Overview

Though research on dementia has been conducted many times throughout scientific history, we would like to explore this world ourselves. We have taken two datasets from a public source that include many demographic factors about demented and nondemented patients, and we will use those datasets to perform an exploratory analysis of fluctuations in brain volume. Additionally, using numerical values of normal brain volume in male and female patients, we want to perform Pearson's Correlation Coefficient to compare normal brain volume to the brain volume of someone who has dementia separated by gender. Moving forward into our project, we will prototype a predictive model to predict dementia using various neural images found on a publicly available dataset. Using computer vision with a python package called 'tensorflow', we will demo our predictive model using images ranging from nondemented, very mild demented, and mild demented. Our purpose for using not as severe case images for diagnosing dementia patients is because we want to analyze whether dementia can be predicted and caught early on. Which, in turn, could create new opportunities for better treatment plans and diagnosis.

Research Question

How does brain atrophy differ between patients with Alzheimer's disease and those without Alzheimer's disease? Is it possible to predict a patient's dementia level using fMRI scans (neural images of their brain atrophy levels), given there is a difference between the brain atrophy levels?

Hypothesis

H1: The predictive accuracy of machine learning models, such as Convolutional Neural Networks (CNN), will significantly improve with the inclusion of additional brain imaging features derived from fMRI data. This enhancement will lead to more precise and reliable predictions of Alzheimer's disease progression, as well as a clearer distinction between patients with Alzheimer's disease and those without it.

H0: The inclusion of additional brain imaging features derived from fMRI data will not significantly improve the predictive accuracy of machine learning models, such as Convolutional Neural Networks (CNN), in predicting Alzheimer's disease progression or distinguishing between patients with and without Alzheimer's disease. The accuracy of the predictions will remain statistically similar to models that do not incorporate these additional features.

Background & Prior Work

In this project, our group wants to explore the differences between demented and nondemented patients. This topic piqued our interest particularly because it is a very common symptom in which vast numbers of people and it has been widely studied by other scientists. As a result, creating better diagnostic tools and improving treatment plans and management. We also take into consideration those who take care of loved ones with dementia, as it has been discussed by many people as a physically and mentally exhausting event. There are a plethora of Reddit posts we have found in our research of this topic of people describing the sadness, anger, and frustration that comes along with treating dementia - some even finding humor in their situations.[1] After our findings via the internet, we grew sympathy and a greater understanding of the effects of dementia on not just patients who have it, but those around them as well.

1. ^ lottieslady (Dec, 2023) Those who have had a parent/friend/loved one with dementia, how did you help them? How did you help yourself cope with their declining state? *Reddit*. https://www.reddit.com/r/AskOldPeople/comments/190u5qt/those_who_have_had_a_parentfriendloved_one_with/

According to the Alzheimer's Association, Dementia is a general term for loss of memory, language, problem-solving and other thinking abilities that can vary in severity, overall interfering with a person's daily life. It's not a single disease, rather this umbrella term to describe a collection of symptoms if they are living with a disease, most notably Alzheimer's Disease. [1] Alzheimer's is a very common type of dementia with progressive symptoms, starting with mild memory loss and possibly leading to the loss of ability to carry on a conversation and respond to your general surroundings. According to the CDC, scientists do not fully know what causes Alzheimer’s disease, but there are multiple factors that can affect each person differently: age, family history, changes in the brain, and possibly education, diet, and environment. Most of what is known are the symptoms of Alzheimer’s, typically regarding memory problems being the first warning sign followed by difficulty completing familiar tasks, misplacing things, and changes in mood and behavior. [2] Our group’s decision to focus on brain atrophy in Dementia patients is per our discussion for a need to create better diagnostic and prognostic tools in managing this debilitating condition.

From what we knew before, there is no single test that can determine if a person is living with Dementia. Recently, however, there has been a new usage of biomarkers to help diagnose Alzheimer’s disease, particularly focusing on brain imaging. According to the National Institute on Aging, brain scans are allowing doctors to see different factors that may help in diagnosis via CT, MRI, and PET scan. [3] Our group specifically wanted to focus on MRI for this project due to its versatility. MRIs can show areas of the brain that have shrunk and repeated MRIs can show a person's brain changes over time, which may lead to evidence of shrinkage and can be use in many diagnoses. [3]

Magnetic resonance imaging is a noninvasive technique that uses magnetic fields and radio waves to produce detailed images of body structures, and similar to CT scans, MRIs can show areas of the brain that have shrunk. Additionally, repeated MRIs can show a person’s brain changes over time, which may lead to evidence of shrinkage and can be used in many diagnoses. [4] This has our group wondering, if MRIs can be used to note shrinkage in the brain, and according to the NIA, Alzheimer’s results as

neuronal death which can affect the brain via tissue death and shrinkage, then we can possibly use MRI as a predictive method for Dementia.

