STEM Fellowship Big Data Challenge 2023

Alzheimer's Diagnostic with OASIS

Devender[1], Diljit Singh[1], Jagpreet Singh[1], and Karman Singh Bains[1]

[1]Lambton College

June 12, 2023

Abstract

Alzheimer's is a nervous system disease that affects human memory and thinking abilities. Doctors do not consider it curable, but its progression can be slowed if detected early.

Open Access Series of Imaging Studies (OASIS) brain data can be used for Alzheimer's disease detection. It includes MRI(Magnetic Resonance Imaging) scans of the brain, which can help detect structural changes in the person's brain diagnosed with Alzheimer's disease.

The project aims to detect Alzheimer's disease at an early stage using an OASIS brain data set. This project involves implementing machine learning techniques and exploring different algorithms and methods to detect the disease through the given data accurately. This model will detect the structure change in specific brain parts and the abnormalities that lead to Alzheimer's disease.

The results of the projects have a potential for improvement in the development of tools for diagnostics and further understanding of the disease in detail.

Keywords
Alzheimer's disease, OASIS data set, Neuroimaging, Machine learning, Diagnostic model

1 Introduction

An estimated 40 million people, mainly older than 60 years, have dementia worldwide, and this figure is projected to double every 20 years until at least 2050[1]. Dementia of Alzheimer's Type (DAT) is the most common form of dementia, affecting 1 in 9 people over 65 years and as many as 1 in 3 people over the age of 85 [2]. Thus, it is a significant health concern among all the other modern health issues.

OASIS contains MRI scans of the brain images with neuroimaging and related clinical data, publicly available for research and analysis. It contains data to understand the brain and helps in developing treatment approaches for various brain-related diseases, including Alzheimer's disease.

Currently, diagnostics of Alzheimer's disease diagnosis rely on a combination of clinical evaluations, cognitive assessments, and neuroimaging techniques. However, the accuracy and reliability of existing diagnostic methods can be limited, especially in the early stages of the disease.

Diagnosing the disease through machine learning would be a better and much more effective way as the model will classify if the person's brain is normal or have some patterns that reflect the presence of Alzheimer's disease.

2 Materials & Methods

The data set consists of MRI of 150 individuals aged 60 to 96 years, all scanned in a similar environment. Everyone was scanned on two or more visits, separated by at least one year for 373 imaging sessions [3]. This data set contains brain images and demographic data of the person being scanned.

Implemented Convolution Neural Network (CNN) for image recognition and applied Transfer Learning on pre-trained VGG16(Visual Geometry Group 16) CNN model. VGG16 has 16 hidden layers and 14,714,688 parameters. The model has been trained on 1000 images of 1000 different categories with coloured images. The layers of the VGG16 model are freezed; so that the weights will not get updated in further training, the input layer is chopped off, and a new input layer is added for the current input data. After the pre-defined model(VGG16), the output is flattened and sent to a fully connected layer with 64 neurons with Leaky ReLU (alpha = 0.1) as the activation function. The final output layer consists of three neurons (One for each class) with softmax as the activation function.

3 Results

The data set has MRI images of 3-dimensional black-and-white images with shape (256, 256, 128). But, the pre-trained model used has been trained on images of shape (224,224,3). Hence the data set was transformed into a shape in the format required for the model, and specific frames (i.e., 75th, 100th and 125th) were selected. The labels/target column (i.e., demented, non-demented and converted) were extracted from each subject's Demographic (DM) data for the respective images. These labels, along with the MRI images, were combined and used for training the model.

