SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V11I8P109

Volume 11 Issue 8, 82-89, August 2024
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*Original Article*

# Enhanced Breast Cancer Detection in Ultrasound Imaging Using an Attention Based U-Net++ Architecture for Improved Tumor Segmentation

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Received: 02 June 2024 Revised: 16 July 2024 Accepted: 09 August 2024 Published: 31 August 2024

***Abstract*** - *Breast cancer, the most commonly occurring cancer among women and a leading reason of cancer mortality worldwide, necessitates early detection to reduce mortality rates. Breast Ultrasound (BUS) imaging, coupled with Computer Aided Diagnosis (CAD) systems, has emerged as a crucial, non-invasive, non-radioactive and low cost method for early breast cancer detection. Its suitability for large-scale screening and diagnosis, particularly in low-resource settings, further underscores its importance. However, the automatic segmentation of tumors in BUS images remains disputing due to the lower quality of the image, characterized by speckle noise, low contrast, feeble boundaries and artifacts. A histogram equalization was used as a pre-processing model to overcome such an issue. Additionally, the significant variation in tumor shape, size and echo strength across patients complicates the application of conventional segmentation methods that rely on strong priors to object features. This work proposes a novel attention-based U-Net++ architecture designed to address these challenges and achieve highly accurate breast cancer segmentation in BUS images. This model integrates an attention mechanism to boost the network's ability to attention to pertinent image regions, improving tumours' delineation despite noise and artifacts. The architecture incorporates the U-Net++'s strength in handling biomedical image segmentation tasks, incorporating skip connections to preserve spatial information and attention gates to filter and refine features at multiple scales. Through extensive experimentation and evaluation using Python, the attention-based U-Net++ demonstrates superior performance in segmenting tumors in BUS images, outperforming conventional models in terms of accuracy and robustness.*

***Keywords*** - *Attention gates, Attention-based U-Net++, BUS image, CAD systems, Histogram equalization.*

## 1. Introduction

One of the most common malignancies that greatly affects women and results in a large number of deaths each year is breast cancer [1-3]. Since the causes of breast cancer are still unknown, timely prediction is essential to reducing the death rate (by at least 40%). Risk factors for breast cancer include aging, inheritance, radiation exposure, dense breast tissue, consuming alcohol, and other variables [4-6]. Early detection and treatment considerably increase The probability of survival [7, 8].

Mammography and ultrasound are commonly used to diagnose breast cancer. However, breast cancer detection is challenging, particularly in the early stages of mammography [9]. When diagnosing breast cancer, breast ultrasonography is a common non-radiation clinical technique that patients tolerate well [10-12]. Ultrasound is especially helpful for further assessing concerning results from mammography since it uses sound waves to produce real time images of breast tissue. It provides crucial information regarding the type and features of breast lesions by differentiating between fluid filled cysts and solid masses [13, 14]. Though its accuracy depends on the clinician's skill, misdiagnosis is possible [15]. To address these issues, CAD algorithms based on BUS imaging can help medical staff accurately interpret breast cancer images. Some conventional methods are used for segmenting breast cancer images.

In [16], a greater patch token number is in suspense while a single MLP head is constructed on the class token for supervised training, although the standard ViT is used for BUS image classification. The ViT models often overfit on limited training datasets as a result of this unbalanced architecture. The model can localize tumors based on patches due to the enhanced architecture, which significantly enhances the performance of the main task (malignant detection) on the class token by providing additional task based supervised information. However, as the size of the patches reduces, so

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does the complexity of the second task itself. A neural network with a new classification branch added to the segmentation net is built and tuned in [17].

The model maintained its sensitivity for images containing tumors while producing incredibly few false-positive predictions on normal images. The model demonstrated high transferability on an external test set and outperformed the state of the art models in segmentation. However, malignant tumors exhibit a somewhat poorer segmentation result than benign ones, presumably as a result of their border roughness, greater heterogeneity in shape, echo density, and other factors. An automated pipeline comprising several layers of specialized CNN ensembles is presented in [18] for the end-to-end segmentation and classification of BUS images.

