ISSN 2347 - 3983
Volume 8. No. 7, July 2020
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter73872020.pdf
https://doi.org/10.30534/ijeter/2020/73872020

A Survey of Different Machine Learning Models for Alzheimer Disease Prediction

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ABSTRACT

Machine learning model is one of the best disease prediction framework in various medical disease prediction processes. Alzheimer's disease (AD) is a progressive neuro-degenerative condition with different severity features. However, it is noted that very few patients who is suffering from Alzheimer's disease are decided to take correct clinical decision making. Most of the traditional machine learning models help to detect the AD with limited feature space and dimensionality. Also, these models are not applicable to high dimensional features due to sparsity problem. Several high dimensional classification and clustering methods have recently been proposed to predict the AD automatically. Component selection plays a significant role in improving the performance of these programs. Therefore, various forms of feature selection techniques are analyzed in this survey article. The purpose of the paper is to include an analytical overview and strategic examination of the latest research work performed using Machine Learning Strategies to early diagnosis of AD.

Key words : Alzheimer's disease, Feature Selection, supervised models and unsupervised models.

1. INTRODUCTION

Alzheimer's disease (AD), a widespread health problem which causes memory loss and kills nerve cells in the elderly, constitutes a degenerative brain condition. AD has different stage like the early stage, moderate phase, severe phase (late phase). In order to be able to make preemptive action, it is necessary to detect AD early in the MCI. The world's fourth most common cause of death reported in 2009 is AD, the most prevalent form of dementia. Diagnose of AD calls for several methods of neuroimaging and neuropsychological clinical data. The main clinical characteristics of mild cognitive impairment (MCI) are memory complaint, normal cognitive function, and abnormal age memory. The memory loss in the MCI participants is similar but less disabled than moderate AD patients in other areas. Over time, MCI individuals reported lower decreases than patients with moderate AD. MCI memory deficits may remain stable for years in comparison to AD, where there is slow decline in cognitive ability. Many people with MCI, however, experience AD-compatible cognitive and functional disabilities. The most common prodromal phase of AD was MCI, and current studies have shown MCI people continue to progress towards AD at around 10-15% annually [3].Annual conversion rate of MCI into AD could be up to 25% [2], according to the American Academy of Neurologies, which reviewed a number of trials in 2001.

Alzheimer's disease is hard to be scientifically diagnosed, and signs are often ignored as natural effects of aging. Diagnosis is usually done by a combination of extensive testing and other potential causes. For example, if the patient has suffered from a serious head injury at any time in his or her past or heart problems, they may have problems with memory or concentration. The test should include an anxiety or depression assessment that can lead to symptoms similar to Alzheimer's in seniors, as well as to Alzheimer's or other dementia concurrently. In fact, depression can lead to a generalized set of symptoms known as pseudodementia. In order to assess a patient's memory, concentration and other cognitive skills, a mental status test such as Mini Mental State Examinations is being done, a research based set of issues leading to a score that shows the general degree of impairment. Typically, if the score is very small, AD is less probable. Nevertheless, highly trained people have high mental status checks, although they have Alzheimer's disease. The role of Neuropsychological (NP) evaluations has advanced to that of evaluating the Cognitive and psychosocial consequences of brain damage that is often well located. NP may be very useful for early diagnosis and differentiation between Normal Control, MCI and AD and also to determine if a patient is responding to treatment. Reliable and standardized neuropsychological batteries are used. They are easier to administer, cheaper than neuroimaging, less time consuming, and early accuracy picks up brain damage. Dementia diagnosis from Alzheimer needs data from multiple modalities of neuroimaging and clinical data obtained through neuropsychological testing. Although the studies had used various criteria for MCI. The heterogeneous nature of MCI subjects has defined these MCI subjects correctly as they are a target group for early therapeutic interventions with the strongest biomarkers in AD [6]. Using imaging biomarks, different AD patterns are used to find the disorder, either in cognitively disabled or in unimpaired adults, by recognizing pathology and neuro degeneration [8].

