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CNN-based Wound Segmentation: A Review of Models and Performance Evaluation

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Abstract

Deep learning, particularly convolutional neural networks (CNNs), has altered medical image processing by automating and precisely segmenting complex medical pictures. Wound segmentation, a critical application in automated wound assessment, is essential for wound size estimation, classification, and healing progress monitoring. This study presents a comprehensive review of CNN-based wound segmentation models, focusing on their architectures, methodologies, and performance on diverse datasets. Four deep learning models, including two U-Net variants (5-layer and 4-layer), SegNet, and MobileNetV2, were evaluated on three datasets: AZH Woundcare Dataset, WoundSeg Dataset, and Medetec Wound Dataset. The models were analyzed using standard metrics such as Dice coefficient and loss values. By comparing the strengths and limitations of these models, this review highlights the impact of dataset size and architectural variations on segmentation performance. The findings shed light on the status of wound segmentation research and suggest directions for future advancements.

Keywords: Wound segmentation, convolutional neural networks, U-net, Segnet, Mobilenetv2, deep learning, medical image analysis, segmentation

INTRODUCTION

Image segmentation is a fundamental task in computer vision that involves partitioning an image into meaningful regions or objects. In the medical domain, precise segmentation of images is crucial for accurate diagnosis and effective treatment planning. This is particularly important in chronic wound care, where accurate segmentation aids in quantifying wound size, classifying wound types, and monitoring healing progress over time. Traditional segmentation methods often relied on manual efforts, which are time-consuming, error-prone, and difficult to standardize.

Convolutional Neural Networks (CNNs) have transformed image analysis by learning hierarchical features from data without the need for manual feature engineering. These networks have performed exceptionally well in a variety of picture segmentation tasks, including medical applications. For instance, CNN-based frameworks have been developed for fully automatic wound segmentation, showcasing significant advancements in this area [1]. Additionally, frameworks like MIScnn have been introduced to provide comprehensive tools for medical image segmentation using CNNs [2].

Recent advancements in CNN architectures, such as attention mechanisms, hybrid models, and multi-scale processing, have further enhanced their accuracy and robustness. For example, studies have proposed hybrid feature extraction networks that

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integrate CNNs and Transformers to utilize their combined strengths in feature extraction [3]. Furthermore, attention-based models have been applied to medical image segmentation, improving the focus on relevant regions and thereby enhancing segmentation performance [4].

This study reviews the existing literature on CNN-based wound segmentation models, evaluates their performance on diverse datasets, and discusses potential future research directions to advance the field. This review seeks to guide future research on wound segmentation using CNNs by highlighting the strengths and limitations of current models and examining trends identified in recent publications. Our findings highlight the need of addressing existing difficulties to realize the full potential of CNNs in therapeutic applications.

LITERATURE REVIEW

Wang *et al*. explored the superiority of DL-based segmentation methods over traditional algorithms, such as thresholding and K-means clustering, in RGB image segmentation [5]. Models like U-Net, SegNet, and Fully Convolutional Networks (FCNs) significantly outperform classical methods in terms of accuracy, precision, and recall. Additionally, DL models scale effectively with higher-resolution images, demonstrating their adaptability and robustness across diverse datasets and applications.

Segmentation for brain tumor identification is highlighted in one study, which emphasizes the importance of partitioning MRI images into regions representing tumor types, such as enhancing tumors, necrotic tissues, and peritumoral edema. Daimary *et al*. discussed the limitations of manual segmentation, which is time-intensive and error-prone, and demonstrates the effectiveness of DL architectures like U-Net and SegNet [6]. U-Net's encoder-decoder structure with skip connections preserves fine spatial details, while SegNet's computationally efficient design simplifies operations, making it suitable for resource-limited environments. Hybrid models such as Seg-UNet and Res-SegNet combine these strengths, enhancing accuracy and boundary delineation for improved diagnostic outcomes.

Daniel *et al*. focused on segmenting fluorescence microscopy images of the endoplasmic reticulum (ER) network, a critical task for understanding cellular conditions and disease mechanisms [7]. The paper introduces advanced models such as VGG-UNet and VGG-SegNet, which leverage the VGG19 architecture to achieve segmentation accuracies exceeding 98%. These models integrate U-Net’s precise encoder-decoder structure and SegNet’s computational efficiency. The study also incorporates innovations like 16 to 8-bit data conversions and advanced preprocessing, showcasing the potential of VGG-SegNet for clinical-grade ER network analysis.

Huang *et al.* offer a deep learning algorithm that can segment the median nerve in ultrasound pictures [8]. The architecture integrates VGG16 in the encoder path and attention mechanisms to focus on critical regions, with variants such as A-VGG16-UNet, S-VGG16-UNet, and AS-VGG16-UNet. Trained on 910 images and tested on 207, the model achieved high performance, with A-VGG16-UNet attaining the best results. The model's 3D nerve reconstructions provide clinical insights, though the study highlights dataset limitations and suggests expanding to diverse populations.

The use of deep learning (DL) in wound image analysis, highlighting advancements in classification, detection, and segmentation. It emphasizes architectures like U-Net, ResNet, and YOLO, along with specialized models such as Mask R-CNN for tasks like burn and diabetic foot ulcer analysis. Public datasets and preprocessing techniques are discussed as key to improving performance. Zhang *et al.* identified challenges, including limited datasets and annotation variability, and suggests future directions like standardized datasets and real-world model optimization, showcasing DL’s potential to transform wound diagnosis and care [9].

