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Segmentation of Brain subjects for the classification of Alzheimer's disease in MR Images using hybrid Classifier

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Abstract:
Alzheimer's disease (AD) is generally detected from the structural variation in brain subjects. Grey Matter (GM) decrease and reduction in hippocampus are the essential estimation parameters for classifying the nature of disease. Earlier detection of AD is very helpful to the physicians in the diagnostic,which is possible with volumetric measure of brain subjects. Magnetic Resonance imaging (MRI) is preferable imaging technique among various modalities, because of its better visualization and higher resolution. Segmentation plays a crucial task inmedical application to identify different stages of disease. Four different labels are assigned to cluster various brain tissue category depending upon the similarity of pixels. Intuitionistic Fuzzy algorithm is employed to segment GM, White Matter (WM), Hippocampus region and the cerebrospinal Fluid (CSF) regions. Essential features are selected from the pre and post segmented brain image using Grey Level Co-occurrence Matrix (GLCM). The severity of the disease has been classified using the chosen features. Stable and progressive Mild Cognitive Impairment (MCI) as well as the AD subjects are classified using hybridSupport Vector Machines (SVM) and naïve bayesclassifier. The results of our proposed approach is analyzed with previous works and the performance of classification approach is 95.2%.

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1. Introduction

AD generally predictedby the anatomical structural variation in brain which happens over some years of time period. According to 2018 world report, 50 million people are affected by AD across the globe and it is estimated more than 152 million will be suffered by AD until 2050. AD is differentiated depending upon the death cells in the brain tissues, initially which starts in medial lobe. [10] The major reason for causing problems in neurofibrillary and protein plaques is the death cells, which reduces the usual neural function. The appearance of atrophy can be clearly predicted in structural magnetic resonance imaging, and the disease progression have been monitored by the structural variations. Initially AD starts slowly and progressively affects the thinking capability, remembering new events, meeting trouble in usual activities. [12] Volume reduction in GM and the areacontraction in hippocampus region were essential measures to detectthe AD in the earliest. There are lot of previous studies have been focused on the segmentation of tissues in brain for the volumetric analysis and the classification of AD. [8] Among those techniques, clustering is majorly utilized technique in the accurate segmentation of brain tissues. Pixel based detailed spatial information was obtained more accurately using intuitionistic fuzzy algorithm. Cluster initialization has been carried out with the fuzzy membership function and a slight modification is done in the FCM membership function. Essential features are selected from the segmented images. [11] The severity of AD has been differentiated using Support Vector Machine (SVM), naïve Bayes and radial basis function classifier. According to the classification results AD, MCI and normal subjects were differentiated.[1]Rachina.J et al were proposed convolution neural network based deep learning classification model for categorizing the stages of AD. Mathematical based transfer learning is implemented to reduce the data for training the neural network. The performance of classifier provided 95.37% results and it is compared with state of the art.[2]Feddevan.D.L et al have proposed spatial energy and intensity energy based segmentation principle to segment exact hippocampus region. The label has assigned for the hippocampus based on probabilistic atlas method. AD stages has been evaluated using the hippocampal volumetry. [3] Elaheh et al, have developed a machine learning framework to distinguish progressive and stable MCI from the AD subjects using support vector machines. [4] P.R.Kumar et al were used K means with graph cut segmentation principle for grouping various brain matters. Volumetric measurement of all the segmented brain regions and some essential features have been selected to differentiate the stages of AD using game theory classifier.

2. Methodology

2.1 Fuzzy C Means algorithm

The FCM principle works based upon the memberships, which allocates pixel to all the individual category. Let$X = (x_1, x_2, \ldots . x_n)$represents an image with pixels N which is to be segregated into C clusters and x_i denotes multi spectral data [5]. This algorithm executes optimization iteratively that reduces the cost function represented in equation (1),

$$J = \sum_{j=1}^{N} \sum_{i-1}^{c} u_{ij}^{m} \left\| x_j - v_i^2 \right\| \quad (1)$$

u_{ij}denotes membership of x_j in the i^{th} cluster, v_i cluster center and m is the constant. The fuzziness is controlled by m and the value allocated to $m = 2$ in this case. The larger membership values have allocated when the cluster center nearer to the pixels and the lower values are allotted when the pixels far from the cluster center [6]. The probability of a pixel that exists to a particular cluster denoted by membership function. The probability of the FCM algorithm is measured the distance between the pixels. The updated cluster center and the membership function are following equation (2), (3).

