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Deep Learning for breast ultrasound analysis: a CNN-based tumor segmentation and classification for improved diagnosis

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Abstract
Breast ultrasound imaging is an essential tool in early breast cancer detection, yet its interpretation remains a challenging task due to image variability and noise. This study explores deep learning-based approaches for tumor segmentation and classification in breast ultrasound images, aiming to improve diagnostic accuracy and assist medical professionals in decision-making. An encoder-decoder architecture utilizing two pre-trained convolutional neural networks, DeepLabV3+ and U-Net, is proposed for the segmentation task. The segmentation performance was evaluated against a semi-automatic Local Graph Cut method using the Dice similarity coefficient. DeepLabV3+ achieved superior results compared to U-Net and Local Graph Cut.
Further, a deep learning framework incorporating MobileNetV2, VGG16, and EfficientNetB7 is employed for classification. The proposed approach is novel in its ability to extract and analyze features from both the lesion and the surrounding tissue, leveraging morphological operations (erosion and dilation) to improve the model's interpretability. Transfer learning allows for the optimization of classification performance. The system was trained and validated using the BUS-BRA and BUSI datasets. High accuracy and AUC scores were achieved for the classification of both benign and malignant lesions. These results confirm the effectiveness of CNNs in segmentation and classification tasks, highlighting the potential of deep learning for automated breast cancer diagnosis. The proposed methodology paves the way for more robust, interpretable, and clinically relevant AI-driven diagnostic tools in breast imaging.

Keywords: breast lesion, US images, convolutional neural networks, tumor segmentation, tumor classification.

1. INTRODUCTION

Breast cancer continues to be one of the leading causes of mortality among women worldwide, recording a significant number of new cases annually. Early diagnosis remains essential for increasing survival chances, which is why imaging screening methods are constantly being improved [1]. Although mammography is considered the gold standard in the early detection of tumors and microcalcifications, its effectiveness is diminished in the case of dense breast tissue and involves the use of ionizing radiation [2]. In this context, breast ultrasound (BUS) becomes an important alternative, offering the advantages of a non-invasive, radiation-free method that is more accessible and effective in detecting breast lesions, including in dense breast tissue. Due to the variability in tumor appearance and the high noise level specific to this imaging technique, the interpretation of ultrasound images is still challenging. Moreover, a large stack of images required for a complete breast evaluation significantly demands the attention and time of radiologists. For these reasons, automated systems for the segmentation and classification of breast lesion development, based on artificial intelligence, have become a priority.

The correct segmentation of breast tumors plays an essential role in the diagnostic process, allowing for a clear delineation of lesions from normal tissue. Initially, automatic segmentation methods were developed within computer-aided diagnostic (CAD) systems, aimed at supporting doctors in medical image analysis. With the advancement of AI, with a particular focus on convolutional neural networks (CNNs), significant progress has been made in medical image processing. CNNs, through their specific architecture that includes convolutional layers, pooling, and dense connections, have demonstrated a high capacity to learn complex representations of imaging data [3]. In this context, the use of encoder-decoder architectures, such as DeepLabV3+ and U-Net, has been explored for the automatic segmentation of tumors in breast ultrasound images. Their performances have been compared with semi-automated methods like Local Graph Cut [4-6]. Furthermore, for the classification of lesions as benign or malignant, we employed pre-trained networks including MobileNetV2, VGG16, and EfficientNetB7. To enhance feature extraction, morphological operations such as erosion and dilation were integrated, enabling the capture of meaningful features not only within the tumor regions but also in the surrounding tissues [7-9]. This approach can improve the interpretability of the models and refine the diagnostic process.

2. MATERIALS AND METHODS

To improve breast cancer diagnosis through ultrasound, this paper highlights recent advances in using CNNs to emphasize improvements in tumor segmentation and lesion classification. Currently, most studies on breast cancer classification use deep learning models and raw images or tumor features, neglecting important clinical stages such as feature optimization and image preprocessing. In this context, we propose the analysis of approaches based on pre-trained CNN networks for tumor segmentation and lesion classification to improve diagnostic accuracy.

