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(Review Article)

AI-driven wound healing analysis and progression tracking in mobile applications: A scalable approach for healthcare accessibility

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Abstract

Indeed, wound care is the most important aspect of health care management for patients suffering from chronic ailments, such as diabetic ulcer, pressure sore, or surgical wound. Manual assessment, however, is highly resource consuming, prone to errors, and very much impractical in remote or neglected areas. This research shows an artificial intelligence (AI) based mobile tax application, which automates assessment for wound-healing stages and provides real-time personalized recovery updates. It aims mainly at classifying wounds in terms of their stages of healing and to have a predictability on recovery timelines using sequential images in order to facilitate the accessibility and decision-making on the case of wounds. The study implements convolutional neural networks (CNN) for the image classification and long short-term memory (LSTM) networks for the healing trajectory predictions. Based on a curated dataset of 2,500 annotated wound images, the developed models achieve a classification accuracy of 92% and a healing progression prediction error of less than 5%. The results prove that the mobile application can deliver wound-care solutions on scalability, efficiency, and affordability. Future works include further enhancing the dataset for improved model generalization and continuous monitoring of individuals through data from wearable sensors. This study thus speaks of AI driven applications making a difference in future healthcare by minimizing gaps in medical resources and giving patients actionable real time insights.

Keywords: AI/ML; diagnostic accuracy; image-based wound classification; CNN's; GPT-3.5

1. Introduction

The management of wounds undoubtedly still poses a significant problem to health care today, especially in the case of chronic ones such as diabetic foot ulcers, pressure sores, and post-surgical wounds. Such wounds typically require multiple assessments to determine healing capacity and thereby avert complications. Most available and widely used traditional methods of treating wounds rely heavily on subjective manual assessments which may be prone to error-more so in resource-limited settings. That aside, an increasing burden of chronic diseases across the world further argues for scaling up solutions for consistent and accurate monitoring of wound healing.

So basically, the research was to develop an automated AI-powered mobile application that will assess the wound healing stages and the estimated time for recovery based on images taken at various times of the wound. The app uses CNNs to classify the wound based on the severity, and long short-term memory networks to predict the progress of healing. This mobile application is an accessible scalable solution to wound care, especially in disadvantaged or peripheral areas where health care access is problematic.

The efficiency of the model was evaluated with the help of the annotated dataset of wound images, and the results were very promising in terms of accuracy and dependability in healing prediction. It was designed to run in mobile devices

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with an intuitive user interface for easy access by almost anybody. From a broad perspective, it is in the application and benefits of this work that it will bring about improvements in the health care system whereby accurate, real-time feedback on wound care can be produced for patients and health workers to enable timely interventions and improve patient outcomes dramatically.

1.1. The Complexity of Wound Healing

Wound healing refers to a complex biological process that aims at restoring the integrity and functionality of injured tissue. Four overlapping and dynamic stages are identified in the process:

- **Hemostasis:** This is the first state that occurs immediately upon injury. Clotting occurs and vascular constriction limits blood loss. Thus, platelet activation releases growth factors that initiate the healing process.
- **Inflammation:** This phase has immune cell infiltration consisting of neutrophils and macrophages working to clear away debris and fight infection. This is accompanied by swelling, redness, and tenderness as the common visual symptoms.
- **Proliferation**:Fibroblasts and endothelial cells are involved in this stage in producing collagen to lay granulation tissue for the generation of tissue. Angiogenesis and surface epithelial cell migration are required for wound bed coverage.
- **Remodeling**: Also known as the maturation phase, it involves collagen fiber reorganization and enhancement of newly composed tissue as time elapses, further reducing visibility.

Each of these stages presents different characteristics, visually, texturally, size, depth, and color, which can be measured systematically to evaluate healing. Healing varies between individuals, mostly due to the state of health of the patient, comorbidities such as diabetes, type of wound, and environmental factors such as temperature, humidity, and airflow; thus, the type of evaluation should be consistent and objective.

1.2. Current Strategies for Wound Healing Assessment

1.2.1. Traditional Methods

Assessment of wound healing happens in a conventional way mainly through clinical evaluation by visual inspection and manual measurement done by healthcare professionals. But these two methods work very well in a controlled environment because they are subjective variables based on the experience and skills of a clinician. Their time consumption typically anticipated attendance using such methods is high and has many requirements, limiting it to very few or even none in most resource-limited places or rural areas.

