Segmentation of thyroid nodules using Improvised U-Net Architecture

Nayana R Shenoy, Anand Jatti

Abstract: ***Thyroid nodules are considered as most common disease found in adults and thyroid cancer has increased over the years rapidly. Further automatic segmentation for ultrasound image is quite difficult due to the image poor quality, hence several researcher have focused and observed that U-Net achieves significant performance in medical image segmentation. However U-net faces the problem of low resolution which causes smoothness in image, hence in this research work we have proposed improvised U-Net which helps in achieving the better performance. The main aim of this research work is to achieve the probable Region of Interest through segmentation with better efficiency. In order to achieve that Improvised U-Net develops two distinctive feature map i.e. High level feature Map and low level feature map to avoid the problem of low resolution. Further proposed model is evaluated considering the standard dataset based on performance metrics such as Dice Coefficient and True positive Rate. Moreover our model achieves better performance than the existing model.***

Keywords: thyroid cancer, segmentation, Improvised U-Net, ROI.

I. INTRODUCTION

Human body comprises several endocrine organ, thyroid is one of the essential endocrine organ that lies in the near the neck below the cartilage [], thyroid hormone regulates the metabolism of human body. Further some of the thyroid nodules are of proper margins, some of them are irregular in shape. In general thyroid nodules are categorized into three distinctive form i.e. crystic, solid and integration of both crystic and solid nodules, also sometimes classification of thyroid is known as isoechoic, hypopechoic or hyperechoic. Hypoechoic nodules that has irregular boundaries has highly probability of becoming malignant nodules [1]. Moreover according to the epidemiologic research palpable nodues are found in nearly 4-7% of population, however nodules shown in ultrasound examination only shows 19-67% of the portions [2]. Thyroid nodules are classified as hypoechoic, isoechoic, or hyperechoic. Previous studies have shown that hypoechoic nodules with irregular boundaries are more likely to develop into malignant nodules [3]. The incidence of malignant thyroid nodules is 0.1%-0.2%.Thyroid nodules are pretty common in general population that can be detected through high resolution ultrasound, further in last 30 years it has become fifth most common cancer found in women. Moreover Ultrasonography is of the important and popular tool to evaluate the thyroid nodule. Ultrasonography is mainly used due to its cost effective and high sensitivity occurrence.

Revised Manuscript Received on June 30, 2020.
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However it requires clinical experience of radiologists to identify the thyroid cancer since the radiologists performs the diagnosis based on the nodule characteristics and this makes very much challenging for thyroid cancer detection [4]. Hence several researcher work on Computer Added Design aka CAD to automatically classify the thyroid nodules. In general CAD comprises three component i.e. detection of nodule, image feature extraction and classification. Detection of nodule is carried through process known as segmentation, segmentation is the process of finding probable ROI (Region of interest). US (Ultrasound)-Image segmentation is influenced through the data quality, further segmentation is complicated process as there are several factors such as signal dropout, shadows, speckle and attenuation. These might result in missing boundaries, hence this gets complicated, further complication occurs due to rise in contrast among the ROI (Region of Interest). Moreover there has been various researches regarding improvising the information from an ultrasound image. . [5] developed an automatic method for segmenting the thyroid glands in 2D images, this method was named on RBFNN. Further 3D thyroid volumes were estimated based on 2D image. Here segmentation is considered in four step i.e. Image enhancement and probable region identification, extracting features and training RBFNN along with thyroid recovery. Moreover Image processing was carried out to speckle noise and enhance the ultrasound image and hence reduce the computation amount. Furthermore in few methods 2D thyroid ultrasound image, vertical projection is carried out to for locating the probable region. It used AWMF and morphological operation is proposed for speckle noise reduction, further gray level compensation is used for contrast adjusting between the thyroid and background. They applied six texture feature which includes mean, variance, coefficient, histogram and block difference and intensity difference. RBFNN comprises three layers namely input layer, hidden layer and output layer. [6] adopted the segmentation of thyroid gland based on the machine learning methods and support vector machine, here the whole segmentation was parted into two distinctive parts i.e. thyroid gland segmentation and nodule recognition. Thyroid gland segmentation contains three parts i.e. image enhancement, speckle noise and increasing the image quality. [7] Proposed FNN for segmentation purpose, here nine different features were considered which includes the thyroid gland region, histogram energy, histogram kurtosis, histogram skewness, histogram entropy, histogram variance standard deviation, mean, HAARV and HAARM, their accuracy was better, however they considered only limited set of images. [8] Developed a method which was trained with supervised learning algorithm for constructing the classifier, the main drawback was that it was tested on dataset of 5 images.

