INDIAN INSTITUTE OF INFORMATION TECHNOLOGY,ALLAHABAD

MAJOR PROJECT PRESENTATION

Left Heart Segmentation In Echocardiographic Images Using DNN Models

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INTRODUCTION

1. Echocardiography is a non-invasive imaging technique done using high-frequency sound waves.
2. It is used in clinical practice to assess the structure and function of the heart
3. This imaging modality plays a crucial role in diagnosing various cardiac conditions, including heart valve disorders, cardiomyopathies, and congenital heart defects.
4. Deep learning has emerged as a promising approach to address the challenges of manual interpretation.

WHY SEGMENTATION?

1. Involves accurately outlining cardiac structures in 2D echocardiographic images
2. Extract high-level features
3. Semantic segmentation
4. Segmentation of the left ventricle and left atrium is essential for measuring cardiac morphology
5. LV and LA abnormalities are closely related with left ventricular dysfunction, left atrial enlargement and left heart failure (how related to heart)

LITERATURE SURVEY

S.No	Title	Authors	Dataset	Method Used	Evaluation Matrix	Conclusion
1.	Residual Dilated UNet for Left Ventricle Segmentation from Echocardiographic Images[2020][1]	Alyaa Amer, Xujiong Ye	STACOM	ResDUnet	Mean Dice - 86.7%	Performance gains achieved when state-of-the-art u-net is integrated with innovative concepts such as residual.
2.	Dual-Branch TransV-Net for 3-D Echocardiography Segmentation [2023][2]	Jiapeng Zhang, Yongxiong Wang	Self Collected Dataset (120 3-D echocardiographic images)	TransV-net	Mean Dice - 90.2%	Self-attention-based 3-D transformer module used on the bottom layer can reduce the risk of over or under segmentation.
3.	CLA-U-Net: Convolutional Long-short-term-memory Attention-gated U-Net for Automatic Segmentation of the Left Ventricle in 2-D Echocardiograms[2022][3]	Zihan Lin, Po-Hsiang Tsui	EchoNet-Dynamic	CLA-U-Net	Mean Dice - 93%	The CLA-U-Net model outperforms state-of-the-art methods in LV segmentation and has a lower number of parameters

[1] Amer, Alyaa, et al. "ResDUnet: Residual dilated UNet for left ventricle segmentation from echocardiographic images." 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2020.
[2]Zhang, Jiapeng, et al. "Dual-branch TransV-Net for 3D echocardiography segmentation." IEEE Transactions on Industrial Informatics (2023).
[3] Lin, Zihan, et al. "CLA-U-Net: Convolutional Long-short-term-memory Attention-gated U-Net for Automatic Segmentation of the Left Ventricle in 2-D Echocardiograms." 2022 IEEE International Ultrasonics Symposium (IUS). IEEE, 2022.
LIGht

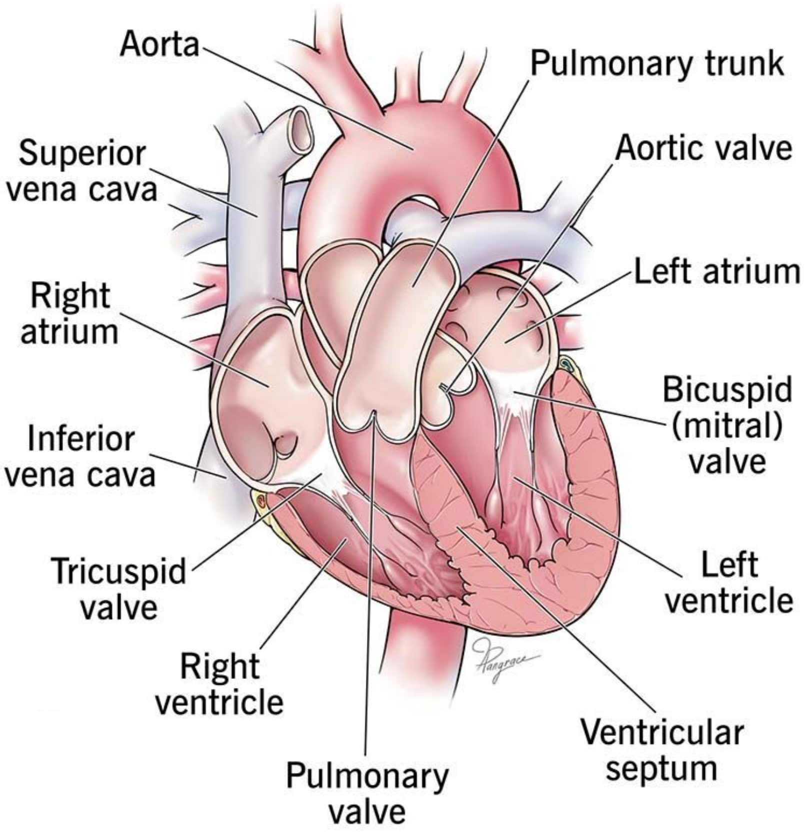
S.No	Title	Authors	Dataset	Method Used	Evaluation Matrix	Conclusion
4.	Segmentation of Five Components in Four Chamber View of Fetal Echocardiography[2020][4]	Tingyang Yang, Jiancheng Han	Self Collected dataset of 301 patients	Unet + DenseNet	Mean Dice - 88.9%	Through data augmentation and data proportion balance strategy, the segmentation effect of the group with a small proportion is improved.
5.	Bayesian Optimization of 2D Echocardiography Segmentation [2021][5]	Tung Tran, Joshua V. Stough	CAMUS	Unet	Mean Dice - 92%	Optimal candidate boasts tighter limits of agreement and vastly improved outlier performance.
6.	Improved Segmentation of Echocardiography With Orientation-Congruency of Optical Flow and Motion-Enhanced Segmentation[2022][6]	Wufeng Xue, Heng Cao	CAMUS	SOCOF	Mean Dice - 81%	It achieves accurate automatic segmentation for multiple cardiac structures by applying motion-enhanced segmentation.

[4] Yang, Tingyang, et al. "Segmentation of five components in four chamber view of fetal echocardiography." 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI). IEEE, 2020.
[5] Tran, Tung, et al. "Bayesian optimization of 2D echocardiography Segmentation." 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI). IEEE, 2021.
[6] Xue, Wufeng, et al. "Improved segmentation of echocardiography with orientation-congruency of optical flow and motion-enhanced segmentation." IEEE Journal of Biomedical and Health Informatics 26.12 (2022): 6105-6115.

S.No	Title	Authors	Dataset	Method Used	Evaluation Matrix	Conclusion
7.	The Segmentation of the Left Ventricle of the Heart From Ultrasound Data Using Deep Learning Architectures and Derivative-Based Search Methods[2020][7]	Gustavo Carneiro; Jacinto C. Nascimento	Self Collected dataset	ANN + DBN	Jaccard Index- 80%	The use of deep belief networks and the decoupling of the rigid and non-rigid classifiers showed robustness to large and rich training sets.
8.	(ACNNs): Application to Cardiac Image Enhancement and Segmentation [2019][8]	Ozan Oktay; Enzo Ferrante	UK Digital Heart Project	ACNN	Mean Dice - 86%	VGG features tend to be more general purpose representations that are learnt from ImageNet dataset containing natural images of a large variety of objects.

[7] Carneiro, Gustavo, Jacinto C. Nascimento, and António Freitas. "The segmentation of the left ventricle of the heart from ultrasound data using deep learning architectures and derivative-based search methods." IEEE Transactions on Image Processing 21.3 (2020): 968-982.
[8] Oktay, Ozan, et al. "Anatomically constrained neural networks (ACNNs): application to cardiac image enhancement and segmentation." IEEE transactions on medical imaging 37.2 (2019): 384-395.
[9] Yang, Tingyang, et al. "Segmentation of five components in four chamber view of fetal echocardiography." 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI). IEEE, 2020.

HEART ANATOMY



src - https://my.clevelandclinic.org/health/body/21704-heart

RESEARCH GAP AND OBJECTIVE

- Deep learning applications remains limited in this field.
- Current researches have achieved round 90% dice score which can be improved further.
- We will evaluate the performance of different encoder-decoder DCNN methods.
- Performance will be evaluated on the basis of dice coefficient, hausdorff distance, MAD, MAE, precision, recall and accuracy.
- Potentially aiding early diagnosis and personalized treatment to protect the hearts of patients.

