





Radboud Universiteit



**Fast** and **Interactive** Multi-class Segmentation in CBCT Volumes













# Organizers





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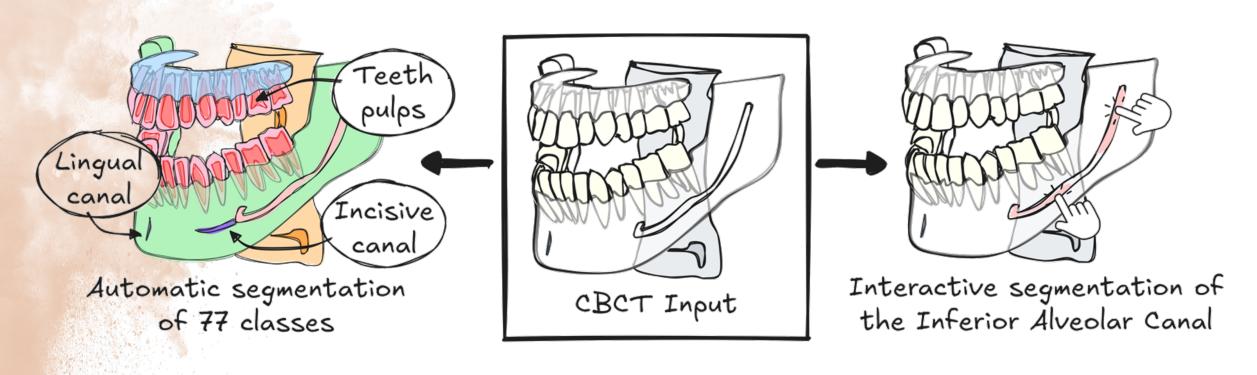
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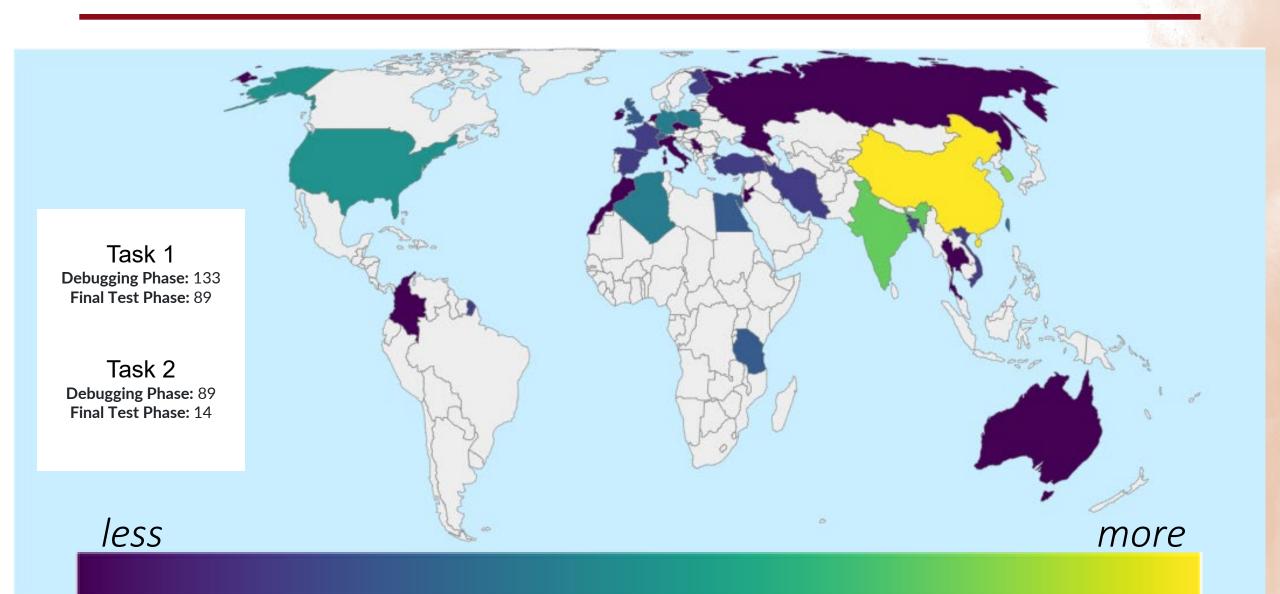
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# Challenge Tasks

- Task 1 Fast Multi-Structure Segmentation in CBCT Volumes
- Task 2 Interactive Segmentation of the Inferior Alveolar Canal (IAC) in CBCT Volumes