The images used come from two public datasets: BUSI and BUS-BRA. The BUSI dataset [10] contains 780 8-bit grayscale ultrasound images (437 benign, 210 malignant, 133 normal), collected at Baheya Hospital in Egypt, accompanied by manual segmentations performed by radiologists. The BUS-BRA dataset [11] includes 1875 images from 1064 patients, classified into 1268 benign and 607 malignant images, confirmed by biopsy.

For the automatic segmentation of tumors in breast ultrasound images, two encoder-decoder architectures, DeepLabV3+ and U-Net, were explored to evaluate their effectiveness and accuracy in delineating tumor boundaries. The encoder-decoder architecture of the DeepLabV3+ network [12] uses Xception-65 as the backbone, atrous spatial pyramid pooling (ASPP) for extending the field of view, and a decoder with progressive upsampling to restore spatial details. The CNN U-Net network [13] has a symmetric architecture based on convolution and transposed convolution operations, with connections between the encoder and decoder for feature extraction and reconstruction. Also, a semi-automated Local Graph Cut method was used for segmentation and performance comparison. The segmentation performance was quantified using the DICE similarity coefficient, which provides an objective measure of the overlap between the automatically segmented regions and the manually annotated ground truth.

To enhance the detection of affected areas and facilitate more effective feature extraction, the raw images are preprocessed using morphological operations such as erosion and dilation [14-16]. Erosion reduces the tumor size by 10 pixels, allowing feature extraction only from the internal tumor tissue. Dilation expands the tumor region to include both the tumor and the peritumoral tissue within a radius of 10 pixels. These operations allow for the capture of relevant information about the internal structure of the tumor and how it interacts with the surrounding tissue, essential aspects for differentiating between benign and malignant lesions. Following this preprocessing, three versions were obtained for each image: the image retaining only the region of interest (ROI), the eroded image, and the dilated image. They were subsequently used in the classification process. The preprocessed images were fed into a suite of pre-trained CNN models (MobileNetV2, VGG16, and EfficientNetB7) for feature extraction and lesion classification. MobileNetV2 [17] is a model optimized for computational efficiency, using inverted residual blocks and depthwise separable convolutions. It is ideal for fast medical classification applications. VGG16 [18] is a classic deep network architecture, composed of 13 convolutional layers and 3 fully connected layers, known for its robustness in extracting complex visual features. EfficientNetB7 [19] is a model scaled simultaneously in depth, width, and resolution, capable of learning detailed features from images with reduced computational costs. The entire training process was carried out using transfer learning and fine-tuning. Initially, the models were pre-trained on the ImageNet database, which contains over a million labeled images.

3. RESULTS AND DISCUSSION

BUS images were segmented using the Local Graph Cut algorithm in the MATLAB environment, and the results were used as reference images, alongside the ground truth segmentations performed by radiologists. Figures 1 and 2 present examples of segmented images with analyzed convolutional networks. The results generated by DeepLabV3+ (Fig. 1, columns c and f) are more closely aligned with the reference images compared to those obtained with the U-Net network (Fig. 2, columns b and d).

