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# Automated Detection of Alzheimer Disease Using Region Growing technique and Artificial Neural Network

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***Abstract*—**Alzheimer is known as the loss of mental functions such as thinking, memory, and reasoning that is severe enough to interfere with a person's daily functioning. The appearance of Alzheimer Disease symptoms (AD) are resulted based on which part of the brain has a variety of infection or damage. In this case, the MRI is the best biomedical instrumentation can be ever used to discover the AD existence. Therefore, this paper proposed a fusion method to distinguish between the normal and (AD) MRIs. In this combined method around 27 MRIs collected from Jordanian Hospitals are analyzed based on the use of Low pass -morphological filters to get the extracted statistical outputs through intensity histogram to be employed by the descriptive box plot. Also, the artificial neural network (ANN) is applied to test the performance of this approach. Finally, the obtained result of t-test with confidence accuracy (95%) has compared with classification accuracy of ANN (100 %). The robust of the developed method can be considered effectively to diagnose and determine the type of AD image.

***Keywords*—**Alzheimer disease, Brain MRI analysis, Morphological filter, Box plot, Intensity histogram, ANN.

## I. Introduction

ALZHEIMER disease is the most common causes of dementia in the elderly. The disease usually becomes clinically apparent of higher intellectual function with alteration in mode and behavior later progressive disorientation memory loss and aphasia indicted severe cortical dysfunction and over the next 5 to 10 years the Alzheimer disease is 3% for individual 65 to 74 years old, 19% for 75 to 84 years and 47% for 85 years or more. This increasing incidence with age has given rise to major medical social and economic problems in countries with growing number of elderly although pathologic examination patient becomes profoundly disabled mute and immobile. Death usually occurs from inter-current pneumonia or other infections then considered by age groups the incidence of brain tissue remains necessary for the definitive diagnosis of Alzheimer disease the combination of clinical assessment and modern radio logic method allow accurate diagnosis in 80% to 90% of cases [1]. The most popular 10 warning signs of Alzheimer's disease as: Memory loss, Difficulty performing, Problems with language, Poor or decreased judgment, Problems with abstract thinking, Misplacing things, Changes in mood, or behavior, Changes in personality, Loss of initiative.

The MRI systems are the best medical imaging modalities to represent the human brain components, but still variations on the contrast of the same tissue are found in an image due to RF noise or shading effects due to magnetic field variations, resulting in tissue misclassification later on. In order to study each segment in the brain MRIs, the segmentation techniques are become necessarily important in partitioning an image into different regions. In MRI, segmentation consists of partitioning the image into different neuroanatomical structures which corresponds to different tissues. Therefore, analyzing the neuroanatomical structures and the distribution of the tissues on the image, brain disorders can be figured out. Hence, dealing with the variety of brain tissues is growing fast and becomes a fact to modify a certain tool for this mission.

These tools are usually trained to recognize the three basic tissue classes found on a healthy brain MR image: white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). All of the misrecognized tissues or fluids are classified as suspect, to be pathological. There are two ways for segmentation process: (1) the manual delimitation of the structures present within an image by an expert, (2) an automatic segmentation technique [2]-[8]. There are several automatic segmentation techniques. Some of them use the information contained in the image based -histogram. This way, since different contrast areas should correspond with different tissues, the image histogram can be used for partitioning the image. Other methods use statistical based- classifiers based on the expectation maximization algorithms [9]-[11]. Other segmentation techniques are based on artificial neural network classifiers [5], [12]–[15].

In this work, we have introduced a double check approach to identify the MRIs with AD from the normal one. The first way is performed using the low pass filter, morphological filter and then the histogram for the AD- MRI was found for the WM, GM, and SCF. From the obtained histogram the statistical extracted information such the mean value and standard deviation were calculated to undertake the further statistical analysis. In the second way, the extracted feature from threshold histogram was employed to train and test the ANN

In the literature, there are many attempts about the biomedical application of ANN were reported. Patil et al [16] proposed technique consists of three stages, namely, normalization of 3D MRI, feature extraction, and classification.

