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Development of ResNet-18 architecture to lesion identification in breast ultrasound images

Silfia Andini[1], Sumijan[2], Iskandar Fitri[2]
[1]Department of Informatics Management, Universitas Putra Indonesia YPTK Padang, West Sumatera, Indonesia
[2]Department of Information Technology, Universitas Putra Indonesia YPTK, Padang, West Sumatera, Indonesia

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ABSTRACT

Breast ultrasound (USG) is widely used for early breast cancer detection, but challenges such as noise, low contrast, and resolution limitations hinder accurate lesion identification. This study proposes a modified residual network-18 (ResNet-18) architecture for breast lesion segmentation, aimed at improving detection accuracy. The methodology involves preprocessing steps including red green blue (RGB) to Grayscale conversion, contrast stretching, and median filtering to enhance image quality. The modified ResNet-18 model introduces additional convolutional layers to refine feature extraction. The proposed model was trained and validated on 30 breast ultrasound images, with evaluation metrics including accuracy, sensitivity, and specificity. Experimental results indicate that the modified architecture outperforms the baseline model, achieving an average accuracy of 0.97093, sensitivity of 0.90056, and specificity of 0.97705. Validation by a radiology specialist confirms the model's clinical relevance. These findings suggest that the enhanced ResNet-18 model has the potential to assist radiologists in more accurately identifying breast lesions. Future research should focus on expanding the dataset, integrating multi-modal imaging, and optimizing model generalizability for real-time clinical applications. The study contributes to advancing artificial intelligence (AI)-driven breast cancer diagnostics, supporting early detection, and improving patient outcomes.

Corresponding Author:

Silfia Andini
Department of Informatics Management, Universitas Putra Indonesia YPTK Padang
25221, Padang, West Sumatera, Indonesia
Email: silfiaandini68@upiyptk.ac.id

1. INTRODUCTION

Breast cancer remains one of the leading causes of mortality among women worldwide, with early detection playing a crucial role in improving survival rates [1]. In developing countries like Indonesia, late-stage diagnosis is a prevalent issue due to limited access to advanced diagnostic tools and variability in ultrasound imaging interpretation [2]. Ultrasound (USG) is widely used for early breast cancer screening due to its non-invasive nature and ability to detect abnormalities in dense breast tissue [3]. However, the accuracy of ultrasound-based diagnosis is often hindered by several challenges, including image noise, low contrast, and operator dependency, making it difficult to distinguish malignant from benign lesions [4].

The rapid development of digital image processing technology has greatly benefited medical imaging, facilitating more accurate and reliable diagnoses [5]. Image processing techniques aim to enhance image quality and extract meaningful information for better analysis [6]. Among the advanced methods, convolutional neural networks (CNNs) have shown remarkable performance in image analysis and medical applications due to their ability to learn hierarchical features directly from image data [7]. CNNs consist of multiple layers, including convolutional and pooling layers, which help capture spatial features at different levels of granularity. One of the popular CNN architectures used for image analysis is residual network (ResNet) [8]. ResNet, introduced to overcome the vanishing gradient problem, allows deeper networks by incorporating shortcut connections, which improve training and performance. ResNet-18, a specific variant of ResNet, has been widely adopted in medical image analysis due to its balance between complexity and performance. Researchers have been leveraging and modifying ResNet-18 for various tasks, such as lesion detection and classification, to enhance accuracy and reliability. The flexibility of the ResNet architecture, along with data augmentation and transfer learning techniques, enables the development of models capable of handling different challenges in medical imaging, including noise reduction, feature extraction, and high-accuracy classification.

Previous studies have explored the potential of CNN-based architectures, particularly ResNet-18, for breast lesion detection and classification. Wang and Huang [9] introduced a framework using CDeep3M, a CNN-based model, which demonstrated promising results in breast tumor segmentation. This approach highlighted the capability of deep learning in assisting comprehensive diagnoses, showing significant flexibility in real-time cancer prediction [9]. Similarly, Das and Rana [10] investigated various ResNet architectures (ResNet-18, -34, -50, -101, and -152) to detect breast cancer from ultrasound images. Their results showed that ResNet models, especially with transfer learning, could achieve high precision, recall, and accuracy, indicating their effectiveness for medical image analysis. In another study, Yu *et al.* [11] proposed an augmented data framework called scaling and contrast limited adaptive histogram equalization data augmentation (SCDA) combined with ResNet-50, yielding an average specificity of 98.55% and sensitivity of 92.83%. This enhanced the overall model accuracy to 95.74% [11]. Furthermore, Dai *et al.* [12] presented a real-time detection network, STA-Net, built on ResNet-18 for video ultrasound breast lesion detection. Their model reached an impressive 54 frames per second processing rate with an average precision of 38.7 mAP, outperforming existing methods and demonstrating the potential of CNN-based real-time analysis [12].

Several computational approaches have been proposed to enhance breast lesion detection in ultrasound images. Traditional machine learning techniques, such as texture analysis and handcrafted feature extraction, have shown promise but often lack robustness due to variations in image quality. Recently, deep learning models, particularly CNNs, have been widely adopted for medical image analysis. Studies by Wang and Huang [9] and Yu *et al.* [11] demonstrated the effectiveness of CNN-based segmentation models in improving lesion detection accuracy. However, these methods still face challenges related to limited training data, overfitting, and the need for improved feature extraction tailored to breast ultrasound imaging.

