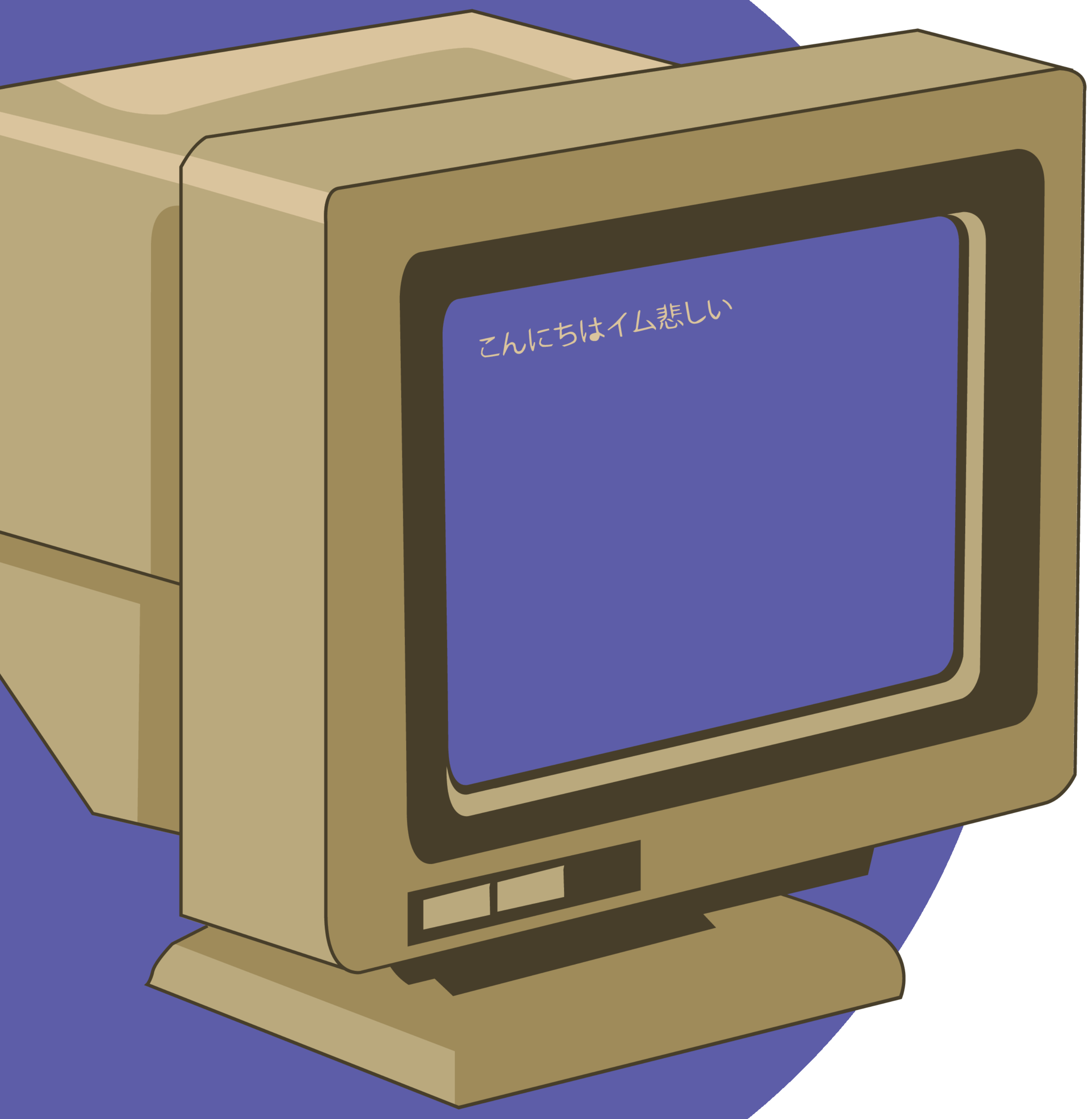


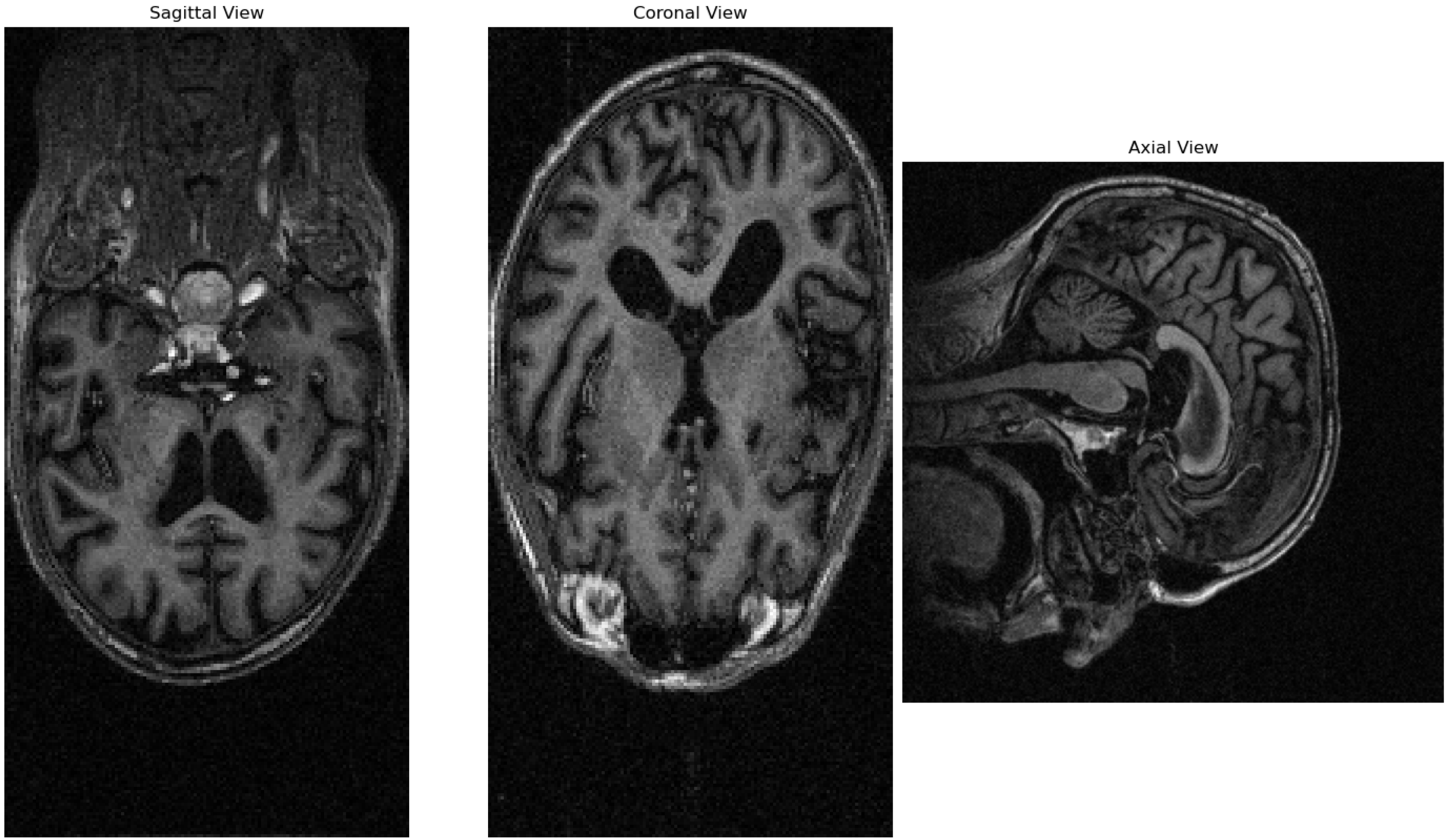
3D CNN BASED ALZHEIMER'S DISEASE DETECTION

DATASET:

HTTPS://SITES.WUSTL.EDU/OASISBRAINS/HOME/OASIS-2/

ABOUT THE PROJECT

- Objective:
  - Develop a deep learning model to classify Alzheimer's disease (nondemented vs. demented) using MRI scans and tabular data.
- Dataset:
  - OASIS-2 dataset: 373 T1-weighted MRI scans from 150 subjects, with demographics (Age, EDUC, SES, MMSE).
- Class distribution: 206 nondemented, 167 demented (imbalanced).
- Approach:
  - Hybrid CNN3DTabular model: 3D CNN for MRI (128x128x128x1) + MLP for tabular features.
  - Training: 15 epochs, Adam optimizer, BCEWithLogitsLoss with pos_weight for imbalance.
- Expected Outcomes:
  - Achieve high balanced accuracy (>0.75) with minimal train-val gap.
  - Reliable AD detection: High recall, low false negatives for clinical relevance.



Shape of MRI scan: (256, 256, 128, 1)
This is a visualization of a 3D MRI scan from the OASIS-2 dataset. The scan is one of the many .nii.gz files located in the OAS2_RAW directory, each representing a longitudinal brain scan session. The sagittal, coronal, and axial views give us a comprehensive look at the brain's structure, which forms the core input to our 3D CNN model.

