**International Journal of Computer Engineering & Technology (IJCET)**
Volume 8, Issue 4, July-August 2017, pp. 31–44, Article ID: IJCET_08_04_004
Available online at
http://www.iaeme.com/ijcet/issues.asp?JType=IJCET&VType=8&IType=4
Journal Impact Factor (2016): 9.3590(Calculated by GISI) www.jifactor.com
ISSN Print: 0976-6367 and ISSN Online: 0976–6375


# A COMPREHENSIVE SURVEY: EARLY DETECTION OF ALZHEIMER'S DISEASE USING DIFFERENT TECHNIQUES AND APPROACHES

**S. Sambath Kumar**
Research Scholar, Department of Computer Science,
Pondicherry University, Puducherry, India

**Dr. M. Nandhini**
Assistant Professor, Department of Computer Science,
Pondicherry University, Puducherry, India

**ABSTRACT**

*The accurate diagnosis of Alzheimer's diseases (AD) and prodromal stage like Mild Cognitive Impairment (MCI) play a vital role in preventing them. This survey paper is focused on computer-aided diagnosis with identification algorithm found in the literature. Many researchers have attempted with feature extraction, feature selection, and classification method consists of three categories of feature extraction approach; viz the Voxel-based approach, Region based approach and Patch based approach and four categories of classification, including, the Random Forest, Support Vector Machine, K-Nearest Neighbor and Artificial Neural Network. Our comparison part shows many recently developed algorithms for classifying the AD from elderly Normal Control (NC) with high-level accuracy, whereas major challenge arises from classifying the Mild Cognitive Impairment (MCI) from NC or AD.*

**Key word:** Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), Computer Aided Diagnosis, Medical Imaging, Feature Extraction, Classification.

**Cite this Article:** S. Sambath Kumar and Dr. M. Nandhini, A Comprehensive Survey: Early Detection of Alzheimer's Disease using Different Techniques and Approaches. *International Journal of Computer Engineering & Technology*, 8(4), 2017, pp. 31–44.
http://www.iaeme.com/ijcet/issues.asp?JType=IJCET&VType=8&IType=4

## 1. INTRODUCTION

In the United States, the Alzheimer's disease (AD) is the sixth leading cause of death. More than 5.4 million Americans are living with Alzheimer's disease. It affects people aged more than 65. Alzheimer's disease, the neurological disorder causes memory loss and cognitive degeneration[1] leading to brain death. It is a most common form of dementia nowadays. Dementia, a neuro disease initially proceeds milder and gets worse progressively. At regular intervals, someone is affected by AD in the United States. So far there is no treatment for affected patients. Patients suffering from AD at a prodromal stage are mostly classified as mild cognitive impairment (MCI). At each of the stages, the researcher has improved diagnosis to prevent AD diseases[2].

In that respect, there are three examples of AD: preclinical, Mild Cognitive Impairment, and Dementia. Preclinical means early-onset of Alzheimer's and so happens to those younger and below 65 years. It's a rare case in medical history with 5% of people catching these early-onsets of Alzheimer's. Mild Cognitive Impairment (MCI) is a transitional stage[3]. This is associated with language, thinking, memory changes and judgment greater than the normal condition. Finally, dementia is a wide category of brain diseases[4]

The early stage of dementia will have some common symptoms. It has long term effect on linguistic ability and it will bear upon daily functioning in a person's lifetime[5]. Dementia will cause different conditions, which include Huntington's disease, Creutzfeldt-Jakob disease (CJD), Lewy body disease, and vascular dementia, Parkinson's disease, and Wernicke-Korsakoff syndrome[6]. In Fig-1 some common symptoms of Alzheimer's are shown.

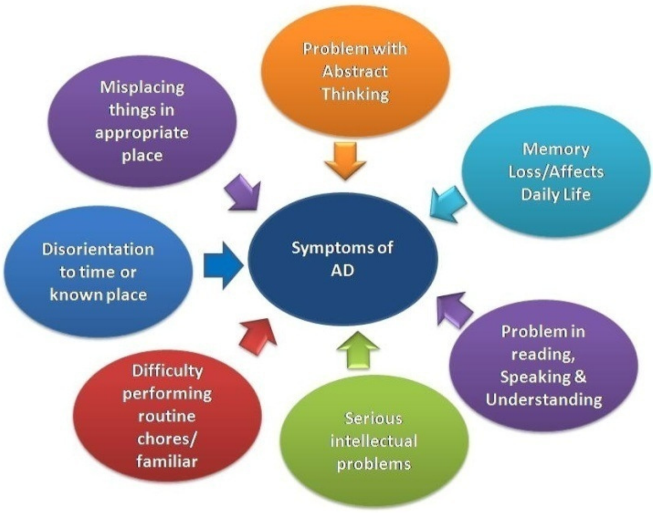


**Figure 1** Symptoms of Alzheimer's Diseases

Medical imaging plays a vital role in dementia. Imaging biomarkers are a set of indicators computed from image modalities and can be used for the early detection of AD diseases. Some commonly used medical images to diagnosis dementia at an early stage include magnetic resonance imaging (MRI), positron emission tomography (PET)[7], Cerebro-spinal Fluid (CSF), single-photon emission computed tomography (SPECT), Computerized Tomography (CT scans), electroencephalogram (EEG) signal[8][9]. It assesses the whole brain signals. Structural MRI uses radio waves and a magnetic field to image tissues and organs in the human body. This technique gives many advantages, including better soft tissue contrast, lower cost, greater accessibility and regional atrophy. Structural MRI image is obtained as a data set from Alzheimer's disease Neuroimaging Initiative (ADNI) for identifying AD progression. Functional PET having some various radioactive tracers, for example, 18C-Pittsburgh Compound (11C-PiB), and 2-[18F] Fluoro-2-deoxy-D-glucose (FDG) can detect the slight changes in amyloid deposition or cerebral metabolism prior to anatomical changes is a symptomatological diagnosis of dementia. Functional SPECT is analogous to PET images by using a radioactive isotope and imaging gamma rays from it[10][11][12]. SPECT scan is less expensive than PET scans but has lower spatial resolution compared to PET scans[13].

In medical research, acquiring the data sets is very difficult, acquiring 3-D dataset images is mostly unexplored and a comparatively low volume of work is entirely based on visual assessment of slice by slice search of 3-D datasets for affected diseases patterns. This will require enormous knowledge, effort, cost and time. Inasmuch as the doctor's opinion, computer aided classification and identification of dementia is still the most promising tool at an early stage. Those approaches are classified into three categories: (1) differentiating AD from NC (2) identifying the different stages of AD: MCI from AD (3) and AD from FTD. There are many databases available for diagnosis of AD, including the Alzheimer's Disease Neuroimaging Initiative (ADNI)[14], and Open Access Series of Imaging Studies (OASIS)[15]. These databases are mainly used for identification and classification of dementia an early stage in the research.

