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Comparative Analysis of Machine Learning Models over Alzheimer's Disease Suspected MRI Images

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ABSTRACT

Alzheimers disease (AD) is neurodegenerative disease and pathogenesis that primarily affects older age people and is the common cause of dementia. The first manifestation of Alzheimer's disease is selective memory impairment. Although some symptoms can be relieved by treatment, but there is currently no cure. Modern day diagnostics uses Magnetic Resonance Imaging (MRI) of patients' brain with suspected AD. Using Machine Learning (ML) techniques to accurately predict a patient's progression from mild cognitive impairment to dementia could be one of the boosting steps in the medical sciences. This could advance the early detection process of the non-curable condition. This paper presents the application of different ML models on the brain MRI images for detecting Alzheimer's disease and also carried out the comparison among the results of them. AD detection is carried out by using 3 techniques namely SVM, Random Forest and KNN, resulting in accuracies of 81.5, 86.84 and 70% respectively.

Keywords: Alzheimers disease (AD), Magnetic Resonance Imaging (MRI), Support Vector Machines (SVM), K-Nearest Neighbors (KNN)

I. INTRODUCTION

Dementia is a form of brain condition that causes problems with memory, thinking and behaviour of a person. Symptoms develop gradually and become worse over time, severe enough to interfere with daily routine. Dementia is not a part of normal aging. The greatest known risk factor is advanced age, with most patients with Alzheimer's disease being aged 65 and over. But Alzheimer's disease is not just a disease of old age. About 200,000 Americans under the age of 65 have early-onset Alzheimer's disease (also called early-onset Alzheimer's disease).

Figure 1 shows the human brain conditions with (severe) and without dementia (normal)[6]. The brain with severe demented condition possesses more shrinkage of cortex and hippocampus along with enlarged ventricles when compared with the normal brain with no dementia.

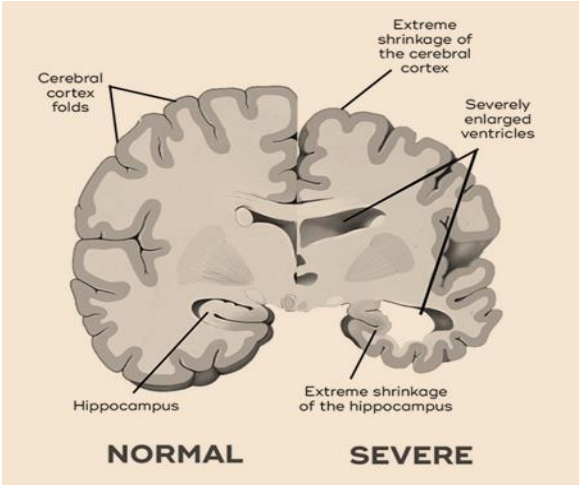

Fig.1. Human Brain condition with and without Dementia[15]

Alzheimer's disease is the sixth major reason of death in the US. People with Alzheimer's symptoms live an average of 8 years after others notice them, but this ranges from 4 to 20 years, depending on age and other health conditions [8].

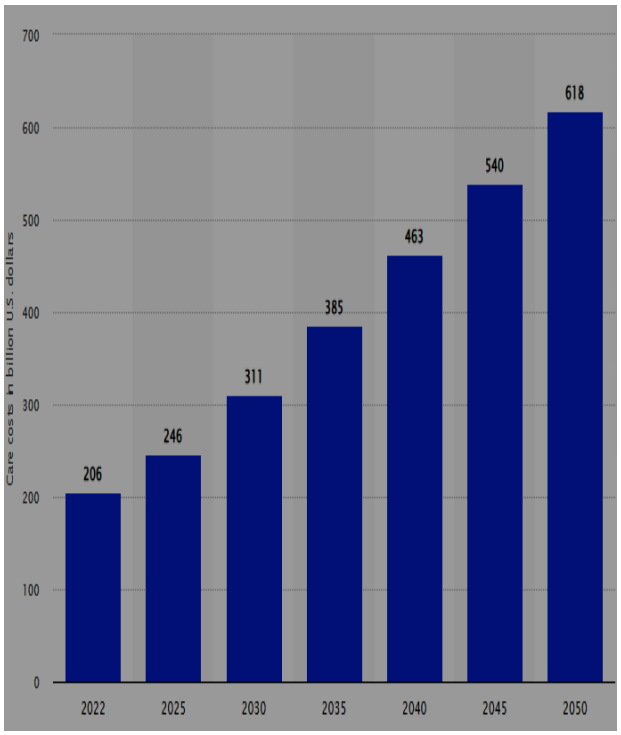

Fig.2. The Alzheimer's costs of Medicare and Medicaid until 2050[17].

