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CSCI 113i Final Project

CAD System with Dementia Prediction for Healthcare

Business Understanding

1.1 Determine Business Objectives

Background

According to the World Health Organization (WHO), dementia is a syndrome that leads to progressive or chronic deterioration of cognitive functions such as memory and behavior. It is also the seventh leading cause of death among all diseases, affecting especially the elderly. Dementia results from an umbrella of diseases, most commonly Alzheimer's disease which causes 60–70% of cases of dementia. It is estimated that dementia cases in Southeast Asia will be 12.09 million (236%) by 2050. Symptoms of dementia include disorientation, mood and behavior changes, serious memory loss, and difficulty speaking, swallowing and walking. Though there is no treatment for dementia, caring for dementia relies on early diagnosis to provide the best possible management and support. The sooner the diagnosis is made, the better it is for both the patient and caregiver.

Computer-Aided Diagnosis (CAD) is an Artificial Intelligence (AI)-based system that is used in hospitals for detecting different ailments such as tuberculosis and pneumonia and assisting radiologists in increasing the accuracy of diagnoses. While there are CAD systems being used in hospitals, these are focused on other diseases such as respiratory diseases. With this, a CAD is being introduced to a hospital in order to possibly develop technical solutions that will help improve early diagnosis and treatment strategies of dementia patients. This will in turn improve the care provided by healthcare professionals and caretakers of these patients, as well as improve the performance of the hospital by enabling better use of their resources (e.g. therapies, medicines).

Business Objective: Analyze the cases of dementia using features from MRI data

- What are the underlying relationships of variables that affect dementia?
    - Understand the relationships of features in the data
    - Determine if a certain feature is consequential to their chances of getting dementia
- Based on the data, can we predict the onset of dementia of a patient?

Business Success Criteria

- Obtain useful insights into the relationships of different factors towards dementia
- Increase diagnostic accuracy to about 80% (according to a study by Bron et. al.)
- Improve patient safety through better determination of treatment criteria and risk factors
- Obtain a patient satisfaction rating of at least 70%

1.2 Assess Situation

Inventory of Resources

- Personnel: data analysts, technical support, business analysts, medical personnel (i.e. neurology department who is in charge of dementia patients, radiology department in charge of taking medical images to help with diagnosis of diseases)
- Data: dataset from OASIS (Longitudinal MRI Data in Nondemented and Demented Older Adults)
- Hardware: MacOS for producing model
- Software: Jupyter notebook, Python
    - Classification models from sklearn (DTC, LR, RFC, KNN, SVC, MLP, GNB, KNN)
    - Clustering model from sklearn (KMeans)

Requirements, Assumptions, and Constraints

- Requirements
    - Schedule of completion of diagnostic model: May 23
    - Schedule of completion of CAD system: third quarter of 2022
- Assumptions
    - Dataset is complete, no null or missing values
    - Hospital has enough personnel and other resources to treat dementia patients
- Constraints:
    - Lack of time (since preliminary model should be done by May 23, and given the schedule of other personnel, there may be scheduling issues)
    - Lack of data (dataset comes from 150 subjects only)

Risks & Contingencies

- Internet outage
    - Solution: Work at a cafe or use another source of Internet

Terminology

The dataset contains different features of the patients, such as MMSE, eTIV, CDR, nWBV, and ASF. The following section explains these terminologies:

- Mini–Mental State Examination (MMSE)
    - The MMSE is a 30-point questionnaire for measuring cognitive impairment of patients. Cognitive impairment means that a person has trouble with memory, concentration, and the like. This exam is used for estimating the severity of cognitive impairment with regards to dementia.
    - Any score greater than or equal to 24 points (out of 30) indicates a normal cognition. Below this, scores can indicate severe (≤9 points), moderate (10–18 points) or mild (19–23 points) cognitive impairment. The raw score may also need to be corrected for educational attainment and age (i.e. a maximal score of 30 points 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

- Clinical Dementia Rating (CDR)
    - The CDR is a 5-point scale that characterizes the performance of Alzheimer's disease patients based on their memory, orientation, judgment & problem solving, community affairs, home and hobbies, and personal care. This is done through an interview with the patient and the caregiver. The CDR table provides a guide to the physician to make the appropriate ratings for the patients
    - The CDR is based on a scale of 0–3: no dementia (CDR = 0), questionable dementia (CDR = 0.5), MCI (CDR = 1), moderate cognitive impairment (CDR = 2), and severe cognitive impairment (CDR = 3).

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

- Estimated Total Intracranial Volume (eTIV)
    - ICV, or total intracranial volume (TIV), is a standard measure to correct for head size in different brain studies. This is one of the factors that help in investigating neurological brain disorders such as Alzheimer's disease. Helps evaluate age-related changes in the structure of premorbid brain, determine characterizing atrophy patterns in subjects with mild cognitive impairment (MCI) and Alzheimer's disease (AD)

- Atlas Scaling Factor (ASF)
    - The ASF is an automated solution to the issue of correcting for head size variation in regional and whole-brain morphometric analyses of dementia patients based on age by using TIV measurement as a reference.

- nWBV
    - Normalized whole-brain volume, expressed as a percent of all voxels (“constant” for any value of estimated total intracranial volume)
    - is another measure used to correct the head size variation across subjects. Using this may be more appropriate when interest is in how the brain structure volume changes with respect to the brain as a whole.

