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Segmentation of intracranial hemorrhage in CT scans using machine learning

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Agenda

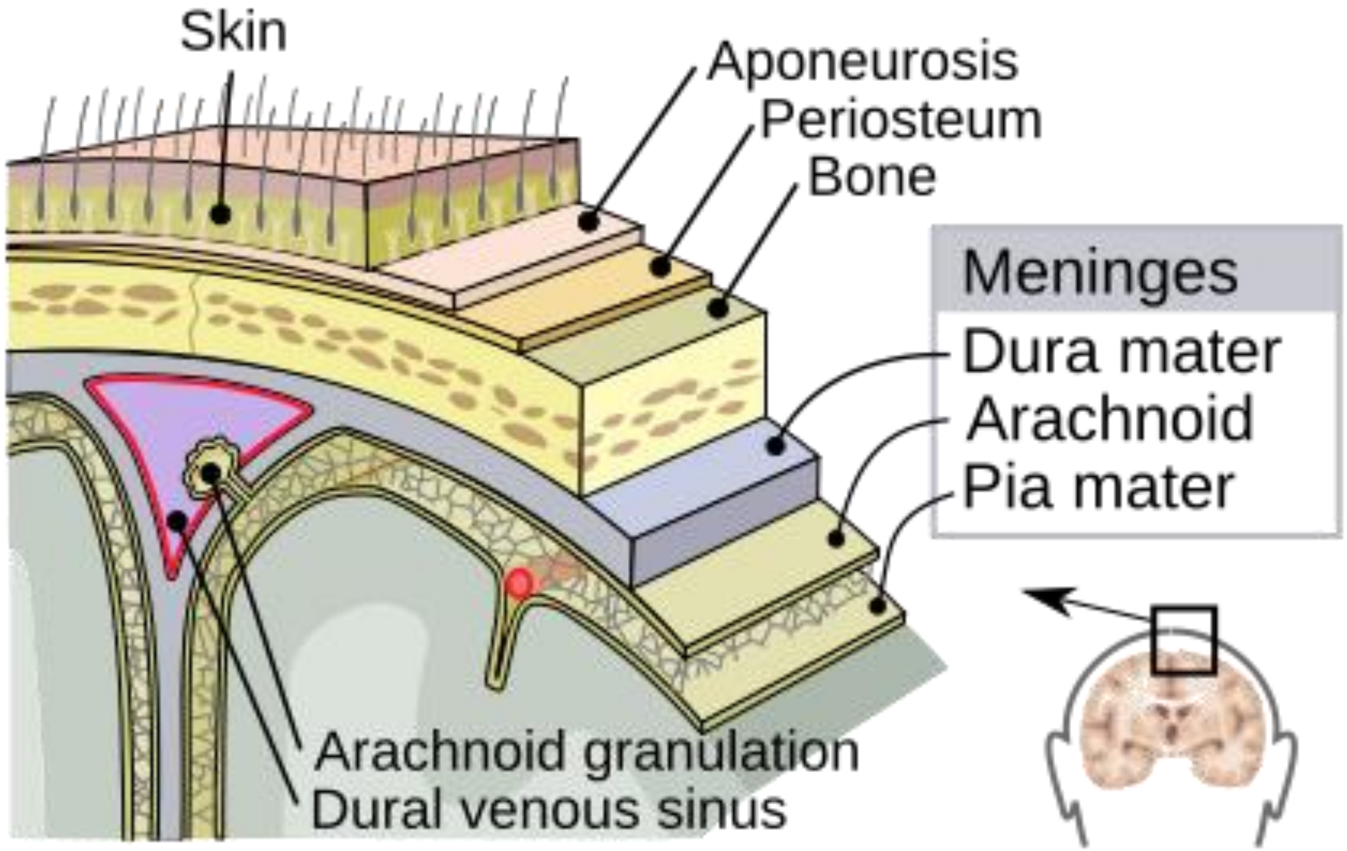
1. Problem
2. Methodology
3. Results
4. Conclusions

1. Problem

Introduction

- **What is Intracranial Hemorrhage (ICH)?**
  - Bleeding within the skull, requiring treatment within hours
  - 5 main types: EDH, SDH, SAH, IPH, IVH *(see next 2 slides)*
  - Usually diagnosed with non-contrast CT head scans
- **Importance of Multiclass Segmentation**
  - Treatment depends on type, location, and volume of hemorrhage.
  - Manual segmentation is slow and expertise-dependent.
- **Challenges**:
  - Poor segmentation of certain ICH types (e.g., EDH, SDH).
  - Limited validation on public benchmarks.
- **Goal**: Enhance multiclass ICH segmentation.