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|} \right)^{2/(m=1)}} (2)$$

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} (3)$$

Benning with the primary assumption for each cluster center, the algorithm concentrates a forward solution.$v_i$denotes the saddle point or local minimum of the cost function. According to the variation in the membership function leads to detect the convergence.

2.2 Intuitionistic Fuzzy algorithm

Fuzzy set theory has been demonstrated as an essential application in various research fields. This principle is most acceptable because of its ambiguity and uncertainty. [7] The membership value of an element in fuzzy set theory is lice between zero and one. Nevertheless in existence, it might not be real that the non-membership element is equal to 1 minus the membership degree, because of some hesitation degree. In order to overcome these issues Atanassov was introduced simplification of fuzzy sets as

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Intuitionistic Fuzzy sets that integrated the degree of hesitation denoted as hesitation margin. The mathematical representation of finite set$X = (x_1, x_2, \dots . x_n)$ in the fuzzy set A, which is written equation (4)

$$A = \{(x, \mu_A(x) \mid x \in X\} \quad (4)$$

The belongings of degree of element x in finite set X can be calculated using the fuzziness $\mu_A(x): X \to [0,1]$ and non-belonging measure is represented as$1 - \mu_A(x)$. The hesitation degree is represented as $\pi_A(x)$. Non membership degree will not be complemented the membership degree in the fuzzy set, same time it might be less than or equal to the membership degree. The mathematical expression of a finite set X of IF set A is denoted as followingin equation (5),

$$A = \{(x, \mu_A(x), V_A(x)) \mid x \in X\} \quad (5)$$

The non-membership and membership functions are $v_A(x): X \to [0,1], \mu_A(x)$respectively with significant conditions of an element x in equation (6),(7)

$$0 \le \mu_A(x) +, V_A(x) \le 1 \quad (6)$$

$$\pi_A(x) + \mu_A(x) + V_A(x) \le 1 \quad (7)$$

Segmentation of an image is crucial before the development. In order to highlight the meaningfulorganization of the image. Segmentation executes using IF sets. This task has been performed after completing the preprocessing work, where the image is segmented to separate various brain subjects based on its pixel values.[7] The principle clustering segregates an image into few region. This similar characteristic of pixel are grouped and assigned labels to each group depending upon the similarity measure. Different types of tissue regions and abnormalities presenting in a particular region can be identified using the clustering. So, this technique is preferable in the detection and monitoring the progression of disease. The membership values are associated with every pixel and the pixels might be in various cluster. The hesitation of membership function also consider in intuitionistic fuzzy.

3. Volume estimation and Feature extraction

Texture based features are widely preferred traditional feature analyzing concept because various texture features show the different aspect of an image. GLCM based feature selection process has been executed for extracting the features from the image. [12] Additionally morphometric features have been taken from the segmented image. On the other hand voxel based volumetric analysis is very helpful to predict the WM,GM, CSF and Hippocampus region using (8), (9),(10).

$$Volume_{GM} = \sum_{slice=1}^{n} \sum_{i=1}^{x} \sum_{j=1}^{y} f(i,j) == thresh \quad (8)$$

$$Volume_{WM} = \sum_{slice=1}^{n} \sum_{i=1}^{x} \sum_{j=1}^{y} f(i,j) > thresh \quad (9)$$

$$Volume_{CSF} = \sum_{slice=1}^{n} \sum_{i=1}^{x} \sum_{j=1}^{y} f(i,j) < thresh \quad (10)$$

4. Classification

Further, the probable of studying the organizational MR imaging feature vector s for detecting mild AD subjects. [9] The comparison has been done with widely used machine learning classifiers: a naïve bayas and Support Vector Machines (SVM). The radial basis function kernel is utilized to parameterize the SVM and the complexity parameter c is equal to 1. Three various strategies has been followed in classification analysis: 1) Normal Cognitive vs MCI. 2) Progressive MCI vs Stable MCI. 3) Stable MCI vs Alzheimer's disease. For each classification process, each feature vectors

