SSRG International Journal of Computer Science and Engineering
ISSN: 2348–8387 / https://doi.org/10.14445/23488387/IJCSE-V11I12P104

Volume 11 Issue 12, 23-30, December 2024

Original Article

Improved Segmentation of Skin Lesions Using Attention-Enhanced Residual U-Net

Saleh Alghamdi

Department of Information Technology, College of Computers and Information Technology, Taif University, Taif, Saudi Arabia.

Corresponding Author : s.algamedi@tu.edu.sa

Received: 14 October 2024 Revised: 18 November 2024 Accepted: 12 December 2024 Published: 30 December 2024

Abstract - *Accurate segmentation of skin lesions is critical for early skin cancer identification and treatment. Conventional U-Net architectures have been widely utilized in medical image segmentation for their ability to capture intricate details effectively. However, these models often encounter challenges in grasping contextual information and managing complex lesion boundaries. We propose an enhanced segmentation model, the attention-based residual U-Net, which incorporates attention mechanisms and residual connections into the traditional U-Net architecture. The attention mechanism enables the network to concentrate on relevant regions of the input image, improving feature extraction, while residual connections aid in training deeper networks by tackling the issue of vanishing gradients. Assessed on a publicly available dermoscopic image dataset (PH2 dataset), our model demonstrates significant improvements in segmentation accuracy (96.55%) and boundary outlining, attaining higher dice coefficients (89.54%) and reduced segmentation errors. The proposed model displays resilience across various lesion variations and imaging conditions, making it a promising tool for clinical applications in dermatology.*

Keywords - *Skin lesion segmentation, Attention mechanism, Residual U-Net, Deep learning, Medical image analysis.*

1. Introduction

Skin cancer is regarded as one of the most common types of cancer worldwide, with early detection being critical for effective treatment and improved patient outcomes [1]. Skin cancer is closely related to skin lesions but not all skin lesions are cancerous. Skin lesions are any irregularities on the skin's surface that differ from surrounding healthy tissue. These variations can arise from various causes. Injuries, infections from bacteria or viruses, allergic reactions, and even inflammatory conditions like eczema or psoriasis can all manifest as skin lesions. In some instances, however, a skin lesion could be a sign of skin cancer. Basal cell carcinoma, squamous cell carcinoma, and melanoma, are examples of malignant lesions, while moles and freckles are benign. Basal cell carcinoma is the most common and typically slow-growing, while squamous cell carcinoma can become more aggressive if left untreated. Melanoma is recognized as the most severe type of skin cancer, known for its rapid spread if not identified and treated early [2].

Figure 1 shows examples of various skin cancer types. Dermoscopic imaging has become a vital tool in the diagnosis and analysis of skin lesions, enabling detailed visualization of skin structures. Segmentation of skin lesions in dermoscopic images through manual methods is a laborious and subjective task. This process is susceptible to variations among observers due to factors such as lesion intricacy and physician expertise.. Thus, accurate and automated segmentation of skin lesions from dermoscopic images remains a challenging task [3]. Deep learning methods have become effective tools for automating activities related to the segmentation of medical images, such as skin lesions. The U-Net architecture, [4] introduced by Ronneberger et al. , has been widely adopted for medical image segmentation due to its ability to capture fine-grained details and its robustness in various medical imaging tasks. Despite its success, standard U-Net models often struggle with capturing complex contextual information and accurately delineating irregular lesion boundaries. Moreover, challenges associated with dermoscopic images, such as low contrast between lesions and surrounding skin and significant variations in lesion size and shape, can limit the segmentation accuracy of U-Net models [5]. Enhancements to the basic U-Net architecture are necessary to address these limitations and improve segmentation performance [6].

In this paper, we propose to use an improved U-Net architecture, termed attention-based residual U-Net (AB-ResU-Net) for enhanced skin lesion segmentation. This model integrates attention mechanisms and residual connections into the U-Net framework. Inspired by recent advancements in deep learning, it leverages an attention mechanism to selectively focus on informative features within the lesion [7]. This mechanism suppresses less relevant regions in the image, leading to more accurate segmentation, particularly for lesions with intricate and challenging borders. It uses residual connections to get around the vanishing gradient issue, which can make it difficult to train deeper networks. Because of these connections, the network can learn from the identity mapping, which speeds up the training process and makes it possible for the model to extract more contextual information from the dermoscopic images, improving segmentation performance in the process [8].

We evaluate the proposed model on a publicly available dermoscopic image dataset, PH^2 [9], demonstrating its ability to achieve superior segmentation accuracy compared to the standard U-Net and other existing methods. Our experimental results show notable enhancements in dice coefficient and boundary delineation, indicating the model's robustness and accuracy across various lesion types and imaging conditions.

