

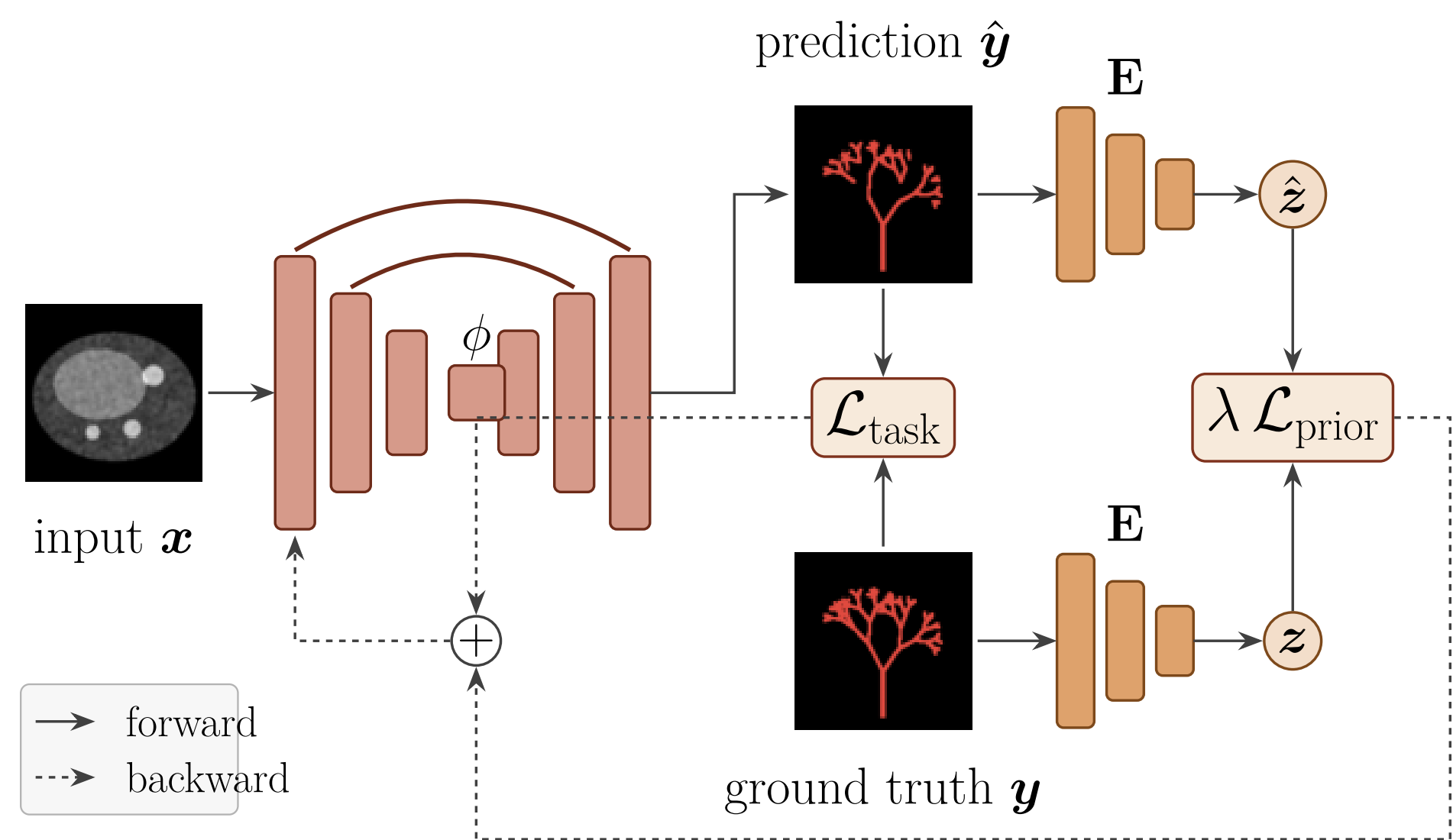
# A SHORT AND CLEAR TITLE FOR YOUR RESEARCH POSTER

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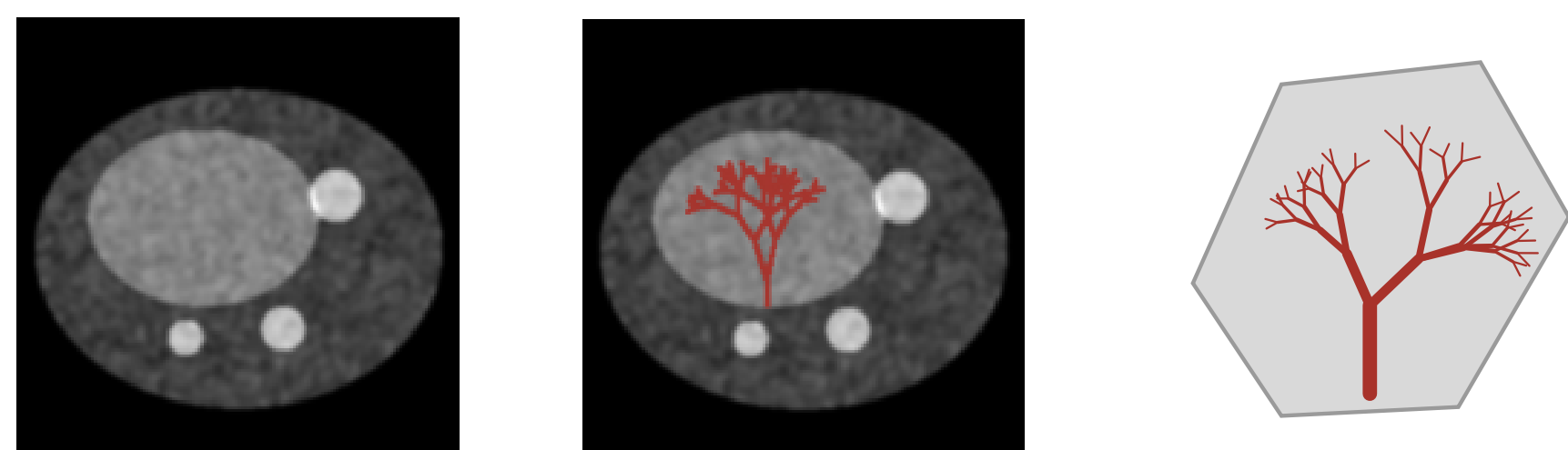
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## GRAPHICAL ABSTRACT



**CONTRIBUTION:** State your contribution in two or three sentences: what you propose, what it changes compared with existing work, and why it matters. This is the block most visitors will read, so keep it short and concrete.