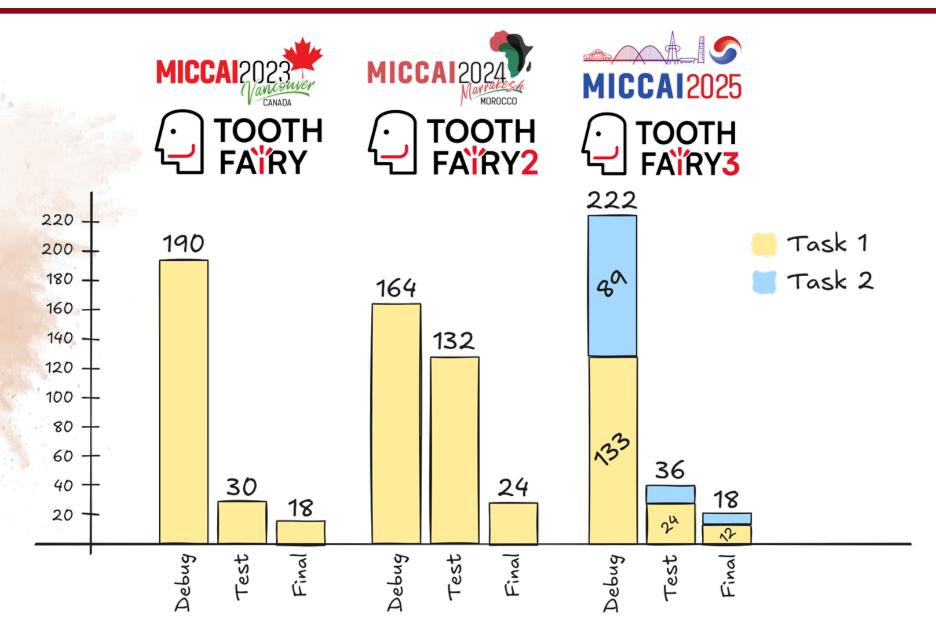


#### Submissions from all over the world!



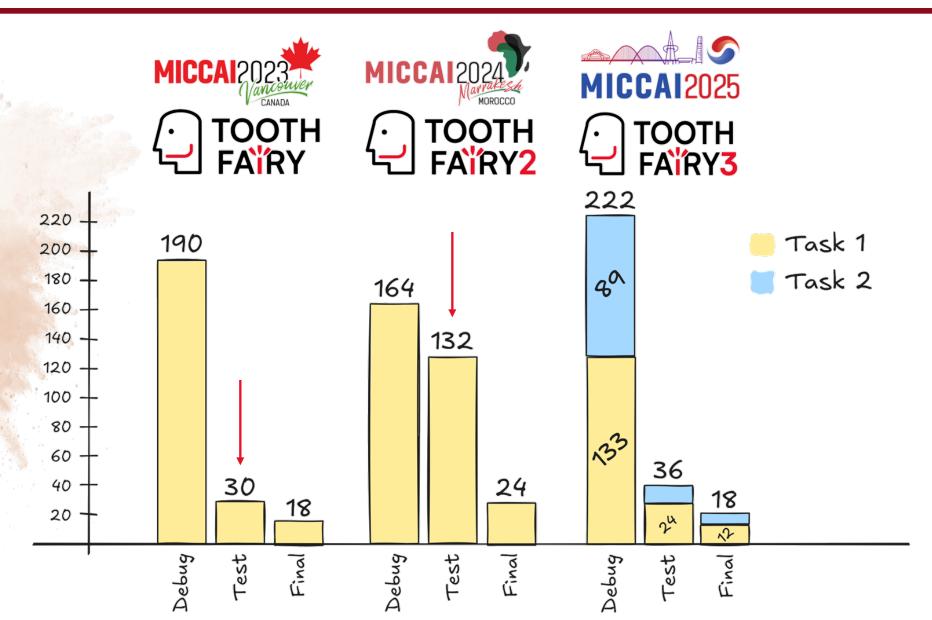
# But with a decreasing trend ...





# But with a decreasing trend ...





# Thanks to all the participants!





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#### ToothFairy3: Fast and Interactive Multi-class Segmentation in CBCT Volumes

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Dataset





52 more volumes;





3D annotations on all volumes;

**532** CBCTs for training, **50** test volumes from two external institutions;

77 labeled classes (42 on GC) + clicks;

Challenges:



Large **number** of **classes** (VRAM requirements);



Non-uniform class distribution and missing classes;



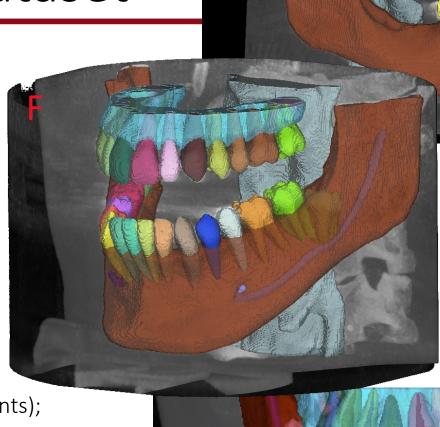
Considerable difference in label sizes;



Varying field of view (P, F and C cases);

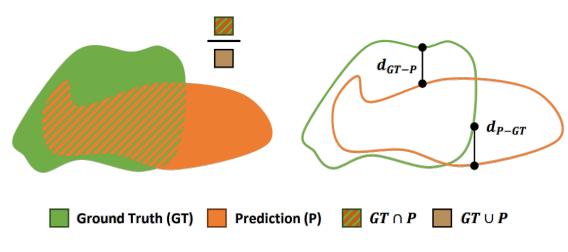


Inference time as a major constraints.

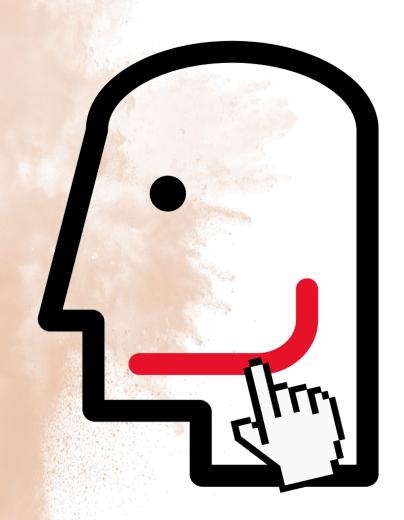


# Task 1 - Metrics & Ranking

- 1. For each class and for each volume, calculate the **Dice score (DSC)** and the **HD95**. Measure also the **inference** time (Time) and the **maximum used memory** (Mem);
- 2. Average the DSC and the HD95 for each class across all volumes and compute the average Time across all volumes.
- 3. Rank all the DSC, HD95, Time, and maximum used memory independently (93 rankings);
- 4. Average the rankings obtained at point 3 for each DSC, HD95, and Time to produce the final rank. Average Time is weighted as much as the number of classes included in the dataset to balance its importance with respect to the other metrics;
- 5. If two or more final ranks obtained at point 4 are equal, Mem will be used to break ties;
- 6. If two or more ranks are still equal, it is a tie: the prize will be evenly split.



### Task 2 - The Interactive Segmentation Initiative

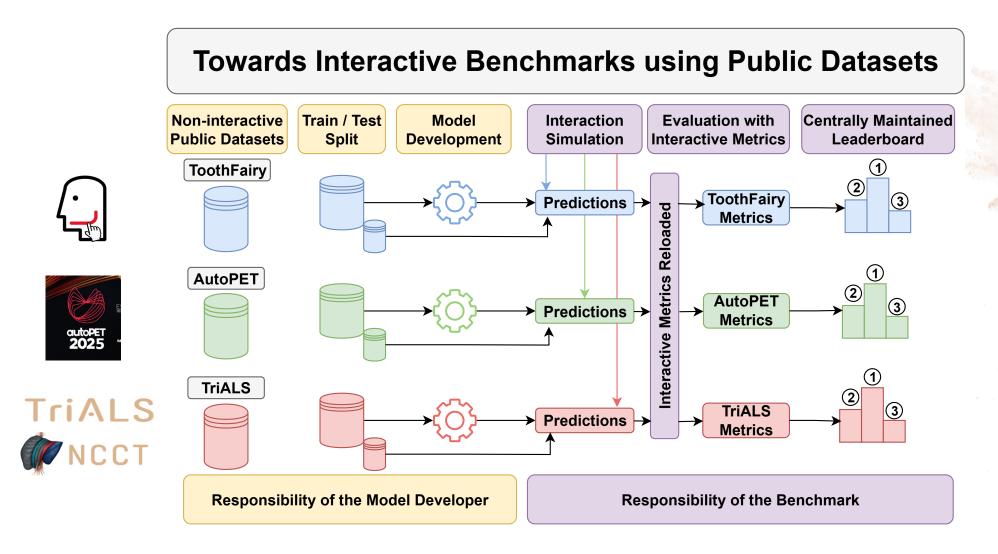


Task 2: Interactive Segmentation of Inferior Alveolar Canal:

- Novel task since 2025 (MICCAI + CVPR)
- Use human clicks to help the model

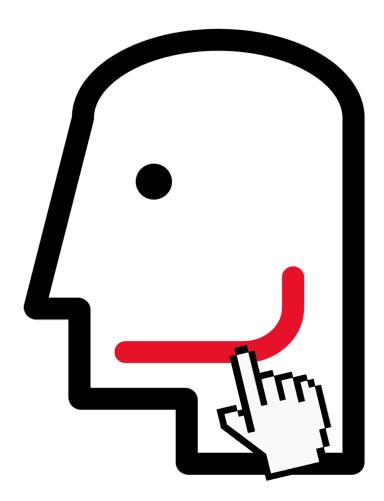
### The Interactive Segmentation Initiative

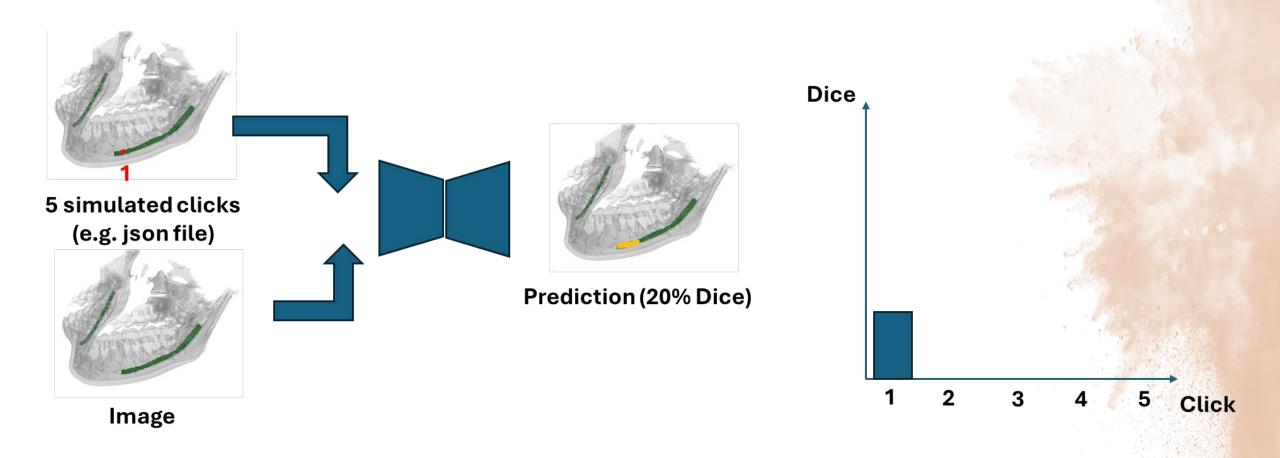
How it all started...

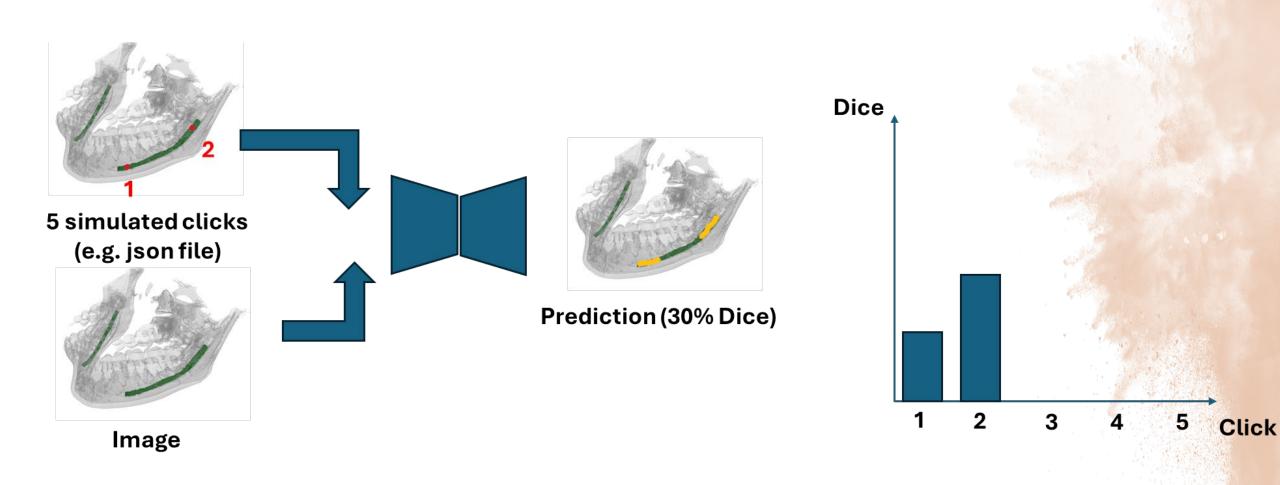


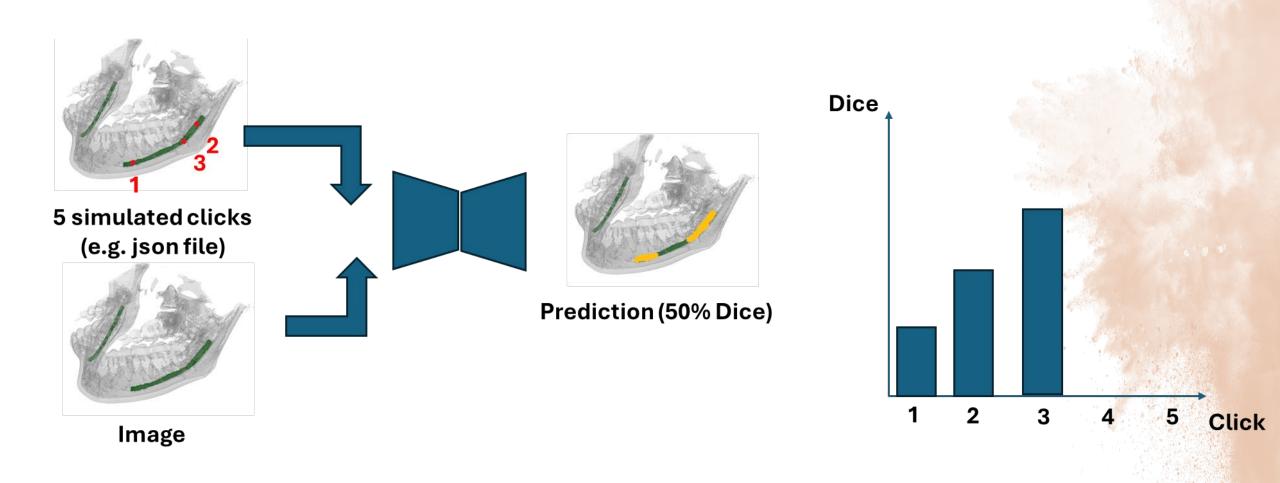
Reasons for using interactive segmentation models:

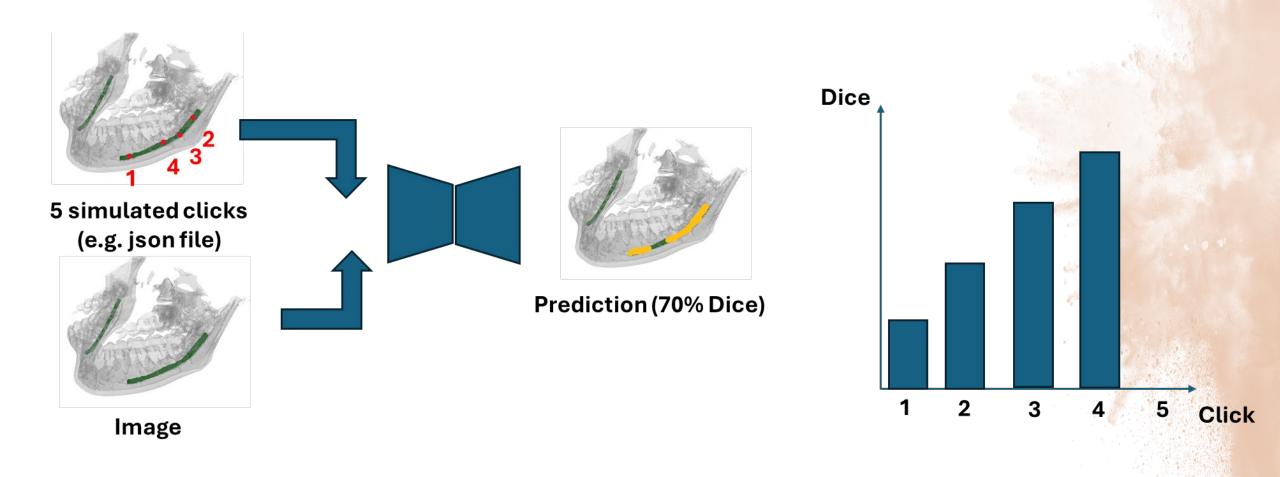
- Click-based annotation tools
- Bridge the gap for difficult tasks
  - o Clicks encode expert knowledge
- Make models more trustworthy and reliable
  - o Implicit quality control → User continuously corrects model's mistakes

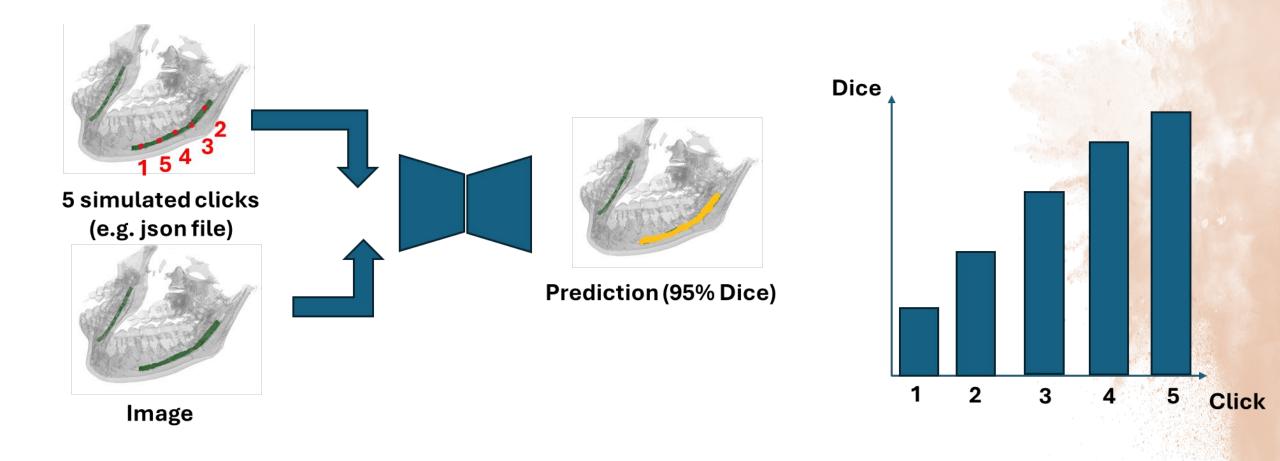








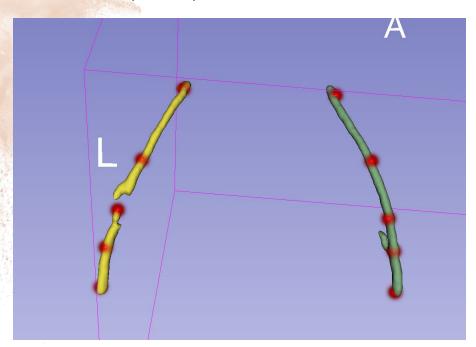


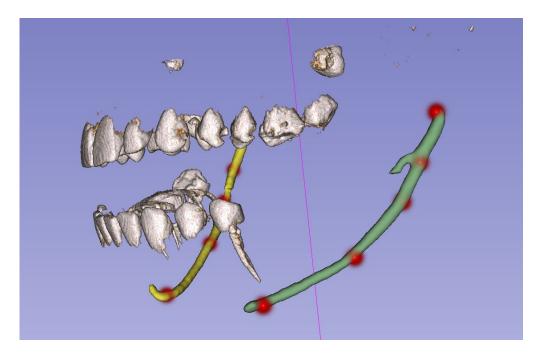


#### Clicks simulation

#### Simulation method is the same for all volumes

- Aim: method can later be used as an annotation protocol
- Approach:
  - o First / last click is always 0-5 voxels from the first / last axial slice of the IAC
  - o The other 3 clicks are placed (almost) uniformly across the middle axial slices
  - o Each of the 5 clicks is placed in the center of the mask in the slice + small perturbation
- All participants receive the same clicks → fair evaluation

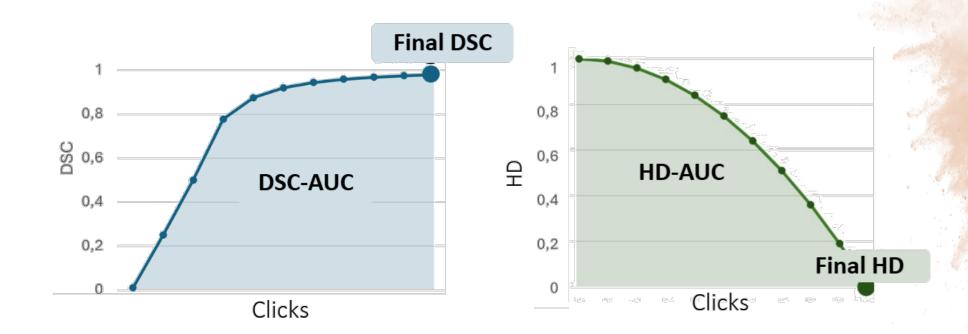




#### Interactive Metrics

Use same metrics as Task 1, but extend them to be interactive!

