
MICCAI
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25th International Conference on
Medical Image Computing and
Computer Assisted Intervention
September 18-22, 2022
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We create generalizable domain-aware loss and provide pretrained 3D models!

DOMINO: Domain-aware Model Calibration in Medical Image Segmentation

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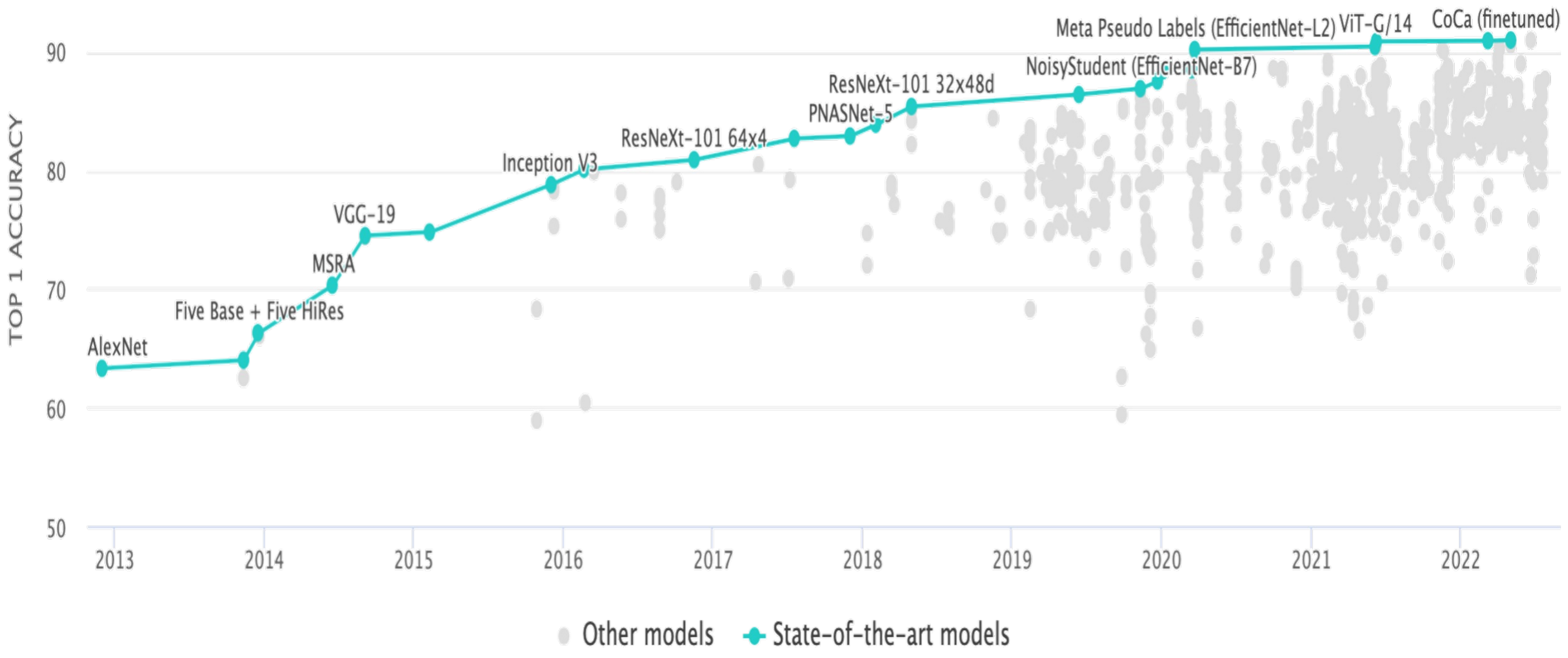
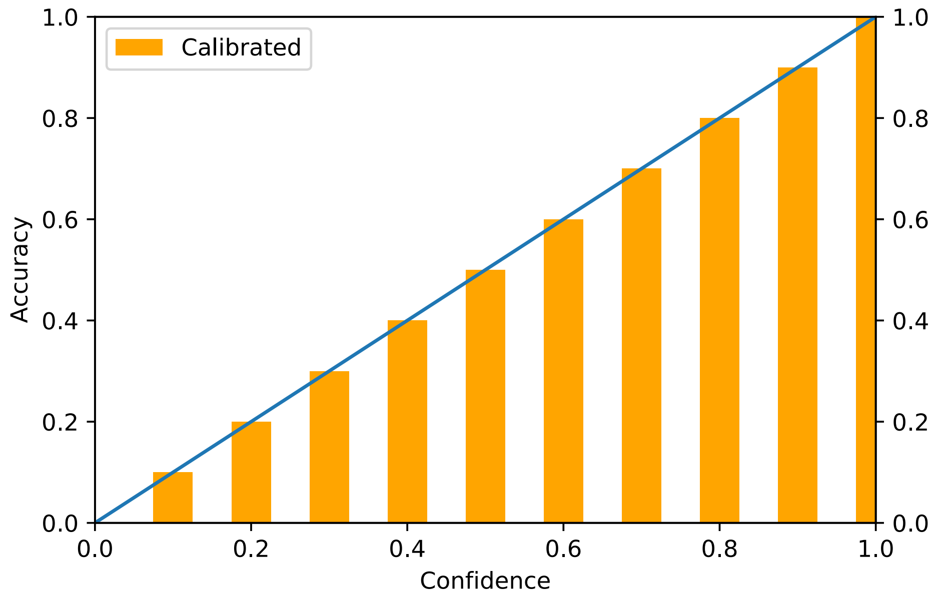
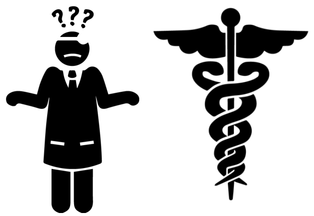
Goal: High Accuracy + Good Calibration





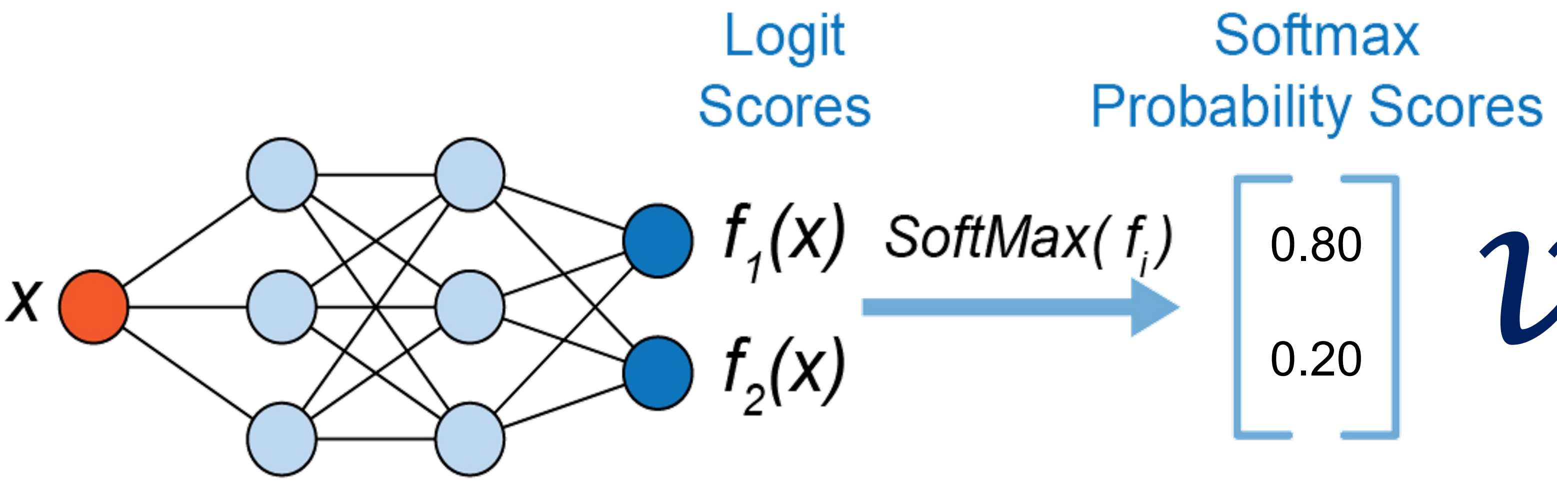
Confidence vs. Accuracy Vital in medicine!



