AN IMPROVED ALZHEMEIR'S DISEASE DETECTION USING IMPROVED UNSUPERVISED MAPPING TECHNIQUE

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Abstract : **The Alzheimer's disease (AD) is currently ranked as the sixth leading cause of death in the United States and recent estimates indicate that the disorder may rank third, just behind heart disease and cancer, as a cause of death for older people. So, predicting in its early stage may prevent it from progressing and may be of great importance. The diagnosis of Alzheimer's disease (AD) requires a range of medical tests, which leads to huge amounts of multivariate heterogeneous data. It can be difficult and exhausting to manually compare, visualize, and analyze this data due to the heterogeneous nature of medical tests; therefore, an efficient computational approach for accurate prediction of the changes in the brain through the classification of magnetic resonance imaging (MRI) images is greatly beneficial and yet very challenging. In this paper, a novel approach is proposed for the diagnosis of very early stages of AD through an efficient mapping technique for differentiating affected MRI images from normal .This employs unsupervised learning framework with improved adaptive moving self organizing mapping(AMSOM) method. We first apply median filter for denoising and then feature extraction to extract some of the most critical AD-related features of brain images from the original MRI volumes and also gray matter (GM) segmentation volumes. The 24 features are captured with most discriminative properties that vary between a healthy and Alzheimer-affected brain. Next, we perform a clustering over the set of vectors for classifying and clustering faster. To use the best extracted features, we present a hybrid learning framework which embeds the feature vectors in a subspace. Next, using a small set of subjects, we apply clustering method in the created space to predict the labels of the remaining images and classify them in the two groups of mild Alzheimer's and normal condition (MCI/NC).** .

IndexTerms **- Adaptive moving fuzzy self organize mapping, clustering, Feature extraction, Self organised mapping(SOM) .**

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I. INTRODUCTION

The World Alzheimer 5Report states that 46.8 million people worldwide were living with dementia in 2015 and this number is believed to be greater than 50 million people in 2018. Every 20 years, there is increase in growth which may be 75 million in 2030 and 131.5 million in 2050. Because of the living style and eating habits 58% of people with dementia live in low and middle income countries, but by 2050 this will rise to 68% with fastest growth in China, India, and their south Asian and western Pacific neighbors(World Alzheimer Report 2015, Census of India-2011).

AD is confirmed with behavioral assessments and cognitive tests. This is followed by brain imaging techniques such as magnetic resonance imaging (MRI), Computer Tomography(CT) or PET scan which shows certain changes in the brain .These heterogeneous changes in the brain leads to dead nerve cell and tissue loss throughout the brain, resulting to extreme shrinkage of the hippocampal volume , extreme reduction of its cortical thickness, as well as a severe enlargement of the internal ventricles some biomarkers(S. Matoug, 2015, O. B. Ahmed 2015).

Medical image processing and machine learning tools can help neurologists to diagnose whether a subject is developing the Alzheimer disease. So MRI classification is one of the most important and challenging tasks in disease prediction as it explores different measurement parameters with structural and other analysis for delineating pathological regions, and for surgical planning and image-guided interventions.

There is extensive literature based on classification which can be either through separating the pixels (segmentation) which is based on dividing the image into groups based on certain criteria or grouping the pixels(clustering)which is based on collecting pixels together as per assumptions. There are different clustering techniques like hard clustering or Fuzzy clustering and K-means(Biju et al . 2017).This standalone can efficiently divide the image in different groups so acts as preprocessing step for most of the algorithm but fails to cluster noisy images so we have employed this method in the later steps.

Some used extracted salient features for segmentation and detection purpose in which two phase visual saliency was used but faced the problem loss of information. Ashraf et al 2013. and Rowayda et al. 2013 worked over abnormality of brain and Alzheimer's disease detection at early stage by volume based and ROI based for limited volume of data .Some used local binary pattern for AD detection. Convolutional encoder using neural networks was used for automatic detection its 3D implementation. Some implemented multimodal feature extraction for Alzheimer disease detection using machine learning and deep learning methods(Sarraf et al 2016,Liu et al 2015) .Pre-computed medical descriptors were represented biomedical image with approximate measurements of volume and the cerebral metabolic rate of glucose (CMRGlc).The segmented 3D brain was extracted for regions of interest (ROI), and were used for AD classification with Support Vector Machine (SVM), Bayesian method or other methods . There are several constraints in such work-flows. Ortiz et.al. 2013 improved the SOM performance by introducing Growing Hierarchical Self-Organizing Map (GHSOM) and multi-objective based feature selection technique to optimize the performance of segmentation. The main drawback of SOM is that size of the output map need to be selected before classification. GHSOM is a variant of SOM which grows dynamically and allow discovering inherent hierarchies on the data. GHSOM contains several SOM layers of variable size. During training process, the number of SOM maps and size of map is determined. The feature vectors selected from an image has greater influence in segmentation process because the odd features may cause misclassification. Selecting discriminative features may improve the performance of classifications. Spanakis et al. in 2016 introduced AMSOM (Adaptive MovingSelf-Organizing Map) that creates more flexible structure where neuron positions are dynamically altered during training and on the other hand tackles the drawback of having a predefined grid by allowing neuron addition and/or removal during training. It improves training performance of SOM and leads to a better visualization of the input dataset and provides a framework for determining the optimal number and structure of neurons. D Sarwinda et.al 2016 used principal component analysis (PCA) and factor analysis as feature selection and SVM classifier for the classification. Medical image processing is one of the hot topic for today's researchers. They have suggested various techniques for segmentation , clustering and mapping techniques to identify AD in its early stage.

