Diagnosing Wound and Transfigure Wound care Analysis

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***Abstract*— Chronic wounds affect millions of people across the world and are very expensive. Recent advances in machine learning and deep learning are taking the management of wound care to a new level. Research has proposed mobile applications for the classification of insect bites using Random Forests that attain higher accuracy than Support Vector Machines. Mobile device-based approaches for the detection of wounds have focused on measurement size and color analysis. While assessment risk for acne scarring seems to have greatly improved using convolutional neural networks, further improvement of models is still needed in more complex scenarios. Deep learning models outrank traditional tools, such as PUSH and BWAT, at predicting outcome in chronic wounds healing. Methods to improve segmentation like FANet and IFANet boost accuracy, with new methods for monitoring wound growth and boundary demarcation setting up a huge improvement. A scoping review identified progress in wound size and tissue type classification but indicated that larger datasets and future research are required.**

***Keywords* — Chronic Wounds, Machine Learning, Deep Learning, Convolutional Neural Networks (CNNs), Segmentation**

I. INTRODUCTION

Chronic wounds are one of the most significant health care challenges, with millions of people suffering from them worldwide, thereby incurring large economic burdens. With respect to treating chronic wounds, innovative approaches in diagnosis, monitoring, and management are clearly needed as their treatment is complex and time-consuming. Conventional techniques for measuring wound size and assessing progress in healing, such as ruler-based measurements and manual assessment, are inaccurate, time-consuming, and very variable.

Recent advances in ML and DL bring along transformative potential for the improvement of wound care. They allow for much more accurate and efficient wound classification, risk assessment, and segmentation through image analysis in support of clinical decision-making. Applications of machine learning algorithms like random forests and support vector machines have been reported in the literature for classifying types of wounds and the prediction of outcomes. Deep learning techniques, like CNN, have shown better performance in tasks as acne scarring risk estimation and chronic wounds healing prediction.

This survey represents a landscape view of integration of ML and DL techniques in wound care and represents substantial progress in areas such as mobile-based applications toward monitoring wounds, newer segmentation methodologies, and improvements made in predictive modelling. The conducted scoping review provides one an overview of ongoing progress and identification of areas that require further research, including larger data sets and improved algorithmic approaches. The paper reviews how ML and DL are likely to reshape wound care practice for more accurate, efficient, and accessible medical interventions by synthesizing current developments and challenges.

II. LITERATURE REVIEW

Akshaykrishnan. V et al [1] proposed a model for classification of insect bite marks using machine learning models for better diagnosis and treatment, especially Random Forests and Support Vector Machines. The experiments conducted on five common species of biting insects proved that the performance of Random Forests in terms of accuracy and speed was better in comparison with the results obtained from the Support Vector Machines. This work contributes to the possibility of ML applications in mobile-based wound classification. Maintaining the Integrity of the Specifications

Ameya Wagh et al [2] this work will compare some traditional segmentation methods, like the Associated Hierarchical Random Field, with some deep learning approaches—more specifically, Fully Convolutional Networks (i.e., FCN), U-Net, and DeepLabV3—in the same line of the smartphone-based wound image analysis. It has been found that, though AHRF works well with small datasets, deep learning methods significantly outperform it with respect to both accuracy and speed—especially when the datasets become very large.

Berra Z. Barkana et al [3] The appearance of wounds in individuals can lead to significant health problems if not promptly and correctly treated. Early detection and continuous monitoring are essential for effective treatment. However, during the ongoing pandemic, many people avoid hospital visits, exacerbating the risk associated with untreated wounds.

Chin-lung lin et al [4] The paper presents the TOSD system, using multispectral imaging and ResNet34-based U-Net algorithms for wound segmentation. The system achieved a Dice score of 93.49% and effectively differentiated the wound healing phases by monitoring StO2 levels, which gave an early detection compared to LSCI.

