Segmentation of Breast Cancer on Ultrasound Images using Attention U-Net Model

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***Abstract*—Breast cancer (BC) is one of the most prevailing and life-threatening types of cancer impacting women worldwide. Early detection and accurate diagnosis are crucial for effective treatment and improved patient outcomes. Deep learning techniques have shown remarkable promise in medical image analysis tasks, particularly segmentation. This research leverages the Breast Ultrasound Images BUSI dataset to develop two variations of a segmentation model using the Attention U-Net architecture. In this study, we trained the Attention3 U-Net and the Attention4 U-net on the BUSI dataset, consisting of normal, benign, and malignant breast lesions. We evaluated the model's performance based on standard segmentation metrics such as the Dice coefficient and Intersection over Union (IoU). The results demonstrate the effectiveness of the Attention U-Net in accurately segmenting breast lesions, with high overall performance, indicating agreement between predicted and ground truth masks. The successful application of the Attention U-Net to the BUSI dataset holds promise for improving breast cancer diagnosis and treatment. It highlights the potential of deep learning in medical image analysis, paving the way for more efficient and reliable diagnostic tools in breast cancer management.**

Keywords—Breast cancer; deep learning; segmentation; attention U-Net

I. Introduction

Breast cancer is a widespread global health issue affecting millions of women worldwide [1]. Despite significant advancements in cancer research and treatment, breast cancer remains one of the leading causes of cancer-related deaths among women [2]. Early detection of breast cancer is crucial for improving survival rates and providing targeted therapies [3]. Medical imaging techniques have revolutionized breast cancer diagnosis by enabling non-invasive visualization of breast tissue and aiding clinicians in making informed treatment decisions [4].

Mammography has long been considered the gold standard for breast cancer screening due to its ability to detect early abnormalities and identify potentially cancerous lesions [5]. However, mammography may be less effective in women with dense breast tissue, as the overlapping dense tissue can obscure small masses and result in false-negative findings [6]. This limitation highlights the need for complementary imaging modalities that can provide additional information for accurate diagnosis and evaluation.

Ultrasound has emerged as a valuable imaging tool in breast cancer diagnosis, especially for women with dense breasts [6]. Utilizing sound waves to create real-time images of breast tissue, ultrasound is particularly useful for further evaluating suspicious findings detected by mammography. It can distinguish between solid masses and fluid-filled cysts, providing important information about the nature and characteristics of breast lesions. Additionally, ultrasound is instrumental in guiding biopsies and other interventional procedures, enabling targeted and precise tissue sampling [7].

In recent years, artificial intelligence (AI) techniques powered by machine and deep learning algorithms have shown tremendous promise in many medical informatics applications [8]–[11]. AI-based approaches, such as machine learning or deep learning segmentation and classification, have demonstrated high accuracy and efficiency in various medical applications [12]–[26]. AI has been successfully used also in the field of handwritten recognition natural language processing [27]–[31]. Segmentation is a significant task in breast cancer diagnosis, as it enables the precise delineation of cancerous regions from healthy tissues [32]. Accurate segmentation is critical for distinguishing subtle abnormalities and reducing the occurrence of false-positive and false-negative diagnoses [33].

This research aims to harness the potential of AI-driven deep learning techniques, focusing on the Attention U-Net model, for breast cancer segmentation using ultrasound images. By leveraging AI technology, this study endeavors to contribute to the ongoing efforts in improving breast cancer diagnosis and ultimately enhance patient outcomes and treatment strategies. Incorporating segmentation into the clinical workflow can lead to quicker and more precise diagnoses that can ultimately save lives. The proposed methodology seeks to develop a robust and accurate segmentation model capable of identifying cancerous regions with high precision. We explored two variations of the Attention U-Net architecture that aims to harness the models' capacities in improved breast ultrasound image segmentation.

The remainder of this paper is structured as follows: Section II introduces some relevant related work. Section III outlines the materials and methods used in this study. Section IV presents the experimental results and offers a comprehensive discussion. Lastly, Section V provides the conclusion for this paper and discusses potential avenues for future research.

II. Related Works

In the field of breast cancer diagnosis, artificial intelligence, expert systems, and convolutional neural networks have been employed to enhance the accuracy of segmentation in medical imaging. Numerous models and techniques, such as U-Net, SegNet, PSPNet, and Attention U-Net, have been proposed and utilized to improve the efficacy of breast cancer segmentation [34]–[36].