This paper is structured as follows: Section II examines previous research in the area of skin lesion segmentation. Section III details the proposed attention-based residual U-Net architecture, dataset used, and performance metrics. Section IV details the experimental setup, presents the performance results, and provides a discussion. Section V, which wraps up the paper, also suggests possible directions for future research.

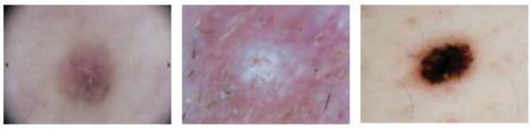


Fig. 1 Various types of malign skin lesions, melanoma and both types of carcinoma

2. Related Work

Traditional skin lesion segmentation methods face limitations due to the diverse nature of skin lesions in terms of sizes, colors, shapes, and textures, making segmentation challenging [10]. These methods are often time-consuming and inefficient, hindering quick and accurate results in skin cancer diagnosis [11]. Additionally, the existing similarity between lesions complicates the examination and visualization process, leading to potential misinterpretations [12]. Moreover, traditional methods may struggle with understanding long-distance spatial relations within images, limiting their segmentation accuracy and efficiency. Traditional methods for skin lesion segmentation usually relied on handcrafted features and machine learning algorithms.

Thresholding and morphological operations were used for segmentation based on intensity variations in the image. However, their performance suffered due to factors like low contrast between lesions and surrounding skin [13]. Active contour models were employed to segment lesions by iteratively refining their position based on image features. While offering some level of automation, these methods were sensitive to initialization and computationally expensive [14]. Feature extraction techniques like texture analysis and local binary patterns (LBP) were used in conjunction with classifiers like Support Vector Machines (SVM) or Random Forests [15]. These methods achieved moderate success but required significant domain knowledge for feature engineering.

Hence, the need for improved performance and comprehensive information extraction has led to the integration of deep learning approaches to enhance skin lesion segmentation and diagnosis. Skin lesion segmentation underwent a revolutionary change with the advent of deep learning systems. Due to their capacity to extract hierarchical information directly from images, Convolutional Neural Networks (CNNs) have emerged as the standard method. Pioneering work by Long et al. [16] introduced FCNs for semantic segmentation tasks. While effective for general image segmentation, FCNs lacked the ability to capture fine-grained details crucial for accurately segmenting skin lesions. U-Net is a specially created architecture for biomedical image segmentation, as suggested by Ronneberger et al. [4]. Skip connections in the encoder-decoder part of U-Net facilitate efficient learning of spatial and contextual information, leading to significant performance improvements in skin lesion segmentation compared to FCNs [12].

Zhou et al. [17] present a lightweight multi-scale U-shaped network (LMUNet) for skin lesion segmentation, offering improved performance with significantly reduced parameters and computational complexity compared to UNet. Additionally, it makes use of an asymmetric atrous spatial pyramid pooling-based technique that improves the network's capacity to extract multi-scale information from the input images. LMUNet showcases its potential to streamline the process of analyzing skin lesions, potentially aiding in early detection, diagnosis, and treatment planning for skin conditions. However, the authors did not address the computational efficiency of LMUNet in terms of inference time or resource utilization on different hardware platforms, which could be crucial considerations for practical implementation and deployment of the network in healthcare systems or medical devices. In a subsequent effort [18], by removing Fast Fourier Transform (FFT) features from input images and feeding them into a U-Net design while simultaneously feeding the original image into a different U-net architecture, the authors suggested a unique method for skin lesion segmentation. The final output is then created by concatenating the findings from both designs. The PH^2 and ISIC-2018 datasets were used to train and evaluate the system, showcasing its effectiveness in accurately segmenting skin lesion images. The study did not address potential issues related to data augmentation techniques, model interpretability, or the strength of the suggested method to variations in image quality or artifacts commonly encountered in dermatological imaging tasks.

Residual connections, as introduced in the ResNet architecture by He et al. [19], have also been leveraged to improve skin lesion segmentation. These links make it possible to train much deeper networks and lessen the impact of the vanishing gradient issue. Residual U-Net, a model combining the strengths of U-Net and ResNet, has shown improved accuracy and convergence in medical image segmentation tasks. A ResNetl01 based U-Net architecture was designed by Manivannan and Venkateswaran [20] in order to accurately segment lesions from the healthy portion of the skin. Extensive data augmentation techniques were employed, contributing significantly to the model's improved efficiency and performance. The model's generalizability to different types of skin lesions or datasets is not thoroughly explored, potentially limiting its applicability in diverse clinical settings. Combining predictions from multiple U-Net models with different hyperparameters or training strategies has been shown to enhance robustness and generalizability [21].

