Multi-Approach Alzheimer's Disease Detection

Combining Neuroimaging and Clinical Risk Factor Analysis

Hack4Health AI for Alzheimer's Challenge | Author: Aron | December 2025

Abstract

This project presents a multi-approach framework for Alzheimer's Disease detection using two complementary methodologies: (1) deep learning classification of MRI brain scans using ResNet50 transfer learning, achieving **82.62% accuracy** on 4-class dementia staging, and (2) neural network analysis of clinical risk factors, achieving **85.35% accuracy** on binary diagnosis prediction. Our approach demonstrates that combining neuroimaging with clinical data mirrors real-world diagnostic practice and provides comprehensive disease assessment.

1. Problem Framing

Alzheimer's Disease (AD) affects over 55 million people worldwide, with numbers projected to triple by 2050. Early and accurate detection is crucial for intervention planning and patient care. Current diagnostic approaches rely on expensive imaging, cognitive assessments, and clinical expertise. This project addresses the challenge of automated AD detection through two complementary machine learning approaches:

- **Neuroimaging Analysis**: Automated classification of brain MRI scans into 4 dementia stages (Non-Demented, Mild, Moderate, Very Mild)
- **Clinical Risk Assessment**: Prediction of AD diagnosis from 32 patient clinical features including demographics, lifestyle factors, and cognitive assessments

By exploring both modalities, we demonstrate how AI can support clinical decision-making across different diagnostic contexts, mirroring the multi-modal approach used by clinicians in practice.

2. Methods

2.1 MRI Classification

Dataset: 5,120 training MRI brain scans across 4 classes: Non-Demented (724 samples), Mild Demented (49 samples), Moderate Demented (2,566 samples), and Very Mild Demented (1,781 samples). The significant class imbalance was addressed using weighted loss functions and weighted random sampling.

Model Architecture: ResNet50 pretrained on ImageNet with a custom classification head. Transfer learning allows the model to leverage features learned from 14 million images, then fine-tune for brain scan classification. The architecture includes dropout regularization (0.5) to prevent overfitting.

Training: 15 epochs using AdamW optimizer (lr=1e-4) with cosine annealing learning rate scheduler. Data augmentation (random horizontal flip, rotation up to 15°, color jitter) was applied to increase effective training data. Gradient clipping (max_norm=1.0) prevented training instability.

2.2 Clinical Risk Model

Dataset: 2,149 patients with 32 clinical features including demographics (age, gender, education), lifestyle factors (BMI, smoking, physical activity), medical history (family history, cardiovascular disease, diabetes), cognitive assessments (MMSE, functional assessment, ADL scores), and symptoms (confusion, disorientation, memory complaints). Data source: Rabie El Kharoua (2024), Kaggle.

Model Architecture: Multi-layer perceptron with architecture 32→128→64→32→2, including batch normalization after each hidden layer and dropout (0.4) for regularization.

Training: 100 epochs using Adam optimizer (lr=0.001) with step learning rate decay. Features were standardized using StandardScaler before training.

3. Evaluation & Results

Metric	MRI Model (ResNet50)	Clinical Model (MLP)
Task	4-class staging	Binary diagnosis
Accuracy	82.62%	85.35%
F1 Score (weighted)	83%	85%
Training Samples	4,096	1,719
Validation Samples	1,024	430

3.1 MRI Model Performance

The MRI model achieved strong performance on Non-Demented (precision: 0.98, recall: 0.84) and Very Mild Demented classes (precision: 0.68, recall: 0.97). The main confusion occurred between Moderate and Very Mild stages, which is clinically expected as these stages represent a continuum of disease progression. Class 1 (Mild Demented) achieved perfect scores but had only 10 validation samples, limiting statistical reliability.

3.2 Clinical Model Performance

The clinical model showed balanced performance: No Alzheimer's (precision: 0.88, recall: 0.90) and Alzheimer's (precision: 0.80, recall: 0.78). Feature importance analysis identified MMSE score, Functional Assessment, ADL score, and Memory Complaints as top predictors, aligning with established clinical diagnostic criteria.

3.3 Explainability

Grad-CAM Visualization: We implemented Gradient-weighted Class Activation Mapping to visualize which brain regions influence predictions. The model focuses on: (1) ventricular regions—consistent with ventricular enlargement as an AD biomarker, (2) temporal and frontal cortex—where AD-related atrophy occurs, and (3) hippocampal regions—the primary area affected in AD. This alignment with known pathology validates that the model learns clinically meaningful features.

4. Limitations & Future Work

- **No true multimodal fusion:** MRI and clinical datasets contain different patients, preventing patient-matched fusion
- **Class imbalance:** Mild Demented class has only 49 samples (0.96% of data), limiting statistical reliability
- **Synthetic clinical data:** The Kaggle clinical dataset is synthetic, requiring validation on real patient data
- **Image-level splitting:** Train/test split at image level, not patient level, may cause optimistic estimates

Future work: Obtain matched multimodal datasets (MRI + clinical for same patients), integrate genetic risk factors (APOE genotype), develop attention-based fusion architectures, and validate on external datasets (ADNI, OASIS).

5. Conclusion

This project demonstrates that deep learning can effectively classify Alzheimer's disease from both neuroimaging and clinical data. The MRI model achieved **82.62% accuracy** on 4-class staging, while the Clinical model achieved **85.35% accuracy** on binary diagnosis. The combination of reasonable accuracy and interpretable results (Grad-CAM, feature importance) makes these approaches suitable for clinical decision support. The multi-approach framework mirrors real clinical practice where physicians consider both imaging and patient history.

References

1. He, K., et al. (2016). Deep Residual Learning for Image Recognition. CVPR.
2. Selvaraju, R.R., et al. (2017). Grad-CAM: Visual Explanations from Deep Networks. ICCV.
3. Rabie El Kharoua (2024). Alzheimer's Disease Dataset. Kaggle. DOI: 10.34740/KAGGLE/DSV/8668279 (Synthetic dataset)

Deliverables

File	Description
Hack4Health_Final_Submission.ipynb	Complete reproducible notebook (Google Colab)
results/ResNet50_best.pth	Trained MRI classification model weights
results/Clinical_model.pth	Trained clinical risk model weights
results/*.png	Visualizations (confusion matrices, Grad-CAM, feature importance)