Kesaraju R. International Journal of Computer Science and Mobile Applications, Vol. 12 Issue 11, November-2024, pg. 01-19.

ISSN: 2321-8363
Impact Factor: 6.308

(An Open Accessible, Fully Refereed and Peer Reviewed Journal)

AI-Driven Wound Healing Analysis and Progression Tracking in Mobile Applications: A Scalable Approach for Healthcare Accessibility

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Received Date: 27 Nov 2024, Manuscript No. IJCSMA-24-153387; **Editor assigned:** 29 Nov 2024, Pre QC No. IJCSMA-24-153387 (PQ); **Reviewed:** 06 Dec 2024, QC No. IJCSMA-24-153387 (Q); **Revised:** 12 Dec 2024, Manuscript No. IJCSMA-153387 (R); **Published date:** 16 Dec 2024

Abstract

Wound care is a crucial element of healthcare management, particularly for patients with chronic conditions like diabetic ulcers, pressure sores, or surgical wounds. However, the manual assessment of wound healing is resource-intensive, error-prone, and often impractical in remote or underserved regions. This research introduces an Artificial Intelligence (AI)-powered mobile application designed to address these challenges by automating the assessment of wound healing stages and providing real-time, personalized recovery progress. The primary objectives are to classify wounds based on their healing stage and predict recovery

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timelines using sequential images, thereby improving accessibility and decision-making in wound management. The study utilizes Convolutional Neural Networks (CNNs) for image classification and Long Short-Term Memory (LSTM) networks for healing trajectory prediction. Using a curated dataset of 2,500 annotated wound images, the proposed models achieve a classification accuracy of 92% and a healing progression prediction error of less than 5%. The results indicate that the mobile application can provide scalable, efficient, and accessible wound care solutions. Future work includes expanding the dataset to enhance model generalization and integrating wearable sensor data for continuous monitoring. This study highlights the potential of AI-driven applications to revolutionize healthcare by bridging the gap in medical resources and providing patients with actionable insights in real-time.

Keywords: AI-driven healthcare; Wound healing analysis; Progression tracking; Mobile health applications; Scalable healthcare solutions; Healthcare accessibility

1. Introduction

The management of wound care remains a critical challenge in healthcare, particularly for individuals with chronic wounds, such as diabetic foot ulcers, pressure sores, and post-surgical wounds. These types of wounds often require frequent assessment to ensure proper healing and prevent complications. Traditional wound care methods rely heavily on manual assessments, which can be subjective and prone to error, particularly in resource-limited settings. Furthermore, the increasing global burden of chronic diseases has heightened the need for scalable solutions that can provide consistent and accurate monitoring of wound healing.

The primary aim of this research is to develop an AI-powered mobile application that provides automated, real-time assessments of wound healing stages and predicts recovery timelines based on sequential wound images. The application leverages Convolutional Neural Networks (CNNs) to classify the severity of the wound and Long Short-Term Memory (LSTM) networks to predict the healing progression. This mobile application represents a scalable solution that could significantly improve wound care, particularly in underserved or remote areas where access to medical professionals is limited [1].

The effectiveness of the model was evaluated using a dataset of annotated wound images, with results showing high classification accuracy and reliable healing predictions. The application was built with the goal of making it accessible on mobile devices, ensuring ease of use and widespread adoption. The significance of this work lies in its potential to enhance healthcare delivery by providing patients and healthcare professionals with accurate, real-time insights into wound care, thus enabling timely interventions and improving patient outcomes.

2. Background

2.1. The Complexity of Wound Healing

Wound healing is a multifaceted biological process aimed at restoring the integrity and function of injured tissue. It proceeds through four overlapping and dynamic stages:

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2.1.1. Hemostasis: Occurs immediately after injury, where vascular constriction and clot formation prevent blood loss. Platelet activation also releases growth factors that initiate the healing process.

2.1.2. Inflammation: This stage is characterized by immune cell infiltration, including neutrophils and macrophages, which work to clear debris and combat infection. Redness, swelling, and pain are common visual markers of this phase.

2.1.3. Proliferation: In this stage, fibroblasts and endothelial cells promote tissue regeneration by producing collagen and forming granulation tissue. Angiogenesis (new blood vessel formation) and epithelial cell migration are critical for covering the wound bed.

2.1.4. Remodeling: Also known as the maturation phase, this involves the reorganization of collagen fibers and strengthening of the newly formed tissue, reducing scar visibility over time.

Each of these stages exhibits unique visual and textural features, such as changes in size, depth, and coloration, which can be systematically analyzed to assess healing progression. Variability in healing rates is influenced by factors such as patient health, comorbidities (e.g., diabetes), wound type, and environmental conditions, underscoring the need for consistent and objective evaluation methods.

