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Research Article

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Role of Smart Image Segmentation in Infection Diagnosis and Monitoring of Acute Surgical Wounds

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Abstract Background/Purpose: There are challenges in applying artificial intelligence (AI) for acute wound healing assessment due to limited data availability, the dynamic nature of healing, and inter-patient variability. These challenges require further research on data collection, algorithm design, and validation techniques specific to each wound type. This study proposes a computer vision model for identifying acute surgical wounds using image segmentation techniques. Methods: The ACW.ai model was used to segment wound images and assign various labels to different wound features, mimicking a clinician's perspective. The model was trained and validated using ACW.ai on a chronic wound dataset (FUSeg). Results: The ACW.ai model achieved a DICE score of 90.9%, outperforming existing methods. Additionally, the model was trained on a private dataset of 59 acute wound images, achieving a DICE score of 87.90% and a mean average precision of 82.10%. Conclusion: Image segmentation is crucial for the early detection of surgical site infections (SSIs) and facilitates better assessment of wound healing. Healthcare professionals may identify potential signs of infection and monitor healing progress by segmenting wounds and analyzing specific features, enabling them to take preventive actions and improve patient outcomes.

Keywords Post Operative Wound Healing · Surgical Site Infections · Computer Vision · Image Segmentation

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INTRODUCTION

Surgical site infections (SSIs), sometimes referred to as postoperative infections or surgical wound infections, are a major factor in prolonged hospital stays and lead to higher morbidity and mortality rates (Owens & Stoessel, 2008). They are the most common hospital infection cases, affecting over 800,000 patients annually in Europe, and may occur for up to 30 days following a surgical intervention (or within 1 year in patients with prosthetic implants) (Cassini et al., 2016). One SSI can result in additional costs of up to 47000 USD (Badia et al., 2017), making it one of the most expensive healthcare events and resulting in significant financial losses.

Data-driven and smart applications, such as artificial intelligence (AI)-based approaches, have been shown to transform healthcare systems by improving efficiency, accuracy, accessibility, and patient outcomes (Rajpurkar et al., 2022). These applications could also be applied to SSIs or general wound healing for tracking and prediction. Smart segmentation of the wound imaging is crucial for further quantifying and predicting the possibility of SSIs.

The fundamental problem of image segmentation in computer vision (CV) and artificial intelligence (AI) research is splitting an image into numerous coherent and significant parts (Antonelli et al., 2022). The objective is to recognize and categorize various objects or areas within an image, making it easier for machines to comprehend and process visual input (Arbeláez et al., 2011). Image segmentation is essential in many different applications, such as object recognition (Ullman, 2007), autonomous driving (Kabiraj et al., 2022), medical imaging (Chan et al., 2020; Jin et al., 2022), and video surveillance (Gruosso et al., 2021).

Semantic segmentation is a term used to describe a typical image segmentation method (Shelhamer et al., 2014). The goal of semantic segmentation is to provide each pixel in an image with a unique label that describes a particular object or class. This method enables computers to identify various objects or areas of interest within an image.

"Instance segmentation" is a different approach to picture segmentation. Instance segmentation separates distinct instances of objects within the same class and categorizes pixels into several object classes (X. Wang et al., 2021). For instance, instance segmentation would give each person a picture of many people and their own label, enabling accurate localization and tracking of individuals.

Deep learning methods, especially convolutional neural networks (CNNs), are frequently used in image segmentation. These networks learn to extract useful features from visual data and forecast pixel-level segmentation maps by being trained on enormous labeled image datasets (Girshick et al., n.d.). U-Net (Weng & Zhu, 2015), Mask R-CNN (He et al., 2017), and DeepLab (L. C. Chen et al., 2016) are a few examples of CNN-based models that have excelled in image segmentation tasks and are now considered innovative approaches.

Finally, this study suggests a CV model to identify an acute wound through a custom algorithm to segment and further process it with different labels, e.g., annotations, to mimic a clinician’s perspective. It has established a DICE score of over 90.90%, which is comparable to that of chronic wound segmentation algorithms, with a higher number of wound images to train the model.

Healthcare AI applications: Segmentation

Numerous healthcare applications have significantly improved because of picture segmentation developments. In medical imaging, segmentation is essential for activities such as tumor identification (Tiwari et al., 2020), organ segmentation (Linguraru et al., 2010), and disease diagnosis (Kumar et al., 2022).

Magnetic resonance imaging (MRI) and computed tomography (CT) are two examples of medical imaging that require image segmentation to recognize and delineate malignancies (Sharma et al., 2010; Zhang & Sejdić, 2019). By precisely segmenting tumor locations, doctors can measure tumor size, track its growth, and develop effective treatment plans. Additionally, it allows for tumor boundaries to be observed, which helps surgeons plan operations and radiation oncologists specify treatment zones.

Organ Segmentation: Image segmentation is essential for separating organs from medical images, allowing for easier study of certain organs and assisting in the diagnosis and treatment planning. Segmenting the various areas of the brain during brain imaging enables the identification and localization of anomalies such as tumors (Horská & Barker, 2010), hemorrhages (Patel et al., 2019; Xu et al., 2021), and ischemiac lesions (Kabir et al., 2007). Segmenting the heart from cardiac imaging allows for cardiac function evaluation, anomaly detection, and intervention planning (Counseller & Aboelkassem, 2023; Gosling & Al-Mohammad, 2022; Malahfji & Chamsi-Pasha, 2019).

Image segmentation aids in the identification and delineation of lesions or anomalies within medical images. For instance, segmenting skin lesions in dermatology helps in the diagnosis of melanoma (Chen et al., 2003) or other skin malignancies (Dildar et al., 2021) by examining different traits such as shape, color, and texture (Khan et al., 2018). Segmentation techniques can also help in locating anomalies in retinal pictures, such as age-related macular degeneration or DR.