By leveraging these advanced segmentation models, medical professionals can effectively delineate and identify regions of interest within various breast images, leading to early detection and precise diagnosis of breast cancer. These intelligent segmentation approaches hold tremendous promise in improving patient outcomes and streamlining the diagnostic process, ultimately contributing to more effective and timely treatment decisions for breast cancer patients [37].

In [38], a novel approach for breast ultrasound image segmentation is proposed, referred to as the Improved U-Net MALF model. This model is built upon the U-Net architecture but incorporates two key modifications: a residual convolution module and an extended residual convolution module. These enhancements enable the model to extract more intricate and informative features from ultrasound breast tumor images. Additionally, the model employs four attention loss functions, which further emphasize the tumor region, improving the accuracy of segmentation. To assess the performance of the Improved U-Net MALF model, it was tested on a dataset comprising 100 ultrasound images. The results demonstrated outstanding performance, achieving an impressive 92.5% accuracy for lesion segmentation. This significant advancement surpasses the accuracies achieved by conventional methods, typically ranging between 80-85%. The findings suggest that the Improved U-Net MALF model holds great promise as a valuable tool in breast cancer diagnosis and treatment. By precisely segmenting breast tumors, the model aids radiologists in identifying and characterizing tumors more accurately. Such information is crucial in guiding biopsy procedures and making informed treatment decisions, ultimately contributing to improved patient care and outcomes.

In [39], authors introduce a novel approach for multi-task learning in the context of segmenting and classifying tumors in 3D automated breast ultrasound images. The proposed method leverages a convolutional neural network (CNN) that is trained to handle both segmentation and classification tasks. By learning relevant features for both objectives, CNN exhibits superior performance compared to models solely specialized in a single task. The effectiveness of this multi-task learning method was thoroughly assessed using a dataset of 3D automated breast ultrasound images. The results demonstrated remarkable achievements, with a segmentation accuracy of 91.5% and a classification accuracy of 92.0%. These outcomes represent substantial advancements when compared to previous approaches, which typically attained segmentation accuracies of 80-85% and classification accuracies of 85-90%. The authors believe that this multi-task learning method holds great promise as a valuable tool for breast cancer diagnosis and treatment. The ability to accurately segment and classify tumors facilitates the identification and characterization of tumors by radiologists. Ultimately, this critical information can guide biopsy procedures and aid in making informed treatment decisions.

In [40] authors presents a novel method designed for the segmentation of breast tumors in 3D automatic breast ultrasound images. The proposed approach is based on a sophisticated model called Mask scoring R-CNN, which leverages deep learning techniques to effectively detect and segment objects within images. Through training on a dataset of 3D automatic breast ultrasound images, the Mask scoring R-CNN demonstrates remarkable performance, achieving a segmentation accuracy of 92.5%. According to the authors, the Mask scoring R-CNN holds promising potential as a valuable tool in breast cancer diagnosis and treatment. Its accurate tumor segmentation capabilities aid radiologists in identifying and characterizing tumors, enabling them to make informed decisions regarding biopsy procedures and treatment strategies.

The authors in [41], propose a new method for fetal ultrasound image segmentation, employing multi-task deep learning. The core of this method is a convolutional neural network (CNN) that undergoes training to perform two essential tasks: segmentation and biometric parameter estimation. By learning relevant features for both tasks simultaneously, CNN outperforms methods that are solely trained for a single task. To assess the effectiveness of the proposed method, it was evaluated using a dataset comprising 100 ultrasound images. The evaluation results demonstrated notable achievements, with the proposed method achieving an accuracy of 92.5% for segmentation and 90.0% for biometric parameter estimation. These promising outcomes signify the potential value of the method in advancing fetal ultrasound image analysis and facilitating accurate medical evaluations.

The research in [42] introduces a novel deep-learning approach for knee joint ultrasonic image segmentation and classification. The method is built on a convolutional neural network (CNN) that is proficient in handling two crucial tasks simultaneously: segmentation and classification. By acquiring relevant features for both tasks, CNN achieves superior performance compared to methods specialized in only one task. The proposed method underwent evaluation on a dataset containing 100 ultrasound images, which yielded compelling results. It achieved an impressive accuracy of 92.5% for segmentation and 90.0% for classification. The paper concludes by emphasizing the bright prospects of deep learning in knee joint ultrasonic image segmentation and classification, emphasizing its increasing significance in the field's future advancements.