- Additionally:
  - o Inference time
  - Maximum memory (only for tie breakers)

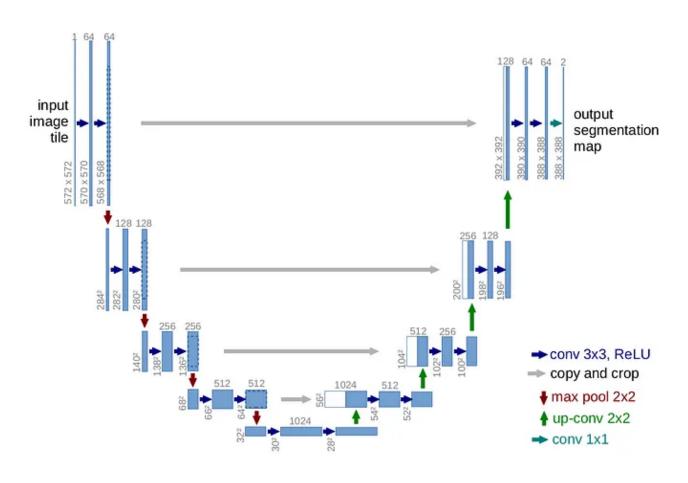


# Task 2 - Ranking

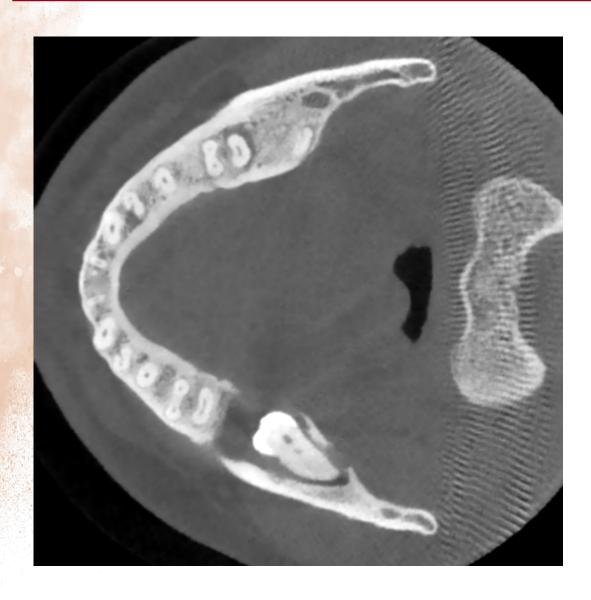
- 1. For each branch of the IAC (left and right) and for each volume, calculate the four metrics:
  - a) DSC@FinalClick;
  - b) HD95@FinalClick;
  - DSC-to-Click AUC, for a fixed number of 5 interaction steps;
  - d) HD95-to-Click AUC, for a fixed number of 5 interaction steps;

The result is 4 metrics \* 2 IAC branches, 8 scores in total. Measure also:

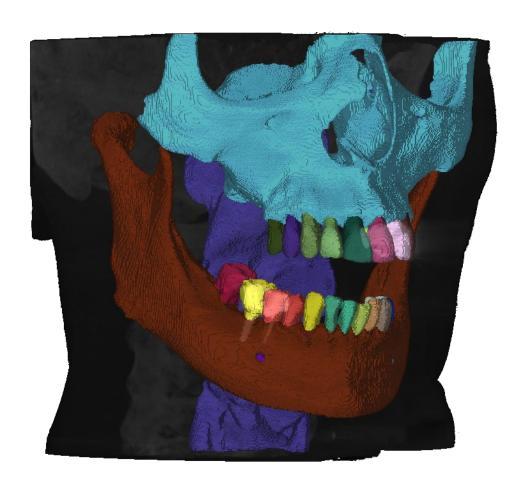
- e) average inference time of the five interaction steps (Time);
- f) and (f) maximum used memory (Mem), for all cases;
- 2. Average DSC- and HD95-based metrics for each IAC branch across all volumes.
- 3. Rank all ten metrics independently;
- 4. Average the eight rankings obtained at point 3 for each DSC- and HD95-based metric and the rankings obtained for Time to produce the final rank (9 rankings in total);
- 5. If two or more final ranks obtained at point 4 are equal, use the Mem ranking to break ties;
- 6. If two or more ranks are still equal, it is a tie: the prize will be evenly split.



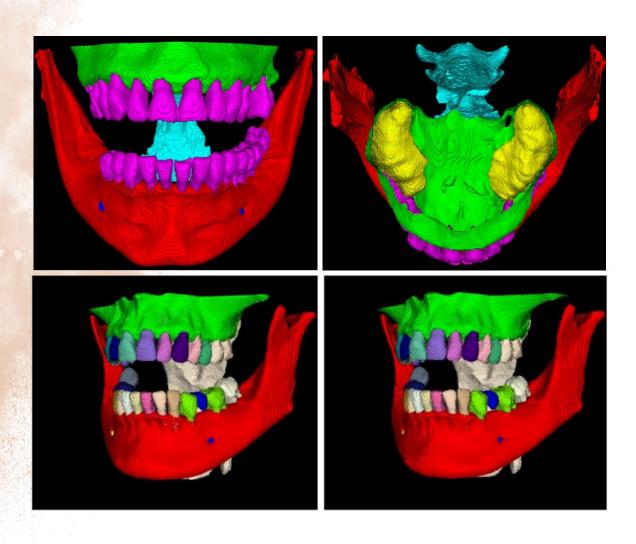
- Many participants used Unet with the nnUnet Framework;
- Approaches integrating Mamba placed in the top section of the final ranking;
- 3D SegResNet has been employed as well;
- nnInteractive and VISTA for the interactive task;



