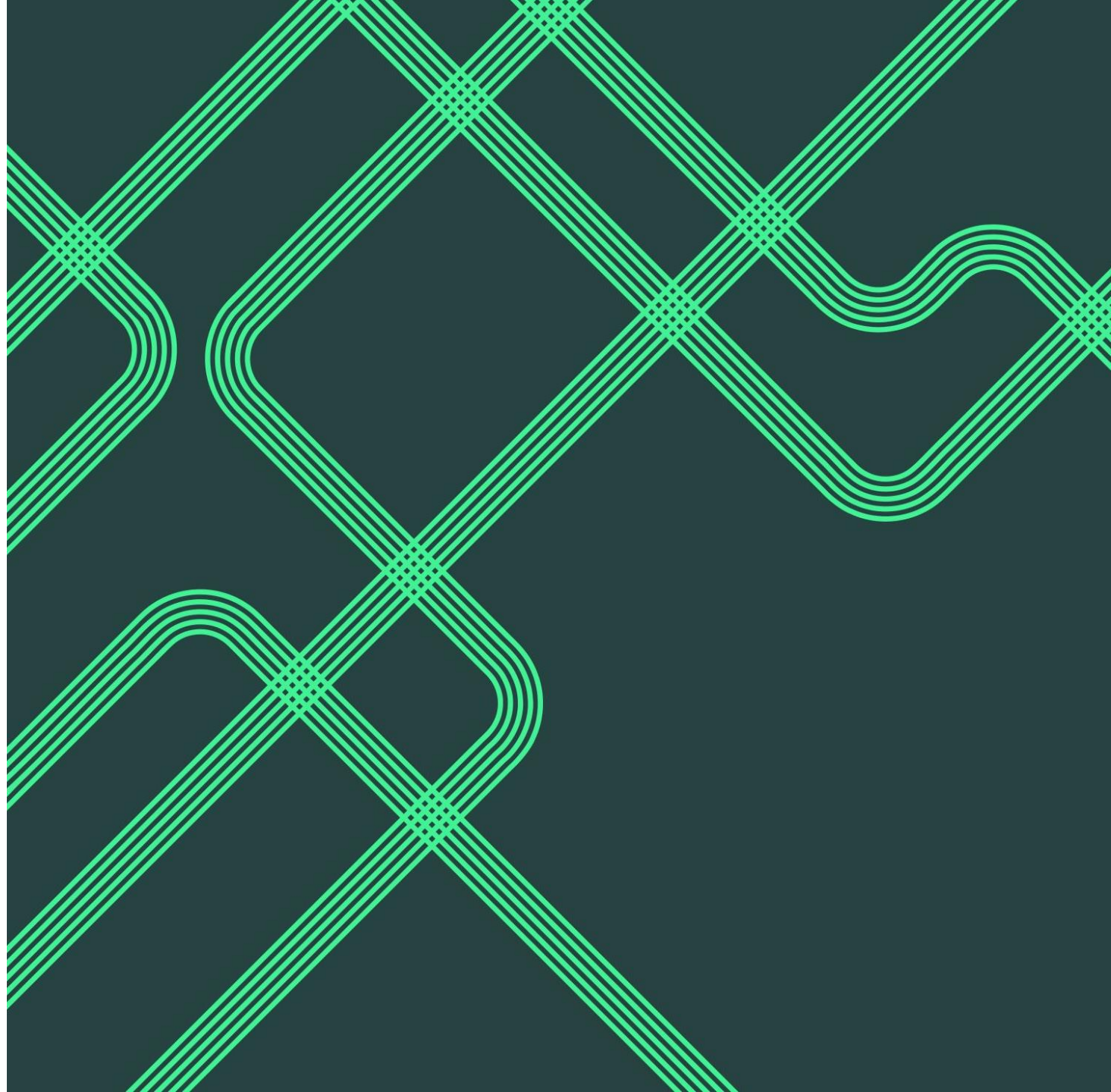


# Vessel Detection in 3D Brain MRA

Dataset: VesselMNIST3D  
(MedMNIST3D)

