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

Mamata Lohar
Department of Electronics and Telecommunication
MMIT
Pune, India

Rashmi Patange
Department of Electronics and Telecommunication
MMIT
Pune, India

***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 inhomogenities, 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

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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]:

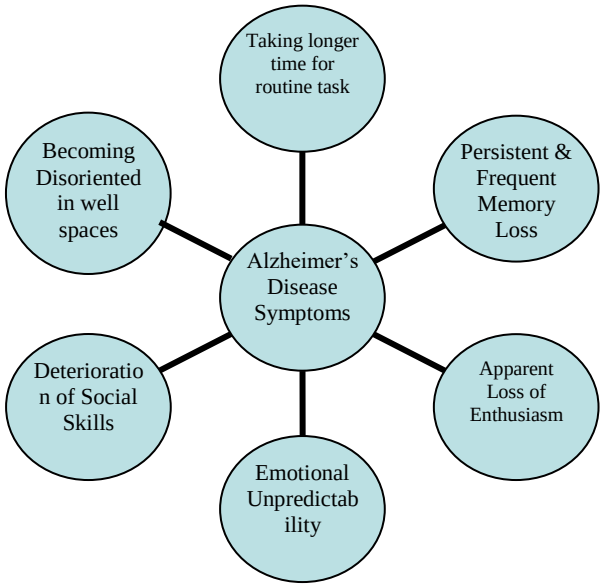
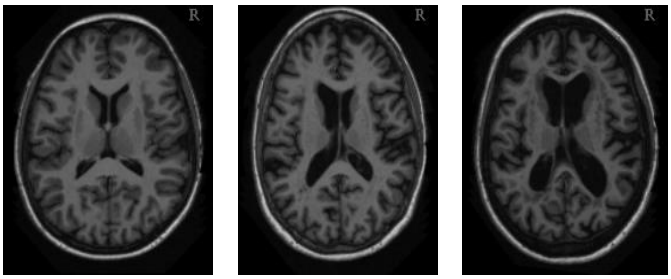


Fig. 1. Symptoms of Alzheimer's Disease

B. Role of MRI in Diagnosis of AD

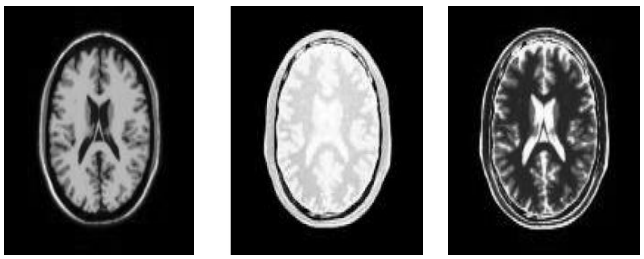
Neuroimaging techniques enable in assessment of brain changes and are therefore promising in the field of early detection of AD. Understanding the brain of Alzheimer's and dementia patients is of a great clinical importance. MRI could help detect Alzheimer's disease at an early stage before irreversible 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.



NC MCI AD

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.



T1 Image PD Image T2 Image

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

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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 / TANNN 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 NC-AD / Test set / 85.4 / 91.3 / 80 / 92.2 NC-MCI / Calibration set / 80.2 / 86.2 / 70.4 / 86.4 NC-MCI / Test set / 78.5 / 80.5 / 75 / 84.1 MCI-AD / Calibration set / 83.8 / 47.6 / 94.1 / 83.8 MCI-AD / 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 λ1, λ2, Energy	For Normal vs AD Features / Acc (%) / Sen (%) / Spe (%) Orientation: 76.1 / 71.34 / 72.43 Anisotropy index: 65.76 / 62.54 / 59.85 λ1: 51.17 / 48.46 / 45.32 λ2: 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 λ1: 47.3 / 47.1 / 46.3 λ2: 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 λ1: 43.6 / 42.5 / 40.5 λ2: 75.2 / 68.3 / 70.5 Energy: 79.1 / 74.7 / 76.7

