Detecting Presence of Brain Aneurysms- A Deep Learning Approach

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Problem / Question

- Intracranial aneurysms are small (~3 mm) and often missed in manual detection.
- Early detection is critical due to high mortality after rupture.
- **Can deep learning improve aneurysm detection and spatial localization to support radiologists?**

Objective

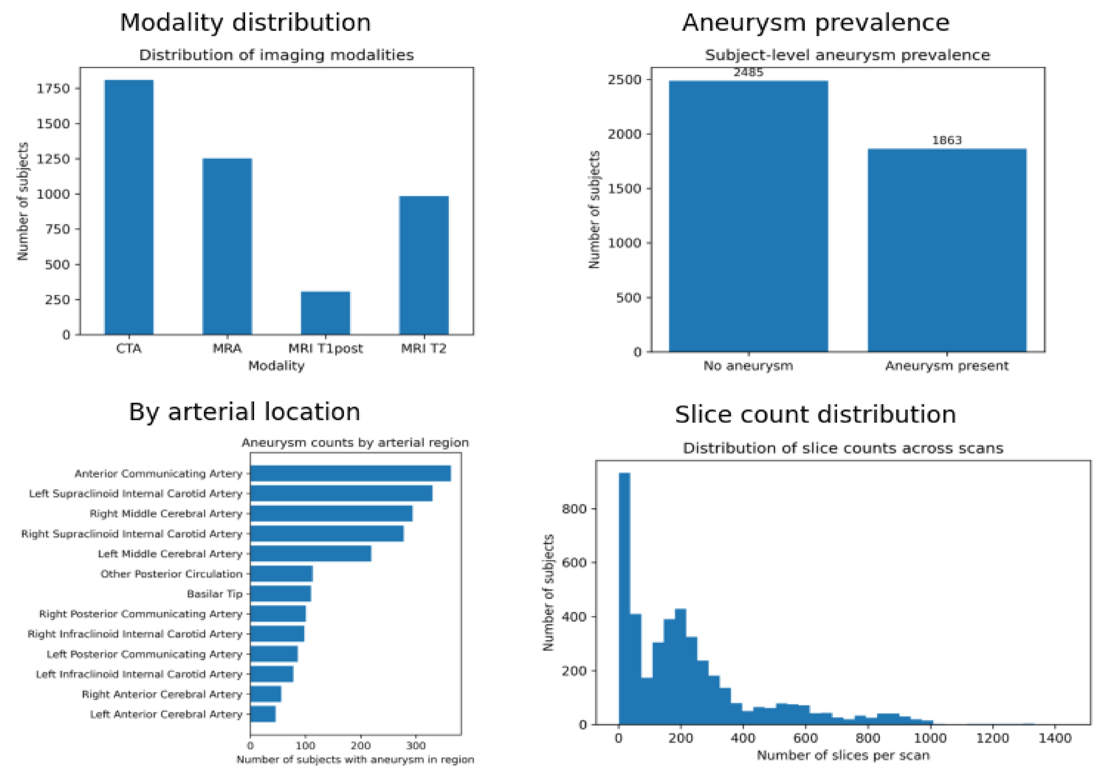
Develop a deep learning pipeline using 3D brain imaging to:

1. Detect whether an aneurysm is present.
2. Localize aneurysms across key intracranial arterial regions.

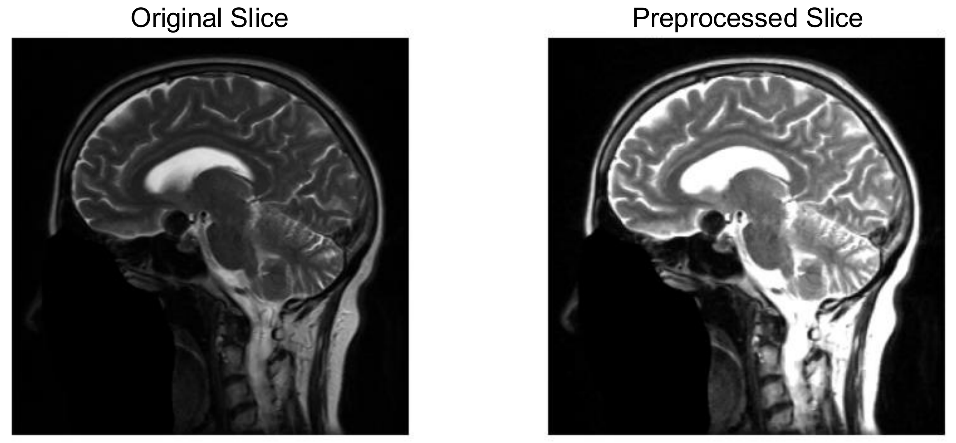
We compare a **one-step** (joint) model and a **two-step** (decoupled) model to assess accuracy and interpretability.

