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US-Net: A Breast Ultrasound Image Segmentation using Deep Learning

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***Abstract*—Segmentation of medical images is a crucial step in many clinical applications, including the precise diagnosis and treatment of diseases like breast cancer. Therefore, automated segmentation of breast tumors from breast ultrasound images remains a challenging task. In this paper, we developed a new model, called Ultrasound Network (US-Net), which uses the U-Net architecture with attention gates embedded in the skip connections to assign weights to feature maps based on their importance for the segmentation task. Our method underwent evaluation on three public datasets: BUSI, UDIAT, and STUHospital, using the Dice coefficient as the primary metric for segmentation performance. Notably, US-Net achieved impressive Dice coefficients of 86.99%, 94.38%, and 94% on BUSI, UDIAT, and STUHospital, respectively. Experimental results showed that our network outperformed the latest image segmentation methods for lesion segmentation in breast ultrasound.**

***Index Terms*—Breast Ultrasound, Image Pre-processing, Segmentation, Deep learning, U-Net, Attention mechanism.**

I. Introduction

Breast cancer is the most diagnosed cancer and the leading cause of cancer-related deaths among women worldwide. Although breast cancer can also affect men, it is more prevalent in women, which raises significant public health concerns. The United States of America has reported that 43,250 women and 530 men will die of breast cancer in 2022 [1]. In Morocco, breast cancer is a major public health problem with 11,747 newly diagnosed cases and an age-standardized incidence rate of 56.4 per 100,000 women. Globally, breast cancer is responsible for approximately 630,000 deaths yearly, including 3,700 in Morocco alone [2]. Therefore, early detection and diagnosis are essential to improve survival rates.

Breast cancer screening typically uses mammography and breast ultrasound as imaging methods to detect and diagnose breast cancer. However, mammography has limitations in detecting subtle masses, especially in women with dense breast tissue. In contrast, Breast Ultrasound Imaging (BUI) is a very effective modality for the early identification of breast cancer [3]. It has several advantages over mammography, including no radiation exposure, high sensitivity, easy accessibility, and lower cost [4].

Segmentation is a crucial step in computer-aided diagnosis that involves identifying and isolating specific regions of interest, such as organs or tumors, to facilitate diagnosis and therapy. The emergence of Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized breast cancer diagnosis [5], [6]. DL models can directly extract high-level features without requiring human expertise [7]. Previous attempts at breast mass segmentation have run into difficulties. However, Ronneberger et al. [8] presented a promising model called U-Net that solves these problems. U-Net is a neural network architecture based on the Convolutional Neural Network (CNN) and designed specifically for image segmentation tasks, providing high accuracy and computational efficiency. Although these segmentation methods have yielded promising results, there is always an opportunity for enhancement.

This work used three publicly available breast ultrasound datasets to validate the proposed ultrasound model (US-Net), named BUSI, UDIAT, and STUHospital, respectively. In addition, we perform pre-processing that involved enhancing the contrast of the images, resizing them to an optimal size for segmentation, and applying data augmentation techniques, such as rotation and flipping, to improve the efficiency of our results. Compared to other methods, our network is very

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competitive. After introducing breast ultrasound segmentation, the subsequent sections are laid out as follows. Section II reviews the related work and Section III describes our proposed approach. Experimental results are described in Section IV. The key conclusions are presented in Section V.

II. Related Work

Deep learning has become the dominant technique for medical image segmentation [9], including breast ultrasounds. In this section, we will provide an overview of the most advanced deep learning networks, focusing on those relevant to our proposed work.

