Benchmarking Evaluation Metrics for Tubular Structure Segmentation in Biomedical Images

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Introduction

- **Tubular tree-like structures** are common in biology and medicine : vascular networks airways, neuronal trees

- The **segmentation** of these structures is crucial for many downstream applications : tracing, numerical simulation

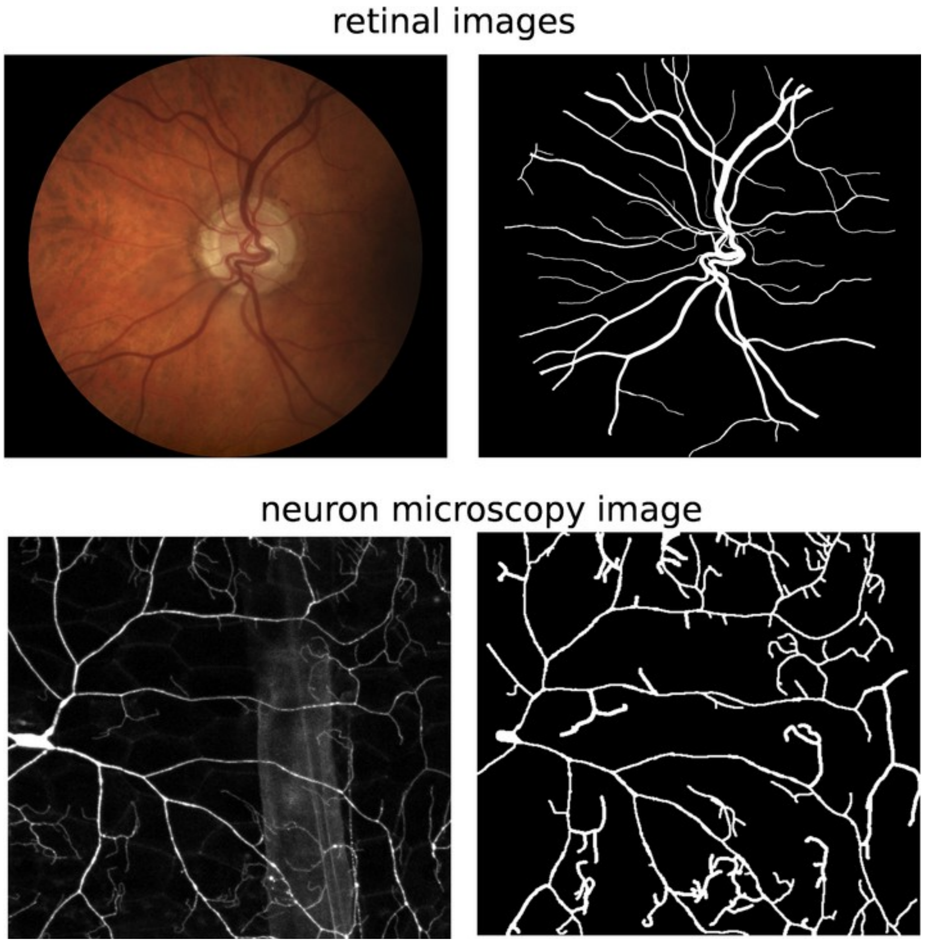


Figure 1. Example of biomedical images showing tubular, tree-like structures and the target segmentation.

Introduction

- **Deep learning** has led to tremendous progress in biomedical image segmentation.

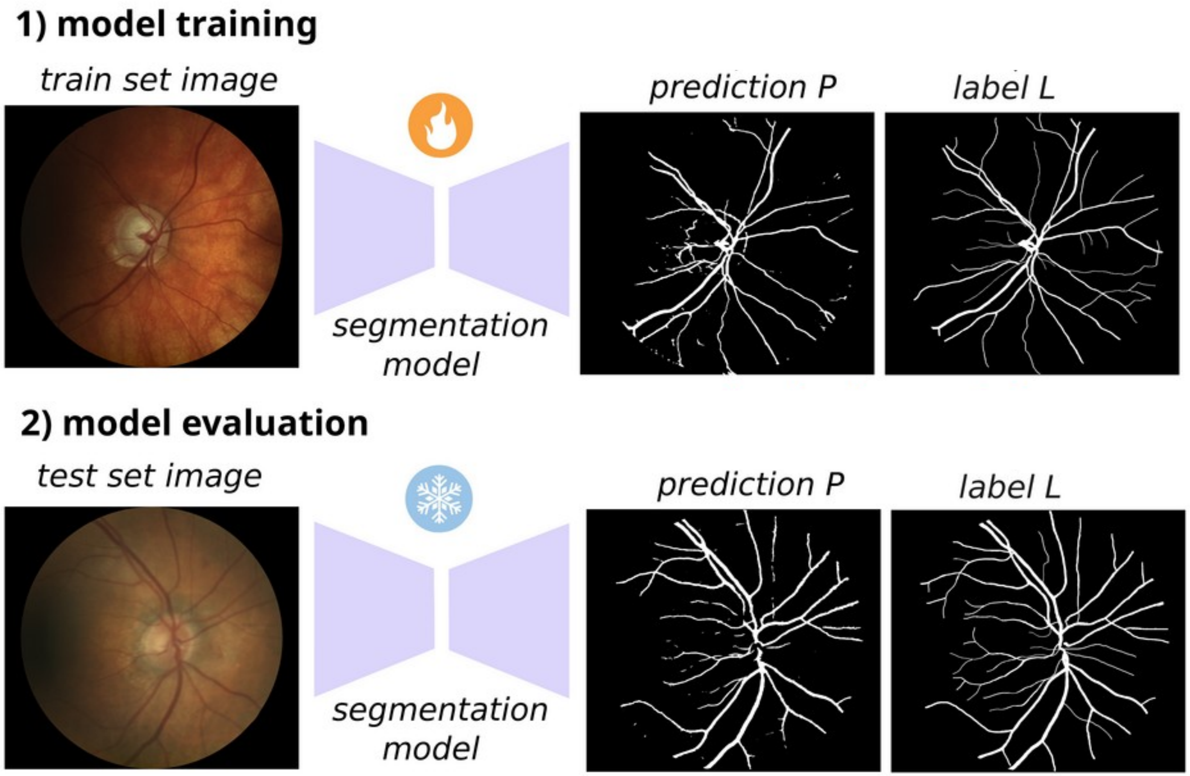


Figure 2. Importance of quality metrics.

Introduction

- To **train and evaluate** segmentation models, we need to design **metrics** measuring the **quality** of a predicted segmentation compared to the ground-truth labels.

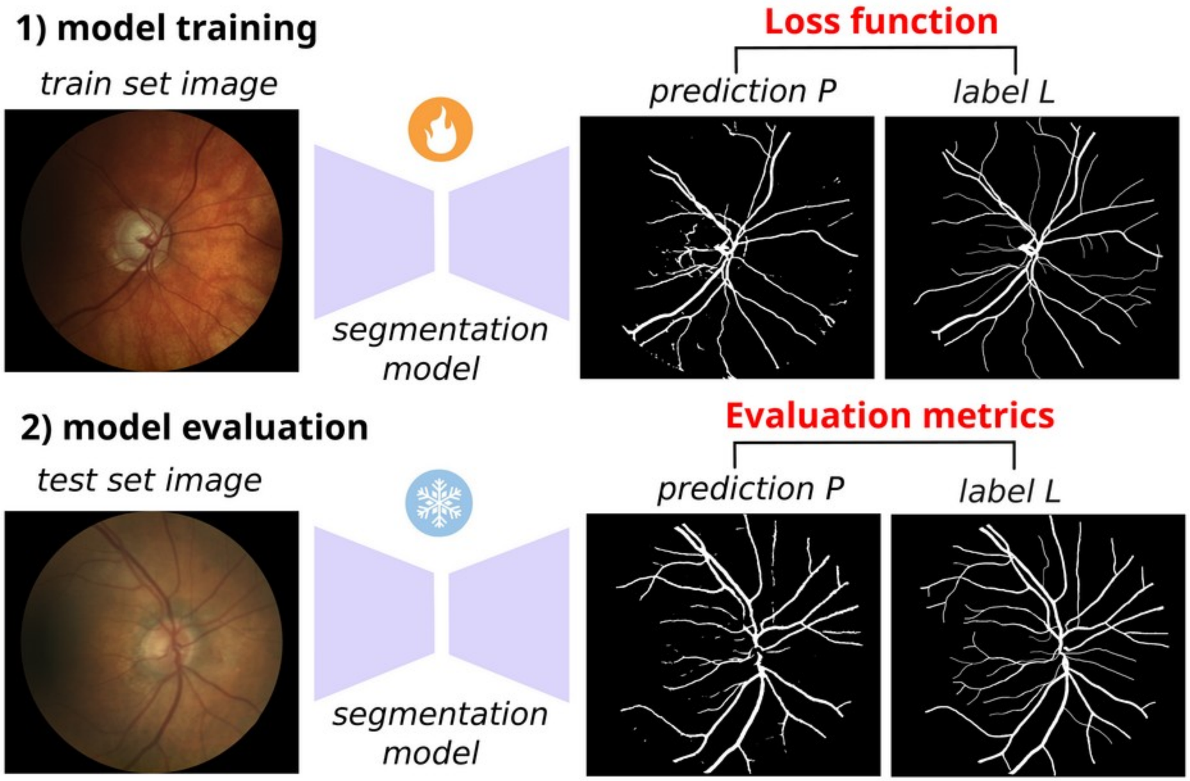


Figure 2. Importance of quality metrics.

Introduction

- Tubular structure segmentation offers unique **challenges**, leading to the design of **various metrics and loss functions** in recent years.