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In the first stage, normalizing the 3D MR images used Voxel-based morphometry (VBM) analysis spatially filtered and slice averaged in order to obtain 2D MR slice. In the second stage, the extracted features by DWT are fed to FP-ANN with accuracies of 74% and 67% using Daubechies wavelet and Haar wavelet respectively. Ahmed et al. have provided have been used an active contour modeling to enhance the MRIs to be applied for segmentation process, where the targeted segments were detected by the ANN [17]. The ANN has been used for cross talk scatter correction during the simultaneous dual isotope imaging (Tc-99m/I-123) [18], [19]. Torabi et al. [20], [21] proposed a novel method for Alzheimer's disease investigation using the texture analysis technique to form a vector containing 336 elements to be forwarded to ANN. A combined method between Voxel-based morphometry and Artificial Neural Network to diagnose the AD was demonstrated by Chengzhong et al. [22]. El-Sayed et al. [23] developed a hybrid technique to classify the healthy abnormal brain MRIs based on three steps: feature extraction using Discrete wavelet transform, features reduction using principal component analysis, and classification using feed forward back propagation artificial neural network (FP-ANN) and the second classifier is based on k nearest neighbor (k-NN). A classification with a success of 97% and 98% has been obtained by FP-ANN and k-NN, respectively.

This paper is structured in the following way: Section II provides details on the proposed enhancement techniques. Section III provides a comparative performance evaluation of this approach and the experimental results. Finally, Section IV provides a summary of the paper and its main conclusions.

## II. Materials and Method

The proposed technique was built based on the extracted data from AD MRIs for normal and abnormal cases by applying image processing techniques, where the results were evaluated by the T-test descriptive analysis and compared with ANN. In this Section, the theoretical backgrounds for both approaches are introduced.

### *A. Image Database*

We have a total of 37 real MR brain images were used in this study. All these normal and pathological benchmark images are axial, T2-weighted, MR images of 256 x 256 size. The algorithm of preprocessed images was tested on two sets of AD brain images. Specifically, we tested (17) images of AD abnormal images and set of (20) images are normal. All images were provided by Jordanian hospitals, especially the King Hussein Medical City (KHMC), Jordan.

All images were a variety of patients and were taken from several transverse slices.

### *B. Enhancement*

In this paper, the enhancement of AD MRIs was performed as described in the following steps using the LabView 7.1 software:

Step 1. After converting all images to the gray scale low pass filter is applied. Calculates the inter-pixel variation between the pixel being processed and those pixels surrounding it. If the pixel being processed has a variation greater than a specified percentage, it is set to the average pixel value as calculated from the neighboring pixels.

Step 2. Morphological filters: Performs grayscale morphological transformations. All source and destination AD image types must be the same. The connected source image for a morphological transformation must have been created with a border capable of supporting the size of the structuring element. A 3 × 3 structuring element requires a minimal border of 1, a 5 × 5 structuring element requires a minimal border of 2, and so on. The border size of the destination image is not important (Fig. 1).

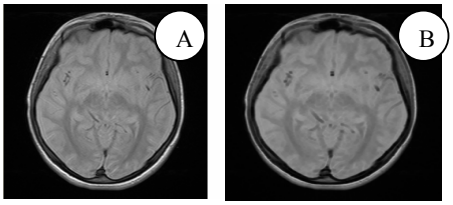


Fig. 1 A original brain image B after morphological filter

Step 3. Equalizer filter: Produces a histogram equalization of an image. This VI (Labview code) redistributes the pixel values of an image to linearize the accumulated histogram. The precision of the VI is dependent on the histogram precision, which in turn is dependent on the number of classes used in the histogram (Fig. 2).

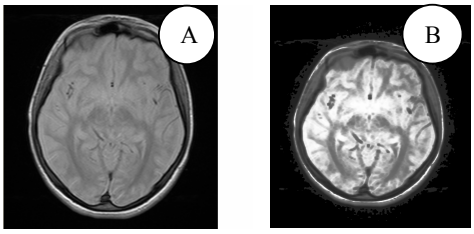


Fig. 2 A original brain image B equalizer output image

Step 4. Histogram transformation: A histogram of an image provides information about the intensity distribution of pixels in the image. The simplest form of histogram is the plot of occurrence of specific gray level values of the pixels in the image.

$$H(r_i) = n_i \qquad \text{for i} = 0,1,2,\ldots..\text{L-1} \qquad (1)$$

$r_i$ is the ith gray level in the image for a total of L gray values and $n_i$ is the number of occurrences of gray level $r_i$ in the image. The information that obtains from histogram is:

**Mean Value:** Mean value of intensities found in the image or selected regions in the image.

**Standard Deviation:** Standard deviation of the pixel intensities.

**Number of Pixels:** Number of pixels used to calculate the histogram.

Step 5. In this work for the results evaluation, the T- test and ANN have been used.