One of the advanced models is the SK-U-Net proposed by Byra et al. [10], which used an attention mechanism to adjust the receptive fields of the network for breast mass segmentation in ultrasound images. Wang et al. [11] presented a fusion network with coding, decoding, and central fusion flow paths (FSPs), achieving high Dice scores on public datasets. An enhanced Pyramid Attention Network that integrates the Attention mechanism and Multi-Scale features (AMS-PAN) developed by Lyu et al. [12] for breast ultrasound image segmentation. To evaluate the performance of this architecture, the authors used two publicly available datasets, BUSI and OASBUD. Furthermore, H. Yang and D. Yang [13] proposed a novel approach that combined CNN and Swin Transformer to achieve more accurate breast lesion segmentation in ultrasound images. The proposed method utilized the self-attention mechanism of the Swin Transformer to construct an RSTB, while the CNN is responsible for feature localization. Chen et al. [14] proposed a new method for breast tumor segmentation from ultrasound images, utilizing the residual refinement convolutional network (RRCNet) on two publicly available datasets: BUSI and UDIAT. The RRCNet comprised three main modules, including SegNet with a deep supervision module, a residual miss detection network, and a residual false detection network, to improve the accuracy of segmentation. Farooq et al. [15] introduced a framework called the residual-attention-based uncertainty-guided mean teacher, which utilized residual and attention blocks. The residual block enabled the deep network to optimize the flow of high-level features, while the attention module enhanced the model's focus by adjusting its weights during the learning process. Ma et al. [16] suggested a neural network called ATFE-Net that combined the benefits of Transformer and CNN models. The model was evaluated using two public datasets, BUSI and UDIAT, for ultrasound breast mass segmentation. The approach demonstrated strong performance. Additionally, HCTNet is a proposed method by He et al. [17] for improving breast lesion segmentation in ultrasound images. It combined CNNs and TEBlocks in the encoder to extract features and learn global contextual information. The decoder used an SCA module based on the spatial attention mechanism to reduce semantic divergence with the encoder. This method employs a dual encoder architecture consisting of U-Net and Swin-Transformer, as well as additional modules such as the Spatial Interaction Block (SIB), Feature Compression Block (FCB), and Relationship Aggregation Block (RAB). Chen et al. [18] proposed the DSEU network as a novel method for segmenting medical ultrasound images. This network utilized a deeper U-net as a benchmark to capture enough information on target features from complex ultrasound images. Additionally, the Squeeze-and-Excitation (SE) block is used to connect the encoder and decoder and focus attention on the significant regions of the object. In a similar vein, Ru et al. [19] proposed the Att-U-Node framework for the segmentation of breast tumors in medical images. The approach leveraged attention modules integrated into the U-Node architecture and was thoroughly evaluated on three publicly available datasets to gauge its effectiveness. Table I reviews all of these studies and recent algorithms used for breast ultrasound images and their corresponding performance.

TABLE I
THE SUMMARY OF THE STUDIES THAT USED THE ULTRASOUND DATASET.

Paper	Model	Dataset	Dice(%)
Byra et al. [10]	SK-U-Net	UDIAT	79.1
		OASBUD	72.6
		BUSI	70.9
Wang et al. [11]	CNN	Ultrasoundcases	84.71
		BUSI	83.76
		STUHospital	86.52
Lyu et al. [12]	AMS-PAN	BUSI	80.71
		OASBUD	70.62
Yang et al. [13]	CSwin-PNe	UDIAT	87.25
		BUSI	83.68
Chen et al. [14]	RRCNet	UDIAT	80.40
		BUSI	70.79
		M	78.85
Farooq et al. [15]	RA-UGMT	UDIAT	83.56
		BUSI	80.82
Ma et al. [16]	ATFE-Net	BUSI	82.46
		UDIAT	86.78
He et al. [17]	HCTNet	BUSI	82
		UDIAT	84.13
		Dataset B	97.23
Chen et al. [18]	DSEU-net	BUSI	78.51
		UDIAT	81.50
		KUS	94.32
Ru et al. [19]	Att-U-Node	BUSI	76.88
		UDIAT	77.76
		OASBUD	59.96

III. Methodology

In this work, we followed the proposed flowchart to perform an image segmentation task, as shown in Figure 1. We started by pre-processing the data, enhancing the contrast, and resizing the images, and then used data augmentation techniques to increase the amount of training data. Subsequently, we trained our model. Finally, we tested the model on 20% of each dataset to evaluate its effectiveness.

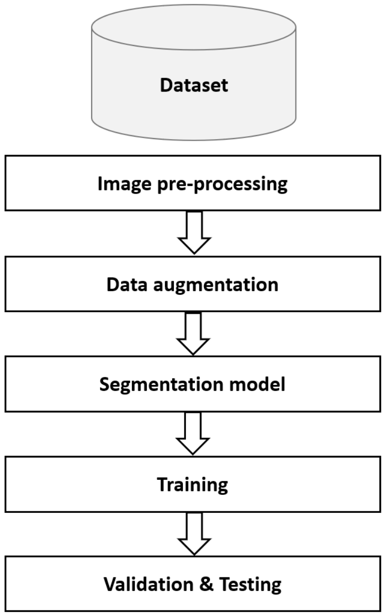


Fig. 1. Our proposed flowchart.

