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A Comparison of Machine Learning Methods on Diagnosing MCI and AD using Multimodal Neuroimaging

R.Ramya[1], Mr.S.P.Sivagnana Subramanian[2], and ADNI[3]

[2]Assistant Professor, Sri Venkateswara College of Engineering, Sriperumbudur, (TN)

E-Mail: ramyaravi678@gmail.com

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A Comparison of Machine Learning Methods on Diagnosing MCI and AD using Multimodal Neuroimaging

R.Ramya[1], Mr.S.P.Sivagnana Subramanian[2], and ADNI[3]

[1]P.G.Scholar, [2]Assistant Professor,
Sri Venkateswara College of Engineering, Sriperumbudur, (TN)

E-Mail: ramyaravi678@gmail.com

ABSTRACT

Machine learning approach is to be used for identification of 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 machine learning methods. We proposed a Support vector machine(SVM), Naive Bayes (NB)and Quadratic Discriminant Analysis (QDA) classifiers are used to characterize Normal, MCI and AD patients. Finally, the performances of the different classifiers are compared and results of the classifiers clearly indicate that gives good performance for Normal, MCI, and AD detection.

IndexTerms –Image Registration, Feature Extraction, Support vector machine, Naïve Bayes, Quadratic Discriminant Analysis.

I.INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative disorder. AD is considered to be one of the most common causes of dementia among elderly persons. Around 60−80% of age-related dementia is caused due to AD. Alzheimer's disease (AD) is a progressive brain disorder that slowly leads to memory loss, confusion, disorientation and inability to communicate.AD is a degenerative brain disorder that is characterized by progressive dementia that is characterized by the degeneration of specific nerve cells.

Mild Cognitive Impairment (MCI) is a represents has early-Stage of AD.MCI is an Intermediate state between normal and AD. Memory problems are typically one of the first symptoms of cognitive impairment related to AD. Peoples are affected with more memory problems than normal for their age, have a condition called mild Cognitive impairment (MCI).Symptoms of MCI do not interfere with their everyday lives.

Another way of detecting AD and MCI is by using Neuroimaging or brain imaging techniques. Machine learning was performed for Multimodal brain images, that is MRI and PET images that are widely applied in the early detection of MCI and AD. A Normal, MCI and AD patient classifies using Neuroimaging and machine learning algorithms are a promising area of research. Neuroimaging datasets 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 to geometrically align two Neuroimages. Classification of Normal, MCI, and AD patients are difficult because of high dimensional features.

The Gray level co-occurrence matrix(GLCM) features are the widely used for dimensionality reduction in multimodal Neuroimages classification.GLCM feature extraction technique is applied to pre-processed images and features of images are the input of the classification system. Finally, images are classified into the responsive classes by the suitable techniques such as Support vector machine (SVM), Naive Bayes (NB) and Quadratic Discriminant Analysis (QDA) classifier and performance are evaluated.

The process of proposed system includes image acquisition, pre-processing, feature extraction, classification and performance evaluation.

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.

III. MATERIALS AND METHODS

A.SYSTEM ARCHITECTURE OVERVIEW

The design of this system architecture is shown in Fig. 1. We first obtained the Neuroimaging data of 300 patients with Alzheimer's disease Neuroimaging Initiative (ADNI). In pre-processing the image Registration technique is used for Multimodal Neuroimages that is PET and MRI images. 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 different classifiers to characterize Normal, MCI, and AD patients, and compare its performance.

B.IMAGE ACQUISITION

Alzheimer's disease Neuroimaging Initiative (ADNI) was designed to detect Alzheimer's disease at earlier stages. ADNI studies include Neuroimaging or brain imaging techniques, such as positron emission tomography (PET) and Magnetic Resonance Imaging (MRI). PET is a non-invasive medical imaging modality that provides 3D maps modeling the glucose consumption rate of the brain and MRI scanners use magnetic fields and radio waves to form images of the Body.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 system.