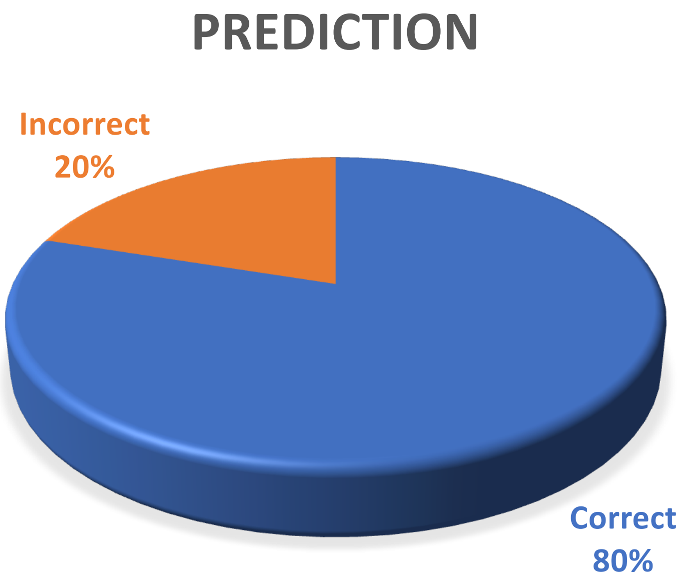
https://paperswithcode.com/sota/image-classification-on-imagenet

Deep Learning Calibration

Confidence vs. Accuracy



vs.



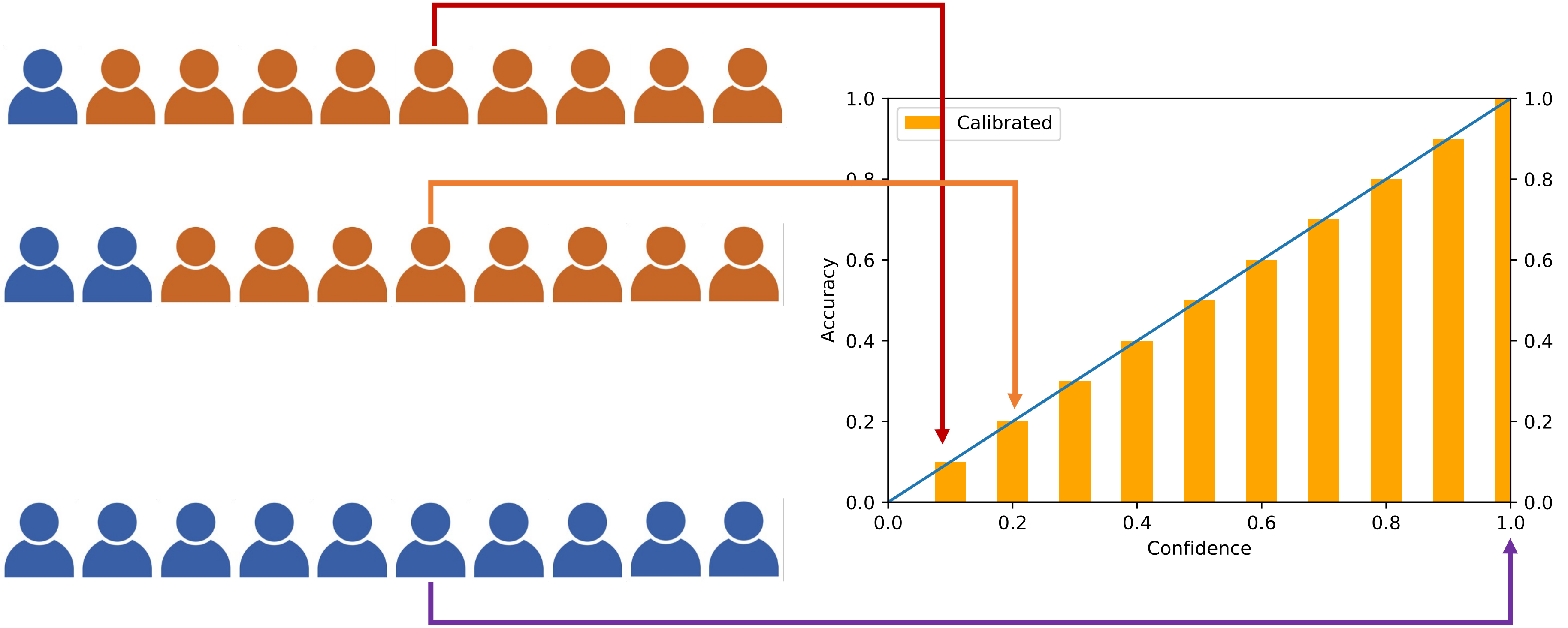
Calibration and Trustworthiness

- Confidence = 0.1
- Accuracy = 1/10 = 0.1

- Confidence = 0.2
- Accuracy = 2/10 = 0.2

…

- Confidence = 1.0
- Accuracy = 10/10 = 1.0



Calibration in Medical Triage

Uncalibrated Model Decision

- Individual has positive diagnosis?
  - **Yes** → Treat individual
  - **No** → Send individual home

