affiDementia Detection Binary Classification CNN Using 3D Convolution

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Abstract

Alzheimer's disease is a growing global concern, affecting over 50 million people and projected to triple by 2050. Early diagnosis is critical for slowing progression and improving patient outcomes. Current diagnostic methods such as the Mini‑Mental State Examination (MMSE) are often subjective, time-consuming, or require expert interpretation. This project addresses these challenges by developing a deep learning model that analyzes brain MRI scans for early detection of dementia. Our approach combines convolutional neural networks (CNNs) for image classification with advanced preprocessing techniques to improve diagnostic accuracy.

Problem Statement

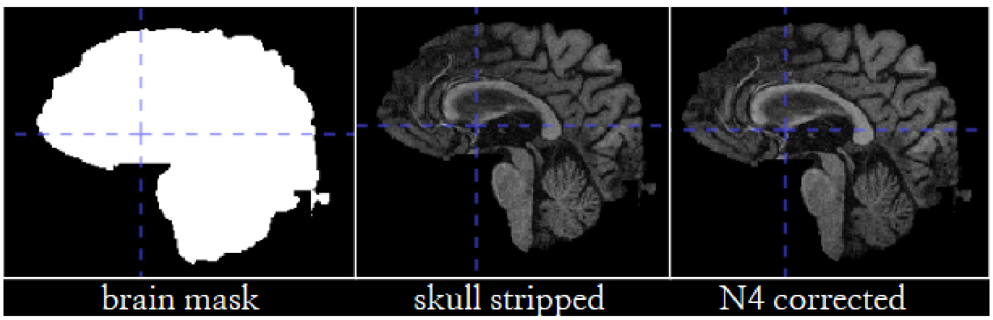
The primary goal of this project is to detect cognitive decline and dementia from high-resolution MRI scans, potentially improving diagnostic speed and accuracy. We based our study on prior research demonstrating the effectiveness of CNNs in medical image analysis, including the Open Access Series of Imaging Studies (OASIS) dataset.

Methods

1. **Dataset**: For our dataset, we used the OASIS-2 dataset, containing labeled T1-weighted MRI scans in the NIFTI-1 file format. These images were categorized as Nondemented, Demented, and Converted. The Converted label denotes a patient that, during a previous MRI session, was classified as Nondemented, but during the current MRI session was reclassified as Demented. For the purposes of this project, Converted labels were treated as Demented. There are a total of 1368 MRI images we extracted, and "this set consists of a longitudinal collection of 150 subjects aged 60 to 96. Each subject was scanned on two or more visits, separated by at least one year for a total of 373 imaging sessions[7]." Each image had dimensions of 128 x 256 x 256
2. **Pre-processing Overview:** We used a paper which evaluated various DNN and CNN models as a basis for the pre-processing steps we performed[2]. Images were preprocessed by extracting the z-axis view, co-registered, and skull-stripped to isolate brain tissue features. Finally, N4 Bias Correction was applied as noise removal[6].
3. **Preprocessing Pipeline**:
   - **Resampling and Registration**: We used Nibabel Pytorch library[8] and SimpleITK library[9]. SimpleITK was used to resample the images to a continuous grid

representation. Then we applied linear interpolation and affine transformations for image alignment and registration.

- **Skull Stripping**: The old method, which we later replaced, used the ICBM 2009c Nonlinear Symmetric template[3]. This was a static 3D brain mask to "skull strip" or remove image features outside of the brain matter. As shown in the figure below, the new method used a pre-trained model (PARIETAL), which was trained using the same OASIS image set that we used [8]. Isolated brain tissue using custom and pre-trained neuroimaging masks, overcoming template limitations.



- **Noise Removal**: Performed N4 Bias Field correction to eliminate low-frequency intensity non-uniformity, crucial for consistent intensity distributions.
- **Conversion**: Converted processed data into HDF5 file format (using HDF5 Pytorch library) to optimize storage and facilitate large-scale batch processing.

