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# A Survey on Classification Methods of Brain MRI for Alzheimer's Disease

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**Abstract**— Alzheimer's disease (AD) is the most typical type of dementia. There are no available treatments that stop or reverse the progression of the disease which is harmful and eventually leads to death. There are currently no specific techniques that can confirm with a 100% certainty AD diagnosis. A combination of brain imaging and clinical assessment checking for signs of memory impairment is used to identify patients with AD. There is a need for automated techniques to be developed in order to detect the disease well before irreversible loss is made. Currently there are lot of advances in the area of biomarkers for assessment of risk, diagnosis and monitoring disease progression. In recent years, Neuroimaging combined with machine learning techniques have been studied for the detection of Alzheimer's disease. Our research work is focused on the automatic classification methods for the detection of Alzheimer's disease, with a primary focus on improving the prediction accuracy which will be helpful for practitioners for detection of Alzheimer's disease and even its progression stages as Normal Control (NC), Mild Cognitive Impairment (MCI) and Alzheimer's disease (AD). This paper is about the survey on recent studies in related field that are towards development of semi or fully automatic computer aided diagnosis of the AD progression. Paper presents comparison of methods implemented, classes considered, Data base used, evaluation parameters considered and the results obtained with detailing about the disease.

**Keywords**—Alzheimer's disease (AD); Classification Techniques; Database; Feature Extraction; Magnetic Resonance Imaging (MRI); Computer Aided Diagnosis (CAD)

## I. INTRODUCTION

Abnormality detection in Magnetic Resonance (MR) brain images is a challenging task. The difficulty in brain image analysis is mainly due to the requirement of detection techniques with high accuracy within quick convergence time. The detection process of any abnormalities in the brain images are a two-step process. Initially, the abnormal MR brain images are classified into different categories (Image Classification) since treatment planning varies for different types of abnormalities. Further, the abnormal portion is extracted (Image Segmentation) to perform volumetric analysis which verifies the success rate of the treatment given to the patient. Conventionally, the detection process is performed manually which is highly prone to error because of the intervention of human perception [27].

Dementia is the general brain disorder of which Alzheimer's disease is most common, progressive and fatal brain disease. It destroys brain cells, interfering with memory,

thinking, and behavior severely enough to affect a person's work, hobbies, and social life. Alzheimer's disease gets worse over time and is fatal. In diagnosis of this, Image pre-processing is one of the preliminary steps which are highly required to ensure the high accuracy of the subsequent steps. The raw MR images normally consist of many artifacts such as intensity inhomogeneities, extra cranial tissues, etc. which reduces the overall accuracy. Grayscale cross sectional MRI images as well as pre-processed, segmented versions of each raw image. Custom normalizing and preprocessing methods for were implemented for the unprocessed brain images for testing consistency for this study. The next step in the automated diagnosis process is feature extraction. Feature extraction is the technique of extracting specific features from the pre-processed images of different abnormal categories in such a way that the within – class similarity is maximized and between – class similarity is minimized. The important process in the diagnosis system is brain image classification. The main objective of this step is to differentiate the different abnormal brain images based on the optimal feature set. This image classification technique is able to give the information about the presence of abnormality in the input brain image which is used to detect the dementia and Alzheimer's disease. The main objective of classification step is to differentiate the different abnormal brain images based on the optimal feature set [27]. Several conventional classifiers are available for categorization such as K-NN, SVM, Naïve Bayes, PCA, ICA, LDA, ANN, Decision tree, fuzzy technique etc. which gives the best results for basic feature extraction used for the diagnosis of Dementia and Alzheimer's disease. The K –Nearest Neighbors (K-NN), a technique that compares the test sample to the 'k' nearest points and assigns a class based on the majority class of the nearest points. The Naïve Bayes, which classifies a test sample based on the most probable class. Support Vector Machines (SVM), which attempts to find the hyper plane which best separates the data into the respective two classes [13]. PCA is commonly used to decrease the dimensionality of images and get most of information. ICA is a probabilistic and multivariate method which ensures the identification of original components. LDA is used to make the feature extraction and to classify samples of unknown classes based on training samples with known classes. ANN is used to improve the accuracy of the classifiers. The goal of this comparison is to determine which technique would yield the best results using a standard set of image features. The results could then be applied to more efficient feature extraction of many samples, while assigning the class using the best classical classification technique.

The rest of the paper is organized as follows: An effects of AD and role of MRI in Diagnosis of AD is presented in

section II, A comprehensive literature survey of work done towards computer-aided diagnosis of AD is presented in section III, Section IV provides Procedure for AD MR Image Classification, Section V gives the information about Feature Extraction and Selection. Section VI provides different classification techniques followed by conclusion in section VII.

## II. ALZHEIMER'S DISEASE

### A. Alzheimer's Disease and it's Symptoms

Dementia is a general term for a group of brain disorders. It is a decline of intellectual function, medically called decline of cognition. Alzheimer's disease is a progressive dementia caused by a progressive degeneration of brain cells. Alzheimer's disease results in impaired memory, thinking and behavior. It is named after Alois Alzheimer, the German doctor who first described it in 1907. As Alzheimer's disease affects different areas of the brain, specific functions or abilities are lost. Memory of recent events is often the first to be affected, but as the disease progresses, long-term memory is also lost. The disease also affects many of the brain's other functions and consequently language, attention, judgment and many other aspects of behavior are affected.