In a longitudinal OHSU study done to analyze the rate of brain volume loss in Dementia patients, it was found that the rate of brain volume loss differed greatly among those with intact cognition and stable mild cognitive impairment. It was suggested that monitoring brain volume loss is a key indicator in predicting dementia before symptoms appear. [5] Additionally, in a prior study done in Sporadic Alzheimer's Disease, it was found that volume loss across the brain can predict the likelihood of developing dementia. [6] Essentially, the quantification of volume loss across the brain might provide a good prediction of who is in the early stages of diseases like Alzheimer's.

Therefore, quantifying volume loss throughout the brain could offer valuable insights into identifying individuals in the early stages of diseases like Alzheimer's, aiding in early intervention and management strategies. For this project, we would like to take into account the possibility of a difference between gender in Dementia diagnosis. This is especially so since women have a higher risk of developing Dementia during their lifetime where around twice as many women have Alzheimer's Disease compared to men. [7]

Thus, for this project, we chose to separate it into two parts.

1. Comparisons in normal brain volume and demented brain volume between males and females
2. Computer vision application of multiple MRI images of patients to prototype a predictive model for the prediction of Alzheimer's Disease

1. ^ Centers for Disease Control and Prevention. (2020, October 26) Alzheimer’s Disease and Related Dementias. *Alzheimer's Disease and Healthy Aging*. https://www.alz.org/alzheimers-dementia/what-is-dementia
2. ^ Alzheimer's Society. (n.d.) What is Dementia? *Alzheimer's Disease and Dementia*. https://www.alz.org/alzheimers-dementia/what-is-dementia
3. ^ National Institute on Aging. (2022, January 21) How Biomarkers Help Diagnose Dementia. *Alzheimer's symptoms and diagnosis*. https://www.alz.org/alzheimers-dementia/what-is-dementia
4. ^ John Hopkins Medicine. (n.d.) Magnetic Resonance Imaging (MRI). *Treatments, Tests and Therapies*. https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/magnetic-resonance-imaging-mri
5. ^ Oregon Health & Science University. (2004, April 28). OHSU Study:Rate of Brain Volume Loss Predicts Dementia. *OHSU News*. https://news.ohsu.edu/2004/04/28/ohsu-study:rate-of-brain-volume-loss-predicts-dementia
6. ^ National Library of Medicine. (2013, October 11). Biomarker-based prediction of progression in MCI: Comparison of AD signature and hippocampal volume with spinal fluid amyloid-β and tau. *Front Aging Neuroscience*. https://pubmed.ncbi.nlm.nih.gov/24130528/
7. ^ Alzheimer's Society. (2024, March 8). Why is dementia different for women?. *About Dementia*. https://www.alzheimers.org.uk/blog/why-dementia-different-women#:~:text=Women%20have%20a%20greater%20risk,of%20dementia%20–%20compared%20to%20men.

Part 1: Whole Brain Volume Test

In the first part of our project, we will be focusing on 2 datasets taken form Oasis, a publicly available source for data on demented and nondemented patients.[1] In the next parts, we will clean the data and perform an exploratory analysis to better understand what the data is demonstrating.

1. ^ Open access series of imaging studies (OASIS). (n.d.). https://sites.wustl.edu/oasisbrains/

Dataset #1

- Name: Oasis_cross_sectional
- Link to dataset: https://sites.wustl.edu/oasisbrains/home/oasis-1/
- Number of observations: 436
- Number of variables: 12

For this dataset, we will be particularly focused on gender (M/F), Estimated total Intracranial volume measured in mm3 (eTIV), and the Clinical Dementia Rating (CDR) - (0 = no dementia, 0.5 = very mild AD, 1 = mild AD, 2 = moderate AD). The dataset also includes other demographics such as:

- Handedness (Hand)
- Age (Age)
- Years of Education (EDUC)
- Socioeconomic status (SES)

And clinical information:

- Mini-Mental State Examination Score (MMSE)
- Estimated total intracranial volume (eTIV)
- Atlas Scaling Factor (ASF)
- Normalized Whole-Brain Volume (nWBV)

As we delve into exploratory analysis, we really only care about the gender of the patient and their normalized whole-brain volume. With this dataset, we will clean it and merge it with Dataset #2 to create a larger dataset to perform more analysis.