Head anatomy



Introduction

	Intraparenchymal	Intraventricular	Subarachnoid	Subdural	Epidural
Location	Inside of the brain	Inside of the ventricle	Between the arachnoid and the pia mater	Between the Dura and the arachnoid	Between the dura and the skull
Imaging					
Mechanism	High blood pressure, trauma, arteriovenous malformation, tumor, etc	Can be associated with both intraparenchymal and subarachnoid hemorrhages	Rupture of aneurysms or arteriovenous malformations or trauma	Trauma	Trauma or after surgery
Source	Arterial or venous	Arterial or venous	Predominantly arterial	Venous (bridging veins)	Arterial
Shape	Typically rounded	Conforms to ventricular shape	Tracks along the sulci and fissures	Crescent	Lentiform
Presentation	Acute (sudden onset of headache, nausea, vomiting)	Acute (sudden onset of headache, nausea, vomiting)	Acute (worst headache of life)	May be insidious (worsening headache)	Acute (skull fracture and altered mental status)

Image source: A. Stein, C. Wu, C. Carr and others, RSNA intracranial hemorrhage detection, Kaggle, 2019. url: https://kaggle.com/competitions/rsna-intracranial-hemorrhage-detection.

Problem Formulation

- **Task**: semantic segmentation
- **Input**: 3D voxel array of CT scan, each voxel is radiodensity in Hounsfield Units
- **Output**: 3D segmentation mask:
  - 0: background
  - 1: EDH (**e**pi**d**ural **h**emorrhage)
  - 2: IPH (**i**ntra**p**arenchymal **h**emorrhage)
  - 3: IVH (**i**ntra**v**entricular **h**emorrhage)
  - 4: SAH (**s**ub**a**rachnoid **h**emorrhage)
  - 5: SDH (**s**ub**d**ural **h**emorrhage)

2. Methodology

Overview

- **Base model**: nnU-Net[1]: automatic configuration of U-Net for medical image segmentation, SOTA for many medical tasks (2024)[2]
- Try to **improve using two methods**:
  - Changing CT windowing settings for data preprocessing
  - Ensemble learning

[1]F. Isensee, P. F. Jaeger, S. A. A. Kohl, J. Petersen and K. H. Maier-Hein,"nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation," Nature Methods, jourvol 18, number 2, pages 203–211,2021, ISSN: 1548-7105. DOI: 10.1038/s41592-020-01008-z. url:https://doi.org/10.1038/s41592-020-01008-z.
[2]F. Isensee, T. Wald, C. Ulrich and others, "nnU-Net revisited: A call for rigorous validation in 3d medical image segmentation," in Medical Image Computing and Computer Assisted Intervention – MICCAI 2024 M. G. Linguraru, Q. Dou, A. Feragen and others, editors, Cham: Springer Nature Switzerland,2024, pages 488–498, ISBN: 978-3-031-72114-4.

Data Preparation

- Public **Brain Hemorrhage Segmentation Dataset (BHSD)**[1]:
  - **Training**:
    - 96 ICH-positive + 200 ICH-negative CT volumes
    - 80% for training + 20% for validation
  - **Test**: 96 positive CT volumes.
- **CT scan preprocessing**:
  - **CT Windowing**: Truncate HU values to a smaller range to focus on relevant features
  - **Normalization**: Map each voxel value x to $\frac{x-\mu}{\sigma}$, where μ and σ are mean and std. dev. of training set foreground voxel values
  - **Resampling**: Ensure consistent voxel spacing among CT scans, target spacing = 5x0.5x0.5mm

[1]B. Wu, Y. Xie, Z. Zhang and others, "BHSD: A 3d multi-class brain hemorrhage segmentation dataset," in Machine Learning in Medical Imaging X. Cao, X. Xu, I. Rekik, Z. Cui and X. Ouyang, editors, Cham: Springer Nature Switzerland, 2024, pages 147–156, ISBN: 978-3-031-45673-2.

