Final Project

Neural Networks and Deep Learning

Alzheimer's Diagnostic with OASIS

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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 [1].

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[2]. 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 [3]. Thus, it is a significant health concern among all the other modern health issues.

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 expected or has some patterns that reflect the presence of 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 accurately detect the disease through the given data. This model will detect the structure change in specific brain parts and the abnormalities that lead to Alzheimer's disease.

1 Dataset

OASIS contains MRI scans of the brain images with neuroimaging and related clinical data, which are publicly available for research and analysis. It includes data to understand the brain and helps in developing treatment approaches for various brain-related diseases, including Alzheimer's disease. 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 [4]. This data set contains brain images and demographic data of the person being scanned.

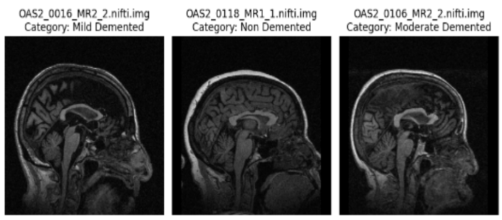

Figure 1. Sample Images with Default Axes.

2 Exploratory Data Analysis

The most common type of dementia is mild dementia, with 123 patients. There are significantly fewer patients with moderate dementia (41) and highly demented (3). The number of non-demented patients is 206.

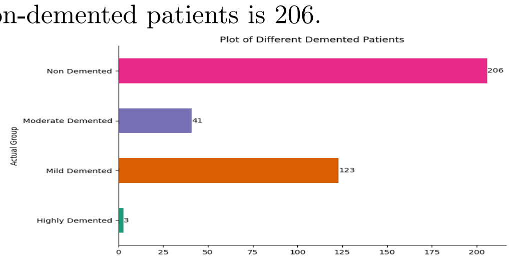

Figure 2. Count of Different Categories.

The proportion of non-demented people is highest between 60 and 70 years old. It then steadily declines until 100 years old while the proportion of demented people is very low and relatively constant across all ages. There is a small number of people in the "converted" category.

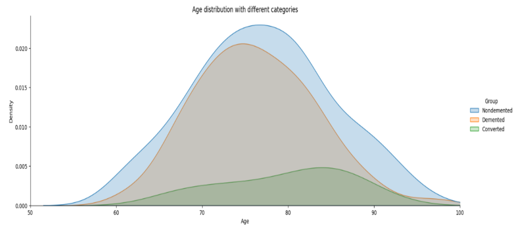

Figure 3. Distribution of Different Categories.

The age group with the most people is 70-75 years old. There are fewer people in the age groups below and above this range. The distribution is roughly symmetrical, with similar numbers of people in the 60-65 and 80-85 year old age groups.

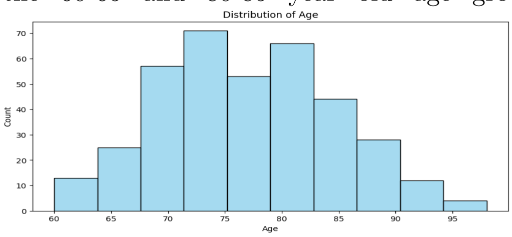

Figure 4. Distribution of Age.

3 Dataset Preprocessing

This section elaborates on the preprocessing steps to prepare the dataset for analysis. We took help from Conor to understand the data and do the extraction process [5].

1. **Selection of Dimension**: Out of the three dimensions provided in the MRI images, we specifically chose the first dimension, which represents the side view of the brain. This choice was motivated by the fact that Alzheimer's disease initially affects regions such as the hippocampus, which can be distinctly observed in this particular view[6].

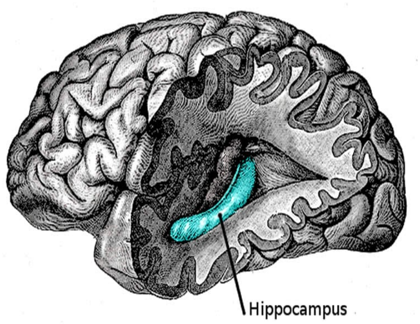

Figure 5. Location of Hippocampus[7].

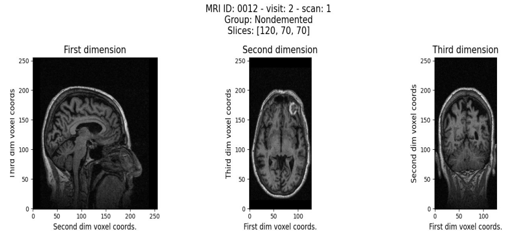

Figure 6. All 3 Axes of Same Image.

