Enhancing MRI Analysis in Temporal Lobe Epilepsy: Sequential Classification and Segmentation of Hippocampal Structures

Authors: Vihan Bhattacharjee , Kamalashree Sudhakar, Dr. Sindhu Ghanta

Presenter's Name: Vihan Bhattacharjee , Bellarmine College Preparatory School, 11th Grade
Presenter's email: v.bhattacharjee27@bcp.org

Vihan Bhattacharjee

- High school student, Bellarmine College Preparatory, San Jose, CA

I am conducting research on diagnostics of diseases using deep learning algorithms for the past two years. My previous research on Cancer detection using YOLO AI was published on IEEE CAI 2025.

Bellarmine College Preparatory

Introduction

HEALTHY BRAIN → EPILEPTIC BRAIN
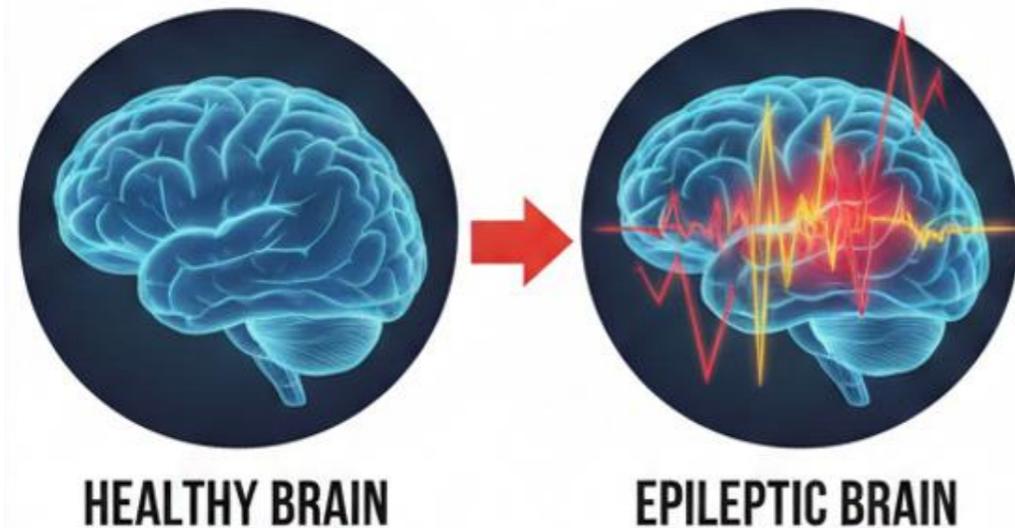
The Problem:

- Temporal Lobe Epilepsy (TLE) affects **50 million people worldwide**
- It is the **fourth most common neurological disorder**, and it impacts people of all ages
- Electroencephalograph (EEG) is the primary diagnostic tool; interpretation of EEG scans are very **subjective** and often **misdiagnosed**
- Studies have shown that **38%** of epilepsy patients experience misdiagnosis
- Manual hippocampal analysis to look for damage or structural changes is useful however it is **time-intensive and subject to inter-observer variability**
- Automation can assist; however, processing MRI images presents challenges due to the **substantial computational resources needed and the extensive time required** for completion
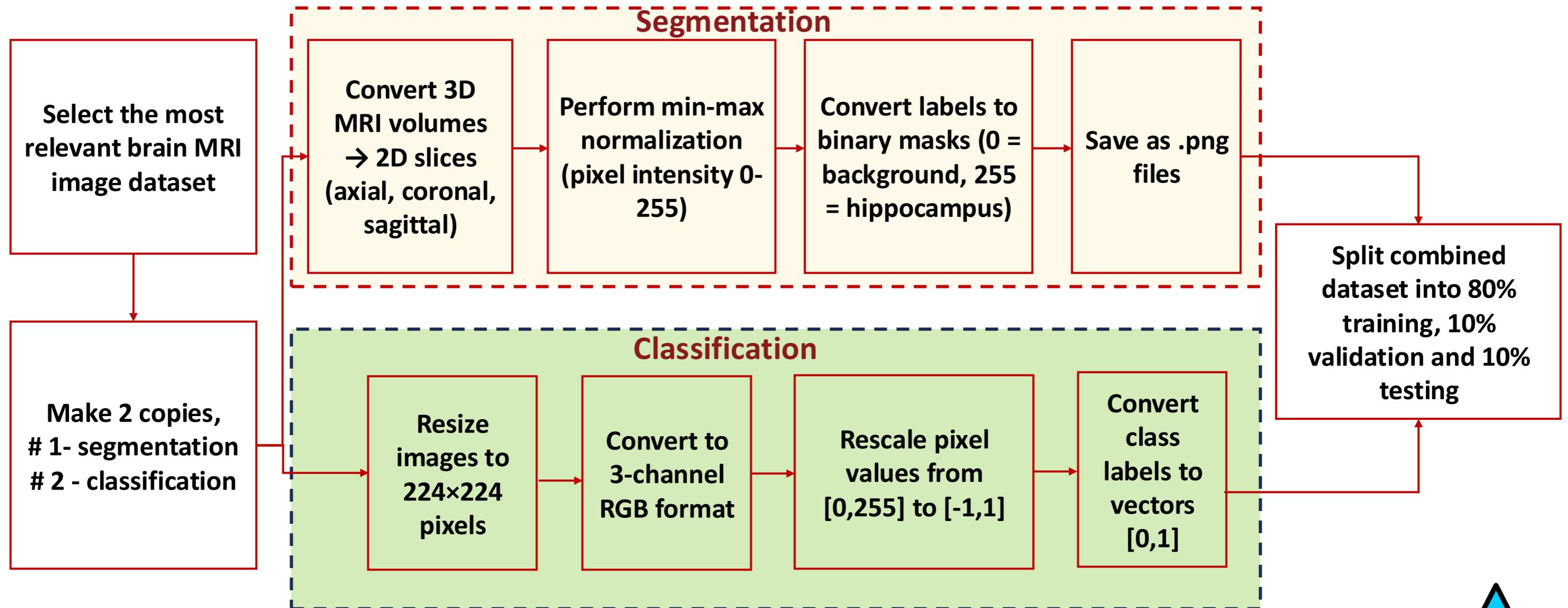
Our Solution:

- **Two-stage workflow**, first screen for abnormalities, then precisely localize
- Integrated deep learning approach combining **MobileNet** model for classification + **U-Net model** for segmentation

Key Results:

- MobileNet: **94%** classification accuracy
- U-Net: **0.902 IoU** for segmentation

.

Data Preprocessing

Select the most relevant brain MRI image dataset

Make 2 copies,
1- segmentation
2 - classification

Segmentation

Convert 3D MRI volumes → 2D slices (axial, coronal, sagittal)

Perform min-max normalization (pixel intensity 0-255)

Convert labels to binary masks (0 = background, 255 = hippocampus)

Save as .png files

Classification

Resize images to 224×224 pixels

Convert to 3-channel RGB format

Rescale pixel values from [0,255] to [-1,1]

Convert class labels to vectors [0,1]

Split combined dataset into 80% training, 10% validation and 10% testing

Bellarmine College Preparatory

IARIA

Computational Analysis

U-Net for Segmentation

- **Encoder-decoder** structure with skip connections

- Optimal for small datasets due to automatic augmentation

- Divide-and-conquer strategy with 5 feature maps

- End-to-end training on broad medical images

- Hyperparameters tested:
  - Learning rates: **0.000001-0.05**
  - Epochs: **10-50**

- Evaluation metric:
  - Intersection over Union (IoU)

MobileNet for Classification

- **Lightweight CNN** with depth wise separable convolutions

- Efficient for high-volume screening

- Requires **fewer parameters** than similar CNNs

- Binary classification:
  - Healthy vs. Unhealthy

- Same hyperparameter ranges as U-Net

- Evaluation:
  - Accuracy & confusion matrices

Transfer Learning

- **Pre-trained weights** accelerate convergence

- **Improves performance** with limited dataset

Bellarmine College Preparatory

Results
Segmentation using U-Net

Best Performance

- IoU: **0.902**
- Optimal hyperparameters: **40 epochs**, learning rate **0.01**
- Loss: **0.0064**