We are using fMRI imaging datasets from patients with Alzheimer's disease, supplemented by datasets from the Oasis project, which provides data on brain volume and relevant clinical information such as age and gender. The Oasis dataset gave us a better understanding in our research as it provides data on brain volume and clinical information for both healthy individuals and patients with Alzheimer's disease. This multi-source approach helps ensure the diversity and completeness of our dataset, limiting bias in our data modeling. Furthermore, we focused on the Alzheimer's fMRI imaging dataset, which contains a collection of images showing brain atrophy levels in patients with Alzheimer's disease. This integration of analyzing both datasets helps provide a comprehensive view of the factors contributing to Alzheimer's disease progression. These images

have undergone preprocessing steps to correct and normalize spatially, and remove non-brain tissues. Any incomplete or corrupted imaging files have been excluded from the dataset.

Dataset #2

- Name: Oasis_longitudinal_demographics
- Link to dataset: https://sites.wustl.edu/oasisbrains/home/oasis-2/
- Number of observations: 373
- Number of variables: 15

Similarly with the first dataset, we will be particularly focused on gender (M/F), Estimated total Intracranial volume measured in mm3 (eTIV) and the Clinical Dementia Rating (CDR) - (0 = no dementia, 0.5 = very mild AD, 1 = mild AD, 2 = moderate AD).

The dataset also includes other demographics such as:

- Handedness (Hand)
- Age (Age)
- Years of Education (EDUC)
- Socioeconomic status (SES)

And clinical information:

- Mini-Mental State Examination Score (MMSE)
- Atlas Scaling Factor (ASF)
- Normalized Whole-Brain Volume (nWBV)

After cleaning the data below, we will merge this dataset with Dataset #1 by their Clinical Dementia Rating (CDR).

In the cell below, to make the dataset easier to work with, we will merge the dataset on their CDR and M/F columns. All columns with '_x' will be data from Dataset #1 and '_y' will be data from Dataset #2. We will be left with a dataset joined together by their clinical ratings to make an easier distinction between, for example, female patients with mild dementia, male patients with moderate dementia, etc. The values will be in descending order from 0.0-2.0.

- Name: brain_volume
- Number of observations: 6164
- Number of variables: 4

Data Visualization

The CDR Scoring Table offers descriptive references to assist clinicians in assigning suitable ratings using interview information and clinical assessment. Alongside domain-specific ratings, an overall CDR™ score can be computed using a CDR™ Scoring Algorithm. [1] This scoring system is valuable for defining and monitoring a patient's degree of impairment or dementia over time:

0 = Normal
0.5 = Very Mild Dementia or Questionable
1 = Mild Dementia

2 = Moderate Dementia

1. ^ Washington University School of Medicine in St. Louis. (n.d.). Knight Alzheimer Disease Research Center. *Department of Neurology* https://knightadrc.wustl.edu/professionals-clinicians/cdr-dementia-staging-instrument/

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Findings:
Between the two datasets in their brain volume, their averages lie between 1200 to 1600 mm3. Additionally, it's important to note that the highest values recorded are different and have the potential to average out. In Dataset #1 and #2, the highest calculated brain volume is 2000 mm3. Using the histogram with combined data, it's much easier to specify that the most frequent brain volume in demented patients is between 1400-1500 mm3.

Bar plot for CDR by Gender

A stacked bar plot is effective for comparing the distribution of Clinical Dementia Rating (CDR) across male and female (M/F) categories, allowing clear visualization of differences in dementia severity between genders and providing a comprehensive view of subgroup compositions within each CDR level. You can see below that there are more very mild demented participants that are than female.

Findings

There are not very many moderate dementia patients. After performing more intricate analysis, we believe it is important to show the counts of data compiled that are either male or female. This is a possible limitation due to the 984 more female participant data that may skew the visualizations we see above. Overall though, men on average according to the data present very mild dementia more than any other category, women perform similarly but at a much lower rate.

Scatter plot for CDR and eTIV association

Findings:

- There is a very interesting visualization presented in the scatterplot. In Dataset #1, most of the Clinical Dementia Rating is as a value of 0.00 (Normal) while in Dataset #2, the Clinical Dementia Rating is most common at a value of 0.50 (Very Mild Demented). It's important to note there are a few outliers in the data where very few cases present a CDR of 2 (Moderate Dementia).
- Taking into account the brain volume, let's separate the analysis for easier understanding:
    - Dataset #1: eTIV lowers as the CDR increases. The highest volume was measured at 0.850 with a CDR value of 0.0. Suggesting a negative correlation
    - Dataset #2: eTIV lowers as CDR increases. The highest volume was measured at slightly above 0.80 with a CDR value of 0.50. As well suggesting a negative correlation with some tweaks, but overall it shows a similar trend to that of the first dataset

After combining the datasets, one can note a very distinct trend in patients who have a CDR rating of 0.50. That is, their brain volumes tend to hang around the 1300-1500 value. There are also some peculiarities in the data such that the CDR rating of 2.0 contains a higher brain volume than some of those two have a CDR rating of 0, suggesting there could be some skew in the data.

