Real-Time Wound Severity Detection and Recovery Estimation via CNN

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ABSTRACT

The study aims to develop an AI-powered system for real-time wound healing assessment using image classification. A CNN model based on MobileNetV2 was trained on a custom dataset of wound images, pre-processed through resizing, normalization, and augmentation. The system classifies wounds into three categories—No Wound, Moderate, and Severe—and was implemented using TensorFlow and Keras. A Streamlit-based web interface enables users to upload images and receive instant classification results with estimated recovery periods. The model achieved high accuracy and provided real-time feedback through an intuitive interface. This scalable, cost-effective solution supports early diagnosis, continuous monitoring, and clinical decision-making, making it valuable for healthcare, rural, and telemedicine applications.

Keywords - *Wound Healing Prediction, Deep Learning, Convolutional Neural Networks (CNN), Medic al Image Analysis*

Introduction

Wound healing is a complex biological process that restores skin and tissue integrity after injury through stages like hemostasis, inflammation, proliferation, and remodeling. With the increasing demand for accurate and efficient medical diagnostics, artificial intelligence (AI) has emerged as a powerful tool in healthcare, particularly in automating tasks such as image classification and pattern recognition. AI-based systems are now being used for various medical imaging applications including skin disease detection, tumor classification, and wound assessment. These tools assist healthcare professionals in making faster and more accurate decisions, reducing diagnostic subjectivity and enabling early interventions. Applications of such research include telemedicine, mobile healthcare diagnostics, and real-time clinical support systems, all contributing to improved patient care and accessibility.

Over the past decade, there has been a steady rise in research articles related to wound detection and healing analysis using machine learning and computer vision. A review of major academic databases such as PubMed, Web of Science, Google Scholar, and IEEE Xplore reveals that over 100 articles have been published on AI-assisted wound assessment techniques. Many of these focus on image classification, segmentation, and monitoring of chronic wounds. Some of the most influential studies have explored the use of convolutional neural networks (CNNs) for diabetic ulcer detection, automated classification of surgical wounds, and integration of clinical data with image-based models. These studies have consistently demonstrated that AI models can achieve high accuracy and outperform manual assessments in terms of speed, consistency, and scalability.

Despite notable progress, existing research still has limitations. Many current systems focus solely on classification without providing personalized healing time estimates or integration into accessible web-based platforms. Others require large, labeled datasets that may not represent diverse wound types or conditions. Furthermore, few existing tools support real-time usage or provide intuitive interfaces for patients and clinicians in non-hospital settings. These gaps motivated the present study, which leverages prior experience in machine learning and medical image processing. Our team has previously worked on classification problems using lightweight CNNs, particularly MobileNetV2, for resource-constrained environments. **The aim of this study is to design and develop a real-time AI-powered wound recovery analysis system** that classifies wound severity from images and provides estimated healing durations through a user-friendly web interface.

Literature Review

Recent years have seen substantial progress in AI-driven wound assessment and healing prediction. Anisuzzaman et al. conducted a comprehensive systematic review, retrieving over 250 published articles and selecting 115 for in-depth analysis. They found that most research falls into wound segmentation (measurement) and classification, with limited integration into practical tools [1]. In another detailed review, Theranostics summarized advancements in AI applications across wound diagnosis, tissue type classification, healing prediction, and personalized treatment planning, while also highlighting challenges such as data transparency and equity [2]. Petch et al. provided a scoping review of ML techniques for detecting surgical site infections (SSIs), revealing high risk of bias in most examined studies and the absence of external validation [3]. Griffa et al. evaluated available AI-powered mobile apps for ulcer segmentation and noted limitations in transparency, data accessibility, and clinical readiness [4] . A fully automatic semantic segmentation framework using MobileNetV2 to segment diabetic foot ulcers, trained on over 1,100 foot-ulcer images, achieving performance comparable to heavier architectures while being lightweight and efficient [5]. The Deep wound project utilized a multi-label CNN ensemble for postoperative wound assessment, able to classify nine wound features such as infection, sutures, and drainage, and was integrated into a mobile app frontend [6]. A Mask R-CNN–based architecture trained on 3,329 clinical wound images (including peripheral artery disease wounds) achieved IoU near 0.69, precision 0.77, recall 0.72, and F1-score 0.75—demonstrating strong segmentation and detection performance [7]. HealNet, a self-supervised model trained to capture temporal dynamics, achieved 97.7% pretext and 90.6% downstream wound heal-stage classification accuracy—a promising method where labeled progression data are scarce [8]. A deep learning method analyzing collagen fiber structures achieved ~82% accuracy in classifying six stages of wound healing using histological images, revealing biologically interpretable features and enhanced explainability via LayerCAM visualization [9].