There is currently no cure for Alzheimer's disease, but there are treatments for the symptoms and research is ongoing. Although current treatments for Alzheimer's disease cannot halt the progression of the disease, they can temporarily slow the worsening of dementia symptoms and improve the quality of life of patients with Alzheimer's disease and their caregivers. Regressive research is going on to find better ways to diagnose and treat the disease, delay its onset and prevent its progression.

II. LITERATURE REVIEW

A review presented by Peter J Nester et.al. [7] describes the combined aging of the population and the prospects for disease-modifying therapies that will become available in the near future. The early stages of Alzheimer's disease (AD) are characterized as an active research topic. This study reviews recent advances in our understanding of the course of early AD with specific reference to symptomatic pre-dementia termed 'mild cognitive impairment', focusing on early cognitive profiles and neuro-imaging efforts related.
Luis Javier [1] addressed two distinct problems: the first is to develop a classification. Classify MRI images into normal or Alzheimer affected images, and the second class is used for identification and classification between normal subjects, MCI patients and AD patients. This work provided a tool to help in the early diagnosis of dementia. Outlines of the method include wavelet feature extraction from MRI using support vector machines, dimensionality reduction, test-train splitting, and classification.
[3] Suhad et.al. presented a brief literature review on Alzheimer's disease detection using deep learning techniques. [9] A deep learning model with stacked auto encoders and softmax layer to detect AD and Mild Cognitive impairment (MCI) having capacity to analyze multiple classes in one setting along with less labeled data with minimum prior domain information, had achieved high classification accuracy.[10] M. Khojaste-Sarakhsi et.al. presented comparative analysis among the alzheimer's disease detection techniques focusing on challenges categorized and explained from data-related, methodology-related, and clinical adoption aspects.

III. PROPOSED WORK

The work consists of applying Machine learning techniques to the dataset of different of groups and compared the classification accuracy of each algorithm. The MRI images of group of 150 subjects having age 60 to 96 years taken for the classification. Each subject was scanned at two or more visits, at least one year apart, for a total of 373 imaging sessions. For each subject, include 3 or 4 separate T1-weighted MRIs acquired in a single scanning session. The subjects were all right-handed, male and female. Throughout the study, 72 subjects were characterized as not having dementia. Sixty-four of the subjects were described as having dementia at their initial visit and remained so on subsequent examinations, including 51 people with mild to moderate Alzheimer's disease. Fourteen additional subjects were characterized as not demented at the initial visit and then characterized as demented at a subsequent visit. We will be using the following algorithms to track the detection of Alzheimer's disease:-

- SVM
- RANDOM FOREST ALGORITHM
- KNN

Using the following dataset and using these algorithm we will detect individual is suffering from Alzheimer or not.