Image segmentation is used to recognize and separate individual cells or nuclei inside microscopic pictures in disciplines such as pathology (Aeffner et al., 2019; Vu et al., 2019; Wienert et al., 2012) and cytology (Bao et al., 2020; Landau & Pantanowitz, 2019). This enables the automated characterization and quantification of cell characteristics, assisting in the detection, evaluation, and study of cancer. Studies involving blood analysis also use cell segmentation techniques to separate red and white blood cells for various analyses (Carvalho et al., 2021; Prinyakupt & Pluempitiwiriyawej, 2015; Mohd Safuan et al., 2018).

Wound healing segmentation

An application of image segmentation known as "wound healing segmentation" focuses on segmenting and examining wounds to track the healing process (Glinos et al., 2017; Y. Wang et al., 2022). In the literature as well as commercially available products, some examples of picture segmentation in use in the study of wound healing are provided below:

1. Measurement of wound size: Image segmentation techniques can be used to precisely define the limits of wounds from pictures or images (Lucas et al., 2021; Privalov et al., 2021). Healthcare providers can quantify the wound area and monitor changes over time by segmenting the wound region. This quantitative assessment helps track the healing process, evaluate treatment efficacy, and provide factual information for clinical research (Curti et al., 2023).
2. Wound Tissue Classification: Image segmentation can be used to categorize several types of tissues within a wound (Ramachandram et al., 2022a). Segmenting granulation tissue (Mukherjee et al., 2014a), epithelial tissue (Wagh et al., 2020), and necrotic (dead) tissue (Mukherjee et al., 2014b) enables a thor-

ough examination of the wound's makeup. This information aids medical professionals in determining the stage of wound healing and directing suitable therapies, such as debridement or the use of specialist dressings.

3. Wound Depth Estimation: In some circumstances, image segmentation may be used to assess the depth of a wound (Anisuzzaman et al., 2022; Carrión et al., 2022). Algorithms can roughly determine a wound's depth by segmenting its various layers, such as the epidermis, dermis, or subcutaneous tissue. This information is useful for determining the wound severity and making the best course of treatment, which may include surgical interventions or wound closure.
4. Wound Infection Detection: Image segmentation techniques can help identify and classify diseased wound areas (Anisuzzaman et al., 2022). Algorithms can identify potentially infected areas by segmenting the wound area and examining characteristics such as color, texture, or the presence of exudate (Wu et al., 2020). This helps medical professionals spot infections early, enabling quick treatment and averting problems.
5. Wound Healing Assessment: Image segmentation enables the ability to follow and analyze how a wound heals over time (Barakat-Johnson et al., 2022). Algorithms can spot changes in wound features, such as a reduction in wound size, closure of the wound borders, and re-epithelialization, by segmenting wounds in sequential images or by employing time-lapse imaging (Chairat et al., 2023; Howell et al., 2021). These quantitative evaluations may aid in determining the effectiveness of therapies, direct clinical research, and provide crucial information for studies on wound healing.

Overall, segmenting wound healing offers medical personnel quantifiable metrics and visual insights to evaluate wound development, direct treatment choices, and improve patient care (Anisuzzaman et al., 2022; Curti et al., 2023; Ramachandram et al., 2022b). Clinicians can receive precise and thorough information about wounds from image segmentation techniques, thereby facilitating efficient wound management and better patient outcomes.

Materials and Methods

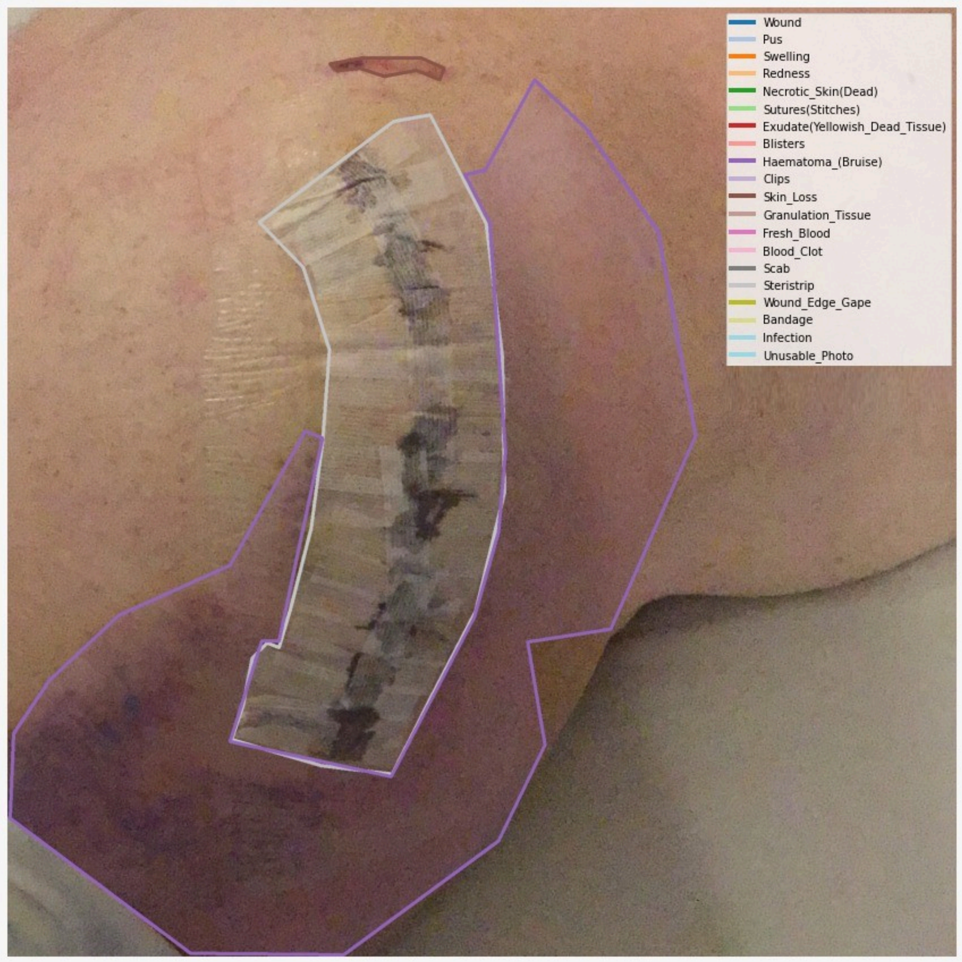
A custom CV model, ACW.ai, is a Python-based wound detection model that depends on widely used and maintained open-source Python packages, such as PyTorch (Paszke et al., 2019), NumPy (Harris et al., 2020), OpenCV (Bradski, 2000), and Matplotlib (Hunter, 2007).

