

## **Title**

Automated segmentation of the thyroid nodules

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## **Abstract**

Thyroid nodule segmentation from ultrasound images is an important step for early diagnosis of thyroid diseases. In this paper, an end-to-end thyroid nodule automatic recognition and segmentation system is designed based on CNN. In this work, we have developed models based on U-net architecture with the dataset. Experimental results demonstrate that the proposed U-net model segmentation has excellent performance in diagnosing thyroid diseases. We have obtained the validation accuracy of 96.78% and test accuracy of 96.2%.

## **Introduction**

The thyroid gland is a butterfly-shaped endocrine gland that is normally located in the lower front of the neck. It secretes indispensable hormones that are necessary for all the cells in your body to work normally. The term thyroid nodule refers to an abnormal growth of thyroid cells that forms a lump within the thyroid gland.

Most recently, machine learning has been introduced in US imaging-mediated diagnosis. ML is defined as a set of methods that automatically detect patterns in data and then utilize the patterns to predict future data or enable decision-making under uncertain conditions. Deep learning is a special type of artificial neural network that resembles the multilayered human cognition system. Deep learning algorithms such as convolutional neural networks (CNN) are currently utilized in multiple aspects of healthcare, especially in imaging-based diagnosis and prognostic analysis in cancer.

Thyroid nodule can appear anywhere and have any kind of contrast, shape and size, hence segmentation process needs to be designed carefully; several researchers have worked in designing the segmentation mechanism, however most of them were either semi-automatic or lack with performance metric, however it was suggested that U-Net possesses great accuracy. Hence, in this paper, we proposed U-Net to find the probable Region of interest and segment further. Moreover the proposed model is evaluated considering the important metrics such as Dice Coefficient and pixel accuracy.

## **Design problem formulation**

In any image processing technique segmentation plays an important role as inaccurate segmentation might lead to misdiagnosis, especially which are boundary based. Segmentation is very important in gland segmentation and nodule segmentation. Moreover Ultrasound Image segmentation has been part of research from past few decades and most of them were machine learning based as machine learning performs better than any traditional model, However machine learning method does face some serious issue such as these method requires adequate amount of marked dataset and it takes lot of time to train the model. Considering these facts we have developed a U-net model to find the region of interest.

## **Possible methods to solve the problem**

This paper proposes a mark-guided ultrasound deep network segmentation model of thyroid nodules. By comparing with Inception V3 model, DenseNet model, segmentation edge and network operation time which were already obtained, it is found that the algorithm in this paper has relative advantages.

## **Work Done**

### [Source code](#)

Succinctly, we implemented the Unet model, a segmentation model using the Pytorch machine learning library and have used the Ultrasound Thyroid [Image database](#) (dataset) for the model training part.

The first step was to preprocess the available data. There are a total of 476 images (size: 288 x 432) and to obtain the segmentation images, we must train the model with the original ultrasound image and it's respective mask. There weren't mask images readily available, hence we created them by plotting and obtained the mask of the nodule area using ImageJ software for all the ultrasound images using the coordinate points inside the xml files available in the dataset. After having all the components of the data, we started building the Unet model based on our understanding of the official Unet model paper and few other references.

### **How does the Model work?**

This model was specifically designed for medical image segmentation purposes. The model basically contains two paths, where one side of the path is the contraction path which captures the context of an image. In this path we apply regular convolutions and max pooling layers, due to which the size of the image gradually reduces while the depth gradually increases, thereby capturing all the features.

The other path is the symmetrical expanding path involving transposed convolutions along with regular convolutions. Here, the size of the image gradually increases and the depth gradually decreases majorly assuring the recovery of the data of localization. To get better precise locations, at every step of the expanding path, we use skip connections by concatenating the output of the transposed convolution layers with the feature maps from the contracting path. Thus it is an end-to-end fully convolutional network i.e. it only contains Convolutional layers because of which it can accept images of any size. In the end, the output segmented image will have the same dimensions as the input image.

## **Results and Analysis**

To check the accuracy of the model, pixel accuracy between the original mask and the output segmented mask is taken as the measure to calculate.