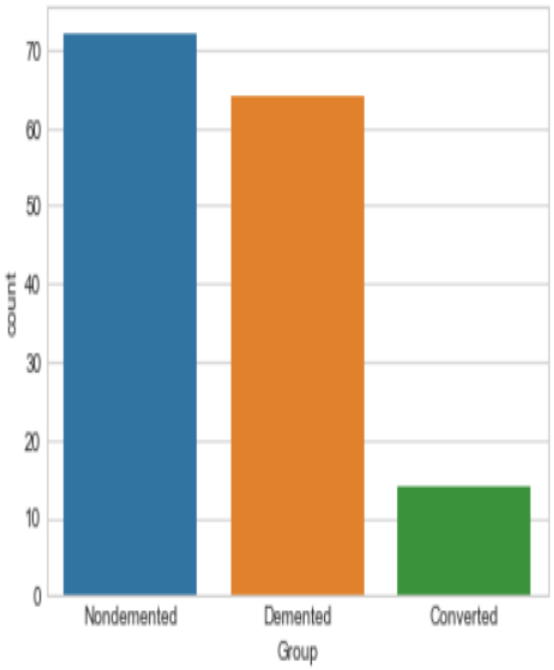

Fig 3. Individual Data Set of different groups

III.a Data Description

We used longitudinal MRI data. Fig. 3 represents the counts of demented, non demented and converted groups.
- Dataset contains longitudinal MRI data from 150 subjects aged 60-96.
- Every subject has been scanned at least once.
- Everyone is right-handed. Throughout the study,
- 72 subjects were classified as having "dementia".
- 64 subjects were classified as "disordered" at initial visit and remained so throughout the study.
- 14 subjects classified as "unbalanced" at initial visit and subsequently "unbalanced" at subsequent vi- sits. It falls into the "converted" category.

COL - Description
EDUC - Years of Education
SES - Socioeconomic Status
MMSE - Mini Mental State Examination
CDR - Clinical Dementia Rating
eTIV - Estimated Total Intracranial Volume
nWBV - Normalize Whole Brain Volume
ASF - Atlas Scaling Factor

III.b Mini–Mental State Examination (MMSE)

The Mini-Mental State Examination (MMSE) or Folstein test is a 30-item questionnaire widely used in clinical and research settings to measure cognitive impairment. It is commonly used in medicine and related health fields to screen for dementia. It is also used to estimate the severity and progression of cognitive impairment and to track the progression of an individual's cognitive changes over time, making it an effective method for documenting an individual's response to treatment. The MMSE itself is not intended to provide a diagnosis for a specific nosological entity.

III.c Cognitive Impairment

When a person has trouble remembering, learning new things, concentrating, or making decisions that affect their daily life, it is called cognitive impairment. Any score greater than or equal to 24 out of 30 indicates a normal level of cognition. The following scores may indicate severe (≤9 points), moderate (10-18 points), or mild (19-23 points) cognitive impairment. Raw scores may also need to be corrected for education and age. That said, a maximum score of 30 can never rule out dementia.

Method	Score	Interpretation
Single Cutoff	<24	Abnormal
Range	<21	Increased Odds of Dementia
	<25	Decreased Odds of Dementia
Education	21	Abnormal for 8th Grade Education
	<23	Abnormal for High School Education
	<24	Abnormal for College Education
Severity	24-30	No Cognitive Impairment
	18-23	Mild Cognitive Impairment
	0-17	Severe Cognitive Impairment

Fig 4. Cognitive Impairment

III.d Clinical Dementia Rating (CDR)

The CDR is a 5-point scale that characterizes six domains of cognitive and functional performance applicable to Alzheimer's disease and related dementias: memory, orientation, judgment and problem solving, community affairs, family, leisure, and self-care. The information required for each assessment was obtained through semi-structured interviews with patients and reliable informants or indirect sources such as family members. The CDR form provides descriptive anchors to guide the clinician in making an appropriate assessment based on interview data and clinical judgment. In addition to the ratings for each domain, an algorithm can

be used to calculate an overall CDR score. This score can be used to describe and track a patient's level of disability/dementia:

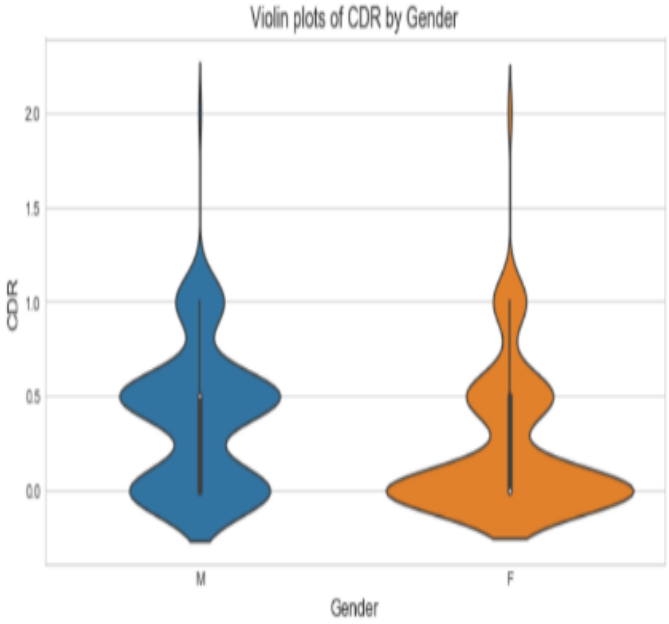

Fig 5.CDR violin graph

Score	Description
0	Normal
0.5	Very Mild Dementia
1	Mild Dementia
2	Moderate Dementia
3	Severe Dementia

Fig 6.CDR score and description

III.e Estimated Total Intracranial Volume(eTIV)

Total intracranial volume (TIV/VCI) is an important covariate in the analysis of brain volume and brain regions, particularly in the study of neurodegenerative diseases, where it can provide an approximation of premorbid peak brain volume.

1. Unlike brain atrophy in AD patients, TIV does not change over time. Mean TIV did not differ significantly between subject groups. There was no association between TIV and age or age at symptom onset. The only significant predictor of TIV was gender. Men had 12% more eTIV than women.
2. We measured TIV using a semi-automated segmentation technique on T1- and T2-weighted MRI images of 55 controls, 10 patients with AD, and two individuals at risk for familial AD. Whole brain volumes were also measured and normalized using the VTI.
3. TIV normalization of cross-sectional brain volumes significantly reduced interindividual variability; the coefficient of variation (CV) in the control group decreased from 10.0% to 6.0% ($P < 0.001$). The VTI measured on T1-weighted images had low variability (CV, 0.16%) and was not significantly different from the VTI measured on T2-weighted images ($P = 0.16$). In 10 controls and 5 AD patients, TIV normalization of serial brain volume measurements reduced frame-to-frame variability caused by voxel-scale variation (CV decreased by 1. 3% to 0.5%, P=0.002).

III.f Atlas Scaling Factor (ASF)

A Unified Approach to Analyzing Morphometric and Functional Data of Young, Older, and Demented Adults Using Automatic Atlas-Based Head Size Normalization: Reliability and Validation Against Total Intracranial Volume of Head Size the head measured manually.
Basically, the total intracranial volume was found to be related to the determinants of the transformation matrix used to align the image with the atlas. This work shows that a one-parameter scale factor provides a reasonable estimate of the TIV.

III.g Work

The goals of our project are:-

1. Predicting Alzheimer's disease.
2. Using different models to make predictions.
3. Finding the best predictive model for the data.