CAMUS DATASET

1. Camus (Cardiac Acquisitions for Multi-structure Ultrasound Segmentation)

2. Fully-annotated dataset for 2D echocardiographic assessment

3. Consists of images of 500 patients with left ventricular ejection fraction,

4. Acquired at the University Hospital of St Etienne (France)

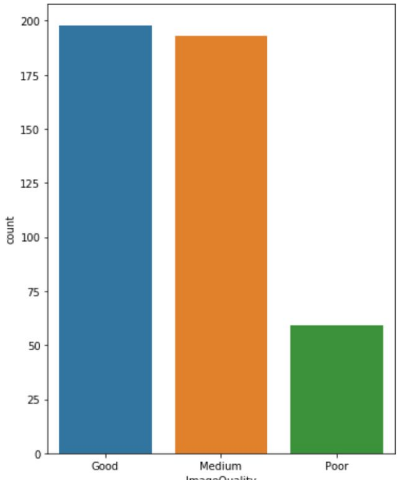
5. It contains 2D apical 2CH view acquired from 500 patients

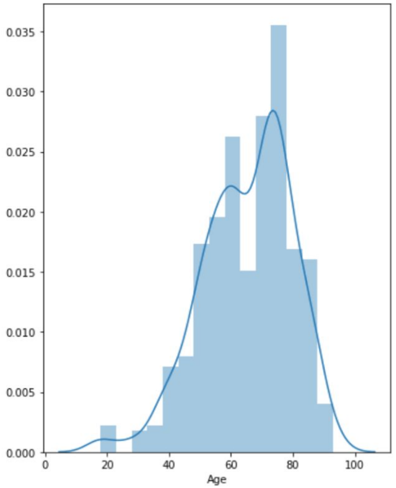
    i) A training set of 450 patients (400 patients for training and 50 for validation)

    ii) A testing set composed of 50 new patients.

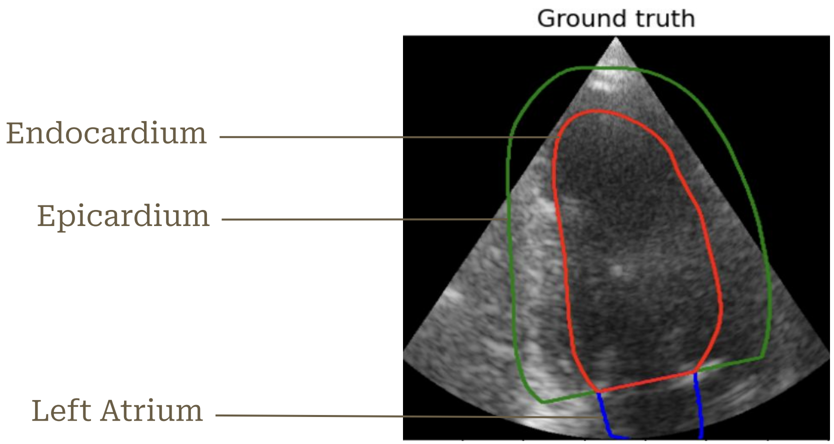
6. Dataset includes images of varying quality (good, medium, and poor)

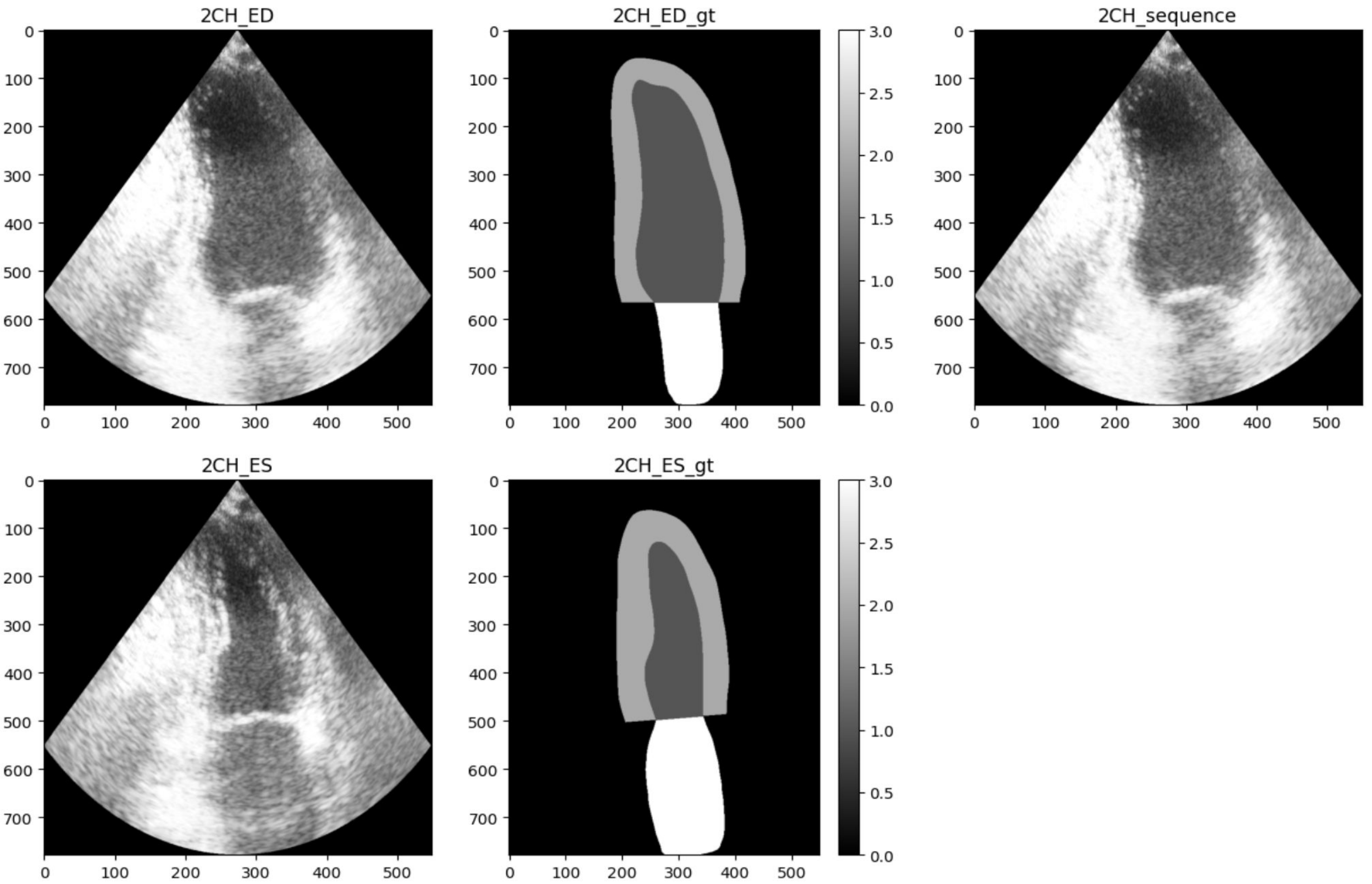
Link - https://humanheart-project.creatis.insa-lyon.fr/database/#collection/6373703d73e9f0047faa1bc8