2. **Image Slicing**: To ensure clarity and maximize information extraction, the NIfTI (Neuroimaging Informatics Technology Initiative) medical images were sliced at frames between 60 to 70. This range was selected based on the clarity and information content assessment within these frames.

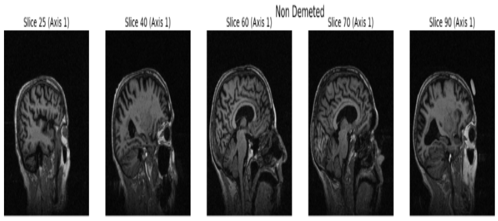

Figure 7. Slicing the Images.

3. **Categorization Adjustment**: Initially, the highly demented category contained limited images, potentially skewing the analysis. Therefore, to better align with the focus on mild dementia, these images were reclassified into the moderate dementia category. Data augmentation techniques were also employed to address the class imbalance and balance the number of images across the three remaining categories.

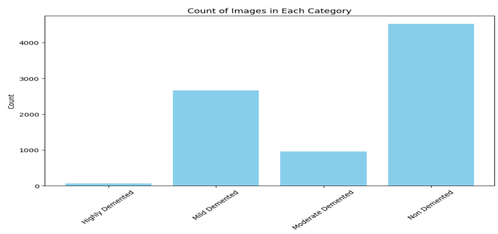

Figure 8. Count Plot before Processing.

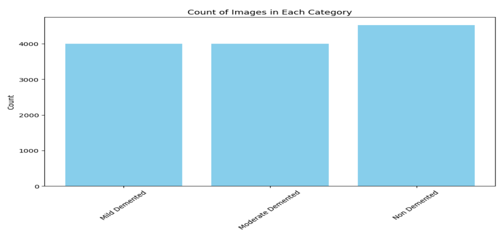

Figure 9. Count Plot after Processing.

4. **Data Splitting**: The preprocessed dataset was divided into three subsets: training, testing, and validation.

4 Materials and Methods

4.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a class of deep neural networks most commonly applied to analyzing visual imagery. CNNs are particularly effective in image classification tasks due to their ability to learn and extract hierarchical features from images automatically.

We implemented a CNN architecture for our image classification task. The CNN model comprised several convolutional and pooling layers and fully connected layers for classification. The architecture was designed to extract relevant features from input images and make predictions based on these features.

The total number of parameters in the CNN model is 34,719,268, with all parameters being trainable. This model architecture was utilized for our image classification task, achieving promising results.

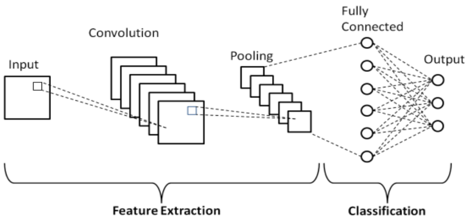

Figure 10. CNN Architecture.

4.2 VGG16 Model

The VGG16 (Visual Geometry Group 16) model is a pre-trained deep convolutional neural network architecture developed by the Visual Geometry Group at the University of Oxford. VGG16 is known for its simplicity and effectiveness in image recognition tasks.

In our study, we employed the VGG16 model as a feature extractor. The pre-trained VGG16 model was loaded without the top (classification) layers, and custom classification layers were added on top to adapt the model for our specific classification task.

The VGG16 model is a deep convolutional neural network architecture proposed by Karen Simonyan and Andrew Zisserman in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition." It consists of 16 convolutional layers and is widely used for image classification tasks[8].

The key features of VGG16 are:

- **Depth:** VGG16 has 16 layers with weights, consisting of 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers.

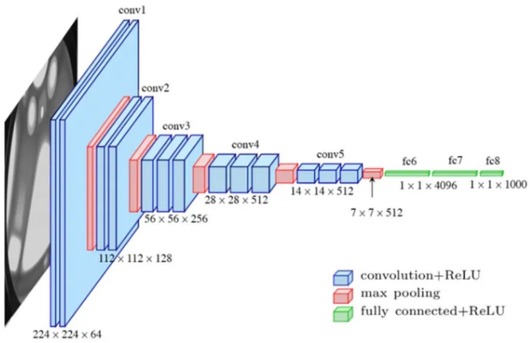

Figure 1: VGG16 Architecture[9]

- **Simplicity:** The VGG16 architecture is relatively simple, using only 3x3 convolution filters and 2x2 max-pooling layers consistently throughout the network. This makes the model easy to understand and implement.