Backbone Selection and Training

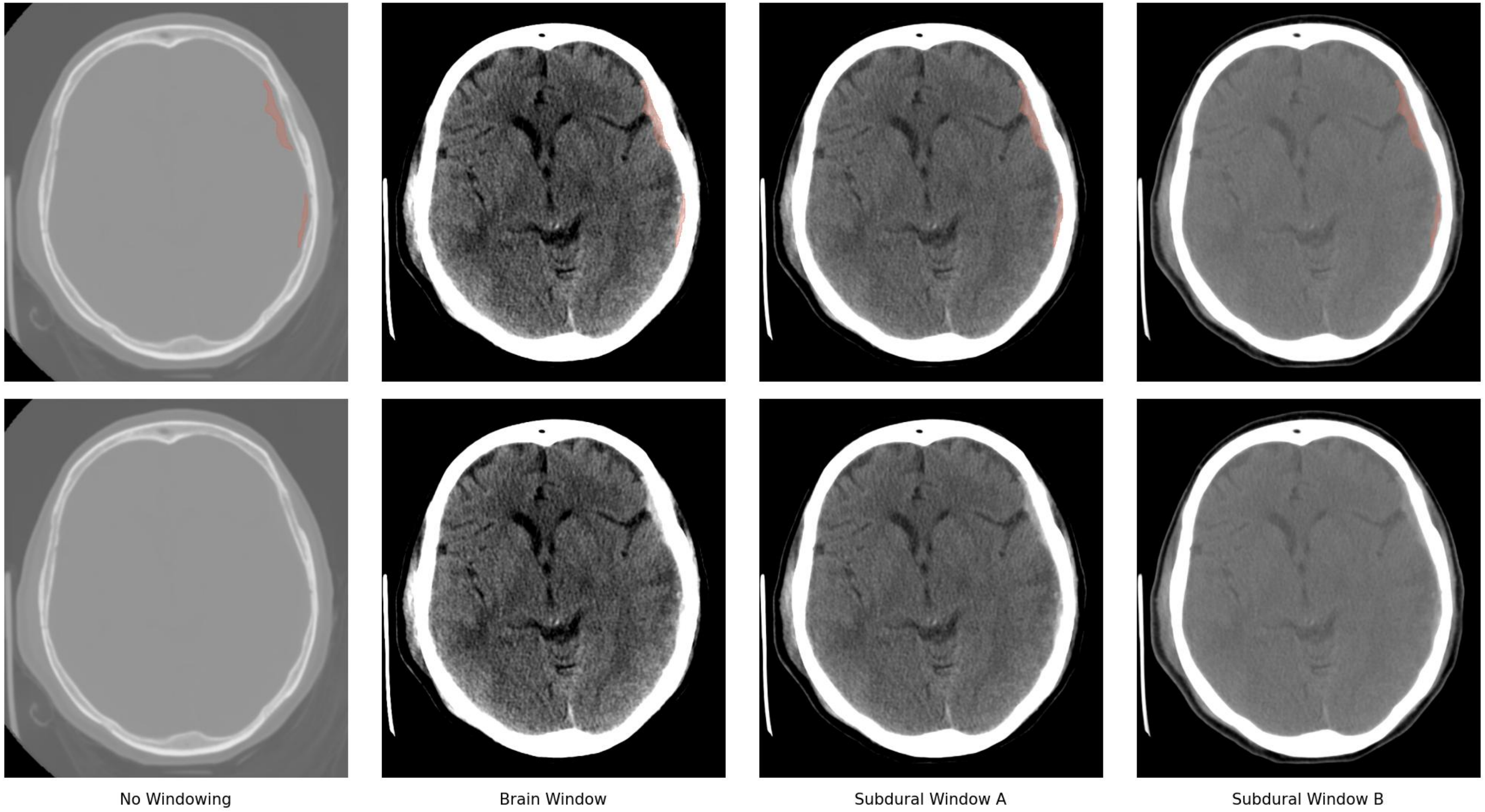
- **Architectures**:
  - 2D nnU-Net: input patch size 512x512
  - 3D nnU-Net: input patch size 256x256x28
- **Training**:
  - 1000 epochs, 250 minibatches/epoch
  - Batch size: 12 for 2D nnU-Net, 2 for 3D nnU-Net
  - Loss function: Cross Entropy Loss + Dice Loss
- **Selection**: 3D nnU-Net (higher validation set macro-average DSC)