Exploratory Data Analysis

The following figures show on overview of the dataset, including imaging modalities, aneurysm prevalence, arterial distribution, and scan characteristics.



Preprocessing



Slice Level

Slices are ordered using DICOM geometry metadata, resized to a uniform grid, and intensity-normalized across modalities. CTA slices are converted to Hounsfield units; MRI slices remain in native units. **All slices undergo modality-appropriate windowing, clipping, grayscale correction, and normalization.** Final inputs are down sampled to 128 x 128 to meet memory constraints.

We use **3,726 subjects**, selected to create a balanced sample with respect to aneurysm presence, not by localization category.

One-Step Approach

- **3D Convolutional Neural Network**:
  - 3 blocks of 2 3x3x3 convolutional layers with LeakyReLU activation and max-pooling layers.
  - Classifiying head: 3 feedforward layers and 1 dropout layer.
  - Softmax generates probabilities over 14x1 output.
  - Loss: multi-label classification cross entropy weighted to emphasize detection over localization.

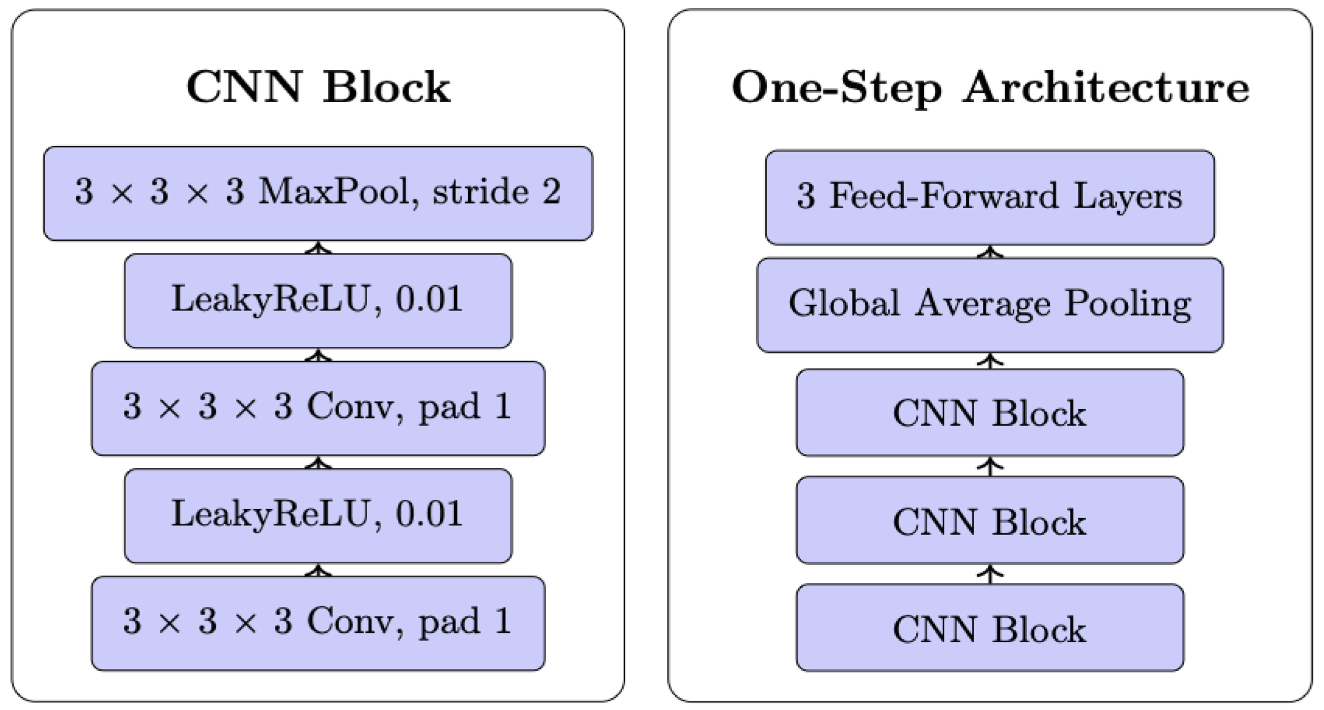


Figure 1: One-Step Approach Architecture

Two-Step Approach

- Divide aneurysm identification and localization into 2 3D CNN.
- **Step 1: 3D CNN with single output targeting presence of aneurysm**
  - Similar convolutional structure to One-Step Approach; BCE Loss
- **Step 2: 3D CNN with 13x1 output**
  - Use weights of step 1, with new feed-forward head; cross entropy loss