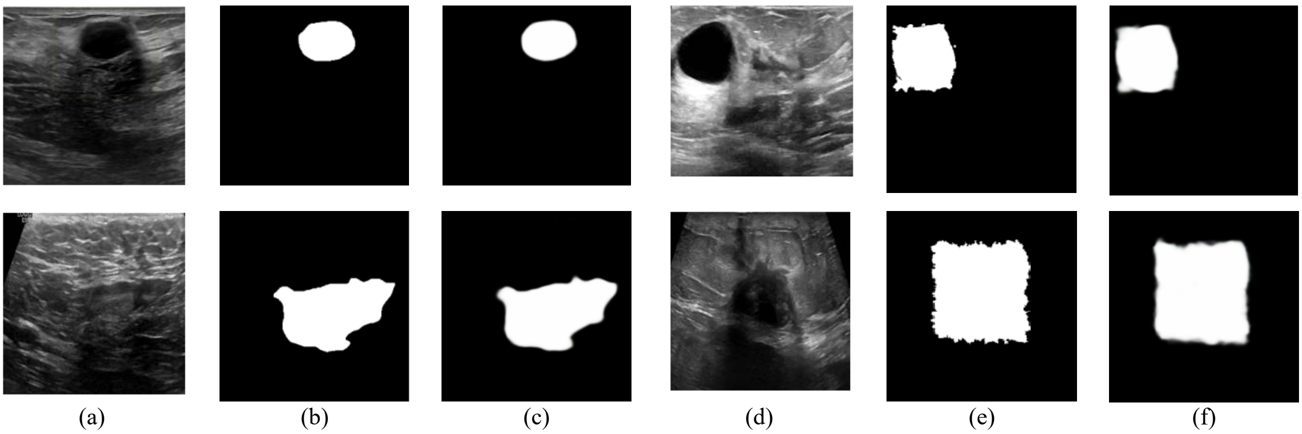


Fig. 1. Segmentation by DeepLabV3+ results. (a), (c) original raw image; (b) ground truth segmentation by radiologists; (c), (f) segmentation result by DeepLabV3+; (e) ground truth segmentation by Graph cut algorithm; First row: benign lesion; Second row: malignant lesion.

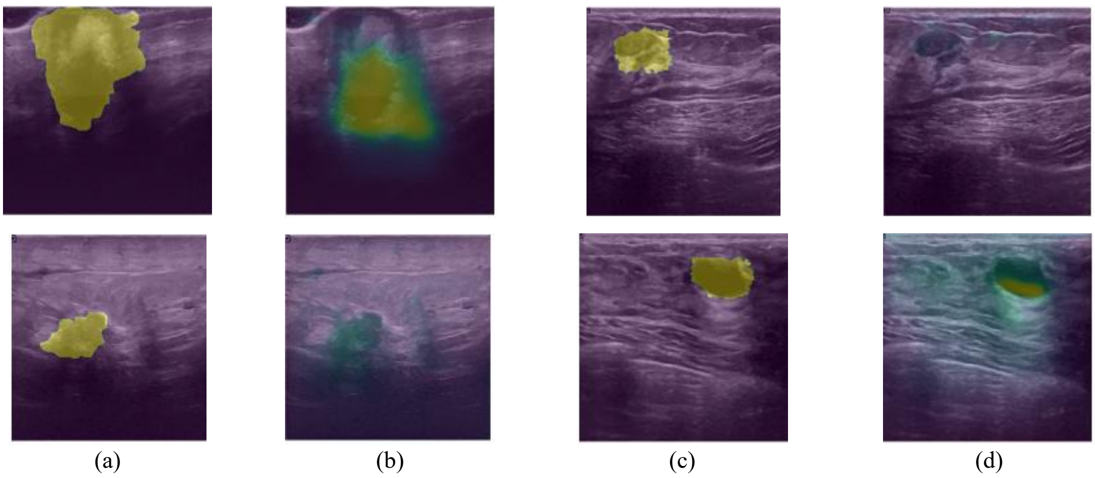
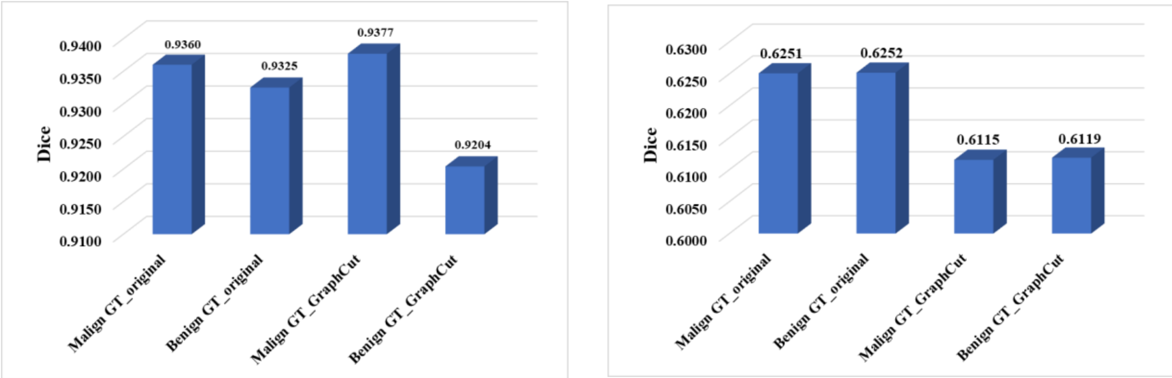


