A Nesting Segmenting and Categorizing Model for Diabetic Wound Depth Detection in Foot Using Convolutional Neural Networks

Omprakash Dewangan [1*], Ankita Tiwari [1]

Abstract

Background: Traditional methods of Diabetic Foot Ulcers (DFUs) assessment and segmentation using computer vision and Machine Learning (ML) have faced limitations in accuracy and automation. Recent advancements in Deep Learning (DL) offer potential improvements, but challenges remain in the precise quantification and categorization of DFUs. Methods: This study explores a framework combining Mask Region-based Convolutional Neural Networks (R-CNN) with a nested structure for DFU segmentation. The approach involved collecting and preprocessing DFU images from Xiangya Hospital and the DFU Challenge (DFUC) 2020. A Region Proposal Network (RPN) was employed to identify potential regions of interest, which were then analyzed using Mask R-CNN with ResNet-FPN as the backbone. The model aimed to enhance feature extraction and categorization of DFUs through a layered approach that integrates regional proposals and segmentation masks. Results: The proposed method achieved superior results in DFU categorization compared to existing techniques. The use of Mask R-CNN with ResNet-FPN improved segmentation accuracy, with the framework achieving notable enhancements in F-score and accuracy metrics—0.79%, 16.30%, and 3.24% improvements over other algorithms. The method effectively learned and categorized complex DFU structures, providing a more accurate assessment of wound severity levels. The performance was validated against various models, including R-CNN, YOLO, DetNet, and EfficientDet, demonstrating the robustness of the proposed method. Conclusion: The integration of Mask R-CNN with a nested feature extraction framework offers a promising advancement in DFU segmentation. This approach addresses existing limitations in automated DFU assessment by improving accuracy and consistency.

Keywords: Diabetic Foot Ulcer, Deep Learning, Mask R-CNN, ResNet-FPN, Segmentation

Significance | This research demonstrates a novel Mask R-CNN with ResNet-FPN framework for improved segmentation and classification of Diabetic Foot Ulcers, enhancing diagnostic accuracy.

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Introduction

A Diabetic Foot Ulcer (DFU) is a common long-term complication of diabetes that arises when insulin cells or receptors malfunction (Eriksson et al., 2022). DFUs are associated with high risks of morbidity and mortality. Often, computer vision and Deep Learning (DL) techniques are employed to assess DFUs, though several limitations hinder the accuracy of wound quantification (Wang et al., 2022). One study utilized a sorting method to categorize wounds based on a DFU grading system, with stacked ring shapes illustrating increasing severity levels. The study collected 1,426 DFU images, with 967 featuring stacked tags and 460 containing unique tags (Ahmad, 2022). The images were annotated with rings indicating varying degrees of wound severity. Researchers developed a DL model using Mask Region-based

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Convolutional Neural Networks (R-CNN) to accurately segment DFUs, allowing for the extraction of wound severity data at multiple levels. The study evaluated the model's effectiveness, showing it outperformed current methods in segmenting, classifying, and identifying diabetic foot wounds (Barakat-Johnson et al., 2022). The stacked segmentation and multi-level categorization approach demonstrated its usefulness. The document offers recommendations for assessing, detecting, and treating DFUs. The COVID-19 pandemic in 2020 impacted global healthcare systems, particularly wound care. Another approach involves using computer-assisted techniques for wound area segmentation, providing advantages such as increased speed, automation, enhanced morphological parameter acquisition, and simplified data management (Du et al., 2020).

Research on Diabetic Foot Ulcer (DFU) segmentation is divided into two main categories: traditional image analysis combined with Machine Learning (ML) and various Deep Learning (DL) techniques (Alamer, Alqahtani, & Shadadi, 2023). Thota et al. (2024) explored four segmentation methods—k-means, edge recognition, thresholds, and area expanding—to analyze DFU images. They optimized settings using Grid search and the Nelder-Mead method and employed Multi-Layered Perceptrons (MLP) and Radial Basis Functions (RBF) for classification. Fauzi et al. (2021) used Cr-Conversion and Luv-Conversion techniques to enhance and separate wound areas using a Fuzzy C-means Clustering (FCM) approach. These methods face limitations, including the need for feature engineering, sensitivity to skin color, lighting, and manual variable tuning, and lack of comprehensive automation and extensive database evaluation. These constraints can be partially addressed by DL algorithms.