An adversarial learning-based system named EGAN was suggested by Innani et al. [22] for better skin lesion segmentation. The architecture includes a generator module, which features a top-down squeeze excitation-based compound scaled path and an asymmetric lateral connection-based bottom-up path. Additionally, there is a discriminator module designed to differentiate between original and synthetic masks. In comparison to the current techniques for skin lesion segmentation, EGAN showed a 1% increase in accuracy, a 2% rise in dice coefficient, and a 1% improvement in Jaccard index. The framework's success in achieving higher accuracy metrics indicates its effectiveness in accurate skin lesion segmentation from dermoscopic images. Woo et al. [23] proposed the Convolutional Block Attention Module (CBAM) that focuses the network's attention on informative regions within the lesion, leading to improved segmentation accuracy, especially for lesions with intricate borders. In order to create a model, Rehman et al. [24] combined the fundamental UNet architecture with squeeze and excite units, residual connections, atrous spatial pyramid pooling, and attention gates. This method has shown to be effective in handling the variability in lesion appearance and achieving higher segmentation accuracy.

Our proposed model, AB-ResU-Net, builds upon these advancements by incorporating both attention mechanisms and residual connections within a U-Net architecture. This combination aims to achieve superior segmentation accuracy compared to existing methods by focusing on relevant features within the lesion and facilitating the training of a deeper network for capturing a wider range of contextual information in dermoscopic images.

3. Methodology

As illustrated in Figure 2, the proposed system for skin lesion segmentation employing the attention-based residual U-Net (AB-ResU-Net) follows a systematic pipeline consisting of several key stages. First, dermoscopic images are loaded and undergo preprocessing, which involve resizing and data augmentation, an essential step, to artificially expand the training dataset by creating variations of existing images through techniques like flipping and rotating. This helps the model better generalize to unseen data during real-world use. The preprocessed images are then fed into the core of the system for model training. Critically, the AB-ResU-Net incorporates two key improvements: attention mechanisms and residual connections. Attention processes allow the model to concentrate on informative sections of the lesion, which is especially useful for those with irregular borders or small alterations. Residual connections facilitate the transmission of data through deeper layers, allowing the network to understand intricate relationships within the image. Additionally, skip connections within the AB-ResU-Net architecture preserve spatial details crucial for accurate segmentation.

The output of the model is a binary segmentation mask. With the help of this mask, every pixel is given a probability value that represents how likely it is that it is located in the lesion region. As a final step, postprocessing techniques such as morphological operations are applied to refine the mask by removing noise and smoothing the segmentation boundaries. The evaluation stage compares the generated mask with ground truth labels (manually segmented lesion areas) to calculate performance metrics and assess the effectiveness of the system.

