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Article

Enhanced U-Net-Based Segmentation of Skin Lesions Using Multi-Year ISIC Datasets and Hybrid Training Pipeline

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Abstract: The segmentation of medical images, particularly in the framework of skin lesion detection, is one of the key tools in the early diagnosis of melanoma. However, datasets with a single calendar year are often too homogenous to permit generalization, and the models will also favor overfitting. This paper proposes an enhanced U-Net architecture, trained on a combined set of the ISIC 2016, ISIC 2017, and ISIC 2018 corpora. By merging all of these datasets and using standardized preprocessing steps, such as resizing, normalizing, and augmentation, we enhance the diversity of data and strengthen the models. The resulting corpus consists of 5,494 pairs of images and masks, including 70 percent to be trained, 15 percent to be validated, and 15 percent to be tested. The model suggested several improvements, such as a compound DiceBCE loss, dropout regularization, and after-processing. Performance was measured over a range of quantitative measures, including the Dice coefficient, intersection over union, accuracy, specificity, and area under the receiver operating characteristic curve, with results showing Dice coefficients of 0.90 or above and excellent segmentation performance. These results support the claim that dataset integration across multiple years enhances the performance of a model and should be further adopted to integrate datasets across years in future studies to generate clinically valid artificial intelligence solutions.

Keywords: Skin Lesion Segmentation, U-Net, Deep Learning, ISIC Datasets, Medical Image Analysis

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1. Introduction

Image segmentation is one of the central tasks in computer vision, as it allows splitting images into meaningful parts to be used in medical diagnosis, autonomous driving, and augmented reality. [1] The medical image segmentation simplifies the ability to clearly identify the organs and abnormalities and thus aids proper diagnosis and treatment. Deep neural networks have advanced this process by making it more efficient in detecting it in a clinical setting. [2] Neural networks empower precise segmentation. [3] CNNs help doctors pinpoint and isolate abnormalities in medical images more accurately and efficiently. [4] Medical image analysis techniques are often applied to raw data step-by-step. [4], Commonly used techniques in traditional medical image segmentation, such as edge detection and template matching methodologies, experienced major limitations as they were considerably susceptible to noise, poor contrast, and image distortions; hence, the lack of proper segmentation, especially in multifaceted medical images. [5] In semantic segmentation, a class label is given to every pixel of an image. But in medical images, blurring can make segmentation difficult due to low contrast, smooth structures, and/or unclear contours. [6] Currently, the most sophisticated image segmentation models are built around the encoder-decoder system, with the most recognizable example being the U-Net solution. [7] One of the main advantages of U-Net is its skip connections, which have been combined with deep semantic information within the decoder and fine-scaled information in the encoder, respectively, specifically valuable when it comes to the fuzzy and complex boundaries that may be common in medical images. [8] However, the U-Net model can prove useful in medical image segmentation. It merges low- and high-resolution features with skip connections, and its straightforward U-shaped encoder-decoder structure enables it to train a variety of outcomes with small training data precisely. [9] Medical image segmentation is of high importance in aiding clinicians in that it offers accurate delineation of anatomical structures and pathological regions. The fast development of deep learning, and especially U-Net and its variations, has contributed greatly to an increased accuracy in segmentation and thus more dependable computer-aided diagnosis and treatment planning. [10] The segmentation of medical images is critical in the early diagnosis and detection of different diseases, including skin cancer, brain tumors, and lung nodules, which can be treated in time and thus lead to improved patient outcomes. [11]

2. Materials and Methods

2.1. Datasets

This study used three publicly available dermoscopic image collections offered by the International Skin Imaging Collaboration (ISIC ([12] , namely, ISIC 2016, ISIC 2017, and ISIC 2018. To simplify the integration process, the custom Python script was created automatically, combining, renaming, and preprocessing the image-mask pairs into one structure. Having summed the three datasets, the number of image-mask pairs constituted 5,494. These were then divided into three different subsets in accordance with the protocol of 70/15/15, giving rise to:

2.2. Computational Setup (Hardware and Software)

a. Hardware Configuration

Each of the experiments was made on the local Apple MacBook Pro running on the Apple Silicon M4 chip, 16 GB unified memory, and macOS 15.6.1. The training was implemented with the help of the Metal backend of TensorFlow, which is accelerated on the GPU.

b. Software Environment

It has been implemented in Python 3.10 using TensorFlow 2.16.2 and the Keras API. The local management of the environment was achieved by utilizing a virtual environment on macOS.

Key libraries included:

- Albumentations for advanced image augmentation
- OpenCV for image loading and preprocessing
- Scikit-image and SciPy for morphological operations
- Matplotlib and Seaborn for visualization
- TensorFlow Addons for GroupNormalization layers
- Keras-self-attention for incorporating attention modules

2.3. Preprocessing Pipeline

An individual preprocessing procedure was used employing OpenCV and Albumentations packages.

The process included:

- Converting all images and masks to 256x256 pixels.