The methodology used two distinct data sources to evaluate the model performance:

- **FUSeg Dataset (Task 1):** The *Foot Ulcer Segmentation Challenge 2021* (Wang et al., 2022) was used to train the model for high-precision chronic wound segmentation (for one label: wound).
- **Private Dataset (Task 2):** A dataset of 59 acute wound images (37 with visible wound areas) was used for complex feature classification (Fig. 1). Images were resized to 1024 1024 pixels, ±15° rotation.

Figure 1

An image from the acute wound dataset, where different areas have been segmented (drawn and annotated), which would go into training/validation subset for ACW.ai



- **Annotation Protocol:** Images in the private dataset were annotated using a custom tool inspired by Meta's SAM2 (Ravi et al., 2024). This allowed for precise mask generation across 19 distinct clinical labels (Table I):

Table 1

19 clinical labels used for complex feature classification

Category	Specific Clinical Labels
Wound State	wound, granulation tissue, skin loss, wound edge gap
Exudate/Fluid	pus, exudate (yellowish dead tissue), fresh blood, blood clot
Tissue Pathology	necrotic skin (dead), scab, bruising, blisters, swelling, redness
External/Clinical	sutures (stitches), clips, steri-strip, bandage, infection

The system employs a two-stage modular pipeline:

1. Stage 1 (Instance Segmentation): A custom Mask-RCNN model was implemented to detect and segment the wound regions. This model was initially pre-trained on the FUSeg dataset.
2. Stage 2 (Classification): The resulting segmented ROIs were passed into a standalone ResNet-50 architecture for final multi-label classification.

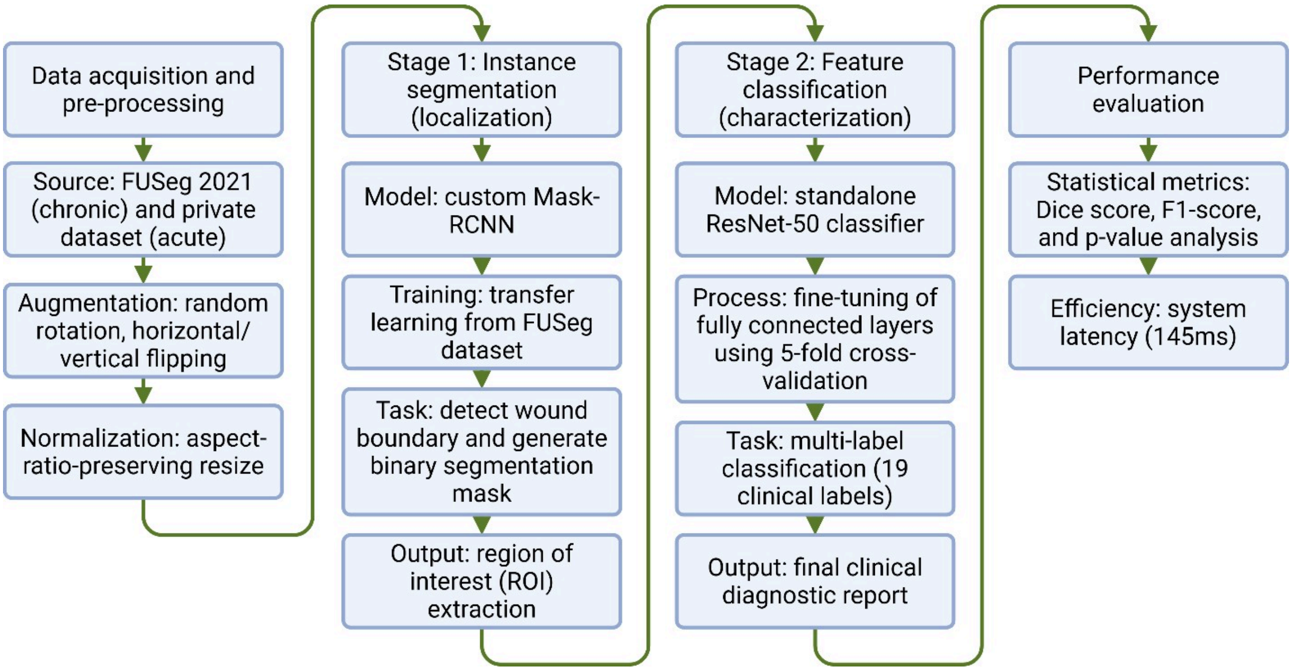
3. Transfer Learning (TL): To adapt the system from chronic to acute wounds, TL was utilized to fine-tune the pretrained weights from the FUSeg domain onto the smaller private dataset, ensuring robust feature extraction despite limited data.

All quantitative results are presented as the Mean ± Standard Deviation (SD) across the 5-fold cross-validation cycles. To determine the statistical significance of the ACW.ai pipeline's performance compared to baseline models (U-Net, DeepLabv3+, and vanilla Mask-RCNN), a paired Student's t-test was employed for the Dice Similarity Coefficient (DSC) and mAP metrics. A p-value of < 0.05 was considered statistically significant. For multi-label classification of the 19 clinical indicators, performance was evaluated using Precision-Recall curves and the F1-score to account for potential class imbalances within the private dataset. All statistical computations were performed using the SciPy library in Python, ensuring that the reported improvements in segmentation accuracy are mathematically robust and not the result of stochastic variation during training.