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<table>
<tr>
<td>Bibo Shi (IEEE) 2014 [6]</td>
<td>Large margin nearest neighbors (LMNN), relevant component analysis (RCA), Distance Informed metric learning (DIML), K-NN</td>
<td>MRI</td>
<td>NC=161 MCI=104 AD=56</td>
<td>ADNI</td>
<td>Structural features -Cortical thickness, hippocampal volume/ shape, voxel tissue probability map, atrophy</td>
<td colspan="6">AD vs NC results
<table>
<tr><th>Classifier</th><th>ACC (%)</th><th>SEN (%)</th><th>SPE (%)</th><th>PPV (%)</th><th>NPV (%)</th></tr>
<tr><td>K-NN</td><td>76.67</td><td>56.33</td><td>97</td><td>94.64</td><td>81.33</td></tr>
<tr><td>RCA</td><td>81.46</td><td>70.67</td><td>92.24</td><td>85.28</td><td>86.03</td></tr>
<tr><td>LMNN</td><td>81.93</td><td>69.67</td><td>94.18</td><td>88.83</td><td>85.77</td></tr>
<tr><td>DIML</td><td>82.52</td><td>72.67</td><td>92.36</td><td>84.83</td><td>86.86</td></tr>
</table>
MCI vs NC results
<table>
<tr><th>Classifier</th><th>ACC (%)</th><th>SEN (%)</th><th>SPE (%)</th><th>PPV (%)</th><th>NPV (%)</th></tr>
<tr><td>K-NN</td><td>62.63</td><td>67.9</td><td>57.36</td><td>71.95</td><td>54.6</td></tr>
<tr><td>RCA</td><td>61.23</td><td>71.54</td><td>50.91</td><td>69.15</td><td>55.9</td></tr>
<tr><td>LMNN</td><td>64.2</td><td>71.58</td><td>56.82</td><td>72.29</td><td>57.56</td></tr>
<tr><td>DIML</td><td>71.56</td><td>77.57</td><td>65.55</td><td>77.59</td><td>69.25</td></tr>
</table></td>
</tr>
<tr>
<td>Fayao Liu (IEEE) 2014 [7]</td>
<td>Multiple kernel learning (MKL), Random Fourier feature (RFF), SVM</td>
<td>MRI CSF</td>
<td>Nc=70 MCI=50</td>
<td>ADNI</td>
<td>Structural Features WM, GM, CSF</td>
<td colspan="6"><table>
<tr><th>Method</th><th>ACC (%)</th><th>SEN (%)</th><th>SPE (%)</th><th>MCC (%)</th></tr>
<tr><td>MKL</td><td>87.06</td><td>87.89</td><td>86.68</td><td>74.57</td></tr>
<tr><td>RFF+L1</td><td>81.94</td><td>83.83</td><td>78.97</td><td>63.31</td></tr>
<tr><td>RFF+L2</td><td>85</td><td>85.49</td><td>84.28</td><td>69.41</td></tr>
<tr><td>RFF+L21</td><td>90.56</td><td>93.26</td><td>87.49</td><td>81.98</td></tr>
</table></td>
</tr>
<tr>
<td>Filipa Rodrigues (IEEE) 2014 [8]</td>
<td>SVM</td>
<td>PDG -PET</td>
<td>NC=66 MCI=109 AD=48</td>
<td>ADNI</td>
<td>Multi-region analysis, Voxel-based analysis</td>
<td colspan="6"><table>
<tr><th colspan="2">Group</th><th>CN/AD</th><th>CN/MCI</th></tr>
<tr><td rowspan="4">Multiregion Analysis</td><td>Baseline</td><td>81.1 ±11.1</td><td>68.5± 9.5</td></tr>
<tr><td>Baseline+ Change</td><td>83.3 ± 9.7</td><td>68.9 ±9.7</td></tr>
<tr><td>12 Months</td><td>87.4 ± 9.8</td><td>65.1 ±11.3</td></tr>
<tr><td>12Months+ Change</td><td>87.8 ± 9.1</td><td>65.6 ±9.6</td></tr>
<tr><td rowspan="4">Voxel based analysis</td><td>Baseline</td><td>84.2 ± 10.0</td><td>68.1 ± 10.6</td></tr>
<tr><td>Baseline+ Change</td><td>91.2 ± 8.0</td><td>69.3 ± 10.9</td></tr>
<tr><td>12 Months</td><td>92.8 ± 6.3</td><td>69.7 ± 10.6</td></tr>
<tr><td>12Months+Change</td><td>92.6 ± 6.7</td><td>70.2 ± 9.0</td></tr>
</table></td>
</tr>
<tr>
<td>Helena Aidos (IEEE) 2014 [9]</td>
<td>SVM, KNN, Naïve Bayes</td>
<td>FDG -PET</td>
<td>MCI=59 AD=59</td>
<td>ADNI</td>
<td>Voxel intensities (VI)</td>
<td colspan="6"><table>
<tr><td rowspan="6">Highest Accuracy with lower no of features and vice versa</td><td></td><td>Best</td></tr>
<tr><td>SVM + KNN</td><td>ROI (Automatic)</td></tr>
<tr><td>Naïve Bayes</td><td>ROI (Automatic+ Expert)</td></tr>
<tr><td></td><td>Accuracy (%)</td></tr>
<tr><td>AD vs CN</td><td>85</td></tr>
<tr><td>MCI vs CN</td><td>65~79</td></tr>
</table></td>
</tr>
<tr>
<td>Saima Farhan (HPC) 2014 [10]</td>
<td>SVM, MLP, J48</td>
<td>MRI</td>
<td>NC=37 AD=48</td>
<td>OASIS</td>
<td>Volume of WM, GM, CSF</td>
<td colspan="6"><table>
<tr><td rowspan="2">Ensemble Classifiers</td><td>Acc (%)</td><td>Sen (%)</td><td>Spe (%)</td></tr>
<tr><td>93.75</td><td>100</td><td>87.5</td></tr>
</table></td>
</tr>
<tr>
<td>Andrea Rueda (IEEE) 2014 [11]</td>
<td>Saliency Based Pattern Recog-nition</td>
<td>MRI</td>
<td>G1=> NC=66 ,MCI= 20G2=> NC=98, MCI= 28 G3=> NC=66, MCI= 70 G4= >NC=98, MCI=100</td>
<td>OASIS-MIRIAD</td>
<td>Intensity, Orientation, Contrast (18 Features)</td>
<td colspan="6"><table>
<tr><th>Parameter</th><th>G1</th><th>G2</th><th>G3</th><th>G4</th></tr>
<tr><td>Accuracy</td><td>86.05</td><td>80.16</td><td>76.47</td><td>70.2</td></tr>
<tr><td>Sensitivity</td><td>85</td><td>75</td><td>87.14</td><td>70</td></tr>
<tr><td>Specificity</td><td>86.36</td><td>81.63</td><td>69.7</td><td>73.47</td></tr>
<tr><td>BAC</td><td>85.68</td><td>78.32</td><td>76.28</td><td>70.23</td></tr>
<tr><td>F-Measure</td><td>73.91</td><td>62.29</td><td>78.71</td><td>69.65</td></tr>
<tr><td>EER</td><td>0.86</td><td>0.79</td><td>0.79</td><td>0.69</td></tr>
</table></td>
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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	66.33	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	31.8	50.6	
						Standard deviation	2.9	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	NC vs AD	nMCI vs cMCI	MCI to AD	
						ACC (%)	93	75	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 (%)	AUC
						Single	86.43	83.89	88.64	0.928
						Ensemble low level	89.7	86.89	92.11	0.939
						Multiple	92.04	90.92	92.98	0.9518
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	82	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	95.30
						Sensitivity	88.90	88.90	91.90	91.10
						Specificity	91.80	89.80	89.80	95.90
						Accuracy	90.40	89.40	90.40	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	Acc
						KNN	0.935	0.917	0.826	91.04
						SVM	0.912	0.812	0.831	91.17
						Naïve Bayes	0.868	0.916	0.828	86.76
						Multi-boost AB	0.91	0.91	0.829	91.04
						Rotation Forest	0.971	0.285	0.971	97.06
						VFI	0.742	0.049	0.93	74.16
						J48	0.96	0.314	0.958	95.98
						Random Forest	0.91	0.271	0.97	97.01