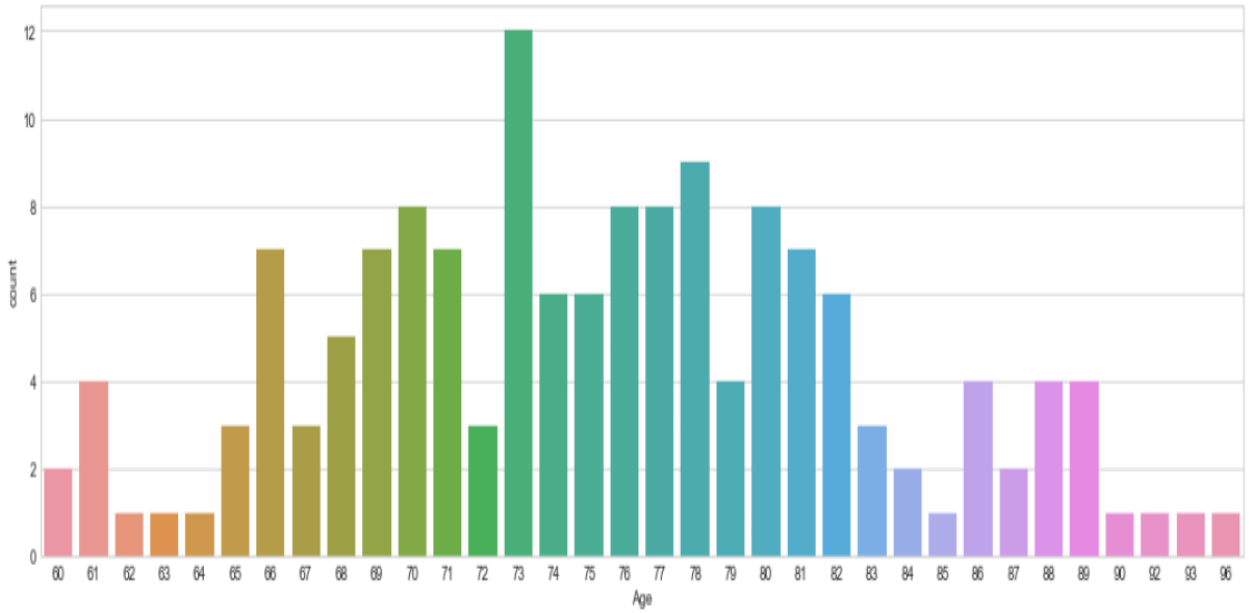

Fig 7. Dataset age count

STEP 1.CLEANSING

We inspect the data to identify the data problems, null values and outliers. We have to solve identified problem to begin the analysis without any problem. There are few null values which were taken care of. We have used numerous libraries for an entire process like data exploration and visualization.

Let's understand the process of getting the best hyper parameters. First of all we need to make sure the data is clean i.e. we need to remove null values from the data set. There are many ways to suppress null values in a dataset.

1) We can try to drop the column with the most null values in the dataset. These columns may be irrelevant and have little meaning to the data.

2) If there are zero values in the column, We try to remove them by replacing the zero values with mean, median or mode etc. It depends on the value in the column.

3) If there are categorical values in the dataset, these values can be replaced using a hot encoding method. Hot encoding is the way to which categorical variables are transformed into form that can passed to ML algorithms for better prediction.

Once we are sure that all null values are handled, we can start further analysis

	A	B	C	D	E	F	G	H	I	J	K	L
1	ID	M/F	Hand	Age	Educ	SES	MMSE	CDR	eTIV	nWBV	ASF	Delay
2	OAS1_000	F	R	74	2	3	29	0	1344	0.743	1.306	N/A
3	OAS1_000	F	R	55	4	1	29	0	1147	0.81	1.531	N/A
4	OAS1_000	F	R	73	4	3	27	0.5	1454	0.708	1.207	N/A
5	OAS1_000	M	R	28					1588	0.803	1.105	N/A
6	OAS1_000	M	R	18					1737	0.848	1.01	N/A
7	OAS1_000	F	R	24					1131	0.862	1.551	N/A
8	OAS1_000	M	R	21					1516	0.83	1.157	N/A
9	OAS1_000	F	R	20					1505	0.843	1.166	N/A
10	OAS1_001	M	R	74	5	2	30	0	1636	0.689	1.073	N/A
11	OAS1_001	F	R	52	3	2	30	0	1321	0.827	1.329	N/A
12	OAS1_001	M	R	30					1574	0.842	1.115	N/A
13	OAS1_001	F	R	81	5	2	30	0	1664	0.679	1.055	N/A
14	OAS1_001	F	R	19					1525	0.856	1.151	N/A
15	OAS1_001	M	R	76	2		28	0.5	1738	0.719	1.01	N/A
16	OAS1_001	M	R	82	2	4	27	0.5	1477	0.739	1.188	N/A
17	OAS1_001	M	R	21					1689	0.845	1.039	N/A
18	OAS1_001	M	R	39	3	4	28	0	1636	0.813	1.073	N/A
19	OAS1_001	F	R	89	5	1	30	0	1536	0.715	1.142	N/A
20	OAS1_002	F	R	48	5	2	29	0	1326	0.785	1.323	N/A
21	OAS1_002	F	R	80	3	3	23	0.5	1794	0.765	0.978	N/A
22	OAS1_002	F	R	69	2	4	23	0.5	1447	0.757	1.213	N/A
23	OAS1_002	M	R	82	2	3	27	0.5	1420	0.71	1.236	N/A
24	OAS1_002	F	R	24					1240	0.893	1.415	N/A
25	OAS1_002	F	R	58	5	1	30	0	1235	0.82	1.421	N/A
26	OAS1_002	F	R	43					1194	0.834	1.47	N/A
27	OAS1_002	F	R	86	2	4	27	1	1449	0.738	1.211	N/A