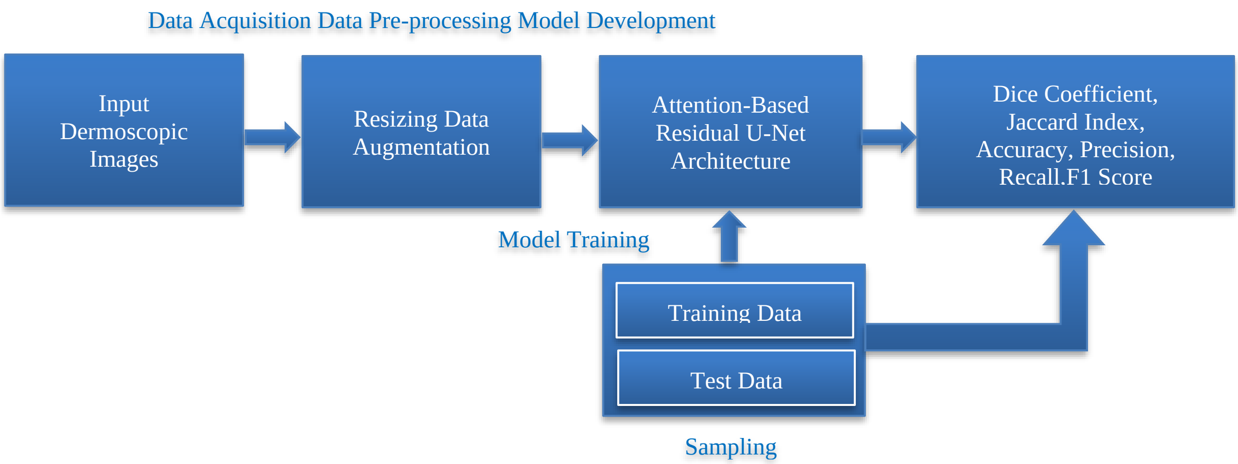


Fig. 2 The overall stages of the proposed system for segmenting skin lesions

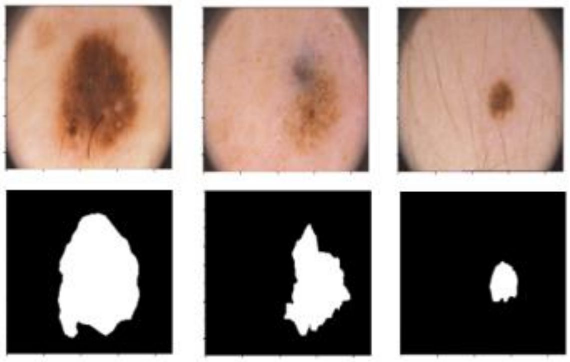
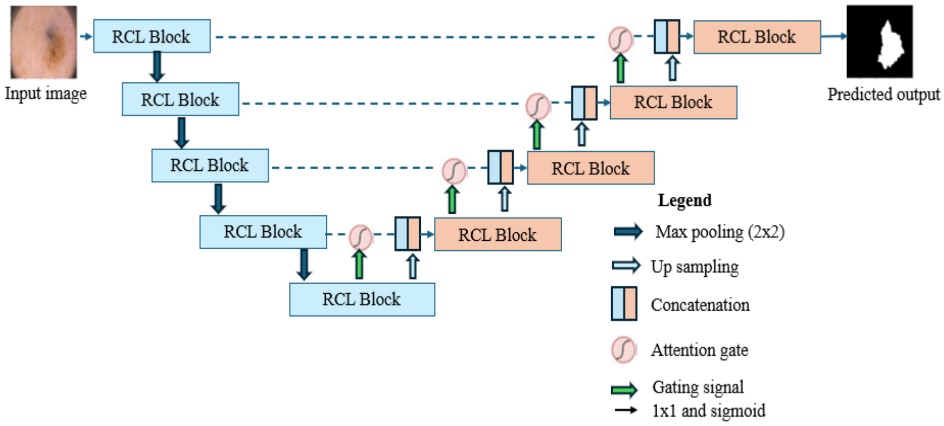
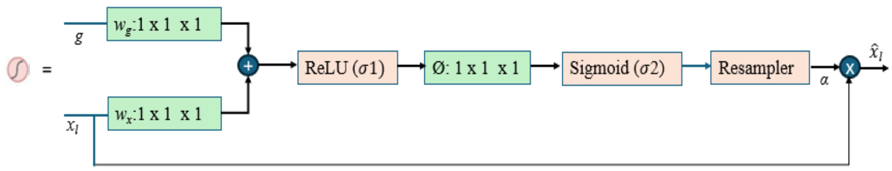


Fig. 3 Some sample images (top row) and corresponding masks (bottom row) from the PH2 dataset



(a)



(b)

Fig. 4 (a) AB-ResU-Net architecture based on the U-Net architecture, which incorporates convolutional encoding and decoding units using residual convolutional layers (RCL). Decoding residual units are integrated with the attention gate (AG) [6], (b) Schematics of the attention gate (AG) [7]

3.1. Dataset Description and Pre-Processing

We have used PH^2 dataset [9] to train and evaluate our skin lesion segmentation system. This dataset is a freely accessible collection of dermoscopic images specifically curated for skin lesion segmentation research. It contains 200 images depicting melanocytic lesions. These lesions are categorized into 80 common nevi (benign moles), 80 atypical nevi (atypical moles), and 40 melanomas (skin cancers). Each image is 768x560 pixels in 8-bit RGB format. In addition, each image is accompanied by a high-quality segmentation mask outlining the exact lesion boundary, providing essential ground truth data for training and validating segmentation models. Figure 3 shows sample images and the corresponding mask from the dataset.

We performed several preprocessing steps on the training and test images prior to training and evaluating the model. Initially, the input dermoscopic images are preprocessed to ensure uniformity and enhance model robustness. The preprocessing steps include resizing the images to a standard size (224x224 pixels). It standardizes the input data, ensuring all images have the same dimensions, which is essential for compatibility with the U-Net model that requires fixed input sizes. This consistency avoids errors during training and inference and eliminates the need for additional handling of varying image dimensions.