In this survey report, we explain about an automated identification of dementia approaches from the pattern classification point of view in detail. Section 2 explains three different types of feature extraction methods and four types of classification technique used in following approaches. Finally, we present a comparison of performances in different approaches.

## 2. METHODS

Computer Aided identification using brain medical images to diagnose the AD at early phases based on a pattern recognition problem has two types: Pattern classification and feature extraction. During the training stage of the implementation, the brain image feature represents the various stages of dementia or the patterns. Quantitative image analysis is used to recognize these patterns. Before training stage, all the features are identified or pooled and feed into some specific algorithm to reduce the dimensionality under supervised learning[16]. Sometimes the trained phase is treated as a "black box technique". Secondly, to predict the class label[17], features are extracted, combined or selected and in a similar way applied to the classifier to create a classification which shows the stage of the diseases**.** In Fig-2. The design of Computer Aided Diagnosis of Dementia is shown.

And so, we will focus on state-of-the-art feature extraction technique and classification technique to identify the AD disease.

### 2.1. Feature Extraction Technique

The feature extraction method for extracting features from the brain image dataset is classified into three approaches: voxel-based, ROI based, and Patch based ones[18].

#### *2.1.1. Voxel-Based Approaches*

The voxel-based approach is a neuroimaging technique. It allows the study of focal differences in brain diagnosis by using the statistical approach of statistical mapping. In morphometry, the volume of entire brain or subparts is calculated by determining volumes of regions of interest on brain images from brain scanning and calculation. The Voxel-Based Morphometry (VBM) will register for every template, which gives a clear idea about the brain disease among people. Finally, brain volume is compared in every voxel. VBM cannot differentiate small differences in volumes. scores regression and clinical status identification for MRI and PET images. The accuracy level of ADAS-Cog reached .716% and of MMSE .655%.

Jussi Tohka et al.(2012)[19] discussed on feature selection and classification method for aMRI images. Filter based approach is used for feature selection and voxel-based method for classification. Mainly two classification problems are implemented AD vs NC and AD vs

MCI. Further, it discussed stability selection and LASSO method for good generalization performance.

D Salas-Gonzalez et al.(2010)[20] elaborated on computer aided diagnosis technique for Alzheimer's disease and calculated the mean ATD images and mean normal. Further, it calculated Welch's t-test for both images in each and every all voxel. Then the classifier approach reached an accuracy level of 96.2% J. Ramfrez et al.(2009)[21] discussed on CAD system to improve the diagnosis of Alzheimer Type Dementia (ATD) in early stages by using the SPECT images. The proposed approach is feature selection and classification technique. Further, it discusses on voxel as feature approach and SVM for better classification. The proposed approach reached an accuracy level of 90%.

Ayşe Demirhan et al.(2016)[22] discussed on White Matter (WM) voxels for abnormal patients by using the DTI fractional anisotropy maps to classify the AD, MCI, and healthy normal control. Further, it discussed on a ReliefF algorithm to select the subset of WM voxels for classification. Rémi Cuingnet et al[18] discussed on ten approaches from 509 ADNI subjects. 5 voxel-based approaches and 3 cortical thicknesses and 2 hippocampi are automatically select between affected patients having AD, MCI, and elderly normal control by using the T1 scans. Further, the work discussed on voxel or cortical thickness approaches achieved 81% sensitivity and 95% specificity and reduced computation time to find the AD diseases.

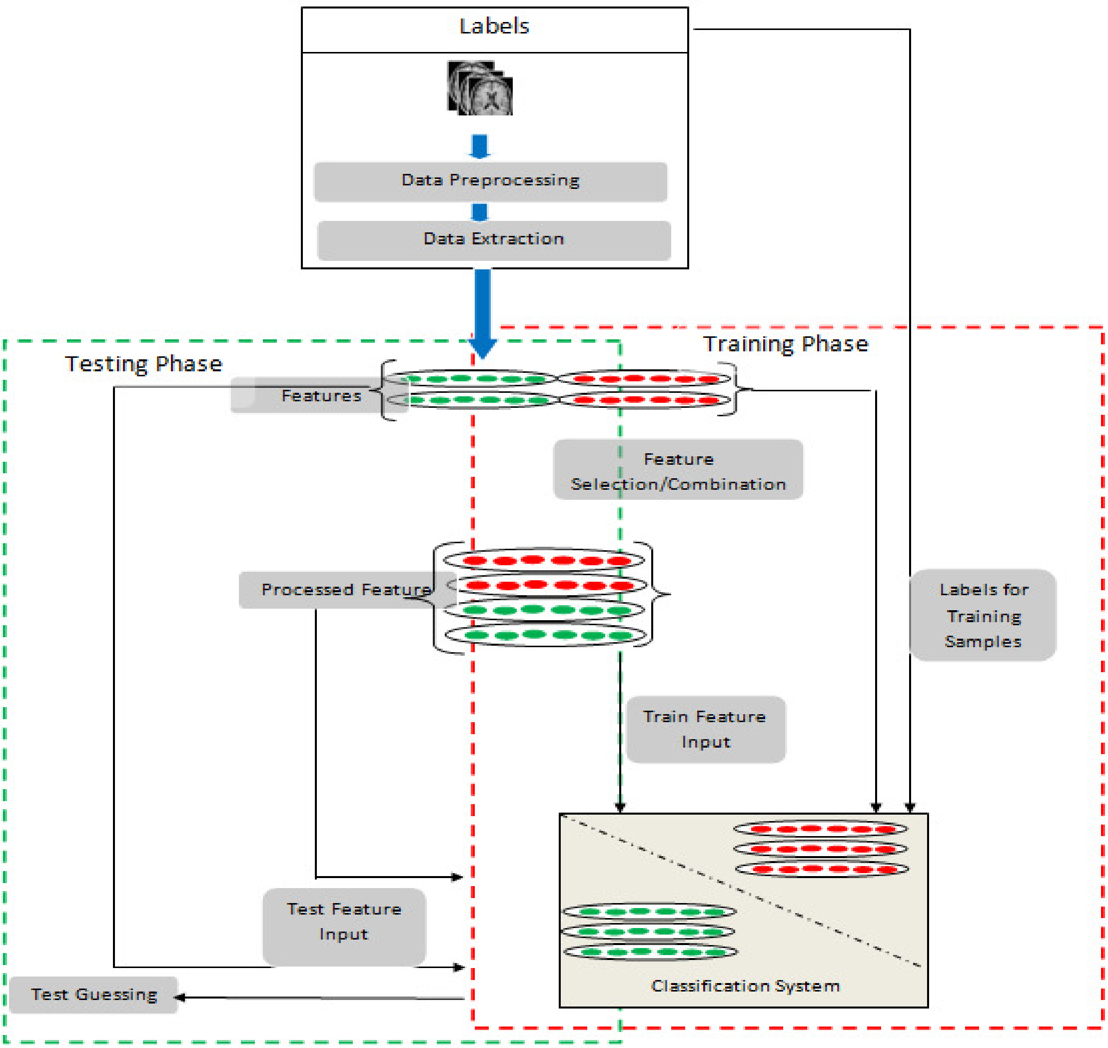


**Figure 2** The design of Computer Aided Diagnosis of Dementia

Xiaofeng Zhu et al.(2015)[23]introduced space multi-task learning for feature selection by using the canonical features. The proposed algorithms are N3 and FAST. It jointly achieved predictable clinical scores regression and clinical status identification for MRI and PET images. The accuracy level of ADAS-Cog reached .716% and of MMSE .655%.