The approach can be a useful decision support system because it demonstrates a good level of robustness and reliability. Further work is necessary to improve the method in this direction because analyzing extremely difficult cases those with indistinct tissue structures or noise in the image that makes it difficult to discern from the healthy tissue- is typically the most challenging task for human operators.

In [19], a benchmark for B-mode BUS image segmentation is developed, identifying the key elements needed to boost segmentation performance. However, it does not assess the ratio of successfully segmented non-tumor zones. Hence, it is not an accurate segmentation. By incorporating segmentation-based attention data into the deep convolution network to classify breast cancers, [20] created a novel segmentation to classification technique.

That scheme's autonomous segmentation significantly improves the system's operability. The classification scheme's possible drawback is that it requires two phases, increasing training time and complexity, and is not an end-to-end method. Artifacts, noise, and other troubles generate problems for radiologists in segmenting the BUS images. It is resolved by using a histogram equalization for pre-processing, effectively reducing the noise presented in the breast image and improving image quality.

Furthermore, traditional segmentation techniques that rely on strong priors to object attributes are complicated by the notable variance in tumor size, shape, and echo strength among patients. To overcome these challenges and obtain extremely precise breast cancer segmentation in BUS images, this work proposes a unique attention-based U-Net++ architecture. The main goals of this work are,

- BUS imaging and CAD systems have emerged as a crucial approach for early breast cancer detection.
- The pre-processing based on histogram equalization is employed to eliminate text, spackle noise and artifacts from raw BUS images.
- An attention-based U-Net++ mainly focuses on specific regions of the breast image, which can assist in increasing segmentation accuracy.

## 2. Proposed Methodology

Breast cancer is one of the main cancers that affects women the most and results in a large number of fatalities each year. Targeted therapy and larger survival rates are dependent on early identification of breast cancer. In order to accurately distinguish cancerous from healthy tissue, segmentation is a vital stage in breast cancer diagnosis. Therefore, this work proposes a novel attention-based U-Net++ approach designed to address the challenges and attain highly accurate segmentation of breast cancer in BUS images. Figure 1 depicts the proposed block diagram.

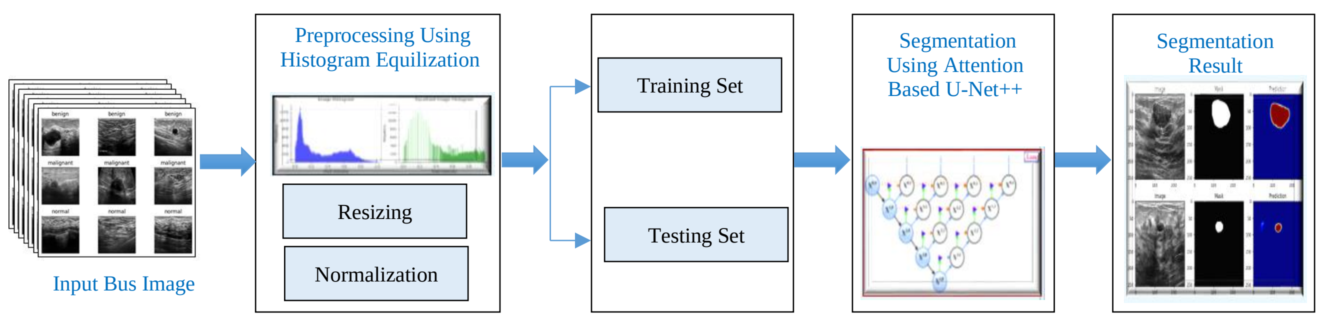


**Fig. 1 Proposed work's block diagram**

Initially, the breast cancer image is considered an input image and is pre-processed by using histogram equalization. The pre-processing step involves image resizing to alter the image to the required size, and equalization is utilized to improve the image's contrast. Then, the pre-processed data is separated into training and testing datasets with an 8:2 ratio.

Next, the data is entered into an attention-based U-Net++ architecture. The attention model is employed to enhance the ability of the network to focus on relevant regions of the image, and the U-Net++ is utilized to segment the abnormal cells from the BUS image, thereby ensuring highly accurate segmentation.