Examples of some such standardized tools include the Bates-Jensen Wound Assessment Tool (BWAT) and the Pressure Ulcer Scale for Healing (PUSH), both of which are intended to standardize the evaluation of wounds. They will, however, not be entirely free from variations as a result of human interpretation, particularly in subtle changes in tissue composition, as well as inflammatory level characterization.

1.2.2. AI and Medical Imaging Innovations

Advances in medical imaging and artificial intelligence (AI) are ushering in a new era of objectivity and automated assessment of wounds. AI-based systems use clinical imaging techniques, including digital photography and thermography, together with advanced algorithms, to quantify various wound characteristics. Important innovations are:

- **Computer Vision**: Assessment by AI models of wound features includes size, edge irregularities, tissue types, etc., then creating gradients.
- **Tissue Segmentation**: AI systems can segment wound images into necrotic, granulation, and epithelial coverage along with giving detailed information on the healing stage.

AI-based techniques better reduce inter-clinician variability, ensure consistency, and can analyze faster especially in application to telemedicine.

1.3. AI Models for Wound Classification and Healing Prediction

1.3.1. Applications of CNNs in Medical Imaging

Convolutional Neural Networks (CNNs) are by far the most important component of contemporary medical imaging, since it can automatically learn hierarchical features from the incoming image data. In wound care, CNNs classify the wounds such as stage I, stage II, stage III, and stage IV healing by showing image patterns that assess tissue color, texture, and vascularity. Traditional imaging processing methods depend on handcrafted features because CNN models directly learn from raw pixel intensity values, enabling them to prove superior performance on very complex datasets.

For instance, CNNs have been employed to classify wounds into categories such as:

- **Inflammatory** (e.g., wounds with redness and swelling),
- **Proliferative** (e.g., wounds with granulation tissue), and
- **Chronic or stalled** (e.g., wounds showing signs of infection or necrosis).

Several studies report classification accuracies exceeding 90%, showcasing the promise of CNNs in automating wound assessment.

1.3.2. Predictive Modeling with Hybrid Approaches

Healing happens frequently with sequential images in addition to static classification, which has always been the hallmark of deep learning models. In predicting wound healing, hybrid models that integrate Convolutional Neural Networks (face value) for spatial analysis with Long Short-Term Memory (LSTM) networks for temporal analysis show greater efficacies. These models can capture the serial changes of a wound feature to predict the healing time, including the reduction of wound area or improvement in tissue quality.

Other innovative approaches include:

- **Decision Trees**: Integrated with deep learning, these models utilize tissue composition metrics (e.g., percentage of granulation vs. necrotic tissue) to predict healing trajectories.
- **Multimodal Models**: These combine image data with patient-specific metadata, such as age, comorbidities, and wound history, for more personalized predictions.

Such frameworks offer improved accuracy and reliability over traditional methods by accounting for both the visual complexity and the temporal dynamics of wound healing.

1.4. Challenges and Future Directions in AI-Based Wound Care

Despite the potential of AI in wound care, several challenges remain:

- **Data Diversity**: Most wound datasets lack representation of rare wound types and diverse patient demographics, leading to model bias.
- **Generalizability**: AI models trained on controlled datasets may struggle to perform in real-world settings, where lighting, angles, and image quality vary.
- **Clinical Validation**: Limited clinical trials hinder the adoption of AI models in practice, necessitating rigorous validation to ensure safety and efficacy.

To address these challenges, future research should prioritize the collection of larger, more diverse datasets, the development of explainable AI models to improve clinician trust, and the integration of real-time sensing technologies, such as wearable devices that track wound moisture levels or temperature.

2. Dataset

2.1. Overview of the Dataset

The dataset utilized for this project was specifically curated to ensure comprehensive coverage of wound types, healing stages, and demographic diversity. It consists of 2,500 high-resolution wound images sourced from three primary repositories:

- **Medical Image Database for Diabetic Foot Ulcers (MIDF-U)**: This database includes annotated images of diabetic ulcers, providing detailed metadata for each case.
- **Wound Progress Dataset**: A specialized dataset focusing on wound healing progress over time, offering sequential image data for longitudinal analysis.
- **Publicly Available Clinical Repositories**: These repositories include various wound types, such as pressure ulcers, venous leg ulcers, and surgical wounds, annotated with clinical insights.

The combined dataset ensures a robust foundation for training and testing deep learning models by encompassing a wide range of wound characteristics, environmental conditions, and patient demographics.

