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RESEARCH ARTICLE

EARLY DETECTION OF ALZHEIMER'S DISEASE USING MACHINE LEARNING TECHNIQUES.

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Abstract

Alzheimer's *Disease* (AD) is believed to be the most widely recognized reason for dementia and it is assessed that lone 1-in-4 individuals with Alzheimer's are accurately diagnose*d* in an opportune manner. While no authoritative fix is accessible, when the weakness is still mellow the side effects can be overseen and treatment is best when it is begun before critical downstream harm happens, i.e., at the phase of mild cognitive impairment (MCI) or considerably prior. *AD* is clinically analyzed by physical and neurological assessment, and through neuropsychological and intellectual tests. There is a need to grow better diagnostic tools, which is the thing that this postulation addresses. *OASIS* is an open access dataset accessible online for improving the determination strategy of *A*lzheimer's malady. Information gathered at meeting is recorded and one point of the work in this theory is to investigate the utilization of machine learning strategies to produce a classifier that can help with screening new people for various phases of AD. Contrasted with the past work processes, our technique is fit for breaking down different classes in a single setting and requires less marked training samples and insignificant *domain* earlier information. A *notable performance* gain on *classification* of all *diagnosis groups* was accomplished in our examinations. The model is prepared at first on *416* analyzed cases got from OASIS database. We at that point test our prepared model on the whole arrangement of *entries provided* by OASIS dataset to affirm the *accuracy* of discovery by our framework. Our outcomes produce 9*4.37*% exactness in AD *detection and classification*.

Introduction:-

Alzheimer's Disease (AD) is a degenerative mind sickness that impacts people and is believed to be the most well-known reason for dementia, however dementia can likewise be brought about by different ailments and conditions. It is portrayed by a decrease in memory, capacity to figure and utilize language, critical thinking and other intellectual aptitudes and these attributes influence an individual's capacity to perform regular exercises. This decrease in human capacities happens in light of the fact that nerve cells (neurons) in the pieces of the mind engaged with intellectual capacity have been harmed and never again work typically. In Alzheimer's illness, neuronal harm in the long run influences portions of the mind that empower an individual to do fundamental substantial capacities, for

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example, strolling and gulping. Alzheimer's Disease is a fatal ailment with no ailment-changing treatment available up 'til now. Dementia is an umbrella term which is utilized to portray a lot of side effects, and there are a wide range of kinds of dementia including Alzheimer's Disease, vascular dementia, dementia with Lewy bodies and others**.** However**,** dementia of the Alzheimer's sort (AD) is by a wide margin the most well-known reason for dementia and this is the kind of dementia this postulation is worried about.

Until this point in time, the conclusion of most types of mental issue has been founded on clinical perception. Explicitly these incorporate the distinguishing proof of manifestations that will in general group together**,** the pace and propensity of the symptoms to resolve, recur or become recurrent**.** There is as of now no solution for Alzheimer's Disease and we do not have any type of solid and powerful early demonstrative instruments**.** Alzheimer's Disease is clinically identified by performing physical and neurological assessments and checking different indications of scholarly disability through standard neuropsychological and psychological tests. The general methodology is based around analysis by disposal, for example administering everything else out until Alzheimer's Disease remains the last alternative. Notwithstanding the above clinical measures, as per Dubois et al. [6] the rules for the determination of Alzheimer's Disease accentuate the job that can be played by utilizing different biomarkers.

These incorporate measures from magnetic resonance imaging (MRI), positron emission tomography (PET), cerebrospinal liquid (CSF) protein profiles just as examination of hereditary hazard profiles. However these are costly and hard to scale to enormous quantities of appraisals. Unmistakably, there is a need to grow better diagnostic tools for Alzheimer's Disease diagnosis, perhaps utilizing data mining and data analysis procedures, which is the thing that we investigate in this thesis. In the event that new medications or aversion methodologies were created and demonstrated to be successful, at that point an early analysis may empower mediation at a prior stage which would be of demonstrated advantage, yet we are still when clinical conclusion is done utilizing just the signs and side effects of the disease and this is gruelling. There is no single test that can show whether an individual has or doesn't have Alzheimer's Disease. While doctors can quite often decide whether an individual has dementia, it might be hard to decide the accurate reason.

