

Decision support system for the diagnosis of chronic wounds using Machine Learning algorithms with images

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Abstract: A solution is proposed that consists of supporting the professional in deciding how to act on the wound by offering a diagnosis proposal. Artificial Intelligence (AI) and Machine Learning (ML) algorithms have been developed to allow the extraction of the most relevant wound characteristics through an image and providing similar wound assessment cases from the health center itself. In this way, the professional would have a diagnostic reference of other wounds similar to the one under assessment, and this be able to make the right decision. The solution is embedded in a software as a medical device, which is CE marked and is also capable of tracking wounds through images and data. A total of 795 images were processed and analyzed in order to obtain their most identifying morphological and textural characteristics. From each image, the five most similar images in terms of characteristics were searched for and clinically validated by comparing them using an objective scale and widely used in chronic wound care called. The results showed a similitude in 73.71% of cases, calculated by comparing the clinical scale of the image performed by a specialist clinician with the proposed scale of the algorithm. With this solution, clinicians improve their confidence in clinical practice by having support in decisions making, observing favorable outcomes and progression of chronic wound.

Keywords: Chronic wound; similar cases; diagnosis; Machine Learning; Artificial Intelligence

1. Introduction

There are many causes of a wound: a simple fall, a surgical intervention, dependency-related factors such as the application of pressure or friction, as well as pathological conditions such as diabetes or vascular disease [1]. The need for a longer time for a wound to heal causes it to become a chronic wound. Some authors [2,3] determine that the time to heal must be longer than six weeks to categorize a wound as a chronic as they heal by second intention, a complex process in which damaged tissue is first removed and then replaced. While an acute wound follows a sequential healing process with anatomical and functional restoration in a timely way, chronic wounds lack normal restoration due to various physiological alterations [4]. Chronic wounds have a negative impact on people's quality of life, causing difficulties to cope with situations such as the presence of pain, difficulty in performing basic daily activities or the need for periodic wound healing, triggering dependence. In some cases, such as diabetic foot wounds, the situation can worsen and lead to limb loss and even mortality.

In Europe, the prevalence of patients with at least one chronic wound is estimated to be 3.7 per 1000 population [1,5], matching the mortality rate associated with cancer in some cases of chronic wound typology [6]. In addition, the care of chronic wounds by healthcare personnel and services entails an economic cost estimated at 5% of the total healthcare expenditure in Spain for pressure wounds only [5].

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Specific wound care skills are required to assess and treat a chronic wound, as there is a great variability of healing processes depending on the type of wound, among other factors that may also influence the wound care process. New technological solutions are seen as a catalyst for more informed wound care practice [7] and can therefore aid specialization in chronic wounds clinical area. Using technological systems such as apps with AI and ML implementations, clinicians can capture large volumes of data, as well as have the tools, the security and the confidence to understand areas of concern and the changes needed to standardize practice. AI combined with accurate, patient-centred human intelligence translates into better outcomes in terms of healing and closure time. Whereby, the use of new technology solutions with the integration of Electronic Health Records (EHR) is driving change in the healthcare system. This allows, on the one hand, patients to benefit from better care and, on the other hand, providers to deliver more efficient care and reduce costs [8].

There are many research groups that are working in different projects to provide a support in chronic wounds diagnosis. Many of these studies consist of providing the clinician with information on wound characteristics related to wound healing. Some provide a classification of tissue types [9–11], others detect the presence of infection [12–14] or measures such as area [15–17]. There are also other studies that classify the type of chronic wound [18–20]. The aim of this work is to combine both image and clinician information in order to compare chronic wound cases in a health centre. In this way, taking advantage of the chronic wound assessment previously performed by clinicians and the consequent outcome, the aim is to provide real-time information that can be used to correctly diagnose a patient's chronic wound in the hospital consultation. This information would consist of an assessment of the chronic wound, providing information on the type of tissue in the wound, the type of wound edges, the exudate, the depth, whether there are any signs of infection and the approximate area.

