Early Detection of Alzheimer's Using MRI Image Analysis

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1. Introduction and Problem Statement

Alzheimer's disease (AD) is a progressive, neurodegenerative disorder that impacts cognitive and functional abilities. It affects over 6.5 million people in the U.S. alone, 10.7% of individuals over age 65. The goal of our project is to develop a convolutional neural network (CNN) that classifies MRI scans of brains into one of four labels: non-demented, very mild dementia, mild dementia, and moderate dementia. We hope to achieve a classification accuracy that is competitive with other modern existing solutions.

We specifically wanted to improve accuracy for classifying mild and very mild cases, as existing models tend to struggle more with these borderline cases. If our model could achieve strong performance for these two labels, we believe it could possibly be applied to early detection efforts, which are critical in providing effective treatment to patients. We will also utilize specific image preprocessing techniques. Additionally, we attempted transfer learning by training our model on one dataset and evaluating it on a second dataset. However, we were unable to successfully implement transfer learning due to large differences between our datasets.

Initially, our model achieved a classification accuracy of 99.9%. This abnormal performance made us realize that we had to treat multiple 2D MRI images as one 3D scan, and failing to do this caused our data to leak between our test and training datasets. Once we stacked images together, our performance dropped drastically. Due to time constraints, this caused us to change our approach to the problem to binary classification where our model succeeded.

2. Related Work:

Deep learning has already been used extensively for AD detection in brain MRIs, with state-of-the-art models achieving classification accuracy >95%. Variations of CNNs are the most common models. Most studies use the OASIS and/or ADNI datasets as they are the largest, most easily available MRI datasets for AD classification. One of the primary goals of our project is to combine effective techniques used by recent research to see if we can build an even better model.

We will preprocess our MRI images using a pipeline inspired by [1], which successfully applied these steps to achieve high AD detection accuracy with an ensemble of transformers. The steps are i) reorientation, ii) registration, iii) skull-stripping, and iv) histogram equalization.

For our actual CNN model, we are utilizing a similar structure to the DEMNET model [2]. This recent CNN performed exceptionally well and utilized four custom feature extraction blocks in sequence, as well as four fully connected layers. When implementing our neural network, we primarily followed the description from this article.

3. Data Sets

OASIS MRI Dataset [4]

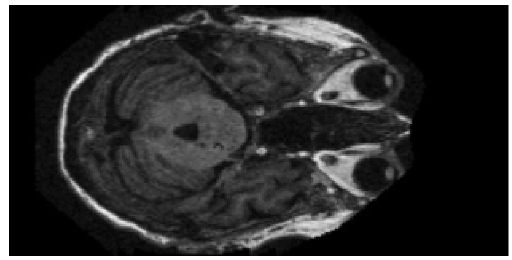

Figure 1. OASIS Dataset

The OASIS dataset is widely recognized as a resource for studying Alzheimer's disease as it contains 80,000 MRI scans from 461 patients. These scans are classified into four different stages non-demented, very mild dementia [Figure 1], mild dementia, and moderate dementia. After the original data formats were standardized, the MRI scans were sliced along the z-axis. This created 256 slices for each patient, and slices 100 to 160 were used for this dataset as they contained the most relevant information. These slices were then converted into .jpg, as that is the format that is most compatible with Alzheimer's research.

The OASIS dataset, available at [Kaggle](), is an amazing resource for Alzheimer's disease research. Its large size and vast representation of different stages of dementia provide a foundation for developing and testing deep learning models. By covering a wide spectrum of the progression of Alzheimer's, the dataset enables researchers to design solutions for the early detection and classification of this disease.

