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Segmentation of Mammogram Images using Deep Learning based MultiRes U-Net

Ganta Venkata Manideep Kumar, Chilakabathini Praveen, Kolla Naga Pavani, Desaboyina Akshaya

Dept. of Electronics and Communication Engineering,
R.V.R. & J.C. College of Engineering,
NAAC A+ grade, Approved by AICTE, Affiliated to Acharya Nagarjuna University,
Chowdavaram, Guntur-522 019 (A.P.)

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Abstract - *Cancer stands as the second leading cause of death worldwide, accounting for approximately one out of every six deaths. Among the various types of cancer, breast cancer is a prevalent malignancy affecting both women and, to a lesser extent, men. Early detection of cancer is crucial in reducing mortality rates for patients.*

In this project, we utilized the MultiRes U-Net architecture for the segmentation of mammogram images using the Mini-DDSM (Digital Database for Screening Mammography) dataset. The project was executed in three main phases. First, the dataset was preprocessed, and ground truth masks were obtained. We employed image enhancement and augmentation techniques to improve the quality and diversity of the dataset. Second, a MultiRes U-Net model was constructed and trained using the preprocessed mammogram images and their corresponding ground truth masks. The training and testing of the model were implemented using Python. Lastly, the model's performance was assessed using two key metrics: Intersection over Union (IoU) and accuracy. The achieved testing accuracy was 99.71%, with an IoU score of 95.74%.

By segmenting mammogram images, this project contributes to the field of medical imaging by potentially assisting radiologists in the early detection of breast cancer. This advancement can significantly improve diagnostic accuracy and patient care.

Key Words: breast cancer, deep learning, U-Net, mammogram, segmentation

1. INTRODUCTION

Breast cancer is a significant global health concern, representing one of the most common malignancies affecting women worldwide. Early detection of breast cancer plays a pivotal role in improving patient outcomes and reducing mortality rates. Mammography, a widely utilized imaging modality for breast cancer screening, enables the detection of suspicious lesions and abnormalities at early stages when treatment is most effective [1]. However, the manual interpretation of mammogram images by radiologists is labor-intensive, time-consuming, and subject to inter-observer variability, potentially leading to missed diagnoses or false positives.

To address these challenges, automated image segmentation techniques have emerged as promising tools for assisting radiologists in the detection and characterization of breast abnormalities on mammograms. Image segmentation refers to the process of partitioning an image into meaningful regions or objects, facilitating quantitative analysis and aiding in clinical decision-making. Deep learning-based approaches, in particular, have shown remarkable success in various medical image segmentation tasks, leveraging convolutional neural networks (CNNs) to learn complex patterns and features directly from the data [2].

In this context, this paper utilizes a deep learning-based MultiRes U-Net model for the segmentation of mammogram images using a deep learning-based MultiRes U-Net model. The U-Net architecture [11], originally introduced for biomedical image segmentation, exhibits a unique symmetric encoder-decoder structure, allowing for precise localization of objects within images. The MultiRes U-Net variant enhances the model's performance by incorporating multi-resolution features, capturing both local details and global context crucial for accurate segmentation.

Furthermore, to train and evaluate the segmentation model, we leverage the Mini DDSM (Digital Database for Screening Mammography) dataset [3]. DDSM provides a rich collection of mammogram images annotated with clinically relevant information, making it well-suited for training deep learning models in breast cancer research. By harnessing the power of deep learning and utilizing a comprehensive dataset like DDSM, we aim to develop an automated segmentation system capable of accurately identifying and delineating regions of interest within mammogram images, including tumors, calcifications, and other abnormalities.

2. LITERATURE SURVEY

Recent advancements in mammogram image segmentation using deep learning models have yielded significant progress in the detection of breast masses.