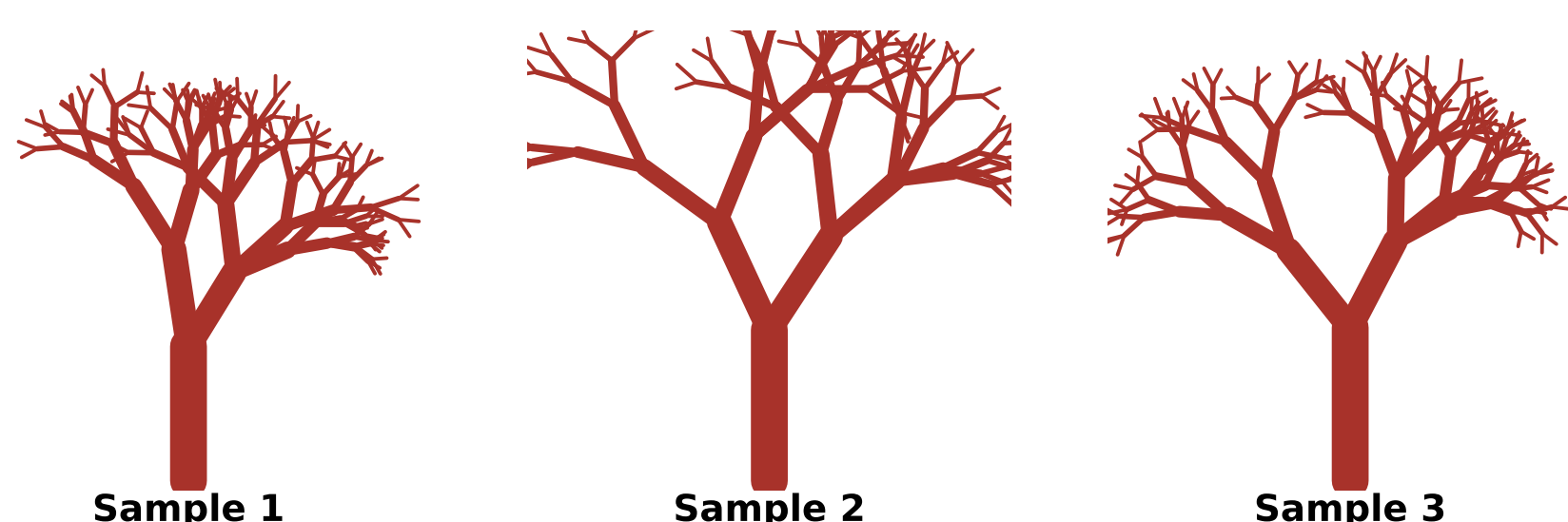
## BACKGROUND



Example data: raw image, image with annotation overlay, and a 3D view of the structure of interest.

- Introduce the application and why it is important.
  - Explain how the task is done today and what limits it (cost, time, expertise, reproducibility).
- Need for an automated, reliable approach

## CHALLENGES & AIMS



Three samples of the same structure showing the variability between cases.

- Strong variability between cases in shape, size and appearance.
