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Survey on Identification of Alzheimer Disease Using Magnetic Resonance Imaging (MRI) Images

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Abstract*: *Alzheimer's disease (AD) is a neuro-degenerative disorder which is characterised functional and cognitive deficits that take place progressively. Early detection of the AD is important for the therapy to be early and this may slow down the disease and its progression. For the purpose of bringing about an improvement to the incidence of early detection of the AD, there may be certain Normal Controls (NC) that is based on the structural analysis of Magnetic Resonance Imaging (MRI). In fact, an early detection of the AD by means of using an MRI can help both patients, as well as physicians, to a great extent since it is of a low cost and is also a procedure that is non-invasive providing objective diagnosis by avoiding human errors. This has been connected to the accumulation of the amyloid and the tau proteins found in the brain which is probably the commonest cause for a case of dementia and also accounts for almost 70% of cases of dementia. The MRI is an extremely promising technique in terms of detection of functional or structural brain differences observed among both these patient populations. For the purpose of this work, there had been a new survey that had been made for the identification of a new case of Alzheimer's disease by means of using the MRI images.

Index Terms*: *Alzheimer's disease (AD), dementia, Magnetic Resonance Imaging (MRI).

I. INTRODUCTION

In the World Alzheimer Report 2018, there had been an estimation of 50 million people all over the world who are suffering from dementia and the projection for an increase of this was about 152 million people before 2050. One of the most common reasons for dementia has been identified to be Alzheimer's disease (AD) which accounts for about 60-70% of the cases of dementia (WHO, 2017). The AD has been characterised by a cell death that is abnormal mainly in the medial temporal lobe. Such a disease can have a major impact on the society since it involves health services along with a conglomerate of the family care, psychological and social issues. Thus, these neurodegenerative diseases like the AD have been one of the major challenges faced in the 21st century [23].

The actual emergence and the improvement of technologies of imaging like the Magnetic Resonance Imaging (MRI), electroencephalography (EEG), Positron Emission Tomography (PET), Functional MRI (fMRI) and so on have now resulted in a breakthrough in the diagnosis process. anatomical variability that is caused by the AD within the brain structure is captured by the MRI which is not an important tool to classify cases of AD.

Another important area which is being extensively researched and investigated is the neuroimaging. For example, the measurements of the MRI in terms of volume reduction in multiple regions of the brain found in cortical thickness are predictive of the ones that convert from the MCI to the AD. Speaking specifically, the hippocampus is studied extensively along with the hippocampal volume or shape that has a predictive value in terms of conversion. There are some more such predictions for conversion observed in certain other imaging modalities that may include Diffusion Tensor Imaging, Positron Emission Tomography Acetylcholinesterase activity, Amyloid Imaging, Fluoro-deoxy Glucose Positron Emission Tomography and so on.

II. RELATED WORK

Beheshti et al [1] had developed a new and novel computer-aided diagnosis (CAD) system employing the feature-ranking along with a Genetic Algorithm for analysing the Structural Magnetic Resonance Imaging data. By employing this system, it is possible to predict the conversion of any Mild Cognitive Impairment (MCI)-to the Alzheimer's disease (AD) during a time between one and three years even before a clinical diagnosis is made. The CAD system had been developed in four different stages. Firstly, there was the voxel-based morphometry technique that had been applied for investigating any local or global Grey Matter (GM) atrophy found in the AD compared to the Healthy Controls (HCs). The regions have a significant amount of reduction in the GM volume was segmented to be Volumes of Interest (VOIs). After this, there were VOIs that were used for the extraction of voxel values that were made from the regions of atrophy in the HC, the AD, the stable MCI (sMCI) and in the progressive MCI (pMCI) based patient groups. These voxel values had been extracted within a feature vector. Thirdly, there was a stage of feature selection were all the features had been ranked in accordance with their t-test scores along with a genetic algorithm which was designed to identify an optimal feature subset. There was a Fisher criterion that had been used as one part of the objective function found in the Genetic Algorithm. Lastly, there is a classification that was carried out by making use of

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a new Support Vector Machine (SVM) that uses a 10-fold cross-validation.