## III. Results and Discussion

This work has an effective study of several images for patients with AD and compared with normal sample using image processing techniques conducted by filtration steps (low pass filter and morphological filter) then it was followed by the histogram for the whole image. As the main objective of our algorithm is to distinguish normal brain MR images from pathological brain MR images, we have considered that all images pertaining to Alzheimer's disease belong to the same class. Each image is a gray image and each pixel has an 8-bit representation of its corresponding image intensity. For each image, the two extreme ends of the intensity spectrum are given by 0 (representing black) and 255 (representing white). The figures below show the image processing results for normal and Alzheimer images respectively. It is seen that the histogram for all images contain many statistical variable and by observing the original image and the output image, it has proven that the output image has higher quality than input image.

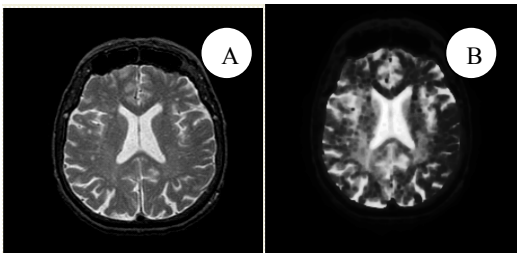


Fig. 3 Normal image before A and after B steps of enhancement

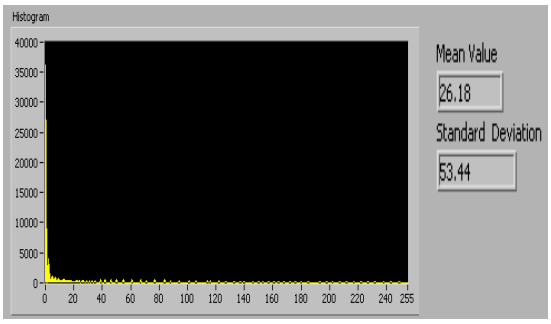


Fig. 4 The histogram and extracted statistical values for normal image

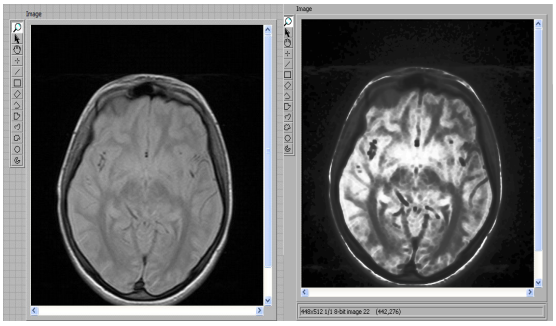

Fig. 5 The original Alzheimer disease, before and after (right side) enhancement

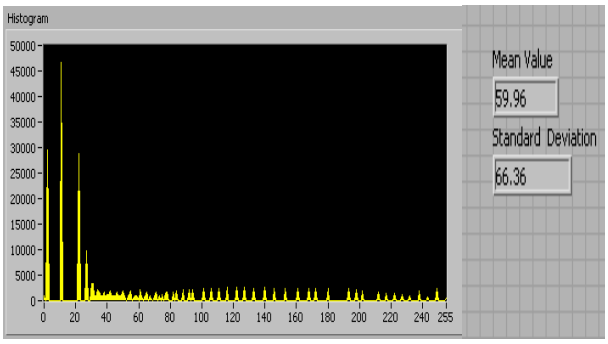


Fig. 6 The histogram and statistical values for Alzheimer image

The Box Plot (Fig. 7) clearly indicates the average value of the AD which are in the range of (58-64) is higher than the average values of the normal cases which are in the range of (25-30).

### *A. Two-Sample T-Test and CI: Normal; Alzheimer*

A two-sample T-test was performed to test the hypothesis claiming that mean for AD is the same mean for the normal case. It is clear from the test results that the hypothesis is rejected and concluded that there will be a difference between the two means as illustrated in Table I.

TABLE I
Two-Sample T for Normal vs. Alzheimer

| | N | Mean | St. Dev. | SE Mean |
|---|---|---|---|---|
| Normal | 20 | 26.61 | 1.93 | 0.43 |
| Alzheimer | 17 | 62.31 | 2.71 | 0.66 |

Difference = mu (Normal) - mu (Alzheimer)
Estimate for difference: -35.6976
95% CI for difference: (-37.3082; -34.0869)
T-Test of difference = 0 (vs not =):
T-Value = -45.40, P-Value = 0.000 DF = 28

The used ANN has a simple structure in Fig. 8, where the achieved performance was better than the T- test. Table II represents all parameters and results of ANN for AD classification. Fig. 9 shows the best performance that ANN was achieved during training - testing - validation procedure.