Some change in memory is normal as we grow older, but the effects of Alzheimer's disease are more severe than simple lapses. They include difficulties with communicating, learning, thinking, and reasoning impairments severe enough to have an impact on an individual's work, social activities, and family life in the early and middle stages. Some of the most common symptoms of that people with Alzheimer's disease experience are [37]:

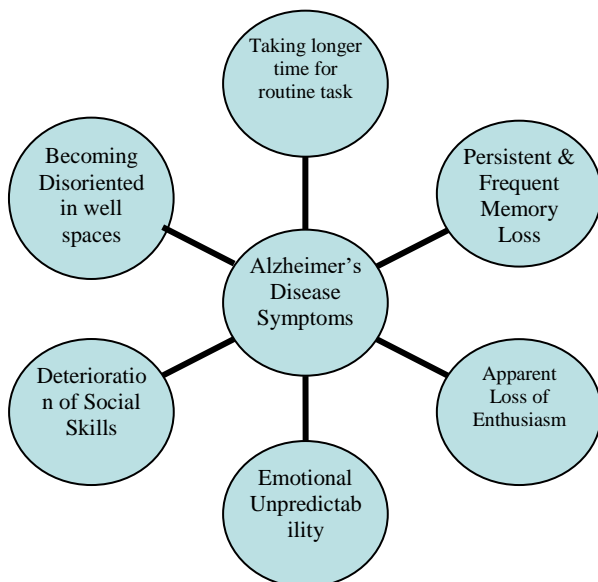


Fig. 1. Symptoms of Alzheimer's Disease

### B. Role of MRI in Diagnosis of AD

Neuroimaging techniques enable in assessment of brain changes and are therefore promising in the field of early detection of AD. Understanding the brain of Alzheimer's and dementia patients is of a great clinical importance. MRI could help detect Alzheimer's disease at an early stage before irreversible damage has been done. Analyzing MRI exams of healthy patients as well as those with mild cognitive impairment (MCI) and early Alzheimer's, examined specific biomarkers of the disease process. Fig 2 shows the various stages of Alzheimer's disease.

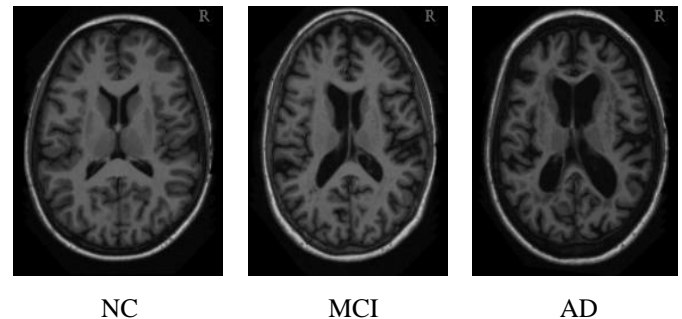


Fig. 2. Normal, MCI and AD T1 Weighted Axial Brain MR Images

All MR images are to some degree affected by each of the parameters that determine tissue contrast (i.e., T1, T2, and proton density), but the Repetition time (TR) and Echo time (TE) can be adjusted to emphasize a particular type of contrast. T1-weighted images best depict the anatomy, and, if contrast material is used, they may also show pathologic entities; however, T2-weighted images provide the best depiction of disease, because most tissues that are involved in a pathologic process have higher water content than in normal, and the fluid causes the affected areas to appear bright on T2-weighted images. Proton-density weighted MR images usually depict both the anatomy and the disease entity [42]. The three weighted MR images are shown in Fig. 3. T1-weighted MR image offers high contrast between the brain soft tissues. On the contrary, T2-weighted and Proton density images exhibit very low contrast between GM and WM, but high contrast between CSF and brain parenchyma. Fig 3 shows a comparison of T1, PD and T2 weighting.

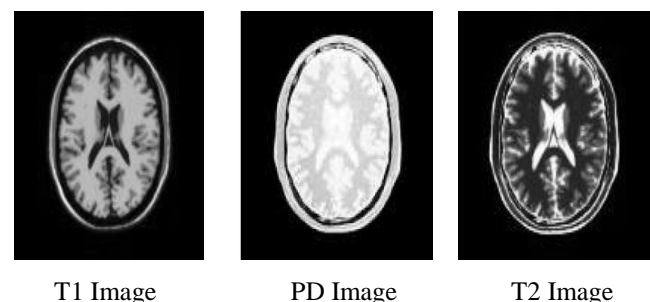


Fig. 3. T1, PD and T2 Weighted Axial Brain Images

### III. LITERATURE SURVEY

Automated brain disorder diagnosis with MR images is becoming increasingly important in the medical field. The automated diagnosis involves two major steps: (a) Image classification and (b) Image segmentation. Image classification is the technique of categorizing the abnormal images into different groups based on some similarity measure. The accuracy of this abnormality detection technique must be significantly high since the treatment planning is based on this

identification. Many research papers with different approaches for image classification are reported in the literature. TABLE I gives the extensive literature survey on types of classifiers, different stages of AD, sources of publically available databases, extracted features, results of classification etc. which is used for abnormality detection in brain images.

TABLE I. SURVEY ON AUTOMATIC CLASSIFICATION TECHNIQUES FOR ALZHEIMER'S DISEASE DETECTION

Author Name	Classifier Used	Modality	No of Images	Source of Image	Features	Results											
Kajal Gulhare (IJARCSSE) 2017 [1]	Deep Neural Network (DNN)	MRI	AD+MCI +NC= 150	OASIS	Textural Features, Intensity	DNN Accuracy = 96.6 %											
Rupali Kamathe (ICTACT) 2017 [2]	K-NN , Adaboost	MRI	AD=26 MCI=68 NC= 107	OASIS	Contrast, Correlation, Energy, Homogeneity, Absolute Value, Information Measure of Correlation	Model Name		Accuracy (%)									
								K-NN			Adaboost						
						Abnormal vs Normal		76.92			87						
						AD vs MCI		92.31			100						
						AD vs NC		92.75			100						
						MCI vs NC		83.33			90.28						
Eman M Ali (IJCA) 2016 [3]	TANNN	MRI	AD+MCI +NC=416	OASIS	Statistical, Symmetry, Texture	Accuracy (%)											
						Seg.	DA	NN	NB	SVM	DT	KNN	TAN NN				
						OASIS	94.4	93.6	95.2	92.5	96.4	96.6	99.2				
Antonio Martínez (HPC) 2015 [4]	Logistic Regression Classifier	MRI PET	NC= 469 MCI=893 AD= 280	ADNI	Correlation based features Forward selection and Backward elimination of features	Analysis		Cohort		Acc (%)		Sen (%)		Spe (%)		AUC (%)	
						NC-AD	Calibration set		87.7		84.9		90.5		94.5		
							Test set		85.4		91.3		80		92.2		
						NC-MCI	Calibration set		80.2		86.2		70.4		86.4		
							Test set		78.5		80.5		75		84.1		
						MCI-AD	Calibration set		83.8		47.6		94.1		83.8		
							Test set		80		33.3		93		81.5		
						Archana M (IEEE) 2014 [5]	SVM	MRI	NC=92 MCI=97 AD=45	OASIS	Structural features Orientation Anisotropy index $\lambda_1$ , $\lambda_2$ , Energy	For Normal vs AD					
Features		Acc (%)		Sen (%)								Spe (%)					
Orientation		76.1		71.34								72.43					
Anisotropy index		65.76		62.54								59.85					
$\lambda_1$		51.17		48.46								45.32					
$\lambda_2$		87.39		85.56								83.45					
Energy		88.67		87.65								84.87					
For Normal vs MCI																	
Features		Acc (%)		Sen (%)								Spe (%)					
Orientation		65.8		71.3								65.8					
Anisotropy index		57.1		55.1								54.8					
$\lambda_1$		47.3		47.1								46.3					
$\lambda_2$		75.8		73.6								74.4					
Energy		80.3		76.4								78.3					
For MCI vs AD																	
Features		Acc (%)		Sen (%)								Spe (%)					
Orientation		66.7		64.3								62.5					
Anisotropy index		53.3		52.6								53.3					
$\lambda_1$		43.6		42.5								40.5					
$\lambda_2$		75.2		68.3								70.5					
Energy		79.1		74.7								76.7					