A flowchart of the methodology is shown below (Fig. 2).

Figure 2

Flowchart of the data processing pipeline



Results

ACW.ai outperformed the state-of-the-art (SOTA) methods in the treatment of chronic wounds (Table II). The model outperforms the current state-of-the-art model with a dice score of 90.9% with the test set in the FUSeg dataset (Fig. 3).

Figure 3

Several images of testing from the FUSeg dataset, to visually compare ACW.ai with the ground truth dataset.

Table 2

Comparative Performance on the FUSeg 2021 Benchmark. The ACW.ai model is the "Reference" against which the p-values of other models are calculated.

Model Architecture	Dice similarity coefficient (DSC)	mAP_{50}	p-value
U-Net	82.4 ± 2.1%	0.76	< 0.01
DeepLabv3+	86.7 ± 1.8%	0.81	< 0.05
Mask-RCNN (Baseline)	88.4 ± 1.5%	0.84	0.042
ACW.ai (Proposed)	**90.9** ± **1.2%**	**0.89**	< 0.05
Source:(derived from https://fusc. grand-challenge.org/leaderboard , accessed Jan 8, 2026)			

Furthermore, the ACW.ai model obtained a dice score of 87.90% and a mean average precision of 82.10% on acute wound images (Fig. 4), with only 37 images without bandages (Table III).

Figure 4

Segmentation of several images from the private acute wound dataset before and after the wound area with ACW.ai

Table 3

Establishment of ground truth for clinical indicators via SAM2-assisted expert annotation to ensure pixel-level boundary precision

Clinical Indicator	Precision	Recall (Sensitivity)	F1-Score
Sutures and clips	0.97	0.95	0.96
Pus and exudate	0.78	0.74	0.76
Redness (Erythema)	0.74	0.79	0.76
Necrotic skin	0.86	0.82	0.84
Wound edge gap	0.72	0.68	0.70

Discussion

Wound healing segmentation is crucial in the context of surgical site infections (SSIs) and their prevention. Image segmentation can help in the early diagnosis of surgical wound infections. Algorithms can discover possible indicators of infection (Bawa et al., 2023) by segmenting the wound region and examining particular characteristics, such as color, texture, or the presence of exudate, as shown in animal models (Hughes et al., 2023). Early detection enables medical professionals to take immediate action, initiate suitable treatment plans, and halt the spread of the infection (Shen et al., 2019). The objective evaluation of the wound healing process provided by image segmentation allows healthcare professionals to evaluate the efficacy of preventive interventions in lowering the risk of SSIs (Tomsic et al., 2020). Clinicians can assess the effects of interventions, such as customized dressings or wound care procedures, by comparing segmented wound pictures over time and establish their effectiveness in encouraging optimal wound healing and lowering the risk of infection. SSI risk classification benefits from accurate wound segmentation and analysis (Scala et al., 2022). Clinicians can identify high-risk wounds that require additional preventive measures by assessing wound parameters such as size, depth, or tissue composition (Lucas et al., 2021; Wu et al., 2020). This enables the creation of individualized care plans for every patient, improved infection control methods, and SSI reduction.

Comparing acute wound healing to chronic wound healing using AI may be challenging. Several factors make measuring acute wound healing more difficult, including the following:

1. Limited Data Availability: Acute wounds often heal within a short time, frequently within a few weeks. Because there may not be as many photos of acute wounds as there are of chronic wounds due to the short timescale, it will be harder to train AI models successfully. For effective and reliable AI algorithms, a broad and representative dataset is essential.
2. Dynamic Nature of Healing: As they heal, acute wounds undergo rapid changes in both appearance and personality. This dynamic nature can prove challenging for AI systems that must adapt and generalize effectively over diverse stages of healing. Artificial intelligence-based quantification techniques may not be as accurate over time because of changes in color, texture, tissue composition, and wound size.
3. Interpatient Variability: Surgical treatments, traumatic experiences, or different types of injuries can all result in acute wounds. Each patient's wound could be distinct in terms of its depth, form, and placement. Since AI models must consider these various wound appearances to precisely evaluate healing progress, this inter-patient variability can add to their complexity.

4. Limited Time for Benchmarking: Because acute wounds tend to heal quite quickly, there might not be much time to compare and test AI algorithms against real-world data. Collecting accurate and reliable annotations or reference measures for acute wounds within the limited healing window can be difficult, which can affect how well the AI model functions.

However, measuring chronic wounds with AI has its own difficulties.

1. Complex and Prolonged Healing Process: Chronic wounds, such as diabetic ulcers or pressure ulcers, frequently take a long time to heal; they may persist for weeks, months, or even longer. Accurately measuring and quantifying the healing progress over time can be difficult because of the complexity and prolonged healing process.
2. Variability in Wound Characteristics: Chronic wounds show a great deal of variation in terms of size, shape, depth, tissue composition, and the presence of biofilms or necrotic tissue. Due to these variances, creating AI models that can accurately quantify and capture the many features of chronic wound healing is difficult.
3. Infection and Complications: Compared with acute wounds, chronic wounds are more prone to infections, sluggish healing, and other problems. These aspects may add complexity when assessing the healing process using AI because the presence of infections or other non-healing traits may necessitate special analysis procedures.
4. Longitudinal Analysis: Analyzing longitudinal data, considering several time points, and evaluating changes over long periods of time are frequently necessary to quantify chronic wound healing. Long-term monitoring and data collection may be required to fully capture the healing trajectory, necessitating powerful AI systems capable of handling such longitudinal investigations.