Costs & Benefits

- Costs
    - Deployment of diagnostic and predictive models to the new CAD system. This will depend on the current hardware and software used by hospitals (i.e. if current systems are powerful enough for this model)
    - New testing and treatment for patients, if any (e.g. pharmacological treatment for specific symptoms)
- Benefits
    - Averted medical costs for patients
    - Valuation of quality of life gained due to earlier diagnosis and treatment of patients
    - Increased caregivers’ productivity

1.3 Determine Data Science Goals

Data Science Goals

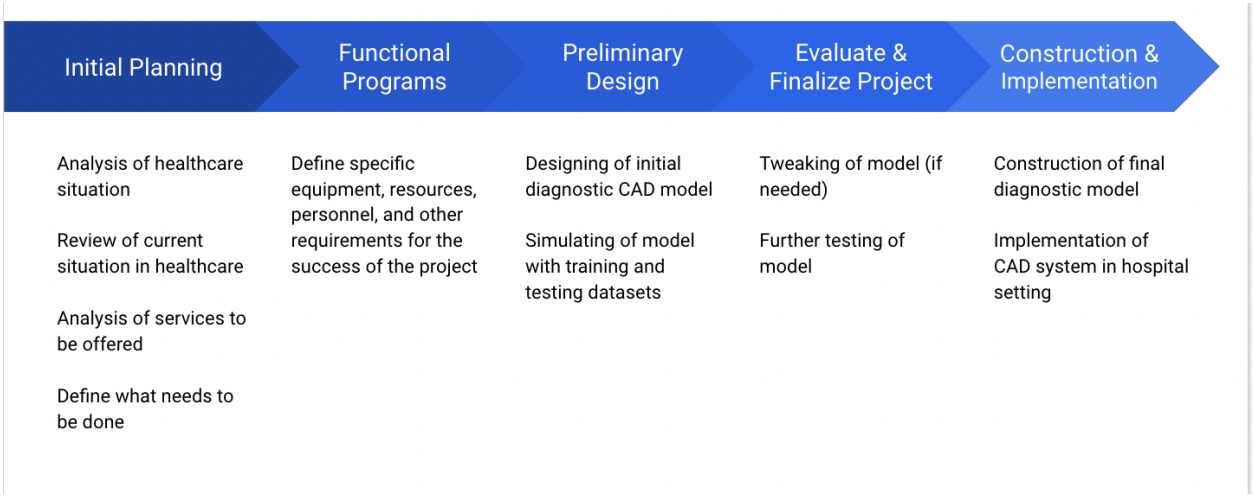
- Predict the occurrence of Dementia by estimating the classification of Dementia in patients using a logistic model with relevant features in the MRI dataset
    - Analyze the correlation between the different features
    - Understand the influence of certain features on the disease

Data Science Success Criteria

- Adapt a model with at least 80% accuracy, precision, and sensitivity
- Deploy a diagnostic and predictive model with at least 0.8 F1 score

1.4 Produce Project Plan

Given these business and data science objectives, the plan for the project was then created. Below is the chart for the project.



The initial planning phase includes the analysis and review of the healthcare business situation. Apart from the prominence of dementia especially in the Philippines, the CAD system was looked into as a possible solution to it. This phase also includes the analysis of what services are to be provided by the hospital, which includes diagnosis and treatments of dementia patients. From these, the objectives were defined.

The second phase involves the functional programs of the business and project. This includes the equipment, resources, and other requirements for the completion of the project, such as the software to be used, the dataset to be extracted, and the personnel involved.

The third phase involves the designing of the preliminary diagnostic model for the CAD system. This is done using Python as the coding language and Jupyter Notebook as the platform. The model is then trained and tested using the dataset.

The fourth phase is the evaluation and finalization of the project, which requires evaluation of the performance of the model through more testing and tweaking it if needed.

The final step is the construction and implementation of the project in completion. This involves deploying the chosen model in the CAD system of the hospital and using it for dementia diagnosis.

- Dataset
    - Data were provided by OASIS: Longitudinal: Principal Investigators: D. Marcus, R, Buckner, J. Csernansky, J. Morris; P50 AG05681, P01 AG03991, P01 AG026276, R01 AG021910, P20 MH071616, U24 RR021382
    - Longitudinal MRI Data in Nondemented and Demented Older Adults:
        - “This set consists of a longitudinal collection of 150 subjects aged 60 to 96. Each subject was scanned on two or more visits, separated by at least one year for a total of 373 imaging sessions. For each subject, 3 or 4 individual T1-weighted MRI scans obtained in single scan sessions are included. The subjects are all right-handed and include both men and women. 72 of the subjects were characterized as nondemented throughout the study. 64 of the included subjects were characterized as demented at the time of their initial visits and remained so for subsequent scans, including 51 individuals with mild to moderate Alzheimer’s disease. Another 14 subjects were characterized as nondemented at the time of their initial visit and were subsequently characterized as demented at a later visit.”

Data Understanding

2.1 Collect Initial Data

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2.0	27.0	0.0	1987	0.696	0.883
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2.0	30.0	0.0	2004	0.681	0.876
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23.0	0.5	1678	0.736	1.046
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	NaN	28.0	0.5	1738	0.713	1.010
4	OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12	NaN	22.0	0.5	1698	0.701	1.034
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
368	OAS2_0185	OAS2_0185_MR2	Demented	2	842	M	R	82	16	1.0	28.0	0.5	1693	0.694	1.037
369	OAS2_0185	OAS2_0185_MR3	Demented	3	2297	M	R	86	16	1.0	26.0	0.5	1688	0.675	1.040
370	OAS2_0186	OAS2_0186_MR1	Nondemented	1	0	F	R	61	13	2.0	30.0	0.0	1319	0.801	1.331
371	OAS2_0186	OAS2_0186_MR2	Nondemented	2	763	F	R	63	13	2.0	30.0	0.0	1327	0.796	1.323
372	OAS2_0186	OAS2_0186_MR3	Nondemented	3	1608	F	R	65	13	2.0	30.0	0.0	1333	0.801	1.317

