Harnessing 3D U-Net For Classifying CongenitalCardiovascular Diseases On Cardiac Images

Bensen Mathew[1], Bineetta Mary[2], Rahul Ajith[3], Santa Mariam Saji[4] Dr. Dhanya S.
[1234] Department of Electronics and Communication Engineering, Muthoot Institute of Technology and Science, Varikoli, India

Abstract— The deep learning technique, U-Net architecture, are used to achieve accurate and efficient segmentation of congenital heart vessels. Congenital heart disease stands as a major cause of mortality, affecting 1 in every 110 births. Timely diagnosis through automatic cardiac segmentation is crucial. Leveraging state-of-the-art neural network architectures, our approach focuses on the automated extraction and precise delineation of intricate vascular structures within the heart. The proposed methodology involves preprocessing the data, training the deep learning model on a diverse dataset, and fine-tuning the network to achieve accurate segmentation results. By automating vessel segmentation, our system contributes to expediting diagnosis and treatment planning, ultimately improving patient outcomes in the realm of congenital heart diseases.

Keywords— Segmentation, Cardiac MRI, Classification, 3D U-Net

I. INTRODUCTION

Our research focuses on classifying different forms of congenital heart disease (CHD) and segmenting congenital heart vessels utilizing the cutting-edge 3D U-Net design. Congenital heart defects (CHDs) are intricate structural defects that impact cardiac function and may involve complex changes in heart arteries. Precise diagnosis, treatment planning, and patient monitoring for congestive heart failure depend heavily on accurate segmentation of these arteries. Our goal is to improve and automate the process of separating heart vessels from MRI or CT scans, giving medical practitioners precise and comprehensive anatomical insights. We will achieve this by utilizing deep learning and medical image analysis.

Moreover, our work goes beyond segmentation to include the critical work of categorizing various forms of CHD. By utilizing extensive datasets and machine learning methods, our goal is to create a reliable classification system that can classify CHD situations according to segmented vessel patterns. This classification capacity is extremely valuable for clinical practice because it allows physicians to quickly identify particular forms of CHD, which allows for more individualized treatment plans and better patient outcomes.

Our project intends to transform pediatric cardiology's diagnostic and treatment landscape by integrating state-of-the-art technologies, such as machine learning for classification and deep learning for segmentation. Through the provision of automated, precise, and effective methods for heart vessel segmentation and CHD classification, our goal is to make a substantial contribution to improved clinical decision-making, patient care, and congenital heart disease research developments.

II. DATASET

Our dataset encompasses 178 3D CT images acquired using a Siemens biograph 64 machine, capturing patients aged between 1 month and 40 years, predominantly within the 1-month to 2-year age range. The images exhibit dimensions of $512 \times 512 \times (129\text{-}357)$, with a typical voxel size of $0.25 \times 0.25 \times 0.5 mm^3$, ensuring high-resolution representation. The dataset comprehensively covers 16 types of congenital heart disease (CHD), including both common and less common variants.

For classification purposes, the dataset includes images of eight common CHD types, namely atrial septal defect (ASD), atrioventricular septal defect (AVSD), patent ductus arteriosus (PDA), pulmonary atresia (PuA), ventricular septal defect (VSD), coarctation (CA), tetralogy of Fallot (TOF), and transposition of great arteries (TGA). Additionally, it encompasses eight less common types, such as pulmonary artery sling (PAS), double outlet right ventricle (DORV), common arterial trunk (CAT), double aortic arch (DAA), anomalous pulmonary venous drainage (APVC), aortic arch hypoplasia (AAH), interrupted aortic arch (IAA), and double superior vena cava (DSVC).

Moreover, the dataset provides comprehensive segmentation labels for seven substructures: left ventricle (LV), right ventricle (RV), left atrium (LA), right atrium (RA), myocardium (Myo), aorta (AO), and pulmonary artery (PA). Venae cavae (VC) and pulmonary veins (PV) are also delineated as part of RA and LA, respectively, for ease of processing. Anomalous vessels are labeled according to their connections, contributing to the detailed annotation provided by a team of four experienced cardiovascular radiologists.

Through the integration of segmentation and classification data, our dataset serves as a valuable resource for advancing research in automated CHD diagnosis and management, facilitating the development of robust algorithms capable of accurately segmenting cardiac structures and classifying diverse CHD types.

III. METHODOLOGY

A. *Methodology for Disease Segmentation*

The methodology for whole heart and blood vessel segmentation using the 3D U-Net architecture begins with acquiring a diverse dataset of 3D medical images showcasing various heart structures and blood vessels. These images undergo rigorous preprocessing, including standardization, augmentation for increased diversity, and noise reduction. The 3D U-Net model is then configured, featuring a contracting path for feature extraction and an expansive path for segmentation map generation, interconnected by skip connections. The model is trained on the augmented dataset, with hyperparameters fine-tuned based on validation set performance to prevent overfitting. Evaluation metrics like dice coefficient and IoU are used to assess segmentation accuracy, followed by post-processing techniques for refining results. Finally, the trained 3D U-Net model is deployed for real-world applications in automated whole heart and blood vessel segmentation tasks within medical imaging systems.

B. *Methodology for Disease Classification:*

There are numerous crucial steps in the process of identifying various forms of congenital heart disease (CHD) utilizing the VGG architecture. First, a collection of medical photos with labels indicating different types of congenital heart disease (CHD) is gathered. To make sure these photos are suitable for input into the VGG model, preprocessing techniques like scaling, normalization, and augmentation are applied. Next, the deep convolutional layers-based VGG architecture is set up for classification tasks. By starting the model using pre-trained weights from a sizable dataset, such as ImageNet, and honing it on the CHD dataset, transfer learning can be used. The dataset is separated into test, validation, and training sets. To avoid overfitting, the model is trained using the training set and its performance is tracked on the validation set. Evaluation measures are employed to evaluate the model's classification performance on the test set, including accuracy, precision, recall, and F1 score. When the model performs well enough, it can be implemented in real-world scenarios and help with automatic and precise CHD categorization in medical settings.

