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Exploiting of Classification Paradigms for Early diagnosis of Alzheimer's disease

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Abstract: Alzheimer's disorder is an incurable neurodegenerative disease that ordinarily affects the aged population. Coherent automated assessment methods are essential for Alzheimer's disease diagnosis in early from distinct images modalities using Machine Learning. This article focuses on exploring various feature extraction and classification methods for early detection of AD proposed by researchers and proposes a modern predictive model that includes Voxel based Texture analysis of brain images for extract features and Optimized Classifier Deep Convolution Neural Network (DCNN) employed for enhance accuracy.

***Keywords*: Alzheimer's disease (AD), DCNN, Feature Extraction.**

1. Introduction

Alzheimer's disease (AD), a type of dementia is portrayed by revolutionary thinking problems and behavior, beginning in the middle or old age. Alzheimer's disease leads to poor memory, perception, and Behavior. In year 1907 Alois Alzheimer's German neuropathologist first described about Alzheimer's [1]. The pathological characteristics of neuritis are brain plaques and explicit brain degeneration cells. In general, the symptoms develop slowly and get serious enough to be interfere in everyday life. While the Oldness is a paramount risk factor, AD is not merely a sickness of old age. In time, Alzheimer's disease gets worse and is fatal, Alzheimer's disease is difficult to recognizing by Doctors before reaches to clinical stage by reason of diagnosis process done manually it leads to highly significance to error due to interference of perception of patients, even if warning signs are not recognized by patients themselves [2].

Dementia is the general brain disorder the most common, progressive and debilitating brain disease of which is Alzheimer's disease. It breaks down brain cells, interfering significantly enough with memory, thinking, and behavior to influence the job, hobbies, and social life of a person. An assessment and analysis of the existing studies, number of common trends and shortcomings identified. The patterns most evident include a short one AD detection and forecast growth using the methods of machine learning. Machine learning also plays a vital role in diagnosis and prediction of AD. Among the bigger gaps was a too many attributes selection, use of Unconventional data set, class inequality, overtraining and inadequate objective assessments or Validation. However, the better designed and the better the Studies validated showed that machine learning approaches enhance AD accuracy.

Machine learning is expanding under Artificial intelligence, it's more powerful than standard statistical tools, better understanding of problem and consist of different tools for probabilistic, statistical decision depends on prior learning. Uses previous experience to identify current events and recognize existing patterns.

Alzheimer's disease is getting worse over time and fatal. In diagnosing of AD using Machine learning it consists of sequence of steps. The initial steps are preprocessing takes the unprocessed MRI contains of numerous artifacts, including intensity similarity, extra corpuscular tissue and more, step is important because it should be taken to make certain high accuracy in preceding steps. The second step in the diagnostic procedure is Feature extraction; a method that extracts peculiar features from pre-processed images in various anomalous groups therefore, "within class similarity is maximized and between class similarities is minimized". This image classification technique is capable of providing information on the existence anomalies of input brain image used to diagnose dementia and Alzheimer's., Brain image classification is an important process in diagnostic systems. The main aim of the classification process is to determine between distinct anomalousness of brain images predicated on the best possible feature set. [1].

Many traditional Machine Learning algorithms are available for classification, such as K-Nearest Neighbors (KNN), Naïve Bayes , Support Vector Machine (SVM) , Random Forest (RF), Decision tree and more, which offers the best results for extraction of features used in the diagnosis of dementia and Alzheimer's disease.

In this article give a predictive model which includes novel feature extraction and hybrid optimal classifier DCNN for detection of Alzheimer's using MRI images.

2. 2. Alzheimer's Disease

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Alzheimer's Disease (AD) which is also known as Senile Dementia [3]. It's a progressive disease that causes brain cells to waste, degenerate and die., it is a uninterrupted decline in thinking, behavioral and mental skills that disrupts a person's capability to function on one's own. A person with this disease will develop severe memory impairment. There is no complete cure or alteration of this disease. Instead of curing, we can take several programs and treatments which maximize the better functionality of the brain.

A. Symptoms:

Loss of memory is that the main symptom of Alzheimer's disease. Recalling recent events or conversations is sometimes a tough early sign of the disease. Memory impairments worsen because the disease progresses, and different symptoms develop [4].