Moreover, uniform image sizes optimize memory usage and computational resources, allowing for efficient batch processing and faster training and testing. Resizing images also facilitates the use of consistent data augmentation approaches, which improves the generalization capacity of the model. To improve the model's capacity to generalize to new data, we used data augmentation methods including random rotation and horizontal flipping to expand the training dataset. The training dataset that results after augmentation has 360 images in it. The validation and test sets contain 90 images and 50 images respectively.

3.2. Model Architecture

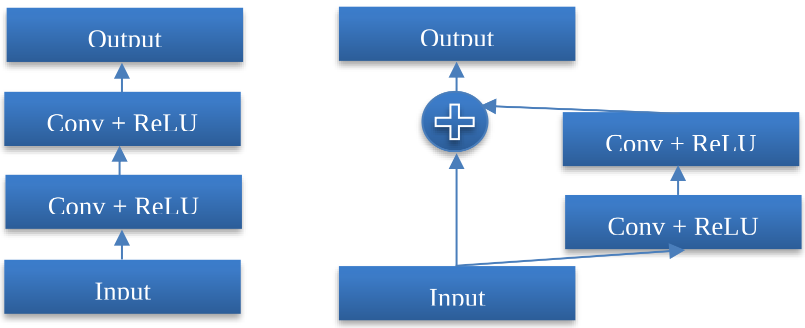
The suggested model for efficient segmentation of skin lesions integrates two advanced neural network architectures: the residual CNN based on U-Net (ResU-Net) [8] architecture by incorporating an additive attention gate (AG) [7] mechanism. This combined model, AB-ResU-Net, aims to leverage the advantages of both approaches for improved skin lesion segmentation.

3.2.1. Base Architecture

The base architecture (ResU-Net) leverages the well-established U-Net architecture for segmenting skin lesions. It maintains the structure of the encoder-decoder, in which high-level features are extracted from the input image by the encoder by gradually shrinking it, and spatial details that are necessary for precise segmentation are recovered by the decoder by upsampling these features. To solve the vanishing gradient issue, a prevalent deep learning challenge, ResU-Net incorporates residual blocks within both the encoder and decoder pathways. Figure 5 (b) shows an example residual convolutional block. These blocks contain convolutional layers, batch normalization for training stability, and rectified linear units (ReLU) activation for introducing non-linearity. Notably, a residual connection adds the block's input straight to its output, facilitating more gradient flow and allowing the network to Figure out complex relationships within the dermoscopic images. ResU-Net also makes use of skip connections, which fill in the space among the encoder and decoder at matching resolutions. These linkages aid in the retention of early stages of processing spatial features, leading to improved localization of lesion boundaries in the final segmentation mask. Figure 4 (a) shows the overall architecture of the residual convolutional neural network based on U-Net (ResU-Net) by incorporating an additive attention gate (AG).

3.3. Integration of Additive Attention Gate (AG)

Our proposed enhancement to ResU-Net involves incorporating an additive attention gate (AG) mechanism within the residual blocks [7]. This addition aims to improve the model's capacity to concentrate on informative regions specifically appropriate for lesion segmentation. The AG is strategically placed after the second convolutional layer within each residual block as illustrated in Figure 4 (a) and (b) displays the schematics of the attention gate. First, a squeeze operation reduces the feature map's spatial dimensions, capturing global feature statistics. Then, an excitation operation utilizes fully-connected layers to generate an attention weight map. This map emphasizes the significance of several channels inside the feature map, emphasizing those informative for lesion segmentation, such as channels capturing color variations or specific texture patterns. Finally, the output from the second convolutional layer is element-wise added with this attention weight map. This process essentially modulates the feature map by emphasizing informative channels based on the learned attention weights. By incorporating the AG mechanism, AB-ResU-net aims to achieve a two-fold benefit: focusing on informative regions within the lesion and potentially improving feature learning through the combined effect of residual connections and the attention mechanism.



(a) **(b)**

Fig. 5 (a) Basic convolutional unit for U-Net, (b) Residual convolutional layer (RCL) block

Table 1. Performance results obtained from training, validation and test data

Data	Results				
	IoU	**Dice Coeff.**	**Accuracy**	**Precision**	**Recall**
Training	99.07	94.52	99.08	98.13	98.91
Validation	97.51	91.95	97.37	95.53	96.31
Test	96.42	89.84	96.55	94.03	94.40

3.4. Evaluation Metrics

A number of metrics are employed in the performance evaluation of the suggested model in order to provide a thorough evaluation. The Intersection over Union (IoU), also known as the Jaccard Index, is a metric that represents the proportion of their intersection in relation to their union that quantifies the overlap between the ground truth and the projected segmentation. Another overlap metric called the Dice coefficient determines the harmonic mean of recall and precision, offering a fair assessment of accuracy. The precision measure of a model's ability to prevent false positives is the percentage of accurately predicted positive pixels out of all projected positive pixels. The percentage of accurately predicted positive pixels among all real positive pixels is known as recall, or sensitivity, and it indicates how well the model can identify true positives. Finally, accuracy determines how much of the total number of pixels, both positive and negative, are correctly identified, hence evaluating the overall correctness of the model.

