Segmentation of Mammography Breast Images using Automatic Segmen Adversarial Network with Unet Neural Networks

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Abstract
Breast cancer is the most dangerous and deadly form of cancer. Initial detection of breast cancer can significantly improve treatment effectiveness. The second most common cancer among Indian women in rural areas. Early detection of symptoms and signs is the most important technique to effectively treat breast cancer, as it enhances the odds of receiving an earlier, more specialist care. As a result, it has the possible to significantly improve survival odds by delaying or entirely eliminating cancer. Mammography is a high-resolution radiography technique that is an important factor in avoiding and diagnosing cancer at an early stage. Automatic segmentation of the breast part using Mammography pictures can help reduce the area available for cancer search while also saving time and effort compared to manual segmentation. Autoencoder-like convolutional and deconvolutional neural networks (CN-DCNN) were utilised in previous studies to automatically segment the breast area in Mammography pictures. We present Automatic SegmenAN, a unique end-to-end adversarial neural network for the job of medical image segmentation, in this paper. Because image segmentation necessitates extensive, pixel-level labelling, a standard GAN's discriminator's single scalar real/fake output may be inefficient in providing steady and appropriate gradient feedback to the networks. Instead of utilising a fully convolutional neural network as the segmentor, we suggested a new adversarial critic network with a multi-scale L1 loss function to force the critic and segmentor to learn both global and local attributes that collect long- and short-range spatial relations among pixels. We demonstrate that an Automatic SegmenAN perspective is more up to date and reliable for segmentation tasks than the state-of-the-art U-net segmentation technique.

Keywords: *Convolution neural network; SegmenAN; deep learning; medical image segmentation; computer aided diagnosis; DC-UNet*

1.INTRODUCTION

Breast cancer is the world's second most frequent cancer and one of the maximum frequent malignancies in women. Breast cancer accounts for 30 percent of all incident cancer cases reported in women in both developed and developing countries, according to the International Agency for Cancer Research (IARC) [1]. It is the important reason of cancer deaths between women in poor countries. It kills more people than any other disease and is the seersarial Networkcond important reason of cancer death among women in developed countries, following lung cancer. [1]. Mammography has played a significant role in breast cancer screening and has resulted in a reduction in disease mortality. The fundamental purpose of these investigations is to appropriately detect cancer cells. Incorrect detections in mammography pictures due to radiologists' errors of diagnosis analysis due to physician fatigue or optical illusion prompted the search for a way to automate the process. In 10 to 30% of cases, radiologists fail to identify tissue. Automatic segmentation algorithms were employed to eliminate human errors in segmentation. One of the most important phases in image processing is segmentation. For better analysis, it separates digital images into various sections. Patients with breast cancer who are diagnosed early have a better chance of surviving [2]. Mammography has been the best perfect for breast cancer screening, despite its efficacy in lowering mortality rates [3], and its performance is determined by breast density. Mammography also exposes women to higher levels of radiation and is less effective in younger women [4] [5]. Thermography, on the other hand, is non-ionizing, non-contact, and low-cost, making it a feasible non-invasive breast cancer screening alternative to mammography [5]. Modern thermography-based analysis methods, according to research, are capable of accurately diagnosing breast cancer [6].

In this paper, we recommend Automatic SegmenAN, a novel end-to-end Adversarial Network planning for semantic segmentation with a multi-scale L1 loss function. The training technique for SegmenAN is analogous to a two-player min-max game in which a segmentor network (S) and a critic network (C) are qualified in an irregular way to minimise and maximise an objective function, as inspired by the original GAN [9].

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However, there are numerous fundamental changes between our SegmenAN and the original GAN that make SegmenAN far superior for picture segmentation.

SegmenAN may right absorb spatial pixel needs at many scales by training the complete system end-to-end with back propagation and alternate the optimization of S and C. Our SegmenAN network uses a new multi-scale loss to enforce the learning of hierarchical features in a more easy and efficient manner than prior methods that used multi-scale multi-path CNNs to learn hierarchical features [7]. Extensive testing shows that the proposed SegmenAN delivers comparable or superior results than state-of-the-art CNN-based architectures, such as U-net.

SegmenAN has the possible to be a better strategy to segmenting infrared breast images than our previous model, according to the findings.