- **Performance:** VGG16 achieved a top-5 error rate of 7.3% on the ImageNet dataset, which was highly competitive at the time. It is considered one of the best vision model architectures. As we were having issues with high validation error thus this the best choice.

5 Results

5.1 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) model has trained over 70 epochs, with periodic evaluations on the validation dataset. During the training process, the model significantly improved accuracy and loss metrics. Notably, the validation accuracy steadily increased from an initial value of 64.58% in the first epoch to a peak of 91.35% in the 27th epoch. This improvement demonstrates the effectiveness of the model in generalizing to unseen data. However, after the 27th epoch, the early stopping mechanism was triggered, indicating that further training did not lead to substantial improvements in performance. The final test accuracy achieved by the CNN model was 89.02%, with a corresponding test loss of 0.3389. These results validate the efficacy of the CNN architecture in accurately classifying dementia severity levels based on brain MRI images.

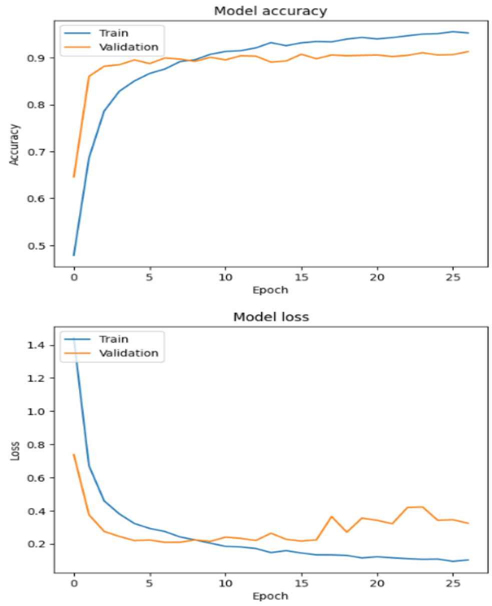

Figure 11. Error and Accuracy for CNN.

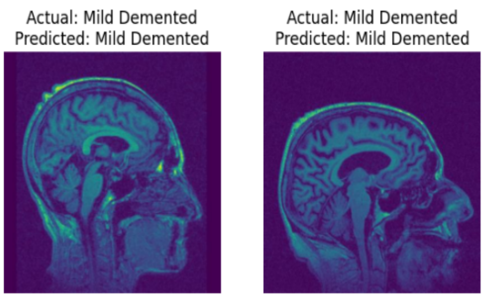

Figure 12. CNN Predicted Samples.

5.2 VGG16 Model

The training of the VGG16 model was conducted over 50 epochs, with periodic evaluations of the validation dataset. Initially, the model achieved an accuracy of 54% and a loss of 0.92 on the training data in the first epoch. However, the validation loss did not improve from 0.1415 after the 14th epoch. Notably, the VGG16 model outperformed the CNN model in terms of both accuracy and loss metrics. The final test accuracy achieved by the VGG16 model was 93.03%, with a corresponding test loss of 0.2525. This superior performance validates the effectiveness of the VGG16 architecture in accurately classifying dementia severity levels based on brain MRI images.

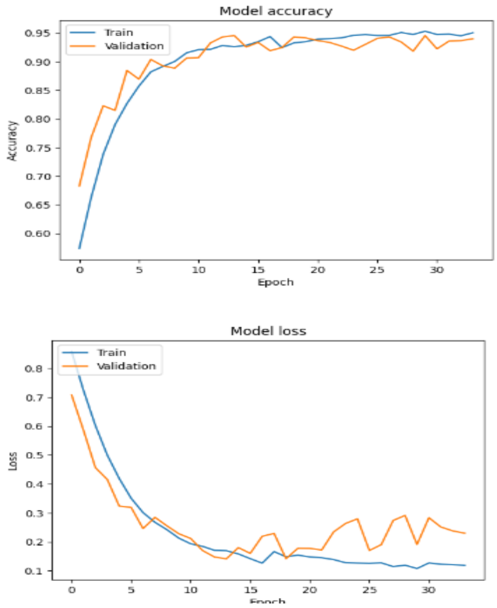

Figure 13. Error and Accuracy for VGG16.