Several studies have contributed to this field, showcasing various approaches and their outcomes. Heyi Li et al. (2018) introduced a Conditional Residual U-Net architecture for breast mass segmentation in mammograms, showcasing promising results in accurate delineation [4]. Following this, Shuyi Li et al. (2019) proposed an Attention Dense-U-Net model tailored for automatic breast mass segmentation, further advancing segmentation accuracy in digital mammograms [5]. Building upon these works, N Ravitha Rajalakshmi et al. (2020) developed a Deeply Supervised U-Net for mass segmentation, demonstrating notable performance metrics and highlighting the potential for improved accuracy [6]. Md Zahangir Alom et al. (2019) expanded the scope to include medical image segmentation, presenting a Recurrent Residual U-Net model with high accuracies across diverse datasets, indicating the robustness of the approach [7].

Furthermore, Jingyao Li et al. (2021) proposed a Multi-Scale Fusion U-Net specifically for breast lesion segmentation, showcasing impressive recall, precision, and Dice Similarity Coefficient scores [8]. In addition to these specific works, the broader literature on medical image analysis using deep learning provides valuable insights into the overarching methodologies and trends in the field. Anwar et al. (2018) conducted a comprehensive review of convolutional neural networks for medical image analysis, shedding light on the advancements and challenges [9]. Moreover, Litjens et al. (2017) surveyed the application of deep learning in medical image analysis, underscoring the significance of this approach in various clinical domains.

3. DATASET AND PREPROCESSING

The Mini DDSM (Digital Database for Screening Mammography) dataset is a subset of the full DDSM dataset [9], which is widely used for research in the field of computer-aided detection (CAD) [10] and diagnosis of breast cancer using mammograms. The DDSM is a collection of digitized film mammograms that were obtained from several mammography centers. The Mini DDSM dataset is a smaller version of the original DDSM dataset, containing a reduced number of mammogram images. It was created to facilitate research and development by providing a more manageable dataset while still retaining the essential characteristics of the full DDSM dataset. The dataset encompasses both normal and abnormal mammogram images. It includes benign and malignant lesions, facilitating comprehensive research [19].

We have used 1600 images for training, 200 images for validation and 200 images for testing. The ground truth masks are prepared using ImageJ software [15] with the help of annotations made by radiologists and doctors.

Given the low signal-to-noise ratio in mammogram images, proper preprocessing is crucial for effective detection. Existing literature suggests that histogram equalization and its variations are advantageous for enhancing mammogram images. In our study, we employed the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique [16] to enhance the contrast in mammogram images. This approach has been shown to enhance the image edges.

Data augmentation is crucial in enhancing the robustness and generalizability of deep learning models, especially when dealing with limited datasets like mammograms. In mammogram image processing, augmentation techniques such as rotation, flipping, zooming, and contrast adjustment can be applied. These transformations help the model to learn invariant features and patterns from different variations of the original images, thereby improving its performance and reducing overfitting.

Figure 1 displays sample images from the Mini DDSM dataset, enhanced using the CLAHE technique.

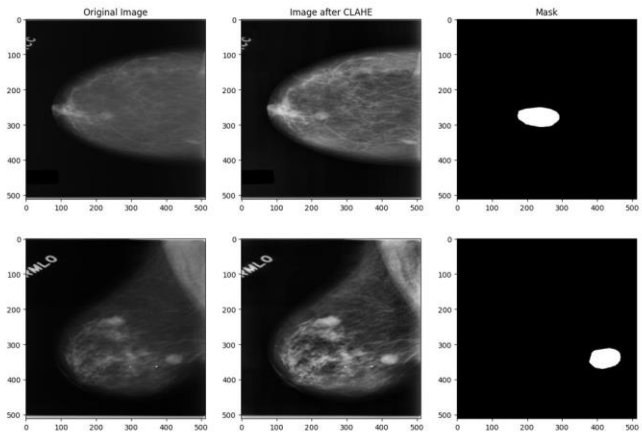

Fig -1: Illustration of CLAHE on mammogram images.

4. ARCHITECTURE OF U-NET

The architecture of U-Net is unique in that it consists of a contracting path and an expansive path. The contracting path in U-Net is responsible for identifying the relevant features in the input image. The encoder layers perform convolutional operations that reduce the spatial resolution of the feature maps while increasing their depth, thereby capturing increasingly abstract representations of the input. This contracting path is similar to the feedforward layers in other convolutional neural networks. On the other hand, the expansive path works on decoding the encoded data and locating the features while maintaining the spatial resolution of the input. The decoder layers in the expansive path up-sample the feature maps, while also performing convolutional operations. The skip connections from the contracting path help to preserve the spatial information lost in the contracting path, which helps the decoder layers to locate the features more accurately.

