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Machine Learning Based Method for Alzheimer's Disease Detection

Preeti Deshmane-Topannavar
Research Scholar, AISSMSIOIT, Pune
Maharashtra, India

Dr. D. M. Yadav
Principal, SVPM'sCOE, Baramati
Maharashtra, India

ABSTRACT

Alzheimer's disease (AD), the most common form of dementia, is a degenerative disorder of the brain that leads to memory loss. Anatomical changes observed in samples of Alzheimer's are dramatic shrinkage of the cerebral cortex, fatty deposits in blood vessels, atrophied brain cells, neuro bifilarly tangles and senile plaques. Neuroimaging is a promising area of research for detecting AD. There are multiple brain imaging procedures that can be used to identify abnormalities in the brain, including PET, MRI, and CT scans. Each scan involves a unique technique and detects specific structures and abnormalities in the brain.

Inference problem(Confusion) in the diagnosis of AD as the Biomarkers obtained from MRI, PET, SPECT images are similar for the diseases like brain tumor, brain cancer, hormonal disorders etc. Combining the different biomarkers from different neuroimaging techniques at different stages of diagnosis to make it personalize.From the literature review, it is clear that there is need of designing new system for Alzheimer's disease detection which will be a personalize and help the doctors to detect the AD more accurately, which is reflected in the necessity of developing sensitive and specific biomarkers, specific vector reduction technique and a particular efficient classifier.

KEYWORDS

Alzheimer's Disease, Neuroimaging, Computer Aided Detection (CAD), Machine Learning.

INTRODUCTION

Alzheimer's disease (AD) is a degenerative disorder of the brain that leads to memory loss, difficulty with speech, agitation, and confusion. AD affects 5.3 million of the people and is the seventh leading cause of death. In Alzheimer's disease, there is a dramatic shrinkage of the cerebral cortex, fatty deposits in blood vessels and atrophied brain cells. The neurofibrillary tangles and senile plaques are also the indicative of AD. By identifying the current stage of the disease, physicians can predict what symptoms can be expected in the future and possiblecourses of treatment.

Neuroimaging is a promising area of research for detecting AD. There are multiple brain imaging procedures that can be used to identify abnormalities in the brain, including PET, MRI, and CT scans.Each scan involves a unique technique and detects specific structures and abnormalities in the brain. Fusion of these techniques improves the classification accuracy. Most of the recent computer aided machine learning approaches uses the fusion of neuroimaging techniques and apply the same classification model to all patients with no tailoring of the diagnostic decisions i.e. they assume that all biomarkers are readily available at once [14].

But in practice, the clinician decides which tests are most appropriatefor each patient. If the results are conclusive, a diagnosis isestablished. Otherwise, the clinician orders other tests for clarification.All these decisions are tailored to the patient. This is a rare case that, the patients need to undergo a considerable number of clinicalprocedures for detection of disease, which may be costly and/or invasive, even thoughsome tests may not be relevant for them. Thus, it is desirableto develop new approaches to support clinicians in the early,more effective (in terms of number of tests and/or cost), andpersonalized detection of disease. [1]

LITERATURE REVIEW

Several studies have been conducted previously for detection of Alzheimer's disease which address the issues of high diagnosis cost, inference problems and complexity of the system, optimum accuracy. From that, some of them had focused processing of MRI scans or PET scans and few of them had focused on improvement in the classification.These are discussed as follows:

Javier Escudero, Emmanuel Ifeachor in 2013presented a machine learning approach for personalized and cost-effective diagnosis of AD is described here. It uses personalized classifier model to each patient and computes the sequence of biomarkers most informative or cost-effective to diagnose patients. The system assumes that not all biomarkers are available at once and it could be modified according to requirements. But the authors acknowledge that the classification performance of the system lower than that obtained considering allvariables at once.[1]

Jonathan H. Morra, Zhuowen Tu, Liana in 2010 presented anadvanced method in which, Hippocampus from 3D MRI scan is segmented and processed by using different machine learning algorithms:1) hierarchical AdaBoost, 2) support vector machines(SVM) with manual feature selection, 3) hierarchical SVM withautomated feature selection (Ada-SVM), and 4) a publicly availablebrain segmentation package (FreeSurfer) to detect the Alzheimer's disease.TheAdaBoost and Ada-SVM segmentations compared favorably.But still proposed a method Ada-SVM which performs better than performs better than AdaBoost in AD detection. [3]