Fig. 1. Raw Dataset from OASIS

Dataset/s acquired
- MRI and Alzheimer's Dataset

Data sources
- Data were provided by OASIS: Longitudinal: Principal Investigators: D. Marcus, R, Buckner, J. Csernansky, J. Morris; P50 AG05681, P01 AG03991, P01 AG026276, R01 AG021910, P20 MH071616, U24 RR021382
- Open Access Series of Imaging Studies (OASIS) where neuroimaging data sets of the brain are collected

Methods used to acquire the datasets
- Importing data using CSV in python

Any problems encountered
- Missing values
- Different types of data

2.2 Describe Data

Format of the data
- float, int, object data types

Quantity of data (e.g. the number of records and fields in each table)
- Df2: 373 rows × 15 columns

Identities of the fields
- ID Identification
- Group Demented or Nondemented
- Visit The visit number
- M/F Gender
- Hand Dominant Hand

- Age Age in years
- 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
- Delay Delay

2.3 Explore Data

Initial Findings

After obtaining the dataset, the different features were explored and analyzed using graphs.

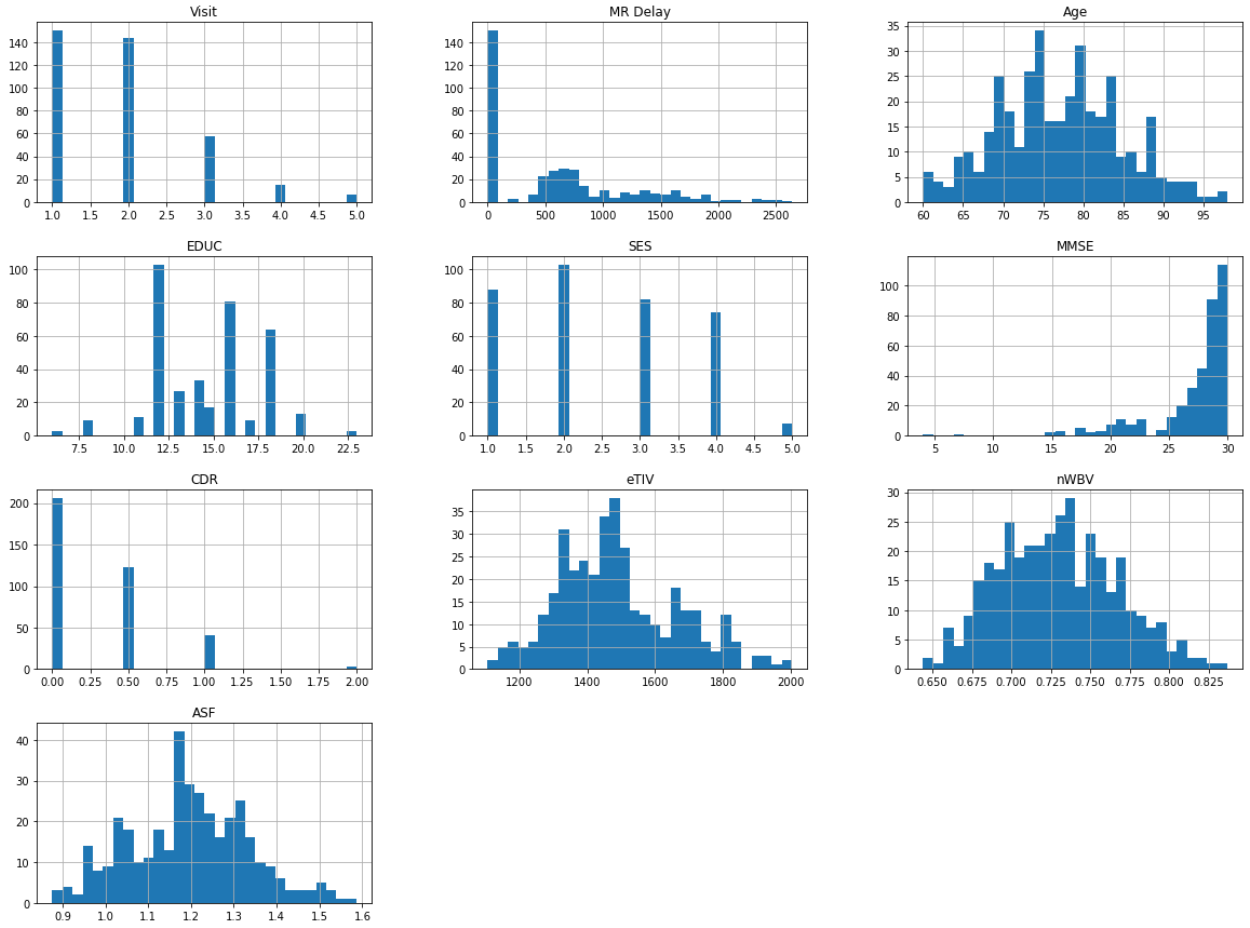


Fig. 2. Analysis of Preliminary Dataset from OASIS

Based on the graphs above, it was found that:

- All are right handed
- More females than males
- Majority of ages fall under 70’s
- Majority are from second SES

- Majority from second level of education
- Majority have had less than 12.5 years of education
- There is an extra group called “converted”, wherein they were first nondemented but turned out to be demented after a later visit
- Majority of patients had visited once only
- MMSE values are skewed to the right (around 30), which means that majority of patients have normal cognition
- CDR is mostly 0-0.5 (no dementia)
- eTIV is about 1450-1500
- Highest nWBV is at around 0.73 to 0.74
- Highest ASF is about 1.5 to 1.7

2.4 Verify Data Quality

- Data can be understood easily since all necessary information is logged
- There are some missing values, so imputation of data needs to be done
- There is a mix of categorical variables and numerical variables. One hot encoding should be done to make all data numerical
- No outliers based on inspection

Data Preparation

3.1 Select Data

To select the relevant features, the dataset was first examined. It was seen that there were features not related to the patient’s personal information in relation to dementia. Thus, these features were removed.

