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The early diagnosis of alzheimer's disease using deep learning

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ABSTRACT

The accurate diagnosis of Alzheimer's disease (AD) is essential for patient care and will be increasingly important as disease modifying agents become available, early in the course of the disease Mild Cognitive Impairment (MCI), the early stage of Alzheimer's (AD), is used for clinical trials. Different imaging techniques have been used to help diagnose the disease. A few of them are magnetic resonance imaging (MRI), computed tomography, positron emission tomography. These features from MRI and PET images are extracted for diagnosis. Fusion of these features can improve the accuracy of diagnosis. Due to some defects of original PCNN for data fusion, the dual channel PCNN is used to implement multimodal image fusion. This method gives additional features for better diagnosis of AD.

Keywords: Alzheimer's disease, MRI and PET scan, Preprocessing Resize wiener filtering, Features Homogeneity, Contrast.

INTRODUCTION

Alzheimer's disease (AD) is a degenerative brain disorder that is characterized by a progressive dementia that is character by the degeneration of specific nerve cells, presence of neuritic plaques, and neurofibrillary tangles. A decline in memory and other cognitive functions are the usual early syndromes. AD will be a global burden over the coming decades, due to the increasing age of societies. It was reported that in 2006, there were 26.6 million AD cases in the world, including about 56% of the cases that are at the early stage. In 2050, population of the AD patients is predicted to grow fourfold to 106.8 million. Still an exact treatment is not found early detection of Alzheimer's disease (AD) important for a successful treatment. MRI and PET Images are considered to be the most widely used technique for the detection of Alzheimer's disease. It is a complex task to analyze these images as they are projected images. A medical expert has to make extensive knowledge of anatomy and imaging techniques [1-10].

Magnetic resonance imaging (MRI)

Alzheimer's is a deadly disease, where dementia symptoms slowly worsen over a number of years. Brain cell connections and the cells degenerate and die, gradually destroying memory and other mental functions.

In the early stages, the memory loss is mild, but with late stage AD, individuals lose their ability to carry on a conversation and respond to their environment. The current Alzheimer's treatments cannot stop Alzheimer's from progressing, they can slow the worsening of symptoms and increase the quality of life for those with Alzheimer's [11-20].

MRI image can detect brain abnormalities related with mild cognitive impairment (MCI) and can be used to tell which patients with MCI may eventually develop AD. Magnetic resonance

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imaging (MRI) uses a powerful magnetic field, radio frequency pulses and a computer to produce detailed pictures of organs, soft tissues, bone and virtually all other internal body structures. MRI can detect brain abnormalities associated with mild cognitive impairment (MCI) and can be used to predict which patients with MCI may eventually develop Alzheimer's disease. In the early stages of Alzheimer's disease, an MRI scan of the brain may be normal. In later stages, MRI may show a decrease in the size of different areas of the brain (mainly affecting the temporal and parietal lobes).

High-Field MRI Scanners

High-Field MRI scanners are usually closed or tube or tunnel like due to their use of stronger magnets ranging from at least 1.5T up to 3.0T. A 1.5T MRI scanner is useful because it provides a really great quality image. It can also boast fast scan times and the ability to evaluate how certain structures in the body others may not. The 3.0T MRI scanner, which is double in strength, becomes great for visualizing very fine detail such the vessels of the brain or heart. There is also an ultra-high field scanner which has a strength of 7.0T. It is not widely available and is typically used for research.

Low-Field MRI Scanners

Low-Field MRI scanners are typically identified as open MRI scanners and have a magnet range of 0.23T-0.3T. These scanners are useful for people who are claustrophobic or unable to have a closed MRI scan due to weight or size. Low-field scanners are typically open on the sides rather than having the magnets completely surrounding the patient. Low-field MRI scanners have decreased image quality and require a longer scan times compared to high-field MRI scanners, but they provide an alternative for those who otherwise might not be able to have an MRI scan.

Uses of MRI

Magnetic resonance imaging (MRI) is a safe and painless test that uses a magnetic field and radio waves to produce detailed pictures of the body's organs and structures. An MRI differs from a CAT scan (also called a CT scan or a computed axial tomography scan) because it doesn't use radiation.

POSITRON EMISSION TOMOGRAPHY (PET)

A positron emission tomography (PET) scan is a diagnostic examination that uses small amounts of radioactive material (called a radiotracer) to diagnose and determine the severity of a variety of diseases.

One study shows that PET imaging using florbetapir F 18 as a tracer was able to distinguish between 68 people with suspected Alzheimer's disease, 60 people who showed signs of mild cognitive impairment, and 82 healthy older people with no signs of cognitive impatient.