Key Findings

- Learning rates from **0.0001-0.01** consistently yielded higher IoU, **> 0.85**)
- **40** epochs provided optimal convergence
- **50** epochs showed no improvement (potential overfitting)
- **Lower** learning rates required more epochs to converge
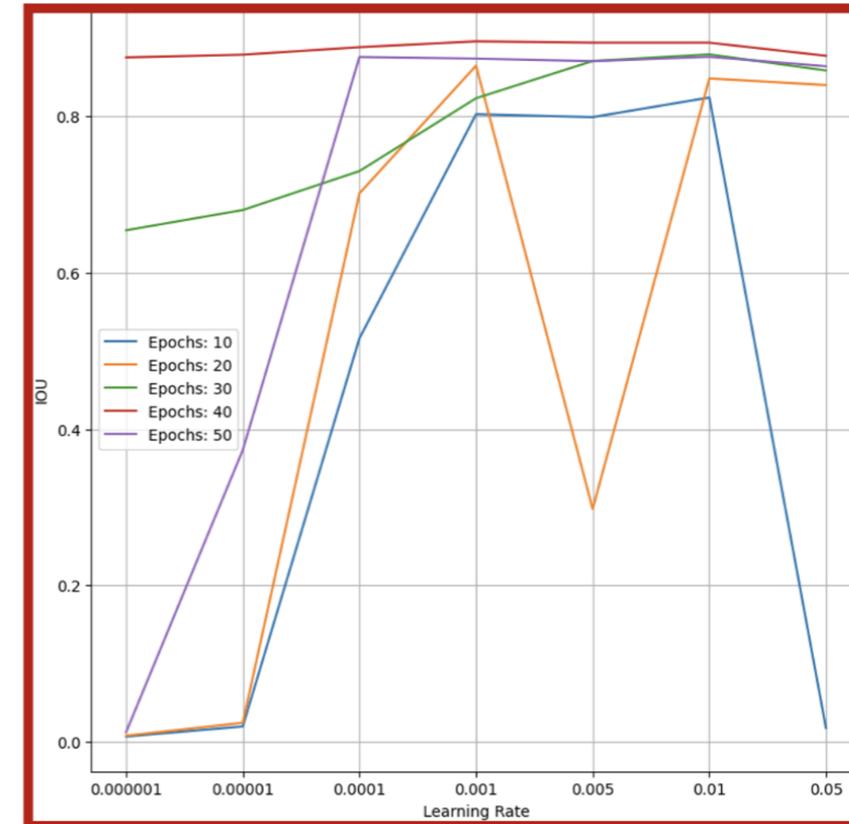
Segmentation IoU Results

Epochs	Learning Rate						
	0.000001	0.00001	0.0001	0.001	0.005	0.01	0.05
10	0.0064	0.0193	0.5159	0.8028	0.7991	0.8242	0.0175
20	0.0074	0.024	0.7015	0.865	0.2977	0.8486	0.8401
30	0.6543	0.6802	0.73	0.8233	0.8709	0.8794	0.8588
40	0.8755	0.879	0.8886	**0.8961**	0.8944	0.8944	0.8776
50	0.0121	0.373	0.876	0.874	0.8707	0.8763	0.8642

