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Preoperative planning for Coronary Artery Disease using 3D Segmentation and Mixed Reality

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***Abstract*—Coronary arteries are crucial for keeping the function of our heart muscles by delivering the necessary resources like oxygen and nutrients. However, many problems may arise that can lead to potentially serious health issues such as Coronary Artery Disease, Myocardial Infarction, Dissection, Aneurysms and many more. Sometimes, surgery like Percutaneous Coronary Intervention is needed to fix a blocked artery. The surgery needs an intensive planning to prevent perioperative complications. To perform a proper planning the anatomy of coronary arteries needs to be studied. From the technical point of view automatic segmentation of coronaries can provide information related to the 3D anatomy and is essential for the diagnosis and quantification of coronary artery disease. In clinical practice the manual and semi-automatic segmentation of coronary arteries for quantification of narrowing part and treatment planning is still being used. In this study, the 3D Dense-U-Net architecture was proposed for precise segmentation of the coronary arteries. Additionally, Mixed Realty solution was introduced for pathology assessment during planning stage. The dataset consists of 1000 computed tomography angiography of patients. The dataset was divided in three subsets. Training, validation and test sets in ratio $70 : 15 : 15$. The segmentation results were evaluated using Dice and Hausdorff metrics. The proposed method achieved 0.8206 and $22.06mm$ respectively. The segmentation results are combined with the Computed Tomography volumetric rendering in Mixed Reality. The operator wearing the head-mounted display can assess the anatomy of coronary arteries, analyse the potential blockages and evaluate his/her approach for the surgery during preoperative planning and also intraoperatively.**

***Index Terms*—coronary artery; segmentation; 3D Dense U-Net; mixed reality; computed tomography (CT)**

I. Introduction

Cardiovascular diseases are the leading cause of death worldwide [1] and are mainly due to coronary artery disease. Computed Tomography Angiography (CTA) is one of the main imaging tools used for coronary artery visualization. It is an important diagnostic tool commonly used across the globe to detect coronary artery disease. Cardiologists examine CT angiographs to diagnose plaques and lesions in the coronary artery for preoperative planning of surgical treatments. The use of volumetric CT images allow clinicians to strategically plan surgical procedures and treatment according to the anatomy of each patient, while thoroughly evaluating all potential risks and complications. Since, precision is vital during surgical and interventional procedures, particularly within the fields of cardiothoracic surgery and cardiology. During surgery, a minor error in a few millimeter measurements can lead to complications and adverse effects, such as stroke and valve embolization [2]. However, manual examination requires a lot of time to look into the smallest details, while examinations may have interobserver variations due to experience and quality of CT angiographs. As a result, an automatic segmentation of coronary artery is necessary to prepare the data for 3D volumetric visualization.

However, Automatic segmentation of the coronary artery is a challenging task. Several factors affect the anatomy of the coronary artery. Depending on the individual, the coronary artery can be surrounded by fat or located in the heart muscle. In addition, noise in CT angiographs and the presence of artifacts highly compromise the segmentation quality. Furthermore, the coronary artery has an irregular tubular morphology [3]. For instance, the arteries contain a significant number of bifurcations and a limited proportion of the coronary arteries, as observed in the transverse planes.

Several studies have been conducted to address the aforementioned challenges. Coronary artery segmentation using conventional techniques is often classified into four categories: active contour model, centerline method, region growing method, and statistical model. Zhao et al. [4] employed the Hessian matrix approach to increase the contrast of blood vessels on CT angiographs. Subsequently, the moving sphere model was applied to generate the centerline of the coronary artery. However, the application of the Hessian matrix can subsequently amplify the noise of the CT angiograph.