2.MAMMOGRAPHY IMAGES

Mammography is a form of radiography that is designed exclusively for women's breasts. Its goal is to distinguish anomalies as soon as possible, such as a palpable nodule, skin changes, discharge, inflammation, and so on. [7]. The attenuation of an X-ray beam as it permits over the various breast tissues creates the mammography image. The makeup of the tissues through which this beam passes determines its attenuation the most. The grease is classified as a transparent radio zone due to its low physical density. As a result, it appears very dark on a mammography. The clear radio zones correspond to fibro glandular flesh and calcium, which are essential components of breast tumours [7]. Incidences are a set of directions in which mammography is frequently done. The easiest method to see as much breast tissue as possible on an X-ray plate is to stretch it out as much as possible. Depending on the part of the breast is being examined, different implications are used. The most widely used occurrences are the occurrence of the face, also known as Cranio Caudal (CC), the oblique outside incidence, also known as Medio Lateral Oblique (MLO), and the incidence of profile (Figure 1).

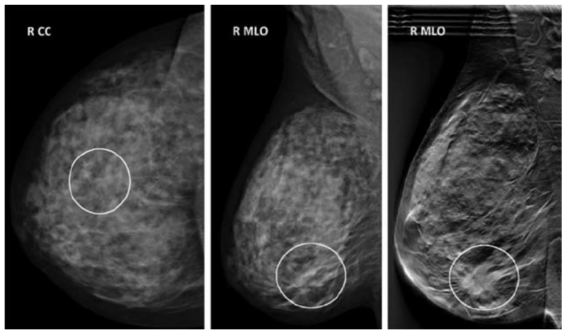


Fig.1.Different directions of mammography acquisition

3.RELATED WORK

Narinder Singh [2022] [8] proposes an effective outstanding cross spatial attention guided beginning U-Net (RCA-I Unet) typical with low training parameters for tumour segmentation using breast ultrasound imagery to improve segmentation performance of shifting tumour sizes. On double widely accessible datasets, the proposed model's segmentation performance is validated using traditional segmentation evaluation criteria, and it outperforms previous state-of-the-art segmentation models.

Arindam Chaudhuri [2021] [9] was announced as the winner. Modified Fast Region-based CNN (Hierarchical Fast R-CNN) and Hierarchical Fast Region-based CNN (Hierarchical Fast R-CNN) (Mod Fast R-CNN) Deep CNNs are combined with a modified Fast region-based CNN (HMod Fast R-CNN) that takes category hierarchy into account. To distinguish the easy classes, coarse classifiers are utilised. The tough classes are classified using fine classifiers. On the MS-COCO, PASCAL VOC 2007, and VOC 2012 datasets, the proposed network outperforms alternative object detectors in terms of performance. The HMod Fast R-CNN architecture can have more than five levels. This, in theory, will improve experimental findings in terms of item detection accuracy while also speeding up the overall procedure.

Lazaros Tsochatzidis [2021] [10] present a comprehensive analysis of current state-of-the-art semantic picture segmentation algorithms learning based methods that can work in real time to facilitate autonomous driving scenarios. To that end, the provided overview focuses on the presentation of all strategies that reduce inference time, as well as an analysis of existing procedures based on their end-to-end functionality and a comparison study using a uniform evaluation framework.

Wessam M. Salama [2021] [11] presents a new context for breast cancer picture segmentation and classification. The Digital Database for Screening Mammography (DDSM), the Mammographic Image Analysis Society (MIAS), and the Curated Breast Imaging Subset of DDSM (CBIS-DDSM) use models such InceptionV3, DenseNet121, ResNet50, VGG16, and Mobile-NetV2 to classify images as benign or malignant. This paper covers all aspects of convolutional neural networks (CNNs) from start to finish. The recommended technique of employing data mining algorithms with a modified U-Net model and InceptionV3 produces the best results with the DDSM dataset. This has a 98.87 percent accuracy, 98.88 percent AUC, 98.98 percent sensitivity, 98.79 percent precision, 97.99 percent F1 score, and 1.2134 second processing time on DDSM datasets.

Rashmi R [2022] [12] discusses a number of traditional and deep learning-based algorithms for analysing breast cancer histopathology pictures in her review study. First, the features of histologic breast cancer images are discussed. There is a comprehensive description of the many potential areas of interest, which is essential for the creation of Computer-Aided Diagnostic systems. They give a rundown of current developments and decisions in the arena of medicinal image processing. Finally, a comprehensive assessment of the several challenges that BCHI analysis entails, as well as the future scope, is provided.

The Connected-UNets concept, proposed by Asma Baccouche [2021] [13], employs added improved skip connections to join two UNets. In the two standard UNets, they adopt Atrous Spatial Pyramid Pooling (ASPP) to emphasise additional context inside the encoder–decoder network design. The proposed design is also used in the Attention UNet (AUNet) and the Residual UNet (RUNet) (ResUNet). Two public datasets, the Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM) and INbreast, as well as a private dataset, were used to test the proposed designs. Experiments were also conducted among two unmatched datasets utilising extra synthetic data to supplement and improve the pictures exploitation the cycle-consistent Generative Adversarial Network (Cycle GAN) model. With a high Dice notch of 89.51 percent, 95.28 percent, and 95.88 percent, respectively, and an Intersection over Union (IoU) score of 80.02 percent, 91.03 percent, and 92.27 percent on CBIS-DDSM, INbreast, and the private dataset, qualitative and quantitative outcomes establish that the planned planning can attain healthier involuntary mass segmentation.

