

DemCare Application for Dementia Diagnosis Using Machine Learning Classifiers

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ABSTRACT

Technology-based solutions have revolutionized people's lives in a more stable and safer environment in every area and service. Solutions to prevent, manage and detect certain diseases are also applied. The suggested system presents a technological approach to facilitate and support people with dementia. This study effort offers support for day-to-day regular tasks, dose medicines, particularly to aid individuals with Dementia suffering from worry and tension. Furthermore, the system contains Quiz Games for the recall of patient history, monitoring and monitoring of caregivers from wherever in the event of patient confusion. The method presented also comprises brain imaging through MRI, for the testing of probable dementia patients. MRI results show a shrinking of brain tissues both locally and generally. But physicians and scientists need to utilize a machine learning methodology to precisely anticipate the patient's development from moderate impairment to dementia to achieve this.

Keywords - Demcare, caretaker application, dementia disease, android, smartphone, MRI (Magnetic Resonance Imaging), machine learning techniques.

Introduction

Health services are of primary importance to individuals trying to alter and help people through technology. Increased technology-based solutions are driven by the world's ageing population. Older population for today's developing and developed worlds is one of the dreadful issues. For long-term independence and robustness, it necessitates a trustworthy solution. The emergence of wireless and omnipresent technology provides ageing society a tremendous potential [26].

Since we can observe individuals living with dementia have a short-term memory, they confront certain typical challenges like getting away, having no food, forgetting the faces and names of their families. To fix this problem, have with you a caregiver, who cares for you and helps you all day long.

What if an application takes care of the patient rather than the human caregiver, helping the patient remember the faces/names, reminding them of medications, keeping them in line with the Plan, etc. Plan. Patients also might assess their progress reports by means of a questionnaire the problem contest will assist him to boost the functioning of the brain. This application is intended as far as possible to make patients autonomous [27].

We have developed a proposal to help the elderly and caregivers. We have devised and developed our suggested Demcare system for adults up to the fourth stage of dementia.

Stage	Description
Stage-1	Cognitive activities do not decline
Stage-2	Very little decrease in cognitive activity (Not noticed)
Stage-3	Modern decrease in cognitive activity
Stage-4	Reduce cognitive activity from moderate to modest
Stage-5	Declines in cognitive activities moderate and serving

Stage-6	Cognitive activities serve decreases (Middle Dementia)
Stage-7	Very Serve Condition Dementia (Serve Dementia)

Table.1. Stages of Dementia

Machine learning is an efficient technique based on training and testing. The ML is effective and efficient in field. It is a subsection of Artificial Information (AI) centred on the objective of prediction. One of the large fields of machine learning is for machines to penalise the development, empower or teach human capabilities for further predictive analyses using past data. Machine learning systems, on the other hand, are taught in processing and data utilisation. Machine learning is named this combination technique. The algorithm for machine learning needs proper training and testing information. The performance of the models can be improved if the machine learning model is given balanced data. Moreover, if relevant characteristics are picked from a data collection, the capacity and accuracy of the prediction model may be increased. A balanced data collection and the selection of functions are essential to increasing the performance of the model. In addition, the machine learning technique that was addressed in this research is employed for the prediction of dementia.

A complete research has been proposed in this work to diagnose dementia utilizing machine study methods. This section contains a related work. Neuroimaging of Dementia Disease Initiative datasets to compare different selection techniques utilizing anatomical brain anatomical dementia learning MRI. SVM and logistic regression as classifiers are utilized and it has been demonstrated that the removal of age enhances the average accuracy for all classifiers after application of features [28].

In general, the diagnosis of dementia has three phases. The first step is MMSE testing of cognitive capacity (Mini-Mental state Examination). The second part consists of a neuropsychological test for those who are not generally diagnosed in the screening. The ultimate stage is the diagnosis of dementia or cognitive moderation. After the third phase the suspicious patients will be diagnosed using MRI or CT. There are patients therefore categorized into normal, MCI and dementia groups [29].

We present in this research Early dementia model of two layers, which is based on the diagnostic technique employed and utilized machine learning processes in centres of dementia support. The first is a screening test for normal or anomalous patients, while the second is a careful evaluation of cases, identifying them as MCI or dementia.

Data pre-processing based on MMSE data is carried out in the first step. The next step is to choose the functions you want. The data is learnt from the chosen function and categorized in both normal and cognitive decline groups after the feature selection is accomplished. In the second phase of study, CDR data are used to classify MCI and dementia using machine-learning algorithms [30].

The data from visiting patients are gathered and dementia evaluated. Including age, sex, education, and test results we have collected patient information with MMSE and CDR. We implemented machine learning algorithms to this data that are valuable for data analysis and employed in several fields. We employed supervised learning techniques such as the Vector Support Machine, Naïve Bayes, Logistic Regression, and Precision and Random Forest Assessment Method [31-35].

We first looked at the impact of each feature utilizing information gain methods through the selection of features. Consequently, the maximum normal MCI value and dementia value shown in the Random Forest method.

This is how the remaining paper gets constructed. Section 2 describes research on Dementia. Section 3 presents an analysis of the proposed work presented by the author. Section 4 shows the module, design, and architecture of Demcare application. The findings of exploratory data analysis are presented in Section 5. Section 6 provides information of all trials and outcomes for implementation. Section 7 finally describes the author's research effort and finishes it.

Literature Review

Frank Sposaro et.al [1], The smartphone app iWander has been developed. It is operated on numerous Android-enabled smartphones having a global positioning system (GPS). It permits hearing alerts for patients, monitors them in their homes, sends warnings to the caregiver on the patients' present position, transmits the patient-at-home communications and makes a party call between them. Relatively, a research investigation into the suggested system which will make it easier and safer for cognitively challenged individuals to use public transport services and to aid family and careers monitor and monitor.

Louise Robinson.et. al [2] Contributes to the event of confusion between a person with moderate cognitive impairment and his family.

Christiana.et.al [3] Work carried out in the state that wanderings have become a major concern for the elderly and their related caretakers. They suggested the design and technological analysis of a localization service to promote and manage a person with a minor cognitive impairment's likely spatial disorientation.

Mahammad Fahim.et.al [4] Proposed android system enabled application to help older individuals live independently and actively. The load of the healthcare provider and hospital facilities on the other is reduced. It is organized into three different layers: intelligent home, cloud computing and the app layer. In addition, the "People remind the application and caregiver's helper application" application layer has been built to monitor daily living activities. The main system is organized through the Android Studio platform open-source tool.

John K. et.al [5] A further smartphone application widget has been developed that reminds its user to promptly take the right medication and retain records for medical doctors to evaluate later. It was built using the.NET framework calendar on Windows mobile 8.0.

Jane K. et.al [6] A mobile application that supports and monitors patients and offers ageing diseases monitoring has been suggested and developed. It works with any smartphone for iOS, Android or Windows. It forges a synergy for the monitoring and mental wellbeing of seniors amongst doctors, careers, physicians and elders.

Study [7] Study A mobile test application to find and sort for memory sharpening, orientation and other cognitive activities healthy persons and dementia groups. Compared to its employees, the proposed system includes a wide variety of multimedia technologies.

Williams.et.al [8] Discussion of mobile-technology breakthroughs has cleared the path for interesting new apps. Smartphones may be used for mobile blood pressure measurement instruments, glucose measurement, mobile ultrasonography even STD testing. The aim is to enhance the capacity of persons to carry out everyday tasks to foster independence and social

involvement. The goal is to reduce the load of caregivers by boosting the perception of skill and capacity of dementia patients to deal with difficulties of behavior.