2.2. Dataset Characteristics

2.3. Image Resolution

Images in the dataset were initially captured at varying resolutions, reflecting the diverse sources and equipment used. For uniformity and compatibility with convolutional neural networks (CNNs), all images were resized to 224x224 pixels. This resolution balances computational efficiency with the retention of critical visual features such as wound edges, tissue composition, and color variations.

2.4. Annotations

Each image in the dataset is accompanied by detailed annotations, including:

- **Wound Type**: Identifying the specific wound category (e.g., diabetic ulcer, pressure sore, traumatic wound).
- **Healing Stage**: Classifying the wound into one of the four healing stages: inflammatory, proliferative, maturation, or chronic/stalled.
- **Wound Dimensions**: Measurements such as area, perimeter, and depth, essential for assessing healing progress.
- **Segmentation Masks**: Pixel-wise annotations delineating the wound boundary and identifying tissue types (e.g., necrotic, granulation, epithelial). These masks enhance the model's ability to focus on relevant regions of the image.

2.5. Diversity

To ensure the model's generalizability, the dataset includes diverse demographic and clinical factors, such as:

- **Patient Demographics**: Representation across age groups, genders, and ethnicities.
- **Comorbidities**: Images from patients with varying underlying conditions, including diabetes, obesity, and vascular diseases, which impact wound healing.
- **Wound Environments**: Images captured under different lighting conditions, angles, and clinical settings, simulating real-world variability.

2.6. Preprocessing Techniques

Effective preprocessing is essential to enhance the quality and utility of the dataset for AI models.

2.7. Normalization

All images were normalized to a pixel intensity range of [0, 1], ensuring consistency in brightness and contrast. This standardization improves the convergence rate during training and minimizes sensitivity to illumination differences.

2.8. Data Augmentation

To mitigate overfitting and increase dataset diversity, various augmentation techniques were applied:

- **Rotations**: Random rotations up to 30 degrees to simulate different image orientations.
- **Flipping**: Horizontal and vertical flipping to account for varying perspectives.
- **Brightness Adjustments**: Random brightness changes to replicate differences in lighting conditions.
- **Zoom and Cropping**: Random zoom-in effects to highlight specific regions of the wound.

These augmentations expanded the effective dataset size by 40%, introducing variability while preserving the integrity of the underlying data.

2.9. Data Splitting Strategy

To maximize the reliability of model evaluation, the dataset was divided into three subsets using a **stratified approach**:

- **Training Set (70%, 1,750 images)**: Used for model training, this set includes a balanced representation of all wound types and healing stages to ensure robust learning.
- **Validation Set (15%, 375 images)**: Used during training to monitor model performance and prevent overfitting. This set helps fine-tune hyperparameters.
- **Testing Set (15%, 375 images)**: Reserved for final evaluation, ensuring unbiased assessment of the model's ability to generalize to unseen data.

2.10. Stratification and Balancing

The stratification process ensured that all wound types, stages, and demographic characteristics were proportionally represented in each subset. For instance, diabetic ulcers, which constitute 40% of the dataset, were allocated proportionately across training, validation, and testing sets. This approach prevents skewed performance metrics caused by overrepresentation or underrepresentation of specific wound types.

2.10.1. Dataset Analytics and Visualizations

To further understand the dataset distribution and ensure its quality, exploratory data analysis (EDA) was conducted. Key insights include:

Class Distribution:

- Diabetic Ulcers: 40%
- Pressure Ulcers: 30%
- Venous Leg Ulcers: 20%
- Other Wounds: 10%

Healing Stage Distribution:

- Inflammatory: 25%
- Proliferative: 35%
- Maturation: 30%
- Chronic: 10%

Demographic Representation:

- **Age Groups**: 20–40 years (15%), 41–60 years (40%), 61+ years (45%).
- **Gender Distribution**: Male (55%), Female (45%).

2.10.2. Visualization:

- Bar charts depict the distribution of wound types and healing stages.
- Heatmaps of segmentation masks illustrate tissue type annotations.

These analyses confirmed the dataset's comprehensiveness and highlighted areas for potential augmentation, such as increasing the representation of rare wound types.

2.10.3. Challenges and Limitations of the Dataset

While the dataset is robust, certain challenges persist:

- **Class Imbalance**: Rare wound types, such as arterial ulcers, are underrepresented, potentially biasing model predictions. Synthetic data generation or targeted augmentation strategies may address this gap.
- **Image Quality**: Variability in image resolution and lighting conditions can affect model performance, necessitating preprocessing and data cleaning.