The automatic CAD system that was proposed had been analysed by means of applying some of the baseline values from the data set known as Alzheimer's Disease Neuroimaging Initiative (ADNI) (160 AD, 162 HC, 65 sMCI and 71 pMCI). The results of the experiment had indicated that the system proposed could distinguish between the sMCI and pMCI patients, this would be suitable for any practical use that is found in clinical settings.

B¨ohle et al [2] had further proposed making use of a Layer-wise Relevance Propagation (LRP) for the purpose of visualizing the Convolutional Neural Network and the decisions for the AD that is based on the MRI data. In the case of the other methods used in visualization, the LRP can also produce a new heat map within the input space that indicates the criticality of every voxel that contributes to its final classification. Contrastingly, the susceptibility maps which are produced by the guided backpropagation (“That change in the voxels that will be able to change the outcome the most?”), where the LRP method can directly be able to highlight the positive contributions to the classification of the network within their input space. So, all of the highlighted areas have been interpreted as ‘positive evidence’ that is used by different networks to decide if an individual is an AD. Identify the LRP-evidence: (1) this is very specific for individuals (“Why will a person have an AD?”) that have a high level of inter-patient variability, (2) there was only very little evidence for the healthy control of the AD and (3) the areas will exhibit plenty of evidence that correlates well for the literature. In order to be able to quantify the latter, there was a major need that was observed compute the metrics that are size-corrected for the summed evidence for each brain area such as ‘evidence gain’ or ‘evidence density’. Even though these metrics were able to produce some individual fingerprints of the patterns of relevance for the patients of AD, there may be plenty of importance placed on different areas that were observed in the temporal lobe which also includes amygdala and hippocampus. It has been thus concluded that an LRP can provide a powerful tool assisting clinicians to identify evidence for conditions of AD (and other diseases as well) within a structural MRI based data.

Brickman et al [3] had employed the data that was obtained from the cross-sectional and the longitudinal study based on the community of several residents that are eligible for Medicare in northern Manhattan that was ideally followed once every 18–24 months (where n = 1,175 and mean age is 78 years). There were also some white matter hyper intensities, hippocampal volumes, cortical thickness and infarcts quantified from the MRI and this was combined for the generation of an MRI measure that had been connected to such an episodic memory. This combined measure of MRI had been duly replicated and further validated by using data from an autopsy, CSF biomarkers, amyloid PET from Alzheimer’s Disease Neuroimaging Initiative and clinical analysis. There was also a new quantitative measure of MRI had been developed within a group of the community participants (n =690) and this was further replicated within a second group (n = 485). On being compared with certain other healthy controls, this quantitative MRI measure was identified to be lower among patients suffering from Mild Cognitive Impairment. Those who were clinically diagnosed with the AD were lower still in number. This measure had the need to be correlated with the neurofibrillary tangles, infarcts at the post-mortem during an autopsy subset, atrophy and neuronal loss. They had been connected with the PET amyloid imaging along with the CSF levels of the total tau, the phosphorylated tau, and the β-amyloid 42. There was also a new MRI measure conversion that was predicted to the MCI along with the clinical AD among various healthy controls.

Bron et al [4] had further investigated one more diagnostic value that was added in connection to the Arterial Spin Labelling (ASL) along with a Diffusion Tensor Imaging (DTI) to that of the structural MRI in classification that was computer-aided of the Alzheimer's disease (AD), the Frontotemporal Dementia (FTD), and their controls. This type of retrospective studies employed with the MRI data from 24 early-onset of the AD and about 33 early-onset FTD patients along with 34 controls (CN). There was yet another classification that was based on the voxel-wise feature maps which was obtained from that of the had been obtained from the MRI, the ASL, and the DTI. There were several other Support vector machines (SVMs) that had been trained for the purpose of classification of the AD against the CN (AD-CN), FTD-CN, AD-FTD, and AD-FTD-CN (multiclass). Making use of these significance maps of the SVM was helpful in the analysis of various regions of the brain and also their contributions. Both the ASL and the DTI were combined to be able to obtain better performance in differential AD diagnosis with the FTD (AUC=84%; p=0.05) compared for making use of another structural MRI on its own (AUC=72%). The ASL performance with the DTI could not bring about any improvement to the structural MRI. There were some more classifications that had been driven by certain brain regions that were used for the ASL and the DTI when compared to the structural MRI that had suggested such complementary information.

