Single/Two-frame(s) Volume Estimation of the Left Ventricle using Convolutional Neural Networks

information fusion lab

ERSP Early Research Scholars Program

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Background

Congenital Heart Disease is a heart birth defect that could lead to life-threatening conditions. In medicine today, there is an increasing trend use of deep learning and computer vision to aid in early disease detection and diagnosis.

Motivation

Our goal is to develop an efficient way of estimating left ventricle heart volume, a metric that can be used to analyze heart function and aid in the early detection of Congenital Heart Disease.

Most existing CNN solutions work on multiple frames of the imaging dataset. However, we plan to work on two MRI frames: short and long-axis view using 2D and 3D CNN.

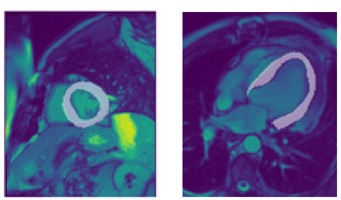

Figure 1: (a) short-axis view (b) long-axis view Regions that are enclosed by the circle are the left ventricles

Research Questions

1. Will one frame 2D CNN perform better than two frames 3D?
2. Will the central frames yield a better volume estimate than the edge frames?
3. Will our model yield a better end-diastolic volume prediction with the frames that have the greatest surface area?

Data collection

The dataset used is open-sourced from the Left Ventricle Segmentation Challenge (LVSC) dataset. We partitioned our dataset by patients i.e train, test, and validation sets to not have overlapping images from the same patient. Our train set has 7044 data points (80%), the validation set has 880 data points (10%), and test set has 880 data points (10%).

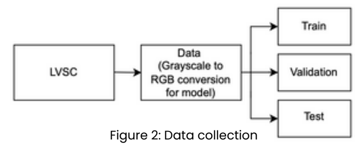

Figure 2: Data collection

Methods

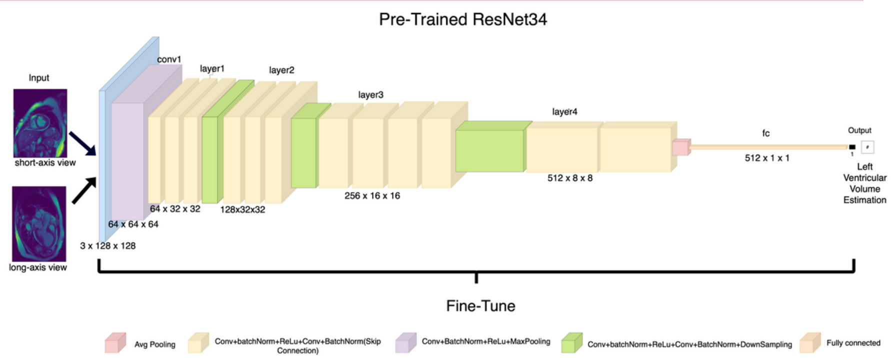

Figure 3: Model of a pre-trained ResNet34

A pre-trained ResNet34 model (CNN) is used to speed up the training process. A special feature of ResNet is the use of skip connection.

We use transfer learning to copy n layers of a previously trained residual network on imageNet, then re-initialize and fine-tune the head (fc) of the network.

Next, we are going to fine-tune every conv layer by alternately freezing and unfreezing to stabilize performance.

Acknowledgements

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Results

RQ 1:

The CNN that has the smallest train loss is highlighted, and losses of different CNNs are shown below and the data was partition by patients.

Type of CNN	Smallest Train Loss	Smallest Val Loss
One Frame 2D CNN	6.703	18.569
Two Frame 2D CNN	2.821	56.638
Two Frame 3D CNN	7.223	20.633

RQ 2 :

This table shows the MSE loss on the testing set and we trained our model with only the edge frames or central frames. The data was not partition by patients.

Type of Single Frame in 2D CNN	Loss on the testing set (MSE)
Edge frames	3.235
Central frames	2.436

RQ 3 :

This table shows the MSE loss on the testing set and we trained our model with all the frames except EDV and non-EDV frames. The testing set contains EDV or non-EDV frames. The data was not partition by patients.

Type of volume frame	Loss on the testing set (MSE)
Non-end diastolic	5.495
End diastolic	9.367

Conclusion

Important findings:

- 2D and 3D CNN perform similarly.
- The model is memorizing instead of learning from the training data.
- It is easier to extract the key features of the left ventricle with central frames.

Future Work

- Get a loss <1 on the testing set by fine-tuning and trying different models.
- Use the attention branch network (ABN) to boost the performance.
- Hyper-parameters tuning