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Classification and Feature Extraction of Alzheimer's from Structural MRI

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Abstract: Alzheimer's Disease (AD) is a neuro-degenerative disease which causes cell death and damage for the tissues in the brain. AD condition causes memory loss which disrupts their daily activity and they ultimately gets detached from their own surroundings. The Progression of Alzheimer's disease can be controlled by early detection. The proposed methodology uses structural Magnetic Resonance Image (MRI) for AD detection. From MRI data AD can be classified into three different stages such as Cognitive Normal (CN), Mild Cognitive Impairment (MCI) and Alzheimer's Disease. Initially MRI image is preprocessed which includes contrast enhancement and skull stripping. Then preprocessed image is segmented to gray matter, white matter and cerebrospinal fluid. After feature extraction, by some machine learning models the brain image is classified as normal vs Alzheimer's.

Keywords: Alzheimer's Disease, Magnetic Resonance Image, Support Vector Machine, Random Forest.

I. INTRODUCTION

Alzheimer's disease is a neural disorder that affect people with an average age of 65 years old. It affects the cells and tissues in the brain, which results in its shrinking and the disruption of various brain functions. In 2010 nearly 35.6 million people are affected by AD. It is caused due to tau tangles, beta amyloid plaques and loss of connection between nerve cells. Due to plaques and tangles communication between nerve cells becomes difficult. Advances in brain imaging technique allow us to see the development of tangles and plaques in the living brain as well as changes in brain structure. Some brain imaging techniques are Computed Tomography (CT), Single Photon Emission Computed Tomography (SPECT), Positron Emission Topography (PET) and MRI. CT is an imaging technique that slices tissues from multiple directions. A rotating gamma camera with many detector heads is used in SPECT and PET uses nuclear imaging technique and provide better resolution. MRI is a noninvasive technique which uses RF (.2 GHz to 2GHz) which provide clear vision and high resolution [2].

Due to cell death and tissue damage, AD affected brain shrinks. Hippocampus seen in the inner folds of the bottom middle section of the brain also get damaged by AD. It also affects the volume of Gray Matter (GM), White Matter (WM) and Cerebrospinal Fluid (CSF) to a great extent. Gray matter is the area of brain in which real processing takes place. White matter communicates to and from GM and rest of the body. The mechanical and immunological protection to the brain is provided by Cerebrospinal fluid. There is a slight reduction in WM volume along with simultaneous expansion of CSF volume in AD. The proposed methodology is used to extract Alzheimer's from normal subjects.

The rest of the paper is structured as follows: Section II covers the works which are related to the AD detection. Section III discusses the methodology comprises of block diagram, database collection, preprocessing, feature extraction, image segmentation and classification. Section IV contains the results obtained for the proposed methodology and final part gives the conclusion.

II. RELATED WORKS

Mohamed Mahyoub et al. [3] studied about different machine learning models to rank AD risk factor by importance. Risk factors are categorized as behavioral and biological factors, which includes medical history, family dementia background and life style. Different machine learning models used are Random Forest (RF), Neural networks with Principal Component Analysis (pcaNNet), Support Vector Machines with Linear Kernel (SVMLinear), and Multi-Layer Perceptron (MLP). It has been found that subject specific risk factors like demography and lifestyle are much relevant than medical history risk factors.

Deevi Sarwinda et al. [4] proposed a method in which feature selection is done using Kernel Principal Component Analysis (PCA). This method detects AD from 3D MRI. PCA maximizes the variance of a linear combination of variables, Kernel PCA is used for non-linear structures. Support vector machine is adapted to classify CN from AD, CN from MCI and MCI from AD.

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Chen Fang et al. [5] suggested a novel Gaussian Discriminant Analysis (GDA) based on Computer Aided Diagnosis (CAD) system for classifying different stages of AD. It can classify into three different stages, CN, MCI and AD in a single scan. Brain image is separated to left and right hemispheres and then classification is performed. Finally, their outputs are combined.