Bouts et al [5] primarily aimed at determining the actual generalizability of the MRI-based probability of classification that scores the detecting of the MCI on the basis of an individual inside a general population. For determination of the scores of classification probability, there is an AD, a mild-AD and a moderate AD and its detection. There were several measures of the AD, the moderate AD and the mild AD that were detection model that had been created with an anatomical diffusion of the MRI measures. These were applied subsequently to a cohort based on the population using about 48 MCI and another 617 subjects ageing normally. The AD model and the mild-AD identified MCI which are from the controls having a better one than the chance level (AUC = 0.600, p = 0.025; AUC = 0.619, p = 0.008). contrastingly, there was a moderate model of the AD that could not separate the MCI from that of normal ageing (AUC = 0.567, p = 0.147). This MCI-model could separate the MCI from the controls which were better than the chance (p = 0.014) having the mean AUC values that were comparable to an AD-model (AUC = 0.611, p = 1.0).

inside the cohort that was based on population, there were several models of classification that were detected and the rates of performance had been identified as moderate and at times insufficient for facilitating any robust MRI-based detection of MCI. This data indicated the fact that the MRI-based multi-parametric classification was effective in their clinical cohorts and did not always translate to the applications to the general population.

Canu et al [6] had further explored this approach which was a combination of a structural (a cortical thickness with the White Matter (WM) microstructure) one along with the resting state functional MRI was able to help the differentiation that had been identified between a total of 62 early onset Alzheimer's disease (EOAD) along with about 27 patients of behavioural variant of frontotemporal dementia (bvFTD). There was also a new random forest along with a receiver operator characteristic curve to analyse the ability of the MRI in the classification of two different clinical syndromes. The patients showed a pattern of distribution of alterations to the brain that had been related to the controls. On being compared to the bvFTD, the patients of the EOAD were able to show a bilateral and also an inferior parietal cortical thinning along with decreased default mode network functional connectivity. Compared to the EOAD, the patients of bvFTD had shown a bilateral orbitofrontal with temporal cortical thinning, along with a WM damage of a condition of the corpus callosum, the bilateral uncinate fasciculus, along with the left superior longitudinal fasciculus. There was also a Random Forest Analysis which proved that the left inferior parietal cortical thickness (with an accuracy of about 0.78, a specificity of about 0.76, and a sensitivity of about 0.83) along with an integrity of WM for the right uncinate fasciculus (an accuracy of about 0.81, a specificity of about 0.96 and a sensitivity of about 0.43) that were identified as the best predictors of their clinical diagnosis. One more combination of its cortical thickness with the measures of DT MRI could distinguish patients having EOAD and bvFTD at an accuracy of 0.82, a specificity of 0.76, and a sensitivity of 0.96. This ability of diagnosis of the MRI models was confirmed by the subsample of patients that was also with a biomarker-based clinical diagnosis. Also identified was a multi-parametric MRI employed for the identification of any alterations made to the brain in accordance with the EOAD and the bvFTD. Yet another severe cortical involvement was suggestive of the EOAD, and it was one more prominent damage of the WM which was indicative of the bvFTD.

Farooq et al [7] had made a proposal of a novel neural network based pipeline of deep convolution for the diagnosis of the Alzheimer’s disease. AD can result in permanent damage to brain cells. This diagnosis of the AD in the elderly people which is challenging and needs a discriminative representation of features for the classification owing to similar pixel intensities and brain patterns. There are several deep learning techniques that can learn these representations. Another 4-way classifier had been implemented for the classification of the Alzheimer’s (AD), the Mild Cognitive Impairment (MCI), the late Mild Cognitive Impairment (LMCI) and the healthy persons. There were several experiments that had been performed at the time of a graphical processing system with results that were state-of-the-art. The technique proposed will result in an accuracy of prediction of about 98.9%.

Feng et al [8] made a proposal of another novel method for integrating the shape analysis and texture which was made in a way that was anatomically informed. More specifically, a Poisson map had been employed for the purpose of stratification of that of the hippocampus was employed for stratifying the hippocampus into several layers with the bag-of-words (BoW) model which was based on image intensity. There was one more level of the BoW model that had been employed for the encoding the texture over the subjects and also across layers. There was yet another Bayesian non-parametric (BNP) method for the inferring and further adjusting the layers and their variability. Validation of the model on the hippocampus-based Alzheimer’s disease (AD) along with the Mild Cognitive Impairment (MCI) diagnosis. There was a thorough comparison of all related features that was performed. The results proved that the method was able to achieve a performance which was state-of-the-art during the time of employing any hippocampus information.