Dilan Dogru et al [5] describes a U-net deep learning method for microscopic image segmentation in photobiomodulation studies on wound healing processes. The segmentation is very critical in the analysis of recovery from wounds, where this model achieved more than 90% success in most metrics of performance. In terms of Dice similarity coefficients, the model returned 0.953 for validation sets and 0.939 for test sets.

D. M. Anisuzzaman et al [6] proposed a model for automated wound localizer using the YOLOv3 model, developed as part of an iOS mobile application for diagnostics in wounds. The localizer isolates wound regions, which aids in further processing, such as segmentation and classification. Trained on datasets including the AZH and Medetec datasets, YOLOv3 obtained a very high mean average precision of 97.3%, hence outperforming the SSD model.

Filipe Ferreira et al [7] literature review of methods for wound size measurement and explores the possibility of using the information on wound colour to determine other health parameters. It also refers to the decrease in hospital visits during the pandemic, emphasizing the importance of early detection and easy monitoring of wounds. This study suggests the use of off-the-shelf mobile devices as the detector for wound detection. Furthermore, it also discusses future work on the implementation of the wound size correction into an Android application.

Jordan Aguilar [8] It estimates the risk with respect to acne-induced scarring by image analysis using convolutional neural networks. For this purpose, a custom-trained CNN model was developed from images rated by dermatologists into low, moderate, and high-risk classes. It did very well in binary classification, where accuracy reached 93.15% at an AUC of 0.931, but was significantly poor in threefold classification.

Pengfei Zhang et al [9] This paper proposes a new feature augment network, namely FANet, for automatic skin wound segmentation to assist dermatological diagnosis and treatment. In this network, not only edge and spatial relationship features are integrated into one network, but also the interactive version called IFANet offers users further adjustment to improve segmentation. Experiment results on several wound image datasets indicate that our proposed FANet works well and IFANet further brings an improvement in accuracy with very simple user inputs. Comparison experiments were conducted to prove the effectiveness of both networks in wound analysis by comparing the results against other segmentation methods.

Rishabh Gupta et al [10] proposed a model for the deficiencies of the available tools for wound prognosis, such as the Pressure Ulcer Scale for Healing and the Bates-Jensen Wound Assessment Tool, which rely on manual and subjective measurements. The study made use of deep learning-based objective features extracted from wound images and developed prognostic models that significantly improved the prediction of wound healing. Trained on a very large data set of 2.1 million evaluations, the models improved by 5-13% compared to traditional methods.

R. Niri et al [11] The paper presents a Multiview imaging approach for wound segmentation, hence circumventing the limitations of a single view in deep learning. Capturing a sequence of images to reconstruct a 3D wound model by choosing the most accurate view for segmentation and backprojecting it to enhance neural network training significantly improves accuracy.

Ruyi Zhang et al [12] reviews deep learning applied in wound image analysis with classification, detection, and segmentation tasks, publicly available datasets, preprocessing techniques, and the various models used to evaluate different types of wounds, such as burns and diabetic ulcers. Further, the work adumbrates the existing challenges and gives an idea of the prospective development directions of this area in the future.

Sawrawit Chairat et al [13] study focus on deep learning applied in wound image analysis with classification, detection, and segmentation tasks, publicly available datasets, preprocessing techniques, and the various models used to evaluate different types of wounds, such as burns and diabetic ulcers. Further, the work adumbrates the existing challenges and gives an idea of the prospective development directions of this area in the future.

Teiteira Paula A et al [14] assessment and healing of chronic wounds are critical to diagnosis and treatment, with millions affected and billions spent annually. Current methods, however, still rely on subjective human evaluation, even with the many advancements in this area. A scoping review of 109 articles on computer vision for wound assessment has pinpointed the key clinical challenges and identified areas needing further research and larger datasets. There have been developments regarding wound size and tissue classification, but further research on solving other clinical challenges and integration into routine clinical practice will still be necessary.