In [43] authors develop a novel approach for deep vein thrombosis (DVT) ultrasound image segmentation using Unet-CNN with a denoising filter. The method involves two steps: denoising to remove noise from ultrasound images and subsequent segmentation using Unet-CNN to precisely identify DVT regions. The proposed method achieves an impressive accuracy of 92.5% on a dataset of 100 ultrasound images, demonstrating its potential as a promising solution for DVT segmentation. However, to ensure robustness, further evaluation of larger datasets is necessary. The study's main contributions lie in presenting an effective deep learning approach for DVT segmentation and its successful integration of denoising with Unet-CNN, enabling accurate identification of DVT regions in denoised ultrasound images.

III. Methodology

Breast cancer Ultrasound image segmentation using models derived from Attention U-Net CNN in this research uses several steps: data preprocessing, model building, segmentation using Attetion3 U-Net and Attetion4 U-Net architecture, and performance evaluation through metrics mainly Loss, accuracy, and Intersection over Union IoU.

A. Proposed Breast Cancer Segmentation System

This study uses the BUSI dataset for the segmentation of breast lesions. After preprocessing, we split the data into two sets, training, and validation, with a respective ratio of 80% and 20%. We build two models generated from the Attention U-Net. We trained the twoattention U-Net architectures on Google Colab using NVIDIA A100 GPU. Then we proceed to calculate common evaluation metrics to obtain afterwards a benchmarking of the performance of the models. Fig. 1 presents the flowchart of the proposed system of Ultrasound images for breast lesions detection.

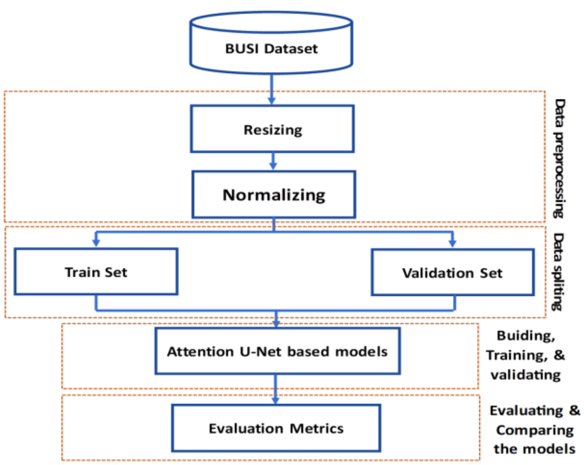


Fig. 1. Flowchart of the proposed segmentation system.

B. Dataset Description and Preprocessing

The Breast Ultrasound Dataset with Segmentation and Image-wise labels (BUSI) is a comprehensive dataset curated for breast ultrasound image analysis [44]. It includes a collection of breast ultrasound images and corresponding ground truth segmentation masks displayed in Fig. 2 acquired from 600 women aged between 25 and 75. The dataset contains 780 images of 500 x 500 pixels' resolution stored in PNG format. Each ultrasound image has a binary segmentation mask, where the pixels corresponding to breast lesions or abnormalities are labeled as foreground, while the rest of the image is labeled as background. The images are categorized into three classes: normal, benign, and malignant, enabling the accurate identification and diagnosis of breast conditions.

Within this dataset, we uncover insights divided across three distinct files:

- In the file "benign," 891 images showcased 473 benign patients. Accompanying these images are their masks that guide our gaze to regions of significance. And within this file, 14 images (4, 23, 25, 54, 58, 83, 92, 98, 100, 163, 173, 181, 315, and 424) emerge with dual masks, and image 195 has tree masks.
- Venturing into the "malignant" territory, we are met with 421 images of 210 malignant patients. Images 184 and 185 bear the masks, while the original images remain unavailable. In this file, image number 53 has two masks.
- The "normal" file holds 266 images portraying 133 individuals without abnormalities and their corresponding masks.

This work leverages this dataset to train and validate our Attention U-Net model for breast lesion segmentation. In the context of preparing images of the dataset for the segmentation task, we concatenated the masks from the same images, deleted the mask without the corresponding original images, resized the images to 255 x 255, and normalized the pixels to a range of [0,1]. Then, we overlayed the segmentation masks on top of the original corresponding image, as shown in Fig. 3.

