MTU-Net: Multi-Task Convolutional Neural Network for Breast Calcification Segmentation from Mammograms

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ABSTRACT

Computer-Aided Detection (CAD) is a technology that helps radiologists identify malignant microcalcifications (MCs) on mammograms. By minimizing observational oversight, CAD enhances the radiologist's detection accuracy. However, the high incidence of false positives limits the reliance on these technologies. Breast Arterial Calcifications (BAC) are a common source of false positives. Effective identification and elimination of these false positives are crucial for improving CAD performance in detecting malignant MCs. This paper presents a model that can eliminate BACs from positive findings, thereby enhancing the accuracy of CAD. Inspired by the successful outcomes of the UNet model in various biomedical segmentation tasks, a multitask U-Net (MTU-Net) was developed to simultaneously segment different types of calcifications, including MCs and BACs, in mammograms. This was achieved by integrating multiple fully connected output nodes in the output layer and applying different objective functions for each calcification type instead of training different models or using one model with a shared objective function for different classes. The experimental results demonstrate that the proposed MTU-Net model can reduce training and inference times compared to separate multi-structure segmentation problems. In addition, this helps the model converge faster and delivers better segmentation results for specific samples.

Keywords-deep learning; image segmentation; U-Net, mammogram; breast calcification

I. INTRODUCTION

Breast cancer is among the most common cancer types. Early detection of this cancer is essential to reduce its risk. Mammography screening techniques are important for the early detection of breast cancer. Mammography is an X-ray imaging technique used to examine the breast's internal structure. Among the various types of visual information provided by mammography, calcifications can be either suspicious (for breast carcinoma) or benign.

Micro-Calcifications (MCs) are suspicious calcifications that appear as white regions in the mammograms and are caused by the micro-calcium deposited on the breast tissues. It is an indication of the cell death located in that region. However, the segmentation of MCs is complicated because of their diversity, tiny structure, and unclear visibility. Breast Arterial Calcifications (BACs) are benign calcifications that linearly deposit on the vessel wall of breast arteries [1]. BACs are one of the most false positive findings in the detection of breast cancer and are easily defined by screening radiologists as nonsuspicious calcifications. However, this task is difficult for a CAD system. Thus, the removal of BACs as positive findings can increase the performance of automated cancer detection systems. An example of a case containing both MCs and BACs is shown in Figure 1. This figure was drawn using a mammogram image from the Miami dataset [2]. Figure 1(c) shows magnified segments from one of the standard mammographic views known as the mediolateral oblique (MLO). The MC is shown in the upper image as a white region, while the BAC is shown in the lower image as linear deposits of bright spots along the walls of the arteries. Figure 1(d) shows the related masks the Miami dataset [2] provided for these calcifications.

Various studies have investigated the possibility of automatic detection of BACs in computer vision. For instance, image filters, k-segment clustering, and classifiers have been combined into a single model to detect BACs [3]. Another two-step model defines the task as vessel tracking using calcification points [4-6]. The first step detects the BAC path using an uncertainty tracking point algorithm. The second step applies a compiling and linking algorithm to connect the detected points to the BAC. Finally, a GentleBoost classifier is applied to pre-extracted features to detect BACs as false positives [7]. Despite the effectiveness of these studies, the automatic detection of BACs in mammograms remains challenging.

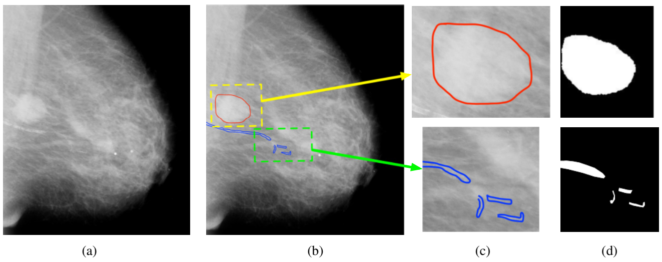

Fig. 1. An illustration of the difference between the MC and BACs from a clipped mammogram MLO view. (a-b) A mammogram image. (c) Examples of different appearance patterns of calcifications. (d) The related masks for the selected calcifications provided in the dataset [2].