### *2.1.2. Region of Interest (Roi) -Based Approaches*

The region of Interest based approach is used for image features and it will categorize a number of parts in brain element, like the corpus callosum, superior longitudinal fasciculur, hippocampi, uncinate fasciculus, and cingulum. Pathological studies will show the neurodegeneration in Alzheimer's disease starting to appear in the temporal lobe and limbic system, hippocampus, and neocortical regions[24][25][26]. Hippocampi astorphy is used as a marker in many areas of AD. The selected features from brain images include the hippocampi shape or the volume or weighted combination.

In ROI based approach, ROI segmentation happens before applying feature extraction technique[27][28]. In one hand manual segmentation involves time-consuming and operator-related bias and in another the automated segmentation of a region of interest is poor.

Tingting Ye et al.(2015)[29] proposed a discriminative multi-task feature selection for multiple modalities. It discussed group-sparsity regularization for joint selection of multi-image modalities. Further, it discussed discriminative regularization term for intercourse and intraclass Laplacian matrix for each subject. The accuracy value of 95.92% was reached. Siqi Liu et al.(2015)[30] proposed zero masking strategy to extract complimentary information from multi-data modalities with SAE and achieve the best performance for multi-class Alzheimer's diseases. The SAE used for to get high-level features. Further 2SAE+MKSVM achieved high-level accuracy of 91.4% and specificity of 91.67%

Chen Zu et al.(2016)[31] Chen developed two main components (i.e.) multimodal classification and multi-task feature selection for AD/MCI patients. Further, it discussed on joint feature selection for AD and relevant features are selected jointly by group sparsity regularizer. Multi-kernel SVM method shows an accuracy value of 95.95%. Daoqiang Zhang et al.(2011)[32] proposed in kernel combination method for multi-modality biomarkers and linear SVM is used for better classification. The experimental method shows better performance in AD/MCI classification and better measurements from MRI, PET and CSF biomarkers. 11 top regions are selected from MRI and PET for MCI classification. High-level accuracy, sensitivity, and specificity levels are achieved. Andre Santos Ribeiro et al.2015[33] introduced new Multimodal Imaging Brain Connectivity Analysis (MIBCA) tool, which they used for processing fMRI image and PET scans. This toolbox is able to process aMRI from high resolution scanned images, fMRI image from Blood Oxygen Level Dependent (BOLD) and dMRI from DTI. P. Padilla et al.(2012)[34] proposed computer aided diagnosis for AD in early stages by using the Fisher Discriminant Ratio (FDR) and Nonnegative Matrix Factorization (NMF) for relevant feature selection and classification technique by using SVM. This NMF and FDR attained an accuracy level of 91% and sensitivity, specificity more than 90%

### *2.1.3. Patch-Based Approach*

The patch based approach is proposed for image representation and restoration. This method is primarily used for point-wise selection of given image patches of exact size in the variable select of each picture element. Each pixel has some weights of the data within the adaptively selected data. This approach will demonstrate the hopeful results in medical research.

Pushkar Bhatkoti et al.(2016)[35] proposed for the computer aided multi-class diagnosis of AD with efficient manner. The classification technique has improved by k-Sparse Autoencoder (KSA) approach. The modified KSA method and deep learning framework will provide the accurate results in AD diagnosis. The classification method shows an accuracy value of 83.14%. Xiaofeng Zhu et al.(2014)[36] proposed multi-model canonical feature selection for MRI and PET data. This method selects canonical cross-modality feature for multi-class identification and clinical scores regression. Further, it discussed the jointly predicted the clinical scores from MMSE and ADAS-Cog, and identify the AD in early stages. The proposed 3-JRMI and 4-JRMI method achieved 10.01% accuracy level, 0.045% on CCA and 0.081% on CC-M. Jun Shi et al.(2017)[37] proposed an MM-SDPN algorithm to learn feature for finding the AD in an early stage. This algorithm achieves the best performance in comparison with the multi-modality algorithm. Further, it discussed two stages of SDPN and four stages of SDPN applied to MRI and PET images for ROI features. Heung-Il Suk et al.(2013)[38] proposed stacked autoencoder (SAE) for AD/MCI diagnosis. The SAE model permits us to determine the best possible parameter in adjustment with the exact sample data from ADNI (51 AD patients, 99 MCI52, HC subjects). This method involved SAE learned feature representation in brain diseases and it achieved maximum accuracy based on the classification. The accuracy value of 98.8% was achieved.

Bo Cheng et al.(2016)[39] proposed multi-domain transfer learning to diagnose the AD in early stages. Mainly two key components are used in this MDTL. To select the future subset from more than one domain data by using future selection and classification technique used for finding the AD detection in early stages. Josephine Barnes et al.(2010)[40] discussed on hippocampal atrophy rates from MRI image. This atrophy rate is useful for tracking and diagnosing Alzheimer’s disease patients. Further, it discussed on meta-regression and Meta-analysis of the given datasets. The mean rate was found as 4.66% (95%). Saman Sarraf et al.(2016)[41] proposed on Convolutional Neural Network (CNN) and deep learning architecture (LeNet) to train and test the enormous image data. Using CNN and LeNet-5 architecture both are extracted and classified MRI data to recognize the AD during a clinical scan. The classified data from AD to NC reached 98.84% and the Privacy of clinical data is compromised. Francesco Carlo Morabito et al.(2016)[42] discussed the use of different biomarkers yielding promising accurate outcome and various image modalities, giving a different view of the function of brain images for diagnosing AD/MCI using CNN approach. For example, EEG signals classify EEG pattern of AD from the prodromal version of dementia. CNN approach attained an accuracy level of 95%.

Ehsan Hosseini-Asl et al.(2016)[43] introduced structural MRI scans using a deep learning approach (3D CNN). The proposed method involved 3D ACNN classifier approach, which is enabled to find the AD using structural MRI in an accurate manner (210 subjects of ADNI). The performance of the ACNN classifier approach reached an accuracy level of 95%. Yi-Wei Chen et al[44] discussed on combining classification using SVM technique and feature selection. Some techniques are using filter type approaches and some are wrapper methods. Further, it discussed future selection method applied to SVM for classification and modification of SVM for training and testing. These are the datasets used Madelon, Gisette, Dorothea, Dexter, and Arcene for better classification and performance.