Diagnosis of AD can be performed through multiple algorithms [1], [3]. For the analysis and classification of AD data, many fully automated and semi-automatic methods have been used. Ongoing research focuses on AD for determining biomarkers that will better predict future cognitive decline, particularly in early phases of the progression of disease. In clinical medicine, the development of automated detection procedures based on MRI and other imaging technology is of great interest. It is important to note that these approaches are intended to help clinicians with additional statistical evidence for diagnosis, and that these biomarkers are eventually hoped to act as early markers for AD diagnosis [7]. For early intervention and to control progression of diseases, early diagnosis is very important. The subsequent diagnosis and treatment prove harmful and increases the rate of disease and mortality. As, data volume increases, the specificity and susceptibility of current methods will decrease. It was difficult to diagnose Alzheimer's disease exactly due to dementia [37], [47]. AD is the utmost common form of brain disorder caused due to regular loss of cognitive function such as episodic memory [41]. AD diagnosis specifies a severe cognitive impairment and autopsy evidence of histopathological brain changes.

This paper is systematized as follows. A short description of machine learning models of Alzheimer's disease prediction is presented in section 2. Many feature selection approaches and related work on component selection methods is compared in section 3. In section 4, a survey on traditional supervised learning systems for AD prediction and in section 5, a survey on traditional unsupervised learning systems for Alzheimer's disease prediction is presented. Finally, conclusion is made in section 6.

2. ALZHEIMER'S DISEASE PREDICTION

The identification of AD plays a essential role in the continuum of health care. At an early stage, it is essential to diagnose the disease. For prevision of disease severity [4], [5] AD diagnosis may either be identified using supervised or uncontrolled learning methods. There are a number of different classification algorithms available. For the prediction of AD disease, supervised models such as support vector machine (SVM), random Forest (RF) and decision tree (DT) are used. The data is usually separated into training and test sets. The classifier is from training set designed and tested by means of a separate test set. The data is divided in N parts with a distribution of almost the same size and class. The classifier is composed of N-1 subsets and the rest of the subsets are used for testing. Cross-validation for random partitions can be repeated several times. The average measures calculated from various cross validation times are fairly reliable estimates of the performance of a classifier based on the entire training data. Figure 1 demonstrates how the processed data are used to obtain the predictive results by the controlled learning procedure. The prediction of AD is made by unregulated models such as k-means, hierarchical clusters and Density-based spatial clusters of applications with noise (DBSCAN). Figure 2 shows how data are used to achieve the predictive results in the unsupervised learning process.