Empirical superiority and clinical relevance

The success of ACW.ai in achieving a Dice score of 90.9% on the FUSeg benchmark is not merely a technical milestone; it is a critical prerequisite for the early diagnosis of SSIs. As highlighted in the literature, segmenting the wound region allows for the examination of specific characteristics, such as color, texture, and exudate—all of which are precursors to infection (Bawa et al., 2023). By outperforming current SOTA models, ACW.ai provides the high-fidelity "smart segmentation" necessary to quantify these parameters. This precision enables medical professionals to move beyond subjective observation, allowing for the immediate initiation of treatment plans that can halt the spread of infection and reduce the 47,000 USD financial burden per SSI event (Badia et al., 2017; Shen et al., 2019).

Bridging the Acute and Chronic Gaps

The primary innovation of this study lies in its ability to handle the "Dynamic Nature of Healing" inherent in acute wounds. Acute wounds change rapidly in appearance, making AI systems' adaptation challenging (Tomsic et al., 2020). ACW.ai demonstrates that a hybrid Mask-RCNN and ResNet-50 pipeline can effectively generalize across the quick transitions of color, texture, and tissue composition that defines the acute healing window by achieving an 87.90% Dice score on the private acute dataset.

While chronic wounds—such as diabetic ulcers—present complexities involving biofilms and necrotic tissue over months, acute wounds require rapid benchmarking within a narrow window. The high mAP_{50} of 82.10% on acute images suggests that the model can navigate inter-patient variability (depth, form, and placement) to provide the objective evaluations needed to assess customized dressings or surgical interventions (Lucas et al., 2021).

This study directly addresses the "Limited Data Availability" bottleneck common in acute wound research. Because acute wounds heal quickly, collecting representative datasets is notoriously difficult compared with longitudinal studies of chronic wounds. The methodology proves that TL effectively bridges this gap. By using the "foundation" learned from chronic wound morphology (FUSeg) and fine-tuning it with ten times augmented private dataset, the model avoided overfitting.

Unlike semantic segmentation, which provides a simple binary mAP_{50}, the instance segmentation approach separates distinct clinical instances. This mimics a clinician's diagnostic process by assessing specific tissue compositions, such as "granulation tissue", "pus", or "necrotic skin" (Wu et al., 2020).

- Early Detection: The F1-score of 0.76 for "pus" and 0.76 for "redness" provides empirical evidence that ACW.ai can identify high-risk wounds requiring additional preventive measures (Scala et al., 2022).
- Surgical Precision: The near-perfect detection of "sutures" (0.97 precision) allows clinicians to monitor surgical site integrity alongside biological healing, a dual capability that is often missing in standard chronic wound models.

Conclusion

Assessing healing using artificial intelligence is challenging in both acute and chronic wounds. Chronic wounds present difficulties because of the intricacy of the healing process, variety in the characteristics of the wound, and possibility of infections or consequences, whereas acute wounds may have limited data availability and show quick changes. Thorough data collection, algorithm design, and validation techniques specific to each type of wound are required to overcome these obstacles. Future research will move toward the "Longitudinal Analysis" mentioned in the introduction, tracking the 19 clinical labels across multiple time points to capture the full healing trajectory of acute wounds. ACW.ai offers a scalable solution to lower SSI risks, improve infection control, and transform postoperative care into an objective, data-driven discipline by automating this quantification.

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References

Aeffner, F., Zarella, M. D., Buchbinder, N., Bui, M. M., Goodman, M. R., Hartman, D. J., Lujan, G. M., Molani, M. A., Parwani, A. V., Lillard, K., Turner, O. C., Vemuri, V. N. P., Yuil-Valdes, A. G., & Bowman, D. (2019). Introduction to Digital Image Analysis in Whole-slide Imaging: A White Paper from the Digital Pathology Association. Journal of Pathology Informatics, 10(1). https://doi.org/10.4103/JPI.JPI_82_18

Anisuzzaman, D. M., Wang, C., Rostami, B., Gopalakrishnan, S., Niezgoda, J., & Yu, Z. (2022). Image-Based Artificial Intelligence in Wound Assessment: A Systematic Review. Advances in Wound Care, 11(12), 687–709. https://doi.org/10.1089/WOUND.2021.0091

Antonelli, L., De Simone, V., Daniela Di Serafino, ·, Di, D., & B, S.-D. (2022). A view of computational models for image segmentation. ANNALI DELL'UNIVERSITA' DI FERRARA, 68, 277–294. https://doi.org/10.1007/s11565-022-00417-6

Arbeláez, P., Maire, M., Fowlkes, C., & Malik, J. (2011). Contour detection and hierarchical image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 33(5), 898–916. https://doi.org/10.1109/TPAMI.2010.161

Badia, J. M., Casey, A. L., Petrosillo, N., Hudson, P. M., Mitchell, S. A., & Crosby, C. (2017). Impact of surgical site infection on healthcare costs and patient outcomes: a systematic review in six European countries. The Journal of Hospital Infection, 96(1), 1–15. https://doi.org/10.1016/J.JHIN.2017.03.004

Bao, H., Sun, X., Zhang, Y., Pang, B., Li, H., Zhou, L., Wu, F., Cao, D., Wang, J., Turic, B., & Wang, L. (2020). The artificial intelligence-assisted cytology diagnostic system in large-scale cervical cancer screening: A population-based cohort study of 0.7 million women. Cancer Medicine, 9(18), 6896–6906. https://doi.org/10.1002/CAM4.3296

Barakat-Johnson, M., Jones, A., Burger, M., Leong, T., Frotjold, A., Randall, S., Kim, B., Fethney, J., & Coyer, F. (2022). Reshaping wound care: Evaluation of an artificial intelligence app to improve wound assessment and management amid the COVID-19 pandemic. International Wound Journal, 19(6), 1561–1577. https://doi.org/10.1111/IWJ.13755

Bawa, A., Kansal, R., Kalra, V., Rengan, V., Sundaram, P., & Ramana, B. (2023). OC-004 CAN AI HELP IN EARLY PREDICTION OF SURGICAL SITE INFECTIONS? British Journal of Surgery, 110(Supplement_2). https://doi.org/10.1093/BJS/ZNAD080.011

Bradski, G. (2000). The OpenCV Library. Dr. Dobb's Journal of Software Tools.

