Latent Space Exploration for Automated Detection of Myocardial Infarction in Echocardiograms

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Understanding Myocardial Infarction (MI)

Statistics

- Myocardial infarction (MI) is the major cause of death in the world. Solely in the United States, nearly 4 million people suffering from cardiac pain go to the emergency every year and more than half of the accepted patients are treated in the hospitals for their recovery.

Limitations of Traditional Techniques

- The electrical activity in the heart, which is measured by ECG, cannot differentiate between MI and myocardial ischemia .
- The ECG also relatively depicts the MI with a significant delay compared to the imaging technique so that non-diagnostic ECG still maintains as an unsolved problem.

Dataset

The HCM-QU dataset is created by the collaboration between Hamad Medical Corporation Hospital and Qatar University.

The Dataset has 109 A4C videos in .avi format with a total of 72 MI and 37 non MI patients.

For each echo/video we are provided with around 30-60 frames and also their corresponding masks.

Google Docs

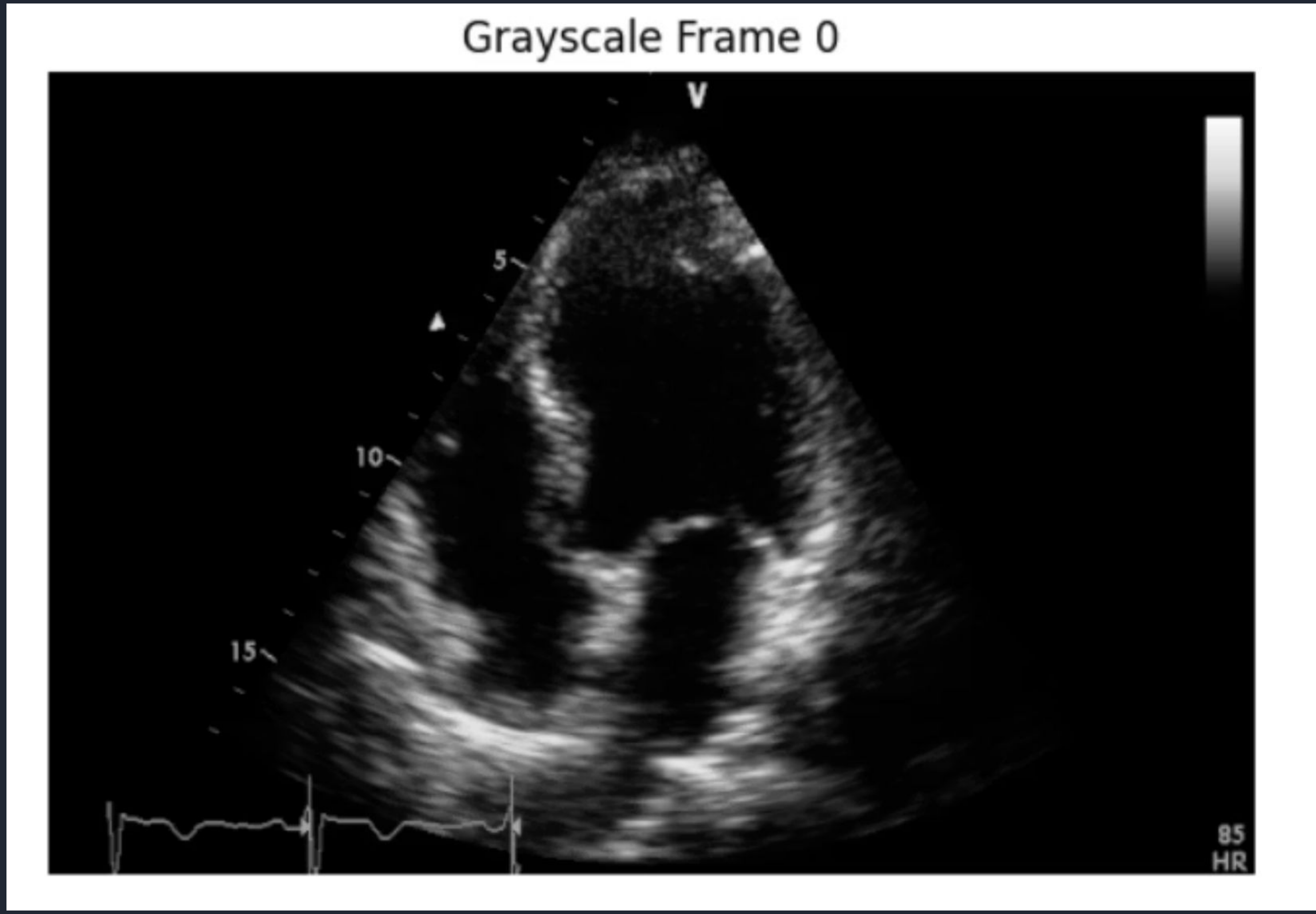
ES0001 _4CH_1.avi

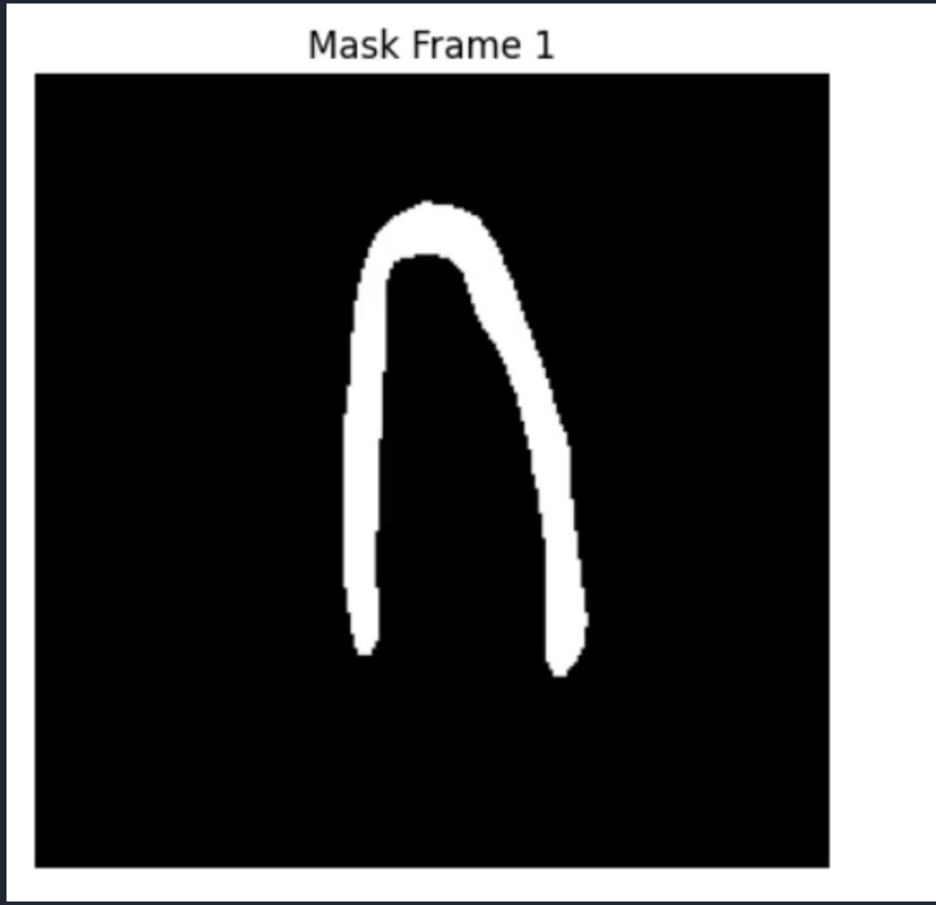
1	ECHO	LABEL						One cardiac-cycle frames		LV Wall Ground-truth Segmentation Masks
2		SEG3	SEG9	SEG14	SEG16	SEG12	SEG6	Reference Frame	End of Cycle	Available: ✓ Not Available: ×
3	ES0001 _4CH_1	MI	MI	MI	MI	MI	non-MI	1	20	✓
4	ES00010 _4CH_1	non-MI	non-MI	MI	non-MI	non-MI	non-MI	1	21	✓
5	ES000102 _4CH_1	non-MI	non-MI	MI	MI	non-MI	non-MI	1	22	✓
6	ES000103 _4CH_2	MI	MI	MI	MI	non-MI	non-MI	1	16	✓
7	ES000105 _4CH_1	non-MI	MI	MI	non-MI	non-MI	non-MI	1	20	✓
8	ES000106 _4CH_1	MI	MI	MI	MI	non-MI	non-MI	1	18	✓
9	ES000107 _4CH_1	MI	MI	MI	MI	MI	MI	45	61	✓
10	ES000108 _4CH_1	non-MI	non-MI	MI	non-MI	non-MI	non-MI	1	16	✓
11	ES000109 _4CH_2	non-MI	non-MI	MI	MI	non-MI	non-MI	1	16	✓
12	ES00011 _4CH_1	non-MI	non-MI	non-MI	non-MI	non-MI	non-MI	1	17	✓