ABOUT THE DATASET

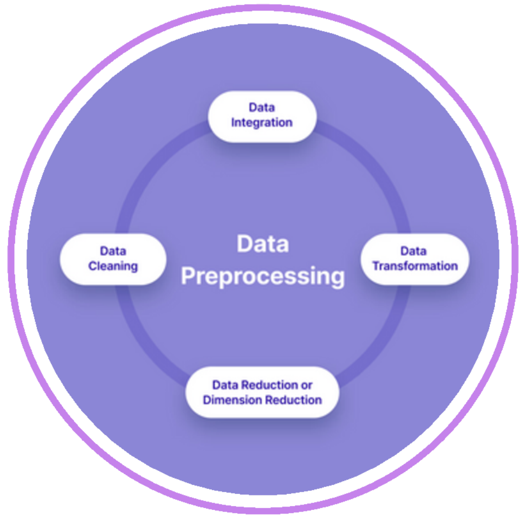
OASIS-2

- The dataset comes with 3 files:
  - OAS2_RAW_PART1
  - OAS2_RAW_PART2
  - oasis_longitudinal_demographics-8d83e569fa2e2d30.xlsx
- Source: OASIS longitudinal dataset
- Subjects: 150 right-handed individuals, aged 60–96, scanned over 2+ visits (1+ year apart).
- Size: 373 samples (206 nondemented, 167 demented).
- Features:
  - 3D MRI scans
  - Longitudinal Visits: Each subject has 2–5 visits (yearly scans)
  - Tabular: Age, Education (EDUC), Socioeconomic Status (SES), Mini-Mental State Examination (MMSE).
- Split: 297 training, 76 validation (20% split, GroupShuffleSplit).
- Classes: 72 always non-demented, 64 demented (51 with mild/moderate AD), 14 converted to demented.

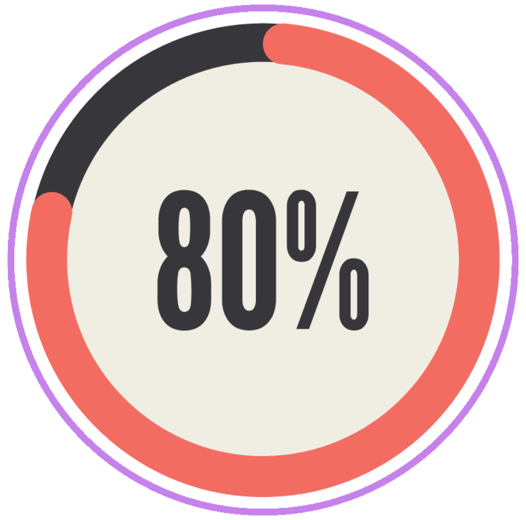
OUTLINE OF THE MODEL

IMAGE DATASET:
T1-weighted MRI scans from OASIS-2

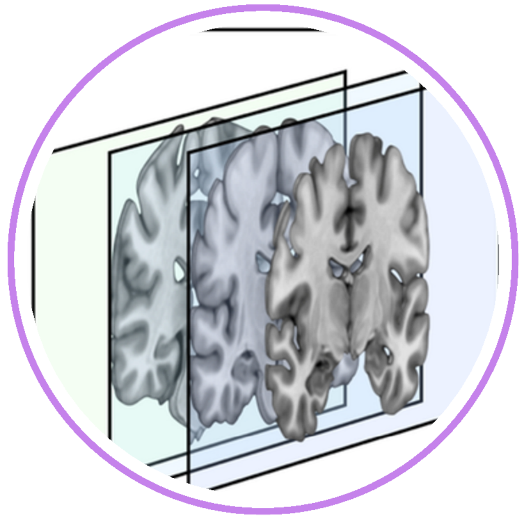
DATA EXPLORATION:
Analyzed MRI dimensions, tabular features, and DEMENTIA labels



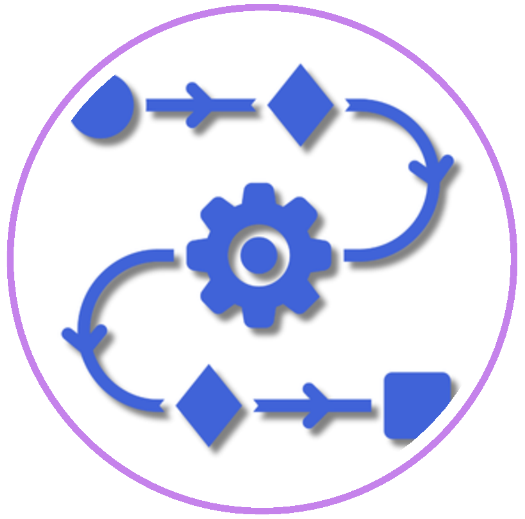
DATA PREPROCESSING:
Resized and normalized MRI images Augmentation and reshaping.