Baccouch *et al*. evaluated U-Net and CNN architectures for automatic segmentation of cardiac MRI images, focusing on the left and right ventricles using the ACDC database [10]. Data augmentation increased the training dataset size fourfold. U-Net, with its encoder-decoder structure and skip connections, outperformed CNN in terms of Dice Similarity Coefficient (DSC), Hausdorff Distance (HD), and segmentation accuracy, achieving a mean DSC of 97.9% for the left ventricle and 95.75% for the right ventricle. U-Net also required less training time due to its lack of fully connected layers, making it more computationally efficient. The paper highlights U-Net's superiority in segmenting smaller anatomical structures and reducing reliance on manual segmentation in cardiac diagnostics.

U-Net is a deep learning architecture specifically designed for medical image segmentation, characterized by its symmetric encoder-decoder structure. Siddique *et al*. studied the whole process as well as the separate variants [11]. The encoder path extracts classification features through successive convolutional layers, max-pooling, and non-linear activation functions. The decoder path, by contrast, utilizes up-convolutions and concatenates features from corresponding encoder layers to recover spatial resolution and create detailed segmentation maps. This architecture's hallmark U-shape ensures precise pixel-level classification. U-Net variants, such as 3D U-Net, Attention U-Net, and Residual U-Net, extend its capabilities to volumetric data, emphasize relevant features, and address deep network training challenges, respectively. These advancements have made U-Net a cornerstone in medical imaging for segmenting modalities like MRI, CT, and ultrasound.

Malhotra *et al*. explores deep neural network architectures for medical image segmentation, addressing challenges like intensity variations and complex textures [12]. U-Net, a key focus, features an encoder-decoder structure that combines high-level contextual information with precise localization using skip connections. Variants such as U-Net++, Attention U-Net, and SD-UNet enhance performance through innovations like dense skip connections, attention mechanisms, and structured dropout. Other architectures, including FCN, VNet, and Mask R-CNN, adapt to specific tasks with features like volumetric kernels, region proposal networks, or multi-task learning. These models are applied across modalities such as MRI, CT, and X-rays, advancing segmentation accuracy and efficiency.

MATERIAL AND METHODS

Datasets

The performance of the proposed segmentation models was assessed using three publicly available wound segmentation datasets. These datasets vary in size, wound types, and augmentation strategies, offering a diverse set of challenges to evaluate the models comprehensively.

AZH woundcare dataset

The AZH Woundcare Dataset is a large-scale collection consisting of 4040 wound images obtained from 889 patients, primarily capturing cases of foot ulcers [13]. Each image is provided with a corresponding binary mask that precisely marks the wound regions. The dataset was further augmented to enhance its diversity, including transformations such as rotations, cropping, and intensity adjustments, which help mitigate overfitting and improve the generalization ability of the models. Due to its substantial size and augmentation, this dataset serves as a robust benchmark for wound segmentation tasks.

WoundSeg dataset

The WoundSeg Dataset comprises 2686 images, representing a wide variety of wound types [14]. Like the AZH Woundcare dataset, each image includes an associated binary mask that delineates the wound area. However, unlike the AZH Woundcare dataset, the WoundSeg dataset was used in its original form without applying any data augmentation techniques. This dataset poses a unique challenge as its unaugmented nature may require the models to rely solely on the inherent variability in the dataset for learning, as well as the multiple diverse types of wounds like diabetic, pressure, trauma, etc. prove a challenge to multiple segmentation models. The inclusion of this dataset in the study ensures the evaluation of model performance on datasets with varying levels of diversity and preprocessing.

Medetec wound dataset

The Medetec Wound Dataset is the smallest of the three, consisting of 200 images focused exclusively on foot ulcers [15]. While the full Medetec Wound Dataset is large and encompasses various types of wounds, we specifically selected the foot ulcer subset for our study. Each image is complemented by a binary mask for accurate wound delineation. Given the small sample size, data augmentation techniques were used to artificially enlarge the dataset and give a more thorough training set for the models. These augmentations included transformations such as scaling, cropping, and intensity variations, ensuring that the dataset was sufficient to train and test segmentation algorithms effectively. Despite its smaller size, this dataset remains significant due to its specific focus on foot ulcers, helping us evaluate segmentation models in more specific context.

Together, these datasets provide a diverse set of challenges in terms of wound type, dataset size, and augmentation. This diversity is crucial for ensuring that the segmentation models are not only accurate but also robust and generalizable to real-world clinical scenarios.

Segmentation Models

To evaluate wound segmentation performance, three deep learning models: U-Net, SegNet, and MobileNetV2, were employed in this study. These models represent a diverse set of architectural paradigms and capabilities, enabling a comprehensive assessment of their strengths and limitations in the context of wound image segmentation. A full overview of each model is represented in Figure 1.

U-Net

U-Net is one of the most popular networks for biomedical image segmentation applications due to its ability to produce precise results even with little training data [16]. The network architecture consists of three major components:

1. *Contracting path:* This method decreases the spatial dimensions of the input image while extracting more abstract elements. It employs convolutional layers followed by ReLU activation and max-pooling operations to achieve feature extraction and downsampling.
2. *Bottleneck:* Positioned between the contracting and expanding paths, the bottleneck serves as the transition point where the network focuses on extracting high-level features at the lowest spatial resolution. This component helps the model capture the most essential and complex features of the input image, providing a rich feature representation for accurate segmentation.
3. *Expanding path:* This path restores the spatial dimensions of the feature maps through upsampling and concatenates them with equivalent feature maps from the contracting path using skip connections. These skip connections allow the model to retain fine-grained spatial details, critical for accurate segmentation of small or irregularly shaped wounds.