3. Current Strategies for Wound Healing Assessment

3.1. Traditional Methods

Historically, the assessment of wound healing has relied on clinical evaluations, which involve visual inspection and manual measurements by healthcare professionals. While effective in controlled settings, these methods are inherently subjective, with outcomes influenced by the clinician's expertise and experience. Moreover, the process is time-consuming, requiring frequent follow-ups, and it is resource-intensive, limiting its scalability in low-resource settings or rural areas.

Standardized tools like the Bates-Jensen Wound Assessment Tool (BWAT) and Pressure Ulcer Scale for Healing (PUSH) attempt to provide structure to wound evaluation. However, they remain limited by the variability of human interpretation, particularly when distinguishing between subtle changes in tissue composition or inflammation levels.

3.2. AI and Medical Imaging Innovations

Advancements in medical imaging and Artificial Intelligence (AI) are paving the way for more objective and automated approaches to wound assessment. AI-driven systems leverage imaging technologies such as digital photography and thermography, combined with powerful algorithms, to quantify wound characteristics. Key innovations include:

- **Computer Vision:** AI models use computer vision to analyze wound features such as size, edge

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irregularities, tissue types, and color gradients.

- **Tissue Segmentation:** AI tools can segment wound images to identify necrotic tissue, granulation tissue, and epithelial coverage, providing granular insights into healing stages.

These AI-based methodologies reduce inter-clinician variability, ensure consistency, and enable rapid analysis, especially in telemedicine applications.

4. AI Models for Wound Classification and Healing Prediction

4.1. Applications of CNNS in Medical Imaging

Convolutional Neural Networks (CNNs) have emerged as the backbone of modern medical imaging solutions due to their ability to automatically extract hierarchical features from image data. In wound care, CNNs are widely used to classify wounds based on their healing stages by identifying visual patterns such as tissue color, texture, and vascularization. Unlike traditional image analysis, which requires handcrafted features, CNNs learn directly from raw pixel data, enabling superior performance in complex datasets [2].

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.

4.2. Predictive Modeling with Hybrid Approaches

Deep learning models are not limited to static classification; they can also predict healing outcomes using sequential image data. Hybrid models, which combine Convolutional Neural Networks (for spatial analysis) with Long Short-Term Memory (LSTM) networks (for temporal analysis), are particularly effective in wound healing prediction. These models analyze changes in wound features over time, such as reductions in wound area or improvements in tissue quality, to forecast recovery timelines.

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.

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

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

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

4.3.1. Data Diversity: Most wound datasets lack representation of rare wound types and diverse patient demographics, leading to model bias.

4.3.2. Generalizability: AI models trained on controlled datasets may struggle to perform in real-world settings, where lighting, angles and image quality vary.

4.3.3. 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.

5. Dataset

5.1. 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:

5.1.1. Medical Image Database for Diabetic Foot Ulcers (MIDF-U): This database includes annotated images of diabetic ulcers, providing detailed metadata for each case.

5.1.2. Wound Progress Dataset: A specialized dataset focusing on wound healing progress over time, offering sequential image data for longitudinal analysis.

5.1.3. 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.

6. Dataset Characteristics

6.1. Image Resolution

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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 224 × 224 pixels. This resolution balances computational efficiency with the retention of critical visual features such as wound edges, tissue composition, and color variations [3].

6.2. 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.

6.3. 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.

7. Preprocessing Techniques

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

7.1. 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 [4].

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7.2. Data Augmentation

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

7.2.1. Rotations: Random rotations up to 30 degrees to simulate different image orientations.

7.2.2. Flipping: Horizontal and vertical flipping to account for varying perspectives.

7.2.3. Brightness Adjustments: Random brightness changes to replicate differences in lighting conditions.

7.2.4. 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.

7.3. Data Splitting Strategy

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

7.3.1. Training Set (70%, 1,750 Images): Used for model training, this set includes a balanced representation of all wound types and healingstages to ensure robust learning.

7.3.2. Validation Set (15%, 375 Images): Used during training to monitor model performance and prevent overfitting. This set helps fine-tune hyper parameters.

7.3.3. Testing Set (15%, 375 Images): Reserved for final evaluation, ensuring unbiased assessment of the model's ability to generalize to unseen data.

7.4. 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 [5].

7.5. Dataset Analytics and Visualizations

To further understand the dataset distribution and ensure its quality, Exploratory Data Analysis (EDA) was conducted. Key insights include:

7.5.1. Class Distribution:

- **Diabetic Ulcers**: 40%

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

7.5.2. Healing Stage Distribution:

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

7.5.3. Demographic Representation:

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

7.6. Challenges and Limitations of the Dataset

While the dataset is robust, certain challenges persist:

7.6.1. 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.

7.6.2. Image Quality: Variability in image resolution and lighting conditions can affect model performance, necessitating preprocessing and data cleaning.

7.6.3. 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.

8. Method

8.1. 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:

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8.1.1. Feature Extraction: Wound images are processed through a CNN to extract meaningful visual features such as size, texture, color, and tissue composition.

8.1.2. 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.

8.1.3. 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.