Changes in brain associated with Alzheimer's disease cause increasing problems with:

i. Loss of memory which disrupts everyday life
ii. Challenges in planning or solving problems
iii. Difficulty carrying out common roles
iv. Confusion of time and place
v. Misplacing things and lose the opportunity to retrace steps
vi. Mood shifts and attitude changes
vii. Wrong or poor judgment

B. Stages:

There are seven stages in the Alzheimer disease which helps to understand that the person is in which stage by its symptoms [5].

Stage 1: No Impairment*:* In this Stage No Symptoms, no memory problems and Alzheimer's disease are undetectable.

Stage 2: Very Mild Decline: during this stage dementia can be recognized by a clinical assessment or family members. They may forget where they left things, but person do well with memory.

Stage 3: Mild Cognitive Decline: At this stage, the family members, co-workers and friends of the aged may begin to identify difficulties. Duration of stage is seven years.

Stage 4: Moderate Cognitive Decline: In stage four of Alzheimer's, explicit symptoms of the disease are supposed. Maybe forgot about own personal history become moody

Stage 5: Moderately Severe Decline: starting of stage major memory gaps present, person need assistance with activities of day-by-day, unable to recollect phone number and address.

Stage 6: Severe Cognitive Decline: also called Middle Dementia, during this stage person need supervision symptoms are inability to identify closed friends and family members, experience loss of bowel and bladder control, and speech

Stage 7: Very severe cognitive decline: It is final stage in the Progress of AD, people will have lost their ability to speak or convey information. They regularly require assist with the majority of their exercises, which includes washing, toileting, dressing, eating, and different day- by- day exercises.

3. Machine Learning:

"Machine learning is subset of artificial intelligence it provides machine ability to learn automatically and improve from experience without explicitly programmer". It learns from previous experiences and build a Model when new data is comes easily predicts belongs to which category. Machine learning is statistical models, aim is to analyze and recognize structure of data [6]. The machine learning is help to analysis of data to diagnosis of Diseases in medical field. What to create good machine learning model it requires Data pre-processing capabilities, Algorithms, Automation and iterative process, scalability and Ensemble modeling and better Model gives high accuracy.

3.1 Types of Machine Learning Techniques:

There are 4 types of machine learning Algorithms

A. Supervised learning
B. Unsupervised learning
C. Semi supervised Learning
D. Reinforcement Learning

A. Supervised learning:

Supervised learning is approach in which can be teach machine by labeled data. The outcome (dependent variable) is predicted from the previous experience (independent variables), it creates mapping function Y =f(X) it maps input to expected output, where X input variable and Y is output variable [7]. It can help to get Optimized performance for predictions for new unlabelled data from experiences. Decision Tree, Regression, KNN, Random Forest are Supervised Learning approaches. Supervised learning has two types' a) classification b) Regression.

Classification is process of assign a class label to input data. There are two categories of classifications. One is Binary classifier involve two class labels either "YES" or "NO", another one is Multi label Classifier refers one or more class.

Regression is process of " Predict continuous outcome (dependent variable) from one or more input (independent variable), Y=bX+c where X is independent variable, Y is Dependent Variable and b, c is Co-efficient " .

B. Unsupervised learning:

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Unsupervised learning is approaching the machine trained on unlabelled data without any supervisor, have not any outcome/target to estimate. it consists of input variable X and responding Output variable. K-means, Principal Component Analysis, Apriori algorithm for association rule learning are Unsupervised learning algorithms.

Unsupervised learning has categorized 2 types a) Clustering b) Dimensionality Reduction.

Clustering is process of group the objects based on homogenous characteristics. Clustering is based on Density, Centroid and Distribution.

Dimensionality Reduction method is minimizing the no of features there two components in one is feature selection and feature extraction.

C. Semi supervised Learning:

Semi supervised Learning is Combination of Supervised (less labeled data) and unsupervised (more Unlabelled data), in the process first cluster the data by using unsupervised learning then use labeled the data to label remain unlabelled data [8].

