Summary/Critique

of

Automatic segmentation of intraluminal thrombosis of abdominal aortic aneurysms from CT angiography using a mixed-scale-driven multiview perception network (M2Net) model

Summary:

The paper presents M2Net, a novel deep-learning approach for automated intraluminal thrombus (ILT) segmentation in abdominal aortic aneurysm (AAA) cases using contrast-enhanced CT angiography (CTA) images. ILT is an important factor in AAA progression, but detecting it accurately is challenging because it has low contrast. It blends in with surrounding tissues, and it is unevenly spread within the aorta, making it difficult for traditional methods to segment. Additionally, manual segmentation is time-consuming and can vary between experts, leading to inconsistencies. To solve these issues, M2Net uses a two-step process: first, a 2D segmentation model called ZoomNet analyzes CTA images from three different views (axial, sagittal, and coronal), using multi-scale learning to detect ILT more effectively. These 2D segmentations are then combined into a 3D image using the Context-aware Volume Integration Network (CVIN), which improves accuracy by preserving both global structure and fine details. CVIN uses dilated convolutions to capture important patterns and anisotropic pooling to enhance local features. To improve detection of small or irregular ILT regions, the model is trained with Tversky loss, which helps balance false positives and false negatives. M2Net was tested on 80 CTA scans and achieved a Dice Similarity Coefficient (DSC) of 0.88, meaning it performed better than other deep-learning models in accurately identifying ILT. By automating ILT detection, M2Net could help doctors assess AAA risks more effectively and improve treatment planning, making it a valuable tool for medical imaging and diagnosis.

Strength:

One of the biggest strengths of this paper is its innovative multiview segmentation approach, which takes information from three different views (axial, sagittal, and coronal) instead of relying on a single perspective. This helps create a more accurate and detailed 3D representation of ILT, making it easier to detect even in challenging cases. Many previous methods depended on single-view imaging or manual segmentation, which could lead to inconsistencies and errors due to differences in how different experts annotate images. By using a multiview approach, M2Net reduces human bias and ensures greater consistency in segmenting ILT. Another major strength is the context-aware fusion method (CVIN), which combines the segmented results from different views into one unified 3D model. This is especially useful for detecting small or irregular ILT regions, which are often overlooked by other models due to their low contrast and scattered distribution. The paper also explains its methodology very clearly, providing detailed diagrams, experimental results, and comparisons with other advanced models to prove that M2Net performs

better. Additionally, the study highlights how manual ILT segmentation is a slow and difficult task for doctors, and by automating this process, M2Net could save time, reduce errors, and make ILT detection more reliable in real-world medical settings. This contribution is important for medical imaging and AI-based diagnostics, as it has the potential to improve AAA treatment planning and help doctors make better decisions.

Weakness:

Although the study makes valuable contributions, it has some limitations that need to be considered. One of the main issues is that the dataset used for training and testing includes only 80 CTA scans, which is a relatively small sample size. While this is enough to show that M2Net works well, it may not fully represent all types of patients, especially those with different ILT shapes, sizes, and imaging conditions. A larger and more diverse dataset would help confirm that the model can work reliably in real-world medical settings. Another challenge is that the ground truth ILT segmentations were labeled by human experts, which introduces some degree of subjectivity and potential errors. Since ILT is difficult to separate from surrounding tissues, different experts might mark the boundaries slightly differently, leading to variations in the training data. The study also only focuses on CTA images, but other medical imaging techniques like MRI and ultrasound could provide more detailed information about ILT composition and structure. Combining these imaging methods could help create a more complete and accurate segmentation system. Lastly, while M2Net is more accurate than previous methods, it takes a long time to train, with the CVIN model alone requiring 40 hours. This high computational cost could make it difficult to use in real-time clinical settings, unless further improvements are made to speed up processing without reducing accuracy.

Potential Improvement:

To make the study more useful and widely applicable, the researchers could increase the size and diversity of the dataset by including more CTA scans from different medical centers. This would help ensure that M2Net works well for a broader range of patients, including those with different ILT shapes, sizes, and imaging conditions. Another way to improve the model is by using semi-supervised learning, which allows the system to learn from a mix of fully labeled and partially labeled data. This would help reduce the need for experts to manually mark ILT regions, making the training process faster and less prone to human errors. Additionally, instead of relying only on CTA images, the study could integrate other imaging methods like MRI or ultrasound, which can provide extra details about ILT structure and composition. Using multiple imaging techniques together could improve segmentation accuracy, especially in difficult cases where CTA alone may not be enough. Finally, the model's long training time is a major challenge, so researchers could optimize CVIN by making it more efficient. Techniques like lighter architectures or knowledge distillation could help reduce computational costs, allowing the model to train and run faster without sacrificing accuracy. These improvements would make M2Net more practical for real-time use in hospitals and clinics, helping doctors analyze ILT quickly and accurately.