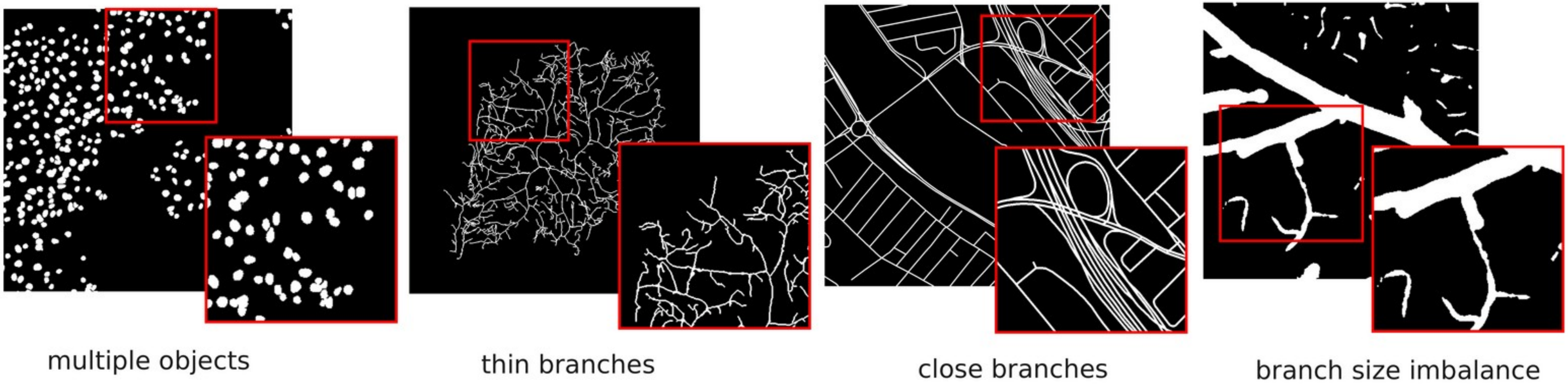


Figure 3. Challenges of tubular structure segmentation.

Introduction – Overlap-based quality metrics

- The **Dice** score is based on the pixel-wise mismatch between label and prediction.

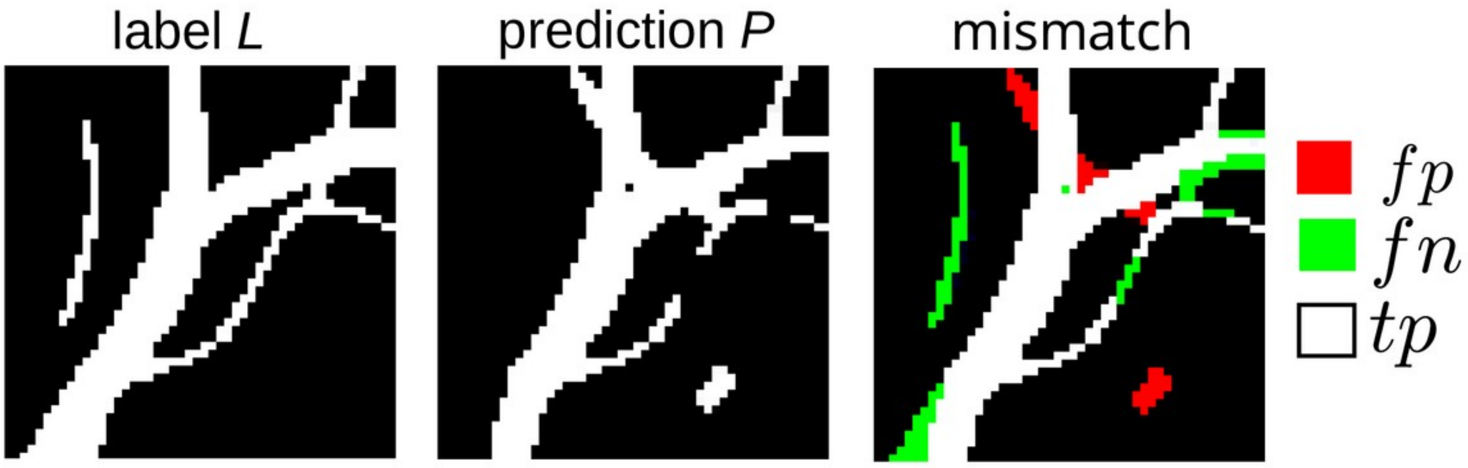


Figure 4. Illustration of the Dice calculation.
(tp = true positives, fn = false, fp = false postives)

Introduction – Skeleton-based quality metrics

- The **clDice**[1] relies on the **skeleton** mismatch.
- The **cbDice**[2] includes the **distance to boundaries.**

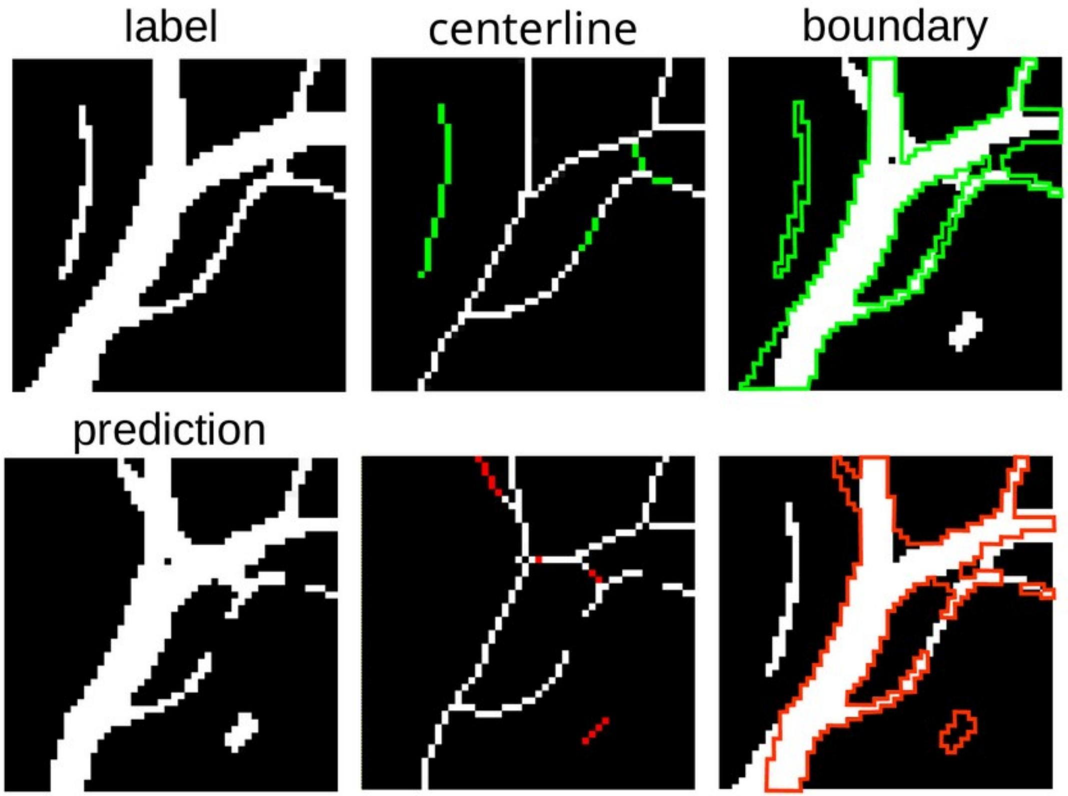


Figure 5. Illustration of the clDice and cbDice.

[1] Shit, Suprosanna, et al. "clDice-a novel topology-preserving loss function for tubular structure segmentation." IEEE/CVF, 2021.
[2] Shi, Pengcheng, et al. "Centerline boundary dice loss for vascular segmentation." MICCAI, 2024.

Introduction –
Algebraic topology quality metrics

β_0 = number of **connected components CC**
β_1 = number of **holes** in the image

- The **Betti error** β^{err} is the difference between the Betti numbers of the label and prediction.