Final dataset includes:

Group - classifies whether demented or not
M/F - see relationships of gender to dementia (if any)
Age - to gain more insights into relationship of age to dementia
Educ - see if education has correlation with dementia
SES - see if SES has relationship with dementia
MMSE (Mini Mental State Examination) - the effects of the MMSE values
CDR - to see the Clinical Dementia Rating and how it relates to dementia
eTIV - Estimated total intracranial volume
nWBV - Normalize Whole Brain Volume
ASF- Atlas Scaling Factor

Excludes:

- Unique values (i.e. MRI ID, Subject ID)
- Number of visits (pertains to how many times a patient has visited)
- Hand since all are right-handed
- MRI delay (denotes the delay between visits)

3.2 Clean Data

To clean the dataset, the following steps were accomplished:

- Imputing data using median and mode imputation
    - Mean imputation for numerical variables
    - Mode imputation for categorical variables
- One hot encoding for converting categorical data to numerical
    - M/F: 1 if M, 0 if F
    - Group: 1 if Demented or Converted, 0 if Nondemented
- Dropping unnecessary data features
- Data normalization since the data ranges vary widely among features and so all attributes fall within the same range

3.3 Construct Data

The final dataset to be used came from the original OASIS dataset with only the necessary attributes. Further analysis of the finalized dataset was done, the results of which are listed below:

- In the dataset, there is a higher rate of dementia in males than females. Dementia is more prevalent in patients aged 70-80, whereas non-demented patients are typically younger (around 60).
- Based on the correlation heatmap and scatterplot, there is a negative correlation between nWBV and age.
- Majority of patients have 0 to 0.5 CDR scores, meaning they have normal to very mild dementia.
- MMSE scores seem to be higher for nondemented patients than those with dementia. The MMSE scores for dementia patients seem to be more scattered (16-30), while those with no dementia only ranged from 26-30. Any MMSE score greater than or equal to 24 points indicates a normal cognition, hence why those without dementia have higher scores. MMSE scores for demented patients ranges from moderate (10–18 points) to mild (19–23 points) cognitive impairment.
- eTIV in dementia patients is more prominent in the 1300-1600 range than in non dementia patients. However, both demented and nondemented patients fall within the same range of eTIV. eTIV is also more scattered in non dementia patients. It can also be seen that eTIV and ASF fall linearly, showing that eTIV and ASF are negatively correlated. This is because ASF is the volume-scaling factor necessary to fit each individual, and should be proportional to eTIV.
- nWBV in dementia patients is lower than that in non dementia patients. Dementia patients have nWBV typically falling within 0.70 - 0.76, while that of non dementia patients falls within 0.72 - 0.78. Hence, subjects with lesser nWBV value are more likely to be demented.
- ASF is less spread out for demented patients (ranges from 1.1 to 1.4) than for nondemented patients. Results are similar to eTIV since these are negatively correlated on a 1-1 basis.
- Years of education for those with dementia is less compared to those without dementia. This aligns with findings suggesting that less education relates with higher probability of dementia.

- SES of those with dementia is more spread out. This may mean that the SES of a patient does not increase the probability of having dementia.