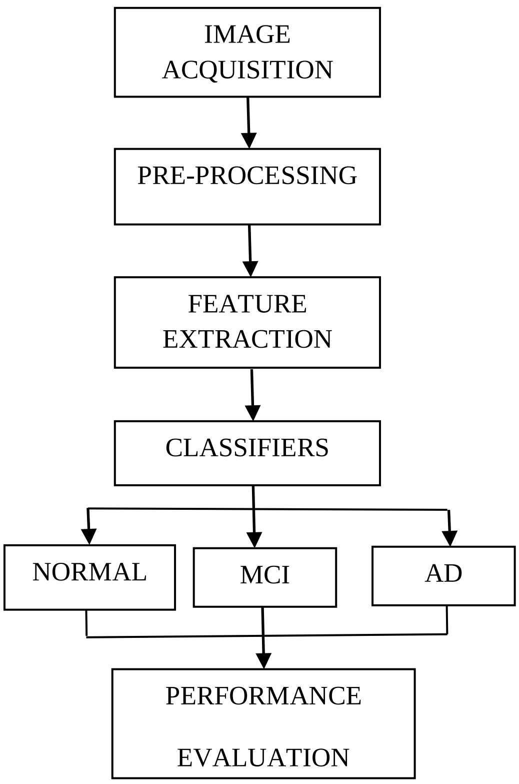

Fig. 1. System Architecture

C. STEPS OF SYSTEM ARCHITECTURE

1. Obtain a DICOM image such as MRI and PET from ADNI site.
2. About 300 DICOM images are taken and it equally divided the images into three categories as Normal, MCI, and AD.

3. In Pre-Processing stage is applied for multimodal Neuroimages for geometrically to align two DICOM images using Image Registration.
4. Pre-processed images are applied as an input to extract GLCM features.
5. Finally the Efficient Machine learning methods are applied and performance is evaluated

D. PRE-PROCESSING

PET and MRI images are used as different imaging modalities in Machine learning method. Image registration is the process of overlaying PET and MRI Neuroimages of the same scene taken at multimodal analysis and it geometrically aligns two images properly, typically on the image is consider as a target image and other is consider as a source image. It is a process of that source image is transformed to match the target image.

E.FEATURE EXTRACTION

Feature extraction technique mainly used for dimensionality reduction for a large dataset and it describes the dataset with sufficient accuracy. When the input dataset is too large to be processed and it will be transformed into a reduced representation features set. The extracted features are expected to contain more relevant information from the input datasets.

EXTRACTION OF GLCM FEATURES

Gray Level Co-Occurrence Matrix (GLCM) is a popular method of extracting features from pre-processed Neuroimages. The extracted features are contrast, correlation, Energy, homogeneity, mean and standard deviation are computed using MATLAB.

CONTRAST

Contrast measures an amount of local changes in an image. It measures of intensity contrast between a pixel and its neighborhood in an image.

$$\text{Contrast} = \sum_{n=0}^{N_g-1} n^2 \sum_{[i-j]=n} . P_d\,(\mathrm{i, j}) \quad (1)$$

CORRELATION

Correlation measures how the connection between pixels is to its neighborhood. It is the measure of gray tone linear dependencies in the image.

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

ENERGY

The energy is also known as Uniformity or Angular second moment (ASM). It provides the sum of squared elements in GLCM. Energy is 1 for a constant image.

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

HOMOGENEITY

Homogeneity measures the correspondence of pixels.

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

Mean

The mean takes the average level of intensity of the image.

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

STANDARD DEVIATION

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

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

IV.CLASSIFICATION BASED ON EFFICIENT MACHINE LEARNING METHODS

The extracted features are given as an input to the machine learning methods such as Support vector machine (SVM), Naive Bayes (NB) and Quadratic Discriminant Analysis (DA) to characterize Normal, MCI and AD patients.

A.SUPPORT VECTOR MACHINE CLASSIFIER

Support vector machine is a machine learning method that analyzes data points used for classification and it is formally separating by a hyperplane **.** After extracting GLCM features, it applied as an input to SVM classifiers and it classifies different stages of Alzheimer's disease such as normal, MCI and AD patients. If the number of features is applied and it is much greater than the number of data points, then the SVM method gives very poor performances. SVM gives a less overfitting in a data points and it is a computationally expensive.

B.NAIVE BAYES CLASSIFIER

Naive Bayes classifier is fully based on applying Bayes' theorem with an assumption of independence between each and every pair of features. NB is very easy to build and it is mainly used for very large datasets. Extracting features of GLCM is applied to NB classifier to characterize of normal, MCI and AD patients. Naive Bayes classifiers provide a greater amount of information about the Alzheimer's disease stages because of the independence assumption.