Xin Hong et al. [6] developed a method for predicting Alzheimer's disease using Long Short-Term Memory (LSTM). LSTM connects previous information to present task by encoding temporal relation between features and next stage of AD. Images are extracted from Alzheimer's Disease Neuroimaging Initiative (ADNI) database. Their results show that Coral Thickness Average (TA) is an essential feature to predict the development of AD.

Srinivasan A et al. [7] proposed Magnetic resonance image analysis using Discrete Wavelet Transform (DWT) with fractal feature analysis. Proposed action consists of two stages. First stage consists of image enhancement and skull stripping. Then the preprocessed image is transformed to wavelet domain followed by fractal analysis. They used image slices from OASIS dataset.

K A N N P Gunawardhana et al. [8] suggests that pre-detection for AD can be done using Convolutional Neural Networks (CNN). By using different datasets and image segmentation techniques the proposed CNN model was tested. CNN offers more accuracy than SVM.

III. METHODOLOGY

A. *Block Diagram*

Fig. 1. shows the block diagram for AD detection system. The main processes in the system are dataset collection, data preprocessing which includes contrast enhancement and skull stripping, image segmentation, feature extraction and classification. The dataset is obtained from ADNI. The first task is to preprocess the brain MRI'S. Image segmentation is used to segment gray matter, white matter and cerebrospinal fluid [9]. After segmentation optimal features were extracted. Selected features are trained using different classifiers. After training the system will be able to predict whether a particular MRI is CN or AD [12].

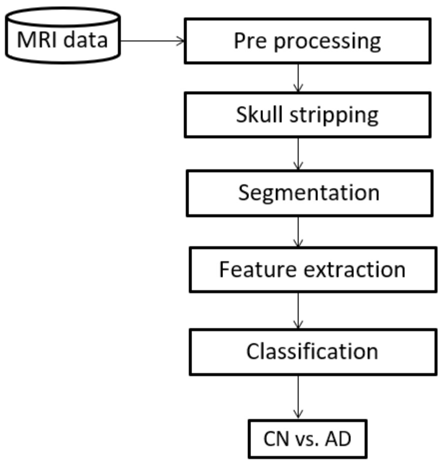

Fig. 1. Block diagram for AD detection

B. *Dataset Collection*

The Magnetic resonance imaging data for the proposed system has been obtained ADNI. The data includes MRI and PET images and the dataset had nifti files. Each nifti file is in nii format which gives a 3-Dimensional image showing all three views of the brain. The data set consists of 100 subjects including 50 CN and 50 AD Data. For training 70 MRI data is considered and for testing 30 data is considered.

C. *Image Preprocessing*

Preprocessing improves the image quality. Contrast enhancement is done by histogram equalization. Skull stripping is one of the major phases in AD detection. It refers to the extraction of cerebral tissues and removal of non-cerebral tissues. Those resultant brain region images are analyzed for AD detection. There are different steps for skull stripping. Initially the gray scale MRI brain image is converted to binary image. All the pixel values greater than luminance are replaced by one and others by zero. Interior gaps are filled by ones. So, we obtain a cleaned binary image. Erosion is performed by placing zeros at the outer boundary. Eroded binary image is used as a mask which multiplies all the pixel values of the eroded binary image with the pixel values of the original image, which results in desired skull stripped MRI brain image.

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D. *Image Segmentation*

Image segmentation is the process of splitting a digital image into different segments. The goal is to simplify the image analysis and obtain more accurate information. Multiple Otsu's segmentation is used to segment gray matter, white matter and cerebrospinal fluid. In this case the image is segmented into three regions and two thresholds must be selected.

E. *Feature Extraction*

Feature extraction is the process of extracting essential and unique information by performing some functional and filtering operations. The goal is to extract a set of features from the dataset. Grey Level Cooccurrence Matrix (GLCM) features, Gray matter proportion, white matter to cerebrospinal fluid ratio, skewness and kurtosis are the extracted features. GLCM is a measure of how often different combinations of grey levels occur in an image. Using GLCM different texture features such as contrast, correlation, homogeneity and energy can be defined. Contrast is a measure of local level variations. Correlation defines the association between pixels in two different directions. Homogeneity measures the level of similarity or uniformity in the intensities of an image. Energy gives the amount of information in the image [2].