## 2.2. Classification Technique

This section briefly describes various classification techniques used for categorizing the diseases. All the classifier technique could be trained and then applied to find the diagnosis of a test case. The commonly used classifier technique in Alzheimer's disease identification includes the Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Artificial Neural Networks (ANN).

### *2.2.1. Random Forest (RF)*

Random forests or random decision forests is used as an ensemble learning method for regression, classification, and other tasks. It constructs a multitude of decision trees at training time and gives the output of the class which is the mode of the mean prediction (regression) or classes (classification) of the individual trees. It gives the better results when compared to the other classification techniques.

Tong Tong et al.(2017)[45] elaborated on a number of important factors such as age correction, registration accuracy, feature selection and selection of training data. Further, it discussed on novel grading biomarkers for MCI-AD conversion and used a sparse representation technique with Random Forest. Finally, the classification accuracy improved from 62% to 73%. Mingxing Zhang et al.(2016)[46] discussed on multi-view classification technique $l_{2,p}$ norm regularization for AD diseases. This work considers inter structure and intra-structure relations. The proposed method compared among Random Forest, SVM, and Decision Tree. S. R. Bhagya Shree et al.(2014)[47] proposed data mining approach to finding the AD and discussed on various classification technique for Alzheimer's disease. The techniques are Random Forest, Naïve Bayes classifier, and decision tree algorithm and achieved high accuracy.

Rosalia Maglietta et al.(2016)[48] discussed on hippocampal segmentation in MRI images using the RUSBoost algorithm. Further, it compared with AdaBoost and Random forest classification. This method is suitable for segmentation, accurate classification of hippocampal. Andreas Merentitis et al.(2015)[49] elaborated on feature extraction as hierarchical and coming under unsupervised in deep learning. It reduces the gap between methods and feature extraction. To learn the important features the author used RF classifier for feature ranking capability.

### *2.2.2. Support Vector Machine (SVM)*

SVM plays a vital role in machine learning. It is a supervised learning machine model and its associated learning algorithm studies. Processed data is used for regression analysis and classification or another task[50]. SVM, having finite training samples, is mostly used to solve pattern classification problem. Classification technique has classified into two main steps. First classification training considers a group of the binary label. Second classification training considers an unlabeled data[51].Chester

V. Dolph et al.(2014)[52] proposed feature classification method that is used to find segmentation tissue in MRI images. The proposed method of feature extraction is classified into three categories GM, WM, and CSF. This SVM-RBF attained an accuracy level of 0.866%. Xiaohong W.Gao et al.(2016)[53] introduced an unsupervised automatic computer aided the process of CNN on the segmentation, classification, and measurement of Alzheimer's diseases. The accuracy value of 95.6% was achieved. The classification of AD, lesion, and normalcy achieved the accuracy of 88%, 76.6%, and 95% respectively.

Feng Lie et al.(2015)[54] discussed Multi-kernel SVM classifier to classify AD and MCI from MRI, PET, and CSF. Feature Extraction technique, including PCA, Stability Selection, and dropout technique improves the classification technique. The classification accuracy level has improved by 5.9%. Saman Sarraf et al.(2016)[55] discussed deep learning architecture (LeNet) to train and test the enormous image data. CNN and LeNet-5 architectures are used for classifying fMRI, MRI, and state functional magnetic resonance imaging (rs-fMRI) data to recognize the AD during a clinical scan. The accuracy value of 96.85% was achieved. Tien Duong Vu et al.(2017)[56] proposed a learning algorithm for SVM classification performance. It was achieved using three layer neural networks with softmax function, and AD/NC achieved an accuracy of 90.3% and MCI/NC accuracy of 87.9%

### *2.2.3. K-Nearest Neighbour (KNN)*

K-nearest neighbors (k-NN) is a non-parametric method and it is data mining algorithm. KNN used for regression and classification in the image processing domain. In both the regression and classification cases, the input consists of the k closest training data in the feature space. The output consists of whether k-NN is used for classification or regression depending on the data.

Emrana Kabir Hashi et al.(2017)[57] discussed diabetes disease using k-nearest neighbors and decision tree algorithm. This classifier algorithm mainly used to predict the exact diseases at an early stage, which will avoid patient's ailment. Abdalla R. Gad et al.(2017)[58]Proposed automated classification of giving subjects from MRI images and two classification techniques are proposed. The first technique is KNN and second technique is SVM. The author found for which one accuracy is higher for identification of the class of the selected feature. KNN and SVM attained best average accuracy level of 95.833% and 97.92%. Charlotte Cecere et al.(2014)[59] discussed on machine learning approach by using the EEG feature and then compared different classification techniques. Those techniques are SVM, KNN, CART trees, naïve Bayes and AdaBoost algorithm. SVM achieved the highest accuracy of 78.5%. Bibo et al.(2015)[60] developed the nonlinear metric learning model for diagnosis the AD and MCI at an early stage. Further, it's discussed patch based feature selection approach to extract the longitudinal and cross-sectional feature from MRI images.

### *2.2.4. Artificial Neural Networks (ANN)*

In Machine Learning, connectionist system or Artificial Neural Networks (ANN) is a computational model. It is based on a large collection of associated simple units called artificial neuron in computer science or other research domain.

M. M. Patil, et al.(2013)[61] proposed on Discrete Cosine Transform (DCT) coefficients as a feature for the classification of ANN. The derived feature is classified as for whether it is AD or NC or MCI. This ANN attained an accuracy value of 100% for a set of MRI. Almir Aljovic et al.(2016)[62] discussed ANN for the classification of healthy control people and Alzheimer's disease. They used five biomarkers for classification of input data for AD: it includes Aβ40 (CSF), albumin ration, Aβ42 (CSF), t-total (CSF) and tau-phosphor (CSF). AD patient's diagnosis achieved a sensitivity of 95.5%, from 32 subjects and exactly classified a specificity of 91.43 %. Pedro Rodrigues et al.[63] Proposed Logistic Regression for the identification of Alzheimer's diseases and ANN in EEG classification. The wavelet transform is the main technique here for signal processing. These selected features feed into ANN and LR by using PCA analysis. This ANN achieved an accuracy of 84.2%, a sensitivity of 77.6% and specificity of 90.8%. And LR achieved an accuracy of 75.7%, a sensitivity of 77.6% and specificity of 73.7%.