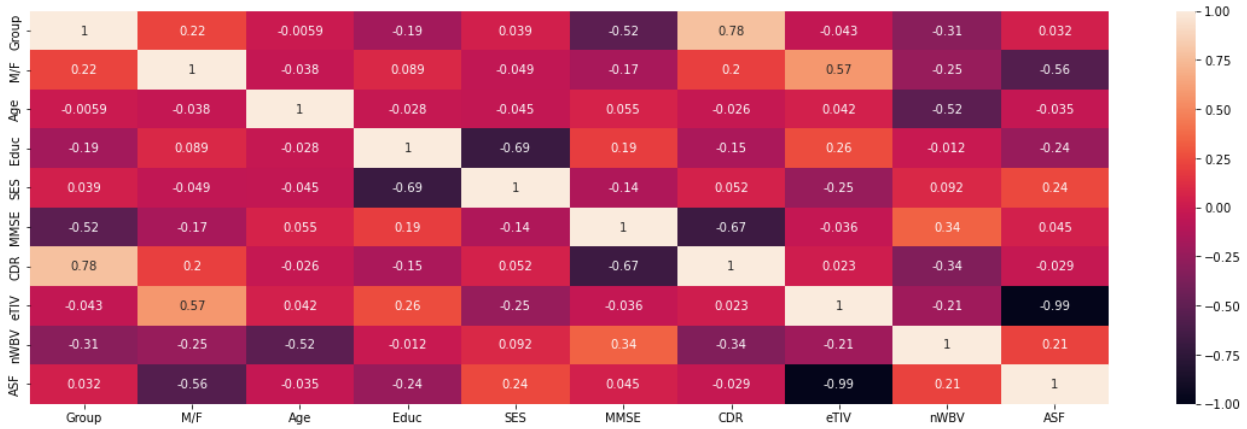


Fig. 3. Correlation Heatmap of Constructed Dataset

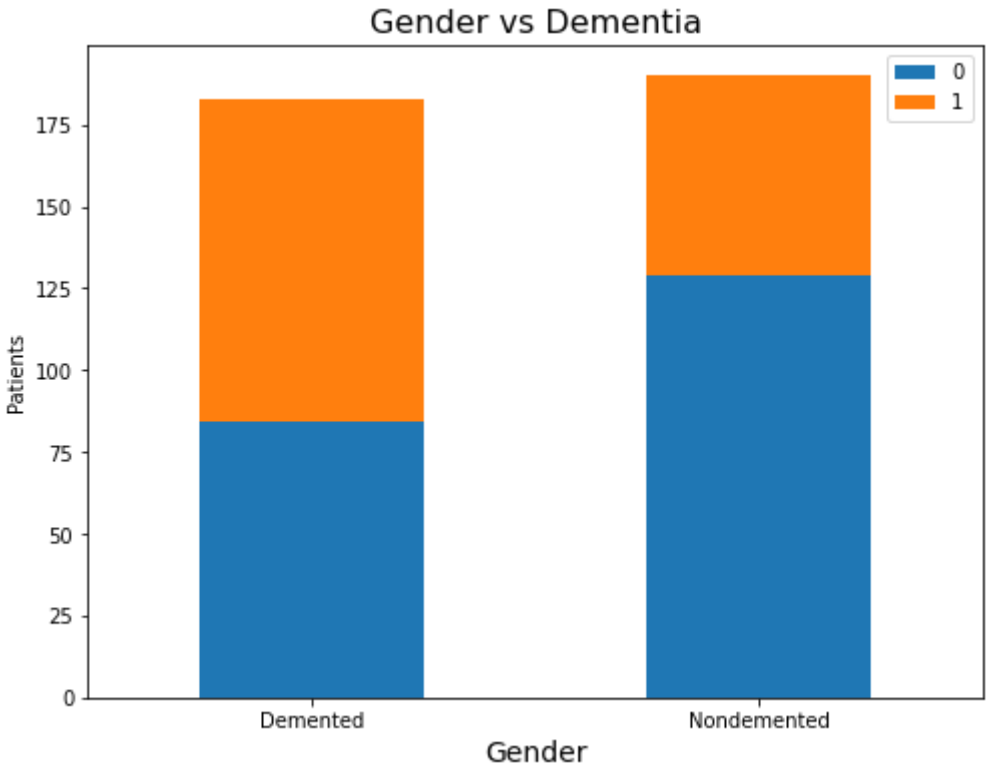


Fig. 4. Gender vs. Dementia Data

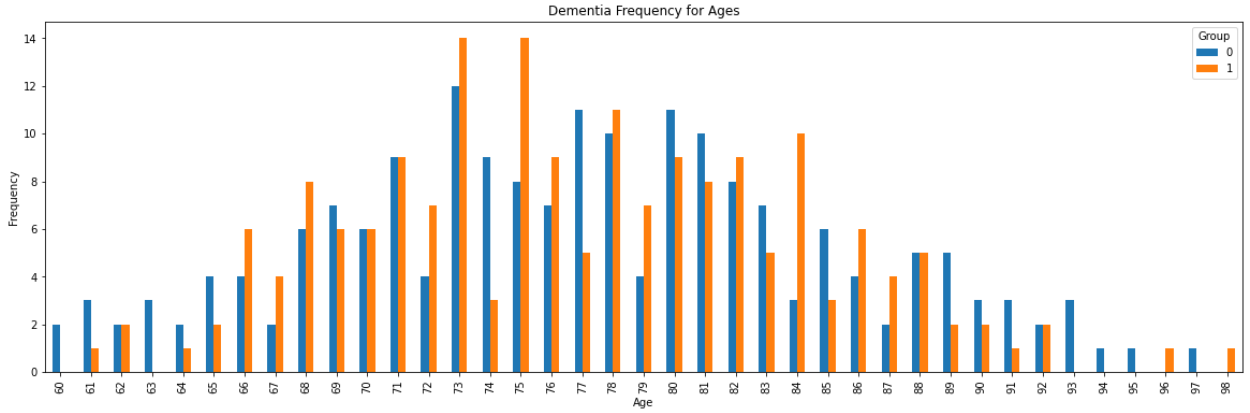


Fig. 5. Dementia Frequency for Ages

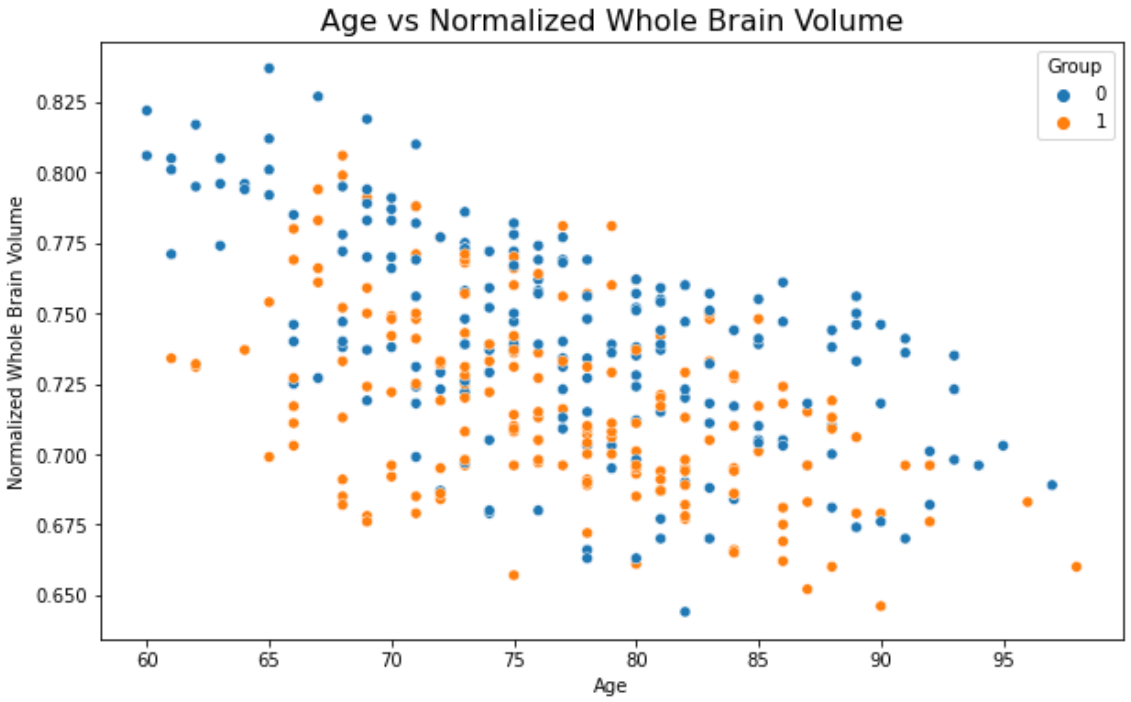


Fig. 6. Age vs. Normalized Whole Brain Volume

3.4 Integrate Data

- No merged data

3.5 Format Data

Modeling

4.1 Select Modeling Technique

Since we want to obtain insights into the relationships of different factors towards dementia of patients as well as predict whether one has dementia or not based on their data,

classification modeling should be used. Since the data has labels (demented or nondemented), supervised learning can be used for this model. It is assumed that the supervised learning model that is used will classify whether one has dementia or not. In addition, clustering was also explored to see the patterns or groupings of the features depending on the presence or absence of dementia.

4.2 Generate Test Design

With the dataset from OASIS, different supervised learning models were used to train the dataset. The dataset was divided into training and testing (where 80% of the data falls under the training dataset and 20% will fall under the testing dataset). The dataset was scaled using StandardScaler to ensure that all columns have values within the same ranges. Each model was used to predict the patients' classifications and was scored based on their accuracy. To evaluate the models, a confusion matrix was used to show the accuracy, precision, sensitivity, and f1 scores. The model with the highest score in accuracy will be used for deployment.

4.3 Build Model

To build the most appropriate model, various supervised learning classification methods were used, as adapted from the sklearn library of Python. These include the MLPClassifier, RandomForestClassifier, LogisticRegression, DecisionTreeClassifier, GaussianNB, SVC, XGBClassifier, GradientBoostClassifier, ExtraTreesClassifier, and KNeighborsClassifier. RandomizedSearchCV was used, which is a method for finding the best "fit" and "score" depending on the model used. It takes into account the hyperparameters of each model.

Multi-layer Perceptron classifier (MLP Classifier) is a type of artificial neural network (ANN) model that maps sets of input data onto a set of appropriate outputs.

Logistic Regression models the probability of a discrete outcome given input variables. The most common logistic regression models a binary outcome; in this case, the output is whether the patient has dementia or not. It does not require a linear relationship between inputs and output variables, but rather follows a nonlinear log transformation. A probability of 0.5 or less classifies the output as 0, otherwise it is classified as 1.

