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Deep Learning-Based Segmentation of Cardiac Structures in MRI Image

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Abstract: Deep learning is now the most common technique for segmenting cardiac images, having recently eclipsed all previous approaches. In this research, we demonstrate a complete application of deep learning for cardiac image segmentation. This usage covers a broad variety of popular imaging modalities as well as the primary anatomical components that are significant (ventricles, atria, and arteries). In addition, we provide an overview of open-source software repositories as well as cardiac imaging datasets in order to encourage research that can be reproduced. Finally, we emphasize the limitations and restrictions of current deep learning-based approaches (a lack of labels, domain-general designs, and a lack of interpretability), and we offer future research pathways to address these issues.

Keywords*: cardiac imagine segmentation, deep learning datasets*

1. Introduction

Diseases of the cardiovascular system (CVDs) are still the leading cause of mortality and disability on a global scale.[1] Coronary artery disease is the biggest cause of death throughout the globe, and it is responsible for a significant portion of the fatalities that occur annually.Imaging methods such as CT, CMR, echocardiography, etc., etc., have been developed together with other types of technology in order to facilitate the non-invasive examination of cardiovascular diseases (CVDs) [2].CMR is currently the gold standard for non-invasively evaluating heart chamber volume, ejection fraction, mass and wall thickness, and wall motion abnormalities of many CVDs [3]. This is because CMR can measure all of these parameters simultaneously. This is because the pictures that are created are of a very high quality, there is no need for ionizing radiation, and there is a very clear contrast between the different types of tissues. Chamber segmentation is now done manually by specialists using a technique called outlining. This is the current best clinical practice. Manual segmentation requires a lot of effort and time, and it yields varying results depending on who is doing it. As a result, it is essential to include automation into this system in order to quicken the segmentation process and make it more streamlined [4]. In recent years, approaches that use image processing to differentiate between the left ventricle (LV) and the right ventricle (RV) have been developed, and these methods range from semi-automatic to completely automated. When attempting to describe the progression of a disease, clinical researchers have, historically speaking, concentrated their attention on the LV. Because of the numerous significant discoveries that have been made about the treatment of illnesses such as dysplasia cardiomyopathies, coronary heart disease, and pulmonary hypertension, researchers are focusing their attention on RV at a higher level than they ever have previously [1-4]. On the other hand, as compared to LV segmentation, RV segmentation is considered to be a great deal more challenging. Because a solution to the problem of segmenting the RV has not been found, the RV is often regarded as being of lower importance than the LV [6-7].The ability of deep learning algorithms to automatically recognize features is one factor that has led to the rise in popularity of these algorithms over the last several decades. Traditional methods of feature extraction make use of prior knowledge, which helps in the better extraction of features for a given application [8]. However, deep learning may be used to do this task based on the requirements of the specific application. Deep learning gives users the capacity to discover very relevant qualities that were unavailable in the past. Picture classification with just a single label for a class is the usage scenario that best showcases the power of convolutional networks. One of the many areas in which it is vital to classify each pixel with a particular category is the field of biomedical image processing. In addition, one of the most challenging obstacles that biological

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image processing must overcome is the collection of enormous amounts of training data. data [9]. A convolutional neural network is utilized in order to automatically separate the left and right ventricles from cardiac MRI images. This process is called segmentation. Details on one hundred individuals, including information on their systolic and diastolic pauses. A brief review of the contributions made by the several research communities to the RV segmentation process to this point The technique, in addition to the findings and the analysis, are described in extensive detail.

With the advent of deep learning (DL), which is propelled by richer data and tremendous processing capacity and has its roots in artificial neural networks (ANNs), the area of computer vision (CV) has been rapidly transformed. DL is a method that relies heavily on training data to create smart systems. fast dataset storage, a surge in processing power, and parallelization using graphics processing units (GPUs) have all contributed to the technology's fast uptake. In recent years, advances in the field of image classification have mostly focused towards the job of semantic segmentation (SS) due to its quick predictive capacity.

In the context of computer vision, the challenge of semantic picture segmentation may be seen as the problem of pixelwise categorization. This ability to effectively generate semantic interpretation from incoming data has profound implications for the development of artificial intelligence (AI).

