ML Detection of Alzheimer's in Brain Scans

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AGENDA

One Background & Approach

Two Datasets

Three Preprocessing

Four Data Modeling

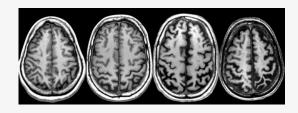
Five Conclusion



Background & Approach

Background

- Alzheimer's...
 - o 1/9 elderly, 6 million Americans
 - impaired memory
 - neurodegenerative
- ML-powered detection...
 - o prevention, planning, research



Approach

- 21 different models that prioritize accuracy, 90% threshold
 - correctly classify as many cases as possible
 - paying attention to FNs via confusion matrices





2 Datasets Overview

Dataset 1

- size = 6.4k
- image dimensions = 128×128
- **preprocessed** = True
- **number of unique brains** = unknown
 - every image treated independently

- size = 86k
- image dimensions = 244×488
- preprocessed = False
- number of unique brains = 1.5k
 - every 61 images stacked → 3D brain

Single MRI from each class



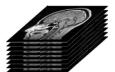
Non Demented



Very Mild Demented

Shared Characteristics

- axial = True
- **classes** = non-demented, very mildly demented, mildly demented, moderately demented





Mild Dementia



Single MRI from each class





Moderate Dementia

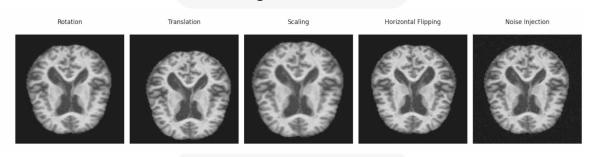


Dataset 2

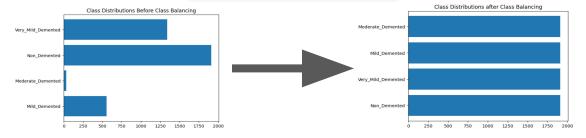
Dataset 1 Preprocessing

60/20/20 Split

Augmentation



Balancing





Modeling Dataset 1

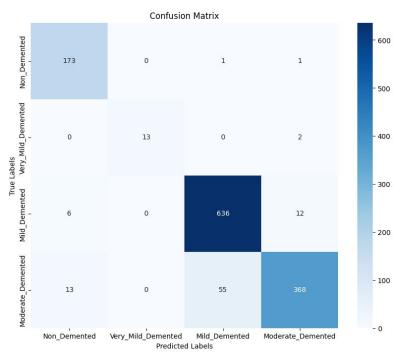
Model	Baseline results	Fine-tuned results
Logistic Regression	Train Accuracy: 0.4566 Val. Accuracy: 0.4906 Test Accuracy: 0.5063	Train Accuracy: 0.8515 Val. Accuracy: 0.8555 Test Accuracy: 0.8609
Decision Tree	Train Accuracy: 1.0000 Val. Accuracy: 0.6898 Test Accuracy: 0.6695	
Random Forest	Train Accuracy: 0.9946 Val. Accuracy: 0.7852 Test Accuracy: 0.7633	Train Accuracy: 1.0000 Val. Accuracy: 0.8680 Test Accuracy: 0.8633
CNN	Train Accuracy: 0.8360 Val. Accuracy: 0.7141 Test Accuracy: 0.7203	Train Accuracy: 0.8371 0.9297 Val. Accuracy: 0.7461 0.9258 Test Accuracy: 0.7492 0.9297
Transfer Learning	Train Accuracy: 0.6484 0.9850 Val. Accuracy: 0.6313 0.8539 Test Accuracy: 0.6469 0.8562	Train Accuracy: 0.9953 Val. Accuracy: 0.9008 Test Accuracy: 0.9031



Dataset 1 - CNN Models

- Addition of a third 2D convolutional layer with 64 filters slightly improved test accuracy from baseline (72% to 74%) in the first improvement
- Changing third 2D convolutional layer to 128 filters and increasing dense layer units to 256 improved test accuracy to 93%
- Final model confusion matrix shown on right:

Advanced CNN Model #2





Dataset 1 - Transfer Learning Models

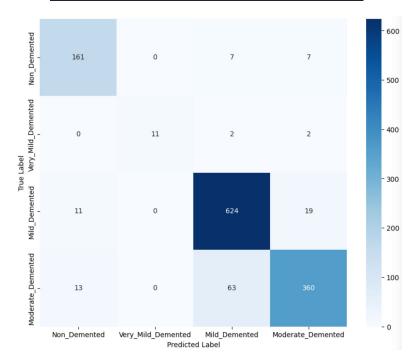
EfficientNetB0 Baseline Model

- Weights pre-trained on ImageNet
- Fine-tuned last 17 layers (237 total layers)
- Accuracies were around 64% across split data