Building on the foundation of existing research, this study aims to further develop a segmentation method for identifying breast lesions in ultrasound images using a modified ResNet-18 architecture. The focus will be on enhancing the ResNet-18 model by adding and modifying convolutional layers to create a novel model capable of producing more accurate results. The developed model will undergo evaluation, training, and validation to measure its accuracy, sensitivity, and specificity. The goal is to identify the best-performing model with optimal values for these parameters, which would represent a significant contribution to the field. The novelty of this research lies in the modifications made to the original ResNet-18 architecture and its application in breast ultrasound image analysis. The anticipated outcome is that this enhanced model can be implemented in medical ultrasound equipment to support radiologists and oncologists in diagnosing breast lesions more accurately and efficiently. The results could lead to better clinical recommendations and improved early detection, ultimately contributing to lower mortality rates from breast cancer.

This study aims to address these challenges by developing an improved segmentation method based on a modified ResNet-18 architecture. By introducing additional convolutional layers, we seek to enhance the model's capability in extracting critical features, thereby improving the accuracy, sensitivity, and specificity of breast lesion identification. The primary objectives of this research are: (1) to develop a deep learning model that enhances breast lesion segmentation accuracy, (2) to evaluate the model's performance compared to standard ResNet-18 and existing approaches, and (3) to explore its potential application in clinical diagnostic workflows. By optimizing lesion detection in ultrasound imaging, this study aspires to contribute to early breast cancer diagnosis, ultimately improving patient outcomes.

2. METHOD

2.1. Research framework

In Figure 1 is the research framework conducted in this study. The framework above is divided into four stages consisting of the first stage, namely image input. The image input stage is the first stage in this study that enters image data into the system to be analyzed in the study. The second stage is preprocessing or preprocessing which consists of three preprocessing sub-steps, namely the color conversion of the image from red green blue (RGB) to Grayscale, then improving image quality (image enhancement) using the contrast stretching method, then reducing noise (noise reduction) using the median filter method. The third stage in this study is processing which consists of seven sub-steps of the process, namely the first region of interest (ROI), the second training and validation of ROI data, the third image segmentation, the fourth application of the ResNet-18 architecture and the development of the ResNet-18 architecture, the fifth evaluation, training and validation of the ResNet-18 model before development and after development (evaluation, training and validation are carried out on three values, namely accuracy, sensitivity, and specificity), the sixth model test using test data before development and after development, the seventh is the evaluation of test result data before development and after development (evaluation of test result data is carried out on three values, namely accuracy, sensitivity, and specificity). The fourth stage in this study is the results of lesion detection in breast ultrasound images from architectures that have not been developed with architectures that have been developed. This study follows a structured research framework designed to enhance breast lesion identification in ultrasound images through a modified ResNet-18 architecture. The framework consists of four main stages: data acquisition, preprocessing, model development, and evaluation. The research workflow is illustrated in Figure 1.

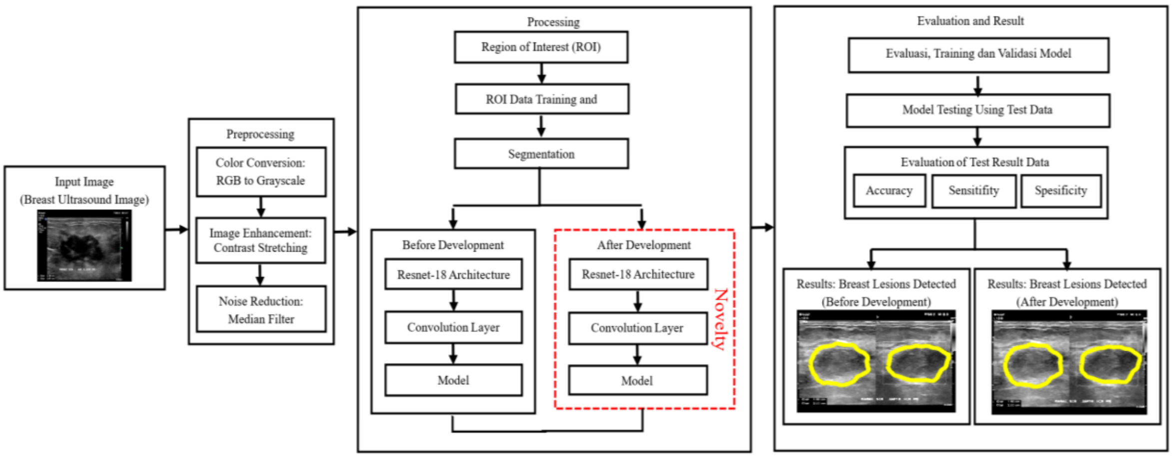


Figure 1. Research framework

2.2. Input image (breast ultrasound image)

The ultrasound images used in this study were collected from Prof. Dr. MA Hanifiah SM Batusangkar Hospital, obtained using a Philips Affiniti 50 G ultrasound machine. The dataset comprises 30 breast ultrasound images from patients diagnosed with suspected lesions. Ethical approval was obtained, and the images were anonymized before processing. The dataset includes various lesion types to ensure model robustness. The ultrasound image produced by the device is in the form of a digital file format with the extension *.jpg, in the form of an RGB image because the ultrasound image from a patient identified with a breast tumor is RGB, as in Figure 2.