According to Jennifer K. Chukwu [2021] [14], an android programme for breast cancer categorization was constructed using a deep learning approach based on a Convolutional Neural Network (CNN). The programme is designed to tell the alteration among benign and aggressive breast tumours. Experiments on histopathological pictures using the BreakHis dataset revealed that the DenseNet CNN typical had high processing performances with 96 percent accuracy in the breast cancer classification test when compared to state-of-the-art algorithms.

4.PROPOSED APPROACH

Our experiments have a major goal: to help detect early signs of breast cancer, which can help lower women's death rates and considerably increase their chances of surviving by delivering individualised, effective, and efficient treatment. Our present work focuses in this interpretation, and it may be broken down into the following steps: Pre-processing, segmentation, and classification are all performed on mammographic pictures. Following picture quality improvement, the next step is to extract the ROI, i.e., the region containing the microcalcifications identified in prior work for image segmentation methodologies, hence the name segmentation phase. The goal of segmentation is to make an image's representation meaningful and easy to analyse. The most basic definition of segmentation is the dividing of a picture into different sections based on some criteria in order to recognise and find objects and boundaries in a specific environment. Tissues, structures, lesions, and other medical imagery can be used.

4.1Overview of U-Net Architecture

U-Net uses convolutional layers to achieve semantic segmentation. The symmetric network is made up of 2 portions: an encoder and a decoder. The encoder is based on a convolutional network's design, which extracts spatial data from images. In a convolution block, two 3×3 convolution operations are followed by a max-pooling operation with a pooling size of 2×2 and stride of 2. This block is frequent 4 times, with the number of filters in the convolution doubling after each down sampling. Finally, the encoder and decoder are linked by a series of two 3× 3 convolution processes. The decoder receives the encoder's information and constructs the segmentation map. The decoder utilises a 2× 2 transposed convolution process. After that, a series of two 3 ×3 convolution processes are conducted once more. As the encoder, this process of upsampling and convolution layer processes is repeated four times, reducing the number of filters at every iteration.

Finally, the last segmentation map is generated using a 1× 1 convolution process. Except for the last layer, which employs a 1× 1 convolutional layer and Sigmoid activation function, all convolutional layers in the U-Net use the ReLU (Rectified Linear Unit) as a beginning purpose.

A skip link is also used in the U-Net design to convey the encoder's output to the decoder. The production of the up-sampling process is concatenated with these feature maps, and the concatenated feature map is spread to the subsequent layers. The skip connections allow the network to recover spatial details that have been lost as a result of pooling processes. In Figure 2, the U-Net architecture is depicted.

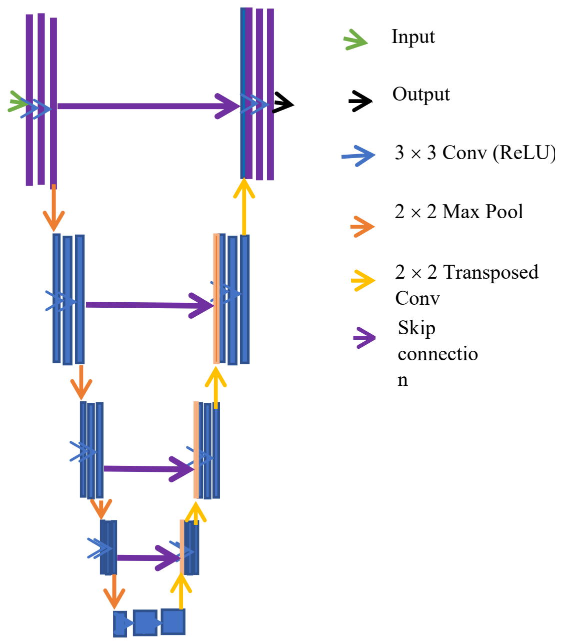


Fig. 2. Architecture of U-Net

4.2DualC-UNet

U-Net is a remarkable and widely used architecture in medical image segmentation, and the SegmenAN can produce significantly better results than the U-Net due to its ability to give varied scaling characteristics. However, the SegmenAN fails to perform effectively in several particularly difficult medical picture scenarios, like as fuzzy objects and background interference (part of medical equipment). The purpose of the MR block is to give different-scale characteristics to aid in the separation of objects from the entire image. As a result, we tweaked the SegmenAN block to make it more functional. This concept inspired us to create a new enhancement block.