VGG16 Models

- Both: fine-tuned last 8 layers (16 total layers)
- Improved: 1/2 dense layer units
- Test accuracy improved by 5% to 90%, with less overfitting

VGG16 Improved Model Results

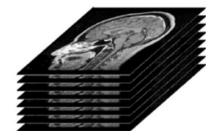




Dataset 2 Preprocessing

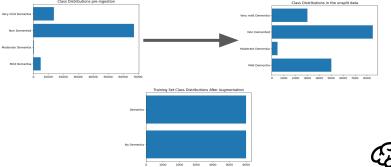
3D Pipeline

- **stacked** 61 axial scans during ingestion
- **transformed** data
- class **merged** → binary, multiclass
- 80/20 **split**
- augmented (some) training volumes



2D Pipeline

- undersampled during ingestion
- transformed data
- class **merged** → binary
- 60/20/20 **split**
- augmented training images





Modeling Dataset 2 - 3D Pipeline

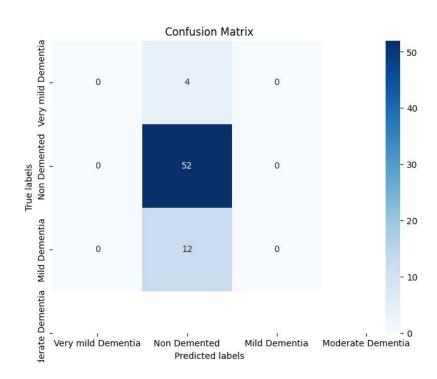
Model	Results	Takeaways
CNN	Test Accuracy: 0.7794 Test Loss: 0.7982	Skewed predictions based on confusion matrixMissing Class
Binary CNN	Test Accuracy: 0.7647 Test Loss: 0.5505	- Similar performance to multi-class, likely due to class imbalance
CNN with Slice Augmentation	Test Accuracy: 0.4450 Validation Accuracy: 0.4699 Test Loss: 2.3780 Validation Loss: 1.3218	 Performs worse than volume-augmentation Lower results than no augmentation are likely due to lower epochs
CNN with Volume Augmentation	Test Accuracy: 0.5532 Validation Accuracy: 0.6933 Test Loss: 1.7072 Validation Loss: 1.0582	Performs better than slice-by-sliceSpatial relations are importantRoom for more training



Dataset 2, 3D Pipeline - Simple CNN Model

Simple CNN Model

- Data-points heavily reduced
- Large class imbalance
- Memory issues
 - Generators
 - dat files
 - Compression
- Despite this...
 - Test Accuracy: 77.94%
 - Test Loss: 0.7982

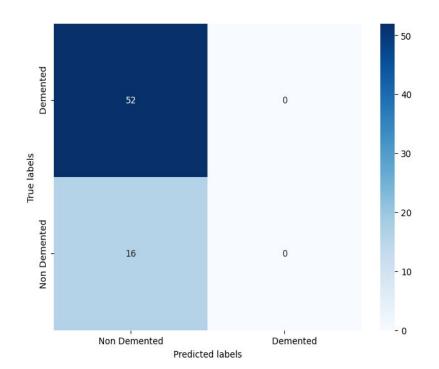




Dataset 2, 3D Pipeline - Binary CNN Model

Binary CNN Model

- Same preprocessing steps and model architecture
- Similar performance
 - Lack of sensitivity within predictions, likely due to class imbalance

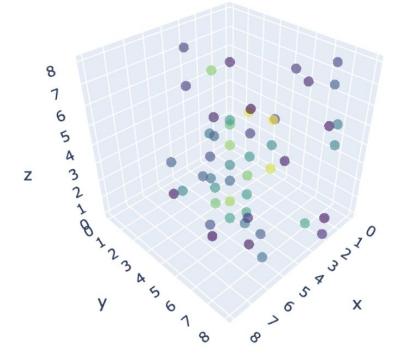




Dataset 2, 3D Pipeline - CNN, Augmentation 1

Slice Augmentation CNN

- Augmenting Slice-by Slice
- Initial Theory:
 - Model resiliency
 - Resistant to noisy and missing data
 - Lose value of spatial relationships
- Visualization: too much scatter

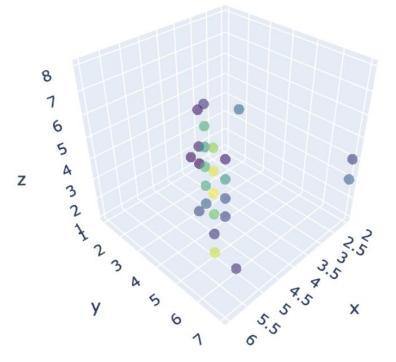




Dataset 2, 3D Pipeline - CNN, Augmentation 2

Volume Augmentation CNN

- Augmenting by Volume
- Initial Theory:
 - Introducing unrealistic artifacts within the volume
 - Maintain spatial relationships