CT Windowing

- **Definition**: Truncate voxel value I to a range $[I_{lower}, I_{upper}]$:
  - $I_w = \max\{\min\{I, I_{upper}\}, I_{lower}\}$
- **Purpose**: help radiologist/neural net focus on relevant features, because raw HU range is too wide
- **nnU-Net default**:
  - Method: [0.5^{th} percentile, 99.5^{th} percentile] of foreground voxel values
  - For BHSD: [10, 81] (effectively brain window[1])
- **Custom windows**: inspired by clinical practice
  - Subdural window[1] A: [-15, 115]
  - Subdural window B: [-100, 200]

[1]A. Murphy, J. Feger, M. Ismail and others, Windowing (ct), Radiopaedia.org,2025. DOI: 10.53347/rID- 52108. url: https://doi.org/10.53347/rID-52108.

CT Windowing



Red mask: SDH

Ensemble Learning

- **Ensemble method**: average probability distributions predicted by multiple models
- **Aim**: utilize complementary strengths of models to improve overall performance
- **Ensemble selection**: highest mean DSC on validation set

3. Results

Backbone selection

Validation set DSC of 2D nnU-Net and 3D nnU-Net

(blue: better)

Model	2D nnU-Net	3D nnU-Net
EDH	0.00%	0.00%
IPH	37.41%	63.95%
EVH	31.31%	48.29%
SAH	17.35%	19.62%
SDH	25.76%	20.12%
Macro Avg	**22.37%**	**30.40%**

Ensemble selection

Validation set DSC of ensembles of 3D nnU-Net

- Model names:
  - **M1**: 3D nnU-Net with CT window [10, 81]
  - **M2**: 3D nnU-Net with CT window [-15, 115]
  - **M3**: 3D nnU-Net with CT window [-100, 200]
- Blue: best

Ensemble	M1 & M2	M2 & M3	M1 & M3	M1 & M2 & M3
EDH	0.00%	1.98%	0.00%	0.00%
IPH	62.84%	62.36%	63.28%	66.67%
EVH	48.04%	47.14%	53.77%	47.78%
SAH	22.21%	21.55%	23.36%	24.42%
SDH	22.01%	25.44%	25.21%	34.52%
Macro Avg	**31.02%**	**31.69%**	**33.12%**	**34.68%**

Final model results (test set DSC)