### *2.1. Preprocessing Using Histogram Equalization*

The input BUS images are pre-processed by removing unnecessary information, such as text fields, directional markers, and manufacturer labels, which skew the image's interpretation and produce inaccurate findings when noise reduction is applied. This process guaranteed a sharp and distinct image. In order to handle the images efficiently, they were then normalized and converted to a standard format and size. Resizing the images to an identical size and aspect ratio is essential since variations in resolutions and aspect ratios compromise the analysis's accuracy.

Ultimately, the data is verified before being input into the algorithm. Here, histogram equalization improves an image's contrast through pre-processing. This is because it does not need a lot of computer power and is simple to implement. The process involves mapping the image's gray levels according to the input gray levels' probability distribution. The quality of the real image produced by the scanner and the examiner's experience determine the reliability of a high-quality BUS examination.

In order to increase the likelihood of more accurate lesion ROI recognition, the Preprocessing phase addresses the problem of ensuring the homogeneity of the original ultrasound images. To accomplish the homogeneity guarantee in the proposed approach, data is pre-processed by using a histogram equalization model. Similar to contrast stretching, Histogram equalization aims to broaden the dynamic range of the pixel values in an image. This is not interactive, though, as using a histogram equalization technique on an image with a limited bin number continuously provides the same output, unlike contrast stretching. Take

$$P_r(r_j), j = 1,2, \dots, l \qquad (1)$$

Let $P_r(r_j)$stand for the histogram corresponding to a specific image's intensity levels. Keep in mind that the values within a normalized histogram represent estimates of the likelihood that each level of intensity will appear in the image. With discrete quantities, the transformation of equalization is,

$$S_k = T(r_k) = \sum_{j=1}^{k} P_r(r_j) = \sum_{j=1}^{k} \frac{n_j}{n} \qquad (2)$$

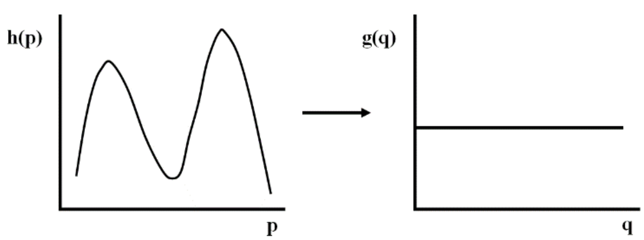


**Fig. 2 Histogram equalization**

In this case, $k = 1,2, \dots, L$, where n is the total number of pixels and $n_j$ is the number of pixels in bin $j$. Additionally, $S_k$ is the intensity value in the output image that corresponds to the value $r_k$ in the input image. Figure 2 displays the graph for histogram equalization. After pre-processing, the data is split into 2 groups, a training and a testing set, with an 80:20 ratio. In other words, just 20% of the data is employed to validate the approach, and 80% is employed to train it.

### *2.2. Bus Image Segmentation Using Attention Based U-NET++ Architecture*

After pre-processing, an attention-based U-Net++ model integrates attention models to boost the network's ability to focus on the image's relevant regions, improving the tumours' delineation. Image segmentation is the model of assembling parts of an image that are members of the same object class. It involves breaking up images into many objects or segments.

There are two methods to define image segmentation (instance segmentation): assigning semantic labels to each pixel (semantic segmentation) or dividing the image into individual objects. Using a collection of item categories, semantic segmentation assigns a pixel-by-pixel label to each and every image pixel. In image classification, a single label is predicted for the whole image or frame; this is usually more difficult. Instance segmentation extends the reach of semantic segmentation by finding and classifying every item of interest in an image.

Deep learning models have created a novel class of image segmentation approaches with significant gains in performance. Industry standards for image segmentation have changed dramatically due to deep learning-based models often accomplishing the maximum accuracy rates on popular benchmarks. Image segmentation improves medical images such as BUS by precisely dividing the homogeneous regions at the pixel level.

The Attention-UNet++-based deep learning algorithm segments the BUS image from the pre-processed image. Because traditional UNet produces efficient results, it is frequently used to carry out segmentation operations. Although the computing overhead is reduced by including skip links, the precision of the segmentation is still limited by the inability to take local contextual variables into account. Therefore, the UNet model incorporates stacked dense connections and attention modules to improve segmentation accuracy by considering local and global information.