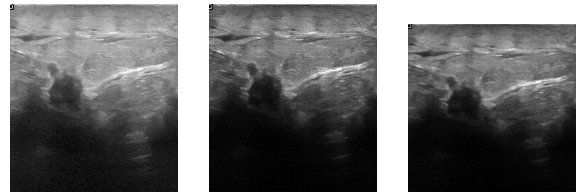
A. Ultrasound Datasets

The approach employs three different publicly available datasets of breast ultrasound for conducting a comparative experimental analysis. Al-Dhabyani et al. [20] created the first breast ultrasound dataset (BUSI), which consists of 647 images. The collection of Yap et al. [21] is the second public breast ultrasound dataset (UDIAT) that yielded 163 images. The third dataset is STUHospital which includes 42 breast ultrasound images obtained at Shantou University Hospital [11].

B. Image Pre-processing

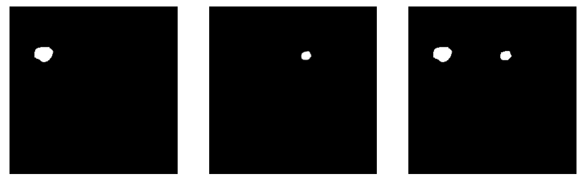
The breast ultrasound images used in this work were subjected to a MATLAB-based pre-processing step to improve their quality. In this step, we applied an amelioration contrast function. The purpose of using this function is to improve the visual quality of the image and to facilitate its analysis. In addition, the datasets were resized to a standardized resolution of 256×256 to ensure consistency in size across the dataset, as seen in Figure 2. Therefore, resizing the image ensures that all input images have similar dimensions, which makes it easier to learn the models.

It is important to cite that some BUSI images include two annotated masks for each image. Therefore, we used MATLAB to combine those two masks to enhance segmentation accuracy. As shown in Figure 3, the fused masks provided a more precise ground truth for evaluating the performance of our segmentation method.



(a) (b) (c)

Fig. 2. Pre-processing steps for enhancing image quality in malignant breast ultrasound image: (a) Original Image, (b) Adjusted Image, and (c) Resized Image.



(a) (b) (c)

Fig. 3. Example of Mask Fusion Technique for Enhanced Ground Truth Generation in BUSI Database: (a) Mask 1, (b) Mask 2, and (c) Fused Masks.

C. Data Augmentation

One of the main challenges facing medical image processing systems is the lack of available image data to train and evaluate system performance. To solve this issue, we employed a data augmentation approach to improve the effectiveness of our deep learning model for segmenting breast cancer based on ultrasound images. Therefore, we applied rotation and flipping (Figure 4) to create additional images from the original dataset. The main objective of this approach was to increase the size of the training dataset to enhance the model's performance.

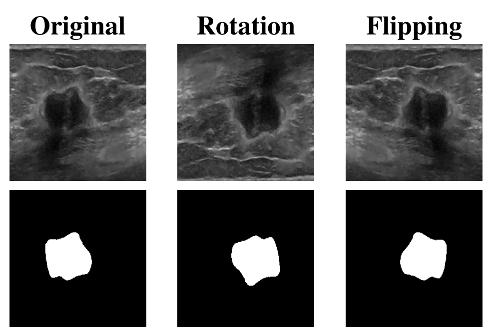


Fig. 4. Data augmentation example with rotation and flipping.

Table II shows the number of images in each dataset before and after the augmentation techniques.

D. Segmentation Method

The U-Net architecture [8] is a convolutional network that consists of an encoder and a decoder path as illustrated in Figure 5. Attention mechanisms have been added to the U-Net architecture to selectively focus on interested regions of the

TABLE II
ULTRASOUND IMAGE DATASET SIZE BEFORE AND AFTER AUGMENTATION.

Dataset	Before	After
BUSI	647	1,666
UDIAT	163	1,107
STUHospital	42	1,042

input image, thus improving the accuracy of the segmentation results.