Enhanced Kaggle Alzheimer's Dataset with Synthetic MRIs [3]

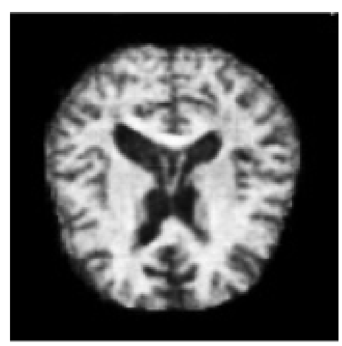

Figure 2. Kaggle Dataset

This dataset included 6,400 brain MRI scans from 100 patients with no impairment, 70 with very mild impairment, 28 with mild impairment, and 2 with moderate impairment [Figure 2], which are all categorized into four separate classes. The dataset was preprocessed to remove the skull and used 1.5 Tesla T1-weighted MRI images, but the severe class imbalance caused some issues when it came to providing valuable data. In order to solve this imbalance, WGANS-GP (Wasserstein GAN with Gradient Penalty) was employed to generate synthetic MRIs for the classes that were underrepresented, which was the main reason for how the dataset increased to 11,500 images.

The dataset resulted from this whole process of synthetic and real 2D MRI images in .jpg format with a resolution of 128x128 pixels. This balanced dataset helped to improve the model's balanced accuracy to 99% compared to the original 87%. Overall, this dataset came from a source in Kaggle and is a valuable resource for researchers focused on Alzheimer's disease classification.

Transfer Learning Between Datasets

The Kaggle dataset enhanced with the synthetic MRI was used as a transfer learning dataset. The model was trained using the OASIS dataset. This model was then evaluated on the Kaggle dataset to test the comprehensive feature extraction capabilities learned from OASIS, as well as the strength of our preprocessing techniques. This approach helps to check the generalizability of our model which is crucial to improve the accuracy and performance of the Alzheimer classification process, due to the reality of processing data from different sources.

4. Description of Technical Approach

Data Loading and Image Preprocessing

All data was downloaded locally for both datasets, with different folders for each label. A pandas dataframe was used to efficiently load all data, and an 80/20 training and testing split was created. The dataframes were then converted into a custom PyTorch dataset where transformations were applied for preprocessing. For both datasets, our preprocessing approach involved ImageNet pixel normalization and resizing of the images. ImageNet pixel normalization scales the pixel values to ensure consistency across the images in the data set by scaling each pixel's intensity based on the mean and standard deviation values derived from the dataset. Pixel normalization stabilizes the training process and speeds up convergence on a model. Additionally, all JPG images were resized to 176x176 pixels.

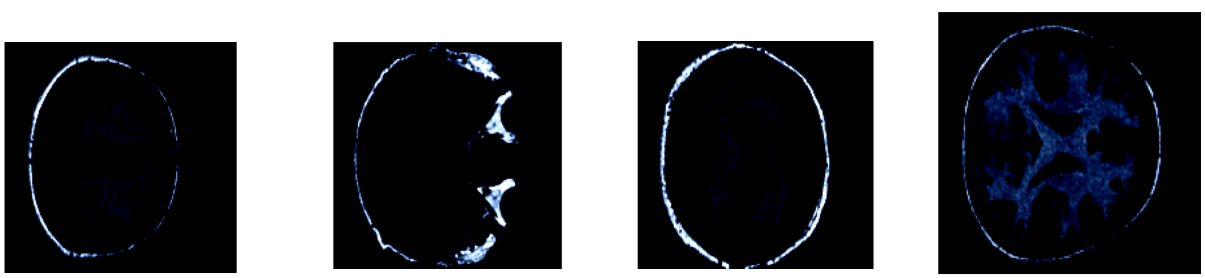

Figure 3: OASIS MRI scans after preprocessing

CNN Design

We design our CNN by closely following the description of the DEMNET model [2], and making it compatible with our data pipeline. Figure 4 shows the complete architecture. The inputted scan first passes through two convolutional layers using ReLU activation. Next are four consecutive feature extraction blocks, which each double the output. These blocks are meant to abstract high level features from the scan to help in the multi-class prediction. Each block contains two additional convolutional layers as well as ReLU activation, batch normalization, and max pooling.

Next, a dropout rate of 0.25 is applied and the spatial dimensions are flattened. The result is then forwarded through four fully connected layers, downsizing from 512 to the amount of labels to output the final classification.