Ma et al. [5] developed technique to separate the coronary artery according to the spherical regions and the growth of the annular. The proposed approach integrates elements of 2D and 3D image analysis to efficiently detect the coronary artery. Based on the shape of blood vessels in 2D, the target region is marked in a series of circular regions. Meanwhile, the spatial feature is defined by the spherical region, which conforms to the trajectory of the blood vessel in 3D images. However, the approach struggles with interference information on the CT angiograph. In [6] Ansari et al. applied the region-growing method with an optimal threshold. The extracted features were applied to the Hessian-based computed density measurement of the blood vessel, layer by layer, to detect the coronary artery. The proposed method identifies

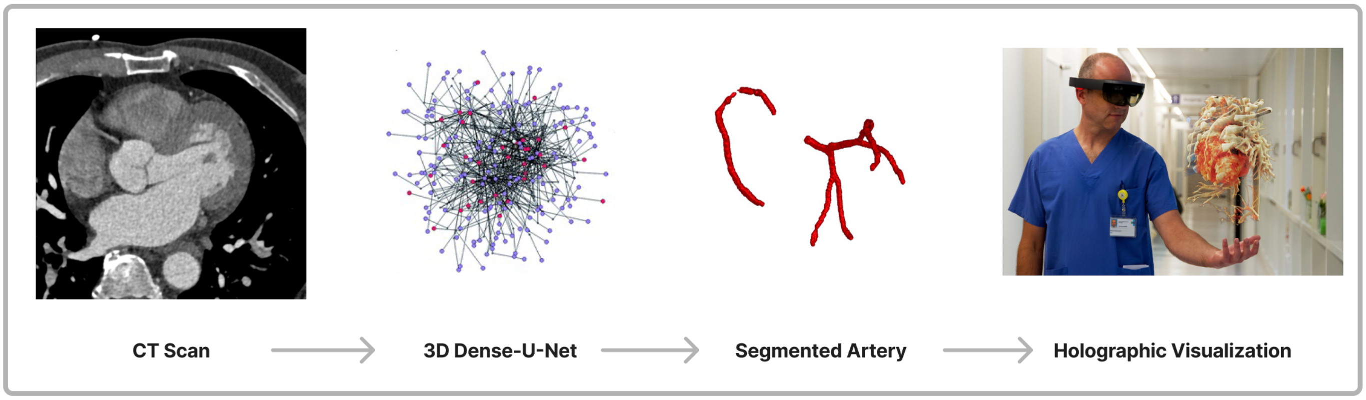

Fig. 1. Multi-dimensional Approach to Segment Coronary Artery and Identify Plaque

the coronary artery continuously, but the implementation of the threshold can result in the loss of some information. The application of traditional methods to segment the coronary artery mainly involves image pre-processing of the coronary artery, generation of the coronary center-line, and setting the growth rules. The aforementioned techniques can detect the coronary artery automatically or semiautomatically. However, conventional methods face challenges with burification and identification of small branches in the coronary artery.

In recent times, there has been a significant surge in the use of deep learning technology. Many deep learning algorithms have been applied in the field of medical image processing. In the study [7], Wolterink et al. implemented a graph convolutional network to determine the spatial position of the vertices within the tubular surface mesh that segmented the coronary artery. GCN is observed to be able to extract the coronary artery network. However, the identification of small lesions in the coronary artery remains a challenging task. Recently, the U-Net architecture, which consists of deep CNN layers, has shown promising results for automated segmentation in the medical field. In [8], Kjerland et al. implemented a two-stream CNN architecture that was trained on varying input scales. Volume data was generated from centerline data. In the study [9], a novel approach is introduced, comprising a 3D CNN classifier to estimate the radius and direction of the artery in the CT angiograph. However, the studies mentioned above demonstrated limited performance and have been evaluated using a small dataset. The primary objective of this study is to employ a deep learning approach to precisely segment the arteries and a 3D holographic representation of plaques. This methodology is intended to improve the understanding of physicians, allowing more precise surgical planning in the least amount of time. The pipeline of this study is shown in Fig. 1. Segmentation of the coronary artery is achieved by implementing a 3D Dense-U-Net architecture, which is based on the U-Net model. The dice loss function is applied to ensure significant segmentation results. Additionally, to provide a complete understanding of vascular health, segmented results are visualized on 3D holographs, allowing for detailed identification and in-depth analysis of plaques.