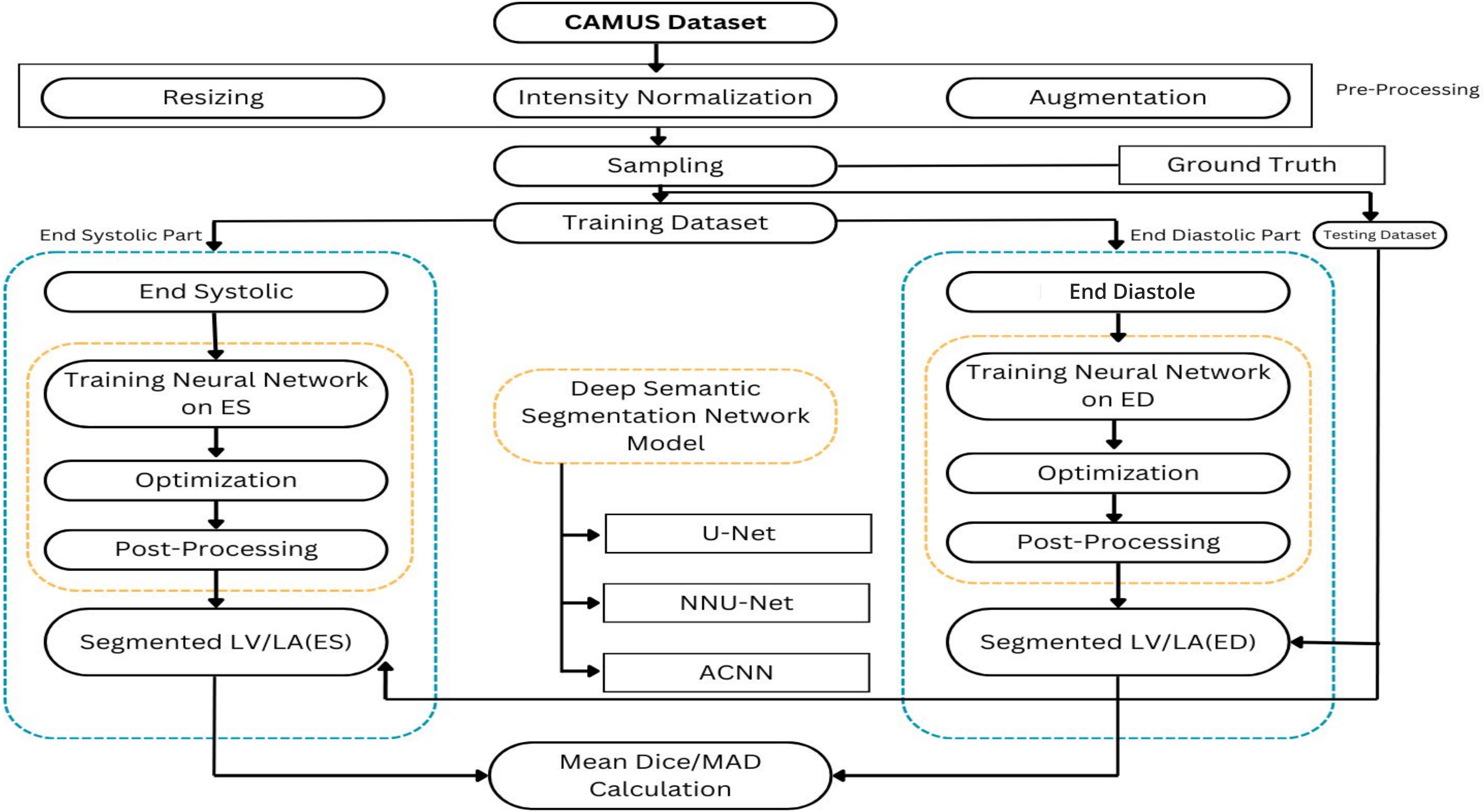
- Each image in the CAMUS dataset is fully annotated with labels for cardiac structures.
- The labeling process involves assigning pixel-level annotations to delineate the boundaries of cardiac structures such as the left ventricle and left atrium.
- These annotations serve as ground truth data for training and evaluating machine learning algorithms.





2CH_ED
2CH_ED_gt
2CH_sequence
2CH_ES
2CH_ES_gt

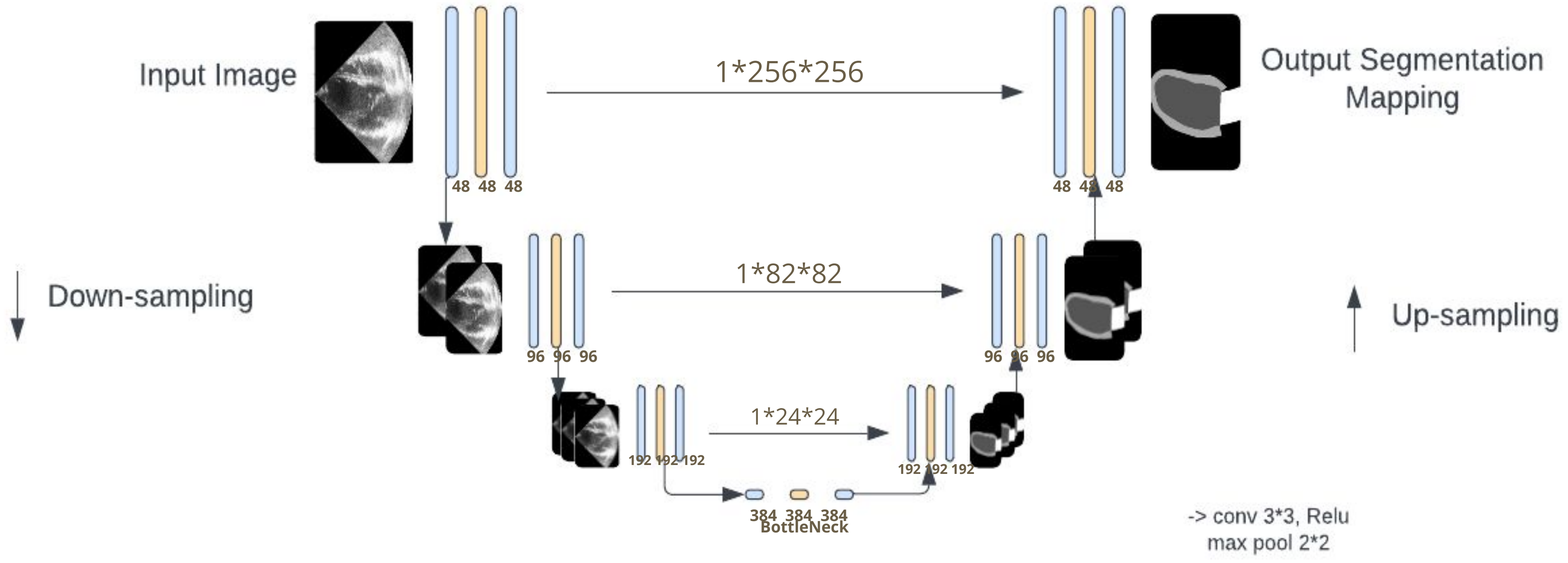
METHODOLOGY



U-Net

1. It has U-shaped design where contracting path captures context (downsampling), expanding path recovers details (upsampling) with skip connections for precise segmentation.
2. Skip connections help maintain spatial information for accurate object boundary prediction.
3. Contracting path extracts high-level features for understanding the entire image and distinguishing components.
4. Requires less training data compared to some architectures, making it suitable for limited datasets.