In this study, two variants of U-Net were explored:

1. *U-Net (5-layer):* This architecture features a U-shaped encoder-decoder design with five layers in both the contracting and expansive paths. The skip connections ensure precise localization by preserving spatial information, making it highly effective for medical image analysis.
2. *U-Net (4-layer):* This is a modified version of the standard U-Net with four layers instead of five. It is designed to test whether a smaller U-Net can achieve similar performance while being computationally more efficient.

U-Net's flexibility, combined with its ability to capture both contextual and detailed information, makes it highly suitable for wound segmentation applications.

SegNet

SegNet is a deep convolutional neural network designed specifically for pixel-wise image segmentation [17]. Its architecture is characterized by an encoder-decoder structure, which facilitates effective feature learning and segmentation output, as shown in Figure 2.

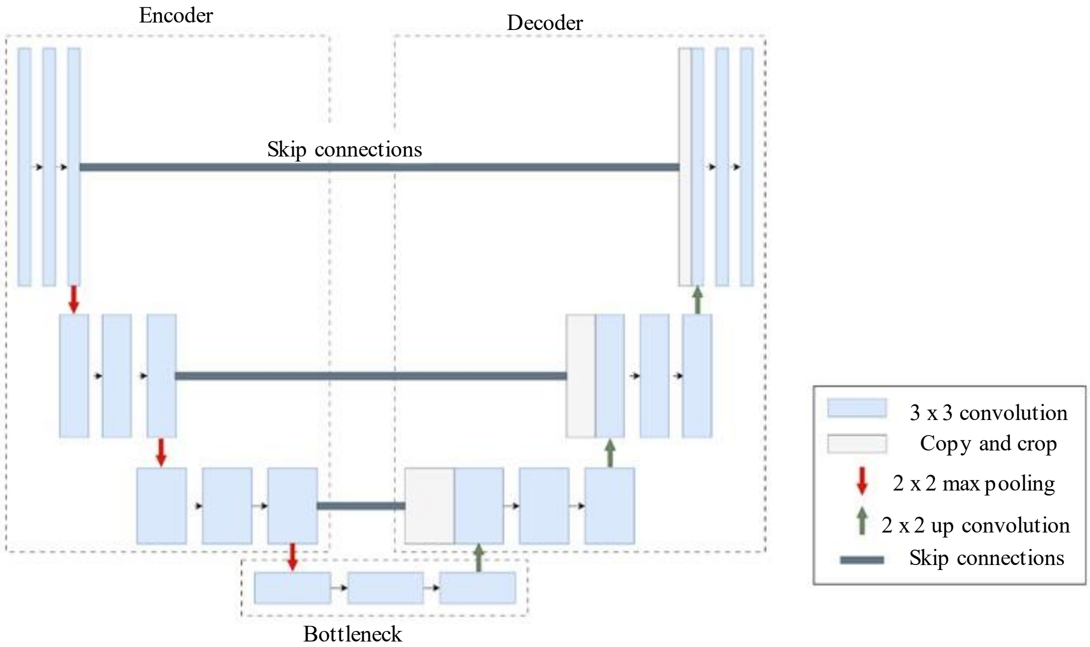


Figure 1. UNet architecture.

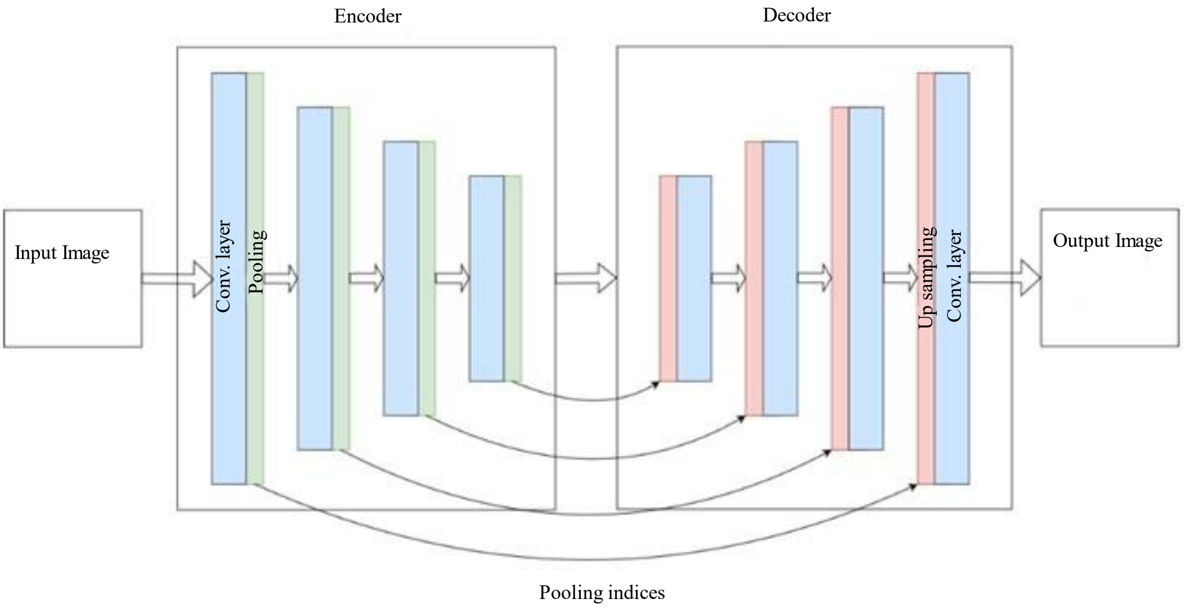


Figure 2. SegNet architecture.