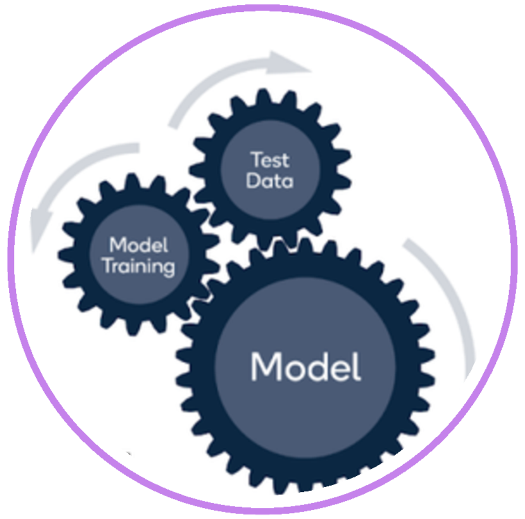
DATASET SPLIT:
297 training, 76 validation (20% split no test set).



MODEL ARCHITECTURE:
CNN3DTabular (3D CNN for MRI + MLP for tabular data, binary output).



MODEL COMPILATION:
BCEWithLogitsLoss (pos_weight ~1.2336), Adam optimizer (lr=1e-3, weight_decay=1e-4).



MODEL TRAINING:
15 epochs, batch size 4

EVALUATION & RESULTS:
Validation balanced accuracy, confusion matrix, classification report.

KEY PREPROCESSING STEPS

- MRI Preprocessing (preprocessing.py):
  - Loaded raw T1-weighted MRI scans (Analyze/NIfTI format) from OASIS-2 (OAS2_RAW_PART1/2).
  - Removed singleton dimensions (e.g., X,Y,Z,1 → X,Y,Z), normalized to [0,1].
  - Resized to 128x128x128 using anti-aliasing, saved as .npy files (float32).
- Tabular Data Handling (train.py):
  - Extracted features: Age, EDUC, SES, MMSE (4 features per subject).
  - Normalized using StandardScaler for consistent scaling.
- Data Cleaning (train.py):
  - Matched MRI .npy files with tabular data using MRI IDs; skipped missing files.
  - Labels derived: CDR > 0 → demented (1), else nondemented (0).
- Dataset Splitting & Balancing (train.py):
  - Split 80:20 (297 train, 76 val) using GroupShuffleSplit to avoid subject overlap.
  - Applied WeightedRandomSampler to address class imbalance (206:167).

LIBRARIES AND TOOLS

- Python: Core programming language for development.
- PyTorch (torch, torch.nn, torch.utils.data): Deep learning framework for building, training, and evaluating the 3D CNN model.
- NumPy: Used for numerical operations and MRI array manipulation.
- Pandas: Dataframe management for demographics data.
- OS: To interact with the file system (e.g., loading .npy files).
- Scikit-learn:
  - GroupShuffleSplit for train-validation split.
  - StandardScaler for tabular feature normalisation.
  - Classification report, confusion matrix for evaluation.
- Torchvision: Data augmentation (RandomRotation, HorizontalFlip).
- Matplotlib & Seaborn: Plotting (loss, accuracy, confusion matrix).
- Nibabel – Loading and handling of NIfTI (.nii.gz) MRI files

- Key Modules:
  - torch.nn.BCEWithLogitsLoss: For binary classification loss with pos_weight.
  - torch.utils.data.WeightedRandomSampler: For handling class imbalance in training.

HYPERPARAMETERS

- Batch Size: 4 (for training and validation).
- Epochs: 15 (total training iterations).
- Learning Rate (lr): 1e-3 (Adam optimizer).
- Weight Decay: 1e-4 (for regularization in Adam).
- Validation Split: 0.2 (20% of data, 76 samples).
- Pos Weight: ~1.2336 (BCEWithLogitsLoss, based on class imbalance).
- Metrics: Balanced Accuracy, Classification report, Confusion matrix
- Image Dimensions: 128 × 128 × 128 × 1 (depth × height × width × channels, preprocessed MRI scans)
- Number of Classes: 2 (Non-Demented, Demented)
- Augmentation:
  - Random Rotation: 15 degrees.
  - Horizontal Flip: Probability 0.3 (training only).

INITIAL APPROACHES

UNDERSTANDING INITIAL APPROACHES:

Initial approaches typically involved simpler models, basic preprocessing, and standard training setups. Challenges like class imbalance, overfitting and data leakage often lead to iterative improvements.

INITIAL DATA HANDLING:

- Loaded raw T1-weighted MRI scans and demographics data (OASIS dataset).
- No augmentation; used raw MRI dimensions (64x64x64x1 after resizing) which suffered major information loss.