One of the first challenges to address is that wound management systems remain technologically backward, and most caregivers rely solely on inaccurate optical assessment. This can cause risk of infections and inaccurate measurements, resulting in a wrong assessment of the wound. Another issue identified is the lack of adequate practice and expertise, especially in primary care settings where a large number of wounds with high variability in wound typology are usually first assessed. This further increases the economic burden and patient discomfort.

2. Materials and Methods

2.1. Data capture

The data used for the development of this work consisted of taking images of chronic wounds together with the answers to the questions on a wound evolution assessment scale. From each of the images, the wound outline was additionally drawn and saved. The data was captured by healthcare professionals at the Hospital Santa Creu from Vic, Barcelona (Spain), using an application called Clinicgram. This required a smartphone mobile device with WIFI or data connectivity and a back camera with at least 10-megapixel resolution.

2.1.1. Clinical scale RESVECH 2.0

Las escalas se definen como instrumentos de medición objetiva, sobre todo cuando hay múltiples factores que pueden llevar a una valoración subjetiva de lo que se pretende medir [2]. En este trabajo se pretende valorar la similitud entre imágenes de heridas crónicas y para ello se utilizará una escala de medición ampliamente usada en el seguimiento y evaluación de las heridas crónicas llamada RESVECH 2.0, una evolución de la RESVECH 1.0 creada en 2010 para medir el proceso de cicatrización de heridas [21]. Para abarcar completamente la evaluación de la cicatrización de una herida es necesario tener en cuenta diferentes características de ésta, incluyendo todos los ítems del lecho de la herida (tamaño, profundidad, infección, exudado y tipo de tejido) así como prácticamente todos los elementos del borde (maceración, tunelizaciones y forma del borde). Con la escala de evaluación

RESVECH 2.0 se tienen en cuenta dichos componentes físicos y fisiológicos que deben ser recojidos por los expertos y se listan a continuación: 88

- Wound size 90
 0. 0 cm² 91
 1. < 4 cm² 92
 2. 4 < 16 cm² 93
 3. 16 < 36 cm² 94
 4. 36 < 64 cm² 95
 5. 64 < 100 cm² 96
 6. ≥ 100 cm² 97
- Depht 98
 0. Heated intact skin 99
 1. Impact of the dermis-epidermis 100
 2. Involvement subcutaneous tissue (adipose tissue without the muscle fascia) 101
 3. Muscle involvement 102
 4. Involvement of bone or tissue attached (tendons, ligaments, joint capsule or bedsores can see no black fabric below) 103
104
- Edges 105
 0. No distinguishable (no wound edges) 106
 1. Fuzzy 107
 2. Delimited 108
 3. Damaged 109
 4. Spoiled (“aged”, “inverted”) 110
- Tissue Type 111
 0. Closed / healing 112
 1. Epithelial tissue 113
 2. Granulation tissue 114
 3. Necrotic tissue or spheres in the wound bed 115
 4. Necrotic (dry black or dry scald) 116
- Exudate 117
 0. Moist 118
 1. Wet 119
 2. Saturated 120
 3. Dry 121
 4. Leaking 122
- Infection Signs 123
 1. Increasingly painful 124
 2. Erythema around the wound 125
 3. Edema around the wound 126
 4. Rising temperature 127
 5. Increasing exudate 128
 6. Purulent exudate 129
 7. Tissue is friable or bleeds easily 130
 8. Wound stationary, no progress 131
 9. Tissue compatible with biofilm 132
 10. Odor 133
 11. Hyper granulation 134
 12. Wound increasingly larger 135
 13. Satellite lesions 136
 14. Pale tissue 137

Cada una de las características le corresponde una puntuación la cual está directamente relacionada con la severidad que la caracteriza. La puntuación oscila entre 0 y 35, siendo 0 una herida completamente curada [22].

Por cada imagen, el clínico ha indicado cuáles de las características le corresponden a la herida en el momento de la evaluación y, adicionalmente, se ha registrado la etiología de la herida.