Most applications in medical image processing need high-quality segmentation outcomes. Convolutional neural networks (CNNs) have recently emerged as a consequence of DL and have shown to provide remarkable outcomes, greatly benefiting the medical imaging research field. Although DL segmentation models might have a significant effect on healthcare automation, few have been developed in the context of medical imaging. Conventional ML algorithm performance has been stifled by the advent of SS architectures, which are founded on fully convolutional auto encoder-decoder (CNN) based architectures.

Imaging techniques in medicine and biology provide important details on the structure and function of an organ, from the cellular to the systemic level.

Cellular, Tissue, and Organ-Related Diagnostic Data, Such as Reports, News, and Facts or the patient's health state may be determined by looking at the size and form of the patient's body as a whole. As a result, health informatics plays a crucial role in illuminating the patient's difficulties, which are often complicated, individual, and problem-specific. Automated medical imaging analysis is crucial in contemporary medicine because it allows for objective evaluation of pictures, which are otherwise very subjective. Segmenting biological images has traditionally been done manually, which is a time-consuming and error-prone process. Later, with the advent of machine learning algorithms, this task became somewhat automated, however it still falls short of human performance levels. Recently, DL approaches for medical image processing have been more widely available, allowing for the development of an intelligent diagnostic system for biomedical imaging. Many people in the field of biomedical imaging use a segmentation architecture called U-Net because of its proven success. Many other scientists quickly followed suit, creating U-Net variations that use more nuanced and informative feature data to better define the objects of interest. The ability of radiologists to make precise diagnoses has been boosted by these innovations.

The study of coronary arteries, one of the heart's main blood vessels, has therefore been motivated by health informatics. Due to the severity of the situation, prompt detection of coronary artery stenosis is essential. In order to examine and analyze the artery's function, it must first be located and segmented from the image using the cardiac MRI modality.

This work was motivated by a desire to create an effective architecture for coronary artery segmentation in cardiac MRI data. The authors of this study start with the SegNet model for accurate coronary artery segmentation in cardiac MRIs, but they then suggest an improved solution based on the U-Net model with pooling indices and residual connections. The qualitative and quantitative results of SegNet, U-Net, and SegUnet models are very encouraging in achieving the semantic segmentation (SS) task of coronary artery, which led to the development of the proposed model with even higher accuracies to meet the health care demands of modern society.

The goal of this research is to use an input dataset (the original cum ground truth) to automatically segment the coronary artery area in cardiac MRI images. In the most basic form, the dataset is split into three distinct parts: training, validation, and testing. When it comes to analyzing medical images, even a little increase in segmentation accuracy may play a major role in pinpointing the problem, which is sometimes invisible to the naked eye. As a result, segmentation is a thriving field of study, allowing for faster, more accurate clinical diagnosis for the patient. All of the work is divided into four stages, each of which employs a different fully convolutional auto encoder decoder based network design. The model weights for each of the four architecture are stored once they have been trained on the input pictures from a training dataset. There is no need to enhance the picture data for training purposes since a large enough dataset already exists. These models are implemented with the help of Keras and TensorFlow. Positive experimental findings from one stage to the next have been shown, suggesting that this effort should be continued.

MRI, being a less intrusive technique, has received a lot of praise and attention for its effectiveness in detecting CAD. Excellent soft tissue contrast is provided by MRI scans, and the scans may be acquired in any anatomical plane. It is crucial to know the framework of the diagnostic value provided by the MRI in CAD in order to mobilize patient care and begin early diagnosis. Because MRI shields the patient against ionizing radiation, it has been put through considerable testing. Recent advances in technology, especially the introduction of 3.0 T MRI equipment, have greatly enhanced the diagnostic values for detecting CAD.

2. Literature Review

Kamal Raj Singh et.al (2022) To improve LV, MYO, and RV segmentation in short-axis CMRI, a Deep Residual U-Net is proposed in this article. The structure of the model is quite similar to that of U-Net, and it is built using residual connections. There are three benefits to using it: To begin, deep network training is simplified by residual connections. Second, the network's abundant skip connections facilitate feature propagation, leading to the development of networks that are simpler to construct yet exhibit exceptional performance.

Roshan Reddy Upendra et.al (2021) In this paper, we detail the process of creating patient-specific, dynamic models of the right ventricle (RV) for use in assessing RV function using motion and kinematic analysis, using both normal individuals and patients with RV abnormalities. We utilize a deep learning-based deformation-resistant network to come up with isosurface corresponds of the cardiac mathematics at all cardiac defines by generating the end-diastole (ED) isosurface mesh with the reconstructed motion field..

