Indian Institute of Technology, Mandi

EE-511 Computer Vision

PROJECT REPORT

Computer Vision for Ultrasound Beamforming

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Submission Date : 14/01/2024

1 Introduction

Biomedical imaging provides a very good source of diagnosing deadly diseases. Those diseases that form within our body but cannot be seen by us are diagnosed using ultrasound. In some of these diseases a particular kind of cyst gets formed in between the normal tissues of our body. Some of these cysts are anechoic, some are hypoechoic and some are hyperechoic. Anechoic cysts are those cysts which do not reflect any wave back to the transducer and hence appears completely black in the ultrasound image produced. Any disturbance in the tissues caused due to some phantom gets detected by the process of ultrasound.

So, to generate the ultrasound image, there is a transducer that emits high freuqency waves into our body and if any disturbance is found, then there is difference in the reflected waves and hence identified in the ultrasound image. The probe contains almost around 50 such transducers which emit the waves at different angles. As the angles are different the recieved Radio frequency waves are concatenated to produce the final ultrasound image that can be read by the doctor. This step is called beamforming.

As there are around 50 such channels that are to be concatenated, there is a high possibility that if the probe is not very accurate in the process, the beamforming step will result in not very good image. High quality probes are very expensive. Therefore to overcome this problem of accurately constructing the B-mode image, deep learning can be employed. On researching through various research papers on this topic, we got a method to resolve this issue.

Our research on this topic revealed that an U-Net model can be employed to get rid of this problem. As there were no proper datasets available for this, we simulated the dataset using Field II toolbox provided by Mathworks. All of this is discussed in great detail further in this report.

In the further sections of this report, we will be talking about the architecture of the employed model, the simulation of the dataset and hence the implementation of SOTA. Further, we will also be talking about the novelty and references used.

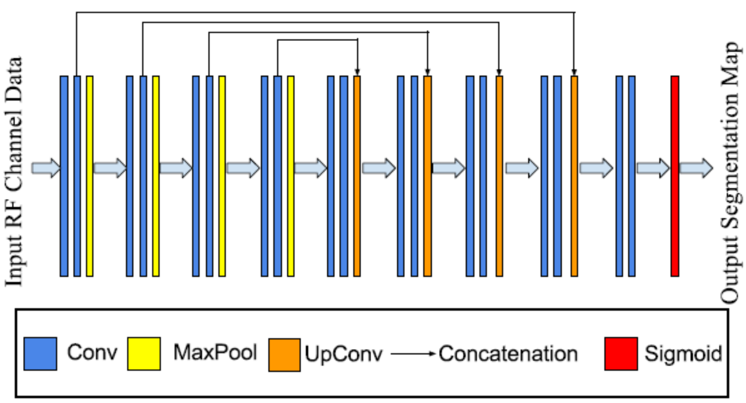


Figure 1: Architecture of the employed U-Net model

2 Dataset Simulation

The simulation of dataset was done using MATLAB. The Field II toolbox provides us with the platform to do so. All the simulations had a cyst of a particular radius in between a given region. These cysts were anechoic which means they should be completely black in colour, so the amplitude inside the cyst was set to 0. This generated the RF channel data. Further using MATLAB, transducer was set up and the beamformed image was generated.

3 U-Net Model

U-Net is a model that is widely used for image segmentation particularly semantic segmentation. It majorly comprises of 2 parts that are the encoder and the decoder part which are connected by skip connections. The encoder path is contracting and consists of convlayers to extract the useful features and the maxpool layer to reduce the dimension to half hence contracting. The decoder part of the model reverses the doings of the encoder part hence doing the segmentation.

ReLu function was used for introducing non linearity by keeping only the positive part of the input data. Sigmoid function was used in the final output layer to bring the values in between 0 and 1 thus providing a probability like measure to predict whether the pixel belongs to the cyst phantom or not.

The accuracy of the model was calculated using the dice coefficient which denotes the number of overlapping pixels in the ground truth image and the predicted image mask as a fraction of the total number of pixels. Below is the formula for the same where X denotes the pixels in the predicted mask and Y denotes the pixels in Ground truth image generated in the simulation.

