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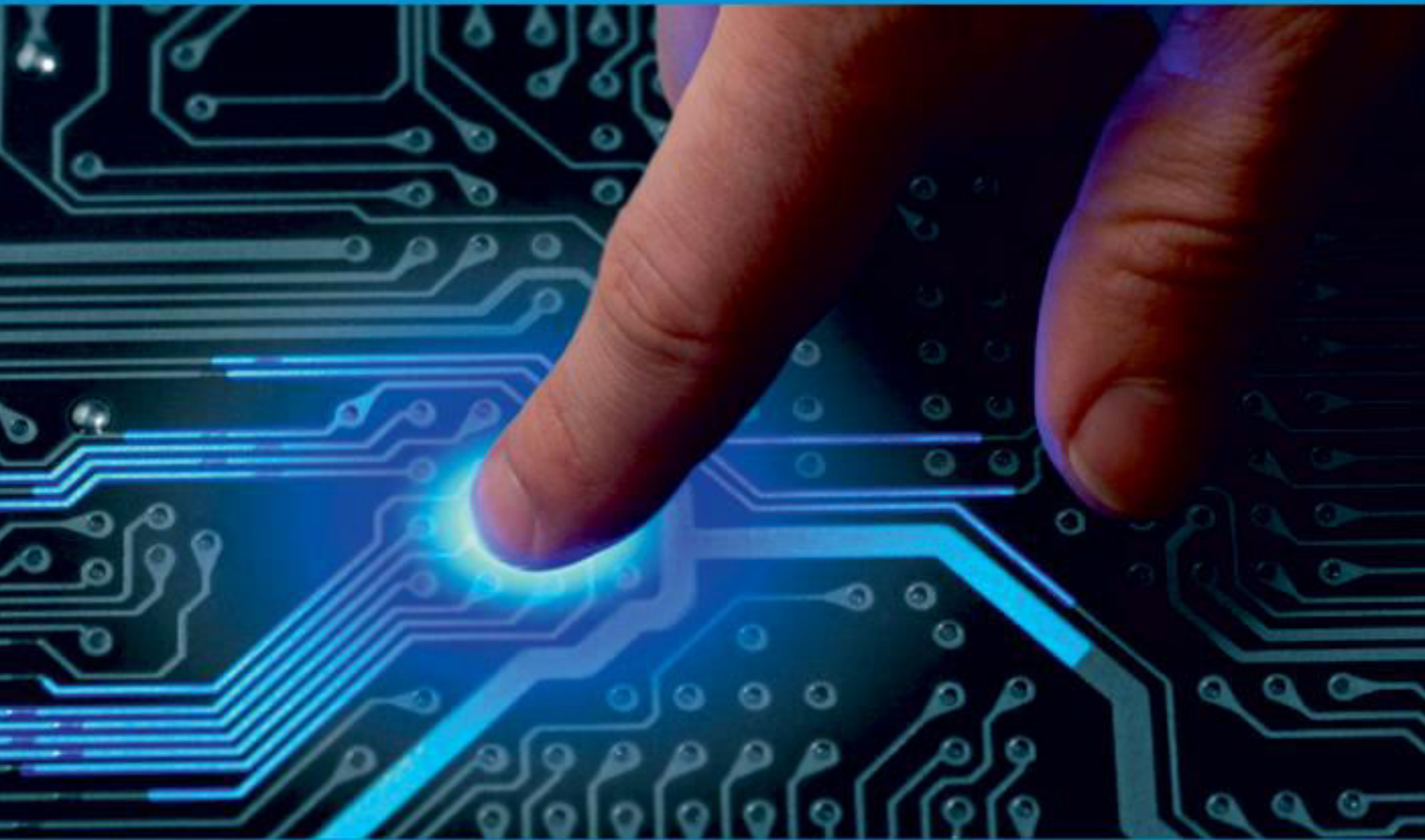

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ResUnet++: A Deep Learning-Based Cardiac Segmentation for Echocardiographic Images

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ABSTRACT: Cardiovascular illnesses can be brought on by abnormalities in the heart structures. To reduce cardiac risks, it is necessary to monitor the various heart structures. The segmentation of the left ventricle, myocardium, and left atrium of the heart is carried out in the proposed study. Due to the uncertain boundaries and uneven intensity distribution, segmenting these cardiac structures from echocardiographic images is a difficult task. As a result, ResUNet++ is suggested as a model for segmenting cardiac structures. For the segmentation of cardiac images, ResUNet++ is an enhanced version of the original ResUNet design. On a publicly available CAMUS dataset, performance metrics were assessed. The mean dice coefficient and precision obtained is 0.768 and 0.987 respectively.

