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Leveraging Mixed Reality and 3D Segmentation in the Efficacious Detection, Diagnosis and Treatment for Coronary Artery Disease[1]

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ABSTRACT

The coronary arteries are essential for maintaining heart muscle function by supplying oxygen and nutrients. However, various conditions such as Coronary Artery Disease, Myocardial Infarction, Dissection, and Aneurysms can severely impact their health. Surgical interventions like Percutaneous Coronary Intervention are often necessary for treating blocked arteries, requiring meticulous planning to avoid complications. A comprehensive understanding of coronary artery anatomy is crucial for effectively planning, diagnosing, and treating coronary artery disease. While manual and semi-automatic segmentation methods are traditionally used in clinical settings, automatic segmentation offers advancements in 3D anatomy assessment.

This study introduces the 3D Dense-U-Net architecture for precise segmentation of coronary arteries. But the real excitement lies in the proposed Mixed Reality solution, a cutting-edge tool that revolutionizes pathology assessment during the planning stage. The dataset comprises 1000 computed tomography angiography scans, divided into training, validation, and test sets at a ratio of 70:15:15. Segmentation performance is evaluated using Dice and Hausdorff metrics, achieving scores of 0.8206 and 22.06mm, respectively. The segmented results are integrated with volumetric rendering in Computed Tomography for Mixed Reality visualization. Operators using head-mounted displays can analyze coronary artery anatomy, identify blockages, and refine surgical approaches during preoperative planning and intraoperative stages.

INTRODUCTION

Cardiovascular diseases rank as the primary cause of global mortality [1], prominently driven by conditions such as coronary artery disease. Computed Tomography Angiography (CTA) is a vital imaging modality for visualizing coronary arteries, which is crucial for diagnosing arterial plaques and lesions and planning surgical interventions effectively. Utilizing volumetric CT images enables clinicians to strategize treatments tailored to each patient's anatomy, meticulously assessing risks and complications. Precision is paramount in cardiothoracic surgery and cardiology; minor measurement errors during procedures can lead to severe outcomes like stroke or valve embolization [2]. Manual scrutiny is time-intensive and subject to interobserver variability based on experience and image quality, necessitating automated coronary artery segmentation for 3D volumetric visualization.

Automatic segmentation of coronary arteries poses challenges due to anatomical variability—arteries may be surrounded by fat or embedded in heart muscle—and imaging artefacts that compromise segmentation quality. Moreover, coronary arteries exhibit irregular tubular morphologies with numerous bifurcations, complicating

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segmentation in transverse planes [3]. Traditional approaches to coronary artery segmentation include active contour models, centerline methods, region growing, and statistical models. For instance, Zhao et al. [4] enhanced blood vessel contrast using the Hessian matrix but risked amplifying CT noise. Ma et al. [5] employed spherical region segmentation, combining 2D and 3D analysis, but faced interference in CT images. Ansari et al. [6] utilized region growing with optimal thresholds, achieving continuous artery detection but at the cost of information loss.

Recent advancements in deep learning have revolutionized medical image processing. Wolterink et al. [7] utilized a graph convolutional network (GCN) to extract coronary artery networks, yet small lesion detection remains challenging. U-Net, a deep convolutional neural network (CNN), has shown promise in medical segmentation tasks. Kjerland et al. [8] applied a two-stream CNN for coronary artery segmentation but with limitations due to the small dataset evaluation. This study employs a 3D Dense-U-Net architecture to address these gaps for precise coronary artery segmentation and visualization of holographic plaque.

The primary objective is to enhance surgical planning efficiency through deep learning-based segmentation and 3D holographic visualization of coronary arteries. Fig. 1 illustrates the study pipeline, which employs a 3D Dense-U-Net architecture integrated with the U-Net model and dice loss function for robust segmentation. Segmented results are visualized in 3D holograms to facilitate detailed plaque identification and comprehensive vascular health analysis.