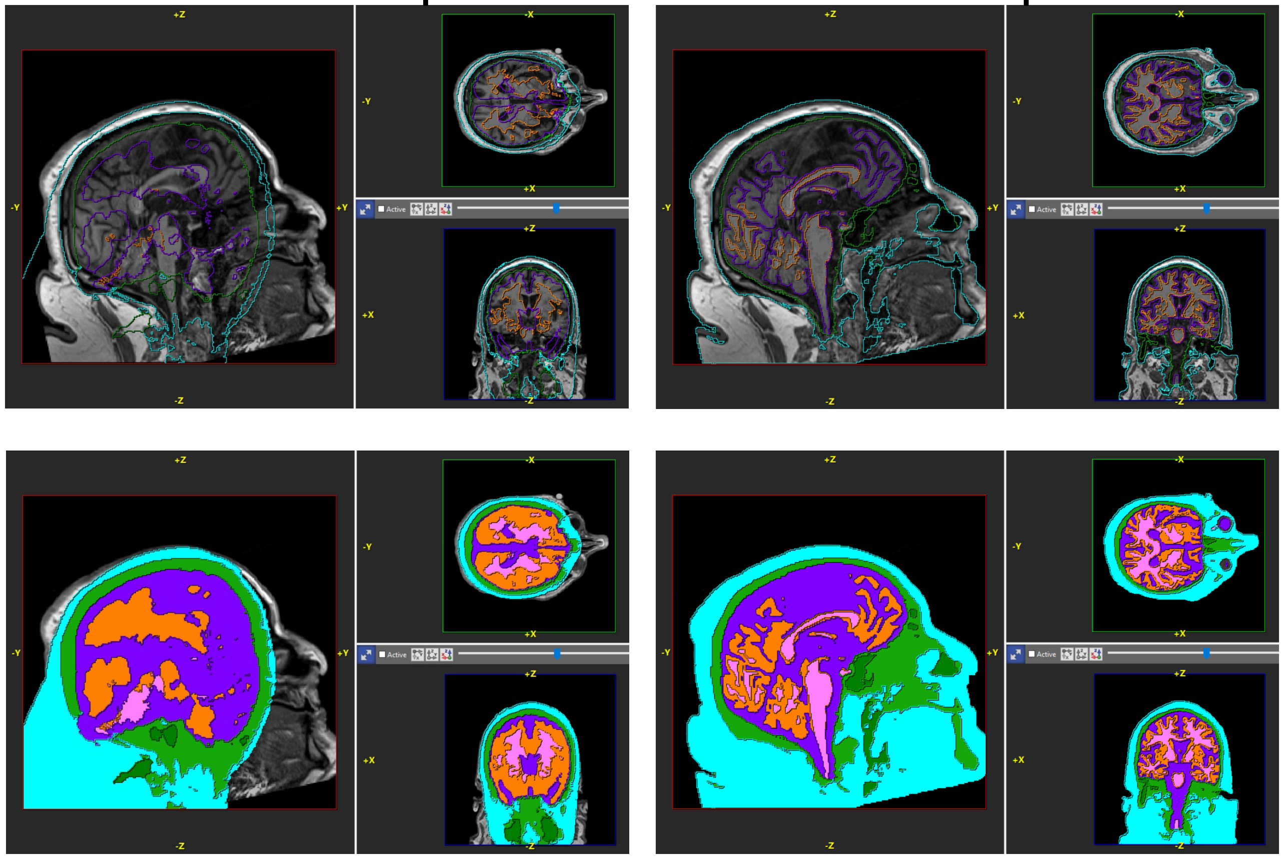
Calibrated Model Decision

- Individual has positive diagnosis?
  - **Yes** → Treat individual
  - **No** → Is the confidence high?
    - **Yes** → Send individual home
    - **No** → Ask individual to follow-up

Uncertainty in Segmentation

- Out-of-Distribution (OOD) data:
  - Rarer tissues (e.g., air, blood, tumor)
  - Quality differences (i.e., ringing artifact)
  - Anatomical differences
- Pixel-wise classification:
  - More data
- Most uncertain at tissue boundaries:
  - Partial volume effects

ROAST Output: Our Output:



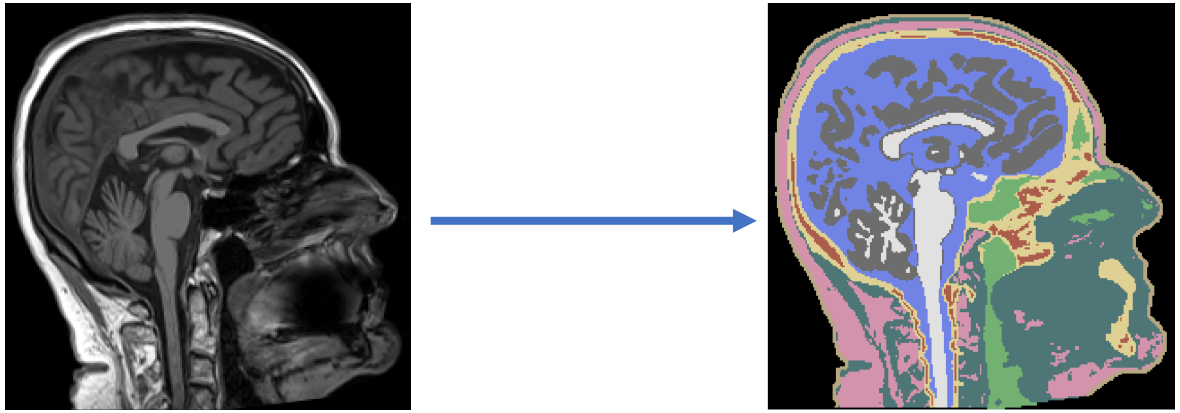
Dataset and Network

Data:

- Augmenting Cognitive Training in Older Adults (ACT) trial (NCT02851511)
- NIH-R01 Phase III clinical trial
- Cognitive training + tDCS for cognitive improvement
- 379 participants
- University of Florida (UF) and University of Arizona (AZ)
- 65-85 years of age

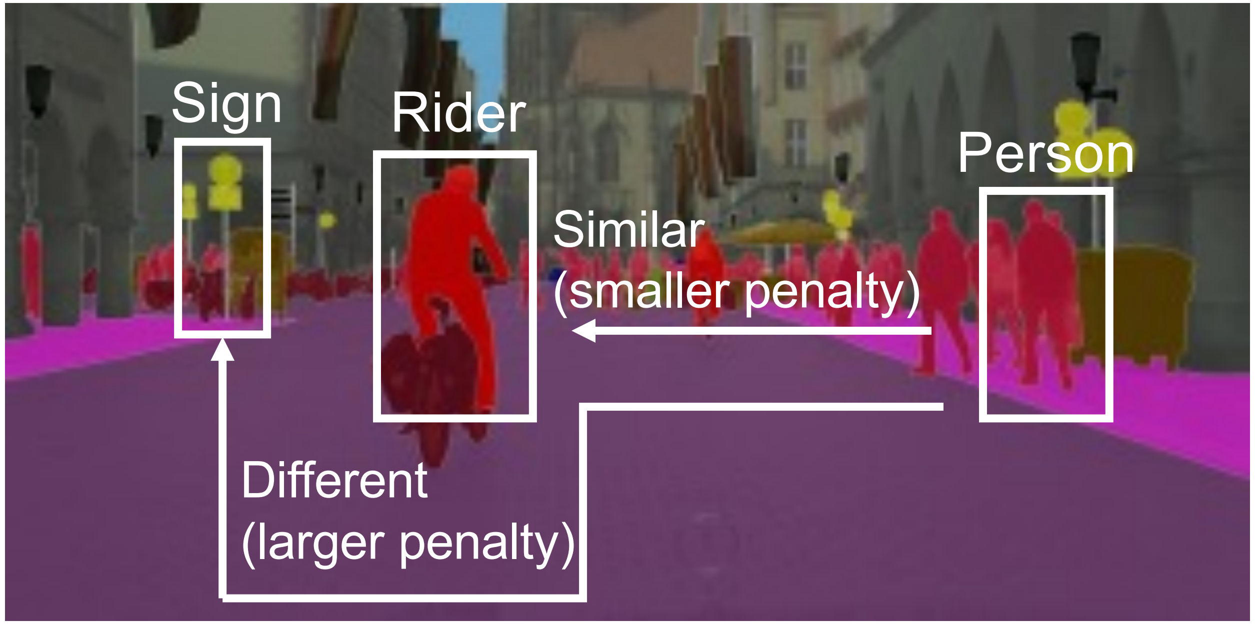
Two Deep Learning Frameworks:

- **U-Net Transformer (UNETR)**
- DeepLab-v3+



Loss Concept

- Estimate meaningful uncertainty
- Uncalibrated loss:
  - Arbitrarily increase confidence
  - Equally confuse classes
- Proposed loss:
  - Similarity is assigned based on task



Example: Task-oriented = Avoid hitting human

Different task could be detecting number of vehicles (person and sign would be closer)

Loss Derivation

$$L(y,\hat{y}) = \ell(y,\hat{y}) + \beta(y^T * W * \hat{y})$$

$\ell =$ Cross entropy (CE), DiceCE, etc.

$\beta =$ constant

True Class: Person

$$y^T = [0 \quad 1 \quad 0]$$

$$W = \begin{bmatrix} 0.0 & 0.9 & 2.2 \\ 0.7 & 0.0 & 2.0 \\ 1.9 & 1.7 & 0.0 \end{bmatrix}$$

$$y^T * W = [0.7 \quad 0.0 \quad 2.0]$$

Multiply $(y' * W)$ by softmax vector to get penalty

True Label: Person | Rider | Person | Sign

Model	Softmax Output	Loss
Model 1 (BEST = CORRECT)	$\hat{y} = \begin{bmatrix} 0.25 \\ 0.50 \\ 0.25 \end{bmatrix}$	CE + $(0.25 * 0.7) +$ $(0.50 * 0.0) + (0.25 * 2.0) =$ 1.00 + 0.675
Model 2 (2^{nd} Best)	$\hat{y} = \begin{bmatrix} 0.90 \\ 0.10 \\ 0.00 \end{bmatrix}$	CE + $(0.90 * 0.7) +$ $(0.10 * 0.0) + (0.0 * 2.0) =$ 3.32 + 0.630
Model 3 (3^{rd} Best)	$\hat{y} = \begin{bmatrix} 0.45 \\ 0.10 \\ 0.45 \end{bmatrix}$	CE + $(0.45 * 0.7) +$ $(0.10 * 0.0) + (0.45 * 2.0) =$ 3.32 + 1.215

DOMINO-CM

- Steps:
  1. Generate confusion matrix using uncalibrated model (UNETR-Base)
  2. Normalize confusion matrix by class
  3. Subtract matrix from identity matrix
  4. Set diagonal values to all zeroes
  5. Scale by a constant (e.g., 3)

	Background	White Matter	Grey Matter	Eyes	CSF	Air	Blood	Cancellous	Cortical	Skin	Fat	Muscle
Background	0	3	3	3	3	3	3	3	3	3	3	3
White Matter	3	0	2.8	3	3	3	3	3	3	3	3	3
Grey Matter	3	2.9	0	3	2.8	3	3	3	3	3	3	3
Eyes	3	3	3	0	2.9	3	3	3	3	2.9	2.9	2.8
CSF	3	3	2.7	3	0	3	3	3	2.8	3	3	3
Air	3	3	3	3	3	0	3	3	2.7	3	3	2.9
Blood	3	3	3	3	2.5	3	0	2.9	2.8	3	2.4	0.91
Cancellous	3	3	3	3	3	3	3	0	2.4	3	3	2.8
Cortical	3	3	3	3	2.9	2.9	3	2.9	0	3	3	2.7
Skin	2.6	3	3	3	3	3	3	3	3	0	3	2.9
Fat	3	3	3	3	3	3	3	3	3	2.9	0	2.9
Muscle	3	3	3	3	3	3	3	3	2.9	2.9	2.9	0

Machine learned

DOMINO-CM

Machine learned

- Steps:
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True Class \ Predicted Class	Class 1	Class 2	Class 3
Class 1	47980212	187436	21978
Class 2	548989	2244321	90464
Class 3	7718	7712	20457763

DOMINO-CM

Machine learned

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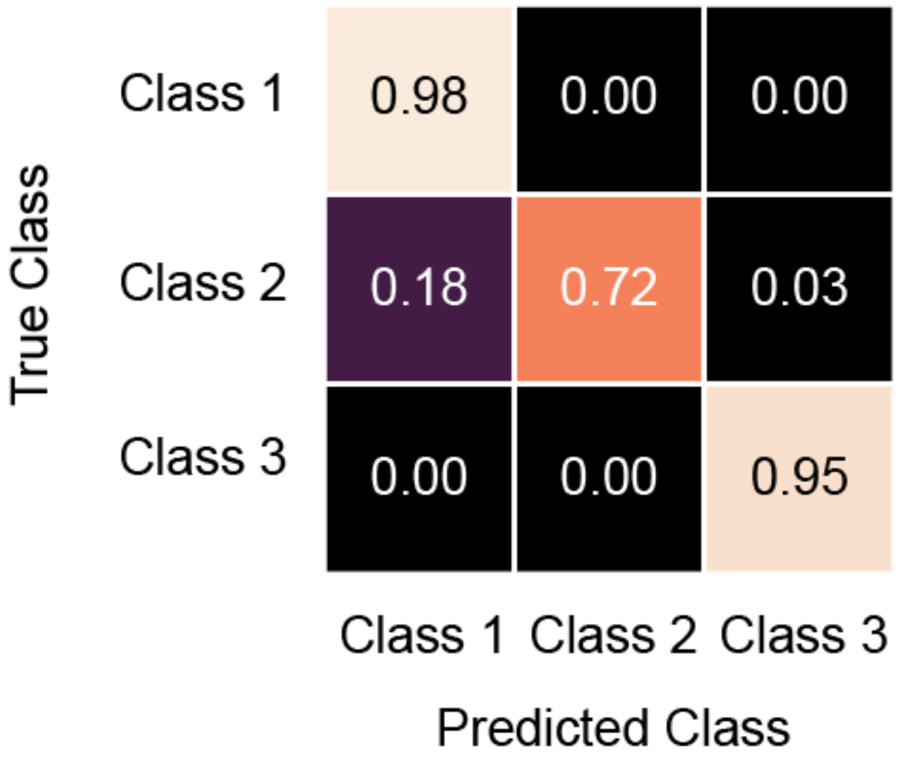

