71	0.71	0.77	0.66
ISO	0.97	0.97	0.81	0.72
KMeans	0.71	0.71	0.77	0.66
OTSU	0.97	0.97	0.81	0.72

Figure 2: Speckle Noise Vs DC



	0	5	10	15
2 D ANN	0.98	0.89	0.93	0.93
3DANN	0.97	0.91	0.91	0.91
FCM	0.98	0.77	0.77	0.77
ISO	0.98	0.79	0.79	0.79
KMeans	0.98	0.77	0.77	0.77
OTSU	0.98	0.79	0.79	0.79

Figure 3: Speckle Noise Vs DC

V. CONCLUSION AND FUTURE SCOPE

After successfully generation of medical dataset, we apply traditional segmentation techniques and neural network on it. The result concludes that, as we increase the noise, neural network approach gives higher DC value, it means closer to ground truth compare to traditional segmentation technique.

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