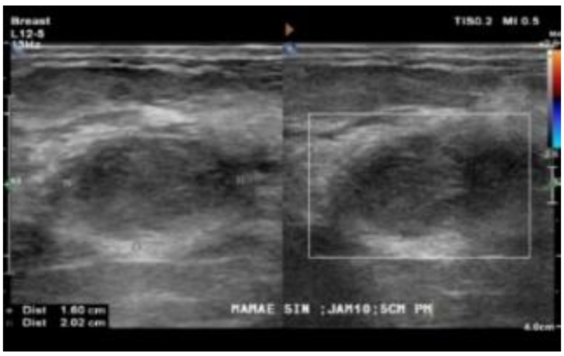


Figure 2. USG image of breast lesions with affiniti 50 G Philip Brand Machine at Prof. Dr. MA. Hanifiah SM Batusangkar Hospital

2.3. Preprocessing (color conversion (RGB to Grayscale), image enhancement, noise reduction)

Preprocessing is the initial step in data processing that aims to clean and format data before it is used in analysis. With preprocessing, data becomes more consistent and high quality, can increase the accuracy and effectiveness of the model built.

a) Color conversion (RGB to Grayscale). The image pre-processing stage is a research step carried out before the main processing process of the image being studied [13]. The main purpose of this stage is to provide the best and most accurate image data before the main processing process is carried out, so that after the main processing process the results obtained are better, more precise, and more accurate [14], [15]. In this study, the first image pre-processing stage was carried out, namely converting the input image color from RGB to Grayscale. This step is taken so that the resulting image only consists of white, black and gray.

b) Image enhancement. The second step in preprocessing is image enhancement, which is a step taken to clarify and sharpen certain characteristics/features of the image so that the image is easier to perceive or analyze more carefully [16]. In addition, the aim is to highlight a certain characteristic in the image or to improve the appearance aspect [17]. This step is carried out after the RGB to Grayscale color pre-processing stage for the USG Breast Lesion image quality improvement stage [18]. The method used to improve this image quality is the contrast stretching method. This contrast stretching method can be used to improve the quality of digital images related to lighting, namely by adjusting the brightness level and contrast of a digital image so that it can be used for the next pre-processing stage.

c) Noise reduction. The third step in preprocessing is image noise reduction, which is a step taken to clean or eliminate or reduce noise from the image so that the image is easier to perceive or analyze more carefully [19], [20]. In addition, the aim is to highlight a certain feature in the image or to improve the appearance aspect [21]. This step is carried out after the pre-processing stage of improving the image quality of the USG Breast Lesion image. The method used to improve image quality is the median filter method. This median filter method can be used to reduce image noise associated with black or white spots that are irregularly positioned and irregularly shaped.

2.4. Processing

The first step in the processing stage is the ROI. ROI in digital imagery refers to a specific area within an image that is of primary focus or interest in further analysis or processing [22]. ROI is used to limit our attention to the most relevant or interesting areas within an image, thereby reducing the time and resources required to analyze or process the entire image [23]. ROI can be a rectangle, square, circle, or other shape, depending on the needs and type of analysis being performed. ROI can be manually defined by the user by drawing a box or other shape around the area of interest, or in some cases, ROI can be determined using a computer algorithm that detects specific features or objects within the image. The second step in the processing stage is training and validating the ROI data. Training and validation data are two important stages in the process of developing a machine learning model. ROI refers to a specific part of the data that is the focus of the analysis. Training data is the data set used to train the machine learning model. At this stage, the model will learn patterns and relationships in the data to make predictions or make decisions. In the context of ROI, training data will include relevant data only from certain parts that are considered important or interesting to the ROI. Validation data is a separate data set used to evaluate the performance of the trained model. Validation data is not used during training, but is used to provide an unbiased assessment of the model’s ability to generalize to new data. In the context of ROI, validation data also focuses on specific parts that are considered important.

2.4.1. Segmentation

The third step in the processing stage is image segmentation. Image segmentation is the process of breaking down or grouping based on the characteristics of pixels in the image [24]. Image segmentation can be in the form of separating the foreground from the background or grouping pixel regions based on similarity in color or shape [25]. The purpose of segmentation is to facilitate image analysis by focusing on certain areas or objects. The image segmentation process is based on the similarity of color between the color of each pixel and the background color in the breast ultrasound image. Multi-thresholding is an image segmentation method where pixels in the image are divided into several classes or groups using more than one threshold value. The main purpose of multi-thresholding is to separate pixels into more than two groups, according to the level of pixel intensity. This is useful when the image has more than two types of objects or structures with different levels of intensity. At this stage the image is converted into a binary image using several thresholds, so that pixels can be classified into several segments according to the threshold used.

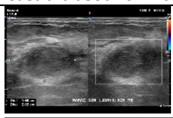
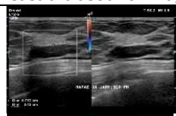
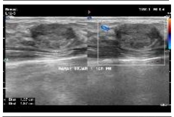
A. ResNet-18 architecture before and after development

ResNet-18 is part of the ResNet family developed to address common problems in deep neural networks, such as vanishing gradients and the difficulty of training very deep networks [26]. ResNet introduces the concept of residual learning, which allows layers in a neural network to learn to identify the difference (residual) between the input and the desired output, rather than trying to learn a direct map [27]. For more details, the complete structure of the ResNet-18 architecture can be seen in Table 1. The modified ResNet architecture with the addition of convolution layers can be seen in Table 2.

