Radial Basis Function Neural Network Based Classifier For Diagnosing Of MCI/AD Using Multimodal Neuroimaging

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Abstract: Neuroimaging has played a very important role in the diagnosis of brain degeneration disorders, such as Alzheimer's disease (AD) and Mild Cognitive Impairment (MCI). To identify different stages of Alzheimer's disease and efficient analysis system has been developed for magnetic resonance Imaging (MRI) and positron emission tomography (PET) Neuroimages using radial basis function neural network (RBFNN) classifier.Normal, MCI and AD identification by using RBFNN classifier. The proposed model performance was assessed based on three parameters such as sensitivity, specificity and accuracy.

Index Terms: Image Registration, Feature Extraction, Radial basis function neural network, performance evaluation.

I. INTRODUCTION

Alzheimer's disease (AD) is a physical disease that causes the nerve cells. AD in which the death of brain cells that destroys memory loss and other important mental functions**.** Neurodegenerative disorder is a loss of thinking, remembering, and communication that interferes with a person's daily life and activities. AD is a loss of connections between neurons in the brain. Mild cognitive impairment (MCI) is a brain disorder and it is an intermediate stage between the normal and AD patients.MCI is a condition in which people have mental abilities such as mildly thinking and remembering. Another way of identification AD and MCI is by using Neuroimaging Normal, MCI and AD patients can classify by using Neuroimaging and machine learning algorithms are a promising area of research. Neuroimaging datasets which are collected from Alzheimer's disease Neuroimaging Initiative (ADNI) for 300 patients. In Multimodal Neuroimages such as MRI and PET are subjected to pre-processing initially where the image Registration technique is used. The Gray level co-occurrence matrix (GLCM) feature extraction technique is applied to pre-processed images and where the extraction features of images are given as an input to the classification system. Finally, Neuroimages are classified into the responsive classes by Radial basis function neural network (RBFNN) classifier and performance are evaluated. The process of proposed system design includes image acquisition, pre-processing, feature extraction, classification and performance evaluation.

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II. EXISTING ALGORITHM

Carlos Cabral, Pedro M.Morgado, Durval Campos Costa and Margarida Silveira constructed an Elastic net (EN) and Two-One-Sided-Test (TOST) model by supervised learning to classify DICOM Neuroimages. The idea behind EN and TOST model it classify two groups of class, highly correlated data and it is capable of using a minimum number of prediction classes but it cannot take a large number of data sets which is the major drawback of this method. Nho K, Shen L, Kim S and Risacher S.L, proposed a Support vector machine (SVM) are used to differentiate between AD and normal subjects, and then it is used to predict conversion from MCI to AD. The SVM classification was based on the Structural Magnetic Resonance Imaging data. The highest accuracy achieved was 72.3% accuracy for predicting MCI and AD patients. J.Ramirez and J.M.Gorriz proposed a computer-aided diagnosis system for the early diagnosis of Alzheimer's disease using Single Emission Computed Tomography (SPECT) Neuroimages. The proposed method is based on random forests as a predictor. Obtained extracted features give the highest accuracy achieved.

III. METHODOLOGY

A.SYSTEM ARCHITECTURE OVERVIEW

The Methodology of the proposed system is shown in Fig. 1. We first obtained the Neuroimaging data of 300 patients from Alzheimer's disease Neuroimaging Initiative (ADNI),100 normal subjects, 100 subjects with MCI and 100 subjects with AD and were consequently selected in this system. In pre-processing the image Registration technique is used for Multimodal Neuroimages that is PET and MRI Neuroimages. The Pre-processed image will be applied to feature extraction techniques to reduce dimensionality problems for the large set of data. We used the extracted features were applied as an input to classifier to characterize Normal, MCI, and AD patients, and performance is evaluated.

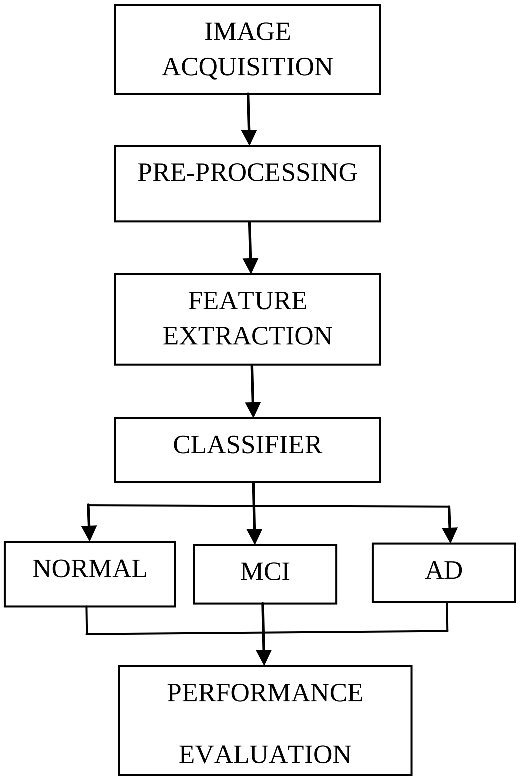

Fig.1. System design

B. STEPS OF SYSTEM DESIGN

1. Obtain a DICOM Neuroimages from ADNI site such as MRI and PET.
2. About 300 Neuroimages are taken from ADNI and it equally divided the images into three categories as Normal, MCI, and AD patients.
3. Multimodal Neuroimages were undergone to pre-processing step, initially, where the image Registration technique is used.
4. Pre-processed images are applied as an input to extract features by using GLCM technique.
5. Finally extracted features are applied as an input to RBFNN classifier and performance is evaluated.