Ilkay Oksuz et al (2020). In this study, we present an end-to-end architecture whereby this is used in conjunction with a segmentation network. All three of these processes—detection of image artifacts, correction of image artifacts, and segmentation of images—are optimized by our training.

Adan Lin et.al(2020) Using the right ventricle shape model as registration data, this research proposes a deep learning-based approach to RV segmentation. Training samples are used to create a probability model of the RV form. Then, the registration method is used to train aU-Net with the shape prior probability. To estimate the shape of a probability map, we register the network's predictions to the shape model, and we define loss as the sum of the Kullback-Leibler deviations between the prediction and the map, and between the map and the ground truth

3. Deep Learning

Deep learning has had an effect on several areas of real-time data processing.It efficiently handles the problem of dealing with high-dimensional data on its own via the use of feature extraction.In contrast to most standard ML techniques, which need substantial time and effort from data scientists, DL automatically constructs a feature set to categorize data. When the user's collection of characteristics is insufficient to adequately characterize the objects, DL approaches may be highly helpful since they rely on learning the features as opposed to extracting them. Objects of interest in photographs may be quickly and correctly identified with the use of DL approaches that train the images or search among millions of accessible images.The availability of massive amounts of training data and powerful computational resources in the age of cloud computing and big data [4] is crucial for DL systems to reach an acceptable degree of accuracy.

However, the development of hardware requirements opened the door to the possibility of developing and testing huge NN [4] with more extensive training data, leading to significant improvements in speed, efficiency, and accuracy. The feature extraction stage is skipped in DL, making it more appealing than previous versions of NN, which instead put more emphasis on pre-trained models.

Analysis of cardiac MR images is hindered by the spatial intensity fluctuations that characterize these pictures. Magnetic field intensity fluctuations and long-term magnetic field gradients are the primary causes of inhomogeneity. based (persistent) interfaces. Due to the inhomogeneity, tissue intensities often overlap and are incorrectly assigned. Since the intensity-inhomogeneity cannot be understood without first estimating the bias field, using bias field correction is essential.

Figure 1 depicts a work flow that provides an overview of the process of automated ventricular analysis. Different illumination correction techniques, including as Bias Corrected Fuzzy C-Means (BCFCM), LS, and MICO, are used in the pre-processing of the obtained CMR pictures.

Statistical characteristics and multifractal analysis are used to verify the accuracy of these procedures. Segmentation utilizing the suggested Sobel with Optimized Chan Vese (S-OCV) hybrid approach is then used to the preprocessed images for ventricular detection.. The approaches provided for precise ventricular delineation are compared so that the best one may be chosen. The ventricles' intensity and geometric properties are retrieved, and the relevant features are selected using PCA. Further, the images are classified using NBC, PNN and SVM classifiers.