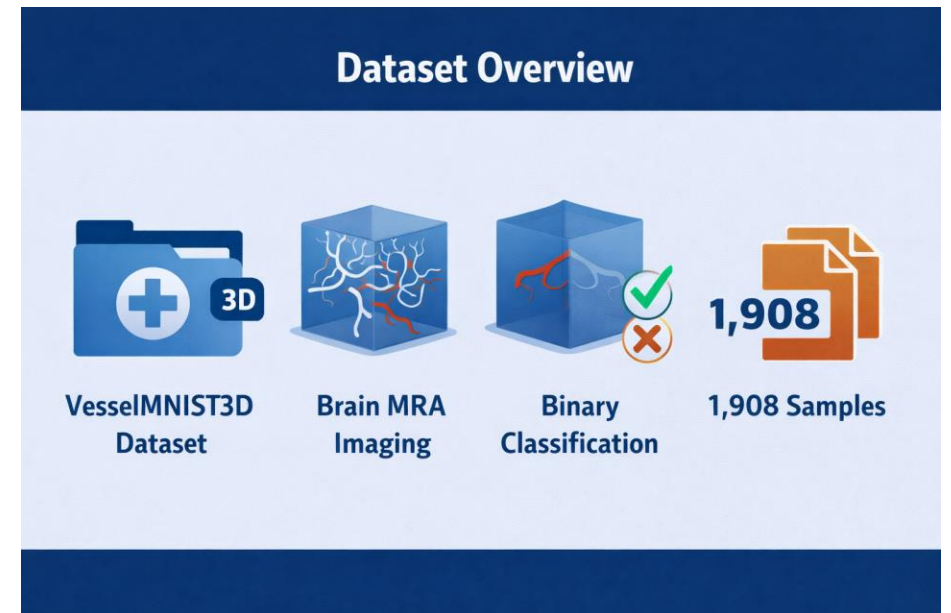


BY: DAVID & ABDUL



# Dataset Overview

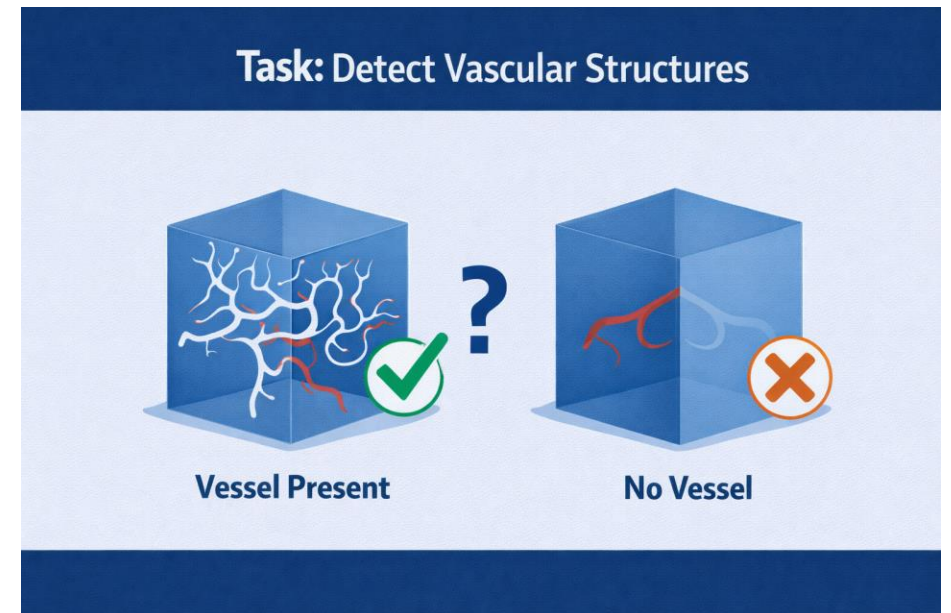
- "For our project, we worked with VesselMNIST3D dataset from the MedMNIST3D collection"
- VesselMNIST3D consists of 3D volumes derived from brain MRA scans, each image having a 28x28x28 voxels.
- The images were derived from 3D medical imaging techniques, such as a angiography, which are commonly used to visualize vascular structures.