When we examine the outcomes of segmentation using the standard UNet and SegmenAN, we can see that different-scale features considerably aid segmentation. As a result, we anticipated that if we could give more different-scale (more effective) features, the most difficult jobs would be accomplished. We discovered a simple residual connection in the SegmenAN block based on this assumption. As the author points out, the residual link here just adds a few extra spatial elements, which may be insufficient for some of the most difficult tasks. The potential of the different-scale feature in medical image segmentation has already been demonstrated. To address the issue of insufficient spatial features, we used a three-layer convolutional layer sequence to replace the residual connection in the SegmenAN block. As illustrated in Fig. 3, we named this block Dual Channel.

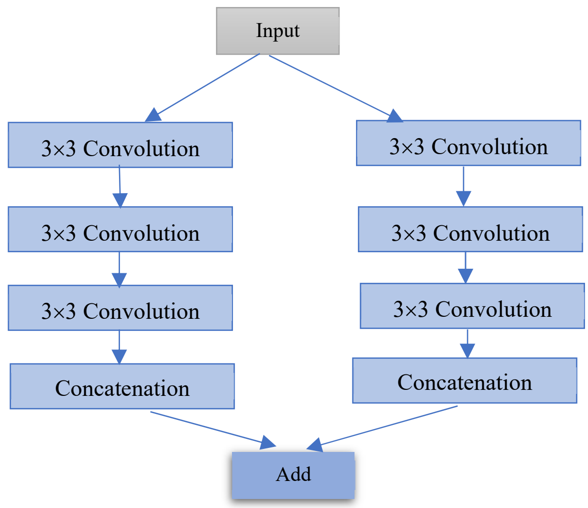


Fig 3. Dual-Channel block

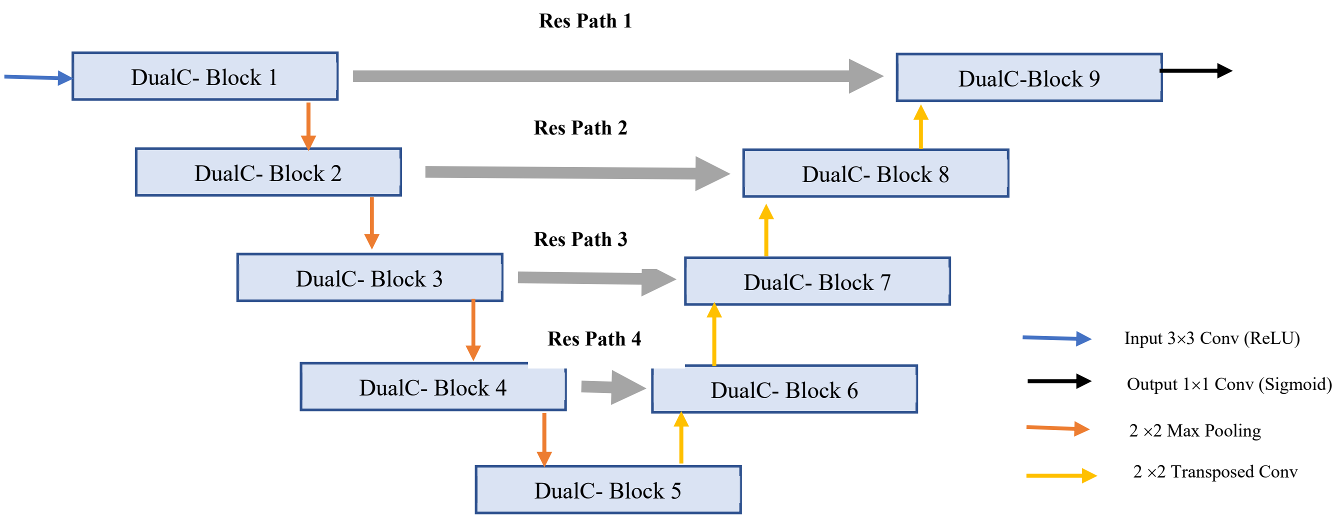


Fig. 4. Architecture of DualC-UNet

4.3. PROPOSED WORK

The proposed SegmenAN is finished up of two pieces, as exposed in Figure 5, the segmentor network S and the critic network C. The segmentor is a completely convolutional encoder-decoder system that uses input images to build a probability label map. Image features masked by ground truth name mapping and original images masked by projected label maps from S are supplied into the critic network. The S and C networks are qualified in a counter-intuitive manner: S is taught to minimise our suggested multi-scale L1 loss, while C is trained to maximise the same loss function.

