GR-95 Using Machine Learning to Detect Early Alzheimer's

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Abstract

More than 6 million Americans are currently living with Alzheimer's Disease (AD). AD requires lab / imaging tests for proper diagnosis, but even with current diagnostic tools, accuracy can vary. For our project, we utilize Machine Learning to accurately classify different stages of AD. We use 2 datasets*: (1) a 35 MB dataset from Kaggle which contains 4 classes of MRI images: Mild Demented, Moderate Demented, normal, and Very Mild Demented. (2) The OASIS dataset.* (2) was used for testing and validation. We tested four Machine Learning techniques and a convolutional neural network (CNN) on both datasets.

Introduction

AD is the most common form of dementia, accounting for 60-80% of cases; Dementia is a general term for describing symptoms associated with decline in memory, reasoning, and other cognitive skills severe enough to impact daily life. AD is a specific type of dementia.

There are 3 stages of AD – Early stage, Mid stage & Late stage. During the early stage, the person can still function independently, though they may feel they are having lapses in memory (e.g remembering names when introduced to new people, losing/misplacing an important object). The first stage is crucial because the symptoms themselves may not be widely obvious. It is also possible for the individual to have MCI (Mild Cognitive Impairment), which is not considered to be a part of Dementia.

Research Question(s)

1. What are the drawbacks of current diagnostic tests used for diagnosing Alzheimer's Disease?
2. What trade-offs exist between using simpler methods for diagnosis versus a more complicated model?

Materials and Methods

The project was conducted on a Windows 10 Laptop with an RTX 2060 GPU. We used Python Version 3.7. For building the CNN, we used the TensorFlow and Keras libraries. The four Machine Learning methods used include: Decision Tree, Random Forest, Support Vector Machine and Gradient Tree Boosting, a neural network with 10 layers, and XGBoost.

For dataset (1), we conducted two experiments with the Machine learning models. Experiment 1 focused on distinguishing normal from AD. Experiment 2 focused on identifying different stages of AD. The CNN was tested 3 times on dataset (1) with adjustments to batch size, epochs and test-size. For dataset (2) we tested the machine learning models on longitudinal MRI data, which had 150 subjects aged 60 to 96. The machine learning models were tested 6 times. Runs 4-6 had different parameters.

Results

Table 1: Machine Learning Models results - Experiment 1 (Kaggle Dataset)

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.78	0.87	0.88	0.87
Random Forest	0.86	0.86	0.995	0.924
Gradient Tree Boosting	0.86	0.87	0.9927	0.926
Neural Network	0.86	0.88	0.98	0.92

Table 2: Machine Learning Model results – Experiment 2 (Kaggle Dataset)

Algorithm	Accuracy
Decision Tree	0.479
Random Forest	0.626
Gradient Tree Boosting	0.643
Neural Network	0.579

CNN Plots for Kaggle Dataset

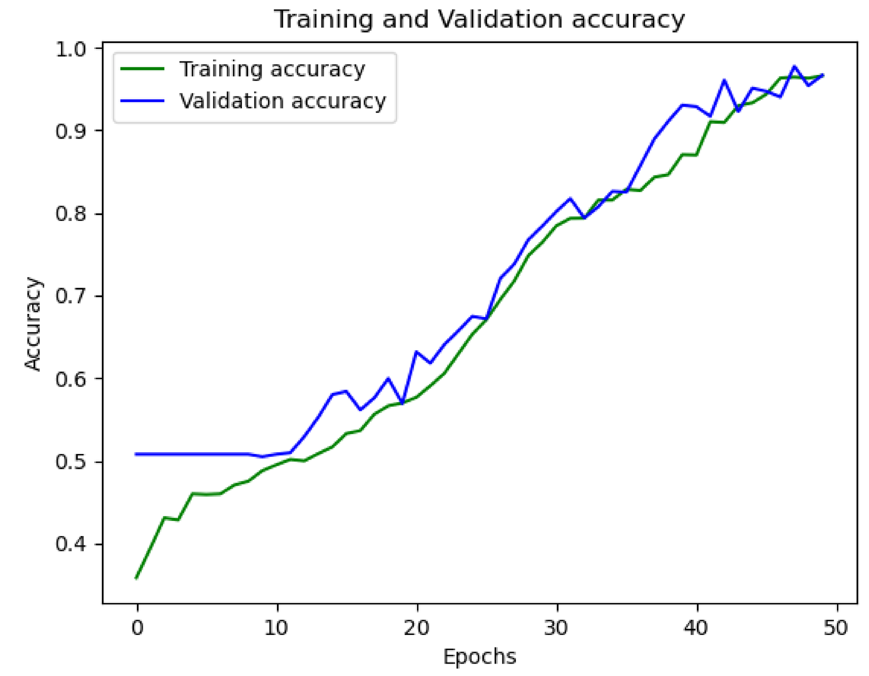

Table 3: Machine Learning Models Results: OASIS Dataset – no parameters changed

Test 1: Testing size: 30%	
Random Forest	0.8392857143
SVM	0.7767857143
Decision Tree	0.7946428571
XGBoost	0.8392857143
Test 2 – Testing size: 20%	
Random Forest	0.7866666667
SVM	0.76
Decision Tree	0.6933333333
XGBoost	0.8
Test 3 – Testing size: 10%	
Random Forest	0.8421052632
SVM	0.7894736842
Decision Tree	0.6578947368
XGBoost	0.8421052632

Table 4: Machine Learning Models Results: OASIS Dataset – parameters changed

Test 4: Testing size: 30%	
Random Forest	0.8421052632
SVM	0.7894736842
Decision Tree	0.6578947368
XGBoost	0.8421052632
Test 5: Testing size: 20%	
Random Forest	0.8
SVM	0.76
Decision Tree	0.8
XGBoost	0.8
Test 6: Testing size: 10%	
Random Forest	0.81578947368421
SVM	0.789473684210526
Decision Tree	0.684210526315789
XGBoost	0.842105263157894

Conclusions

The results obtained prove that Machine Learning can be used as a reliable diagnostic tool for detecting early AD and distinguishing between different early stages of AD. Additionally, there was a trade-off regarding speed, since the CNN model took 3 to 4 hours for training and testing. For the OASIS dataset, the highest accuracy was above 80%, with the XGBoost classifier achieving the best performance of 84%. However, we still need to fine-tune these models in order to account for overfitting.

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