Fig. 2. U-Net segmentation results. (a) ground truth segmentation by radiologists; (b), (d) segmentation result by U-Net; (c) ground truth segmentation by Graph cut algorithm; First row: benign lesion; Second row: malignant lesion.

The Dice score values clearly highlight the differences in accuracy between the DeepLabV3+ and U-Net architectures, as illustrated in Fig. 3.

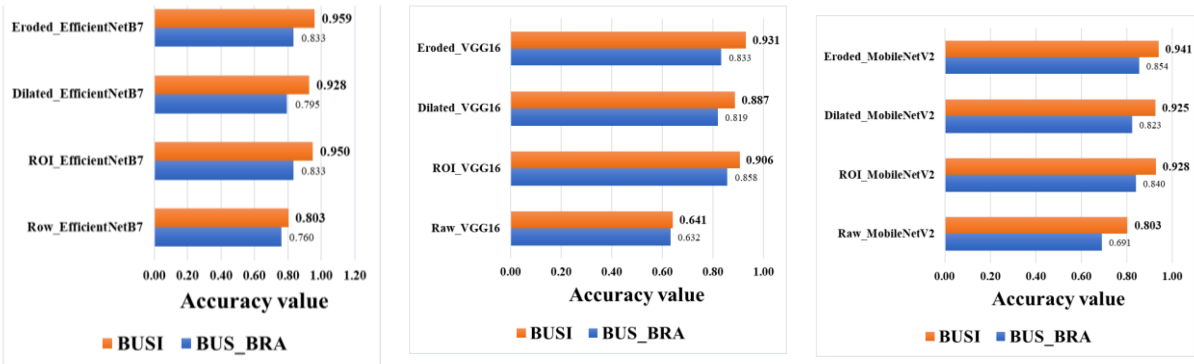


(a) (b)

Fig. 3. Segmentation performance for (a) DeepLabV3+; (b) U-Net.

DeepLabV3+ demonstrated superior performance when evaluated against both the original ground truth images provided by radiologists and the segmentations generated by the Local Graph Cut algorithm, thereby confirming its robustness and capacity to generalize across different reference standards. In contrast, U-Net exhibited significantly lower segmentation accuracy, particularly when the original radiologist annotations served as the reference, indicating its limited ability to accurately delineate lesion contours. When using segmentations obtained through the Local Graph Cut method as references, U-Net's performance declined further, underscoring its sensitivity to the quality and variability of training data. These findings suggest that DeepLabV3+ is more effective in capturing the morphological features of breast tumors, likely due to its advanced architecture incorporating atrous spatial pyramid pooling (ASPP) and a high-performance decoder. Although U-Net remains a widely used model in medical image segmentation, it appears less capable of handling the high structural variability characteristic of BUS images and is more dependent on high-quality training annotations.