As an alternative, Convolutional Neural Network (CNNs) models have been successfully applied to various medical image segmentation tasks, including MC and BAC segmentation. One of the first models [8] employed a pixel-wise, patch-based, two-class classification CNN with 12 layers to detect BACs. Each pixel was processed according to the surrounding patch. This model achieved results comparable to those obtained by human experts. However, it only processes the patch of the specified pixel and thus limits the data used by the model for the global features of the input. Inspired by the successful results achieved using the U-Net models for various biomedical segmentation tasks [9], various BAC segmentation models have been proposed. Dense U-Net (or DU-Net) [2] extends U-Net with dense connectivity for automatically detecting BACs in mammograms. Simple context U-Net (SCU-Net) [10] is another extension of U-Net, where the images are cropped into multiple patches and fed to the U-Net with dilated convolutional layers. For MC segmentation, authors in [11] presented connected-UNets that combined two U-Net models with additional skip connections. They emphasized contextual information using Atrous Spatial Pyramid Pooling (ASPP) in their U-Net models. In [12], the U-Net was extended with the VGG16 encoder for semantic segmentation. The tuned model was then used to predict breast cancer in earlier stages. Despite these approaches, the distinction between MCs and BACs in mammograms remains an unresolved problem. In this study, we investigated the applicability of U-Net to automatically detect both MCs and BACs in mammograms and develop a fully automated calcification detection method. Inspired by the good results achieved using multitask CNNs [13, 14] over single models, we implemented a multitask convolutional neural network (MTU-Net) to segment both MC and BAC in mammogram images simultaneously. An MTU-Net can be developed by adding multiple objectives or fusing features trained for different objectives. When tested on a public database of mammogram images, the proposed model achieved better results than state-of-the-art segmentation methods. The contribution of this paper can be summarized as follows:

- The MTU-Net is introduced to simultaneously segment multiple anatomical structures, namely BAC and MC, in mammogram images.
- MTU-Net simply extends the U-Net by integrating multiple fully connected output nodes in the output layer and applying different objective functions for each calcification type.
- A new dataset of mammogram images with the ground-truth of both BAC and MC is presented. This dataset, with the annotations, will be available to foster future research in this area.

II. APPROACH

In this study, the calcification-detection task was considered a multi-class segmentation task in which each type of calcification could be segmented simultaneously. The MTU-Net model comprises three classes: MC, BAC, and background. Based on the conventional U-Net model, we propose the MTU-Net, as illustrated in Figure 2.

A. U-Net

Fully Convolutional Networks (FCNs) [15] are special CNN versions developed for semantic segmentation. In contrast to traditional CNNs, FCNs do not make predictions; thus, they do not require dense layers to change the spatial resolution of a segmentation map. In contrast, an FCN contains only a combination of convolutional and upsampling layers. A specialized extension of FCN is the U-Net [16], which has an architecture specifically designed to implement symmetric skip connections. The U-Net contains two paths: an encoder path on the left side to extract the features from the entire image and a decoder path on the right side to generate a segmentation with the input resolution. The encoder consists of duplicates of four steps of two 3×3 convolutions, each followed by a rectified linear unit (ReLU) and a 2×2 max pooling layer for downsampling. After each step, the number of feature channels is doubled. The decoder consists of duplicates of four upsampling steps, followed by a 2×2 transposed convolution and two 3×3 convolutions, each followed by a ReLU. Finally, a 1×1 convolution layer is used to output the segmentation map. Between these two paths, long skip connections are applied to directly connect the opposing layers from the encoder to the decoder paths [17]. These connections allow the spatial information lost during subsampling in the encoder path to be recovered in the decoder path by sending equal-resolution features from the former to the latter. This helps the model incorporate context information from the coarse layer and detailed image features at a finer scale, leading to remarkable results in various biomedical segmentation tasks.

B. MTU-Net

This study aimed to segment both MC and BAC in mammogram images simultaneously. Multiple-class segmentation tasks can be solved using various methods. One method involves addressing each class separately and training multiple CNNs to segment different classes sequentially. Another method considers a task as multiple classes and trains a single CNN with a single objective function to output multiple probability maps. However, the segmentation area of BAC can morphologically overlap with the MC field [18]. Therefore, the softmax activation function, typically used in multi-class classification tasks and requires that the segmented area belong exclusively to a single class, does not apply to this task. Another method to perform this task is to train a multitask CNN that generates multiple segmentation masks using a common base.