4. Results and Discussions

This section presents the performance results from training and evaluating our suggested skin lesion segmentation model.

4.1. Experimental Configuration

The training process leveraged Python 3.8 and TensorFlow 2.6 on an Nvidia P100 GPU. Key hyperparameters include 120 epochs, a batch size of 8, an initial learning rate of 0.003, the Adam optimizer, and the Jaccard distance loss function. To prevent overfitting and optimize training, we employed several callback functions such as ModelCheckpoint, EarlyStopping, and ReduceLROnPlateau. To guarantee that the most optimal model was retained throughout the training process, ModelCheckpoint was used to save the model that performed the best on the validation set. In order to prevent overfitting, EarlyStopping was used to stop training if no improvement in validation loss was seen after a predetermined number of epochs. Furthermore, when a validation loss plateau was identified, ReduceLROnPlateau lowered the learning rate, which facilitated a more efficient convergence of the model.

4.2. Analysis of Results

The proposed AB-ResU-Net model was evaluated on training, validation, and test datasets to assess its performance in segmenting skin lesions. The model demonstrated promising results as shown in Table 1 across all metrics, highlighting its effectiveness in skin lesion segmentation tasks. Evaluating performance on the test set reveals a generalizable performance that is lower than the training results, as expected. The test set IoU of 96.42% demonstrates a slight drop compared to training, but still indicates a very good level of overlap between predictions and ground truth. The Dice coefficient of 89.84% reflects a similar trend. Precision of 94.03% suggests the model maintains a good ability to identify true lesion pixels, while the recall of 94.40% indicates it captures a significant portion of the actual lesion area. Overall accuracy of 96.55% aligns with these observations. The validation set results, with an IoU of 97.51% and Dice coefficient of 91.95%, fall between the training and test set performance, suggesting the model is not overfitting significantly. While the training results are very promising, the gap between training and test performance indicates that the model generalizes well but could benefit from further fine-tuning or additional data to bridge the gap between validation and test performance.

The training and validation loss curves as shown in Figure 6, indicated a steady decline in loss, demonstrating that the model effectively learned the features necessary for accurate segmentation. The segmentation performance was enhanced by explicitly optimizing the overlap between the ground truth and anticipated masks by using the Jaccard distance as the loss function.

In addition to quantitative metrics, we conducted a qualitative evaluation by visually inspecting the model's predictions on unseen images from the test set as presented in Figure 7. The output segmentation masks and the matching ground truth masks showed a high degree of similarity in these images. This qualitative assessment aligns with the performance results obtained on the test set, particularly the Intersection over Union (IoU) of 96.42% and Dice coefficient of 89.84%. These metrics indicate a good intersection between the predicted lesions and the actual lesions in the unseen images. The visual confirmation provides further evidence that the model can generalize its segmentation capabilities to unseen data, which is crucial for real-world application. This suggests the model has learned meaningful features that translate well to identifying lesions in new images.