Topu Biswas et al [15] With the rise in diabetes and obesity rates worldwide, chronic wounds are becoming both a health and an economic burden. Treatments are frequently performed inaccurately and inconsistently, using conventional measuring techniques such as ruler-based and tracing methods. In this paper, we propose a novel method for solving the problem of demarcating the boundaries of a wound with the integration of deep learning and superpixel segmentation. It was experimentally proven that the presented approach was more than 90% accurate when compared with the classical methods.

III. METHODOLOGY

In this section [1] we will detail the training and testing processes for our classifiers. The dataset is divided into 98% for training and 2% for testing. Since there didn't already exist any pre-built dataset for this task, we manually created one with five classes of insect bites (mosquito, tick, bedbug, bee sting, fire ant) and two false classes: skin lesion and snake bite.

The images are being processed with OpenCV: they are changed to grey scale, after that to binary, then morphological operations are carried out, among them contour finding and erosion. Erosion will help detect round models and fill gaps. After that, images are returned to grey scale for conducting feature extraction via the Gray Level Co-occurrence Matrix method. Extracted key features, such as energy, entropy, contrast, correlation, and homogeneity, using functions from the Scikit-learn library and normalized within the range 0 to 1, are stored in a CSV file.

While at the testing stage, the user captures and uploads the images of bite marks by means of an application in Android. All the test images undergo the same steps of pre-processing as were done in training. The extracted features are matched against CSV data using Random Forest and SVM classifier to determine the most likely label. The architecture of the system is shown in

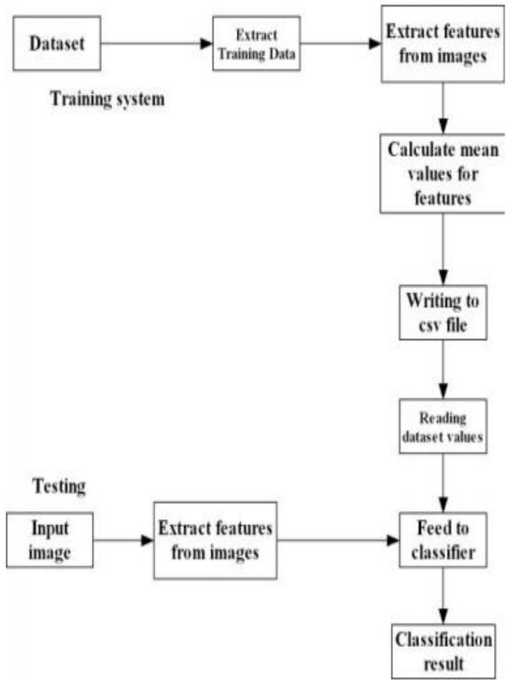

Fig. 1. System Architecture.

[3] FCNs are distinct from traditional CNNs applied for image classification tasks by removing fully connected layers, leaving only convolutional layers followed by pooling and activation. This makes FCNs quite flexible in terms of handling images with arbitrary sizes and segmenting them. Long et al. introduced FCNs that had marked success on benchmarks as PASCAL VOC 2012, NYUDv2, and SIFT Flow in 2015. An FCN is constructed through classification networks by removing the classifier layers at the end and appending a 1×1 convolutional layer that predicts the classes. While the class predictions are coarse initially, it refines through skip connections that combine lower and higher layer features to capture fine details. Furthermore, it reconstructs the high-resolution output through upsampling with deconvolution layers, hence improving the segmentation accuracy by incorporating detailed local information with the global context.

Deep Learning Models: Discuss the use of convolutional neural networks (CNNs), fully convolutional networks (FCNs), and U-Net architectures for wound segmentation, prediction of healing outcomes, and acne scarring risk estimation. Highlight the superior performance of CNNs over traditional methods. Emphasize the importance of continuous research in wound segmentation, mobile applications, and AI-based solutions to address existing challenges in wound care.