DOMINO-CM

Machine learned

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DOMINO-CM

Machine learned

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DOMINO-CM

Machine learned

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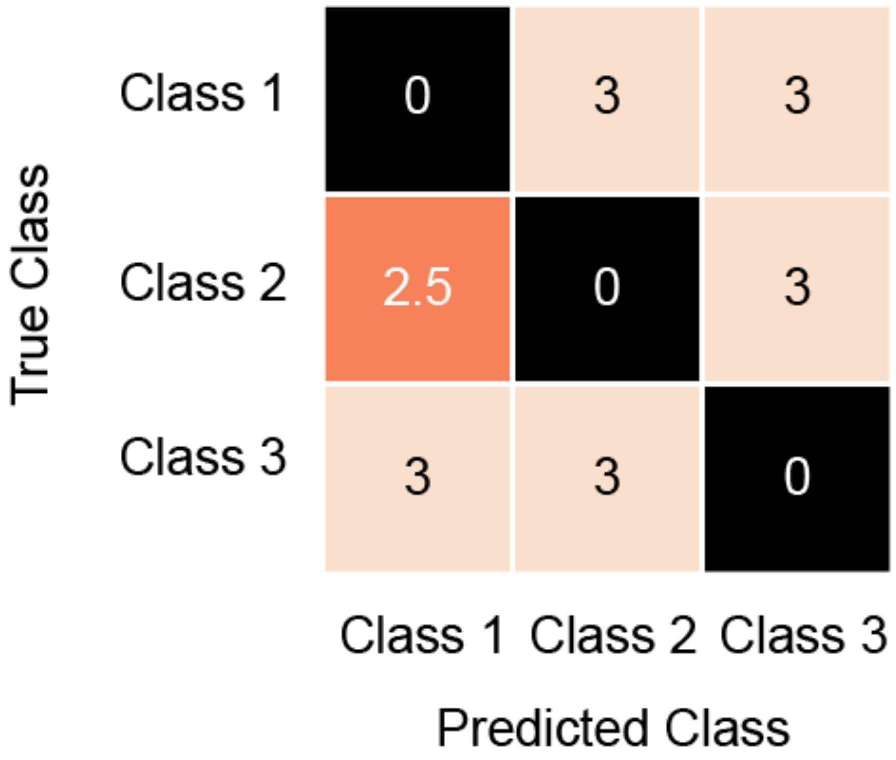

DOMINO-CM

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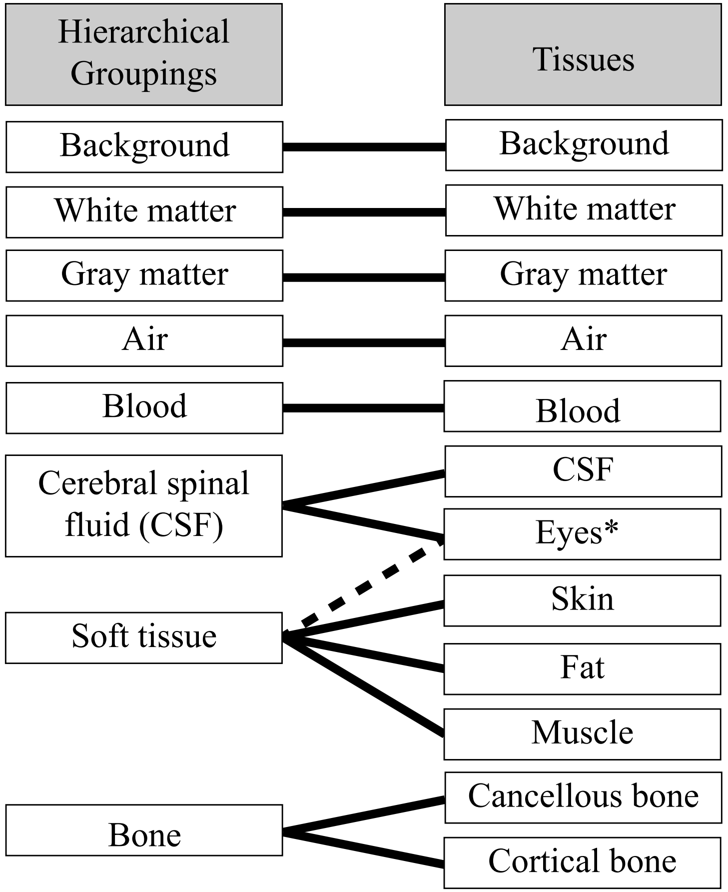
Eyes	3	3	3	0	2.9	3	3	3	3	2.9	2.9	2.8
CSF	3	3	2.7	3	0	3	3	3	2.8	3	3	3
Air	3	3	3	3	3	0	3	3	2.7	3	3	2.9
Blood	3	3	3	3	2.5	3	0	2.9	2.8	3	2.4	0.91
Cancellous	3	3	3	3	3	3	3	0	2.4	3	3	2.8
Cortical	3	3	3	3	2.9	2.9	3	2.9	0	3	3	2.7
Skin	2.6	3	3	3	3	3	3	3	3	0	3	2.9
Fat	3	3	3	3	3	3	3	3	3	2.9	0	2.9
Muscle	3	3	3	3	3	3	3	3	2.9	2.9	2.9	0

Machine learned

DOMINO-HC Expert learned



	Background	White Matter	Grey Matter	Eyes	CSF	Air	Blood	Cancellous	Cortical	Skin	Fat	Muscle
Background	0	3	3	3	3	3	3	3	3	3	3	3
White Matter	3	0	3	3	3	3	3	3	3	3	3	3
Grey Matter	3	3	0	3	3	3	3	3	3	3	3	3
Eyes	3	3	3	0	2.4	3	3	3	3	2.7	2.7	2.7
CSF	3	3	3	2.4	0	3	3	3	3	3	3	3
Air	3	3	3	3	3	0	3	3	3	3	3	3
Blood	3	3	3	3	3	3	0	3	3	3	3	3
Cancellous	3	3	3	3	3	3	3	0	2.1	3	3	3
Cortical	3	3	3	3	3	3	3	2.1	0	3	3	3
Skin	3	3	3	2.7	3	3	3	3	3	0	2.1	2.1
Fat	3	3	3	2.7	3	3	3	3	3	2.1	0	2.1
Muscle	3	3	3	2.7	3	3	3	3	3	2.1	2.1	0

Top-N Accuracy

- 11 tissue accuracy scores show superiority of the DOMINO-CM method
- 6 tissue model also shows that DOMINO-CM is superior