4.4The multi-scale L1 loss

The objective loss function of traditional GANs [9] is defined as:

$$minmaxL(X_r, X_g) = E_{xr\sim X_r}[\log(D(x_r))] + E_{xg\sim X_g}\left[1 - \log\left(D(x_g)\right)\right] \quad (1)$$

g is a random participation for the producer derived from a probability distribution, and x is the real picture from an unidentified circulation X_r in this impartial purpose (such as Gaussian) The parameters for the generator and discriminator in GAN are X_g. X_r and X_g, respectively. The multi-scale objective loss function L is specified as follows in our proposed SegmenAN for a dataset with N training pictures x_n and accompanying ground truth label mappings y_n:

$$\min maxL(\theta_S, \theta_C) = \frac{1}{N}\sum_{n=1}^{N} \ell_{mse}(f_C(x_n \circ S(x_n)), f_C(x_n \circ y_n)) \ (2)$$

where ℓ_{mse} is the Mean Absolute Error (MAE) or L_1 distance; $x_n \circ S(x_n))$ is the input picture disguised by segment to predicted label map (i.e., pixel-wise multiplication of predicted label map and original image); $x_n \circ y_n$ is the input image masked by its ground truth label map (i.e., pixel-wise increase of ground truth label map and normal picture); and $f_C(x)$ represents the hierarchical features extracted from image x by the critic network. More specifically, the ℓ_{mse} function is defined as:

$$\ell_{mse}(f_C(x), f_C(x')) = \frac{1}{L}\sum_{i=1}^{L} \| f_C^2(x) - f_C^2(x')\|_1 \quad (3)$$

where L is the total number of layers (i.e., scales) in the critic network, and $f_C^i(x)$ is the extracted feature map of image x at the ith layer of C.

4.5.SegmenAN Architecture

Segmentor: For the segmentor S network, we adopt a fully convolutional encoder-decoder structure. For down sampling, we use a convolutional layer with kernel size 4x4 and stride 2, while for up sampling, we use a factor of 2 image resize layer and a convolutional layer with kernel size 3× 3 stride 1. We also follow the U-net and add skip connections between the encoder and decoder's appropriate layers.

Critic: The critic C is structured similarly to the decoder in S. The multi-scale L1 loss is computed using hierarchical features taken from various levels of C. Using these hierarchical characteristics, such as pixel-level features, low-level (e.g., super pixels) features, and middle-level (e.g., patches) features, this technique may capture long- and short-range spatial interactions between pixels. Figure 5 shows other information, such as activation layers (e.g., leaky ReLU), batch normalisation layers, and total of feature maps utilised in each convolutional layer.