Exploratory Data Analysis

Source #1: https://mode.com/blog/violin-plot-examples#how-to-read-violin-plot

Carron, J. (2021, December 13). *Violin plots 101: Visualizing Distribution and Probability Density*. Mode. https://mode.com/blog/violin-plot-examples#how-to-read-violin-plot

Describe Violin Plot:

A violin plot is a data visualization tool that combines the features of a box plot and kernel density plot, using the distribution of numerical data to highlight the density of the data points. It is useful for comparative analysis between different categories or groups and allows us to draw summary statistics.

Looking at the violin plot, the white dot in the middle of the violin plot represents the median. The thick gray bar in the center represents the interquartile range and the thin gray line represents the rest of the distribution, excluding the outlier points. Each side of the gray line shows the kernel density estimation which helps us see the distribution shape of our data. The wider the violin plot, the higher the probability.

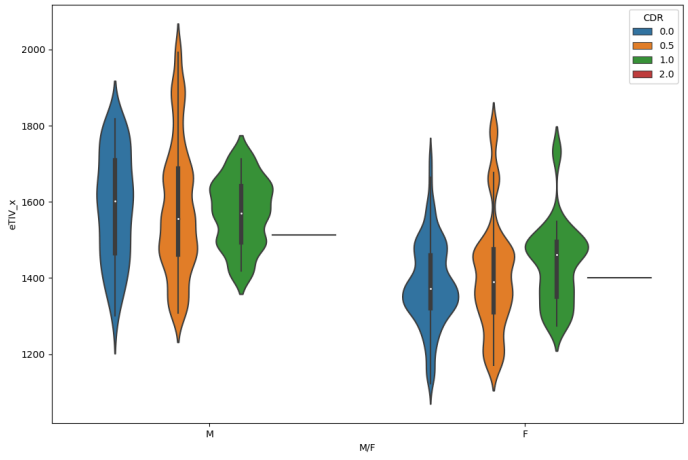
The Clinical Dementia Rating (CDR) is a clinical tool that measures the severity of dementia through an assessment of cognitive and functional performance. It scales from 0-3 point numeric scale derived from a clinician's rating.

Violin Plot #1:

In this violin plot, the x-axis has two areas, males and females. The y-axis represents the estimated total intracranial values, which can be abbreviated as eTIV and essentially refers to brain volume data. Looking at the violin plot, you can see that in Males shown on the left side, there is a broader spread in eTIV values and that in Females shown on the right side, more concentrated with lower variability and lower eTIV values.

Blue (0.0): No dementia
Orange (0.5): Very mild dementia
Green (1.0): Mild dementia
Red (2.0): Moderate dementia

Distribution by Gender:



What's very interesting is that among all the plots, even when brain volume was not merged, the brain volume demonstrated in demented patients was lower on average for female patients than male patients. In the plot above, we generally have more representation for female patients in the CDR index, showing that their medians are at a lower eTIV value than males. Additionally, there are only median horizontal lines on the plot which represent the 0.0 CDR index for males and the 2.0 CDR index for females. This could suggest there is very minimal data form the merged sets. However, from the plots above, we can see that there is data present for those two ranges in the second dataset. The simplest answer for this observation is that of error in the means when combining the two datasets.

In [35]:

Above is a visualization which filters data for males and females respectively. Demonstrated on an overlaid histogram, we can see that between both datasets, there are very few female participants that have a mean brain volume higher than 1500-1600. The heavier portion of brain volume for males lies skewed to the left as does the data for women, but differently demonstrating a strong average of 1400 mm3 in brain volume.

For the sake of accuracy, we will be abandoning our combined dataset 'eTIV_combined' to perform a Pearson Correlation Coefficient task. Our reasoning for a PCC is to determine if there is a linear component associated between our two variables of concern: gender and associated brain volume. In seeing the strength of the correlation, we can make a good deterministic decision that brain volume in demented patients does differ between gender.

The output Pearson correlation coefficient: 0.302982850979866 indicates a moderate positive correlation between the 'eTIV_x' and 'eTIV_y' columns in the dataset.