Yang et al .2007 used independent component analysis based classification and coefficients are fed into an SVM-based classifier for diagnosis of individuals with or without AD.Y Zhang et al. 2016 proposed eigenbrain and machine learning method for the detection of AD using 3D MRI scan data. This method achieved high accuracy 92.36±0.94 and they reported eigenbrain method is effective in AD subject prediction and discriminant brain region detection in MRI scanning. I.Beheshti et al 2016 introduced feature ranking and classification error using voxel based morphometric technique to compare the gray matter of AD patients and health control. The features used were statistical dependency (SD), information gain (IG), mutual information (MI), Pearson's correlation coefficient (PCC), t-test score(TS), Fisher's criterion (FC), and the Gini index (GI).

Ehsan et al. 2016 used convolutional method but faced problem of homogeneity issue. Suddenly work over visualisation techniques came into existence considering unsupervised method which overcomed the existing issues of homogeneity, volume data. Oritiz et al. 2013 in three different papers worked on unsupervised method based over SOM and other SOM based strategies.

Some mapping methods considers only fixed neuron mapping ,some, homogeneous regions or complete object for segmentation to retrieve the affected area whereas in this method we have introduced adaptive technique in which neuron position can be varied as it is adaptive. In this paper ,we have used mapping method as it is efficient than prevailing methods. So, these variety of algorithm were thoroughly studied and among which FCM ,SOM-FKM, FKM , used for comparison . The testing algorithm were applied to four groups of dataset which consists of different age groups. In our integration we eliminated manual interaction, saved time, retained image information and avoided irrelevant segmentation. The proposed algorithm is compared among various mapping method .The methodology and results are highlighted in different sections of the paper.

II. RESEARCH METHODOLOGY

2.1 Self Organizing Map(SOM)

SOM (self organised mapping) is one of the most common and efficient neural network techniques. It is unsupervised learning and main objective is to gather similar type of group data and features into two or more dimensional lattice whereas distinct will appear at output space. SOM is defined as number of neurons and distance which defines the lattice structure and weight factor. The process include training data whose information has to be known before which corresponds to distance between input vector and corresponding weight factor which is related to output vector. Here neurons corresponds to the mapping area from high dimensional space onto a plane. Its topology means that the mapping preserves the relative distance between the points which are near each other in the input space are mapped to nearby map units in the SOM. There is a very important parameter to be calculated that is Best Matching Unit (BHU) whose value is updated (Isha et al 2016, Selvaraj etal 2013).

The layers are typically located on a regular low-dimensional grid which may be either rectangular or hexagonal. A model of SOM network with M=10 inputs and L=10 x 10=100 neurons and data set with 300 inputs vector space .

Here input vector is x(t) = [x1,.., xM] and each input is connected to all of neurons via corresponding weights wj=[w1,w2…..wN] where t=1,2,…,L ,i= 1 to Land j=1,2,…,M. The Figure 2 shows the training and initialisation stage.