Carrión, H., Jafari, M., Bagood, M. D., Yang, H. Y., Isseroff, R. R., & Gomez, M. (2022). Automatic wound detection and size estimation using deep learning algorithms. PLOS Computational Biology, 18(3), e1009852. https://doi.org/10.1371/JOURNAL.PCBI.1009852

Carvalho, V., Gonçalves, I. M., Souza, A., Souza, M. S., Bento, D., Ribeiro, J. E., Lima, R., & Pinho, D. (2021). Manual and Automatic Image Analysis Segmentation Methods for Blood Flow Studies in Microchannels. Micromachines, 12(3). https://doi.org/10.3390/MI12030317

Cassini, A., Plachouras, D., Eckmanns, T., Abu Sin, M., Blank, H. P., Ducomble, T., Haller, S., Harder, T., Klingeberg, A., Sixtensson, M., Velasco, E., Weiß, B., Kramarz, P., Monnet, D. L., Kretzschmar, M. E., & Suetens, C. (2016). Burden of Six Healthcare-Associated Infections on European Population Health: Estimating Incidence-Based Disability-Adjusted Life Years through a Population Prevalence-Based Modelling Study. PLoS Medicine, 13(10). https://doi.org/10.1371/JOURNAL.PMED.1002150

Chairat, S., Chaichulee, S., Dissaneewate, T., Wangkulangkul, P., & Kongpanichakul, L. (2023). AI-Assisted Assessment of Wound Tissue with Automatic Color and Measurement Calibration on Images Taken with a Smartphone. Healthcare (Basel, Switzerland), 11(2). https://doi.org/10.3390/HEALTHCARE11020273

Chan, H. P., Samala, R. K., Hadjiiski, L. M., & Zhou, C. (2020). Deep Learning in Medical Image Analysis. Advances in Experimental Medicine and Biology, 1213, 3–21. https://doi.org/10.1007/978-3-030-33128-3_1

Chen, J., Stanley, R. J., Moss, R. H., & Van Stoecker, W. (2003). Color analysis of skin lesion regions for melanoma discrimination in clinical images. Skin Research and Technology : Official Journal of International Society for Bioengineering and the Skin (ISBS) [and] International Society for Digital Imaging of Skin (ISDIS) [and] International Society for Skin Imaging (ISSI), 9(2), 94. https://doi.org/10.1034/J.1600-0846.2003.00024.X

Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2016). DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834–848. https://doi.org/10.1109/TPAMI.2017.2699184

Counseller, Q., & Aboelkassem, Y. (2023). Recent technologies in cardiac imaging. Frontiers in Medical Technology, 4, 99. https://doi.org/10.3389/FMEDT.2022.984492

Curti, N., Merli, Y., Zengarini, C., Giampieri, E., Merlotti, A., Dall'Olio, D., Marcelli, E., Bianchi, T., & Castellani, G. (2023). Effectiveness of Semi-Supervised Active Learning in Automated Wound Image Segmentation. International Journal of Molecular Sciences, 24(1), 706. https://doi.org/10.3390/IJMS24010706/S1

Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., Alsaiari, S. A., Saeed, A. H. M., Alraddadi, M. O., & Mahnashi, M. H. (2021). Skin Cancer Detection: A Review Using Deep Learning Techniques. International Journal of Environmental Research and Public Health, 18(10). https://doi.org/10.3390/IJERPH18105479

Girshick, R., Donahue, J., Darrell, T., & Malik, J. (n.d.). Rich feature hierarchies for accurate object detection and semantic segmentation Tech report (v5). Retrieved May 28, 2023, from http://www.cs.berkeley.edu/˜rbg/rcnn.

Glinos, G. D., Verne, S. H., Aldahan, A. S., Liang, L., Nouri, K., Elliot, S., Glassberg, M., Cabrera DeBuc, D., Koru-Sengul, T., Tomic-Canic, M., & Pastar, I. (2017). Optical coherence tomography for assessment of epithelialization in a human ex vivo wound model. Wound Repair and Regeneration, 25(6), 1017–1026. https://doi.org/10.1111/WRR.12600

Gosling, R. C., & Al-Mohammad, A. (2022). The Role of Cardiac Imaging in Heart Failure with Reduced Ejection Fraction. Cardiac Failure Review, 8. https://doi.org/10.15420/CFR.2021.33

Gruosso, M., Capece, N., & Erra, U. (2021). Human segmentation in surveillance video with deep learning. Multimedia Tools and Applications, 80(1), 1175–1199. https://doi.org/10.1007/S11042-020-09425-0/FIGURES/11

Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., del Río, J. F., Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. Nature, 585(7825), 357–362. https://doi.org/10.1038/S41586-020-2649-2

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. IEEE Transactions on Pattern Analysis and Machine Intelligence, 42(2), 386–397. https://doi.org/10.1109/TPAMI.2018.2844175

Horská, A., & Barker, P. B. (2010). Imaging of Brain Tumors: MR Spectroscopy and Metabolic Imaging. Neuroimaging Clinics of North America, 20(3), 293. https://doi.org/10.1016/J.NIC.2010.04.003

Howell, R. S., Liu, H. H., Khan, A. A., Woods, J. S., Lin, L. J., Saxena, M., Saxena, H., Castellano, M., Petrone, P., Slone, E., Chiu, E. S., Gillette, B. M., & Gorenstein, S. A. (2021). Development of a Method for Clinical Evaluation of Artificial Intelligence–Based Digital Wound Assessment Tools. JAMA Network Open, 4(5), e217234–e217234. https://doi.org/10.1001/JAMANETWORKOPEN.2021.7234

Hughes, C. M. L., Jeffers, A., Sethuraman, A., Klum, M., Tan, M., & Tan, V. (2023). The detection and prediction of surgical site infections using multi-modal sensors and machine learning: Results in an animal model. Frontiers in Medical Technology, 5, 24. https://doi.org/10.3389/FMEDT.2023.1111859

Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. Computing in Science & Engineering, 9(3), 90–95. https://doi.org/10.1109/MCSE.2007.55

Jin, C., Udupa, J. K., Zhao, L., Tong, Y., Odhner, D., Pednekar, G., Nag, S., Lewis, S., Poole, N., Mannikeri, S., Govindasamy, S., Singh, A., Camaratta, J., Owens, S., & Torigian, D. A. (2022). Object recognition in medical images via anatomy-guided deep learning. Medical Image Analysis, 81. https://doi.org/10.1016/J.MEDIA.2022.102527

Kabir, Y., Dojat, M., Scherrer, B., Forbes, F., & Garbay, C. (2007). Multimodal MRI segmentation of ischemic stroke lesions. Conference Proceedings, 2007, 1595. https://doi.org/10.1109/IEMBS.2007.4352610

Kabiraj, A., Pal, D., Ganguly, D., Chatterjee, K., & Roy, S. (2022). Number plate recognition from enhanced super-resolution using generative adversarial network. Multimedia Tools and Applications, 82(9), 13837–13853. https://doi.org/10.1007/S11042-022-14018-0/TABLES/5

Khan, M. A., Akram, T., Sharif, M., Shahzad, A., Aurangzeb, K., Alhussein, M., Haider, S. I., & Altamrah, A. (2018). An implementation of normal distribution based segmentation and entropy controlled features selection for skin lesion detection and classification. BMC Cancer, 18(1), 1–20. https://doi.org/10.1186/S12885-018-4465-8/TABLES/16

Kumar, Y., Koul, A., Singla, R., & Ijaz, M. F. (2022). Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. Journal of Ambient Intelligence and Humanized Computing, 1, 1. https://doi.org/10.1007/S12652-021-03612-Z

Landau, M. S., & Pantanowitz, L. (2019). Artificial intelligence in cytopathology: a review of the literature and overview of commercial landscape. Journal of the American Society of Cytopathology, 8(4), 230–241. https://doi.org/10.1016/J.JASC.2019.03.003

Linguraru, M. G., Pura, J. A., Chowdhury, A. S., & Summers, R. M. (2010). Multi-Organ Segmentation from Multi-Phase Abdominal CT via 4D Graphs using Enhancement, Shape and Location Optimization. Medical Image Computing and Computer-Assisted Intervention : MICCAI ... International Conference on Medical Image Computing and Computer-Assisted Intervention, 13(Pt 3), 89. https://doi.org/10.1007/978-3-642-15711-0_12

Lucas, Y., Niri, R., Treuillet, S., Douzi, H., & Castaneda, B. (2021). Wound Size Imaging: Ready for Smart Assessment and Monitoring. Advances in Wound Care, 10(11), 641. https://doi.org/10.1089/WOUND.2018.0937

Malahfji, M., & Chamsi-Pasha, M. A. (2019). Advanced Cardiac Imaging for Complex Adult Congenital Heart Diseases. Methodist DeBakey Cardiovascular Journal, 15(2), 99. https://doi.org/10.14797/MDCJ-15-2-99

Mohd Safuan, S. N., Md Tomari, M. R., & Wan Zakaria, W. N. (2018). White blood cell (WBC) counting analysis in blood smear images using various color segmentation methods. Measurement, 116, 543–555. https://doi.org/10.1016/J.MEASUREMENT.2017.11.002

Mukherjee, R., Manohar, D. D., Das, D. K., Achar, A., Mitra, A., & Chakraborty, C. (2014a). Automated Tissue Classification Framework for Reproducible Chronic Wound Assessment. BioMed Research International, 2014. https://doi.org/10.1155/2014/851582

Mukherjee, R., Manohar, D. D., Das, D. K., Achar, A., Mitra, A., & Chakraborty, C. (2014b). Automated tissue classification framework for reproducible chronic wound assessment. BioMed Research International, 2014. https://doi.org/10.1155/2014/851582

Owens, C. D., & Stoessel, K. (2008). Surgical site infections: epidemiology, microbiology and prevention. The Journal of Hospital Infection, 70 Suppl 2(SUPPL. 2), 3–10. https://doi.org/10.1016/S0195-6701(08)60017-1

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury Google, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Xamla, A. K., Yang, E., Devito, Z., Raison Nabla, M., Tejani, A., Chilamkurthy, S., Ai, Q., Steiner, B., … Chintala, S. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library.

Patel, A., Schreuder, F. H. B. M., Klijn, C. J. M., Prokop, M., Ginneken, B. van, Marquering, H. A., Roos, Y. B. W. E. M., Baharoglu, M. I., Meijer, F. J. A., & Manniesing, R. (2019). Intracerebral Haemorrhage Segmentation in Non-Contrast CT. Scientific Reports 2019 9:1, 9(1), 1–11. https://doi.org/10.1038/s41598-019-54491-6

Prinyakupt, J., & Pluempitiwiriyawej, C. (2015). Segmentation of white blood cells and comparison of cell morphology by linear and naïve Bayes classifiers. BioMedical Engineering OnLine, 14(1). https://doi.org/10.1186/S12938-015-0037-1

Privalov, M., Beisemann, N., Barbari, J. El, Mandelka, E., Müller, M., Syrek, H., Grützner, P. A., & Vetter, S. Y. (2021). Software-Based Method for Automated Segmentation and Measurement of Wounds on Photographs Using Mask R-CNN: a Validation Study. Journal of Digital Imaging, 34(4), 788. https://doi.org/10.1007/S10278-021-00490-X

Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. Nature Medicine, 28(1), 31–38. https://doi.org/10.1038/S41591-021-01614-0

Ramachandram, D., Ramirez-GarciaLuna, J. L., Fraser, R. D. J., Martínez-Jiménez, M. A., Arriaga-Caballero, J. E., & Allport, J. (2022a). Fully Automated Wound Tissue Segmentation Using Deep Learning on Mobile Devices: Cohort Study. JMIR MHealth and UHealth, 10(4). https://doi.org/10.2196/36977

Ramachandram, D., Ramirez-GarciaLuna, J. L., Fraser, R. D. J., Martínez-Jiménez, M. A., Arriaga-Caballero, J. E., & Allport, J. (2022b). Fully Automated Wound Tissue Segmentation Using Deep Learning on Mobile Devices: Cohort Study. JMIR MHealth and UHealth, 10(4). https://doi.org/10.2196/36977

Ravi, N., Gabeur, V., Hu, Y. T., Hu, R., Ryali, C., Ma, T., … & Feichtenhofer, C. (2024). Sam 2: Segment anything in images and videos. *arXiv preprint arXiv:2408.00714*.