D. Reinforcement Learning

Reinforcement learning is the preparation of machine learning models to make a series of decisions. The agent learns how to accomplish a target in an unknown, potentially complex system. The machine uses a trial and error to fix the issues. In order to get the system to do what the programmer wishes; the artificial intelligence is either praised or punished for the acts it performs [9]. The aim is to optimize the overall reward. Reinforcement implemented by using 3 methods value based, policy based and model based. Markov Decision Process is a Reinforcement algorithm.

4. Literature Survey

Image classification is approach of recognizes various objects in the abnormal images and categorizing them based on similar characteristics, planning of treatment is done based on the outcome of abnormality detections. In Many research articles are use Varity of technique for image classification to Predict Alzheimer's Disease are presented in the Table. The literature survey includes summary of types classifiers are used, sources of publically available databases, type of Image modality, relevant features extracted and performance of classifier.

Author	Dataset	Methodology	Image modality	Features	Target	Performance		
						Accuracy	Sensitivity	Specificity
Peng et al. [10]	ADNI	SVM(multi kernel)	sMRI,PET, SNP	Volume + Mean intensity features	CN vs AD	96.1	97.3	94.9
					CN vs. MCI	80.3	85.6	69.8
					MCI vs.AD	80.3	85.6	69.8
Kar et al. [11]	ADNI	ANN	sMRI ,CT	ROI	CN vs.AD	100	100	100
Sheng et al. [12]	ADNI	SVM	fMRI	RF-Score	CN vs.AD	95.8		
Spasov et al. [13]	ADNI	CNN	MRI	ROI, APOe4	sMCI vs. pMCI	92.5	86.5	85
Fritsch et al. [14]	Pitt Corpus	LSTM	Linguistic	n-gram	CN vs.AD	85.6		
Gosztolya et al. [15]	ADNI	SVM -Linear	Acoustic signal	MFCC	CN vs MCI	80		75.9
					CN vs mAD	86		87.5
					MCI vs mAD	80		85.7
Krishnakumar Vaithinathan et al [16]	ADNI	KNN	MRI	Textural Features (RROI)	NC vs MCI	63.73	55.26	67.14
Casanova *et al.* [17]	ADNI	SVM	MRI	cortical	AD vs NC	100	100	100
Mattsson *et al.* [18]	FINDER	F-AV	MRI,tPET	regional cortical	AD	93		
Das, D et.al. [19]	ADNI	SHIMR	MRI,CSF,PET	protein	AD vs NC	82		
Ji, H.,et al. [20]	ADNI	CNN	MRI	ROI	AD vs MCI	100	100	96

Table 1: Overview of Classification Paradigms for Detection of Alzheimer's disease in 2019

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Author	Dataset	Methodology	Image modality	Features	Target	Performance		
						Accuracy	Sensitivity	Specificity
Liu et al. [21]	ADNI	Multi task multi channel-DNN	MRI	Patch	CN vs.AD	93.7	94.6	93.2
Sun et al. [22]	ADNI	Group lasso SVM	sMRI	VBM ,PCC	CN vs.AD	95.1	93.8	83.8
					CN vs.MCI	70.8	72.1	69.1
					MCI vs.AD	65.7	63.2	67.3
Basaia et al. [23]	ADNI	CNN	MRI	GM, WM, CSF	CN vs. AD	98.2	98.1	98.3
Lahmiri et al. [24]	ADNI	SVM	MRI	VBM	CN vs.AD	100	100	100
Lu et al. [25]	ADNI	MDNN	FDG-PET	ROI	CN vs. AD	93.58	91.54	95.06
Li et al. [26]	ADNI	DenseNet	MRI	Patch	CN vs. AD	89.5	87.9	90.8
					CN vs MCI	73.8	86.6	51.5
Liu et al. [27]	ADNI	MKBoost , SVM	MRI	Atlas	CN vs.AD	95.37	92.49	96.08
					MCI vs.AD	90.41	92.83	88.82
					CN vs.MCI	86.56	90.74	84.83
Zheng et al. [28]	ADNI	MFN	MRI	ROI	CN vs. AD	98.7	98.59	98.79
					CN vs. MCI	97.93	98.64	96.97
					AD vs. MCI	73.83	64.08	80.09
Dominguez et al. [29]	Pitt Corpus	RF	Audio	Cov + lin	CN vs. AD	94	100	86
					CN vs.MCI	87	87	86
Cui et al. [30]	ADNI	ANN+BGRU	MRI	VBM	CN vs.AD	89.69	86.87	92.58
Jain et al. [31]	ADNI	CNN	MRI	Entropy	CN vs. AD	99.14		
Zhou et al. [32]	ADNI	TrAdaBoost	MRI	Atlas	CN vs. AD	93.75	87.5	100
Cheng et al al. [33]	ADNI	rMLTFL	sMRI	VBM	CN vs.AD	95.2	95.2	95.3
					CN vs.MCI	82.4	86.7	73.8
					MCI vs. AD	76.7	61.4	81.8
Li et al. [34]	ADNI	Subspace alignment	fMRI	VBM	CN vs.AD	84.6	92	79
Kim et al. [35]	ADNI	MSH-ELM	MRI,PET, CSF	Atlas	CN vs.AD	97.2	98.08	94.12