9. CNN Model Architecture

9.1. Architectures Used

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

9.1.1. 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.

9.1.2. Mobile Net:

- **Overview:** A lightweight architecture optimized for mobile and embedded devices, Mobile Net 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:** Mobile Net was also pretrained on Image Net and fine-tuned to classify wound stages efficiently.

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9.2. 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.

9.3. Evaluation Metrics

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.

9.4. 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.

10. LSTM Model for Healing Prediction

10.1. 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.

10.2. Architecture and Implementation

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10.2.1. 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.

10.2.2. LSTM Layers:

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

10.2.3. Output Layer:

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

11. Training Process

11.1. 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.

11.2. Workflow of the Combined Model

11.2.1 Input Image Preprocessing: Images were preprocessed (resized, normalized, and augmented) and fed into the CNN model.

11.2.2. Feature Extraction and Classification: The CNN outputs feature maps and classifies the wound stage.

11.2.3. Sequential Data Creation: For each patient, features from sequential images were aggregated into a time-series dataset**.**

11.2.4. Healing Prediction: The LSTM analyzes the sequential data to predict the expected healingtrajectory.

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12. Model Performance

12.1. 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.
- **Mobile Net:** achieved an accuracy of 89%, with reduced computational cost, making it ideal for real-time applications.

12.2. 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.

12.3. Advantages Of The Hybrid Approach

12.3.1. Improved Classification Accuracy: The CNN effectively distinguished wound stages, addressing limitations of manual inspection.

12.3.2. Temporal Modeling: The LSTM captured dynamic healing trends, enabling accurate predictions of healing durations.

12.3.3. Scalability: Mobile Net's lightweight design ensures the model can be deployed on portable devices for real-world use.

12.4. 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 1** below: Key Observations

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%

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12.4.1. 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.

12.4.2. 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.

12.5. 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.

12.6. 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:

12.6.1. 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)**.

Table 2. MAE and MSE values.

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

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12.7. Limitations and Outliers

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

12.7.1. 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.

12.7.2. Visual Ambiguities: Variations in wound lighting, occlusion from bandages, or inconsistent imaging angles introduced noise into the feature extraction process, impacting temporal predictions.

12.8. 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.

13. Hyper parameter Tuning and Model Optimization

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

13.1. 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.

13.2. 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 [6].

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14. Error Analysis

Despite the strong results, certain limitations were noted:

14.1. Misclassifications between Moderate andSevere Wounds

- **Overlapping:** visual characteristics causedfrequent errors in classification.
- **Solution:** Augmenting the model with additional clinical data or developing explainable AI mechanisms to identify subtle feature differences could mitigatethis issue.

14.2. 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.

14.3. Impact of Image Quality

- **Poor Lighting:** Occlusions, and inconsistent imaging angles affected bothclassification and regression accuracy.
- **Solution**: Developing Preprocessing pipelines to enhance image quality or using Generative Adversarial Networks(GANs) for image enhancement could address these challenges.

15. Future Improvements

15.1. 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 [7].

15.2. Advanced Model Architectures

- Exploring Vision Transformers (ViTs), which capture global image features more effectively than traditional CNNs, could improve classification accuracy.

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- Investigating ensemble models combining multiple architectures (e.g., ResNet, MobileNet, and ViTs) for enhanced robustness.

15.3. 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 [8].

15.4. 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.

15.5. Explain Ability and Trust

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

16. Conclusion

This research presents an AI-driven mobile application for the classification and progression tracking of wound healing, combining advanced machine learning techniques with the potential to revolutionize wound care management. Using ResNet50 and Mobile Net for wound severity classification and a CNN-LSTM model for healing progression prediction, the application achieved promising results. The classification accuracy of 93.2% and a Mean Absolute Error (MAE) of 3.2 days in healing predictions highlight the feasibility of automating and scaling wound care assessments through AI.

Despite these successes, challenges remain. Misclassifications, particularly between "moderate" and "severe" wounds, reveal the need for more nuanced features and contextual clinical data. Similarly, outliers in healing progression predictions underscore the importance of addressing external factors, such as comorbidities and inconsistent imaging quality, to improve reliability further.

The study underscores the transformative potential of integrating AI into mobile healthcare applications, especially for underserved regions with limited access to skilled medical professionals. By automating wound care assessments, this tool could help bridge gaps in healthcare accessibility, reduce diagnosis time, and provide cost-effective support for chronic wound management.

Future advancements, including dataset expansion, multi-modal data integration, and the exploration of cutting-edge model architectures like Vision Transformers, will enhance the tool's accuracy and robustness. Additionally, real-world validation in clinical environments will be critical for refining the application and ensuring its practical utility.

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This research lays the groundwork for broader adoption of AI in healthcare, demonstrating how technology can enable more efficient, personalized, and accessible care. By addressing existing challenges and incorporating further innovations, AI-driven solutions can play a pivotal role in improving health outcomes and quality of life for patients worldwide.

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