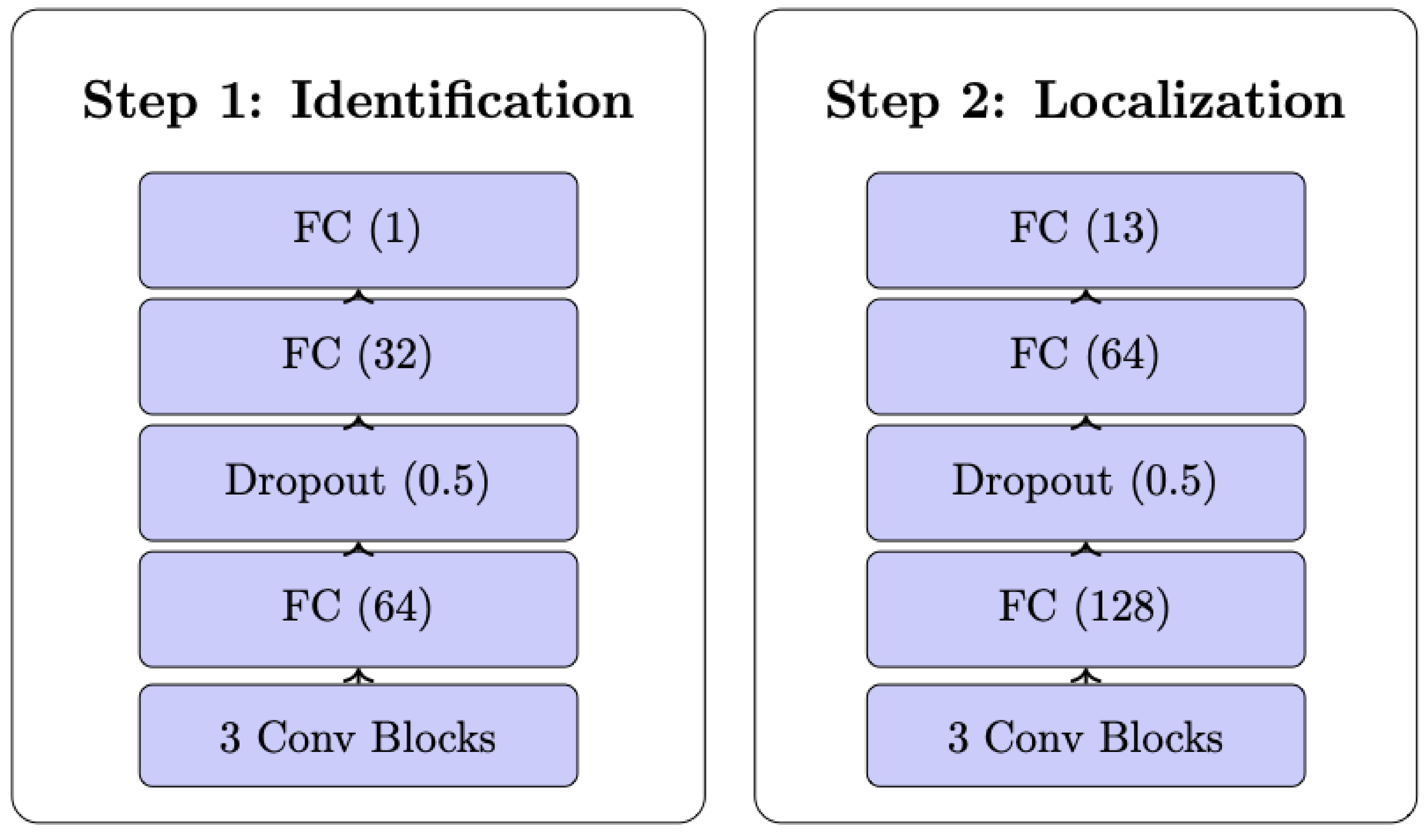


Figure 2: Two-Step Approach Architecture

Results

Training

- Perform 70-10-20 train, validation, test split across subjects.