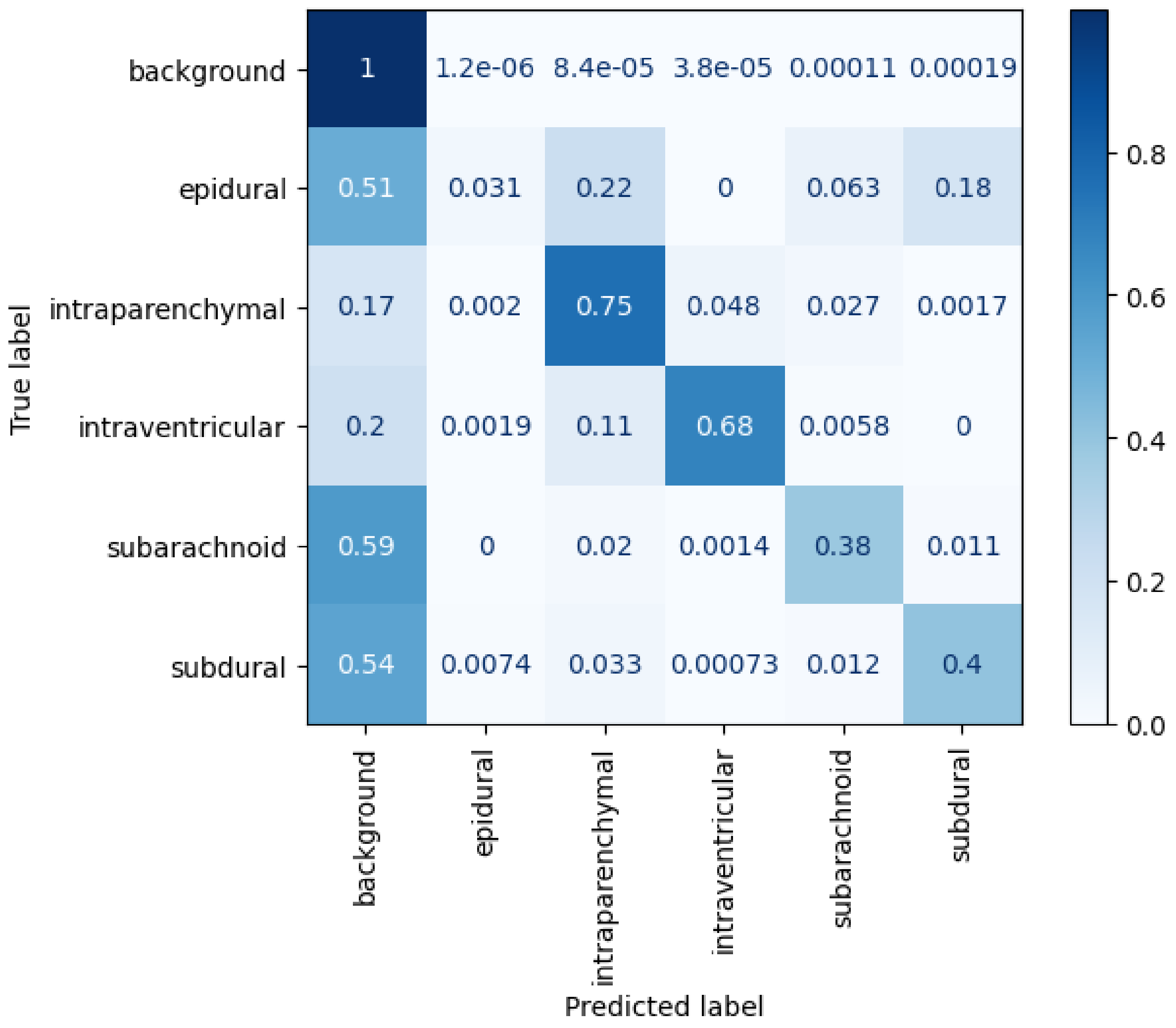
- **Baseline**: 3D nnU-Net with CT window [-40, 120] (Wu et al., 2023)[1]
- My models:
  - **M1**, **M2**, **M3** *(see previous slide)*
  - **Ensemble** of M1, M2, and M3

- Notation:
  - **Bold**: highest
  - <u>Underline</u>: highest among my models
  - Green: better than baseline
  - Red: worse than baseline

Model	Baseline	M1	M2	M3	Ensemble
EDH	9.77%	6.38%	6.54%	<u>10.01%</u>	7.61%
IPH	56.90%	<u>57.72%</u>	55.02%	54.27%	57.18%
IVH	**58.53%**	<u>52.31%</u>	51.09%	48.37%	51.12%
SAH	**29.98%**	21.69%	<u>22.08%</u>	19.93%	21.44%
SDH	**21.73%**	11.22%	<u>16.88%</u>	16.46%	16.54%
Macro Avg	**35.38%**	29.86%	30.32%	29.81%	<u>30.78%</u>
Foreground	45.10%	57.52%	<u>59.14%</u>	58.42%	58.61%

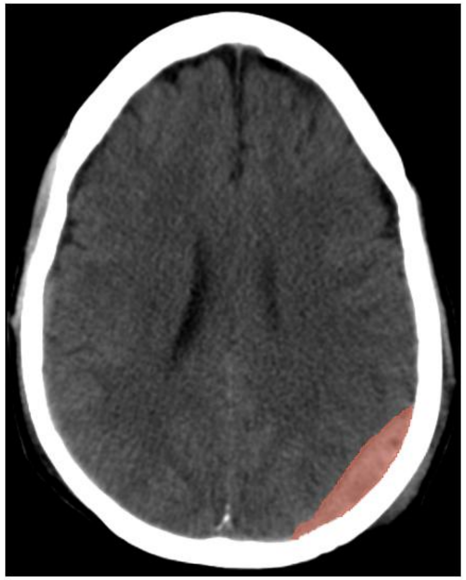
[1]B. Wu, Y. Xie, Z. Zhang and others, "BHSD: A 3d multi-class brain hemorrhage segmentation dataset," in Machine Learning in Medical Imaging X. Cao, X. Xu, I. Rekik, Z. Cui and X. Ouyang, editors, Cham: Springer Nature Switzerland, 2024, pages 147–156, ISBN: 978-3-031-45673-2.