P. Padilla,M. López, J. M. Górriz, J. Ramírez in 2014 presented a Non- negative Matrix Factorization – Support Vector Machine (NMF-SVM) based technique for computer aided diagnosis of Alzheimer's disease. The proposed technique is based on the combination of nonnegative matrix factorization (NMF) for feature selection and reduction and SVM for classification. The NMF-SVM CAD tool is validated with two brain functional image databases: a SPECT data set which provides information about the blood perfusion in the brain and a PET data set which yields information about the glucose metabolism. The validation results of the proposed NMF-SVM method yields up to 91% classification accuracy with high sensitivity and specificity values (upper than 85%) for both data sets. The cost of SPECT scan and PET scan is morecomparatively. [2]

Qi Zhou, Mohammed Goryawala, Mercedes Cabrerizo, proposed to combine MRI data with a neuropsychological test and mini-mental state examination (MMSE) score and use it as input to a multi-dimensional space for the classification of Alzheimer's disease (AD). The general structure of the proposed approach is acquisition of the MRI scans, sorting and selection of features that will constitute the decisional space for the classification using the well-established SVM classifier. This method provides an average accuracy of 92.4%. This study has shown that volumetric MRI measures can better predict AD when combined with MMSE score. [4]

ChaturaphatTanchi, NiponTheera-Umpon in 2012 proposed a new automatic method to segment the whole brain in magnetic resonance (MR) image series and calculates its volume for detecting Alzheimer's disease (AD). The results show that the volumes of AD patients, mild cognitive impairment (MCI) patients, and normal persons are 828±49mm3, 922±30 mm3, and 1056±102 mm3, respectively. The classification performance of 87% on the test sets of the four-fold cross validation is achieved using the Bayes classifier. This demonstrates that the proposed segmentation method provides another promising alternative Alzheimer's disease detection.[8]

The summary of literature considering MRI, PET and SPECT scan used previously for detection of Alzheimer's disease with used feature extraction, reduction and classification techniques is given in the table below:

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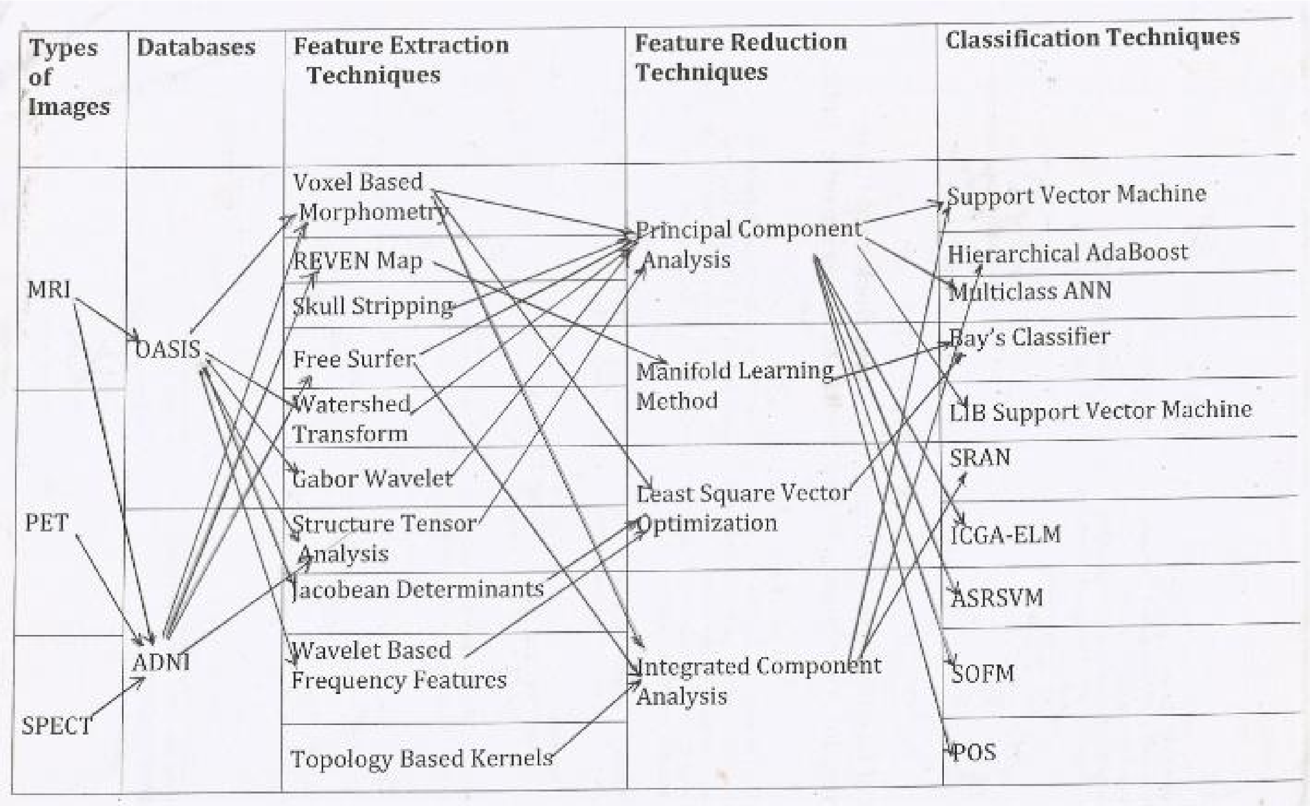
Table 1. Methods of feature extraction, reduction and classification