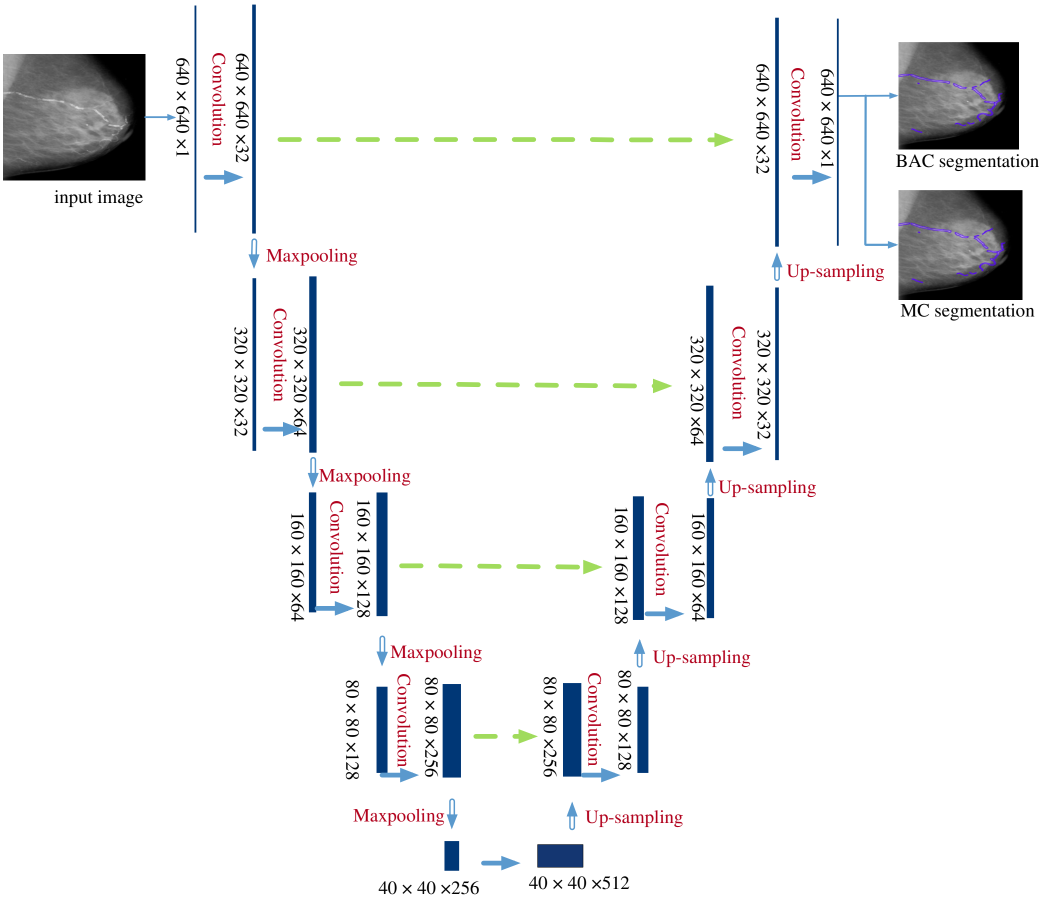

Fig. 2. An illustration of the proposed MTU-Net model, which extended the U-Net model for multi-task segmentation.

A multitask CNN aims to integrate multiple outputs with multiple objective functions on top of a shared base model. This implies that the model has multiple outputs sharing the same feature pools. To train a model that optimizes detection and segmentation tasks, the feature pool may eventually contain two sets of features that complement each other. In U-Net, low-resolution layers are also considered contextual information for finer output layers. In the multitasking U-Net, context information was also enriched. Thus, three output nodes were added in the final layer to the output segmentation masks for the three different classes, each with a loss function. In this study, a negative Dice coefficient was used as the loss function for each type of calcification. The weighting factor for all objective functions was set to 1.0, indicating that both calcifications were equally important.

$$NegDICE(a,b) = -2\frac{a.b}{\|a\|+\|b\|} \quad (1)$$

where a is the ground truth mask and b is the predicted mask.