C.QUADRATIC DISCRIMINANT ANALYSIS CLASSIFIER

The Quadratic discriminant analysis is used in machine learning method used for separating two or more classes by a quadratic function and is a technique mainly useful

for classification. Extracted features are applied to QDA to classifies different stages of Alzheimer's disease.QDA classifier it fits the dataset just as well as a complicated model and it will be better on the test dataset.

V.EXPERIMENTAL AND RESULTS

The complete ADNI data set consists of 300 samples. The three machine learning methods are trained and tested such as Normal, MCI, and AD based on the different datasets which are collected from ADNI. Here nearly 300 DICOM Neuroimages are taken and 6 GLCM features are extracted for 50% total samples for training and the remaining for testing and for having a comparison between different classifiers. By using six extracted features for finding efficient classification which improves the class prediction accuracy from different classifiers. So that, the computation time will be reduced and improve classification stages such as Normal, MCI, and AD. The Machine Learning approach provides efficient classification and gives good accuracy on the GLCM features set for DICOM Neuroimages analysis.

ACCURACY

Accuracy is able to measure the true amount of samples are how good and efficient. It is the proportion of correctly diagnosed disease stage from the total number of disease stage.

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

SENSITIVITY

Sensitivity measures the proportion of positives disease that is correctly identified. Sensitivity measures the ability to identify disease stage.

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

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) - people which have disease are correctly identified
False Positive (FP) - people have without disease are incorrectly identified
True Negative (TN) - people have without disease are correctly identified
False Negative (FN) - people which have disease are incorrectly identified

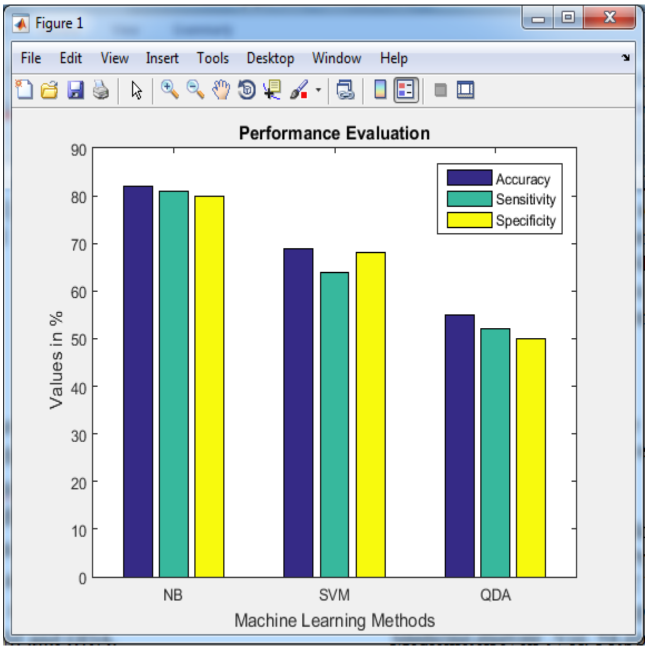

Fig.2.Performance comparison of different classifiers

Fig.2. shows the extracted six features are given to different classifiers. Support vector machine (SVM), Naive Bayes (NB) and Quadratic Discriminant Analysis (QDA) classifiers are performed for identification mechanism of Normal, MCI, and AD. SVM optimally it classifies of two stages when compared to NB and QDA classifier. NB correctly classifies all three stages when compared other two methods such as SVM and QDA.

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)
NB	82	81	80
SVM	69	64	68
QDA	55	52	50

Table.1. Parametric Results for Classification

Table.1. shows the comparison of three different classifiers. The Accuracy of SVM 55%, an accuracy of NB 80% and accuracy of QDA 45%. NB gives better performance because it identifies three stages correctly than other two methods.To improve more accuracy by applying large dataset and increase more features set.

VI.CONCLUSION AND FUTURE WORK

This system was developed to diagnose of disease analysis by using DICOM Neuroimages classification is a most important stage. But it is not a simple way for finest identification of early detection of diseases such as MCI and AD.

Generally, the Multimodality DICOM Neuroimages is a more valuable and most reliable method used for detection of disease in different stages. DICOM is useful for brain scans and most effective technique to detect the dissimilarity in Neuroimages. In this paper different classifier approach is proposed for DICOM image classification and performance is evaluated. The approach consists of Pre-Processing, feature extraction, classification and performance Evaluation. The classification consists of Support Vector Machine (SVM), Naive Bayes (NB) and Quadratic Discriminant Analysis (QDA). Classification is done on the fully based on parameters extracted by GLCM a feature extraction technique. Classifiers mainly used to the characterization of the Normal, MCI and AD patients. In SVM and QDA it optimally separates two groups and less overfitting datasets problems are overcome by NB algorithm is its capability. The NB gives results better and quick as compared to other two classifiers it is beneficial where large datasets have to compute rapidly.