Bibo Shi (IEEE) 2014 [6]	Large margin nearest neighbors (LMNN), relevant component analysis (RCA), Distance Informed metric learning (DIML), K-NN	MRI	NC=161 MCI=104 AD=56	ADNI	Structural features -Cortical thickness, hippocampal volume/ shape, voxel tissue probability map, atrophy	AD vs NC results								
						Classifier	ACC (%)	SEN (%)	SPE (%)	PPV (%)	NPV (%)			
						K-NN	76.67	56.33	97	94.64	81.33			
						RCA	81.46	70.67	92.24	85.28	86.03			
						LMNN	81.93	69.67	94.18	88.83	85.77			
						DIML	82.52	72.67	92.36	84.83	86.86			
						MCI vs NC results								
						Classifier	ACC (%)	SEN (%)	SPE (%)	PPV (%)	NPV (%)			
						K-NN	62.63	67.9	57.36	71.95	54.6			
						RCA	61.23	71.54	50.91	69.15	55.9			
						LMNN	64.2	71.58	56.82	72.29	57.56			
						DIML	71.56	77.57	65.55	77.59	69.25			
Fayao Liu (IEEE) 2014 [7]	Multiple kernel learning (MKL), Random Fourier feature (RFF), SVM	MRI CSF	Nc=70 MCI=50	ADNI	Structural Features WM, GM, CSF	Method	ACC (%)		SEN (%)		SPE (%)		MCC (%)	
						MKL	87.06		87.89		86.68		74.57	
						RFF+L1	81.94		83.83		78.97		63.31	
						RFF+L2	85		85.49		84.28		69.41	
						RFF+L21	90.56		93.26		87.49		81.98	
Filipa Rodrigues (IEEE) 2014 [8]	SVM	PDG -PET	NC=66 MCI=109 AD=48	ADNI	Multi-region analysis, Voxel-based analysis	Group			CN/AD			CN/MCI		
						Multiregion Analysis	Baseline		81.1 ±11.1			68.5± 9.5		
							Baseline+ Change		83.3 ± 9.7			68.9 ±9.7		
							12 Months		87.4 ± 9.8			65.1 ±11.3		
							12Months+ Change		87.8 ± 9.1			65.6 ±9.6		
						Voxel based analysis	Baseline		84.2 ± 10.0			68.1 ± 10.6		
							Baseline+ Change		91.2 ± 8.0			69.3 ± 10.9		
							12 Months		92.8 ± 6.3			69.7 ± 10.6		
							12Months+Change		92.6 ± 6.7			70.2 ± 9.0		
Helena Aidos (IEEE) 2014 [9]	SVM, KNN, Naïve Bayes	FDG -PET	MCI=59 AD=59	ADNI	Voxel intensities (VI)	Highest Accuracy with lower no of features and vice versa			Best					
							SVM + KNN		ROI (Automatic)					
							Naïve Bayes		ROI (Automatic+ Expert)					
									Accuracy (%)					
							AD vs CN		85					
							MCI vs CN		65~79					
Saima Farhan (HPC) 2014 [10]	SVM, MLP, J48	MRI	NC=37 AD=48	OASIS	Volume of WM, GM, CSF	Ensemble Classifiers	Acc (%)		Sen (%)		Spe (%)			
							93.75		100		87.5			
Andrea Rueda (IEEE) 2014 [11]	Saliency Based Pattern Recognition	MRI	G1=> NC=66 ,MCI= 20 G2=> NC=98, MCI= 28 G3=> NC=66, MCI= 70 G4=> NC=98, MCI=100	OASIS-MIRIAD	Intensity, Orientation, Contrast (18 Features)	Parameter	G1		G2		G3		G4	
						Accuracy	86.05		80.16		76.47		70.2	
						Sensitivity	85		75		87.14		70	
						Specificity	86.36		81.63		69.7		73.47	
						BAC	85.68		78.32		76.28		70.23	
						F-Measure	73.91		62.29		78.71		69.65	
						EER	0.86		0.79		0.79		0.69	