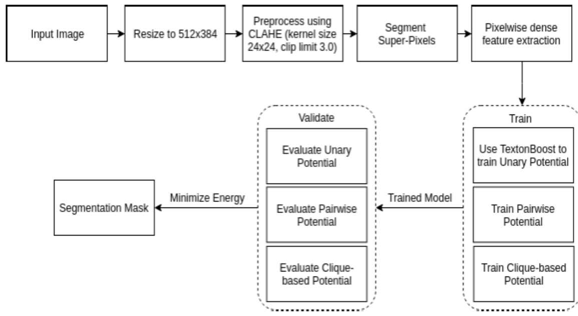

Fig. 2. Proposed sequence of methods for wound area measurement.

[12] Performance will then be ranked against some baseline metrics: Dice similarity coefficient, map, and silhouette coefficients. A comparative analysis will further be conducted by applying the models to small and large datasets to test them for varying different conditions. This new model and approach with improved standard tools like PUSH and BWAT will, therefore, be benchmarked and contrasted to establish improvements that can generalize across clinical settings.

IV. CONCLUSION AND FUTURE WORKS

Accuracy and Efficiency: Random Forest outperformed SVM in its training speed apart from hitting a high accuracy for insect bite classification. The indication of higher accuracy with which Random Forest performs demonstrates it's capable of being used effectively for a mobile-based wound classification system.CNNs were highly accurate in all binary classification tasks where the risk estimation of acne scarring was concerned, but poor accuracies arose in cases of threefold classification. So, for this specific case, the scenarios might need a model of higher level to target further complexities.

U-Net and FANet Segmentation: The U-Net and FANet (and their variants like IFANet) have been proved to be very effective in the wound segmentation process. They surpass traditional approaches such as the Pressure Ulcer Scale for Healing (PUSH) and the Bates-Jensen Wound Assessment Tool (BWAT). Pengfei Zhang et al. documented better edge and spatial relationship feature extraction by FANet, thereby giving an enhanced boundary demarcation of the wound. Wound Localization using YOLOv3 Wound localization application on mobile was performed using the YOLOv3 model that produced a mean average precision of 97.3% and thus proved strong for the identification of wound areas[6]

Studies were conducted that demonstrated the ability of diagnosing and monitoring the wounds through mobile application. These were viable alternatives during the time of COVID-19 pandemic when hospital visits had significantly been reduced [8].There was potential for analysis of real-time wound color and size through smartphone to become part of routine wound care. [10] Designed deep learning models based on image data to predict wound healing and have been claimed to improve the accuracy 5-13% over traditional BWAT models of prediction. Improved prognosis models can also guide more precise strategies in chronic wound treatment.

This approach of applying machine learning models in the form of Random Forests with DL methods such as CNNs and

U-Net improves both the speed and accuracy in the diagnosis and prognosis of wound healing. In comparison to classical ruler-based measurements and visual assessments, the above methods exhibit significantly reduced variability in estimating the size of the wound and predicting healing.

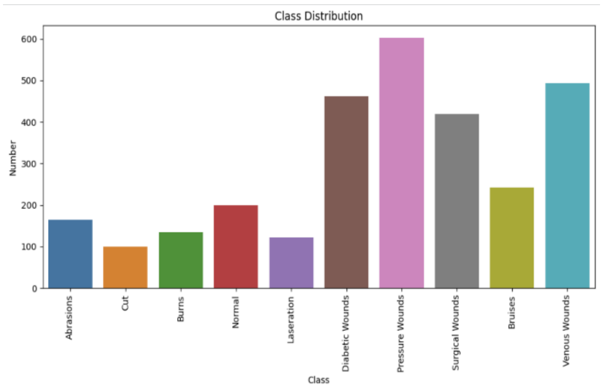

Fig. 3. Wound class Distribution

Improved segmentation capabilities in the model U-Net and FANet compared with their state-of-theart predecessor; this shows significant superiority, particularly when the dataset is large enough. The capacities of the models in doing precise demarcation of the boundary are crucial for exact assessment and treatment planning. The interactive models, IFANet improve segmentation through the simplest user inputs, opening new possibilities for semi-automated tools in wound care.