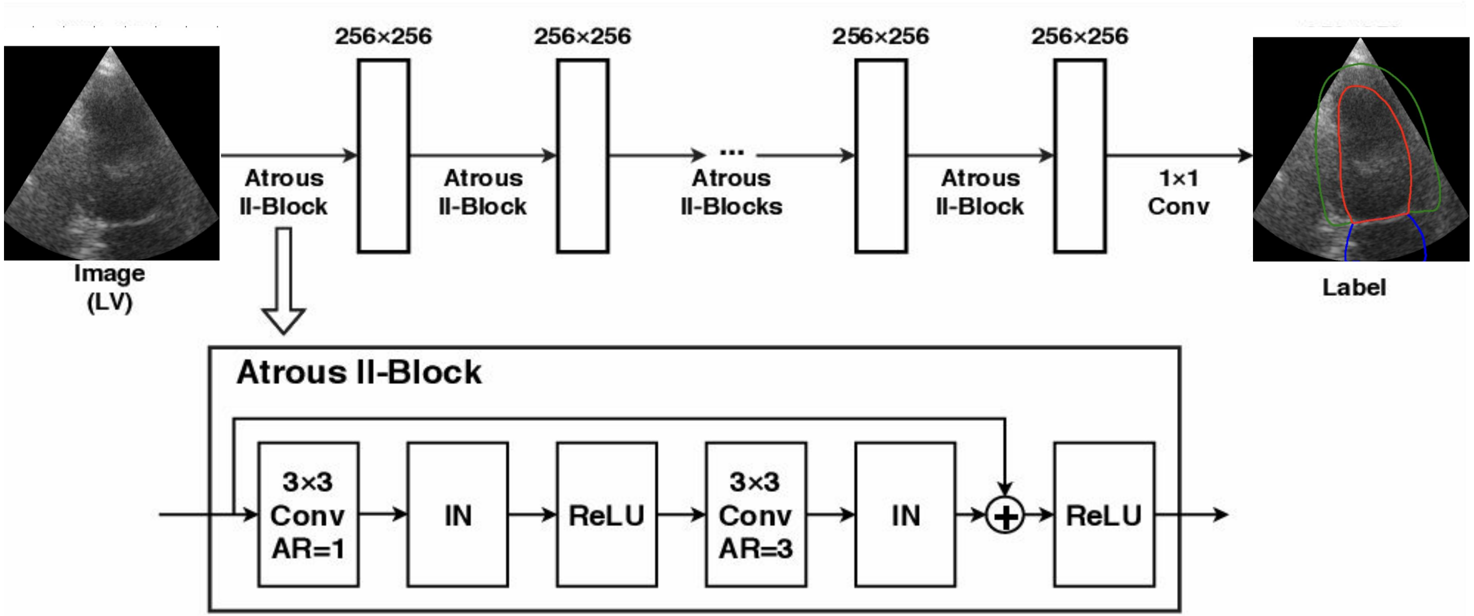
U-Net ARCHITECTURE



ACNN

1. Atrous Convolution Neural Network (ACNN), as a pooling-free network structure
2. Achieve full-resolution feature processing using a theoretically optimal dilation setting for a larger receptive field, even with fewer parameters.
3. Atrous convolution is an alternative for the down sampling layer.
4. Incorporates cascaded atrous II-blocks, residual learning and Instance Normalization (IN).
5. Achieve higher segmentation Intersection over Union (IoU) – and much less trainable parameters and model sizes.

ACNN ARCHITECTURE

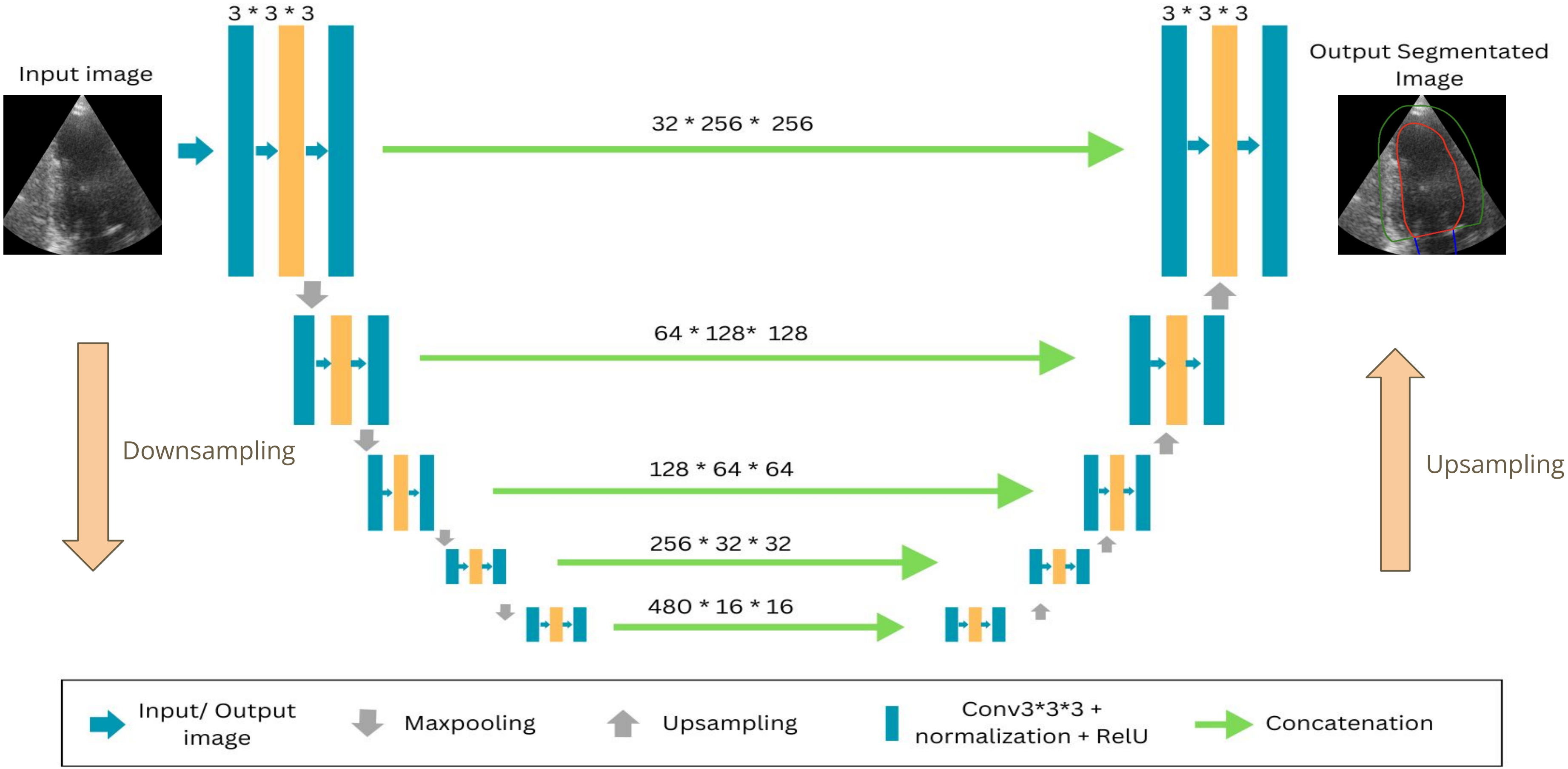


Total of 129 Atrous II blocks have used

NN-Unet

1. No-New-Unet uses semantic segmentation method that automatically adapts to a given dataset
2. Automatically configures itself, including preprocessing, network architecture, training and post-processing.
3. Provides training cases and automatically configure a matching U-Net-based segmentation pipeline
4. It has set of fixed parameters, interdependent rules and empirical decisions.