Grey Matter Proportion and White Matter Volume to Cerebrospinal Volume Ratio are other important features. Grey matter proportion can be obtained by extracting pixels in image. It is measured due to the atrophies seen in regions like Hippocampus and Amygdala [11]. For Alzheimer's affected people there is a slight reduction in white matter volume along with the simultaneous expansion of cerebrospinal volume. Kurtosis and skewness are other important texture related features. Kurtosis measures the sharpness of peak of probability distribution function. It can be defined as positive, normal and negative kurtosis. Skewness refers to the measure of asymmetry and it can be positive, zero or negative.

F. *Machine Learning Algorithms*

After the feature's extraction, the next step is to apply machine learning algorithms and train the classifiers. Different machine learning models used for classification are Random Forest and Support Vector Machine [10]. Random Forest (RF) is an ensemble classier using many decision trees models. Support Vector Machine (SVM) is a supervised learning model and a binary classier which performs well in AD detection. The basic principle of SVM is to choose an optimal hyperplane that reduces the classification error of the test sample.

IV. RESULTS

The preprocessing stage of Alzheimer's detection is done. Fig. 2. shows the original image, skull stripped image, gray matter and white matter extraction.

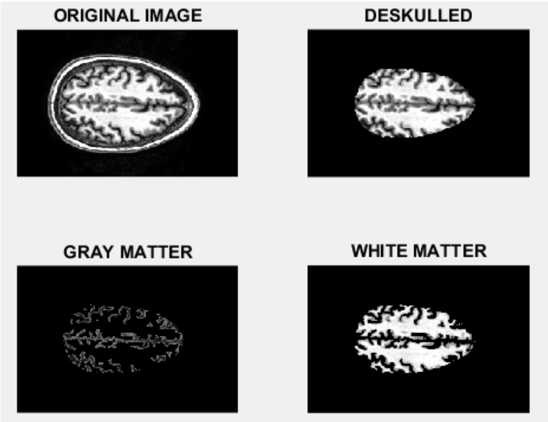

Fig. 2. Skull Stripping, GM and WM Extraction

The accuracy of the classifiers, Random Forest and Support Vector Machine is compared for the training data.

Table I: Performance of SVM & Random Forest Classifiers

Classifier	No of training data	Misclassification cost	Accuracy
SVM	35	5	92.9
Random Forest	35	1	98.6

Table I shows the comparison of SVM and RF classifiers based on their performance in the proposed approach. Random Forest classifier gives better accuracy than Support Vector Machine for normal vs Alzheimer's classification. RF classifier provides an accuracy of 98.6% whereas SVM provides only 92.9%. Both SVM and RF provides 100% testing accuracy for this classification.

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V. CONCLUSION & FUTURE WORKS

The proposed system is able to automatically detect Alzheimer's disease from structural MRI. MRI image of the brain is obtained from ADNI. It is subjected to preprocessing which includes contrast enhancement and skull stripping. Image segmentation is done using multiple Otsu's segmentation to extract GM, WM and CSF. GLCM features, GM volume, white matter to cerebrospinal fluid ratio, kurtosis and skewness were extracted and these features are given to different machine learning models such as Random Forest and Support Vector Machine. Random Forest provides better accuracy than support Vector Machine for recognition of Alzheimer's from structural MRI. Mild Cognitive Impairment can also be classified from the structural MRI. Some of the MCI will leads to AD and some will not convert to AD. The features obtained from neuroimages are also used to classify MCI-c (MCI that convert to AD) from MCI-nc (MCI that not convert to AD). Long Short-term Memory (LSTM) can be used to predict the development of Alzheimer's Disease.

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