The output Pearson correlation coefficient for males: -0.00029160691475869574 indicates a very weak negative correlation (close to zero) for males, and Pearson correlation coefficient for females: 0.009529753739218721 indicates a very weak positive correlation (close to zero) for females. These values suggest that there is almost no linear relationship between the 'eTIV_x' and 'eTIV_y' columns for both males and females in this dataset.

According to a paper published by the National Library of Medicine, the mean brain volume for men is 1209 mm^3 while for women is is 1056 mm^3.[1] Using these values, let's create a function that can take an input and determine whether that falls inside or outside the normal range for males or females. If the inputted value is less than the mean brain volume for the respective gender, it will output that it is a possible red flag. Our hope is that our small demo could be used as a small tool in diagnosis.

1. ^ National Library of Medicine. (2020, May). Aging and the Brain: A Quantitative Study of Clinical CT Images. *National Center for Biotechnology Information* https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7228157/#:~:text=Brain%20Parenchymal%20Volume&text=The%20mean%20brain%20volume%20for,1056%20%C2%B1%20107.4%20cm3).

Summary of Findings

The findings from the analysis include:

1. **CDR Scoring and Brain Volume Distribution:**
    - The CDR Scoring Table helps clinicians assign ratings for dementia severity, with scores ranging from 0 (Normal) to 2 (Moderate Dementia).
    - Brain volume distributions in demented patients from two datasets average between 1200 to 1600 mm^3, with the highest recorded brain volume reaching 2000 mm^3.
    - The most frequent brain volume range for demented patients is between 1400-1500 mm^3.
2. **Gender Differences and Dementia Severity:**
    - Visualizations show more very mild dementia cases in males than females, with overall fewer moderate dementia cases observed.
    - The analysis reveals differences in brain volume between genders, with males tending to have higher brain volumes, particularly in the 1400 mm^3 range.
3. **Association between CDR and Brain Volume:**
    - Scatter plots demonstrate a negative correlation between Clinical Dementia Rating (CDR) and brain volume, suggesting lower brain volumes with increasing dementia severity.
4. **Pearson Correlation Coefficients:**
    - A moderate positive correlation is observed between brain volumes from the two datasets.
    - When examining male and female subsets separately, very weak correlations (close to zero) are found, indicating almost no linear relationship between brain volumes.
5. **Brain Volume Analysis by Gender:**
    - Histograms and violin plots show brain volume distributions by gender and CDR levels, indicating variations in brain volumes between males and females across dementia severity levels.

These findings suggest significant gender-based differences in brain volume distributions among demented patients, with implications for understanding dementia progression and potential diagnostic insights. Additionally, the function created to check if a patient's brain volume falls within the normal range for males or females based on mean values could suggest a potential diagnostic tool as it provides a possible red flags for volumes below the normal range

Part 2: Predictive Model Prototype

Data Overview: Wrangling & Cleaning

Dataset #3: Alzheimer's dataset

In our data cleaning process, we performed data cleaning on the Oasis dataset for research purposes only since we will not be utilizing it for our data modeling and prepared the Alzheimer's dataset for analysis. In total, the dataset comprises a substantial collection of 6,401 neural images. We eliminated incomplete or corrupted imaging files to ensure data quality.

Dataset #1

- Name: Alzheimer MRI Preprocessed Dataset
- Link to dataset: https://www.kaggle.com/datasets/sachinkumar413/alzheimer-mri-dataset
- Number of images: 6400 MRI images

For this dataset, there are four different classes, folders, that is categorized into four severity levels:

- Class - 1: Mild Demented (896 images)
- Class - 2: Moderate Demented (64 images)
- Class - 3: Non Demented (3200 images)
- Class - 4: Very Mild Demented (2240 images)

##

FOR THE HEATMAPS: In particular, we can see that represented in the 2D Heat maps illustrating the differences between the images of those who present dementia and those who do not. In this manner, our intention was to highlight that there needs to be opposite ends of severity levels for there to be observable differences in the graphs. In this manner, this is why we combined moderate and very mild neural images versus those with no dementia to attempt to see some differences.