Qi Zhou (IEEE) 2014 [12]	Support vector machine	MRI	NC=59 aMCI=6, naMCI=5 6AD=127	Private MSMCI	Statistical Features & Ranking Mechanism	Accuracy		92.40%	
						Sensitivity		84.00%	
						Specificity		96.10%	
Carlos Cabral (IEEE) 2013 [14]	SVM, Random forest (RF)	FDG -PET	NA	ADNI	Voxel intensity	RBF SVM		L-SVM	RF
						Accuracy (%)		66.78	64.63
Francesco Carlo Morabito (IEEE) 2013 [15]	Wavelet transform, compres- sive sensing, time frequency analysis	EEG	NC=4 MCI=4 AD=4	IRCCS	NA	NC		MCI	AD
						Mean		28.3	50.6
						Standard deviation		3.5	4.8
Javier Escudero (IEEE) 2013 [16]	Instance based classifier i.e. K-NN logistic regression	MRI PET	NC=45 cMCI=12 nMCI=59 AD=41	ADNI	NA	MRI, PET , Biochemistry		nMCI vs cMCI	MCI to AD
						ACC (%)		93	67
Dr. G. Wiselin (IEEE) 2013 [17]	SVM, Ada- SVM	MRI	Training AD,MCI, NC=10 Testing AD=20 NC=20	ICBM	Intensities, Gradients, Curvatures, Tissue classifi. Local filters ,	Adaboost and Ada-SVM gives Superior accuracy			
Eric Westman (Springer) 2012 [18]	Multiva- riate Analysis	MRI	NC=255 MCI=287 AD=187	ADNI	Regional Volume, Cortical Thickness, Gray Matter Volume	AD vs NC		MCI vs AD	
						Accuracy		91.50%	75.90%
Manhua Liu Springer (2012) [19]	Single classifier, ensemble low level classifier, Multilevel Classifier	MRI	NC=229 AD=189	ADNI	Correlation contex Features	Classifier	Acc (%)	Sen (%)	Spe (%)
						Single	86.43	83.89	88.64
						Ensemble low level	89.7	86.89	92.11
						Multiple	92.04	90.92	92.98
Mohamed Dessouky (IJCA) 2013 [20]	Support Vector Machine	MRI	NC=71 AD= 49	OASIS	Intensity Level	Acc (%)		Sen (%)	Spe (%)
						100		100	100
Stefano Diciotti (IEEE) 2012 [21]	SVM, Naïve Bayes	MRI	NC=29 MCI=30 AD=21	Clinical	Volume , thickness	Acc (%)		Sen (%)	Spe (%)
						NC vs AD		86	90
Zhuo Sun (IEEE) 2012 [22]	LDA, K- NN, SVM	MRI	AD= 20 NC= 20	ADNI	Correlation based features	Classifiers	Accuracy %		
							Non- scaled		Scaled
						LDA	87.1		87.1
						K-NN	83.33		93.55
						SVM	90.32		90.32
Jayapathy Rajeesh (Asian Biome- dicine) 2012 [23]	Support Vector Machine	MRI	NC=146 AD=133	ADNI	Textural Features- Entropy, Variance, Skewness, Symmetry, Mean	Case 1 (%)	Case 2 (%)	Case 3 (%)	Case 4 (%)
						Precision	90.90	88.90	89.10
						Sensitivity	88.90	88.90	91.90
						Specificity	91.80	89.80	95.90
						Accuracy	90.40	89.40	93.60
Lavneet Singh IJREISS (2012) [24]	SVM, KNN, Naïve Bayes, Multiboost AB Rotation forest, VFI, J48, Random Forest	MRI	Normal and Abnormal MRI Image	NA	Wavelet based Feature extraction	Classifiers	TP	FP	Preci
						KNN	0.935	0.917	0.826
						SVM	0.912	0.812	0.831
						Naïve Bayes	0.868	0.916	0.828
						Multi-boost AB	0.91	0.91	0.829
						Rotation Forest	0.971	0.285	0.971
						VFI	0.742	0.049	0.93
						J48	0.96	0.314	0.958
						Random Forest	0.91	0.271	0.97



T. R. Sivapriya (IJRAI) 2012 [25]	Clustered Z-Score Least Square, Support Vector Machine(C ZLSSVM)	MRI	NC=229 MCI=397 AD=193	OASIS-ADNI	Cross Validation	Acc (%)		Sen (%)		Spe (%)					
						94		96		99					
Nabil Belmokhtar (IJCA) 2012 [26]	Binary Support Vector Machine	MRI	AD=193	OASIS	VBM Analysis= Mean, Standard Deviation Cross validation (K=10)	SVM karnel		Global Accuracy (%)		Total Process Time (ms) (%)					
						Linear		84.9		178					
						Polynomial		100		125					
						RBF		62.26		109					
Anil Rao (IEEE) 2011 [29]	SLR, SRSLR, PLR, MLDA	MRI	NC=60 AD=69	NINCDS ADRDA	Voxel based features WM,GM segmented	Classifier		Sen (%)		Spe (%)		Acc (%)			
						SLR		90.77±3.67		80.26±3.93		85.26±1.39			
						SRSLR		90.35±3.73		80.26±3.93		85.26±1.81			
						PLR		85.85±3.67		79.85±4.88		82.95±2.23			
Daoqiang Zhang (IEEE) 2011 [30]	MLapRL, mRLS	MRI PET CFS	NC=52 MCI=99 AD=51	ADNI	WM, GM, CSF	MLDA		85.10±4.38		79.85±4.88		82.95±2.23			
						AUC									
						mLapRLS		98.50%							
						mRLS		94.60%							
Javier Escudero (IEEE) 2011 [31]	LR, SVM, RBF, C4.0	MRI	NC= 180 MCI=222 AD= 122	ADNI	Filter method, Forward selection	Experiment		Classifier		Acc (%)		AUC			
						NC vs AD	LR		85.63		0.919				
							SVM		89.17		0.884				
							RBF		87.94		0.874				
							C4.0		83.93		0.833				
						NC vs MCI	LR		72.51		0.803				
							SVM		72.65		0.726				
							RBF		70.92		0.710				
							C4.0		72.69		0.725				
Dong Hye Ye (IEEE) 2011 [32]	SVM	MRI	NC=63 cMCI=68 ncMCI= 169 AD=53	ADNI	RAVENS maps as a feature characterizing the images	Racall rates between cMCI vs ncMCI									
								Sen (%)		Spe (%)		Acc (%)			
						Embedding+LapSVM		94.1		40.8		56.1			
						Embedding+SVM		88.2		42		55.3			
						Compare +SVM		89.8		37		52.3			
Murat Seckin Ayhan (IEEE) 2010 [33]	SVM, Naïve Bayes	PET =394	NA	ADNI	Correlation based features 15964 features	Feature selection procedure improves the classification accuracy									
Xiaojing Long (IEEE) 2010 [34]	SVM, MDS, Quick shift clustering, symmetric log domain diffeo-morphic demons	MRI	NC=40 AD=35	OASIS	NA	Method		Target structure		Correctly Classified					
						MDS		Hippocampus		60~75					
						SVM		Gray Matter		85.6~95.6					
						Proposed Method		Gray/White Matter		94.67~97.33					
Jonathan H. Morra NIH Access (IEEE) 2010 [35]	ADA-BOOST and SVM	MRI	NC=10 MCI=10 AD=10	ICBM53	Intensity Distributions, Adjacency Priors, Mean (100 Features)			Ada-SVM		Manual SVM					
								Left		Right		Left		Right	
						Precision		0.785		0.802		0.364		0.755	
						Recall		0.851		0.848		0.973		0.719	
						R.O		0.691		0.701		0.36		0.582	
						S.I		0.814		0.822		0.526		0.732	
						Hausdroff		4.34		4.63		6.05		6.83	
						Mean		0.029		0.034		0.384		0.047	