# TASK?

"The task for VesselMNIST3D is a binary classification problem."

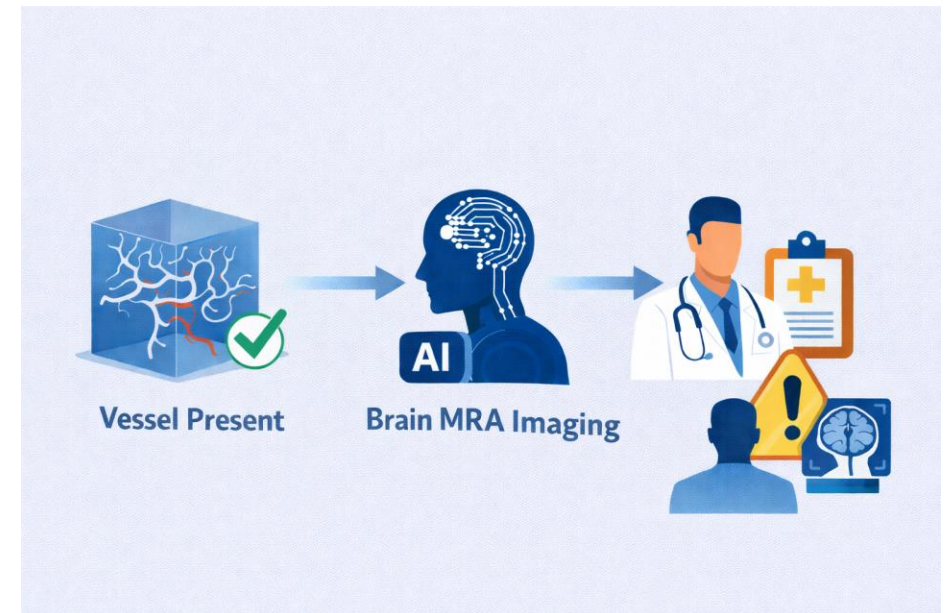
- Each image is labeled to indicate detecting vascular abnormalities.
- The underlying medical question is:
  - Can a neural network automatically detect vascular structures in 3D medical scans?
- Why is accurate vessel detection important:
  - Supports diagnosis of vascular diseases
  - Helps in surgical planning
  - Can assist radiologists by reducing manual workload



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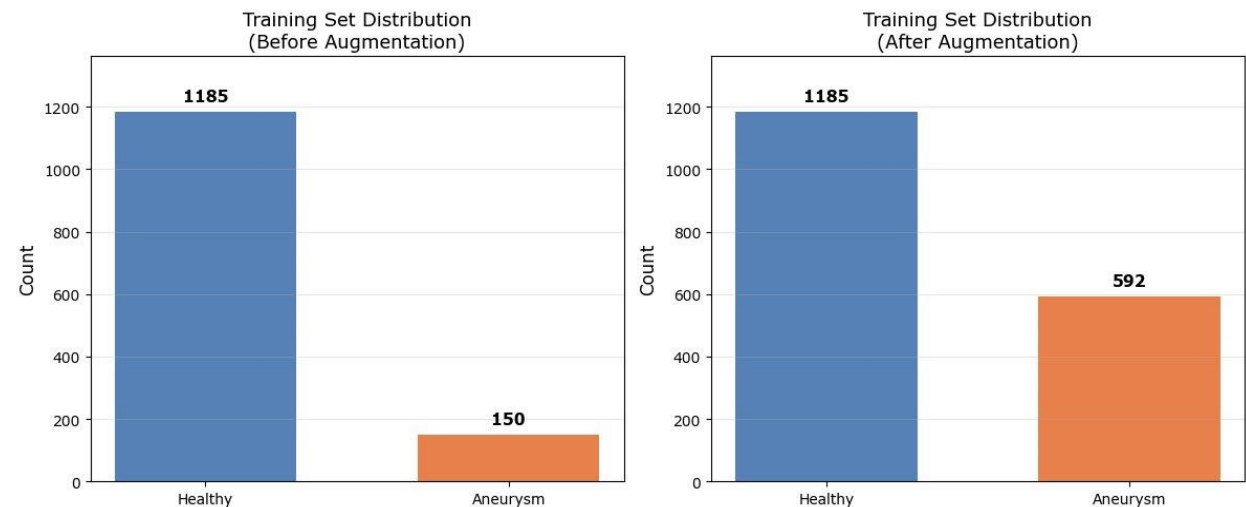
# What Medical Question Are We Trying To Answer?