To assess the efficiency of the approach, the test set was evaluated using the Dice similarity coefficient (DSC) and the Hausdorff distance (HD). Furthermore, the segmented artery is visualized through a 3D hologram, which improved the understanding of the plaque regions. Consequently, providing an extensive analysis of vascular condition.

II. Methodology

A. Dataset

In this study, ImageCAS dataset [10] is used which was collected between April 2012 and December 2018 at the Guangdong Provincial People's Hospital. Two radiologists independently labeled the left and right coronary arteries. Additionally, the labels are also cross-validated. In case of discord, the third radiologist performed the annotations and the final outcome was decided by consensus. The study included 586 males and 414 females, aged 57.68 on average and 59.98 on average, respectively. A total of 1,000 3D CT angiographs were acquired. CT scans have a dimension of (512 * 512 * (206 - 275)) with a spacing of 0.25 to 0.45 mm.

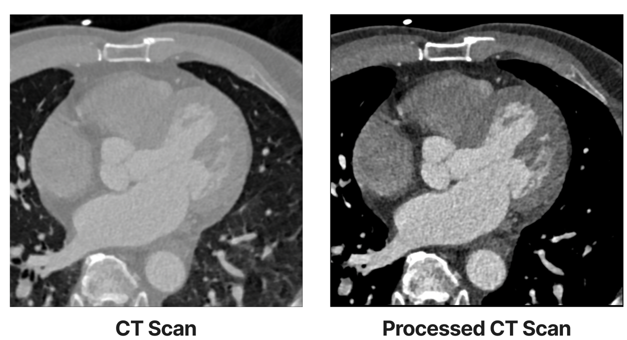

Fig. 2. Visualisation of CT Image Preprocessing

B. Preprocessing

During the preprocessing phase, the dataset is processed and organised in the following manner:

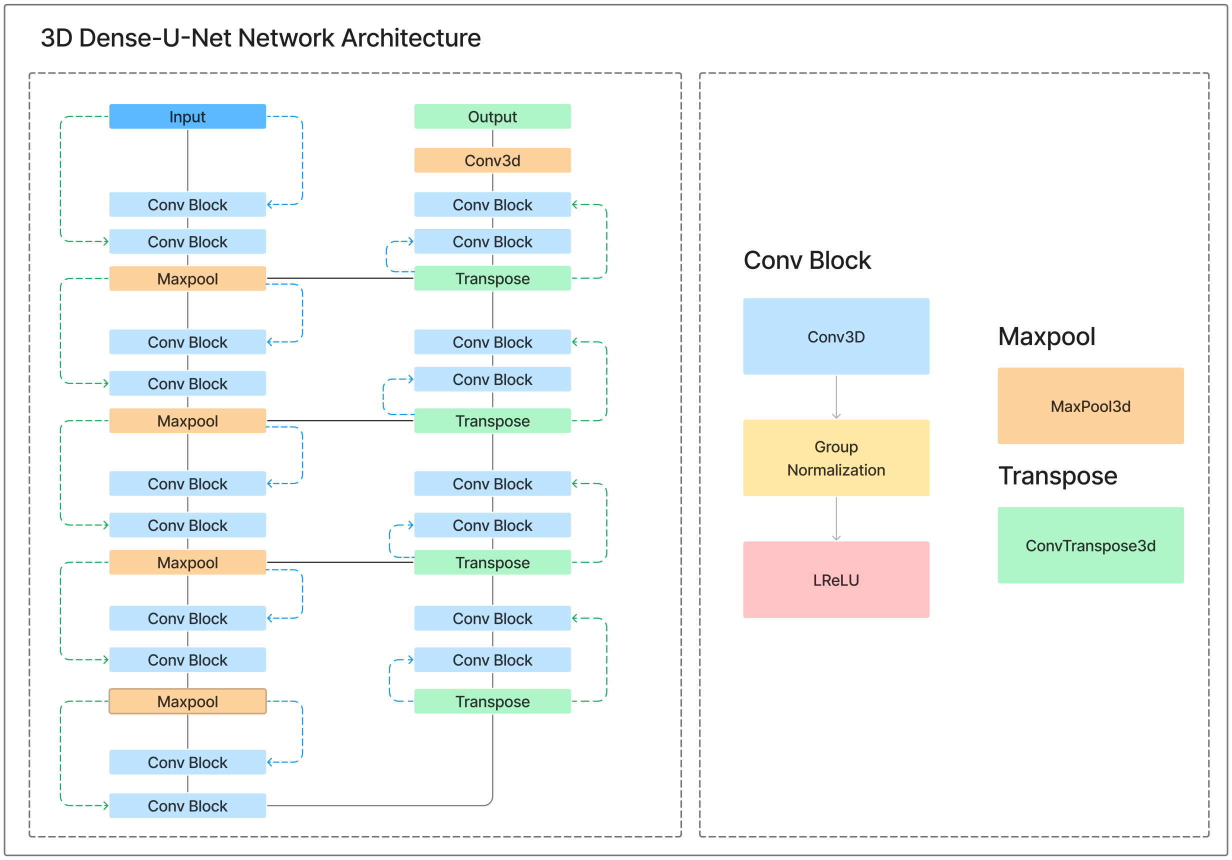

Fig. 3. The Architecture of Dense-U-Net network model

1) CT employs Hounsfield Units (HU) as a quantitative metric to determine density of various tissues in the body. CT scans are clipped from the [-200, 500] HU scale. The given range filters out the noise and irrelevant information. Furthermore, it emphasizes the coronary artery for accurate identification.
2) CT images have varying intensities, so they are normalized to the [0, 1] range. Normalization simplifies the computation, which contributes to a smoother training process.
3) Processing high-resolution volumes is a challenging task due to memory constraints on the GPU. As a result, the sample size of each CT scan is reduced by a factor of 2.

The final results of the preprocessing stage are illustrated in Fig. 2.

C. 3D Dense-U-Net Network Architecture

A 3D Dense-U-Net [11] network composed of residual interconnections and dense interconnections and employs a U-Net structure is implmented. The residual interconnections only interact within the down-sampling and up-sampling blocks. However, dense interconnections facilitate the flow of information between down-sampling and up-sampling blocks.

The architecture of the netwrok is shown in Fig. 3. Residual interconnections are shown in green, whereas dense interconnections are illustrated in blue. The network consists of four down-sampling and four up-sampling blocks, which are interconnected. Each downsamling block consists of conv blocks and maxpool. The Max-pooling layer decreases the size of the sample and extracts features. The upsampling block consists of conv blocks and a transposed conv layer. The size of the feature is doubled after each upsampling block.

The flow of information across interconnections is achieved by the zero padding. Following each conv layer, the extracted vector is filled with zeros to restore its original length. Thus, both conv layers operate on the same size of the input vector. For results, the feature map is computed with the 3D conv layer and a sigmoid layer. The feature map has two categories: background (0) and segmented coronary artery (1).

D. Post-processing

In the post-processing, the up-sampling is performed which transforms the segmented artery to its original size. Subsequently, false positives are removed using morphological approaches.

E. Network Training and Testing

The dataset was divided into three subsets. The Network is trained on 700 CT scans, validated on 150 CT scans, and

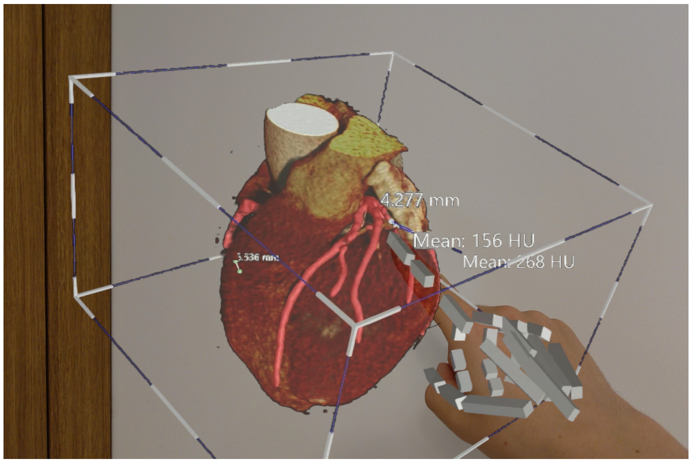

Fig. 4. Holographic visualization of CT DICOM with segmentation results in CarnaLife Holo (MedApp S.A., Poland) Mixed Reality solution.

tested on 150 scans. The Adam optimizer [12] is implemented with a learning rate of 0.0001, 200 epochs. The dice loss function is utilized during the training phase of the network. The function optimizes the network performance, ensuring precise segmentation.