Table 1. ResNet-18 architecture before and after development

ResNet-18 architecture before develpoment		ResNet-18 architecture after develpoment	
Layer	Type	Layer	Type
1	Input layer	1	Input layer
2	Conv1 (*Lapisan Konvolusi Awal*)	2	Conv1 (*Lapisan Konvolusi Awal*)
3	Conv2_x (Residual Block 1)	3	Conv2_x (Residual Block 1)
4	Conv3_x (Residual Block 2)	4	Conv2D + ReLU (Added)
5	Conv4_x (Residual Block 3)	5	Conv3_x (Residual Block 2)
6	Conv5_x (Residual Block 4)	6	Conv2D + ReLU (Added)
7	Fully connected layer	7	Conv4_x (Residual Block 3)
8	Output layer	8	Conv2D + ReLU (Added)
		9	Conv5_x (Residual Block 4)
		10	Fully connected layer
		11	Output layer

Table 2. Input image

Patient	Breast ultrasound image	Patient	Breast ultrasound image	Patient	Breast ultrasound image
1		4		7	
2		5		8	
3		6			

In the before development ResNet-18 diagram, each stage consists of two convolutional layers followed by max pooling (in the encoder section) and upsampling (in the decoder section) with skip connections connecting the corresponding layers from the encoder to the decoder. In the After development ResNet-18 diagram, additional convolutional layers (labeled as "Conv2D + ReLU (Added)") are inserted at some stages to improve the feature extraction capability. The addition of convolutional layers in the ResNet-18 architecture is expected to improve the model's performance in breast lesion segmentation. Additional convolutional layers allow the model to learn more complex and diverse features. Each convolutional layer captures various patterns and textures from the input data. By adding more layers, the model can capture higher-level features, such as fine edges, texture patterns, and more complex shapes that may be present in breast lesion images. With more convolutional layers, the model can identify finer details in the image. This is especially important in medical segmentation, where small details can indicate the presence or characteristics of significant lesions. More detailed feature detection improves the model's ability to distinguish between normal tissue and tissue containing lesions.

B. Convolution layers ResNet-18

The convolution layer in ResNet-18 is the core of the architecture that processes the input image, the details of which are as follows:

- Initial convolution layer (Conv1): this is the first convolution layer that uses 64 filters with a large kernel (7x7) [28]. This kernel size is larger than usual to capture more context of the overall image at the beginning of the network. Padding of 3 is used to ensure the output has the desired dimension.

Stride 2 is used to reduce the image size. Followed by a max pooling operation that further reduces the spatial dimension.
- Residual blocks (Conv2_x, Conv3_x, Conv4_x, Conv5_x): each residual block consists of two convolution layers, with filters of size 3x3 [1]. Padding 1 is used to maintain the same output dimension as the input (except when stride is applied). Batch normalization is applied after each convolution to stabilize the output distribution. ReLU activation function is applied after normalization. These convolutional layers are designed to work with shortcut connections that allow the output of one block to be passed to the next block without modification (or with minor size adjustments if necessary).

C. Model ResNet-18

This sub-chapter will discuss in detail the ResNet-18 model, which is one of the most influential deep learning architectures. The ResNet-18 model as a whole is a deep learning model consisting of 18 layers, including convolutional layers and residual blocks. Some important points about this model can be explained as follows:
- Effectiveness of residual learning: this model utilizes shortcut connections to skip one or more convolutional layers [29]. This allows the network to more easily learn the identity function, which means that the network only needs to learn the difference (residual) between the input and the desired output.
- Training advantage: due to the residual architecture, ResNet-18 is easier to train even when the network is very deep [30]. This overcomes a common problem in traditional neural networks where the deeper the network, the harder it is to train it effectively due to vanishing gradients.
- Applications: ResNet-18 is commonly used for image classification tasks on large datasets such as ImageNet [31]. However, due to its flexible architecture, ResNet-18 can also be adapted for various other tasks such as object detection, image segmentation, and more. Using transfer learning, the model can be applied to smaller datasets and tailored for different applications.
- Efficiency: ResNet-18 is lighter and less complex than larger ResNet variants (such as ResNet-50 or ResNet-101), making it faster to train and more efficient in memory usage [32]. This makes it suitable for applications that require deep networks but are limited in computing resources.
- ResNet-18 offers a balance between depth and efficiency, making it a popular choice for many computer vision applications, especially in situations where resources are limited or speed is a priority [33].