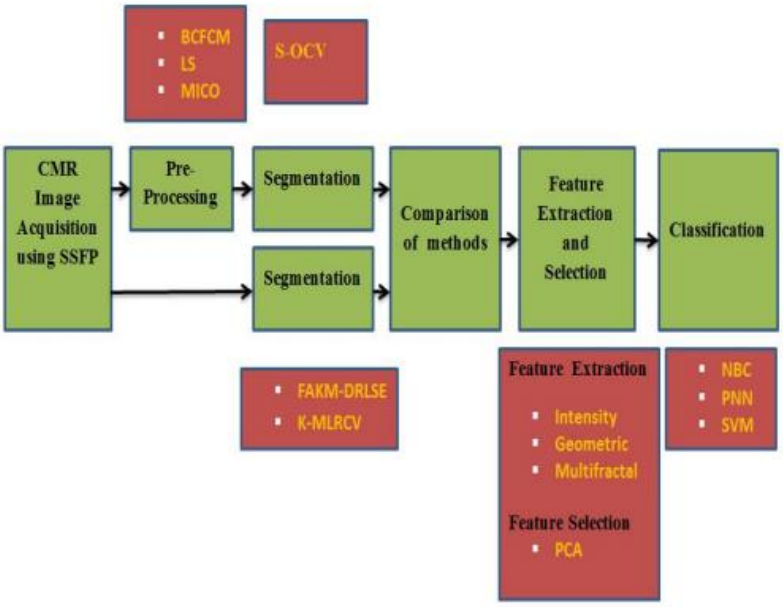

Fig 1 Work flow description

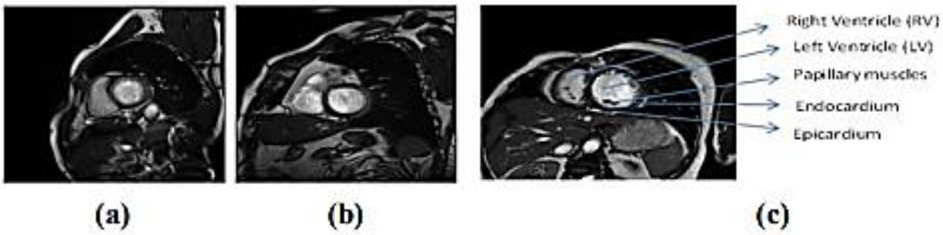

Fig 2 Original Cardiac MRI Short Axis Slices (a) Normal and (b), (c) Abnormal

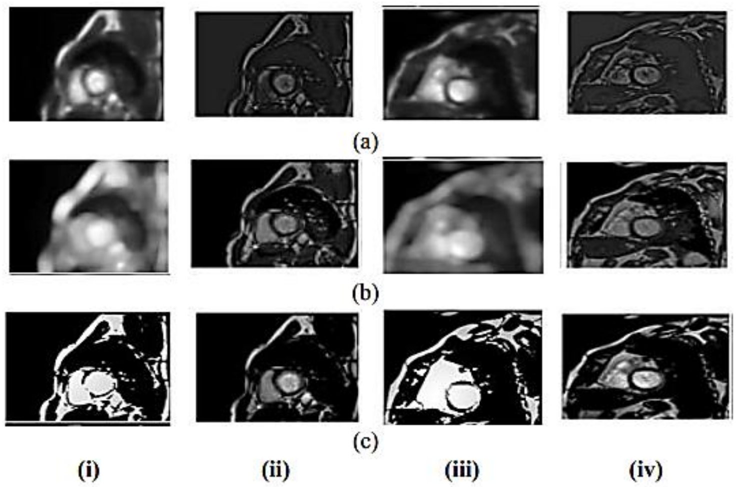

Fig 3 Bias estimation and Correction using (a) BCFCM, (b) LS and (c) MICO. i, iii - Estimated images and ii, iv - Corrected images

Due of the bias field's ability to dampen the high frequency component of a CMR image, sharp edges and contours are muddled. Below a magnetic field intensity of 3T, the impact of inhomogeneity on CMR images is negligible. With the advent of 3T+ scanners and multi-channel phased array coils, images may have high intensity-inhomogeneity throughout the whole 'K' space, necessitating post-scan processing.The estimated bias and its corrected images using the BCFCM, LS, and MICO methods are shown in Figure 3. When bias is taken into consideration, the intensity levels become relatively consistent and the boundaries become distinguishable because similar intensities are assigned to similar tissue categories. After inspecting the bias-free versions of the photographs, we can say, qualitatively, that the processes seem to be working as intended.

This work brings forth both the qualitative and quantitative results after applying the cardiac 2D image dataset to the SURNet architecture. The tables 1 and 2 represents the accuracies and evaluation metrics for train, test and validation sets.

Table 1: Illustrates the accuracies and losses for training, testing and validation datasets

Value → / ***Dataset ↓***	*Accuracy*	*Loss*
Training	0.9903	0.01027
Testing	0.9846	0.04984
Validation	0.9926	0.0123

Evaluation metric → / Architecture ↓	**Mean IoU (%)**		**Precision(%)**		**Recall (%)**		**F1-score (%)**	
	Train	Test	Train	Test	Train	Test	Train	Test
SURNet	98.5	97.8	83.15	82.21	88.15	86.27	96.19	94.65