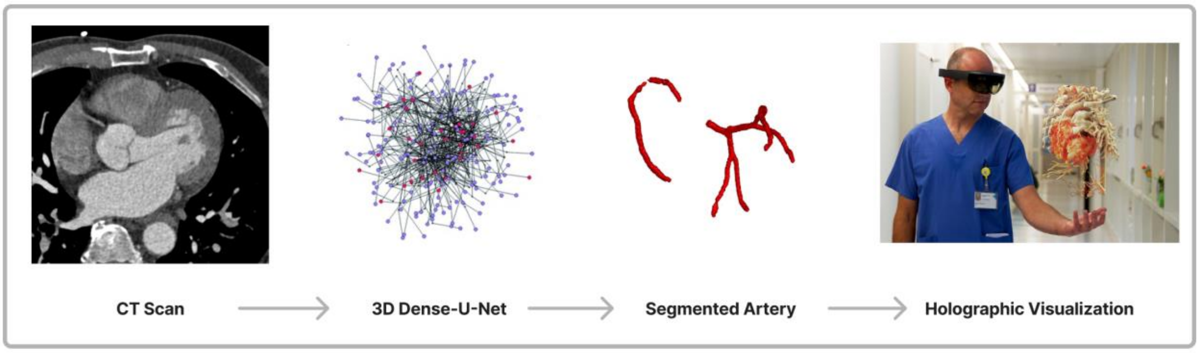

Fig. 1. Multi-dimensional Approach to Segment Coronary Artery and Identify Plaque

Evaluation on a test set utilizes Dice similarity coefficient (DSC) and Hausdorff distance (HD) metrics, ensuring accurate artery segmentation. Integrating 3D holograms enhances understanding of plaque distribution and vascular conditions, promising enhanced surgical planning and diagnostic precision.

METHODOLOGY

A. Dataset

This study utilized the ImageCAS dataset [10], collected between April 2012 and December 2018 at Guangdong Provincial People's Hospital. Two radiologists independently labelled both left and right coronary arteries, with cross-validation of labels. A third radiologist resolved discrepancies through consensus. The dataset included 586 males and 414 females, averaging 57.68 and 59.98 years old. 1,000 3D CT angiographs were acquired, with CT scans measuring (512 512 (206 - 275)) and spaced 0.25 to 0.45 mm.