Chengzhong Huang et al.(2008)[64] Elaborated on automatically detecting the grey matter loss of AD-affected patients with MRI images. Further, it discussed VBM with ANN. PCA is used for feature dimensionality and back propagation algorithm with ANN and was trained in Alzheimer's disease classification and then achieved an accuracy of 100% from AD to NC. Shih-Ting Yang et al.(2010)[65] proposed the computer aided diagnosis of AD using ANN classification. Shape features and volumetric features are extracted from MRI images. And then PCA has been used to decrease the dimension, back propagation algorithm with ANN trained for AD disease classification. The proposed accuracy level reached up to 92.17%

So far we have summarized four pattern classification techniques to identify dementia on early stage. Analysis of the exact disease is very important for supervised classification technique, and then the advance pattern classification and supervised machine learning technique finds the best application on this survey.

## 3. PERFORMANCE COMPARISON

We have a number of comparative studies in this literature survey. Chen Zu et al. [31] applied 202 patients from ADNI database to diagnosis the ad diseases. Which is the ROI-based approach. ROI calculated from every image of 51 AD, 52 NC, and 99 MCI patients, and applied the best classifier of support vector machine to classify the diseases.Chen developed two main components (i.e.) multimodal classification and multi-task feature selection for AD/MCI patients. Further, it discussed on joint feature selection for AD and relevant features are selected jointly by group sparsity regularizer. Multi-kernel SVM method achieves the best and highest accuracy with cross-validation method. Feng Li et al [54] discussed on patch based approach and the data collected from ADNI database, which includes 202 subjects from 51 AD, 52 NC, and 99 MCI. In Patch-based approach, Multi-Kernel SVM and Feature Extraction technique, including Principal Compound Analysis, Stability Selection, and dropout technique improves the classification technique. The classification accuracy level has improved by 5.9%.Rémi Cuingnet et al. [18]discussed on ten approaches from 509 ADNI subjects. 5 voxel-based approaches and 3 cortical thicknesses and 2 hippocampi in automatically select between affected patients with MCI, AD, and elderly normal controls by using the T1 scan. The best classification technique SVM is applied to classify the exact diseases. The first section belongs to voxel-based approach and the features are segmented tissue probability maps selected from MRI voxel. Particularly, the probability of the tissue is Gray matter(GM), white matter(WM) and cerebrospinal fluid(CSF) from the T1 weighted scan. The second section belongs to cortical thickness and ROI-based approaches. The features selected from based on the cortical surface. The last method belongs to hippocampi, it includes the shape and volume of the right and left hippocampus. Voxel base approach and cortical thickness approach achieved the highest accuracy of 81% sensitivity and 95% specificity and reduced computation time to find the AD diseases.

Table 1 demonstrates the overall performance about the Computer Aided Diagnosis of Dementia methods published from last ten year. most of the author achieved an accuracy of more than 90% with smaller datasets. This table shows various feature selection and classification technique in a voxel, ROI, and Patch based approach. Feature selection technique includes canonical loss function, canonical regularization, row sparsity, Welch's t-test for both classes like AD and Norma. Classification technique includes SVM, CT, Linear SVM and Gaussian SVM.

## 4. CONCLUSIONS

A detailed survey and summary of computer aided diagnosis of dementia from the pattern classification point of view can be divided into two main parts: Feature extraction technique and classification technique. Feature extraction including, Voxel based, ROI based, and Patch based and classification including, Random Forest, Support Vector Machine, K- Nearest Neighbor and Artificial Neural Network algorithm and approaches are presented in this paper. We compared the performance with recently developed algorithms. The comparison part displays the diagnosis of Alzheimer's disease (AD), Mild Cognitive Impairment (MCI) and elderly Normal Control (NC) achieved high accuracy by recently developed algorithms.