Acc=Accuracy, Sen=Sensitivity, Spe=Specificity, HC=Hippocampus, EC=Entorhinal Cortex, NC=Normal Control, MCI=Mild Cognitive Impairment, AD=Alzheimer's Disease, SVM=Support Vector Machine, KNN=K-Nearest Neighbour, ANN= Artificial Neural Network, DNN= Deep Neural Network, LDA= Linear Discriminant Analysis, PCA= Principal Component Analysis, ICA= Independent Component Analysis, OASIS= Open Access Series for Imaging Studies, ADNI=Alzheimer's Disease Neuroimaging Initiative, NINCDS-ADRDA=National Institute of Neurological and Communicative Disorders and Stroke-Alzheimer's Disease and Related Disorders Association, ICBM=International Consortium for Brain Mapping, MIRIAD=Minimal Interval Resonance Imaging in Alzheimer's Disease, GM= Gray Matter, WM= White Matter, CSF= Cerebrospinal Fluid, VI= Voxel Intensities

#### IV. PROCEDURE FOR CLASSIFICATION OF AD MR IMAGES

The general procedure for classification of AD MR Images is described in Fig. 4. The MR Images are selected from the database. After selection of MR images, features are first extracted and then selected. Training and testing of the database is done. Then data is given as an input to the classifier. Classifier classifies the images into desired categories. The performance of classifier is evaluated in terms of accuracy, error rate, sensitivity, specificity, AUC, etc. Results are then validated from the authority.

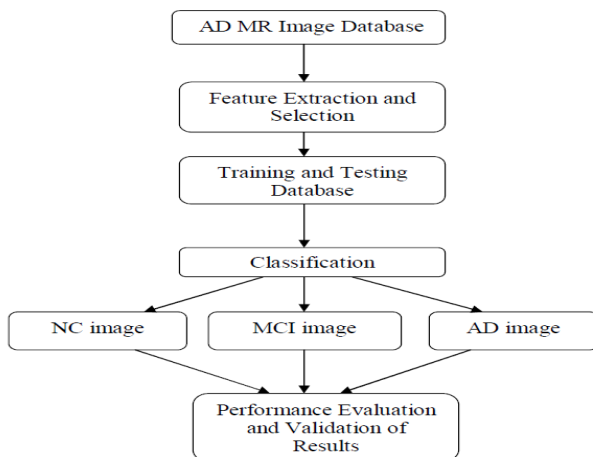


Fig. 4. Procedure for Classification of AD MR Images

#### V. FEATUTE EXTRACTION AND SELECTION

In image pre-processing, one of the preliminary steps in the automated diagnosis of AD process is feature extraction which extracts specific features from the pre-processed images of different abnormal categories. The feature extraction stage is designed to obtain a compact, non-redundant and meaningful representation of observations. It is achieved by removing redundant and irrelevant information from the data. These features are used by the classifier to classify the data. It is assumed that a classifier that uses smaller and relevant features will provide better accuracy and require less memory, which is desirable for any real time system and improves the computational speed of the classifier [28]. After feature extraction, features are selected in which only some of the features from the dataset are selected and used in the training process of the learning algorithm. In this process the aim is to find the optimal subset that increases the efficiency of the learning algorithm. Feature extraction and selection aims to achieve a compact pattern representation which also leads to the decrease of measurement cost and the increase of the classification accuracy. Consequently, the resulting classifier will be faster and will use less memory [12].

Feature selection (FS) algorithms [41] occupy the approach to dimension reduction by finding the "best" least subset of the original features, without transforming the data to a new set of dimensions. Feature selection enables combining features from different data models. Potential difficulties in feature selection (a) small sample size, (b) what criterion function to use. Feature selection can be done using:

##### a. Supervised Learning:-

In supervised learning there is a specified set of classes, and example objects are labeled with the appropriate class. The goal is to generalize from the training objects that will enable novel objects to be identified as belonging to one of the classes.

##### b. Unsupervised Learning:-

In unsupervised feature selection the object is less well posed and consequently it is a much less explored area. Often the goal in unsupervised learning is to decide which objects should be grouped together, in other words, the learner forms the classes itself [37].

Features are used as inputs to classifiers which assign them to the class that they represent. Feature extraction enable to reduce the original data by measuring certain properties of images which have relevant data, or features, that distinguish one pattern from another pattern. There different types of features like shape based, color based, texture based [38], wavelet based [36], region based, histogram based, GLCM based [38], etc are extracted from the brain image for the diagnosis of AD. Features can be selected using filter method, wrapper method [40], Sequential forward selection and backward elimination method, correlation based method, mutual information based method and wavelet based techniques.

#### VI. CLASSIFICATION TECHNIQUES

The important process in the automated system is brain image classification. The main objective of this step is to differentiate the different abnormal brain images based on the optimal feature set. Image classification is one of the sub-categories of pattern recognition system in which an input image is categorized into any one of the pre-defined classes. The image classification is performed with the whole image rather than with pixels. In other words, image classification can be termed as 'between images' operation.