F. Mixed Reality preoperative planning

Mixed Reality is a novel technique that enables using of digital information in 3D space thanks to the stereoscopic head mounted displays. In opposition to Virtual Reality (VR), where the user is immersed in a fully artificially created world, the mixed reality approach merges both worlds by overlaying the digital layer on the real world. Additionally, the mixed reality creates immersion based on the intuitive hand gestures, voice commands and virtual menus. The user has an impression of interacting with digital images as if they were real objects.

Proposed solution combines two types of visualization, surface rendering for segmentation results and volumetric rendering for CT data.This approach simplifies the result analysis for the doctors because of easiness of understanding the 3D structures in holographic space which is hard to accomplish on classical screens. Mixed Reality gives also an opportunity to bring the visualization to the intra-operative scenario while maintaining the possibility to create new measurements and customize the visualization based on ad-hoc needs during the surgery. Sample visualization in Mixed Reality is presented in the Fig. 4.

III. Results

Trained 3D DenseNet architecture is evaluated on a test dataset composed of 150 CT scans. DSC and HD are widely used in the evaluation of volume segmentation and image identification within the medical domain. The DSC is used to quantify the overlap between the ground truth and the predicted results. The mathematical representation is as follows:

$$DSC = \frac{2\left|P \bigcap G\right|}{|P| + |G|} \tag{1}$$

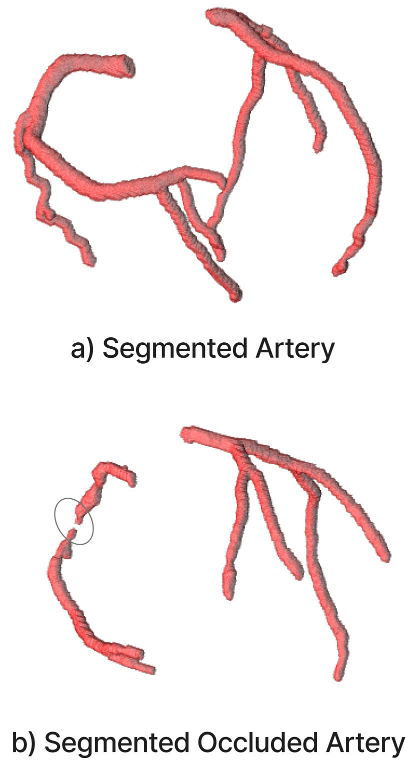

Fig. 5. Segmented Results: Comparison between two different segmented cases

The ground truth is represented by G, while P shows the predicted results.

The HD is a mathematical measure employed to determine the maximum distance in two structures.

$$\begin{aligned} HD(X,Y) &= max\left\{d_{XY}, d_{YX}\right\} \\ &= max\left\{\max_{x\epsilon X}\min_{y\epsilon Y} d(x,y), \max_{y\epsilon Y}\min_{x\epsilon X} d(x,y)\right\} \end{aligned} \tag{2}$$

The variable d_{XY} denotes the maximum distance between the minimum distance from boundary X to boundary Y. while d_{YX} represents the maximum distance between the minimum distance from the boundary Y to the boundary X.

The table I presents the results in comparison to the other methods. The state-of-the-art segmentation approaches [7], [13]–[15] were recreated and validated on ImageCAS datased by Zeng et al. [10].