2.1.2. Clinicgram

The Clinicgram application (version 2.3.1) is a Class I medical device software with CE marking following the Declaration of Conformity, signed by the manufacturer Skilled Skin SL, according to Directive (EU) 93/42/EEC. This application has several software functionalities which allow the integration of medical history data with images. In this case, the Clinicgram application has been used to take the images with the camera of the device where it has been installed, as well as to draw the outline of the wound and enter the data associated with the RESVECH 2.0 scale by means of an integrated questionnaire, so that the data capture has been carried out quickly and optimally.

2.2. Ethics Committee approval

The clinical protocol has been approved by the CEIC (Clinical Research Ethics Committee) of the Hospital Santa Creu de Vic, Barcelona (Spain) (XXXXXXXXXX).

2.3. Data processing

Los datos obtenidos consisten en un conjunto de imágenes con las respuestas de los elementos asociados correspondientes a la escala clínica usada. Tanto las imágenes como los cuestionarios han sido registrados por los clínicos mediante la aplicación Clinicgram. Las imágenes han sido procesadas segmentando la parte correspondiente a la herida y quitando el fondo (Figure 1). Se ha aplicado un zoom en la parte donde se encuentra la herida de la imagen para poder identificar y analizar la herida más fácilmente y se ha realizado un reajuste del tamaño a 224 x 224.

Paralelamente, se han observado las respuestas a los ítems de la escala clínica y se han balanceado por tal de que haya la misma proporción de tipología de heridas. Para ello, se ha reducido el tamaño de muestras hasta igualar el número de cada tipo.

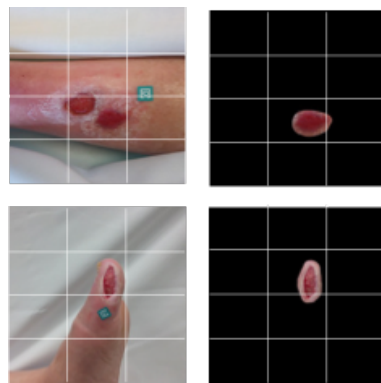


Figure 1. On the left is the normal image of the chronic wound, on the right is the segmentation of the wound from the clinician's contour. Part of the skin has been taken so that the wound edges can also be visualised.

2.4. Feature extraction

Una vez procesadas las imágenes, se han extraído sus características mediante dos fases. En una primera fase se han usado algoritmos de IA implementando técnicas de Deep Learning para caracterizar las imágenes. En una segunda fase, se han extraído características relacionadas con la textura y el color. Para ello se ha usado Gray Level Co-occurrence Matrix (GLCM) para buscar parámetros matemáticos como el contraste,

la correlación, la entropía, la uniformidad y la energía de la imagen en escala de grises. Finalmente, se ha hecho una extracción de los colores más relevantes presentes en las heridas. Los resultados de cada algoritmo se han unido representando cada imagen en forma de vector numérico.

2.4.1. AI algorithms

Using Deep Learning techniques, the images were processed to extract the most relevant shape and texture features. To obtain the best way to extract features, different pre-trained Convolutional Neural Networks (CNN) are used with a technique called transfer learning. La técnica de transfer learning nos permite utilizar el conocimiento generado en una CNN entrenada previamente con una cantidad de datos muy grande, y adaptar el problema y la arquitectura ya diseñada al conjunto de datos que disponemos. Para ello se han usado los pesos de la CNN entrenada con el conjunto de datos Imagenet y se han establecido como datos de entrada el conjunto de nuestras imágenes con el tamaño ajustado a 224x224x3. Adicionalmente, se ha configurado para que la salida de la CNN sea un vector de características que represente la imagen, en lugar de la capa de clasificación habitual. Concretamente, se han probado las redes preentrenadas Mobilenet, ResNet50, InceptionV3, VGG16 y VGG19. Con cada una de las CNN pre-entrenadas se han usado el mismo conjunto de imágenes pero con cuatro procesamientos previos diferentes: sin aplicar la segmentación de la herida, sin aplicar la segmentación pero con un zoom en la zona de la herida, aplicando la segmentación y aplicando la segmentación y cogiendo parte de la zona perilesional. El objetivo de usar cinco redes pre-entrenadas distintas y cuatro conjuntos de datos con cada una de ellas, es conocer cuál es la combinación que da mejores resultados. Posteriormente, con el objetivo de mejorar el rendimiento de las fases posteriores del proceso, se ha probado de implementar una técnica para reducir características llamada Principal Component Analysis (PCA). Esta técnica se usa para reducir los vectores de características resultantes de las CNN a un vector de menores dimensiones eliminando aquellas características que son dependientes o irrelevantes.