Rose.et.al [9] GPS tracking is location surveillance using the Global Positioning System (GPS) for remotely monitoring the whereabouts of any individual or item. In an application, the technology may be utilized for tracking the whereabouts of dementia patients with The GPS location tracking functionality is longitude, latitude, ground speed and direction. Reminder is an application feature that enables users to create lists for themselves and set notifications. It calls upon its users to take the proper medicine in due course and to record schedules for following career exams. Patients might be alerted via a push or alert about possible drug/drug interactions. It is alerted to some medicines around 5-15 minutes before the appointed time. Until the user cancels it the notice is given again. It records the period when its user cancels an intake warning and considers that it was used when a certain drug was consumed. These records for medicinal products can be saved on board and synced with the database.

Geofrey.et.al [10] the system presented an essential instrument for personal protection and safety is the personal emergency notification system. There are two sorts of prevalent methods of emergency reporting. One is to allow the user to utilize a designed button at home, which connects to the device host. Another functional device is particularly developed with the back button SOS. Users are able to swiftly hit the predefined SOS button to make messages or telephone calls to the correct emergency person.

Mathotaarchchiet.et.al [11] Used SVM and regularized logistic regression ADNI-GO/2 studies for the PET images. A pilot research was also carried out using several algorithms of machine learning: random forests, naïve bays, J48, and J48 is the least between all algorithms. J48 is the least successful. OASIS data set MRI images from Gabor filters, Grayscale Co-occurrence Matrix and RBF classification independent component analysis and functionality fusion with high precision, recall and accuracy classification. The projected CDR scores and clinical diagnoses using the four models: SVM, decision tree, NN and Naïve Bayes, with neuro psychological and demographic data included. Average values have replaced the missing data and the best accuracy is shown in Naïve Bayes. A 10-fold cross-validation with a connection between the genetic, the picture, the biomarker and neuropsychological data is employed. The morphometry based on Voxel is used on OASIS Dataset MRI images.

Shankleet.al [12] Apart from two simple cognitive and functional skill tests, the evaluation of FAQ and BOMC information for improving the screening of dementia is conducted in Naïve Bayes, IB1. C4.5. The figures were collected from the University of California, Irvine ADRC. There were seven non-parametric categories compared to the categories. The 10 neuropsychological tests used to predict dementia are shown to be highly accurate, specific, discriminatory, and sensitive in both random forest and linear.

Shankleet.al. [13] Using the University of California dataset based on the Mini Mental State Examination (MMSE), the questionnaire of Functional Activities and the ICP (ICP) Tasks. 93 percent susceptibility and 80 percent specificity is achieved by decision tree students, Naïve Bayes, and rule students. In comparison to the two statistical techniques, SVM, Bayesian's Inverted Tree Structure (BNCIT), Bayes Naïve Decision Tree and many layers perceptron's are studied. In MRI images derived from Washington University, logistic regression and discriminatory analysis have been implemented.

Cunignet et.al [14] Comparing 10 ADNI pictures using the MRIs, the entire brain approaches were shown to have excellent precision, 81 percent sensitiveness and 95 percent specificity. The Naïve Bayes and the J48 dementia diagnosis classifier demonstrated that naïve Bays

exceed J48. All four classification approaches were evaluated using 24 database features from many neuropsychological studies and demonstrated that Naïve Bayes is best.

Machine learning framework for early MRI-based Alzheimer's conversion prediction in MCI subject. [15] in the MCI system as the transitional period between age-related decline in cognition and dementia. This system identifies MCI. The group intends to use new machine learning techniques to produce an MRI-based biomarker. They used information accessible from the ADNI database of the Alzheimer's Neuroimaging Initiative. The article says that their A total of ten fat cross validation areas below 0.09020 (AUC) attained by an aggregate biomarker with progressive MCI (pMCI) and stability of the MCI (sMCI).

This study deals with the early diagnosis and demographic details of dementia using neuropsychological tests. The common measures in neuropsychology These are the Mini-Mental State Examination (MMSE), the Cognition Consortium in Montreal (MoCAs), a brief interview with a Dementia Diagnosis Information Agency (AD8), and the General Practitioner Cognition Assessment (GPCOG) each providing information on disease detection (AD8). A brief interview with the general practitioner is available. MMSE and CERAD are now the most often utilised as they may be used irrespective of gender, education, culture or age. [16].

Joshi et.al.[17], To enhance the accuracy of existing dementia screening instruments, MMSE and functional activity questionnaires, Network methods to machine learning were applied to categories dementia stages. The results reveal, by integrating both tests using machine and neural network, the accuracy may be optimized. Trambaiolli and Lorena.et.al.[18] Previously used electroencephalographical information By learning EEG patterns in SVM algorithm patients with Alzheimer, patients with normal cognitions, dementia, and/or MCI should be classified. EEG Epochs showed relatively good precision (79.9%) and the findings for the SVM amounted to about 87%.

Weakley and Williams [19] The CDR score and dementia screening methods were examined with the usage of Naïve Bayes, Decision Tree, Neural Network and SVM. The evaluation reveals that Naïve Bayes is the most precise and SVM the lowest. The most accurate is the SVM. Cho and Chen presented a two-layer hierarchy for early dementia diagnosis [20]. This model predicts that the Bayesian network uses an early diagnosis of dementia in the top layer after the diagnosis of the base-layer FCM and PNN algorithms in a Cognitive testing like CERAD and MMSE. However, when comparing normal, the MCI and dementia were not adequately classified, this model exhibited 74 and 69 percent of the accuracy of FCM and PNN. Shanklea and Mani [21] made the CDR forecasts using machine and electronic medical records. Naïve Bayes was around 70 percent accurate, while it was lower than Bayesian for other algorithms.

Proposed Work

The data set from the OASIS-Brain.org is gathered in the proposed effort. The Open-Access Imaging series (OASIS) has been developed, which enables the brain MRI data set to be freely available. There are two types of data available in the OASIS dataset: transversal MRI data and longitudinal MRI data of demeaning and demeaning elderly people. Age, sex, education, socioeconomic position, minimal OASIS has all parts of the State test, clinical dementia rates, atlas scaffolding factor, projected total intracranial volumes and standardized brain-wide volume [36]. Figure 1 shows the suggested layout.



The steps in the work planned are as follows

1. Data collection

Data are gathered from the Oasis-brain.org system by 416 participants in transverse data and 37 documents in longitudinal information.

2. Data Pre-processing

The pre-treatment of data has shown to be a significant matter for data mining since real-world data is incomplete and inconsistent. The missing entries are completed with the average values.

3. Feature Selection

A subset of functions is assessed with a degree of redundancy in each predictive capacity of the entire feature.

4. Classification

- Naïve Bayes

Naïve Bayes, as one of the most used techniques of classification, is a classification of probability using the Bayesian theorem as in text and document categorization. Bayes uses algorithms which are based not on a single method, but on broad concepts. At a supervised learning scenario, Naïve Bayes is highly successful in estimating parameters using Maximum Likelihood estimates [22]. The Naive Bayes classification is a blend of probability and decision rule discussed before, and it finds the most probable class. The Naïve Bayes method calculates the set of probability by counting the values in the data set.