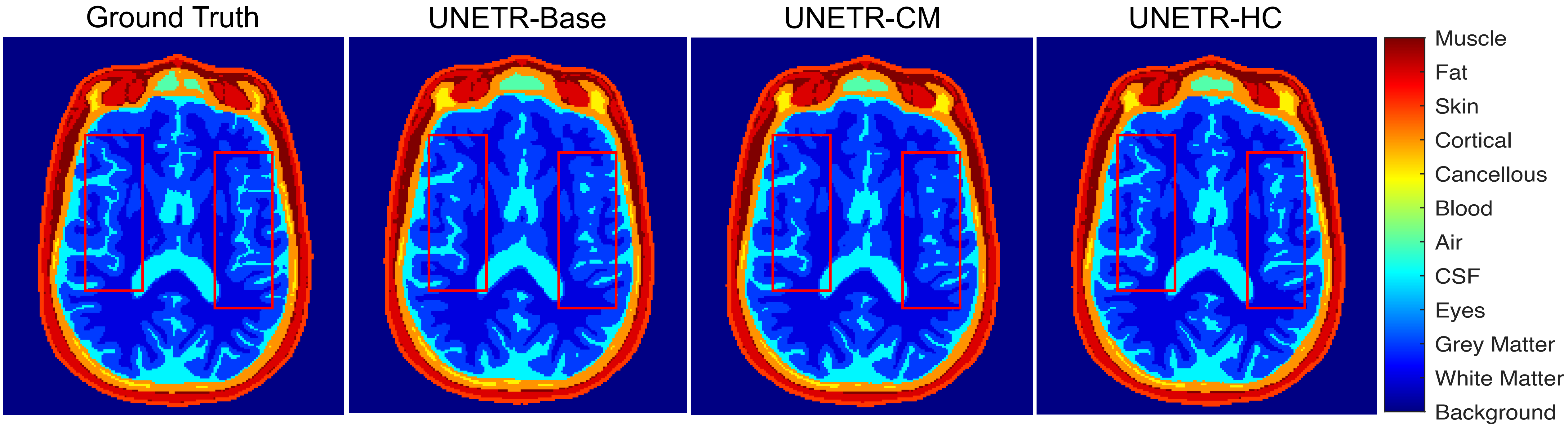
Method	Top-1	Top-2	Top-3
UNETR-Base	0.876	0.979	0.990
UNETR-HC	0.891	0.984	0.993
UNETR-CM	**0.895**	**0.986**	**0.996**

Method	Top-1	Top-2	Top-3
HEADRECO	0.905	0.977	0.983
UNETR-Base	0.913	0.993	0.998
UNETR-HC	0.924	0.995	0.998
UNETR-CM	**0.928**	**0.996**	**0.999**