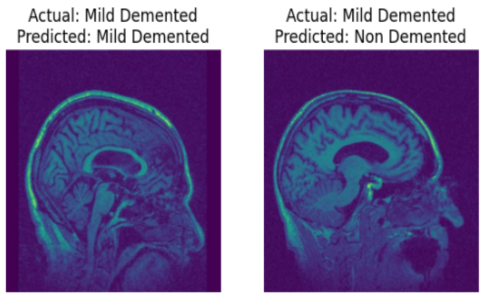

Figure 14. VGG16 Predicted Samples.

6 Evaluation

Based on the classification reports for the CNN and VGG16 models, it is evident that both models perform well in detecting Alzheimer's disease, particularly in identifying Non Demented cases with high precision, recall, and F1-score. However, when it comes to Mild Demented cases, there is a slightly lower performance in terms of precision and recall, especially for the CNN model.

Considering that the primary objective of the model is to detect Alzheimer's disease at an early stage, it is crucial to minimize the misclassification of Mild Demented cases as Non Demented or Moderately Demented. Even if a Mild Demented case is classified as Moderately Demented, it can still be considered beneficial for the patient, as it provides an early indication of cognitive decline and allows for necessary preparations and interventions before the condition worsens. Therefore, false positives in this context may not necessarily be considered detrimental.

In evaluating the models, it is essential to focus on their ability to detect Mild De-

Table 1: Train Error and Accuracy Comparison

Model	Error	Accuracy
CNN (Train)	0.1035	0.9536
CNN (Val)	0.3243	0.9135
CNN (Test)	0.3720	0.8902
VGG16 (Train)	0.1656	0.9298
VGG16 (Val)	0.1415	0.9455
VGG16 (Test)	0.2525	0.9302

Table 2: Classification Reports

Model	Metrics		
	Precision	**Recall**	**F1-score**
CNN	0.85	0.75	0.80
	0.80	0.89	0.84
	1.00	1.00	1.00
VGG16	0.96	0.81	0.88
	0.85	0.97	0.90
	1.00	1.00	1.00

mented cases accurately while maintaining high precision and recall for other classes. Additionally, considering the clinical implications, the emphasis should be on minimizing false negatives for Mild Demented cases to ensure early detection and intervention.

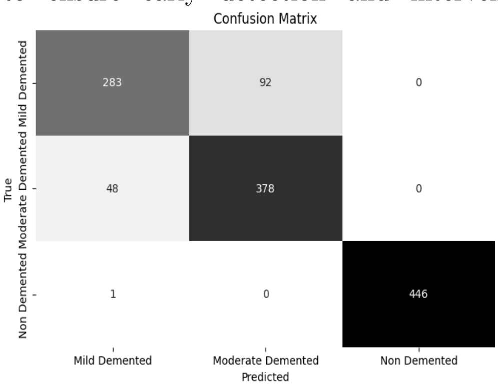

Figure 15. CNN Classification Report

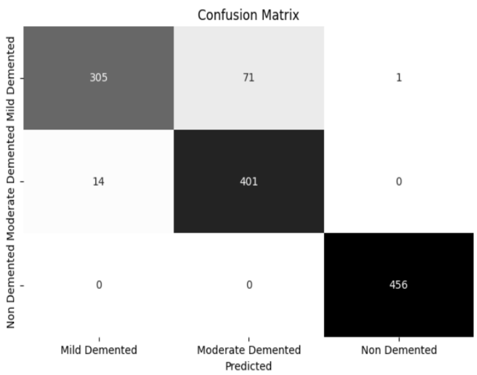

Figure 16. VGG16 Classification Report

Overall, both the CNN and VGG16 models demonstrate promising performance in detecting Alzheimer's disease at an early stage, with a focus on minimizing false negatives for Mild Demented cases while maintaining high precision and recall for other classes. Further refinement and optimization of the models could improve their performance in this critical task.

7 Experimentation's

During the experimentation phase, we explored the possibility of incorporating Principal Component Analysis (PCA) as a dimensionality reduction technique to enhance the performance of our models. However, upon analysis, we found that while PCA could reduce the dimensionality of the input data, retaining 95% variance required retaining 28 principal components out of the total 32 components, which did not significantly impact the overall performance of the models.