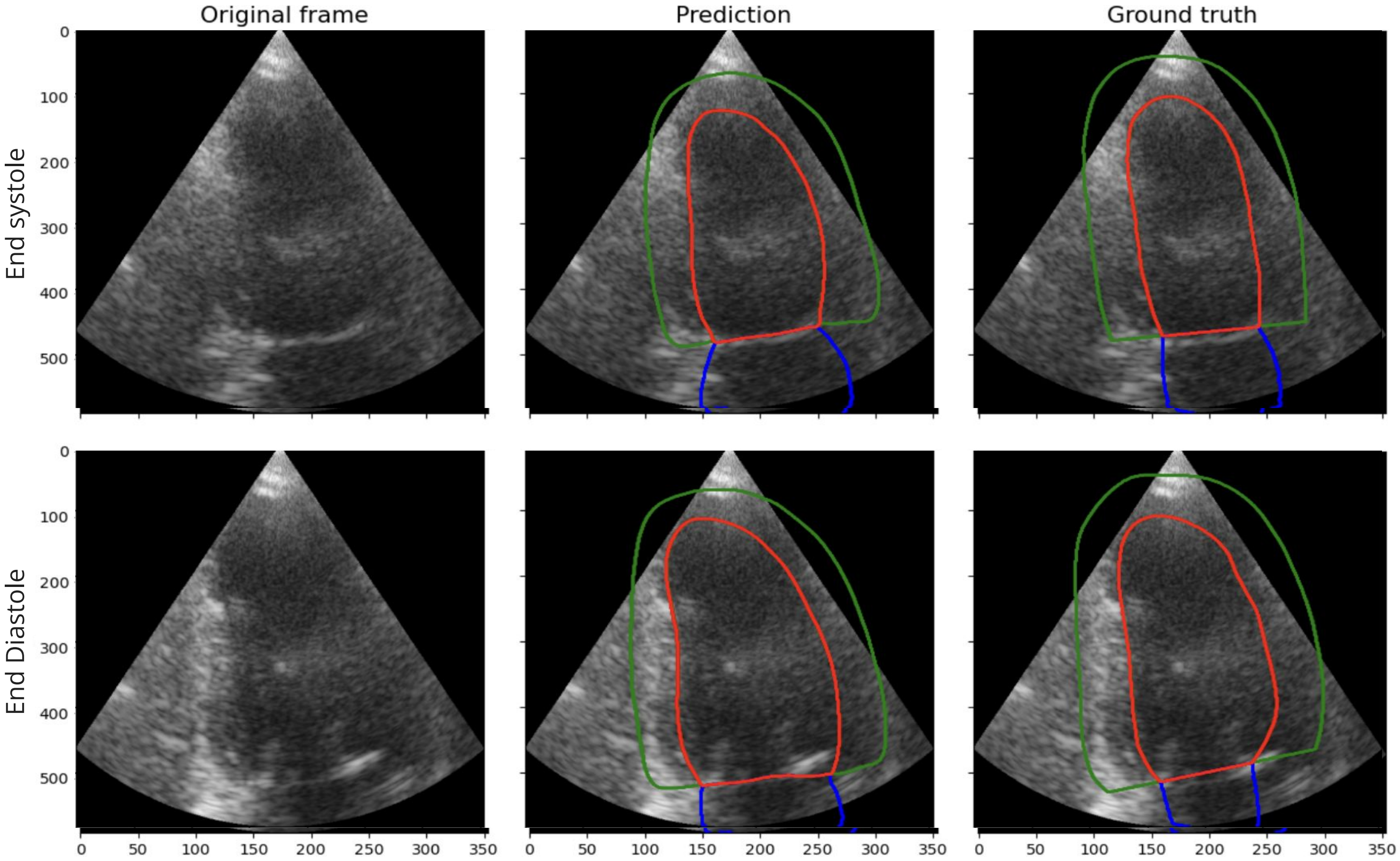
NN-Unet ARCHITECTURE



MODEL CHARACTERISTICS

Architectures	Lowest Resolution	Upsampling Scheme	Downsamplin g Scheme	Normalization Scheme	Batch Size	Learning Rate	Loss Function	Trainable Parameters	Optimizer
U-Net	24 * 24	3 * 3 repeats	3 * 3 repeats	None	32	1e-4	Multi-class Dice Loss	18M	ADAM
ACNN	32 * 32	Deconvolutio n	Convolution	Batch normalization	32	1e-4	Multi-class Dice Loss	5.5M	ADAM
NNU-Net	16 * 16	Deconvolutio n	Convolution	Batch normalization	32	1e-4	Multi-class Dice Loss	2.4M	ADAM

PREDICTION VS GROUND TRUTH



EVALUATION MATRICES

1. **Mean dice -** measuring the similarity or overlap between two sets. It quantifies how well the predicted region (e.g., object boundaries) aligns with the ground truth region (the actual location of objects in the image). Range of Mean dice coefficient lies from 0 to 1.

   Dice coefficient $= 2 * |X \cap G| / (|X| + |G|)$

   $|X|$ represents the number of pixels in predicted mask

   $|G|$ represents the number of pixels in Ground Truth mask

   $|X \cap G|$ represents the number of overlapping pixels in both masks

2. Mean hausdorff - Mean Hausdorff can be calculated as the mean of the directed average Hausdorff distance from X to Y. The directed average Hausdorff distance from point set *X* to *Y* is given by the sum of all minimum distances from all points from point set *X* to *Y* divided by the number of points in *X*.

$$d_{AHD(x,\,y)} \;=\; \left(\frac{1}{X}\sum_{x\in X}\min d\,(x,\,y) \,+\, \frac{1}{Y}\sum_{y\in Y}\min\, d\,(x,\,y)\right)/2$$

dAND - average Hausdorff distance between two finite point sets X and Y. Lower the MH means lesser is the distance between predicted mask and ground truth mask.

3. Mad - the average distance between their observation and the mean. Lower values are associated with closely related data points.

$$MAD = \sum \frac{|x_i - \overline{x}|}{n}$$

m(x) = average value of the data set
n = number of data values
xi = data values in the set

4. Correlation Coefficient - is used to measure the extent of the relationship between two variables. It ranges from -1 to +1.

$$r_{xg} = \frac{n \sum_{i=1}^{n} x_i g_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} g_i}{\sqrt{n \sum_{i=1}^{n} x^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \cdot \sqrt{n \sum_{i=1}^{n} g_{i^2} - \left(\sum_{i=1}^{n} g_i\right)^2}}$$

n = Data quantity or number of data available

Σx = Total of the predicted data point

Σg = Total of the ground truth data point

Σxg = Sum of the Product of predicted & ground truth data points

Σx2 = Sum of the Squares of the predicted data point

Σg2 = Sum of the Squares of the ground truth data points

5. Jaccard Index (I0U) - It measures the similarity measures the similarity between finite sample sets A,B as the Intersection over Union (IoU). Its values lies between 0 to 1.

$$\mathrm{IoU} = \frac{\text{predMask} \cap \text{groundtruthMask}}{\text{predMask} + \text{groundtruthMask - predMask} \cap \text{groundtruthMask}}$$

6. MAE - It measures the average of the errors' magnitude between the predicted and actual values. Its value ranges from 0 to ∞.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \overline{y_i}|$$

Where,
n: number of observation
yi: the actual value of the ith observation
yi': the predicted value of the ith observation

7. Precision - It is the number of true positive results divided by the number of all positive results. Its value ranges from 0 to 1.

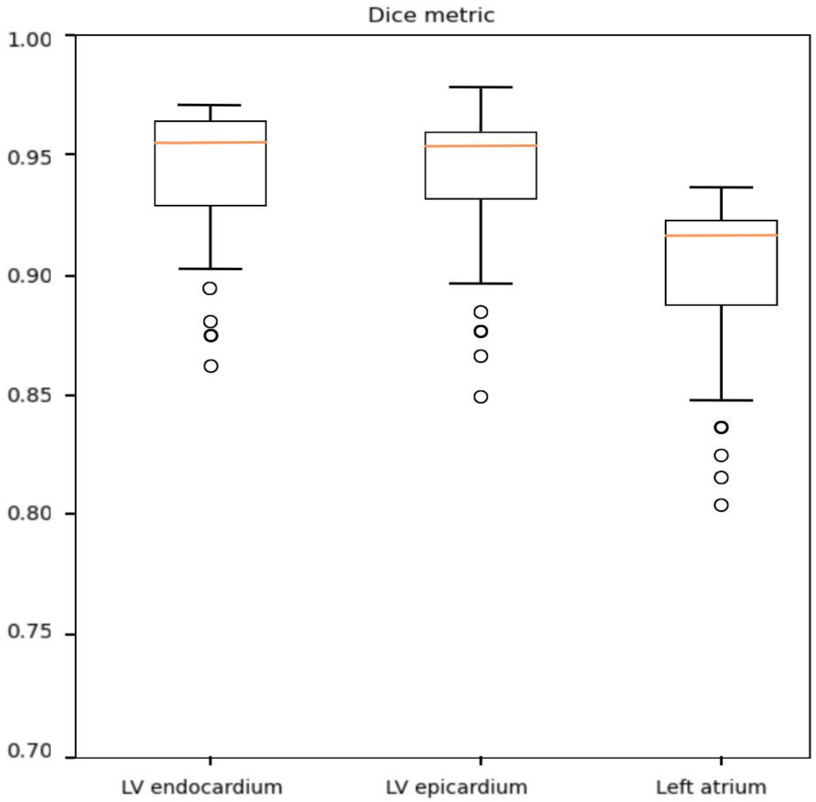
Precision = (predMask ∩ groundtruthMask) / predMask

8. Recall - It is the number of true positive results divided by the number of all samples that should have been identified as positive. Its value ranges from 0 to 1.

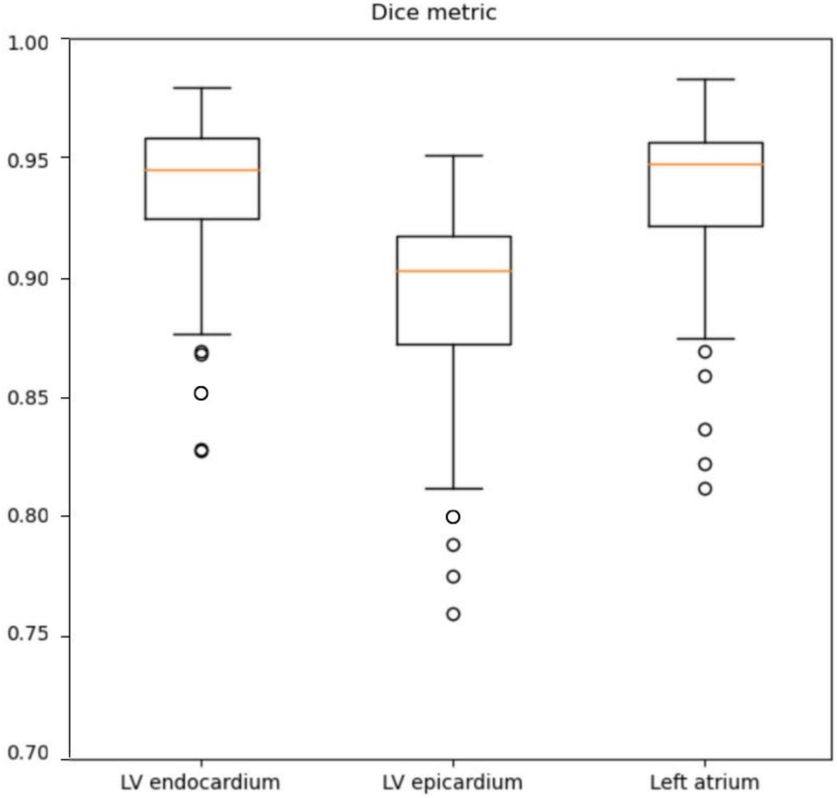
Recall = (predMask ∩ groundtruthMask) / groundtruthMask

