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Survey of Different Techniques to Detect Alzheimer's Disease

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***Abstract*: Dementia is a condition marked by the deterioration of certain cognitive faculties. The effects are a high death rate and a high cost of discovery, treatment, and patient care. Even though there's no remedy for dementia, early location helps give required help, appropriate medication, and, to the degree attainable, keeping up mental, social, and physical exercises. Early identification of Alzheimer's disease (AD) is critical for enhancing patients' and their family's quality of life. This paper shows the different works related to detecting Alzheimer's disease with other datasets using various machine learning calculations like SVM, Irregular timberland, and Calculated relapse with diverse strategies**

Keywords: Alzheimer, Classification, Machine Learning, RF, Regression, Segmentation, SVM.

1. INTRODUCTION

Dementia is a medical condition characterized by cognitive and emotional dysfunction. Common symptoms affecting mental health and quality of life include memory, thinking, language, and perceptual interpretation. Based on a unique combination of these symptoms, several types of dementia are categorized, with Alzheimer's infection (advertisement) being the most common (62 percent of cases) and affecting the elderly. The stated figures, however, are increasing globally and in the UK for people under 65 [1]. The loss of episodic memory and problems acquiring new material are two early indications of Alzheimer's disease. Individuals with Alzheimer's disorder persevere more memory misfortune, cognitive impedances, and behavioral anomalies as the illness creates. Meandering and getting misplaced are common issues, as are doubts of family and caregivers, taking longer to do everyday obligations, and the failure to have a conversation, type in or walk accurately[2]. When Alzheimer's disorder is found, the neuronal harm has now gone distant sufficient to be

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irreversible [3]. The damage is irreversible because neurons cannot increase and replenish themselves like other cells [2]. As a result, it is critical to recognize dementia early to slow down the rate of deterioration [4–6]. Early identification is also crucial to ensure that the patient receives appropriate therapy and improves their quality of life [7]. Another factor to consider is the expense of dementia treatment. The worldwide toll of dementia is $818 billion, and it is anticipated to reach a trillion by 2018 [8]. In 2013, the fetched of dementia within the Joined together Kingdom was predicted to be 26.3 billion pounds, with 4.3 billion going through healthcare uses with a generally 85 million went through on diagnosis [1]. As a result, developing economic diagnosis and treatment options is critical. Assistive technology helps control the rising costs connected with dementia. One of the suggested approaches is to send e-health (data and communication innovation (ICT)) arrangements to cut costs and make wellbeing frameworks and setups broadly open [9–11]. The advantages of e-health technologies, according to Arief et al. [8], include improved access to healthcare administrations for older adults, cost-effectiveness, and productivity in overseeing wellbeing assets.

The signs of Alzheimer's illness are being investigated to improve the results of existing strategies or to create modern and more precise conclusion instruments based on cutting-edge, open, and publically recognizing Alzheimer's infection separated into two categories: There are two sorts of invasiveness: intrusive and non-invasive. Obtrusive approaches require strategies such as lumbar cut or blood extraction to procure information from the insides of the patient's body. These invasive approaches aim to identify possible biomarkers that can be used to predict Alzheimer's disease accurately [12]. Most of them are not always safe or comfortable for the patient, and they can be very painful sometimes. Non-invasive diagnostics, on the other hand, are safer and more convenient throughout the diagnostic procedure.

Related Work

A. Alzheimer's disease and its Symptoms:

Dementia may be a cover term for a set of mental ailments. It's a misfortune of mental work, too known as decreased cognition in restorative terms. Alzheimer's could be dementia that develops over time as brain cells deteriorate. Alzheimer's disease causes memory, cognitive, and. Alzheimer's disease affects distinct brain parts, and specific skills or talents are lost. Recent event memory is frequently the first to be impacted, but long-term memory is often lost as the disease advances. The condition also affects many other brain processes, including language, attention, judgment, and other elements of behavior.

B. Role of MRI in Diagnosis of AD

Neuroimaging strategies permit the evaluation of brain changes and are, in this way, promising in early Alzheimer's infection locations. Understanding the brains of Alzheimer's and dementia patients from a clinical standpoint is crucial. MRI may be able to diagnose Alzheimer's disease early on before permanent damage has occurred. Researchers looked at

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particular indicators of the disease process by analyzing MRI scans of healthy people and those with moderate cognitive impairment (MCI) and early Alzheimer's disease. The phases of Alzheimer's disease are depicted in Figure 1