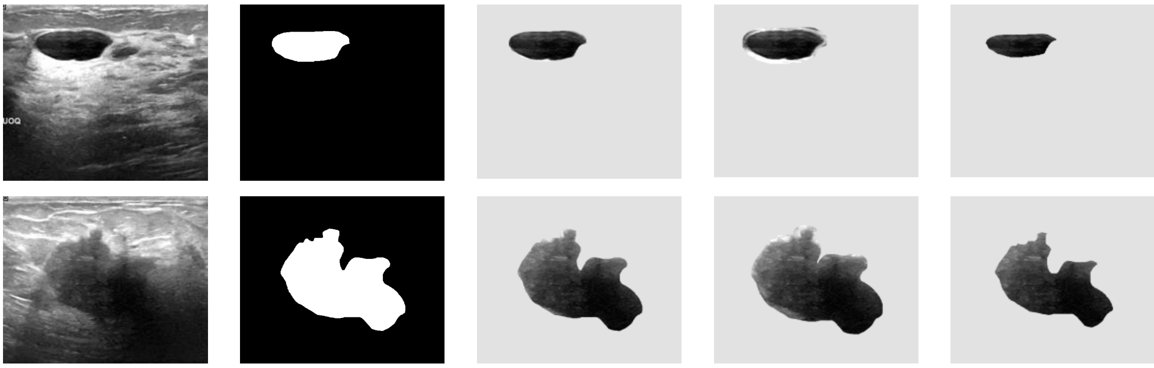
Additionally, lesion regions were classified as benign or malignant using three pre-trained networks—EfficientNetB7, VGG16, and MobileNetV2—via transfer learning. Figure 4 shows how the imaging characteristics of the lesion and surrounding tissues influence classification performance, using accuracy as the metric.



(a) (b) (c)

Fig. 4. Classification performance for (a) EfficientNetB7; (b) VGG16; (c) MobilNetV2.

A comparative analysis of the accuracy across the three pre-trained networks reveals that EfficientNetB7 consistently outperforms the others across all types of processed images, achieving the highest accuracy particularly on eroded images. MobileNetV2 also demonstrated strong performance on eroded images, indicating its robustness in feature extraction following preprocessing. Conversely, VGG16 showed more modest results, especially when applied to raw images, where it attained the lowest accuracy among the three models. In all scenarios, preprocessing of images significantly improved classification performance compared to using raw images, underscoring the beneficial impact of image enhancement techniques. These experimental findings emphasize the critical role of integrating segmentation and morphological preprocessing steps to enhance breast tumor classification accuracy (Fig. 5). Segmentation plays a vital role by isolating the tumor region, effectively reducing background noise, and enabling deep learning models to focus on relevant features for distinguishing benign from malignant lesions. Erosion operations facilitated the extraction of fine internal details within the tumor, which are valuable for identifying malignancy indicators. Meanwhile, dilation operations accentuated features in adjacent peritumoral tissues, providing critical information for evaluating invasive tumors. Collectively, these preprocessing strategies enhance the morphological context and improve the overall performance of the classification models.



Original raw image   Ground truth image   ROI image   Dilatated image   Eroded image

Fig. 5. Morphological pre-processing results.
First row: benign lesion; Second row: malignant lesion.

Another important aspect of the experiment pertains to the application of transfer learning techniques, which played a significant role in reducing the amount of training data required and accelerating the convergence of the pre-trained CNN models. This approach enabled efficient utilization of existing knowledge embedded in the models, thereby enhancing training efficiency and performance. We also observed that the models' responses to different types of preprocessing varied, suggesting that an ensemble approach, based on combining the results of multiple classifiers, could lead to further improvements in overall performance.

4. CONCLUSIONS

The comparative analysis of segmentation and classification approaches underscores that deep learning-based models, when trained on properly preprocessed ultrasound images, can attain performance levels comparable to, or even surpassing, human evaluations, particularly in screening and initial sorting tasks. Encoder-decoder network architectures have demonstrated effectiveness in supporting breast cancer diagnosis by providing precise tumor segmentations in ultrasound images, thereby facilitating more accurate assessments. A key insight from the study is the substantial impact of preprocessing on model performance. The use of eroded and dilated images notably enhanced the networks' capacity to learn salient features, both within the tumor regions and in the peritumoral tissues. This morphological preprocessing enables the models to better capture critical details and improve diagnostic reliability. In conclusion, for automatic segmentation of breast tumors in ultrasound images, DeepLabV3+ offers superior accuracy and robustness compared to U-Net, regardless of the ground truth standard employed.