Encoder: The encoder network in SegNet mirrors the convolutional layers of the VGG16 architecture, consisting of 13 convolutional layers. Unlike VGG16, SegNet discards the fully connected layers to preserve higher-resolution feature maps, significantly reducing the number of trainable parameters. Max-pooling is used in the encoder to downsample the feature maps while capturing spatial invariance. To address the loss of spatial information caused by pooling, SegNet stores the max-pooling indices for subsequent use in the decoder.

Decoder: The decoder network mirrors the encoder structure, using the stored max-pooling indices to upsample feature maps efficiently. This method restores spatial resolution while keeping boundary features required for successful segmentation.

SegNet's ability to efficiently store and utilize spatial information makes it particularly effective in scenarios where precise delineation of wound boundaries is critical.

MobilenetV2

MobileNetV2 is a lightweight neural network architecture designed for efficient performance on resource-constrained devices is shown in Figure 3 [18]. Despite its compact size, it delivers state-of-the-art results for various image analysis tasks, including segmentation. The architecture is based on an inverted residual block structure and depthwise separable convolutions, which reduce computing cost while retaining good accuracy.

Inverted residuals: Unlike traditional residual networks, which expand the input features in intermediate layers, MobileNetV2 employs bottleneck layers, compressing the input features before expanding them for transformation. This approach increases efficiency while preserving expressiveness.

Depthwise separable convolutions: These convolutions function separately on each input channel before combining them using a pointwise convolution. This minimizes the number of parameters and processes in the model, making it more computationally efficient.

Adaptation for segmentation: In this study, MobileNetV2 was used in conjunction with a reduced version of the DeepLabV3 framework, enabling it to perform semantic segmentation. This adaptation makes MobileNetV2 a strong candidate for real-time wound segmentation tasks, particularly on mobile or edge devices.

The models selected for this study cover a wide spectrum of architectural complexities and resource requirements. U-Net focuses on precision and contextual understanding, SegNet emphasizes efficient handling of spatial information, and MobileNetV2 offers a balance between accuracy and computational efficiency. Together, these models provide a robust framework for evaluating wound segmentation across diverse datasets and application scenarios.

RESEARCH METHODOLOGY

Research Setup

The experiments were conducted on our college machine learning server. Python 3.8.0 was utilized for the implementation, along with TensorFlow 2.6.0, Keras 2.6.0, and NumPy 1.19.2 for deep learning and numerical computations. The server is equipped with the following features listed in Table 1.

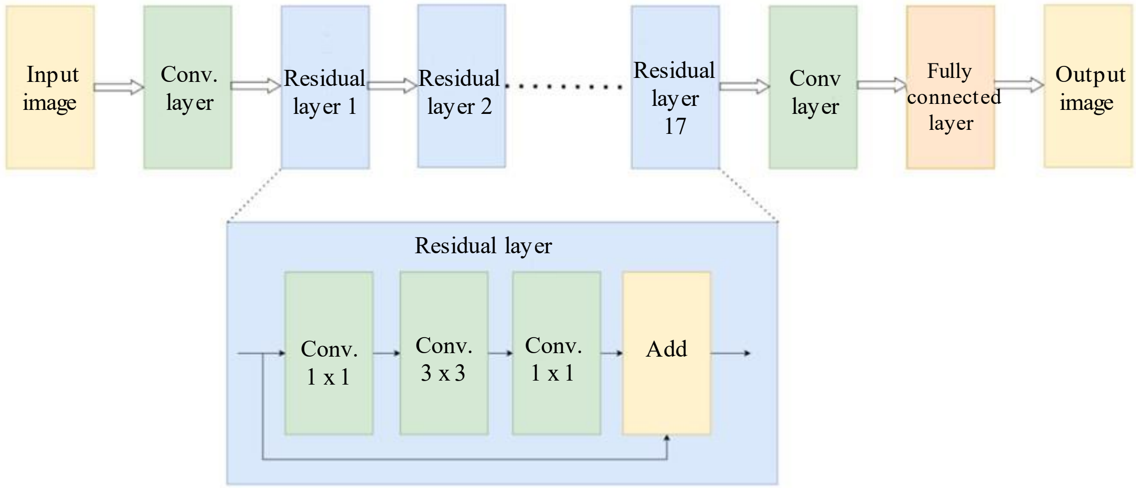


Figure 3. MobileNetV2 architecture.

Table 1. System configuration.

Processor	**Intel Xeon (2 units×16 cores each =32 cores)**
Clock Speed	2.1 GHz
GPU	Nvidia Tesla V100s
GPU Memory	32 GB
RAM	16 GB
Storage	12 TB HDD ×3=36 TB

Performance measures

Multiple criteria were used to evaluate the performance of the selected deep learning models for wound segmentation, ensuring a thorough assessment. These measurements quantify the segmentation outputs' accuracy in comparison to ground truth labels, assisting in the selection of the most effective model for the task.

Test loss and train loss

The segmentation models were also evaluated using test loss and train loss to measure their performance during training and testing phases. Train Loss refers to how well the model matches the training data during the learning phase. Test Loss measures the model's ability to generalize to previously unseen data.

Precision

Precision is defined as the proportion of correctly predicted positive pixels among all pixels anticipated as positive. It demonstrates the model's capacity to avoid false positives.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

Where:
- *TP*: True Positives, and
- *FP*: False Positives.

Recall

Recall, also known as sensitivity, calculates the proportion of correctly predicted positive pixels out of all actual positive pixels. It indicates the model's ability to identify relevant pixels.

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

Where:
- *TP*: True Positives, and
- *FN*: False Negatives.