- Medical Question:
  - Can a deep learning model automatically detect and distinguish vascular structures in 3D brain MRA scans, supporting early identification of abnormalities such as intracranial aneurysms?
- Intracranial aneurysms can be difficult to detect?
- Missed detection may lead to hemorrhagic stroke
- Manual review of 3D scans is time consuming



# Data Augmentation for Imbalanced Distribution

- **Problem:** VesselMNIST3D dataset had severe class imbalance ( $\sim 8:1$  ratio of Healthy to Aneurysm cases)
- **Solution:** Applied 3D augmentation (rotation  $\pm 15^\circ$ , flipping, small shifts, light noise) to minority class only
- **Strategy:** Used lighter 2:1 oversampling instead of full 1:1 balancing to prevent model from memorizing augmented copies
- **Implementation:** Generated synthetic aneurysm samples, concatenated with original data, and shuffled the combined dataset
- **Result:** Improved class balance from  $\sim 8:1$  to  $\sim 2:1$  ratio



# Architecture

## 3D CNN Architecture for Binary Classification



Total Parameters: ~870,000

Key Features: Residual Connections • SE Attention • Progressive Dropout

Input/Output   Convolution   Residual Blocks   Classifier





# Ensemble Method

**Approach:** Trained 5 identical 3D CNN models with different random seeds (42, 123, 456, 789, 1010)

## Why Ensemble?

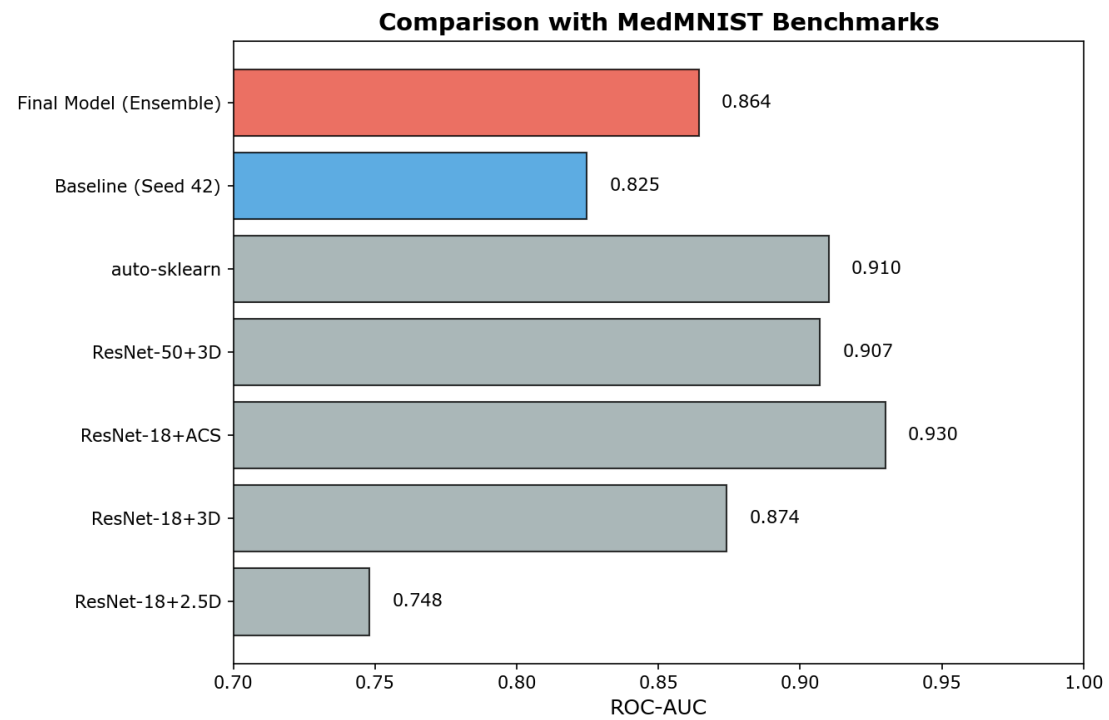
