Early Alzheimer’s Detection

Deep Learning on OASIS MRI Images

Brad Richardson

Applied Computer Science, BS Post-Baccalaureate, University of Colorado Boulder, brri6685@colorado.edu

1 MOTIVATION

As the primary caregiver for my 87-year-old grandmother diagnosed with Alzheimer's, I've witnessed firsthand the critical importance of early detection and accurate staging of the disease. Motivated by this personal experience and my decade in healthcare, I aim to apply deep learning techniques, specifically convolutional neural networks (CNNs), to classify MRI brain images into four categories reflecting Alzheimer's progression stages. Utilizing the extensive OASIS MRI dataset of 80,000 images, I seek to explore how effectively CNNs can detect and differentiate subtle brain changes in early Alzheimer's stages. By investigating whether a multi-class CNN model can improve early detection compared to traditional binary classification, I hope to uncover new patterns or indicators that might enhance diagnostic accuracy. Ultimately, this research aims to contribute to improved patient care and treatment strategies, potentially benefiting families like mine who are affected by Alzheimer's.

2 LITERARY SURVEYS

Oh, K. et al (2019) developed a deep convolutional neural network (CNN) model to classify Alzheimer's disease stages using structural MRI data. Their model achieved high classification accuracy by automatically

learning relevant features from the MRI images without manual feature extraction. They employed visualization techniques to highlight the brain regions that contributed most to the classification decisions, enhancing the interpretability of the model. The results demonstrated that the CNN could effectively identify patterns associated with Alzheimer's disease progression.

Islam, J & Zhang, Y (2018) presented an ensemble approach using deep convolutional neural networks for the diagnosis of Alzheimer's disease from brain MRI scans. They constructed multiple CNN models and combined their predictions to improve diagnostic accuracy. The authors utilized data augmentation and transfer learning techniques to address the limited availability of medical imaging data. Their ensemble system showed superior performance compared to individual CNN models, achieving higher accuracy in classifying patients with Alzheimer's disease versus healthy controls.

Korolev, S et al (2017) compared the performance of plain and residual convolutional neural networks for classifying Alzheimer's disease using 3D brain MRI data. They explored how deeper network architectures could improve classification accuracy by capturing complex features from volumetric data. The study found that residual networks, which incorporate shortcut connections to mitigate vanishing gradient problems, outperformed plain CNNs in this task. Their results demonstrated that using 3D CNN architectures with residual connections could enhance the detection of Alzheimer's disease from MRI scans.

Bassaia, S. et al (2019) developed an automated system using deep convolutional neural networks to classify Alzheimer's disease and mild cognitive impairment (MCI) from single structural MRI scans. They designed a 3D CNN model that could process whole-brain images without the need for region-of-interest segmentation. The model achieved high accuracy in distinguishing between Alzheimer's patients, MCI individuals, and healthy controls. By using a single MRI scan, their approach offers a practical solution for clinical settings where additional imaging modalities may not be available.

Wen, J et al (2020) provided a comprehensive overview of convolutional neural network applications for Alzheimer's disease classification using MRI data. They conducted a reproducible evaluation of various CNN architectures and training strategies to assess their effectiveness. The study emphasized the importance of standardized evaluation protocols to ensure fair comparisons between models. By making their code and models publicly available, the authors aimed to improve transparency and reproducibility in the field.

3 PROPOSED WORK

In this project, I aim to develop a multi-class convolutional neural network (CNN) model for early Alzheimer's detection using the OASIS MRI dataset. I will begin with data exploration to understand the dataset's structure and characteristics, followed by

basic preprocessing steps including pixel normalization and image resizing. I will develop a simple custom CNN architecture, consisting of 2-3 convolutional layers with max pooling, 1-2 fully connected layers, and an output layer with softmax activation for multi-class classification. I will train the model on the preprocessed dataset, with basic hyperparameter tuning and dropout regularization implemented to optimize performance and prevent overfitting. If time permits, I will fine-tune a pre-trained model such as VGG16 or ResNet50 for comparison with my custom CNN.

My evaluation will focus on calculating key performance metrics including accuracy, precision, recall, and F1-score for each class. I will create and analyze a confusion matrix to understand model misclassifications, and plot learning curves to assess potential overfitting or underfitting issues. I will also include visualization of sample predictions to gain insights into model performance. My approach differs from previous works by focusing on multi-class classification of Alzheimer's stages, demonstrating how beginner-level practitioners can approach complex medical imaging tasks within time constraints. By balancing the complexity of multi-class Alzheimer's detection with practical limitations, I aim to contribute valuable insights into early Alzheimer's detection while gaining experience in applying CNN techniques to medical imaging problems.