Gupta et al [9] made a proposal with a cortical thickness along with subcortical volumes to distinguish the binary and the tertiary classification from the National Research Center for Dementia dataset (NRCD), with 326 subjects. There were five other experiments of classification that were performed: the binary classification, i.e., the AD versus HC, the HC vs mAD (MCI because of AD), and mAD versus aAD (asymptomatic AD), and the tertiary classification, which is, AD versus HC versus mAD and the AD versus HC versus aAD making use of the cortical and the sub-cortical features. There were some datasets that had been divided in a ratio that was 70/30 and after this, about 70% had been used for training while 30% was used for obtaining an unbiased performance estimation. For the purpose of the reduction of dimensionality, there was a Principal Component Analysis (PCA) that was employed. Once this was done different classifiers such as the Naïve Bayes (NB), the K-Nearest Neighbours, the Support Vector Machine (SVM) and the Softmax were used. The experiments conducted on the NRCD dataset had demonstrated the softmax classifier to be the one that was well-suited for the classification of AD versus HC that had a F1 score of 99.06. The SVM classifier was well-suited for an HC versus mAD, mAD versus aAD, and AD versus HC versus mAD classifications that are with F1 scores which are 99.51, 97.5, and about 99.99, respectively. Additionally, in the case of the AD versus the HC versus the AD, there was an NB performed having a score of about 95.88. additionally, in order to check the efficiency of the proposed model, there was an OASIS dataset to compare it with the other 9 methods that were state-of-the-art.

Islam and Zhang [10] had made a proposal yet another deep convolutional neural network that had been used for diagnosis of the Alzheimer’s Disease. This model was could identify all the different stages of the AD along with a superior level performance in terms of an early-stage diagnosis.

There were also several other experiments that were conducted for demonstrating the model that outperformed the baselines on an Open Access Series of the Imaging Studies dataset.

Lahmiri et al [11] had made an evaluation of the features along with fractals form the surfaces based on the MRI of the cerebral cortex, the gyrification index, the cortical thickness and the Alzheimer's disease assessment scale (ADAS) based scores of cognitive tests which were informative to classify patients of the AD. The results proved that the Support Vector Machine (SVM) had trained with the cortical thickness, the gyrification index and the ADAS cognitive test scores that distinguish between the healthy control subjects and the AD. This CAD system was able to achieve an ideal level of accuracy to outperform other systems.

Lama et al [12] had proposed a new presentation and further compared the diagnosis of the AD with the structural Magnetic Resonance (sMR) images for discriminating the AD, the Mild Cognitive Impairment (MCI) along with the Healthy Control (HC) with the Support Vector Machine (SVM), the Import Vector Machine (IVM), with a Regularized Extreme Learning Machine (RELM). Additionally, there was also a new kernel-based discriminative approach duly adopted for the purpose of dealing with some of the complex aspects of data distribution. For the purpose of comparing the performance of these classifiers that were used for volumetric sMR image data taken from the Alzheimer's Disease Neuroimaging Initiative (ADNI) datasets. These experiments conducted on the datasets of the ADNI that showed that the RELM along with the approach to feature selection that can improve the accuracy of that of the classification of AD from the MCI and the HC.

Liu et al [13] had focused the review of all existing research using methods of Artificial Intelligence and Statistical Machine Learning for the purpose of performing Quantitative Analysis that was for the diagnosis and the prognosis of the AD in the preclinical stages. Reviewing a current word was conducted in a total of three sub-areas: the diagnosis, the prognosis, and the methods that handle mission data modality-wise. The factors contributing to missing data will also include lack of imaging equipment, the cost, the difficulty of the consent of the patient and the patient drop-off (for longitudinal studies). Finally, there were also some more major findings providing recommendations for directions in the future.