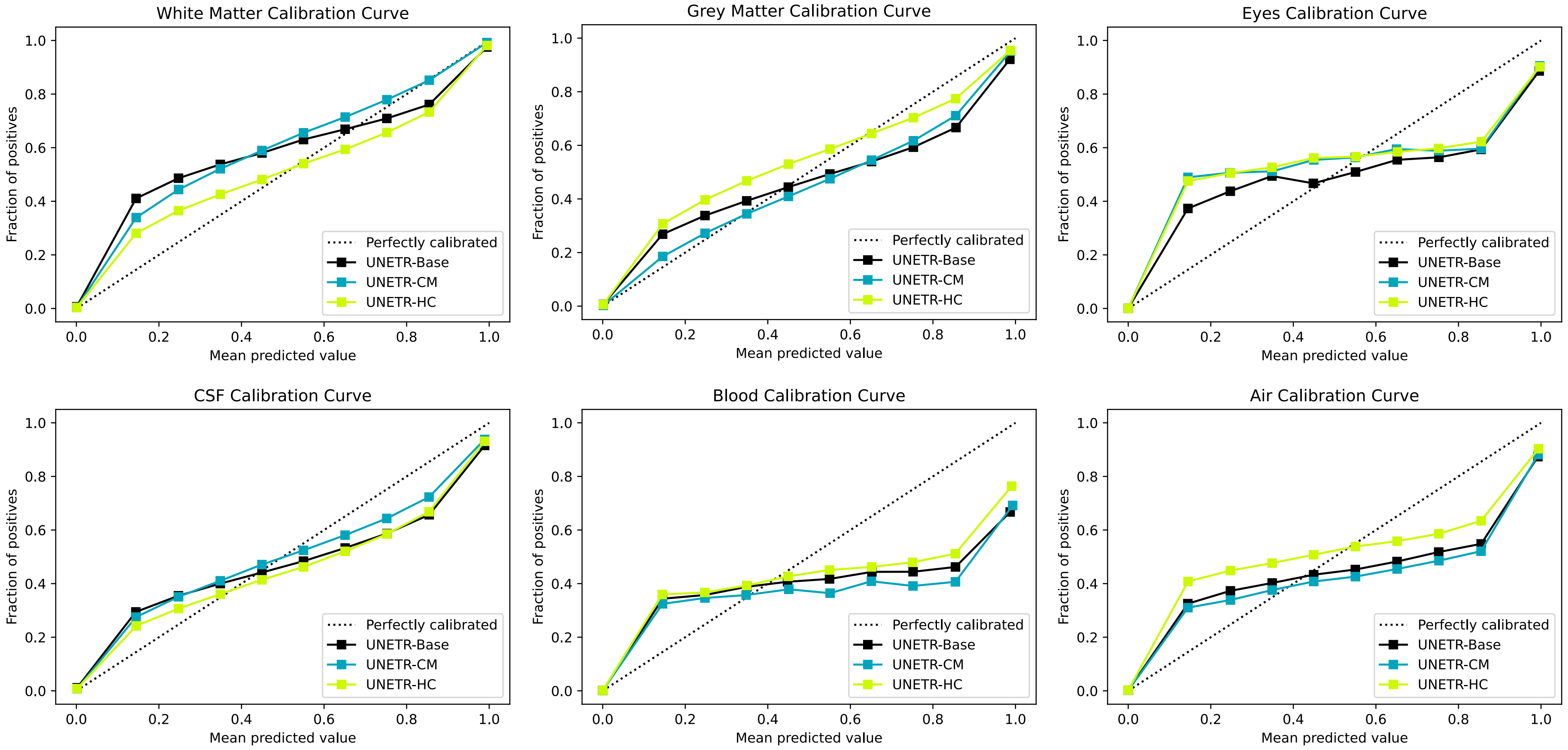
Better Regional Accuracy →

Visual Results on 11 tissues

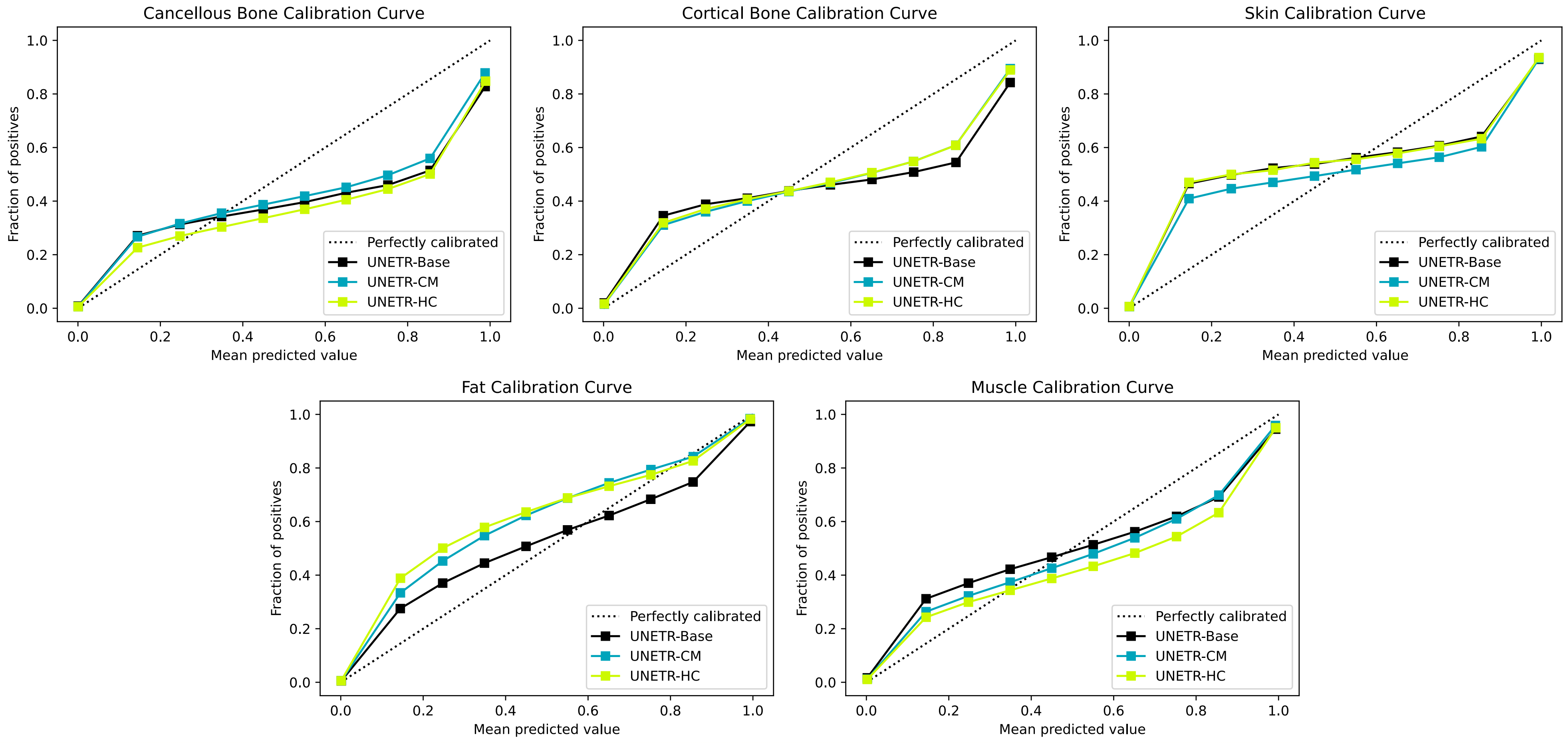
Better Boundary Detection



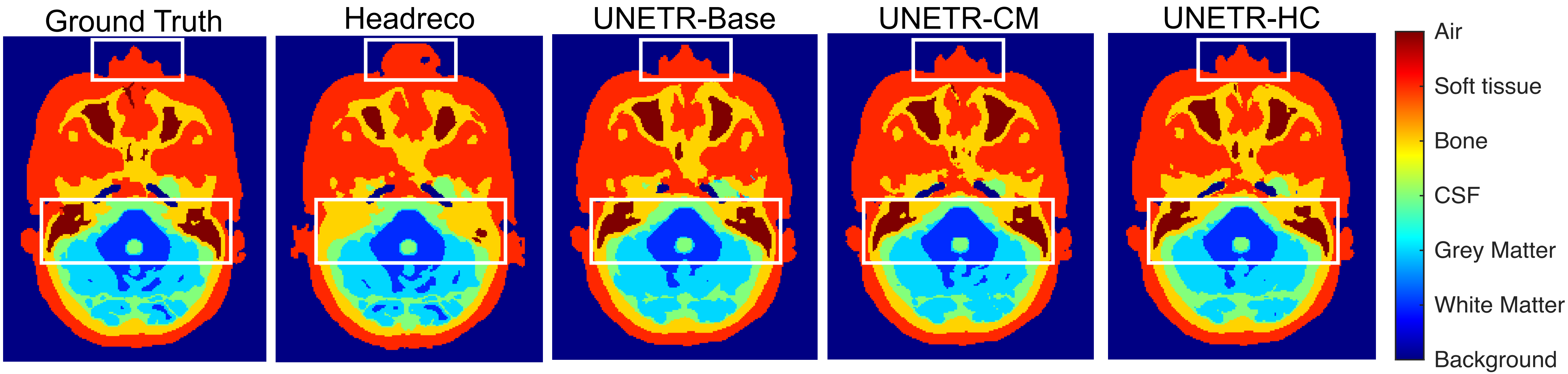
Model Calibration Results (11 tissue)



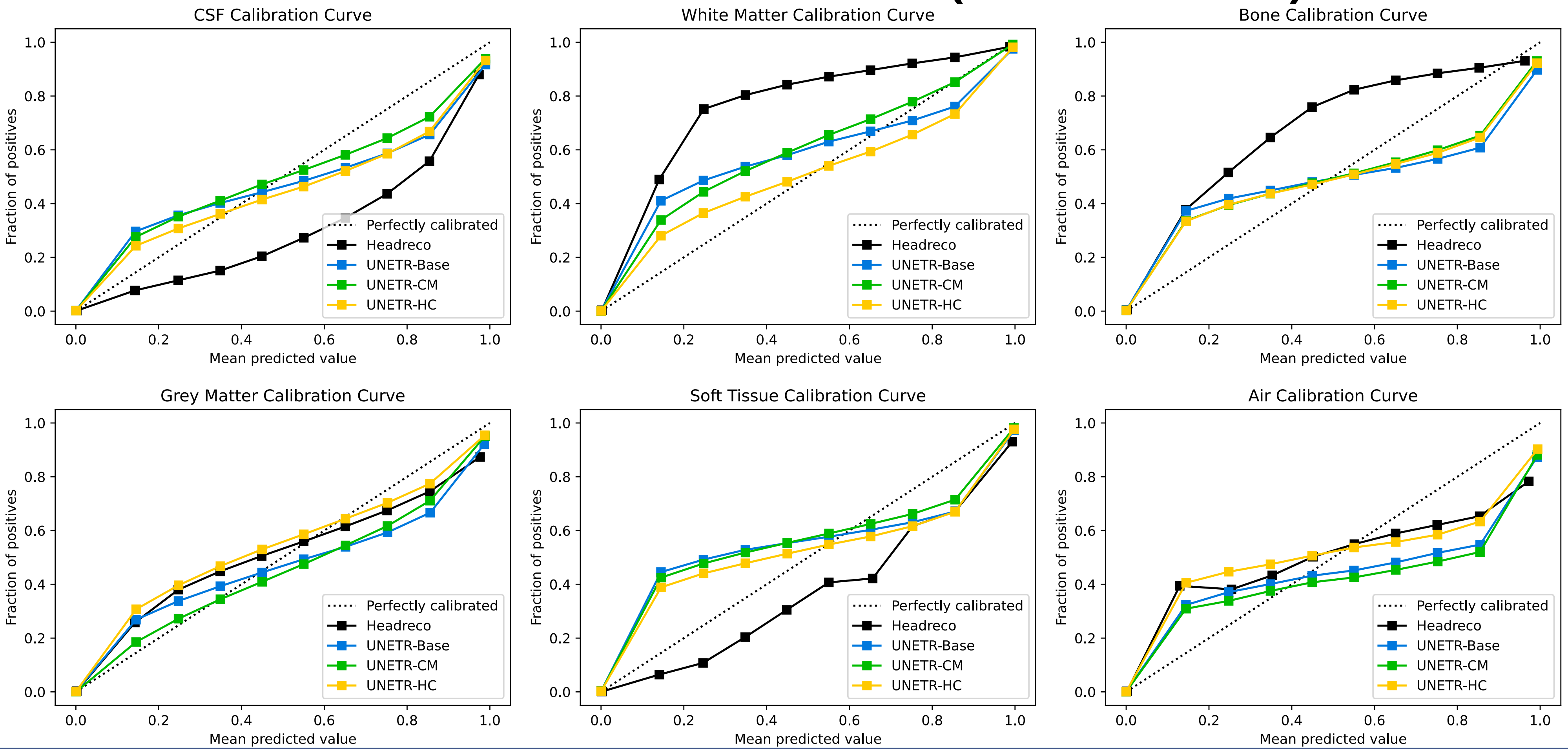
Model Calibration Results (11 tissue)