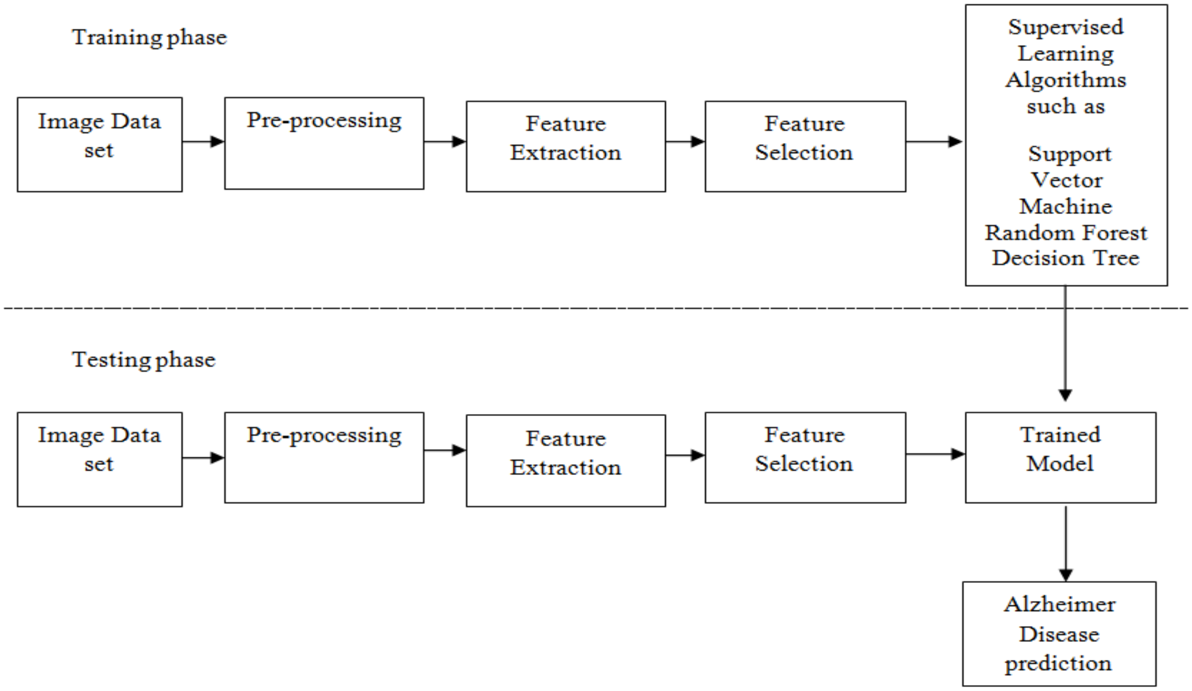

Figure 1: Supervised learning process

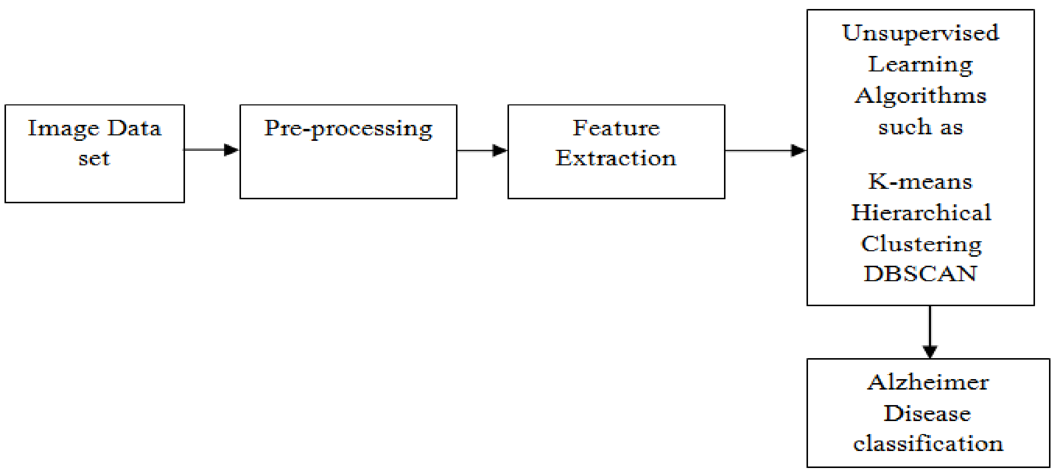

Figure 2: Unsupervised learning process

3. TRADITIONAL FEATURE SELECTION MODELS

Feature selection is one of the significant steps in data mining and machine learning. Feature selection techniques in domains where many features exist are often used. It is a time-consuming job to use all the features for classification of diseases. Moreover, a few features may help Alzheimer's disease more while the rest may contribute little. In medical diagnoses, the most important risk factors related to Alzheimer's disease are very important to identify. Relevant feature identification helps to remove superfluous, redundant attributes from the images data set, reducing training time and improving prediction performance [30].

In recent years different approaches to identifying features in health data sets have been used to provide more valuable information. Few methodologies for selecting the optimal feature set were studied [29]. This protocol proposes a multi-tasking hypergraph approach to select AD / MCI classification, which is used as one function for each modality and integrates group-sparsity regularizer in order to pick similar features together across multiple modalities. This approach is built on the selection of each model. In order to model high-order structural relations between subjects shao et al. [24] introduced the hyper graph based regulation term for a standard selection of the multi-tasking function. Lastly, a multi-kernel SVM is used in order to combine the selected features of various classification modalities. Anatomical parceling by registration with an atlas to group voxels of the different anatomical regions was one approach used in this study [3]. In multi-class scenarios, it is important to delineate the narrow boundary between several classes, which is explored by specific sampling techniques and feature selection techniques in current Alzheimer's Dementia studies [9]. Ramesh et al. [35] compares diagnostic approaches to structural magnetic resonance imaging using the SVM, the import vector machine, and the regularized extreme learning machine to discriminate against AD, MCI and healthy-constrained subjects (HC-subjects). The greedy score based technique for the selection of important functional vectors is used.