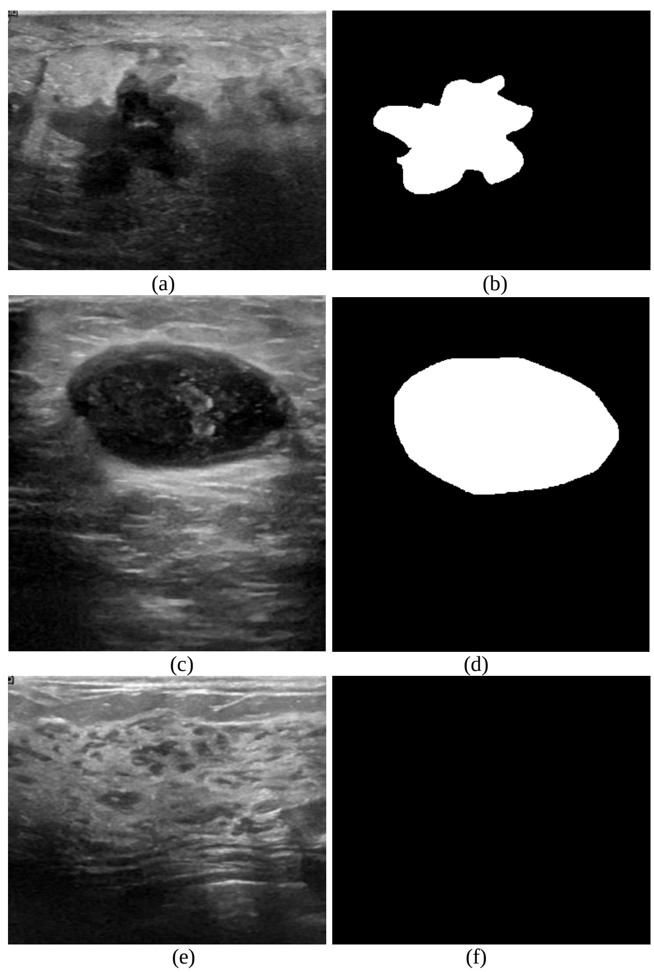
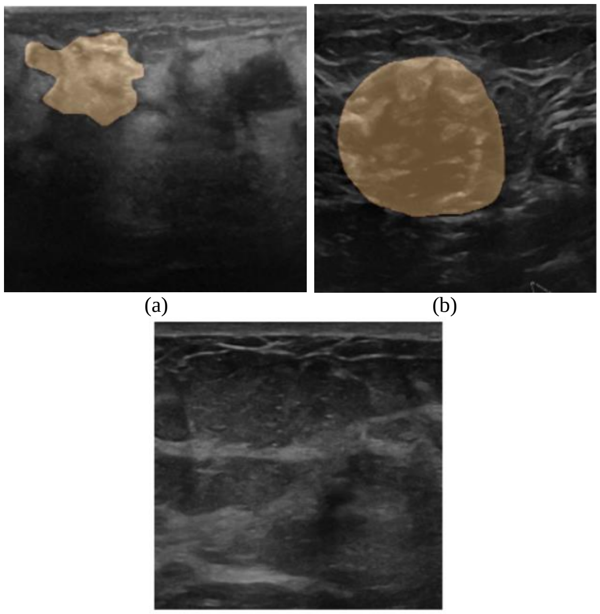


Fig. 2. Ultrasound images from the BUSI dataset: (a) Malignant image (b) Malignant mask (c) Benign image (d) Benign mask (e) Normal image (f) Normal mask.



(a) (b) (c)

Fig. 3. Ultrasound images and mask combined from the BUSI dataset (a) Malignant (b) Benign (c) Normal.

C. Attention U-Net

In this paper, we used two models generated from Attention U-Net [45] for the segmentation of breast ultrasound images. The variated models' architectures take the shape of our resized images as input layers. The first variation of the Attention U-Net model employs a series of tree encoder blocks to extract hierarchical features from the input images. Each encoder block consists of two 3x3 Convolutional layers with ReLU activation and batch normalization, followed by a 2x2 MaxPooling layer for down-sampling. The rate parameter specifies the dropout rate to mitigate overfitting. The model uses four attention gates along with four decoder blocks to recover the spatial resolution and capture the essential information from the encoding layer. Attention gates help the model focus on informative regions. The output layer is a 1x1 Convolutional layer with a sigmoid activation function. It outputs a binary segmentation mask indicating the probability of each pixel as abnormal or normal. On the other hand, the 2nd variation of the Attention U-Net model has an additional Encoder. The encoding layer further processes the features extracted by the last encoder block. Fig. 4 presents the Attention U-Net architecture.