Labelled Data

This excel file shows the cardiac cycle frames and they are using each fragment of the mask to predict MI or non-MI.

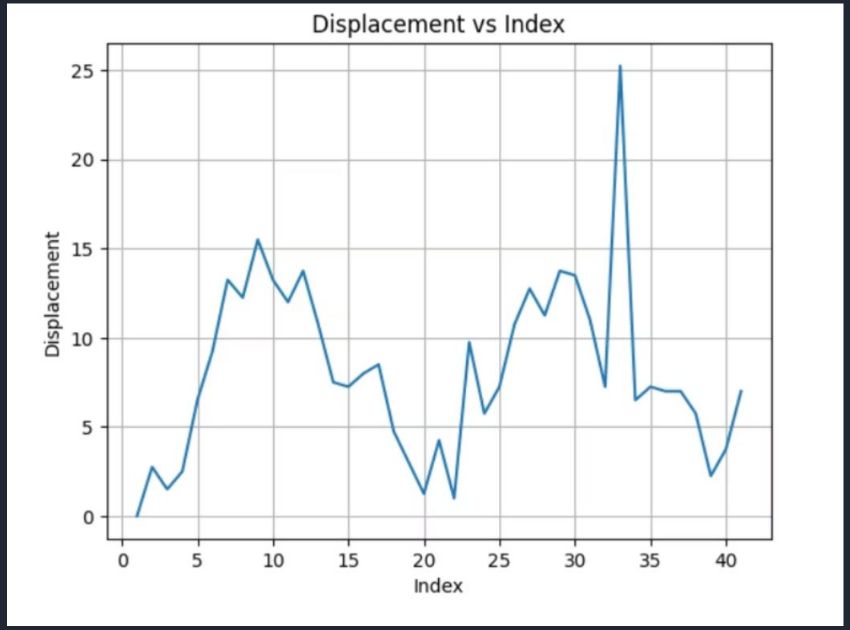
LV Ground Truth Segmentation



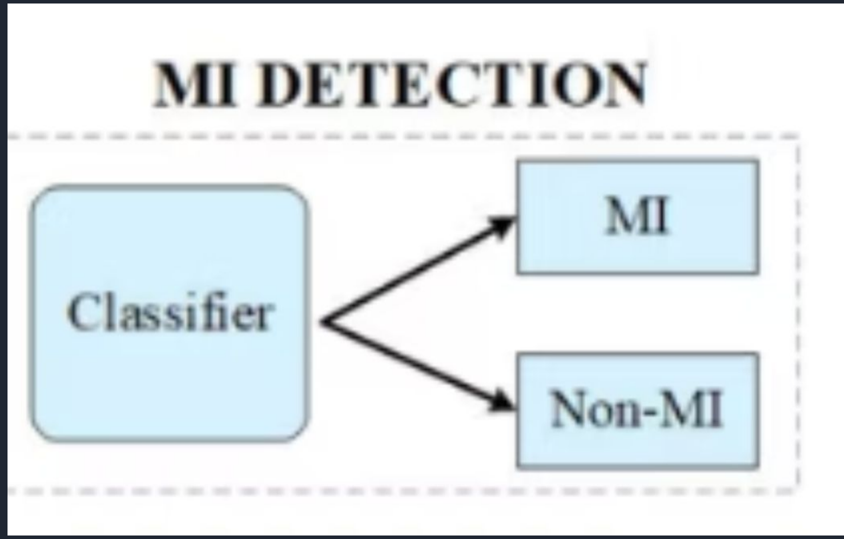


Methodology for Myocardial Infarction

Segmentation



Feature Extraction



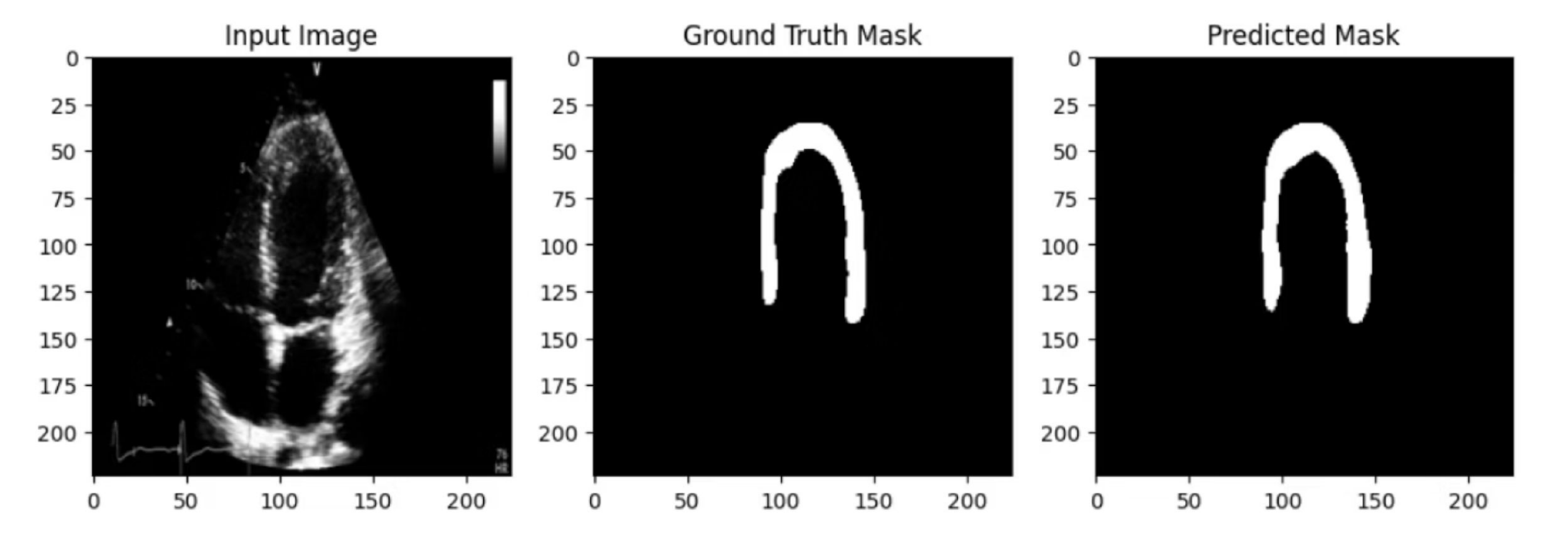
Classification

Segmentation

1. For preprocessing we have resized all images to 224X224 size and normalized them.
2. For segmenting the walls of the Left Ventricle we have used two models and chosen the one with the best accuracy : encoder-decoder U-net architecture with attention (attention unit).
3. For increasing the dataset we used 3 data augmentation techniques.