4 DATA SET

I am utilizing the OASIS MRI dataset, a comprehensive collection of 86,437 brain MRI images specifically curated for Alzheimer's disease research. Available on Kaggle, this 1.3 GB dataset consists of .jpg images converted from original .nii format MRI scans of 461 patients. Each patient's MRI was sliced along the z-axis, with multiple slices selected per patient to create 2D images suitable for deep learning applications. The images are classified into four categories based on Alzheimer's progression: non-demented (77.77%), very mild demented (15.88%), mild demented (5.79%), and moderate demented (0.56%). My initial data exploration has revealed consistent image dimensions of 496x248 pixels across all samples, with varying intensity distributions between classes that may provide valuable features for classification.

5 EVALUATION METHODS

To evaluate my model, I will employ a comprehensive set of metrics including accuracy, precision, recall, and F1-score for each of the four classification categories. I will generate confusion matrices to visualize the model's performance across all classes and use ROC curves with AUC to assess its ability to distinguish between stages. For model interpretability, I'll implement Grad-CAM to highlight influential regions in the MRI images, potentially uncovering new patterns or indicators of early Alzheimer's stages. To ensure robustness, I'll use k-fold cross-validation and compare my multi-class CNN model against a baseline binary

classification model to quantify improvements in early detection capabilities. Finally, I'll conduct error analysis on misclassified images, particularly focusing on cases where the model confuses adjacent stages, to identify areas for future improvement.

6 TOOLS

For this project, I have established a comprehensive Python-based development environment that leverages multiple specialized libraries for medical image processing and deep learning. At the core of my image processing pipeline, I utilize OpenCV and PIL for efficient loading and manipulation of the MRI scans, enabling consistent preprocessing across my large dataset. I handle data manipulation and numerical computations through Pandas and NumPy, which provide the foundation for my statistical analysis workflows. For visualization needs, I employ Matplotlib and Seaborn, allowing me to create detailed representations of my data distributions and model results. I will implement the deep learning components using TensorFlow and Keras, chosen for their robust ecosystem and extensive documentation. To support my statistical analysis requirements, I have integrated SciPy, particularly for calculating distribution moments and other advanced metrics. I am accelerating development and training through Google Colab's GPU resources, while maintaining version control through Git and GitHub, ensuring reproducibility and systematic progress tracking.

7 MILESTONES

My project has progressed significantly since its inception, with several key milestones already achieved and others clearly defined for the remaining timeline. In Phase 1, completed in October, I successfully established a robust data infrastructure, implementing a comprehensive loading and verification pipeline that has processed all 86,437 images in my dataset. This initial phase included thorough integrity checks and dimension verification, confirming consistent image specifications across all samples. My exploratory data analysis has yielded valuable insights into class distributions and image characteristics, informing my future modeling decisions. I've also completed the development of my preprocessing pipeline, which effectively normalizes image intensities and standardizes input formats for my planned neural network architecture.

The data preparation phase has been particularly successful in establishing quality control measures. I've implemented automated checks for image corruption, dimensional consistency, and proper class labeling. My statistical analysis tools are now in place, allowing me to monitor class distributions and image characteristics throughout the development process. Additionally, I've created visualization tools for monitoring model performance and data distributions, which will be crucial for the upcoming modeling phases.

Looking ahead, my immediate focus will be on model development, scheduled for early November. This phase will encompass

several critical components: first, the implementation of my initial CNN architecture with carefully chosen layer configurations based on my dataset characteristics. Second, I'll develop targeted data augmentation strategies to address the class imbalance I've identified, particularly for the underrepresented moderate dementia class. Third, I'll establish proper data splits for training, validation, and testing, ensuring stratified sampling to maintain class distributions across all sets.

By mid-November, I will transition into the training and optimization phase. This stage will focus on addressing the class imbalance challenges identified in my exploratory analysis through implementation of weighted loss functions and balanced batch sampling strategies. I'll conduct systematic hyperparameter optimization, including learning rate scheduling, dropout rate tuning, and architecture refinement. This phase will also include the development and implementation of early stopping criteria based on validation performance to prevent overfitting.

Late November will be dedicated to model evaluation and refinement. I'll implement my comprehensive evaluation metrics suite, including class-specific performance measures and confusion matrix analysis. If initial results indicate areas for improvement, I'll explore architectural modifications or advanced training techniques. I'll also begin comparing my results with baseline models and existing literature benchmarks.

The final phase, extending into early December, will focus on comprehensive performance analysis and documentation of my findings. This will include detailed error analysis of misclassified cases, visualization of model decision boundaries, and investigation of model interpretability using techniques like Grad-CAM. I'll prepare visualization tools for presenting my results and compile comprehensive documentation of my methodology and findings. The project will culminate in the final report due December 9, which will include both technical achievements and potential clinical implications of my work.