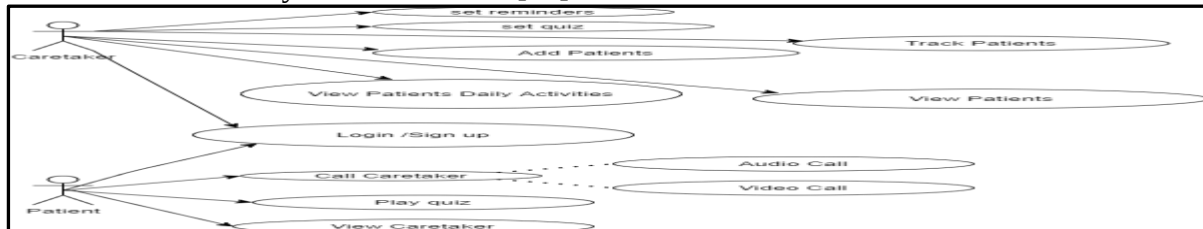
- Random Forest

The three predictors in random forests are merged, where each tree has the same distribution for all trees, depending on the value of the random vector collected individually. The algorithm Random Forest is a supervised method used for classification and regression issues. It follows the principle of ensemble learning, combining several classifications to tackle complicated issues and to improve the performance of a model [37]. It comprises in general of numerous decision trees which create a subset of a certain dataset and improve the predicted accuracy of the data set. The final output is predicted by Random Forest Classifier in comparison with the forecast from each of the trees based on choice such as majority vote.

- Support Vector Machine (SVM)

The Sustainable Vector Machinery (SVM) mapping approach consists of A data analysis and pattern detection mapping methodology. The main uses of regression analysis and categorization are. A SVM approach creates a binary linear classification model that is unlikely to find its widest border when a series of data belonging to one of the two categories is provided. It is beneficial for both linear and nonlinear

classification. Data on a high-dimensional characteristic space must be mapped for non-linear classification. To do this efficiently, a kernel approach can be used. Assistance One of the greatest supervised learning algorithms is Vector Machine. It is useful for both issues with regression and classification. This approach is nonetheless utilized to classify the dataset used [24].



- **Logistic Regression**

Regression is a stochastic model to estimate the probability of a situation using a linear combination of indigenous variables when there is a binomial problem with a dependent variable. Therefore, it is described as a specific function and used for future model projection [25][38] as a link between the dependent variable and the independent variable. In addition, logistic regression analyses often serve to categorize and predict data outcomes in categories when data is provided to category data, as opposed to linear regression analyses. When data is supplied, the data is classified.

5. Results

Finally, the accuracy of the categorization is achieved and examined. The accuracy of classification is defined as the proportion of the number of samples that are successfully categorized divided by total samples collected.

$$\text{Classification Accuracy} = \frac{\text{Correctly classified samples}}{\text{total number of samples}} \cdot 100$$

Module design & architecture

The general design and workflow mechanism of the Demcare application are shown below.

The application perspective has two aspects: the caregiver and the patient. Cognitive tasks are a prominent element of our memory since they are repeated every now and then. When doing necessary core everyday activities, especially for a patient with dementia, oblivion is not required. Demcare delivers services from both points to execute such activities in a timely way. Caretaker module services are the patient monitoring system, the history of all prior sites visited by the patient, testing games to avoid more impairment in the patient's memory and making them recall all things essential and always connect to the patient. Patient Module service includes updated medication reminders, a quiz to sharpen the memory and save items that pertain to him and connecting to the maintainer in all situations.

More significantly, the system produced include tests and games to keep your mind and body going by assigning some helpful chores to you. Video calls/audio calls for patients, if they are imprisoned in a dangerous circumstance, is another crucial element of our solution. Three user roles are developed: caregiver, patient, and manager for this system. Each position is permitted with certain rights.

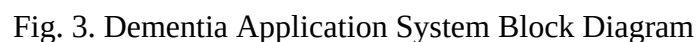
Fig. 2. Demcare system design- use case diagram

A. Module for Caregiver:

- Medication reminders
- Track patients and view location history
- Set quiz games for patient
- Registering a patient

In this module a patient may register and log in as a patient, amend pill memories by caretaker, call a caretaker to help and participate in test games for the sharpening of memory and the improvement of the cognitive learning domain.

- ## Approach



- **Personal Information** - The username, age, address, and number of providers save all data within the database.
- **Daily schedule**- This includes timetables for every user daily work from mornings to nights such as lunch times, books or journals, medical schedules and so on. This schedule is kept again for simple recovery in the database.
- **Family information**- The user must first give each member with his/her family member picture data, such as user-member relationships.
- **GPS tracking and browsing**- Initially home settings are provided as input by the maintainer. When the user exits home parameters, location mapping will start with GPS and navigation. When the user forgets the way home, then GPS will enable the user to chart the road to return by saving the coordinates in the database.

To identify people with moderate to modest dementia for the purpose of training multiple machine learning models, the data package will be generated utilizing the Open Access Series of image studies (OASIS).

<http://annalsofrscb.ro>

- The longitudinal MRI data are going to be used.
- A sample of longitudinal MRI data includes 150 aged 60 to 96 years.
- At least once every topic is scanned.
- Everybody's right.
- During the whole investigation 72 patients were classified as 'Nondemented.'

64 of the individuals categorized on their initial visits as 'demented' and stayed so for the whole research.

- 14 themes categorized at the first visit as 'Nondemented' and afterwards described at the latter visit as 'Demented.' These are complete in the category 'Converted.'

COL	FULL-FORMS
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

Table.2. Full forms of Data

Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2	27	0	1987	0.696	0.883
OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2	30	0	2004	0.681	0.876
OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12		23	0.5	1678	0.736	1.046
OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12		28	0.5	1738	0.713	1.01
OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12		22	0.5	1698	0.701	1.034

Table.3. Dataset of Longitudinal MRI (OASIS)

	Visit	MR Delay	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
Count	373	373	373	373	354	371	373	373	373	373
Mean	1.882	595.1	77.01	14.597	2.46	27.34	0.29	1488.1	0.72	1.195
Std	0.922	635.48	7.64	2.876	1.134	3.683	0.37	176.12	0.037	0.138
Min	1	0	60	6	1	4	0	1106	0.644	0.87
25%	1	0	71	12	2	27	0	1357	0.7	1.09
50%	2	525	77	15	2	29	0	1470	0.729	1.194
75%	2	873	82	16	3	30	0	1597	0.75	1.29
Max	5	2639	98	23	5	30	2	2004	0.837	1.587

Fig.4. Output of Statical Comparison

Data Preprocessing

In the SES column, 8 rows have been discovered with missing values. We have 2 ways to this issue. One is to delete missing row values. The other is the missing values, often known as 'imputations,' to be replaced with the appropriate values. As we only have 150 data, I guess the imputation might contribute to our model's performance.

Subject ID	0
Group	0
MR Delay	0
M/F	0
EDUC	0
SES	0
MMSE	0
CDR	0
eTIV	0
nWBV	0
ASF	0
dtype: int64	

Table.4. Output of Missing value

Cross validation

This part contains five-fold cross-validation for optimum model parameters, logistic regression, SVM, decision-tree, random forests and AdaBoost. As precision is the performance metric, the optimal tuning parameter will be found by precision. In short, for each model we compare the precision, reminder, and AUC [33].

Model

Performance Measure

The use of the area under the recipient functional curve as our key metric of performance. In the event of non-life-threatening terminal disease medical diagnoses such as most neurodegenerative diseases, it is crucial for all people with dementia to be found as quickly as feasible; But we also want to guarantee that this fallout is as limited as possible, because we do not want the demented and medical treatment of a healthy adult to be misdiagnosed. Consequently, AUC appeared like the appropriate solution for performance measurement. In addition, for each model we shall see for precision and recall [34]. You might consider crucial factors as demented topics in the diagram below. Accuracy and recall. Precision.