This image classification technique is able to give the information about the presence of abnormality in the input brain image. Broadly, the image classification is divided into two subclasses: (a) Binary classification and (b) Multi-level classification. In the binary classification system, the number of pre-defined classes is only two and hence the details of the presence or absence of the abnormality in the brain image can be obtained. The output of such systems is able to differentiate the normal images and the abnormal images. Practically, this information is insufficient since the nature of the abnormality is necessary for treatment planning. The next level of classification is multi-level classification in which the number of pre-defined classes is more than two. These classification techniques have the capability of differentiating the different types of abnormalities which aids in treatment planning. The complexity of such techniques is quite high but these classification systems are more suitable for real-time applications [11]. There are various methods classification of images used in MRI scan for detection of Alzheimer's and Dementia such as K-NN [2,6,9,13,16,22,28,24], SVM[5, 7, 8, 9,10,12,17,20,21, 22,23,24,26,31,32,33,34,35], Naïve Bayes [9,21,24,28,33], PCA [20], ICA [28], LDA [20, 22], ANN [27], Decision tree, fuzzy technique etc. which gives the best



results for basic feature extraction used for the diagnosis of Dementia and Alzheimer's disease.

#### A. K-Nearest Neighbour (K-NN)

K-Nearest Neighbour (KNN) is a data mining algorithm with a wide range of applications in the image processing domain. There are three key elements of this approach: a set of labeled training examples, a distance measure to compute the distance between the training set examples and the test example, and the value of  $k$ ; i.e., the number of nearest neighbours to the testing example. We used Euclidean and Riemannian distance measures in our work to classify the testing set examples from the three classes which can be mathematically expressed as:

$$\text{Euclidean distance} = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (1)$$

$$\text{Riemannian distance} = \| \log x_i - \log y_i \| \quad (2)$$

The  $k$  training images that were identified as being closest to the test image were then tallied as to which class they fell into, normal or positive for Alzheimer's disease. The class with the most points was assigned to the test image as the classification [2,6,9,13,16,22,28,24].

#### B. Support Vector Machine (SVM)

Support vector machine (SVM) is a versatile data classification method widely used in the machine learning domain. It can be used to classify both linearly and nonlinearly separable data. Kernel trick is used to separate examples that are non-linearly separable in the space of the inputs and might be separable in a higher dimensionality feature space given a suitable mapping. We made use of the inverse multiquadratic kernel which is defined as follows:

$$1 / \sqrt{(\|x_i - x_j\|^2 + c)} \quad (3)$$

Where,  $c$  is a constant greater than zero while  $x_i$  and  $x_j$  are variables dependent on the available data [5, 7, 8, 9,10,12,17,20,21, 22,23,24,26,31,32,33,34,35].

#### C. Naïve Bayes

The Naïve Bayes assigns a class to a test sample based upon the highest-class probability. It is the almost insensitive to synthetic oversampling; although best results are observed when the technique is not applied (oversampling of 0%). In this study we also considered applying kernel density estimation to achieve better estimations of the features pdfs. However, results were slightly worse than with the typical Gaussian assumption. Naive Bayes has one of the best performances achieving a balanced classification model. It also achieves the highest AUC. It should be noted that, whereas with the full feature set no oversampling was required, the optimal case after feature selection was achieved after synthetic duplication of AD instances. Naïve Bayes classifier naturally leads with missing values; when computing the instance likelihood it disregards any feature value that is missing [9, 21, 24, 28, 33].

#### D. Principle Component Analysis (PCA)

PCA is known as the best data representation in the least-square sense for classical recognition. It is commonly used to decrease the dimensionality of images and get most of information. The central idea behind PCA is to find an

orthonormal set of axes pointing at the direction of maximum covariance in the data. It is often used in representing facial images. The idea is to find the orthonormal basis vectors, or the eigenvectors, of the covariance matrix of a set of images, with each image treated as a single point in a high-dimensional space. It is supposed that the facial images form a connected sub region in the image space. The eigenvectors map the most significant variations between faces and are preferred over other correlation techniques that assume that every pixel in an image is of equal importance. PCA is a powerful tool for analyzing data and once we have found these patterns in the data and compress the data by reducing the number of dimensions, without much loss of information [20].

Methods:

Step 1: Get some data.

Step 2: Subtract the mean.

Step 3: Calculate the covariance matrix.

Step 4: Calculate the eigenvectors and Eigen values of the covariance matrix.

Step 5: Choose components and form a feature vector.

Step 6: Derive the new data set.

#### E. Independent Component Analysis (ICA)

ICA is a probabilistic and multivariate method for learning a linear transform of random vectors. The basic goal of ICA is to search for the components which are maximally as independent and non-Gaussian as possible. Its fundamental difference to classical multivariate statistical methods such as PCA and linear discriminate analysis (LDA) is in the assumption of non-gaussianity, which ensures the identification of original components, in comparison with these classical methods. ICA can be mathematically modeled as,

$$X = A \times S \quad (4)$$

Where,  $X$  is the observed data vector,  $A$  is the mixing matrix and  $S$  is the source matrix. In practice, we use of the Fast ICA matlab toolbox to compute both  $A$  and  $S$  from  $X$ . The mixing matrix  $A$  has been considered in the subsequent steps of feature selection and classification [28].

#### F. Linear Discriminate Analysis (LDA)

LDA is used to make the feature extraction and to classify samples of unknown classes based on training samples with known classes. It get a linear transformation of  $k$ -dimensional samples into an  $m$ -dimensional space ( $m < k$ ), so that samples pertinence to the same class are close together, but samples from different classes are far apart from each other. This method maximizes the ratio of between-class variance to within-class variance in any data set; thereby, the theoretical maximum separation in the linear sense will be guaranteed. Since LDA require directions that are efficient for discrimination, it is the optimal classifier for specializing classes that are Gaussian distribution and have equal covariance matrices. LDA requires a transformation matrix that in some sense maximizes the ratio of the between scatter matrix to the within scatter matrix [20,22].