Related Work:-

A lot of research has been done for the exact diagnosis of psychological ailments, for example, Alzheimer's as of late, and various approaches have been proposed for this reason. Generally, the data separated from structural and functional brain imaging data or the cerebrospinal liquid is used for a superior determination. In addition, various endeavors have been made for the grouping and prediction of various phases of AD recently. In the accompanying, the absolute most focused works that have been done around there as of late are depicted:

Farouk et al. [2]: The authors have displayed an image analysis strategy for the forecast of Alzheimer's Disease. The system consolidates texture features removed from gray level co-occurrence matrix and voxel-based morphometry neuroimaging analysis to group Alzheimer's sickness patients by the methods of support vector machine classifier. Dataset here that has been used by the authors is ADNI [3].

Khajehnejad et al. [4]: A method is presented for analyzing OASIS [5] dataset. The technique depends on semi-supervised learning which requires just a little level of the dataset as the training data to precisely foresee the labels for the rest of the test information.

Hosseini-Asl et al. [6]: The technique proposed in this paper is fundamentally founded on a 3D convolutional auto-encoder. This is a model which applies deep 3D convolutional neural network to extract AD-related features and gain from them. At long last, the classification assignment is accomplished for various binary combinations of three gatherings of subjects (AD, MCI, and NC) just as a ternary arrangement among them. Here, ADNI dataset is used by the authors.

Moradi et al**.** [7]**:** In this approach, to make another biomarker of MCI to AD change, a semi-supervised learning technique is applied. While performing feature selection by means of regularized logistic regression on the MRI images, the aging impacts are evacuated. At last, for the final classification which is done by using a random forest classifier, the built biomarker is bound together with age and cognitive measures about the MCI subjects utilizing a supervised learning method. Information was obtained from ADNI dataset.

Suk et al. [8]: In this paper, Authors have proposed the strategy for a significant level inactive and shared feature depiction from neuroimaging modalities by means of deep learning. They have utilized Deep Boltzmann Machine (DBM), a deep network with a limited Boltzmann machine as a structure obstruct, to locate a latent hierarchical feature portrayal from a 3D fix, and afterward contrived a precise technique for a joint feature representation from the combined patches of MRI and PET with a multimodal DBM. To approve the viability of the proposed technique, they have performed investigations on ADNI dataset contrasting with the cutting edge strategies.

Savio et al. [9]: Authors have utilized OASIS dataset and performed activities on deformation based features, got from the deformation vectors figured by non-linear registration processes. Feature selection depends on the relationship between the scalar values processed from the deformation maps and the control variable.

Overview of Dataset:-

We have downloaded the general public dataset from Open Access Series of Imaging Studies (OASIS). The URL (Uniform Resource Locator) is http://www.oasis-brains.org/. OASIS contains cross-sectional MRI data, longitudinal MRI data and supplementary data for each subject. During this study, we select the longitudinal dataset in consistent with the MRI scan of individual human beings at a single point in time. The OASIS dataset consists of 416 subjects aged 60 (sixty) to 96 (ninety six).

The dataset includes the below measurements:

Age:
Age at time of image possession (years)

Sex:
Sex (M or F)

Education:
Years of education

SES:
Socioeconomic Status as assessed by the Hollingshead Index [10] of Social Position and classified into orders from 1 (highest status) to 5 (lowest status)

MMSE:
Mini-Mental State Examination score (range is from 0 = worst to 30 = best)

CDR:
Clinical Dementia Rating (0 = no, 0.5 = very mild, 1 = mild, 2 = moderate)

ASF:
Atlas Scaling Factor (unitless). Quantified scaling factor that converts native-space brain and skull to the atlas target (i.e., the determinant of the transform matrix)

ETIV:
Estimated Total Intracranial Volume (cm3)

NWBV:
Normalized Whole-Brain Volume, expressed as a percent of all voxels within the atlas-masked image that are tagged as gray or white matter by the automated tissue segmentation procedure.