  - Thin, multi-scale structures that are easy to break or miss.
- Use prior knowledge to obtain plausible results

## METHODOLOGY

### PROBLEM FORMULATION

Given an input  $\mathbf{x}$ , a network  $f_\theta$  predicts a label map  $\hat{\mathbf{y}}$ . The reference  $\mathbf{y}$  is defined, in a binary setting, as:

$$\mathbf{y}(v) = \begin{cases} 1 & \text{if } v \in \mathcal{S} \\ 0 & \text{otherwise} \end{cases}$$

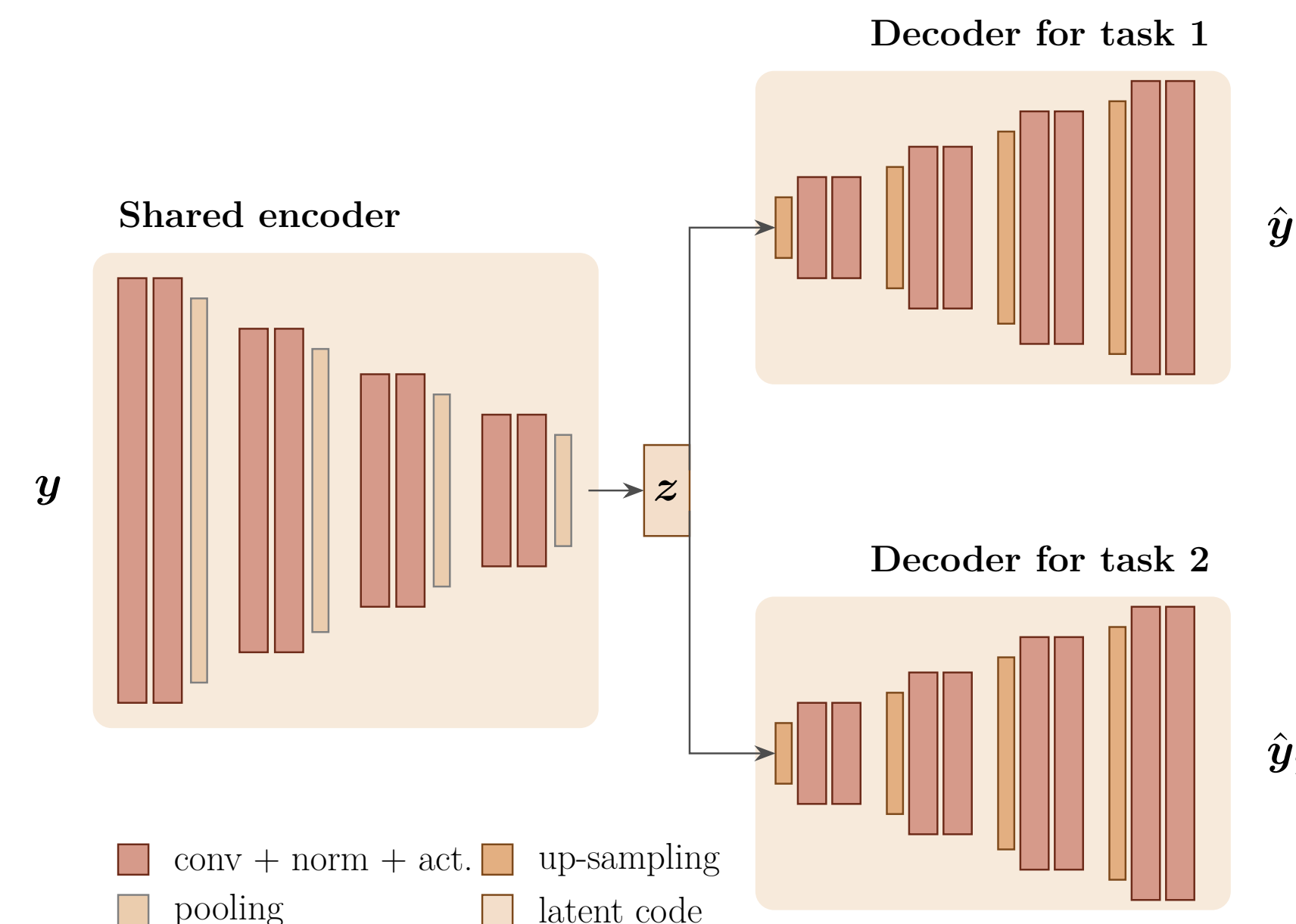
where  $v$  is a pixel and  $\mathcal{S}$  the region of interest.