##

First we test to see if the moderate.jpg image opens. We utilized the Python Imaging Library (PIL) to do this. We first retrieved the image path and then used that path to process it through Image.open(). This method essentially opens the file and reads its components. Following this step, we wanted to convert that image into an array. Now that we know this works, we now want to turn the folders, which contain the different ranges of demented data, themselves into arrays. .[1]

1. ^ Romanov. (1964, February 1). Iterate through folder with pillow image.open. Stack Overflow. https://stackoverflow.com/questions/51178166/iterate-through-folder-with-pillow-image-open

The os.listdir() method allows us to parse through a folder of files, in the case of our project it is a folder full of images, and return a list of all of the allocated files. [1] In the code below, we are parsing through each of the Datasets containing MRI images and turning those images into arrays. We utilized Mangesh Deshpande, the medium article author, to help us parse through the allocated datasets folders to ensure they are .jpg and .jpeg images. [2] Additionally, with each of the images, we used the img_to_array() to convert each of the i-th images into an array. We then appended each of the i-th images to the assigned array ist. The last step was to convert the array list to an array.

1. ^ GeeksforGeeks. (2024, January 16). Python: Os.listdir() method. https://www.geeksforgeeks.org/python-os-listdir-method/
2. ^ Deshpande, M. (2023, June 23). Working with image dataset to build CNN model in tensorflow. Medium. https://medium.com/@mangesh8374/working-with-image-dataset-to-build-cnn-model-in-tensorflow-f3dba0f72bfa

Now, we want to visualize some of the array data. So in this case, we used a 2-D Heat Map. In the code below implemented from Geeks for Geeks heat maps of the two dimensional array containing the very mild and moderate demented data, labeled as "two_dim_modterate_very_mild_data". [1]

1. ^ How to draw 2D heatmap using Matplotlib in Python?. GeeksforGeeks. (2024b, March 21). https://www.geeksforgeeks.org/how-to-draw-2d-heatmap-using-matplotlib-in-python/

In the code below implemented from Geeks for Geeks heat maps of the two dimensional array containing the non demented data, labeled as "two_dim_Non_Demented_array". [1]

1. ^ How to draw 2D heatmap using Matplotlib in Python?. GeeksforGeeks. (2024b, March 21). https://www.geeksforgeeks.org/how-to-draw-2d-heatmap-using-matplotlib-in-python/

According to the sklearn website, the make_blobs() function essentially creates 'isotropic (spherical) gaussian blobs'. This means that the data is normally distributed, and when displayed creates like a bell curve. [1] Essentially, we use kmeans as a method of unsupervised machine learning. [2] Since the MRI neural images do not have labels, our goal with Kmeans was to cluster the different four different classes of dementia. We utilized the documentation on the sklearn website to generate data and visualize our results. [3]

1. ^ Kmeans. scikit. (n.d.). https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans
2. ^ Khan, M. (2017, August 2). KMEANS clustering for classification. Medium. https://towardsdatascience.com/kmeans-clustering-for-classification-74b992405d0a
3. ^ KmeaDemonstration of k-means assumptions. scikit. (n.d.). https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_assumptions.html#sphx-glr-auto-examples-cluster-plot-kmeans-assumptions-py

Notes: two groups: dementia, non_demented have x and y, have labels bc we have the 4 classes

- adjusted grand score, accuracy score is more for supervised.
- adj. grand score does it fit one or more categories.
- look at the most severely dementia and non_demenetd and then have two clusters.

CNN

 # cite: https://www.youtube.com/watch?v=jztwpsIzEGc Install Dependencies and Setup

We followed Nicholas Renotte's tutorial guide to aid us in setting up a CNN image classifier. We then played with the optimizer, data inputs, and other aspects to better fit our needs. The image classifier

as a whole is a basic template that can be seen in many other websites such as tenserflow's website.[1]

We also took note of Amy Jang's project, which was similar to ours. It used a different dataset and a different methodology, but in essence, attempted to do the same task. We compared our accuracies, losses, and trends with Jang's project, to test if our program is able to get similar results. [2]

1. ^ Nicholas Renotte (25 April 2022) Build a Deep CNN Image Classifier with ANY Images https://www.youtube.com/watch?v=jztwpsIzEGc
2. ^ Amy Jang (2020) Alzheimer MRI Model + TensorFlow 2.3 Data Loading https://www.kaggle.com/code/amyjang/alzheimer-mri-model-tensorflow-2-3-data-loading/notebook

This loads the data, then assigns the dataset into the variable "data". Using the next 2 lines, mixes the data into a random group, then separates the data into batches.

Batch 0 represents the size of the batches, having 256 by 256 images in 3 separate layers. There are 32 images in each batch. batch[1] goes to show the pattern in the first batch, the 1 and 0 representing a data point from either the demented or nondemented datasets.