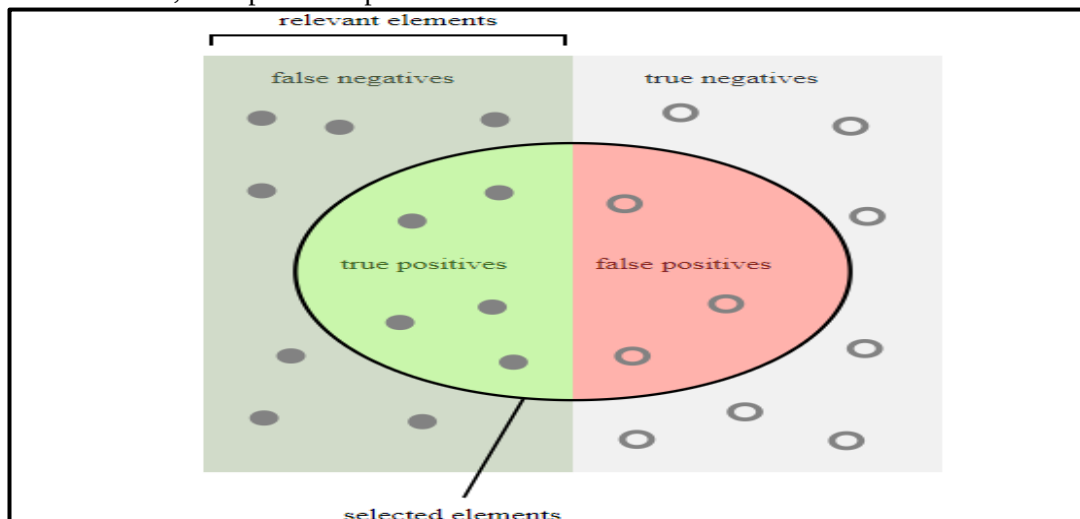


Fig.5. Comparison of Relevant and Selected element

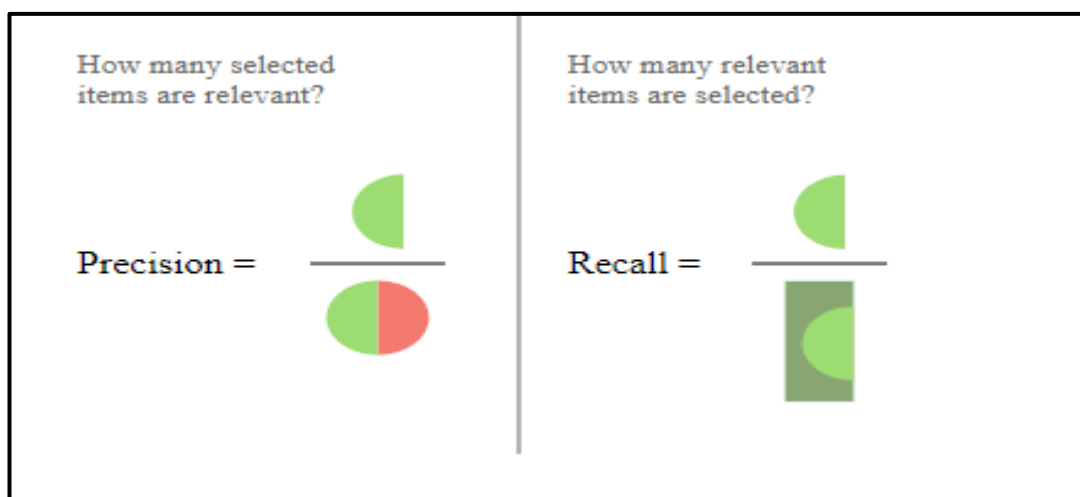


Fig. 6. Comparison of Precision and Recall

Exploratory Data Analysis (EDA)

The relation between each RMI test feature and the patient's dementia was investigated in this section. This process clearly explains the data relation a graphic, so that before data extraction or data analysis we may assume correlations. It may assist us understand the nature of the data and then pick the correct method for the analysis of the model.

Each function for graph implementation shows the lowest, maximum, and average values.

	Min	Max	Mean
Educ	6	23	14.6
SES	1	5	2.34
MMSE	17	30	27.2
CDR	0	1	0.29
eTIV	1123	1989	1490
nWBV	0.66	0.837	0.73
ASF	0.883	1.563	1.2

Table.5. Feature Graph Implementation

Figure 7 displays in our figure data set the number of female and male data. There are 72 "men" and 78 "females." There are 72.

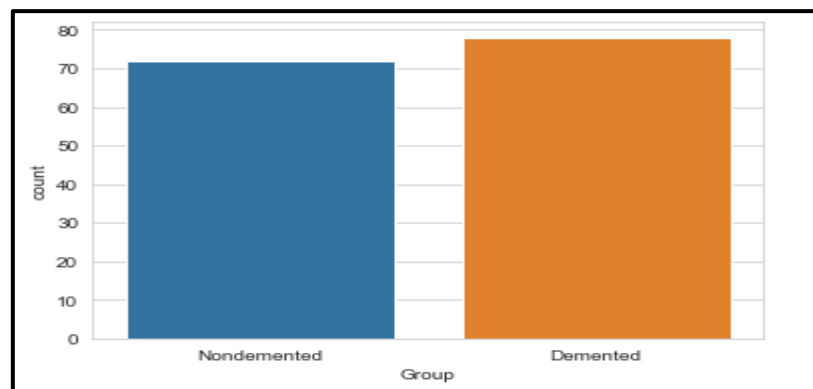


Fig. 7. Counts of Male and Female

Figure 8 shows a correlation graph among attributes, using the syntax:

`plot_correlation_map(df)`

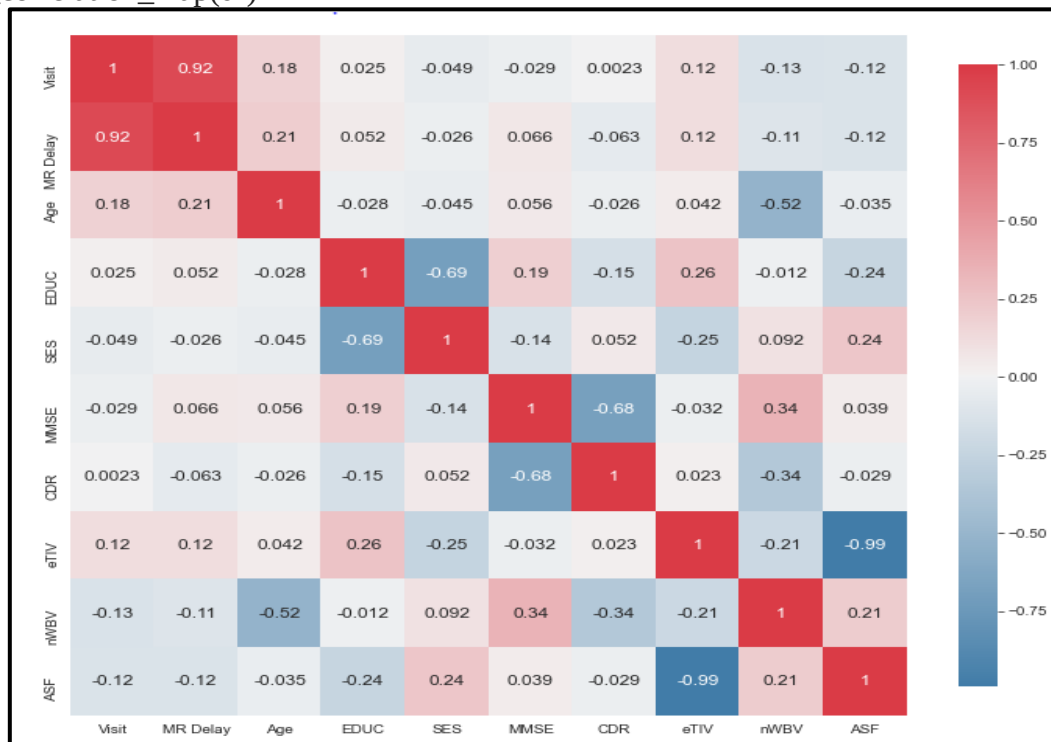
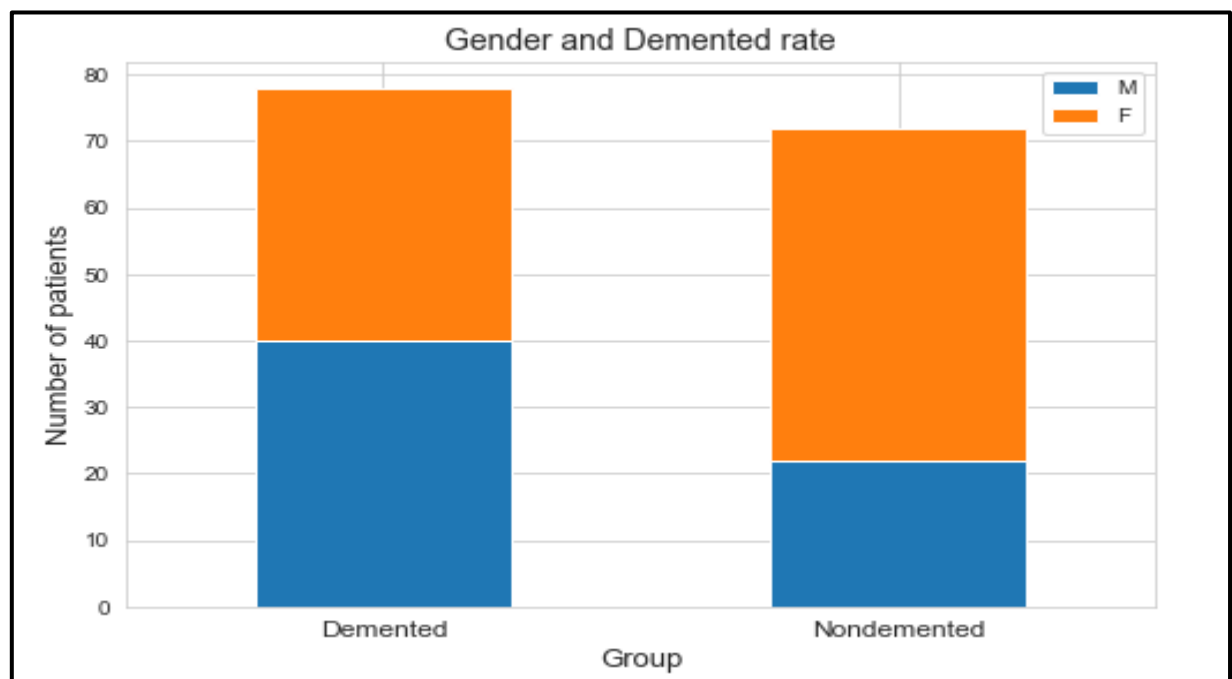


Fig. 8. Attributes Correlation Matrix

In each sex, male and female, figure 9 displays Gender numbers and '0.5' and '1.0' demented rate predictions. We infer those 40 guys are susceptible to dementia, and 22 guys are non-

conscious. Likewise, 38 "females" are demented, and in comparison, to males, 50 "females" are demented.

Fig. 9. Demented and Non-demented Male/Female



The distribution of age is seen in Figure 10 and generally seems dispersed. In the demented group of individuals, the concentration is between 70 and 80 years greater than in non-demented people. Patients who have such a condition have a decreased survival rate, which means that they are only about 90 years old.

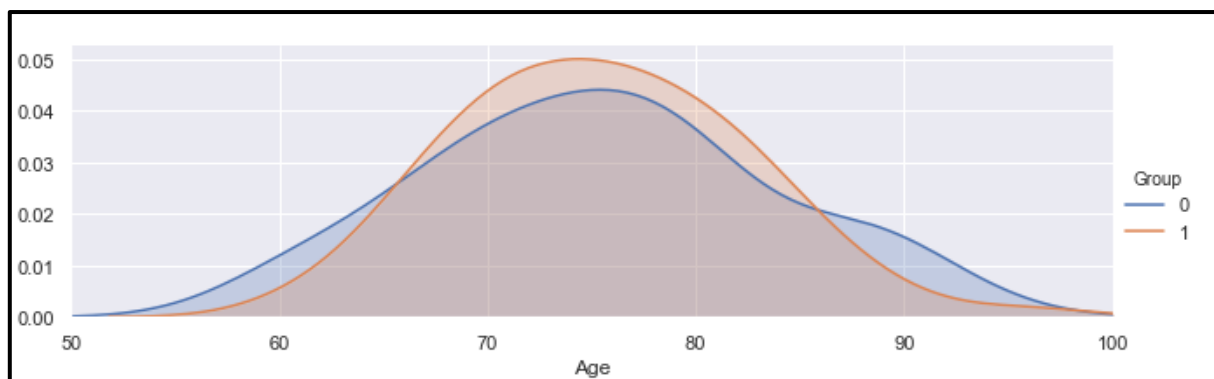


Fig. 10. Age distribution (normalized)

Implementation Details

Experimental Design Setup

Setup:

1. Patient personal information:
The user must initially provide basic patient information like name, age and contact number.
2. Caregiver personal information:

Users should give the person taking care of the patient basic information like the name, the contact no and the email address.

3. Location setup:

The user must give the right patient home location co-ordinates.

4. Reminder setup:

By clicking the 'Add Event' button, users will be able to set a new event. By clicking the "Remove Event" button, you may remove an existing event.

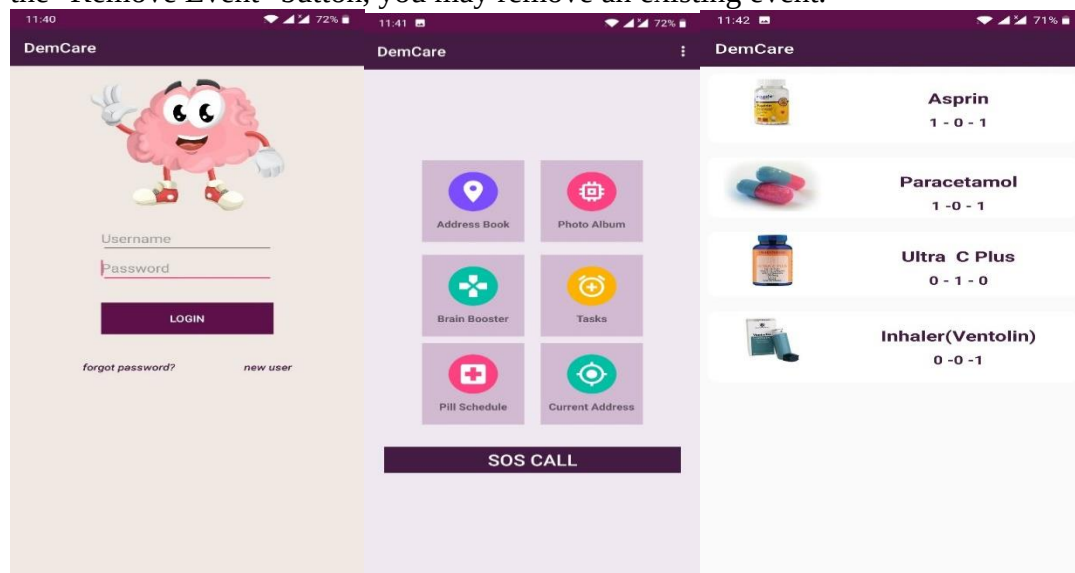


Fig. 11. (Login Page, Home Page, Pill Schedule)