[9] Proposed U-net model to segment the whole segment considering encoder and decoder, here encoder is responsible classifying and identifying the ultrasound image pixel and decoder was used for finding the specific part of the location. Here to avoid the overfitting data augmentation is carried out, this model considers the fair amount of data for model evaluation and achieves better than the other model. However the smoothening of image was main issue and it could have been enhanced further.

1.1 Motivation and contribution of research work

In any image processing technique segmentation plays an important role as inaccurate segmentation might lead to misdiagnoses, especially which are boundary based. Moreover accurate segmentation is considered as the basis of difference between malignant and benign, further thyroid gland segmentation is basic need for estimation of thyroid volume. Thyroid volume is used for analyzing the secretion of thyroid hormone, this needs to be considered as priority as it helps in finding the thyroid abnormality. However clinically it is highly improbable for estimating these characteristics through humans. Hence, 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 segmentation model to find the region of interest. The contribution of this research are highlighted through the below points.

- At first we address issue of conventional U-Net architecture, these issue includes the problem of low image resolution, high resolution and optimization in number of pooling
- We propose an improvised U-net for thyroid cancer image segmentation, the main aim of proposed model is to find the ROI.
- Improvised U net focuses on achieving the High level feature map and low level feature map to avoid the resolution problem occurred in basic U-Net architecture.
- Proposed model is evaluated considering standard dataset.
- Further Improvised U-Net is evaluated considering performance metric such as Dice Coefficient and truth positive rate.

This research work has been designed in a standard work, as first section involves background about thyroid, thyroid cancer and its various aspect, further in the same section we highlight the shortcoming of some of the existing segmentation model. Further in same section we discuss motivation and contribution of this research work. Second section discuss the overall Improvised U-net model along with its mathematical formulation, Improvised U-Net is evaluated in third section considering various performance metrics.

II. PROPOSED METHODOLOGY

Segmentation is one of the primary steps in identification of thyroid cancer, further U-Net has gained popularity due to its capability of analysing the biomedical image and promises better efficiency. However conventional U-Net architecture has several drawbacks. Main drawback is low resolution image information in designed feature maps, this directly effects the efficiency of the model. Other drawback is it is very difficult to optimize the pooling operations, hence to avoid such issue we developed Improvised U-net where apart from the conventional U-net two feature map are designed namely high level and low level which helps in avoiding the low resolution issue. In here at first we design the U Net which is biomedical architecture of convolution neural network, later two feature maps are designed.

1.2 Improvised U-Net

U-net has Convolution layer which comprises two operations i.e. Convolution and activation along with pooling; convolution layer reduces the computational complexities through distributing kernel co-efficient for each feature map. Further it generates various features in spatial domain and each layer has several kernels. Moreover output of convolution layer and pooling in fully connected layer is computed in fully connected network. Fully connected network is given in the below equation

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

Similarly kernel is given as

$$\mathcal{Y}^k = \{\mathcal{Y}_1^k, \mathcal{Y}_2^k, \dots \dots, \mathcal{Y}_{m_k}^k\} \quad (2)$$

And bias value is given as

$$\mathcal{D}^k = \{\mathcal{D}_1^k, \mathcal{D}_2^k, \dots \dots, \mathcal{D}_{m_k}^k\} \quad (3)$$

Activation in the kth layer is given in the below equation.

$$e_l^k = h\left(\mathcal{D}_l^k + \mathcal{Y}_l^k \otimes \mathcal{F}(\mathcal{E}^{l-1})\right) \in \mathcal{E}^k, 1 \leq k \leq L_{j,}, \quad (4)$$

$$e^k \equiv \mathcal{E}^k(\mathcal{F}(e^{k-1}); \delta^k), 1 \leq k \leq n \quad (5)$$