Liu et al [14] had made a new proposal of another method of feature selection for the diagnosis of the AD by means of choosing the interesting structures in the Brain MRI. The method proposed had the P-Value which was used for obtaining the independent and principal features. The P-Value for each voxel was computed using the T-test between various classes of the image with the average P-Value for each brain tissue. As soon as all these operations are complete, this Statistical Parametric Mapping (SPM) based software will be employed for the purpose of pre-processing the MRI. Finally, these images are classified for the diagnosing the AD by means of a collaborative representation based classification (CRC). There were also some more extensive experiments that had been conducted for the evaluation of the method proposed and the results had indicated better performance that was in contrast to the other algorithms.

Long et al [15] had proposed a new method of machine learning for the discrimination of patients with either the AD or a Mild Cognitive Impairment (MCI) and the healthy elderly for the prediction of the AD conversion. The actual distance that existed between every such pair of subjects had been quantified from the symmetric diffeomorphic registration and this was followed by an embedding algorithm which was within the learning approach to its classification. by the embedding algorithm within a learning approach to classification. The method proposed had an accuracy of about 96.5% in bringing about an ideal differentiation of a Mild AD from that of healthy elderly with a grey matter or a temporal lobe in the Region of Interest (ROI), about 91.74% which was in the differentiating progressive MCI from that of the healthy elderly and finally about 88.99% in the classifying progressive MCI vs stable MCI with amygdala or a condition of hippocampus as ROI. Such methods were based on deformation and made use of the pair-wise shape that was macroscopic among groups having an increased discriminatory power.

Luk et al [16] had aimed at determining if the MRI may be used for converting the MCI to an AD. There was a 3-dimensional, analysis of the whole-brain texture method that was used for the computing of the texture features from the T1-weighted MR images. For the purpose of assessing their predictive values, there were texture changes that had been compared between the MCI converters and the non-converters over an observation period of 3 years. There was another predictive model that made use of clinical and texture factors. The model was further tested based on tested on the basis of randomly chosen test groups that were ten in number. These texture features were also found to be significantly different from the normal controls (n5225), the patients with MCI (n5382), and the patients with the AD (n5183). There was one more subset of patients having MCI that had been used for comparing between the MCI converters (n 5 98) and the non-converters (n 5 106). There was yet another composite model having texture features, the APOE-ε4 genotype, sex, which was a Mini-Mental Status Examination score along with the hippocampal occupancy that had resulted within an area that was under the curve of about 0.905. The application of the composite model to a total of about ten test groups randomly chosen (the non-converters of 5 26 and the converters of 5 24) that had been predicted in the MCI conversion having a mean accuracy of about 76.2%.

For investigating the applicability aspect of the subtraction MRI found in the ARIA-E detection by making use of the ARIA-E-rating scale is employed. Martens et al [17] had included a total of 75 AD patients receiving the treatment of bapineuzumab that includes about 29 ARIA-E cases. There are a total of five neuro-radiologists that had rated their brain MRI scans either with or without images of subtraction.

The evaluation accuracy of the presence of the ARIA-E, the intra-class correlation coefficient (ICC) that had a specific agreement had been computed. This type of subtraction had resulted in a higher level of sensitivity (of about 0.966) and a lower specificity (of about 0.970) compared to native images (of about 0.959 and about 0.991, respectively). This further had an individual rate detection that was excellent. The ICC scores ranged from a level of excellence to the level of good for the gyral swelling (moderate). There are excellent negative and good positive agreement among the features of ARIA-E imaging that were reported in the groups. There was also a combination of the sulcal hyper-intensity along with the the gyral swelling had increased significantly this type of positive agreement of the subtraction images.

Mathew et al [18] had made a proposal of one more new method for diagnosing the AD from the MRI images. There are some more primary methods of diagnosis of the Alzheimer’s disease are: the measuring of the atrophy rate of the Hippocampus and also the total brain volume; the next one was the extraction of information from the grey matter, Cerebro Spinal Fluid (CSF) and also the white matter of the brain. For the purpose of this work, there had been several statistical features like correlation, homogeneous and contrast where the shape features that were extracted from the images of the MRI. For each image, there were several features that were fed to classifiers. These images had been grouped into three different classes: Alzheimer’s Disease (AD), Mild Cognitive Impairment (MCI) and the Normal Control (NC). The approach also makes a comparison between the performance of the Probabilistic Neural Network (PNN), the K-Nearest Neighbour (KNN) and the Support Vector Machines (SVM) with regard to their sensitivity, specificity, and finally accuracy. There were MRI images that were obtained from the database of the ADNI which was a database that was clinically validated of the MRI, the PET and the FMRI images of the subjects.