Fig.8 Before Cleaning (having null values)

	A	B	C	D	E	F	G	H	I	J	K	L
1	ID	M/F	Hand	Age	Educ	SES	MMSE	CDR	eTIV	nWBV	ASF	Delay
2	OAS1_000	F	R	74	2	3	29	0	1344	0.743	1.306	N/A
3	OAS1_000	F	R	55	4	1	29	0	1147	0.81	1.531	N/A
4	OAS1_000	F	R	73	4	3	27	0.5	1454	0.708	1.207	N/A
5	OAS1_001	M	R	74	5	2	30	0	1636	0.689	1.073	N/A
6	OAS1_001	F	R	52	3	2	30	0	1321	0.827	1.329	N/A
7	OAS1_001	F	R	81	5	2	30	0	1664	0.679	1.055	N/A
8	OAS1_001	M	R	76	2		28	0.5	1738	0.719	1.01	N/A
9	OAS1_001	M	R	82	2	4	27	0.5	1477	0.739	1.188	N/A
10	OAS1_001	M	R	39	3	4	28	0	1636	0.813	1.073	N/A
11	OAS1_001	F	R	89	5	1	30	0	1536	0.715	1.142	N/A
12	OAS1_002	F	R	48	5	2	29	0	1326	0.785	1.323	N/A
13	OAS1_002	F	R	80	3	3	23	0.5	1794	0.765	0.978	N/A
14	OAS1_002	F	R	69	2	4	23	0.5	1447	0.757	1.213	N/A
15	OAS1_002	M	R	82	2	3	27	0.5	1420	0.71	1.236	N/A
16	OAS1_002	F	R	58	5	1	30	0	1235	0.82	1.421	N/A
17	OAS1_002	F	R	86	2	4	27	1	1449	0.738	1.211	N/A
18	OAS1_003	F	R	65	2	3	29	0	1392	0.764	1.261	N/A
19	OAS1_003	M	R	88	1	4	26	1	1419	0.674	1.236	N/A
20	OAS1_003	M	R	89	4	1	28	0	1631	0.682	1.076	N/A
21	OAS1_003	F	R	80	4	2	29	0	1323	0.735	1.326	N/A
22	OAS1_003	M	R	51	5	1	29	0	1538	0.831	1.141	N/A
23	OAS1_003	F	R	84	3	2	28	1	1402	0.695	1.252	N/A
24	OAS1_003	M	R	70	4	3	29	0.5	1463	0.772	1.2	N/A
25	OAS1_004	F	R	62	2		28	0.5	1350	0.758	1.3	N/A
26	OAS1_004	M	R	80	4	2	29	0.5	1854	0.709	0.947	N/A
27	OAS1_004	F	R	47	4	2	30	0	1346	0.829	1.304	N/A

Fig.9 After cleaning (no null value)

Here we have omitted several visits to avoid confusion and only the first visit is taken into account. We also

convert the string value to a binary or numeric equivalent to complete the process. Here is a visualization of the male to female ratio:

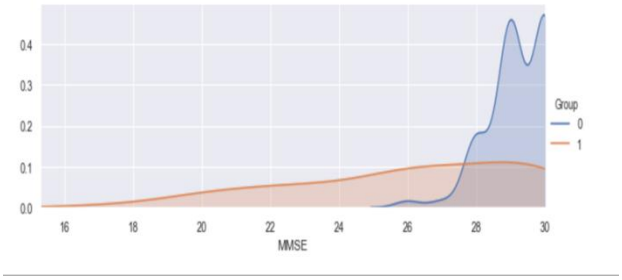

Fig 10. Male and female demented graph

From the graph above, we can see that there are almost equal numbers of males and females with dementia. On the other hand, we note that there are fewer non-demented women than men This suggests that men can have Alzheimer more likely than women to develop disease. Above is a graphical comparison of the Mini-Mental State Exam (MMSE) with max score of 30 points. The graph above shows that the group without dementia had more high MMSE scores than the group with disease. From various graphs, We concluded that the non demented group have a higher brain volume ratio than demented group. It is believed to be because the disease affects the brain, causing its tissues to be shrink. In addition, we draw the following conclusions from the graph:

1) Men are more likely to have dementia, a type of Alzheimer's disease, than the women.
2) People with dementia have fewer years of education.
3) The brain volume of the group without dementia is greater than that of the group with dementia.
4) The group of 70-80 year olds in the dementia group is higher than that of the non-dementia group.

