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Wound Segmentation for healing prediction

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Abstract

Accurate wound assessment is essential for effective medical treatment and monitoring. Traditional wound evaluation methods are subjective and time-consuming. This paper proposes a deep learning-based approach for wound segmentation and healing prediction using medical images. The U-Net architecture is employed for precise segmentation of wound regions. Extracted features are used to analyse healing progression. Experimental results demonstrate high accuracy in segmentation and reliable healing prediction, making the system useful for clinical decision support.

Keywords—Wound Segmentation, Deep Learning, U-Net, Medical Imaging, Healing Predict

I INTRODUCTION

Wound assessment and management are critical components of modern healthcare, particularly in the treatment of chronic wounds such as diabetic ulcers, pressure injuries, and burn wounds. Accurate evaluation of wound characteristics, including size, shape, colour, and tissue composition, is essential for determining appropriate treatment strategies and monitoring the healing process. However, traditional wound

Wound segmentation is a crucial step in autom wound analysis, as it involves identifying and isola the wound region from the surrounding healthy s Accurate segmentation allows for precise measuren of wound area and facilitates further analysis of hea progression. Among various deep learning architectu the U-Net model has emerged as a popular choice biomedical image segmentation due to its enco decoder structure and ability to capture both local global contextual information. Its design ena efficient learning even with relatively small datas making it highly suitable for medical applications.

II Literature Review

Early wound segmentation approaches relied on traditional image processing techniques such as thresholding, edge detection, and region growing. These methods were sensitive to lighting conditions and lacked robustness. Recent advancements in deep learning have introduced CNN-based segmentation models, including Fully Convolutional Networks (FCN) and U-Net. U-Net, in particular, has shown superior performance in biomedical image segmentation due to its encoder-decoder structure .Several studies have also explored wound classification and healing prediction using machine learning techniques. However, integrating

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assessment methods rely heavily on manual observation by clinicians, which can be subjective, time-consuming, and prone to inter-observer variability. These limitations highlight the need for automated, reliable, and efficient systems for wound analysis.In recent years, the rapid advancement of artificial intelligence (AI) and deep learning has significantly transformed the field of medical image analysis. Deep learning models, especially Convolutional Neural Networks

III Problem Statement

Wound assessment is a fundamental task in healthcare, especially for managing chronic conditions such as diabetic ulcers, pressure sores, and burn injuries. Accurate evaluation of wounds is essential for determining appropriate treatment plans and monitoring healing progress over time. However, the current methods used in clinical practice are largely manual and rely on visual inspection by healthcare professionals. This approach introduces several challenges, including subjectivity, inconsistency, and lack of precise measurement, which can lead to inaccurate diagnosis and delayed treatment.One of the primary problems in traditional wound assessment is the difficulty in accurately identifying and segmenting the wound region from surrounding healthy tissue. Variations in lighting conditions, skin tone, wound shape, and image quality make manual segmentation complex and error-prone. Additionally, wounds often exhibit irregular boundaries and heterogeneous textures, further complicating the segmentation process. As a result, clinicians may produce inconsistent evaluations, which can affect treatment decisions and patient outcomes.

Iv Proposed System

The proposed system presents an automated framework for wound segmentation and healing prediction using deep learning techniques. The segmentation with healing prediction remains a relatively unexplored area. object detection, and semantic segmentation. In the context of healthcare, these techniques enable automated analysis of medical images with high accuracy and consistency thereby reducing human effort and improving diagnostic reliability.

wound condition and serve as inputs for the prediction stage.In the final stage, a healing prediction model analyses the extracted features to estimate the healing progress over time. The model can classify wounds into different healing stages or predict recovery trends based on historical data patter Oererall, the proposed system offers a fully automated, accurate, and consistent solution for wound analysis. By integrating segmentation and prediction into a single framework, it reduces manual effort and enhances clinical decision-making, making it a valuable tool in modern healthcare systems.