Figure 2 illustrates the architecture of classic U-Net. During the contracting path, the input image is progressively reduced in height and width but increased in the number of channels. This increase in channels allows the network to capture high-level features as it progresses down the path. At the bottleneck, a final convolution operation is performed. The expansive path then takes the feature map from the bottleneck and converts it back into an image of the same size as the original input. This is done using up-sampling layers, which increase the spatial resolution of the feature map while reducing the number of channels. The skip connections from the contracting path are used to help the decoder layers locate and refine the features in the image. Finally, each pixel in the output image represents a label that corresponds to a particular object or class in the input image. In this case, the output map is a binary segmentation map where each pixel represents a foreground or background region.

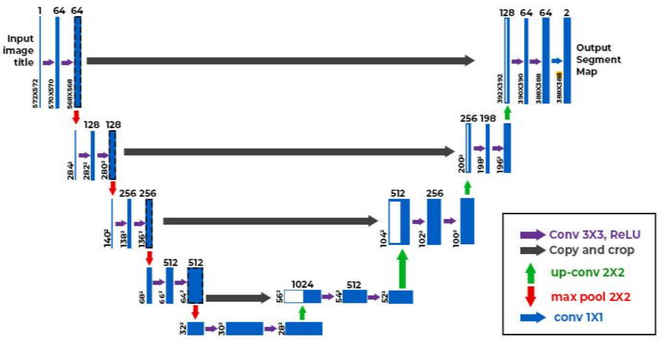

Fig -2: Architecture of U-Net.

5. PROPOSED MODEL - MULTIRES U-NET

The U-Net architecture has been widely acclaimed in medical imaging for its effectiveness in segmentation tasks, but upon closer examination and drawing parallels to advancements in computer vision, we have identified areas for enhancement. One critical observation pertains to the variation in scale within medical images, where objects of interest, such as cell nuclei or tumors, can vary significantly in size. While this issue has been addressed in computer vision, it remains underexplored in medical image segmentation. To address this, MultiRes U-Net is proposed for augmenting the U-Net architecture with multi-resolution analysis capabilities akin to the Inception network, enabling the network to analyze objects at different scales more effectively.

To achieve this, MultiRes blocks are introduced, replacing standard convolutional layers, to reconcile features learned from images at different scales. The MultiRes blocks are depicted in figure 3. By incorporating parallel convolutional operations of varying kernel sizes and gradually increasing the number of filters in successive layers, the network can extract spatial features from multiple scales more efficiently. This approach significantly reduces memory requirements while improving performance.

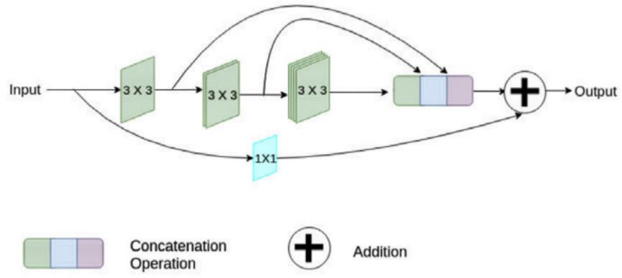

Fig -3: MultiRes block.

Additionally, we address the potential semantic gap between encoder and decoder features introduced by shortcut connections in the U-Net architecture. To mitigate this, we have incorporated convolutional layers along shortcut connections, termed Res paths. The Res path is depicted in figure 4. These additional layers, accompanied by residual connections, facilitate the alignment of features from encoder and decoder stages, enhancing the network's ability to preserve spatial information throughout the segmentation process.

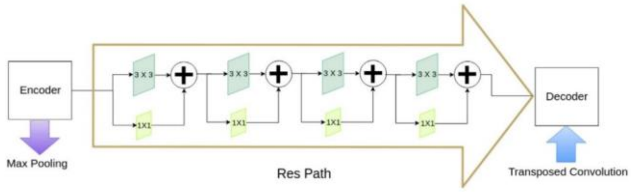

Fig -4: Respath.