KEYWORDS: ResUnet++; Cardiac Segmentation; Echocardiography

I. INTRODUCTION

Segmentation of medical images tries to enhance the visibility of changes to anatomical or diseased features in images. Due to the significant advancement in diagnostic effectiveness and accuracy, it frequently plays a crucial part in computer-aided diagnosis and smart medicine. Cardiac image segmentation is a common medical image segmentation task. A crucial organ in the human body is the heart. The primary cause of death is cardiovascular diseases (CVDs). Therefore, knowing how the heart works and its properties could help with heart disease treatment and prevention. The inevitable can be prevented by early diagnosis of diminished heart functioning. By employing a deep learning approach to segment, the heart structures, the risk of CVDs is decreased.

In recent years, the most popular method for segmenting cardiac images has been deep learning. Medical ultrasound is risk-free, comfortable, and economical. Because of this, cardiac ultrasound technology has many different clinical uses. Echocardiography is the name given to cardiac ultrasound. It is produced by the high-frequency sound waves reflecting off various human bodily organs. Echocardiography is more cheap than magnetic resonance imaging and computed tomography. These cutting-edge imaging techniques can be utilised to display intricate views of the anatomy of the heart. The segmentation of the left ventricle, myocardium, and left atrium of the heart is carried out in the proposed study. Due to the uncertain boundaries and uneven intensity distribution, segmenting these cardiac structures from echocardiographic images is a difficult task. As a result, ResUNet++ is suggested as a model for segmenting cardiac structures. For the segmentation of cardiac images, ResUNet++ is an enhanced version of the original ResUNet design. On the publicly accessible CAMUS dataset, performance metrics were assessed. Images of 2D echocardiograms can be found in the CAMUS dataset.

A. *Problem Statement:*

The primary cause of death is cardiovascular disease (CVDs). Between adjacent images, there are significant differences in the cardiac structures' appearance and form. Therefore, knowing the functions of the various cardiac structures, such as the left ventricle, etc., could help with heart disease prevention and care. The unavoidable can be avoided by early diagnosis of diminished heart functioning. So, segmentation of the heart structures using deep learning can be performed to know about the various heart structures and reduce the risk of CVDs.

B. *Objectives:*

- The process of extracting coarse to fine characteristics from the original image using residual blocks as the fundamental building blocks. For channel-wise attention, adaptive feature recalibration, and boosting the strength of feature representation, squeeze and excitation units are added to residual blocks.
- Segmentation of cardiac structures i.e., left ventricle, myocardium and left atrium.

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- Validating the model using CAMUS dataset.

II. Related Work

The success of U-net and deep residual learning served as inspiration for integrating their advantages into one system. Deeper networks have been demonstrated to function better. Deep U-net architecture training is challenging, especially with sparse training data, but this problem can be overcome by using a pre-trained network with precise tuning. In order to improve network speed without needing to dig deeper, residual blocks were invented. These blocks all share the same concept of concatenating the input (identity shortcut) and propagating the low fine details. The basic U-net units are therefore replaced with residual blocks. These residual blocks will also aid in the spread of features during the encoding and decoding paths. Additionally, stride convolution is utilised to propagate fine feature details to all coarser layers rather than pooling (which was first employed in U-net). This convolution technique improves feature reuse without the requirement for complex deeper architecture.