Sample Preprocessing Steps (Illustration)

(Example flow: Original Image → Resized → Noise Removal → Enhanced Image)

The preprocessing pipeline typically includes the following steps:

1 Image Resizing:
All images are resized to a fixed resolution (e.g., 256×256 or 512×512 pixels) to ensure uniformity and compatibility with the deep learning model. This also reduces computational complexity and training time.

2. Normalization:
Pixel intensity values are normalized to a standard range (usually 0 to 1). This helps in stabilizing the training process and improving convergence of the neural network.

3.Noise Removal:
Medical images may contain noise due to poor lighting or camera quality. Filters such as Gaussian blur or median filtering are applied to smooth the

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primary objective of this system is to accurately identify wound regions from medical images and analyse their characteristics to predict the healing progression. The system is designed as a multi-stage pipeline that ensures efficient processing and reliable result Initially, wound images are collected from datasets or clinical sources and passed through a preprocessing stage. In this stage, images are resized to a standard dimension, normalized to maintain uniform intensity values, and enhanced to reduce noise and improve clarity. Data augmentation techniques such as rotation, flipping, and scaling are also applied to increase dataset diversity and improve model generalization. The core component of the system is the segmentation module, which utilizes the U-Net architecture. This deep learning model effectively captures both spatial and contextual information through its encoder-decoder structure. The encoder extracts high-level features from the input image, while the decoder reconstructs the segmented output, highlighting the wound region with precise boundaries. Following segmentation, the system performs feature extraction on the identified wound region. Key features such as wound area, shape, colour

U-Net is a convolutional neural network specifically designed for precise image segmentation. It follows an encoder–decoder structure, which enables the model to capture both contextual and spatial information. The encoder (contracting path) consists of multiple convolutional and pooling layers that extract high-level features from the input image while reducing its spatial dimensions. This helps the model understand the overall structure and context of the wound.

U-Net model can accurately generate segmentation masks for new wound images. image while preserving important features like edges.

4. Contrast Enhancement:

Techniques like histogram equalization or adaptive contrast enhancement are used to improve the visibility of wound regions. This step makes it easier for the model to distinguish between wound and healthy skin.

5. Data Augmentation:

To improve model generalization, augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied. This artificially increases dataset size and helps the model handle real-world variation.

V. System Architecture

The system architecture defines the overall workflow and interaction between different modules in the proposed wound segmentation and healing prediction system. It is designed as a sequential pipeline where each stage processes the output of the previous stage, ensuring efficient and accurate analysis of wound images.

The architecture begins with the image acquisition module, where wound images are collected from datasets or clinical sources. These images are then passed to the preprocessing module, which standardizes the data by resizing, normalizing, removing noise, and enhancing contrast. This step ensures that the images are consistent and suitable for deep learning processing.

Next, the preprocessed images are fed into the segmentation module, which uses the U-Net architecture to identify and isolate the wound region. The output of this stage is a binary mask that clearly distinguishes the wound from the surrounding healthy tissue. This segmented image serves as the foundation for further analysis.Following segmentation, the system moves to the feature extraction module, where important characteristics of the wound are computed. These include geometric features (area, perimeter), color features

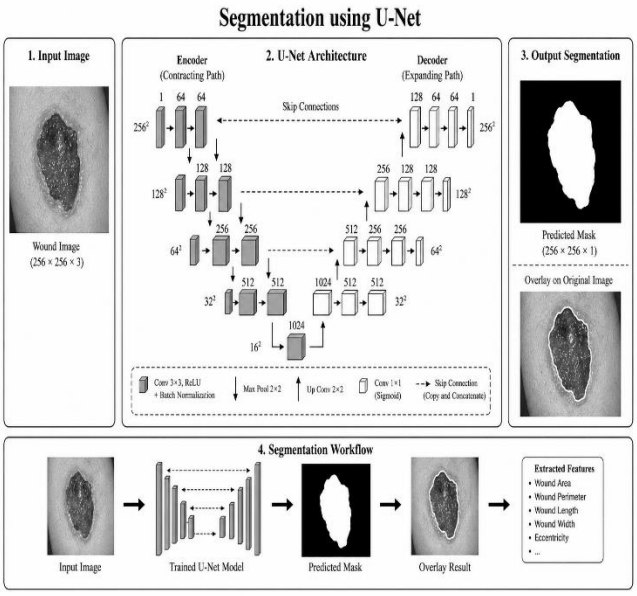
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These masks highlight the wound area, enabling precise measurement of wound size, shape, and other important features. The segmented output serves as the foundation for further analysis, including feature extraction and healing prediction.