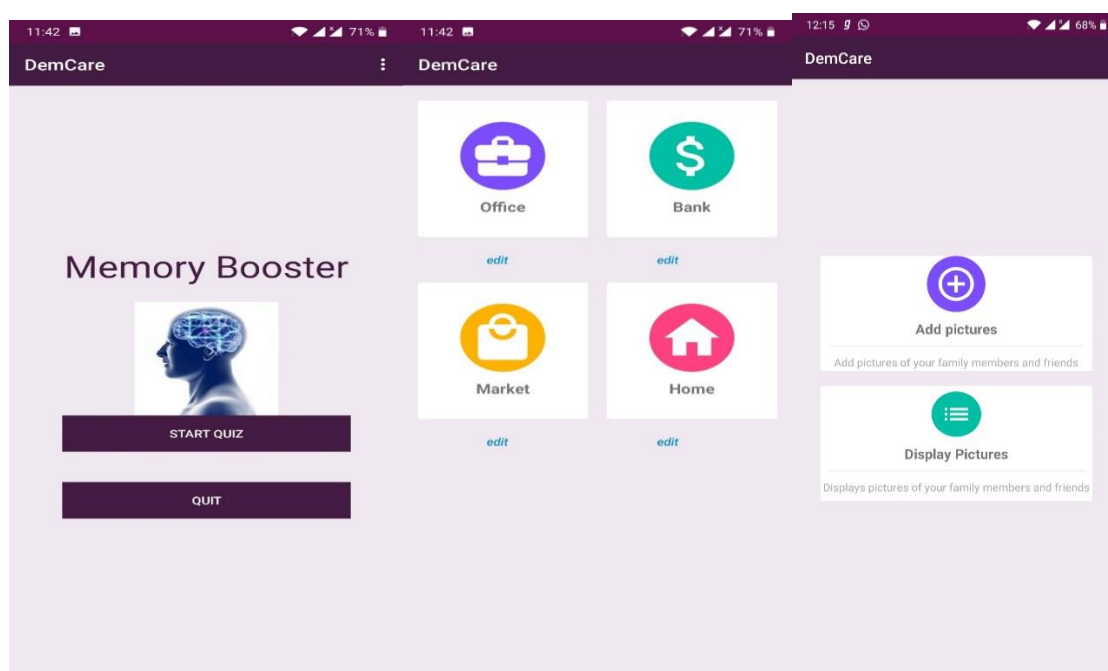


Fig. 12. (Quiz, Task Manager, Album/Photos)

Main page

5. Home:

The following buttons on this page are provided, for example the browsing, timetable, reminder, gallery, quiz and enable me to address some of his everyday concerns.

6. Location tracker:

The user simply needs its source and destination to be specified. Mapping location begins with GPS and navigation when the user leaves home settings. And if the user forgets the way to the source, the co-ordinates which are kept by means of GPS in the database will enable the user to chart the way back.

7. Schedule:

Users will input schedules of every day from dawn to night, such as meals, book or newspaper reading, prescription regimens and so on.

8. Quiz:

The progress report will include specific types of questions that engage the brain of the user and the overall performance.

In this research the potential of detecting dementia and the performance of a classification task is analyzed using supervise Learning used for the machine-learning. The data set was obtained utilizing MRI devices for examination in real time. The dataset comprises of 10 variables, five of which are main, i.e., the CDR of the patient. The following phase includes the Random Forest Classifier, Naïve Bayes, ADA Boost, Tree Classifier, Vector Support Machine, Logistical Regression. The data set was imported through 'read.csv ()' before the model was applied to our obtained data set, and the data were pre-processed. In the second phase, we chose the feature 'StandardScaler ()' in which important patient symptoms have been mostly considered. In addition, 80% training and 20% testing were performed in the dataset. Models have then been used to verify the correctness of the model. Different experimental measures have been calculated in the following stage to assess the classification performance.

Evaluation Metrics

The evaluation metrics of the model are formulated with the confusion matrix. For this, the calculation of values is measured based on:

- TP (True Positive) = Number of successfully determined occurrences.
- FN (False Negative) = number of occurrences which are wrongly forecast and not needed.
- FP (False Positive) = number of wrongly predicted incidents. FP (False Positive).
- TN (True Negative) = the proper and not necessary number of occurrences.

Based on this parameter, we have calculated four measurements with the given formula:

$$1) \text{ ACCURACY} = \frac{TN + TP}{TN + TP + FN + FP}$$

$$2) \text{ PRECISION} = \frac{TP}{TP + FP}$$

$$3) \text{ SENSITIVITY (RECALL)} = \frac{TP}{TP + FN}$$

$$4) \text{ F1 SCORE} = \frac{2 * (\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

Confusion Matrix:				
[[48 12]				
[7 45]]				
Classification Report:				
	precision	recall	f1-score	support
0	0.87	0.80	0.83	60
1	0.79	0.87	0.83	52
accuracy			0.83	112
macro avg	0.83	0.83	0.83	112
weighted avg	0.83	0.83	0.83	112

After executing the machine learning model on the collected dataset, we found the accuracy, sensitivity, precision and F1- score of each algorithm as shown in Table 6. These measurements were calculated with the support of confusion matrix value TP, TN, FP, and FN for each algorithm shown in Figures 13, 14, 15, and 16.