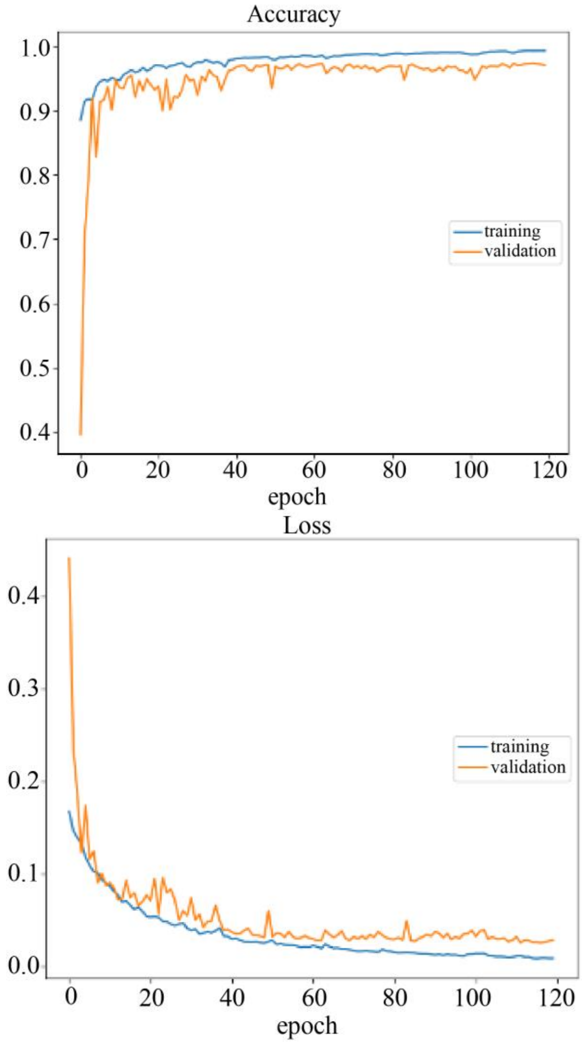


Fig. 6 Accuracy (top) and loss (bottom) curves during training and validation

4.3. Discussion

The segmentation of skin lesions, a critical task in the early identification and diagnosis of skin cancer, including melanoma, is an area in which the proposed model exhibits tremendous potential. The U-Net architecture's incorporation of additive attention gates and residual connections improves the model's capacity to concentrate on relevant features and mitigates the vanishing gradient problem, resulting in improved segmentation performance.

The model demonstrated high performance measures on test dataset, with IoU, Dice coefficient, precision, recall, and accuracy scores indicating its robustness and efficacy in capturing the sophisticated details of skin lesions.

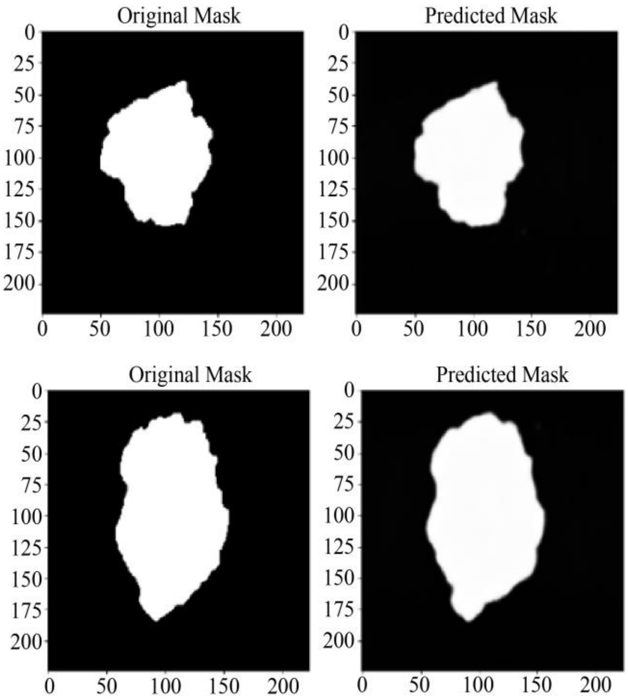


Fig. 7 Comparison of ground truth mask and corresponding predicted mask for sample test images

Moreover, qualitative analysis through visual inspection of the predicted masks for unseen test images further confirmed the model's capability to accurately outline lesion boundaries, closely matching the ground truth masks. This visual similarity underscores the practical applicability of the model, suggesting that it can effectively support clinical decision-making processes by providing precise segmentation results. Despite these promising results, there are several limitations in our study. First, the reliance on the PH2 dataset, which is relatively small and may not fully represent the diversity of skin lesion presentations in broader clinical settings.

This limitation could potentially impact the generalizability of the model when applied to different patient populations or imaging conditions. Additionally, the model's performance, while robust, showed a slight decrease when moving from training and validation datasets to the test dataset. This suggests that further fine-tuning and possibly the integration of more diverse datasets could be beneficial to enhance the model's generalizability and robustness.

5. Conclusions And Future Work

This work presents a residual U-Net model that is based on attention mechanism for the purpose of segmenting skin lesions in dermoscopic images. This is achieved by incorporating attention mechanisms and residual connections into the traditional U-Net architecture. The model is trained and evaluated using a publicly available dermoscopic image dataset and achieves a high value of accuracy (96.55%) and IoU (96.42%) in segmenting skin lesion with a high degree of precision and recall.

Visual inspections confirm that the predicted masks closely match the ground truth, reinforcing the model’s practical applicability for clinical use. As a future work, we envision to concentrate on expanding the dataset to include a broader range of skin lesion types and imaging conditions to enhance the model’s generalizability.