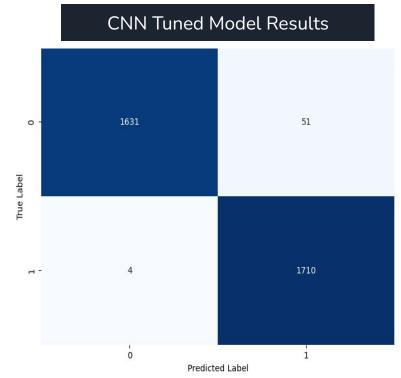
Modeling Dataset 2 - 2D Pipeline

Model	Baseline results	Hyperparameter tuning
Logistic Regression	Train Accuracy: 0.6823 Val. Accuracy: 0.8157 Test Accuracy: 0.8193	Train Accuracy: 0.9312 Val. Accuracy: 0.9049 Test Accuracy: 0.9112
CNN	Train Accuracy: 0.9286 Val. Accuracy: 0.9423 Test Accuracy: 0.9464	Train Accuracy: 0.9903 Val. Accuracy: 0.9838 Test Accuracy: 0.9862
Transfer Learning	Train Accuracy: 0.8205 Val. Accuracy: 0.8716 Test Accuracy: 0.8790	Train Accuracy: 0.9882 Val. Accuracy: 0.9691 Test Accuracy: 0.9714



Dataset 2, 2D Pipeline - CNN Models

- Doubling the number of filters in the final 2D convolutional layer and the dense layer units from the baseline increased test accuracy from 95% to 99%
- Minimal disparity between train and test accuracies suggests robust generalizability
- Hyperparameter tuned CNN was the highest performing model





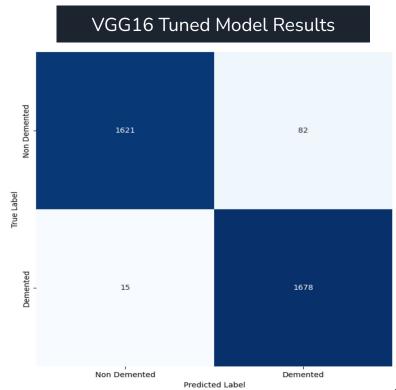
Dataset 2, 2D Pipeline - Transfer Learning Models

EfficientNetB0 Model

- Weights pre-trained on ImageNet
- Fine-tuned last 17 layers (237 total layers)
- Test accuracy was 88%, with no overfit

VGG16 Model

- Fine-tuned last 8 layers (16 total layers)
- Average accuracy was 97%, with no overfit





Conclusion

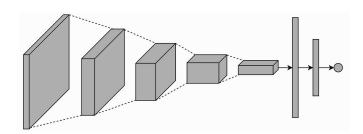
Highlights

- CNNs performed best (test accuracy, FNR, generalization)
 - Dataset 1 Model 8 : 92.97%
 - Dataset 2, 2D Model 4: 98.62%
- Transfer models were a close second
 - Dataset 1 Model 11: 90.86%
 - Dataset 2, 2D Model 6: 97.14%

Takeaways

- Breadth and depth in modeling methodology
 - Breadth: diverse models
 - Depth: Deep learning focus
- Future work: CNNs, Transfer, 3D brain volumes
- **Fairness:** diagnostic automation







THANK YOU Questions?

Dataset 1 - Traditional ML Models

Logistic Regression

- Baseline to improved multiclass logistic regression showed a 36% test accuracy increase (50% to 86%)
- Biggest impact came from dropping learning late from 0.01 to 0.0001 and increasing training epochs from 3 to 20
- Little overfitting across both models

Decision Tree

- Explored decision trees solely to gain insights for potential applications in random forest models
- Highly overfit to training data with a perfect training accuracy but 66% validation and testing accuracies
- Generally recognized for underperforming on image data

Random Forest

- Baseline to advanced demonstrated an ~11% increase in test accuracy (from 76% to 88%)
- Using grid search, we achieved our optimal model parameters
- Both baseline and advanced models indicate some overfitting with training accuracies of ~100%



Dataset 2, 2D Pipeline - LR Model

Model Overview

- Increasing the number of epochs (1 to 20) and changing the Adam optimizer to Stochastic Gradient Descent increased test accuracy 81% to 91%
- Large increase from simple hyperparameter tuning hints at the potential of models with complex layered architectures in learning hierarchical pixel relationships