Dhar et al. (2024) presented a dataset of 650 DFUs, achieving a Dice score of 68.2% using a Fully Convolutional Network (FCN) structure. They acknowledged limitations in detecting small wounds and irregular boundaries due to the model's tendency to produce smooth outlines. To improve this, Dhar et al. (2024) introduced WoundSeg, which integrates MobileNet with varying channel counts and VGG16, achieving a Dice accuracy of 74.8% with a dataset of 950 images. Annotation was performed using a semi-automatic watershed technique. Monroy et al. (2023) employed the MobileNetv2 model on a dataset of 800 training and 250 testing images, achieving a Dice score of 78.21% after a post-processing phase addressed gaps and removed aberrant tissue. Chino et al. (2020) focused on segmenting granulating cells rather than the entire wound area, using 220 images and achieving an Intersection over Union (IoU) score of 50%. Chemello et al. (2022) reviewed AI methodologies for DFU detection and segmentation.

2. Materials and Methods

The framework's general layout is categorized into three distinct components. The research gathered and organized DFU databases from Xiangya Hospital and the DFU Challenge (DFUC) 2020. The research then does expected preprocessing tasks, such as standardizing the picture format and dimensions. The research collaborates with Xiangya dermatologists and DFU specialists to accurately identify the data. The study employs the Regional Proposal Networks (RPN) method to find DFU pictures and utilize a back-boned CNN to extract characteristics. The resulting features are then used as input photos for the subsequent step. To optimize the utilization of the layered DFU characteristic, the system employs Masking R-CNN to provide the ultimate assessment and categorization likelihood for both DFU pictures. The schematic representation of the layout chart for this work is seen in Figure 1.

2.1 Nested feature extraction

By evaluating the layered DFU features and examining the test findings, the research has determined that ResNet-FPN is the optimal backbone design for the Masked R-CNN to achieve standardized abstraction of features. The result of the back-boned CNN is called a feature map, a three-dimensional tensor in mathematics. The success of the proposed method is heavily dependent on the feature-gathering capabilities of the backbone CNN and the accuracy of the collected and chosen information. The additional information can be studied to understand conventional feature extraction CNN comprehensively.

The research integrated the CNN with the Forward Pyramid Networks (FPN) extensions. As the calculation of the bottom-up path advances, the spatial resolution diminishes, and the obtained high-level characteristics have a higher semantic significance. In the top-down pathway, the characteristic mapping of the appropriate level in the path is merged with the feature mapping of the preceding level to create the final characteristic mapping. This results in a high-resolution characteristic mapping with rich semantic information. The DFU nested framework, when combined with FPN and ResNet as the primary system for Masked R-CNN, yields the optimal categorization outcome for DFU.

2.2 Region of Interests (RoI)

The RPN is a compact system that scans the last characteristic mapping generated by the backbone CNN to identify the potential regions that contain the elements. A set of k potential areas called anchors are examined for every position on the feature mapping. These anchors have varying sizes and aspect proportions. The first head is a network that categorizes binary to determine if the k potential areas contain an element. The second head is an estimator head that produces the bounding box of the particle within that area. The significance of the enclosing box diminishes when the category head indicates that that area does not include a particle. The RPN produces areas of interest that indicate potential item locations.