Table I. Hippocampus Segmentation U-Net IoU Results

Results
Classification using MobileNet

Best Performance
- Accuracy: 94%
- Optimal hyperparameters: **20** epochs, learning rate 0.01
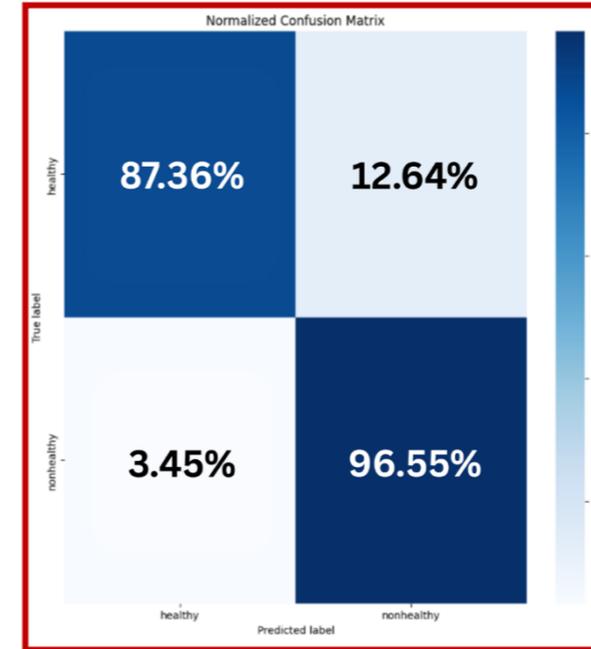
Confusion Matrix
- True Positives (unhealthy): **87.36%**
- True Negatives (healthy): **96.55%**
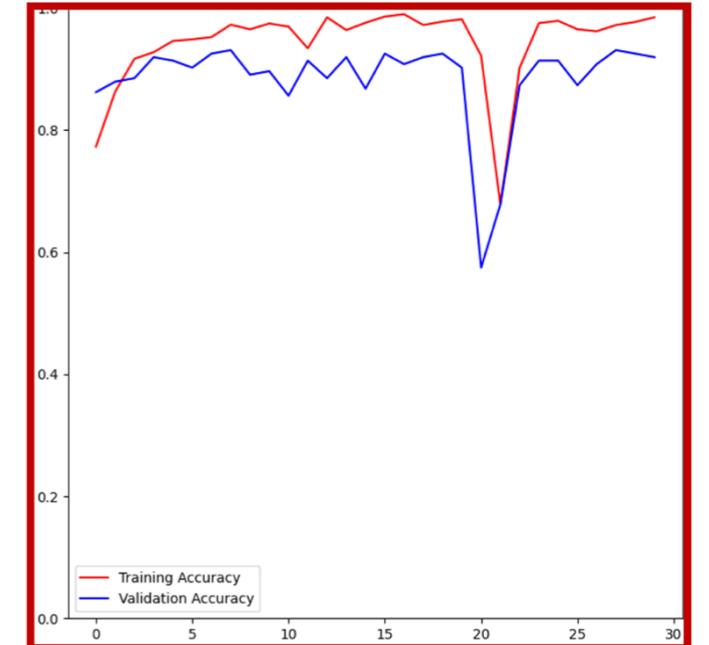
Precision & Recall
- Healthy: Precision **0.96**, Recall **0.87**
- Unhealthy: Precision **0.88**, Recall **0.9**

Key Findings
- Model prioritizes minimizing false negatives which makes it **clinically safer**
- Learning rates **0.001-0.01** are optimal for convergence
- **20** epochs is sufficient with higher learning rate

Confusion Matrix for MobileNet Classification

Classification Accuracy Results

Epochs	Learning Rate						
	0.000001	0.00001	0.0001	0.001	0.005	0.01	0.05
10	0.5345	0.7874	0.8908	0.9195	0.9138	0.9195	0.8851
20	0.7701	0.8506	0.9138	0.9368	0.9425	**0.9483**	0.9195
30	0.7701	0.8678	0.9195	0.9368	0.9368	0.9425	0.5
40	0.7089	0.8678	0.931	0.9368	0.9425	0.931	0.9195
50	0.7759	0.8793	0.9368	0.9253	0.9425	0.9368	0.9253

Table II. Classification MobileNet Accuracy Result

# Results
Combined System

Experiment on test data

- MobileNet screens all MRI slices and flags unhealthy cases and U-Net segments only flags slices