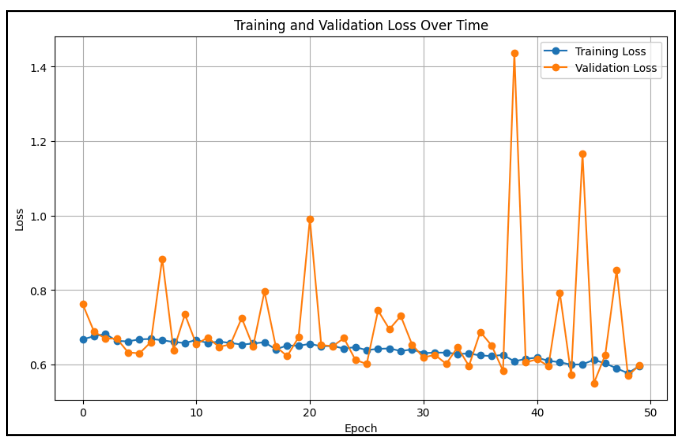
4. **Model Architecture**:
   - We lightly borrowed elements from a ResNet-18 architecture including one skip connection. We also used three 3D convolutional blocks for feature extraction. Due to the small size of our image set, we opted to use a shallower model as a deeper model would not benefit us.
   - Since we used grey-scale images, the initial input channel was 1.
   - Kernel size of 3, and a stride and padding of 1.
   - Optimized using the Adam optimizer with a momentum of 0.1 and Binary Cross-Entropy (BCE) loss for binary classification.
   - Incorporated batch normalization and ReLU activation functions to stabilize training and mitigate vanishing gradient issues.
   - Limited batch size to 4 due to memory constraints, balancing computational feasibility and training performance. Even with a batch size of 4, the model's operations ran at a peak of 40GB GPU RAM, which nearly overwhelmed the A100 GPU we used through Google Colab.

- Employed a learning rate scheduler to dynamically through Adam to adjust learning rates based on validation performance, enhancing training stability and convergence. Initial learning rate was set to 3e-4. We set this small learning rate due to the shallow model architecture and the Adam optimizer being used.
- **Output:** Generated using the Sigmoid function for a predicted score in the range of 0 to 1. A score higher than 0.5 indicates that the model predicts the patient / image to have a positive marker for dementia.

5. **Training and Validation**:
   - The image set was split into training (70%), validation (15%), and test (15%) sets.
   - Pre-processed images using N4 Bias remove and PARIETAL significantly improved model performance compared to training using images with the template brain mask and no noise removal (average accuracy of 54%).
   - Loss Function: Binary Cross-Entropy for binary classification tasks.
   - Validation Protocol: Used accuracy, precision, recall, and F1 scores to evaluate model performance.
   - Regularization: Weight decay was applied to mitigate overfitting, addressing the challenges posed by the dataset's limited size.

Results

The model demonstrated significant improvements following the implementation of advanced preprocessing techniques. Initially, test accuracy was approximately 54%, but after addressing issues such as intensity bias in MRI images through N4 Bias Field Correction and refining the skull-stripping process, the model achieved an F1 score of 70% and a weighted average accuracy of 73%. Training loss steadily decreased across epochs, indicating consistent learning, while validation loss showed an encouraging overall downward trend, despite occasional spikes that suggest areas for further optimization.



Performance metrics highlight the model's strengths: a recall of 92% for the dementia class reflects how the model is better at identifying dementia cases than non-dementia cases, and a precision of 82% for non-dementia cases demonstrates its ability to minimize false positives. These results highlight the potential of CNN-based models in early dementia detection.

Challenges and Future Directions

Key challenges:

- Memory limitations when processing large 3D images. Due to the large size of the image blocks, it was time and resource-intensive to train. The 50 epoch testing using the old and new pre-processed images spent the entirety of our data/resource budget that Google Colab allotted us. Given more processing power, we are interested in longer training.
- Aligning and skull-stripping MRI images with non-standard templates.
- Balancing model complexity to avoid overfitting due to the small dataset size.

Future improvements:

- Expanding the dataset to improve generalizability.
- Deepening the architecture of the model to more closely resemble a Resnet-style model.
- Exploring multi-class classification for various stages of dementia severity.
- Isolating specific brain regions, such as the hippocampus, for targeted analysis of subsets of dementia such as Alzheimers. These brain regions could be isolated by using a technique similar to skull-stripping.
- Increasing training epochs to fully utilize the model's learning potential.

Conclusion

This project successfully demonstrated the potential of CNNs in early dementia detection, leveraging MRI scans as a diagnostic tool. Advanced preprocessing techniques, such as N4 Bias Field Correction and refined skull-stripping, were instrumental in enhancing model performance, achieving an F1 score of 70% and a recall of 92% for dementia cases. These results underscore the viability of deep learning approaches in addressing medical imaging challenges.

While the project faced limitations, including small dataset size and memory constraints, it establishes a strong foundation for future work. Expanding datasets, incorporating multimodal features like genetic markers, and exploring region-specific analyses can significantly improve model accuracy and applicability.

This study highlights the transformative potential of CNNs in neuroimaging, offering a scalable and objective diagnostic method. With further optimization and validation, this approach could pave the way for earlier detection of Alzheimer’s disease, ultimately improving patient outcomes through timely interventions.

Citations

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