**Table 1** (Comparative study) Computer Aided Diagnosis of Dementia method using different medical imaging.

| Year | Author | Targets | Methods | Modality | Data sets | Performance<br>Accuracy(%) | Sensitivity(%) | Specificity(%) |
|---|---|---|---|---|---|---|---|---|
| 2016 | Xiaofeng Zhu et al [27] | AD vs NC | VBM+SVR/SVC | MRI, PET, CSF | ADNI: 51 AD, 52 NC, and 99 MCI | 0.716(ADAS-Cog),0.655(MMSE) | NaN | NaN |
| 2012 | Jussi Tohka et al [28] | MCI vs.NC | VBM+SVM | MRI, PET | ADNI: 200 AD, 231 NC, and 400 MCI | NaN | NaN | NaN |
| 2010 | D Salas-Gonzalez et al [29] | AD vs. NC | VBM(Welch's t-test)+SVM,CT | SPECT | ADNI:180 | 96.2 | NaN | NaN |
| 2009 | J. Ram?rez et al[30] | AD vs. NC | VBM+SVM | SPECT | ADNI:180 | 90.38 | NaN | NaN |
| 2015 | Ay?e Demirhan et al [31] | MCI vs.NC | VBM(EMV)+SVM | DTI | ADNI: 43 AD, 70 NC, and 114 MCI | AD vs NC - 86<br>AD vs MCI - 78.3<br>MCI vs NC - 75.8 | 79.5<br>77<br>86.2 | 92.9<br>89.4<br>65.7 |
| 2010 | Rémi Cuingnet et al [26] | | VBM+SVM | MRI, PET, CSF | ADNI: 69 AD, 67 NC, and 39 MCIc | NaN | 81 | 95 |
| 2015 | Tingting Ye et al [37] | MCI vs.NC | ROI(DMTFS)+SVM | MRI, PET, CSF | ADNI: 51 AD, 52 NC, and 99 MCI | AD vs HC - 95.92<br>MCI VS HC - 82.13 | 94.71<br>87.68 | 97.12<br>71.54 |
| 2015 | Siqi Liu et al [38] | | ROI(SAE)+SVM | MRI, PET, CSF | ADNI: 180 AD, 204 NC, 214 ncMCI and 160 cMCI | MCI-C vs. MCI-NC -71.12<br>NC vs AD- 91.40<br>NC vs MCI - 82.10<br>MRI AND PET - 53.79 | 67.21<br>92.32<br>62.5<br>66.43 | 73.93<br>91.67<br>92.92<br>86.98 |
| 2015 | Chen Zu et al [39] | AD vs. MCI | ROI+SVM | MRI, PET | ADNI: 51 AD, 99 MCI, and 52 NC, | AD vs NC- 95.95<br>MCI vs NC - 80.26 | 95.1<br>84.95 | 96.54<br>70.77 |
| 2010 | Daoqiang Zhang et al [40] | MCI vs AD | ROI+ Linear SVM | MRI, PET, CSF | ADNI: 51 AD, 99 MCI, and 52 NC, | AD vs NC -95.95<br>MCI vs NC - 80.26 | 95.1<br>84.95 | 96.54<br>70.77 |
| 2015 | André Santos Ribeiro et al [41] | MCI vs AD | | MRI, PET | ADNI: 12 AD, 12 MCI and 52 NC, | NaN | NaN | NaN |
| 2012 | P. Padilla et al [42] | MCI vs AD | FS(FDR,NMF)+ SVM | SPECT, PET | ADNI: 800 | NMF-SVM -91.42<br>PET - 86.59 | 90.56<br>87.5 | 92.3<br>85.36 |
| 2012 | Chester V. Dolph et al [61] | MCI vs.NC | ROI+SVM(RBF kernel) | MRI | ADNI: 9 AD, 12 NC, and 9 MCI | NaN | NaN | NaN |
| 2016 | Pushkar Bhatkoti et al [43] | MCI vs AD | PBM+DNN,KSA | MRI, PET, CSF | ADNI: 150 | ZMS - 62.72<br>k-sparse - 63.24<br>?k sparse - 74.05 | NaN | NaN |
| 2014 | Xiaofeng Zhu et al [44] | AD vs. MCI | PBM | MRI, PET | ADNI: 51 AD, 99 MCI, and 52 NC, | 3-JRMI- 10.01 | NaN | NaN |
| 2016 | Jun Shi et al [45] | MCI vs AD | FL(MM-SDPN)+SVM | MRI, PET | ADNI: 51 AD, 99 MCI, and 52 NC, | MM-SDPN-SVM -57.00<br>MM-SDPN-LC -55.34 | 53.65<br>52.49 | 85.05<br>84.18 |
| 2013 | Heung-Il Suk et al [46] | MCI vs AD | PBM+MKSVM | MRI, PET, fMRI | ADNI: 51 AD, 99 MCI, and 52 NC, | AD vs NC -98.8<br>MCI vs NC -90.7<br>MCI vs Cmci -83.6<br>AD vs MCI - 83.7 | NaN | NaN |
| 2014 | Heung-Il Suk et al [47] | MCI vs AD | PBM+MKSVM | MRI, PET | ADNI: 93 AD, 101 NC, 128 76 MCI-NC and 204 MCI | AD vs NC -95.35<br>MCI vs NC -85.67<br>CMCI vs MCI -74.58 | NaN | NaN |
| 2016 | Bo Cheng et al [48] | MCI vs AD | PBM+SVM | MRI, PET | ADNI: 186 AD, 226 NC, and 395 MCI | AD vs NC -94.7<br>MCI vs NC -81.5<br>pMCI vs sMCI-73.8 | 94.1<br>85.8<br>69 | 94.8<br>73.3<br>77.4 |
| 2009 | Josephine Barnesa et al [49] | AD vs NC | Hippocampi shape + SVM | MRI | ADNI: 212 | 95 | NaN | NaN |
| 2015 | Feng Li et al [63] | MCI vs AD | PBM(PCA, SS)+SVM | MRI, PET, CSF | ADNI: 51 AD, 52 NC, and 99 MCI | 5.9 improved | | |
| 2016 | Francesco Carlo Morabito et al [51] | AD vs. MCI | PBM+SVM | EEG | ADNI: 63 AD, 56 MCI | AD-MCI-HC -82<br>MCI vs HC - 85.00<br>AD vs HC - 85<br>MCI vs AD - 78 | 83<br>84<br>85<br>78 | 75<br>81<br>82<br>75 |
| 2016 | Ehsan Hosseini Asl et al [52] | AD vs. MCI | PBM(3D-ACNN)+SVM | MRI, PET, CSF | ADNI: 210 | AD vs MCInc - 89.1<br>AD+MCI vs NC - 90.3<br>AD vs NC -97.6<br>AD vs MCI - 95<br>MCI vs NC -90.8 | NaN | NaN |

# REFERENCES


[1] M. Eroglu S., Toprak S., Urgan O, MD, Ozge E. Onur, MD, Arzu Denizbasi, MD, Haldun Akoglu, MD, Cigdem Ozpolat, MD, Ebru Akoglu, *American Psychiatric Association and American Psychiatric Association (1994) Task Force on DSM-IV, Diagnostic and Statistical Manual of Mental Disorder*, vol. 33. 2012.

[2] N. D. Weder, R. Aziz, K. Wilkins, and R. R. Tampi, "Frontotemporal Dementias: A Review," *Ann. Gen. Psychiatry*, vol. 6, no. 1, p. 15, 2007.

[3] Alzheimer's Association, "2014 Alzheimer's Disease Facts and Figures," *Alzheimer's Dement.*, vol. 10, no. 2, pp. 1–80, 2014.

[4] R. Brookmeyer, E. Johnson, K. Ziegler-Graham, and H. M. Arrighi, "Forecasting the global burden of Alzheimer's disease," *Alzheimer's Dement.*, vol. 3, no. 3, pp. 186–191, 2007.

[5] National Institutes of Health, "Frontotemporal disorders: Frontotemporal dementia •Primary progressive aphasia Movement disorders."

[6] F. Luiz, B. Zadrozny, J. Laks, A. Conci, D. Christina, and M. Saade, "A Bayesian network decision model for supporting the diagnosis of dementia , Alzheimer â€™ s disease and mild cognitive impairment," *Comput. Biol. Med.*, vol. 51, pp. 140–158, 2014.

[7] W. Cai, D. Feng, and R. Fulton, "Content-based retrieval of dynamic PET functional images," *IEEE Trans. Inf. Technol. Biomed.*, vol. 4, no. 2, pp. 152–158, 2000.

[8] D. H. S. Silverman, "Brain 18F-FDG PET in the diagnosis of neurodegenerative dementias: comparison with perfusion SPECT and with clinical evaluations lacking nuclear imaging.," *J. Nucl. Med.*, vol. 45, no. 4, pp. 594–607, 2004.

[9] G. Chetelat and J. C. Baron, "Early diagnosis of Alzheimer's disease: Contribution of structural neuroimaging," *Neuroimage*, vol. 18, no. 2, pp. 525–541, 2003.

[10] J. Stoeckel and G. Fung, "SVM Feature Selection for Classification of SPECT Images of Alzheimer’s Disease Using Spatial Information," *Fifth IEEE Int. Conf. Data Min.*, vol. 11, no. 2, pp. 410–417, 2007.

[11] E. T. Da Rocha, C. A. Buchpiguel, R. Nitrini, S. Tazima, S. V. Peres, and G. Busatto Filho, "Diagnosis of regional cerebral blood flow abnormalities using spect: agreement between individualized statistical parametric maps and visual inspection by nuclear medicine physicians with different levels of expertise in nuclear neurology.," *Clinics (Sao Paulo).*, vol. 64, no. 12, pp. 1145–1153, 2009.

[12] M. P. Page, R. J. Howard, J. T. O'Brien, M. S. Buxton-Thomas, and A. D. Pickering, "Use of neural networks in brain SPECT to diagnose Alzheimer's disease," *J Nucl Med*, vol. 37, no. 2, pp. 195–200, 1996.

[13] M. W. W. S. G. Mueller, N. Schuff, "Evaluation of treatment effects in Alzheimer's and other neurodegenerative diseases by MRI and MRS," vol. 6, no. 9, pp. 655–668, 2008.