Accessibility and Cost-Effectiveness: Mobile applications for wound diagnosis and monitoring are highly beneficial in terms of accessibility in rural or underserved areas. Remote monitoring for healing of a wound helps to reduce hospital visits, thereby reducing healthcare expenditure. However, it increases problems related to user education; improper use can lead to misdiagnosis.

Limitations of Current Mobile Systems: Although promising, the camera quality of the mobile device, lightning conditions, and handling of the user can be a limitation for mobile-based solutions. Inconsistent data input may downgrade the accuracy of the system. One of the major prerequisites for broader acceptance is addressing these limitations by training the user or improving hardware.

AI-driven prognostic tools: The potential for developing AI-based tools that accurately predict the outcome of wound healing is very promising for the practice of personalized medicine. It would be very useful in tailoring treatment plans toward individual patients based on the very unique characteristics of every patient's wound, promising better outcomes and more efficient use of healthcare resources. The future plans of wound care include wearable sensors for monitoring continuously, where the changing conditions of wounds can be traced over time. This information can be integrated into AI models to provide dynamic, personalized recommendations for wound care and alert clinicians to complications before they become critical.

Summarize the main findings and outline how ML and DL technologies are remodelling diagnosis and care of wounds. Emphasise already challenged in this paper-a higher amount of the dataset and better integration into clinical practice-and press forward to overcome the challenges to unlock the potential of an AI-driven wound care system.

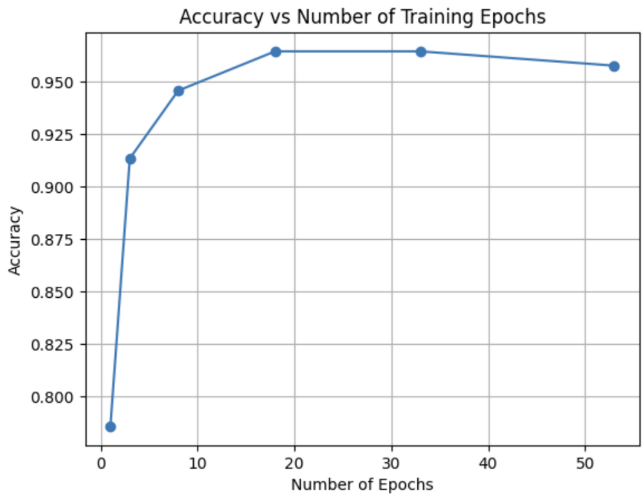

Fig. 4. Accuracy and Number of Training Epochs

IV. CONCLUSION

Deep learning-based techniques in the segmentation of wound imaging have made significant progress and have, at the same time, been challenged by studies. With the edge and spatial relationship features of the nowadays-proposed methods, e.g., the Feature Augment Network and Interactive Feature Augment Network, robust approaches are shown for automatic and interactive wound segmentation. Such a network outperforms methods using traditional methods to open the door to wound-accurate assessment tools.

Deep learning-based models, when associated with the clinical dataset, signify high promise in the management of chronic wounds. This includes models like U-Net with EfficientNet-B2 and further improvements in the methods for wound boundary demarcation through super pixel segmentation and classification. However, improvements over conventional techniques have been considerable. In this regard, multi-view modelling strategies were applied to address dataset-size and perspective effects, further enhancing segmentation accuracy.

It further fuels research, with challenges lying in the need for very large annotated datasets and the influence of camera distance and perspective over segmentation quality. Advanced deep learning, especially by applying Convolutional Neural Networks such as Fully Convolutional Networks, U-Net, and novel architectures used to overcome these limitations, play a major role in this regard.

Such technologies as the proposed automatic systems of wound localization and the use of deep learning for assessment of risks look to the opportunity for improvements in wound care using more reliable and efficient tools, giving accurate information for improved diagnosis and treatment. Continuous research and development in these areas hold much importance with regard to this subject and hold the key to further improvement of the clinical impact of wound image analysis.

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