DICE PLOT

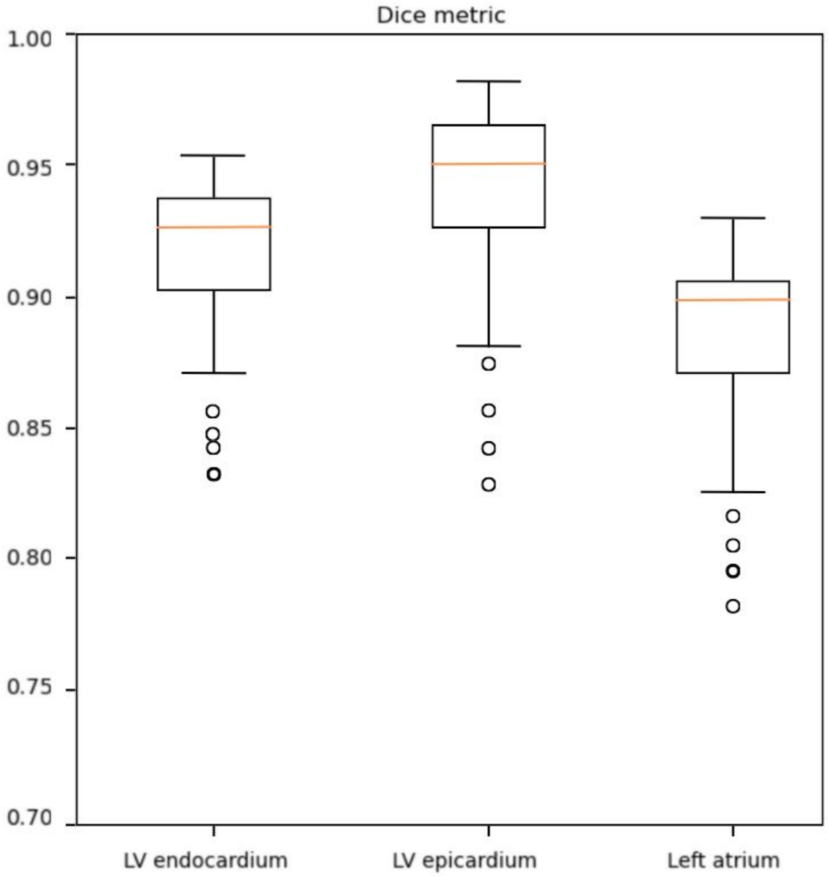
U-Net



ACNN



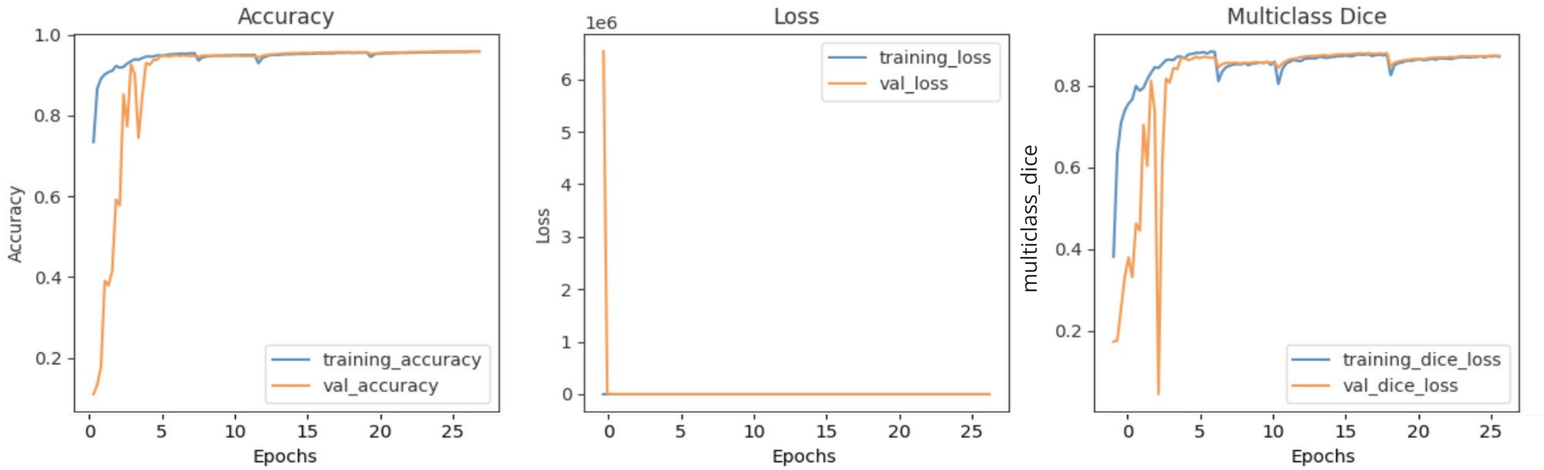
NNU-Net



Dice metric
1.00
0.95
0.90
0.85
0.80
0.75
0.70
LV endocardium
LV epicardium
Left atrium

U-Net

ED



Accuracy
Accuracy
Epochs
training_accuracy
val_accuracy
Loss
1e6
Loss
Epochs
training_loss
val_loss
Multiclass Dice
multiclass_dice
Epochs
training_dice_loss
val_dice_loss

ES

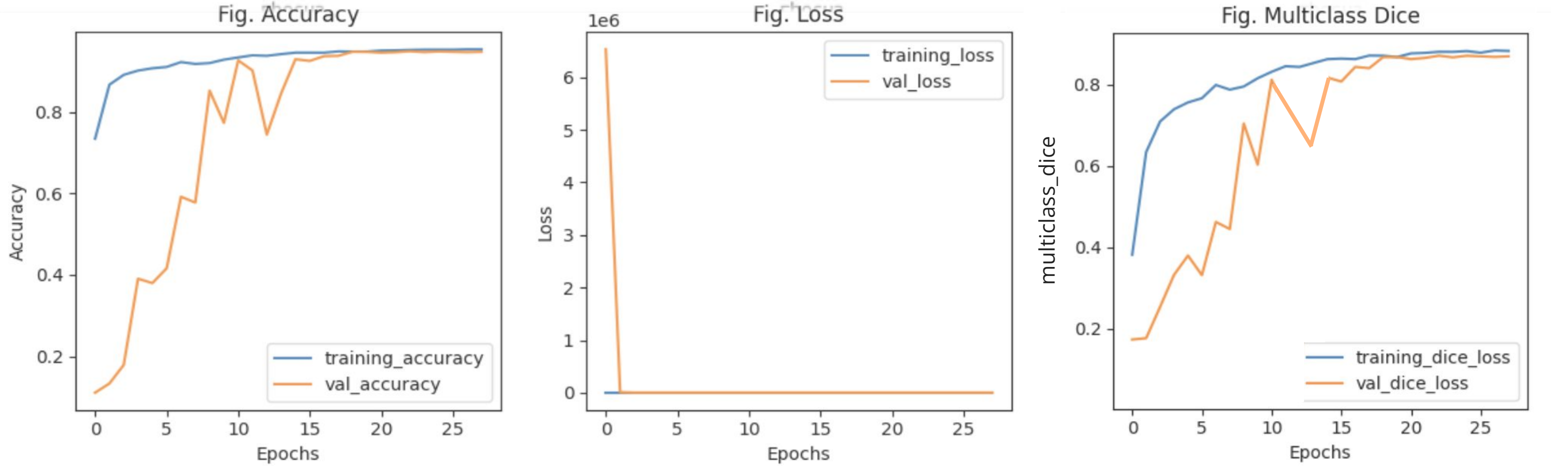


Fig. Accuracy
Accuracy
Epochs
training_accuracy
val_accuracy
Fig. Loss
1e6
Loss
Epochs
training_loss
val_loss
Fig. Multiclass Dice
multiclass_dice
Epochs
training_dice_loss
val_dice_loss

