

FINE-GRAINED DIABETIC WOUND IMAGE ANALYSIS
AND AUTOMATED CLASSIFICATION SYSTEM USING
DEEP LEARNING

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DECLARATION

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ABSTRACT

Diabetic ulcers are a major life-threatening complication among diabetic patients. The existing ulcer diagnosing practices depend on the visual examination of consultants. However, the precise manual diagnosing process is challenging since vision may vary upon the consultant, tedious and time-consuming. In the diagnosing process, the challenging task is to identify the infected areas and the severity of the ulcers.

Accordingly, automatic locating and segmenting of ulcer boundaries and severity stage classification is of significant prominence. Yet a comprehensive computer-aided Wagner scale based severity stage classification system for diabetic foot ulcers is not available in the literature. Even though there are few automated solutions for segmenting and locating of ulcer boundaries available in the literature, they consist of various limitations.

This research proposes solutions to automate two manual processes namely segmenting and locating ulcer boundaries and severity stage classification of diabetic ulcers. Here, a dataset of diabetic ulcers which consists of 2400 images was used for both tasks. Under the segmentation task, the process of instance-based diabetic ulcer segmentation was automated through the Mask-RCNN model. This solution could achieve 0.8605 of average precision value at 0.5 thresholds of Intersection over Union (IoU) and 0.5023 mAP value at 0.5 to 0.95 by the step size of 0.05 Intersection over union (IoU) threshold with ResNet-101 backbone for the DFU segmentation task.

In the meantime, an architecture to classify the severity stages of diabetic foot ulcers was implemented using DenseNet-201 pre-trained CNN architecture. In this approach, the classification head of the DenseNet-201 was removed and used the feature extraction head to extract the feature vectors. Then the feature reduction was done by applying a Global Average Pooling technique and used Singular Value Decomposition (SVD) as a further feature reduction technique. Additionally, SVD helps to optimize the memory consumption and processing time while preserving the accuracy of the proposed classification architecture. This proposed architecture could achieve an accuracy of over 96%.

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LIST OF ABBREVIATIONS

DFU	Diabetic Foot Ulcer
RPN	Regional Proposal Network
GAP	Global Average Pooling
SVD	Singular Value Decomposition
ROI	Region of Interest
AP	Average Precision
CNN	Convolutional Neural Network
IoU	Intersection over Union
SVM	Support Vector Machine
ANN	Artificial Neural Network
SGD	Stochastic Gradient Descent
RGB	Red Green Blue
HSI	Hue (H), Saturation (S), Intensity (I)
FC	Fully Connected
FCN	Fully Connected Network