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Alzheimer's Disease Detection Using DTCWT

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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.

I.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 possible courses 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 appropriate for each patient. If the results are conclusive, a diagnosis is established. 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 clinical procedures for detection of disease, which may be costly and/or invasive, even though some tests may not be relevant for them. Thus, it is desirable to develop new approaches to support clinicians in the early, more effective (in terms of number of tests and/or cost), and personalized detection of disease. [1]

II.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 2013 presented 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 all variables at once. [1]

Jonathan H. Morra, Zhuowen Tu, Liana in 2010 presented an advanced 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 with automated feature selection (Ada-

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SVM), and 4) a publicly available brain segmentation package (FreeSurfer) to detect the Alzheimer's disease. The AdaBoost 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]

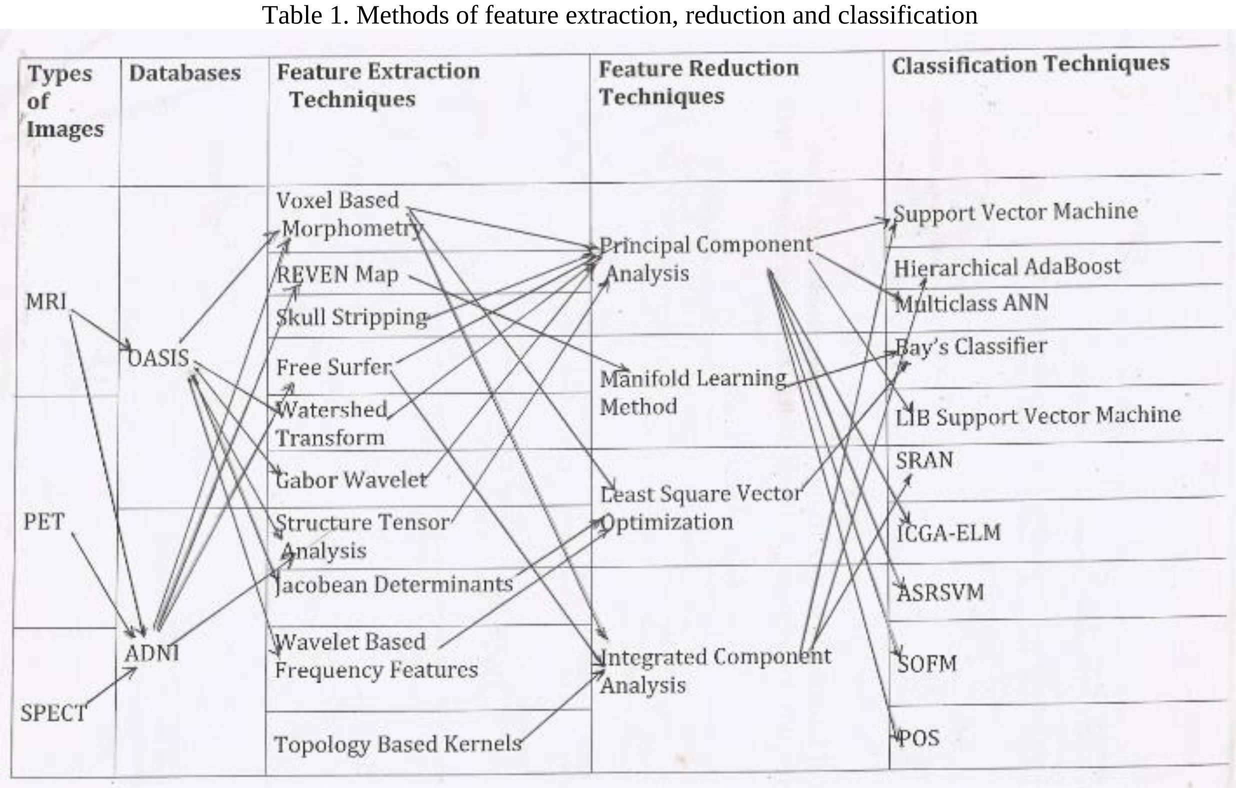
P. Padilla,M. López, J. M. Górriz, J. Ramírez in 2014 presented a Non- negative Matrix Factorization – Support Vector Machine (NMF-SVM) based technique for computer aided diagnosis of Alzheimer's disease. The proposed technique is based on the combination of nonnegative matrix factorization (NMF) for 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 more comparatively. [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]

Chaturaphat Tanchi, Nipon Theera-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:

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.]

This study is based on the comparison and evaluation of related work done to classify Alzheimer's disease detection using different methods using MRI. There are several classification methods for Alzheimer's Disease which are already developed and proposed which perform satisfactorily. Table I shows the analysis of the related works. The accuracy of the detecting system depends on the following factors.

1. The feature extraction method used for extracting the features from brain MRI. The relevant features yields accurate classification result.
2. The selection of feature subset for classification. Feature subset selection should be effective as irrelevant and redundant features should be avoided.
3. The performance of the classifier classifying Alzheimer's Disease. On evaluation of the different techniques, accuracy of each methods have been mentioned in Table I.

A new model is proposed based on the analysis of related works. The proposed model is a method for Alzheimer's disease detection using MRIs using Feature extraction with the help of Gray-Level Co-occurrence Matrix (GLCM) method . This method is used to extract the texture features from brain MRI which gives a good indication of abnormality in brain.
We propose a method for feature reduction using Principal Component Analysis (PCA) approach with the efficient classification method, innovative feed forward network. (FNN). The terms used for the evaluation of proposed work are Specificity, Accuracy, and Sensitivity. This paper can act as a resource for future researches in this field to classify Alzheimer's Disease and Normal Control (NC). In order to execute a strict statistical analysis, stratified cross-validation (SCV) is used. In this experiment 10-fold Cross validation techniques is applied. Our method achieved an accuracy of 92.45%, a sensitivity of 90.00% and a specificity of 85.12%.

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