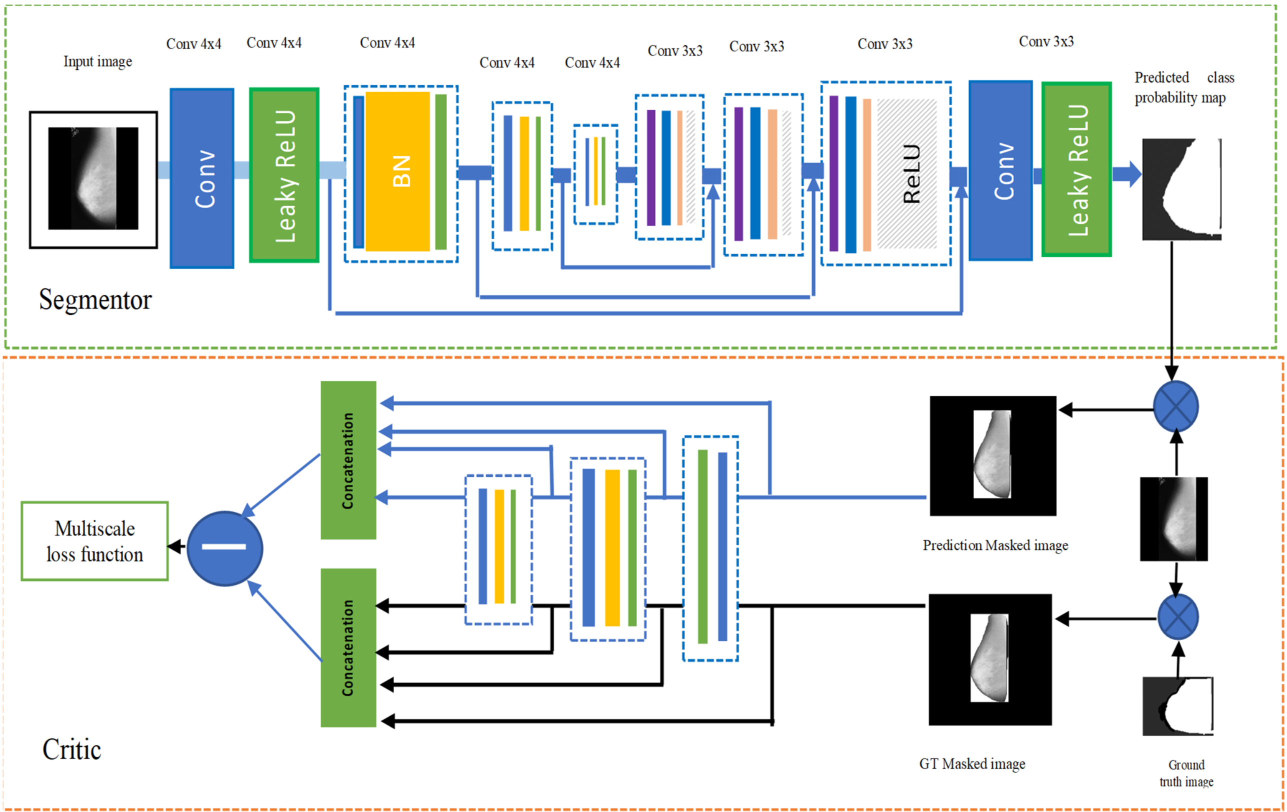


Fig. 5 The proposed SegmenAN architecture, which includes critic networks and segmentor. Encoding is accomplished using 4 x 4 convolutional layers with pace 2 (S2) and the appropriate number of feature maps (e.g., N64), while decoding is accomplished using image resize layers with a factor of 2 (R2) and 3x3 convolutional layers with stride 1. Masked images are created by multiplying a label map with (the various channels of) an input image pixel by pixel. Although only one label map (for complete breast cancer segmentation) is shown here, the segmentor can generate many label maps in one path (e.g., for breast cancer core and Gd-enhanced breast core core).

4.6Training SegmenAN

SegmenAN segmentor S and critic C are trained using backpropagation from the expected multi-scale L1 loss. We fix S and train C in an alternating fashion for one step using gradients computed from the loss function, and then fix C and train S in an alternating fashion using gradients computed from the same loss function provided to S from C. As demonstrated in (2), S and C's training is similar to a min-max game: G strives to reduce multi-scale feature loss, while C tries to maximise it. Both the S and C networks become more powerful as training advances. Finally, the segmentor will be able to anticipate label maps that are extremely close to the ground truth as labelled by human specialists. We also discovered that S-predicted label maps are smoother and have less noise than ground truth label charts obtained manual.

5.EXPERIMENT

The network models were created in the experiments using Keras with a Tensorflow backend in Python 3. The experiments were conducted in a desktop computer with Intel core i7-9700K processor (3.6 GHz) CPU, 16.0 GB RAM, and NVIDIA GeForce RTX 2070 GPU. The mammogram images in the data set are eleven samples from the Mini-mammogram Image Analysis Society (MIAS) record. All the test images are in PGM format. In the experiments, these images are converted into JPG format and resized to 192×256 pixels.

6.RESULTS AND EVALUATION

To the best of our information, our proposed SegmenAN is the first GAN-inspired framework adapted specifically for the segmentation task that produces superior segmentation accuracy. While conventional GANs have been effectively functional to several unsupervised learning tasks and semi-supervised classification, there are very few works that apply adversarial learning to semantic segmentation. The average accuracies of c, SegmenAN, DualC-UNet, and U-Net are 98.52%, 98.07%, and 96.13%, respectively, after applying leave-one-out experiments for the three models as shown in Figure 6, the SegmenAN model performs better than the other models for most test cases. Table 1 shows the average accuracies and time cost of the three models.

Table 1. Average Segmentation Accuracy for 25 Samples

Model	U-Net	DualC-UNet	SegmenAN
Accuracy (Jaccard)	96.13	98.07	98.94
Seconds	63ms	498ms	381ms

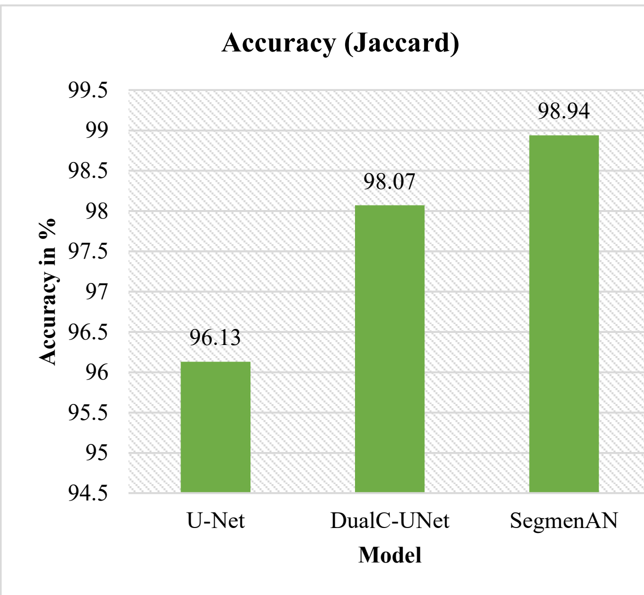
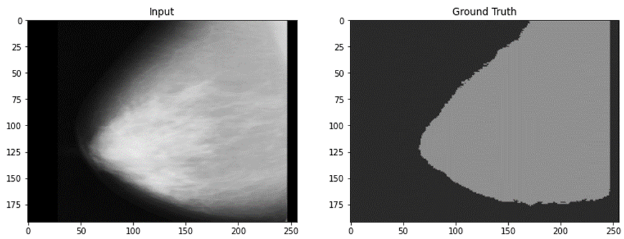
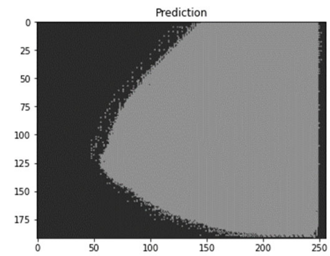