The other study looked at PET scans using fluorine 18-labeled flutemetamol tracer among seven people with normal pressure hydrocephalus, a progressive condition that causes dementia and often mimics Alzheimer's disease. These study participants had undergone brain tissue biopsies during a procedure to treat normal pressure hydrocephalus. Biopsy results correlated with those seen via PET scans.

Uses of PET

A positron emission tomography (PET) scan is an imaging test that allows your doctor to check for diseases in your body. The scan uses a special dye that has radioactive tracers. These tracers are injected into a vein in your arm. Your organs and tissues then absorb the tracer.

Comparision between MRI and PET

One of the main differences between PET scans and other imaging tests like computed tomography (CT) scan or magnetic resonance imaging (MRI) is that the PET scan reveals the cellular level metabolic changes occurring in an organ or tissue.

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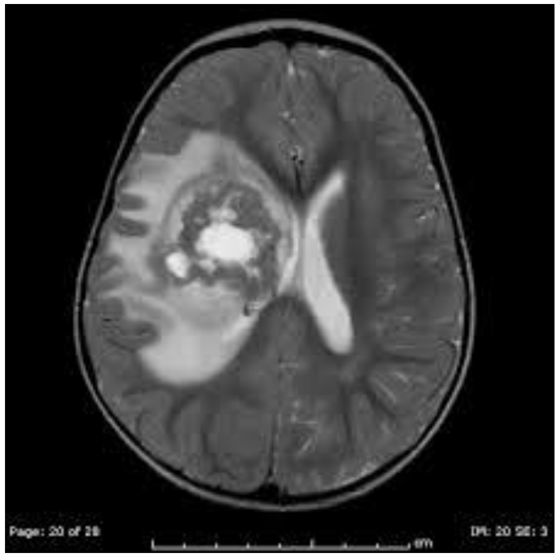

Figure 1.1 An Example of MRI image

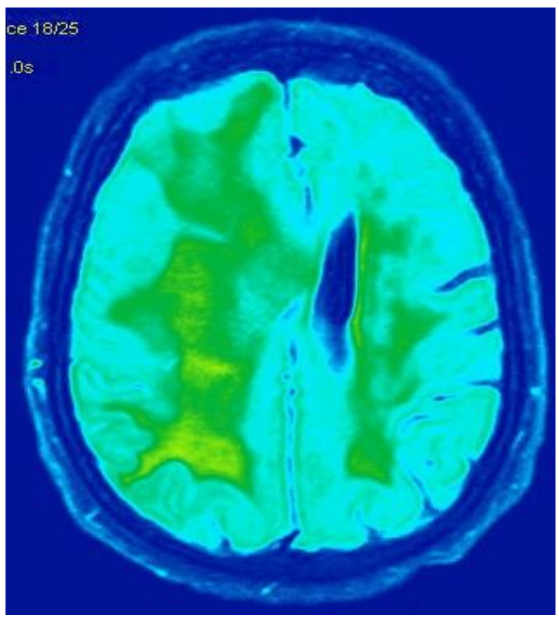

Figure 1.2 An Example of PET image

LITERATURE REVIEW

Alzheimer's disease is the most dangerous disease, the cure of which must be the prime target through scientific investigation. The early detection of AD can be helpful in curing the disease completely. There are several techniques available in the literature for the detection of AD. Many researchers have contributed their ideas in the detection of Alzheimer disease.

This chapter mainly discusses about the existing AD detection techniques available in the literature. Several domains and concepts are used in the detection of Alzheimer disease. The main domains used in this detection technique include neural networks, image processing, nanotechnology etc.

Pulse coupled neural networks in alzheimer detection

The PCNN was originally presented in order to explain the synchronous neuronal burst phenomena- in the cat visual cortex. The information of the input is converted to a set of pulse images which present the objects and edges of the images, so pulse coupled means that the image is analyzed by looking multiple times at different coupled pixels. The pulse coupled neural network is a neural network that has the ability to perform extraction of edges, texture information from images and image segmentation. The PCNN is very generic. Only a few changes are necessary for effectively operate on different types of data. This is an advantage over other image segmentation algorithms which generally require information about the target before they are effective. But the parameters still have to be set manually. When we compare to other artificial neural network models the Pulse coupled neural network is significantly different in both structure and operation. The processing layer consists of many neurons and each neuron corresponds to an image pixel or a set of neighboring image pixels. These are the feeding inputs and are linked to nearby neurons called the linking inputs. The feeding inputs are repeatedly processed and both these inputs together produce a pulse train. The Pulse coupled neural network neuron includes dendritic tree, linking modulation, and pulse generator part. The dendritic tree receives the inputs from two types of channels i.e.; the linking and the feeding. The linking receives external stimulus while the feeding receives external stimulus and local stimulus. The classification based on Pulse Coupled Neural Network is performed using the following equations:

$$F_{i,j}[n] = e^{-\alpha f} F_{i,j}[n-1] + S_{i,j} + F_f \sum_{kl} m_{ijkl} Y_{kl}[n-1]$$

$$L_{ij}[n] = e^{-\alpha L} L_{ij}[n-1] + V_l \sum_{kl} w_{ijkl} Y_{kl}[n-1]$$

$$U_{ij}[n] = S_{ij}[n](1 + \beta L_{ij}[n])$$

$$\theta_{ij}[n] = e^{-\alpha\theta} \theta_{ij}[n-1] + V_\theta Y_{kl}[n-1]$$

$$Y_{ij}[n] = \begin{cases} 1, if\ U_{ij}[n] > \theta_{ij}[n] \\ 0, \text{otherwise} \end{cases}$$

METHODOLOGY

The pipeline of the proposed framework is illustrated in Fig. 2. In this study, MR and PET data are used as two input neuroimaging modalities. All collected brain images are first preprocessed and segmented into 83 functional ROI, and a set of descriptors are computed from each ROI. The dataset is divided into a training set and a testing set .We perform Elastic Net only on the training samples to select the discriminative subset of the feature parameters. A multilayered neural network consisting of several auto encoders is then trained using the selected feature subset in the training dataset. Each layer of the network obtains a higher level of abstraction of the previous layer with non linear transformation. The softmax layer is added on the top of the SAEs for classification. The trained network is then evaluated with the labeled testing samples.

Pre-Processing

Medical images are corrupted with noise and artifacts due to body movements Preprocessing is done to remove unwanted noise and it gives clarity to the images at this stage where filtering is done to remove noise. In our proposed system we are using resize and thus wiener s used to remove noise.

Input Image

Here, the input images are MRI and PET images in JPEG format. First image selected from the file specified by the string filename. The user has to select the required MRI and PET image for further processing. Then each image is resized to 256*256.

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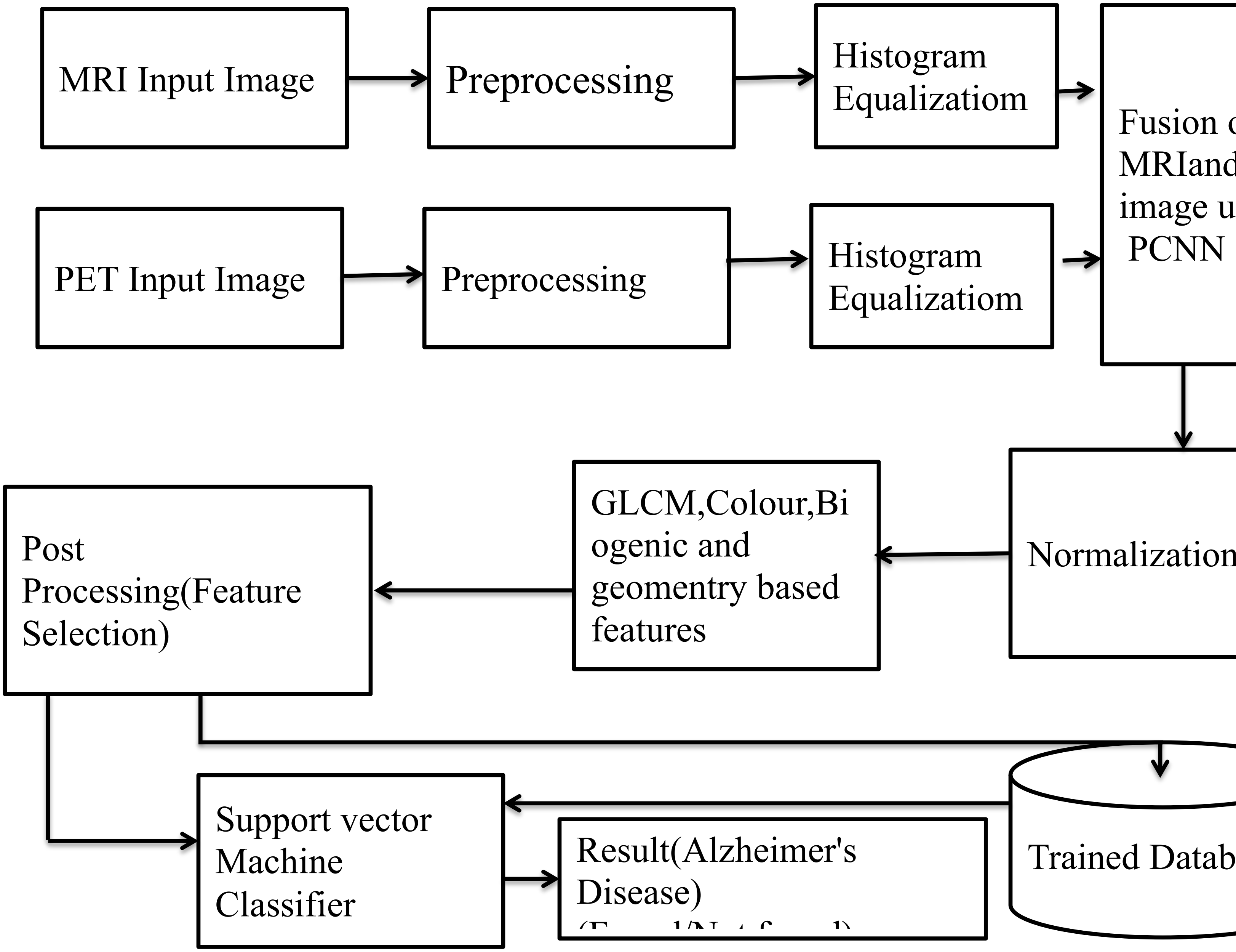