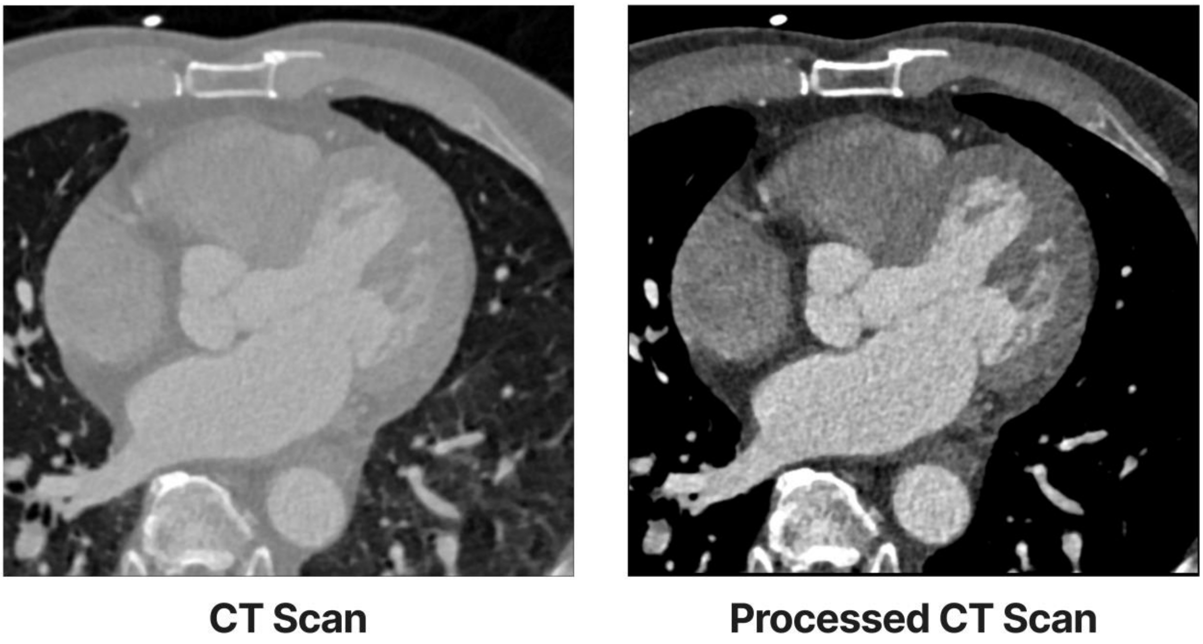

Fig. 2. Visualisation of CT Image Preprocessing

B. Preprocessing

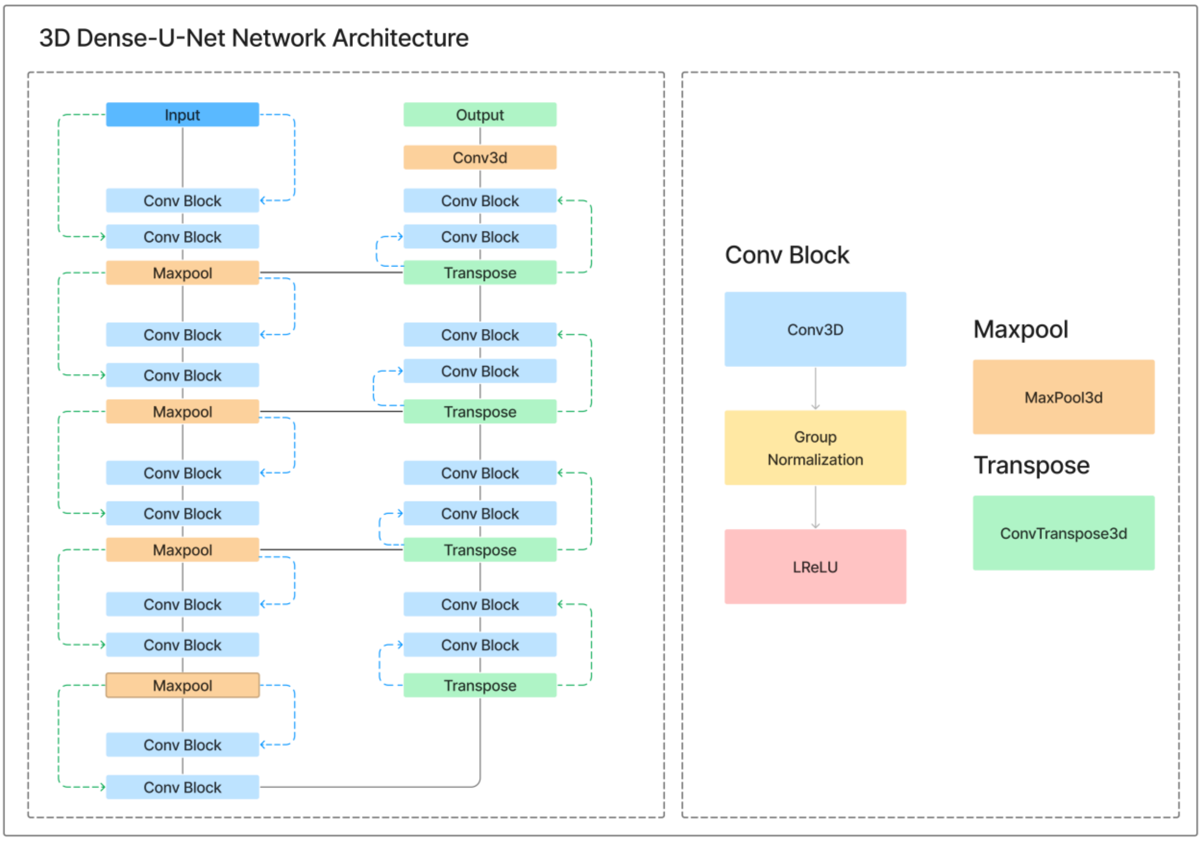

Fig. 3. The Architecture of Dense-U-Net network model

During preprocessing:

1. CT scans, quantified in Hounsfield Units (HU), were clipped to the [-200, 500] HU range to filter noise and enhance coronary artery visibility.