III. EXPERIMENTS AND RESULTS

To test the performance of the MTU-Net model in breast calcification detection, we performed experiments using a subset of a publicly available dataset prepared for this task [2].

A. Dataset

The Digital Database for Screening Mammography (DDSM) [19] is a publicly available dataset used for breast disease detection. A later version, the Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM) [20] consists of images in DICOM format. It consists of about 1,700 scans with three classes related to breast cancer (normal, benign, and malignant). Two views of each breast were presented in most of these cases, including Cranial-Caudal (CC) and mediolateral oblique (MLO) views. Due to the limited sample size, we considered each view a separate image. The dataset also consisted of a Region of Interest (ROI) segmentation, bounding boxes, and pathologic diagnoses for various abnormalities as ground-truth training samples. The size of the images was considered relatively large, with a mean height of 5295 pixels and a mean width of 3131 pixels. This study aimed to distinguish between MCs and BACs in mammograms. Thus, we expanded our ground truth using a dataset published in [2]. This dataset consists of 826 mammogram images, 413 of which have BAC segmentation and the same number of images without BACs. To perform this task, we expanded the BACs dataset with another 413 images containing different MC types chosen randomly from the original dataset [20]. In total, we have 1239 mammogram images for implementation and testing.

B. Experimental Setup

The network was trained and deployed using a PC equipped with an NVIDIA GTX 1080TI 11GB GPU card and a 3584 CUDA parallel processing core. The model uses the Keras framework with a Theano backend [21]. A k-fold cross-validation approach was used to train and test the model. The entire dataset was randomly split into equally sized k-folds with k = 5, where (k-1) folds were used for training and the remaining k^{th} fold for testing. This was performed until all folds were used to test the model, and the overall performance was calculated as the average of all folds. The images were resized to 256 × 256 pixels. The Adam optimizer was employed with a learning rate of 0.0001. The optimization was stopped after 100 epochs.

For further quantitative evaluation of the MTU-Net performance, we implemented a single-class U-Net and a multi-class U-Net for comparison. Two different U-Nets were trained for two different calcifications with a negative Dice coefficient as the loss function for the single-class U-Net. The sigmoid function was used as the activation function for the multi-class U-Net, and categorical cross-entropy was used as the loss function. The setup described above was used for all models.

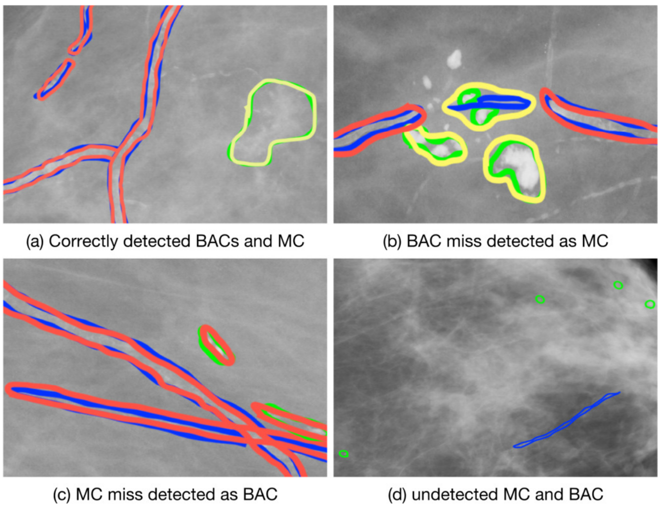

Fig. 3. Illustration of the calcification detection results of the proposed MTU-Net model on mammogram images. The ground-truth BACs and MCs are contoured by blue and green lines, respectively. The automatically detected BACs and MCs are contoured by red and yellow lines, respectively. The magnified images show results with (a) correctly detected BACs and MC, (b) BACs mis-detected as MCs, (c) MCs mis-detected as BACs, and (d) undetected BAC and MC.