FIRST MODEL ATTEMPT:

- Simple 3D CNN (no tabular data integration).
- Standard architecture: Conv3D, pooling, dense layers, sigmoid output.
- Trained with binary cross-entropy loss (no pos_weight for imbalance).

INITIAL TRAINING SETUP:

- Batch size: 4, epochs: 10, Adam optimizer (lr=1e-3).
- No regularization (weight_decay=0), no weighted sampling.
- Metrics: Raw accuracy

CHALLENGES FACED:

- High train-val gap - Overfitting
- Data redundancy and data leakage.
- Class imbalance issues
- Data mismatches: Missing .npy files for some MRI IDs.

IMPROVEMENTS MADE:

- Added MLP for tabular data (Age, EDUC, SES, MMSE) → CNN3DTabular.
- Introduced GroupShuffleSplit (no subject overlap).
- Used pos_weight, augmentation (rotation 15°, flip p=0.3), weight_decay=1e-4.

Final Model:

- CNN3DTabular, a hybrid 3D CNN and MLP model integrating 128x128x128x1 MRI scans with tabular features.
- Training: 15 epochs, batch size 4, Adam (lr=1e-3), BCEWithLogitsLoss (pos_weight ~1.2336), with augmentation (rotation 15°, flip p=0.3).
- Performance: Achieved validation balanced accuracy of 0.7820, reduced train-val gap, & improved precision.

MODEL ARCHITECTURE

Model Overview:

- CNN3DTabular: Hybrid model for Alzheimer's classification.
- Combines 3D CNN (MRI: 128x128x128x1) and MLP (tabular: 4 features).
- Output: Binary classification (nondemented vs demented).
- 3D CNN Component:
    - Input: 128x128x128x1 (depth x height x width x channels).
    - Conv3D Layers:
    - Layer 1: 16 filters, kernel (3x3x3), stride 1, padding 1, ReLU.
    - Layer 2: 32 filters, kernel (3x3x3), stride 1, padding 1, ReLU.
    - Layer 3: 64 filters, kernel (3x3x3), stride 1, padding 1, ReLU.
    - Pooling: MaxPooling3D (2x2x2) after each Conv3D layer.
    - Dropout: 0.3 after each pooling layer to reduce overfitting.
- Output: Flattened feature vector.
- MLP Component (Tabular Data):
    - Input: 4 features (Age, EDUC, SES, MMSE, normalized).
    - Dense Layers:
        - Layer 1: 16 units, ReLU activation.
        - Layer 2: 8 units, ReLU activation.
    - Dropout: 0.2 after each dense layer for regularization.
    - Output: Feature vector (8 units).
- Fusion and Output:
    - Concatenation: Combines 3D CNN output (flattened) and MLP output.
- Final Dense Layer:
    - 1 unit, sigmoid activation for binary classification.
    - Loss: BCEWithLogitsLoss (applied during training).

MODEL ARCHITECTURE

input
1x128x128x128

→

1st Conv 3D layer
8 filters of size 3x3x3
+
ReLU
+
Max Pooling 3D
2x2x2
+
Dropout

→

input
8x64x64x64

→

2nd Conv 3D layer
16 filters of size 3x3x3
+
ReLU
+
Max Pooling 3D
2x2x2
+
Dropout

→

input
16x32x32x32

→

3rd Conv 3D layer
32 filters of size 3x3x3
+
ReLU
+
Max Pooling 3D
2x2x2
+
Dropout

→

input
32x16x16x16

→

Flatten
32×16×16×16=
131,072

→

input
(4, 131072+64)

→

Classifier
(4,1)

