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Alzheimer's Disease Detection in Brain Magnetic Resonance Images Using SOM

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ABSTRACT

Primary diagnosis of Alzheimer's Disease (AD) is of immense importance, since clinical symptoms do not occur until substantial parts of the Substantia nigra (SN) neurons in the brain stem have been irreparably damaged. Furthermore, large sections of the population are regarded by this disease and while AD is currently considered as irredeemable, the symptoms can be reassured by the administration of drugs. Many different imaging modalities have been employed to help diagnose the disease. A few of them include: magnetic resonance imaging, computed tomography(CT), positron emission tomography,magnetic resonance spectroscopy, and functional magnetic resonance imaging. Each of these modalities offers something different towards the detection and possible treatments for Alzheimer's disease. Neuroprotective drugs could shelter neurons of the SN when used at the outset of the disease in the preclinical phase. Therefore a knowledge to detect early SN damage is anticipated for the identification of people at risk for AD. We are giving a loom for MRI brain slices by means of feature extraction and unsupervised clustering. In which clustering is carried out by way of a self-organizing map (SOM). Then, each pixel is classified according to the identified classes. The number of classes is a priori unknown and the artificial neural network that implements the SOM is used to define the primary categories. The detection of the classes in the SOM is done by using a K-means segmentation. This processing is useful for potential diagnosis of Alzheimer's disease in brain stem area. The principle of this solution is shown morphological operations to detection of pathological defects.

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INTRODUCTION

Alzheimer's disease (AD) was mentioned after the German psychiatrist and pathologist Alois Alzheimer after he examined a female patient (post mortem) in 1906 that had died at age 51 after suffering severe memory problems, confusion, and difficulty understanding the questions. Alzheimer reported two common abnormalities in the brain of the patient, "1. Dense layers of protein deposited outside and between the nerve cells. 2. Areas of damaged nerve fibers, inside the nerve cells, which instead of being straight had become tangled" (Pah-Lavan, 2006, p.8). Moreover, these plaques and tangles have been employed to help diagnose AD. MRI scans offer a lighter and more detailed picture of the brain and can read the difference between gray matter(GM) and white matter (WM). The two main types of matter in the brain are grey matter, which forms the outer layer of the brain where information is processed, and white matter, which forms the inner core and provides the 'wiring' for information to move along. MRI scans are powerful enough to reveal understated changes to the blood vessels in the white matter, a common sign of vascular dementia. Research has demonstrated that MRI scans successfully reveal the loss of brain cells in the hippocampus in 80 to 90 percent of cases of people with Alzheimer's disease, even in people who are in the early phases of the precondition.These images are MRI scans showing loss of cells from the hippocampus. a) Shows someone with Alzheimer's disease. b) Shows a control subject.

It is clear that people with Alzheimer's disease, lose brain cells at a higher than normal rate. All the same, the straightforward cell loss cannot be employed to diagnose the condition as brain cells are likewise lost in other types of dementia. But a diagnosis can be made if scans can ascertain the pattern of loss. In Alzheimer's disease, the loss is usually greatest in the area responsible for memory, which is in the middle of the sequential part, whereas cell loss is more widespread and generally in dementia with Lewy bodies and vascular dementia.

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MRI scans can provide researchers with a utilitarian tool for evaluating the effects of anti-dementia drugs in clinical tests. Scans taken at two or three yearly intervals can provide data about the levels and location of cell loss over time, which would bring out valuable information about the positive effects of potential treatments.

