Evaluation of Performance Metrics of Thyroid Segmentation by Deep Learning Technique

Nayana R Shenoy[1], Anand Jatti[2]
[1]AIT, Bangalore 60, India
Email- nayana.rshenoy@gmail.com
[2]RVCE, Bangalore59. India
Email: anandjatti@rvce.edu.in

Received: May 25. Revised: July 15, 2021. Accepted: July 19, 2021. Published: July 22, 2021.

Abstract: Thyroid cancer is one of the commonly seen endocrine system cancer. Thyroid nodules appear as solid or fluid-filled masses on the thyroid. In many cases the thyroid nodules do not show any symptoms and due to this it leads to the critical situation up to death.All nodules are not cancerous and so it is very important to discriminate benign from malignant nodules. For diagnosing thyroid nodule the preferred imaging modality isUltrasound imaging.Due to inhomogeneous structure segmenting thyroid gland is a great challenge.Most of the researchers have implemented semi-automatic and automatic techniques to segment the nodules. In this paper we suggest a model to segment the region of interest by modifyingthe basic U-Netmodel. The performance metrics such as true positive, accuracy, F1-measure and dice coefficient is calculated and compared with basic model.

Keywords:Regionof Interest(ROI),Thyroid Nodules U-Net,Ultrasound(US).

I. INTRODUCTION

The most prominent endocrine gland is the thyroid gland. It is located below the cartilage in the neck and generates thyroid hormone, which regulates the human body's metabolism. Thyroid nodules don't have a fixed shape, few have proper margins and some irregular shapes. Thyroid nodules can be classified as isoechoic,hypoechoic or hyperechoic based on the ultrasound findings.However, there is an increase in thyroid cancer at a rate of 4.5 percent in the recent years [1].According to studies, over two thousand people died in United States as a result of thyroid cancer[2].Thyroid nodules are generally benign, with a risk of cancer of 4.5-6 percent, hence a screening procedure is advocated by researchers and radiologists.

Ultrasonography is widely used diagnostic tool due to its high sensitivity and cost affordability. The nodule identification mainly depends on the expertise of the radiologist and is a great challenge for thyroid nodule detection. Several CAD based systems are developed to classify the thyroid nodules. Segmentation is performed to partition the region of interest (ROI) from the thyroid gland. Deep learning methodology aids in improving the image processing tasks.

In thyroid ultrasound images, segmentation plays a significant function in detecting nodules and creating ROI (Region of Interest); additionally, absolute segmentation of thyroid nodules aids in attaining higher attainment in the computer aided model.Segmentation is a difficult operation since manual segmentation takes time and has a lot of unpredictability. Some researchers have developed semi-automatic methods to segment the ultrasound images, but this only deciphers aportion of the problem because it still requires the input from human , which leads to widespread use of the CAD model. Due to the clinical need and demand, developing a fully automatic approach has been a key priority.Few research has beenconcentrated on the active contour based mechanisms .Active contour aids in the locating the probable region, but reliant on pre-processing and initialization, and as a result, it has a high learning error rate.Other researchers have devised traditional learning methods, these have low success rate, have failed to accomplish absolute segmentation because most of the methods are reliant on human identified characteristics.

The rest of this paper is organized in the following manner. The first section discusses the thyroid and segmentation, while the second section discusses the associated work. The intended work and materials are described in Section III. Section IV presents the experimental results and discussion, followed by Section V's conclusion.

II. RELATED WORK

Segmentation process plays a prominent role in any image processing application. It is accomplished either using semiautomatic technique or fully automatic techniques.[3]implemented a novel multi-output CNN with dilated convolutional layers to perform segmentation of thyroid nodules and cystic components from ultrasound images. A value of 0.76 for dice coefficient was attained.This method works without the use of seedpoints.[4] In this article three non-automatic segmentation algorithms such as pixel-based ,active contours and graph cut are compared. To improve the accuracy, random forest and convolutional neural network are implemented . In article [5] to locate the boundary of the thyroid gland, the spatial location of trachea and carotid artery is utilized. They have implemented this on