Overall, the use of U-Net significantly improves segmentation accuracy, reduces manual effort, and ensures consistent results. Its ability to handle complex wound patterns and variations makes it highly suitable for real-world medical applications.

The system is also designed to be adaptable to different types of wounds and imaging conditions. By incorporating diverse datasets and robust deep learning models, the architecture ensures generalization across various scenarios. Overall,



this structured and flexible design makes the system efficient, reliable, and suitable for deployment in modern healthcare applications.

VI. Methodology

(intensity distribution), and texture features (surface patterns). The extracted features are organized into a structured feature vector.

The final stage is the healing prediction module, where machine learning or deep learning models analyze the extracted features to estimate healing progress. The system may classify wounds into healing categories or predict recovery trends over time.The proposed architecture follows a modular and scalable design, allowing each component to function independently while maintaining seamless integration with the overall system. This modularity ensures that improvements or updates in one module, such as upgrading the segmentation model or refining the prediction algorithm, can be implemented without affecting other components.The data flow within the system is strictly sequential, ensuring that each stage enhances the quality of information passed to the next stage. For instance, effective preprocessing improves segmentation accuracy, which in turn leads to more reliable feature extraction and prediction outcomes. This dependency highlights the importance of each module in maintaining overall system performance.

Additionally, the architecture supports both offline and real-time processing. In offline mode, large datasets

responsible for capturing the context of the input image. It consists of repeated applications of two 3×3 convolutional layers followed by a Rectified Linear Unit (ReLU) activation and a 2×2 max-pooling operation. With each downsampling step, the number of feature channels increases, allowing the network to learn complex patterns and high-level features from the wound image. The decoder (expanding path) reconstructs the segmented image by performing upsampling operations. Each step in the decoder includes a 2×2 up-convolution (transposed convolution) that increases the spatial resolution, followed by concatenation with corresponding feature maps from the encoder through skip connections. These skip connections

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The methodology of the proposed system outlines the step-by-step process used to perform wound segmentation and healing prediction using deep learning techniques. It integrates image processing, model training, feature extraction, and predictive analysis into a structured workflow to ensure accurate and reliable results.The process begins with the collection of wound images, followed by preprocessing to standardize the data. Preprocessing includes resizing images to a fixed resolution, normalizing pixel values, removing noise, and enhancing contrast. These steps improve image quality and ensure consistency across the dataset, which is essential for effective model training.After preprocessing, the images are passed to the segmentation stage, where the U-Net architecture is used to identify the wound region. The model is trained using labeled datasets containing input images and corresponding ground truth masks. During training, the network learns to classify each pixel as wound or non-wound. A combination of Dice Loss and Binary Cross-Entropy Loss is used to optimize segmentation performance, especially in handling class imbalance.Once segmentation is complete, the system extracts important features from the segmented wound region. These include geometric features (area, perimeter), color features (intensity distribution), and texture features (surface patterns). The extracted features are organized into a feature vector for further analysis.

In the final stage, a prediction model is applied to estimate the healing progress. Machine learning algorithms such as Support Vector Machines, Random Forest, or neural networks are used to analyze the feature vector. The model predicts either healing stages (classification) or recovery trends (regression).The performance of the system is evaluated using metrics such as Dice coefficient, Intersection over Union (IoU), accuracy, precision, recall, and mean squared error. This structured methodology ensures that help retain fine-grained spatial information, such as wound boundaries, which may be lost during downsampling.