By introducing these architectural modifications, we aim to improve the U-Net architecture's robustness and effectiveness in medical image segmentation tasks, particularly in handling scale variability and preserving spatial information across encoder-decoder stages.

The MultiRes U-Net model introduces several architectural enhancements compared to the original U-Net. Instead of the standard two convolutional layers, MultiRes blocks are employed to better capture hierarchical features. The number of filters within each MultiRes block is controlled by a parameter, W, calculated based on the number of filters in the corresponding U-Net layer. This ensures the comparability of parameter counts between the two models. By setting $\alpha = 1.67$, the parameter count of MultiRes U-Net is kept slightly below that of U-Net.

Furthermore, within each MultiRes block, the number of filters gradually increases across successive convolutional layers, optimizing feature extraction. Shortcut connections in U-Net are replaced with Res paths, where convolution operations are applied to feature maps propagating from the encoder to the decoder stages. The number of convolutional blocks along Res paths decreases gradually to account for

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diminishing semantic gaps between encoder and decoder feature maps.

The network architecture employs ReLU activation and batch normalization for all convolutional layers except the output layer, which utilizes a Sigmoid activation function. The diagram of the MultiRes U-Net model illustrates its structure. Overall, these architectural modifications enhance feature extraction, promote information flow, and improve the model's capability to capture intricate image details for accurate segmentation.

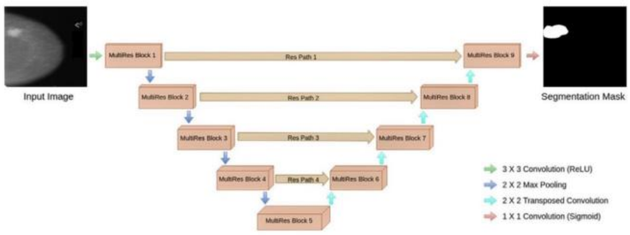

Fig -5: Architecture of MultiRes U-Net.

6. EXPERIMENTAL RESULTS

6.1. Experimental Setup

We conducted our experiments using Python 3 programming language [14]. The network models were implemented using Keras with a Tensorflow backend, leveraging the powerful capabilities of the v100 GPU provided by Google Colab. The use of Google Colab's v100 GPU significantly accelerated the training process, enabling faster convergence and efficient experimentation.

We tested our MultiRes U-Net model on the Mini DDSM dataset, which contains mammogram images with their corresponding ground truth segmentations. The model we used is a modified version of the U-Net architecture, called MultiRes U-Net. For training, we used a batch size of 8, and the Adam optimizer with a binary cross-entropy loss function [20]. We employed early stopping, and the model stopped training at the 47th epoch.

6.2. Metrics

Metrics such as precision and recall can be misleading, often providing an overly optimistic evaluation due to their emphasis on correctly identifying the background. Therefore, the Intersection over Union (IoU) metric, which is calculated as the ratio of the intersection to the union of two sets, has become a popular choice for evaluating and benchmarking image segmentation algorithms. The IoU for the ground truth binary segmentation mask A and the predicted binary segmentation mask B is defined as:

$$IoU = |A \cup B| / |A \cap B|$$

Another metric to evaluate a semantic segmentation is to simply report the percent of pixels in the image which were correctly classified. The pixel accuracy is commonly reported for each class separately as well as globally across all classes.

When considering the per-class pixel accuracy we're essentially evaluating a binary mask; a true positive represents a pixel that is correctly predicted to belong to the given class (according to the target mask) whereas a true negative represents a pixel that is correctly identified as not belonging to the given class.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

This metric can sometimes provide misleading results when the class representation is small within the image, as the measure will be biased in mainly reporting how well you identify negative case (i.e. where the class is not present).

6.3. Training

We monitored the training process using two main plots: the training and validation loss plot, and the training and validation accuracy plot. Both the training and validation losses decrease, which means the model is learning effectively. The model achieves a high training accuracy and IoU, and validation accuracy and IoU also improves, showing that the model can generalize well to new data.