Dice coefficient

The Dice coefficient (DSC), often known as the F1-score, is a commonly used statistic for image segmentation. It computes the overlap between the predicted segmentation and the ground truth by merging precision and recall into a single number. A higher Dice coefficient suggests greater segmentation performance.

$$DSC = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{3}$$

Minimizing both losses while maintaining high Dice, Precision, and Recall scores ensures that the model is accurate and robust without overfitting or underfitting.

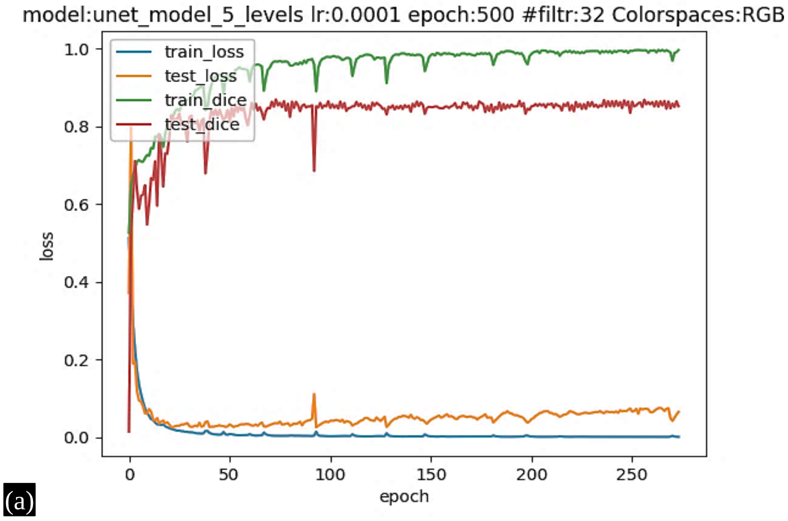
RESULTS

The performance of the four tested models: 5-layer U-Net, 4-layer U-Net, SegNet, and MobileNetV2, was evaluated on three datasets: AZH Woundcare Dataset, WoundSeg Dataset and Medetec Wound dataset. Graphs depicting the variations in training and testing loss during the training process for each model along with the Dice coefficients across the datasets are presented in Figures 4–6. These plots highlight the convergence patterns of the models and provide insights into their stability during the training process.

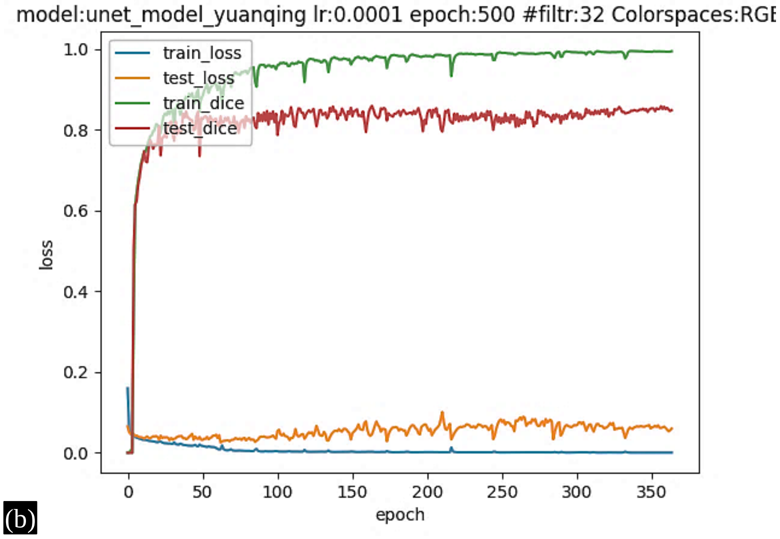
To quantify segmentation performance, test and train losses, along with the Dice coefficient, were calculated for each model. The summarized results are presented in Tables 2–4, showing the comparative performance across all datasets. The Dice coefficient was used as a primary evaluation metric due to its reliability in measuring overlap between predicted and ground truth segmentations.

Table 2. Values of all the models for AZH Woundcare Dataset.

	Train loss	**Test loss**	**Train dice**	**Test dice**
UNet 5 levels	0.0003	0.0249	0.9969	0.8690
UNet 4 levels	0.0005	0.0255	0.9955	0.8594
SegNet	0.0029	0.0404	0.9647	0.7732
MobileNetV2	0.0040	0.0322	0.9575	0.8710



(a)



(b)

