

VessShape: Few-shot 2D blood vessel segmentation by leveraging shape priors from synthetic images

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I. INTRODUCTION

II. RELATED WORKS

- Shape priors for medical images segmentation using neural networks
- Shape priors for vessel segmentation (classic methods) hessian, Frangi filter
- Pre-training with synthetic data deepvesselnet, VesselFM (específicos para determinadas modalidades de imagem (fotografia de fundo, microscopia, ressonância, etc))
- Shape priors for vessel segmentation (neural networks)

III. METHODOLOGY

A. VessShape Dataset

VessShape is a synthetic image dataset that combines tubular, vessel-like shapes with diverse foreground and background textures. The central idea is to provide a robust set that can be used to train blood vessel segmentation models while keeping geometric priors fixed and drastically changing texture, encouraging models to learn shape cues (connectivity, tapering, bifurcations) rather than overfitting to texture.

The geometry of this dataset is based on Bézier curves, which allow a flexible and controlled representation of tubular shapes. Each vascular branch C_k is described by an n -th order Bézier curve with control points $\{\mathbf{P}_{k,i}\}_{i=0}^n$, sampled to produce connected branches and plausible bifurcation angles. Tortuosity is adjusted by small perturbations to the control points, ensuring that vessel geometry is realistic and diverse. The Equation 1 defines the Bézier curve $\mathbf{c}_k(t)$ for each branch k , where t varies from 0 to 1.

$$\mathbf{c}_k(t) = \sum_{i=0}^n \binom{n}{i} (1-t)^{n-i} t^i \mathbf{P}_{k,i}, \quad t \in [0, 1]. \quad (1)$$

To generate connected vascular trees, control points are sampled so that branches share endpoints in order to form

plausible bifurcation angles. Tortuosity is induced by random perturbations to the control points, with amplitude regulated by the displacement scale δ . The number of branches K and the order $n + 1$ of the Bézier curves are also randomly sampled to ensure a wide variety of shapes, and the radius r_0 sets the basal thickness of the vessels during the rasterization process. Table I summarizes the parameters used in the VessShape dataset generation, along with their sampling ranges and descriptions.

The generation of the binary mask M from the curves $\mathbf{c}_k(t)$ is a multi-step process. Initially, each curve is discretized by sampling points at a sufficient resolution to capture its curvature, which are then sequentially connected to form a 1-pixel-thick polyline on the image grid. Subsequently, a binary morphological dilation with a disk-shaped structuring element is applied iteratively until the structure reaches a radius of r_0 , consequently assigning a constant tubular thickness to the branches. Optionally, a morphological closing operation can be employed to seal small gaps at bifurcations or sharp angles.

To compose the final image I from a binary mask M , a foreground texture F and a background texture B are selected from distinct categories, randomly cropped, and resized to the target dimensions ($H \times W$). An alpha matte A is then generated by smoothing M with a Gaussian filter of standard deviation σ and normalizing its values to the $[0, 1]$ range. The textures are subsequently blended using this matte according to Eq. 2, which ensures that vessel regions ($A \approx 1$) preserve the foreground while non-vessel regions ($A \approx 0$) retain the background. The parameter σ directly controls the smoothness of this transition at the vessel boundaries. After composition, the image I undergoes channel-wise normalization using ImageNet statistics for compatibility with pre-trained models. Finally, to ensure spatial consistency, any geometric augmentations are applied identically to both the image I and its corresponding mask M . A sample of the generated images and masks is shown in Figure 1.

$$I(x) = A(x) F(x) + (1 - A(x)) B(x), \quad x \in \Omega. \quad (2)$$

B. Training details

A crucial step is the choice of architecture. We adopt an encoder-decoder arrangement, in which the encoder

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TABLE I. VessShape generation parameters, sampling ranges, and description.

Parameter	Range	Description
Number of curves K	[1, 20]	Number of branches/vessels generated per sample.
Control points $n+1$	[2, 20]	Bézier curve complexity (order n).
Displacement scale δ (px)	[50.0, 150.0]	Controls curvature/tortuosity via the typical amplitude of control-point displacement.
Initial radius $r_{0,k}$ (px)	[1, 5]	Basal vessel thickness; a smooth taper is applied along the branch.
Matting blur σ	[1, 2]	Standard deviation of the Gaussian used for $A = G_\sigma * M$.