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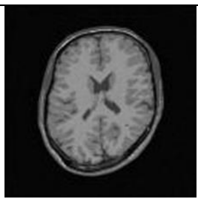
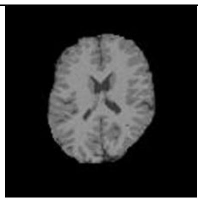
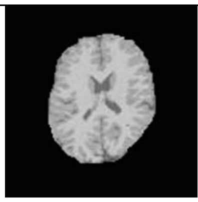
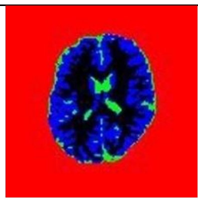
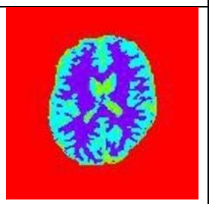
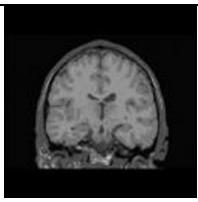
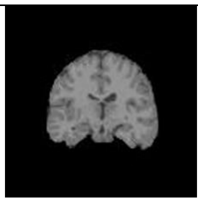
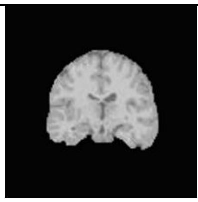
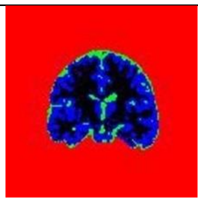
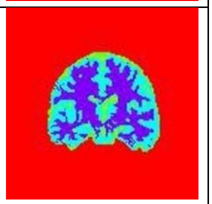
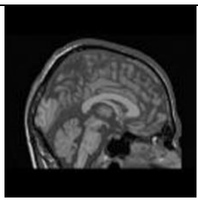
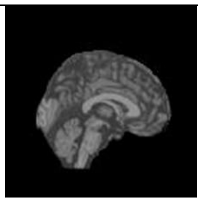
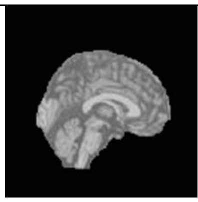
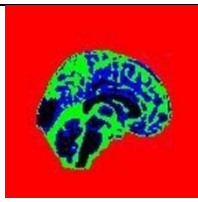
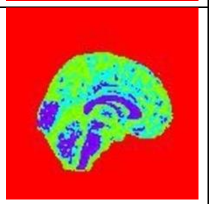
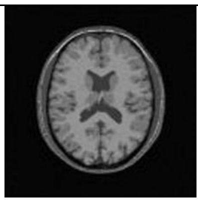
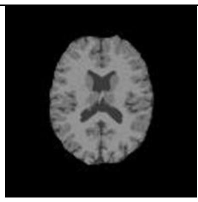
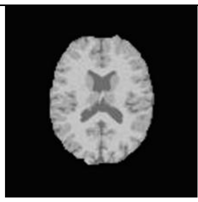
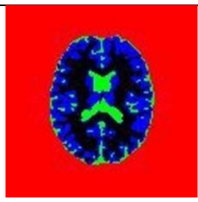
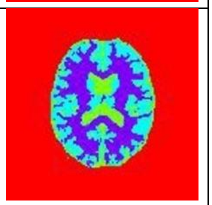
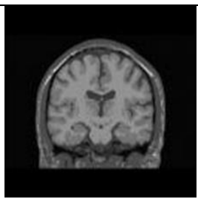
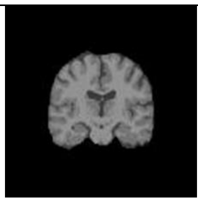
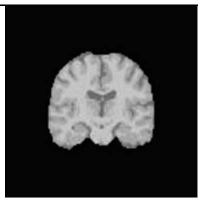
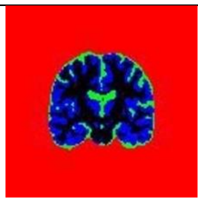
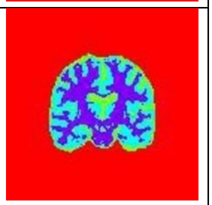
employed as well as two way combination possible feature vector also has been done. In previous works, separately all the feature vectors were fed to the classifier. Later merged feature vectors were given as input for the classification analysis. The efficiency of the hybrid classifier is validated with 10 folds cross validation principle.

5. Results and Discussion

The MRimages involved the study were accessed from the Open Access Series Imaging Studies (OASIS) (https://www.oasis-brains.org/). Some normal MR images are also obtained from standard bench mark image dataset Brain Web database (http://www.bic.mni.mcgill.ca/brainweb/). Around 300 images are involved in the classification analysis to differentiate the severity of AD. 200 images were used in the training process and remaining were used in the testing process. T1 weighted MR noiseless images are preferred in various projection such as Axial, coronal and sagittal views for the sake of clear visualization.