- **Annotation Quality**: Manual annotations, though detailed, are prone to human error. Integrating automated annotation tools could enhance consistency.

Future datasets should aim to include more diverse wound categories, additional metadata (e.g., treatment history), and higher-quality annotations to improve model generalizability and real-world applicability.

3. Method/methodology

3.1. Overview of Model Approach

The proposed methodology leverages the complementary strengths of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to automate wound classification and predict healing progress. The methodology involves three primary steps:

- **Feature Extraction**: Wound images are processed through a CNN to extract meaningful visual features such as size, texture, color, and tissue composition.
- **Classification**: The extracted features are used to classify wounds into distinct healing stages, including inflammatory, proliferative, and maturation stages, providing an initial understanding of the wound's condition.
- **Healing Prediction**: Sequential wound images from the same patient are fed into an LSTM model, capturing temporal dependencies in the healing process. The LSTM predicts the expected healing trajectory and timeline.

This hybrid approach combines the spatial feature extraction capabilities of CNNs with the temporal modeling strengths of LSTMs to address both the static and dynamic aspects of wound healing.

3.2. CNN Model Architecture

3.2.1. Architectures Used

Two CNN architectures were employed to extract features and classify wounds:

ResNet50

- **Overview**: A deep residual network comprising 50 layers, ResNet50 mitigates vanishing gradient issues through residual connections, allowing information to flow more efficiently through the network.
- **Advantages**: Suitable for capturing complex hierarchical patterns in wound images, such as subtle changes in tissue composition or wound boundaries.
- **Implementation**: Pretrained on ImageNet, the ResNet50 model was fine-tuned on the wound dataset to adapt to the task of wound classification.

MobileNet

- **Overview**: A lightweight architecture optimized for mobile and embedded devices, MobileNet uses depth wise separable convolutions to reduce computational overhead without significant performance loss.
- **Advantages**: Ideal for real-time wound analysis on portable devices, enabling deployment in resource-constrained settings such as rural clinics.
- **Implementation**: MobileNet was also pretrained on ImageNet and fine-tuned to classify wound stages efficiently.

3.3. Training Process

The CNN models were trained using the following setup:

- **Loss Function**: Cross-entropy loss for multi-class classification.
- **Optimizer**: Adam optimizer with a learning rate of 0.001.
- **Epochs**: 50 epochs with early stopping to prevent overfitting.
- **Batch Size**: 32 images per batch to optimize training speed and memory usage.

3.4. Evaluation Metrics

3.4.1. The performance of the CNN models was evaluated using:

- **Accuracy**: Percentage of correctly classified wound stages.
- **Precision, Recall, and F1 Score**: For each wound stage to assess the model's ability to differentiate between stages.
- **Confusion Matrix**: To visualize misclassifications and identify areas for improvement.

3.5. Feature Extraction

The output of the CNN models (i.e., feature maps) served as input to subsequent layers or models. Key extracted features included:

- **Wound Size**: Determined by bounding box dimensions around the wound region.
- **Texture Analysis**: Patterns indicating granulation, necrosis, or epithelial tissue.
- **Color Variations**: Indicative of infection or healing progress (e.g., redness for inflammation, pink for granulation).

Feature extraction not only aids classification but also provides interpretable insights for clinicians.

3.6. LSTM Model for Healing Prediction

3.6.1. Overview

The LSTM model was designed to predict wound healing progression by analyzing temporal sequences of wound images. Each patient's wound was imaged over time, creating a sequential dataset. This enabled the LSTM to learn patterns in how wounds evolve and use these patterns to predict the expected healing duration.

3.7. Architecture and Implementation

3.7.1. Feature Input:

- Features extracted by the CNN were aggregated into a time-series dataset for each patient.
- Each time step represents an image, with features including size, texture, color, and healing stage probabilities.

3.7.2. LSTM Layers

- **Units**: 128 hidden units per layer to capture temporal dependencies.
- **Dropout**: A 20% dropout rate was applied to prevent overfitting.
- **Activation**: tanh activation to capture nonlinear healing trends.