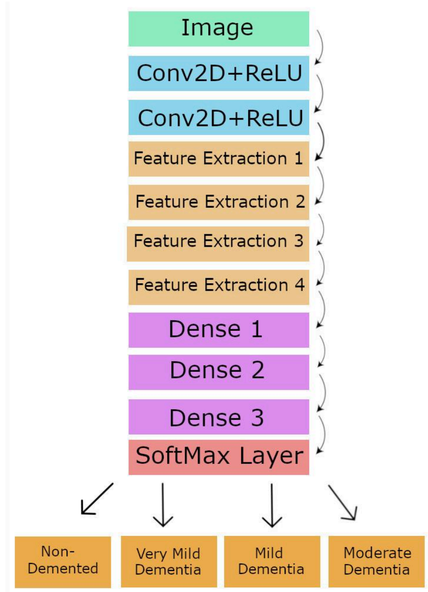

Figure 4: Our Convolutional Neural Network

For our training hyperparameters, we used the Root Mean Square optimizer and Cross Entropy as our loss criterion. We trained our model for 50 epochs with a 0.001 learning rate.

Transfer Learning

For our transfer learning dataset [3], we wanted to apply the following additional preprocessing techniques: reorientation, registration, skull-stripping, and histogram equalization. We used the OpenCV library to design these techniques but were only able to successfully implement reorientation (to match the OASIS dataset) and histogram equalization. Additionally, we used an image-darkening technique to make the scans more similar to the original dataset. We then export our model that was trained on the OASIS dataset [4] to test its performance on the second dataset.

Switching to 3D Approach

As mentioned previously, we eventually realized that we had been handling our data incorrectly. Rather than processing the images individually, each patient's scan was meant to be a group of 61 images. We modified our data loading to stack each group of 61 related images into 3D tensors. At this point, we unfortunately did not have time to redesign our CNN to better learn this increased complexity. We instead reduced our goal to simply determining whether each patient had dementia or not (two labels instead of four). To implement this modification, we assigned the same label for Moderate Dementia, Mild Dementia, and Very Mild Dementia, and changed the output of our model to be binary.

5. Software

Our project involves several different components, separated into scripts and frameworks. These different components enable us to detect Alzheimer's disease through machine learning models trained on MRI datasets.

File	Purpose	Input	Output
3D-AD-Detection-CNN.ipynb	Trains and evaluates CNN for AD classification using OASIS dataset, combines 61 2D images into a 3D scan for classification	3D MRI data slices, hyperparameters	Trained CNN model, performance data
AD-Detection-CNN.ipynb	Trains and evaluates CNN for AD classification using OASIS dataset, processes and classifies individual 2D images	2D MRI images, labels	Classification accuracy, loss curves
test_on_diff_dataset.ipynb	Trains the Kaggle dataset with the model trained with the OASIS dataset.	Kaggle dataset, model weights	Evaluation metrics
transfer_learning.ipynb	Evaluated the trained model on an unseen dataset like the Kaggle dataset to measure generalization capability.	Pre-trained model, Kaggle dataset	Updated model weights, transfer learning data
2d_cnn_model.pth	Stores weights of the trained CNN for individual 2D images.	-	Model weights
3d_cnn_model.pth	Stores weights of the trained CNN for stacked 3D scan.	-	Model weights

6. Experiments and Evaluation

We evaluated the performance of our trained model in classifying AD using precision, recall, and F1 scores. Precision measures the proportion of true positive predictions among all positive predictions made by the model, whereas recall measures the proportion of true positive predictions out of all actual positive instances. F1 score is the harmonic mean of precision and recall, providing a balanced metric of performance. Additionally, a confusion matrix was used for the four labels. This is particularly important to see what kind of misclassifications our model was making. Our goal was to minimize misclassifications of very mild and mild dementia. In all confusion matrices below, the order of the rows is Mild Dementia, Moderate Dementia, Non Demented, and Very Mild Dementia.