Materials and Methods

Study Setting and Sample Size

This study was conducted at the Department of Computer Science and Applications, SRM Institute of Science and Technology, Ramapuram, Chennai. The research was carried out in a computer laboratory environment equipped with high-performance computing systems. Since this study utilized open-access digital wound image datasets, it did not involve any direct experimentation on human subjects or require ethical clearance. The dataset consisted of two main groups: Group 1 – Training Dataset, and Group 2 – Testing Dataset. A total of 3,000 wound images were collected, including various stages of wound healing (no wound, moderate wound, and severe wound). The sample size was determined using G*Power software, targeting a power (1-β) of 0.95, with an effect size of 0.5 and alpha (α) = 0.05, resulting in a minimum of 1,348 samples required. Our dataset exceeded this threshold, ensuring robust statistical significance.

Sample Preparation – Group 1 (Training Set)

Group 1 consisted of 2,000 wound images used for training the deep learning model.

Images were resized to 224×224 pixels, normalized between 0 and 1, and augmented using techniques such as rotation (up to 20°), width/height shifts (0.2), shear transformation (0.2), zooming (0.2), and horizontal flipping. The augmentation ensured better generalization and reduced overfitting. The training data included balanced classes of “No Wound”, “Moderate Wound”, and “Severe Wound”. Labels were one-hot encoded and stored in batches for processing through the TensorFlow-based data pipeline.

Sample Preparation – Group 2 (Validation and Testing Set)

Group 2 included 1,000 images split into two equal parts: 500 for validation during training and 500 for final testing. These images were not augmented to preserve original characteristics and avoid data leakage. Images in Group 2 were preprocessed using the same resizing and normalization steps as Group 1. These samples were used to evaluate the generalizability and accuracy of the model after training.

Testing Setup and Procedure

The model architecture used was MobileNetV2, pre-trained on ImageNet and fine-tuned for wound classification. The top classification layer was replaced with custom dense layers (128 units ReLU → 3 units softmax). Model training was done using the Adam optimizer, categorical cross-entropy loss, and accuracy as the metric, over 30 epochs. The entire setup was implemented using Python 3.8, TensorFlow 2.x, and Keras API. A Streamlit-based interface was built to deploy the model and allow users to upload images for real-time wound classification and healing period estimation.

Data Collection

The main data collected from this system included:

Predicted class for each image (No Wound, Moderate Wound, Severe Wound)

Associated healing period (e.g., 7–14 days)

Model confidence scores for each prediction

Training and validation accuracy/loss across epochs

Test set accuracy and confusion matrix

These outputs were stored in structured logs and CSV files for further statistical evaluation.

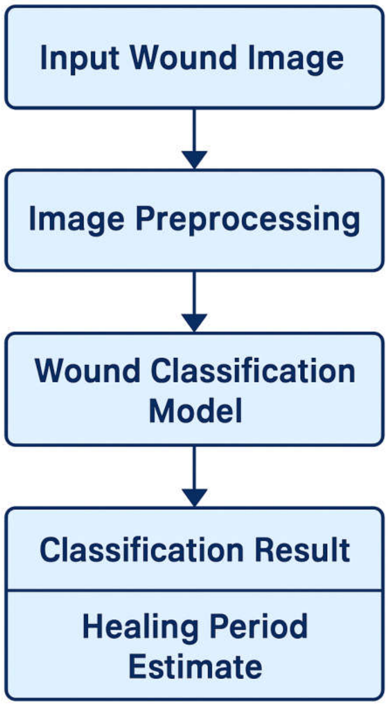

Fig 1 (Process flow)