One Step

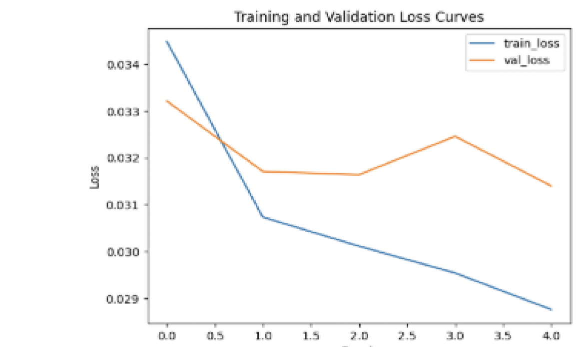


Figure 1: One-Step Approach: Training-Validation Loss Curves

The training and validation loss over 5 epochs with learning rate of 1×10^{-4} and weight decay of 1×10^{-5}.

Two Step

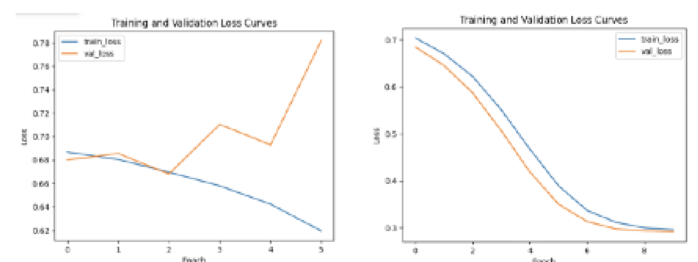


Figure 2: Two-Step Approach: Training-Validation Loss Curves

The training and validation loss over 6 and 10 epochs, respectively, with learning rate of 1×10^{-4} and weight decay of 1×10^{-5}.

Out-of-Sample Evaluation

One Step

For each test subject, aggregate predictions for all mini-volumes. We create a design rule to catch signal even if the aneurysm is not present in all mini-volumes.

Output	Support	Precision	Recall	F1-Score
Presence	276	0.64	0.88	0.74
Loc - 1	13	0.00	0.00	0.00
Loc - 2	21	0.00	0.00	0.00
Loc - 3	59	0.00	0.00	0.00
Loc - 4	48	0.00	0.00	0.00
Loc - 5	37	0.00	0.00	0.00
Loc - 6	41	0.00	0.00	0.00
Loc - 7	71	0.00	0.00	0.00
Loc - 8	9	0.00	0.00	0.00
Loc - 9	9	0.00	0.00	0.00
Loc - 10	13	0.00	0.00	0.00
Loc - 11	24	0.00	0.00	0.00
Loc - 12	15	0.00	0.00	0.00
Loc - 13	15	0.00	0.00	0.00

Table 2: One-Step Approach Evaluation

We report the precision, recall, and F1-Score for all fourteen output categories.

Two Step

First, apply step 1 to the out-of-sample test set. Conditional on the presence of an aneurysm, apply step 2.

Output	Support	Precision	Recall	F1-Score
Presence	288	0.72	0.64	0.68
Loc - 1	27	0.00	0.00	0.00
Loc - 2	15	0.00	0.00	0.00
Loc - 3	18	0.00	0.00	0.00
Loc - 4	11	0.00	0.00	0.00
Loc - 5	20	0.00	0.00	0.00
Loc - 6	12	0.00	0.00	0.00
Loc - 7	41	0.00	0.00	0.00
Loc - 8	54	0.00	0.00	0.00
Loc - 9	43	0.00	0.00	0.00
Loc - 10	28	0.00	0.00	0.00
Loc - 11	9	0.00	0.00	0.00
Loc - 12	3	0.00	0.00	0.00
Loc - 13	73	0.00	0.00	0.00

Table 3: Two-Step Approach Evaluation

We report the precision, recall, and F1-Score for all fourteen output categories.

- Weighted AUC: **0.6317** and **0.6224**, respectively.

Conclusion

- Models successfully **detected aneurysms; struggled to locate** them.
- Limited by computational and memory constraints.
- Move to **Vision Transformers** and **increased model size** could improve localization.

Works Cited

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