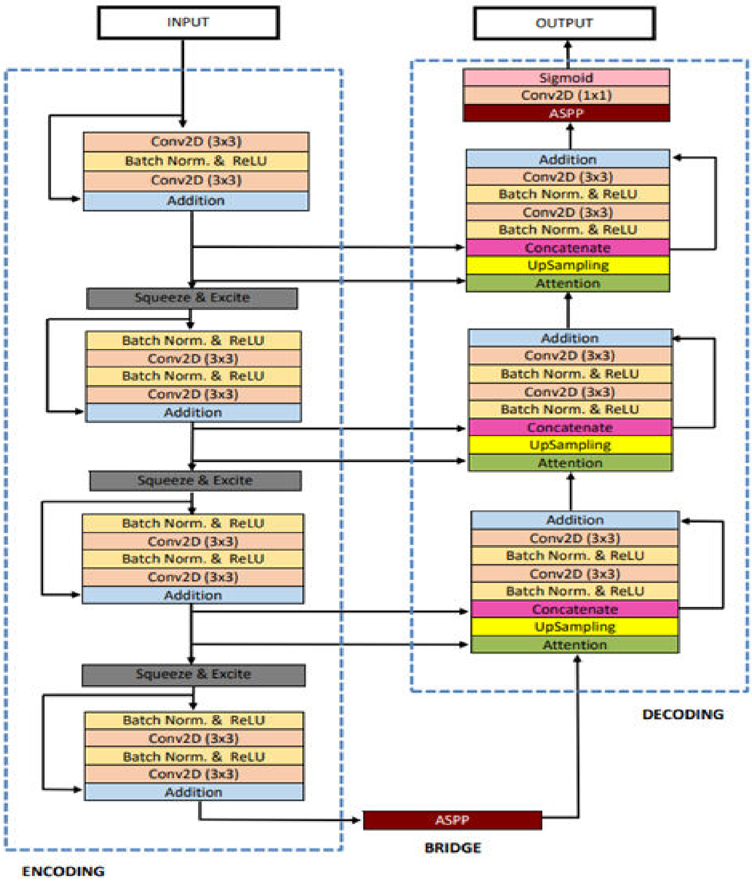

Fig. 1. Block Diagram of ResUnet++ Architecture

The Deep Residual U-Net (ResUNet) architecture, which combines the advantages of U-Net and deep residual learning, is the foundation of the ResUNet++ design. The squeeze and excitation block, ASPP, the attention block, and the residual blocks are all utilised by the proposed ResUNet++ architecture.The residual block allows for the layer-by-layer propagation of information, enabling the construction of a more complex neural network that might address the degradation issue in each of the encoders. This lowers the computational cost while also improving the channel interdependencies. One stem block, three encoder blocks, ASPP, and three decoder blocks make up the proposed ResUNet++ architecture. The proposed ResUNet++ architecture's block diagram is displayed in Figure 1.1. The residual unit in the block diagram is made up of convolutional layers, batch normalisation, and Rectified Linear Unit (ReLU) activation.

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An identity mapping and two consecutive 3 x 3 convolutional blocks make up each encoder block. Each convolution block consists of a convolutional layer, a ReLU activation layer, and a batch normalisation layer. The encoder block's input and output are connected by the identity mapping. In the encoder block's first convolutional layer, a strided convolution layer is used to cut the spatial dimension of the feature maps in half. Squeeze-and-excitation block is used to process the encoder block's output.The ASPP serves as a bridge, expanding the filters' field of vision to take in more context. In line with this, the decoding path also includes residual units. The attention block that comes before each unit makes feature maps more effective. Next, feature maps from the lower level are nearest-neighbor up-sampled before being concatenated with feature maps from the associated encoding path.

The output of the decoder block is passed through ASPP, and finally, we apply a 1 × 1 convolution with sigmoid activation, that provides the segmentation map. The squeeze-and-excitation blocks, ASPP block, and attention blockare extensions of the ResUNet++ and are indicated by light blue, dark red, and green, respectively. Below is a quick explanation of each component:

- **Residual Units**

Training deeper neural networks is comparatively difficult. Accuracy can be increased by training deep neural networks with deeper networks. It might, however, interfere with training and result in a degradation issue. Therefore, a deep residual learning architecture is suggested to aid in the training process and deal with the degradation issue. ResUNet employs residual units with full pre-activation. The skip connection within the networks aids in information propagation without degradation, improving the design of the neural network by reducing the parameters while maintaining or improving performance on the semantic segmentation task. The deep residual unit makes the deep network simple to train. ResUNet is employed as the backbone architecture as a result of these benefits.

- **Squeeze and Excitation Units**

The squeeze-and-excitation network increases the network's representational power by recalibrating feature responses using accurate modelling of channel interdependencies. Squeeze and excite blocks are designed to allow the network to become more sensitive to important features while suppressing irrelevant ones. This objective can be reached in two steps. The first method is called squeeze (global information embedding), in which each channel is compressed using global average pooling to produce statistics broken down by channel. Excitation (active calibration), the next stage, tries to fully capture the channel-wise relationships. To maximise effective generalisation over various datasets and enhance network performance, the squeeze, excitation, and residual blocks are stacked together in the suggested architecture.