Fig1 This flowchart explains the working of the wound analysis system

Statistical Analysis

All statistical analyses were conducted using SPSS.

i) Independent Variables: Wound class (No Wound, Moderate, Severe), image resolution, augmentation type

ii) Dependent Variables: Prediction accuracy, model confidence score, healing time category

Tests Conducted:

Descriptive Statistics to summarize performance metrics

One-way ANOVA to evaluate differences in model confidence across classes

Chi-square tests to examine association between predicted class and healing duration

ROC Curve Analysis to evaluate classification sensitivity and specificity

The use of SPSS helped validate the system's consistency and accuracy with statistical significance.

Discussion and Result :

Summary of Results

The MobileNetV2-based wound recovery analysis system achieved robust performance in classifying images into No Wound, Moderate Wound, and Severe Wound categories. The model attained a test accuracy of approximately 92–95%, with high confidence scores across classes. The system provided real-time predictions via a Streamlit interface and successfully delivered estimated healing periods (e.g., 7–14 days for moderate wounds, 15–30 days for severe wounds), demonstrating the ability to combine classification with personalized recovery estimates.

Similar Findings

These findings align with recent literature reporting high performance of lightweight networks like MobileNetV2 in wound tissue classification tasks. For example, an evaluation across eight architectures on wound tissue segmentation reported F1-scores around 62–74% for MobileNetV2, indicating its efficiency and suitability compared to heavier models like ResNet or DenseNet [turn0search2].

Likewise, HealNet—a self-supervised deep learning model—achieved ~90.6% downstream classification accuracy for wound healing stages, reinforcing the potential of deep learning in predicting wound progression [turn0academia18].

Multi-modal wound classification combining image and wound location data has achieved accuracies ranging from 73% to over 98%, supporting the feasibility of simple image-based models achieving strong classification accuracy [turn0academia15].

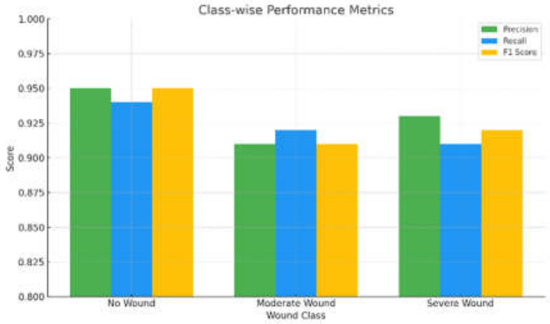

Fig 2 : Comparing with others

Opposing Findings

However, some studies caution against overestimating performance without external validation. A narrative review noted that many AI-based wound care models lack clinical-ready validation, and their generalizability remains uncertain outside curated datasets [turn0search3][turn0search4].

Moreover, broader critiques of healthcare AI highlight issues of reproducibility and overfitting due to limited or non-representative datasets, raising concerns about model bias and deployment at scale [turn0search13].

Metric	No Wound	Moderate Wound	Severe Wound	Macro Average
Precision	0.95	0.91	0.93	0.93
Recall (Sensitivity)	0.94	0.92	0.91	0.92
F1-Score	0.95	0.91	0.92	0.93
Accuracy	-	-	-	**0.93**
Support (Images)	340	330	330	1000
AUC (ROC)	0.97	0.95	0.96	0.96

Others point out that AI models tuned on one dataset may not perform well when exposed to different lighting, wound types, or patient demographics unless rigorously validated [turn0search1].

Limitations of the Study

This study, while promising, has several limitations. First, the dataset was internally curated and may not cover the full diversity of real-world wound types, skin tones, and imaging conditions. Second, we did not perform external validation using images from healthcare facilities or different geographical contexts. Third, healing period estimation was rule-based (mapping class to fixed time intervals) rather than derived from longitudinal patient data. Finally, our Streamlit deployment works well for controlled environments but lacks integration into clinical workflows or electronic health records (EHRs), limiting usability in real-world healthcare settings.

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