C. Evaluation Criteria

The proposed model was evaluated using sensitivity (TPR), specificity, Jaccard index, accuracy, and Matthews Correlation Coefficient (MCC), which are defined as follows:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (1)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (2)$$

$$\text{Jaccard index} = \frac{TP}{TP+FP+FN} \quad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (4)$$

$$\text{MCC} = \frac{TP.TN - FP.FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (6)$$

where *TP*, *TN*, *FP*, and *FN* represent the count of true positives, true negatives, false positives, and negatives, respectively. These values were computed in terms of the number of pixels. Using data augmentation methods, we expanded the dataset to 1000 randomly rotated, scaled, horizontally shifted, and flipped images for actual training.

D. Results

Some examples of the calcification detection results obtained using the MTU-Net model on the mammogram images are shown in Figure 3. The blue and green contours in the figure represent the ground-truth annotations. In contrast, the red and yellow contours are automatically generated by the proposed model for the BACs and MCs, respectively. The first column shows successful examples with a small number of *FP*. Accurate boundaries for both BAC and MC were detected and compared with human experts' annotated calcification performance. The second column shows the failed results where the BAC is considered by the MTU-Net model as the MC. This case contains small groups of overlapping BACs and MCs with non-continuous structures that may confuse the model. The third indicates that the MTU-Net model considered the failed results as BACs. This occurs when the MCs are linearly aligned in a shape similar to the BAC. The last column shows another failed result where the MTU-Net model considered both MC and BAC as the background. These cases occurred in patients with dense breast tissues.

Table I presents the performance of our model compared to the other models defined in Section II-B in terms of sensitivity, specificity, Jaccard index, accuracy, and MCC (in %). MTU-Net outperformed the single- and multi-class models with an overall accuracy of 90.20%, sensitivity of 90.00%, specificity of 91.41%, F-1 score of 91.52, Jaccard coefficient of 83.32%, and MCC of 83.96%. These results show that the MTU-Net model has greater ability than the single- and multi-class U-Net models in distinguishing between MCs and BACs in mammogram images. In addition, they demonstrated significant improvements over other models by using multiple objective functions in addition to a shared base model. The results were also confirmed by the increase in the MCC, showing that our model results matched the ground truth very well.

E. Discussion

In breast cancer detection from mammograms, the presence of BACs is often an *FP*, negatively impacting the system's overall performance. Addressing the challenge of accurately identifying and eliminating BACs from detection results remains an unresolved and complex research task. Using deep learning models, various methods have been proposed to identify the presence of BACs in mammograms [2, 4, 7, 8]. Inspired by these successes, we extended U-Net into a multitask model, MTU-Net, capable of simultaneously segmenting both MCs and BACs. Table I, shows that the proposed model outperformed single- and multi-class U-Net for calcification detection. The MTU-Net model's ability to segment both calcification types concurrently has improved performance metrics.

- Accuracy: The MTU-Net model achieved an overall accuracy of 90.20%, outperforming single-class U-Net (60.40%) and multi-class U-Net (70.20%).
- Sensitivity and specificity: With sensitivity values of 89.3% for BACs and 91.20% for MCs, and specificity values of 89.4% for BACs and 93.41% for MCs, the MTU-Net model reliably identifies *TP* and *TN*, reducing the risk of *FP* and missed detections.
- F1-Score and Jaccard Index: The high F1-scores (90.4% for BACs and 92.62% for MCs) and Jaccard index values (82.7% for BACs and 83.92% for MCs) indicate precise and reliable delineation of calcification boundaries.
- MCC: The MCC values (80.9% for BACs and 83.96% for MCs) reflect a strong correlation between predicted and actual classifications, highlighting the model's robustness.

TABLE I. COMPARISON OF THE PRFORMANCE OF THE PROPOSED MTU-NET IN (%) WITH RELATED METHODS ON CALCIFICATION DETECTION TASK. ALL RESULTS CONSIDER THE AVERAGE OF 5-FOLD CROSS-VALIDATION

Method		Accuracy	Sensitivity	Specificity	F1-score	Jaccard index	MCC
Single-class U-Net	BAC	59.6	54.8	62.5	53.2	59.4	58.6
	MC	61.2	56	65.9	55.9	61.2	58.9
Multi-class U-Net	BAC	68.9	72.1	67.1	67.5	63.8	61.8
	MC	71.5	74.2	67.2	69.9	65.2	62.9
Proposed MTU-Net	**BAC**	**89.3**	**89.3**	**89.4**	**90.4**	**82.7**	**80.9**
	MC	**91.2**	**90.7**	**93.4**	**92.6**	**83.9**	**83.9**