2.4.2. GLCM

Para la extracción de características relacionadas con la forma y la textura de la herida, se ha usado GLCM (Grey-Level Co-occurrence Matrix). GLCM es un método usado en trabajos realizados anteriormente para resolver problemas de tipo similar[23,24] y que permite obtener la distribución de intensidad textural a lo largo de la imagen en escala de grises mediante diferentes medidas estadísticas. Para ello, GLCM caracteriza la textura de una imagen mediante el cálculo de la frecuencia con la que un par de píxeles con valores y relación espacial específicos aparecen en la imagen [23]. La matriz GLCM con nuestro conjunto de imágenes se ha construido considerando una distancia entre pares de píxeles igual a 6 y cuatro direcciones: 0° (derecha), -45° (abajo-derecha), 90° (arriba) y 135° (abajo-izquierda). Como resultado se han obtenido cuatro matrices con el número de veces que cada nivel de gris ocurre a una distancia de 6 píxeles siguiendo la dirección del ángulo correspondiente a cada una.

2.5. Machine Learning algorithms

The similarity algorithm consists of two components or modules. The first is a pre-trained convolutional neural network called MobileNet. This network is used to obtain a feature matrix of the same size for all images. To do this, the images are passed jointly, according to the defined batch size, through the layers contained in this network, without allowing the last classification layer to be reached; specifically, the last fully connected layer (FC15 in Figure 2) is reached. In this way, a vector of 1024 characteristics is obtained for each image, forming a matrix of values. Each vector that defines an image will contain information of this one referring to morphology, size, position, texture, colour, etc., which will have been extracted with the implementation of the functionality applied in each one of the layers of the MobileNet network. Additionally, the information of the wound added

the algorithm. The percentage of similarity is calculated, for each of the features, according to the following relationship:

$$\%similitude = ((Similar1 * 1) + (Similar2 * 0.75) + (Similar3 * 0.50) + (Similar4 * 0.25)) * 100 / 2.5, \quad (1)$$

which assigns a weighting according to whether the feature corresponds to the image with the highest or lowest similarity according to the algorithm. If there is a match between the value of similar images $SimilarN$ is equal to 1, otherwise it is set to 0.

Figure 3 shows the result of the implementation of the similarity algorithm for a particular image. In this example, the similarity results for each item of the RESVECH 2.0 scale show that similar images match 100% with depth being involvement of subcutaneous tissue, delimited borders, no infection, granular tissue type and wound size less than 4 cm². In the case of exudate with a similarity score of 80, three similar images matched the moist exudate type, except for the third most similar image which has a dry exudate type. The total percentage of similarity corresponds to 96.7%.



Figure 3. Result of implementing the similarity algorithm with an image. The percentage of similitude of RESVECH 2.0 items was 100% for depth, edges, infected, tissue type and wound size, and 80% for exudate.

3. Results

A total of 798 images of chronic wounds were recruited from patients, with the wound outline drawn and RESVECH 2.0 scale added by the clinician. Patients have given their informed consent to take a photo of the wound area and to collect the associated data. The data was then securely stored and anonymized so that it could not be accessed. From 798 images recruited, 95 were discarded because they did not meet any of the inclusion criteria or were not of sufficient quality to be included in the study. The remaining 703 images are distributed as 117 arterial wounds, 141 pressure wounds, 124 venous wounds, 15 suture dehiscence, 109 traumatic wounds, 49 mixed wounds, 88 diabetic neuropathic wounds, 5 surgical wounds, 22 hematomas, 8 Martorell hypertensive wounds and 33 assigned as other. (Table 1).