FUTURE WORK

In future, we plan to use hybrid classifier and to increase the data sets thereby investigating the performance.

REFERENCES

1. Carlos Cabral , Pedro M.Morgado , Durval Campos Costa , Margarida Silveira,"Predicting conversion from MCI to AD with FDG-PET brain images at different prodromal stages ", Computers in Biology and Medicine,elseveir ,Vol. 58,pp. 101–109,2015.
2. Pedro M.Morgado , Margarida Silveira ,"Minimal neighborhood redundancy maximal relevance: Application to the diagnosis of Alzheimer's disease ", Neurocomputing ,elseveir,Vol. 155,pp. 295–308,2014.
3. Sidong Liua, Weidong Caia, Lingfeng Wena, David Dagan Fenga, Sonia Pujolb,Ron Kikinisb, Michael J. Fulhama, Stefan Eberla,"Multi-Channel neurodegenerative pattern analysis and its application in Alzheimer's disease characterization ", Computerized Medical Imaging and Graphics ,elseveir,Vol. 38,pp. 436–444,2014.
4. Ben Rabeh Amira, Benzarti faouzi, Amiri Hamid, Mouna Bouaziz ,"Computer-assisted diagnosis of Alzheimer's disease", International Image Processing Applications And Systems Conference, 2013.
5. Biswajit Pathak, Debajyoti Barooah," Texture Analysis Based On The Gray-Level Co-Occurrence Matrix Considering Possible Orientations", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 2, Issue 9, September 2013.
6. Ahmad Ashari, Iman Paryudi and A Min Tjoa," Performance Comparison between Naïve Bayes, Decision Tree and k-Nearest Neighbor in Searching Alternative Design in an Energy Simulation Tool", International Journal of Advanced Computer Science and Applications, Vol. 4, No. 11, pp. 33-39,2013.
7. Eduardo Bicacro, Margarida Silveira, Jorge S. Marques and Durval C. Costa," 3d Brain Image-Based Diagnosis Of Alzheimer's Disease:Bringing Medical Vision Into Feature Selection", IEEE,pp. 134-138,2012.
8. Qian Y, Gao X, Loomes M, Comley R, Barn B, Hui R, Tian z,"Content-based retrieval of 3D medical images", International Conference on eHealth, Telemedicine, and Social Medicine (eTELEMED),Vol. 99,pp 7-12,2011.
9. Pradipta Maji and Sankar K. Pal, "Fuzzy–Rough Sets for Information Measures andSelection of Relevant Genes From Microarray Data", IEEE, Vol. 40, No. 3, P.741-752, 2010.
10. Serkawt Khola , "Feature Weighting and Selection A Novel Genetic Evolutionary Approach", World Academy of Science, Engineering and Technology 73, P.1007-1012, 2011. Ping Yao, "Fuzzy Rough Set and Information Entropy Based Feature Selection for Credit Scoring", IEEE , P.247-251, 2009.
11. El-sayed a. El-dahshan, Abdel-badeeh and Tamer H. Younis, "A Hybrid Technique for Automatic MRI brain Images Classification", Studia Univ. Babes_Bolyai, Informatica, Vol. LIV, No.1, P.55-66,2009.
12. Cai W, Kim J, Feng D,"Content-based medical image retrieval", Biomedical information technology, Elsevier,Vol. 66, pp 83–113,2008.
13. Muller H, Michoux N, Bandon D, Geissbuhler A," A review of content-based image retrieval systems in medical applications – clinical benefits and future directions", IJRRC,pp 1–23,2004.
14. T. Rohlfing, D. B. Russakoff, R. Brandt, R. Menzel, and C. R. Maurer, "Performance-Based Multi-Classifier Decision Fusion for ATLAS-Based Segmentation of Biomedical Images", IEEE International Symposium, 404- 407 Vol. 1,2004.
15. Free borough P.A., Fox N.C., "MR image texture analysis applied to the diagnosis and tracking of Alzheimer's disease ", IEEE Transactions on Medical Imaging, Vol. 17, No.3, P. 475-479, 1998.