Fig2.proposed block diagram

Wiener Filter

The intention of the Wiener filter is to clear out noise that has corrupted a signal. It is based on a statistical approach.Natural filters are designed for a desired frequency response. The Wiener filter approaches filtering from different angle.One are assumed to have knowledge of the spectral properties of the common signal and the noise, and one seeks the LTI filter whose output would come as close to the original signal as possible.

Wiener filters are characterized by the following.

- Assumption: signal and (additive) noise are stationary linear random processes with known spectral characteristics.
- Requirement: the filter must be physically realizable, i.e. causal (this requirement can be dropped, resulting in a non-causal solution).
- Performance criteria: minimum mean-square error.

SEGMENTATION

Algorithms

- Read in the MRI image and convert it to grayscale
- Read in the PET image and convert it to grayscale
- Rearranging the pixels using histogram equalization.
- Filter the images using wiener filter.
- Find the GLCM (Gray Level Co-occurance Matrix using otsu's method.
- Arrange the features using PCNN (pulse coupled neural network).
- Visualize the result.

Read in the color image and convert it to grayscale:

```
I=imread([path,file]);
grayMRI = rgb2gray(I);
grayMRI = imresize(grayMRI,[h,w]);
```

Rearranging the pixels using histogram equalization

Histeq function used to transforms intensity of image. grayMRI = histeq(grayMRI); figure, imshow(grayMRI,[]);

Filter the images using wiener filter

GrayMRI = wiener2 (grayMRI,[3 3]);

Find the GLCM (Gray Level Co-occurance Matrix using otsu's method)

Otsu's method used to automatically perform clustering-based image thresh holding or the reduction of a gray level image to a binary image

```
function feat=GLCM (I)
% Otsu Binarization for segmentation
Level = graythresh(I);
img = im2bw(I,.6);
img = bwareaopen(img,80);
img2 = im2bw(I);
```

Visualize the result

```
Function[result] = multisvm(TrainingSet,GroupTrain)
u=unique(GroupTrain);
numClasses=length(u);
For k=1:numClasses
G1vAll=(GroupTrain==u(k));
Models(k)=
svmtrain(TrainingSet,G1vAll,'ShowPlot',true);
end
result =models;
end
```

Feature Extraction

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features.

Statistical Features: A statistical feature is one of the early methods proposed in image processing. The gray level co-occurrence matrix (GLCM) of the ROI was used as suggested by Haralick. The following features are extracted from the GLCM of the ROI kidney images using MATLAB: Energy, Entropy, Contrast, Homogeneity, Maximum probability and correlation, etc.

Energy is a measure of local homogeneity and it is calculated using

Where, *i* and *j* are the pixel values.

Energy=$\mu = (1/MN) * \sum_{i=1} \sum_{j=1} p(i,j)$

Entropy measures the average, global information content of an image in terms of average bits per pixel. As the magnitude of entropy increases, more information is associated with the image.

Entropy=$f_3=\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,0}(i,j) \log(p_{d,0}(i,j))$

Contrast defines the difference between the lightest and darkest areas on an image.

Contrast=$f_2=$

$\sum_{n=0}^{N_g-1} n^2 \left\{\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,0}(i,j)\right\}$, where $n = |i-j|$

Homogeneity is the state or quality of being homogeneous, biological or other similarities within a group.