With the maturing age, there is progress in each and every area. As far as the medical field is touched on, it also has everyday grown. The medical imaging area in particular, has grown substantially in recent years, and has generated additional interest in methods and tools for the management, analysis, communication of medical image data. There is a growing need in neuroscience research for computational tools to organize, analyze, and visualize the vast amounts of new information being produced about the structure and the function of the brain. A scope of approaches has been proposed for semi-automatic detection of several structures in the brain. These approaches usually require manual interaction, even in most practical implementations, to perform the required segmentation and detection. The fully automated segmentation, however, is yet under research. Image processing in modern medicine is very helpful for diagnosis. In our case we work with a set of MRI images of the brainstem to potential diagnosis of Alzheimer's disease (AD), which is chronic disease depending on the production of dopamine. In ultrasound images is characterized by defects in substantia nigra (SN) area in brain-stem. The goal of this theme is to demonstrate an application which has been developed for ROI SN and searching these defects by thresholding and area comparison followed by statistical analysis. This application is helpful for classification of patients who have AD or not. For analysis of these images we are using a two-stage neural network system. The first phase is a self-organizing principal component analysis (SOPCA) network that is used to see the feature vector onto its leading principal axes found by using principal components analysis. This measure offers an effective foundation for feature extraction. The second phase consists of self-organizing feature map (SOFM) which automatically clusters the input vector into different areas.

1.1 Substantia Nigra and Alzheimer's Disease:

A. Substantia nigra in brain stem:

Substantia nigra (SN; in English "black substance") is a brain structure which is sited in the mesencephalon (midbrain) that acts as an important role in reward, dependence, and motility. SN produces an important dopamine for correct use of CNS (Central Nervous System). Alzheimer's disease (AD) is induced by the destruction of dopaminergic nerve cells. It is a degenerative disease of the basal ganglia in the brain. The primary symptoms of AD include muscle rigidity, tremors and changes in speech and gait, bradykinesia, sleep disorders and more. The following figure shows the position of SN:

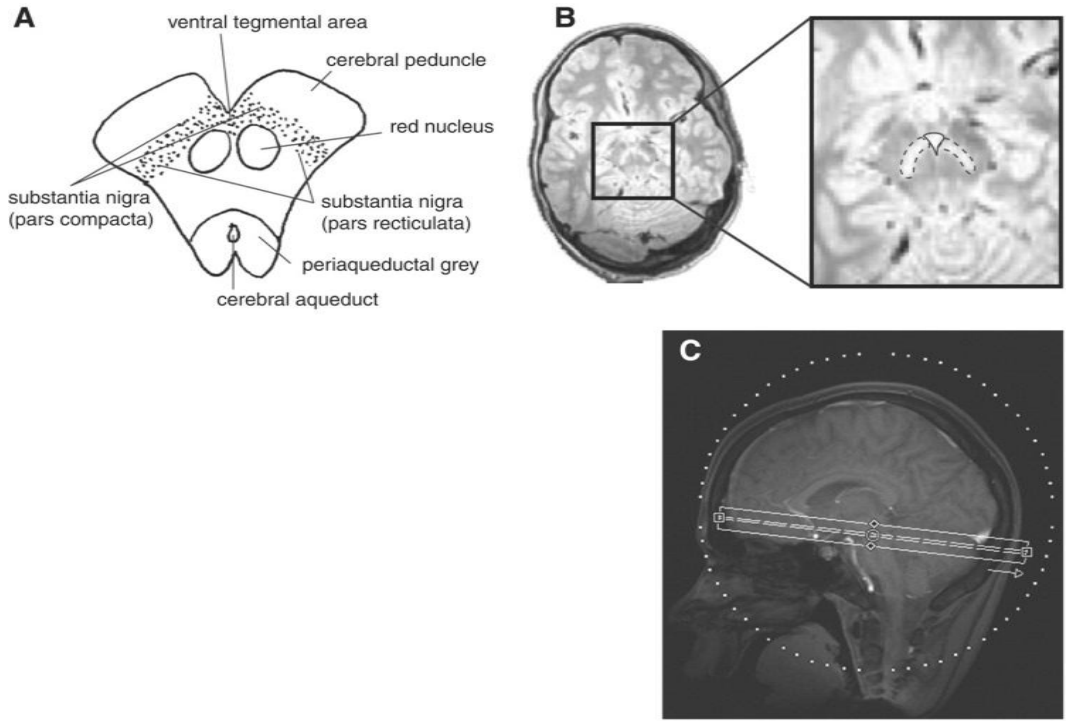

Fig.1: A position of searched SN in midbrain.