3.7.3. Output Layer

- *The final dense layer outputs the predicted healing duration in days.*

3.8. Training Process

3.8.1. The LSTM was trained using:

- **Loss Function**: Mean squared error (MSE) to minimize the difference between predicted and actual healing durations.
- **Optimizer**: Adam optimizer with a learning rate of 0.0005.
- **Epochs**: 50 epochs with early stopping.
- **Batch Size**: 16 patients per batch due to the sequential nature of the data.

3.9. Workflow of the Combined Model

- **Input Image Preprocessing**: Images were preprocessed (resized, normalized, and augmented) and fed into the CNN model.
- **Feature Extraction and Classification**: The CNN outputs feature maps and classifies the wound stage.

- **Sequential Data Creation**: For each patient, features from sequential images were aggregated into a time-series dataset.
- **Healing Prediction**: The LSTM analyzes the sequential data to predict the expected healing trajectory.

3.10. Model Performance

CNN Classification Performance

- **ResNet50** achieved an accuracy of 92% on the test set, with high precision and recall for inflammatory and proliferative stages but slight misclassification between maturation and chronic wounds.
- **MobileNet** achieved an accuracy of 89%, with reduced computational cost, making it ideal for real-time applications.

LSTM Prediction Performance

- **Root Mean Squared Error (RMSE)**: The LSTM achieved an RMSE of 3.8 days on the test set, indicating robust prediction accuracy.
- **Correlation Coefficient**: A strong positive correlation ($r = 0.88$) was observed between predicted and actual healing durations.

Advantages of the Hybrid Approach

- **Improved Classification Accuracy**: The CNN effectively distinguished wound stages, addressing limitations of manual inspection.
- **Temporal Modeling**: The LSTM captured dynamic healing trends, enabling accurate predictions of healing durations.
- **Scalability**: MobileNet's lightweight design ensures the model can be deployed on portable devices for real-world use.
- **Improving Image Quality**: Enhanced preprocessing (e.g., deblurring, contrast correction) and occlusion-aware models could mitigate errors from poor-quality images.

4. Wound severity classification results

The performance of the classification models (ResNet50 and VGG16) was evaluated using key metrics such as accuracy, precision, recall, and F1-score. The results are summarized in the table below:Key Observation.

Table 1 Wound Severity Results from Two Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
ResNet50	93.2%	92.8%	93.1%	93.0%
VGG16	91.5%	91.0%	91.2%	91.1%

- **Model Comparison**: ResNet50 outperformed VGG16 across all metrics. This can be attributed to its deeper architecture and the use of residual connections, which effectively capture complex patterns in wound images while avoiding issues like vanishing gradients.
- **Misclassifications**: Analysis of the confusion matrix highlighted that most errors occurred in distinguishing "moderate" and "severe" wounds. These wound stages often share overlapping visual features, such as redness and tissue granulation, leading to ambiguities in classification.

4.1. Potential Improvements

- **Incorporating Contextual Data**: Including additional contextual information, such as patient history, wound location, and comorbidities, could help differentiate between wound stages with subtle visual differences.
- **Image Augmentation**: Enhancing image preprocessing techniques, such as applying targeted augmentations (e.g., color normalization or contrast enhancement), might reduce misclassification rates by standardizing visual inputs.

4.2. Healing Progression Prediction

The CNN-LSTM model was evaluated for its ability to predict wound healing duration based on sequential wound images. Regression metrics for the model's performance are provided below:Significance of Results

- The MAE of 3.2 days demonstrates strong predictive performance, indicating the model's ability to estimate recovery timelines with a small average error.
- The low MSE value reflects minor deviations in predictions, showcasing the model's reliability and potential utility in real-world clinical scenarios.

Table 2 MAE and MSE values

Metric	Value
Mean Absolute Error (MAE)	3.2 days
Mean Squared Error (MSE)	15.4 days^2

4.3. Limitations and Outliers

While the model performed well overall, some outliers were observed, primarily in cases where:

- **Atypical Healing Patterns**: Certain wounds exhibited delayed healing due to comorbid conditions such as diabetes, poor circulation, or infections. These factors were not captured by the image data alone.
- **Visual Ambiguities**: Variations in wound lighting, occlusion from bandages, or inconsistent imaging angles introduced noise into the feature extraction process, impacting temporal predictions.

4.4. Proposed Solutions

- **Incorporating Metadata**: Integrating patient-specific information, such as medical history, medications, and environmental factors, could improve predictions by accounting for external influences on healing.
- **Improving Image Quality**: Enhanced preprocessing (e.g., deblurring, contrast correction) and occlusion-aware models could mitigate errors from poor-quality images.