**Prior knowledge** is encoded through:

- a shape prior learned from the reference masks;
- a structural prior, for example a distance map  $D$  to the nearest boundary  $\partial\mathcal{S}$ :

$$D(v) = \begin{cases} \min_{u \in \partial\mathcal{S}} \|v - u\|_2 & \text{if } v \in \mathcal{S} \\ 0 & \text{otherwise} \end{cases}$$

### PROPOSED MODEL



A shared encoder maps the masks to a latent code  $\mathbf{z}$  used by two task-specific decoders.

- $\mathcal{L}_{\text{prior}}(\mathbf{y}, \hat{\mathbf{y}}) \propto d(E(\mathbf{y}), E(\hat{\mathbf{y}}))$
- $d(\cdot)$ : distance in the latent space (Cosine,  $L_1$ ,  $L_2$ )

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}}(\mathbf{y}, \hat{\mathbf{y}}) + \lambda \mathcal{L}_{\text{prior}}(\mathbf{y}, \hat{\mathbf{y}})$$

## RESULTS & DISCUSSION

Ablation on the distance  $d(\cdot)$  used in the latent space and on the latent size  $k$  (synthetic numbers). Best in bold, second underlined.

| $d(\cdot)$ | $k$ | Acc. $\uparrow$       | F1 $\uparrow$         | AUC $\uparrow$        | Err. $\downarrow$     | Mem. $\downarrow$ |
|------------|-----|-----------------------|-----------------------|-----------------------|-----------------------|-------------------|
| Cosine     | 16  | 83.0 $\pm$ 1.2        | 76.9 $\pm$ 1.4        | 89.8 $\pm$ 0.9        | 17.0 $\pm$ 1.2        | 3.2               |
|            | 32  | <b>84.1</b> $\pm$ 1.0 | <b>78.2</b> $\pm$ 1.3 | <b>90.6</b> $\pm$ 0.7 | <b>15.9</b> $\pm$ 1.0 | 3.3               |
|            | 64  | 83.6 $\pm$ 1.1        | 77.5 $\pm$ 1.2        | 90.1 $\pm$ 0.8        | 16.4 $\pm$ 1.1        | 3.6               |