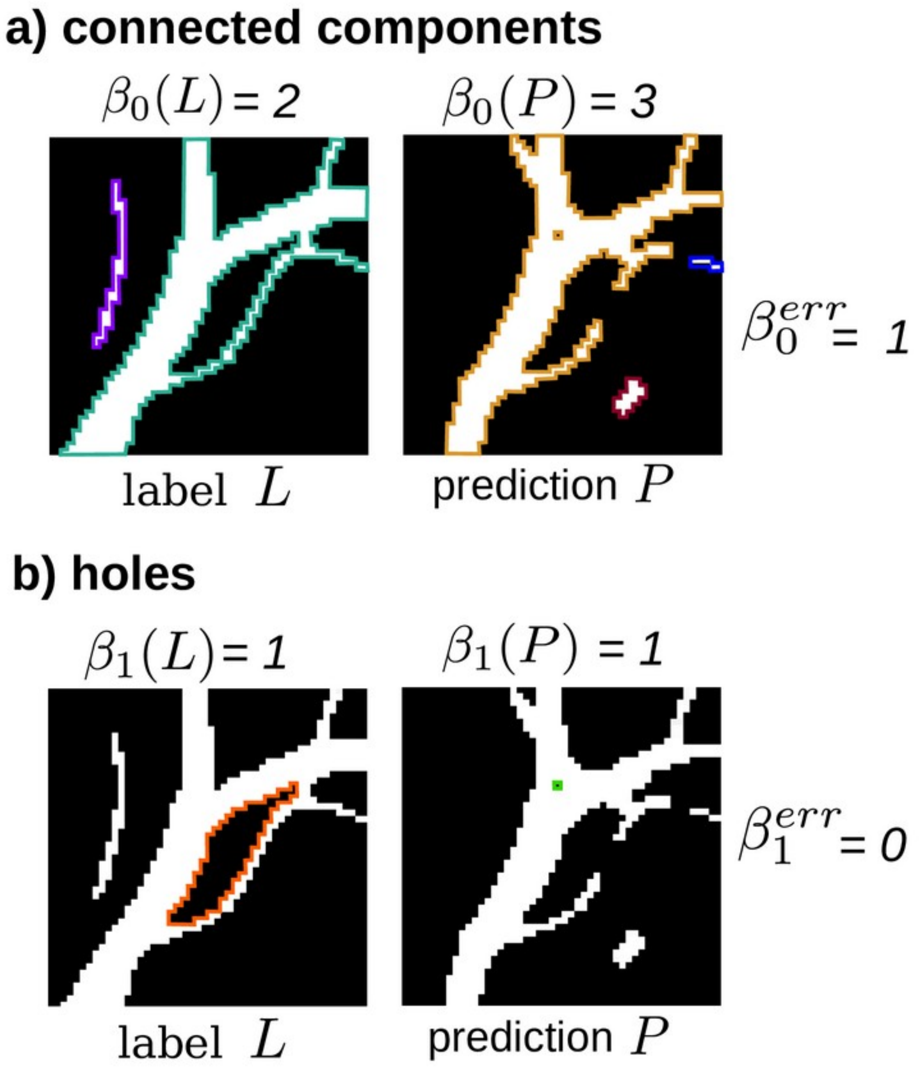
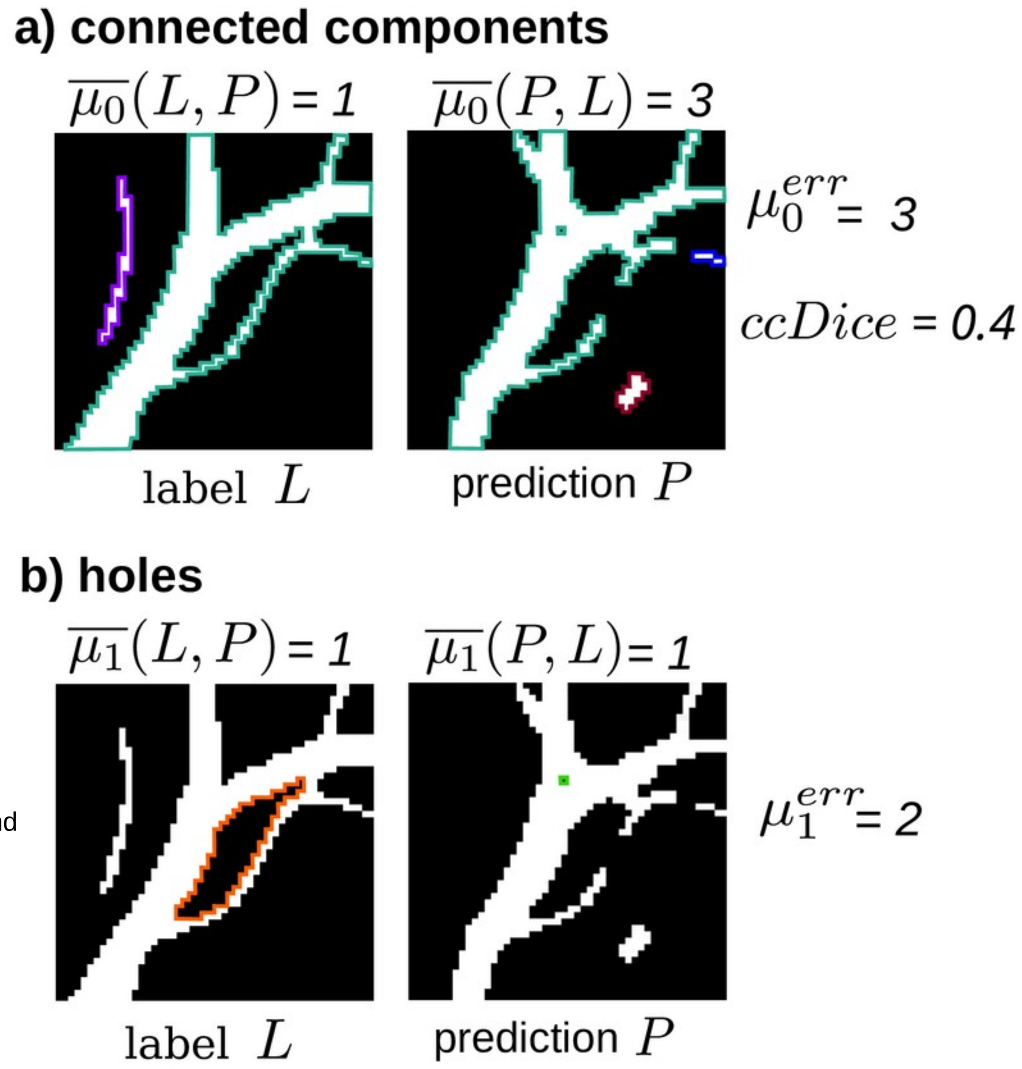


Figure 6. Illustration of the Betti error calculation.

Introduction – Algebraic topology quality metrics

- The **Betti matching error**[3] μ^{err} and the **ccDice**[4] are matching CC and holes.



[3]Stucki, Nico, et al. "Topologically faithful image segmentation via induced matching of persistence barcodes." International Conference on Machine Learning, 2023.

[4]Rougé, Pierre, Odyssée Merveille, and Nicolas Passat. "ccDice: A topology-aware Dice score based on connected components." International Workshop on Topology-and Graph-Informed Imaging Informatics, MICCAI 2024.

Figure 7. Illustration of the Betti matching and ccDice calculation.

Challenge

- Which metric / loss shall I use? How to be sure than the metric reflects my expectations?
  → Quality is **subjective**, making it difficult to assess the **strengths and weaknesses** of each metric.

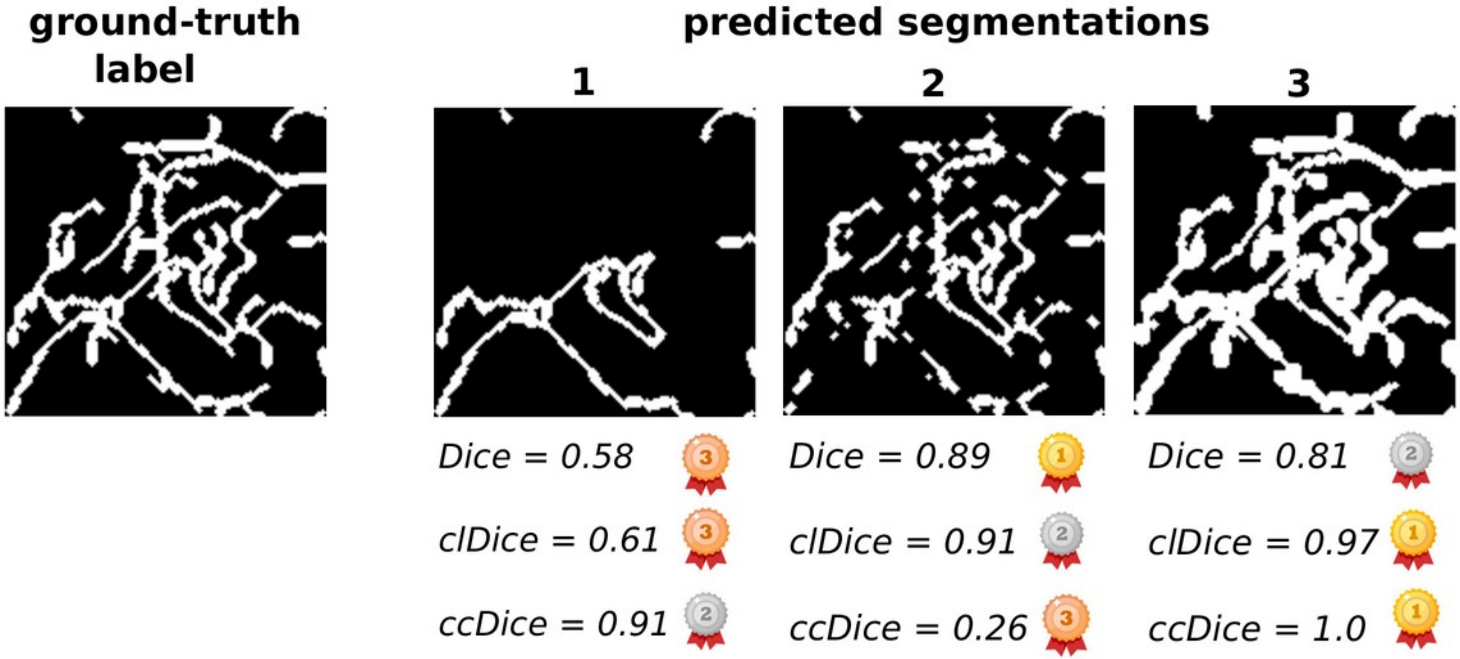


Figure 8. Which is the best segmentation?

State-of-the-art

How the evaluate quality metrics?

1) Use handcrafted examples to show the metric behavior in specific cases[2,4]

2) Ask experts to identify pitfalls and make recommendations (*Metrics Reloaded project*)[5,6]

3) Evaluate metrics based on their correlation to subjective visual scores attributed by experts[7]

[5]Maier-Hein, Lena, et al. "Metrics reloaded: recommendations for image analysis validation." Nature methods, 2024
[6]Reinke, Annika, et al. "Understanding metric-related pitfalls in image analysis validation." Nature methods, 2024
[7]Aydin, Orhun Utku, et al. "An evaluation of performance measures for arterial brain vessel segmentation." BMC medical imaging, 2021

State-of-the-art

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Limitations

- No study focusing on topology-preserving metrics so far
- Relying on experts to grade images or identify pitfalls : time-consuming, hard to apply to new metrics
- Limited to the specific contexts, such as particular application or dataset.

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→ We propose a new approach to benchmark metrics without the need for expert knowledge!

Proposed approach

- Depending on the application, different segmentation errors have different importance or “**weight**”.