Table 2: Highlights the SURNet architecture for various evaluation metrics

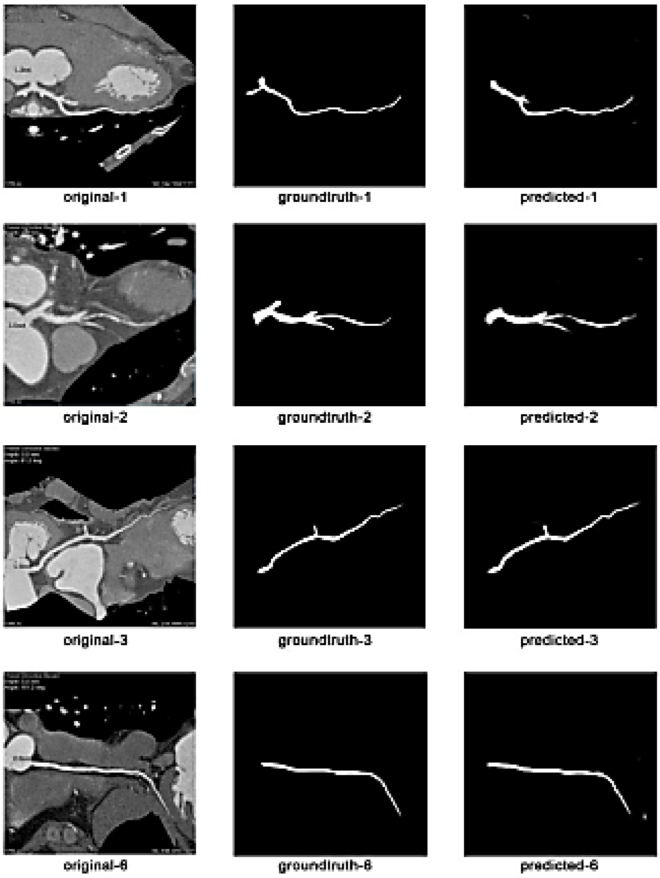

Figure. 4: Qualitative results of SURNet model with original, ground truth and predicted images

It's fascinating to see how each of the four semantic segmentation architectures used in this work—SegNet, U-Net, SegUnet, and SURNet—performs on its own and contributes to the overall quality of the work. A Medium Figure 5 below shows the IoU assessment of all four designs. Among the four models tested, SURNet stands out for its superior accuracy in segmenting the coronary artery in 2D cardiac MRI images.

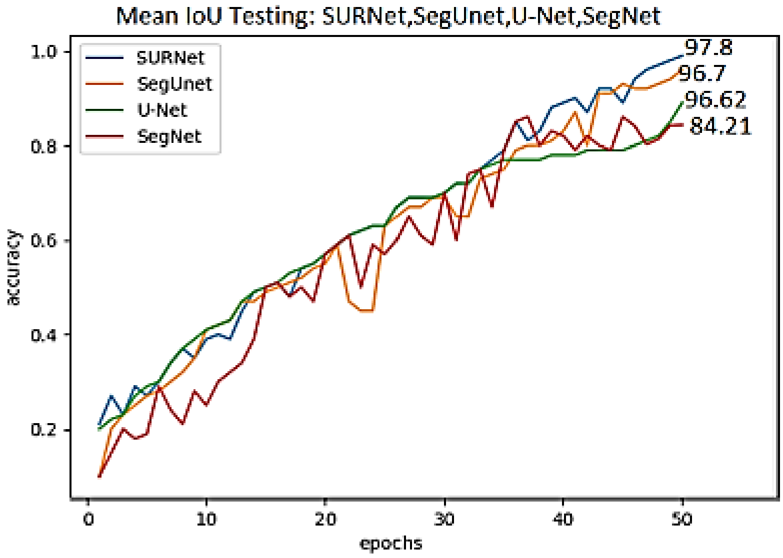

Fig. 5: Represents the MIoU all the four models in a single graph

4. Conclusion

The Deep learning architecture is used so that left ventricular (LV) and right ventricle (RV) segmentation in short-axis MRI images of the human heart may be accomplished. The same motivation leads to the development of a complete convolutional network model that includes training parameters. There are a total of 1328 image-label pairings that are used for training. In addition to the 172 that are used for validation, the approach is evaluated using 366 image-label combinations. 7 hours was the total amount of time needed to train the network. After initial training, the algorithm required just three minutes to successfully segment each of the test images. The accuracy of the system was able to reach a value of 0.90 when measured in terms of the dice coefficient.

As a multiple-class problem, cardiac heart segmentation mapping in the future will include the myocardium as a component of the heart. Combining U-NET with other architectural techniques, such as Attention Gates or Squeeze-and-Excitation, etc., may allow for the performance of U-NET to be improved even further.

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