2. Intensity normalization was performed to scale CT images to the [0, 1] range, simplifying computational processes.

3. To accommodate GPU memory constraints, high-resolution volume processing was optimized by reducing each CT scan size by a factor of 2.

The results of the preprocessing stage are depicted in Fig. 2.

C. 3D Dense-U-Net Network Architecture

A 3D Dense-U-Net [11] network architecture was employed, incorporating residual and dense interconnections within a U-Net structure. Residual interconnections operated exclusively within down-sampling and up-sampling blocks, while dense interconnections facilitated information flow between these blocks. The network structure, illustrated in Fig. 3, comprised four down-sampling and four up-sampling blocks. Each down-sampling block included conv blocks and max-pooling layers to extract features, while each up-sampling block comprised conv blocks and transposed conv layers to double feature map sizes. Information flows across interconnections utilized zero padding to maintain vector length consistency post-convolution. The network output, categorized into the background (0) and segmented coronary artery (1), was processed with a 3D convolutional layer and a sigmoid layer.

D. post-processing

Post-processing involved up sampling to restore segmented artery sizes and morphological techniques to eliminate false positives.

E. Network Training and Testing

The dataset was split into training (700 CT scans), validation (150 CT scans), and testing (150 CT scans) subsets. Training employed the Adam optimizer [12] with a learning rate 0.0001 over 200 epochs, optimizing network performance using the dice loss function to ensure accurate segmentation.

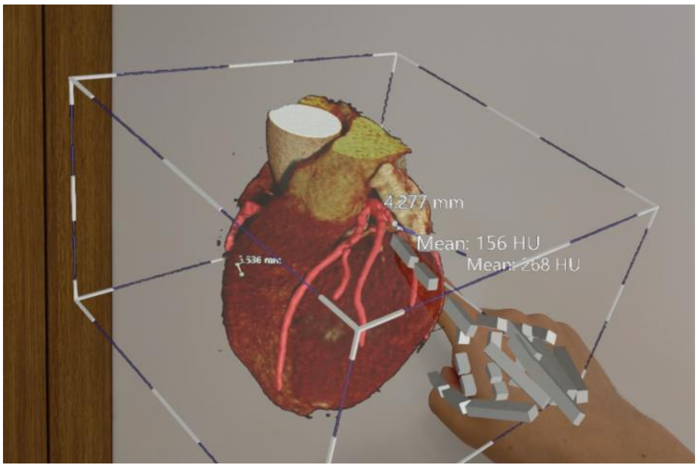

Fig. 4. Holographic visualization of CT DICOM with segmentation results in CarnaLife Holo (MedApp S.A., Poland) Mixed Reality solution.

F. Mixed Reality Preoperative Planning

Mixed Reality integrates digital information into 3D space via stereoscopic head-mounted displays, merging real and virtual worlds. Unlike Virtual Reality (VR), which immerses users in entirely synthetic environments, Mixed

Reality overlays digital layers onto the real world, enabling intuitive interaction through gestures, voice commands, and virtual menus. This approach facilitates a more straightforward analysis of 3D structures via surface rendering for segmentation results and volumetric rendering for CT data, enhancing comprehension compared to traditional screens. Mixed Reality supports intra-operative visualization, enabling real-time adjustments and measurements tailored to surgical needs. Sample visualization in Mixed Reality is shown in Fig. 4.