[14] Jack CR et al, "MRI Methods," *Alzheimer's Dis. neuroimaging Initiat.*, vol. 27, no. 4, pp. 685–691, 2008.

[15] D. S. Marcus, A. F. Fotenos, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open Access Series of Imaging Studies (OASIS): Longitudinal MRI Data in Nondemented and Demented Older Adults Daniel," vol. i, no. 12, pp. 2677–2684, 2010.

[16] K. Doi, "Computer-aided diagnosis in medical imaging: Historical review, current status and future potential," *Comput. Med. Imaging Graph.*, vol. 31, no. 4–5, pp. 198–211, 2007.

[17] C. J. Prashanthi Vemuri, Hasson, G. E. Caldwell, and R. E. A. Van Emmerik, “Alzheimer’s Disease Diagnosis in Individual Subjects using Structural MR Images: Validation Studies,” *Motor Control*, vol. 27, no. 4, pp. 590–609, 2009.

[18] Rémi Cuingnet et al, “Automatic classification of patients with Alzheimer’s disease from structural MRI: A comparison of ten methods using the ADNI database,” *Neuroimage*, vol. 56, no. 2, pp. 766–781, 2011.

[19] J. Tohka and E. Moradi, “Comparison of feature selection techniques in machine learning for anatomical brain MRI in dementia.”

[20] M. Wels, Y. Zheng, and M. Huber, “Computer-aided diagnosis of Alzheimer ’ s disease using support vector machine and classification trees,” *Inst. Phys. Eng. Med.*, pp. 2807–2817, 2010.

[21] I. ´Alvarez J. Ram´ırez, J.M. G´orriz, M. L´opez, D. Salas-Gonzalez and and C. G. P. F. Segovia, “Early Detection of the Alzheimer Disease Combining Feature Selection and Kernel Machines,” *Springer-Verlag Berlin Heidelb.*, vol. 2, pp. 410–417, 2009.

[22] N. J. Ayşe Demirhan, Talia M. Nir, Artemis Zavaliangos-Petropulu, Clifford R. Jack Jr, Michael W. Weiner, Matt A. Bernstein, Paul M. Thompson, “Feature Selection Improves The Accuracy Of Classifying Alzheimer Disease Using Diffusion Tensor Images Ayşe,” *Proc IEEE Int Symp Biomed Imaging*, no. Mci, pp. 126–130, 2016.

[23] X. Zhu, H. S. S. Lee, and D. Shen, “Canonical feature selection for joint regression and multi-class identification in Alzheimer ’ s disease diagnosis,” *Brain Imaging Behav.*, pp. 818–828, 2016.

[24] E. V. A. Braak and A. Considerations, “Staging of Alzheimer â€™ s Disease-Related Neurofibrillary Changes,” *Elsevier Sci. Ltd*, vol. 16, no. 3, pp. 271–278, 1995.

[25] “National Institutes of Health (NIH) (2005) p r o g r e s s r e p o r t o n ALZHEIMER’S DISEASE.2 0 0 5 – 2 0 0 6,” *NIH Publ. Number 05-5724*, 2006.

[26] P. R. On, “National Institutes of Health (NIH) (2005) Progress report on Alzheimer’s Disease 2004-2005,” 2005.

[27] G. B. Frisoni, N. C. Fox, C. R. J. Jr, P. Scheltens, and P. M. Thompson, “The clinical use of structural MRI in Alzheimer disease,” *Nat. Rev. Neurol.*, vol. 6, no. 2, pp. 67–77, 2010.

[28] C. R. J. Jr *et al.*, “Steps to standardization and validation of hippocampal volumetry as a biomarker in clinical trials and diagnostic criteria for Alzheimer’s disease,” *Alzheimer’s dementia. J Alzheimer’s Assoc*, vol. 7, no. 4, pp. 474–485, 2012.

[29] T. Ye, C. Zu, B. Jie, D. Shen, and D. Zhang, “Discriminative multi-task feature selection for multi-modality classification of Alzheimer ’ s disease,” *Brain Imaging Behav.*, vol. 10, pp. 739–749, 2016.

[30] S. Liu *et al.*, “Multimodal Neuroimaging Feature Learning for Multiclass Diagnosis of Alzheimer’s Disease,” *IEEE Trans. Biomed. Eng.*, vol. 62, no. 4, pp. 1132–1140, 2015.

[31] C. Zu, B. Jie, M. Liu, S. Chen, and D. Shen, “Label-aligned multi-task feature learning for multimodal classification of Alzheimer ’ s disease and mild cognitive impairment,” *Brain Imaging Behav.*, vol. 10, pp. 1148–1159, 2016.

[32] D. Zhang, Y. Wang, L. Zhou, H. Yuan, and D. Shen, “Multimodal classification of Alzheimer â€™ s disease and mild cognitive impairment,” *Elsevier*, vol. 55, pp. 856–867, 2011.

[33] A. S. Ribeiro, L. M. Lacerda, N. André, and H. A. Ferreira, “Multimodal Imaging Brain Connectivity Using the MIBCA Toolbox : Preliminary Application to Alzheimer ’ s Disease,” *IEEE Trans. Nucl. Sci.*, vol. 1, no. Suppl 1, pp. 604–611, 2014.

[34] P. Padilla, M. Lopez, J. M. Gorriz, J. Ramirez, D. Salas-Gonzalez, and I. Alvarez, "NMF-SVM based CAD Tool Applied to Functional Brain Images for the Diagnosis of Alzheimer's Disease," *IEEE Trans. Med. Imaging*, vol. 31, no. 2, pp. 207–216, 2012.

[35] P. Bhatkoti and M. Paul, "Early Diagnosis of Alzheimer ' s Disease : A Multi- class Deep Learning Framework with Modified k- sparse Autoencoder Classification," 2016.

[36] D. S. Xiaofeng Zhu, Heung-Il Suk, "Multi-Modality Canonical Feature Selection for Alzheimer's Disease Diagnosis," *Springer Int. Publ.*, vol. 17, no. 2, pp. 162–169, 2015.

[37] J. Shi, X. Zheng, Y. Li, Q. Zhang, S. Ying, and I. Member, "Multimodal Neuroimaging Feature Learning with Multimodal Stacked Deep Polynomial Networks for Diagnosis of Alzheimer â€™ s Disease," *Biomed. Heal. Informatics*, vol. 2194, no. DL, 2017.

[38] H. S. S. Lee and D. Shen, "Latent feature representation with stacked auto-encoder for AD / MCI diagnosis," *Brain Struct Funct*, pp. 841–859, 2015.

[39] B. Cheng, M. Liu, D. Shen, Z. Li, D. Zhang, and I. The Alzheimer???S Disease Neuroimaging, "Multi-Domain Transfer Learning for Early Diagnosis of Alzheimer's Disease," *Springer Sci. Bus. media*, vol. 5, pp. 9318–9323, 2016.