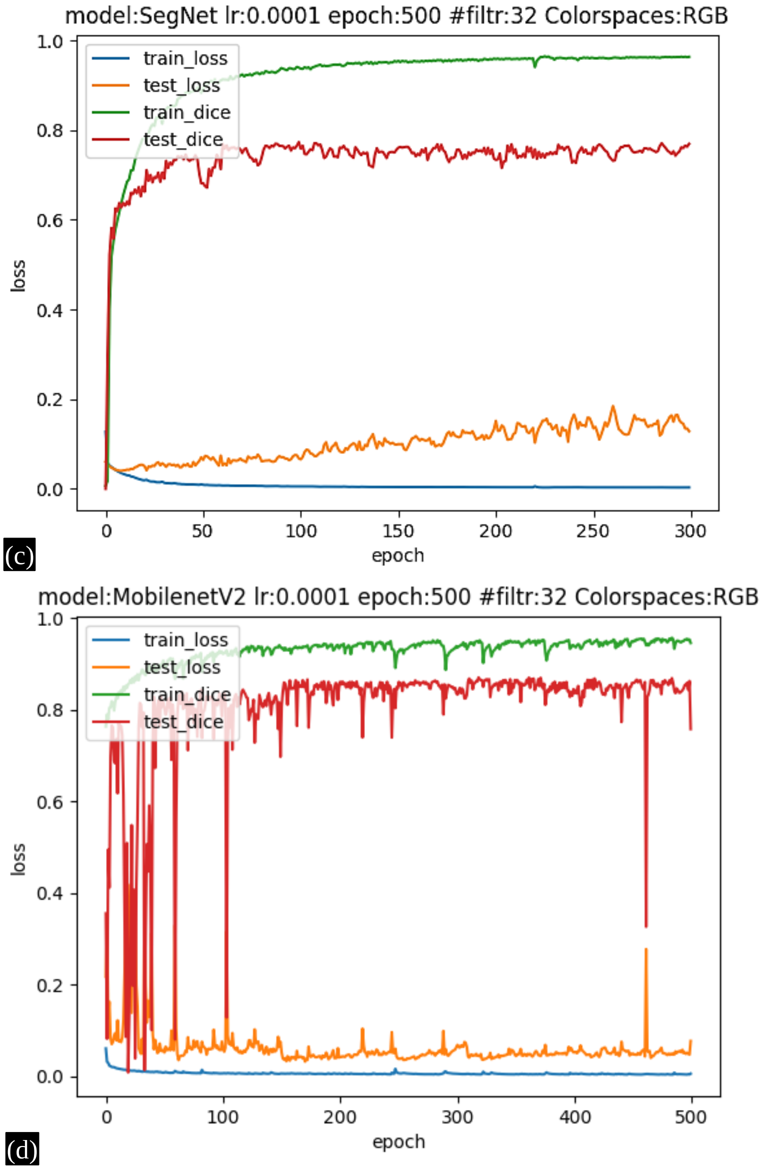
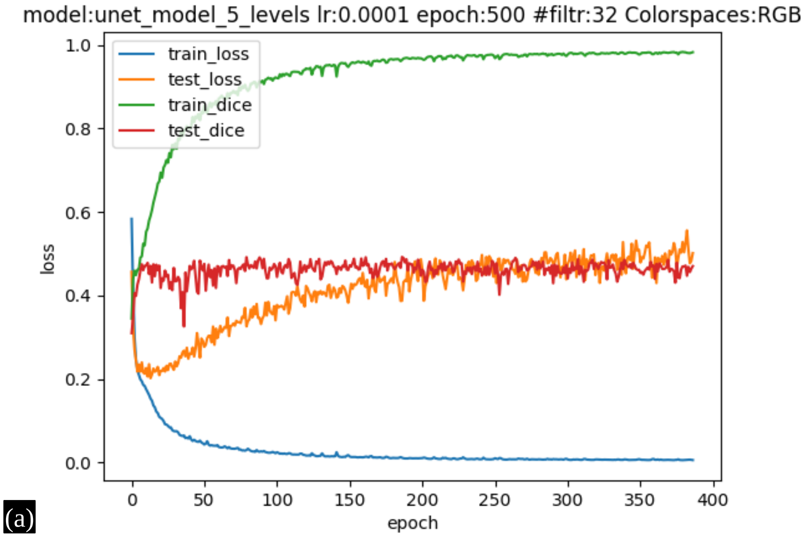


Figure 4. (a–d) Plots of all models on AZH Woundcare dataset.