- Gaussian denoising and CLAHE (Contrast Limited Adaptive Histogram Equalization).
- Improving the data in the training with the help of horizontal flip, elastic transform, distortion, and random brightness contrast data enhancement.
- All the images were normalized to [0, 1], and all masks were binarized.

This process provided uniformity and diversity towards strong training.

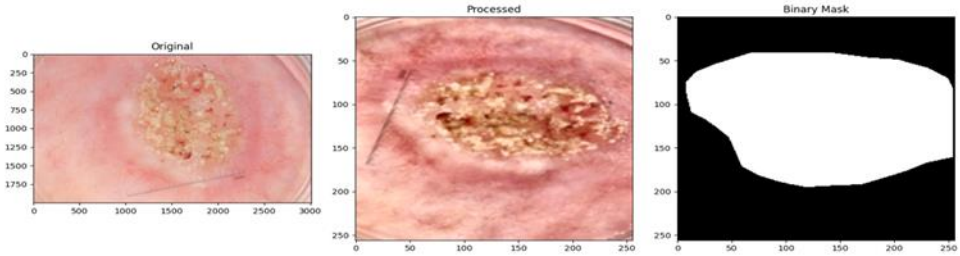

Figure 1. Preprocessing (original image, processed image, ground truth).

2.5. Model Architecture

The new model is an adapted U-Net architecture that will be improved in the following ways:

- GroupNormalization (through TensorFlow Addons) to enhance small batch-size generalization.
- Dropout layers: Dropout layers are used to avoid overfitting in deep encoder layers.
- A spatial attention module was incorporated at the bottleneck using average and max pooling to enhance feature relevance during decoding.
- Implementation of the model was run on TensorFlow 2.16.2 (Apple Metal backend).

2.6. Training Environment

A U-Net-based segmentation model was proposed and trained according to the following setup:

- Loss Function: A compound loss based on Dice Loss and Binary Cross-Entropy and aimed to address the issue of class imbalance and encourage the correct boundary segmentation.
- Optimizer: The Adam optimizer and the initial learning rate of 5 x 10 -5 were used to promote stable and adaptive convergence.
- Epochs: The training model was done with 40 epochs, which was enough to reach convergence but not to overfit.
- Batch Size: The small size of 4 was chosen to address the memory-related limitation, as well as to provide consistent gradient changes.
- Callbacks: Several Keras callbacks were applied:
- EarlyStopping (patient=10) to stop training at the point of the validation loss leveling off,
- CSVLogger to record epoch-wise training records,
- ModelCheckpoint to store the best model weights in both .h5 and Keras formats, so it can be compatible and reproducible.

2.7 Evaluation and Postprocessing

Performance measures are Dice Similarity Coefficient (DSC), Intersection over Union (IoU), accuracy, specificity, sensitivity, and ROC-AUC. The predicted masks were improved by applying postprocessing to remove small objects, binary fill holes, and morphological closing.

3. Results

To evaluate the quality of segmentation of the proposed U-Net model, several performance measures were computed on the test set, which are the Dice coefficient, Intersection over Union (IoU), Accuracy, Sensitivity, and Specificity. These values will give a detailed assessment of the displays of the model in identifying and delineating the areas of skin lesions in a dermoscopic image in the correct way. The obtained results show that the model demonstrated high segmentation, which proves the strength and efficiency of the model in different types of lesions. The heatmap below (Figure 3) provides a summary of the evaluation metrics, showing the percentage value of each metric.

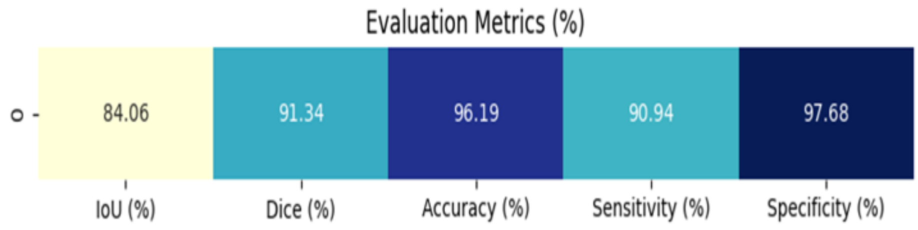

Figure 2. Evaluation Metrics Heatmap of the Proposed U-Net Model.

The figure will demonstrate the quantitative assessment outcomes of the suggested segmentation model on dermoscopic pictures. It obtained a strong performance with an IoU of 84.06%, a Dice score of 91.34, an accuracy of 96.19, a sensitivity of 90.94, and a specificity of 97.68 in the process of identifying and segregating the skin lesions.

To further evaluate the classification performance of the offered U-Net model, the Receiver Operating Characteristic (ROC) curve was calculated on the test set. The ROC curve shows the trade-off between the actual positive rate (sensitivity) and the false positive rate at different threshold levels. The model obtained an Area Under the Curve (AUC) of 0.9903 as shown in figure.