S.No	Brain MR image Input (a)	Brain MR image without skull (b)	Enhanced Images (c)	FFCM output (d)	IF output (e)
1					
2					
3					
4					
5					

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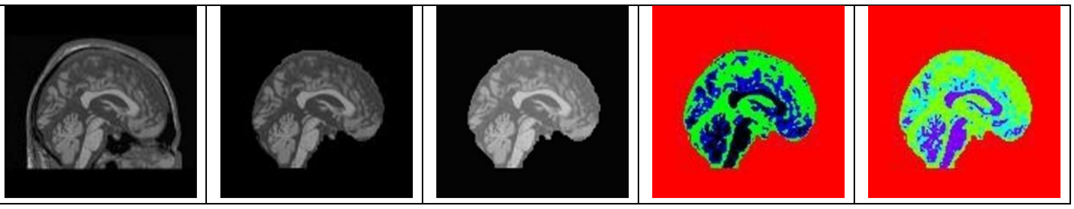

Figure 1: Segmentation outcomes of Intuitionistic Fuzzy principle

Fig 1(a)-6(a) Input brain MR images, 1(b)-6(b) Skull stripped image, 1(c)-6(c) Enhancement results, 1(d)-6(d) Output of FFCM principle, 1(e)-6(e) IF algorithm.

Fig 1 (a) denotes MR brain image in axial projection with skull area. While processing an image, the pixels present in the skull area which reduces the accurate segmentation of brain subjects. In order to perform exact segmentation, skull stripping is essential before processing the image. The skull in the input images are removed using Brain Extraction Tool (BET). The proper threshold value has set after the detailed analysis of pixel distribution in the input images. Fig 1(b) represents the brain image after the skull removal. Generally, lower pixel intensity which makes the segmentation to be ineffective in the biomedical applications. So, the intensity enhancement task is employed in Fig 1(c). After the enhancement task the pixel are distributed uniformly. The intensity variation between two nearer pixels become very less after the contrast enhancement. Fig 1(d) indicates the outcome of Fast Fuzzy C Means algorithm. Advancement of FCM has executed in FFCM. Three different labels are used in this algorithms to differentiate the various types of brain tissues such as WM, GM and CSF region. The membership function initialization is done with FCM principle and the cluster center selection has completed with random selection process. Fig 1(e) denotes the outcome of Intuitionistic Fuzzy algorithm. Cluster initialization task is employed with FCM algorithm. The updated membership function of the cluster is evaluated using equation (2),(3). According to the pixel intensity variations different clusters has been created for grouping the different types of brain subjects. Volumetric measurement of individual clusters are calculated using equations (8),(9),(10). The volumes of all the brain matters are considered one of the important feature for classifying the AD. Texture features have been extracted from the pre and post segmented images using co-occurrence matrix.In classification analysis of AD, three classes used in this work to differentiate the NC, MCI and AD subjects. RBF kernel width is fixed as 0.01 in the parameterization task of SVM.

Number of subjects	Stage	Age (mean ± std)	Gender (M/F)	MMSE (mean ± std)	CDR
145	NC	74.31±6.42	82/63	29.17±1.08	0
112	MCI	76.12±7.39	57/55	27.02±1.92	0.5
43	AD	75.53±8.46	23/20	26.18±2.02	1

Table 1: Classification of AD/MCI

The images preferred for the classification analysis are 300. Among them 145 subjects are normal cognitive. There are no symptoms related to the AD during the analysis. 112 subjects are confirmed as MCI which means progressive as well as stable stages of MCI has been identified. 43 subjects are in the sever stage AD affected subjects. The accuracy of the classifier in the work is 95.2% which is comparably improved than the existing works.

Conclusion

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The stage categorization of AD is the majorattention of the research work. FCM algorithm is employed to the cluster initialization process. Based upon the variation in the pixels labels are allocated for grouping the WM, hippocampus region, CSF, GM.FCM algorithm membership function is modified according to the objective and various clusters are created for the volumetric measurement of all the brain regions. Volume of all the segmented brain subjects and GLCM features are fed into the classifier to make the classification task related to the AD subjects.The stages of AD is analyzed and classified as NC vs MCI and MCI vs AD based on its progression. The hybrid classifier output is compared with the previous research works and that is provided better results. The feature work will be based neural network approach. Radiologists can take decision related to AD in diagnostic.

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