CROWN 2023 Challenge Task1 (AIntropy)

Pengcheng Shi[1], Wei Liu[1], and Ting Ma[1,2](✉)

[1] Electronic & Information Engineering School, Harbin Institute of Technology (Shenzhen), Shenzhen, China
[2] Peng Cheng Laboratory, Shenzhen, China

1 Introduction

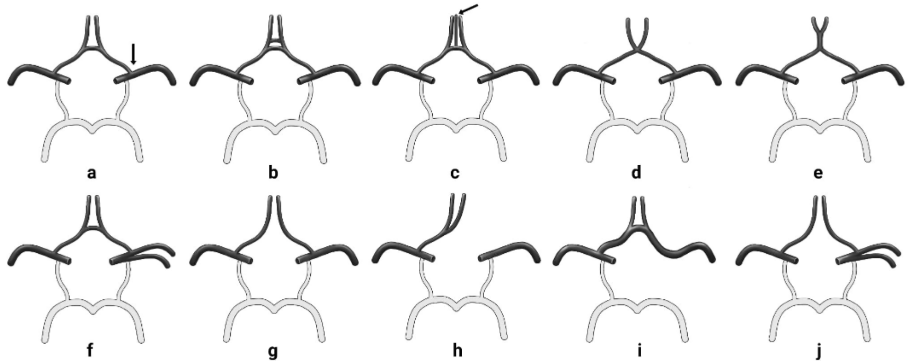
The objective of this research is to classify Circle of Willis (CoW) configuration variants in Time-of-Flight Magnetic Resonance Angiography (TOF-MRA) images. The classification aims to identify two distinct classes for each image: one representing the anterior CoW variant and the other representing the posterior variant, as illustrated in Figure 1. Relevant codes can be found at : https://github.com/PengchengShi1220/NexToU and https://github.com/PengchengShi1220/VesselGrapher.

Convolutional neural networks (CNN) and Transformer variants have led the field in medical image segmentation. However, these methodologies face challenges in integrating information from diverse anatomical regions, and in reducing inter-individual variability. This is particularly apparent when processing the vasculature, given its complex and irregular shapes. Graph neural networks (GNN) have shown potential in addressing these obstacles. Largely due to their superior performance in capturing topological characteristics and non-Euclidean relationships. In this work, we propose a novel approach, VesselGrapher, which leverages GNNs to classify CoW configuration variants on TOF-MRA images. We aim to demonstrate the effectiveness of GNNs in capturing topological information and in reducing inter-individual variability.

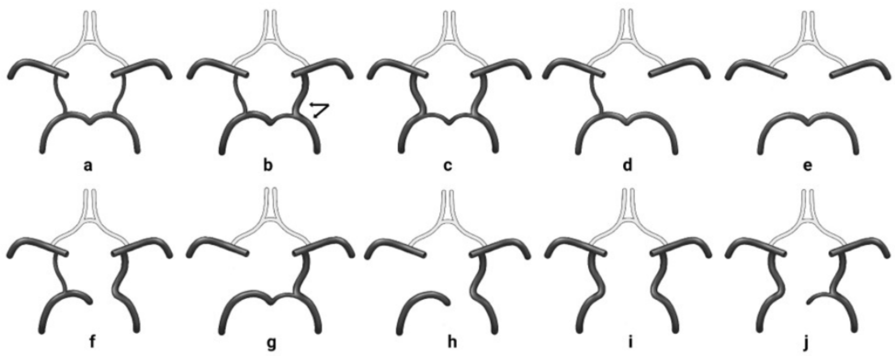
2 Method

Vision GNN: An Image is Worth Graph of Nodes Vision GNN [1] pioneer to study representing the image as graph data and leverage graph neural network for visual tasks (Fig. 2). It divide the image into a number of patches and view them as nodes. Constructing graph based on these nodes can better represent the irregular and complex objects in the wild.