Figure 3 shows the architecture of Attention-UNet++. Here, the high-resolution features are extracted via nested dense connections, which improves the efficiency of mapping the granular features. The combination of the deep supervision, indicated in blue, the dense skip connection, indicated in orange, and the skip connections, depicted in green, results in a nested dense connection that may be used to extract high resolution features. Similarly, Figure 3's red box denotes the attention module responsible for gathering local context data.

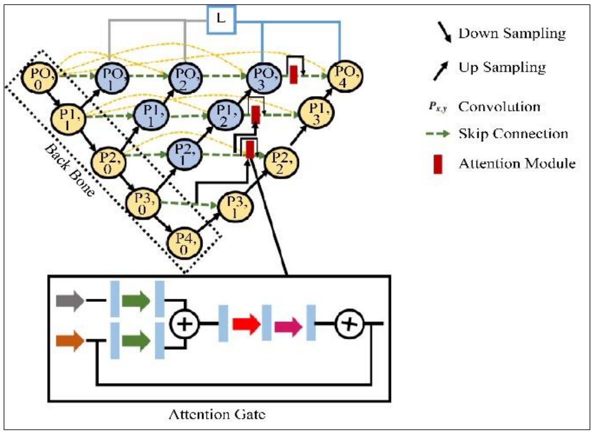


**Fig. 3 Structure of attention based U-Net++**

Due to the consideration of multiscale feature representations, the Attention-UNet++ based segmentation helps to boost the accuracy of BUS image segmentation. The skip connection's feature map is calculated to be

$$P_{x,y} = \begin{cases} C(P_{x-1}, y) & y = 0 \\ C\left(\left[P_{x,z}\right]_{z=0}^{y-1}, a\left(P_{x-1,y-1}\right)\right), & y > 0 \end{cases} \quad (3)$$

Here, the operation of convolution is denoted as ( ), the concatenation is represented as [] and the upsampling is denoted as $a(.)$. The output of the node in the Attention-UNet++ is indicated as$P_{x,y}$ for the corresponding input$P_{x,y}$. The attention block of the Attention-UNet++ is structured in Figure 4.

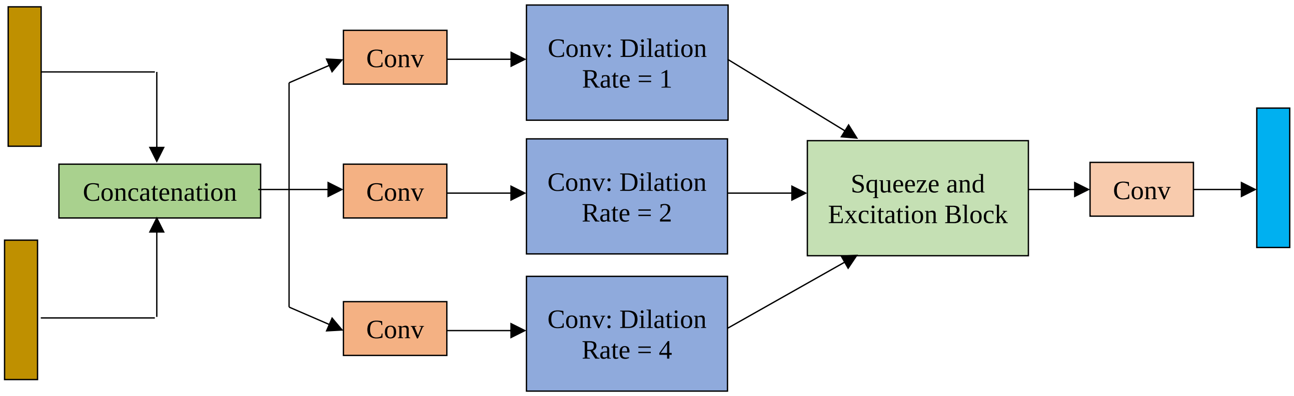


**Fig. 4 Structure of attention gate**

The multi-scale features are captured here, and the raw skip connections are optimized using the attention module. First, low and high level features are combined, and the feature mapping is created by interpolating the data to ensure that both inputs are the same size. Subsequently, dilated convolution at multiple rates facilitates the acquisition of features at different scales, which are subsequently merged to yield multi-scale features. Next, the squeeze and excitation block is used to extract and weigh the most important features from each channel. In the end, the convolutional layer is utilized for dimension reduction. Therefore, considering both the low and high level features with the least computational cost, the BUS image segmentation is used more precisely when utilizing the proposed Attention-UNet++ architecture.