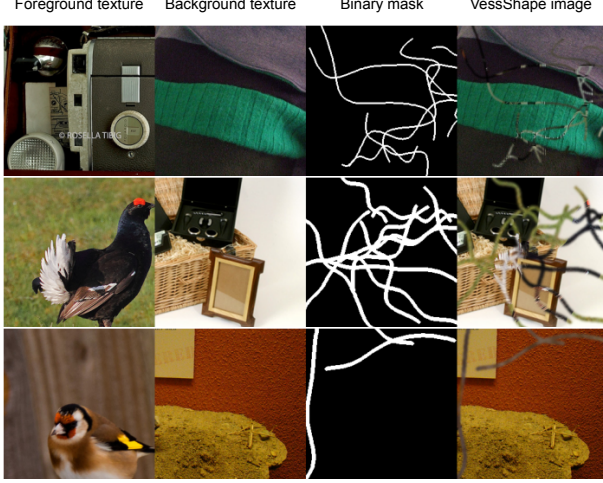


FIG. 1. ??.

extracts visual representations and the decoder performs the segmentation. In the encoder, the architectures actually evaluated were ResNet18 and ResNet50 [1]. The

decoder follows the U-Net design [2], widely used in medical segmentation.

We design three complementary stages with distinct goals: (i) pretraining on VessShape to inject a *shape* bias and reduce dependence on texture, (ii) *from scratch* training on natural datasets (VessMAP, DRIVE) to establish a baseline, and (iii) *few-shot* fine-tuning to measure the transferability and sample efficiency of the learned representations.

C. Pre-training on VessShape

D. Fine-tuning

- Datasets (VessMAP e DRIVE)
- Procedure

IV. RESULTS

V. CONCLUSION

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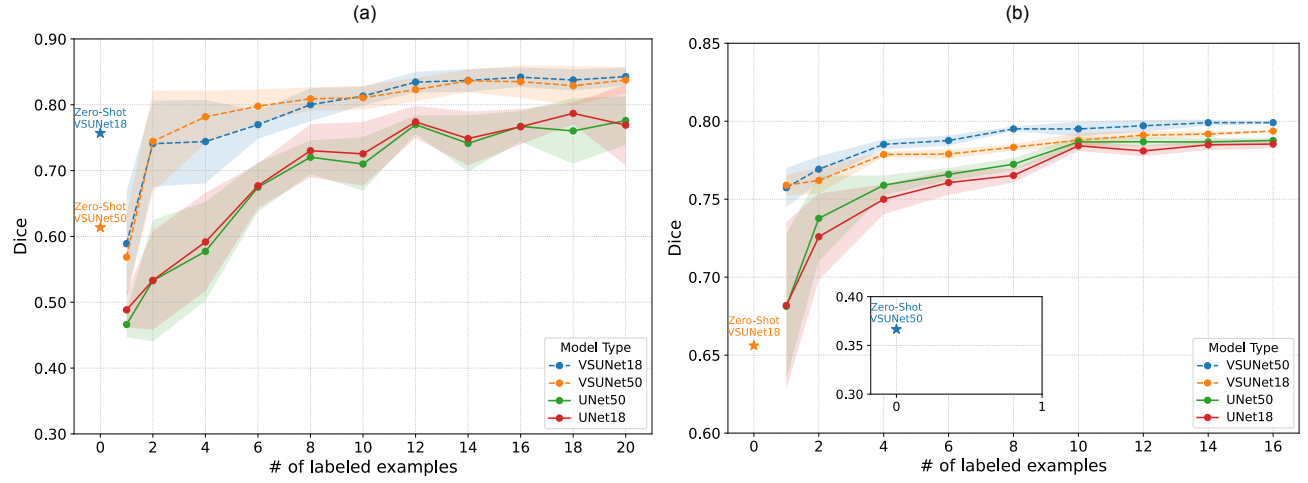


FIG. 2. ??.

TABLE II. Zero-shot segmentation results.

Dataset	Model	Acc	IoU	Prec	Rec	Dice	AUC
VessMAP	ResNet18 - From Scratch	0.886	0.616	0.846	0.696	0.757	0.932
VessMAP	ResNet50 - From Scratch	0.817	0.472	0.746	0.605	0.614	0.854
DRIVE	ResNet18 - From Scratch	0.907	0.490	0.629	0.699	0.656	0.891
DRIVE	ResNet50 - From Scratch	0.888	0.230	0.728	0.275	0.367	0.762