Alzheimer’s Detection Using MRI and Deep Learning – Interview Q&A; Guide

Elevator Pitch:

“This research evaluates deep learning models (Sequential CNN, ResNet50, EfficientNetB0) for detecting Alzheimer’s disease stages from MRI scans using the OASIS dataset. After handling severe class imbalance and applying preprocessing, the CNN Sequential model achieved the best accuracy (99.05%), outperforming ResNet50 and EfficientNetB0. Our study demonstrates how CNNs can provide early and accurate Alzheimer’s detection, enabling timely interventions and improving patient outcomes.”

1. Alzheimer’s Basics

1. Alzheimer’s disease (AD) is a progressive neurodegenerative disorder causing memory loss, cognitive decline, and behavioral changes.
2. Affects over 50 million people worldwide.
3. No cure exists; early detection enables better treatment planning.
4. MRI scans reveal structural changes in the brain, crucial for early diagnosis.

2. Dataset & Preprocessing

1. Dataset: OASIS (80,000 MRI scans from 461 patients).
2. Classes: No Dementia, Very Mild Dementia, Mild Dementia, Moderate Dementia.
3. Problem: Severe class imbalance (mild/moderate over-represented).
4. Solution: Under-sampling majority classes + over-sampling minority classes.
5. Preprocessing: Resized to 128x128, normalized, 80-20 train-validation split.

3. Models – Working, Strengths & Weaknesses

Sequential CNN:
• Working: 3 Conv layers (32, 64, 128 filters) → MaxPooling → Dense → Dropout → Softmax.
• Strengths: Simple yet powerful, best accuracy (99.05%).
• Weaknesses: Less scalable, might miss very complex features.

ResNet50:
• Working: Residual blocks with skip connections to avoid vanishing gradients.
• Strengths: Good at capturing complex patterns, widely used in medical imaging.
• Weaknesses: Higher risk of overfitting on imbalanced datasets. Accuracy = 97.91%.

EfficientNetB0:
• Working: Compound scaling (depth, width, resolution) for efficiency.
• Strengths: Efficient, works well in resource-limited setups.
• Weaknesses: Slightly less accurate (98.76%) than Sequential CNN.

4. Workflow

1. Step 1: Collect MRI scans (OASIS dataset).
2. Step 2: Preprocess images (resize, normalize, balance dataset).
3. Step 3: Train models (Sequential CNN, ResNet50, EfficientNetB0).

4 Step 4: Evaluate using Accuracy, Precision, Recall, F1-score.
5 Step 5: Compare results – CNN Sequential best performer.

5. Results & Interpretation

• CNN Sequential: Accuracy = 0.9905, Precision = 0.9907, Recall = 0.9905, F1 = 0.9905.
• EfficientNetB0: Accuracy = 0.9876, Precision = 0.9879.
• ResNet50: Accuracy = 0.9791, Precision = 0.9792.
• Confusion Matrix shows difficulty in distinguishing mild vs no dementia.
• Cross-validation + early stopping used to reduce overfitting.

6. Limitations & Future Work

1 Imbalanced dataset still affects minority class performance.
2 Models are black-box → limited interpretability for clinicians.
3 Computational limitations prevented deeper model exploration.
4 Future: Multi-modal data (MRI + PET + clinical history) & explainability (Grad-CAM).

7. Common Interview Questions & Answers

Q: Why did you choose CNNs over transformers?
A: CNNs are highly effective in capturing spatial features of MRI scans with lower computational costs. Transformers could be explored in future for multi-modal data but require higher resources.

Q: How did you handle class imbalance?
A: Applied under-sampling for majority classes and over-sampling for minority classes, ensuring 5000 images per class. This improved generalization across all stages.

Q: Why did the Sequential CNN perform better than ResNet50?
A: The dataset was relatively balanced after preprocessing, and Sequential CNN's simpler architecture prevented overfitting compared to the deeper ResNet50. This allowed better generalization.

Q: How do you prevent overfitting in deep models?
A: Used early stopping, cross-validation, dropout layers, and balanced dataset preparation.

Q: What would you do differently with more compute?
A: Experiment with deeper architectures, transformer-based models, and multimodal fusion (MRI + PET).

Q: Why is interpretability important in medical AI?
A: Clinicians require transparency. Techniques like Grad-CAM can highlight brain regions contributing to the model’s decision, increasing trust in AI-driven diagnosis.

Q: What are real-world deployment challenges?
A: Dataset generalization across hospitals, computational resources, explainability, and regulatory compliance are major barriers to clinical adoption.