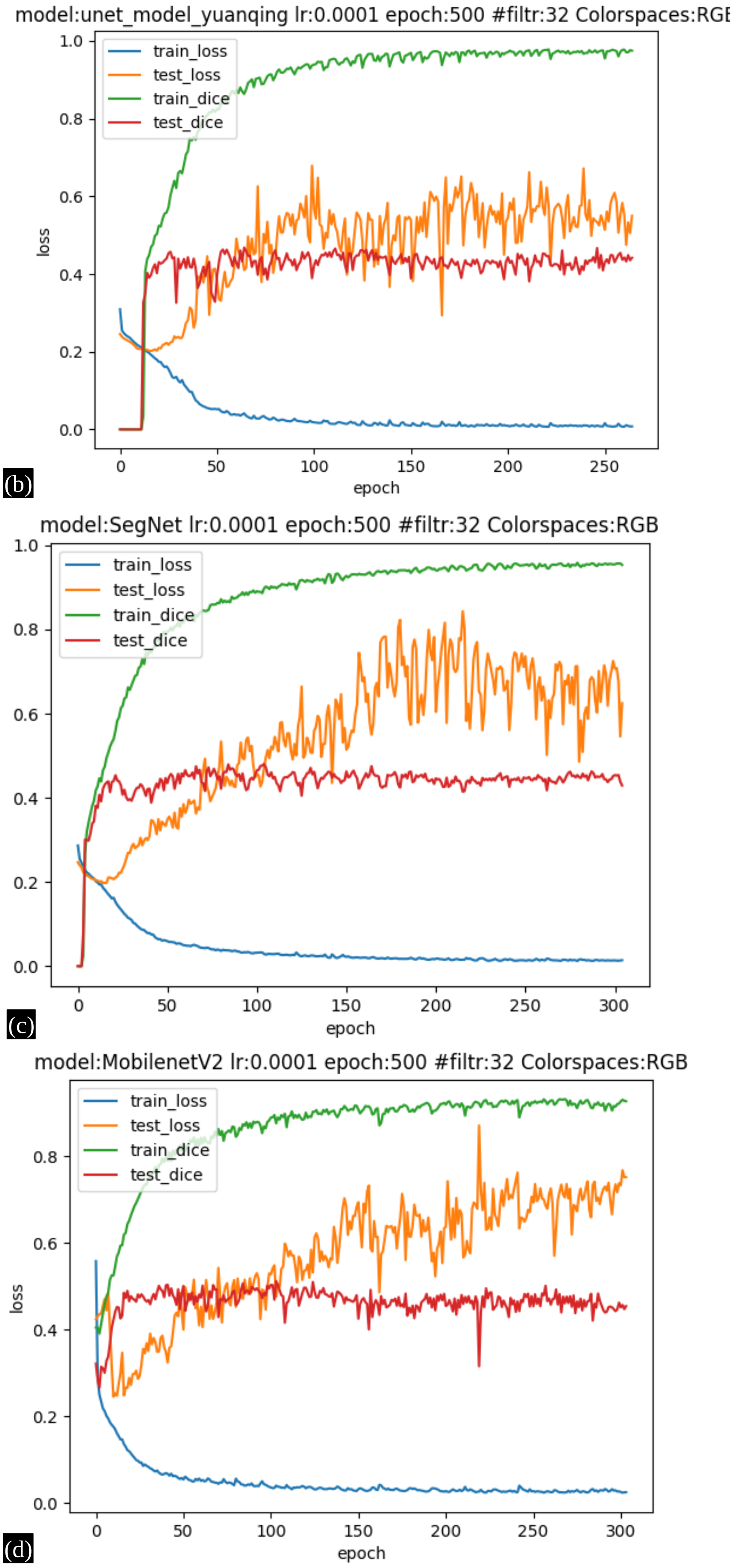
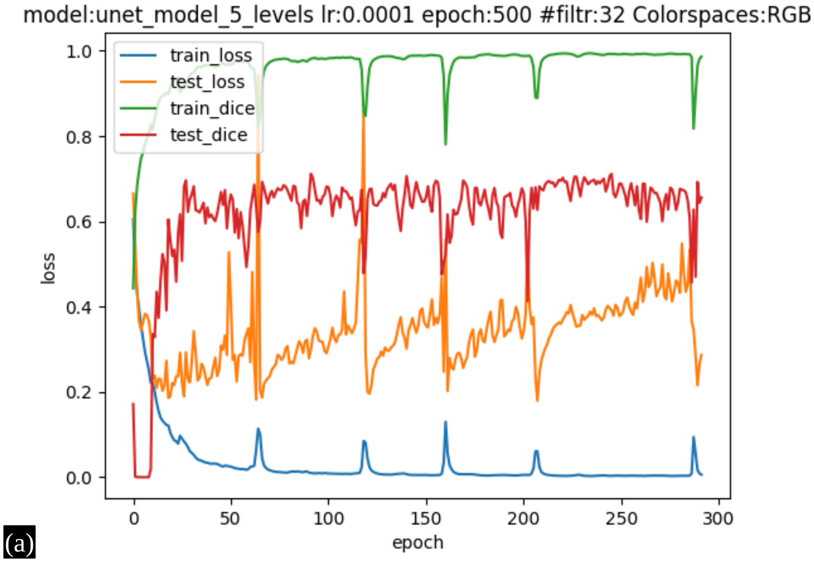
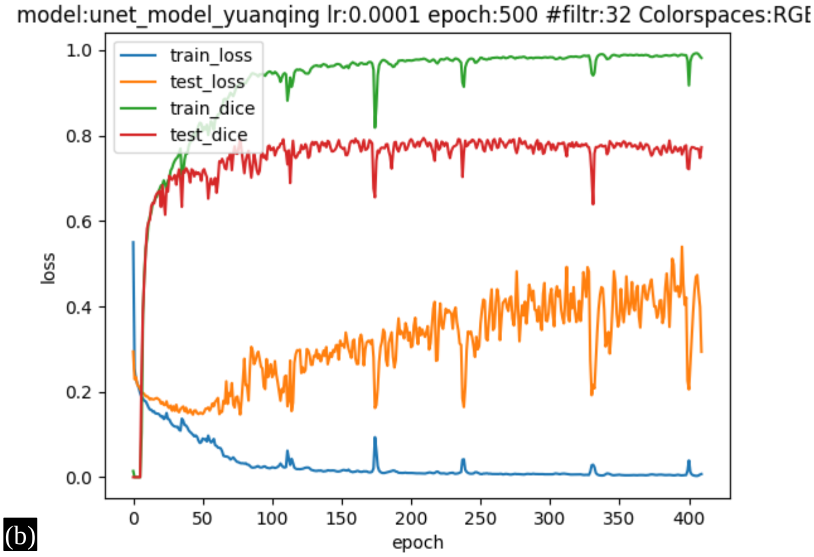


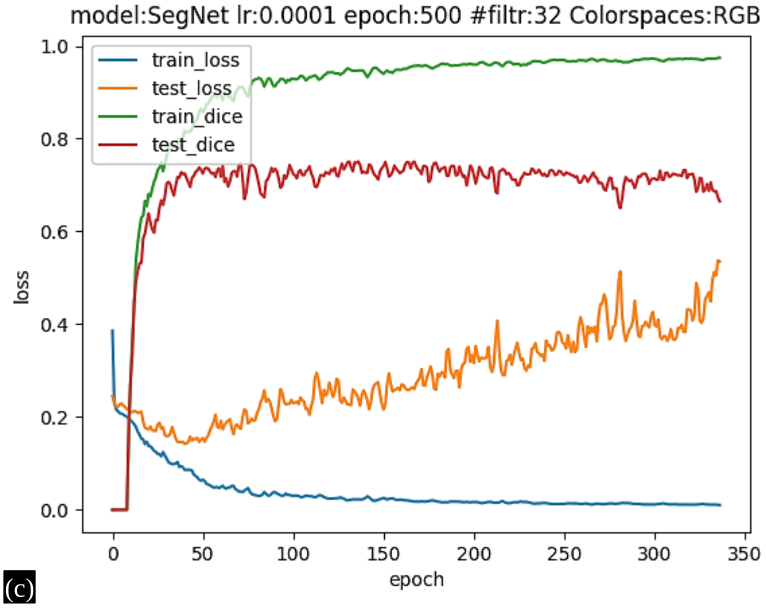
Figure 5. (a–d) Plots of all models on Woundseg dataset.