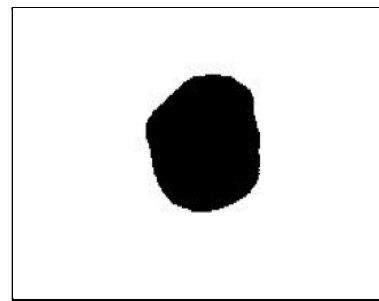
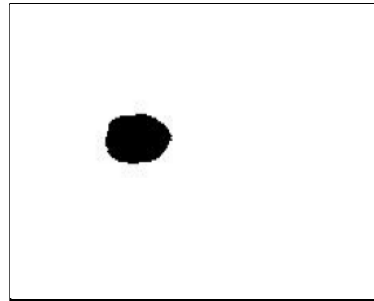
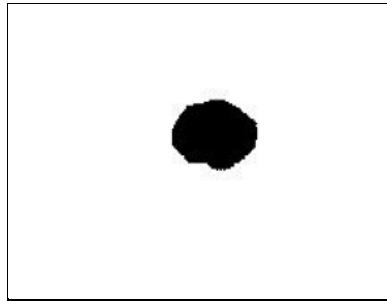
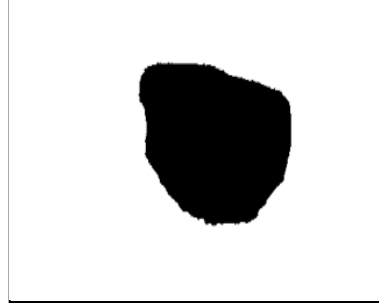
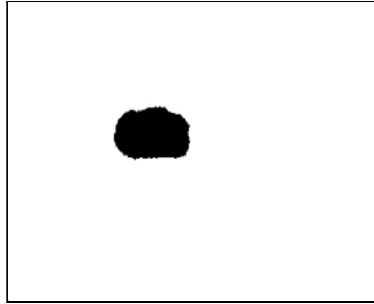
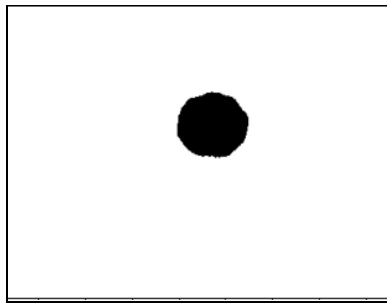
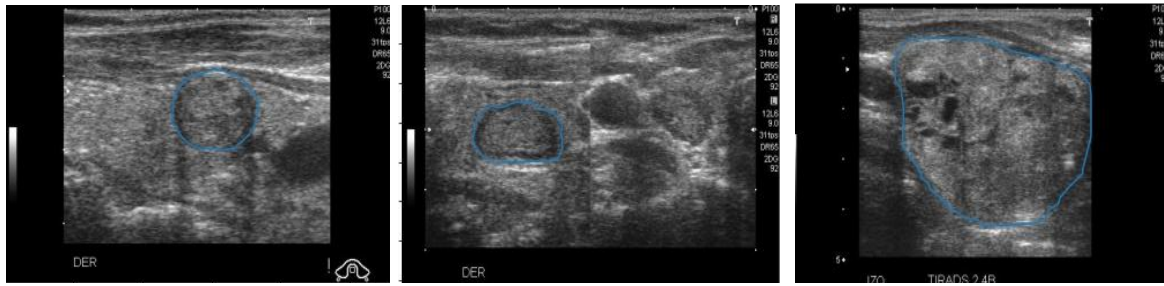
**Table 1**

Validation accuracies obtained for a set of learning rates and number of epochs

<b>Parameters</b> (Learning rate(Rows), Number of epochs(Cols))	<b>3</b> epochs	<b>5</b> epochs	<b>7</b> epochs
<b>1e-4</b>	96.1	96.78	96.22
<b>1e-6</b>	94.35	95.3	96.23
<b>1e-3</b>	91.32	95.06	96.22

On observing the validation scores from Table 1, the model trained with *learning rate* =  $1e-4$  and *number of epochs* = 5 gave the best accuracy of 96.78% and testing accuracy obtained was 96.2%.

With *learning rate* =  $1e-5$  and *number of epochs* = 20, the accuracy on the validation dataset obtained is 97.26%. So, we have trained this model and collected all the segmentation masks of the test dataset of Thyroid nodule image dataset. On comparing the pixel accuracies of the ground truth mask and the predicted mask, the accuracy obtained was 96.63%. Dice score obtained is 0.91. Few segmentation mask images are shown in Fig. 1 (a), (b), (c), (d), (e), (f).



(a)

(b)

(c)