Decision Tree Classifier follows a tree structure where an internal node represents a feature, the branch represents a decision rule, and each leaf node represents the outcome. It first chooses the best feature, which then becomes a decision node and hence breaks the dataset into subsets. This process continues until either 1) there are no more instances left, 2) there are no more features, or 3) all the tuples belong to the same attribute value.

Random Forest Classifier is similar to the Decision Tree such that it takes the prediction from each decision tree based on the majority votes of predictions, and it predicts the final output. The more trees, the higher the accuracy.

Similar to the Random Forest Classifier is the Extra Trees Classifier which creates unpruned decision trees from the training dataset and predicts using majority voting. It then fits each decision tree on the training dataset.

Gaussian Naive Bayes follows the Naive Bayes algorithm which assumes that the particular feature/s in a class is/are unrelated to the other features. It produces an output using probability. This model is easy to build and can work with even large datasets.

Support Vector Machines output the "best fit" hyperplane that divides or categorizes the data into the different classes by using support vectors (training tuples) and margins (defined by the support vectors).

Gradient Boost Classifier and XGBClassifier take a weak hypothesis and tweak it to improve the strength of the hypothesis. This operates similarly to gradient descent in neural networks. The difference of XGBClassifier, which stands for "eXtreme Gradient Boosting", is that the algorithms and methods have been customized to improve performance of the Gradient Boost Classifier.

KNN Classifier stores training examples and delays processing until there is a new instance. It classifies new data based on its similarity to available data. It takes the Euclidean distance of K number of neighbors and counts the number of the data points in each category among these neighbors. It then assigns new data to the category for which the number of the neighbor is maximum.

4.4 Assess Model

Based on the supervised classification models used, MLPClassifier had the highest accuracy at 0.9333333333333333. Multi-layer Perceptron classifier (MLP Classifier) is a type of artificial neural network (ANN) model that maps sets of input data onto a set of appropriate outputs. There are multiple layers and each layer is fully connected to the following one. The simplest MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. MLPClassifier trains iteratively since at each time step the partial derivatives of the loss function with respect to the model parameters are computed to update the parameters.