Table 2: Overview of Classification Paradigms for Detection of Alzheimer's disease in 2018

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Author	Dataset	Methodology	Image modality	Features	Target	Performance		
						Accuracy	Sensitivity	Specificity
Liu et al. [36]	ADNI	MKBoost , SVM	sMRI	Atlas	CN vs AD	94.65	95.03	91.76
					MCIvs AD	89.63	91.55	86.25
An, L.,et al. [37]	ADNI	SVM	MRI + SNP	Discriminative	AD vs. NC	97.4		
Hojjati et al. [38]	ADNI	SVM	fMRI	PCC , Fscore	MCIc-MCInc	91.4	83.24	90.1
Lama et al. [39]	ADNI	PCA , RELM	MRI	Cortical	CN vs AD	77.30	62.12	79.85
Rupali et al. [40]	OASIS	K-NN	MRI	Contrast, Energy, Homogeneity,	AD vs MCI	92.31		
					AD vs NC	92.75		
					MCI vs NC	83.33		
Suk et al. [41]	ADNI	JLLR DeepESRNet	MRI	ROI	CN vs AD	91.02	92.72	89.94
Jha et al. [42]	OASIS	PCA +FFNN	MRI	VBM	CN vs AD	90.06	92.0	87.76
Lei, et al. [43]	ADNI	R2DSLR		GW,ROI	AD vs. NC	97.72	97.9	91.3
					MCI vs. NC	82.6	64.3	86.6
Long et al. [44]	ADNI	SVM	MRI	MDS + PCA	CN vs.AD	96.5	93.85	97.78
Zheng et al. [45]	ADNI	SVM,RBM	MRI PET	Atlas	CN vs AD	88.52 ±8.61	84.60 ±15.24	92.20 ±12.61
Zhang et al. [46]	ADNI	SVM	sMRI	Landmark-based Spatial	AD vs. HC	94.01	79.61	94.69
					MCI vs. HC	85.19	90.46	59.90
Beheshti et al. [47]	JADNI	SVM	MRI	VBM	CN vs AD	84.17	88.83	79.00
					CN vs MCI	70.38	78.17	60.22
Mathotaarachchi, et al.[48]	ADNI	RUSRF	MRI, PET, CSF	Brain voxel	pMCI vs AD	84.0	70.8	86.5
Asgari et al. [49]	-	SVM+RF	Word count	LIWC	AD vs.MCI	74.7	67.51	72.3
Lu et al. [50]	ADNI	RF-RSVM	FDG-PET	VBM	CN vs.MCI	90.53	90.63	93.33
Cheng, D et al. [51]	ADNI	CNN + BGRU	FDG-PET	intra-slice	AD vs. NC	95.28	91.00	91.40
Cheng et al. [52]	ADNI	MDTFS + MDTC	MRI	Atlas	CN vs AD	94.7	94.1	94.8
					CN vs MCI	81.5	85.8	73.3
Alam et al. [53]	ADNI	TWSVM	sMRI	DTCWT	CN vs.AD	96.88	97.72	95.61
Kajal Gulhare et al [54]	OASIS	DNN	MRI	Textural	AD	96.61		
Arpita et al [55]	OASIS	ANN	MRI	Textural	AD vs.MCI	86.8 %		