B. Alzheimer's Disease:

Alzheimer's disease is a neurological complaint in which the death of brain cells causes memory loss and cognitive decline. A neurodegenerative type of dementia, the disease starts slight and gets progressively worse.

Like all types of dementia, Alzheimer's is caused by brain cell death. It is a neurodegenerative disease, which means there is progressive brain cell death that happens over a course of time. The total brain size shrinks with Alzheimer's - the tissue has gradually fewer nerve cells and connections.

While they cannot be seen or tested in the living brain affected by Alzheimer's disease, postmortem/autopsy will always show tiny inclusions in the nerve tissue, called plaques and tangles:

- Plaques are found between the dying cells in the brain - from the build-up of a protein called beta-amyloid (you may hear the term "amyloid plaques").
- The tangles are within the brain neurons - from a disintegration of another protein, called tau.

II. Literature Review:

Development of Early Detection of Alzheimer's Disease some of the earlier tests that were set up in AD are Computed Tomography (CT) scans, structural Magnetic Resonance Imaging (MRI), and neuropsychological tests. CT scans were used to look for atrophy of the brain, and increased ventricle size. It was thought at first that cerebral atrophy was significantly larger in patients with AD than those without. However, it was discovered later that healthy people also have cerebral atrophy. Patients with dementia may not cause cerebral atrophy at least in the early phases of the disease. From these findings it was seen that it can be hard to differentiate between a healthy elderly patient and a patient with dementia. Thus, CT scans have been deemed as clinically unuseful in the principal diagnosis of AD.

After CT was discredited, questions were raised about using structural MRI. Fleisher *et al*. (2008) performed a study to evaluate "predictive models of progression from amnestic MCI (mild cognitive impairment) to AD to assess the added benefit of structural MRI data compared to clinical measures alone". Structural MRI measures the "medial temporal lobe structures, whole brain volumes, and ventricular volumes" (Fleisher *et al*., 2008, p. 192). This turned out similar to the CT scans that were done. It became difficult to differentiate between AD patient's brain atrophy and healthy patient's brain atrophy. " Though we didn't find MRI structural measures, compared to cognitive measures, to be necessary for predicting AD in fields with moderate degrees of MCI, this doesn't necessarily repudiate the utility of anatomic MRI as a potential biomarker for AD" (Fleisher *et al*., 2008, p. 196). Therefore, MRI can be helpful in differentiating between MCI and AD.

1.1 Neuropsychological Tests:

Neuropsychological tests are applied to find out the specific character and level of cognitive deterioration that the patient receives. Schmand (2011) carried a survey using several types of neuropsychological tests. A few of them that were used include, "Rey Auditory Verbal Learning Test, category fluency, Trial Making Test parts A and B, Digit Symbol Substitution Test, Digit Span forward and back, and the Clock Drawing task" (Schmand, Eikelenboom, & Van Gool, 2011, p. 1706).These tests are summarized as follows:

The Rey Auditory Verbal Learning and Category Fluency Tests The Rey Auditory Verbal Leaning Test uses lists to determine how patients recall words. Patients are given a list of 15 unrelated words that are repeated over 5 different trials. Then another list of 15 unrelated words was given to them. The patient then has to repeat the original list of 15 words and then again after 30 minutes. The test takes about 10 to 15 minutes with 30 minutes intervals. The category fluency test is a psychological test where patients have to say as many words as possible in a certain category within about 60 seconds. The categories can be animals, fruits, vegetables, or words that begin with a particular letter of the alphabet.

1.2 The Trail Making Test:

The Trail Making Test is used to measure the function of the brain in general. The test has two parts: Part A uses a series of numbers that the patient has to connect in sequential order (similar to a dot-to-dot). Part B uses a series of numbers and letters that the patient has to alternately connect letters and numbers in sequential order. Part A and Part B are scored separately and measure the amount of time, in seconds, that it takes to finish the trails. The longer the completion time is the more it suggests there is a neurological deficit.