In the above equation, $\otimes$ indicates the convolution operator, $h()$ indicates the activation function, $\mathcal{F}$ () indicates down sample pooling as pooling helps in handling the global feature δ^k indicates parameter set of kth layer. Moreover translation variance from pooling helps in reducing the number of parameter. Further PReLU is employed for activation and given in the below equation.

$$h(v) \equiv \mathrm{A}\, min(0, v) + \max(v, 0) \quad (6)$$

A Is parameter which range between 0 and 1; final output $(\mathcal{K}; \delta)$ of given feed forward is given as

$$(\mathcal{K};\delta) = \tilde{e}^{2k-1}\left(\cdots e^{k+1}\left(e^{k}(\cdots e^{2}(J;\delta^{1});\delta^{2})\cdots;\delta^{2}\right); \delta^{n+1})\cdots;\delta^{2n-1}\right) \quad (7)$$

$\mathcal{K}$ Indicates input signal and δ is parameter set, further we compute the decoding part and convolution output $\tilde{e}^{t}$ is given as in equation 9

$$\tilde{e}_{s}^{t} = h\left(d_{t}^{s} + v_{t}^{s} \otimes \mathcal{W}(\tilde{e}^{s-1})\right) \in \mathcal{E}^{s}, 1 \leq t \leq \mathcal{O}_{s,} \quad (8)$$

$$\tilde{e}^{t} = \tilde{\mathcal{E}}^{t}(v_{t}^{s} \otimes \mathcal{W}(\tilde{e}^{s-1}); \delta^{n+1}), n+1 \leq t \leq 2n-1 \quad (9)$$

In the above equation, $\mathcal{W}()$ indicates up pooling which recovers the original matrix size, further convolution kernel is used for decoding and bias value is used for decoding in rth layer, also $\tilde{e}^{s-1}$ and $e^{s-1}$is equal if $t = n+1$.

Moreover gradient descent algorithm is used for minimizing the pre-defined loss function and it is given as below

$$argmin_{\delta}\mathcal{J}(\mathcal{E}(\mathcal{K};\delta);\mathcal{Q}), \quad (10)$$

$\mathcal{Q}$ Indicates the desired output, $\mathcal{J}()$ indicates the loss function that measures the error. Moreover this produces the good efficiency, however the addressed issue in earlier section can be optimized through below feature maps.

1.3 High level feature and low level feature

U-Net is one of the popular base network, used for segmentation in bio medical image segmentation, however it has problem of low resolution as low resolution might cause smoothing of object boundaries, hence to avoid that we employ high level feature and low level feature. In here we adopt the U net and improvised to achieve absolute ROI, further to achieve that proposed methodology uses two novel feature map, one is for High Level feature and another is for low level feature. Moreover feature map for High level are generated after the residual pass and extracts the given edge information for high level feature, further this is formulated in equation below.

$$r_{IUN}^{n+1} = \mathcal{W}\left(\mathcal{E}^{n}(\mathcal{F}(d^{k-1});\delta^{k})\right) \oplus \mathcal{E}_{u}^{n+1}\left(e^{n-1} - e_{low}^{n-1};\delta_{u}^{n+1}\right) \quad (11)$$

where $e_{v}^{n+1} \equiv e_{low}^{n-1}$

For the low level feature, feature map do not have problem of resolution issue and can used for global feature extraction, IUN indicates Improvised U-Net.

$$r_{IUN}^{n+1} = \mathcal{W}\left(\mathcal{E}^{n}(\mathcal{F}(d^{n-1});\delta^{k})\right) \oplus \mathcal{E}_{t}^{n+1}(e^{n-1};\delta_{t}^{n+1}) \oplus \quad (12)$$

where $e_{u}^{k+1} = 0$

Further these both feature are combined to achieve the better probable detection of Region of interest. Moreover in the next section Improvised U-Net is evaluated.