C. PRE-PROCESSING

Image registration was performed for Multimodal brain images, that is MRI and PET Neuroimages. It is the process of aligning two or more images of the same scene which is taken from different sensors. Image Registration involves designating one image as the reference image and another image as the fixed image. It is a process of that reference image is transformed to match the fixed image.

D. FEATURE EXTRACTION

Feature extraction is mainly used for dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. When the feature vectors are very high and need to be reduced for time computational too. It takes place in terms of storage taken, efficiency in classification and system complexity.

EXTRACTION OF GLCM FEATURES

Gray Level Co-Occurrence Matrix (GLCM) is also called as Gray level Dependency Matrix and it is a best method for the texture in images. GLCM, one of the best-known texture analysis methods and it estimate image properties related to second-order statistics. The extracted features are contrast, correlation, energy,homogeneity, mean and standard deviation features are computed using MATLAB.

CONTRAST

Contrast measures an amount of local changes in an image.

$$\text{Contrast} = \sum_{n=0}^{N_g-1} n^2 \sum_{|i-j|=n} . P_d(i,j) \qquad (1)$$

CORRELATION

Correlation measures how the connection between pixels is to its neighborhood.

$$\text{Correlation} = \frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-\mu_i).P_d(i,j)}{\sigma_i\sigma_j} \qquad (2)$$

ENERGY

The energy is also known as Uniformity or Angular second moment (ASM) and it detects disorders in textures over the whole image.

$$\text{Energy} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_d^2(i,j) \qquad (3)$$

HOMOGENEITY

Homogeneity measures the correspondence of pixels.

$$\text{Homogeneity} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P_d(i,j)}{1+|i-j|} \qquad (4)$$

MEAN

Computes the average values in an image.

$$\text{Mean} = \sum_{K=0}^{L-1} r_k . P(r_k) \qquad (5)$$

STANDARD DEVIATION

Standard deviation is the measurement of the dispersivity of the gray scale from the mean.

$$\text{Standard deviation} = \sum_{K=0}^{L-1}(r_k - \text{mean}).P(r_k) \qquad (6)$$

IV. CLASSIFICATION BASED ON EFFICIENT MACHINE LEARNING METHODS

Normal, MCI and AD identification by using RBFNN classifier. .Neuroimaging is widely used to classify AD, MCI and normal persons. AD and MCI classification are difficult because of high dimensional features, so feature extraction techniques have been increasingly used for dimensionality reduction in Neuroimaging classification. The extracted features are given as an input for Radial basis function neural network (RBFNN) classifier to differentiate Normal, MCI and AD patients.

A. RADIAL BASIS FUNCTION NEURAL NETWORK (RBFNN) CLASSIFIER

The Radial Basis Function Neural Network (RBFNN) is best powerful neural network model that utilizes radial basis functions. It is a combination of both radial basis function and neuron parameters are the output of RBFNN method. RBFNN is a feed-forward network which is trained as a supervised learning method. It typically configured with a single hidden layer of units is selected from a class of functions called basis functions. RBFNN usually train much faster and less susceptible to problems with non-stationary inputs because of the behaviour of the hidden units.

V. EXPERIMENTAL AND RESULTS

The purpose of this section was to evaluate RBFNN classifier to construct classification models for distinguishing between diagnosis of normal, MCI, and AD. The Neuroimaging data of 300 patients are obtained from ADNI,100 normal subjects, 100 subjects with MCI and 100 subjects with AD and were consequently selected in this proposed system. In the proposed system collected image were undergone to pre-processing step, initially, where the image Registration technique is used. Pre-processed image was extracted features by using GLCM technique and are given as input to RBFNN classifier. The proposed model performance was assessed based on three parameters such as sensitivity, specificity and accuracy.

ACCURACY

Accuracy is able to measure the true amount of samples are how good and efficient.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \qquad (7)$$

SENSITIVITY

Sensitivity measures the ability to identify disease stage.

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \qquad (8)$$

SPECIFICITY

Specificity measures the proportion of without disease can be correctly identified. Specificity measures the ability to identify normal stage.

$$\text{Specificity} = \frac{TN}{(FP+TN)} \qquad (9)$$

The effectiveness of the Machine Learning methods has been calculated using the following measures:

True Positive (TP) - Number of correct predictions that an instance is correctly identified.

False Positive (FP) - Number of incorrect predictions that an instance is correctly identified.

True Negative (TN) - Number of correct predictions that an instance is incorrectly identified.

False Negative(FN) - Number of incorrect predictions that an instance is incorrectly identified.

Classifiers	Accuracy (%)	Sensitivity(%)	Specificity(%)
RBFNN	89.7	90	83.2

Table.1. *Parametric Results for Classification*

Table.1. shows the results of RBFNN classifier. RBFNN gives better performance with an accuracy of 89.75% .To improve more accuracy by applying large dataset and increase more features set.

VI. CONCLUSION AND FUTURE WORK

A Proposed system has been designed with an RBFNN algorithm to identify Normal or MCI or AD subjects .Generally, the Multimodality DICOM Neuroimages is a most reliable method used for identification of disease in different stages of AD. The designed methodology has classifier approach is used for DICOM image classification and performance is evaluated. The image analysis module consists of Pre-Processing, feature extraction, classification and performance Evaluation. In Pre-processing, it geometrically aligns Multimodal Neuroimages by using image registration. GLCM features were extracted for Pre-processed image and were classified as Normal, MCI and AD subjects. The Neuroimages were differentiated as Normal or MCI or AD using RBFNN classifier. RBFNN would also perform with high rates of accuracy, with the lowest degree of accuracy for three classes when the efficiently extracted features were used. The proposed method gives results better and Neuroimages were classified as Normal, MCI and AD with an accuracy of 89.7%, the sensitivity of 90% and specificity 83.23%.In future, we plan to use hybrid classifier and to increase the data sets thereby investigating the performance.

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