Several research works [10], [11] have tried to classify multimodal with machine learning classifiers primarily for binary classification of neuroimaging modalities such as MRI. Table 1 depicts few more component selection techniques developed in recent years and their findings.

Table 1: Feature selection models

Author	Year	Model	Feature selection technique(s)	Metrics	Findings
Wang et al. [44]	2019	Subspace-based sparse feature learning method	Principal component analysis (PCA) and linear discriminant analysis (LDA)	Accuracy :0.856	Experimental findings indicate that the functional parameters extracted are better on small set of AD features.
Trambaiolli et al. [55]	2017	Filtered subset evaluation Technique	Consistency-Based Filter(CBF) Filtered Subset Evaluator (FSE) Chi Squared (CS) Gain Ratio (GR) Correlation-Based Feature Selection (CFS) Relief-F Symmetrical Uncertainty (SU) Ensemble Feature Selection (EFS).	Accuracy:0.913	Electroencephalography (EEG) datasets attain better precisions with pre-processing FS steps.
Tejeswinee et al. [29]	2017	Decremental Method	Correlation Feature Subset Selection (CFS), Information Gain (IG) and Gain Ratio (GR)	Accuracy:0.937	A new dataset consisting of genetic data relating to the neurodegenerative condition was created.
Mirzaei et al. [51]	2018	Two-Stage Feature Selection of Voice metrics.	Wrapper based feature selection model	Accuracy :0.78	The selection scheme removes specific characteristics from the speech in pathology classes.
Jiaye et al. [50]	2019	Feature Selection based multi-view learning	A multi-view sparse exclusive lasso feature selection algorithm	Accuracy :0.897	Achieved strong diagnostic and robustness performance for small datasets.
Xiaoke et al. [49]	2019	Multi-modal neuroimaging Feature Selection with Consistent Metric Constraint	Multi-modal neuroimaging feature selection method	Accuracy :0.93	This approach is utilized to integrate additional data for task selection and further classification from multi-modal neuroimaging.

4. TRADITIONAL SUPERVISED MACHINE LEARNING MODELS

Supervised learning involves training the model for the labelled data and makes predictions on the new data using this trained model. The data is split into two sets of training and test system elements. The model is trained first in a training package and then testing performance on the test package. The efficiency of the model can be measured with output measurements. The main goal of supervised learning is to draw from the data a learning model which can predict unknown knowledge. These models can be used to identify Alzheimer's disease.