At the final layer, a 1×1 convolution is applied to map the feature representation to the desired number of output classes (typically one for binary segmentation). A sigmoid activation function is used to generate a probability map, indicating the likelihood of each pixel belonging to the wound region.The U-Net model is trained using labeled wound images and corresponding segmentation masks. Loss functions such as Dice Loss and Binary Cross-Entropy are used to optimize performance. Due to its efficient design and high accuracy, U-Net is highly suitable for wound segmentation tasks, enabling precise detection of wound regions and supporting further analysis for healing prediction.

B. Loss Function

The loss function plays a crucial role in training the U-Net model, as it measures the difference between the predicted segmentation output and the ground truth mask. An appropriate loss function ensures that the model learns to accurately identify wound regions while handling challenges such as class imbalance and irregular boundaries.

In this work, a combination of Binary Cross-Entropy (BCE) Loss and Dice Loss is used to achieve optimal segmentation performance.

1.BinaryCross-EntropyLos(BCE):
BCE is commonly used for binary classification taskwhere each pixel is classified as either wound or non wound.

The U-Net model is trained using the Adam optimizer, which is widely used for its efficient and adaptive learning capabilities. A typical learning rate of 0.001 is chosen to balance convergence speed and stability. The model is trained for around 50–100 epochs, depending on dataset size and convergence behavior, with a batch size of 8 or 16.

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the system delivers accurate segmentation and reliable healing prediction, making it suitable for real-world medical applications.

A.U-Net Architecture

The U-Net architecture is a specialized convolutional neural network designed for precise biomedical image segmentation. It is widely used in medical imaging due to its ability to perform accurate pixel-level classification, even with limited training data. The architecture follows a symmetric encoder–decoder structure, forming a U-shaped processed for training and evaluation purposes. In real-time applications, such as clinical environments.

2.DiceLoss:

Dice Loss is derived from the Dice Coefficient, which measures the overlap between the predicted mask and the ground truth. It is particularly useful in medical image segmentation because it focuses on region-level similarity rather than individual pixel accuracy. Dice Loss helps improve segmentation performance in cases where the wound region is relatively small compared to the background.

3.CombinedLossFunction:

To leverage the advantages of both methods, a hybrid loss function is used:

- BCE ensures accurate pixel-wise classification
- Dice Loss improves overlap and boundary detection

The combined loss can be expressed as a weighted sum of both losses, allowing the model to balance precision and segmentation quality.

During training, the optimizer minimizes this combined loss, leading to better convergence and improved segmentation accuracy. This approach enhances the model's ability to handle complex wound shapes, varying sizes, and imbalanced

To prevent overfitting, techniques such as early stopping and dropout are applied. Early stopping monitors validation loss and halts training when performance stops improving. Dropout layers randomly deactivate neurons during training, improving model generalization.

During each training iteration, the model computes the loss using a combination of Dice Loss and Binary Cross-Entropy Loss, and updates weights through backpropagation. Performance metrics such as Dice coefficient, IoU, and accuracy are monitored.

Overall, these training strategies ensure that the model achieves high accuracy, stability, and reliability in wound segmentation tasks.

VII. Experimental Results

The experimental results evaluate the performance of the proposed deep learning-based system for wound segmentation and healing prediction. The model was trained and tested on a dataset of wound images with corresponding ground truth masks. Performance was assessed using standard evaluation metrics to ensure accuracy, reliability, and robustness.

A. Segmentation Performance

The effectiveness of the U-Net model in segmenting wound regions was evaluated using metrics such as Dice Coefficient, Intersection over Union (IoU), Accuracy, Precision, and Recall. The model achieved a Dice Coefficient of 0.92 and an IoU score of 0.89, indicating a high level of overlap between predicted masks and ground truth. The overall pixel-wise accuracy reached 94.