One key advantage of the MTU-Net model is its ability to leverage the contextual information from MC segmentation to improve BAC segmentation. This multi-task approach enables the model to converge faster and deliver better results than a single-class U-Net trained on single-calcification masks. The image features learned during MC segmentation are beneficial for BAC segmentation, facilitating a higher learning rate - up to 10 times higher - when training the MTU-Net compared to a single-class U-Net focused solely on BACs. However, the baseline single-class and multi-class U-Net models exhibited several errors that impacted their performance:

- Single-class U-Net often misclassified BACs as MCs and vice versa due to the lack of understanding of the differences between the two types of calcifications. This led to lower sensitivity and specificity. Multi-class U-Net showed improved performance but still struggled with overlapping and adjacent BACs and MCs, leading to higher false positive rates.
- Both baseline models had difficulty in accurately defining the boundaries of BACs and MCs, especially in complex cases with dense breast tissues. This resulted in lower F1-scores and Jaccard indices.
- High *FP* rates in detecting BACs, particularly by the single-class U-Net, lower the specificity and high *FN* rates, where actual calcifications were missed, lowered the sensitivity.

The proposed MTU-Net model mitigates these errors through several key mechanisms:

- Multitask Learning: By simultaneously segmenting both BACs and MCs, the MTU-Net model benefits from shared contextual information, improving the accurate identification of each calcification type.
- Improved Boundary Detection: The model's ability to learn and apply features from MC segmentation to BAC segmentation results in more precise boundary detection, enhancing the F1-score and Jaccard index.
- Reduction in *FP* and *FN*: The multitask approach and higher learning rate enable the MTU-Net to achieve higher sensitivity and specificity, reducing the number of false positives and false negatives.

The MTU-Net model's superior performance in detecting calcifications in mammogram images, as evidenced by its high metrics across various performance indicators, underscores its potential as a valuable tool for enhancing the accuracy and reliability of breast cancer screening. Despite the challenges posed by misclassifications and dense breast tissues, the MTU-Net model's ability to segment both BACs and MCs simultaneously represents a significant advancement in mammographic analysis. Further refinement and optimization of the model could lead to even better performance, ultimately contributing to more accurate and reliable breast cancer detection and diagnosis.

IV. CONCLUSION

In this study, a multitask U-Net (MTU-Net) is presented to address the challenge of distinguishing between microcalcifications (MCs) and Breast Arterial Calcifications (BACs) in mammogram images. The proposed MTU-Net model demonstrates significant improvements in simultaneously segmenting both MCs and BACs compared to existing methods. By leveraging a multitask approach with multiple objective functions and feature fusion, our model effectively enhances the accuracy and reliability of calcification detection. Key findings from our study include:

- Enhanced Segmentation Accuracy: The MTU-Net model outperforms other related segmentation techniques by differentiating more precisely between suspicious and benign calcifications. This reduces the likelihood of false positives and improves automated cancer detection systems.

- Multitask Learning Advantage: Integrating multiple objectives within a single U-Net framework allows for more comprehensive analysis and accurate segmentation of both MCs and BACs, addressing the limitations of single-task models that often struggle with overlapping features and varied calcification types.
- New Dataset Contribution: We have introduced a new dataset with detailed ground-truth annotations for both MCs and BACs, which can be used for further research and development in the field. This dataset will support the validation and enhancement of future algorithms to improve mammographic screening processes.

Despite these advancements, several avenues remain for future research. Further exploration of more complex network architectures and feature extraction techniques could yield better results. Additionally, integrating more diverse and extensive datasets could help in developing models with higher generalizability across different populations and imaging conditions. The continuous refinement of CAD systems and expanding annotated datasets will be crucial in achieving more accurate and reliable breast cancer detection and diagnosis.

Overall, our study contributes to the ongoing efforts to enhance mammographic screening through advanced computational techniques and sets the stage for future innovations in breast cancer detection.

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