Segmentation

1. For preprocessing we have resized all images to 224X224 size and normalized them.
2. For segmenting the walls of the Left Ventricle we have used the encoder-decoder U-net architecture with attention (attention unit).
3. Encoder layer comprises of convolution layer (uses ten 2D convolution layers).Decoder layer comprises of up convolution block and attention unit.
4. We have used kernel size =(2,2) , stride=2.
5. For increasing the dataset we used 3 data augmentation techniques.



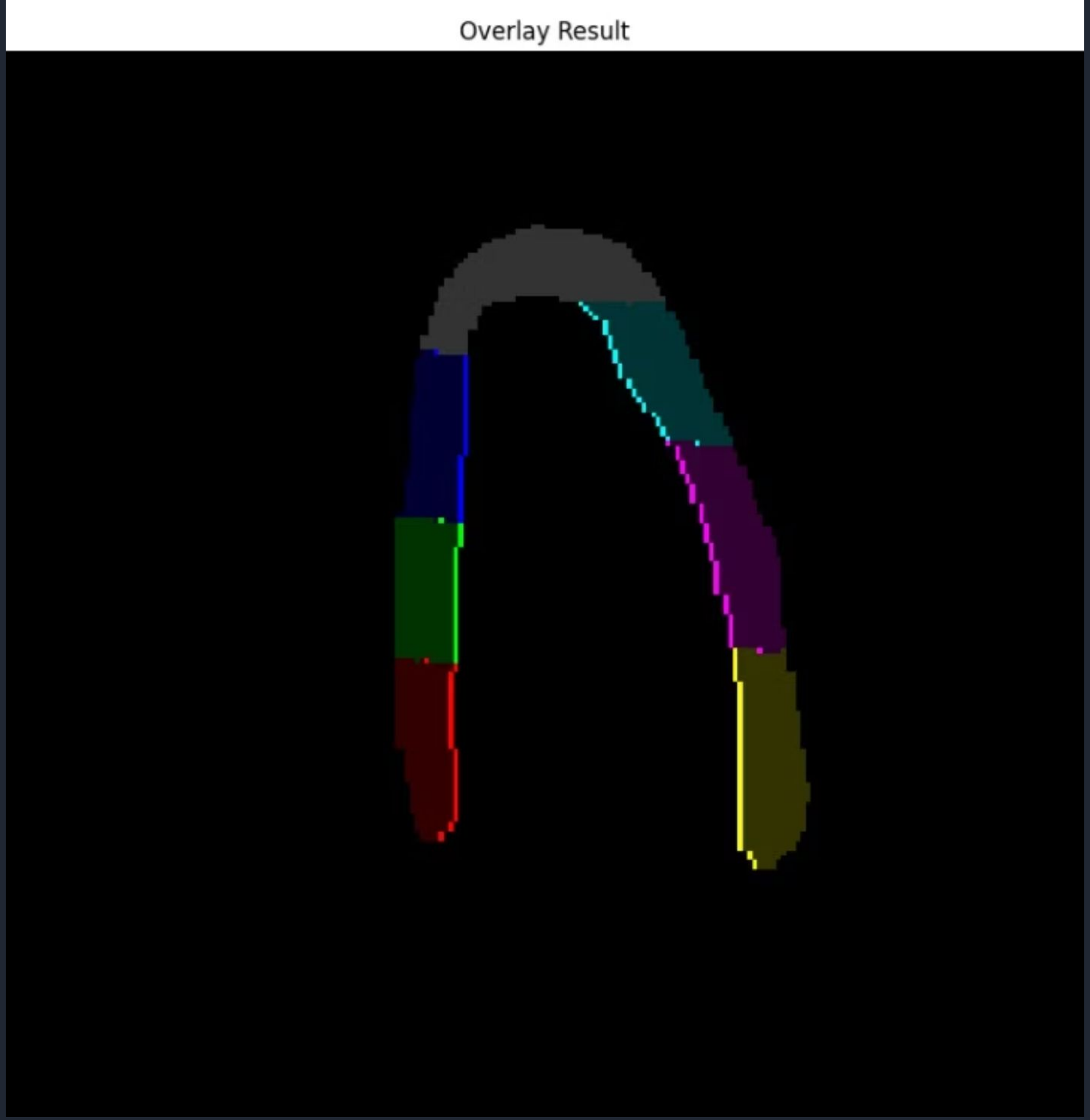
Made with GAMMA

Feature Extraction