D. Evaluation and detection

After creating the ResNet-18 architecture, convolution layers and models, the next step in this research is to evaluate, train and validate the model. Model training is done to train the resulting model. Model evaluation is done to find out whether the resulting model is in accordance with the research objectives. Model training is done to find out whether the resulting model can be applied to the case in this study. Model validation is done to find out whether the resulting model is correct (valid) or not. Testing the new ResNet-18 model using test data to detect breast lesions is the process of evaluating the performance of a segmentation model that has been trained using a new dataset that has never been seen by the model. This test data is used to assess the model’s generalization ability, namely its ability to provide accurate predictions on data that has never been used during the training and validation process. Here are the algorithm 1 in this testing process:

Algorithm 1. Model testing using test data
1. Test data preparation: the test data is a set of breast ultrasound images containing lesions, and this data is separate from the training and validation data. Make sure this data is representative and has the correct annotations.
2. Test data preprocessing: similar to the training and validation data, the test data needs to be preprocessed in the same way, such as converting to grayscale, normalizing, and data augmentation if necessary.
3. Prediction using the model: use the trained ResNet-18 model to perform segmentation predictions on the test data.
4. Thresholding: if the model generates probabilities, apply thresholding to obtain binary segment maps.
5. Performance evaluation: compare the model prediction results with the original annotations to calculate evaluation metrics such as accuracy, sensitivity, specificity, Intersection over Union (IoU), dice coefficient, etc.
6. Results visualization: visualize some examples of prediction results to visually check the segmentation quality.

Evaluation of test data against the ResNet-18 model for detecting breast lesions is a process in which the performance of a segmentation model is assessed using a dataset that was not previously seen during training (test data). This process involves the use of separate test data, consistent preprocessing, comprehensive evaluation metric measurements, and in-depth analysis of the results. With proper evaluation, we can objectively assess the performance of the model and make better decisions about its use in clinical contexts. There are three parameter values used to evaluate, train and validate the resulting model, namely accuracy, sensitivity and specificity values. Accuracy, sensitivity and specificity values are evaluation metrics used to assess the performance of a classification model, especially in the context of medical tasks such as lesion detection in breast ultrasound images.

3. RESULTS AND DISCUSSION

3.1. Input image result

In this research we use 30 USG breast lesion images. In this paper, we only displayed the 8 images for the sample of the result of this research. in the processing stage. We get the image from Prof. Dr. MA. Hanifiah SM Batusangkar Hospital. Table 3 illustrates the set of input images used in the current study, consisting of breast ultrasound images from eight patients. Each image serves as a vital component in the investigation aimed at analyzing and detecting potential breast abnormalities. The images are methodically organized into two columns for patients and their corresponding ultrasound scans, ensuring clarity and structured representation. These scans, derived from diverse cases, form the foundation of the analysis aimed at exploring diagnostic patterns and enhancing image-based assessment techniques. The arrangement provides an accessible reference for comparing the visual characteristics of each image, facilitating further interpretation in subsequent sections of the study.

Table 3. Pre-processing result

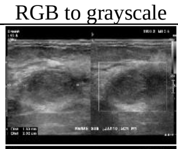
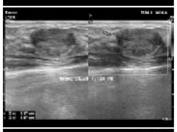
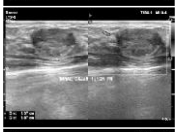
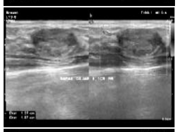
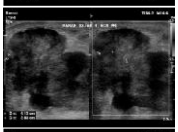
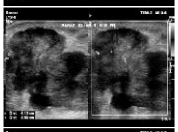
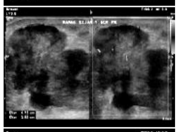
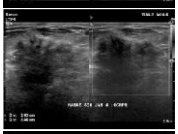
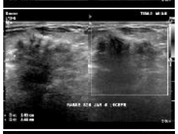
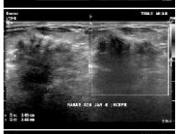
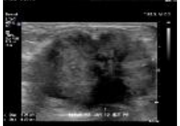
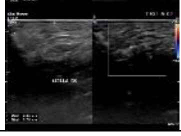
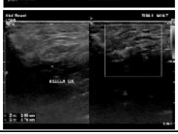
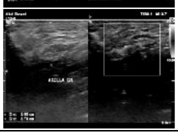
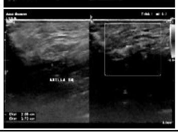
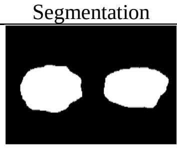
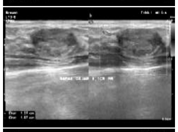
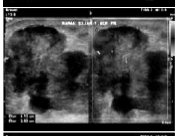
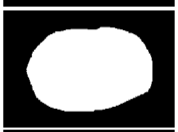
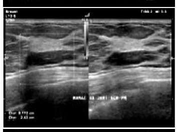
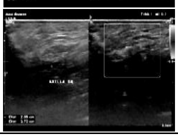
Patient	Breast ultrasound image	RGB to grayscale	Image enhancement	Noise reduction
1				
2				
3				
4				
5				
6				
7				
8				

Table 2 reveals the variability in ultrasound image features across different patients, which is pivotal for thorough diagnostic evaluations. Each scan demonstrates unique attributes that are essential for distinguishing between different types of breast tissue structures. These variations underscore the necessity of a comprehensive assessment method that considers diverse image characteristics, including texture, density, and boundary delineations. The inclusion of multiple patients' ultrasound images enriches the dataset, providing a more robust basis for developing and validating image analysis algorithms. This diverse representation supports the study's aim of ensuring that any proposed diagnostic or detection model can generalize effectively across different cases, ultimately contributing to more reliable and accurate diagnostic outcomes in breast health assessments.