a multivendor dataset yielding Rand index greater than 0.83 and accuracy higher than 94%. O.Ronneberger et.al [6] was pioneer in presenting a network that works with small dataset. Here data augumentation is used. The architecture consists of a one path to capture context and another path for precise localization. End-to-end training is performed with very few images .[7] performs the comparison of segmentation methods and they conclude that direct influence on the final segmentation is accomplished by the graph cut-based approach. [8] here deep convolutional networks was proposed for automatic media-adventitia border segmentation in transverse and longitudinal sections of carotid ultrasound images. It was proposed to combine envelope and phase congruency data in a novel way.An automatic seed selection algorithm based on Higher Order Spectra Entropies from Radon Transform at various angles was proposed by [9].They achieved a similarity index of 80.57 ± 1.06%.[10]have automated the elimination of artefacts in thyroid ultrasound images that were manually induced. Histogram data is used to estimate the artefact intensity. The convex sets method is used to restore the image. In [11]watershed algorithm is implemented to perform thyroid nodule segmentation. The gradient magnitude was used . In article [12] demographic and ultrasound featureshave been utilized to differentiated malignant thyroid nodule.[13]volume estimation of thyroid gland is performed using radial basis neural network.Swarm optimization algorithm is used for evaluation of the parameters.[14] have proposed a method to delineate the thyroid nodules. They have proposed joint echogenicity texture model. We can infer that the semi-automatic methods rely on the human intervention to perform segmentation, so to improve the efficiency adapting deep learning technique is good as the human intervention is negligible.

III. PROPOSED WORK& MATERIALS

In recent decade deep learning techniques are extensively used to implement the semantic segmentation.One of the most frequently used deep learning techniques for medical images is U-Net. It can work with fewer datas and gives a better efficiency; this characteristic makes U-Net the first choice for segmenting medical images which are less in number.The traditional U-Net architecture, on the other hand, has a few flaws. The main disadvantage is image information in the feature maps is of low resolution, which has a direct impact on the model's effectiveness. Another disadvantage is thatpooling operationsare difficult to be optimised therefore, to eliminate this problem, we modify U-Net. Initially we design the basic U-Net and later this is modified by using huge receptive field and optimizing the dropout.

A. Materials

The dataset is crucial for training the model. We used a standard dataset from the Universidad Nacional de Colombia Laboratory's open-access Digital Database of Thyroid Ultrasound Images (DDTI) [15].A total of 299 thyroid ultrasound images were used from the dataset, with 270 instances from females and 29 cases from males of various ages. Each image is having an .xml file which gives the complete description and annotation of thyroid abnormalities. The dataset is validated by the expert radiologist.

B. Proposed Work

The suggested work is separated into two phases: the first is pre-processing, which involves creating a binary mask and the second is training and testing the proposed model.

B.1. Pre-processing

The pre-processing task in our work is to generate the binary mask of the ROI.Each image in the DDTI is having an XML file which contains the metadata about the image.The first task is to read the individual XML file, map all the coordinates of individual nodules associated with the image Thecoordinates are overlayed on the original image. The coordinates are used to create a contour .The image is binarized by setting the intensity value of the pixels within the contour to 255 and outside the contour as zero.The newly constructed image is a mask used for model training.The steps are depicted in the figure1.

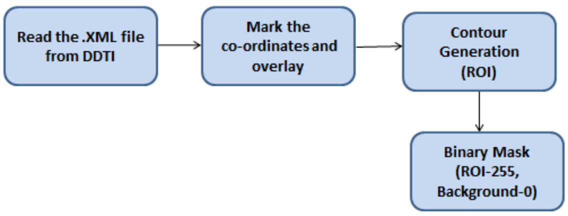

Figure 1: Pre-processing

B.2 Training and Testing

U-Net is a CNN architecture used to segment images quickly and precisely.It learns to focus on target structures of various forms and sizes on its own and doesn't require any seed point in contrast to the traditional methods. The architecture consists two parts: encoder/down-samplingto capture context and decoder/up-samplingfor precise localization.The encoder path consists of convolution ,activation and pooling layers.The decoder path consists of transposed convolution (deconvolution) and activation.The equation below shows a fully connected network.

$$e^k = \{e_1^k, e_2^k, \dots \dots, e_{m_k}^k\} \qquad (1)$$

the kernels can be expressed as

$$y^k = \{y_1^k, y_2^k, \dots \dots, y_{m_k}^k\} \qquad (2)$$

And bias value is given as

$$b^k = \{b_1^k, b_2^k, \dots \dots, b_{m_k}^k\} \qquad (3)$$

The following equation shows activation in the kth layer.