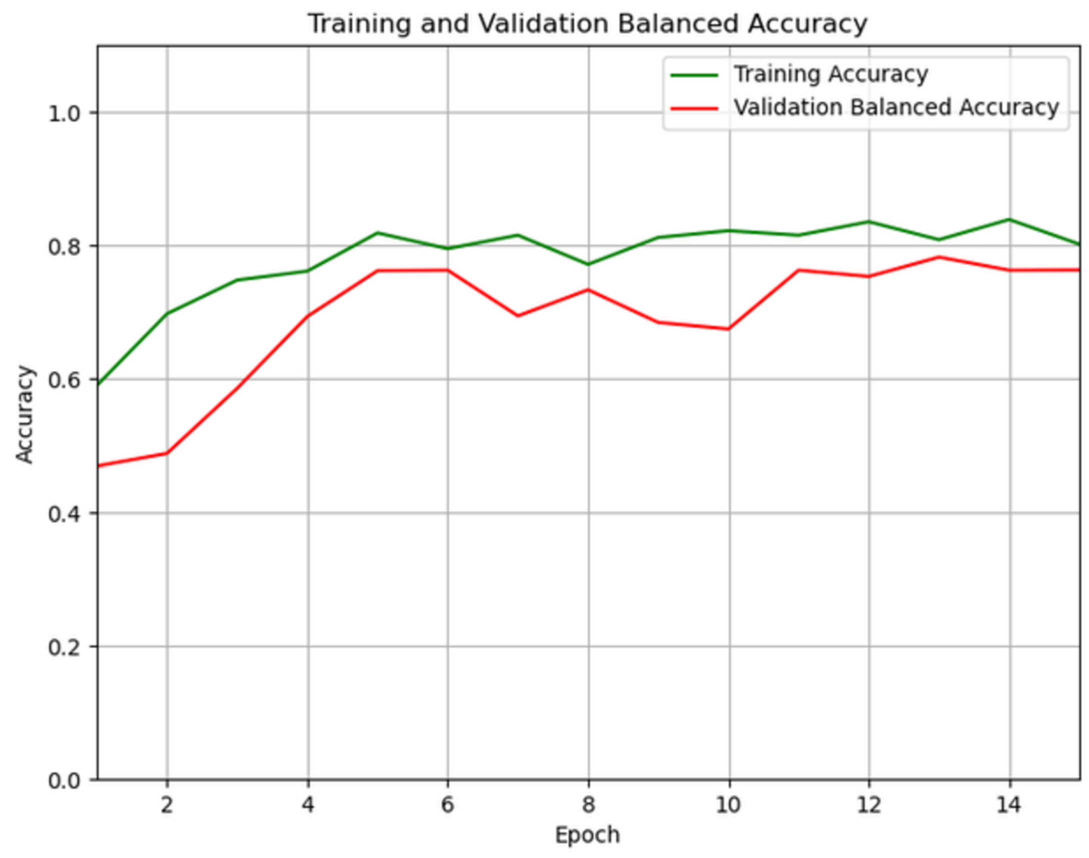
forward Method (Describes the data flow):

- x = self.cnn(x): Processes MRI input through the CNN (output: (batch_size, 32, 16, 16, 16)).
- x = self.flatten(x): Flattens CNN output to (batch_size, 131072).
- tabular = self.tabular_branch(tabular): Processes tabular input to (batch_size, 64).
- combined = torch.cat((x, tabular), dim=1): Concatenates to (batch_size, 131136).
- return self.classifier(combined): Outputs (batch_size, 1).

TRAIN.PY

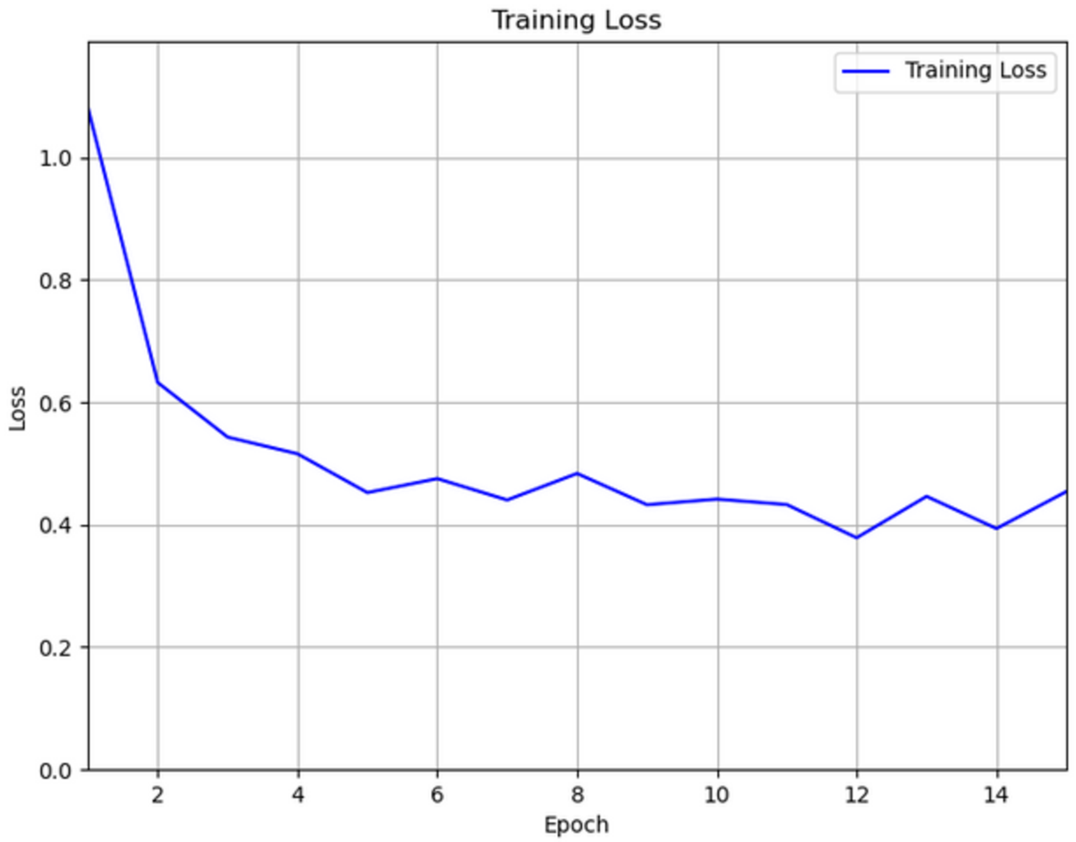
- Model Setup:
  - CNN3DTabular: Hybrid 3D CNN + MLP, trained on MRI (128x128x128x1) and tabular data (4 features).
  - Optimizer: Adam (lr=1e-3, weight_decay=1e-4); Loss: BCEWithLogitsLoss (pos_weight ~1.2336).
- Training Configuration:
  - 15 epochs, batch size 4.
  - Dataset: 297 train, 76 val samples; WeightedRandomSampler for class imbalance (206:167).
- Data Augmentation:
  - Applied to training set: Random rotation (±15°), horizontal flip (p=0.3).
  - Validation set: No augmentation for consistent evaluation.
- Evaluation Metrics:
  - Monitored training loss, train accuracy, and validation balanced accuracy per epoch.
  - Saved best model based on highest validation balanced accuracy.
- Key Outcomes:
  - Best model (Epoch 13): Validation balanced accuracy 0.7820, train-val gap ~0.0193.
  - Generated plots: Loss (loss_plot.png), accuracy (accuracy_plot.png), confusion matrix (confusion_matrix.png).