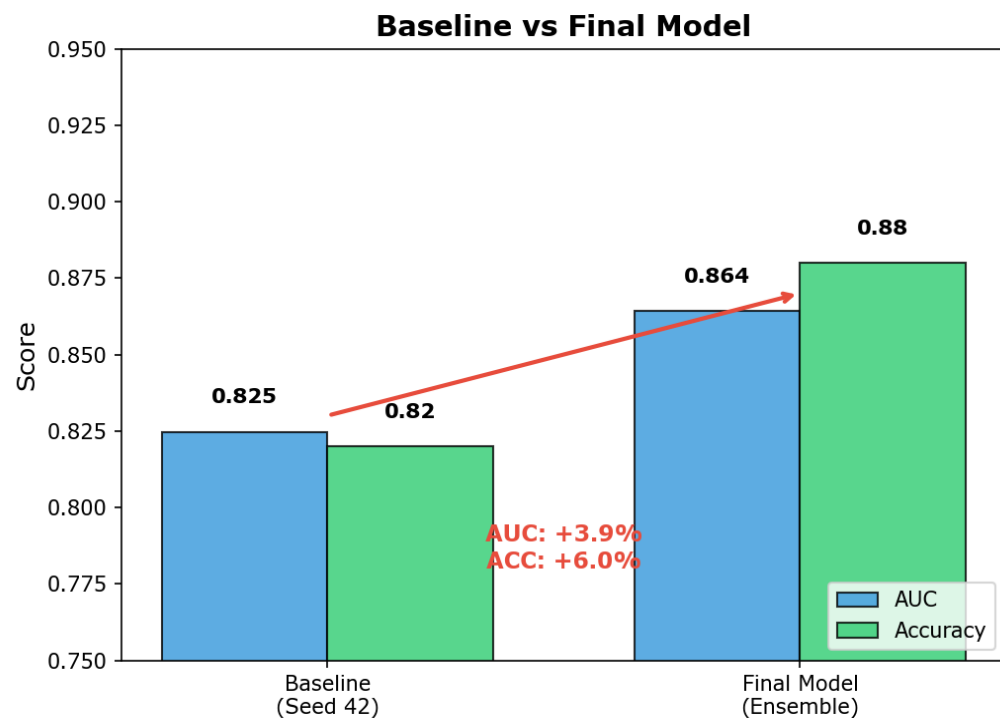
- Same architecture, different weight initializations
- Each model learns slightly different decision boundaries
- Averaging predictions reduces individual model errors

## Implementation:

- Focal Loss ( $\gamma=2.0$ ,  $\alpha=0.7$ ) emphasizing minority class
- Boosted class weights (1.5× for aneurysm)
- Early stopping on validation AUC

**Prediction:** Average probability outputs from all 5 models, then apply optimized threshold

# Results & Benchmarks







# Ethical Considerations

- Ethical Focus: Responsible use of medical AI and avoidance of harm
  - Automated medical image analysis systems can influence clinical decisions.
  - Errors in vessel detection could contribute to misdiagnosis or delayed treatment.
  - Over-reliance on AI outputs poses risk in high-stakes healthcare settings.
- ACM 1.2 – Avoid Harm
  - An ethical concern in this project is how a neural network like ours might be used in real medical contexts. According to ACM Code of Ethics, computing professionals have a responsibility to avoid harm. Even unintended errors from an AI system can have serious consequences, so careful considerations of risks is essential.

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# Summary

- Applied a 3D CNN to VesselMNIST3D
- Addressed a meaningful medical imaging task
- Achieved benchmark-level performance
- Reflected on ethical implications of medical AI