[MRI = magnetic resonance imaging; SPECT = single-photon emission computed tomography; PET = positron emission tomography; OASIS =Open Access Series of Imaging Studies; ADNI = Alzheimer's disease Neuroimaging Initiative, LIBSVM = A Library for Support Vector Machines, SRAN = Selfadaptive Resourse Allocation Network, ICGA-ELM = Integer Coded Genetic Algorithm – Extreme Learning Machine, ASRSVM = Automatic Source Regognition Support Vector Machine, SOFM = Self Organized Feature Map, POS = Partical Optimization Swarm.]

SHORTCOMES FROM THE REVIEW:

- Less accuracy in classification using single neuroimaging technique.
- Inference problem(Confusion) in the diagnosis of AD as the Biomarkers obtained from MRI, PET, SPECT images are similar for the diseases like brain tumor, brain cancer, hormonal disorders etc.
- Fusion of neuro images gives multiple biomarkers and improves accuracy diagnosis of AD. But Number of biomarkers obtained from multiple neuroimages increases complexity of feature vector and eventually increases the complexity of the system.
- Cost of the diagnosis highly increases by using multiple nuero imaging tests.
- Multiple nuero imaging tests makes patient physically and mentally uncomfortable.
- Personalized classification method is suggested in one paper which selects the combination of neuroimaging techniques with respect to the condition of the patient.
- The classification performance of this system lower than that obtained considering all variables at once.

CHALLENGES

- Compute the sequence of biomarkers to make the systemmoreinformative or cost-effective for diagnose patients.
- Extract the efficient biomarkers from the PET, MRI, SPECT neuroimaging techniques to improve the accuracy of the system.
- Reduce dimensions of feature vector in tern reduce the complexity of system.
- Combining the different biomarkers from different neuroimaging techniques at different stages of diagnosis to make it personalize.
- Investigates the impact of combining MRI, PET and SPECT neuroimaging techniques on the accuracy of detection of Alzheimer's disease.

PROBLEM STATEMENT AND OBJECTIVES

From the literature review, it is clear that there is need of designing new system for Alzheimer's disease detectionwhich will be a personalize and help the doctors to detect the AD more accurately,which is reflected in the necessity of developing sensitive andspecific biomarkers, specific vector reduction technique and a particular efficient classifier.

PROBLEM STATEMENT

To develop acomputer aided detection (CAD) tool for iterative Alzheimer's disease detection, along with the adequate description of its forming techniques which includes feature selection, extraction and classification of neuroimagesto support the clinicians for early and more accuratediagnosis.

OBJECTIVES

- Tostudy existing methods to find anatomical changes related tofunctional disturbances indifferent neuroimaging techniques such as MRI,PET and SPECT scans andto investigate the variables those predicts the Alzheimer's disease.
- To test the different approaches on the neuroimaging data to obtain the relevant image biomarkers which are good in agreement with medical expertise and thus validating the approach from medical practice point of view.
- To develop a feature selection and reduction techniques to provide compact features form different types of neuroimages.
- To investigate the impact of combining different neuroimaging techniques on the accuracy of detection of Alzheimer's disease.
- To design the efficient classifier at every stage of iteration to classify thatthe patient is suffering from Alzheimer's disease. or normal.
- To provide competitive results with state of art algorithm for a computer aided detection (CAD) tool for iterative Alzheimer's disease by using variations in the variables to improve accuracy and efficiency and to reduce complexity of system

PROPOSED METHODOLOGY

Following figure illustratethe newapproach for Alzheimer's disease detection. When a new subject arrives,the immediate basic data is collected. These are the variablesavailable at this stage. The approach first tries to classify the newsubject before deciding which biomarker to order. To personalize the classifier, the available variables are compared againstthose of a Pool of already diagnosed people.