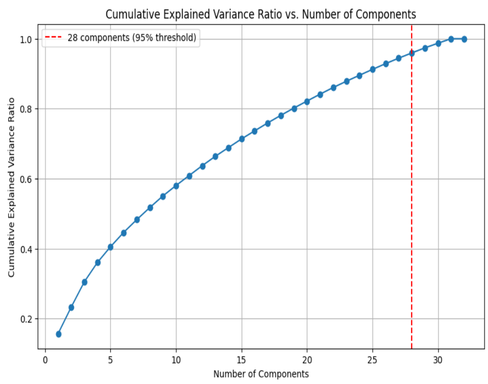

Figure 17. PCA Graph.

Additionally, we initially began with a simple Convolutional Neural Network (CNN) architecture. However, during the training process, we observed signs of overfitting as the model started to perform exceedingly well on the training data but showed a decline in performance on the validation data. This prompted us to explore more complex architectures and regularization techniques to mitigate overfitting and improve generalization performance.

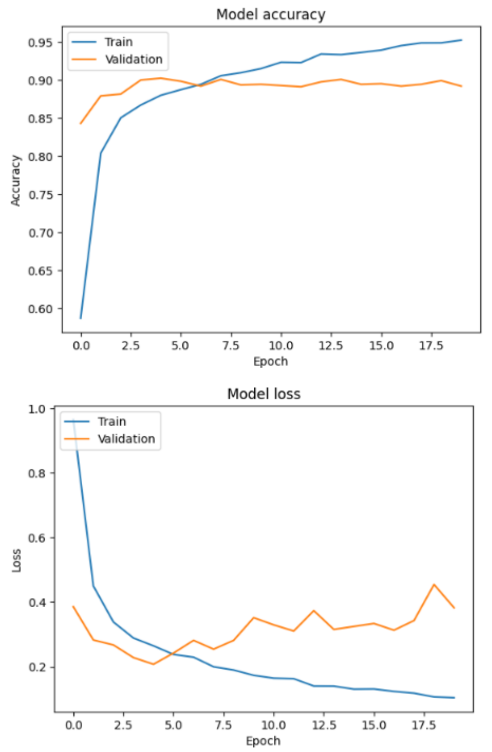

Figure 18. Base CNN model performance. After the best CNN model that we had we tried another model with similart architecture but focusing on validation loss this time. However, during the training process, we observed signs of overfitting and we considered the previous model as our best model which also had better test accuracy and loss.

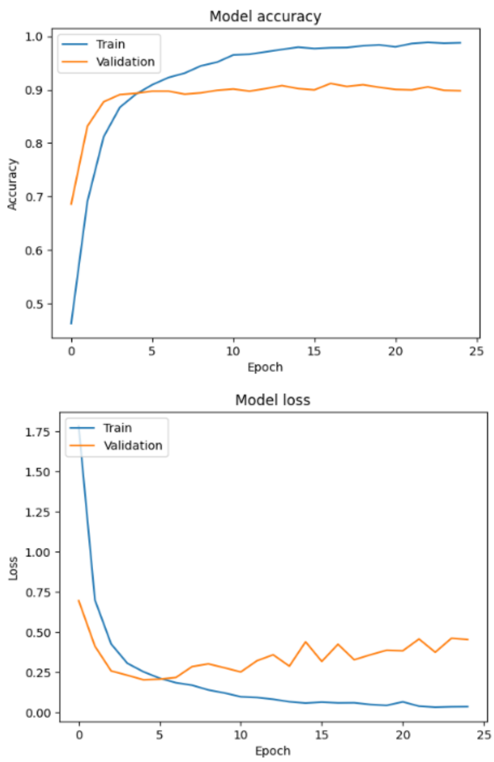

Figure 19. CNN model with focus of loss.

Along with all the experiements we tried working with different libraries such as Med2images, pynifti, nibabel and medpy.io to work with NifTi images.

Conclusions

In conclusion, our project demonstrates the potential of machine learning and neuroimaging techniques in early Alzheimer's disease detection. Through the exploration of CNN and VGG16 models, we achieve promising results in classifying Alzheimer's based on MRI scans.

Our preprocessing efforts and exploratory data analysis enhance dataset quality, improving model performance. While both CNN and VGG16 show high accuracy, VGG16 outperforms CNN, emphasizing the importance of model selection.

Despite limitations in detecting mild dementia cases, our focus on minimizing false negatives underscores the significance of early detection for timely intervention.

Moving forward, refining models and exploring advanced algorithms hold promise for enhancing accuracy and clinical applicability. This project represents a step toward early diagnosis and personalized treatment, highlighting the potential of interdisciplinary collaboration and innovative technologies in addressing Alzheimer's disease.

References

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