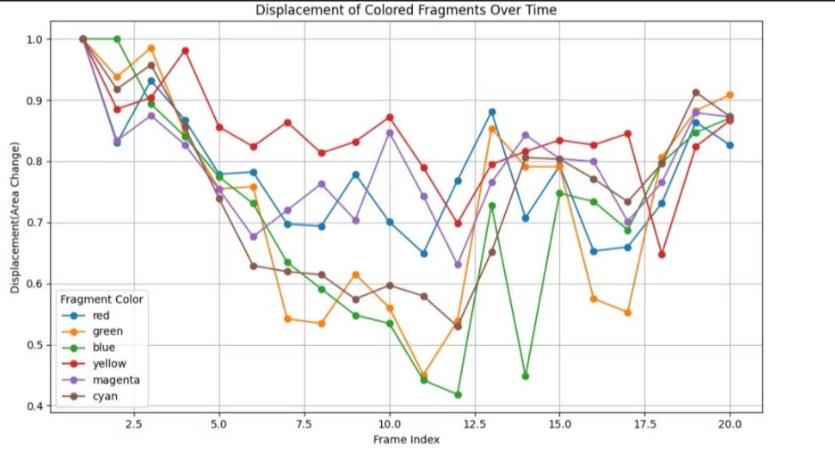
- After segmentation we have divided the mask into 7 parts which we will call as fragments. We have used different color coding to visualize the different segments.
- During our research we observed that these two following features are very important : -

1. Motion of the walls of the LV
2. Thickness of the wall

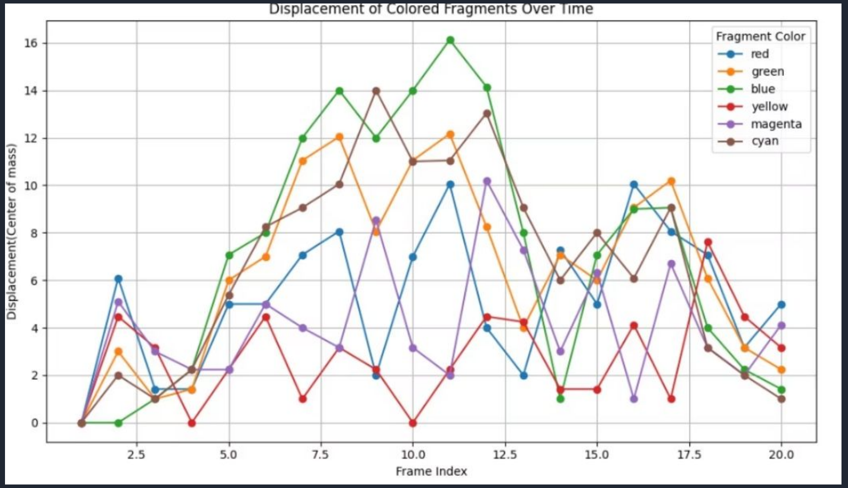
In order to achieve the goal we extracted three features which are : Area of the segment , displacement of the center of mass and the inner boundary of the mask;.