As mentioned previously, we discovered that our approach to this problem was initially incorrect. We were treating each JPG image in our dataset as its scan, when in reality 61 images make up one 3D MRI scan. We only realized this once our initial yielded unrealistically high results due to leakage of data between our test and training sets. Below are the results of our approach of processing each image separately.

Model Results for OASIS dataset when processing images individually:

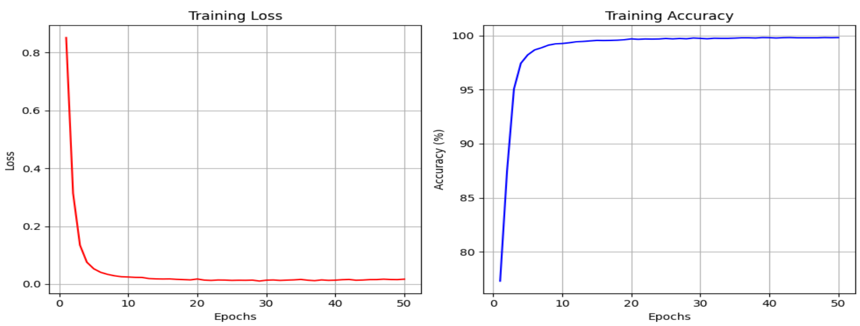

Figure 5: 50 epoch training for initial approach

```
Confusion Matrix of the Test Set
-----------
[[ 1000     0     0     0]
 [    0    98     0     0]
 [    0     0 13442     3]
 [    0     0     1  2744]]
Precision of the Model :        0.9998
Recall of the Model    :        0.9998
F1 Score of the Model  :        0.9998
```

Figure 6: Almost perfect accuracy due to data leakage

Transfer Learning Results:

Unfortunately, we were unable to implement transfer learning successfully as well. We believe this is due to difficulty of effectively implementing the preprocessing steps we intended to include: reorientation, registration, skull stripping, and histogram equalization.

Registration requires a reference image which we were not sure how to handle choosing. Additionally, we did not have time to correct errors to our skull stripping function so we only applied reorientation and histogram equalization to our transfer learning dataset.

Additionally, the JPG images in our transfer learning dataset were significantly smaller than the OASIS images, limiting the features that our model could obstruct. Figure 7 and Figure 8 demonstrate the difference between our preprocessed images from each dataset.

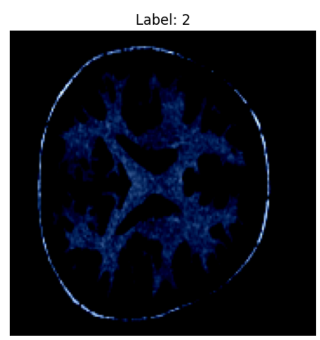

Figure 7: Preprocessed image from OASIS dataset

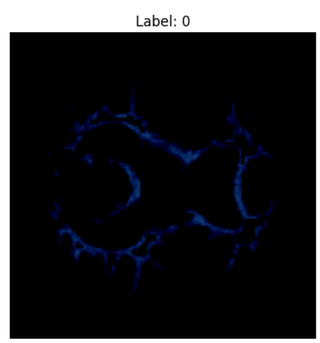

Figure 8: Preprocessed image from second dataset

Once we realized that we had been approaching the problem incorrectly, we stacked the 61 related images into 3D tensors to make up our datasets. We reran training and evaluation using our same CNN architecture and unfortunately, our model performed poorly on the new data points.

```
Confusion Matrix of the Test Set
-----------
[[ 13   0   0   3]
 [  2   0   0   0]
 [ 12   0   5 204]
 [  3   0   0  42]]
Precision of the Model :    0.8293
Recall of the Model    :    0.2113
F1 Score of the Model  :    0.1115
```

Figure 9: Poor performance once we stacked the 2D images

Figure 9 shows our model's poor performance once we switched to treating each data point as a stack of 61 2D images. Interestingly, the confusion matrix shows strong performance for mild and very mild dementia cases (labels 0 and 3), which was one of our goals. However, the main issue is that the majority of non-demented cases were labeled as very mild dementia. This is slightly promising as these are two bordering labels and a false positive is better than a false negative. However, regardless, our model failed once we corrected our approach to the problem.