The importance of such structural Magnetic Resonance Imaging (MRI) and the tau Positron Emission Tomography (PET) for the prediction of both the diagnosis and the cognition of the Alzheimer’s disease (AD) which is unclear. Mattsson et al [19] had tested a total of 56 cognitively unimpaired controls (that included a total of 27 preclinical AD), and 32 patients with a condition of prodromal AD, and finally, 39 patients diagnosed with AD dementia. There were several optimal classifiers constructed by making use of the least absolute shrinkage with a selection operator having 18F-AV-1451 (tau) PET and a structural MRI data (with regional cortical thickness along with subcortical volumes). The F-AV-1451 found in the amygdala, the entorhinal cortex, the Para hippocampal gyrus, the inferior parietal lobule and the fusiform that had about 93% diagnostic accuracy for the AD (either prodromal or dementia). There was also an MRI classifier that involved the same regions along with the hippocampus that had about 83% accuracy and this was not able to improve the tau classifier. The 18F-AV-1451 retention along with the MRI had been associated independently with cognition.

Moradi et al [20] had made a new and comprehensive study to the extent of RAVLT scores that were predictable on the basis of a structural Magnetic Resonance Imaging (MRI) data that makes use of the approaches to Machine Learning and also identify the critical regions of the brain for estimating the scores of the RAVLT. For this purpose, there was a new predictive model that was used to estimate the scores of the RAVLT from the grey matter and its density through the model of elastic net penalized linear regression. Such approaches will have a significant level of correlation which is ideally cross-validated among both estimated and observed RAVLT Immediate (R = 0.50) and the RAVLT Percent Forgetting (R = 0.43) found in the dataset with 806 AD, a condition of Mild Cognitive Impairment (MCI) or the healthy subjects. There are accurate estimates of the RAVLT scores compared to the relevant vector regression that was used before this. There were some top predictors that had been the medial temporal lobe structures along with the amygdala that was used to identify the RAVLT Immediate and the angular gyrus, the hippocampus and the amygdala that had been for estimating the RAVLT Percent Forgetting. Also, the conversion of MCI subjects to the AD within 3 years is predicted on the basis of an estimated or an observed RAVLT score with an accuracy comparable to the biomarkers based on the MRI.

Pan et al [21] had made a proposal of yet another straightforward strategy that tackles the challenge which was to discard subjects that had the PET missing and this can bring down the training subjects to a significant extent. At the same time, as there are certain other modalities (such as the MRI and the PET) had been acquired from this subject. Based on this condition, there was another two-stage framework identified for deep learning that had been proposed. More specifically, for the first stage, there was an impute missing PET data that was based on the corresponding data of the MRI that made use of the 3D Cycle Consistent Generative Adversarial Networks (3D-cGAN) for the purpose of capturing this underlying relationship. During the subsequent stage, making use of a complete MRI and the PET there was a deep multi-instance neural network that was proposed for an AD diagnosis along with a Mild Cognitive Impairment (MCI) prediction of this conversion. The results of the experiment had been that the subjects form an ADNI which demonstrated the synthesized PET images with the 3D-cGAN that had reasonable and with a two-stage method for deep learning to outperform methods which were state-of-the-art in the diagnosis of the AD.

Rieke et al [22] had trained the 3D CNN for the detection of the Alzheimer’s disease with the structural MRI scans. After this, a total of four gradient-based methods were based on the occlusion visualization were employed to explain the classification of the network decisions. All these four methods had been compared using both qualitative and quantitative manner. All these four methods had been involved in the focus of brain regions that were included in the Alzheimer’s disease, like the inferior and the middle temporal gyrus. These methods were based on occlusion focused on a certain level of specific regions and the gradient-based ones picked up the distributed patterns of relevance.

In addition to this, there is a distribution of the relevance that varies across the patients having a stronger focus on their temporal lobe for the other cortical areas that were more relevant. To summarize, identified were several methods of visualization which were critical to understand in the context of the CNN decisions which was a crucial step in increasing the impact and the trust in the decision support systems that were computer-based.