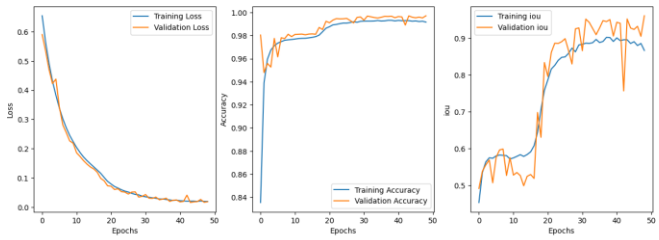

Fig -6: Training plots for loss, accuracy and IoU.

6.4. Performance Evaluation

After training, we tested the model on the test set and achieved an accuracy of 99.71%. The IoU score is a metric that measures how well the predicted segmentation overlaps with the ground truth segmentation. Our model achieved an IoU score of 95.74% on the test set, indicating that the model can accurately segment mammogram images which are tabulated in table 1.

Table -1: Evaluation metrics values in percentages.

Model	**Loss**	**Accuracy**	**IoU**
U-Net	1.98	99.34	92.48
MultiRes U-Net	**1.54**	**99.71**	**95.74**

6.5. Qualitative Results

Here are some sample predictions from the test data to show the model's segmentation performance.

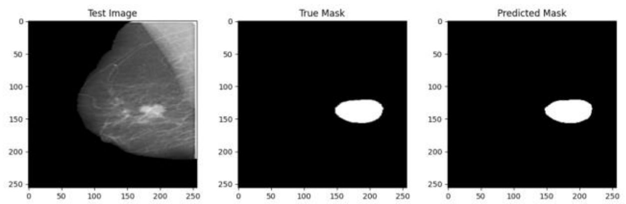

Fig -7.1: Sample Prediction 1: IoU = 94.02%

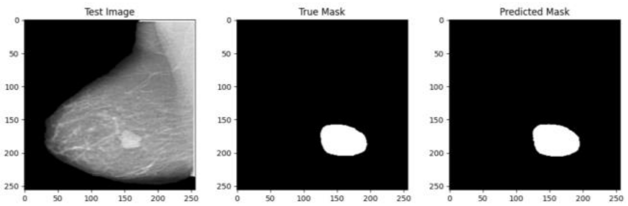

Fig -7.2: Sample Prediction 2: IoU = 96.28%

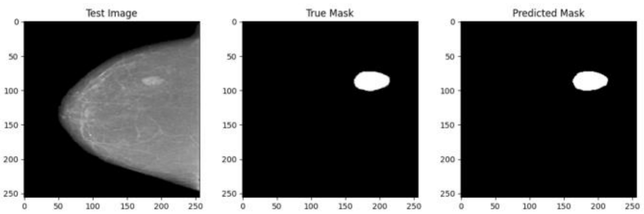

Fig -7.3: Sample Prediction 3: IoU = 92.15%

These sample predictions demonstrate that the model can accurately identify the regions of interest in mammogram images.

7. CONCLUSION AND FUTURE WORK

In conclusion, the segmentation of mammogram images using deep MultiRes U-Net models represents a significant advancement in the field of medical image analysis, particularly in the detection and characterization of breast abnormalities. Leveraging the rich capabilities of deep learning architectures, such as MultiRes U-Net, has enabled the automated and accurate segmentation of regions of interest within mammogram images. Through the integration of multi-resolutional analysis and fusion techniques, these models have demonstrated robust performance in segmenting complex structures, including breast masses and lesions, contributing to more efficient and reliable diagnostic workflows.

To enhance the quality of the input images and subsequently improve the segmentation performance, we employed the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. Metrics such as Intersection over Union (IoU) and accuracy were used to quantitatively assess the performance. The experimental results demonstrated that our MultiRes U-Net model outperformed the classic U-Net model.

In future research, it would be beneficial to explore additional preprocessing techniques and data augmentation methods to further improve the quality of mammogram images and potentially enhance segmentation accuracy. Investigating the integration of other deep learning architectures or ensemble methods could also lead to a more robust segmentation framework.

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