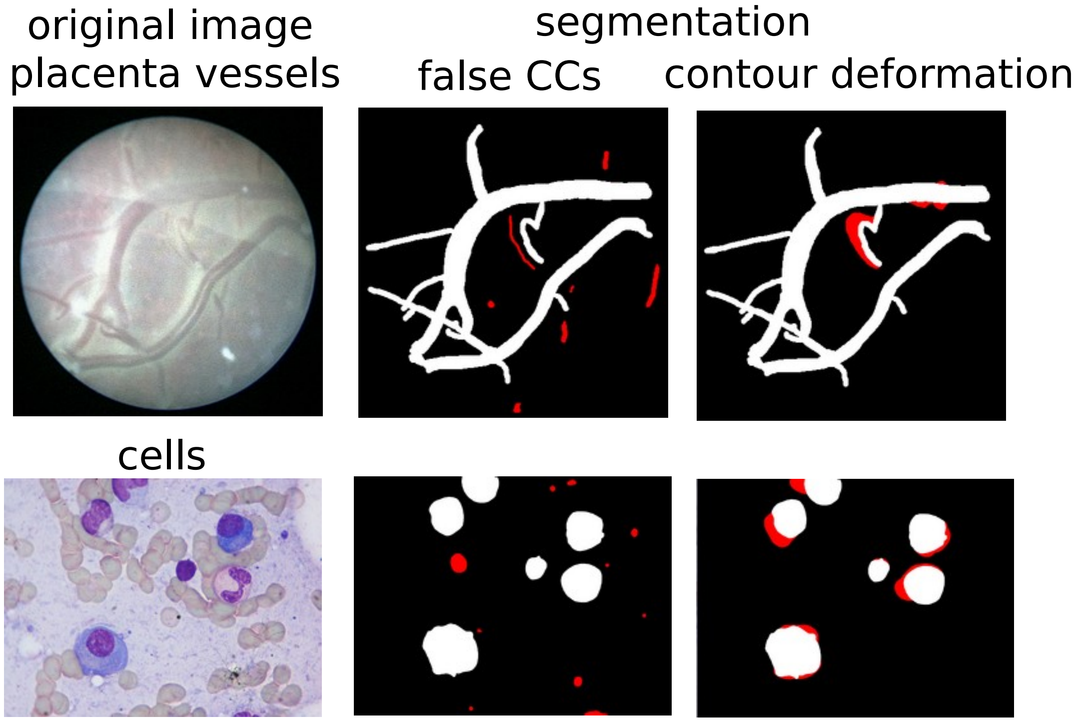


Figure 9. Illustration of different types of segmentation errors. Images from the PSVFM[8] and Neurips 2022 dataset[9].

[8]Bano, Sophia, et al. "Deep placental vessel segmentation for fetoscopic mosaicking." MICCAI, 2020.
[9]Ma, Jun, et al. "The multimodality cell segmentation challenge: toward universal solutions." Nature methods, 2024

Proposed approach

→ **Break down** error types into **easily interpretable categories** (e.g. false component, deformation…)

→ Estimate the “**weight**” that a given metric attributes to each type of errors.

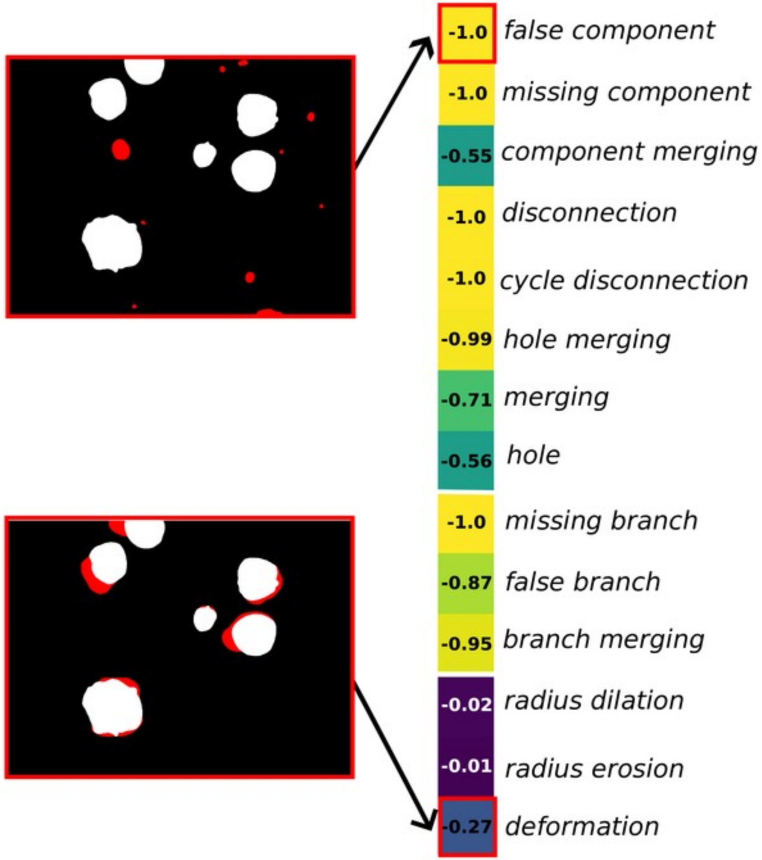


Figure 10. Estimated weights for each type of segmentation errors.

Proposed approach

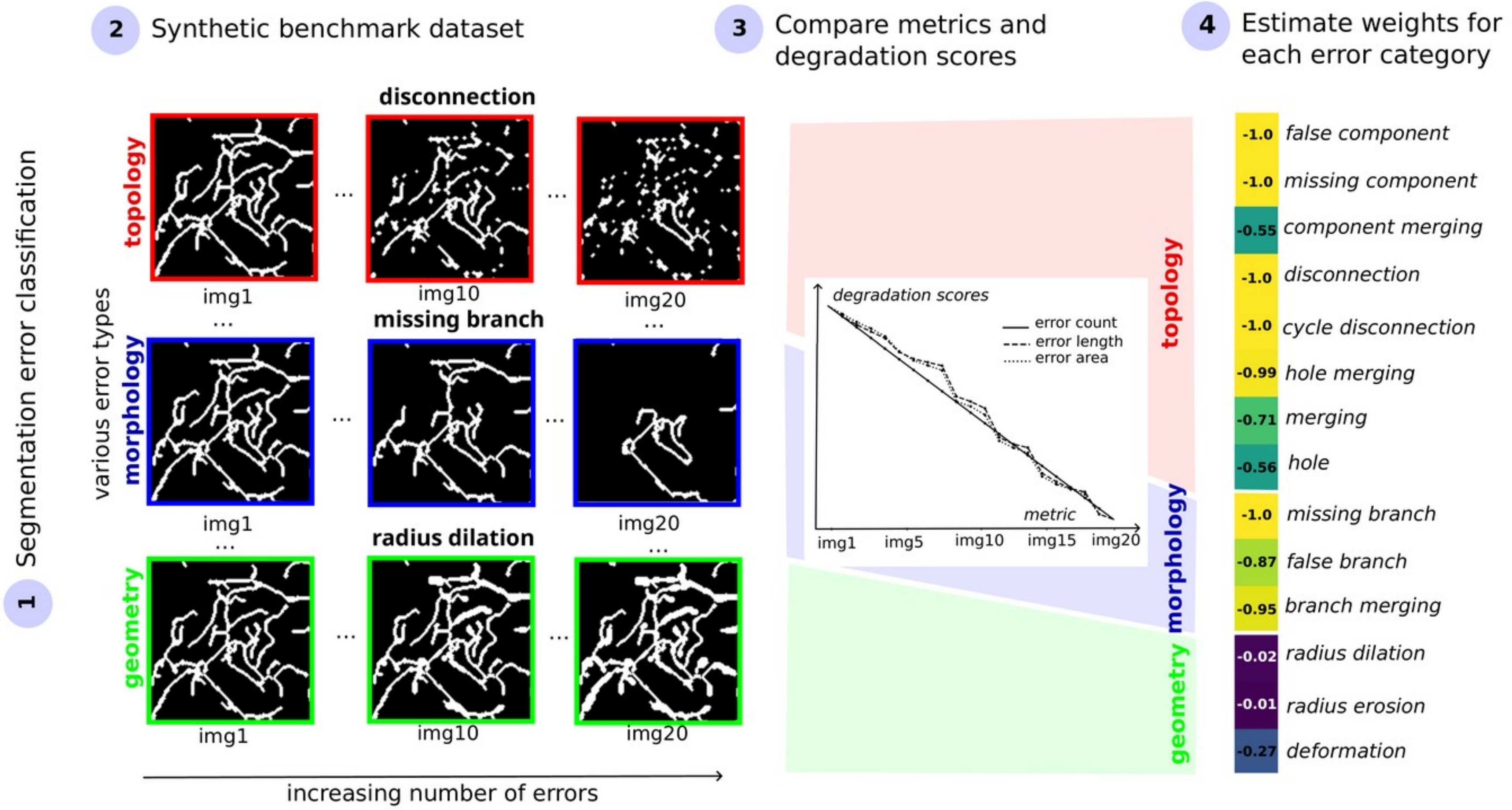


Figure 11. Overview of the proposed method.

Method – Error classification

- We introduce a new distinction between "**topology**", "**morphology**" and "**geometry**".