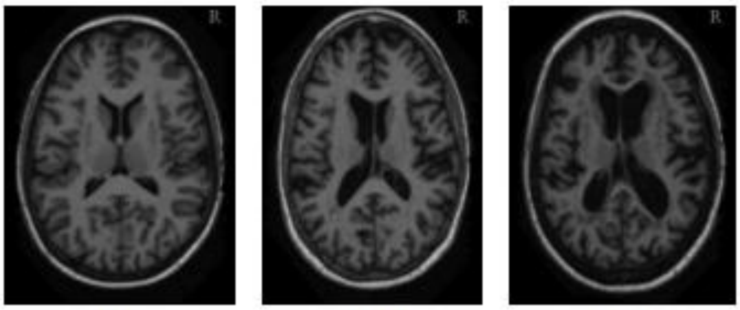

Figure 1: Axial Brain MR Images

Automated brain problem diagnosis using MR imaging is becoming increasingly significant in the medical field. There are two primary processes in automatic diagnosis: (a) image categorization and (b) image segmentation. The process of dividing aberrant photographs into separate categories based on similarity criteria is known as image classification. Because treatment planning is predicated on this identification, the accuracy of this anomaly detection system must be pretty high. In the literature, several research publications describe various techniques to picture categorization. TABLE I has a comprehensive literature review on several types of classifiers, different stages of Alzheimer's disease, publically available datasets, extracted features, classification results, and other topics utilized for anomaly identification in brain pictures. TABLE II has a comparative analysis of the Research study and year, Dataset used, the Method employed & Accuracy achieved.

Author (year)	**Modality/dataset**	**Data processing/ training**	**Classifier**	**ACC**	**SEN**	**SEP**
Suk and Shen(2013)	MRI,PET,CSF	SAE	SVM	95.9	-	-
Liu et al. (2014)	MRI,PET	SAE+NN	softmax	87.76	88.57	87.22
Suk et al. (2014)	MRI, PET	DBM	SVM	95.35	94.65	95.22
Li et al. (2014)	MRI, PET	3DCNN	Logistic regression	92.87	-	-
Li et al. (2015)	MRI,PET,CSF	RBM + Drop out	SVM	91.4	-	-
Suk et al. (2015)	MRI,PET,CSF	SAE + sparse learning	SVM	98.8	-	-
Liu et al. (2015)	MRI, PET	SAE with zero-masking	softmax	91.4	92.32	90.42

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Cheng et al. (2017)	MRI	3DCNN	softmax	87.15	86.36	85.93
Cheng and Liu(2017)	MRI,PET	3DCNN+2D CNN	softmax	89.64	87.10	92.00
Aderghalet al.(2017)	MRI	2DCNN	softmax	91.41	93.75	89.06
Korolev et al.(2017)	MRI	3DCNN	softmax	80	87(AUC)	-
Vu et al. (2017)	MRI, PET	SAE+3DCNN	softmax	91.14	-	-
Liu et al. (2018a)	PET	RNN	softmax	91.2	91.4	91.0
Liu et al. (2018b)	MRI	Landmark detection+3D CNN	softmax	91.09	88.05	93.50
Lu et al. (2018)	MRI, PET	DNN+NN	softmax	84.6	80.2	91.8
Choi and Jin(2018)	PET	3DCNN	softmax	96	93.5	97.8

Table I- literature review on several types of classifiers and Accuracy with other parameters

Research study	**Dataset**	**Models**	**Accuracy**
Albright et al., 2019	ADNI	Neural network model	86.60%
Alickovic & Subasi, 2020	ADNI	Random forest	85.77%
		K- Nearest Neighbours	84.27%
		Naïve Bayes	75.16%
		Artificial Neural Network	76.03%
		Logistic Regression	75.28%
		Support Vector Machine	83.15%
Shahbaz et al., 2019	ADNI	K-Nearest Neighbours	43.26%
		Decision Tree	74.22%
		Rule Induction	69.69%
		Naïve Bayes	74.65%
		Generalized Linear Model	88.24%
		Deep Learning	78.32%
Islam & Zhang, 2018	OASIS	Deep Convolutional Neural Network	93.18%