Homogeneity=$\sum_{i,j=0}^{N-1} \frac{p_y}{1+(i-j)^2}$

Correlation is a measure of the strongest of the relationship between two variables.

Correlation= f3=$\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,0}(i,j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_{x}\sigma_{y}}$

Skewness defines an unbalance and asymmetry from the mean of a data distribution Skewness= (3*(mean-median))/standard deviation

ImageID	Contrast	Correlation	Energy	Homogeneity	Mean	Sensitivity	Specificity	Accuracy%
1	0.2514	0.2007	0.9598	0.9883	0.0015	96.2861	83.3333	96.0758
2	0.1483	0.1396	0.9702	0.9906	0.0018	96.2861	83.3333	96.0758
3	0.2311	-0.0024	0.9906	0.9959	0.0024	96.2861	83.3333	96.0758
4	0.2816	-0.0029	0.9886	0.9950	0.0029	96.2861	84.3333	96.0758

CLASSIFICATION

Support vector machine

Support Vector Machines (SVM) is a set of related, supervised learning methods used in classification and regression. Given a set of training examples, each marked as belonging to one of two categories, SVM training algorithm predicts whether a new example falls into a specific category or not. In training datasets, only regions that could be labeled with high confidence are used whereas in testing datasets, all pixels are labeled because manual segmentation process is used for quantitative assessment of the accuracy of testing results. The SVM classification and manually segmented test data are compared so as to evaluate the performance of the SVM. An Accuracy score is computed through identifying the ratio of correctly classified pixels and total pixels in the region of interest.Support vector machine (SVM) is an algorithm that attempts to find a linear separator(hyper-plane) between the data points of two classes in multidimensional space. SVMs are well suited to dealing with interactions among features and redundant features.

Steps for SVM classifier:

- The goal of a support vector machine is to find the optimal separating hyper plane which maximizes the margin of the training data.
- We could trace a line and then all the data points representing men will be above the line, and all the data points representing women will be below the line.
- Find the optimal hyper plane with the margin.
- We can they find the closest data point.

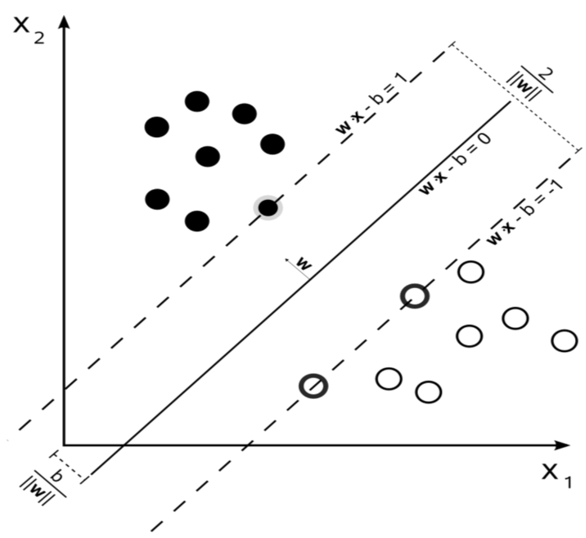

Fig 3 using SVM classifier

Performance analysis

The performance of classifier depends on various factors like Sensitivity, Specificity and the area under Receiver operating characteristics curve (Lu et al. 2004). These values are calculated by considering confusion matrix, which is given as below:

TP	FN
FP	TN

Where,
TP: Number of True Positives,
FP: Number of False positives,
TN: Number of True negatives,
FN: Number of False negatives.

True Positive (TP): The test result is positive in the presence of the alzheimer's disease.
True Negative (TN): The test result is negative in the absence of the alzheimer's disease.
False Positive (FP): The test result is positive in the absence of the alzheimer's disease.

Sensitivity-It is the statistical measure of how well a binary classifier correctly identifies thepositive cases.

Sensitivity=$\frac{TP}{TP+FN}$

Specificity-It is also a statistical measure of how well a binary classifier correctly identifies thenegative class.

Specificity=$\frac{TN}{TN+FP}$

RESULT ANALYSIS

Proposed method has produced 87.5% of accuracy, 75% sensitivity and 100 % specificity values. For further research, improvement can be made by selecting another better filter, as well as by investigation the morphological operation in finding the optimum values for detecting more accurate Alzheimer's disease.

CONCLUSION

This proposed system addresses the image processing techniques to recognize the alzheimer's disease in MRI and PET images. Our Proposed system develops an automatic detection of alzheimer's disease in MRI and PET images using GLCM feature and SVM classifier. Comparatively SVM features give more accurate results than SAE. The accuracy of the disease detected is checked using SVM classification techniques.

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