Deep Learning based model for Ultrasound Beamforming

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***Abstract*—Ultrasound imaging is very often used in medical imaging to spot out structures like cysts, fetal structures, kidney stones and other abnormalities. One of the issues faced by people working by this is beamforming. Even a slight inaccuracy in beamforming that may be caused due to poor quality transducers will even result in challenges in accurately identifying and localizing the abnormal internal structure formed. Current beamforming methods are not able to accurately achieve the perfect localization of cysts leading to limitation in diagnostic accuracies and limiting the treatment planning. To address this issue, we have worked on a deep learning based alternative U-Net model for Ultrasound Beamforming. We will consider the problem as a segmentation problem to segment the abnormally formed structure in the tissue. We have used a dataset that we generated using Field II toolbox of MATLAB. Field II is the open source ultrasound simulation software provided by Mathworks. All simulations have a cyst in normal tissue within a region of -19mm to +19mm in the lateral direction and 30mm and 80mm in the axial direction. Our simulated results produced a mean dice coefficient of 0.98 when measuring the overlap in the ground truth cyst location and the location on the predicted mask. This way our proposed U-Net model solves the problem of ultrasound beamforming efficiently.**

***Index Terms*—Deep Learning, Ultrasound Beamforming, Field-II toolbox, MATLAB, U-Net, Segmentation**

I. Introduction

II. Architecture

The architecture used by our team to solve the problem of ultrasound imaging is by using a Deep Neural Network based model - U-Net which is widely used for image segmentation. As shown in the Fig 1, U-Net is a Fully Convolutional Neural Network architecture consisting of 2 major parts that are the encoder and decoder parts connected through skip connections.

The encoder part is the contracting part of the model which consists of conv layers which are used to capture local patterns formed in an image and maxpooling layers used to reduce the spatial dimensions of input data by retaining most of the important information recieved by the earlier conv layers. Here, in the model, we have used 3 X 3 conv layers with stride of 1. No padding has been done and ReLu function is employed for these conv layers. For MaxPool, the pool size is kept 2 X 2 with stride rate of 2 which means after each of the maxpool layer, the output size is half the size of input.

Medical Ultrasound images are a very good source of disease diagnostics all over the world. These images are used to detect breast cancer, brain tumor and various other deadly diseases. Ultrasound is preferred as it provides real time imaging and is cost effective. The ultrasound imaging uses high frequency sound waves to image the biological tissue. The probe emits these waves and as the waves encounter a biological tissue, the emitted waves reflects back. If any abnormally formed tissue blocks the path of the wave, the waves get reflected from there only and indicates presence of abnormal tissue.

The ultrasound image formation consists of various steps as the image formation takes place out of which the first step is Beamforming which causes a lot of problem as there are multiple angles and even small difference in the angle causes high inefficiency. So, in order to get the accurate diagnostics of disease we need to tackle this problem of beamforming.

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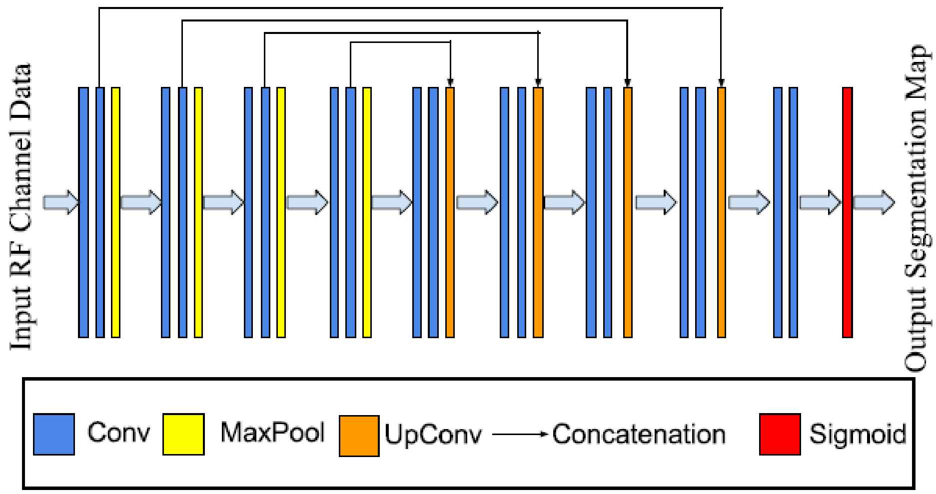