III. PERFORMANCE EVALUATION

In this section we evaluate Improvised U-Net method, further in order to evaluate we have considered the ideal system configuration of windows 10 operating system packed with 8GB RAM, 2GB NVidia graphics with 1TB of Hard disk. Moreover MATLAB is used as programming language with 2016b version,

1.4 Dataset Description

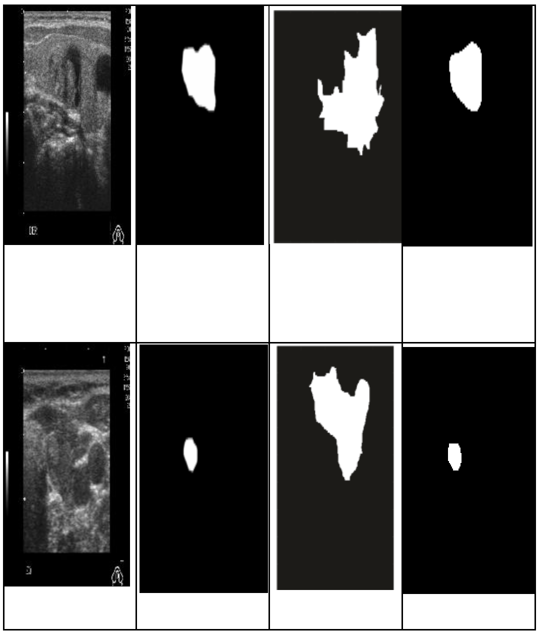
In any machine learning based algorithm dataset plays a major role as data require for model training needs to be sufficient enough to perform the model. In here we have used standard dataset from the open access Digital Database of thyroid ultrasound images from the Universidad Nacional de Colombia Laboratory [11]. Further this dataset is utilized for computation of proposed model. Moreover dataset comprises 92 images of thyroid ultrasound, out of theses 42 were from female and 50 from male from different age group. Moreover these images were captured through TOSHIBA linear transducer and extracted from ultrasound video sequence. These thyroid nodules images are stored in ultrasonography model which includes whole diagnostic description and annotation of thyroid lesions. Further these are carried out under supervision of two radiologist expert using the TI-RADS lexicon.

1.5 ROI comparison

In this section comparative analysis is carried out based on the ROI which is shown in table1, further the comparison is shown considering two images. Table 1 comprises three column, first column shows the original image given in dataset, second column shows the ground truth of original image, third column is ROI achieved through the existing model [14] and fourth column shows the ROI achieved for Improvised U-Net model. Further through the table 1 we observed there is huge difference in the ROI structure of existing model and ground truth, this is occurred due to the image quality used in the segmentation process of existing model whereas our model is nearer to the ground truth.

Table 1Comparison of various methodologies considering ROI

Original Image	Ground truth	SSHOS(existing)	Improvised U-Net



1.6 Performance Metrics

In this section we evaluate improvised U-Net considering True positive and Dice coefficient

1.6.1 True Positive

A true positive is defined as an outcome where the proposed model predicts the positive class of particular model. Precisely, True positive is calculated as the ratio of positive prediction to the total number of positive. Furthermore table 2 presents the comparison of various methodology with proposed model and comparative analysis shows that [12] achieves only 52.26 % of true positive rate, although [13] and NDRLS achieves 93.51 and 95.44 respectively, still it underperforms. Further, existing 96.44 % of true positive rate whereas Improvised U-Net achieves nearly absolute true positive rate of 98.95 %.

Table 2 comparison of various methodologies based on true positive

Methodologies	True Positive
NDRLS[11]	95.44
[12]	52.26
[13]	93.51
SSHOS(existing)[14]	96.44
proposed	98.95

1.6.2 Dice Coefficient

In segmentation, Dice Coefficient is an evaluation metric which is used for gauging the similarity between two given image. In general Dice coefficient is ratio of 2* AoO (Area of overlap) to total number of pixels in given images. Table 3 shows the comparison of various existing model with proposed Improvised U-Net model, in here [12] achieves least dice coefficient pf 67.93, [13] achieves 80.85, existing model SSHOS achieves 92.24, NDRLS achieves 94.2 whereas proposed model achieves 95.60.

Table 3 Dice Coefficient Comparison

Methodologies	Dice_Coefficient
NDRLS[11]	94.2
[12]	67.93
[13]	80.85
Existing (SSHOS)[14]	92.24
Proposed	95.6081

IV. CONCLUSION

In this research work, we have proposed Improvised U-Net for probable identification of ROI through segmentation, to achieve the better efficiency two feature map is considered i.e. high level and low level.