A colormap has been applied to the brain images to visually enhance and show the differences in intensity values to highlight certain features.
The class for each image is labeled above the respective image

- Red: represents the highest intensity values in the image, which might correspond to the most significant areas in terms of atrophy or changes in brain tissue density
- Yellow/Green: represents intermediate intensity values, indicating moderate levels of changes or atrophy
- Blue: represents the lowest intensity values, which the least atrophy or changes

- Training Set ('train'): Contains 70% of the data
- Validation Set ('Val'): Contains 20% of the data
- Test Set ('test'): Contains 10% of the data

Model Creation and Training

This creates 3 layers, with various filters. It uses a 3 by 3 filter size and eventually gives out 1 final output.

We are using 3 layers, with various filters to read through the data. We played around with various filter sizes and found that having 16, 32, and 64 gives the highest accuracy. We also tested various optimizers such as adam and adadelta. We found that using Nadam gave us the best accuracy.

```
Total params: 14,769,697 (56.34 MB)
```

Trainable params: 14,769,697 (56.34 MB)

Non-trainable params: 0 (0.00 B)

The convolutional neural network (CNN) model is designed for a binary classification task, such as distinguishing between images with and without certain features (e.g. presence of brain atrophy). The CNN architecture involves multiple layers of convolutions and pooling to extract features from the input images, followed by dense layers to perform the classification based on these features.

The data that we care about is the validation accuracy and loss. The val_acc plateaus at around 15 epochs and begins to decline. After testing multiple iterations, we saw that this was a trend and decided to settle with 15 epochs. While the loss and accuracy aspects are paramount, they only represent the training data, not the validation aspect. Even if this score is high, if the val values are low, it does not matter. In many of our tests, by increasing the number of epochs, we saw our raw accuracy steadily increase reaching a peak of 0.9993. However, our val_accuracy began to decline, so we decided to cut down the number of epochs.

We see that the val_accuracy is steadily increasing while val_loss is steadily decreasing. This shows that our model is getting better at accurately predicting which class these images belong to.

While the loss and accuracy aspects are important, they only represent the training data, not the validation aspect. Even if this score is high, if the val values are low, it does not matter.

We want to ensure we stop the training and validation process before the val_accuracy begins to decline. This is a sign of overfitting, which is something we want to avoid. Having high loss also means that the program is getting worse at accurately assessing the new data, which is also something we want to avoid. Having high val_acc and low val_loss is the ideal scenario as the program will be the most efficient at categorizing unseen data.

Precision0.9712918400764465, Recall: 0.90625, Accuracy: 0.9503676295280457

This is where we actually test out data. We want the precision, recall and accuracy data points to be high, which means our program is accurately and reliably classifying our test images correctly.

Precision: portion of correctly predicted positive instances, out of all instances predicted as positive: accuracy of positive predictions

Recall: Portion of correctly predicted positive instances, out of all actual positive instances: high recall means few false negatives

Accuracy: How many of the instances are predictive/classified correctly

❑ Discussion of your results and how they address your experimental question

With our aforementioned results presented in part 1 of our project, we concluded that there is small evidence of gender playing a critical role among those who have dementia. Subsequently, the brain volume size of an individual could play a role in the likelihood of them developing dementia. This is based on our findings that those individuals with smaller brain volumes presented more with dementia. These findings address our experimental question as we tried to uncover if brain atrophy, as in loss of neurons, would be a differentiating indicator of dementia.
[¹](#cite_note-1) With the CNN model and the Alzheimer MRI preprocessed dataset, we concluded that there is potential for a model to be able to predict the severity of the disease based on the neural image. In particular, one is not to focus on the accuracy score of 93%. Instead, what matters is the positive increase regarding the accuracy of the values, which is illustrated in the accuracy graph of our project. This indicates that our model is accurately learning and able to successfully classify these neural images. In this manner, we are then able to feed a neural image into the model, and determine if it is correct. Thus, it is plausible to be able to predict the severity of a patient's dementia by utilizing a model and feeding it MRI scans. Based on the fact that there are extreme sides of dementia, those who have early onset versus those who have the worst stage, these kinds of images and data would help train the models accuracy.

1. [^](#cite_ref-1) **professional, C. C. medical. (2022, March 10).** ***Brain atrophy: What it is, causes, symptoms & treatment*****. Cleveland Clinic.** **https://my.clevelandclinic.org/health/diseases/22515-brain-atrophy**

❑ Limitations of analysis discussed

Some limitations we noticed throughout our research and data analysis were that performing CNN requires high-quality neural image data- clear, high-resolution scans. However, we do not know how accurate these scans may be or if they could be affected by the different MRI technology utilized in different hospitals or clinics and may vary in terms of their quality. Thus, poor-quality scans can lead to less effective training in our model.