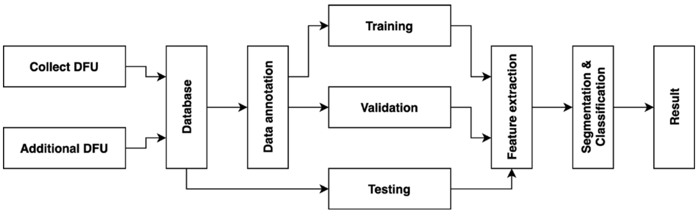

Figure 1. Architecture of the DFU classification process

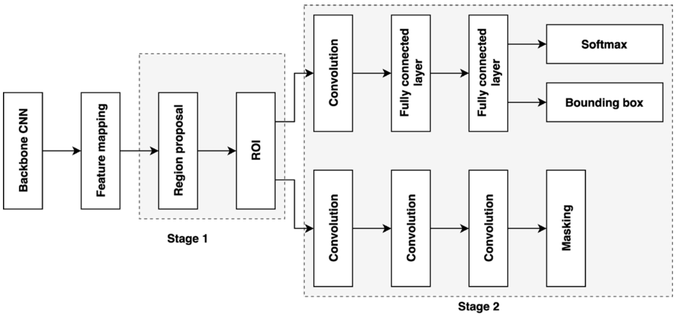

Figure 2. Segmentation and categorization process

Table 1. Confusion matrix analysis

	Actual Results				
		DFU-1	DFU-2	DFU-3	DFU-4
Predicted Results	DFU-1	82.3	8.3	9	0.4
	DFU-2	5.6	81.2	6.8	6.4
	DFU-3	5.9	3.6	80.4	10.1
	DFU-4	6.2	6.9	3.8	83.1

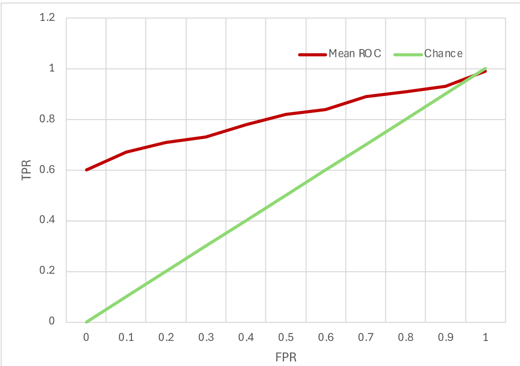

Figure 3. ROC curve analysis

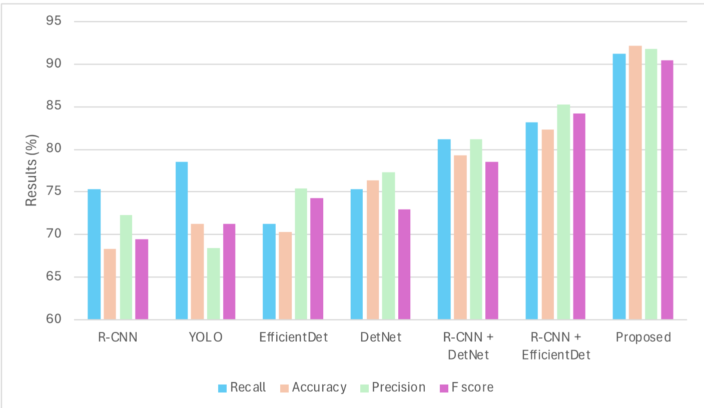

Figure 4. Performance analysis

The methodology the research employs for the automated extraction of pictures relies on the RPN method. The technique has been extensively utilized in the R-CNN family of approaches. The implementation strategy involves generating many potential areas on the input picture. A categorization likelihood value is assigned to each region according to the training sample. The area with the greatest likelihood is then selected as the RoI. This research established the selecting box as a variable number of pixels based on the DFU picture. The study also observed that the proposed framework typically resides in the center of the image. This approach allows us to create a standardized DFU feature mapping.

2.3 Segmentation and Categorisation

The masking R-CNN network design represents the DFU cell through a segmenting and categorizing process. The system's source consists of initial mapping and tagging of the wound masking. The system output includes the expected categorization and box of the wound masking. The particular method flow and specifics can be found in Figure 2. Mask R-CNN utilizes the ResNet-FPN to extract characteristics specifically from ulcerated regions. These characteristics are obtained from the trunk system and used to construct a feature mapping. The feature mapping then produces a set of suggestions across the system. The potential container is aligned with the RoI technique on the characteristic mapping to extract a RoI. It is then linked to two forecasting nodes. One forecasting head is connected to categorization and segmenting tasks, while the remaining is related to an FCN for mask differentiation. The outcomes of box identification and mask identification for the wound are merged. Differential processing involves the utilization of masked sections within the input cell color to prevent the overlapping of pixel characteristics between two layered mask areas during convolution.