## 3. Results and Discussion

A novel, attention-based U-Net++ addresses the issues and produces accurate breast cancer segmentation in BUS images. In order to boost the network's capacity to focus on pertinent areas of the image and improve tumor delineation in the face of noise and artifacts, the proposed model incorporates attention methods. This work is implemented in Python software, and comparative analysis is done using conventional methods to show the better performance of the method.

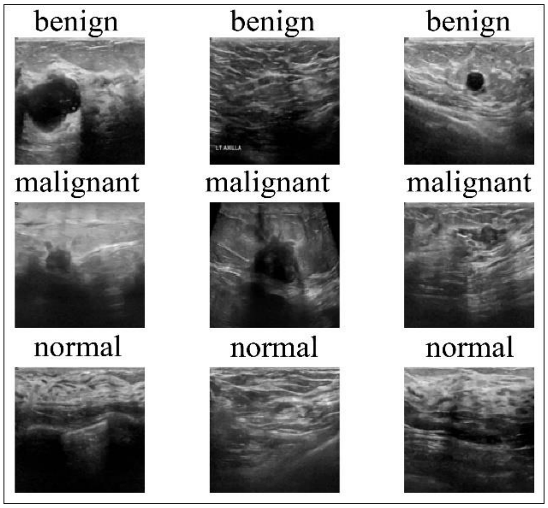


**Fig. 5 Input image**

Figure 5 presents the 256 x 256 pixel input image taken from the BUSI dataset. Every ultrasound image has a binary segmentation mask with background labelling for the remaining pixels and foreground labelling for any breast lesions or anomalies. The ability to accurately find and diagnose breast diseases is made possible by the three classes: malignant, benign, and normal.