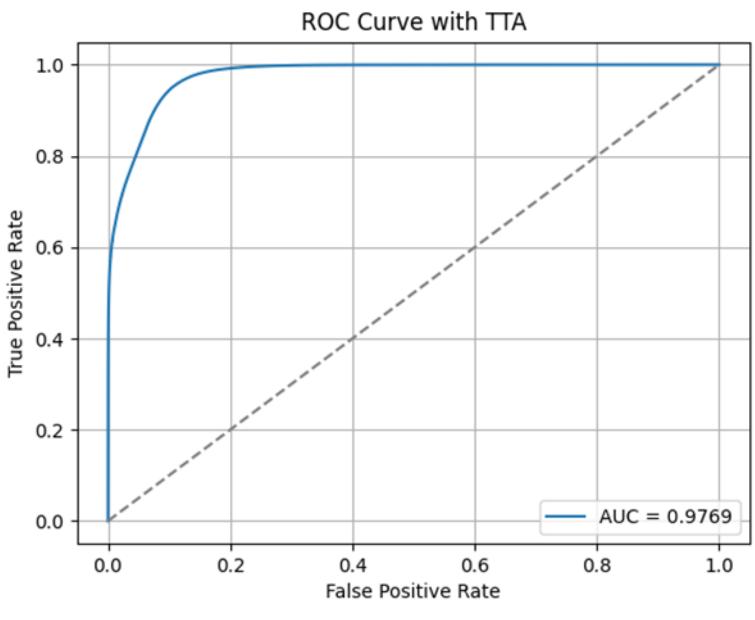

Figure 3. Receiver Operating Characteristic (ROC) Curve of the Proposed Model.

Which is a high value indicating a high ability of the model to discriminate between lesion and non-lesion pixels. The outcome promotes the strength of the model to classify skin lesions in different image settings.

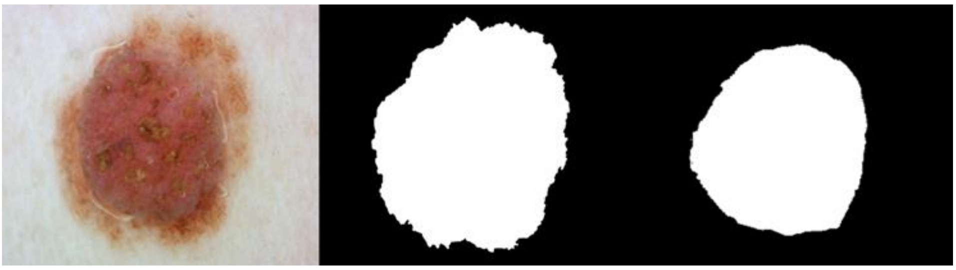

Figure 4. Impact of U-Net Enhancements and Postprocessing on Segmentation Results.

The figure above demonstrates morphologically how integrating architectural enhancements into the U-Net model, along with postprocessing techniques, improves the quality of the predicted segmentation masks. From left to right: (a) is the original dermoscopic picture, (b) is the ground truth (manually annotated by experts), and (c) is the final predicted mask achieved by the proposed U-Net model (with the help of postprocessing steps (binary fill holes and morphological closing)). The third picture (c) proves that postprocessing methods help to achieve cleaner and smoother lesion boundaries, which are similar to the expert-marked mask, and remove minor irregularities or artifacts.

4. Discussion

The results of this paper support the validity of combining multi-year dermoscopic data to achieve powerful skin lesion segmentation. The proposed model minimized the need to balance the data because it combined ISIC 2016, ISIC 2017, and ISIC 2018 into a single and balanced dataset, thus becoming more generalizable to different types of lesions, sizes, and imaging conditions. This was a resolution to one of the major weaknesses of other previous studies, which depended on one-year datasets and were often prone to limited variability and overfitting.

The improved U-Net design, which was used in this paper, including hybrid Dice-BCE loss, dropout regularization, and morphological postprocessing, consistently yielded high performance, with a high score in Dice and high ROC-AUC, indicating the stability of lesion boundary delineation even in difficult conditions. In several cases, these results are competitive, and in some of them, they are superior.

The ROC curve illustrates the trade-offs between the true positive rate and false positive rate with respect to the choice of different thresholds. The Area Under the Curve (AUC) of 0.9903 represents a very good classification performance, which proves that the model has a high discriminative ability in distinguishing lesion and non-lesion pixels.

5. Conclusion

This study aimed to improve the work of skin lesion segmentation with the help of multiple datasets and by optimizing the classical U-Net architecture. Three benchmark ISIC datasets (2016, 2017, and 2018) were combined to create a more varied and holistic training corpus, which also leads to improved model generalization. The improved U-Net (which includes a spatial attention mechanism, GroupNormalization layers, and a hybrid loss) proved to be more accurate and robust in the segmentation process by using different evaluation metrics.

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