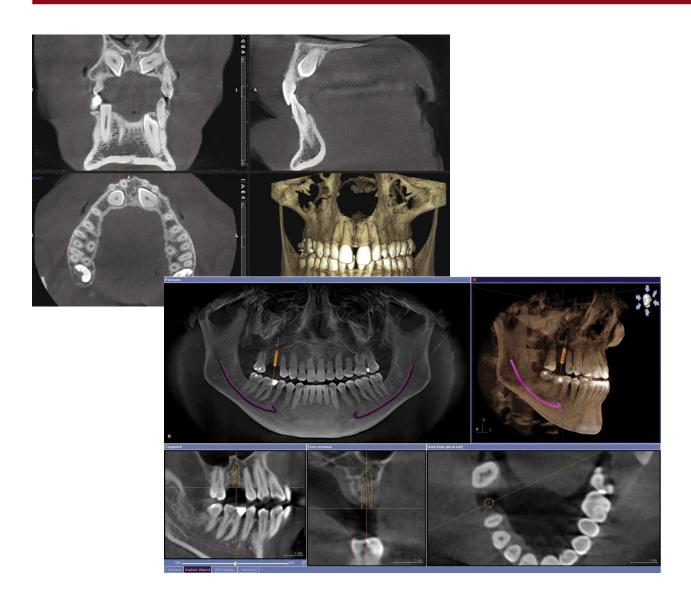
- Many participants used Unet with the nnUnet Framework;
- Moderate use of augmentations but almost no augmentation at test time;



- Many participants used Unet with the nnUnet Framework;
- Moderate use of augmentations;
- Some have preprocessed the dataset by removing training samples, others have included only completely labeled sets in the training;



- Many participants used Unet with the nnUnet Framework;
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- Some have preprocessed the dataset by removing training samples, others have included only completely labeled sets in the training;
- Some employed a multi-stage approach;

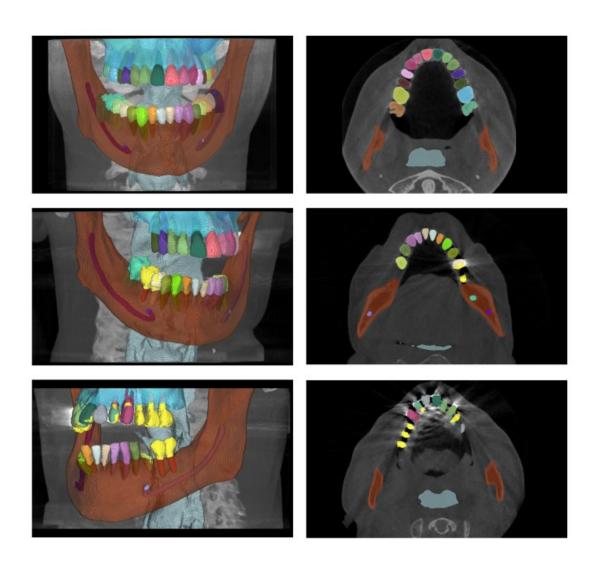


- Many participants used Unet with the nnUnet Framework;
- Moderate use of augmentations;
- Some have preprocessed the dataset by removing training samples, others have included only completely labeled sets in the training;
- Some employed a multi-stage approach;
- As far as we know, only one employed external data from the STSR challenge;

Dice 
$$Loss = 1 - \frac{2 \cdot \sum_{i}^{N} (p_i \cdot g_i)}{\sum_{i=1}^{N} (p_i + g_i)}$$

$$CE Loss = -\frac{1}{N} \sum_{i=1}^{N} [y_i \cdot \log(p_i) + (1 - y_i) \cdot \log(1 - p_i)]$$

- Many participants used Unet with the nnUnet Framework;
- Moderate use of augmentations;
- Some have preprocessed the dataset by removing training samples, others have included only completely labeled sets in the training;
- Some employed a multi-stage approach;
- As far as we know, only one employed external data from the STSR challenge;
- Most sticked on a combination of Dice and Cross-entroy loss;



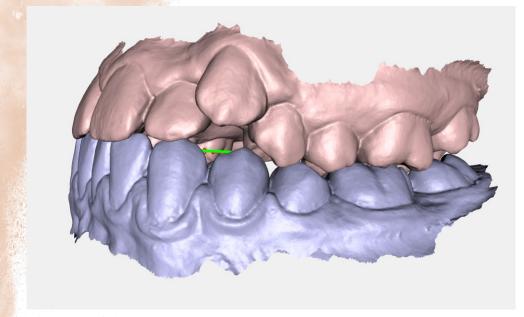
- Most of the participants used Unet with the nnUnet Framework;
- Moderate use of augmentations;
- Some have preprocessed the dataset by removing training samples;
- Some employed a multi-stage approach;
- Some have preprocessed the dataset by removing training samples, others have included only completely labeled sets in the training;
- Some employed a multi-stage approach;
- As far as we know, only one employed external data from the STSR challenge;
- Many have designed solutions to filter output predictions;
- The used of ensemble has been reduced;