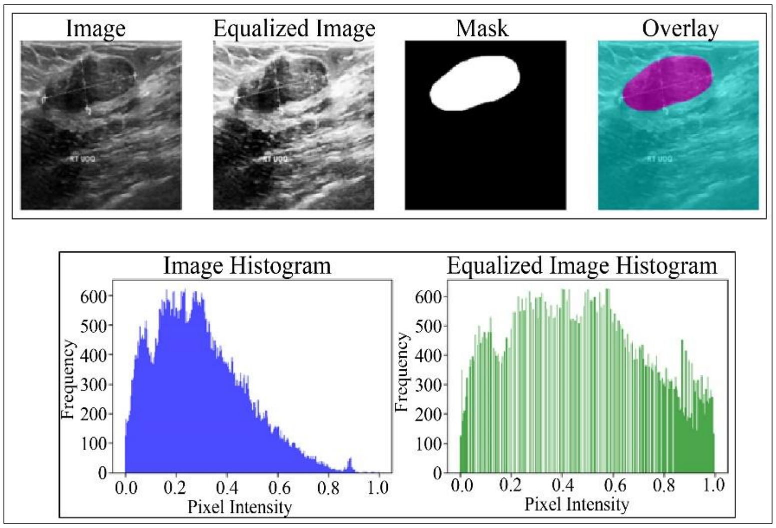


**Fig. 6(a) Pre-processed image for benign class**

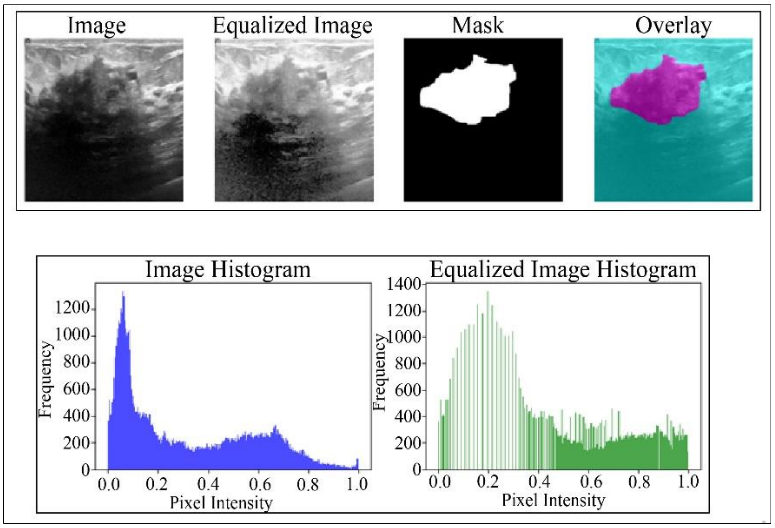


**Fig. 6(b) Pre-processed image for malignant class**

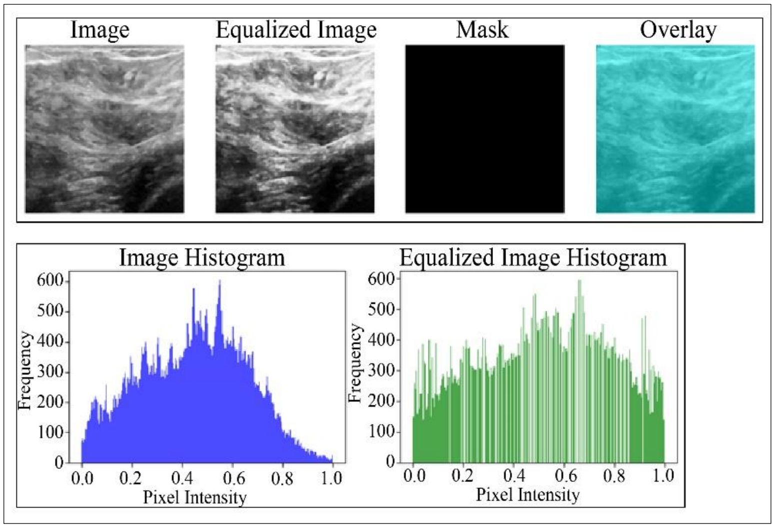


**Fig. 6(c) Pre-processed image for normal class**

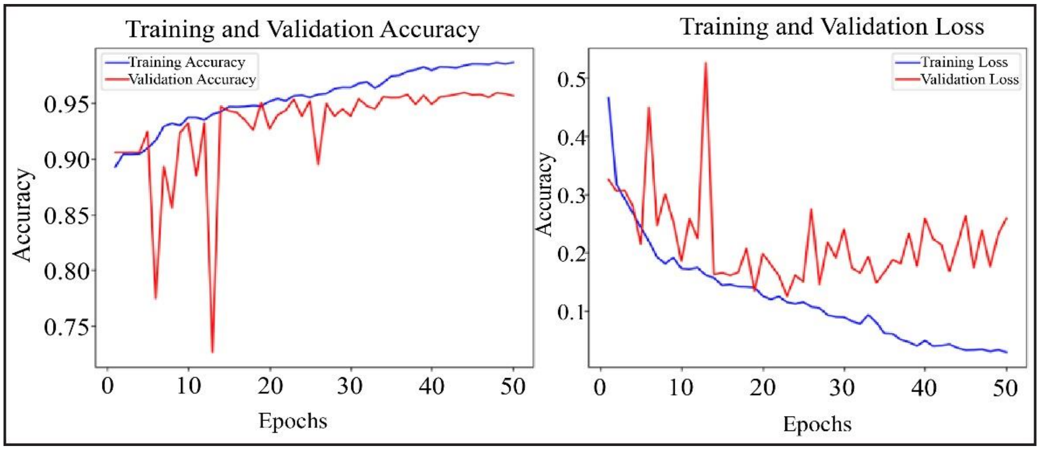


Fig. 7 Attention based U-Net++'s performance

Figures 6(a), (b), and (c) depict pre-processed images for benign, malignant and normal classes of breast image. It consists of a set of ground truth segmentation masks corresponding to a set of BUS images. To prepare for the segmentation task, the dataset's images are scaled, the pixels are normalized, the masks are concatenated from the same images, and the mask without the corresponding original images is erased. Figure 7 displays the performance of Attention based U-Net++. The training and testing datasets are divided with a ratio of 80% and 20%. During training, the model attains an accuracy of 99.4% and a testing accuracy of 95.4%.