The Attention Gate (AG) is a critical component of the Attention U-Net architecture, a neural network framework designed for image segmentation, as detailed in Oktay et al.'s work [22]. This AG module plays a pivotal role in reshaping the representation of image features during the segmentation process. It operates in several key steps, beginning with the reception of feature maps from the encoder. These feature maps, encoding a range of information from low-level spatial details to high-level semantics, are then transformed into attention maps. These attention maps are computed through intricate operations to assess the importance of each pixel or region within the feature maps. Subsequently, the attention maps are used to modulate the original feature maps, selectively enhancing informative regions while diminishing less relevant ones. This process results in a set of feature maps finely tuned to highlight critical image areas, ultimately leading to improved segmentation precision. In essence, the AG module empowers the neural network to allocate its attention intelligently, enhancing its ability to discern and focus on the most vital parts of the image, thereby enhancing the overall quality and accuracy of image segmentation. Our model called Ultrasound Network (US-Net) defines the U-Net with AG, which uses skipped connections to improve model performance. The model takes an image as input and applies convolutional layers with batch normalization and ReLU activation functions to extract feature maps. Then, maximum pooling and dropout layers are employed to reduce the size of feature maps and prevent overfitting.

In the decoder path, transposed convolutional layers are utilized to increase the size of the feature maps, which are then combined with the corresponding feature maps from the encoder path. AG is integrated into the skip connections to assign weights to the feature maps based on their importance for the segmentation task.

Finally, a sigmoid activation function is applied to the output of the last convolutional layer to generate the binary segmentation mask. The entire model is compiled using the binary cross-entropy loss function and the Adam optimizer. In addition, the image segmentation model was developed using the Python programming language and the Keras framework. Table III shows the hyperparameters used during the training of the network.

E. Ablation study

To assess the impact of our network, we performed an ablation study using the U-Net architecture without any attention mechanism. We applied this model to our datasets with identical hyperparameters to assess the generalizability of our findings, as outlined in Tables IV, V, and VI. Nevertheless, based on the results, it is evident that the incorporation of the attention mechanism in US-Net significantly enhanced the performance of the U-Net model.

TABLE III
THE HYPERPARAMETERS UTILIZED TO TRAIN THE MODEL.

Hyperparameter	Value
Input size	$256 \times 256 \times 1$
Training: Test Split	80:20
Epochs	150
Optimizer	Adam
Learning Rate	0.001
Dropout	0.2

IV. RESULTS AND DISCUSSION

A. Evaluation Metrics

This paper uses five segmentation measures to evaluate the performance of our segmentation method. The five segmentation measures used are Accuracy (Acc), Jaccard Index (JI), Sensitivity (Se), Specificity (Sp), and Dice Coefficient (DC). These metrics are used to provide a quantitative evaluation of the segmentation performance of our method.

B. Experimental Results

The proposed approach was evaluated on the three datasets and compared to the latest state-of-the-art models to assess its performance. Tables IV, V, and VI present the segmentation results for the BUSI, UDIAT, and STUHospital, respectively. However, The "-" symbol is used to signify the absence of a result, as the reported results did not include all measurements. The most optimal results are indicated with bold text.

The suggested method outperformed the other approaches, with consistently higher scores on all performance measures, including accuracy, Jaccard coefficient, sensitivity, specificity, and Dice coefficient for all three datasets. Table IV shows US-Net's performance on the BUSI dataset with 98.31% accuracy, Jaccard coefficient of 77.87%, sensitivity of 85.60%, specificity of 99.33%, and Dice coefficient of 86.99%. In addition, Table V reports the results of the model on the UDIAT dataset, achieving the best dice coefficient among the three datasets with accuracy, Jaccard coefficient, sensitivity, specificity, and Dice coefficient of 99.41%, 86.31%, 99.71%, 99.77%, and 94.38%, respectively. Finally, our model achieved 96.86%, 86.36%, 93.71%, 99.45%, and 94% in terms of accuracy, Jaccard coefficient, sensitivity, specificity, and Dice