3.2. Pre-processing result

The first image preprocessing in this study is a process carried out before the main process in the study. First preprocessing result is color conversion from RGB to grayscale. Then the second preprocessing result is image enhancement and after that the third preprocessing result ins noise reduction. Table 4 presents the comprehensive results of the pre-processing steps applied to the breast ultrasound images used in this study. The table systematically illustrates the progression of each patient's ultrasound image through various pre-processing stages, including conversion from RGB to grayscale, image enhancement, and noise reduction. These steps are critical in improving the quality and clarity of the input images, thereby facilitating more accurate analysis and interpretation in subsequent processing stages. The organization of the table allows for an easy comparison of images before and after each pre-processing technique, emphasizing the transformation and improvements at each step.

Table 4. Processing result

Patient	Noise reduction	ROI	Segmentation
1			
2			
3			
4			
5			
6			
7			
8			

A detailed analysis of Table 3 underscores the transformative impact of each pre-processing step on breast ultrasound images and the cumulative benefits they bring to the image analysis process. The initial step, RGB to grayscale conversion, is essential in simplifying the image data by eliminating color information while retaining critical intensity details that are significant for medical image analysis. This step reduces computational complexity and ensures that the focus is solely on the structural and textural details of the tissue. The subsequent image enhancement step serves as a vital process that amplifies the visual contrast and sharpness of the images. This enhancement reveals more defined boundaries and structures, making features such as lesions or tissue abnormalities more discernible. The consistent improvement in image clarity across all patient images in this step demonstrates the reliability and effectiveness of the enhancement algorithm used. The final stage, noise reduction, plays a significant role in refining the quality of the processed images by minimizing unwanted artifacts and background noise. This step ensures that essential image details are preserved while irrelevant visual information is suppressed. Overall, the progression illustrated in Table 3 indicates a systematic and comprehensive pre-processing approach that significantly boosts the interpretability and quality of breast ultrasound images. This multi-stage pre-processing pipeline is vital for achieving reliable image analysis outcomes, as it prepares the data in a way that maximizes the accuracy and efficiency of subsequent diagnostic algorithms. The enhanced clarity, reduced noise, and optimized contrast provided by these pre-processing steps lay the foundation for more robust and accurate feature extraction, which is critical in the early detection and analysis of breast tissue anomalies.

3.2.1. Processing result

The process of calculating the ROI value on an image is to calculate the value of the place to be analyzed on an image. In this study, it is the lesion area found in the breast USG image. Table 5 showcases the processing results obtained from the breast ultrasound images used in this study. The table is structured to display the outcomes at different stages of the image processing workflow, including noise reduction, ROI extraction, and segmentation. Each column in the table highlights a crucial step in the image analysis pipeline, demonstrating how the raw ultrasound images are progressively refined and analyzed to isolate significant regions for further diagnostic evaluation. This comprehensive view of the processing stages provides insight into the effectiveness of each method applied to enhance and segment the images accurately.

Table 5. Evaluation and result

Patient	ResNet-18 architecture					
	Before development			After development		
	Accuracy	Sensitifity	Specificity	Accuracy	Sensitifity	Specificity
1	0.96583	0.99316	0.95961	0.96675	0.99303	0.96078
2	0.98662	0.92924	0.99514	0.97428	0.80231	0.99980
3	0.97848	0.98371	0.97757	0.97992	0.98063	0.97979
4	0.95898	0.99072	0.92081	0.95870	0.98832	0.92309
5	0.86956	0.56590	0.99700	0.86389	0.54103	0.99938
6	0.97020	0.93963	0.99298	0.97009	0.93838	0.99372
7	0.97657	0.69218	0.99989	0.96691	0.56329	1.00000
8	0.96409	0.94203	0.97221	0.93566	0.79752	0.98652

A detailed examination of Table 4 reveals the step-by-step improvements and transformations that the breast ultrasound images undergo during the processing phase. The initial noise reduction column shows the impact of noise minimization techniques, which play a critical role in enhancing image clarity by removing background artifacts and irrelevant visual disturbances. This step ensures that subsequent analyses focus on the meaningful structures within the image without interference from noise, leading to more reliable feature extraction and interpretation. The ROI extraction column further demonstrates the ability of the processing techniques to identify and isolate specific areas within the images that are relevant for diagnostic purposes. The clear demarcation of these regions helps in narrowing the focus to potentially suspicious areas, which can streamline further analysis and aid in targeted medical assessments. The final column, segmentation, shows the segmented output where the regions of interest are delineated with precision. This step is essential in separating the significant tissue structures from the background, enabling a more detailed study of the identified regions. The segmentation results demonstrate how effectively the applied algorithm distinguishes between different tissue types, highlighting areas that may require closer medical evaluation. The uniformity and clarity in segmentation across all eight patient images underscore the reliability and adaptability of the segmentation process to various cases. This comprehensive processing approach is instrumental in supporting more accurate diagnosis and enhancing the overall effectiveness of image-based medical analysis.