- **Atrous Spatial Pyramidal Pooling**

The concept of ASPP was inspired by spatial pyramidal pooling, which was effective in resampling features at various scales. In ASPP, the contextual information is recorded at various scales and the input feature map is fused by numerous parallel atrous convolutions occurring at varying rates. Atrous convolution enables accurate field-of-view control for multiscale data collection. As can be seen in Figure1.1, the suggested design uses ASPP as a link between the encoder and the decoder. By offering multi-scale data, the ASPP model has demonstrated encouraging performance on a variety of segmentation tasks. So, in order to collect the pertinent multi-scale data for the semantic segmentation task, ASPP is used.

- **Attention Units**

The popularity of the attention mechanism is primarily found in NLP (NLP). It concentrates on the portion of its input. Additionally, it has been used for pixel-wise prediction in semantic segmentation tasks. The neural network's attention mechanism chooses which areas of the network need more focus. The attention method also relieves the encoder of the load of encoding the entire cardiac image's information into a vector with a fixed dimension. The simplicity, adaptability to any input size, and improvement in feature quality of the attention mechanism are its key benefits.There exists a direct concatenation of the encoder feature maps with the decoder

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feature maps in U-Net and ResUNet. The success of the attention mechanism in NLP and computer vision tasks served as inspiration for the implementation of the attention block in the decoder portion of the design, which allows users to concentrate on the key regions of feature maps.

A. *Implementation*

The effectiveness of the model is evaluated using the publicly accessible CAMUS dataset. The 2D apical four-chamber and two-chamber views are both included in the CAMUS dataset. The dataset is then prepared by dividing the echocardiographic training images from the masks. Later, the model is trained using ResUnet++. The trained model is then validated. Left ventricle, myocardium, and left atrium of the heart are then segmented.

III. SIMULATION RESULTS

The mean dice coefficient and precision of the test dataset obtained is 0.768 and 0.987 respectively.

- The below figure 2 shows the original image, mask, and the obtained segmented image. In the below figure the dice coefficient obtained is 0.797, precision obtained is 0.992.

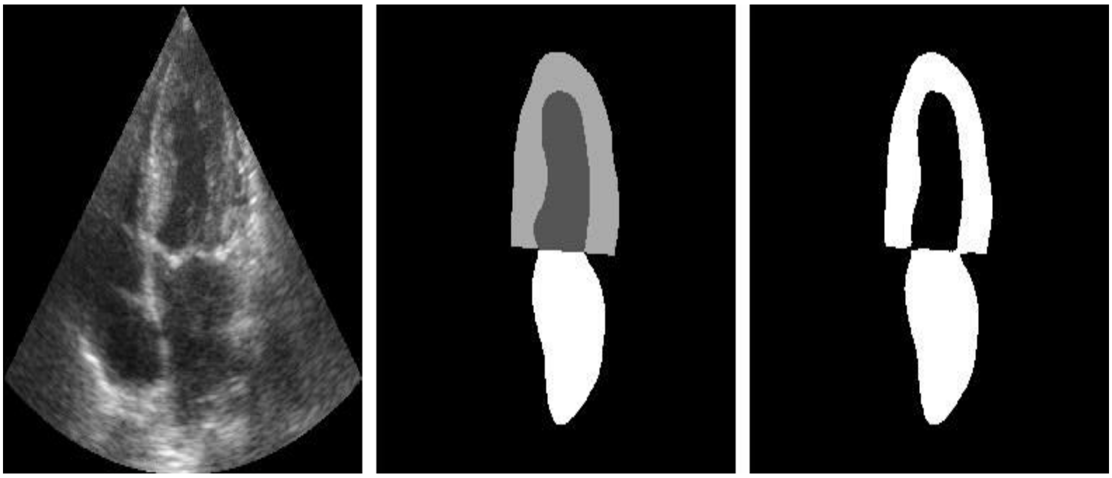

Fig. 2. a) Original image b) Mask c) Segmented image

- The below figure 3 shows the original image, mask, and the obtained segmented image. In the below figure the dice coefficient obtained is 0.791, precision obtained is 0.991.