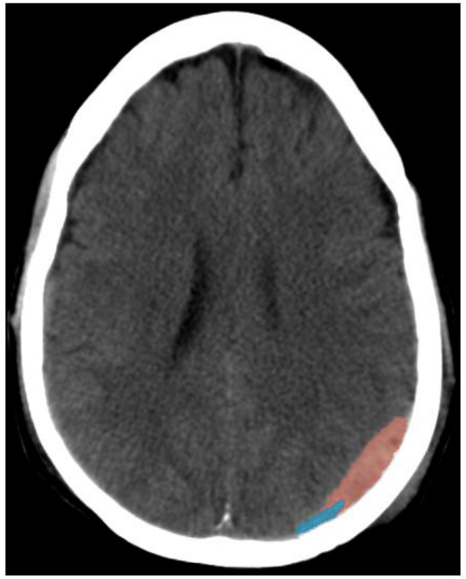
Confusion matrix of Ensemble



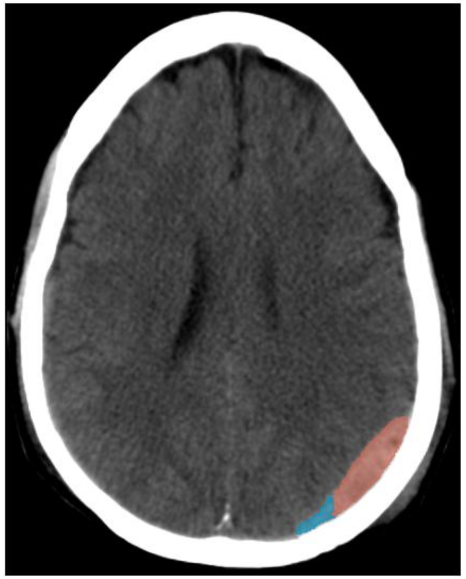
A test case

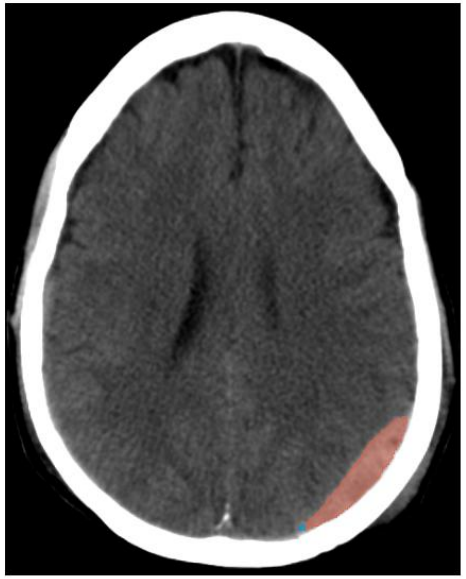

Original CT slice

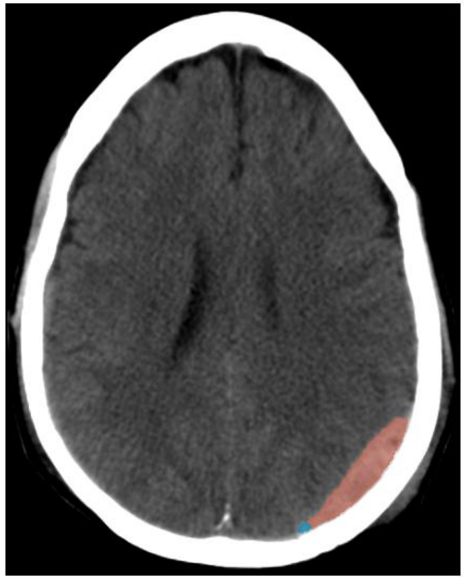

Ground Truth


3D U-Net with Brain Window

Red mask: EDH
Blue mask: SDH


3D U-Net with Subdural Window A


3D U-Net with Subdural Window B


Ensemble Model

4. Conclusions

Conclusions

- **Summary**:
  - Modifying CT window in data preprocessing can improve nnU-Net's segmentation of certain types of ICH while degrading that of other types.
  - Combining models in an ensemble may achieve the best macro-average DSC without the best DSC for any single class.
- **Future work**:
  - Tuning other hyperparameters in nnU-Net (patch size, loss function, optimizer, etc.)
  - Using different neural net architectures (nnU-Net low-resolution cascade, transformer, etc.)
  - Applying proposed techniques to other datasets and other medical imaging problems