III. Proposed Methodology:

The work involves the image processing of MRI images of the brain, feature extraction and finally developing a suitable neural network classifier to classify the normal and abnormal brain images. Images of the brain are obtained from the MRI and the features are extracted using self organized principal

component analysis (SOPCA) technique. These characteristics are utilized to direct the neural net. The artificial neural network model is used for classification. Thus, the proposed work emphasizes on development of Neural Network based method for the classification of MRI brain images. The block schematic diagram shown in figure is the proposed architecture for classification of MRI brain images.

Image Processing: At the first step for every processing is suitable preprocessing for successful application. Thus, the first step is

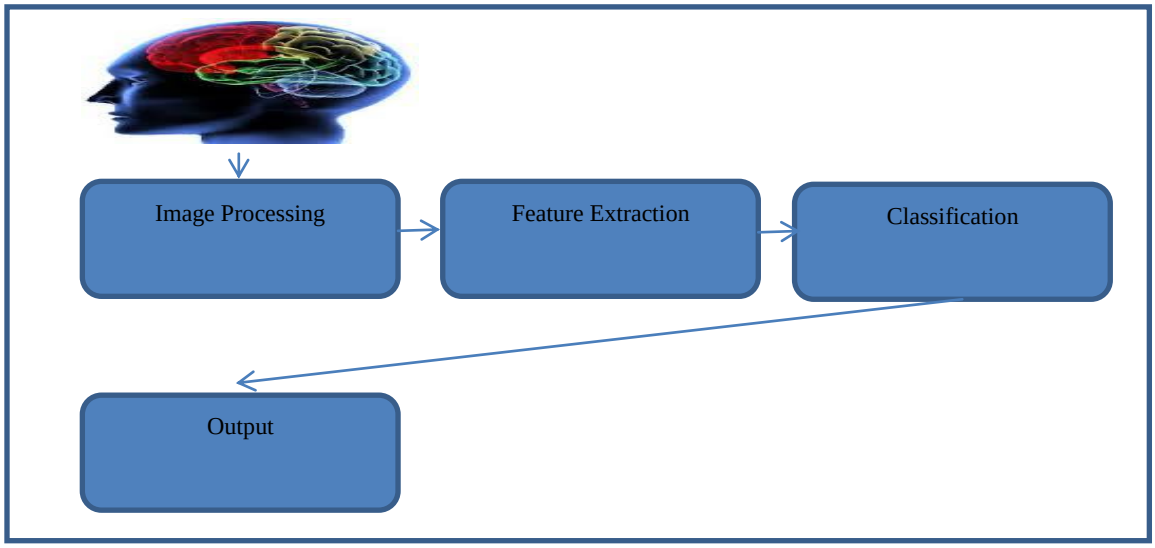

Fig. 2: Our Proposed Architecture

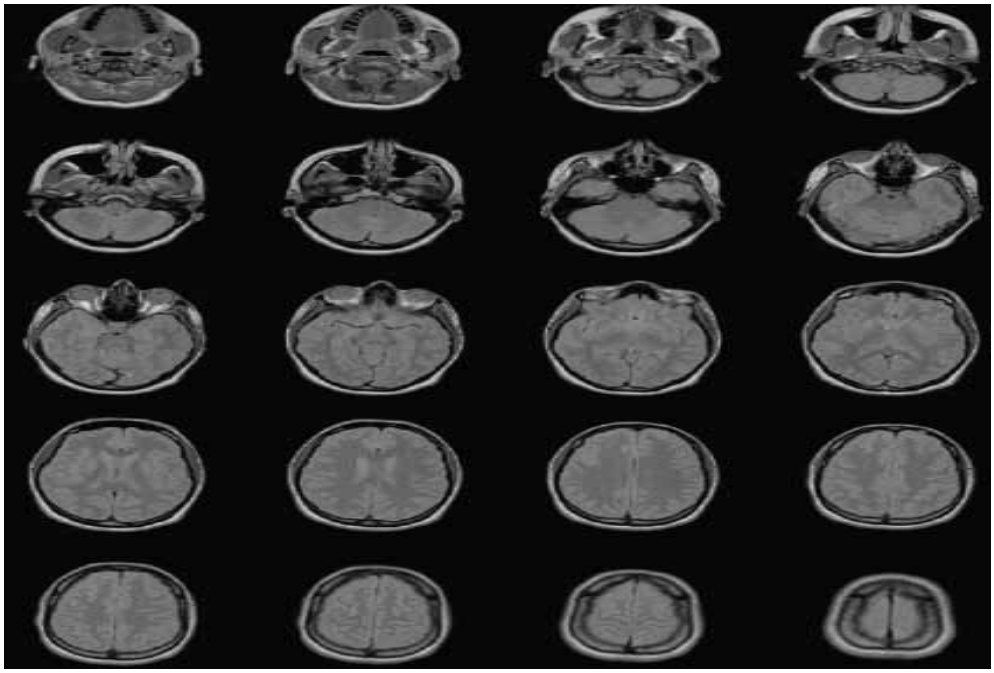

Fig. 3: A typical example of the MRI dataset

Thus, the first step is cropping of images to window with stem area. It is the first step in the algorithm. We considered about the influence of a speckle noise that is typical for sonographical data. MRI images are very sensitive to dynamic speckle noise. The speckle noise arises from different tissues and the actual position of ultrasound investigation. The main problem for the reduction is that speckle is not static noise but dynamic in the image. If we have these small images, then the influence is not very considerable despite the speckle noise should be reduced.

Feature Extraction: The feature extraction is used to reduce the dimension of the input data and minimize the training time taken by the classifier. Multiple features which include geometrical moments,

statistical moments and texture moments are extracted from the region of interest (ROI).

i) Statistical Moments: The basic idea is to characterize the 'content' of an image histogram using some descriptors. Therefore, the following statistical features of the histogram were calculated for quantitative analysis of the gray-level distribution in the ROI. The following statistical features were computed: 1) Mean value, 2) Median value, 3) Standard Deviation, 4) Skewness, and 5) Kurtosis.

ii) Geometrical Moments: Seven moments defined by Hu were computed based on the segmented ROIs. Hu moments have been proven to be invariant to object scale, position and orientation. The moment of inertia is adapted to image processing by interpreting intensity values as inertia values and varies strongly between a uniform and a centrical distribution of the ROI.