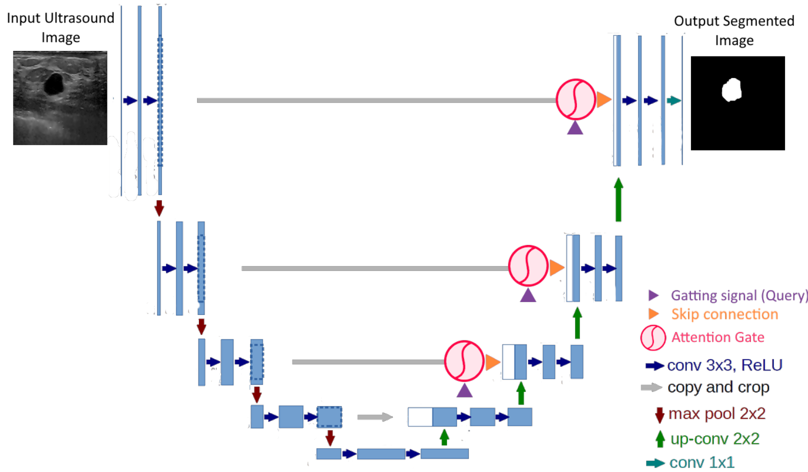


Fig. 5. Ultrasound Net (US-Net) architecture with Attention Gate for breast ultrasound image segmentation.

TABLE IV
THE SEGMENTATION RESULTS OF DIFFERENT COMPETING METHODS ON BUSI DATASET.

Method	Acc (%)	JI (%)	Se (%)	Sp (%)	DC (%)
SK-U-Net [10]	95.6	-	-	-	70.9
CNN [11]	97.17	-	85.21	98.57	83.76
AMS-PAN [12]	97.13	-	-	98.54	80.71
CSwin-PNe [13]	-	-	-	-	83.68
RA-UGMT [15]	95.95	62.67	-	-	80.82
ATFE-Net [16]	96.32	-	82.78	98.32	82.46
HCTNet [17]	96.94	71.84	-	-	82.00
DSEU-net [18]	-	70.36	-	97.42	78.51
Att-U-Node [19]	-	68.67	77.88	97.41	76.88
UNet	98.15	73.59	83.15	99.31	85.15
US-Net	**98.31**	**77.87**	**85.60**	**99.33**	**86.99**

TABLE V
THE SEGMENTATION RESULTS OF DIFFERENT COMPETING METHODS ON UDIAT DATASET.

Method	Acc (%)	JI (%)	Se (%)	Sp (%)	DC(%)
SK-U-Net [10]	98.5	-	-	-	79.1
CSwin-PNe [13]	-	-	-	-	87.25
RRCNet [14]	-	71.81	-	99.01	80.40
RA-UGMT [15]	98.72	78.47	-	-	82.27
ATFE-Net [16]	98.66	-	88.34	99.23	86.78
HCTNet [17]	98.49	73.83	-	-	84.13
DSEU-net [18]	-	73.17	-	99.05	81.50
Att-U-Node [19]	-	69.91	84.28	98.47	77.76
UNet	99.35	85.58	93.69	99.77	93.89
US-Net	**99.41**	**86.31**	**94.71**	**99.77**	**94.38**

coefficient on the STUHospital dataset, respectively, as shown in Table VI.

The segmentation results of the ultrasound images in Figures 6, 7, and 8 clearly showed that our model could accurately extract important anatomical structures from these images. Moreover, The visual results also demonstrated a high correspondence between the segmentation generated by our model and the actual ground truth.

Importantly, our segmentation model could rightly segment multiple masses in a single image, as shown in Figure 6 for the BUSI dataset. Therefore, this ability is crucial for specific diagnosis and treatment of diseases such as breast cancer, which often present as multiple masses of varied sizes and shapes. Overall, our method for ultrasound image segmentation has demonstrated its robustness, reliability, and ability for precise removal of significant anatomical structures.

TABLE VI
THE SEGMENTATION RESULTS OF DIFFERENT COMPETING METHODS ON USTHOSPITAL DATASET.

Method	Acc (%)	JI (%)	Se (%)	Sp (%)	DC (%)
CNN [11]	**98.51**	-	87.21	99.42	86.52
UNet	96.72	85.03	92.40	99.45	93.23
US-Net	96.86	**86.36**	**93.71**	**99.45**	**94.00**

V. CONCLUSION

In this work, we proposed a new approach named US-Net (Ultrasound Network) for breast mass segmentation in ultrasound images. Our model uses U-Net with attention blocks and a triggering mechanism to improve the model