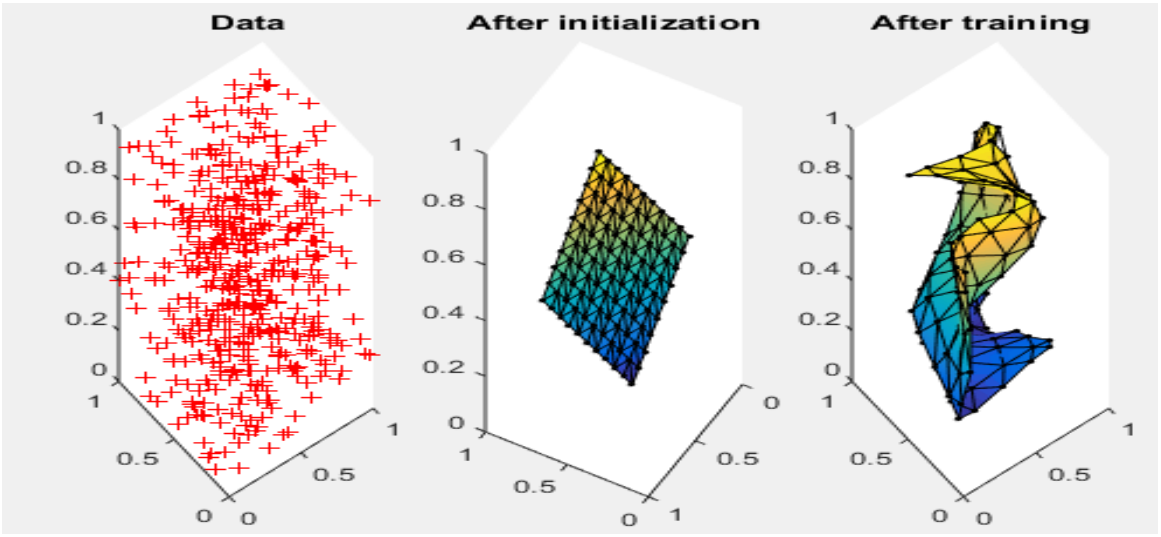

Figure 2 SOM training and initialization output

2.2 Adaptive Moving K-means Self Organizing Map

Proposed algorithm(AMKSOM) includes main four phases first(Initialising phase) comes the initialisation part of neuron vectors is random and same as SOM. Initially, position vectors are set same as positions of the neurons in the hexagonal grid structure. Here the neighbours of each neuron is done in which the initial grid is connected and becomes disconnected after some time .Here to keep track of the changes the orthogonal and symmetrical matrices T and P with same size are used where T(p,q) means 0 for no connection 1 translates to connected neurons and P(p,q) shows the age of edge between neurons p and q(Suwalka. I et al. 2018).When neurons p and q are closest neighbours at current epoch it assumes 0 value but other value implies that neurons p and q were closest neighbours some epochs before (Spanakis et al. 2016).The moving threshold MT is function of data dimension(dD) given by

$$MT = -\ln(dD) * \ln(F) \quad (1)$$

here F is taken as 0.6 .

In second phase(training phase) learning weight of neurons are calculated using the SOM batch algorithm where wi(t + 1) marks neurons i is updated weight at epoch(t+1), t marks current epoch and t +1 is the next , nj(t) marks the number of patterns that are assigned to neuron j, hji(t) marks is the neighbourhood function and is a measure of how close are neuron j and neuron i, xej(t) is the mean feature vector of all x that are assigned to neuron j at epoch t, here rj , ri are the position vectors (in the output space) for neurons j and σ(t) is the adaptation factor, decreasing through training. So,

$$wi(t+1) = \frac{\sum nj(t).hji(t).xej(t)}{\sum nj(t).hji(t)} \quad (2)$$

$$hji(t) = \exp\left(-\frac{\|rj-ri\|^2}{2\sigma(t)^2}\right) \quad (3)$$

Here, at the end of each epoch and after the neuron weight vectors update is over, the distances between the neuron vectors (wi) are computed. These distances depicts the closeness of neurons in the input space and output space can be used as a measure in order to update neuron positions .

$$ri(t+1) = ri(t) + \alpha(t)\frac{\sum nj(t).\delta ji(t).(rj(t)-ri(t)}{\sum nj(t).\delta ji(t)} \quad (4)$$

$$hji(t) = \exp\left(-\frac{\|wj-wi\|^2}{\gamma*\sigma(t)^2}\right) \quad (5)$$

where α(t) is epoch t learning rate, δji(t) is a neighbourhood function ,γ controls the neighbourhood shrinking as a fraction of σ . Here learning rate α(t) is taken as 0.01. In phase III (Smoothening phase)the weight updating process is carried out in which for each input the best matching neuron is determined(Ma) and also the second best matching (Mb). Here, the age of all edges between Ma and its neighbours is increased. The epoch for each incident edge between neurons (i, j), if A(i, j) ≥agemax, then this edge is removed. Regarding the exact position of the two neurons the following process is followed: Neuron with the largest error among Mu's neighbours is spotted say it to be Mv. One neuron will preserve Mu's position and the other one will be placed in the middle between Mu and Mv. The weights and positions of the two new neurons (u1 and u2) are calculated as

$$k_{u1} = (1+\beta) * k_u \quad (6)$$

$$k_{u2} = -(\beta) * k_u \quad (7)$$

$$r_{u1} = r_u \quad (8)$$

$$r_{u1} = \frac{r_u + r_u}{2} \quad (9)$$

where k_{u1} is the weight vector of neuron u and β is a mutation parameter which can take either a fixed or random. Figure 1 shows the flowchart of proposed algorithm. As learning is complete no neurons are added or removed at this phase and no connections between neurons are added or removed but weight and position vector adaptation is continued with a lower rate. These neuron are used for further clustering with last phase using following equation.