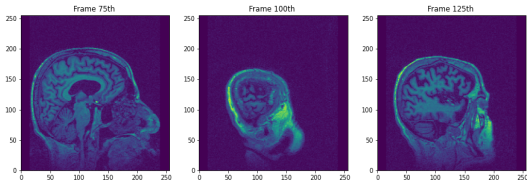

Figure 1. Typical MRI data images. (Frame 75th) Individual scan before defacing. (125th Frame) Atlas-registered gain-field-corrected image. (Frame 100th) Tissue classification image

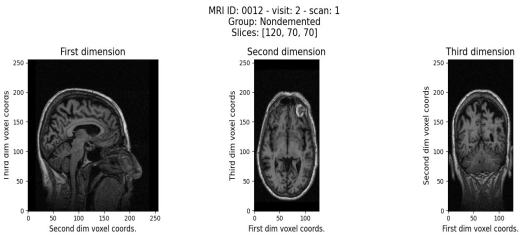

Figure 2. Original images, Subject ID-OAS2 0012, Group Nondemented.

	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	1986.550000	0.696106	0.883440
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2.0	30.0	0.0	2004.479526	0.681062	0.875539
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23.0	0.5	1678.290000	0.736336	1.045710
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	NaN	28.0	0.5	1737.620000	0.713402	1.010000
4	OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12	NaN	22.0	0.5	1697.911134	0.701236	1.033623
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
368	OAS2_0185	OAS2_0185_MR2	Demented	2	842	M	R	82	16	1.0	28.0	0.5	1692.880000	0.693926	1.036690
369	OAS2_0185	OAS2_0185_MR3	Demented	3	2297	M	R	86	16	1.0	26.0	0.5	1688.009649	0.675457	1.039686
370	OAS2_0186	OAS2_0186_MR1	Nondemented	1	0	F	R	61	13	2.0	30.0	0.0	1319.020000	0.801006	1.330540
371	OAS2_0186	OAS2_0186_MR2	Nondemented	2	763	F	R	63	13	2.0	30.0	0.0	1326.650000	0.795981	1.322890
372	OAS2_0186	OAS2_0186_MR3	Nondemented	3	1608	F	R	65	13	2.0	30.0	0.0	1332.944463	0.801248	1.316634

373 rows × 15 columns

Figure 3. Demographic (DM) Data

4 Discussion

Convolution Neural Network(CNN) is a popular algorithm for image recognition because it can detect patterns and objects in the image. We specifically decided to move ahead with VGG16, a pre-trained CNN model, as we had limited data sources, which would not have been enough to train a CNN from scratch due to its complex structure.

Further, it's very interesting to note that in the OASIS2 brain dataset, we have 72 subjects who identified as nondemented throughout the study, 64 subjects as demented in the initial visit and throughout the study, which also includes 51 subjects with mild to moderate Alzheimer's. The remaining 14 subjects were determined as non-demented in the initial visit and marked as demented in the later visits (converted). These 14 subjects (converted) data is crucial for the problem statement, i.e., early detection, as their MRI samples tend to have patterns of the disease that looks like or develops in the early stages.

4.1 Evaluation

The model tends to classify the images as demented, non-demented and converted with an accuracy of 94 percent. Still, accuracy alone cannot give us the whole picture as accuracy metrics only considers the correctly predicted(True Positive + True Negative) output with respect to total outputs. Hence, it can give a false perception in case of unbalanced data.

The Accuracy formula is calculated as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

To overcome the limitation of accuracy score and as a requirement for the defined problem statement, we want to emphasize on reducing False Negative results, i.e. where a subject suffers from Alzheimer's, but the model detects otherwise. Therefore, the metrics we will focus on to evaluate the model are Recall and F1 Score. Recall, the fraction of the items of interest to the user retrieved by the system [4]. The harmonic mean of precision and recall, F1 score, is widely used to measure the success of a classifier when one class is rare [5]. The Recall and F1 score for the given model is 95 percent and 92 percent, respectively.

The Recall formula is calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

The F1 score formula is calculated as:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 1: Metrics

Metrics	Value
Accuracy	94
F1 Score	92
Recall	95

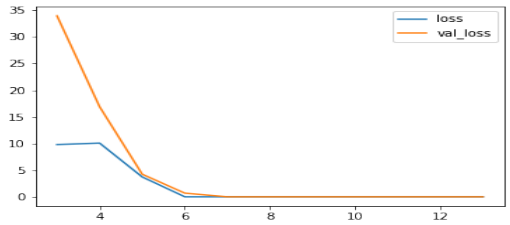

Figure 4.1. Model History: Training Loss vs Validation Loss.