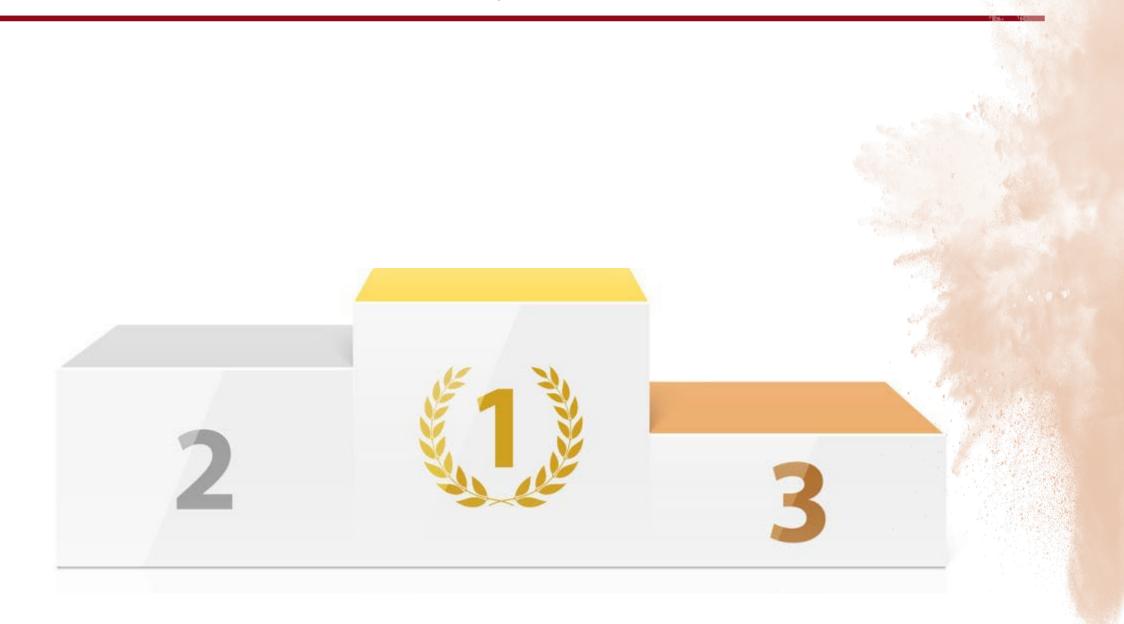


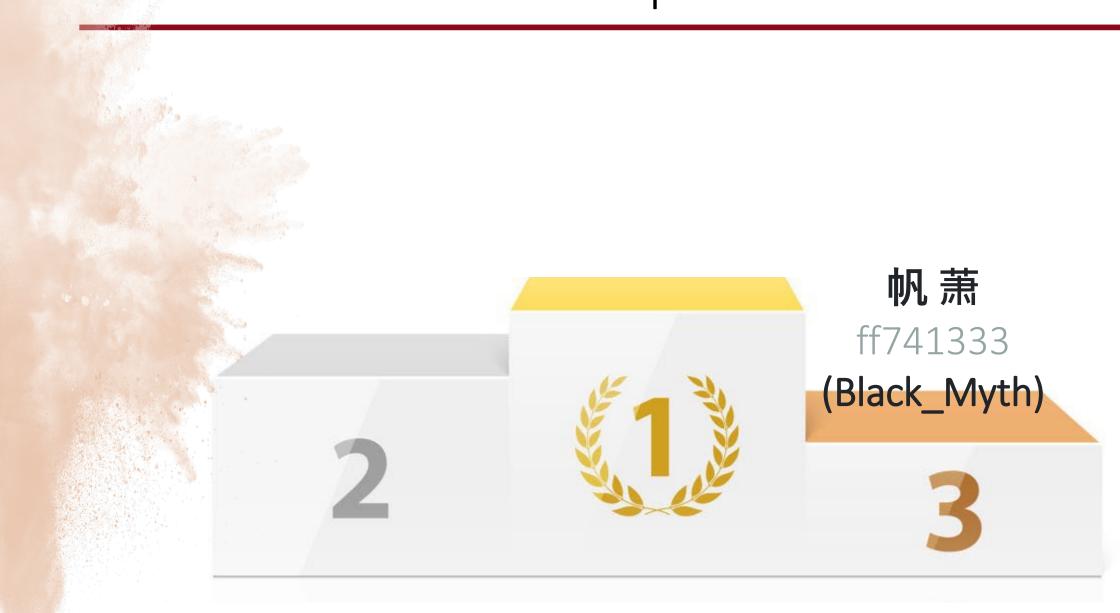




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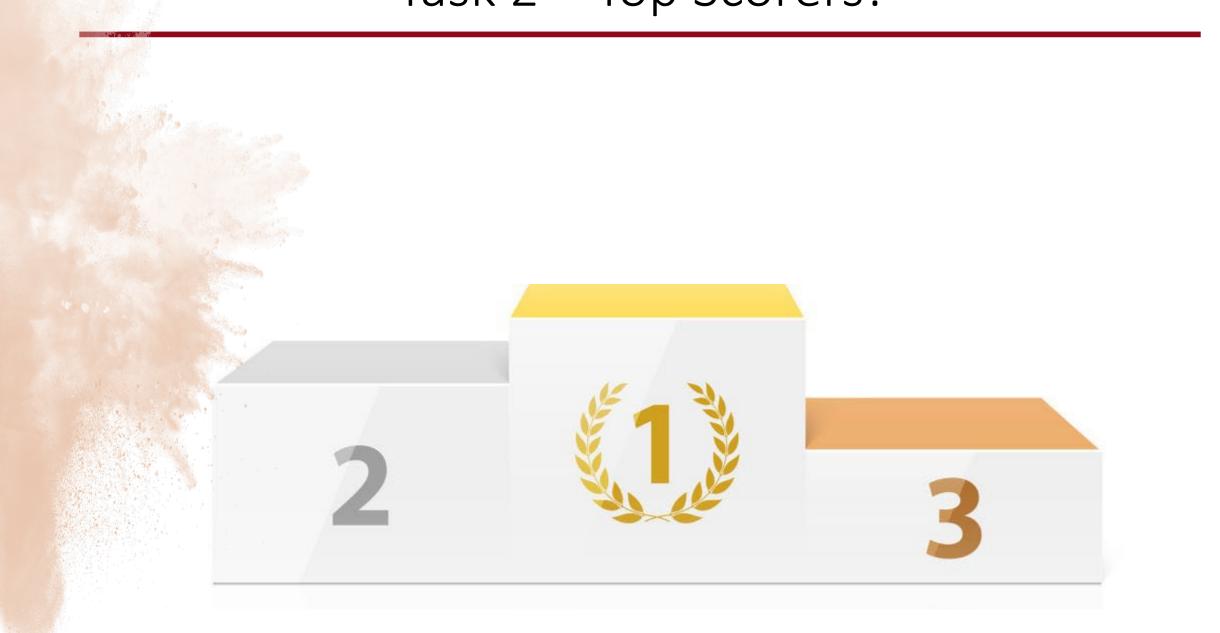