### G. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) is used to improve the accuracy of the classifiers. ANN is dependent on input data and hence a wide variety of pattern is desirable for high accuracy. ANN is a mathematical model or computational model that is inspired by the structural and functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons and it processes information using a connectionist approach to computation. In most cases, an ANN is an adaptive system that changes based on external or internal information which flows through the network during the learning phase. They are usually used to model complex relationships between inputs and outputs or to find patterns in data [27].

## VII. CONCLUSION

With manual techniques for identifying the presence of Alzheimer's disease through brain MRI too expensive and time consuming. Hence we use their classification and analysis for feature extraction and diagnosis. In this paper, a comprehensive information about the different methods of MR image classification such as KNN, Naïve Bayes, SVM, PCA, ICA, LDA, ANN, Decision tree, Fuzzy techniques etc are presented. By reviewing all the classification methods, we can identify the required classifiers are satisfactory in terms of both accuracy and computational speed and has promising results for basic feature extraction and image classification. Thus the classical methods of classification would give the effective identification of Alzheimer's patients with MRI analysis. This work presents significant contribution in the field of automatic classification of brain MRI using different automatic classification techniques. Such system can be proved to be helpful to radiologist and researchers to identify AD classification with improved accuracy.

## REFERENCES

- [1] Kajal Gulhare, S.P. Shukla, L. K. Sharma, "Deep Neural Network Classification Method to Alzheimer's Disease Detection", International Journals of Advanced Research in Computer Science and Software Engineerin, Volume-7, Issue-6, pp. 1-4, June 2017.
- [2] Rupali S. Kamathe, Kalyani R. Joshi, "A Robust Optimized Feature Set Based Automatic Classification of Alzheimer's Disease from Brain MRI Images using K-NN and Adaboost", ICTACT Journal On Image And Video Processing, Volume: 08, Issue: 03, pp. 1665-1672, February 2017.
- [3] Eman M. Ali, Ahmed F. Seddik, Mohammed H. Haggag, "Automatic Detection and Classification of Alzheimer's Disease from MRI using TANN", International Journal of Computer Applications, Volume 148 – No.9, pp. 30-34, August 2016.
- [4] Antonio Martínez-Torteya, Víctor Treviño, José G. Tamez-Peñal, "Improved Diagnostic Multimodal Biomarkers for Alzheimer's Disease and Mild Cognitive Impairment", Hindawi Publishing Corporation BioMed Research International, Volume 2015, pp. 1-11, April 2015.
- [5] Archana M, Ramakrishnan S, "Detection of Alzheimer Disease in MR Images using Structure Tensor", IEEE, pp. 1043-1046, 2014.
- [6] Bibo Shi, Zhewei Wang, Jundong Liu, "Distance-informed metric learning for Alzheimer's Disease Staging", IEEE, pp. 934-937, 2014.
- [7] Fayao Liu, Luping Zhou, Chunhua Shen, Jianping Yin, "Multiple Kernel Learning in the Primal for Multimodal Alzheimer's Disease Classification", IEEE Journal Of Biomedical And Health Informatics, Vol. 18, No. 3, pp. 984-990, May 2014.
- [8] Filipa Rodrigues, Margarida Silveira, "Longitudinal FDG-PET features for the classification of Alzheimer's Disease", IEEE, pp. 1941-1944, 2014.
- [9] Helena Aidos, Joˆao Duarte and Ana Fred, "Identifying Regions Of Interest For Discriminating Alzheimer's Disease From Mild Cognitive Impairment", IEEE, pp. 21-25, 2014.
- [10] Saima Farhan, Muhammad Abuzar Fahiem, Huma Tauseef, "An Ensemble-of-Classifiers Based Approach for Early Diagnosis of Alzheimer's Disease: Classification Using Structural Features of Brain Images", Hindawi Publishing Corporation Computational and Mathematical Methods in Medicine, Volume 2014, pp. 1-11, September 2014.
- [11] Andrea Rueda, Fabio A. González, Eduardo Romero, "Extracting Salient Brain Patterns for Imaging-Based Classification of Neurodegenerative Diseases", IEEE Transactions On Medical Imaging, Vol. 33, No. 6, pp. 1262-1274, June 2014.
- [12] Qi Zhou, Mohammed Goryawala, Mercedes Cabrerizo, Jin Wang, Warren Barker, David A. Loewenstein, Ranjan Dua, and Malek Adjoudi, "An Optimal Decisional Space for the Classification of Alzheimer's Disease and Mild Cognitive Impairment", IEEE Transactions On Biomedical Engineering, Vol. 61, No. 8, pp. 2245-2253, August 2014.
- [13] Kyle S. Marcolini, Stephanie Gillespie, "Comparing classification methods of MRI brain scans for dementia and Alzheimer's disease", University of Miami, Member, IEEE, PP.1-6, 2014.
- [14] Carlos Cabral, Margarida Silveira, "Classification of Alzheimer's Disease from FDG-PET images using Favourite Class Ensembles", 35th Annual International Conference of the IEEE EMBS Osaka, Japan, pp. 2477-2480, July 2013.
- [15] Francesco Carlo Morabito, Domenico Labate, Alessia Bramanti, Fabio La Foresta, "Enhanced Compressibility of EEG Signal in Alzheimer's Disease Patients", IEEE Sensors Journal, Vol. 13, No. 9, pp. 3255-3261, September 2013.
- [16] Javier Escudero, John P. Zajicek, Colin Green, James Shearer, Stephen Pearson, "Machine Learning-Based Method for Personalized and Cost-Effective Detection of Alzheimer's Disease", IEEE Transactions On Biomedical Engineering, Vol. 60, No. 1, pp. 164-168, January 2013.
- [17] Dr. G. Wiselin Jijl, M. Rangini, "Detection of Alzheimer's Disease through Automated Hippocampal Segmentation", IEEE, pp. 144-149, 2013.
- [18] Eric Westman, Carlos Aguilar, J-Sebastian Muehlboeck, and Andrew Simmons, "Regional Magnetic Resonance Imaging Measures for Multivariate Analysis in Alzheimer's Disease and Mild Cognitive Impairment", Springer, Brain Topogr, pp. 9-23, August 2012.
- [19] Manhua Liu, Daoqiang Zhang, Pew-Thian Yap, and Dinggang Shen, "Hierarchical Ensemble of Multi-level Classifiers for Diagnosis of Alzheimer's disease", Springer, Nanjing University of Aeronautics and Astronautics, China, pp. 27-35, 2012.
- [20] Mohamed M. Dessouky, Mohamed A. Elrashidy, Hatem M. Abdalkader, "Selecting and Extracting Effective Features for Automated Diagnosis of Alzheimer's Disease", International Journal of Computer Applications (0975 – 8887) Volume 81 – No.4, pp. 17-28, November 2013.
- [21] Stefano Diciotti, Andrea Ginestroni, Valentina Bessi, Marco Giannelli, Carlo Tessa, Laura Bracco, Mario Mascalchi, Nicola Toschi, "Identification of Mild Alzheimer's Disease through automated classification of structural MRI features", 34th Annual International Conference of the IEEE EMBS San Diego, California USA, pp. 428-431, September 2012.
- [22] Zhuo Sun, Jan. A.C. Veerman, Radu S. Jasinschi, "A Method for Detecting Interstructural Atrophy Correlation in MRI Brain Images", IEEE, pp. 1253-1256, 2012.
- [23] Jayapathy Rajeesh, Rama Swamy Moni, Suyambumuthu Palanikumar, and Thankappan Gopalakrishnan, "Discrimination of Alzheimer's disease using hippocampus texture features from MRI", Asian Biomedicine, Vol. 6, No. 1, pp. 87-94, February 2012.
- [24] Lavneet Singh, Girija Chetty, "Detecting The Brain Abnormalities From MRI Structural Images Using Machine Learning And Pattern Recognition Tools", International Journal of Research in Engineering, IT and Social Sciences Volume 2, Issue 11, pp. 15-30, November 2012.
- [25] T. R. Sivapriya, "Imputation And Classification Of Missing Data Using Least Square Support Vector Machines – A New Approach In Dementia Diagnosis", International Journal of Advanced Research in Artificial Intelligence, Vol. 1, No. 4, pp. 29-34, 2012.