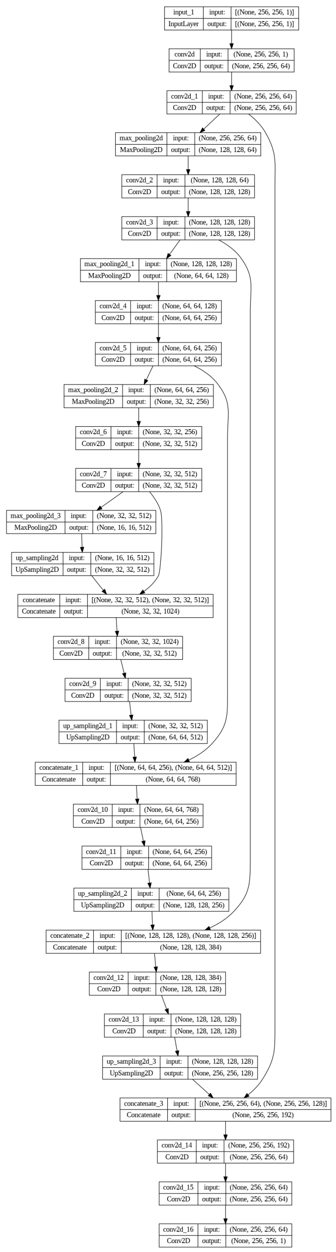
$$Dice(X,Y) = \frac{2|X \cap Y|}{|X| + |Y|}$$