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References

1. Global cancer burden growing, amidst mounting need for services. https://www.who.int/news/item/01-02-2024-global-cancer-burden-growing--amidst-mounting-need-for-services, Accessed on 5.06.2024.
2. Baccouche A., Garcia-Zapirain B., Castillo Olea C., Elmaghraby A.S., Connected-UNets: a deep learning architecture for breast mass segmentation, npj Breast Cancer 7(1) (2021) 1-12.
3. Iman M., Arabnia H. R., Rasheed K. A review of deep transfer learning and recent advancements, Technologies 11(2) (2023) 40.
4. El Adoui M., Mahmoudi S.A., Larhmam M.A., Benjelloun M., MRI Breast Tumor Segmentation Using Different Encoder and Decoder CNN Architectures, Computers 8(3) **(**2019) 52.
5. Gómez-Flores W., Coelho de Albuquerque Pereira W., A comparative study of pre-trained convolutional neural networks for semantic segmentation of breast tumors in ultrasound, *Computers in Biology and Medicine* 126 (2020) 104036.
6. Vakanski A., Xian M., Freer P.E., Attention-Enriched Deep Learning Model for Breast Tumor Segmentation in Ultrasound Images, Ultrasound in Medicine & Biology 46(10) (2020) 2819–33.
7. Dash P.B., Behera H.S., Senapati M.R., Das A.K., Nayak B., Vimal S., Pelusi D., Deep Learning Based Framework for Breast Cancer Mammography Classification Using Resnet50, Computational Intelligence in Pattern Recognition 480 (2022) 625–633.
8. Heikal A., El-Ghamry A., Elmougy S., Rashad M.Z., Fine tuning deep learning models for breast tumor classification, Sci Rep 14(1) (2024) 10753.
9. Roslidar R., Saddami K., Arnia F., Syukri M., Munadi K., A Study of Fine-Tuning CNN Models Based on Thermal Imaging for Breast Cancer Classification, IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom) (2019) 77–81.
10. Al-Dhabyani W., Gomaa M., Khaled H., Fahmy A., Dataset of breast ultrasound images, Data in Brief 28 (2020) 104863.
11. Gómez-Flores, W., Gregorio-Calas, M.J., Pereira, W.C. de A., BUS-BRA: A Breast Ultrasound Dataset for Assessing Computer-aided Diagnosis Systems, Medical Physics (2023).
12. Yan Y., Liu Y., Wu Y., Zhang H., Zhang Y., Meng L., Accurate segmentation of breast tumors using AE U-net with HDC model in ultrasound images, Biomedical Signal Processing and Control 72 (2022) 103299.
13. Ibtehaz N., Rahman M.S., MultiResUNet : Rethinking the U-Net architecture for multimodal biomedical image segmentation, Neural Networks 121 (2020) 74–87.
14. Moradi B., Gity M., Etesam F., Borhani A., Ahmadinejad N., Kazemi M.A., Correlation of apparent diffusion coefficient values and peritumoral edema with pathologic biomarkers in patients with breast cancer, Clinical Imaging 68 (2020) 242–248.
15. Park, N. J.-Y. *et al*. Peritumoral edema in breast cancer at preoperative MRI: an interpretative study with histopathological review toward understanding tumor microenvironment, Sci Rep 11(1) (2021) 12992.
16. Shin, H.J. *et al*. Characterization of tumor and adjacent peritumoral stroma in patients with breast cancer using high-resolution diffusion-weighted imaging: Correlation with pathologic biomarkers, European Journal of Radiology 85(5) (2016) 1004–1011.
17. Sahu A., Das P.K., Meher S., An efficient deep learning scheme to detect breast cancer using mammogram and ultrasound breast images, Biomedical Signal Processing and Control 87 (2024) 105377.
18. Liu Z., Peng J., Guo X., Chen S., Liu L., Breast cancer classification method based on improved VGG16 using mammography images, Journal of Radiation Research and Applied Sciences 17(2) (2024) 100885.
19. Purnama M.M.R. *et al*, Classification of BI-RADS using convolutional neural network and effecientNet-B7, International Journal of Science and Research Archive 11(1) (2024) 1022–1028.