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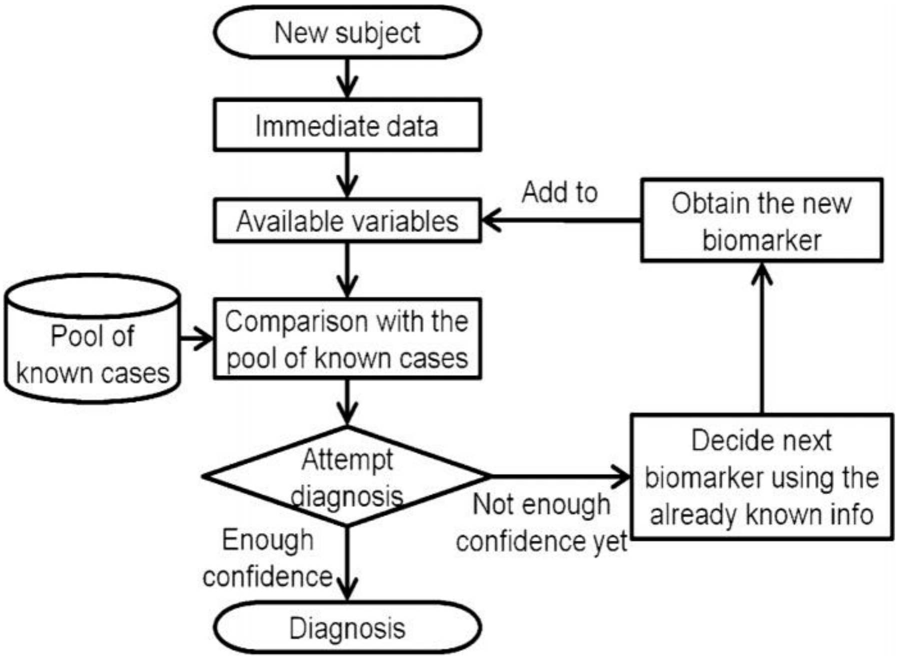

Fig. 1: Block diagram

This comparisonestablishes which cases in the Pool are most similar to the newsubject. Then, a diagnosis is attempted. If it can be established withenough confidence, then the process ends. Otherwise, the systemdetermines which additional biomarker may contribute most tothe diagnosis of the new subject by maximizing the diagnosticinformation. This process uses only the new subject's availablevariables and the Pool of known cases.Once the system selects the next biomarker, it is acquired forthe new subject and added to the set of available variables and again theclassification is reattempted. This iterative process ends whenthe confidence in the diagnosis exceeds a predefined thresholdor no more biomarkers are available.

EVALUATION

The approach can operate in two modes: 1) maximizing the performance (which tries to minimize the *number* of biomarkers for diagnosis) or 2) maximizing the performance per unit of cost (which tries to minimize the *cost* of the diagnosis). The method is assessed against four criteria:final accuracy, final AUC, number of biomarkers to achieve aconfident classification, and cost of such biomarkers.

DISCUSSION AND CONCLUSION

The machine learning approaches for personalized of AD based on multiple neuroimaging techniques is studied [1].Also the advantages and limitations of each neuroimaging technique are studied. From this it is concluded that there is severe need of designing the algorithm for diagnosis of AD which is less complex and eventually cost effective.So the methods for the sequential selection of biomarkers to reduce their number or cost for confident diagnosis are studied. With the multiple biomarkers the dimensionality of feature vector increases a lot, so the classification tasks are studied to differentiate the AD patients and normal subjects.

The approach is closer to the clinical setting, where not allbiomarkers are available at once. It also considers which previouscases are more relevant for the patient.The personalized classifiers tried to minimize the number orcost of the biomarkers included in the process. In this, the classifications were considerably more cost-effective thanthose based on all variables as there can important reductionsin the diagnosis cost. Minimizing the number of biomarkers ledto classifiers with fewer but more expensive features.This new approach suggeststhat expensive, but perhaps more informative, biomarkerstended to be selected in the first iterations of the process.

When compared with the earlier AD detection techniques, the machine learning based approach may show the improvement in the some important parameters of evaluation such as accuracy of diagnosis, number and the cost of biomarkers used in detection, correct classification rate and sensitivity of the system.

If the improvement in the above mentioned parameters is observed, it can make a new proposed algorithm a good candidate for combining the neuroimaging technique for the diagnosis of the AD.

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