In addition, CNN models can easily overfit to the training data, especially if the dataset is small or not diverse enough. In this case, we are using MRI scans of the brain and our dataset contains 6,401 neural images, comprising the different severities of dementia. In this manner, there was not sufficient data for each category. We also recognize that the availability of a much larger and higher-quality dataset of neural images would require substantial computational power. This, in turn, would result in greater computational costs and demand more advanced hardware to process and analyze the data effectively.

Another limitation we faced was finding data that was numerical and free. The data collected from Oasis required access which was to be requested, it was one of few datasets that were not blocked behind a paywall. If the data was not blocked, it did not include information we were particularly interested in using. There is a larger limitation in the datasets we used and that is they contain age data which varies quite largely. In oasis_cross_sectional, the set consisted of 416 subjects aged between 18 and 96 while oasis_longitudinal_demographics had 150 subjects ages 60 to 96 which could have skewed our analysis.

Consequently, the data cleaning and wrangling performed could have gotten rid of some data that could have similarly skewed our data. This leads us into another limitation which we pointed out earlier in our project and that is the merging of our eTIV column, or our brain volume column. This value was unique to a unique ID to its respective dataset. When we merged these columns, many of the eTIV values were dropped and as a result, this significantly reduced the size of our dataset. This is to say because of the small sample size, we cannot take most of the observations we made as definitively true. Rather, they can be used for further research. In the future, it would be best to strictly work on analysis of these two datasets separately. That is because although they contain very similar data, they reflect different demographics which could alter and misrepresent the possibility for an accurate diagnosis for dementia related illnesses.

Subsequently, another limitation that we came across was time. As aforementioned, with the need for more data, we would also require more time to be able to train the model. For the model to be successful, with a zero failure rate, the model would need to be constantly running and learning the differences between brain atrophies and whether someone has or does not have dementia. Some possible solutions may be that we could explore and integrate more advanced cross-validation and techniques to create a better CNN architecture to leverage pre-trained models and reduce our training time.

Aside from time needed to fit the CNN model, we would also require more time to successfully analyze the Kmeans model as having four labels, those being the four different severity levels of dementia. For future exploration, it would be helpful to be able to visually cluster the data into two groups: neural images who have dementia and those who do not. Additionally, this model of

classification could be improved to be able to cluster all four of the severity levels. That is, there would be four clusters of data representing those who do not have dementia, those who have mild, very mild, and moderate severity levels.

- **What additional experiments would be interesting, and what data would you need?**

Additional experiments that would be interesting is to determine if one does or does not have dementia based on their blood work. There have been ample studies suggesting that there is some correlation. [¹](#cite_note-1) In this manner, we could use the data provided from the blood work such as protein, sugar, calcium levels, etc. to be a determining factor aside from their brain atrophy levels. In this manner, we can build a greater understanding of how one would aid against developing dementia in the future by making substantial, if necessary, changes to their lifestyles. Future researchers could utilize machine learning models to determine if the allocated data presents with dementia or not. This could aid in the process of being able to diagnose dementia earlier in someone's life.

1. [^](#cite_ref-1) How biomarkers help diagnose dementia | National Institute on Aging. (2022, January 1). https://www.nia.nih.gov/health/alzheimers-symptoms-and-diagnosis/how-biomarkers-help-diagnose-dementia

Cerebrospinal fluid (CSF) analysis is a valuable diagnostic tool for neurological conditions like Alzheimer's disease and other forms of dementia. The process would involve collecting CSF through a puncture where a needle would be inserted into the lower back to obtain a sample of the fluid surrounding the brain and spinal cord. The analysis would focus on measuring specific biomarkers, as mentioned earlier in our project, associated with neurodegenerative diseases. In Alzheimer's disease, key biomarkers include amyloid-beta and tau proteins. Typically, individuals who have Alzheimer's or other forms of dementia have decreased levels of amyloid-beta and increased levels of tau proteins in their CSF. This information can help with early stage detection and can be used in future analysis. Despite the lumbar puncture's invasiveness, CSF analysis is highly regarded for its accuracy in detecting dementia related changes. [¹](#cite_note-1)

1. [^](#cite_ref-1)

Algeciras, A., Bornhorst, J. (n.d.) Alzheimer's Disease CSF Biomarkers. Mayo Clinic Laboratories. https://news.mayocliniclabs.com/2022/02/07/alzheimers-disease-csf-biomarkers/#:~:text=In%20CSF%2C%20the%20changes%20observed,specific%20marker%20for%20Alzheimer's%20disease