These two feature map helps in avoiding the low resolution. Further Improvised U-Net is evaluated considering standard dataset DDTI in three section, at first ROI is compared which shows that due to low resolution, existing model possesses different ROI in comparison with the ground model whereas our model achieves better ROI.

In further section we compare our model considering True positive Rate and Dice Coefficient and achieves 98.95 and 95.60 respectively.

Moreover through the comparative analysis it is observed that our model achieves 2.51% and 3.36 % efficient than the existing model.

Although Improvised U-Net achieves significant performance when compare to the existing model of segmentation, it can still be improvised considering batch normalization.

REFERENCE

1. M. Schlumberger, M. Tahara, L. J. Wirth, B. Robinson, M. S. Brose, R. Elisei, M. A. Habra, K. Newbold, M. H. Shah, A. O. Hoff, et al.,"Lenvatinib versus placebo in radioiodine-refractory thyroid cancer," New England Journal of Medicine, vol. 372, no. 7, pp. 621–630, 2015.
2. A.G. Unnikrishnan , U.V. Menon , Thyroid disorders in India: an epidemiological perspective, Ind. J. Endocrinol. Metab. 15 (2011) 78–81 .
3. S. L. Bridal, J.-M. Correas, A. Saied, and P. Laugier, "Milestones on the road to higher resolution, quantitative, and functional ultrasonic imaging," *Proc. IEEE*, vol. 91, no. 10, pp. 1543–1561, Oct. 2003.
4. S.V.B. Jardim , M.A.T. Figueiredo , Automatic contour estimation in fetal ultra- sound images, in: Proceedings of International Conference on Image Process- ing, 2003, pp. 1065–1068 .
5. C.-Y. Chang , Y.-F. Lei , C.-H. Tseng , S.-R. Shih ,Thyroid segmentation and vol- ume estimation in ultrasound images, IEEE Trans. Biomed. Eng. 57 (6) (2010) 1348–1357
6. T. Loupas , W.N. McDicken , P.L. Allan , An adaptive weighted median filter for speckle suppression in medical ultrasonic images, IEEE Trans. Circuit Syst. 36 (1) (1989) 129–135 .
7. D. Selvathi , V.S. Sharnitha , Thyroid classification and segmentation in ultra- sound images using machine learning algorithms, in: Proceedings of Interna- tional Conference on Signal Processing, Communication, Computing and Net- working Technologies, 2011, pp. 836–841 .
8. H. Garg , A. Jindal , Segmentation of thyroid gland in ultrasound image using neural network, in: Proceedings of International Conference on Computing, Communications and Networking Technologies, 2013, pp. 1–5.
9. P. Poudel , A. Illanes , C. Hansen , M. Friebe , Evaluation of commonly used al- gorithms for thyroid ultrasound images segmentation and improvement using machine learning approaches, J. Healthcare Eng. 2018 (2018) 1–13 .

10. L. Pedraza, C. Vargas, F. Narv´aez, O. Dur´an, E. Mu˜noz, and E. Romero, "An open access thyroid ultrasound-image database," in *Proceedings of the 10th International Symposium on Medical Information Processing and Analysis*, vol. 9287, Cartagena de Indias, Colombia, 2015.
11. S. Poonguzhali andG. Ravindran, "Acomplete automatic region growing method for segmentation of masses on ultrasound images," in *Proceedings of the 2006 International Conference on Biomedical and Pharmaceutical Engineering, ICBPE 2006*, pp. 88–92, 2006.
12. [40] M. M. Abdelsamea, G. Gnecco, and M. M. Gaber, "A SOMbased Chan-Vesemodel for unsupervised image segmentation," *Soft Computing*, vol. 21, no. 8, pp. 2047–2067, 2017.
13. D. Koundal, S. Gupta, and S. Singh, "Computer aided thyroid nodule detection system using medical ultrasound images," *Biomedical Signal Processing and Control*, vol. 40, pp. 117–130, 2018.
14. Haji, Salih & Yousif, Raghad. (2019). A Novel Neutrosophic Method for Automatic Seed Point Selection in Thyroid Nodule Images. BioMed Research International. 2019. 1-14. 10.1155/2019/7632308.

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