Table 1. Etiology distribution of data.

Eiology	Number of wounds	% of total
Arterial Ulcer (AU)	117	16%
Pressure Ulcer (UPP)	141	20%
Venous Ulcer (VU)	124	18%
Suture Dehiscence (DS)	15	2%
Traumatic Ulcer (TU)	109	15%
Mixed Ulcer (MU)	49	7%
Neuropatic Diabetic Ulcer (UDNN)	88	12%
Surgical Ulcer (SU)	5	1%
Hematoma (H)	22	3%
Martorell hypertensive ulcer (UHM)	8	1%
Other	33	5%

In order to make an overall evaluation of the performance of the algorithm, the percentage of similarity of the features of all the images was calculated and an overall average was made. For this purpose, for each element of the global feature matrix, the similarity algorithm has been implemented and the features of the validation scale have been compared. The result of the average of the similarity percentages corresponds to an overall accuracy of 70.77% and the results of the similarity percentages of each of the parameters of RESVECH 2.0 can be seen in the table 2.

Table 2. Results of similitude calculated with the comparison of RESVECH 2.0 scale values.

RESVECH 2.0 item	mean similitude (%)
Depht	58.75%
Edges	90.13%
Exudate	65.41%
Infected	82.51%
Tissue Type	71.48%
Wound Size	56.33%
Total Accuracy	70.77%

The percentage of similitude has been calculated for each RESVECH 2.0 item with the formula 1. A histogram of all results can be seen in Figure 4, with a prevalence of high coincidences in all of the RESVECH 2.0 items.