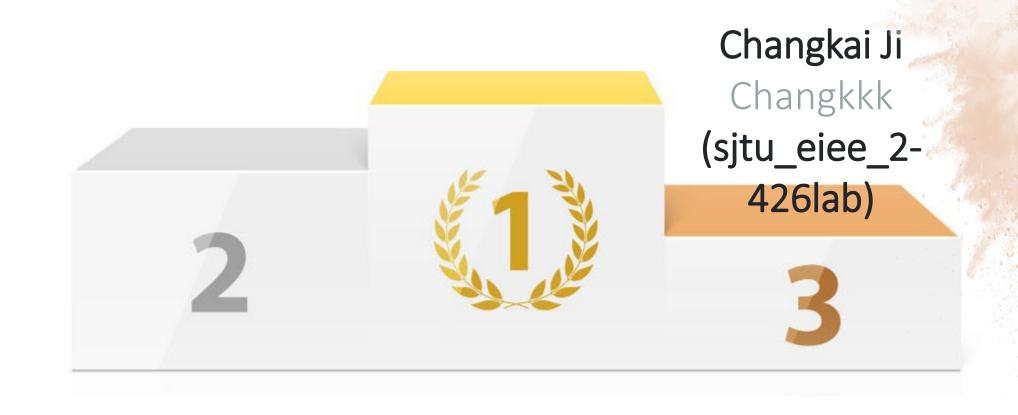


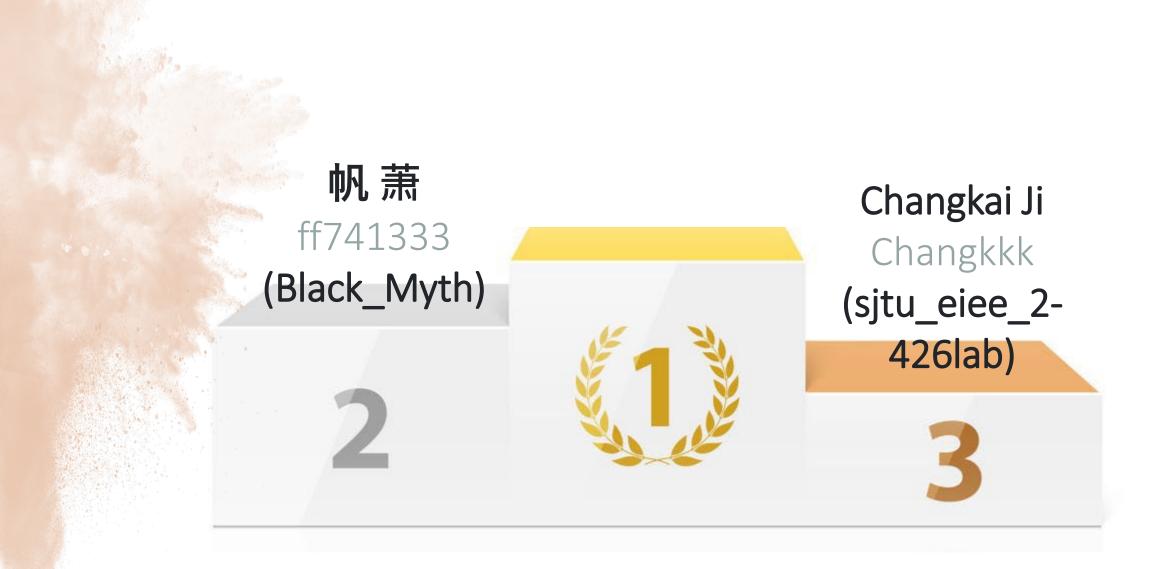


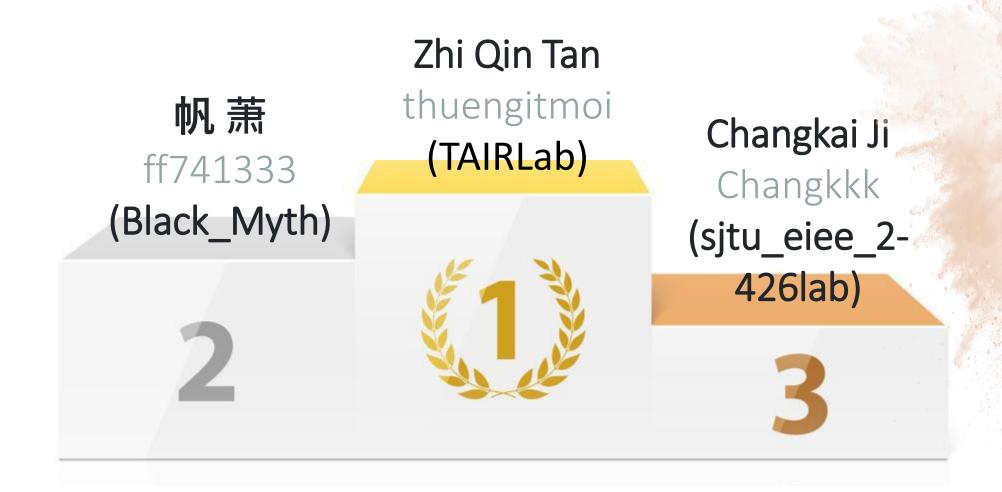
# Final Results

TAIR-Lab	1	Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		40,58	0,84	2,4	38,17	3,0	3,1
sjtu_eiee_2-426lab	2	Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		17,46	0,77	4,9	94,77	5,3	3,7
Black_Myth	3	Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		90,04	0,85	2,0	33,23	2,3	3,8
SMIR		Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		30,30	0,76	4,9	96,40	5,3	4,1
DLaBella29		Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		74,38	0,78	5,0	43,20	3,4	4,5
KiRyum_Prince		Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		97,68	0,82	3,2	50,32	3,7	5,0
gagaha		Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		38,42	0,58	6,9	125,10	6,7	5,5
medlab		Runtime(s)	Dice	Dice Rank	HD95	HD95 Rank	Rank
Aggregated		79,54	0,47	7,3	138,68	7,0	6,8









### Final Results

TAIR Lab	Runtime(s)	Dice_L IAC_AUC	Dice_L IAC_Final	Dice_R IAC_AUC	Dice_R IAC_Final	HD95_L IAC_AUC	HD95_L IAC_Final	HD95_R IAC_AUC	HD95_R IAC_Final	Rank
Nagrogatod	100,64	4,34	0,87	4,31	0,86	11,29	2,26	10,2	2,04	
Aggregated										1.00
Rank	4	1	1	2	2	1	1	1	2	1.66
BlackMyth 2	Runtime(s)	Dice_L IAC_AUC	Dice_L IAC_Final	Dice_R IAC_AUC	Dice_R IAC_Final	HD95_L IAC_AUC	HD95_L IAC_Final	HD95_R IAC_AUC	HD95_R IAC_Final	Rank
\ggregated	168,42	4,3	0,86	4,32	0,87	15,05	2,54	14,55	2,03	
Rank	6	2	2	1	1	2	2	2	1	2.11
changkkk 3	Runtime(s)	Dice_L IAC_AUC	Dice_L IAC_Final	Dice_R IAC_AUC	Dice_R IAC_Final	HD95_LIAC_AUC	HD95_L IAC_Final	HD95_R IAC_AUC	HD95_R IAC_Final	Rank
Aggregated	16,09	3,79	0,76	3,83	0,77	201,75	40,35	131,42	26,28	
Rank	1	3	3	3	3	4	5	4	5	3.44
DLaBella	Runtime(s)	Dice_L IAC_AUC	Dice_L IAC_Final	Dice_R IAC_AUC	Dice_R IAC_Final	HD95_L IAC_AUC	HD95_L IAC_Final	HD95_R IAC_AUC	HD95_R IAC_Final	Rank
Aggregated	152,02	2,98	0,75	2,97	0,74	19,27	4,82	17,82	4,45	
Rank	5	5	4	5	4	3	3	3	3	3.88
gagaha	Runtime(s)	Dice_L IAC_AUC	Dice_L IAC_Final	Dice_R IAC_AUC	Dice_R IAC_Final	HD95_L IAC_AUC	HD95_L IAC_Final	HD95_R IAC_AUC	HD95_R IAC_Final	Rank
Aggregated	26,09	2,64	0,68	2,63	0,7	585,8	11,93	588,75	9,63	
Rank	2	6	5	6	5	6	4	6	4	4.88
ATTIAC	Runtime(s)	Dice_L IAC_AUC	Dice_L IAC_Final			HD95_L IAC_AUC				
Aggregated	83,41	3,18	0,64	3,18	0,64	536,33	107,25	580,63	116,13	
Rank	3	4	6	4	6	5	6	5	6	5