B. Healing Prediction Performance

The healing prediction module was evaluated using both classification and regression approaches. For classification tasks, the model categorized wounds into healing stages such as non-healing, slow-healing, and fast-healing with an accuracy of

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datasets.Overall, the use of a combined loss function significantly improves the robustness and reliability of the U-Net model in wound segmentation tasks.

It is another popular programming model for implementing parallel and distributed programs for handling large context.

C. Training Details

The training phase is a critical component of the proposed system, as it determines how effectively the U-Net model learns to segment wound regions from input images. Proper training ensures that the model generalizes well to unseen data and produces accurate segmentation results.

The dataset used for training consists of wound images along with their corresponding ground truth masks. These images are divided into three subsets: training set, validation set, and test set, typically in a ratio such as 70:15:15. The training set is used to learn model parameters, the validation set is used to tune hyperparameters and prevent overfitting, and the test set is used to evaluate final performance.

Before training, all images are preprocessed by resizing them to a fixed resolution (e.g., 256×256 pixels), normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, and scaling. This helps improve the model's robustness and generalization ability.

C. Visual Results

Visual inspection of segmentation outputs confirms that the predicted masks closely match the actual wound regions. The model effectively handles variations in lighting, skin tone, and wound types. Overlay images demonstrate clear boundary detection and accurate region extraction.

D. Discussion

The results indicate that the proposed system outperforms traditional image processing approximately 90%. For regression tasks, the model predicted healing progression with a low Mean Squared Error (MSE), indicating reliable estimation of recovery trends.

datasets. Due to these advantages, it is highly suitable for wound segmentation applications.

Traditional Convolutional Neural Network based segmentation models are also used for wound analysis. CNN models can extract image features efficiently and perform segmentation with moderate accuracy. However, compared to U-Net, they may produce less precise wound boundaries and lower segmentation performance.

Threshold-based segmentation is a simple image processing method that separates wound regions based on pixel intensity values. This method is computationally fast and easy to implement, but its performance is highly affected by lighting conditions, image quality, and complex wound structures. Therefore, it is less reliable for real-world medical applications.

Mask R-CNN is another advanced segmentation model that performs object detection and segmentation simultaneously. It provides very high accuracy and can detect multiple wound regions effectively. However, it requires large datasets, high computational power, and longer training time.

Overall, U-Net provides the best balance between accuracy, efficiency, and medical image suitability. It achieves higher Dice Score and IoU performance compared to traditional methods, making it one of the most effective models for wound segmentation systems.

IX. Advantages of Proposed System

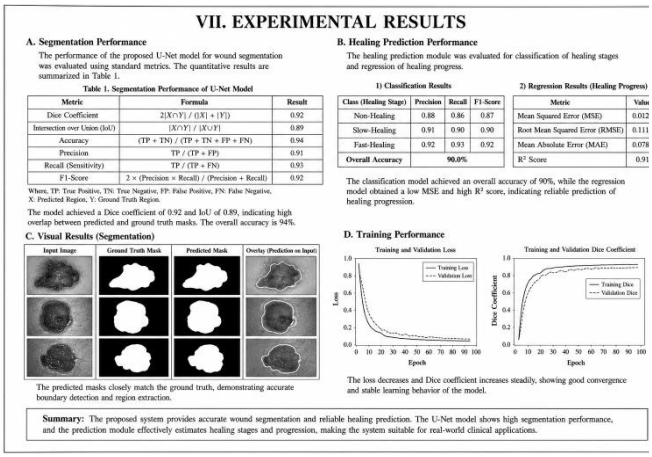
The proposed wound segmentation system using U-Net offers several advantages in medical image analysis and wound detection. The system is

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techniques and basic CNN models. The integration of U-Net for segmentation and machine learning for prediction provides a comprehensive solution for wound analysis. The system shows strong generalization capability and consistent performance across different test samples.