Table II:-Different ML Classifier Comparison with Accuracy

Dataset

One hundred seventeen datasets related to studies on dementia were found by Bell et al. [34]. The majority include clinical data from Alzheimer's patients, including MRI scans, blood tests, and results of cognitive tests (the MMSE, primarily). For instance, the Longitudinal Aging Study Amsterdam (LASA) [35] is a dataset that contains data from interview-based questionnaires for the emotional and cognitive aspects of aging. It is also updated regularly. The information on cognitive deficits is based on research on the aging process in the Dutch population. The AlzGene database [36] contains genotype information that may point to genes that increase the risk of developing AD. The ADNI database contains clinical information such as results from cognitive tests and biomarkers, MR images, PET data, genetic information, and information from biospecimens such as blood, urine, or cerebrospinal fluid. One of the complete databases on Alzheimer's is BRAINnet [37]. From interviews and applications of cognitive testing, general and cognitive information is provided by EEG, ERPs, autonomic arousal measures, MRI, and genomics. SEMdb (Spontaneous Multimodal Database) is a multimodal dataset for recognizing spontaneous emotional reactions. It contains multimodal information (HD RGB, depth and IR frames of the face, EEG signal, and eye gaze data) of nine healthy participants photographed while taking cognitive/visual tests, including five females and four males between the ages of 27 and 60. This Dataset's main objective is to detect Alzheimer's illness. It includes recordings of participants engaging in three tasks: autobiographical activities, numerical search, and gaze calibration.

Evaluation Techniques

A subset of artificial intelligence called machine learning aims to develop methods that let machines learn. Its goal is to identify connections between input variables and outcomes that can be utilized to foresee responses to new input variables.

Methods based on auto-encoders

One of the various deep learning techniques is the deep auto-encoder. It consists of two deep, symmetrical networks, where the first set of layers represents the net's encoding portion and the second set of layers its decoding portion. This paper uses the auto-encoder network to detect AD. For instance, Jha et al. proposed a deep learning approach based on a sparse auto-encoder (SAE) and a Softmax output layer for the diagnosis of Alzheimer's disease (AD) [13]. An unsupervised artificial neural network called an auto-encoder chooses features by reducing reconstruction errors. An auto-training encoder's process is based on cost-function optimization. Before creating a softmax layer, they trained two auto-encoders to recognize the feature vectors.

Methods based on deep feature extraction

Convolutional neural networks (CNN) have been effectively implemented in recent years to extract deep characteristics for AD detection. The profound aspects are unaffected by the nonlinear appearance changes. Several in-depth feature extraction-based solutions have been put out in the literature to solve this problem. For instance, a stacked deep polynomial network (S-DPN) was proposed by Zheng et al. [20] as having the ability to increase characteristic representation from small samples, leading to strong generalization ability. The following stage merges multimodality neuroimaging data and learns features with a multimodality S-DPN (MM-S-DPN) Method. They employed the SVM and the embedded classifier for classification.

Morabito et al. employed CNN to construct adequate characteristics for identifying AD's EEG patterns (electroencephalography) [16]. The non-invasive investigation of cortical neuronal synchronization is made possible by EEG. Five separate, non-overlapping windows are created for each set of EEG channels.
The CNN uses two hidden convolutional layers. Three-channel features are produced by convolving the input vector with 19 masks of 12 elements (one for each channel). The subjects' levels of Alzheimer's illness were then divided into categories using a Multilayered Feed forward Perception (MLP) technique.

CNN was employed by Basher et al. [17] together with the Hough voting strategy. The CNN calculated displacement vectors using many 3-viewpoint patch samples and the voting method. The objective location is then roughly determined by adding these vectors to the sample position. They successfully learned from the samples by combining local and global approaches.

Methods of learning-based transfer
The literature may also contain transfer learning-based strategies that aim to handle the issue of AD detection correctly. This paradigm applies previously acquired information from solving one problem to a related but distinct circumstance.

We single out [18] from among these transfer learning-based methods for AD detection, which used the CNN architecture LeNet-5. In [19], CNN is also utilized. As a feature representation of 2D images, they used a scraped-trained CNN or a pre-trained Alexnet CNN, followed by classification using KNN and Naive Bayes, two straightforward machine learning techniques. A transfer learning approach using 2D CNN and Long Short-Term Memory (LSTM) networks was proposed by Ghahnavieh et al. [20].

Additionally, Jain et al. used the VGG-16 architecture as feature extraction for classification, trained on the ImageNet database [22]. 95.73 percent of the time is accurate. This rate may be raised by using the fine-tuning technique (introducing the model's pre-trained convolution layers); Hon et al. used two CNN architectures in [23]. (Inception V4, VGG-16) The VGG-19 architecture was also used by Khan et al. [24] to identify Alzheimer's illness. The Method used by [25] is based on deep learning. The first step is to process the 3D input volumes and, using the SPM 8 method, extract the grey matter from each volume. Approximately 166 2D segments make up each volume. Next, these slices are sent across two architectures (GoogLeNet and ResNet).

Methods based on Segmentation
The third category of approaches involves using image segmentation to identify the hippocampal area and so correctly detect AD. We identify two types of segmentation-based procedures here: automated and manual.