3.2.2. Evaluation result

Model evaluation is calculating the quality of the resulting model. There are three parameters used, namely accuracy, sensitivity and specificity of the model created. Table 6 presents the evaluation results of the ResNet-18 architecture before and after further development, showcasing its performance on breast ultrasound images from eight patients. The table outlines key performance metrics, including accuracy, sensitivity, and specificity, for each patient. These metrics are essential for understanding the effectiveness of the model in correctly identifying and distinguishing between different tissue types within the images. The comparison between the pre- and post-development performance provides a clear view of the improvements achieved through the model enhancement process, offering insights into the robustness and reliability of the updated ResNet-18 architecture in medical image analysis [34], [35]. To calculate the accuracy, sensitivity, and specificity values of the ResNet-18 architecture before and after development, we use the formula below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ [36]} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \text{ [37]} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \text{ [26]} \quad (3)$$

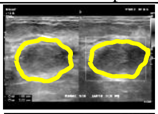
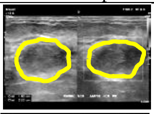
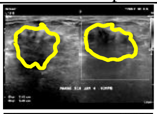
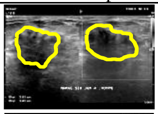
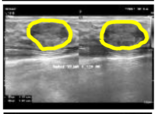
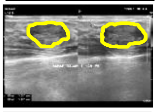
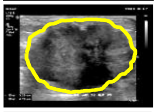
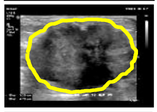
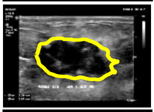
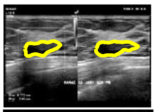
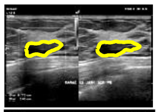
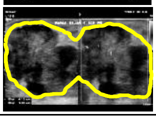
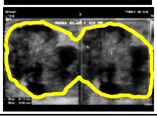
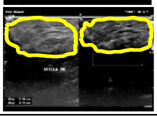
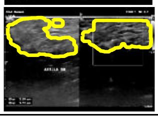
Where: true positive (TP): number of positive cases that were correctly detected., true negative (TN): number of negative cases that were correctly detected, false positive (FP): number of negative cases that were detected as positive (false positive), false negative (FN): number of positive cases that were detected as negative (false negative).

In this study, the evaluation of the model that has been created is carried out by measuring 3 parameters, namely accuracy value, sensitivity value and specificity value. Based on Table 5, it can be seen that the average value of the Res-Net architecture model evaluation before development is an accuracy of 0.96671, sensitivity is 0.98467 and specificity is 0.96314. While the average value of the Res-Net architecture model evaluation after development is an accuracy of 0.97093, sensitivity is 0.90056 and specificity is 0.97705. With these results, it can be seen that there is an increase in the accuracy value that occurs is 0.00422, a decrease in sensitivity value is 0.08411 and an increase in specificity value is 0.01391. With these results, it can be concluded that the model created using the ResNet-18 architecture development is better than the model before the ResNet-18 architecture development in detecting lesions in breast ultrasound images.

Detection is the final result achieved in this study. The detection in question is the detection of lesions in breast ultrasound images. Table 6 illustrates the lesion detection results on breast ultrasound images for eight patients using the ResNet-18 architecture, comparing the outputs before and after the model’s development. The table provides a visual representation of how the enhanced model identifies lesion areas, depicted with yellow outlines, on the breast ultrasound scans. This side-by-side comparison showcases the improvements in detection performance and outlines the refined capability of the model in accurately delineating lesion boundaries post-development. The objective is to assess the advancements made through model optimization and its impact on the quality of lesion detection, which is crucial for supporting medical diagnoses.

A thorough analysis of Table 6 reveals notable improvements in lesion detection after the development of the ResNet-18 architecture. Across all patients, the post-development results exhibit more precise and consistent lesion boundaries, emphasizing the enhancements achieved through model optimization. For example, the detection in patient 1 shows clearer and more accurate delineation of the lesion areas compared to the pre-development stage, suggesting a significant advancement in the model’s ability to accurately identify and outline abnormalities. Patients 3 and 4 display the most pronounced differences, with post-development images indicating more cohesive and continuous lesion outlines, reducing the occurrence of fragmented or incomplete boundaries observed in the pre-development results. This improvement is crucial for comprehensive lesion detection, as well-defined boundaries provide better guidance for further clinical evaluations and potential interventions. For some patients, such as patients 2 and 5, the differences between pre- and post-development detection results appear more subtle, indicating that while the model’s enhancements generally improved performance, the baseline detection was already robust. Nonetheless, the post-development results demonstrate greater consistency in lesion detection, even for these cases. Patient 8’s results show a more substantial enhancement, where the pre-development detection presented partially disjointed outlines, while the post-development model produced smoother and more defined boundaries. This suggests an increased reliability of the improved ResNet-18 model in handling complex lesion structures and differentiating between lesion and non-lesion areas more effectively. Overall, the comparative analysis provided in Table 6 underscores the effectiveness of the model's development in refining lesion detection capabilities.

Table 6. Detection result

Patient	Lesion detection using ResNet-18 architecture		Patient	Lesion detection using ResNet-18 architecture	
	Before development	After development		Before development	After development
1			5		
2			6		
3			7		
4			8		

3.2.3. Discussion result

The results of this study demonstrate the effectiveness of the developed ResNet-18 architecture in segmenting and identifying breast lesions in ultrasound images. The modified model achieved an average accuracy of 0.97093, sensitivity of 0.90056, and specificity of 0.97705, which indicates a significant improvement compared to the baseline model. These results suggest that adding convolutional layers and optimizing the architecture contributes to enhanced feature extraction, leading to improved lesion detection. The validation process, conducted by a radiology specialist, further reinforces the reliability of this approach, highlighting its potential application in clinical settings.