References

[1] Cancer, World Health Organization, 2019. [Online]. Available: https://www.who.int/health-topics/cancer

[2] Skin Cancer, American Cancer Society, 2025. [Online]. Available: https://www.cancer.org/cancer/types/skin-cancer.html

[3] N. C. F. Codella et al., “Deep Learning Ensembles for Melanoma Recognition in Dermoscopy Images,” *IBM Journal of Research and Development*, vol. 61, no. 4/5, pp. 5:1-5:15, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[4] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” *Medical Image Computing and Computer-Assisted Intervention - MICCAI 2015: 18th International Conference*, Munich, Germany, pp. 234-241, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[5] Ozgun Cicek et al., “3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation,” *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016: 19th International Conference*, Athens, Greece, pp. 424-432, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[6] Qiang Zuo, Songyu Chen, and Zhifang Wang, “R2AU-Net: Attention Recurrent Residual Convolutional Neural Network for Multimodal Medical Image Segmentation,” *Security and Communication Networks*, vol. 2021, no. 1, pp. 1-10, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Ozan Oktay et al., “Attention U-Net: Learning Where to Look for the Pancreas,” *1st Conference on Medical Imaging with Deep Learning (MIDL 2018)*, Amsterdam, The Netherlands, pp. 1-10, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[8] Foivos I. Diakogiannis et al., “ResUNet-a: A Deep Learning Framework for Semantic Segmentation of Remotely Sensed Data,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 162, pp. 94-114, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Teresa Mendonca et al., "PH^2 - A Dermoscopic Image Database for Research and Benchmarking," *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Osaka, Japan, pp. 5437-5440, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[10] Omran Salih et al., "An Overview of Skin Lesion Segmentation Methods: Techniques, Challenges, and Future Directions," *2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA*), Benghazi, Libya, pp. 744-749, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Duan Wang, "Skin Lesion Segmentation of Dermoscopy Images Using U-Net," *Applied and Computational Engineering*, vol. 6, pp. 840-847, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Hanene Sahli, Amine Ben Slama, and Mounir Sayadi, "Skin Lesion Segmentation Based on Modified U-NET Architecture," *2023 IEEE International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*, Hammamet, Tunisia, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Nidhal Khdhair El Abbadi, and Abbas Hussien Miry, "Automatic Segmentation of Skin Lesions Using Histogram Thresholding," *Journal of Computer Science*, vol. 10, no. 4, pp. 632-639, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[14] Farhan Riaz et al., "Active Contours Based Segmentation and Lesion Periphery Analysis for Characterization of Skin Lesions in Dermoscopy Images," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 2, pp. 489-500 , 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Lina Liu et al., "Automatic Skin Lesion Classification Based on Mid-Level Feature Learning," *Computerized Medical Imaging and Graphics*, vol. 84, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] Jonathan Long, Evan Shelhamer, and Trevor Darrell, "Fully Convolutional Networks for Semantic Segmentation," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3431-3440, 2015. [Google Scholar] [Publisher Link]

[17] Pengfei Zhou, Xuefeng Liu, and Jichuan Xiong, "Skin Lesion Image Segmentation Based on Lightweight Multi-Scale U-Shaped Network," *Biomedical Physics and Engineering Express*, vol. 9, no. 5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Omran Salih et al., "FFT-Assisted U-Net Architecture for Improved Skin Lesion Segmentation," *2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*, Benghazi, Libya, pp. 480-485, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Kaiming He et al., "Deep Residual Learning for Image Recognition," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 770-778, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[20] S. Manivannan, and N. Venkateswaran, "Skin Lesion Segmentation using Residual U-NET," *2023 10th International Conference on Signal Processing and Integrated Networks (SPIN)*, Noida, India, pp. 405-409, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Dasari Anantha Reddy et al., "Enhanced U-Net Segmentation with Ensemble Convolutional Neural Network for Automated Skin Disease Classification," *Knowledge and Information Systems*, vol. 65, no. 10, pp. 4111-4156, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[22] Shubham Innani et al., "Generative Adversarial Networks Based Skin Lesion Segmentation," *Scientific Reports*, vol. 13, no. 1, pp. 1-10, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Sanghyun Woo et al., "CBAM: Convolutional Block Attention Module," *Computer Vision – ECCV 2018, 15th European Conference*, Munich, Germany, pp. 3-19, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[24] Aasia Rehman, Muheet A. Butt, and Majid Zaman, "Attention Res-UNet: Attention Residual UNet With Focal Tversky Loss for Skin Lesion Segmentation," *International Journal of Decision Support System Technology*, vol. 15, no. 1, pp. 1-17, 2023. [Google Scholar] [Publisher Link]