Scala, A., Loperto, I., Triassi, M., & Improta, G. (2022). Risk Factors Analysis of Surgical Infection Using Artificial Intelligence: A Single Center Study. International Journal of Environmental Research and Public Health, 19(16), 10021. https://doi.org/10.3390/IJERPH191610021

Sharma, N., Ray, A. K., Shukla, K. K., Sharma, S., Pradhan, S., Srivastva, A., & Aggarwal, L. (2010). Automated medical image segmentation techniques. Journal of Medical Physics / Association of Medical Physicists of India, 35(1), 3. https://doi.org/10.4103/0971-6203.58777

Shelhamer, E., Long, J., & Darrell, T. (2014). Fully Convolutional Networks for Semantic Segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(4), 640–651. https://doi.org/10.1109/TPAMI.2016.2572683

Shen, F., Larson, D. W., Naessens, J. M., Habermann, E. B., Liu, H., & Sohn, S. (2019). Detection of Surgical Site Infection Utilizing Automated Feature Generation in Clinical Notes. Journal of Healthcare Informatics Research, 3(3), 267. https://doi.org/10.1007/S41666-018-0042-9

Tiwari, A., Srivastava, S., & Pant, M. (2020). Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019. Pattern Recognition Letters, 131, 244–260. https://doi.org/10.1016/J.PATREC.2019.11.020

Tomsic, I., Heinze, N. R., Chaberny, I. F., Krauth, C., Schock, B., & Von Lengerke, T. (2020). Implementation interventions in preventing surgical site infections in abdominal surgery: a systematic review. BMC Health Services Research, 20(1). https://doi.org/10.1186/S12913-020-4995-Z

Ullman, S. (2007). Object recognition and segmentation by a fragment-based hierarchy. Trends in Cognitive Sciences, 11(2), 58–64. https://doi.org/10.1016/J.TICS.2006.11.009

Vu, Q. D., Graham, S., Kurc, T., To, M. N. N., Shaban, M., Qaiser, T., Koohbanani, N. A., Khurram, S. A., Kalpathy-Cramer, J., Zhao, T., Gupta, R., Kwak, J. T., Rajpoot, N., Saltz, J., & Farahani, K. (2019). Methods for Segmentation and Classification of Digital Microscopy Tissue Images. Frontiers in Bioengineering and Biotechnology, 7(APR), 53. https://doi.org/10.3389/FBIOE.2019.00053

Wagh, A., Jain, S., Mukherjee, A., Agu, E., Pedersen, P. C., Strong, D., Tulu, B., Lindsay, C., & Liu, Z. (2020). Semantic Segmentation of Smartphone Wound Images: Comparative Analysis of AHRF and CNN-Based Approaches. IEEE Access : Practical Innovations, Open Solutions, 8, 181590. https://doi.org/10.1109/ACCESS.2020.3014175

Wang, C., Mahbod, A., Ellinger, I., Galdran, A., Gopalakrishnan, S., Niezgoda, J., & Yu, Z. (2022). FUSeg: The Foot Ulcer Segmentation Challenge. https://arxiv.org/abs/2201.00414v1

Wang, X., Zhang, R., Shen, C., Kong, T., & Li, L. (2021). SOLO: A Simple Framework for Instance Segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(11), 8587–8601. https://doi.org/10.1109/TPAMI.2021.3111116

Wang, Y., Freeman, A., Ajjan, R., Del Galdo, F., & Tiganescu, A. (2022). Automated quantification of 3D wound morphology by machine learning and optical coherence tomography in type 2 diabetes. Skin Health and Disease, e203. https://doi.org/10.1002/SKI2.203

Weng, W., & Zhu, X. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. IEEE Access, 9, 16591–16603. https://doi.org/10.1109/ACCESS.2021.3053408

Wienert, S., Heim, D., Saeger, K., Stenzinger, A., Beil, M., Hufnagl, P., Dietel, M., Denkert, C., & Klauschen, F. (2012). Detection and Segmentation of Cell Nuclei in Virtual Microscopy Images: A Minimum-Model Approach. Scientific Reports 2012 2:1, 2(1), 1–7. https://doi.org/10.1038/srep00503

Wu, J. M., Tsai, C. J., Ho, T. W., Lai, F., Tai, H. C., & Lin, M. T. (2020). A Unified Framework for Automatic Detection of Wound Infection with Artificial Intelligence. Applied Sciences 2020, Vol. 10, Page 5353, 10(15), 5353. https://doi.org/10.3390/APP10155353

Xu, J., Zhang, R., Zhou, Z., Wu, C., Gong, Q., Zhang, H., Wu, S., Wu, G., Deng, Y., Xia, C., & Ma, J. (2021). Deep Network for the Automatic Segmentation and Quantification of Intracranial Hemorrhage on CT. Frontiers in Neuroscience, 14, 1084. https://doi.org/10.3389/FNINS.2020.541817/BIBTEX

Zhang, Z., & Sejdić, E. (2019). Radiological images and machine learning: trends, perspectives, and prospects. Computers in Biology and Medicine, 108, 354. https://doi.org/10.1016/J.COMPBIOMED.2019.02.017