RESULTS

The trained 3D DenseNet architecture was assessed using a test dataset comprising 150 CT scans. Within the medical domain, Dice Similarity Coefficient (DSC) and Hausdorff Distance (HD) are commonly used metrics for evaluating volume segmentation and image identification. The DSC quantifies the overlap between the ground truth (G) and predicted results (P), expressed mathematically as:

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

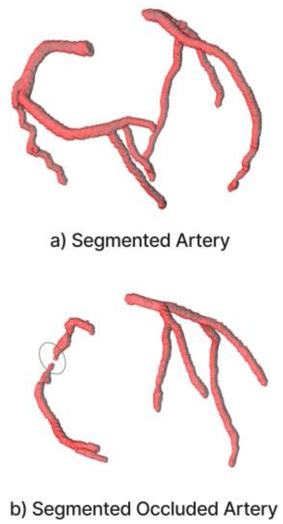

Fig. 5. Segmented Results: Comparison between two different segmented cases

The HD measures the maximum distance between two structures, defined by \(d_{XY} \) as the maximum distance from boundary X to boundary Y, and \(d_{YX} \) as from boundary Y to boundary X.

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

Results are presented in Table I, comparing against state-of-the-art segmentation methods [7], [13]–[15], validated on the ImageCAS dataset by Zeng et al. [10]. Our proposed algorithm has demonstrated its competitive edge, achieving a DSC of 0.8206 and an HD of 22.06 mm, which is on par with or better than existing methods. Notably, some results exhibited lower metrics due to abnormal lumen intensities in coronary arteries. Our method accurately detected healthy arteries but did not cover diseased regions as per the ground truth, aligning with the neural network's intended function to identify arteries with correct lumens.

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

Irregular lumen intensities could result from patient movement during image acquisition, temporal misalignment with physiological parameters, and arterial stenosis. Movement artefacts can blur images and reduce lumen visibility, while cardiac cycle phases can alter arterial intensities. Additionally, plaque buildup due to stenosis can narrow arteries and diminish intensity levels in affected regions.

Figure 5 illustrates two scenarios of segmented arteries, with further visualization in mixed reality for enhanced analysis. In cases involving plaque, our method shows significant potential in aiding surgical planning by accurately depicting plaque locations. This practical application among medical professionals is further demonstrated in Figure 6, which showcases holographic visualization of plaque, distinguishing regions identified as arteries from those missed by the network. Mean Hounsfield Unit (HU) values were calculated for these regions, with the non-classified artery region averaging 150 HU and the vessel-containing region averaging 268 HU, indicating potential plaque presence in close proximity.

CONCLUSION

In conclusion, this study has made a significant contribution by introducing a segmentation framework that integrates deep learning and 3D holography for coronary artery segmentation and plaque identification. The implementation of Dense-U-Net has proven to be effective in segmenting coronary arteries, and the subsequent use of 3D holography has enhanced plaque analysis. This integrated approach not only provides precise artery segmentation and detailed plaque assessment but also paves the way for future research in the field of medical imaging and deep learning.

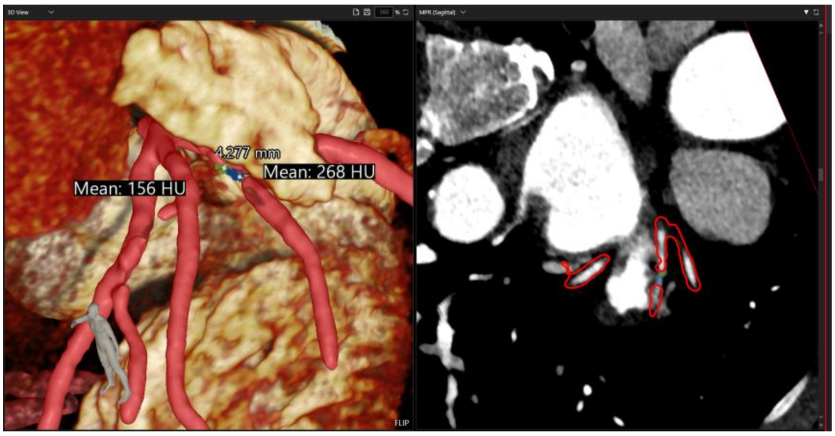

Fig. 6. 3D volumetric rendering of CT DICOM with segmentation results and plaque measurements performed in CarnaLife Holo (MedApp S.A., Poland)

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