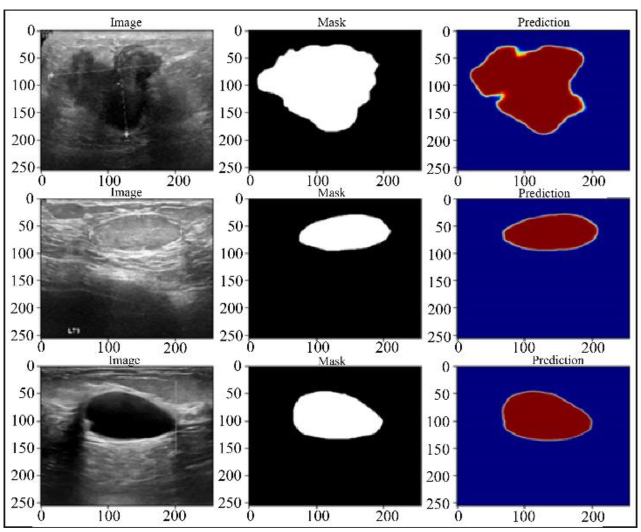


Fig. 8 Segmentation results

Figure 8 highlights the segmentation results of the breast image and shows an arbitrary selection of BUS images from the test set to simplify understanding of the outcomes by comparing mask prediction from our model to the real mask. From the results, the Attention-based U-Net++ model can accurately segment the abnormal area of the BUS image.

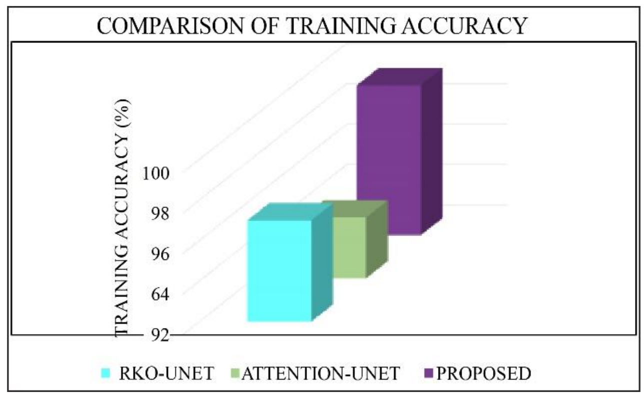


Fig. 9 Comparison of training accuracy

Figure 9 compares training accuracy for RKO-U-Net [15], Attention-U-Net [13] and the proposed method. The proposed approach attains a training accuracy of 99.4%, greater than other methods.

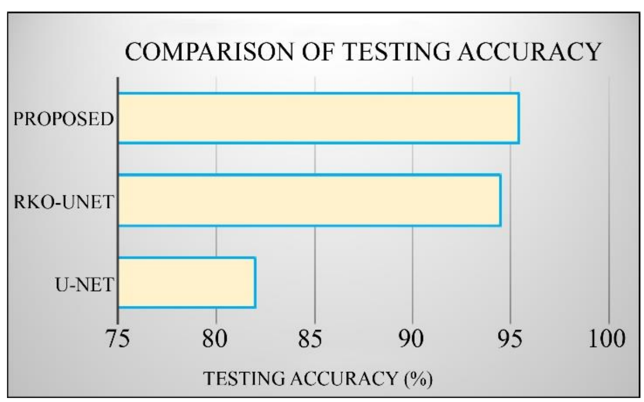


Fig. 10 Comparison of testing accuracy

Figure 10 compares testing accuracy for different methods like RKO-U-Net [15], and U-Net [22], and the proposed method attains a testing accuracy of 95.4%, better than other methods.