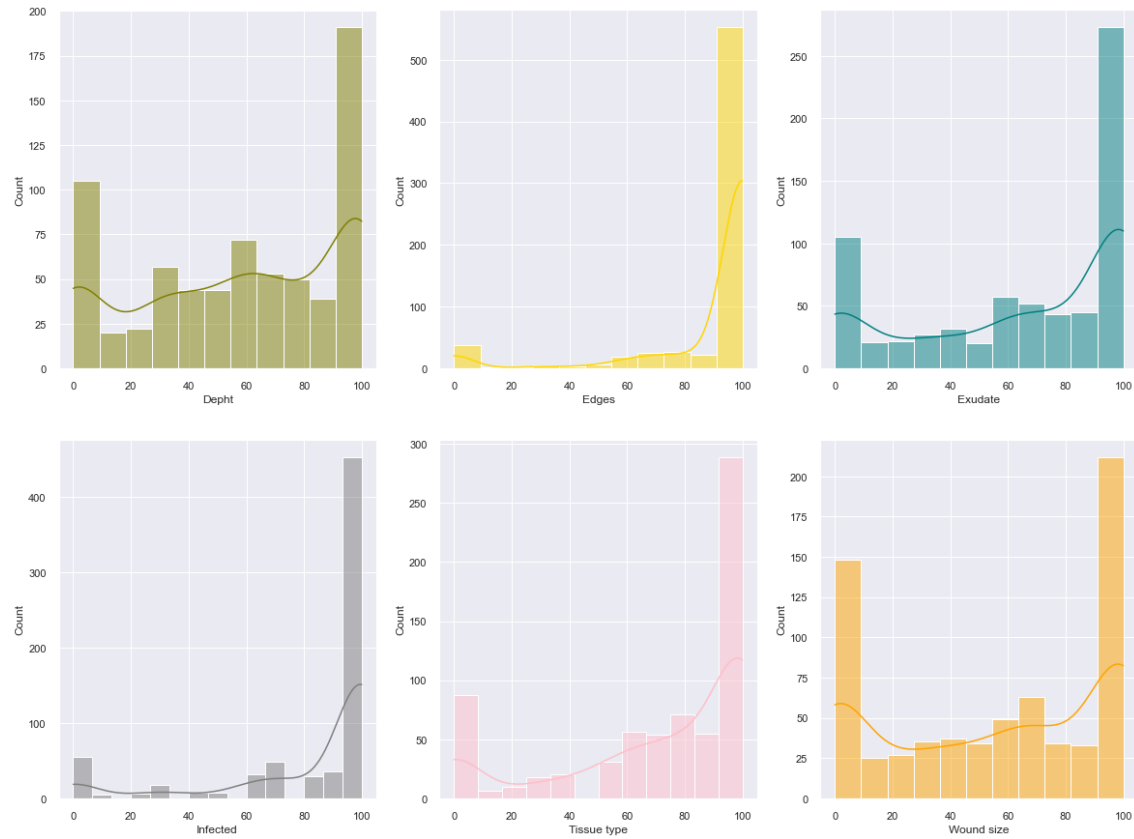


Figure 4. For each RESVECH 2.0 item, the responses of the clinicians have been compared between each image and the similar ones. In each histogram it can be seen the number of samples which have obtained a percentage of similarity according to the RESVECH 2.0 characteristic.

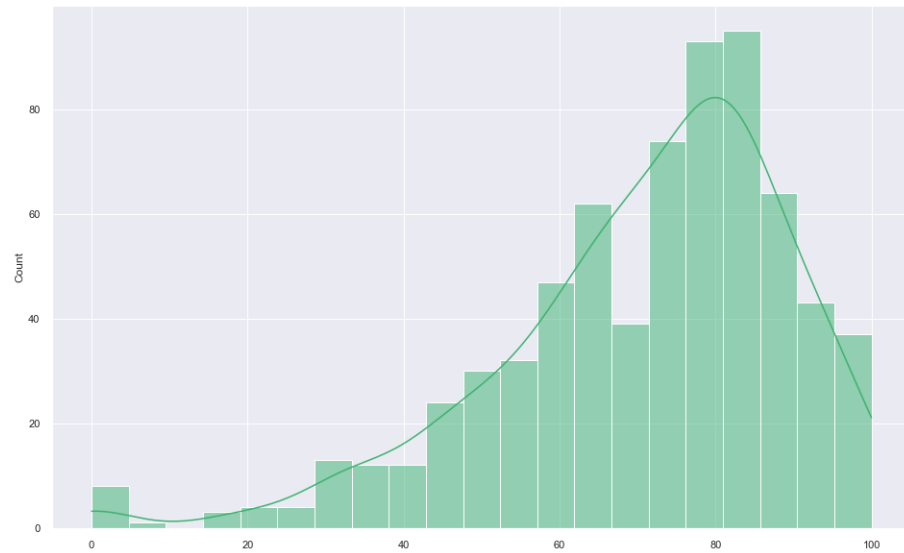


Figure 5. To calculate the overall accuracy, for each similar image, the median of the similar items was calculated and the similarity formula 1 was followed with the results of the averages.

4. Discussion

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

5. Conclusions

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

6. Patents

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Data Availability Statement: In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Please refer to suggested Data Availability Statements in section “MDPI Research Data Policies” at <https://www.mdpi.com/ethics>. If the study did not report any data, you might add “Not applicable” here.

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Abbreviations

The following abbreviations are used in this manuscript:

MDPI Multidisciplinary Digital Publishing Institute

DOAJ Directory of open access journals

TLA Three letter acronym

LD Linear dichroism

Appendix A

Appendix A.1

The appendix is an optional section that can contain details and data supplemental to the main text—for example, explanations of experimental details that would disrupt the flow of the main text but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data are shown in the main text can be added here if brief, or as Supplementary Data. Mathematical proofs of results not central to the paper can be added as an appendix.

Table A1. This is a table caption.

Title 1	Title 2	Title 3
Entry 1	Data	Data
Entry 2	Data	Data

Appendix B

All appendix sections must be cited in the main text. In the appendices, Figures, Tables, etc. should be labeled, starting with “A”—e.g., Figure A1, Figure A2, etc.

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