Machine Learning Tools and Scikit-Learn:-

The programming alternatives we took a gander at included Python with the mainstream SciKit-Learn library [11]. This again is open source and normally tops surveys, for example, those on the KDnuggets site [12] identifying with use of machine learning languages. An elective programming language we considered was the Statistical language R, however Python was our favored decision, fundamentally in view of the SciKit-Learn library augmentations and

the documentation accessible with it. Since its discharge in 2007, scikit-learn has gotten one of the most mainstream open source machine learning libraries. Scikit-Learn (likewise called sklearn) provides algorithms for machine learning tasks including classification, regression, dimensionality reduction and clustering. It likewise gives utilities to feature extraction, handling information and assessing models. It gives in-constructed code to a large number of algorithms. The documentation for Scikit-Learn is extensive, famous and very much kept up. Sklearn is based on developed Python Libraries, for example, NumPy [13], SciPy [14], and Matplotlib [15]. It has a functioning improvement network with regular update arrivals of the library.

Feature Extraction:-

We have followed the following steps for suitable extraction:

1. At first we have downloaded the data from the OASIS website**.** Then we have observed the dataset and identified the unnecessary entries. After that we have cleaned those unnecessary entries.
2. Thus the standardization of the dataset is performed by obtaining a standard scale.
3. Finally, the dependent and non-dependent variables of the dataset are figured out.

After completing the above steps we derive a prepared dataset. The dataset is given below:

```
In [101]: data.head()
```

Out[101]:

	Group	M/F	Age	EDUC	SES	MMSE	eTIV	nWBV	ASF
0	0	1	87	14	2.0	27.0	1987	0.696	0.883
1	0	1	88	14	2.0	30.0	2004	0.681	0.876
5	0	0	88	18	3.0	28.0	1215	0.710	1.444
6	0	0	90	18	3.0	27.0	1200	0.718	1.462
7	0	1	80	12	4.0	28.0	1689	0.712	1.039

Figure 6:-Sample data

Data Visualization:-

Analyzing the dataset we have found certain correlations among the entries. This indicated in the heat-map below:

```
In [67]: sns.heatmap(tc, annot=True,cmap='coolwarm')
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x7f612dafd470
```

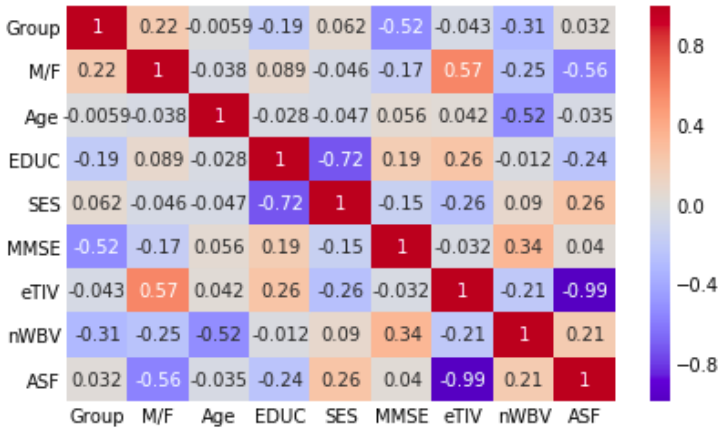

Figure 7:-Heat-map

The correlation among eTIV and MMSE is given below:

```
In [104]: sns.lmplot(x='MMSE',y='eTIV',data=data,hue='M/F',markers=['o','v'],scatter_kws={'s':100})
Out[104]: <seaborn.axisgrid.FacetGrid at 0x7f6123a95b70>
```

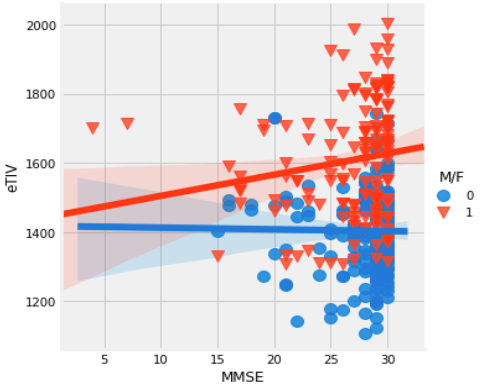

Figure 8:-eTIV-MMSE correlation

The age of the subjects can be visualized by a distribution plot:

```
sns.distplot(data['Age'], kde=False,bins=30)
<matplotlib.axes._subplots.AxesSubplot at 0x7f6131705780>
```