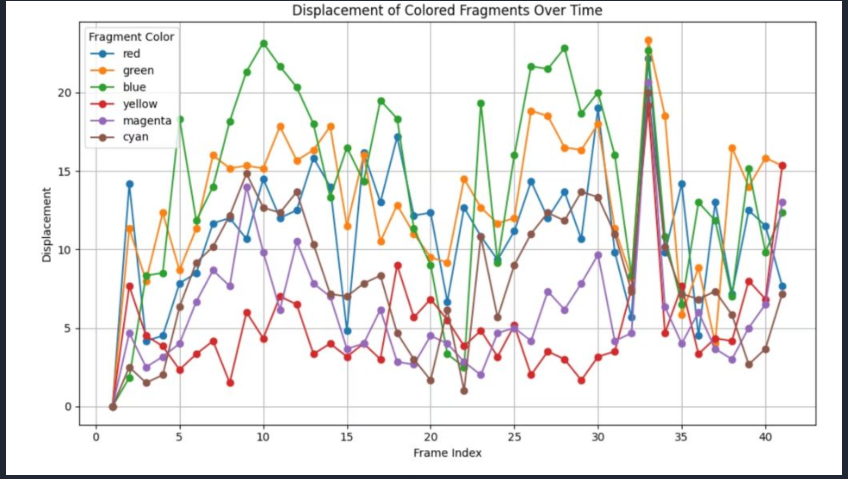
Feature Extraction



Segment Area Curve



Displacement of Center of Mass



Inner Boundary

Classification

- We tried three different models to classify the given echos as MI or non-MI. The three models used were : XgBoost ,SVM & ANN.
- Among these three the ANN provided with the best performance followed by SVM and then by XgBoost.
- Since our dataset had heavy class imbalance we have used different weights for MI & non-MI images to improve the accuracy of the model.

Results and Analysis

Model	Accuracy	F1-Score
ANN	78.78%	0.799
SVM	76%	0.75
XgBoost	70%	0.70

Results

```
Mean Dice Coefficient: 0.9254
```

ResUNet

```
Dice Coefficient: 0.9630
IoU: 0.9287
Precision: 0.9684
Recall/Sensitivity: 0.9577
Pixel-wise Accuracy: 99.69%
```

ED-Unet-Attention Unit

Outputs

```
Classification Report for Segment 1:
              precision    recall  f1-score   support

       No MI       0.73      0.65      0.69        17
          MI       0.67      0.75      0.71        16

    accuracy                           0.70        33
   macro avg       0.70      0.70      0.70        33
weighted avg       0.70      0.70      0.70        33


Overall MI/non-MI Accuracy: 69.70%
```

XgBoost

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
Best Parameters: {'svc__C': 10, 'svc__gamma': 'scale', 'svc__kernel': 'rbf'}

 Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.59      0.71        17
           1       0.68      0.94      0.79        16

    accuracy                           0.76        33
   macro avg       0.80      0.76      0.75        33
weighted avg       0.80      0.76      0.75        33

Confusion Matrix:
 [[10  7]
 [ 1 15]]
```

SVM

```
Accuracy: 0.7878787878787878
F1 Score: 0.7999999999999999
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.71      0.77        17
           1       0.74      0.88      0.80        16

    accuracy                           0.79        33
   macro avg       0.80      0.79      0.79        33
weighted avg       0.80      0.79      0.79        33

Confusion Matrix:
 [[12  5]
 [ 2 14]]
```

ANN

Challenges Faced

Dataset

Every limited amount of data for training of the model.

Noise

No consistent filter which can be used to remove noise from all echos.

Conclusion: Transforming MI Diagnosis

Project Impact

Early, accurate MI detection leads to better outcomes.

Patient Benefits

Reduced healthcare costs and improved survival rates.

Next Steps

Move towards clinical implementation and widespread validation.