ACNN

ED

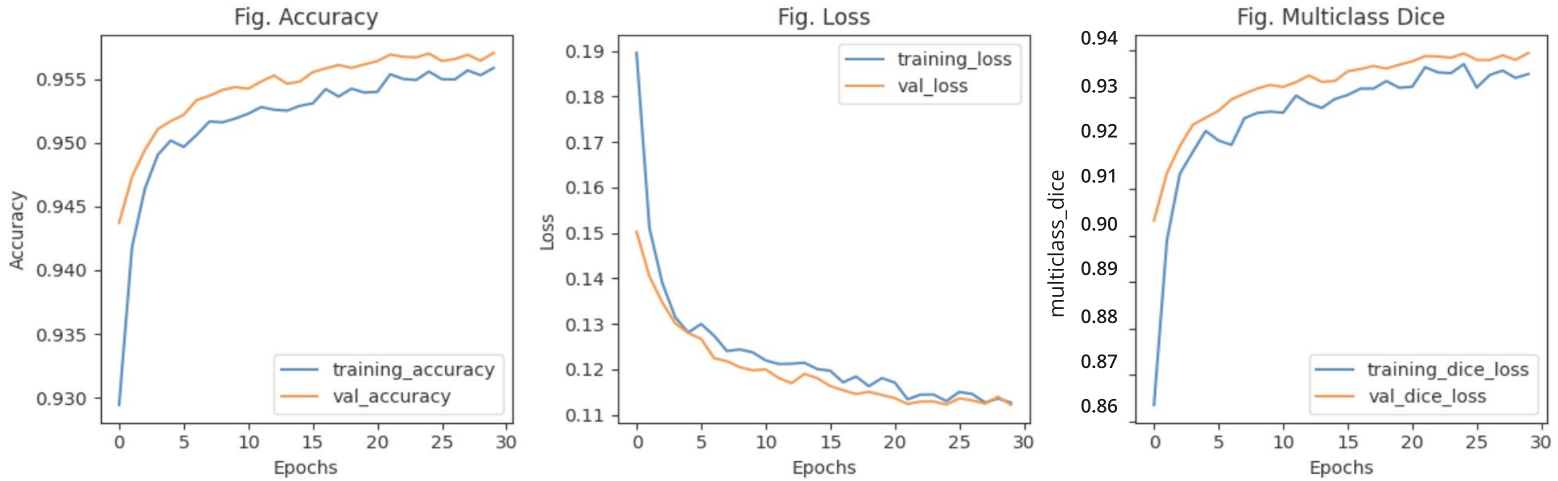


Fig. Accuracy
Accuracy
Epochs
training_accuracy
val_accuracy
Fig. Loss
Loss
Epochs
training_loss
val_loss
Fig. Multiclass Dice
multiclass_dice
Epochs
training_dice_loss
val_dice_loss

ES

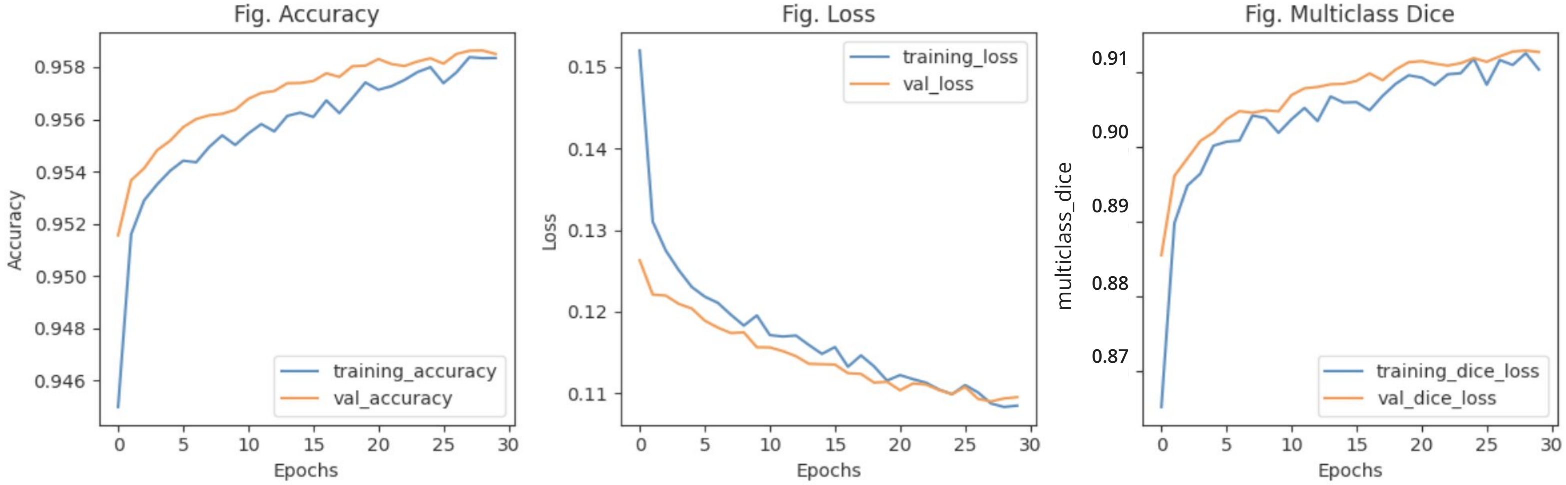
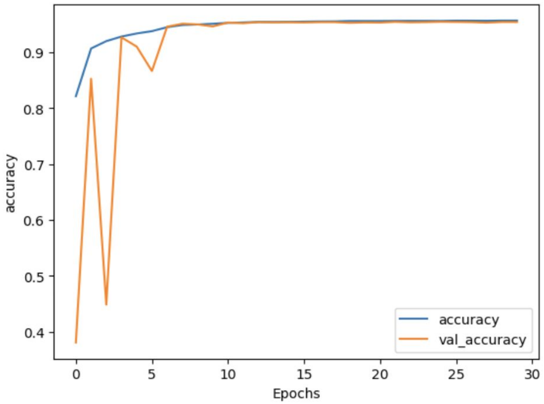
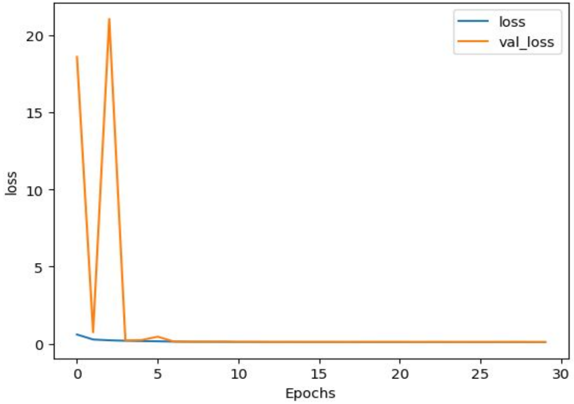


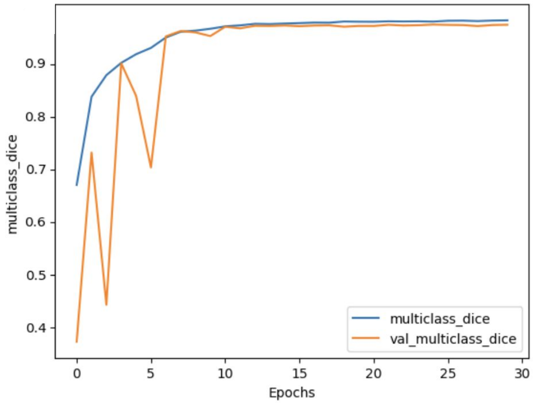
Fig. Accuracy
Accuracy
Epochs
training_accuracy
val_accuracy
Fig. Loss
Loss
Epochs
training_loss
val_loss
Fig. Multiclass Dice
multiclass_dice
Epochs
training_dice_loss
val_dice_loss