STEP 2.MODELS

Here we have created a total of 3 models with the following results:

a. SVM

A support vector machine (SVM) is a discriminating classifier formally defined by a separating hyper plane. In other words, given labelled training data (supervised learning), the algorithm generates a hyper plane to best classify new examples. In two dimensions, this hyper plane is a line that cuts the plane in two, with a class on each side. The goal of the support vector machine algorithm is to find a hyper plane in an N-dimensional space (N - number of features) that can unambiguously classify the data points. In this pattern, I repeat the values of the c and kernel parameters. We are using cross validation to get the accuracy score. We rebuild the model with the best parameters to get the best score. After successfully building the model, the SVM gave an accuracy of 81.5%.

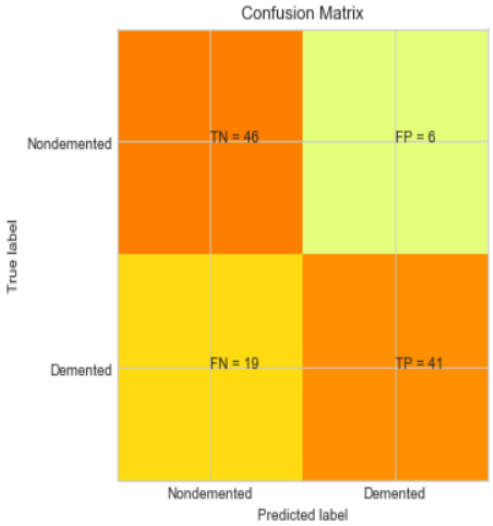

Fig.11. Confusion Matrix of SVM

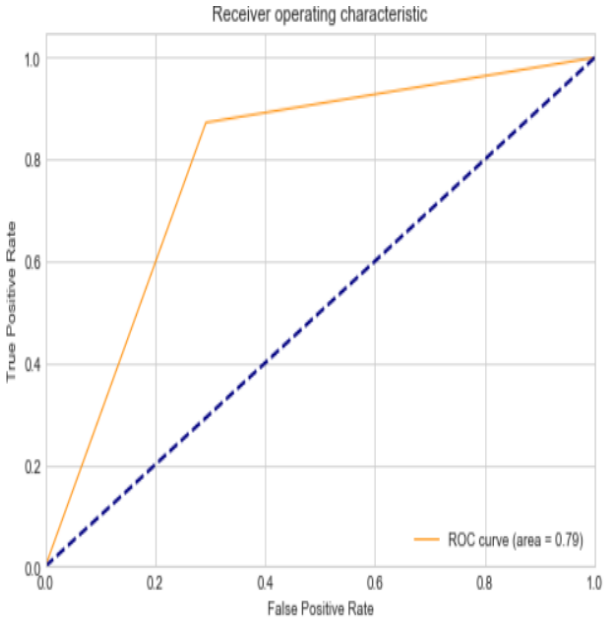

Fig.12.Receiver operating characteristic

b. RANDOM FOREST

Random forests or random decision forests are ensemble learning methods for classification, regression and other tasks by creating ensembles of decision trees during training and generating class models (classification) or individual mean predictions (regression) of trees. Random decision forests correct the habit of decision trees to over-fit their training set. This modeling method is the same as the previous one. But here we got an accuracy of 86.84%.