model:unet_model_5_levels lr:0.0001 epoch:500 #filtr:32 Colorspaces:RGB
train_loss
test_loss
train_dice
test_dice
1.0
0.8
0.6
0.4
0.2
0.0
loss
0
50
100
150
200
250
300
epoch

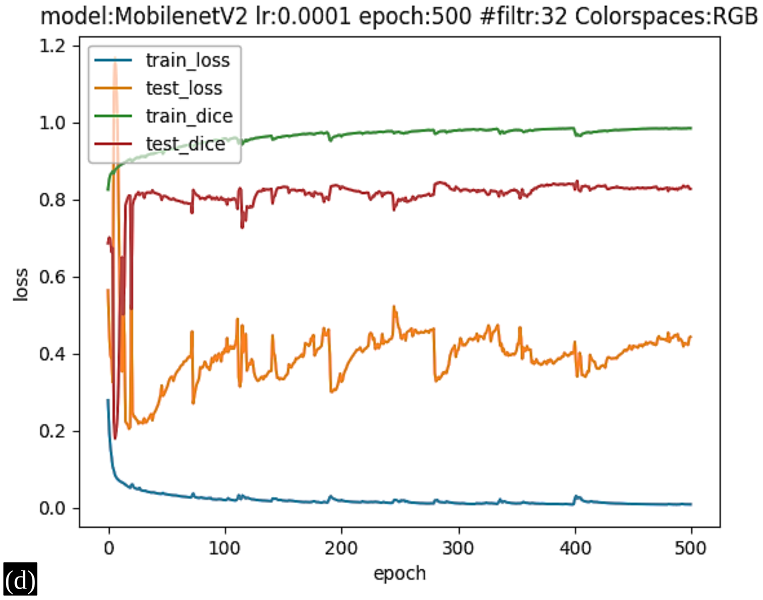
(a)


model:unet_model_yuanqing lr:0.0001 epoch:500 #filtr:32 Colorspaces:RGI
train_loss
test_loss
train_dice
test_dice
1.0
0.8
0.6
0.4
0.2
0.0
loss
0
50
100
150
200
250
300
350
400
epoch

(b)


model:SegNet lr:0.0001 epoch:500 #filtr:32 Colorspaces:RGB
train_loss
test_loss
train_dice
test_dice
1.0
0.8
0.6
0.4
0.2
0.0
loss
0
50
100
150
200
250
300
350
epoch

(c)



(d)

Figure 6. (a–d) Plots of all models on Medetec wound dataset.

Table 3. Values of all the models for WoundSeg Dataset.

	Train loss	Test loss	Train dice	Test dice
UNet 5 levels	0.0055	0.2016	0.9828	0.4920
UNet 4 levels	0.0067	0.2021	0.9784	0.4682
SegNet	0.0126	0.1979	0.9584	0.4805
MobileNetV2	0.0234	0.2450	0.9325	0.5120

Table 4. Values of all the models for Medetec Wound Dataset.

	Train loss	Test loss	Train dice	Test dice
UNet 5 levels	0.0075	0.2043	0.9850	0.8481
UNet 4 levels	0.0152	0.1048	0.9645	0.8374
SegNet	0.0027	0.1793	0.9943	0.7116
MobileNetV2	0.0106	0.1421	0.9742	0.7507

In the Figures 4 to 6, only the loss and Dice coefficient are displayed. The loss provides insight into whether the model is overfitting or underfitting, while the Dice coefficient effectively reflects the model's segmentation performance. Including Precision and Recall would be redundant, as the Dice coefficient offers a more comprehensive measure of model accuracy and adding them would only clutter the graph.

The following Tables 2–4 present only the minimum value over all epochs for each attribute, which is Train loss, Test loss, Train Dice and Test Dice.

CONCLUSION

This study provides a detailed evaluation of CNN-based models for wound segmentation, exploring their performance across diverse datasets. Among the models tested, the 5-layer U-Net and MobileNetV2 demonstrated superior segmentation performance, particularly on larger datasets like the AZH Woundcare Dataset. The findings highlight the significance of dataset size and diversity in achieving accurate and robust segmentation outputs. Datasets like the WoundSeg Dataset presented significant challenges and resulted in poor performance, highlighting an inherent issue with segmentation models. The dataset contained a diverse mix of wound types, which led to inaccurate segmentations, as the models struggled to differentiate between them. This underscores the critical importance of high-quality data, given that wound segmentation is an inherently delicate and nuanced task. The UNet architecture demonstrated similar performance across datasets of varying sizes, reaffirming that minimal amounts of data are sufficient for effective training of the model, unlike SegNet and MobileNetV2. Additionally, the architectural comparison revealed that the 4-layer U-Net offers a computationally efficient alternative with competitive performance, making it suitable for resource-constrained scenarios. Future research should focus on developing hybrid models, improving data augmentation techniques, and exploring transformer-based architectures to further enhance segmentation accuracy and scalability. By addressing these challenges, CNN-based wound segmentation models can continue to play a transformative role in clinical applications, enabling automated and efficient wound care.

Declaration of Interest

The authors declare that there is no conflict of interest related to the publication of this manuscript.

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