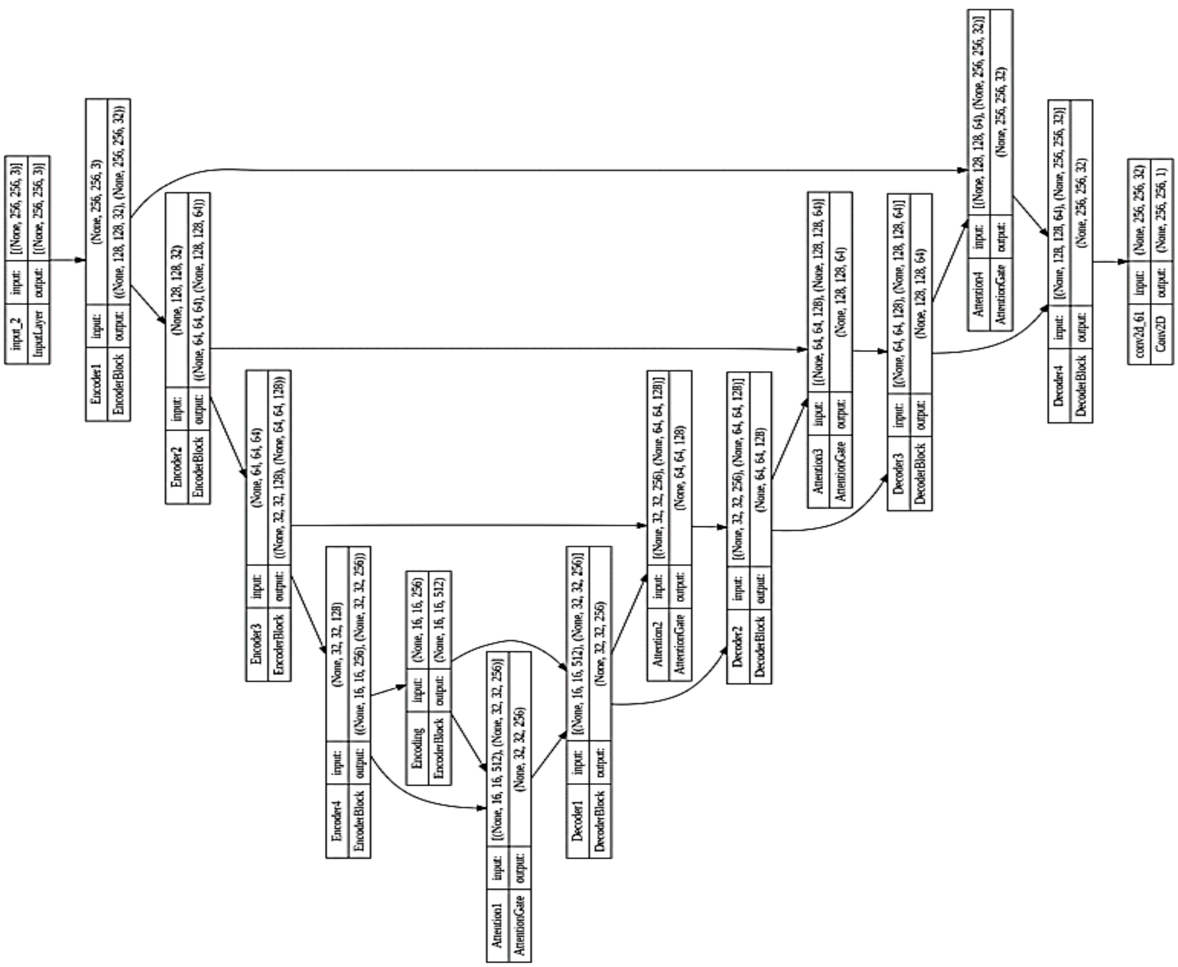


Fig. 4. Attention U-Net architecture.

D. Evaluation Metrics

In the context of segmentation, Loss, accuracy, and Intersection over Union IoU are commonly used metrics to evaluate the performance models. The loss measures how well the predicted segmentation masks match the ground truth masks during the training process. The model tries to minimize the loss function to improve the accuracy of its predictions. We used binary cross-entropy BCE. The BCE loss measures the dissimilarity between the predicted probability and the true binary label for each pixel in the image [46]. Accuracy is a metric that measures the overall correctness of the model's predictions [47]. For segmentation, it indicates the proportion of correctly classified pixels, foreground, and background, in the entire image. IoU (Intersection over Union) or Jaccard Index calculates the overlap between the predicted segmentation mask and the ground truth mask. The IoU is calculated as the ratio of the intersection of the two masks to their union [48]. Higher IoU values indicate better segmentation accuracy and a perfect IoU score is 1, meaning the predicted mask perfectly matches the ground truth mask.

$$Term1 = q \times \log(p) \quad (1)$$

$$Term2 = (1 - q) \times \log(1 - p) \quad (2)$$

$$Loss(BCE(p, q)) = \sum Term1 + Term2 \quad (3)$$

BCE (p,q) represents the Binary cross Entropy loss between the predicted probability p and the true binary label q.