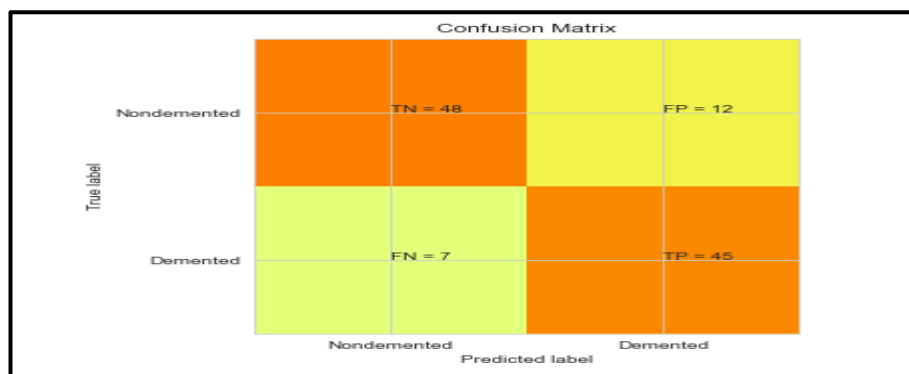


Fig. 13. Random Forest- Confusion Matrix

Fig. 14. Support Vector Machine

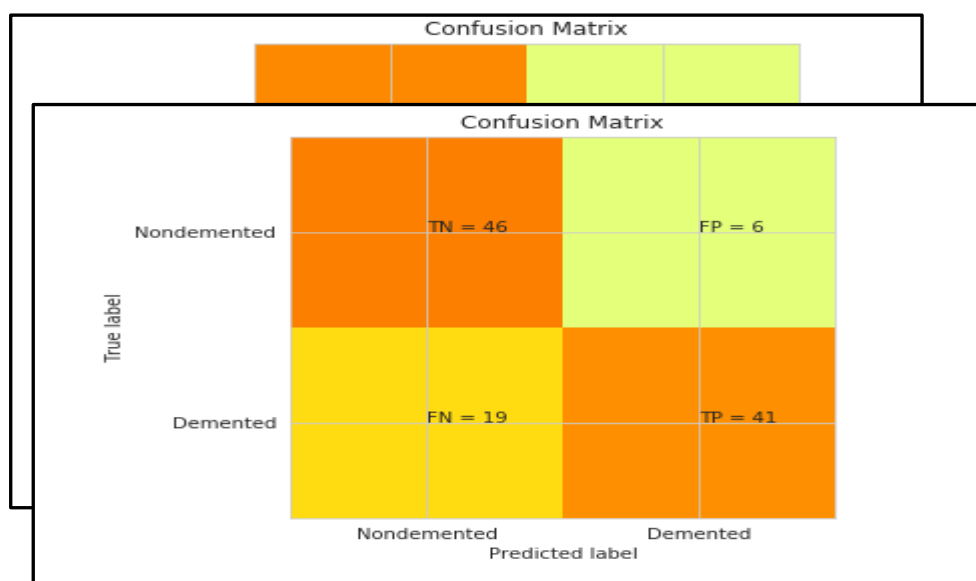


Fig. 15. Decision Tree Classifier

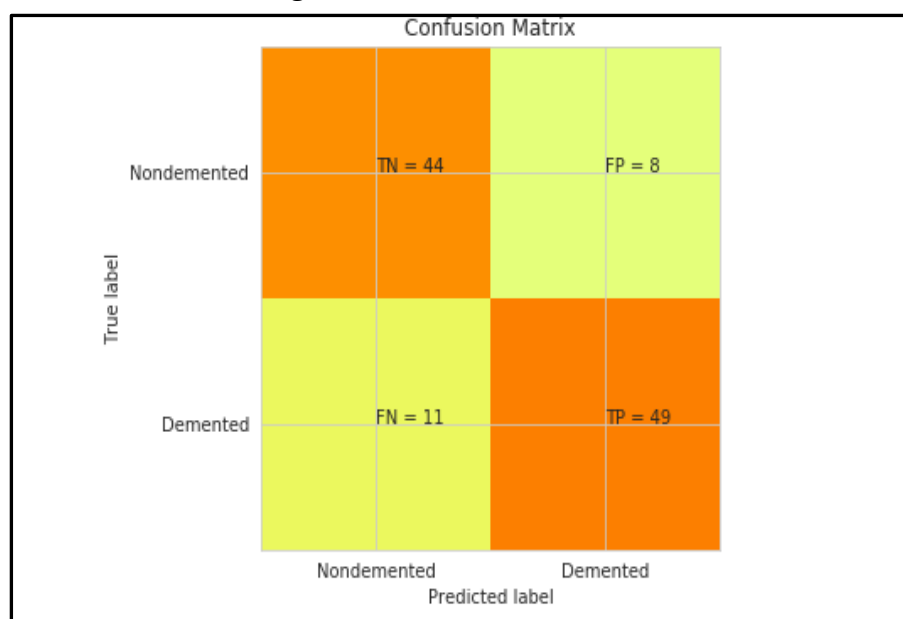


Fig. 16. XG Boost Classifier

Model Performance

	Model	Accuracy	Recall	AUC
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0	Logistic Regression(w/Imputation)	0.789474	0.75	0.791667
1	Logistic Regression (w/dropna)	0.750000	0.70	0.700000
2	SVM	0.815789	0.70	0.822222
3	Decision Tree	0.815789	0.65	0.825000
4	Random Forest	0.868421	0.80	0.872222
5	Random Forest	0.868421	0.80	0.872222
6	Random Forest	0.868421	0.80	0.872222
7	Random Forest	0.868421	0.80	0.872222
8	Random Forest	0.868421	0.80	0.872222
9	AdaBoost	0.868421	0.65	0.825000

Table.6. Accuracy comparison of All Models

From Table, 6, we can conclude that the Random Forest Classifier is the best among all machine learning algorithms a 87% accuracy.

Figures 17, 18, 19, 29 portrays Curve Under Area (AUC) and Curve Receiver Operating Features (ROC). The ROC curve shows the graphics to measure the performance of the model. It shows the true negative and true positive value plotted at distinct levels of the threshold.