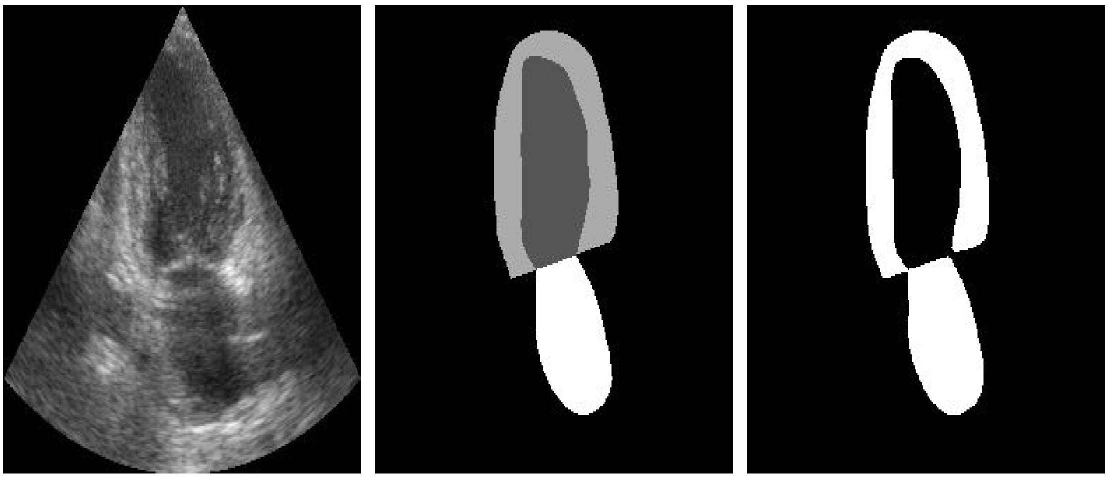

Fig. 3. a) Original image b) Mask c) Segmented image

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- The below figure 4 shows the original image, mask, and the obtained segmented image. In the below figure the dice coefficient obtained is 0.790, precision obtained is 0.992.

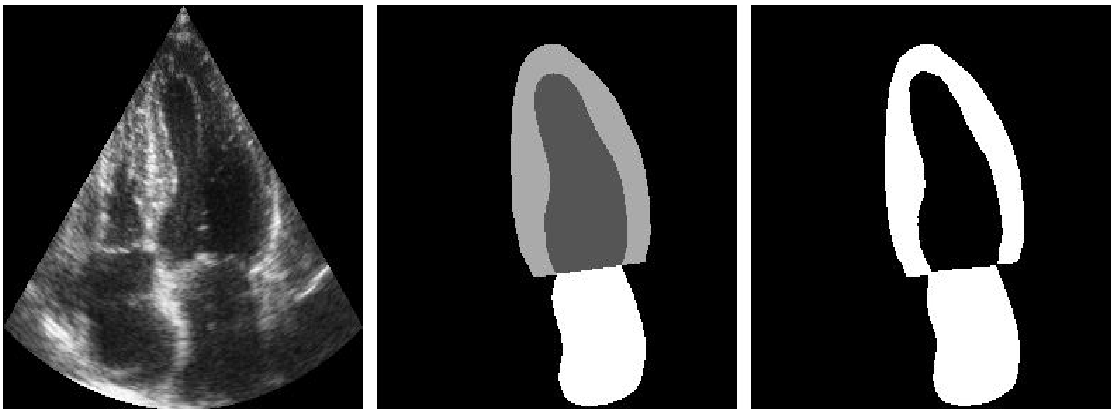

Fig. 4. a) Original image b) Mask c) Segmented image

IV. CONCLUSION AND FUTURE WORK

Knowing the functions and traits of the various cardiac structures, such as the left ventricle, etc., could help with heart disease prevention and care. By employing a deep learning approach to segment, the heart structures, the risk of CVDs is decreased. In this study, the cardiac structures i.e., left ventricle, myocardium, and left atrium from echocardiographic images were segmented using a deep learning ResUnet++. The CAMUS dataset, which is available to the public, was used to assess the model's performance. Through the concatenation of the input layer, which helps to transmit the low fine details, and passing them through the skip connections, residual blocks enhanced the model performance. The mean dice coefficient and precision obtained is 0.768 and 0.987 respectively. ResUnet++ performs well than resunet, unet with vgg16. Future research can look into how the suggested model performs on several other image modalities.

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