The proposed algorithm reached the DSC value equal to 0.8206 and HD equal to $22.06mm$, achieving a baseline level of the state of the art. During the evaluation, we found that some of our results had significantly lower metrics compared to the average score. After further investigation, it turned out that those outliers actually occur in the case of abnormal lumen intensities in the coronary arteries. In the ground truth, the mask represents the entire reconstructed artery, and our

TABLE I
EVALUATION COMPARISON WITH STATE OF THE ART

Segmentation Approaches	Dice	HD (mm)
Tree data-based segmentation (3D reeConvGRU)[13]	0.6878	30.33
Graph based segmentation (GCN) [7]	0.7061	27.87
Patch segmentation (3D U-Net) [14]	0.7201	40.96
Direct segmentation (3D FCN) [15]	0.8058	28.66
Baseline method (3D U-Net and UNet++) [10]	0.8296	27.21
Proposed methodology (3D Dense-U-Net Network)	0.8206	22.06

method detected a healthy artery and did not cover the diseased regions. This is expected behavior, as the neural network is supposed to detect an artery with a correct lumen.

The irregular lumen intensities observed in the arteries may be due to a different range of variables, such as patient movement, measurement timing, and stenosis. During the image acquisition process, sudden movement of the patient may result in distortion and blurring of the image. It can cause the lumen to be less distinct, leading to lower intensity values. Furthermore, the intensity of the artery can be influenced by the temporal alignment between the monitoring process and physiological parameters. For instance, the cardiac cycle can alter the lumen intensities in the artery. In different phases of the cardiac cycle, the intensity of the lumen can vary from one phase to another. Additionally, stenosis frequently arises due to plaque build-up in the artery, leading to narrowing of the artery. In the presence of stenosis, blood flow is restricted in the artery, reducing the intensity level in the affected region. Fig.5 shows two different scenarios of the segmented artery.

The segmented artery is visualized in mixed reality for further analysis. In the case of plaque, visualization in mixed reality is used to represent the plaque. This facilitates enhanced understanding among medical professionals and allows them to effectively plan surgery. The visual representation of plaque in the hologram is illustrated in Fig. 6. In the visualization, two regions are identified. One is where the results identify the artery and the second is where the artery is missing from the results. An average Hounsfield unit (HU) value was calculated for those two regions. It turned out that the region that the neural network did not classify as an artery had a mean value of 150 HU and the one with the vessel has a mean value of 268 HU. The proximity of those regions suggests the existence of a plaque.

IV. CONCLUSION AND FUTURE WORK

In this study, a segmentation framework is described which integrates deep learning and 3D hologram to segment the coronary artery and identify plaques. A Dense-U-Net is implemented to segment the coronary artery, and then the 3D hologram technique is used for plaque examination. This integrated approach precisely segmented the coronary artery and provided an in-depth analysis of plaque analysis.

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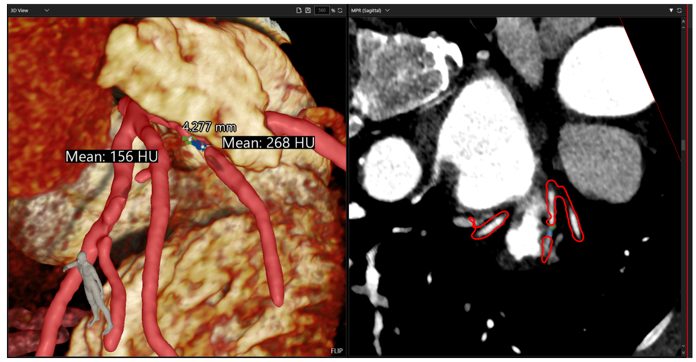

Fig. 6. 3D volumetric rendering of CT DICOM with segmentation results and plaque measurements performed in CarnaLife Holo (MedApp S.A., Poland)

DISCLOSURES

Manahil Zulfiqar, Maciej Stanuch, and Andrzej Skalski are MedApp S.A. employees. MedApp S.A. is the company that manufactures the CarnaLife Holo solution.

REFERENCES

[1] S. M. Szilágyi, M. M. Popovici, and L. Szilágyi, "Automatic segmentation techniques of the coronary artery using ct images in acute coronary syndromes," *Journal of Cardiovascular Emergencies*, vol. 3, no. 1, pp. 9–17, 2017.