ACCURACY & LOSS PLOT



Accuracy Plot (accuracy_plot.png):

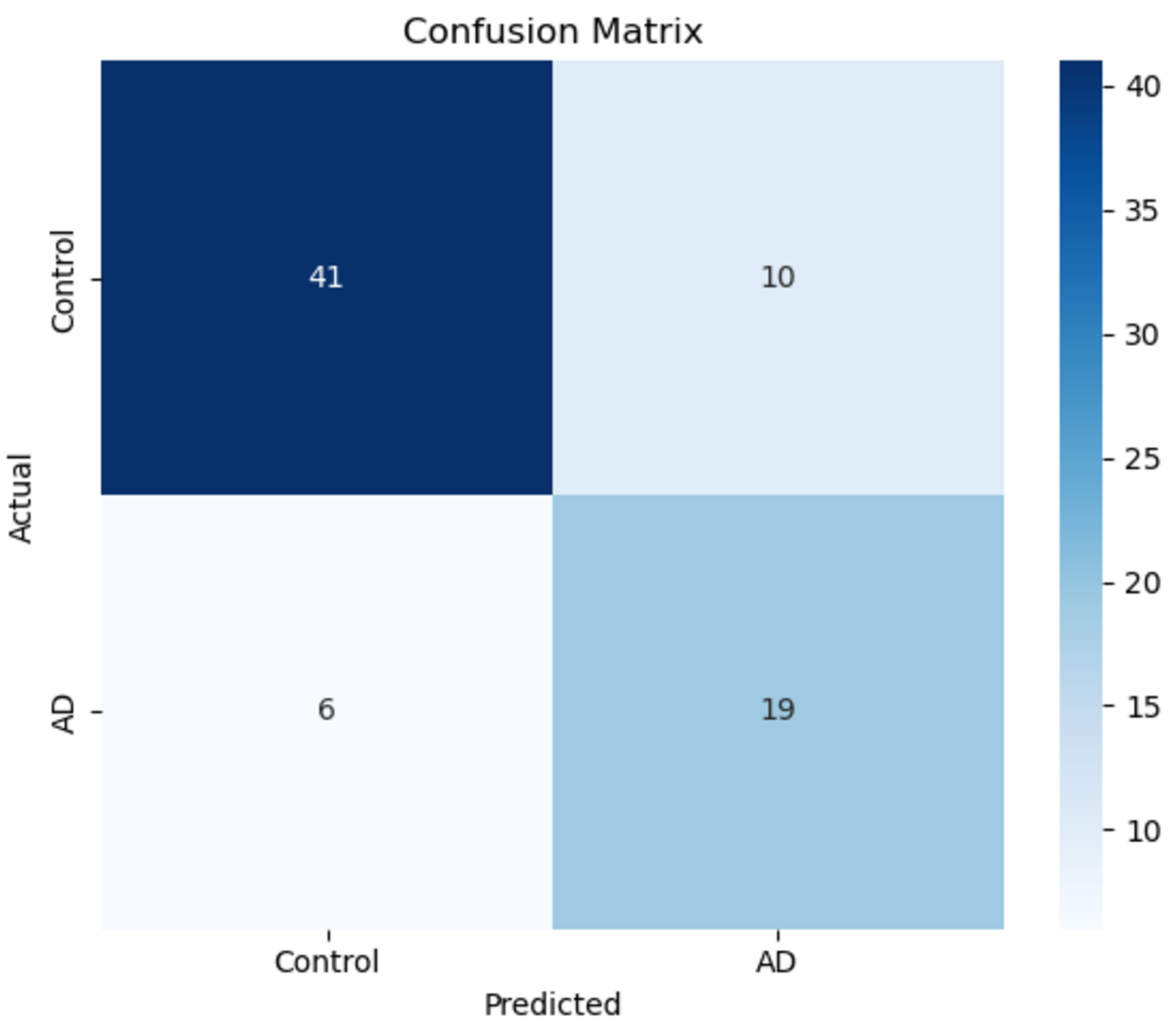
- X-axis: Epochs (1 to 15).
- Y-axis: Accuracy (range 0 to 1).
- Two curves: Training accuracy (green), validation balanced accuracy (red).
- Learning Progress: Both loss and accuracy show the model learns effectively, with early improvements (Epochs 1–5) and later stabilisation.
- Generalisation: The small train-val gap (~0.0193) indicates minimal overfitting, a significant improvement over earlier runs (gap ~0.0794),
- Validation Stability: Validation balanced accuracy stabilises around 0.76–0.78 after Epoch 5, peaking at 0.7820 (Epoch 13), suggesting the model generalises well despite the small validation set (76 samples, 51:25 imbalance).