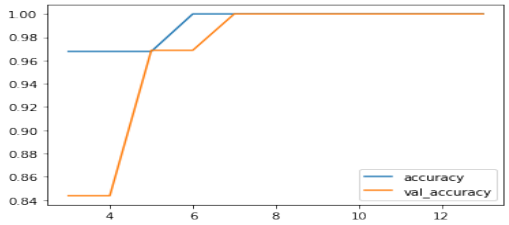

Figure 4.2. Model History: Training Accuracy vs Validation Accuracy.

*Note: Notice the validation accuracy starts from 84 percent because of the pre-trained VGG16 model.

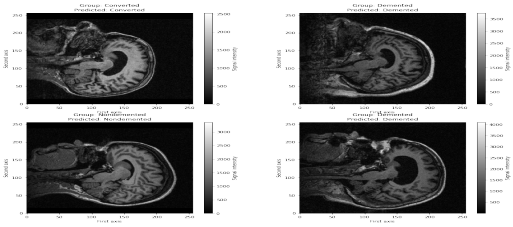

Figure 5. Sample Predictions.

*Note: The model is able to correctly label/predict the images which it has never seen before.

4.2 Limitation

The OASIS2 brain dataset consists of only 150 subjects and 373 MR sessions, all the subjects are aged between 60 and 96, and all the subjects are right-handed. We can see bias in the data as we do not have samples from young and left-handed subjects.

Moreover, due to the data's complexity and large size(3d images), we could only train the model on limited subjects, as training the model on the whole data set would require greater computational power.

4.3 Future Scope

The future scope of the study would be to work with the latest OASIS4 dataset, which has more than 600 subjects and MR sessions. But then, to process extensive data, we require robust systems that can process and transform the data. Further, we would like to collaborate with subject matter experts as they can assist us better in decision-making and understanding the problem.

Conclusions

In conclusion, the study focuses on Alzheimer's disease detection at an early stage using image recognition with CNN. This study can be used in the development of robust diagnostics tools. Additionally, it can further improve Alzheimer's disease detection and highlights the potential of machine learning and neuroimaging techniques in the advanced understanding of structural change in the brain.

Acknowledgements

We want to thank the STEM Fellowship and the IUBDC team, and all those who were behind conducting this competition successfully. Additionally, we appreciate the scientists and researchers involved in collecting the OASIS data set and sharing the concept through the report. Lastly, we want to express our deepest gratitude to our professor Mr. Ashish Gupta, who has motivated and pushed us to participate in the competition and mentored us throughout.

References

[1] Philip Scheltens, Kaj Blennow, Monique M B Breteler, Bart de Strooper, Giovanni B Frisoni, Stephen Salloway, and Wiesje Maria Van der Flier. Alzheimer's disease. *The Lancet*, 388(10043):505–517, 2016.

[2] Karteek Popuri, Da Ma, Lei Wang, and Mirza Faisal Beg. Using machine learning to quantify structural mri neurodegeneration patterns of alzheimer's disease into dementia score: Independent validation on 8,834 images from adni, aibl, oasis, and miriad databases. *Human Brain Mapping*, 41(14):4127–4147, 2020.

[3] Daniel S. Marcus, Anthony F. Fotenos, John G. Csernansky, John C. Morris, and Randy L. Buckner. Open Access Series of Imaging Studies: Longitudinal MRI

Data in Nondemented and Demented Older Adults. *Journal of Cognitive Neuroscience*, 22(12):2677–2684, 12 2010.

[4] Sergio A Alvarez. An exact analytical relation among recall, precision, and classification accuracy in information retrieval. *Boston College, Boston, Technical Report BCCS-02-01*, pages 1–22, 2002.

[5] Zachary Chase Lipton, Charles Elkan, and Balakrishnan Narayanaswamy. Thresholding classifiers to maximize f1 score. *arXiv preprint arXiv:1402.1892*, 2014.