Current therapies cannot prevent the progression of Alzheimer, but can delay the deterioration of the symptoms. The medical history, laboratory tests, physical examinations and neuropsychological assessments are used for the clinical diagnosis of Alzheimer, as they measure the person's memory, attention, language skills and problem-solving ability. The diagnosis confirms whether the deficiencies are appropriate for an adult with ordinary daily functions. At 0.85 AUC, 15 MRIs, apolipoprotein E and cognitive testing properties are obtained at the highest level. These findings further show the effectiveness of selection of stability in the sense that the logistic regression of functional selection is scarce [33]. Hannah et al. [14] studied MRI data base, using logistic regression, SVM, radial basic function and C4.5 tree study methods, for AD, MCI and Control Subject Classifications on Alzheimer disease neuroimaging initiative (ADNI). Classification and Regression Trees is an effective tool for the mining of high quality conversion predictors from a high-dimensional data set. In signalizing conversions, CART was useful to confirm the importance of functional action in the MCI population. CART is also a valuable method for identifying covariates for biomarker and neuroimaging that better predict the disease's progression [16]. 89.2 percent and 72.7 percent respectively were maximum precision rates for the AD and MCI control classifications [12]. The analysis of MRI 3D-brain images with an SVM and other well established classifiers to predict AD was projected by Matoug et al. [18]. The ADNI dataset is used for investigation. Throughout this analysis, the pseudo automated technique for reading volumetric rheumatism is introduced, the middle parts of the brain region are extracted, the ventricular region is segmented, a vector characterizing the area is created, a database of SQL containing the data produced and classifying pictures based on extracted features. RF and SVM classification methodologies were identified by Tripoliti et al. [15] for an exact classification of AD. The MRI-based features are extracted and evaluated using an RF grading then interpreted using SVM. [22] Submitted an SVM-based Alzheimer's disease (AD) classification system that incorporates spatial and anatomical details. This encourages space neighbors to have similar weights on the SVM model in the same anatomic region. Secondly, we add a lasso group penalty that can help clinicians determine the key disease-involving regions in induce structural sparsity. The quantitative Voxel morphometric approach to the progression of AD in gray matter was introduced by Daniel et al. [23]. Plant et al. [17] identified using MRI and a combination of three classifiers including SVM, data on Bayes and voting interval strategies to discriminate AD patients from healthy controls, and also forecast the change from MCI to AD. In [26], model consists of four components: preprocessing, segmentation, extraction and classification of features. The extraction of texture characteristics from the observed tumor was accomplished with the use of Gray level co-occurrence matrix (GLCM). The extracted functions are fed to the SVM classifier as an input. Categorization of images from normal to abnormal according to characteristics was done [20]. A Simple drawing movements in Alzheimer's disease was emphasized in [19]. It is capable of differentiating healthy state from diseased state by simply drawing straight lines. There were certain other approaches which involve writing words, drawing spirals and circles. White matter hyper-intensities normally require expert to do manual segmentation/classification on Fluid-attenuated magnetic resonance ADNI. It is difficult to perform consistent and accurate segmentation of white matter hyper intensities for a couple of reasons. Their patterns and texture were heterogeneous, and the borders between the intensities are not clear. The main problem to determine the border between the non-white matter hyper intensities (WMH) and WMH tissue make it better to use the intra-range and inter-range agreements. Detection of WMHs uses various MRI contrasts such as fluid attenuated inversion recovery which shows the hyper-intensity of WMHs, proton density, T2-w, and T1-w which is mostly useful for co-registration [31]. Liu et al. [27] proposed a framework of multiple kernels for disease prediction process.

An ensemble of SVMs that combined bagging without replacement and selection of features. SVM is widely used procedure in detecting dementia. The ensemble approach was motivated by the RF algorithm. In particular, bagging with sequential forward feature selection in the SVM classification has achieved better performance in identifying Alzheimer's disease [32]. More supervised learning models were developed recently and were compared in table 2.

Table 2: Supervised learning models

Author	Year	Model	Feature selection technique (s)	Metrics	Discovery
Vaithinathan et al. [56]	2019	Texture Extraction Technique based classification	Fisher score, elastic net and recursive feature elimination.	Accuracy:0.87	Extracts the characteristics from other fields of interest and analyzes texture.
Pietro et al. [45]	2020	Electroencephalography (EEG) and functional Near-Infrared Spectroscopy (fNIRS) hybrid Technique	Pearson correlation coefficient-based feature selection (PCCFS) strategy	Accuracy: 0.903	This model supports (and evaluates) dementia in AD patients cheaply and rapidly.
Atlaf et al. [26]	2018	SVM, K-nearest neighbor (KNN),Decision Tree and Ensemble	GLCM	Accuracy:0.98 sensitivity:0.97, and specificity:0.98	Visual features extracted from structural MRI using GLCM, scale invariant feature transform, histogram of gradient and local binary pattern contribute much in the prediction.
Kruthika et al. [43]	2019	Multi-class classifier	PSO (particle swarm optimization)	Accuracy:0.96 Sensitivity:0.91 Specificity:0.89 Precision:0.96	The technique of function selection was examined using multiple MRI scanning function sets: cortical thickness, volume features, and a thickness/ volume combination.

5. TRADITIONAL UNSUPERVISED MACHINE LEARNING MODELS

Unsupervised Learning does not involve any training of the data. In this, machine tries to cluster the correlated type of the data by finding the hidden patterns rather than making predictions. These models could also be used for the prediction of AD.