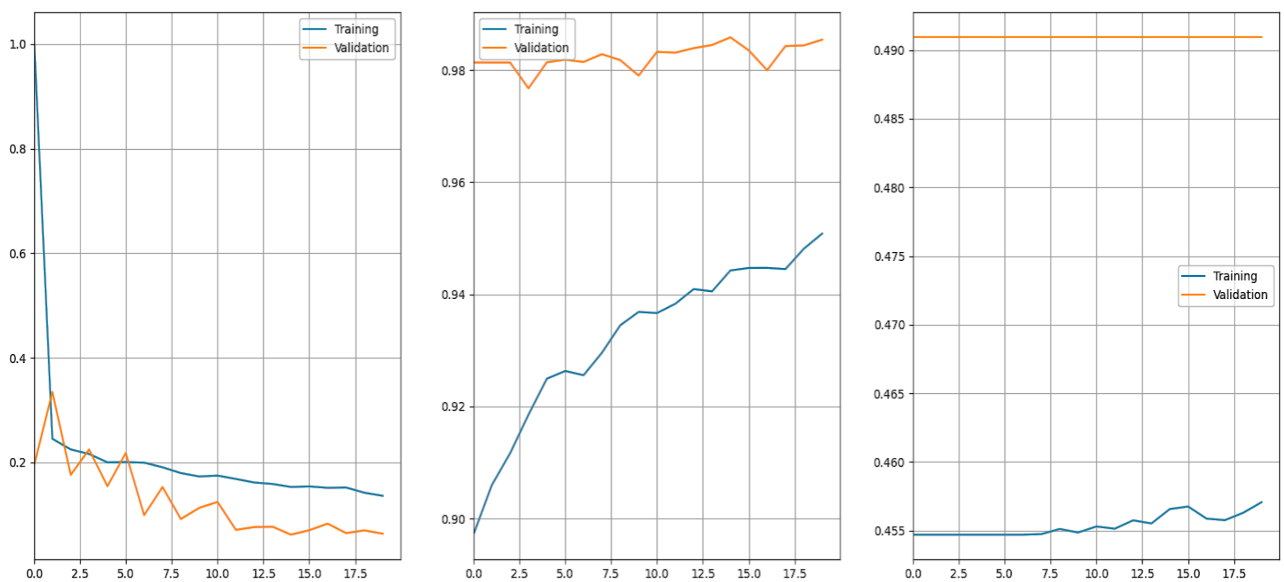
With:

- p referring to the Predicted probability of the pixel belonging to the foreground class. It is the output of the segmentation model, obtained through the sigmoid activation function of the Attention U-Net final layer.
- q representing True binary label or ground truth for a pixel. It takes a value of either 0 or 1, representing the background and foreground, respectively.

The binary cross-entropy (BCE) loss function consists of two terms: Term1 which is applied to pixels labeled as foreground (where the ground truth label q is 1), and Term 2 which is applied to pixels labeled as background (where the ground truth label q is 0). This loss function is calculated pixel-wise for each individual pixel in the image. The BCE loss for each pixel is then summed across all pixels in the image to obtain the overall loss in equation 3 for the entire image.