Unfortunately, we did not have time to optimize our CNN architecture or preprocessing to handle the combined 3D scans and improve performance. Because of this, we decided to simplify the problem to binary classification, predicting either non-demented or demented. This means the scans with moderate dementia, mild dementia, and very mild dementia, now share the same label. Our thought process was that since we increased the complexity of our data points, simplifying the classification goal would allow our model to perform well once again with minimal tweaks.

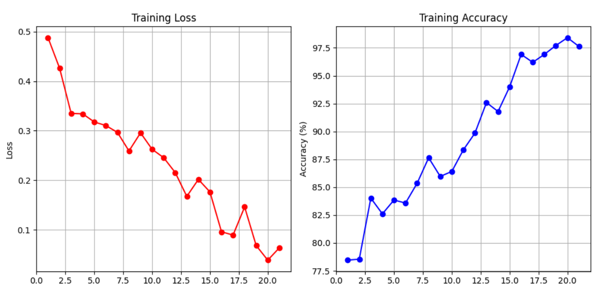

Figure10: Loss and accuracy while training new approach

```
Confusion Matrix of the Test Set
-----------
[[220   1]
 [ 35  28]]
Precision of the Model :        0.8855
Recall of the Model    :        0.8732
F1 Score of the Model  :        0.8543
```

Figure 11: Confusion matrix once switched to binary classification using 3D scans. First row is Non Demented and the second is Demented

As shown in Figure 11, once we switched to a binary classification problem, our model was able to achieve strong performance, even when trained for only 20 epochs. It is important to note that the stacking of images significantly reduced our test dataset. Additionally, there was a strong class imbalance towards Non Demented. These may be factors in our model's performance. However, we are happy that our model was able to succeed without data leakage.

7. Discussion and Conclusion

This project truly helped us to further understand the many challenges and opportunities that lie in applying deep learning techniques for the detection of Alzheimer's disease through the analysis of MRI images. We gained a much deeper understanding of convolutional neural networks (CNN) and their abilities in image classification, as well as the important role proper data preprocessing has.

One major insight was the impact of properly structuring data. Initially, we treated individual 2D slices as separate scans, leading to data leakage and incorrectly high accuracy. Correcting this, we had to stack these 2D slices into 3D tensors revealing to us the true difficulty and complexity of the task ahead of us, while also exposing the limitations of our CNN architecture without more optimizations. Our promising results were achieved in classifying mild and very mild dementia, as the model struggled to recognize cases from very mild dementia, showing the need for more advanced features.

Transfer learning showed extreme limitations as both datasets require different preprocessing and dataset characteristics. The inability of the transfer learning dataset to be able to adapt the preprocessing techniques used to train the model for the OASIS dataset. Despite all this, our exploration of classification (demented vs non-demented) demonstrated that simplifying classification tasks can improve the performance of the model significantly.

Out of the many key lessons, some of the most important lessons that we have learned are the grave importance of properly implementing preprocessing, dealing with data inconsistencies, and being able to properly adapt architectures for more advanced and unique inputs such as the classification into multiple subcategories. Moving forward into the future, we would love to find a way to automate the preprocessing to be able to handle multiple different datasets, explore more advanced architectures, and develop more adaptive techniques. With these further advancements and with more resources, deep learning has a great potential for advancing early Alzheimer's detection and helping change the lives of many by improving treatments in earlier stages.

References:

1. Shaffi, "Ensemble of Vision Transformer Architectures for Efficient Alzheimer's Disease Classification." *Brain Informatics*, 2024, https://braininformatics.springeropen.com/articles/10.1186/s40708-024-00238-7.
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