Fig. 1. U-Net architecture

The second part of the model is the decoder part which inverses the work done by the encoder part of the model. In this part, transposed convolutional layer has been employed. This increases the output size to twice as was reduced in the earlier step. Skip connections here help in reducing the training time and data requirements.

The last layer of this model is a conv layer employed with sigmoid function. The accuracy of the model is calculated using dice score. Dice score is the value that denotes the confidence of whether that particular pixel belongs to the cyst region or not.The dice score is given by the below formula where X represents the vector of predicted segmentation mask and Y represents the vector of ground truth mask.

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

III. SOTA Implementation

A. *Dataset generation*

As there were no earlier available good dataset for the implementation, we simulated a dataset using the open source Field II ultrasound simulation software to train our U-Net model. All the simulated images had a cyst like structure which denoted an abnormality that was to be segmented by the model within the normal tissue region. As the research paper suggested, the simulated cyst was anechoic in nature which means the cyst should be completely black in colour. The amplitude inside the cyst was taken as 0 to implement this. The region of cyst was kept uniform in all the images. The transducer was modeled according to the parameters given in the below table.

Table 1. Ultrasound transducer parameters

Parameter	Value
Element number	128
Pitch	0.30 mm
Aperture	38.4 mm
Element width	0.24 mm
Transmit Frequency	8 MHz
Sampling Frequency	40 MHz

B. *Implementation of the U-Net model*

The U-Net model was implemented using Keras and Tensorflow frameworks. The network was trained on 20 epochs. Final layer was a 1 x 1 convolutional layer which used sigmoid function as its activation function. This outputs the values between 0 and 1 providing probability like interpretation of whether that particular pixel belongs to the cyst region or not.

IV. Results & Comparison with SOTA

As shown in the report, this deep learning based method does not depend on beamforming. We can predict the anechoic cyst abnormality just by using the RF Channel data and hence eliminating the step of beamforming. The U-Net model reads the non human readable RF data along with a lot of advantages like increased speed, accuracy, etc.

The mean dice score of the trained U-Net model as calculated using the formula in the previous section came out to be 0.9786. Taking all the factors into account, the final output image is more interpretable than the earlier used traditional method of creating beamformed image. The model trained output takes less time to predict the mask and is better in

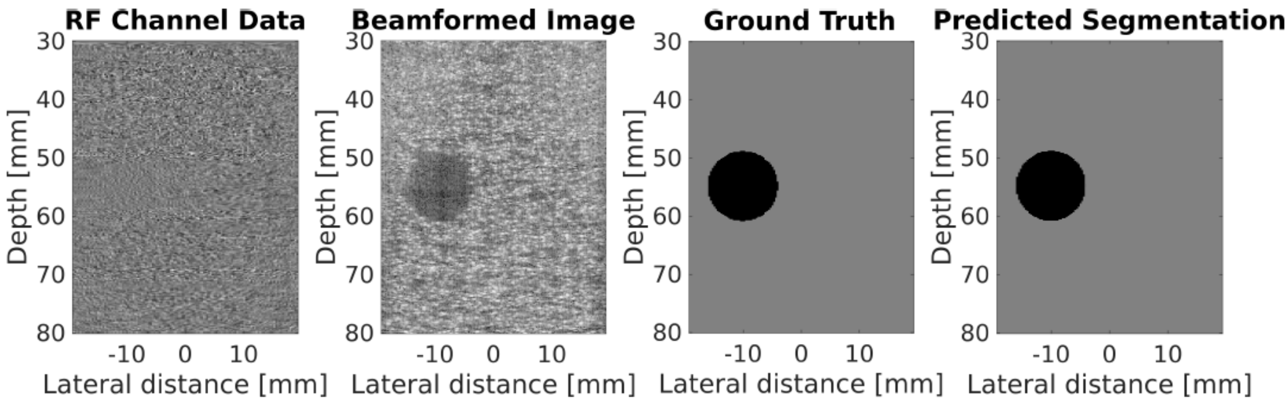

Fig. 2. Field II toolbox simulated images and the predicted mask

many terms than the earlier used method of beamforming the image.