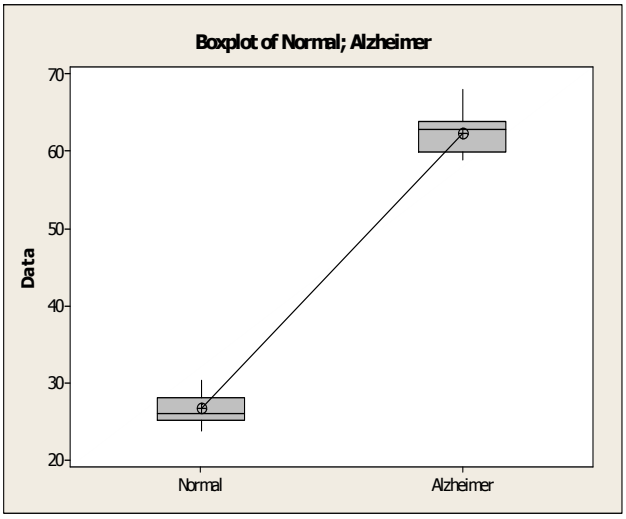


Fig. 7 Box plot of extracted values by histogram for normal and Alzheimer disease

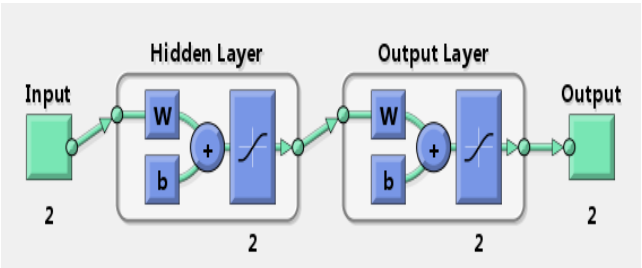


Fig. 8 ANN structure

## IV. Conclusion

In this study we explored the ability to discriminate between 17 AD patients and 20 normal cases. The present paper proposed the development of a statistical-automated brain MRI diagnostic system, which can classify whether the MR image belongs to a normal brain or to a person suffering from Alzheimer's disease. The system implemented a two-stage algorithm. In stage 1, for each image, its intensity histogram is computed after preprocessing steps such a use of morphological and low pass filter and then the extracted data such the mean and standard deviation is employed to the further statistical differential descriptive analysis. It has been proven that this approach as simple as, can efficiently distinguish between the normal and AD with adequate accuracy. The box plot is constructed to distinguish between the two cases of Alzheimer diseases.

The proposed system could provide very good accuracy of 95% based on the descriptive analysis and 100% by the ANN. This showed significant improvement compared to some of the results reported very recently in [16], [17], [21]. This proposed diagnostic method can be used for helping to make a decision on disease as a support tool for radiologists. Some weaknesses of the algorithm, that it was based on small number of samples available at the time of study. To overcome this drawback, it is suggested to increase the number of samples used for the study.

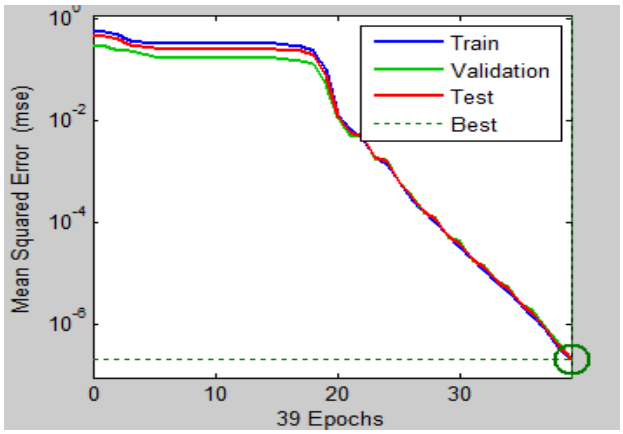


Fig. 9 Data validation with best performance at 39 epoch

TABLE II
The Performance of ANN

| | Training (70%) | Testing (15%) | Checking (15%) | total |
|---|---|---|---|---|
| True positive | 9 | 3 | 4 | 16 |
| False Negative | 0 | 0 | 0 | 0 |
| True negative | 16 | 3 | 2 | 21 |
| False positive | 0 | 0 | 0 | 0 |
| Sensitivity | 100 | 100 | 100 | |
| Specificity | 100 | 100 | 100 | |
| Classification accuracy | 100 | 100 | 100 | |
| RMSE | 4.58e-4 | 4.58e-4 | 4.54e-4 | |

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