Table 3: Overview of Classification Paradigms for Detection of Alzheimer's disease in 2017

5. Critical Evaluation:

Machine Learning is exploit different of probabilistic and optimization techniques, it plays vital role in field of Medical for diagnosis of disease in early stages for that purpose they use various images imaging modalities of brain. Machine Learning methods are integrated with medical images it will help to Predict Alzheimer's disease in early stage. In above section presented overview of different machine learning classifiers proposed by different researches for detection of Alzheimer's.

These studies are used different classifiers like Support Vector Machine, Deep Learning, Artificial Neural Network, and also use different types of features extraction methods to get the accurate results. Several strategies achieved

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promising prediction accuracies; Even though, being able to identify potential issue Such as pre-processing, selection of image modalities, the number of important attributes for feature selection, experiential Design, validation of model, they are not appropriate on detecting the AD disease on time for the earlier diagnosis. Through the analysis of studies, the most common problems are extract relevant characteristics and optimal classifier needed for better accuracy with same datasets.

6. Proposed Model:

To address these limitations of extract relevant characteristics and optimal classifier, a predictive model is proposed shown in figure1. It Consist of 3 stages 1. Pre-processing 2. Extract relevant characteristics 3. Optimized Classifier. Magnetic resonance imaging (MRI) volumetric measures is a standard tool for the detection of development Alzheimer’s Disease (AD) dementia in mild cognitive impairment (MCI). In this study the MRI is data used were acquire from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database.

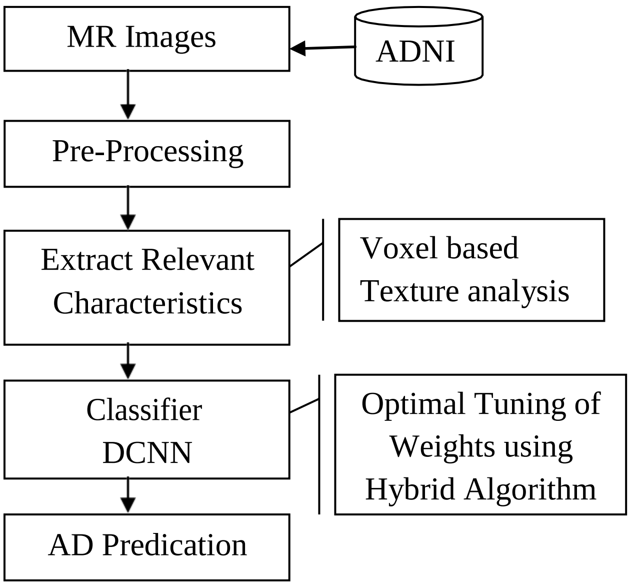

Figure 1. Proposed model for early prediction of AD

The proposed model entails a pre-processing stage for eliminating the issue of class imbalance. It 's important for attributes selection using the machine learning method also help to avoid the problem of too few instances, In Stage 2 perform Voxel based texture analysis of brain MRI, Texture evaluation is a effective quantitative technique for examine Voxel intensities and their interrelationships. Then in stage 3, Optimized Deep Convolution Neural Network (DCNN) will be employed, weight and the activation function in CNN will be optimally tuned by a new “Hybrid” algorithm, which is the hybridized concept of Grey Wolf Optimizer (GWO) and Dragonfly Algorithm (DA). Finally validate the model by using testing data, model may help better to Prediction of Alzheimer’s disease in early stage.

7. Conclusion:

This article contributes comparisons and assessment of recent research done in prediction of Alzheimer’s disease using machine learning techniques. As Recognized from the review much research has been done in early, but crucial need reaming to identify appropriate features and optimized classifiers need to predict AD in early stages. We proposed predicate model for Alzheimer Disease using MRI, it can extract Voxel based textural features and optimized DCNN classifier prefer. Proposed model may increase accuracy and it help to improve predication of AD and offset constraints indicate in previous research

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