Once the backbone structure has completed training on all the weights, ResNet-FPN will be utilized in this particular scenario. These weights have the potential to be used in Mask R-CNN. The research's primary method for identification, categorization, and segmentation is the Mask R-CNN method. The backbone used in the model was ResNet-FPN, and each picture included 16 training ROIs. The most significant number of occurrences identified in one picture was limited to 50. The confidence quality limit was set at 0.97, and all loss factors at each step were uniformly adjusted to 1.0.

3. Results and Discussion

The confusion matrix of the tested findings is represented in Table 1. The confusion matrix offers a comprehensive representation of the algorithm's effectiveness. By evaluating the approach's effectiveness using a nested structure-constrained deep DFU attribute, the research discovered that the proposed method attained the highest overall mean categorization outcomes. Upon assessing the information in Table 1, the categorization accuracy for DFU grades 1 to 4 surpasses that of other studies. This superiority can be attributed to the following factors. Due to the unequal allocation of the data sets, it is difficult to comprehend the features of some DFUs, which are of varying difficulty.

The progression of DFU, which involves complex networks, can effectively explain the different levels of ulceration. The computer program successfully learns the nested patterns of ulcer wounds. To eliminate any missed diagnoses in medicine, the research established a deliberately partial mechanism throughout the categorization process, which resulted in a slightly reduced level of accuracy in cases of DFU 2 and 3. Figure 3 displays the outcome of the Region of Convergence (ROC) curve for the method, which indicates the connection between True Positive Rates (TPR) and False Positive Rates (FPR).

The research assessed the accuracy of the approach in creating an embedded structure-constrained element for learning the structural model of DFU. The study evaluated R-CNN, YOLO, DetNet, EfficientDet, and various R-CNN combinations. Figure 4 displays the recall, accuracy, precision, and F score obtained from the testing dataset for the comparison models used to identify the degree of ulcer of the DFU. The proposed method outperforms others in every aspect. The proposed method is a powerful alternative for identifying diseases with layered structures in DFU.

DFUSC demonstrates substantial enhancements of 0.79%, 16.30%, and 3.24% compared to the other algorithm for F-score and accuracy measures correspondingly—the Masking R-CNN effectively methods the nested-structural link between DFU patches, utilizing distinctive and easily learnable characteristics. As anticipated, the proposed method surpasses other comparison models, demonstrating its capability to integrate DFU illustrations of systems.

For the DFU category with a limited number of samples or imbalanced specimens, incorporating a nested shape into the proposed method might lead to improved recognition accuracy and more excellent recognition results. Conventional CNN models that use only one label cannot accurately represent and identify those categories. However, the layered structure-constrained deep feature fusion can detect these complex DFU cases more effectively. It utilizes multi-class labeling and a layered characteristic vector of DFU.

4. Conclusion

The integration of Mask R-CNN with ResNet-FPN significantly advances DFU segmentation and categorization. This method overcomes limitations of traditional approaches, offering precise, automated, and consistent assessment of DFU severity. By leveraging a nested feature extraction framework, the proposed model achieves higher accuracy and reliability in DFU grading compared to existing methods. The research underscores the potential for this framework to streamline clinical decision-making, improve treatment strategies, and enhance patient outcomes. The results suggest a promising future for automated DFU measurement systems, contributing to better management and reduced complications in diabetic foot care.

Author contributions

OD and AT were responsible for conceptualization, fieldwork, data analysis, original draft writing, editing, funding acquisition, and manuscript review. OD and AT focused on research design, methodology validation, data analysis, visualization, manuscript review, and editing. Additionally, OD handled methodology validation, investigation, manuscript review, funding acquisition, supervision, and editing. All authors have approved the manuscript after reviewing the final version.

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Competing financial interests

The authors have no conflict of interest.

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