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T. R. Sivapriya (IJRAI) 2012 [25]	Clustered Z-Score Least Square, Support Vector Machine(CZLSSVM)	MRI	NC=229 MCI=397 AD=193	OASIS-ADNI	Cross Validation	Acc (%)	Sen (%)	Spe (%)
						94	96	99

Nabil Belmo-khtar (IJCA) 2012 [26]	Binary Suppoert 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
						Sigmoid	7.54	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
						MLDA	85.10±4.38	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		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=Entrohinal 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

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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.

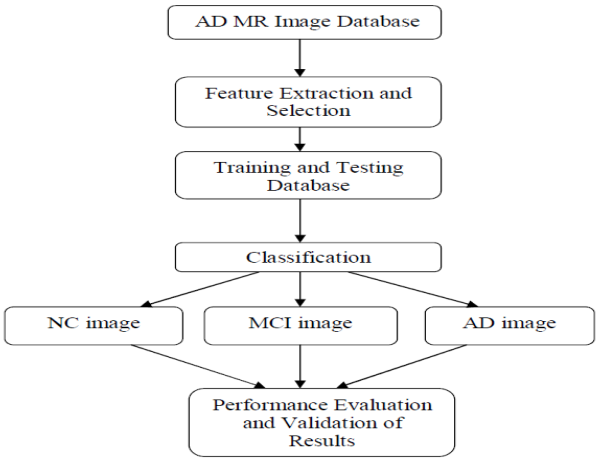

Fig. 4. Procedure for Classification of AD MR Images

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 TECHNIQUIES

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

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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:

$$\text{Euclidean distance} = \sqrt{(\Sigma 4i=1(xi - yi)2} \quad (1)$$

$$\text{Riemannian distance} = \| \log xi - 1yi \| \quad (2)$$

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:

$$1 / \sqrt{(\|xi - xj\|2 + c)} \quad (3)$$

Where, c is a constant greater than zero while xi and xj 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].

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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.

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