|            | 128 | 82.7 $\pm$ 1.4        | 76.4 $\pm$ 1.6        | 89.5 $\pm$ 1.0        | 17.3 $\pm$ 1.4        | 4.2               |
|            | 256 | 82.4 $\pm$ 1.3        | 75.8 $\pm$ 1.5        | 89.0 $\pm$ 1.0        | 17.6 $\pm$ 1.3        | <b>3.1</b>        |
| $L_1$      | 16  | 82.4 $\pm$ 1.3        | 75.8 $\pm$ 1.5        | 89.0 $\pm$ 1.0        | 17.6 $\pm$ 1.3        | <b>3.1</b>        |
|            | 32  | 82.9 $\pm$ 1.2        | 76.6 $\pm$ 1.4        | 89.4 $\pm$ 0.9        | 17.1 $\pm$ 1.2        | 3.2               |
|            | 64  | 82.6 $\pm$ 1.3        | 76.2 $\pm$ 1.5        | 89.3 $\pm$ 1.0        | 17.4 $\pm$ 1.3        | 3.5               |
|            | 128 | 82.1 $\pm$ 1.5        | 75.4 $\pm$ 1.7        | 88.8 $\pm$ 1.1        | 17.9 $\pm$ 1.5        | 4.1               |
|            | 256 | 82.2 $\pm$ 1.4        | 75.6 $\pm$ 1.6        | 88.9 $\pm$ 1.1        | 17.8 $\pm$ 1.4        | <b>3.1</b>        |
| $L_2$      | 16  | 83.1 $\pm$ 1.1        | 76.8 $\pm$ 1.3        | 89.6 $\pm$ 0.9        | 16.9 $\pm$ 1.1        | 3.2               |
|            | 32  | 83.1 $\pm$ 1.1        | 76.8 $\pm$ 1.3        | 89.6 $\pm$ 0.9        | 16.9 $\pm$ 1.1        | 3.2               |
|            | 64  | 82.8 $\pm$ 1.2        | 76.3 $\pm$ 1.4        | 89.4 $\pm$ 0.9        | 17.2 $\pm$ 1.2        | 3.5               |
|            | 128 | 81.9 $\pm$ 1.6        | 75.1 $\pm$ 1.8        | 88.6 $\pm$ 1.2        | 18.1 $\pm$ 1.6        | 4.2               |
|            | 256 | 82.5 $\pm$ 1.3        | 76.5 $\pm$ 1.5        | 89.5 $\pm$ 1.0        | 17.5 $\pm$ 1.4        | 3.8               |

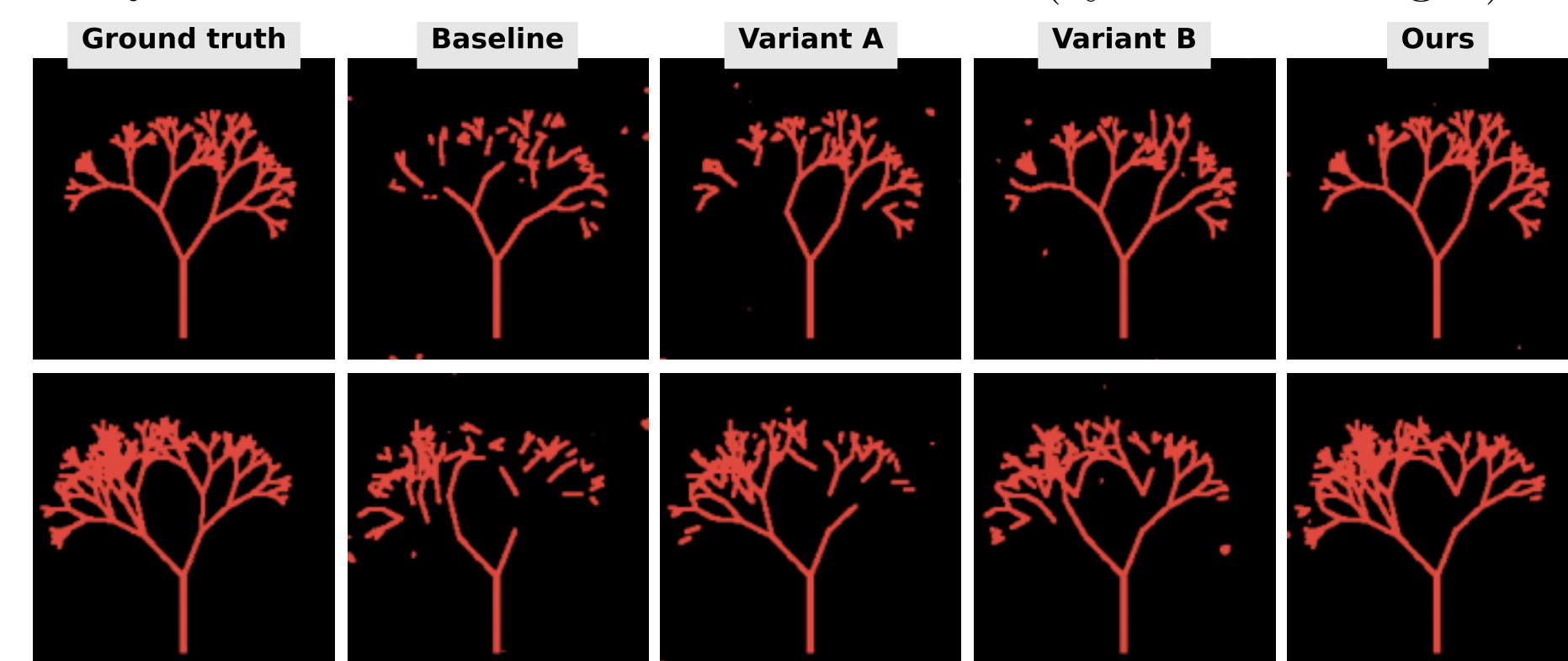
- Comment the ablation in one or two lines: which setting works best, and why.