Loss Plot (loss_plot.png):

- X-axis: Epochs (1 to 15).
- Y-axis: Training loss (BCEWithLogitsLoss, range ~0 to 1.19).
- Single curve (blue) for training loss.
- Trend: Training loss decreases from 1.0817 (Epoch 1) to 0.4539 (Epoch 15), a ~58% reduction, showing effective optimization.
- Convergence: Loss stabilises after Epoch 5 (0.4523), fluctuating between 0.3784 (Epoch 12) and 0.4835 (Epoch 8), indicating convergence with minor oscillations.
- Insight: The model learns well on the training set, with the lowest loss at Epoch 12 (0.3784), though slight increases (e.g., Epoch 15) suggest potential noise or small batch effects (batch size 4).

CONFUSION MATRIX



Confusion Matrix:

- True Negatives (TN): 41 (predicted Control, actual Control)
- False Positives (FP): 10 (predicted AD, actual Control)
- False Negatives (FN): 6 (predicted Control, actual AD)
- True Positives (TP): 19 (predicted AD, actual AD)

- Related Metrics(from classification report):
  - Control (Nondemented): Precision 0.87, Recall 0.80, F1-score 0.84
  - AD (Demented): Precision 0.66, Recall 0.76, F1-score 0.70
  - Balanced Accuracy: 0.7820 (average of recalls: (0.80 + 0.76) / 2)
- Validation Set Distribution:
  - Total samples: 76
  - Nondemented (Control): 51 (67%)
  - Demented (AD): 25 (33%)

Key Insights from the Confusion Matrix:

- Overall Performance:
  - Correct predictions: 41 + 19 = 60 out of 76 samples (78.95% raw accuracy).
- Class-Specific Accuracy:
  - Control (Nondemented): High recall (0.80, 41/51 correctly predicted), meaning 80% of nondemented cases were identified.
  - AD (Demented): Good recall (0.76, 19/25 correctly predicted), meaning 76% of demented cases were identified, crucial for medical diagnosis.
- Class Imbalance Handling:
  - Despite the imbalance (51:25), the model performs well on the minority class (AD), with 19/25 correctly identified, as pos_weight, WeightedRandomSampler were implemented.

CONCLUSION

- Summary: Developed CNN3DTabular using OASIS dataset (373 MRI scans, 150 subjects) to classify nondemented vs. demented cases, integrating 128x128x128x1 MRI scans with tabular features (Age, EDUC, SES, MMSE).

- Model Evolution: Evolved from a basic 3D CNN to a hybrid 3D CNN + MLP model, addressing overfitting (train-val gap reduced from 0.0794 to 0.0193) and imbalance (pos_weight ~1.2336).

- Training & Results: Trained over 15 epochs (batch size 4, Adam lr=1e-3), achieving a validation balanced accuracy of 0.7820, with strong recall (Control: 0.80, AD: 0.76) & AD precision (0.66 vs. 0.61).

- Impact: Robust model for Alzheimer’s detection, with reliable performance (low FNs: 6) but has minor errors (FPs: 10).

THANK YOU!