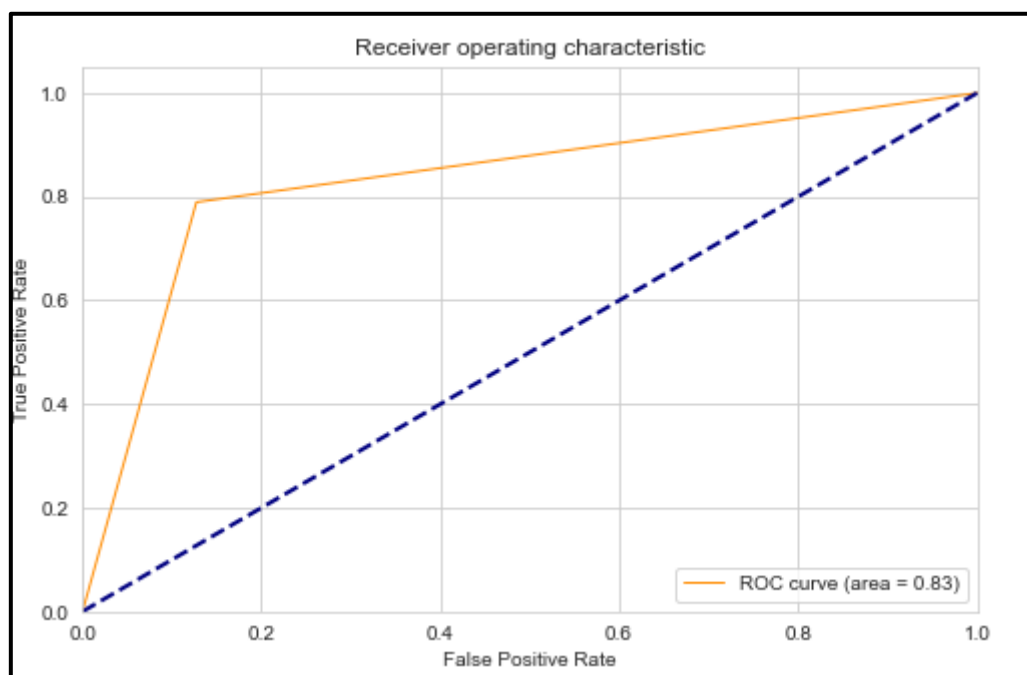


Fig. 17. Random Forest Classifier- ROC curve

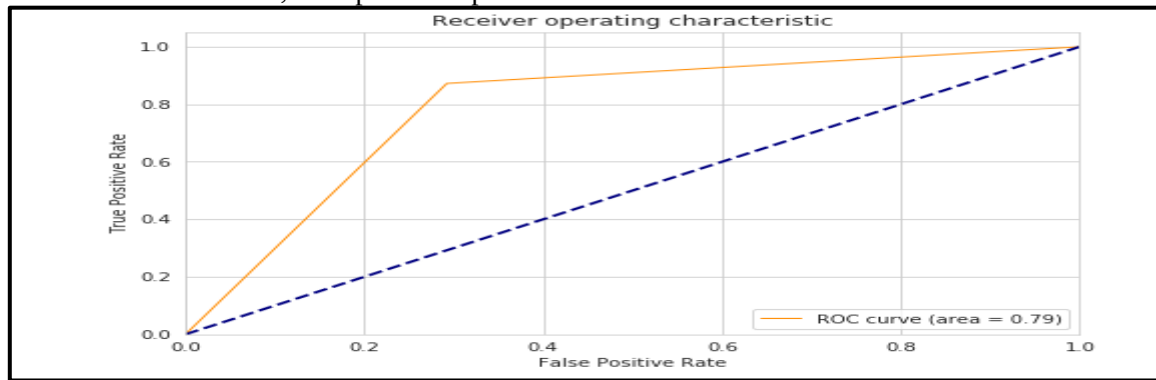


Fig. 18. Support Vector Machine (SVM)- ROC

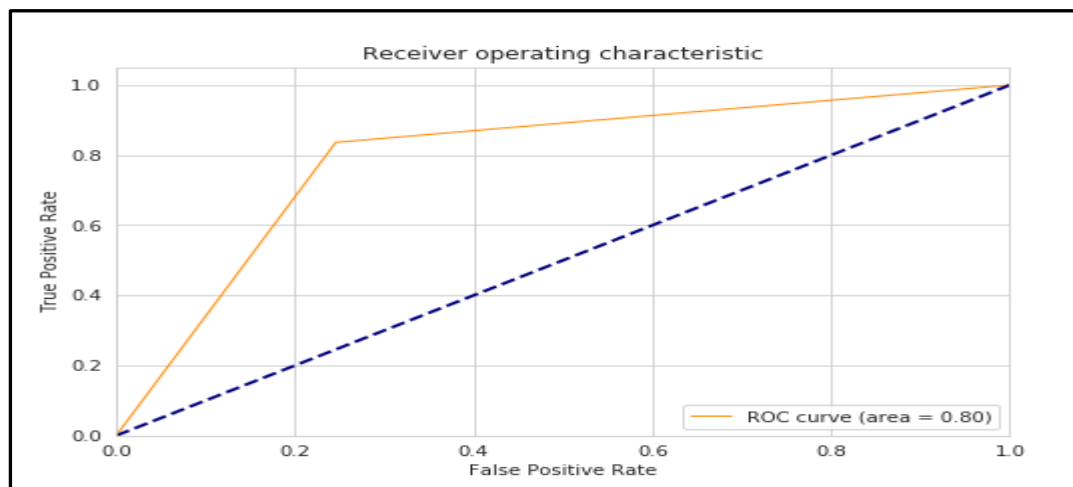


Fig. 19. Decision Tree Classifier- ROC

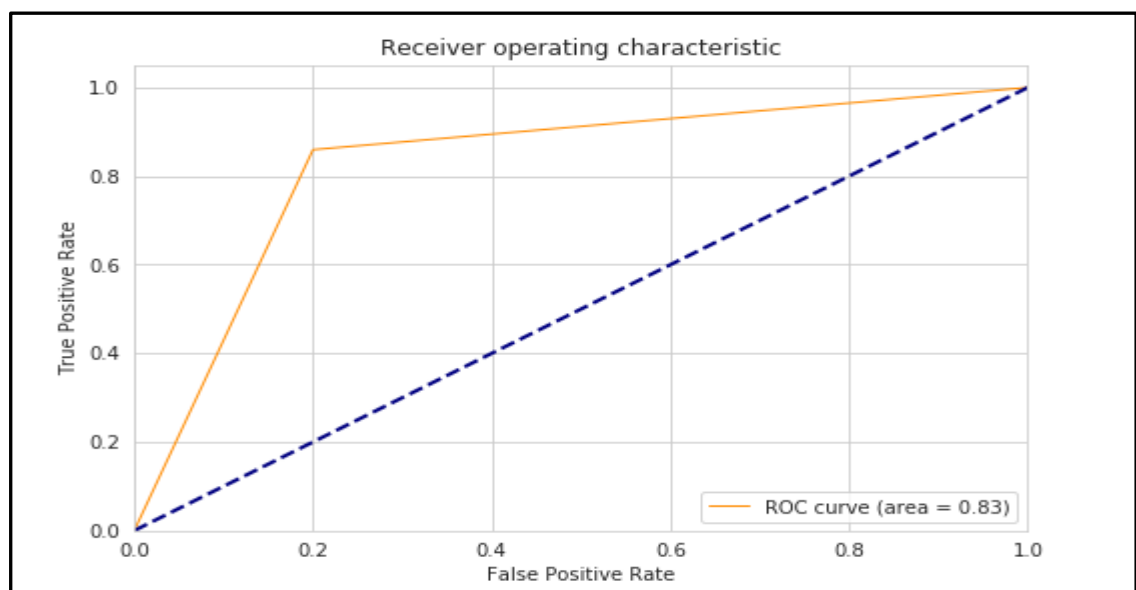


Fig. 20. XG Boost Classifier- RO

Discussion, Conclusion, and Future Work

Discussion

In our study article, we introduced a technology-oriented approach for the usage of Demcare for dementia patient and carers in patients with modest cognitive impairments. The device is also very beneficial for family members who want to monitor fellow dementia sufferers' activities vigilantly. Due to its sustainability, mobility, and flexibility compared to alternative options, the Android based smart phone application has been offered.

Another aspect is the purpose of this article to diagnose and forecast whether the patient suffers from dementia. Six supervised machine learning methods were used for this research: Random Forest Classifier, Support vector Machine, Logistic Regression, AdaBoost algorithm, Decision-Tree, Naïve Bayes, on a real-time data set.

Dataset was split in an 80 percent training set and in a 20 percent test set and pre-processing. On order to achieve precision, the finding was achieved utilizing machine learning techniques in a data set. The result: precision, accuracy, reminder was created by the jupyter notebook's python programming.

Table 12 lists the classification accuracy of each algorithm and compares different methods. 12 Random Forest classifier obtain the greatest precision to recognize patients with dementia from the Table.

Conclusion and Future Work

This research helps to detect and to compare the probability of dementia for gender and age-based patients. The system presented incorporates and delivers so many elements and so acts as a tool to aid patients, carers, and the community in dementia. The results of the evaluation reveal excellent application performance in many circumstances. Possible possibilities for the future include providing online doctor support, preclinical dementia testing and connection with hardware for our application to enhance IOT devices' performance. In our future database, we can additionally save and update AWS. The distinctive technology for each Android application ensures that the consumer does not select another or improved version of comparable technology. So, to stay up with other rivals we need to enhance our app by using some new technologies. Our research aims to identify people with dementia using machine learning models as soon as feasible. In addition, our key contribution reveals the likelihood of survival for individuals with gender and age-based approaches that exceed other algorithms employing two effective ways from the outcome. Thus, the biggest opportunity for us to move forward in the future is that we should maintain the monitoring of dementia and clarify the process in many ways. For the subsequent investigation, a more Our understanding must be enhanced by improved EDA processes with a larger sample. The volume of brain tissue or testing results is pooled together, for instance, not simply the age itself is examined. If the conclusions of this approach are reflected in the process of data clean-up and the positive decision making in the model, the accuracy of this prediction model may also be further strengthened.

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