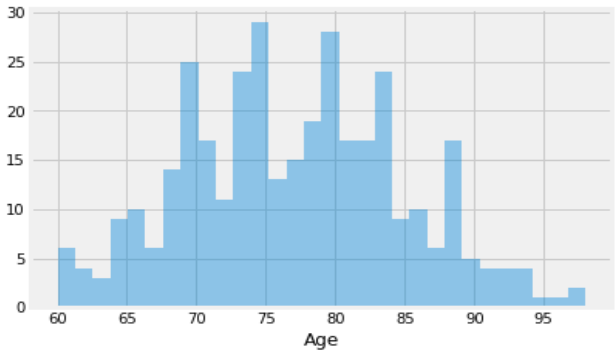

Figure 9:-Age visualization

A box-plot can be derived from education-socioeconomic status regarding male and female subjects:

```
In [26]: sns.boxplot(x='SES',y='EDUC',data=data,hue='M/F')
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6131d57f98>
```

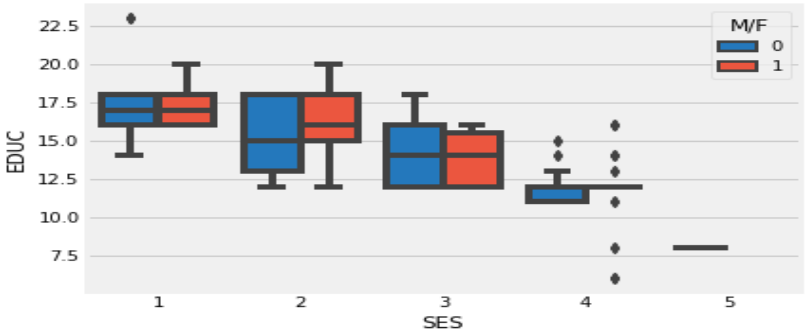

Figure 10:-EDUC-SES visualizatio

Model Evaluation:-

Step 1:

Initially, we haphazardly separate our available data into two subsets: a preparation and a test set. Putting test data aside is a work-around for managing the defects of a non-perfect world, for example, constrained information and assets, and the failure to gather more information from the generating distribution. Here, the test set will speak to new, inconspicuous data to the model; it is significant that the test set is possibly utilized once to abstain from introducing bias when we assess the generalization performance.

Commonly, we assign 80% to the preparation set and 20% of the data to the test set. Other regular preparing/test parts are 60/40, 70/30 or even 90/10 if the dataset is relatively enormous.

Step 2:

In the wake of setting test sample aside, we pick a learning algorithm that we think could be suitable for the given issue. Our learning algorithm consists of parameters titled Hyperparameters**.** Furthermore, we need to determine these hyperparameter values manually – the learning algorithm doesn't take in these from the training data as opposed to the genuine model parameters. Since hyperparameters are not learned during model fitting, we need a type of "additional method" to advance these independently – this holdout approach is less suited for the errand. In this way, for the time being, we need to go with some fixed hyperparameter values – we could utilize our instinct or the default parameters of an off-the-rack algorithm in the event that we are using a current machine learning library.

Step 3:

After the learning algorithm fit a model in the past advance, the following question is: How "great" is the performance of the subsequent model? This is the place the autonomous test set becomes possibly the most important factor. Since the learning algorithm has not "seen" this test set previously, it ought to give a moderately fair-minded gauge of its performance on new, concealed data. Presently, we step through this test set and utilize the model to anticipate the class names. At that point, we take the anticipated class names and contrast them with the "ground truth," the right class names, to appraise the model's generalization correctness or error.

Step 4:

At last, we acquired a gauge of how well our model performs on inconspicuous data. Thus, there is no explanation behind with-holding the test set from the algorithm any more. Since we expect that our examples are i.i.d., there is no motivation to accept the model would perform less well in the wake of bolstering it all the accessible information. As a dependable guideline, the model will have a superior generalization performance if the algorithms utilize more educational data – expecting that it has not arrived at its ability, yet.

Result Analysis:-

Accuracy:

Accuracy in classification issues is the quantity of right expectations made by the model over different sorts forecasts made.