Although the testing accuracy of the proposed Attention -UNet++ (95.4%) is slightly lower than that of the existing Attention- UNet (98.4%), several key factors justify its superiority in practical applications. Attention-UNet++ is designed with advanced mechanisms that enhance its robustness and generalization, making it more reliable across diverse datasets and real-world scenarios. Additionally, it demonstrates improved training efficiency, achieving a higher training accuracy of 99.4%, which suggests faster learning and better convergence with fewer resources.

Its adaptability allows it to handle different types of data and noisy inputs more effectively, making it more versatile than its predecessor. Beyond testing accuracy, Attention-UNet++ excels in other important metrics such as precision, recall, and computational efficiency, which are critical for assessing overall performance.

Furthermore, the architectural innovations in Attention-UNet++ contribute to long-term benefits, including better scalability, ease of integration, and enhanced model interpretability. These factors collectively make Attention-UNet++ a significant improvement over the original, offering notable advantages in a wider range of practical applications.

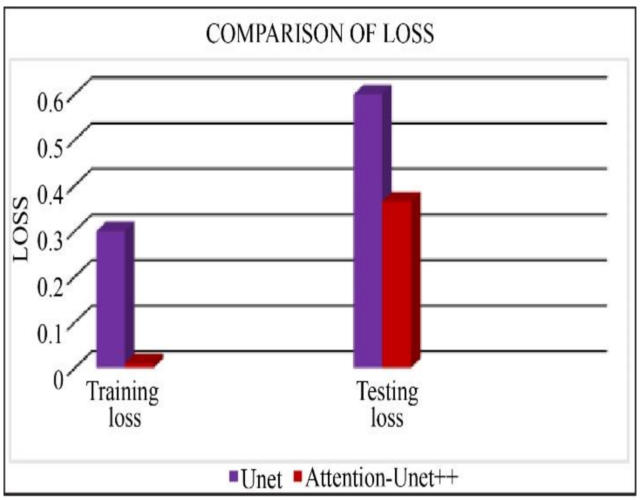


**Fig. 11 Comparison of loss**

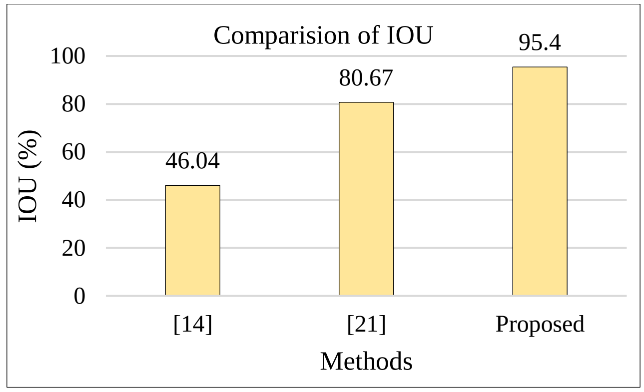


**Fig. 12 IOU comparison**

Figure 11 compares training and testing loss of UNet [15] and Attention-UNet++. It is observed that the proposed method is encouraged by lessened losses of 0.0104 and 0.3650 for training and testing, respectively.

Figure 12 highlights the comparison of Intersection Over Union (IOU) for various methods like Psp-net [14] and RDAU-NET [21] and the proposed method that achieves a testing accuracy of 95.4%, better than other methods.

## 4. Conclusion

For early breast cancer detection, this research proposes an attention-based U-Net++ architecture for the prediction of breast cancer utilizing BUS imaging. The BUSI dataset is utilized to segment breast cancerous cells, and the existence of artifacts, noise, and other problems generates difficulties. So, this model uses a histogram equalization for the pre-processing process, and the dataset is employed to train and test the models using an 80:20 ratio. To handle BUS image segmentation problems, it integrates an attention approach to boost the network's capability to effort on relevant regions of the image, improving the delineation of tumors despite the presence of noise and artifacts. The proposed work is implemented in Python software to show its prominence, and a comparative analysis is made using the other conventional methods. The model achieves an accuracy for training and testing of 99.4% and 95.4% and attains a low loss, thereby ensuring the accurate prediction of breast cancer.

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