IV. ALGORITHM

The U-Net algorithm is a deep learning architecture specifically designed for semantic segmentation tasks, which involve labeling each pixel in an image with a corresponding class label. It is widely used in medical image analysis due to its ability to accurately segment structures of interest, such as organs, tissues, or vessels. The architecture of U-Net consists of two main components: the contracting path and the expansive path.

1. Contracting Path: The contracting path of U-Net is responsible for capturing features and reducing spatial dimensions. It comprises a series of convolutional layers followed by max-pooling layers. The convolutional layers extract features from the input image, gradually reducing its size, while the max-pooling layers downsample the feature maps to capture important information in a more compact representation. This process allows U-Net to learn hierarchical features that are essential for accurate segmentation.

2. Expansive Path: The expansive path of U-Net is responsible for upsampling the features and reconstructing the segmented image. It consists of upsampling layers followed by convolutional layers. The

upsampling layers increase the spatial dimensions of the feature maps to match the original input size, while the convolutional layers refine the segmentation output based on the extracted features. Additionally, U-Net incorporates skip connections, also known as residual connections, that directly connect corresponding layers in the contracting and expansive paths. These skip connections enable the model to preserve fine details and localize segmented objects accurately by combining both global context information from the contracting path and detailed information from the skip connections.

The unique architecture of U-Net, with its contracting and expansive paths and skip connections, allows it to effectively capture both global context and fine details in medical images. This makes it particularly well-suited for tasks like segmenting congenital heart vessels, where precise localization and accurate delineation of structures are crucial for diagnosis and treatment planning.

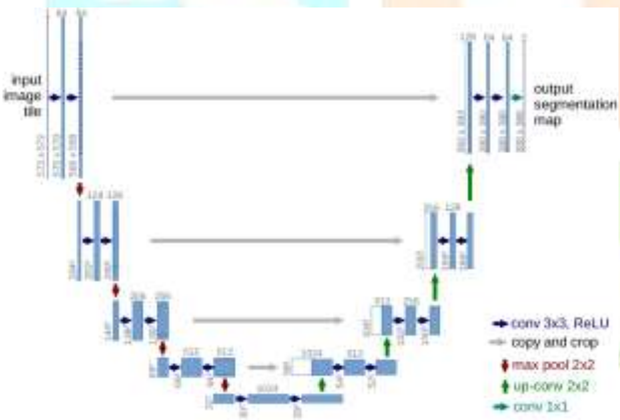

Figure 1: U-Net Architecture

V. EXPERIMENTAL SETUP

The implementation of the 3D U-net in PyTorch was based on, while our 2D U-net largely mirrored the configurations of the 3D U-net with adjustments such as employing 5 levels and setting the initial level's filter count to 16. Both networks employed Dice loss and cross entropy loss, for 2D U-net and 3D U-Net were calculated. Data augmentation and normalization were adopted following the configuration for the 3D U-net.

For both networks, a three-fold cross-validation approach was executed, with approximately 37 images allocated for testing and 73 images for training. The dataset was partitioned to ensure all types of Congenital Heart Diseases (CHD) were represented in each subset. The classification encompassed 17 classes, including 16 types of CHD and normal anatomy. Template selection from the library was randomized, and a selective prediction scheme was employed for evaluation. Dataset partitioning ensured that the structures of CHD were evenly distributed, allowing similar representations in both testing and training datasets, even if not of the same CHD type. Segmentation evaluation utilized the Dice score.

VI. RELATED STUDY

The study involved 68 3D CT images with ground truth labels for seven categories: LV, RV, LA, RA, myocardium, Ao, and PA, covering 14 types of CHD. The framework was able to segment the four chambers and myocardium based on the blood pool using deep learning, and then extract connection information and apply graph matching to categorize all vessels. The proposed framework, which combines deep neural networks and graph matching for whole heart and great vessel segmentation in CHD. The framework employs multiple U-Nets for segmentation, including a 3D U-net and a 2D U-net, to handle the complex structures of the heart and great vessels in CHD. Deep learning is used to process regular structures and refine boundaries, with an average increase of 12% in Dice score compared to the state-of-the-art segmentation method in normal anatomy.

The framework's ability to accurately segment the four chambers, myocardium, and vessels in CHD cases showcases its effectiveness in handling complex anatomical variations. The improved segmentation accuracy, as reflected in the Dice score enhancement, highlights the superiority of the proposed method over existing approaches in normal anatomy segmentation. The segmentation results were evaluated by two cardiovascular imaging specialists using the Van Praagh classification system, and the framework showed good performance in clinical evaluation.The results suggest that the proposed method has the potential for clinical use in the future, paving the way for improved segmentation accuracy in CHD cases.

VII CONCLUSION

In summary, the 3D U-Net architecture for segmenting congenital heart vessels has been effectively implemented by our project, providing a strong basis for precise and thorough examination of the heart structures in patients with congenital heart disease (CHD). In the future, the incorporation of the VGG architecture for CHD classification is expected to improve diagnostic capacities by enabling the accurate classification of various CHD forms according to segmented vessel patterns. Our initiative seeks to greatly improve clinical decision-making, individualized treatment plans, and ultimately better results for patients with congestive heart failure by fusing cutting-edge deep learning techniques with medical image analysis. In order to use technology to improve knowledge and treatment of complex cardiac disorders in pediatric cardiology, it is imperative to go from segmentation to classification.

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