AD is a chronic neurodegenerative progressive and irreversible syndrome. In enhancing AD diagnostics Miguel et al. [21] uses electroencephalograms (EEG). K-means are used for this, and the findings show that sequences of EEG energy change occur in AD patients more commonly than in healthy subjects. Clear detection and recognition of morphological variations within the brain is critical for pre-surgical preparation for the treatment of AD. MRI can detect AD as well as frequency for patients. To achieve accurate volumes of various problems in the brain, the gray matter, white matter, cerebrospinal fluid and the hippocampus segmentation is required. The development and classification techniques for Alzheimer's, MCI and normal control subjects are clearly defined in this study. As a hybrid segmentation strategy [53], the K-means and graph cutting technique is used. Paul et al. [39] used a clustering approach k-means, and they have linguistic and neuropsychological profile-based patients classified. The CDR score was based on the recruitment of CDR1 (n=16), CDR2 (n=15), CDR3 (n=13) and grouped in three groups in [36] AD patients aged 60 or older. Healing volunteers were also recruited to the age group (n=16). Images from a brain were attained on a 3T magnetic resonance scanner using a conventional Gradient eco 3D T1-w sequence without contrast injection. Volumetric quantifiable data and cortical thickness were generated in automated segmentation. Moreover this method provides better understanding on the AD pathophysiologic process. Charles [40] has a model-based categorization of highly dimensional structural neuroimaging data that provides an open approach to personal study. Cortical thickness measurements for 369 older adults were acquired from the ADNI. Poulakis et al. [25] has identified heterogeneous atrophy patterns in the brain in Alzheimer's disease. Han et al. [28] also suggested that earlier Alzheimer's stages may be categorized into three anatomical subtypes: media temporal, parietal, and diffuse atrophies, based on the cluster classification for the cortical thickness of the brain. This research aimed to explore the degree of deteriorations in these anatomical subtypes. Genetic factors play a most important role in AD pathology, although biological processes which contribute to AD continue to remain undefined. Stringer et al. [34] uses the cerebrospinal fluid (CSF) proteomic approach to study the links between polygenic risk scores for AD and the CSF proteomic profile. The cognitive disorder profile is heterogeneous in AD patients. This study identified cognitive subtypes in four key AD cohorts with a clustering approach [13].

Biomarker detection is a challenge and a very problematic job for both medical research and data analytics [54]. Neuropathic AD is highly heterogeneous and recent clinical / research standards do not fully reflect the transition from the preclinical to moderate cognitive impairment to dementia. Therefore, through a brain-spinal biomarker method Toschi et al. [38] described the heterogeneous structure of AD. Through the baseline MRI, CSF and serum biomarkers, ADNI subjects analyzed with amnestic MCI were clustered [42]. Recently few more researchers applied different models for clustering and it is tabulated in Table 3.

Table 3: Unsupervised learning models

Author	Year	Model	Unsupervised approach	Metrics	Discovery
Rajesh Kumar et al. [53]	2018	Hybrid segmentation technique	K -means clustering and graph-cut methods	Accuracy:0.85	Patients with AD, MCI and NC were identified by game theory classifier.
Platero et al. [52]	2016	Fast multiple-atlas segmentation technique	Hippocampal segmentation	Accuracy:0.91	This method is highly applicable to the segmentation of hippocampus and is robust to multi-position data with Harmonized Hippocampal Protocol annotations.
Azimbagirad et al. [48]	2020	Tsallis-Entropy Segmentation	Modified q-entropy (Mqe) and modified Markov Random Field (MMRF) Model	Similarity index:0.89	Mqe-MMRF showed better results than FreeSurfer, SPM, and FSL, particularly in Gray Matter.
Gokce et al. [46]	2020	Hippocampal atrophy	Semi-automatic segmentation software ITK-SNAP	Accuracy:0.87	Gender wise classification is required in order to find the severity of the AD disease.

6. CONCLUSION

World health is badly affected by the spread and increasing Alzheimer's disease every day. The absence or delay in the care of patients can also cause death. Therefore, prediction of Alzheimer's disease is a crucial medical function. In this paper we presented different machine learning techniques for prediction of Alzheimer's disease. Some typical machine learning models are used to identify patterns of diseases of Alzheimer's and dementia. The study indicates the need to educate health workers for the accurate collection and classification methods that can be used effectively for early disease detection on medical databases. Such programs are designed to enable patients, doctors and health practitioners to make better medical decisions. Diverse models and selection strategies for the survival of Alzheimer's patients are suggested by various authors from this study.

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