$$e_l^k = h\left(b_l^k + y_l^k \otimes \mathcal{F}(\mathcal{E}^{l-1})\right) \in \mathcal{E}^k, 1 \le k \le L_{j,}, \qquad (4)$$

$$e^k \equiv \mathcal{E}^k\left(\mathcal{F}(e^{k-1}); \delta^k\right), 1 \le k \le n \qquad (5)$$

In the equation above,$h()$is activation function, δ^k: parameter set of kth layer, $\otimes$: convolution operator, $\mathcal{F}$ () : down sample pooling. The translation variance from pooling aids in the reduction of number of parameters. For activation, a parametric RELU is used. The basic U-Net has low resolution problem due to which the boundaries are smoothed out. So we modify the U-Net by considering the local and global features and high receptive field is maintained. Instead of general pooling non-local transform is applied. To avoid over fitting the loss function is optimized through layer dropouts.As a result, the network feed forward with dropout is depicted in the equation below.

$$t_i^{(n+1)} \backsim g$$

$$\breve{b}^{(n)} = v^{(l)} * t^{(n)}$$

$$a_p^{(n+1)} = b_i^{l+1} + v_i^{(n+1)} \breve{a}^{(n)} \qquad (6)$$

$$b_i^{(l+1)} = h(a_p^{(n+1)})$$

In the preceding collective equation, $t^{(n)}$ denotes a Bernoulli independent random variable and $\breve{b}^{(n)}$ is a thinning output generated by $y^{(l)}$. The network is thinned or capacity is reduced as a result of the above procedure, preventing overfitting. For better learning, more derivatives of back propagation are used to this network.

The dataset is split into two halves, with 80 percent being used for training and 20 percent for testing. The model is trained and we get the ROI segmented. The training phase is depicted in the figure2.

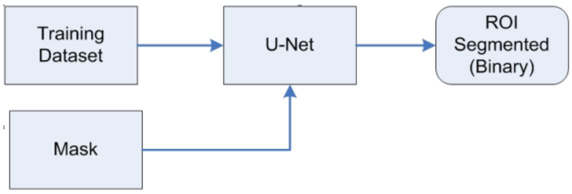

Figure 2: Training Phase

IV. EXPERIMENTAL RESULTS

The experimental findings of the pre-processing, training, and testing phases are discussed in this part, and performance metrics for both the basic and modified U-Net are examined. Python is used as a programming language.The experimental results of pre-processing , training and testing phase is shown in figure 3,4 and 5.

(a) (b) (c) (d)

Figure 3. (a)The outline US input image;(b) ROI Contour;(c)Only ROI ;(d)Mask

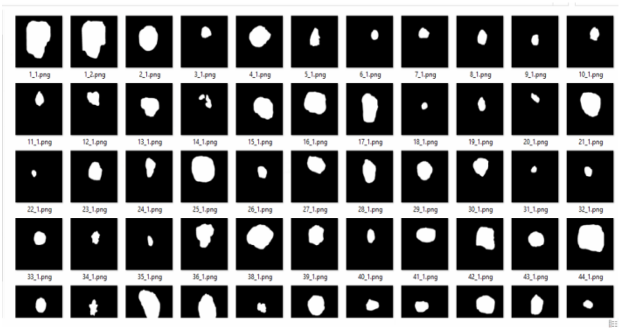

Figure 4:Binary image of ROI segmented

(a) (b)

Figure 5. (a) Original US image ;(b) Binary image of ROI segmented

The performance metrics evaluated are explained as follows.

a)**Accuracy**is the percentage of correctly classified instances.

$$\boldsymbol{Accuracy} = \frac{(\boldsymbol{TP}+\boldsymbol{TN})}{(\boldsymbol{TP}+\boldsymbol{TN}+\boldsymbol{FP}+\boldsymbol{FN})} \quad (7)$$

whereTP is True positive,TN is True negative,FP is False Positive,FN is False Negative

b)**Dice coefficient**is termed as thestatistical tool to measure the similarity between two sets of data.

$$\boldsymbol{Dice\ coefficient} = \frac{\boldsymbol{2} * (\boldsymbol{Area\ of\ overlap})}{\boldsymbol{Total\ number\ of\ pixels\ in\ both\ images}} \quad (8)$$

c)**F1-Measure**is defined as the weighted average of precision and recall

$$\boldsymbol{F1-measure} = \frac{\boldsymbol{2} * (\boldsymbol{Recall} * \boldsymbol{Precision})}{(\boldsymbol{Recall}+\boldsymbol{Precision})} \quad (9)$$

d)**Specificity** is true negative rate

$$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{(\boldsymbol{TN}+\boldsymbol{FP})} \quad (10)$$

A comparative analysis is done with basic and modified U-Net. The Table 1 depicts the various performance metrics.