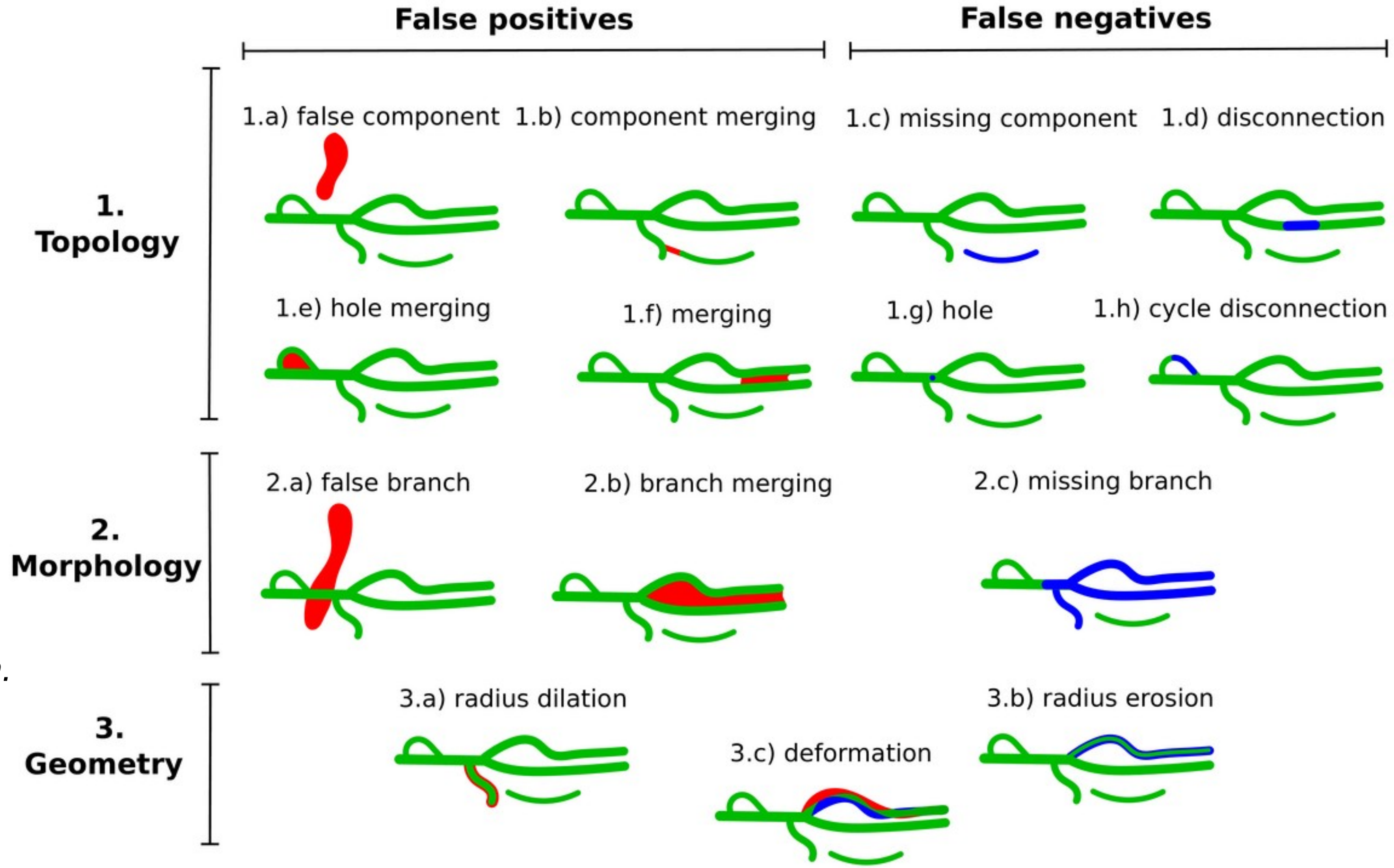
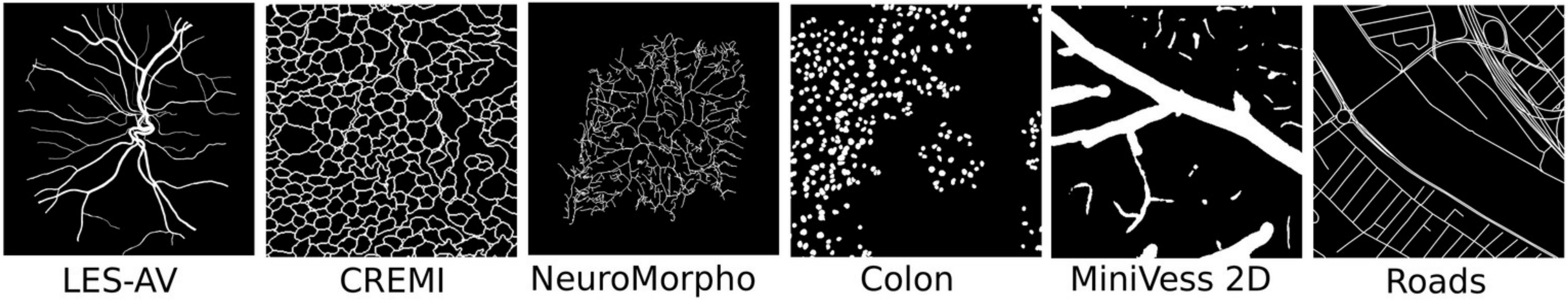


Figure 12. The proposed Segmentation error classification.

Method – Synthetic benchmark dataset

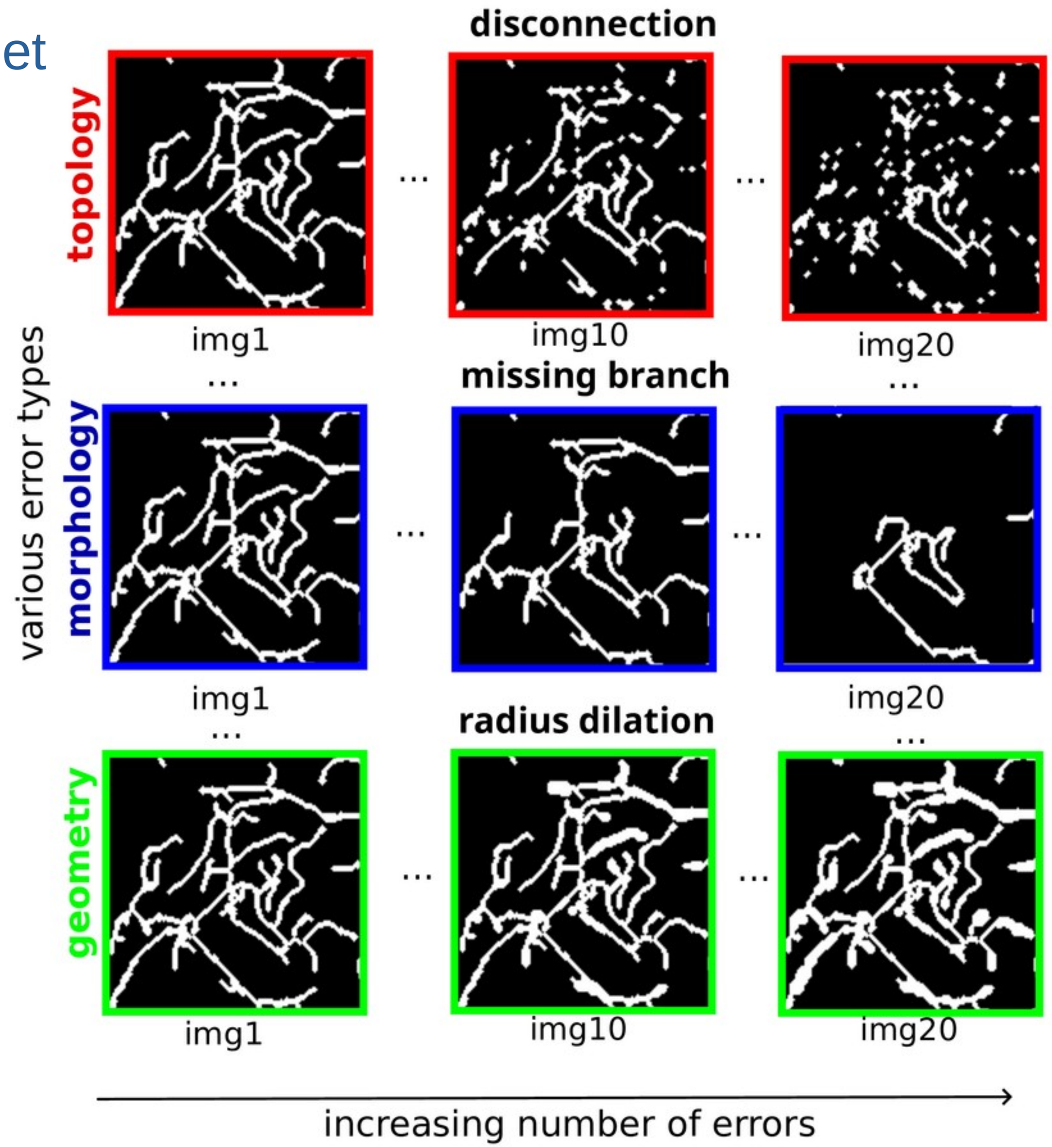
- We selected 3 labels from 6 public datasets.



[10]Cremi. miccai challenge on circuit reconstruction from electron microscopy images https://cremi.org/ (2016), accessed: 2024-02-12
[11]Ljosa, V., Sokolnicki, K.L., Carpenter, A.E.: Annotated high-throughput microscopy image sets for validation. Nature methods, 2012
[12]Tecuatl, C., Ljungquist, B., Ascoli, G.A.: Accelerating the continuous community sharing of digital neuromorphology data. FASEB BioAdvances, 2024
[13]Mnih, V.: Machine Learning for Aerial Image Labeling. Ph.D. thesis, University of Toronto, 2013
[14]Odstrcilik, J., Kolar, R., Budai, A., Hornegger, J., Jan, J., Gazarek, J., Kubena, T., Cernosek, P., Svoboda, O., Angelopoulou, E.: Retinal vessel segmentation by improved matched filtering: evaluation on a new high-resolution fundus image database. IET Image Processing, 2013
[15]Poon, C., Teikari, P., Rachmadi, M.F., Skibbe, H., Hynynen, K.: A dataset of rodent cerebrovasculature from in vivo multiphoton fluorescence microscopy imaging. Scientific Data, 2023

Method – Synthetic benchmark dataset

- We **cumulatively add errors** from each category to mimic predicted segmentations.



Method – Degradation scores

- We design **degradation scores** to quantify the degradation of synthetic images. We consider three **error properties** : the error *“area”*, the error *“length”* and the error *“count”*.