→ Summarise the results in one sentence: what improves, by how much, and at what cost.

Comparison with baselines on a benchmark dataset (synthetic numbers). Best results in bold, second best underlined.

| Method      | $\lambda$              | Acc. $\uparrow$ (%)   | F1 $\uparrow$ (%)     | AUC $\uparrow$ (%)    | Err. $\downarrow$ (%) | Mem. $\downarrow$ (GB) | Time $\downarrow$ (ms) |
|-------------|------------------------|-----------------------|-----------------------|-----------------------|-----------------------|------------------------|------------------------|
| Baseline    | –                      | 81.2 $\pm$ 1.4        | 74.6 $\pm$ 1.9        | 88.1 $\pm$ 1.1        | 18.8 $\pm$ 1.4        | 3.1                    | 42                     |
| + prior A   | $\lambda = 0.5$        | 82.0 $\pm$ 1.2        | 75.3 $\pm$ 1.7        | 88.9 $\pm$ 1.0        | 18.0 $\pm$ 1.2        | 3.4                    | 45                     |
| + prior B   | $\lambda = 1.0$        | 81.8 $\pm$ 1.5        | 75.9 $\pm$ 1.6        | 89.2 $\pm$ 0.9        | 18.2 $\pm$ 1.5        | 3.6                    | 47                     |
| + A + B     | $\lambda = (0.5, 1.0)$ | 82.9 $\pm$ 1.1        | 76.8 $\pm$ 1.5        | 89.7 $\pm$ 0.8        | 17.1 $\pm$ 1.1        | 4.9                    | 61                     |
| <b>Ours</b> | $\lambda = 0.8$        | <b>84.1</b> $\pm$ 1.0 | <b>78.2</b> $\pm$ 1.3 | <b>90.6</b> $\pm$ 0.7 | <b>15.9</b> $\pm$ 1.0 | <b>3.3</b>             | 44                     |

Qualitative results on two test cases (synthetic images).



## CONCLUSION & OUTLOOK

- Main finding of the work and what it means for the field.
- Limitations and next steps: other datasets, other tasks, or a better model of the prior.

## ACKNOWLEDGEMENTS & CONTACTS

This work was funded by Funding Agency (grant XXX-0000) and Another Programme (grant YYY-0000).

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🌐 <https://www.example.org>   🏠 username/repository



Read the paper

- [1] A. Author and B. Coauthor, “A descriptive title for a related method,” in *Proceedings of a Conference*, 2025.
- [2] C. Someone *et al.*, “A public dataset used in this work,” *Journal Name*, 2024.