NexToU: Efficient Topology-Aware U-Net for Medical Image Segmentation In our previous work [5], we introduced the Vision GNN module in the medical image segmentation task for the first time (Fig. 3). At the same time, we proposed Efficient ViG modules (Pool GNN and Swin GNN), in order to aggregate global and local topological representations in the latent space. Besides, we reformulated the topological interaction module based on the nature



(a) Anatomical variations in the anterior part of the CoW



(b) Anatomical variations in the posterior part of the CoW

Fig. 1. automated classification of the circle of Willis configuration variants

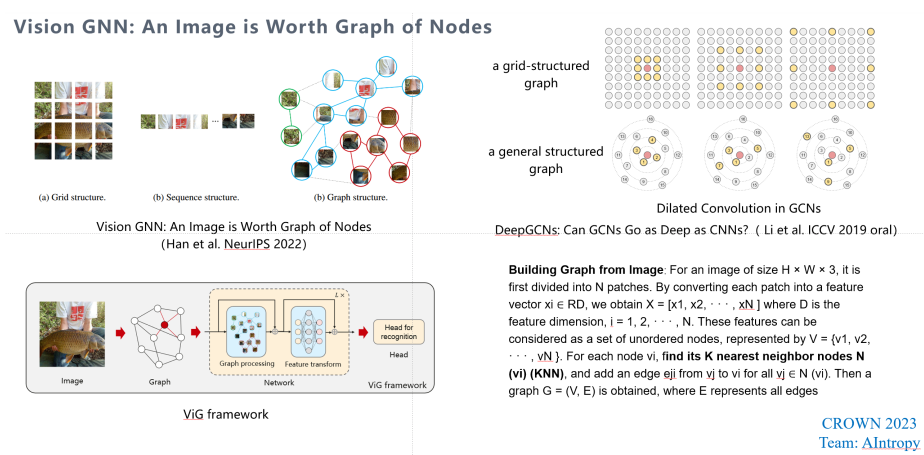


Fig. 2. Vision GNN: An Image is Worth Graph of Nodes

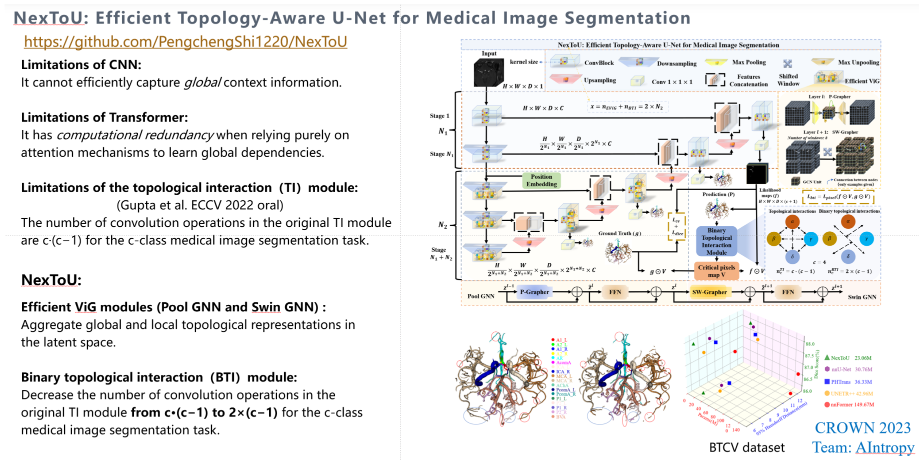


Fig. 3. NexToU: Efficient Topology-Aware U-Net for Medical Image Segmentation

of binary trees, which quickly encodes the topological constraints into NexToU. NexToU outperforms by achieving a higher Dice Score Coefficient and a smaller Hausdorff Distance with fewer parameters required on the BTCV dataset. GNNs became the foundation for NexToU, our proposed hybrid architecture for medical image segmentation. For this task, we used 24 categorized features from 120 multi-center instances, specifically the Circle of Willis. We use the Dice Loss, Cross-Entropy (CE) Loss, centerline Dice (clDice) Loss [6], and Binary Topological Interaction (BTI) Loss [5] to train the model. The final loss function is defined as follows:

$$L = L_{ce} + L_{dice} + L_{clDice} + \lambda_{bti} L_{bti} \tag{1}$$

$$\lambda_{bti} = 1 \times 10^{-6} \tag{2}$$

Replace KNN Graph Construction With Vessel Graph Despite its utility, utilizing the feature similar KNN graph construction in the Vision GNN module for vascular segmentation carries certain limitations. The interpretability of this process still lacks the desired strength, primarily due to parameters like K that must be manually selected. Variations in K significantly influence both computational complexity and performance. Moreover, the current model struggles to accurately represent the vessel graph, particularly in defining the accurate positions of the nodes within the graph and their edge connections. In the 2023 MIDL conference, a work titled Vesselformer [4] introduced an end-to-end approach to generating the vascular graph on synthetic data. However, this work doesn't optimize the process of constructing the vessel graph and the segmentation task together. In our proposed model, VesselGrapher, we employ a vessel graph constructed on the basis of a vascular skeleton, which effectively replaces the KNN graph construction process in the Vision GNN module.

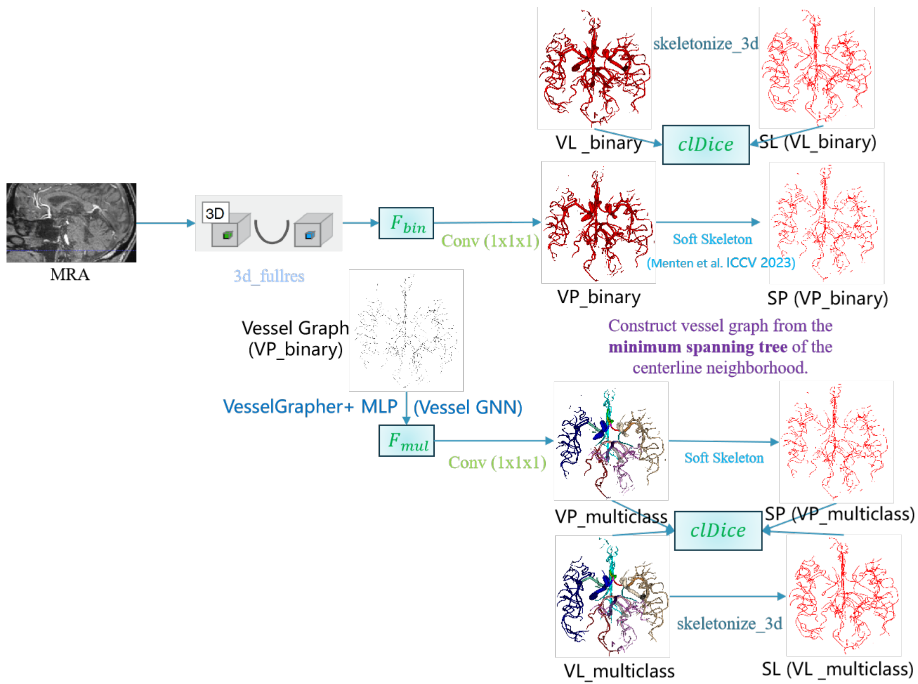


Fig. 4. Network architecture and key implementations

Network Architecture and Key Implementations In our study, we employed a combination of nnUNet [2] framework and our NexToU architecture for 3D full-resolution. Next, we procured the binary segmented prediction mask and used the soft skeleton algorithm from ICCV 2023 [3] to extract its skeleton. Following this, we built the vessel graph from the centerline neighborhood's minimum spanning tree. This process was subsequently utilized to ascertain the topological relationships among features via graph convolution, a key operation within the **VesselGrapher** module. Following the integration of this module with the Multilayer Perceptron (MLP), the resultant system was designated as the **Vessel GNN** module. This module represents a notable divergence from the Vison GNN module, particularly in the methodology adopted for constructing the graph (Fig. 4). To maintain the topological connectivity, we opted for clDice along with the binary topological interaction module from NexToU. Besides these adjustments, our process remained consistent with the nnUNet framework. For data collection, 120 cases were sourced from an internal dataset while the remaining 80 were taken from the CROWN dataset containing Pseudo-labels with 24 anatomical classes. The dataset is summarized in Table 1.

Table 1. Dataset tables.

	Model 1	Model 2
Data Source	120 cases from internal dataset	120 cases from internal dataset
		80 cases from CROWN dataset Pseudo-labels
Classes	24 anatomical classes	24 anatomical classes

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