$$K = \sum_{i=0}^{k} \sum_{i=0}^{n} u_{ij} * hji(t) \quad (10)$$

here u_{ij}membership function ,k is number of clusters produced by AMSOM ,n is number of pixels of input image.

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2.3 Procedure

The methodology involves MRI database taken from OASIS currently includes data sets that is a cross-sectional set which includes 416 subjects aged 18 to 96, among which 100 were clinically diagnosed with Alzheimer's disease. The subjects are preprocessed for skull removing and then noise is removed using thresholding. After that features are extracted the vector set is combined with csv dataset provided by OASIS for each subject data (D. S. Marcus 2007) .. This mapping technique is used for clustering and classifying. The proposed method clusters the featured data and helps in classifying better. The classification may have error rate so it is better to describe this error rate by factors explained below(Govindaraj , 2016).True Positive (TP) which results as positive in the presence of the clinical abnormality. True Negative (TN) gives classification result as negative in the absence of the clinical abnormality. False Positive (FP) gives the classification result as positive in the absence of the clinical

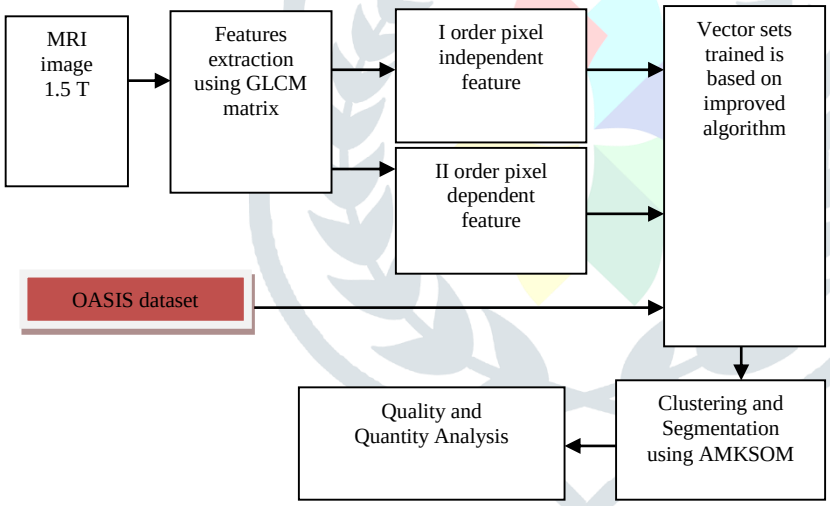

Figure 4 Block diagram of proposed method

abnormality.False Negative (FN) gives the classification result as negative in the presence of the clinical abnormality (Oritiz, 2013).

The result shown in later section comes out to be better enough so that proposed method can be used by clinicians. The block diagram shown in Figure 1 reveals the proposed technique in which flow of method and process explained in earlier sections are shown. Here clustering and classification is done using improved AMSOM where the extracted features are trained mapped and then classified.

III. RESULTS

Wherever In this section we show the results of our proposed algorithm that is obtained from four group of real datasets of MRI. This work was implemented using software version MATLAB (R2014a).We run our experiments on core Intel(R) Core(TM) i3-5005U CPU @ 2.00GHz processor with 4 GB RAM. .The results starts original MRI with skull removing and then filtered with median filter. Thus clustered with proposed algorithm and segmented further based on different features.

The Figure 2 shows preprocessing stage of one of the subject of group 1in which intensity histogram is also shown with the segmented region of MRI data using FCM,FKM. Proposed algorithm to evaluate under same conditions due to efficiency and processing time of segmentation.It seems that with K=3 FCM gave results with 59 iterations but not accurately where as FKM with iteration number 49 gave results with 3 clusters and lesser time.SOM-FKM(Kishore Gunna 2016) gave better results compared to Fuzzy means(FCM and FKM) .We found that with skull processing time of all the algorithm was large.

True Positive (TP) is the ratio of no. of positive having AD to total no.of images.True Negative (TN) is the ratio of no. of negative images not found with AD to total no. of images.False Positive (FP) gives the ration of total no. of images found negative but AD affected to total no. of images.False Negative (FN) gives the ratio of images found positive but not were affected to the total no. of images.