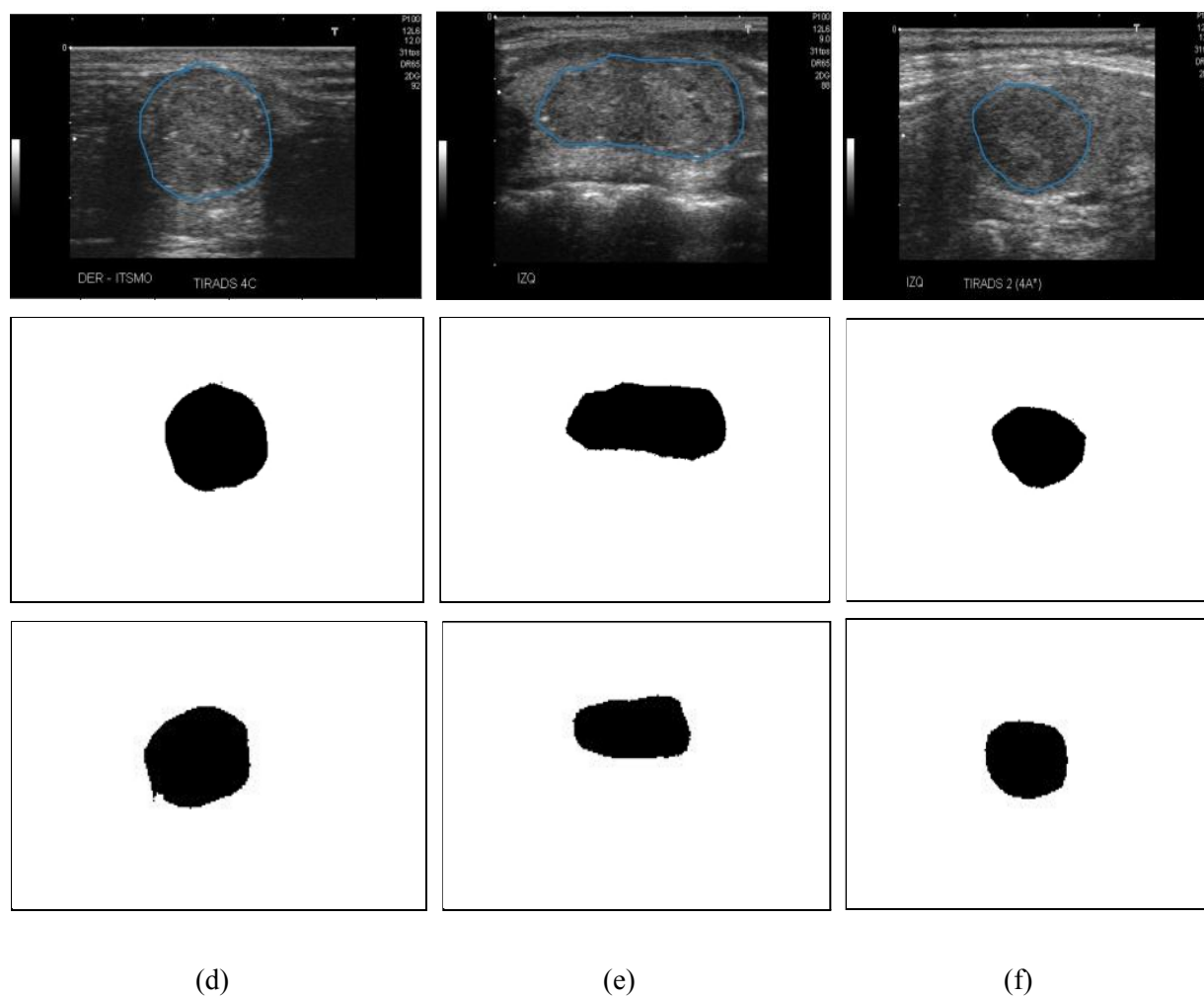


Fig. 1 Sample results of the original ultrasound image (Row 1), original ground truth mask (Row 2) and predicted segmentation mask (Row 3)

The black area is the nodule region, the part of ultrasound image where segmentation needs to be done. In the above samples, the upper image is the ground truth mask and the bottom image is the segmented mask of the ultrasound image done by the model we built.

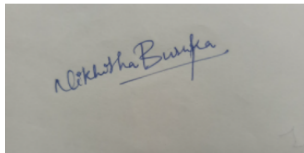
## **Conclusion**

We have conducted research on different machine learning techniques used for segmentation especially in the domain of medical image analysis. Based on deep learning algorithms and concepts of convolutional neural networks, a U-Net segmentation model for thyroid nodules segmentation is chosen. In the case that the segmentation results were pretty good (*few sample images in the results section*) with pixel accuracy upto 96% U-Net.

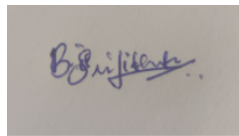
## **References**

- [1] Qing Guan<sup>1</sup>, Yunjun Wang, Jiajun Du, Yu Qin, Hongtao Lu, Jun Xiang, Fen Wang, 2019, “Deep learning based classification of ultrasound images for thyroid nodules: a large scale of pilot study” from ATM. DOI: 10.21037/atm.2019.04.34
- [2] Yifei Chen, Dandan Li, Xin Zhang, Jing Jin, Yi Shen, 2021, “Deep learning based classification of ultrasound images for thyroid nodules: a large scale of pilot study”. DOI: 10.1016/j.media.2020.101819
- [3] Dat Tien Nguyen, Jin Kyu Kang, Tuyen Danh Pham, Ganbayar Batchuluun, and Kang Ryoung Park, 2020, “Ultrasound Image-Based Diagnosis of Malignant Thyroid Nodules Using Artificial Intelligence”. DOI: 10.3390/s20071822

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