NNU-Net

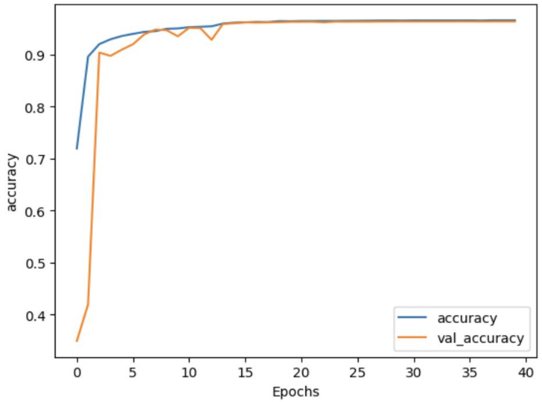
ED

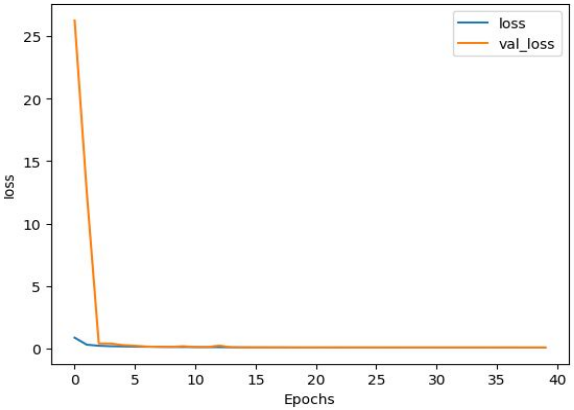

accuracy
Epochs
accuracy
val_accuracy

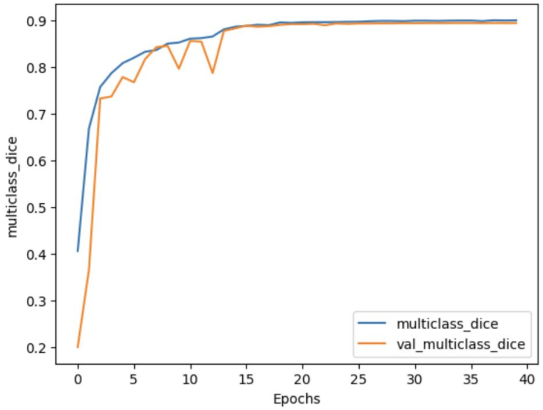

loss
Epochs
loss
val_loss


multiclass_dice
Epochs
multiclass_dice
val_multiclass_dice

ES


accuracy
Epochs
accuracy
val_accuracy


loss
Epochs
loss
val_loss


multiclass_dice
Epochs
multiclass_dice
val_multiclass_dice

RESULTS

Left Ventricle: endocardium

	Mean Dice ED	**Mean Dice ES**	**Mean Hausdorff ED**	**Mean Hausdorff ES**	**MAD ED**	**MAD ES**	**Correlation ED**	**Correlation ES**
U-Net	0.947	0.925	**4.1**	4.4	1.5	**1.3**	0.938	0.959
ACNN	0.933	0.915	5.4	5.2	1.7	1.7	0.930	0.947
NN-Unet	**0.954**	**0.949**	4.5	**4.3**	**1.5**	1.5	**0.978**	**0.983**

	Accuracy ED (%)	Accuracy ES (%)	Precision ED	Precision ES	Recall ED	Recall ES	MAE ED	MAE ES	Jaccard Index ED	Jaccard Index ES
U-Net	95.7	**95.8**	0.938	0.927	0.873	0.912	11.2	7.5	0.889	0.873
ACNN	93.6	94.8	0.932	0.911	0.890	0.934	9.7	6.9	0.905	**0.901**
NN-Unet	**96.7**	94.6	**0.950**	**0.943**	**0.953**	**0.947**	**5.9**	**4.0**	**0.915**	0.891

Left Ventricle: epicardium

	Mean Dice ED	Mean Dice ES	Mean Hausdorff ED	Mean Hausdorff ES	Mean MAD ED	Mean MAD ES	Correlation ED	Correlation ES
U-Net	0.958	0.936	5.2	5.7	1.7	1.9	0.915	0.902
ACNN	0.946	0.953	5.8	5.7	1.8	2.0	0.928	0.910
NN-Unet	**0.968**	**0.928**	**4.6**	**4.4**	**1.5**	**1.5**	**0.948**	**0.953**

	Accuracy ED (%)	**Accuracy ES (%)**	**Precision ED**	**Precision ES**	**Recall ED**	**Recall ES**	**MAE ED**	**MAE ES**	**Jaccard Index ED**	**Jaccard Index ES**
U-Net	93.8	95.6	0.925	0.933	0.907	0.917	9.9	6.7	0.926	0.915
ACNN	94.6	93.2	0.945	**0.949**	0.869	0.892	10.1	7.8	0.893	0.897
NN-Unet	**97.1**	**96.3**	**0.963**	0.915	**0.947**	**0.955**	**6.2**	**5.4**	**0.945**	**0.938**

Left Atrium

	Mean Dice ED	Mean Dice ES	Mean Hausdorff ED	Mean Hausdorff ES	Mean MAD ED	Mean MAD ES	Correlation ED	Correlation ES
U-Net	0.890	0.921	5.6	5.4	2.1	2.0	0.899	0.895
ACNN	0.881	0.870	5.9	6.0	2.3	2.3	0.926	**0.945**
NN-Unet	**0.912**	**0.929**	**5.1**	**4.3**	**2.0**	**1.8**	**0.987**	0.927

	Accuracy ED (%)	**Accuracy ES (%)**	**Precision ED**	**Precisio n ES**	**Recall ED**	**Recall ES**	**MAE ED**	**MAE ES**	**Jaccard Index ED**	**Jaccard Index ES**
U-Net	93.1	92.6	0.874	0.917	0.889	0.845	13.4	10.7	0.889	**0.895**
ACNN	93.8	91	**0.969**	**0.958**	0.937	0.943	10.9	9.8	0.88	0.890
NN-Unet	**94.2**	**94.1**	0.902	0.931	**0.950**	**0.949**	**7.4**	**6.0**	**0.894**	0.883

COMPARATIVE ANALYSIS

Title	Dataset	Method Used	Dice	Hausdorff	MAD	Correlation	Jaccard Index(IOU)	MAE
[3]	STACOM	ResDUnet	0.867	6.5	1.6	-	-	-
[4]	Self-Collected	ACNN + DBN	-	-	-	0.86	0.8	-
[5]	UK Digital Heart Project	ACNN	0.866	-	-	-	-	-
[6]	CAMUS	SOCOF	0.814	-	-	0.918	-	-
[7]	Cardiac US image of canine LV	LVnet	0.902	-	-	-	**0.823**	-

Title	Dataset	Method Used	Dice	Hausdorff	MAD	Correlation	Jaccard Index(IOU)	MAE
[8]	Self-Collected	BEAS	0.825	-	-	-	-	-
[9]	Self-Collected	TransV-Net	0.902	4.9	1.5	-	-	-
[10]	EchoNet-Dynamic	CSS	0.919	4.17	-	-	-	4.9
[11]	CAMUS	PWC Net	0.79	-	-	0.84	-	**2.8**
	CAMUS	U-Net	0.947	**4.1**	**1.5**	0.938	0.889	11.2
	CAMUS	ACNN	0.933	5.4	1.7	0.930	0.905	9.7
	CAMUS	NNU-Net	**0.954**	4.5	**1.5**	**0.978**	**0.915**	**5.9**

CONCLUSION

1. Encoder-decoder networks produced highly accurate segmentation results in 2D echocardiography.
2. Among the different tested architectures, NNU-Net appeared to be most effective in terms of **trade-off between the number of parameters and the achieved performance.**
3. It accurately reproduced expert analysis for left ventricular volumes with high correlation (0.938 for ED and 0.968 for ES) and low absolute mean distance (1.5 for ED and 1.3 for ES).
4. NN-Unet produced high mean dice score i.e around 0.95 in LV ED, 0.912 in LA ED.MH. accuracy and precision.
5. NN-Unet produced high Jaccard index and low MAE values i.e 0.915 and 5.9 respectively.

FUTURE WORK

1. Incorporating Multi-structure Segmentation can improve the results further.
2. Exploring optimal hyperparameters, data augmentation techniques, and training strategies to further improve the accuracy.
3. Dataset Expansion and Diversity.
4. This study can further be extended for right ventricle, right atrium and valves.

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THANK YOU!