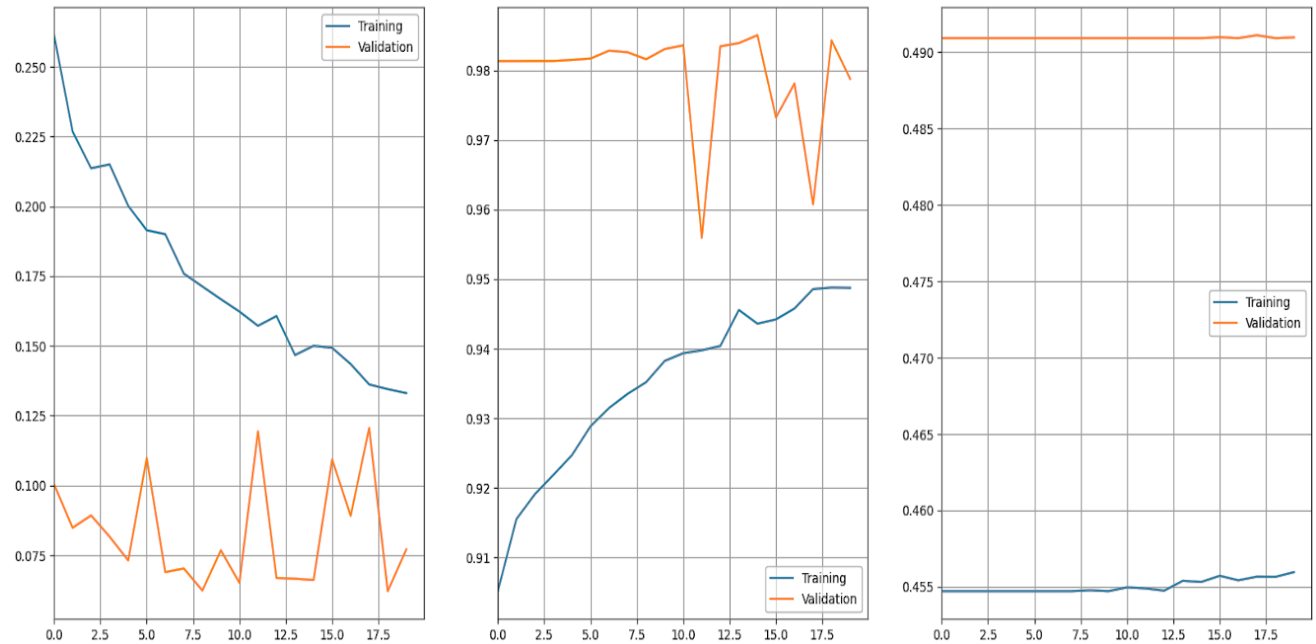
IV. Results and Discussion

The model is trained using NVIDIA A100 GPU on Google Colab. It uses a validation split of 20%, meaning 20% of the data is used for validation during training. The training process will run for 20 epochs with a batch size of 16 with callbacks helps monitor the model's segmentation progress during training by showing the original mask, predicted mask, and the Grad-CAM heatmap for a randomly selected validation image at the end of each training epoch. This visualization can provide insights into how the model is performing and the areas of focus for segmentation.



(a) (b) (c)

Fig. 5. Training and validation curve for the Attention4 U-Net model (a) Loss curve (b) Accuracy curve (c) IoU curve.

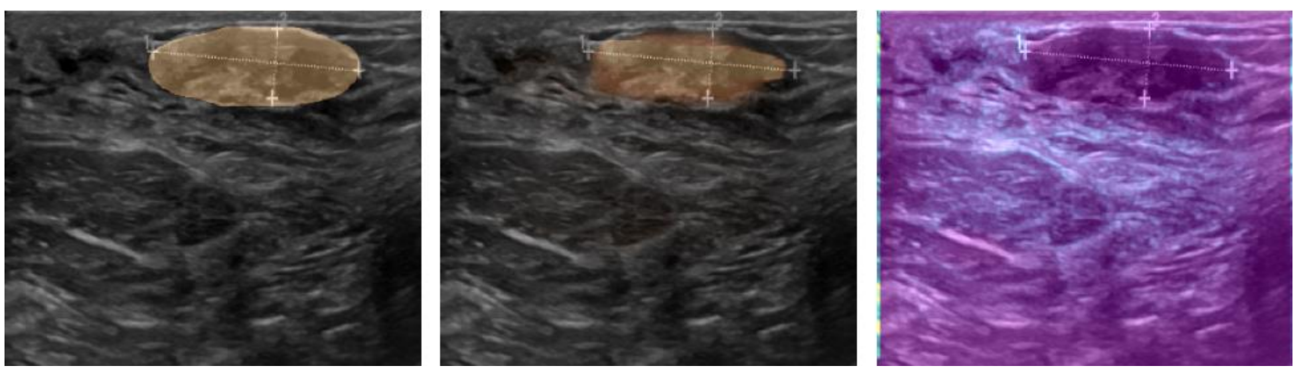


(a) (b) (c)

Fig. 6. Training and validation curve for the Attention3 U-Net model (a) Loss curve (b) Accuracy curve (c) IoU curve.

TABLE I. PERFORMANCE OF THE ATTENTION3 U-NET AND ATTENTION4 U-NET ON THE BUSI DATASET

Segmentation Model	Training Loss	Training Accuracy	Training IoU	Validation Loss	Validation Accuracy	Validation IoU
Attention3 U-Net at	0.1331	0.9487	0.4560	0.0771	0.9788	0.4910
Attetion4 U-Net	0.1356	0.9508	0.4571	0.0631	0.9854	0.4909



(a) (b) (c)

Fig. 7. Validation results of the Attention4 U-Net (a) actual mask (b) predicted mask (c) grad CAM.