Performance on test data

- Confidence score: **1.0**

- Accurate hippocampus localization

- Clinically meaningful outputs

Benefit

- Minimizes computational resources

- Maintains diagnostic precision

- Reflects actual clinical workflow

(a) Sample image from test dataset   (b) Ground truth hippocampus mask   (c) UNet predicted Mask
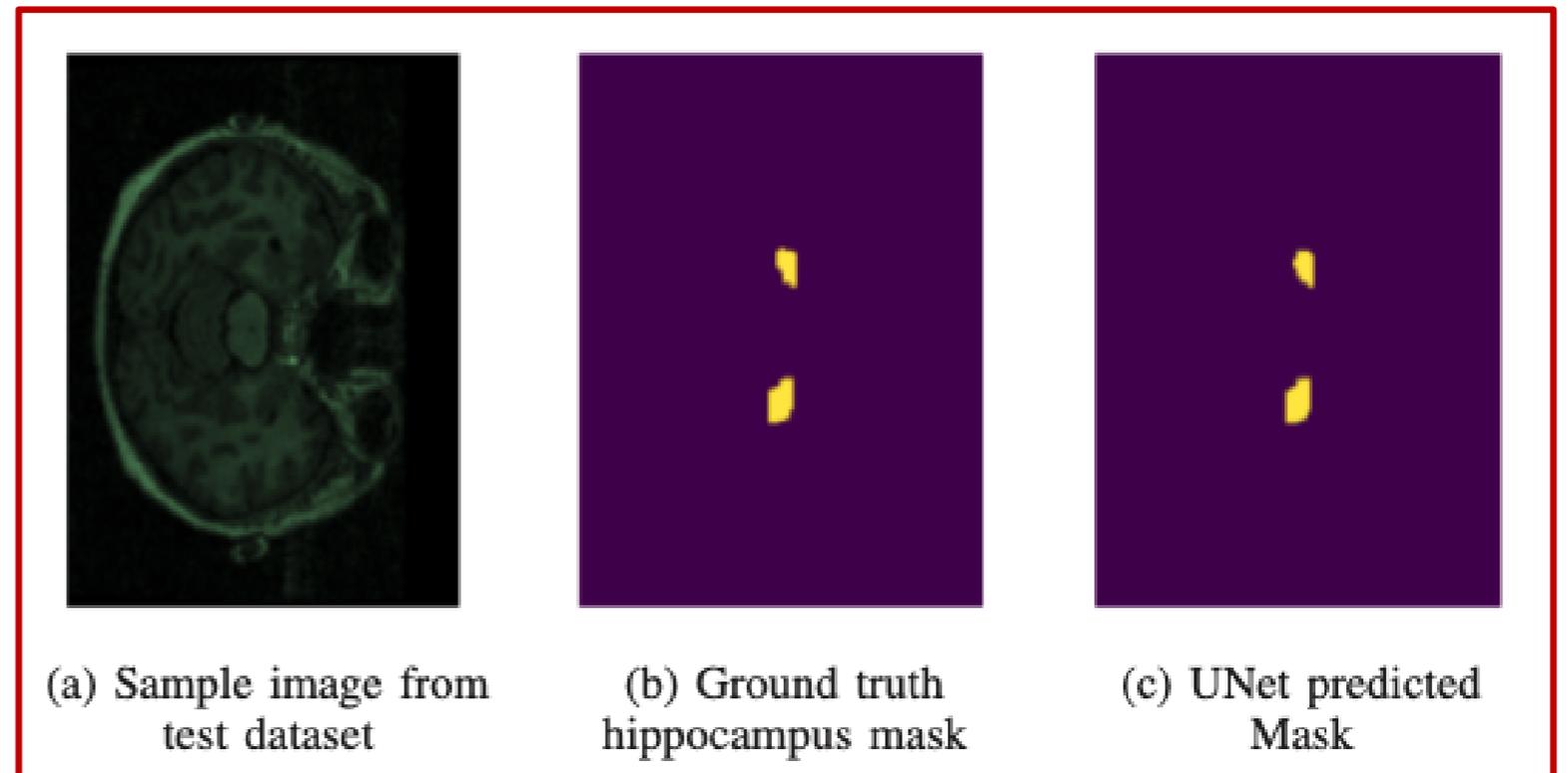
Successful Segmentation of Hippocampal Abnormalities

Conclusion

Key Achievements

U-Net: 0.902 IoU for hippocampal segmentation

MobileNet: 94% accuracy for classification

Successful integration for efficient TLE diagnosis

Minimized false negatives making it clinically safer

Clinical Impact

Assists radiologists in detecting subtle abnormalities

Reduces diagnostic time and human error

Provides objective, consistent analysis

Enables early intervention and better patient outcomes

Limitations

Small dataset (50 scans from single source)

Limited diversity in patient populations

Slice-level rather than 3D volumetric analysis

Future Work

Expand dataset with diverse sources and patient populations

Explore 3D volumetric data analysis

Test additional architectures (optimizer selection, augmentation strategies)

Extend to other epilepsy subtypes and neurological disorders

Thank you