What makes this a good model is that Neural Networks can learn the characteristics of the data on their own. This makes it easier during the feature engineering phase since it does not need expert input for training. From these characteristics, the model combines different representations of the dataset, wherein each identifies a specific characteristic, into a more high-level representation of the dataset. Hence, this type of model can adapt to data on its own. Inputs are combined in a weighted sum and, if the weighted sum exceeds a predefined threshold, the neuron fires and produces an output. For the Multi-layer Perceptron, inputs are combined with the initial weights in a weighted sum and subjected to the activation function (in this model, the stochastic gradient descent), and each result is fed into the next layers (all 108 hidden layers) until it reaches the output layer. Hence, it is feed-forward. This model also uses backpropagation such that any modifications are made from the output layer towards the first hidden layer to reduce the mean squared error.

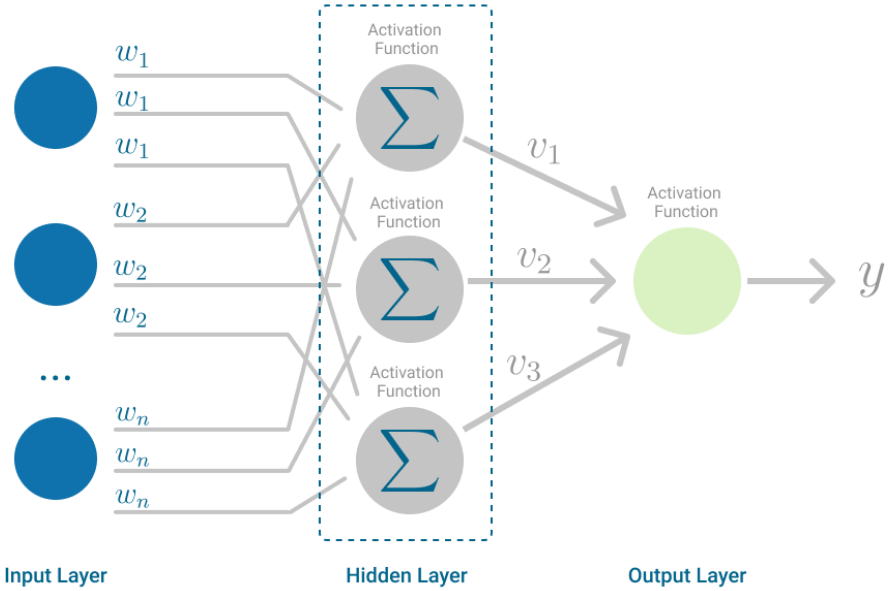


Fig. 7. Visualization of MLP Classification

- Parameters:
  - hidden_layer_sizes : sets the number of layers and the number of nodes in the MLPClassifier. Each element in the tuple represents the number of nodes at the ith position where i is the index of the tuple.
  - max_iter: It denotes the number of epochs or iterations to be done.
  - activation: The activation function for the hidden layers.
  - solver: specifies the algorithm for weight optimization across the nodes.
  - random_state: The parameter allows to set a seed for reproducing the same results
- In this activity, the model used the following parameters: {'solver': 'adam', 'hidden_layer_sizes': 108, 'activation': 'tanh'}
  - Solver adam : stochastic gradient-based optimizer that uses a log-loss function
  - activation tanh : uses the hyperbolic tan function f(x) = tanh(x)
- One weakness of using this however is that it has a long training time

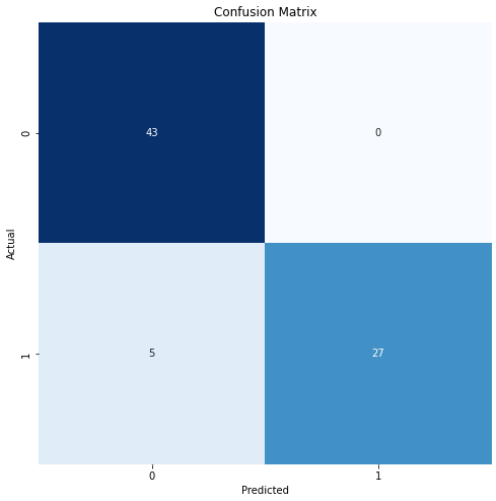


Fig. 8. Confusion matrix of MLP Classification

Classification Report:

	precision	recall	f1-score	support
0	0.90	1.00	0.95	43
1	1.00	0.84	0.92	32
accuracy			0.93	75
macro avg	0.95	0.92	0.93	75
weighted avg	0.94	0.93	0.93	75

The following summarizes the accuracies of the models used:

MLPClassifier: 0.9333333333333333
RandomForestClassifier: 0.92
LogisticRegression: 0.92
DecisionTreeClassifier: 0.92
GaussianNB: 0.92
SVC: 0.92
XGBClassifier: 0.9066666666666666
GradientBoostClassifier: 0.9066666666666666
ExtraTreesClassifier: 0.9066666666666666
KNeighborsClassifier: 0.8933333333333333

In addition to these classifiers, clustering using K-Means was also done to examine the groupings or patterns based on those who have dementia and those who don't. The elbow method was done to find the best number of clusters possible. The results showed that 7 clusters was optimal. However, the clusters based on dementia are unclear. The clusters are grouped in either 0 (no dementia) or 1 (with dementia). Thus, K-Means clustering may not be an optimal model to find the groupings available in the dataset.