[40] I. Josephine Barnes, Scahill, C. Frost, P. Thompson, and N. C. Fox, "A meta-analysis of hippocampal atrophy rates in Alzheimer's Disease," *Elsevier*, vol. 30, no. 11, pp. 1711–1723, 2010.

[41] S. Sarraf and G. Tofighi, "Classification of Alzheimer ' s Disease Structural MRI Data by Deep Learning Convolutional Neural Networks," pp. 1–14.

[42] F. C. Morabito, C. Ieracitano, L. Bonanno, A. Bramanti, S. De, and I. C. N. Bonino-pulejo, "Deep Convolutional Neural Networks for Classification of Mild Cognitive Impaired and Alzheimer ' s Di sease Patients from Scalp EEG Recordings," 2016.

[43] E. Hosseini-asl, R. Keynton, and A. El-baz, "ALZHEIMER ' S DISEASE Diagnostics By Adaptation Of 3d Convolutional Network Electrical and Computer Engineering Department , University of Louisville , Louisville , KY , USA .," pp. 126–130, 2016.

[44] Y. Chen and C. Lin, "Combining SVMs with Various Feature Selection Strategies," no. 1, pp. 1–10.

[45] T. Tong, Q. Gao, R. Guerrero, C. Ledig, L. Chen, and D. Rueckert, "A Novel Grading Biomarker for the Prediction of Conversion From Mild Cognitive Impairment to Alzheimer's Disease," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 1, pp. 155–165, 2017.

[46] M. Zhang, Y. Yang, and F. Shen, "Multi-view feature selection and classification for Alzheimer ' s Disease diagnosis," *Springer Sci. Bus. media*, 2016.

[47] S. R. B. Shree, "An initial investigation in the diagnosis of Alzheimer ' s disease using various classification techniques," 2014.

[48] R. Maglietta *et al.*, "Automated hippocampal segmentation in 3D MRI using random undersampling with boosting algorithm," *Pattern Anal. Appl.*, vol. 19, no. 2, pp. 579–591, 2016.

[49] "Automatic Fusion And Classification Using Random Forests And Features Extracted With Deep Learning Andreas Merentitis , Christian Debes," pp. 2943–2946, 2015.

[50] B. E. Boser, T. B. Laboratories, I. M. Guyon, T. B. Laboratories, and V. N. Vapnik, "A Training Algorithm for Optimal Margin Classi ers," *Proc. COLT'92*, pp. 144–152, 1992.

[51] C. N. Shawe-Taylor J, "Kernel Methods for Pattern Analysis," *2004*.

[52] C. V Dolph, M. D. Samad, and K. M. Iftekharuddin, “Classification of Alzheimer’s disease using structural MRI,” in *Proc MICCAI workshop challenge on computer-aided diagnosis of dementia based on structural MRI data*, 2014, pp. 31–37.

[53] X. W. Gao, “A Deep Learning Based Approach to Classification of CT Brain Images,” in *SAI Computing Conference*, 2016, pp. 13–16.

[54] F. Li, L. Tran, K. Thung, S. Ji, D. Shen, and J. Li, “A Robust Deep Model for Improved Classification of AD / MCI Patients,” *1610 IEEE J. Biomed. Heal. INFORMATICS*, vol. 19, no. 5, pp. 1610–1616, 2015.

[55] S. Sarraf and G. Tofighi, “Classification of Alzheimer ’ s Disease Using fMRI Data and Deep Learning Convolutional Neural Networks,” 2016, pp. 8–12.

[56] T. D. Vu, H. J. Yang, V. Q. Nguyen, A. R. Oh, and M. S. Kim, “Multimodal learning using Convolution Neural Network and Sparse Autoencoder,” in *2017 IEEE International Conference on Big Data and Smart Computing, BigComp 2017*, 2017, pp. 309–312.

[57] E. K. Hashi, S. U. Zaman, and R. Hasan, “An Expert Clinical Decision Support System to Predict Disease Using Classification Techniques,” *Int. Conf. Electr. Comput. Commun. Eng.*, pp. 396–400, 2017.

[58] R. Abdalla R. Gad, Ahmed and A. Seoud, “Automatic Machine Learning Classification of Alzheimer â€™ s Disease Based on Selected Slices from 3D Magnetic Resonance Imagining,” *Int. J. Biomed. Sci. Eng.*, vol. 4, no. 6, pp. 50–54, 2017.

[59] C. Cecere and C. Corrado, “Diagnostic Utility of EEG Based Biomarkers for Alzheimer ’ s Disease,” 2014, pp. 14–15.

[60] B. Shi, Y. Chen, C. Science, K. Hobbs, C. D. Smith, and J. Liu, “Nonlinear Metric Learning for Alzheimer ’ s Disease Diagnosis with Integration of Longitudinal Neuroimaging Features,” pp. 1–13, 2015.

[61] P. M. M. Patil and P. A. R. Yardi, “ANN based Dementia Diagnosis using DCT for Brain MR Image compression,” *Int. Conf. Commun. Signal Process.*, pp. 451–454, 2013.

[62] A. Aljovi, “Artificial Neural Networks in the Discrimination of Alzheimer â€™ s disease Using Biomarkers Data,” in *5th Mediterranean Conference on Embedded Computing*, 2016, pp. 286–289.

[63] P. Rodrigues, J. Teixeira, R. Hornero, J. Poza, and A. Carreres, “Classification of Alzheimer ’ s Electroencephalograms using Artificial Neural Networks and Logistic Regression,” vol. 2, no. Table 1.

[64] C. Huang, B. Yan, H. Jiang, and D. Wang, “Combining voxel-based morphometry with Artifical Neural Network theory in the application research of diagnosing Alzheimer ’ s disease,” *Int. Conf. Biomed. Eng. Informatics Comb.*, pp. 250–254, 2008.

[65] S. Yang, J. Lee, C. Huang, J. Wang, W. Hsu, and Y. Wai, “Computer-Aided Diagnosis of Alzheimer ’ s Disease Using Multiple Features with Artificial Neural Network,” 2010, pp. 699–705.

[66] K.R.Dasegowda, Snehalatha Nadigar, Rahila Banu, Mridula Tripati, Manoj R, Nithin Sadeesh, Chethan GN, DV Srikanth, Alzheimer’s Disease and Its Potential Drug Targets - Review Article. *International Journal of Advanced Research in Engineering and Technology (IJARET),* Volume 5, Issue 9, September (2014), pp. 80-86

[67] Shivamurthy R.C, Manjunatha M B, Pradeep kumar B.P, A Comparative Study On Procedures On Content - Based Image Retrieval In Medical Imaging. *International Journal of Computer Engineering and Technology (IJCET)*, Volume 5, Issue 10, October (20 14), pp. 64-73