4.5. Hyperparameter Tuning and Model Optimization

To achieve optimal performance, key hyperparameters were tuned for both classification and regression tasks:

ResNet50 Optimization

- **Learning Rate**: Set to 0.0001, enabling steady convergence without overshooting minima.
- **Batch Size**: A batch size of 32 balanced computational efficiency and generalization.
- **Dropout**: 30% dropout was applied to reduce overfitting, particularly on complex, high-dimensional image features.

LSTM Optimization

- **Learning Rate**: A slightly higher learning rate of 0.0005 was used, as LSTMs require faster adaptation to capture temporal dependencies.
- **Sequence Length**: The LSTM was trained on sequences of 5-10 images per patient to ensure adequate temporal context without introducing excessive noise.

These optimizations significantly enhanced the models' stability and performance, ensuring robust generalization across both training and validation datasets.

4.6. Error Analysis

Despite the strong results, certain limitations were noted:

- Misclassifications Between Moderate and Severe Wounds:
    - Overlapping visual characteristics caused frequent errors in classification.

- **Solution**: Augmenting the model with additional clinical data or developing explainable AI mechanisms to identify subtle feature differences could mitigate this issue.

Healing Duration Deviations:

- Atypical wounds with delayed healing were not well-represented in the training dataset, leading to prediction errors.
- **Solution**: Expanding the dataset to include diverse cases, particularly those with known comorbidities, could improve the model's handling of edge cases.

Impact of Image Quality:

- Poor lighting, occlusions, and inconsistent imaging angles affected both classification and regression accuracy.
- **Solution**: Developing preprocessing pipelines to enhance image quality or using generative adversarial networks (GANs) for image enhancement could address these challenges.

4.7. Future Improvements

4.7.1. Dataset Expansion

- **More Diverse Data**: Including higher-resolution images, more wound types, and metadata such as patient demographics, wound location, and treatment history.
- **Synthetic Data**: Using GANs to generate synthetic wound images could help augment the dataset and improve model generalization.

4.7.2. Advanced Model Architectures

- Exploring Vision Transformers (ViTs), which capture global image features more effectively than traditional CNNs, could improve classification accuracy.
- Investigating ensemble models combining multiple architectures (e.g., ResNet, MobileNet, and ViTs) for enhanced robustness.

4.7.3. Multi-Modal Data Integration

- Combining image data with sensor readings (e.g., moisture levels, pH, or temperature) from wearable devices could provide a more comprehensive understanding of wound healing.

4.7.4. Real-World Validation:

- Deploying the model in clinical settings to test its performance under real-world conditions.
- Collecting feedback from clinicians to iteratively refine the model and application.

4.7.5. Explainability and Trust

- Incorporating interpretable AI techniques, such as Grad-CAM, to visualize the features influencing predictions could increase trust and adoption among healthcare providers.

5. Conclusion

This research provides an AI-powered mobile app to classify and keep track of wound healing progress using advanced machine learning techniques for potentially revolutionizing wound care management. The application uses ResNet50 and MobileNet for severity classification and a CNN-LSTM model to predict healing progress. In doing so, the application has achieved some encouraging results of: Classification Accuracy - 93.2%; Mean Absolute Error in healing prediction - 3.2 days. This evidence provides a good case for automating and scaling wound care assessment with AI. Even though the above was achieved, still certain difficulties are faced. An example of this can be the misclassification of wounds, such as "moderate to severe," which shows the complicated features and clinical data required for proper classification. Also, the outliers in loss prediction in the healing phase show why external factors should be considered for even more reliable predictions-such as co-morbidities-with the varying quality of imaging input. It illustrates the transformative impact of introducing AI in mobile-enabled healthcare, especially among the poor areas deprived of access to such promising medical capabilities. This application could be transformational in automating wound care assessments and could help close many of those gaps in accessibility, speed of diagnosis, and cost-effective modeling of chronic wound care.

Future extensions such as dataset augmentation, analyses of multi-modal data, and newer architectures such as Vision Transformers will contribute significantly toward making the instrument more accurate and stronger. Furthermore, it will be essential to have real-world validation in a clinical setting for refining the application. This research is the first step for a much broader application of AI in healthcare, showing how technology can facilitate more efficient, personalized, and accessible care to patients worldwide. With regard to some of the challenges that were already outlined, as well as with some others to come, these AI solutions could get very real.

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