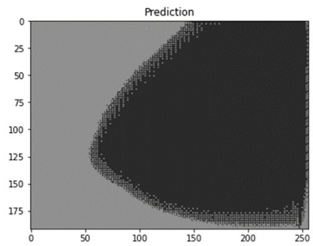
Fig.6. Graphical represent for Average Segmentation Accuracy

Although the Jaccard results of DualC-UNet and SegmenAN are similar and high accurate-Net provides a low accurate breast border as shown in Figure 7. For volunteer 7 shown in Figure 8, the average (over the 15-minute imaging period) accuracy of SegmenAN, DualC-UNet, and U-Net are 99.72%, 99.09%, and 97.62%, respectively, all being high in value. SegmenAN stretches the greatest segmentation outcomes compared to the other models, however, because its associations feature of various resolutions.

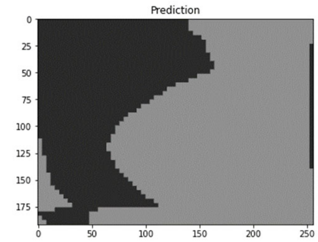


(a) (b)





(c) (d)

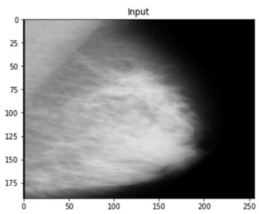


(e)

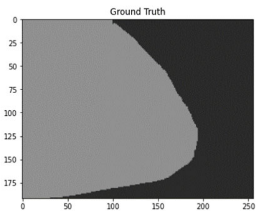
Fig.7. Segmentation results of image1. (a) Cropped Image (b) Manual ground-truth (c) SegmenAN (d) DualC-Net (e) U-Net

Variations among participants and manual segmentation errors, particularly in the top border of the ground-truth image, are to responsibility for the segmentation output faults. Inconsistency in drawing the top and middle limits of the breast region is one of the ground-truth segmentation errors. Figure 7 shows that all models have an upper boundary that is similar to the upper boundary of cropped images; however, the line in the ground-truth segmentation is lower, resulting in a decrease in the accuracy of three models when compared to other cases, despite the fact that this is still regarded as a better segmentation output that encapsulates the breast region.

Furthermore, the accuracy of segmentation is influenced by breast size. The average accuracies of SegmenAN, DualC-UNet, and U-Net for the next image shown in Figure 8 are 98.16 percent, 97.06 percent, and 94.64 percent, respectively; this lower performance is maximum probable due to the size of the breast being significantly smaller than the other cases used for training, which poses a problem for a simple architecture model. This will be addressed in the future by expanding the size and variety of the training set to include more breast shapes and sizes.



(a)



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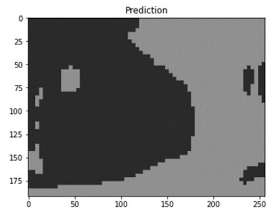
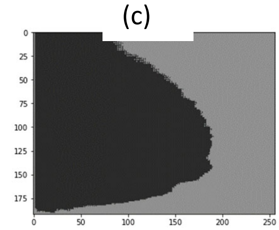
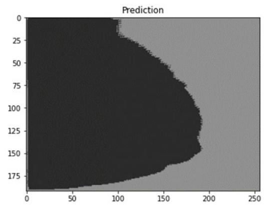


(c)



(d)



(e)

Fig.8. Segmentation results of image2. (a) Cropped Image (b) Manual ground-truth (c) SegmenAN (d) DualC-Net (e) U-Net

In comparison to our earlier filter research, this research used a larger database. In order to overcome the small-breast difficulties, a U-Net based model was compared to the C-DCNN. SegmenAN gives a more accurate border and is more stable to train, according to the outcomes. Instead of using IoU, we employed a novel method called Jaccard-similarity to assess segmentation accuracy. This evaluation eliminates further inaccuracies caused by the Gray-level result thresholding method.