When compared to previous research on CNN-based lesion segmentation, such as Wang and Huang [9] and Das and Rana [10], our modified ResNet-18 model demonstrates competitive performance in terms of accuracy and specificity. Wang and Huang [9] utilized CDeep3M, which showed high segmentation accuracy, while Das and Rana [10] employed various ResNet architectures for lesion classification. Our approach builds upon these works by specifically enhancing ResNet-18 for segmentation, rather than classification, and optimizing the network to improve lesion delineation. A notable strength of this study is the use of real clinical data and validation by radiologists, ensuring practical relevance. However, a key limitation is the relatively small dataset size (30 images), which may affect the generalizability of the model. Additionally, the decrease in sensitivity compared to the baseline model suggests that further tuning is required to improve the detection of small or less distinct lesions. Unexpectedly, some cases showed a decline in sensitivity, likely due to variations in lesion texture and ultrasound noise levels, emphasizing the need for further robustness testing.

This study highlights the potential of deep learning models, particularly a customized ResNet-18, in assisting radiologists with automated lesion detection in breast ultrasound imaging. The improved segmentation accuracy suggests that this model could be integrated into diagnostic workflows to support early breast cancer detection. However, several questions remain unanswered. Future research should explore the impact of larger and more diverse datasets, the integration of attention mechanisms to enhance feature extraction, and the use of hybrid models combining ResNet-18 with transformer-based architectures. Additionally, exploring real-time deployment in clinical environments and testing on ultrasound images from different devices would provide further insights into the model's robustness and generalizability.

4. CONCLUSION

This study presents a modified ResNet-18 architecture for breast lesion segmentation in ultrasound images, addressing the challenges of noise, low contrast, and diagnostic variability. The proposed model achieved an average accuracy of 0.97093, sensitivity of 0.90056, and specificity of 0.97705, outperforming the baseline ResNet-18 architecture. These findings demonstrate the effectiveness of deep learning enhancements, particularly the addition of convolutional layers, in improving lesion detection accuracy.

Furthermore, validation by a radiology specialist reinforces the clinical relevance of the approach. Beyond improving lesion segmentation, this study highlights the potential of deep learning in assisting radiologists by reducing diagnostic subjectivity and supporting early breast cancer detection. However, some challenges remain. The relatively small dataset (30 ultrasound images) limits the generalizability of the model. Additionally, the slight decrease in sensitivity indicates the need for further tuning, particularly in cases with faint or irregular lesion boundaries. Future research should explore larger and more diverse datasets, as well as multi-modal learning that integrates ultrasound with other imaging modalities, such as mammography or MRI, to improve diagnostic accuracy. Another promising direction is the incorporation of transformer-based architectures to enhance feature representation. Additionally, deploying this model in real-time clinical settings and evaluating its usability for radiologists could provide further insights into practical applications. Ultimately, this research contributes to the advancement of AI-driven breast cancer diagnostics, offering a foundation for future innovations that aim to improve early detection, reduce misdiagnosis, and enhance patient outcomes. By refining deep learning methodologies and expanding clinical validation, AI-based breast lesion segmentation could become a reliable tool for medical professionals worldwide.

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BIOGRAPHIES OF AUTHORS

Silfia Andini is a dedicated lecturer in the Information System Study Program within the Faculty of Computer Science at Universitas Putra Indonesia YPTK Padang, Indonesia. She earned his bachelor's degree from Universitas Putra Indonesia YPTK Padang in the Information System program under the Faculty of Computer Science. Subsequently, she pursued a master's degree at UPI YPTK Padang. And right now, she continued a doctoral degree from UPI YPTK Padang. Currently, Silfia Andini is Head of Division Tracer Study from Universitas Putra Indonesia YPTK Padang. Silfia Andini unique identifier, Scopus ID, is 57202958818. Her research endeavors traverse diverse domains, with particular expertise in image processing and information system. Silfia welcomes communication and collaboration. She can be contacted at email: silfiaandini68@upiyptk.ac.id.

Sumijan is a dedicated lecturer and associate professor in the Information Technology (S3) Study Program within the Faculty of Computer Science at Universitas Putra Indonesia YPTK Padang, Indonesia. He earned his bachelor's degree from Universitas Putra Indonesia YPTK Padang in the Information System program under the Faculty of Computer Science. Subsequently, he pursued a Master's Degree at University Technology Malaysia (UTM). And he pursued a doctoral degree from Gunadarma University. Currently, Sumijan is Vice Rector I from Universitas Putra Indonesia YPTK Padang. Sumijan unique identifier, Scopus ID, is 57194787076. His research endeavors traverse diverse domains, with particular expertise in image processing, information system, and web design. Sumijan welcomes communication and collaboration. He can be contacted at email: sumijan@upiyptk.ac.id.

Iskandar Fitri holds the esteemed position of Professor at Universitas Putra Indonesia YPTK Padang, serving as a lecturer in the information technology doctorate program within the Faculty of Computer Science. His academic journey includes completing his undergraduate education (S1) in the electronics engineering study program at Universitas Nasional, followed by Master's (S2) and Doctoral (S3) degrees in the electronics engineering study program at Universitas Indonesia. Presently, he is recognized as a professor specializing in the microwave field at UPI YPTK Padang. Offering a diverse array of courses in the information technology study program, such as microwaves, research methodology, and artificial intelligence. He can be contacted at email: if@upiyptk.ac.id.