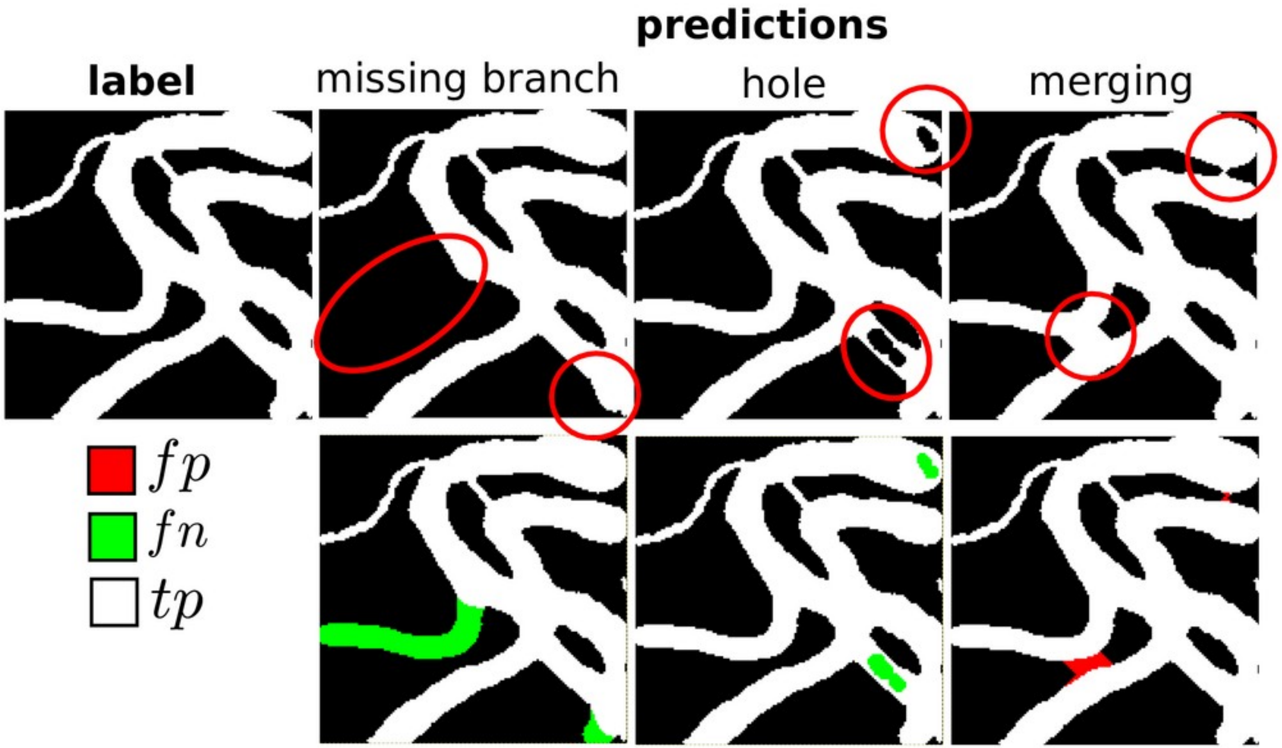


Figure 13. Calculation of the degradation scores for the property “area”.

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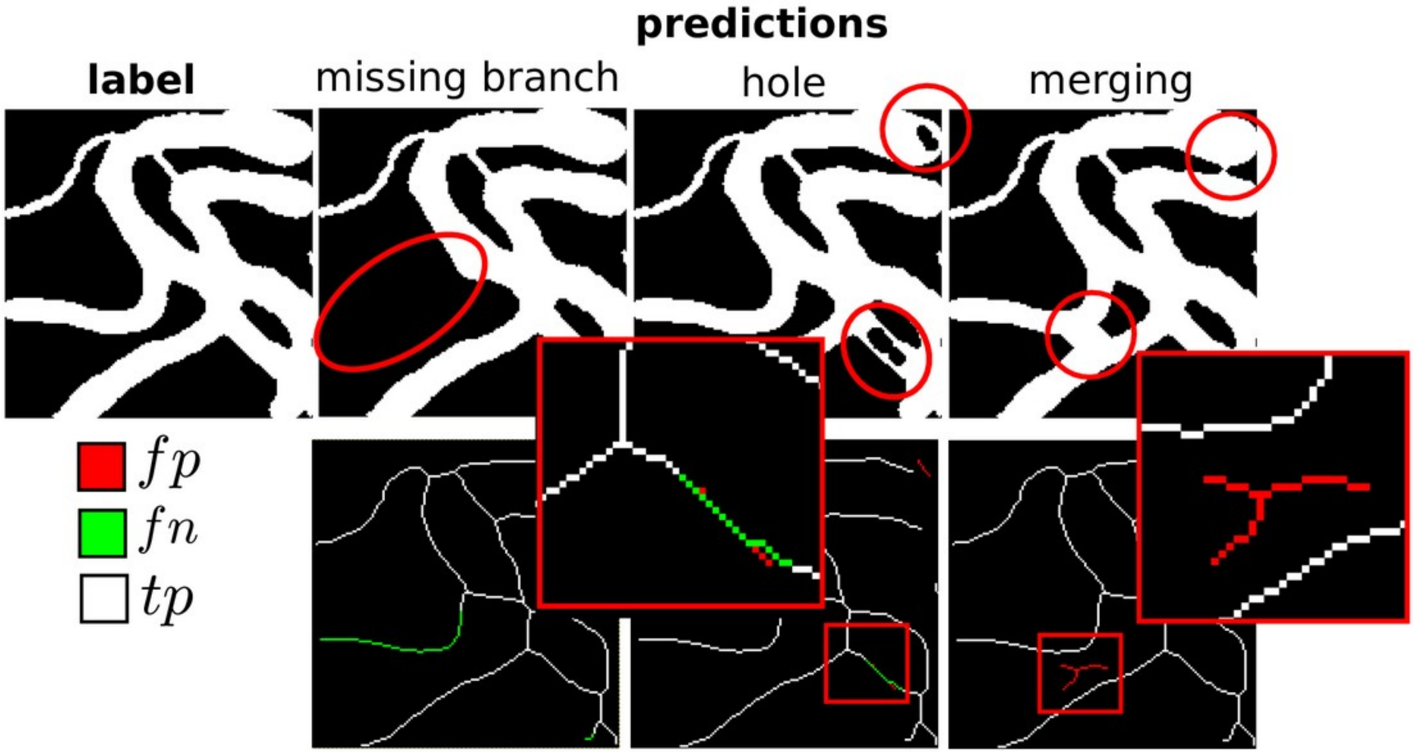
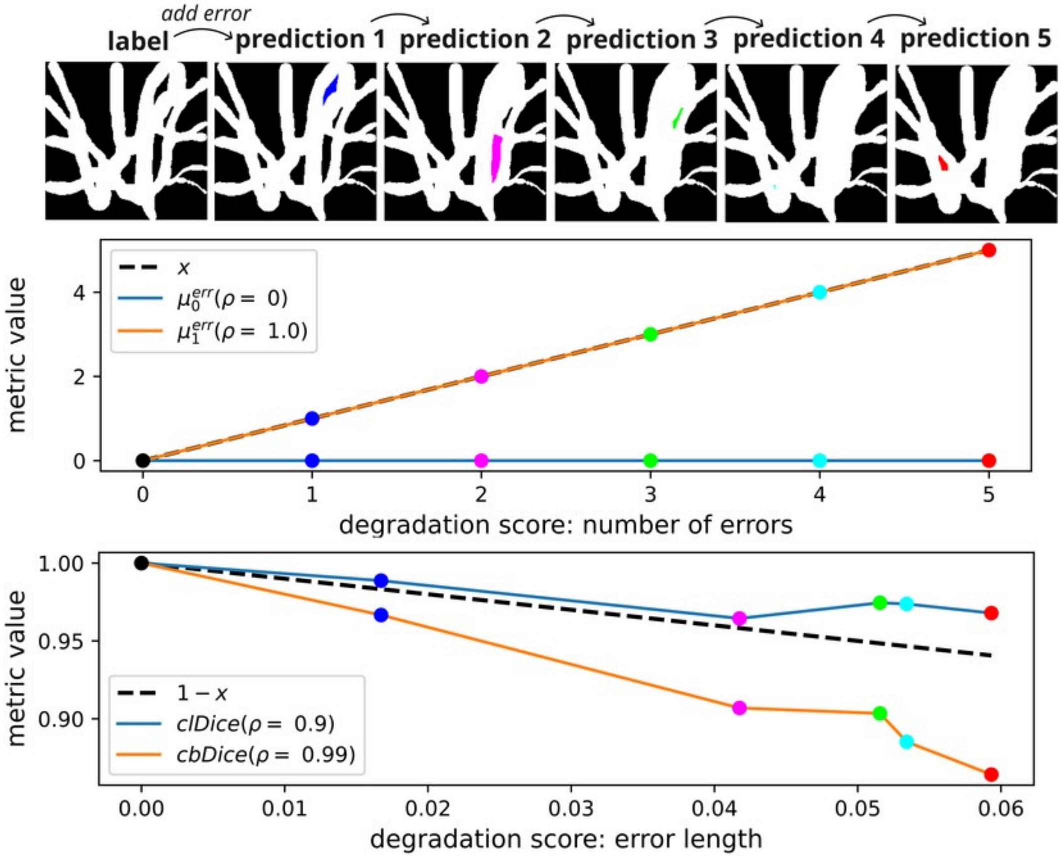


Figure 14. Calculation of the degradation scores for the property “length”.

Method – Correlation and weights estimation



- **Correlation** (absolute Pearson coefficient)

= Is the metric sensitive to one type of error (ρ = 1) or not (ρ = 0)?

- **Weight** (slope of fitted linear function)

= How strongly does the metric penalize a a given type of error?

Results – Correlation analysis

(ρ = 0) : Does not account for this type of error
(ρ > 0.9) : Good estimator of the type of error
(ρ < 0.9) : Influenced by the error (limitation?)