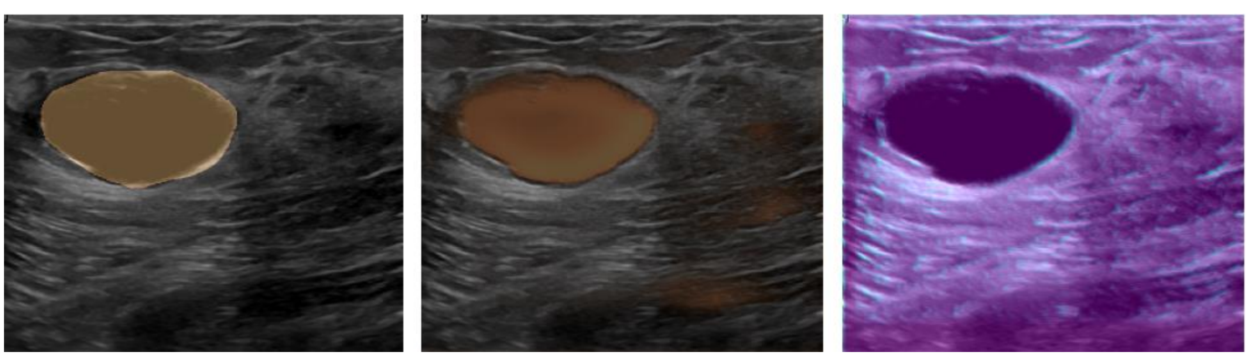


Fig. 8. Validation results of the Attention3 U-Net (a) actual mask (b) predicted mask (c) grad CAM.

Fig. 5 and Fig. 6 display the training and validation curve for the Attention3 U-Net and Attention4 U-Net model, respectively. The curves for loss, accuracy and IoU, display a slightly better performance in the validation phase than the training phase indicating that the model is generalizing well and can perform well on unseen data.

Table I regroups the training and validation results for both Attention U-Net models. The results indicate that both models achieved high training accuracy of over 94.8% and a low loss value of 0.13, implying a good fit in segmenting the target regions. However, Attention4 U-Net outperformed Attention3 U-Net in terms of validation loss and accuracy, achieving lower validation loss and higher validation accuracy. Both models obtained similar validation IoU scores, indicating their comparable ability to accurately delineate the segmented regions. Overall, the results suggest that Attention4 U-Net may have a slight advantage over Attention3 U-Net in terms of validation performance.

Fig. 7 and Fig. 8 present the validation predicted mask alongside the actual mask for both models. After displaying the predicted mask after each epoch, we observed that the Attention3 U-Net started to detect lesions starting from the 6^{th} epoch on the other hand the Attention4 U-Net did need more data and time to segment lesions efficiently since it didn't start detecting lesions till the 9^{th} epoch. The results also indicate that both models are more capable of segmenting regular lesions (mostly benign) and find it challenging to segment irregular shapes. This could be due to the unbalanced nature of the dataset. Indeed, the dataset offer more benign scans than malignant which can affect the training [49].

Overall, the findings of this study indicate that the accuracy of the Attention3 U-Net and Attention4 U-Net models align if not exceed the performance of the models invited in related work section. Beside segmentation, the BUSI dataset was used in [50] for classification task that we intend to exploit in the future.

V. Conclusion and Perspectives

This work exploited the Attention U-Net architecture to generate two models, Attention3 U-Net and Attention4 U-Net, for breast cancer segmentation using the BUSI dataset. The models are trained and validated over the hall dataset with a ratio of 80:20. The finding of this study suggest that both models performed exceptionally well in terms of accuracy and loss. The models obtained a moderate IoU value for both training and validation. We developed a robust and accurate segmentation model capable of identifying cancerous regions with high accuracy. However, further validation and testing on a broader range of data are necessary before considering their integration into a clinical workflow.

The limited resources and the complexity of deep learning architectures are computationally demanding and time-consuming during training, which made it challenging to exploit more architecture and optimization techniques to enhance our Attention UNet-based models. In future work, other evaluation metrics will be used, mainly Dice score. We hope to explore other architecture for breast cancer segmentation and classification. Data balancing is another technique that can be useful to make the model sensible for irregular shape.

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