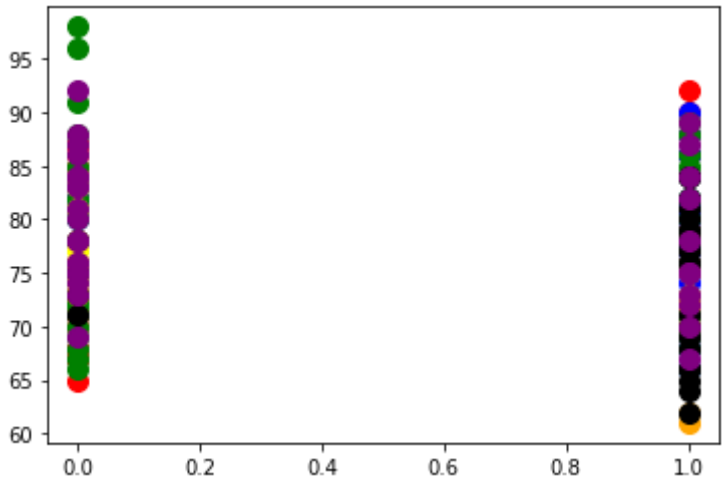


Fig. 9. K-Means Clustering

Evaluation

5.1 Evaluating Results

Conclusion
The following shows the assessment of results for the business objectives.

1. Obtain useful insights into the relationships of different factors towards dementia
    - This objective was successfully implemented. We found that dementia is primarily affected by age, MMSE, nWBV, and years of education based on the exploratory data analysis which involves correlation, histograms, and scatter plots among others.
        - Dementia is more prevalent in patients aged 70-80
        - as age increases, the nWBV decreases
        - MMSE scores seem to be higher for nondemented patients than those with dementia.
        - nWBV in dementia patients is lower than that in non dementia patients
        - Years of education for those with dementia is less compared to those without dementia. This aligns with findings suggesting that less education relates with higher probability of dementia.
2. Increase diagnostic accuracy to about 80% (according to a study by Bron et. al.)
    - This objective was successfully completed. MLP classifier model shows accuracy of about 93.33%, which allows for accurate prediction of dementia in patients
3. Improve patient safety through better determination of treatment criteria and risk factors
    - This objective is partially completed. Through the logistic model, more insights into the critical factors towards dementia were found. This model can be deployed in a real-life setting to examine its reliability and performance further with regards to the treatment of patients
4. Obtain a patient satisfaction rating of at least 70%
    - This objective was not completed since the model needs to be deployed in a real life setting.

From this project, it was seen that all supervised learning models achieved accuracy above 70%. However, the MLPClassifier proved to have higher scores in accuracy, sensitivity, and f1 compared to others. This model can be used for deployment in the healthcare system to aid in faster diagnosis of dementia patients.

5.2 Reviewing the process

Through this process, the following steps were completed:

1. Assessing the business situation in the healthcare industry in terms of diagnosis of Dementia
2. Building the model that can be used for the CAD system
3. Evaluation of model in terms of classification and prediction metrics

Other steps that need to be taken:

1. Testing the model with new data (can use the other datasets from OASIS)
2. Deploy final model in new CAD system
    a. Examine the performance of the model in real life and in relation to dementia patients to find the best possible treatment/s
3. Evaluation of using the proposed CAD system in terms of its costs and benefits

5.3 Determining the next steps

For the data science aspect, one action to take is to deploy a model that can predict the CDR ratings of the patients. The dataset used lacked enough information on the CDR scores, hence why the Group (demented/nondemented) was used as a target variable. Another action is to try other classification and prediction models (since the predictive model focused on using sklearn libraries). One weakness of the MLP Classifier is that it had a longer training time than others. When scaling the model to a larger one, it may further delay the results and hence the diagnosis and treatment of the dementia patients. Another is to try another dataset such as the cross-sectional dataset from OASIS to check if results are the same and evaluate the performance of the model.

For the business aspect, specifically the healthcare industry, a possible action to take after the finalization of the predictive model is to consult with other personnel (e.g. data analysts/ scientists, clinicians) for the possible implementation of this diagnostic tool in the healthcare setup. This is to find out the effectiveness and scalability of this model in a real world setting since the model was developed on a smaller scale (i.e. how do we incorporate this predictive model in diagnosis? Can the model be programmed in existing tools in the hospital for diagnosis, or does the hospital need new resources such as updated desktops to use this model?).

Another action to take is to examine whether the hospital setup has the necessary resources for patients with dementia. Since the model showed the correlation among features such as gender, MMSE, and CDR scores with regards to the onset of dementia, one thing to consider is the availability of (new) treatments that can be done for these patients (especially for those with more severe cognitive impairment). This information is to be provided by health professionals, however.

Another action to take is to scale the proposed model to accompany more datasets with more information. This, however, may need to be done by more researchers. Additionally, patient satisfaction ratings should be obtained to see whether the proposed CAD system is effective in improving the quality of care provided by the physicians with the help of this system.

Lastly, the costs and benefits of using the proposed CAD system should be discussed. Benefits include the early and accurate diagnosis of dementia for patients, which will help patients and caregivers support and maintain the disease with more well-suited treatments. Another benefit may be the reduced amount of time needed for diagnosis, since the proposed model can classify whether one has dementia or not based on the patient's personal information. At the present time, there is no available data in public with regards to the costs of using such a system (if any) for the hospital. This may depend on the setting of the hospital, availability of these technologies, and other important factors. Knowing these can help the hospital company decide what measures to take with regards to the use of the CAD system (i.e. will there need to be an increase in maintenance fees for this system?).

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