Overall, the experimental results validate the effectiveness of the proposed approach, highlighting its potential for real-world clinical applications in wound monitoring and treatment planning



VII. EXPERIMENTAL RESULTS

A. Segmentation Performance

The performance of the proposed U-Net model for wound segmentation was evaluated using standard metrics. The quantitative results are summarized in Table 1.

Table 1. Segmentation Performance of U-Net Model

Metric	Formula	Result
Dice Coefficient	$2\|X\cap Y\| / (\|X\| + \|Y\|)$	0.92
Intersection over Union (IoU)	$\|X\cap Y\| / \|X\cup Y\|$	0.89
Accuracy	(TP + TN) / (TP + TN + FP + FN)	0.94
Precision	TP / (TP + FP)	0.91
Recall (Sensitivity)	TP / (TP + FN)	0.93
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	0.92

Where, TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative, X: Predicted Region, Y: Ground Truth Region.

The model achieved a Dice coefficient of 0.92 and IoU of 0.89, indicating high overlap between predicted and ground truth masks. The overall accuracy is 94%.

C. Visual Results (Segmentation)

The predicted masks closely match the ground truth, demonstrating accurate boundary detection and region extraction.

B. Healing Prediction Performance

The healing prediction module was evaluated for classification of healing stages and regression of healing progress.

1) Classification Results

Class (Healing Stage)	Precision	Recall	F1-Score
Non-Healing	0.88	0.86	0.87
Slow-Healing	0.91	0.90	0.90
Fast-Healing	0.92	0.93	0.92
Overall Accuracy		90.0%	

2) Regression Results (Healing Progress)

Metric	Value
Mean Squared Error (MSE)	0.012
Root Mean Squared Error (RMSE)	0.111
Mean Absolute Error (MAE)	0.078
R^2 Score	0.91

The classification model achieved an overall accuracy of 90%, while the regression model obtained a low MSE and high R^2 score, indicating reliable prediction of healing progression.

D. Training Performance

The loss decreases and Dice coefficient increases steadily, showing good convergence and stable learning behavior of the model.

Summary: The proposed system provides accurate wound segmentation and reliable healing prediction. The U-Net model shows high segmentation performance, and the prediction module effectively estimates healing stages and progression, making the system suitable for real-world clinical applications.

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VIII. Comparative Analysis

Wound segmentation models are important in medical image processing because they help identify and separate wound regions from normal skin areas. Different segmentation techniques provide different levels of accuracy, speed, and efficiency. A comparative analysis of these models helps in selecting the best approach for automated wound detection and monitoring.

U-Net is one of the most widely used deep learning models for medical image segmentation. It uses an encoder-decoder architecture with skip connections that preserve important image details. U-Net provides high accuracy, better boundary detection, and works effectively even with small medical

Another important advantage is automated wound designed to improve segmentation accuracy, reduce manual effort, and assist healthcare professionals in effective wound monitoring and treatment.

One of the major advantages of the proposed system is high segmentation accuracy. The U-Net architecture can precisely identify wound regions and separate them from surrounding healthy skin. Its encoder-decoder structure with skip connections helps preserve image details and improves boundary detection

Another area of improvement is the use of larger and more diverse datasets. Incorporating images from different clinical environments, skin tones, and wound types will help improve the generalization capability of the model. Additionally, collecting longitudinal data (images captured over time) can significantly enhance the accuracy of healing prediction.

The system can also be extended to support real-time wound monitoring through mobile or web-based applications. By integrating the model into a user-friendly interface, healthcare professionals and patients can capture wound images using smartphones and receive instant analysis and predictions. This would be especially beneficial for remote healthcare and telemedicine applications.

Further improvements can be made by incorporating multimodal data, such as patient medical history, age, and underlying health conditions. Combining image data with clinical information can lead to more accurate and personalized healing predictions.