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There are many automated segmentation-based methods; for instance, in [26], Angkoso et al. defined the three brain tissues using a segmentation algorithm based on voxel-based morphometry (VBM) (white matter WM, grey matter GM, and cerebrospinal fluid).
Following that, the properties required to detect the AD using a back propagation neural network were extracted using the Kolmogorov-Smirnov distance approach (BNN).
The authors presented a hippocampus segmentation approach based on the ILLM technique [27]. (iterative local linear mapping). The proposed system is divided into three sections: 1) The LLM is used for preliminary segmentation prediction. 2) The semi-supervised deep auto-goal encoder is to map the samples from the MR patch to the embedded feature manifold in a nonlinear fashion. 3) The ILLM is utilized to accomplish accurate Segmentation. Cabinio et al. [28] segmented the hippocampus using a vertex-wise analysis. The Bayesian technique was used to incorporate direct assessments of subcortical geometric changes.

Classification by several classes
The most common categorization categories are binary and multiclass. The most straightforward classification issues are binary tasks, which involve categorizing data into two groups. One of the most popular binary classifiers, the Support Vector Machine (SVM), was first introduced by Cortes et al. [29] in 1995. In instances involving several classes, it is necessary to divide the presented data into more than two categories. Several binary classifiers or multiclass classifiers can be utilized to solve this issue. With 92% accuracy, Akgul et al. [14] used MRI scans as attributes of an SVM; a classifier was created to separate Alzheimer’s patients from healthy individuals. Binary classifiers including DTW, SVM, and kNN were used by the authors of [26] to categorize participant gait data from AD and healthy individuals. Uses SVM and boost classifiers to classify recent and distant memories using EEG and facial images. When reading text paragraphs, the authors use the Nave Bayes classifier to distinguish between healthy readers and MCI patients by considering factors like gaze length, saccade amplitude, and the overall number of fixations. To find correlations between MRI images and probable explanatory factors for Alzheimer’s disease, the general linear model is constructed in [15]. Vallejo et al. classify tasks using logistic regression binary classification and the features of length and correctness.

Classification into a single category
One-Class Classification (OCC) aims to isolate one type of item and distinguish it from others when the data is badly imbalanced (with training data mainly from one class). Positive samples are drawn from this class’s data. There may be data from other classes, but it isn’t easy to get owing to variables such as cost and ethics. Outliers will be used to classify these data. Three families of OCC techniques have been identified [30]. Density-estimation techniques make up the first family. These require a large quantity of training data and are not resistant to outliers in the data. The clustering-based approaches are dealt with in the second group. These consider the data’s structure and are resistant to outliers, but they require training data to represent the entire class. The third Method in the family constructs a border between the desired class and the others. The selection of this threshold determines their performance and resilience to outliers. According to Rodionova et al. [31], other OCC methodologies for classification that use outliers are compliant and rigorous. The latter

collects all OCC classifiers that exclusively utilize positive data for training, whereas the former incorporates information from certain outliers into the model. Conforming techniques are usually more convenient when the data from the classes overlap.

The automated diagnosis of illnesses [32] is one of the most appropriate uses of OCC because it might be difficult to acquire information from specific conditions owing to restricted resources. The volume of instances, the ethics, or the cost are all factors to consider. To make an early diagnosis of Alzheimer's disease for the categorization of audio signals, Lopez et al. [33] compare OCC and multiclass classifiers. Speech-related Alzheimer's symptoms include aphasia (difficulties speaking and understanding) and emotional response problems. The AZTIAHO database was created by the authors and contains video recordings from twenty people with Alzheimer's disease and fifty healthy individuals. A Multi-Layer Perceptron (MLP) is used by the OCC and multiclass classifier (MCC). At the same time, OCC develops a model representing the healthy group, and MCC models two groups—healthy and AD. Their tests demonstrate that OCC outperforms the multiclass when AD data is sparse.

2. CONCLUSIONS

This research is based on comparing and evaluating previous work in Alzheimer's disease prognosis and prediction utilizing machine learning algorithms. Current machine learning trends have been presented, including the data used and the efficacy of machine learning approaches in predicting Alzheimer's disease in its early stages. It is self-evident that machine learning improves prediction accuracy, particularly compared to traditional statistical techniques. However, according to the review, the clinical diagnosis was not 100 percent correct since pathological verification was not provided, resulting in ambiguity in the expected findings. There is scope for Alzheimer's disease prediction by using different machine learning methods like SVM, Random Forest, Decision Tree algorithm, and Logistic regression also with CNN methods

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