Ruiz et al [23] had proposed another novel fully automatic computer-aided diagnosis (CAD) system which was employed for the detection of the of Alzheimer's disease (AD) that had been based on the methods of supervised learning. The approach had the novelty that had been aimed at the detection of differences in the Regions of Interest (ROI) of the brain. This was also based on the subject recognition using a histogram analysis that was twofold. 1) there was a process of feature extraction aiming at the detection of differences in the Regions of Interest (ROIs) that were relevant for the recognition of subjects using AD and 2) the original greedy algorithm to predict the severity of all effects of the AD on the regions. The algorithm had been considering its progressive nature in connection to the AD that may affect the structure of the brain using various levels of severity. Also, this process can generate a new set of attributes that permit the use of machine learning algorithms. The regions also have a very high influence on the decision of classification in its final stage. There were several other experiments that had been carried out based on the segmented MRI images from a condition of Alzheimer 's disease Neuroimaging Initiative (ADNI) for the purpose of showing the actual benefits of this method. The CAD system that was proposed had achieved competitive results for the classification which was straight forward.

Sørensen et al [24] had made a presentation of a new brain T1-weighted structural Magnetic Resonance Imaging (MRI) biomarker which was a combination of many MRI biomarkers such as hippocampal texture, hippocampal shape, volumetric measurements, the measurements of cortical thickness and so on. This method had been developed, further trained, and finally had evaluated with publicly available datasets: the standardized dataset which was obtained from Alzheimer's Disease Neuroimaging Initiative (ADNI) and an imaging arm of an Australian Imaging Biomarkers and Lifestyle flagship study of ageing (AIBL). Additionally, the method had been evaluated by means of employing participation of Computer-Aided Diagnosis of Dementia (CAD Dementia) challenge. There was yet another cross-validation that had made use of the ADNI and the AIBL data along with a multi-class accuracy of classification of 62.7% that was for discriminating the healthy normal controls (NC), these subjects having a Mild Cognitive Impairment (MCI), and the patients having a condition of Alzheimer's disease (AD). This type of performance was generalized and there was also a challenge of CAD Dementia in which the method was trained by making use of the ADNI and the AIBL data had an accuracy of classification that was about 63.0%. The accuracy of classification obtained ended in the first place in a challenge where the method was better (McNemar's test) compared to the bottom 24 methods that are among 29 methods which were contributed using 15 teams. This method was investigated by employing a new learning curve with experiments of feature selection that use the ADNI and the AIBL data. There was an experiment of the feature selection showing a common and also an uncommon individual MRI wherein biomarkers had biomarkers contributed to their performance. This was the ventricular volume, the hippocampal volume, the hippocampal texture and the thickness of the parietal lobe. The highlight of this study to be a subtle, a localize measurement along with global measurements for discriminating the NC, the AD and the MCI that were based on an MRI scan of a single structure. This will only mean that an additional non-structural MRI feature is required for improving the performance obtained especially among the NC and the MCI.

Zhang et al [25] had made a proposal for a method which is landmark-based feature extraction for diagnosing the AD with longitudinal and structural MR images and they do not need any nonlinear registration or segmentation of tissue in the stage of the application. More specifically, 1) there were some discriminative landmarks that are discovered automatically from the entire brain making use of the training images which were localized efficiently with a method of fast landmark detection for the testing of images that does not involve contextual longitudinal features that were extracted from the detected landmarks characterising the abnormalities of spatial structure and the variations of longitudinal landmarks. Making use of these spatial, as well as longitudinal features, there was a Linear Support Vector Machine (SVM) that was adopted for distinguishing the subjects of AD or a Mild Cognitive Impairment (MCI) form the Healthy Controls (HCs). The results of this experiment that was on the ADNI database and it demonstrated the efficiency of the method along with accuracies of classification of about 88.30% for that of the AD versus HC and about 79.02% for the MCI versus the HC, respectively.

III. CONCLUSION

The work presented a survey made on the diagnosis of the AD using MRI images. For the purpose of this paper, the research was reviewed for the past decade and the focus was of making use of multi-modality imaging data used for the diagnosis and the prognosis of the AD. There were many reviews that were explained using their respective outcomes. This helps in identifying how the MRI images were applied and used in the identification of the diagnosis of the AD. Future work to focus on optimizing selection of features and classifiers to improve the prediction.

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