- [26] Nabil Belmokhtar, "Classification of Alzheimer's Disease from 3D Structural MRI Data", International Journal of Computer Applications, Volume 47, No.3, pp.41-44, June 2012.
- [27] Jude Hemanth D, "Computer Aided Classification And Segmentation Of Abnormal Human Brain Magnetic Resonance Images Using Modified Soft Computing Techniques", a thesis, Doctor Of Philosophy in Electronics and Communication Engineering, a thesis, September 2012.
- [28] Ahsan Bin Tufail, Ali Abidi, Adil Masood Siddiqui, and Muhammad Shahzad Younis, "Automatic Classification of Initial Categories of Alzheimer's Disease from Structural MRI Phase Images: A Comparison of PSVM, KNN and ANN Methods", World Academy of Science, Engineering and Technology Vol:6, PP. 1570-1574, December 2012.
- [29] Anil Rao, Ying Lee, Achim Gass, Andreas Monsch, "Classification of Alzheimer's Disease from Structural MRI using Sparse Logistic Regression with Optional Spatial Regularization", 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, pp. 4499-4502, September 2011.
- [30] Daoqiang Zhanga, Yaping Wanga, Luping Zhoua, Hong Yuana, and Dinggang Shen, "Multimodal Classification of Alzheimer's Disease and Mild Cognitive Impairment", Neuroimage, 55(3), pp.856-867, April 2011.
- [31] Javier Escudero, John P. Zajicek, Emmanuel Ifeakor, "Machine Learning Classification of MRI Features of Alzheimer's Disease and Mild Cognitive Impairment Subjects to Reduce the Sample Size in Clinical Trials", 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, pp.7957-7960, September 2011.
- [32] Dong Hye Ye, Kilian M. Pohl, Christos Davatzikos, "Semi-Supervised Pattern Classification: Application to Structural MRI of Alzheimer's disease", IEEE Computer Society: IEEE International Workshop on Pattern Recognition in NeuroImaging, 2011.
- [33] Murat Seckin Ayhan, Ryan G. Benton, Vijay V. Raghavan, Suresh Choubey, "Exploitation of 3D Stereotactic Surface Projection for Automated Classification of Alzheimer's Disease according to Dementia Levels", IEEE International Conference on Bioinformatics and Biomedicine, pp.516-519, 2010.
- [34] Xiaojing Long, Chris Wyatt, "An Automatic Unsupervised Classification of MR Images in Alzheimer's Disease", IEEE, pp.2910-2917, 2010.
- [35] Jonathan H. Morra, Zhuowen Tu, Liana G. Apostolova, Amity E. Green, Arthur W. Toga, and Paul M. Thompson, "Comparison of AdaBoost and Support Vector Machines for Detecting Alzheimer's Disease through Automated Hippocampal Segmentation", IEEE Trans Med Imaging, 29(1), pp. 30-43, January 2010.
- [36] B. Al-Naami, N. Gharaibeh and A. Khesman, "Automated Detection of Alzheimer's Disease using Region Growing Technique and Artificial neural Network", World Academy of Science Engineering and Technology, Vol. 7, No. 5, pp 204-208, 2013.
- [37] Peter A. Freeborough and Nick C. Fox, "MR Image Texture Analysis Applied to the Diagnosis and Tracking of Alzheimer's Disease", IEEE Transactions on Medical Imaging, Vol. 17, No. 3, 475-479, June 1998.
- [38] Robert M. Haralick, K. Shanmugam and Its Hak Dinstein, "Textural Features for Image Classification", IEEE Transactions on Systems, Man, and Cybernetics, Vol. 3, No. 6, pp. 610-621, 1973.
- [39] Alzheimer's Society, "The progression of Alzheimer's disease and other dementias", leading the fight against dementia, alzheimers.org.uk.
- [40] R. Kohavi and G.H. John, "Wrappers for Feature Subset Selection", Artificial Intelligence, Vol. 97, No. 1-2, pp. 273-324, 1997.
- [41] A. Jain and D. Zongker, "Feature Selection: Evaluation, Application, and Small Sample Performance", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, No. 2, pp. 153-158, 1997.
- [42] [www.mr-trip.com](http://www.mr-trip.com)