Table1: Performance Metrics

Performance Metrics	**Value observed (in percentage)**	
	Basic U-Net	Modified U-Net
Accuracy	92.34	98.39
F1-Meaure	89.67	91.87
Specificity	92.11	98.74
Dice Coefficient	92.57	95.60

The modified U-Net outperforms the original U-Net in the comparative analysis.

V. CONCLUSION

Thyroid segmentation is one of the challenging tasks and essential for quantitative analysis .A good segmented image is basis for a good result from the classifier. In this paper U-Net is used because of its advantage to perform with limited data. U-Net is modified by considering local and global features and deploying dropout layers for optimizing the performance.Despite the fact that our suggested model performs better in terms of defined measures, further work needs to be done with a larger dataset and other metrics.

REFERENCE

[1]. K. BibbinsDomingo, ``Screening for thyroid cancer: US preventive services task force recommendation statement," *Jama*, vol. 317, no. 18, pp. 1882-1887, 2017.

[2]. A. Bikas, K. D. Burman, ``Epidemiology of thyroid cancer", Springer, pp. 541-547, 2019.

[3]. Viksit Kumar, et.al,." Automated segmentation of thyroidnodule,gland and cystic components from ultrasound images using deep learning", IEEE Access, 2020.

[4]. P. Poudel , A. Illanes , C. Hansen , M. Friebe, "Evaluation of commonly used algorithms for thyroid ultrasound images segmentation and improvement using machine learning approaches", J. Healthcare Eng. pp.1-5,2018

[5]. Nikhil S. Narayan, Pina Marziliano, JeevendraKanagalingam, MD and Christopher G.L. Hobbs, MD ,"Speckle patch similarity for echogenicity-based multi organ segmentation in ultrasound images of the thyroid gland" , IEEE Journal Of Biomedical and Health Informatics,2017

[6]. O.Ronneberger,PhilippFischer,ThomasBrox,"U-Net: convolutional networks for biomedical image segmentation", Int.Conf.Med.Images Computer Assist Intervention,Springer 2015.

[7]. T. Wunderling, B. Golla, P. Poudel, C. Arens, M. Friebe, and C. Hansen"Comparison of thyroid segmentation techniques for 3D ultrasound",*Proc. SPIE Int. Soc. Opt. Photon.*, vol. 10133, 2017

[8]. C. Azzopardi, Y. A. Hicks, and K. P. Camilleri,"Automatic carotid ultrasound segmentation using deep convolutional neural networks and phase congruency maps", in Proc. IEEE 14th Int. Symp. Biomed. Imag. (ISBI), pp. 624_628, 2017.

[9]. Haji, Salih&Yousif, Raghad, "A novel neutrosophic method for automatic seed point selection in thyroid nodule images", BioMed Research International, pp1-14,2019.

[10]. Nikhil S. Narayana , Pina Marziliano, Christopher G L Hobbs, "Automatic removal of manually induced artefacts in ultrasound images of thyroid gland", Annual international conference of IEEE –EMB, July2013.

[11]. NarainPonraj, Lilly Saviour, Poongodi, Merlin Mercy,"Segmentation of thyroid nodules using watershed segmentation",ICES,2015.

[12]. Patricio, Miguel ,Oliveira, Carlos, Caseiro-Alves, Filipe," Differentiating malignant thyroid nodule with statistical classifiers based on demographicandultrasound features",ENBENG, pp:1-4, 2017

[13]. Chuan-Yu Chang,Yue-Fong Lei,Chin-Hsiao Tseng, Shyang-Rong Shih,"Thyroid segmentation and volume estimation in ultrasound images", IEEE Trans Biomed Eng. 57(6):1348-57, 2010 .

[14]. Michalis A Savelonas,Dimitris K lakovidis,IoannisLegaskis,DimitrisMaroulis, "Active contours guided by echogenicity and texture for delineation of thyroid nodules in ultrasound images", IEEE Transactions on Information Technology in Biomedicine, Vol: 13, Issue: 4, pp. 519-527,2009.

[15]. L. Pedraza et al, "An open access thyroid ultrasound image database", SPIE proceedings, Vol. 9287, 2015