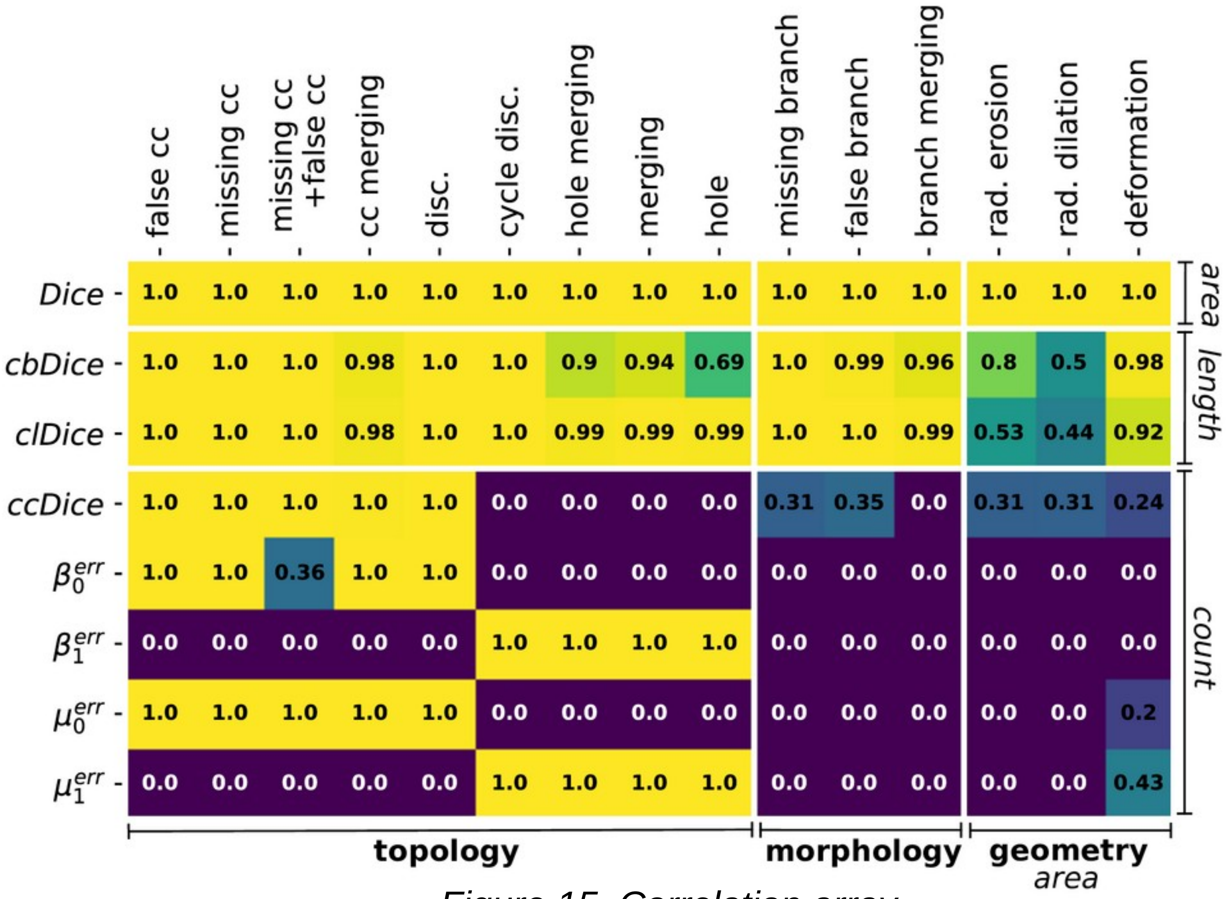


Figure 15. Correlation array.

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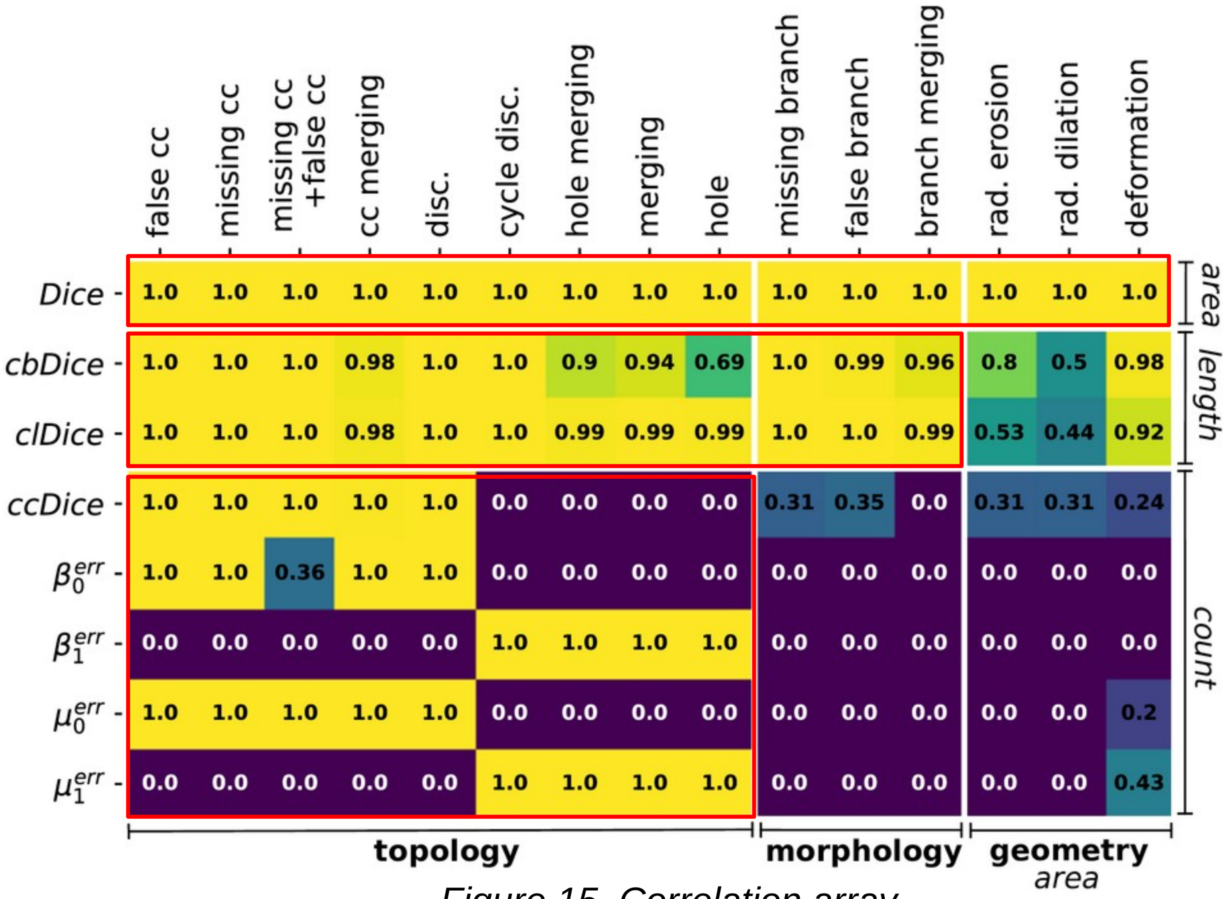

Figure 15. Correlation array.

Results – Correlation analysis

- The clDice is affected by **radius change and deformations**.

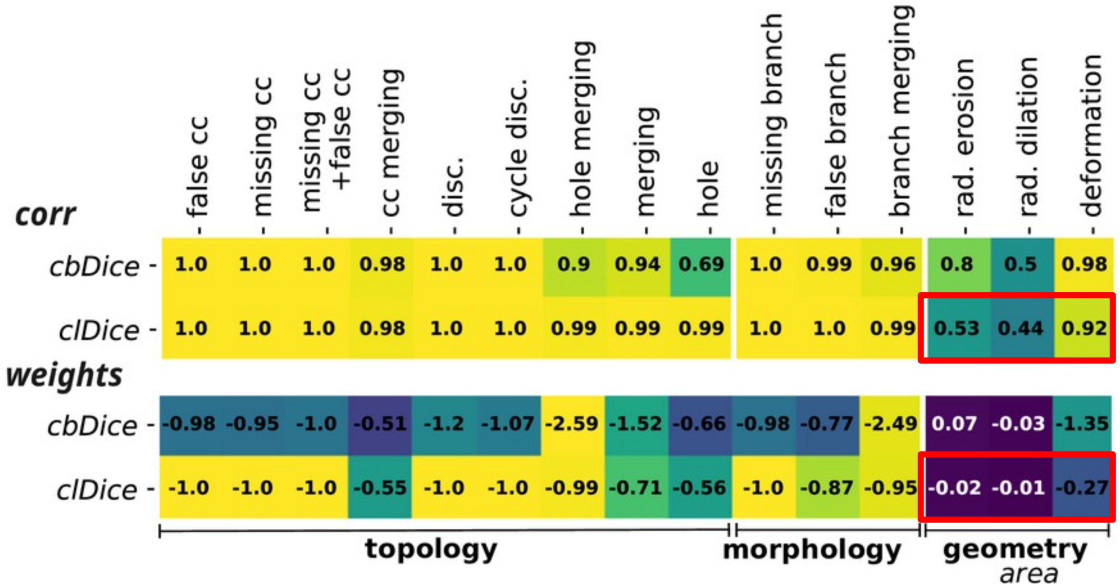

Figure 16. Correlations and weights for the clDice and cbDice.

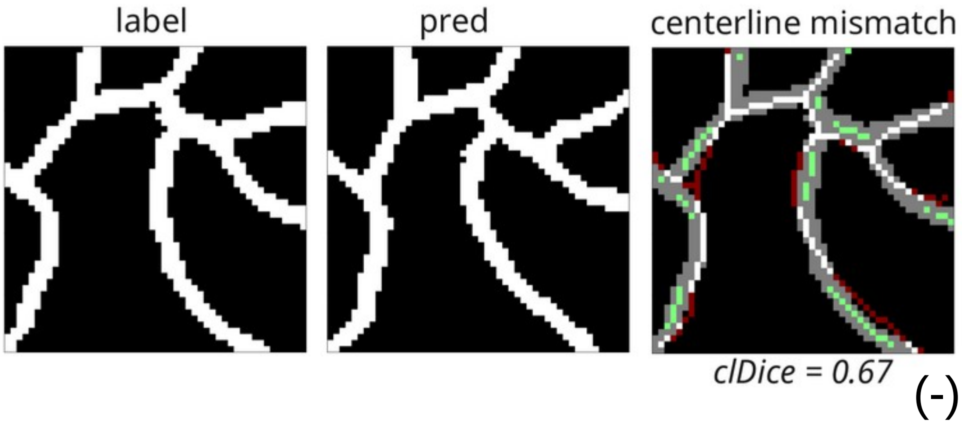

Figure 17. Illustration of the clDice behavior.