Throughout these phases, I maintain weekly progress tracking and regular validation of my approaches against my project objectives. Each milestone includes specific deliverables and quality metrics to ensure I maintain focus on my core goal of improving early Alzheimer's detection while adhering to my academic timeline.

8 RESULTS SO FAR

My initial exploration of the OASIS MRI dataset has yielded fascinating insights into both the technical characteristics and underlying patterns within the brain imaging data. The dataset's scope is substantial, encompassing over 86,000 images that capture various stages of cognitive decline. Through careful analysis, I've discovered that while the dataset is rich in information, it presents an intriguing challenge in terms of class representation that mirrors the real-world distribution of Alzheimer's progression stages.

The majority of my images – nearly four-fifths of the dataset – represent non-demented cases, providing a robust baseline for normal brain structure and appearance. This predominance of healthy brain scans allows me to establish a strong foundation for identifying deviations that might indicate cognitive decline. The remaining cases follow a pattern that reflects the progressive nature of Alzheimer's disease: very mild dementia cases constitute about one-sixth of my dataset, mild dementia cases represent approximately one-twentieth, and moderate dementia cases make up just over half a percent of the total. This distribution, while challenging from a machine learning perspective, actually provides valuable insight into the natural progression of the disease and the relative frequency of different stages in clinical settings.

My technical validation process has revealed remarkably consistent image quality across the entire dataset. Each image maintains precise dimensions of 496 by 248 pixels, suggesting careful standardization during the initial data collection and preparation phases. This uniformity is particularly valuable for my planned deep learning approach, as it eliminates the need for complex resizing operations that might introduce artifacts or distortions in the brain structures I aim to analyze.

Perhaps the most intriguing findings have emerged from my statistical analysis of image characteristics across different diagnostic categories. When examining the intensity patterns within these brain scans, I've noticed subtle but significant variations between healthy and affected brains. Non-demented cases consistently show slightly higher average intensity values, suggesting potentially different patterns of brain tissue density or composition. The statistical distributions of these intensities tell an even more compelling story – healthy brains display more symmetrical patterns in their intensity distributions, while cases involving dementia show more skewed and peaked distributions, possibly indicating structural changes associated with the disease's progression.

These findings have proven invaluable in shaping my approach to the challenge ahead. I've identified the need for sophisticated strategies to address the class imbalance while preserving the essential characteristics that distinguish between different stages of cognitive decline. My preprocessing pipeline has successfully normalized these images while maintaining their distinctive features, providing a solid foundation for my upcoming modeling work. The observed variations in intensity patterns between classes suggest that my neural network might benefit from specific architectural choices that can capture these subtle but important differences.

As I move forward with model development, these insights will guide my decisions in several crucial areas. I'll need to carefully balance my training approach to ensure equal attention to all disease stages, despite their uneven representation in the dataset. The consistent image quality allows me to focus my efforts on feature extraction rather than data cleaning, while the

discovered statistical patterns suggest promising directions for my model architecture design. These early results, while preliminary, have already deepened my understanding of the complex patterns within brain MRI data and strengthened my confidence in the potential for automated early detection of Alzheimer's disease.

The path ahead involves translating these insights into effective modeling strategies, but my thorough exploration of the dataset has provided a strong foundation for this next phase. I've not only confirmed the technical quality of my data but also uncovered subtle patterns that may prove crucial in distinguishing between different stages of cognitive decline. This combination of technical validation and statistical insight positions me well for the modeling challenges that lie ahead.

REFERENCES

[1] Oh, K., Chung, Y. C., Kim, K. W., & Kim, W. S. (2019). Classification and visualization of Alzheimer’s disease using deep convolutional neural networks. *Scientific Reports*, 9, 18150.

[2] Islam, J., & Zhang, Y. (2018). Brain MRI analysis for Alzheimer’s disease diagnosis using an ensemble system of deep convolutional neural networks. *Brain Informatics*, 5(2), 2.

[3] Korolev, S., Safiullin, A., Belyaev, M., & Dodonova, Y. (2017). Residual and plain convolutional neural networks for 3D brain MRI classification. In *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)* (pp. 835-838). IEEE.

[4] Basaia, S., Agosta, F., Wagner, L., Canu, E., Magnani, G., Santangelo, R., & Filippi, M. (2019). Automated classification of Alzheimer’s disease and mild cognitive impairment using a single MRI and deep neural networks. *NeuroImage: Clinical*, 21, 101645.

[5] Wen, J., Thibeau-Sutre, E., Diaz-Melo, M., Samper-Gonzalez, J., Routier, A., Bottani, S., D., Dormont, S., Durrleman, N., Burgos, & Colliot, O. (2020). Convolutional neural networks for classification of Alzheimer’s disease: Overview and reproducible evaluation. *Medical Image Analysis*, 63, 101694.