[2] I. Vernikouskaya, W. Rottbauer, B. Gonska, *et al.*, "Image-guidance for transcatheter aortic valve implantation (TAVI) and cerebral embolic protection," *International journal of cardiology*, vol. 249, pp. 90–95, 2017, ISSN: 0167-5273.

[3] H. Zhu, S. Song, L. Xu, A. Song, and B. Yang, "Segmentation of coronary arteries images using spatio-temporal feature fusion network with combo loss," *Cardiovascular Engineering and Technology*, pp. 1–12, 2022, ISSN: 1869-408X.

[4] J. Zhao, W. Gong, S. Jiang, *et al.*, "Automatic Segmentation and Reconstruction of Coronary Arteries Based on Sphere Model and Hessian Matrix using CCTA Images," *Journal of Physics: Conference Series*, vol. 1213, no. 4, p. 042 049, 2019, ISSN: 1742-6596. DOI: 10.1088/1742-6596/1213/4/042049. [Online]. Available: https://dx.doi.org/10.1088/1742-6596/1213/4/042049.

[5] G. Ma, J. Yang, Y. Huang, and H. Zhao, "A novel automatic coronary artery segmentation method based on region growing with annular and spherical sector partition," *Journal of Medical Imaging and Health Informatics*, vol. 9, no. 1, pp. 148–152, 2019, ISSN: 2156-7018.

[6] M. A. Ansari, S. Zai, and Y. S. Moon, "Automatic segmentation of coronary arteries from computed tomography angiography data cloud using optimal thresholding," *Optical Engineering*, vol. 56, no. 1, p. 13 106, 2017, ISSN: 0091-3286.

[7] J. M. Wolterink, T. Leiner, and I. Išgum, "Graph convolutional networks for coronary artery segmentation in cardiac CT angiography," in *Graph Learning in Medical Imaging: First International Workshop, GLMI 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 17, 2019, Proceedings 1*, Springer, 2019, pp. 62–69, ISBN: 303035816X.

[8] Ø. Kjerland, "Segmentation of Coronary Arteries from CT-scans of the heart using Deep Learning," 2017. [Online]. Available: https://api.semanticscholar.org/CorpusID:55065992.

[9] J. M. Wolterink, R. W. van Hamersvelt, M. A. Viergever, T. Leiner, and I. Išgum, "Coronary artery centerline extraction in cardiac CT angiography using a CNN-based orientation classifier," *Medical image analysis*, vol. 51, pp. 46–60, 2019, ISSN: 1361-8415.

[10] A. Zeng, C. Wu, G. Lin, *et al.*, "ImageCAS: A large-scale dataset and benchmark for coronary artery segmentation based on computed tomography angiography images," *Computerized Medical Imaging and Graphics*, p. 102 287, 2023, ISSN: 0895-6111. DOI: https://doi.org/10.1016/j.compmedimag.2023.102287. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0895611123001052.

[11] M. Kolařík, R. Burget, V. Uher, K. Říha, and M. K. Dutta, "Optimized high resolution 3d dense-u-net network for brain and spine segmentation," *Applied Sciences*, vol. 9, no. 3, p. 404, 2019, ISSN: 2076-3417.

[12] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[13] B. Kong, X. Wang, J. Bai, *et al.*, "Learning tree-structured representation for 3D coronary artery segmentation," *Computerized Medical Imaging and Graphics*, vol. 80, p. 101 688, 2020, ISSN: 0895-6111.

[14] Y.-C. Chen, Y.-C. Lin, C.-P. Wang, *et al.*, "Coronary artery segmentation in cardiac CT angiography using 3D multi-channel U-net," *arXiv preprint arXiv:1907.12246*, 2019.

[15] Y. Shen, Z. Fang, Y. Gao, N. Xiong, C. Zhong, and X. Tang, "Coronary arteries segmentation based on 3D FCN with attention gate and level set function," *Ieee Access*, vol. 7, pp. 42 826–42 835, 2019, ISSN: 2169-3536.