The comparison was done with 4 tested techniques with following performance measures:

$$\text{Precision(Pre)} = TP/(TP+FP) \quad (11)$$

$$\text{Recall(Re)} = TN/(TN+FN) \quad (12)$$

$$\text{Accuracy (Acc)} = (TP+TN)/(TP+TN+FP+FN) \quad (13)$$

TP, TN, FP, FN, Precision , Recall and Accuracy are used to measure the performance of the classifiers.
Here clustering and classification is done using FKM-AMSOM where the extracted features are trained mapped and then classified. Here we can see in figure 3that how proposed method has decreased MSE from 2.3 to 0.44 as for good MSE the value chases zero revealing efficient algorithm. The PSNR has also improved slightly with . 11dB. The time required for simulation and processing of proposed algorithm is 15.119 seconds which is

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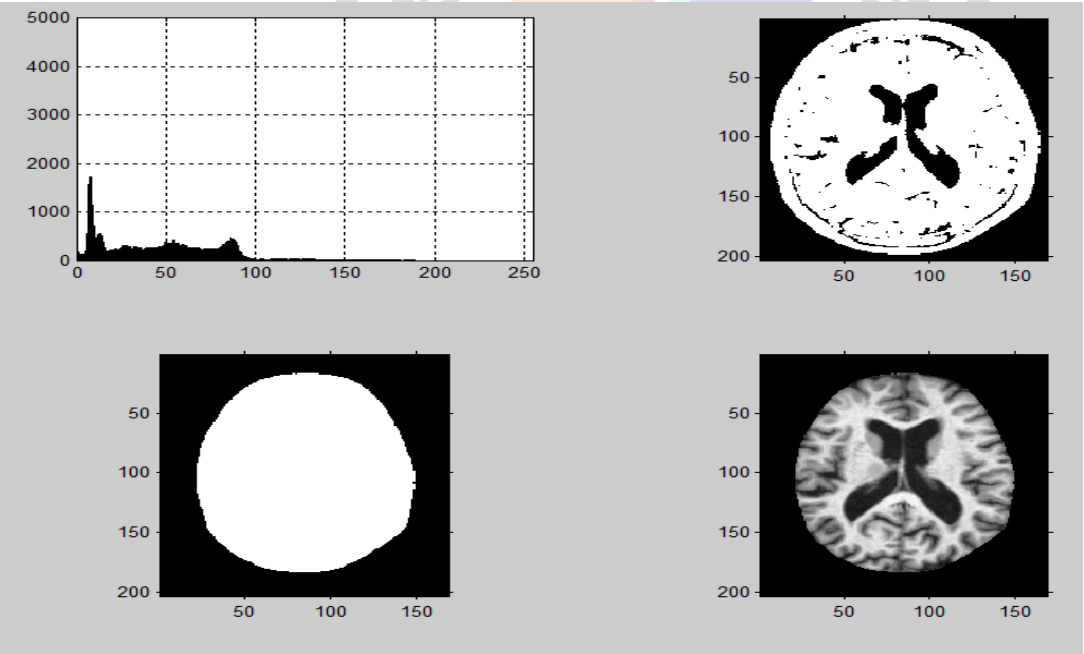

Figure 2 Stages of proposed method

IV. CONCLUSION

The Image clustering plays an important role for medical diagnosis . With advent of new technology there are wide range of techniques such as MRI,CT scan,PET scan and many more.The MRI is better than CT scan but expensive so computational processing may reduce the cost of patients expense if diagnosed at early stage .The K- means can detect faster than FCM and fails to cluster image data with noise. SOM-FKM has improved dimentional reductionality but fails to detect with huge data .So, the new novel attempt to validate the improved mapping algorithm AMSOM for disease detection is carried out in this paper. Oru framework undergoes four stages :pre-processing, clustering, extraction and validation. From the experimental results ,we proved the effectiveness of AMSOM which is efficient enough in satisfying are goal needs. It can be further extended by implementing on PET

and 3-D imaging techniques for other diseases. The result produced using proposed algorithm reveals satisfactory.

V. ACKNOWLEDGMENTS

We would like to express our sincere thanks and deepest gratitude to OASIS group for providing AD brain images as without these images this work would not have been possible. The authors wish to acknowledge Dr. Sunil Joshi (Head, ECE) CTAE, MPUAT, Udaipur, Rajasthan for supporting this work under Ph.D. scheme of department of Electronics and Communication Engineering. We are thankful to all the authors whose research has helped us directly or indirectly.

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