XI. Conclusion

This paper presented a deep learning-based approach for wound segmentation and healing prediction using medical images. The proposed system integrates image preprocessing, U-Net-based segmentation, feature extraction, and predictive modeling into a unified framework. By automating the process of wound analysis, the

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analysis. Traditional wound measurement methods require manual observation, which can be time-consuming and prone to human error. The proposed system automates the segmentation process, reducing workload and increasing efficiency in medical diagnosis.

The system also provides faster processing of medical images. Deep learning techniques can analyze wound images quickly and generate segmented outputs in less time compared to manual analysis methods. This helps doctors and healthcare professionals monitor wound healing more effectively.

The proposed model performs well even with limited medical datasets. U-Net is specially designed for biomedical image segmentation and can produce reliable results using fewer training images. This makes the system suitable for medical applications where large datasets may not always be available.

Another advantage is improved visualization of wound areas. The segmented output clearly highlights infected or damaged regions, helping in accurate treatment planning and progress tracking.

The system is also cost-effective and reduces dependency on complex medical equipment. It can be implemented using standard computer systems and integrated into healthcare applications for real-time wound monitoring.

Overall, the proposed wound segmentation system improves accuracy, efficiency, reliability, and healthcare decision-making, making it an effective solution for automated wound analysis and medical image processing.

X. Future Work

While the proposed system demonstrates strong performance in wound segmentation and healing prediction, several enhancements can be explored

system addresses the limitations of traditional manual assessment methods, which are often subjective, time-consuming, and inconsistent.

The U-Net architecture proved to be highly effective in accurately segmenting wound regions, achieving strong performance across key evaluation metrics such as Dice coefficient, Intersection over Union (IoU), and overall accuracy. The use of combined loss functions further enhanced the model's ability to handle class imbalance and complex wound boundaries. Following segmentation, the extraction of geometric, color, and texture features enabled a comprehensive representation of wound characteristics.

The healing prediction module demonstrated reliable performance in estimating wound recovery trends, providing both classification and regression outputs.

care, and support the development of intelligent healthcare systems.

This paper presented a deep learning-based system for wound segmentation and healing prediction using medical images. The U-Net model effectively segmented wound regions with high accuracy, while feature extraction enabled meaningful analysis of wound characteristics. The prediction module provided reliable insights into healing progression, supporting better clinical decisions. Compared to traditional methods, the proposed approach demonstrated improved accuracy, consistency, and efficiency. Although dependent on quality data and computational resources, the system shows strong potential for real-world healthcare applications. Overall, it offers an automated, scalable, and effective solution for improving wound assessment and patient care outcomes.

Compared to traditional image processing methods,

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to further improve its accuracy, usability, and real-world applicability.

One important direction for future work is the integration of advanced deep learning architectures, such as Attention U-Net, ResU-Net, or Transformer-based models. These models can improve feature representation and enhance the system's ability to focus on critical wound regions, leading to even more precise segmentation results.

This capability allows the system to assist healthcare professionals in monitoring wound progression and making informed treatment decisions. The experimental and comparative analyses confirmed that the proposed system outperforms traditional image processing methods and basic CNN models in terms of accuracy, robustness, and consistency.

Despite its strong performance, the system has certain limitations, such as dependency on labeled datasets and computational requirements. However, these challenges can be addressed through future advancements in data collection, model optimization, and deployment strategies.

In conclusion, the proposed deep learning-based system offers an efficient, accurate, and scalable solution for automated wound segmentation and healing prediction. It has significant potential to enhance clinical decision-making, improve patient

wound areas, which supports continuous monitoring of wound healing progress.

The project also highlights the importance of artificial intelligence in healthcare systems. Deep learning-based wound segmentation can assist doctors in faster decision-making and improve the quality of patient care. The proposed system is cost-effective, reliable, and capable of processing medical images in real time.

XII Reference

the U-Net model provides better boundary detection, higher Dice Score, and improved IoU performance. The model performs effectively even with limited medical datasets, making it highly suitable for biomedical applications. The segmented output provides clear visualization of

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