iii) Texture Features: Gabor filters are effective to extract texture features [18].Given an image I(x, y) with size P × Q, its discrete Gabor wavelet transform is defined by the convolution

$$G_{mn}(x,y) = \sum_{\xi}\sum_{\eta} I(x-\xi, y-\eta) g^{*}_{mn}(\xi,\eta)$$

where ∗ indicates the complex conjugate of gmn. It is assumed that the local area is spatially homogeneous [8]. The filter mask size is indicated by ξ and η. The other two texture features, average gray level and average contrast were computed.

Feature selection using self-organized principal components analysis. A key problem encountered in statistical pattern recognition is that of feature selection. Feature selection refers to a process whereby a data space is transformed into a feature space, in such a way that the data set may be represented by a reduced number of ''effective'' features and yet retain most of the intrinsic information content of the data. Principal Components Analysis PCA is perhaps the oldest and best-known technique in multivariate analysis Haykin, 1994. The practical value of PCA is that it provides an effective technique for dimensionality reduction. The first stage in two-stage network is a neural network that performs principal components analysis of arbitrary size on the input vector.

In, this network is a feed forward network composed of a single layer of linear neurons. The only aspect of the network that is subject to training is the set of synaptic weights {wji} connecting source node i in the input layer to computation node in the output layer, where i=0,1, . . . ,n-1, and j=0,1, . . . ,m-

5. Self-organizing feature-mapping (SOFM):

The principal goal of the self-organizing feature mapping (SOFM) network, developed by Kohonen 1984 is to transform an incoming signal of arbitrary dimension into a one- or two-dimensional discrete map, and to perform this transformation adaptively in a topological order fashion. Many activation patterns are exhibited to the network, one at a time. Each input has a corresponding localized group of nerve cells in the output layer of the network to be active. The essence of the Kohonen's SOFM algorithm is that it substitutes a simple geometric computation for more detailed properties of the Hebb-like rule and lateral interactions. There are three basic steps taken in the application of the algorithm after initialization, namely, sampling, similarity matching, and updating. These three steps are iterated until the map formation is accomplished.