Visual Results on 6 tissues

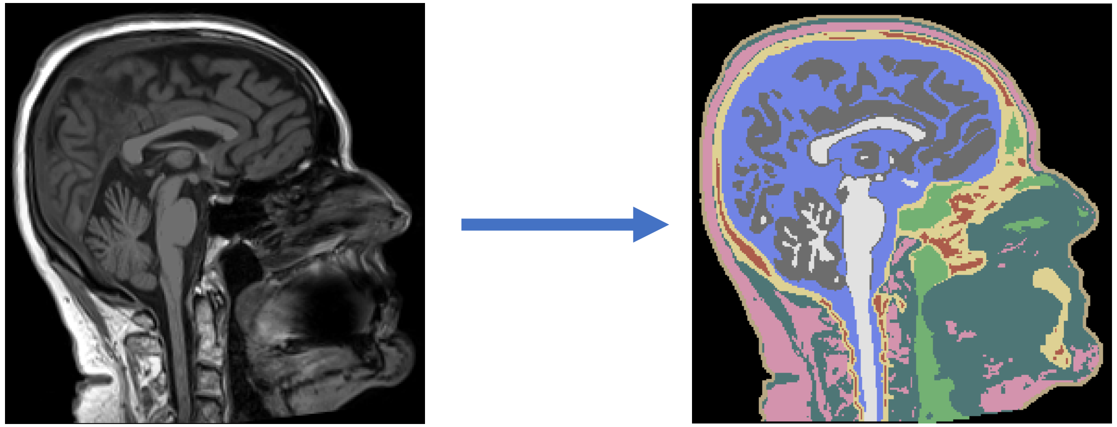


Model Calibration Results (6 tissue)



Conclusions

- Developed two DOMINO methods:
  - DOMINO-CM – better at regional accuracy
  - DOMINO-HC – better at boundary detection
- Model improves calibration without sacrificing accuracy
- Promising results generalizable to public Cityscapes dataset



Source: https://www.cityscapes-dataset.com/

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Poster Session 7

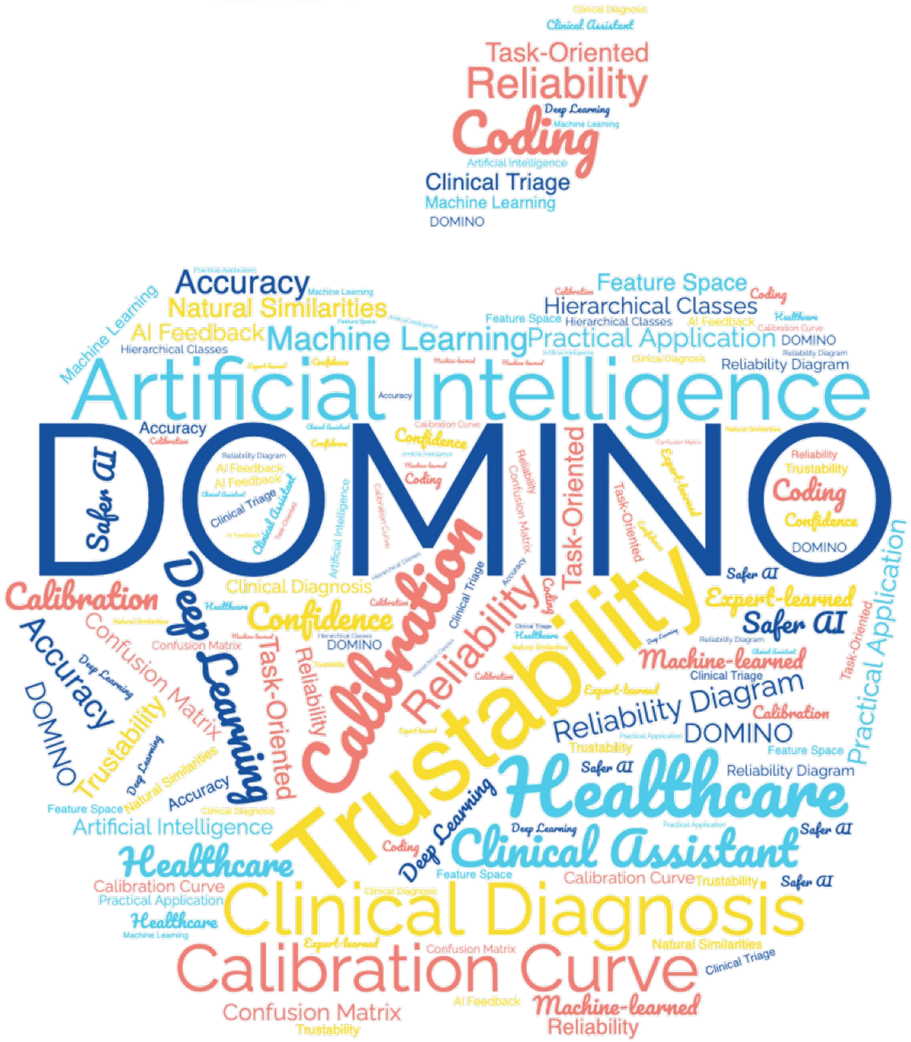
Paper ID: 1693

Image Segmentation, Registration & Reconstruction III

Wednesday, September 21, 2022, 10:30-11:30 AM

Pre-trained models on 11 tissue segmentation from T1 MRIs

github.com/lab-smile/DOMINO


Task-Oriented
Reliability
Coding
Clinical Triage
Machine Learning
DOMINO
Accuracy
Natural Similarities
AI Feedback
Machine Learning
Feature Space
Hierarchical Classes
Practical Application
Reliability Diagram
Artificial Intelligence
DOMINO
Safer AI
Calibration
Deep Learning
Confidence
Clinical Diagnosis
Trustability
Reliability
Task-Oriented
Confusion Matrix
Accuracy
Expert-learned
Machine-learned
Reliability Diagram
Healthcare
Clinical Assistant
Clinical Diagnosis
Calibration Curve
Confusion Matrix
Practical Application
Artificial Intelligence

Thank you!

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