The outcomes presented that U-Net series models can capture critical aspects of breast areas and delineate them in the testing dataset using cross-validation and comparison with ground-truth photos. Based on Jaccard-similarity, adding residual connections to make the model deeper and using multi-resolution features (SegmenAN) raises the average accuracy to 99.72 percent. A model with more features and depth performs better in segmentation. Pre-processing and a larger volume of training data could help deep-learning models perform better in the future. A SegmenAN model can produce more stable segmentation than manual segmentation for the same subject. In contrast, our SegmenAN employs a multi-scale feature loss that assesses the difference among produced and ground truth segmentation at various layers in the critic, trying to force both the segmentor and critic to discover hierarchical features that encapsulate long- and short-range spatial arrangement among pixels. SegmenAN training is final stage and stable since it employs the same loss function for both S and C.

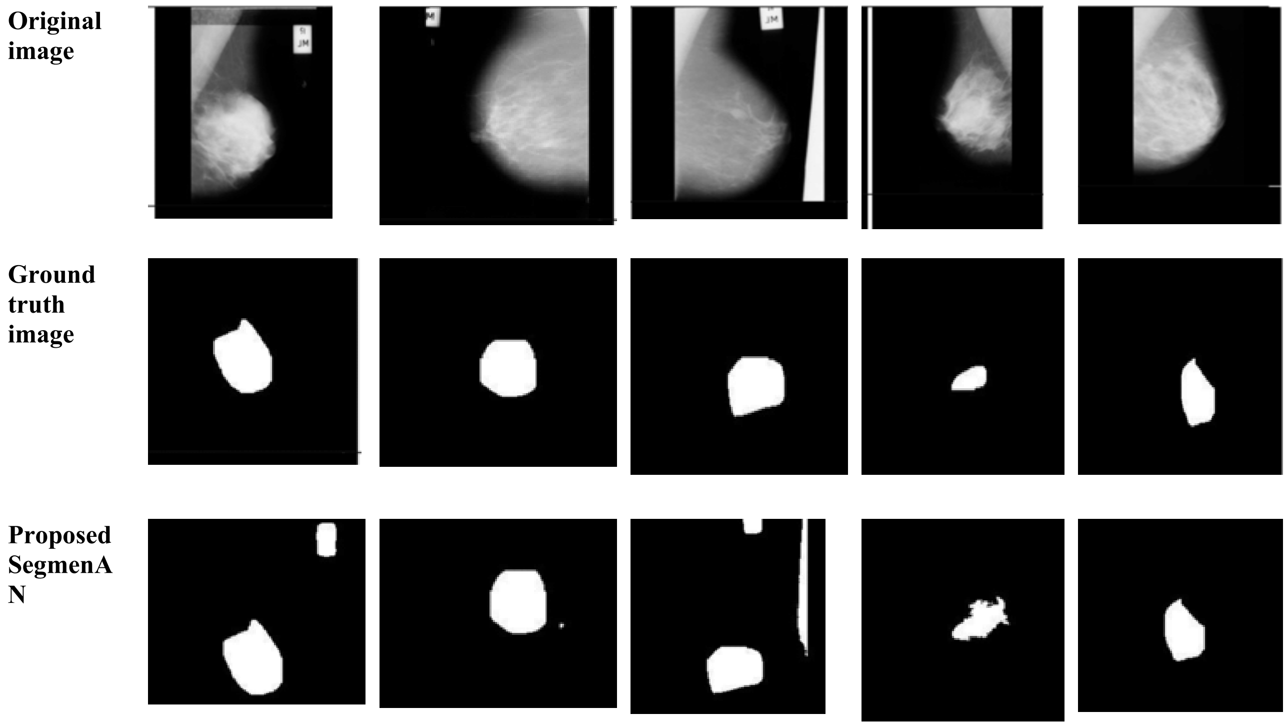


Fig 9. Experimental results of SegmenAN tumour segmentation for breast cancer detection.

7.CONCLUSION

In this paper, we suggest SegmenAN, a unique end-to-end Adversarial Network architecture with a novel multiscale loss for semantic segmentation. Segmenting and isolating the breast area in images is an important step for supervised system algorithms to distinguish breast cancer locations. Manual segmentation is time-consuming and predictable to inter- and intra-observer mistakes. Automatic segmentation employing stable models, on the next side, has the capacity to give precise and consistent breast segmentation with less time and effort. To increase segmentation execution second , In future work, one strategy is to combine a deep-learning model with other approaches to reduce time, expand the dataset, and avoid overfitting.

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