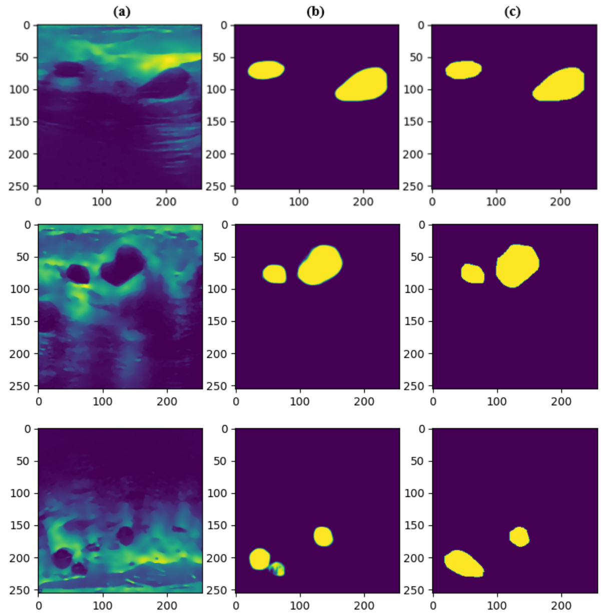


Fig. 6. Visualization of the segmentation results of BUSI dataset generated by our model: (a) Image, (b) Predicted mask, (c) Actual mask.

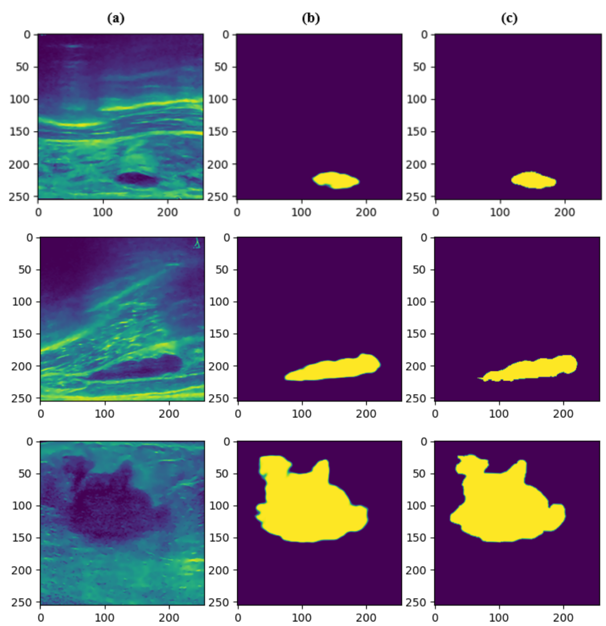


Fig. 7. Visualization of the segmentation results of UDIAT dataset generated by our model: (a) Image, (b) Predicted mask, (c) Actual mask.

performance. Furthermore, experimental results showed that our method achieves the most competitive results for breast mass segmentation. However, we believe that the techniques and knowledge gained in this work could be applied to other imaging modalities. In the future, it would be interesting to extend our approach to other imaging modalities commonly used for breast cancer diagnosis, such as Magnetic Resonance Imaging (MRI) and mammography.

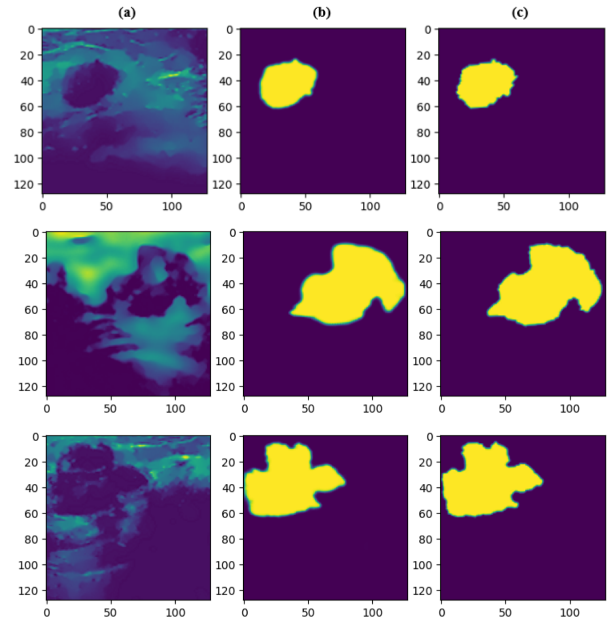


Fig. 8. Visualization of the segmentation results of STUHospital dataset generated by our model: (a) Image, (b) Predicted mask, (c) Actual mask.

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