Results – Correlation analysis

- The clDice may overlook **holes and merging.**

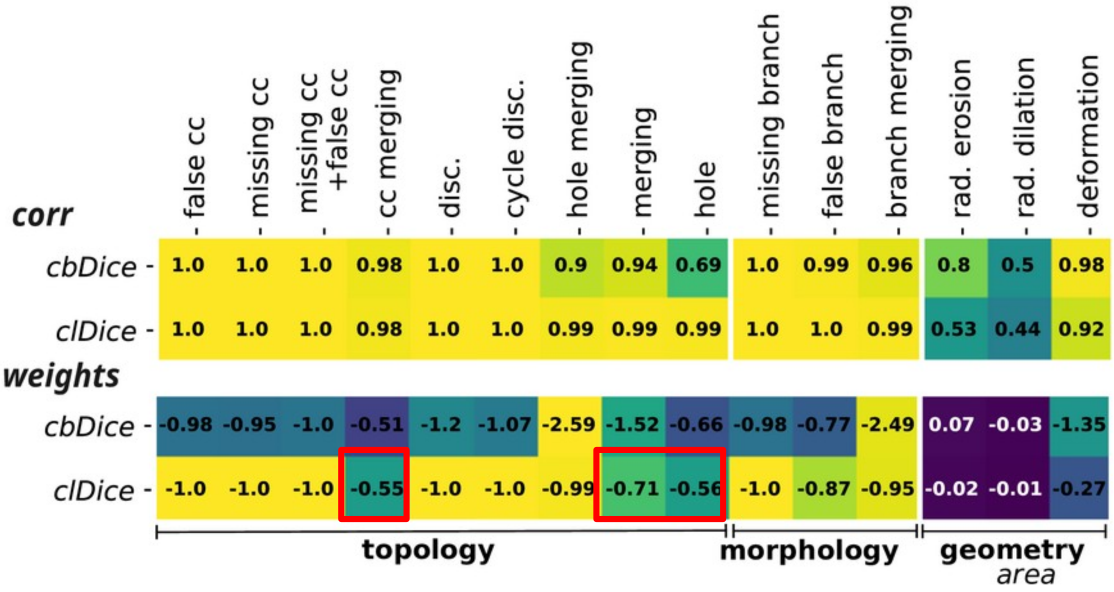

Figure 18. Correlations and weights for the clDice and cbDice.

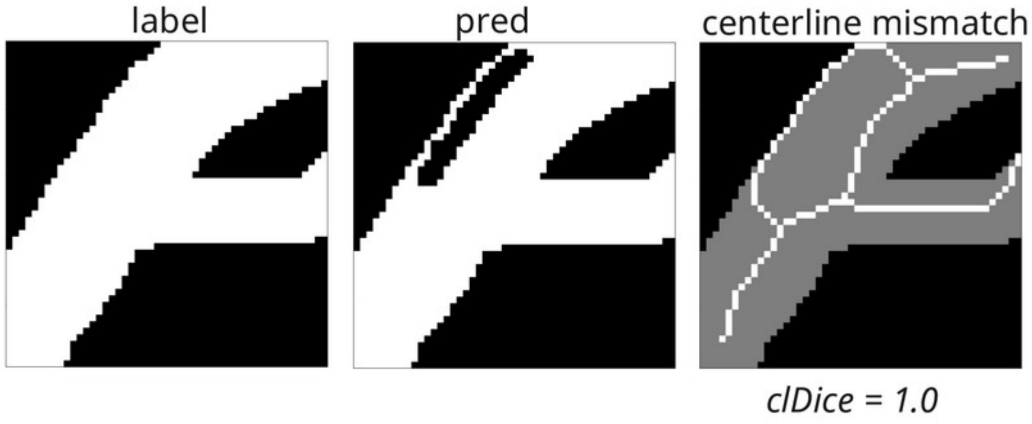

Figure 19. Illustration of the clDice behavior.

(++)

Results – Correlation analysis

- The ccDice and Betti metrics **ignores morphological errors** (e.g. missing branches)

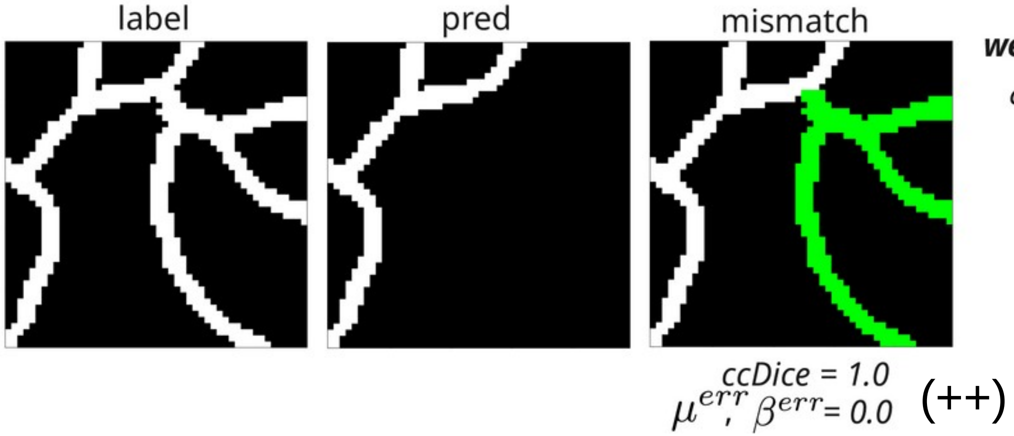

Figure 20. Illustration of the metric's behavior.

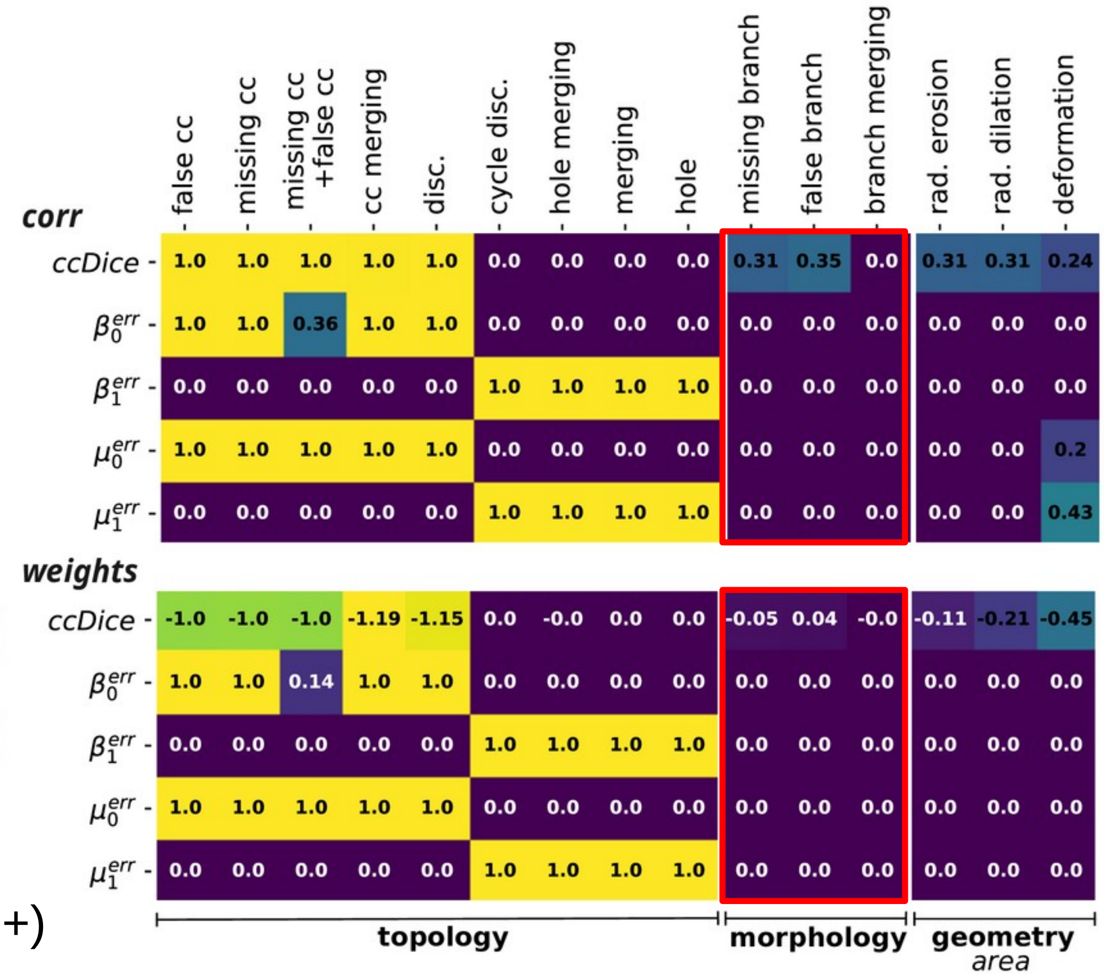

Figure 21. Correlations and weights for the ccDice and Betti metrics.

Conclusion

Contributions

- First classification of segmentation errors for tubular structures
- Method to generate synthetic segmentation with a given type of error
- New approach to visualize and interpret the metrics behavior

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Advantages +

- No need for expert knowledge on the metrics
- Automated (easy to apply to new metrics)
- Covers a large range of applications and contexts (can find unexpected pitfalls!)

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- Method to generate synthetic segmentation with a given type of error
- New approach to visualize and interpret the metrics behavior

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- No need for expert knowledge on the metrics
- Automated (easy to apply to new metrics)
- Covers a large range of applications and contexts (can find unexpected pitfalls!)

Limitations -

- Degradation scores may not reflect the desired metric behavior.
- Necessary to consider more error properties (boundary, center-of-mass)