As suggested by the implemented SOTA, the results produced were accurate as the SOTA suggesteed that the dice score we get from any of the varying dataset should be more than 0.94.

V. Novelty

There are 3 different types of cyst:

Anechoic cyst: Fluid filled cyst structures. Does not reflect any ultrasound wave back to the transducer. It appears completely black in the beamformed image.

Hypoechoic cyst: May indicate a solid tissue or a complex cyst. Reflects fewer ultrasound waves to the transducer, appears dark but not black in the beamformed image.

Hyperechoic cyst: Often contains material more reflective and dense than the surrounding medium. Hence, appear as brighter regions on the ultrasound images.

The research paper focussed on anechoic cyst. To implement Novelty, we extended the simulations to hypoechoic and hyperechoic cysts so as to identify different types of cysts more accurately using the model. For this, simulations containing hypoechoic and hyperechoic cysts were made by handling the amplitude in the cyst region and outside region. To generate hyperechoic cyst, the amplitude inside was changed to 10 times the amplitude outside.

The dice coefficient of this model trained on all these types of cyst came out to be 0.9635.

VI. Conclusion

The proposed solution of deep learning based U-Net model thus solves the problem of ultrasound beamforming. The encoder decoder network we used was able to solve the problem accurately using the input channel data which is in non human readable form improving the diagnostics facility. The cyst identification can hence be classified as a semantic segmentation problem and solved using deep learning.

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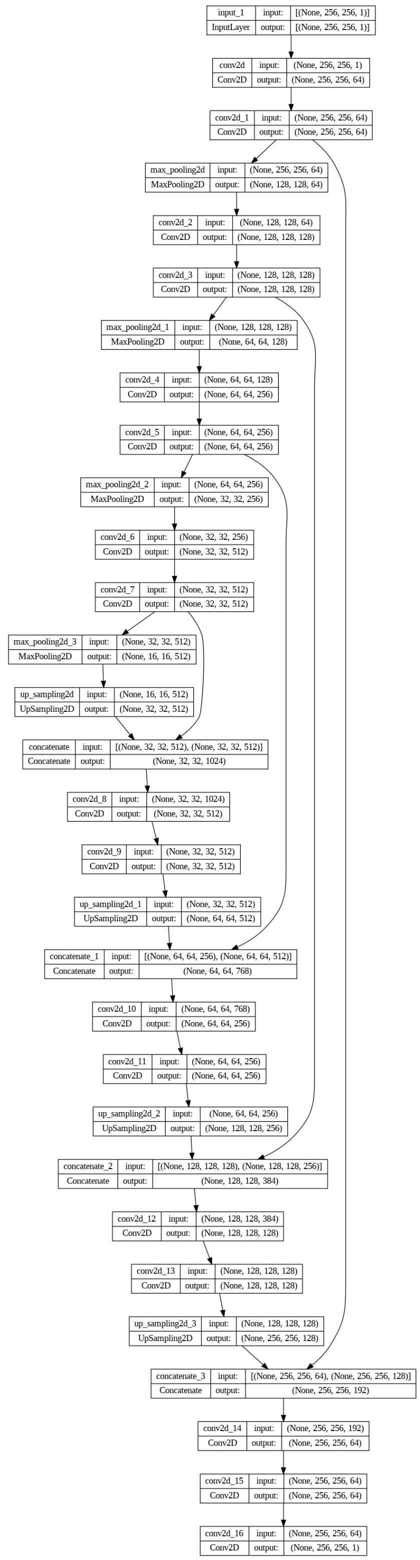

Fig. 3. Architecture of the U-Net model implemented.