Classification: The training and classification is done using Neural Network. Neural network technology provides a number of tools such as learning and adaptation, generalization and robustness, feature extraction and distributed representation. The neural network approach has been shown fruitful in solving classification and identification problems

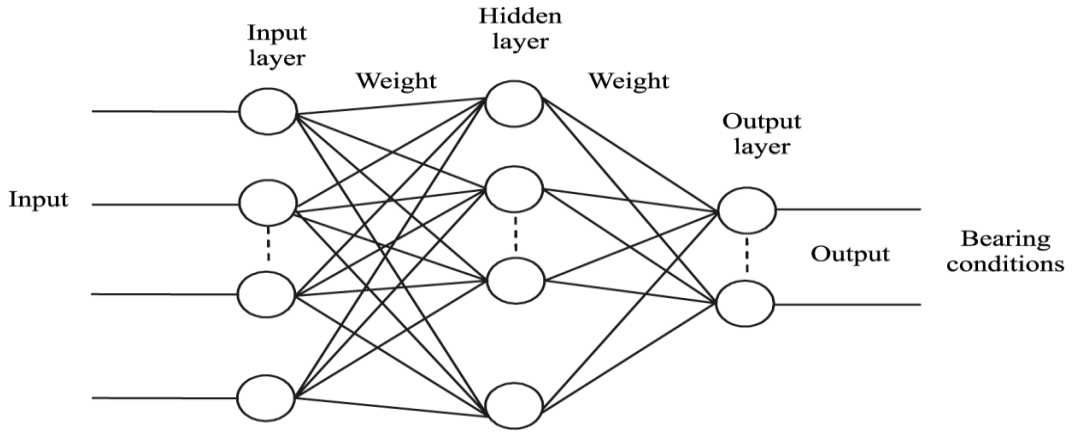

Fig. 5: Neural Network Architecture

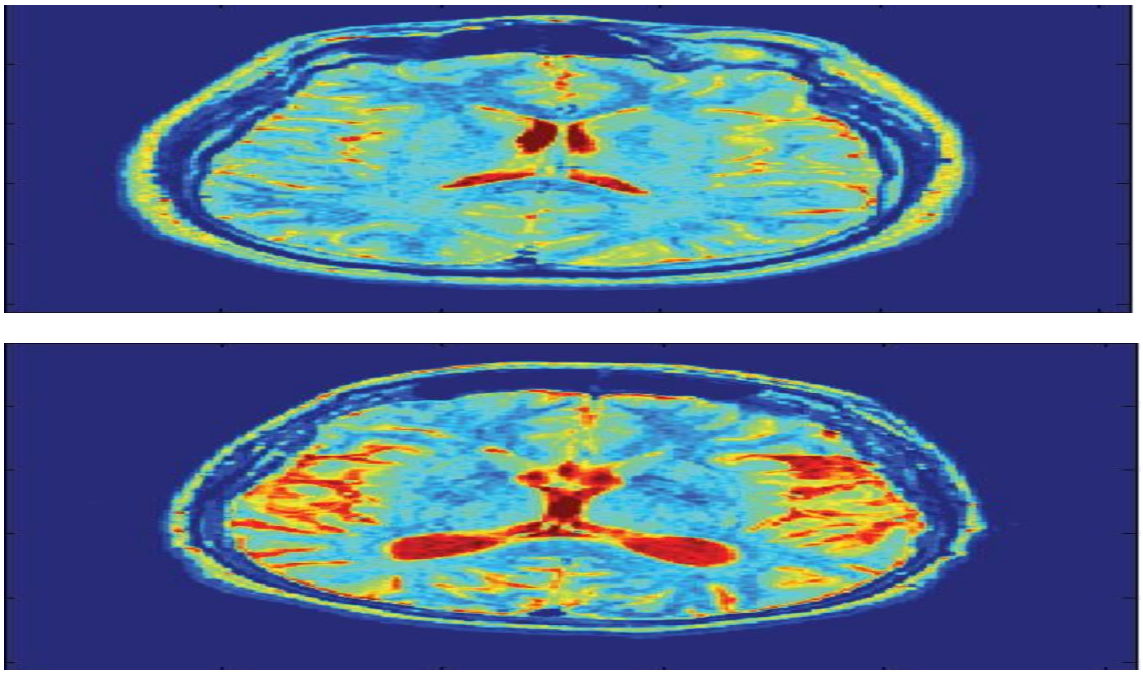

Fig. 6: Healthy image (a) and AD image (b) in double color format.

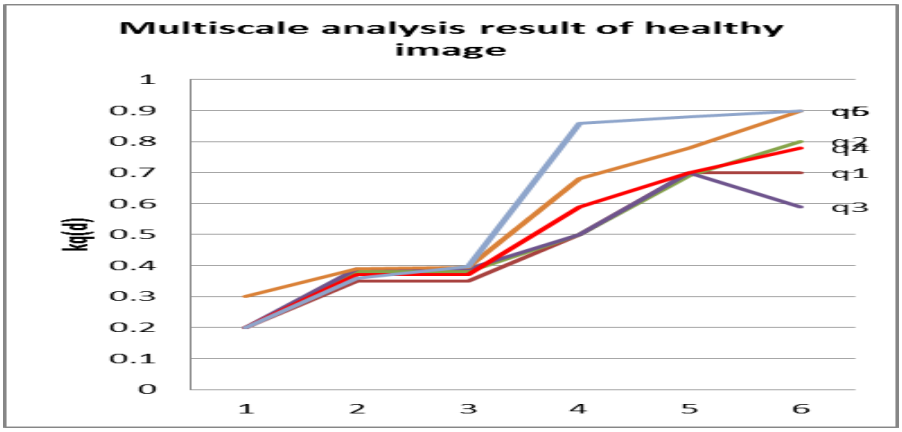

Fig. 7: Multiscale analysis result of healthy image

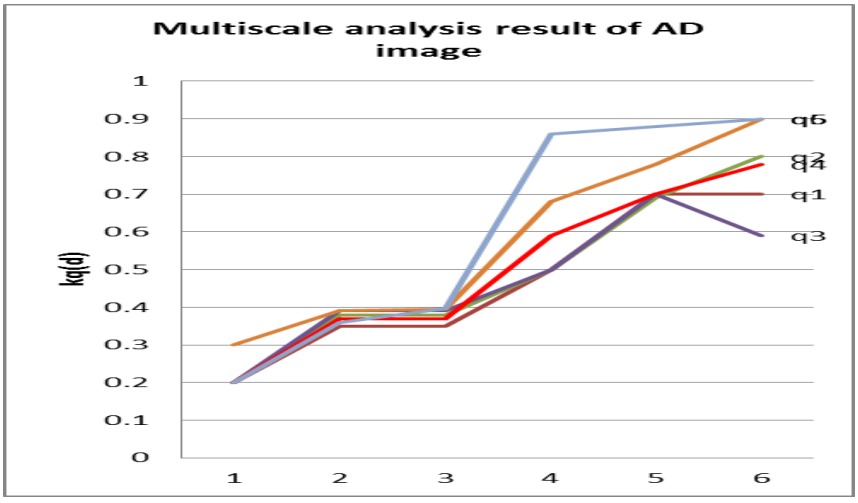

Fig. 8: Multiscale analysis result of AD Image

Conclusion:

A diagnosis of Alzheimer's disease (AD) is challenging problem and there is still a lot of work that needs to be done in this area. Over the past few years, recognition of substantial nigra in brainstem has received substantial attention from researchers in neurology communities. This common interest in this recognition among researchers working in diverse fields is motivated both by the remarkable power to diagnose Parkinson's disease. In this paper, a method was proposed for automatic recognition of substantia nigra in brain-stem SOM for feature extraction.

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