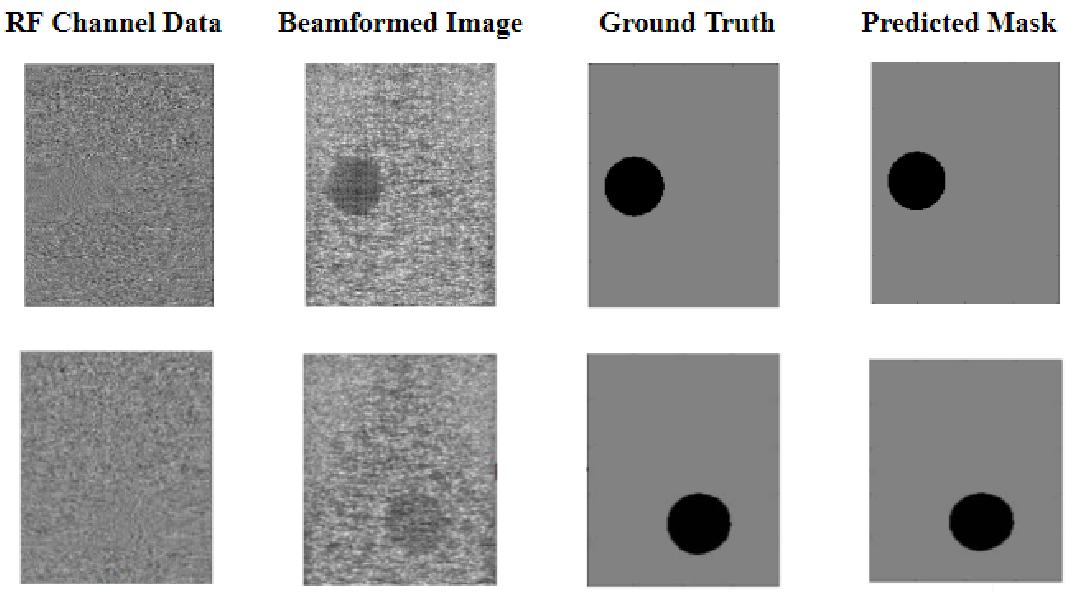
4 Outcomes

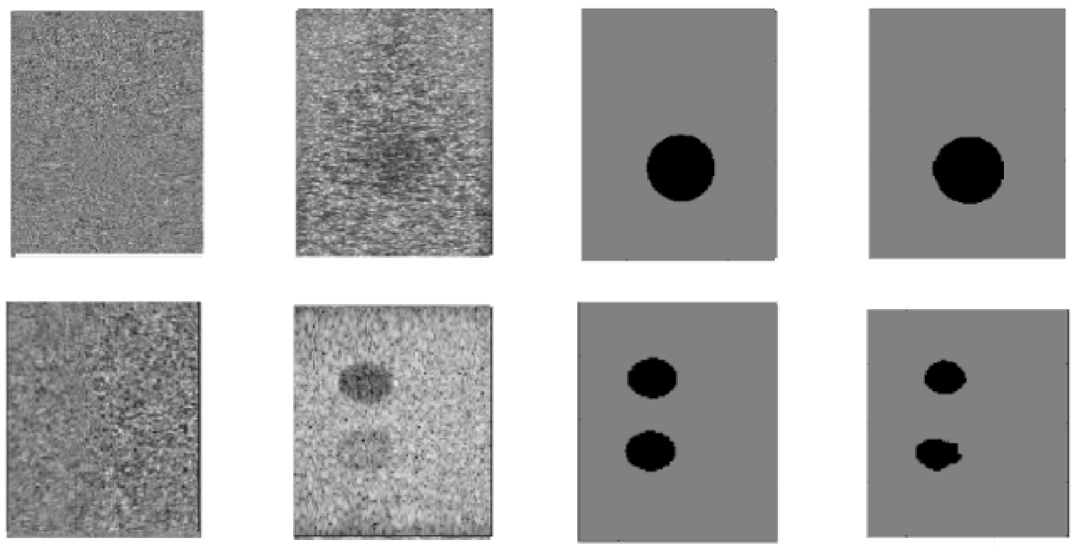
The SOTA stated that the model should have a dice score of more than 0.94 which aligned with our results which gave the dice score of 0.9786. This is the fraction of the pixels that were correctly identified by the model in the predicted image with respect to all the pixels in both te images.

```
Epoch 20/20
36/36 [==============================] - 5s 139ms/step - loss: 0.0176 - dice_coef: 0.9786 - binary_accuracy: 0.9918 - val_loss:
0.0971 - val_dice_coef: 0.9518 - val_binary_accuracy: 0.9768
```

In each case, the mean Dice coefficients was always greater than 0.94, regardless of variations in the four simulated parameters. Varations in Dice coefficients were most sensitive to cyst size. The Dice coefficients were lower for smaller cysts, with performance monotonically increasing as cyst size increased. This increase with size is likely a result




RF Channel Data
Beamformed Image
Ground Truth
Predicted Mask

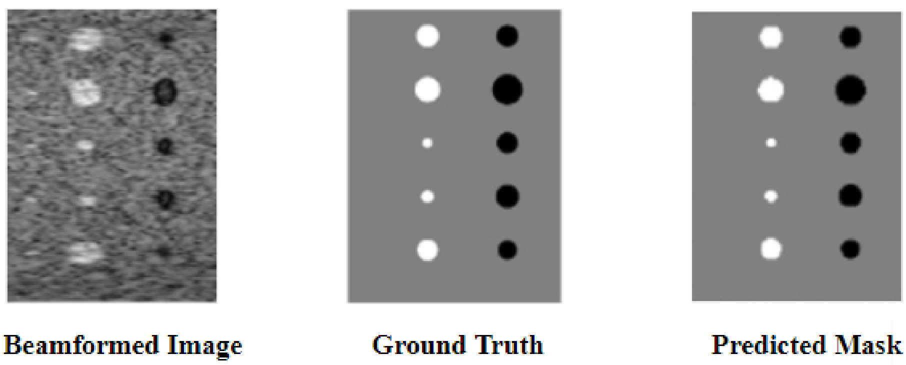


5 Novelty

As discussed earlier, there are 3 types of cyst. The one on which the SOTA focussed was the anechoic cyst. To take into account all the different types of cyst, hypoechoic and hyperechoic cyst should also be considered. Hypoechoic cysts are those cysts which are darker than the surrounding but not completely black. These cysts were generated by setting the outside cyst phantom amplitude greater than the inside amplitude. Hyperechoic cysts are those cysts that appear lighter than the surroundings in the ultrasound image. Therefore to create these, the amplitude in the cyst region was increased to 10 times the amplitude outside creating a lighter spot in the simulated image.

The dataset creation was successful and the model was trained with this dataset which gave a dice coefficient of 0.9635. Hence, the model got extended to classify 3 types of cysts as discussed above.

```
Epoch [20/20], loss: 0.1839 - acc: 0.9817 - dice: 0.9635
Training complete in 79m 10s
```



6 Conclusion

This work demonstrates the feasibility of using deep learning as an alternative for the traditional human reading of ultrasound images and beamforming. The proposed solution of using the U-Net model to solve the problem of ultrasound beamforming. The encoder decoder network used the input channel data which was in non human readable form improving the diagnostic accuracy.

7 References

[1] Field II Cyst simulation: https://field-ii.dk/?examples/cyst_phantom/cyst_phantom.html.

[2] Field II Toolbox: https://field-ii.dk/?papers.html.

[3] Ultrasound terminology: https://www.youtube.com/watch?app=desktop&v=Q6RG4iqXJd4

[4] U-Net implementation for segmentation: https://www.youtube.com/watch?v=azM57JuQpQI&list=PLZsOBAyNTZwbR08R959iCvYT3qzhxvGOE