Precision:

Precision is a measure that reveals to us what extent of patients that we analyzed as having Alzheimer's, really had Alzheimer's.

Recall or Sensitivity:

Recall is a measure that implies what percentage of victims that really had Alzheimer's was detected by the algorithm as having Alzheimer's.

Specificity:

Specificity is a measure that discloses to us what amount of patients that didn't have Alzheimer's, were anticipated by the model as non-Alzheimer.

F1 Score:

We would prefer truly not to convey both Precision and Recall in our toolbox each time we make a model for tackling a classification issue. So it's ideal in the event that we can get a solitary score that sort of speaks to both

Precision (P) and Recall(R). One approach to do that is essentially taking their arithmetic mean. For example (P + R)/2 where P is Precision and R is Recall.

Table 1:-Comparison of Algorithms

Sl No.	Algorithm	Accuracy (%)	Precision (%)	Recall (%)
1	SVM	94.37	93.94	93.94
2	Random Forest	84.12	97.14	68
3	Adaboosting	88.73	87.88	87.88
4	Artificial Neural Network	83.09	88.88	72.72

Comparison with Previous Works:-
After determining the accuracy of our model, we can compare the study with previous works. A comparison shown in the below table indicates that our proposed method gives better performance than others.

Table 2:-Performance Comparison

Sl. No	Authors	Year	Dataset	Method	Accuracy (%)
1	Our Proposed Method	2019	OASIS	Supervised learning (SVM)	94.37
2	Farouk et al. **[**2**]**	2018	ADNI	Supervised learning	88.00
3	Khajehnejad et al. **[**4**]**	2017	OASIS	Semi-supervised method	93.86
4	Hosseini-Asl et al. **[**6**]**	2016	ADNI	10-fold cross-validation	90.80
5	Moradi et al. **[**7**]**	2015	ADNI	10-fold cross-validation	82.00
6	Suk et al**.** [8]	2014	ADNI	10-fold cross-validation	85.70
7	Savio et al. [9]	2011	OASIS	10-fold cross-validation	84.00

In the above comaprison we can see that our proposed model yields considerbale amount of better accuracy than the other models. Among the other models related to OASIS, the model provided by Khajehnejad et al. **[**4**]** has an accuracy of 93.86% using Semi-supervised learning. It is way better than the previous work conducted on the same dataset by Savio et al. [9]. Using 10-fold cross-validation method**,** the model obtained an accuracy of 84%. On the other hand, amongst the researches done on ADNI dataset, the model proposed by Hosseini-Asl et al. **[**6**]** has the most accuracy. It has 90.80% accuracy using 10-fold cross-validation technique. It is clear that the model proposed by us consists of the highest accuracy of 94.37% using SVM . Not only it has such accuracy over OASIS dataset but also it is better than the accuracy attained on other datasets like ADNI (Alzheimer's Disease Neuroimaging Initiative (ADNI). Thus the proposed model performs a better job on regarding the early diagnosis of Alzheimer's Disease.

Conclusion:-

Early discovery of Alzheimer's can prompt halting or easing back the progression of Alzheimer's Disease. Existing work in early diagnosis of AD has been in part fruitful at perceiving AD, yet as far as anyone is concerned, nobody has endeavored such classification into various levels of AD. We have built up an AD diagnosis framework by employing the mathematical technique related with machine learning. Despite the fact that our model gives better bits of knowledge for detecting Alzheimer's at an early age, it is restricted to the OASIS dataset. A greater dataset could assist us with giving progressively rigid outcomes. Our point by point testing on the OASIS dataset accomplishes improved identification rate of 94.37%. Since our framework utilizes SVM (Support Vector Machine), we are confident that if a bigger training data (than the 416 subjects) is utilized to prepare the machine learning model, the classification accuracy will be much higher.

Future Work:-
In the current study we used the clinical data which included neuropsychological assessments, demographic information, physical and neurological examination, cognitive assessments, patient medical history and baseline diagnosis and symptoms**.**

1. In the future, we will try to develop an embedded system with real time data feeds. The device will automatically collect necessary information from the subjects through wearable sensors. Then it will use the data against the machine learning model for disease diagnosis.
2. Also we can use more advanced brain images in conjunction with the clinical data to improve the diagnosis and the prediction processes.

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