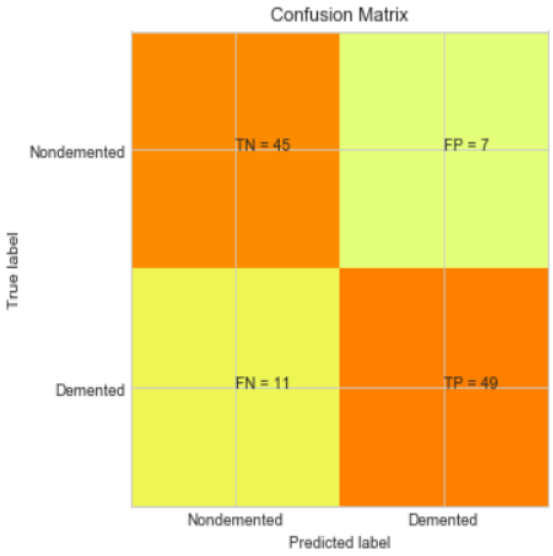

Fig.13. Confusion Matrix of Random Forest

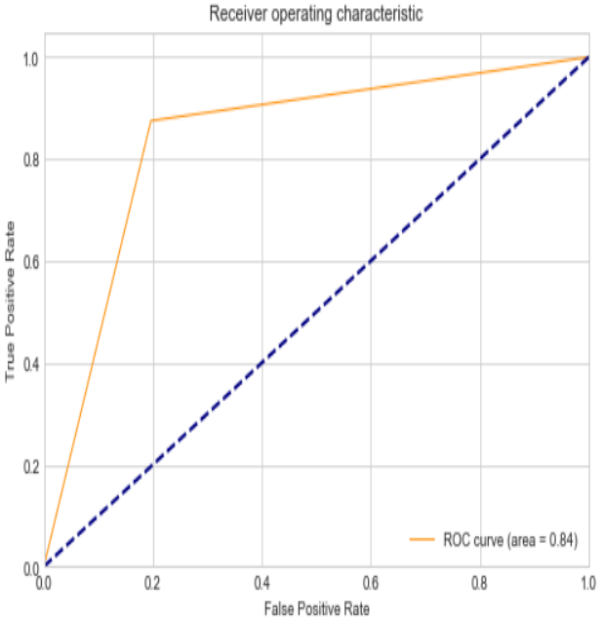

Fig.14. Receiver operating characteristic

c. KNN

K Nearest Neighbors is a simple algorithm that stores all available instances and ranks new instances based on some degree of similarity (e.g. distance function). In the early 1970s, KNN was used as a nonparametric technique for statistical estimation and pattern recognition. Cases are ranked based on the majority votes of their neighbors, and cases are assigned to the most common class among their K nearest neighbors, as measured by a distance function. If K = 1, a case is simply assigned to the class of its nearest neighbor. In this model, data is divided into training and testing. The data were trained on the K-Neighbors classifier and the model was evaluated on the predictions. Here we get an average accuracy of 70%.

IV.CONCLUSION

After going through the all of the analysis we get to see the accuracy or precision of different models. The accuracy is as followed:
SVM = 81.5%
Random Forest = 86.84%
KNN = 70%
Hence, we conclude that Random Forest model is the well model for this data set. It is very simple and efficient compared to all other models.

Parameter	Random Forest Algorithm	SVM Algorithm	KNN Algorithm	Reason
Classification Accuracy	86.4 %	73%	71.2 %	Here, random forest has the highest accuracy. Hence, it is the best model for this data set.
Classification Error	3.7 %	8%	7%	The sum distance of error points to the separation plane is high in SVM model which results in high classification error.
Precision	80.3 %	73%	71.3 %	Random forest algorithm returns more relevant results than irrelevant ones as compared to the other ones.
AUC	High	Low	Low	The classifier can perfectly distinguish between all the Positive and the Negative class points.
Specificity	High	Low	Low	Random forest model's ability to predict true negatives of each available category is comparatively high.
Sensitivity	78%	83.2 %	84.6 %	KNN can be very sensitive to the scale of data as it relies on computing the distances of points.
F - Measure	High	Low	Low	The intuition for F-measure is that both measures(worst and

				perfect) are balanced in Random Forest Algorithm.
Total Accuracy	86.84%	81.5 %	70%	Random Forest is the best model for this data set as it has highest accuracy.

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