IJESRT
INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

MACHINE LEARNING MODEL FOR HEALING ANALYSIS OF HUMAN INJURY

Dr.Shubhangi D C[1], Dr. Baswaraj Gadgay[2], Bhagyashree Sangavi[3]
[1]Department of Computer Science, Vishveshwarayya Technological University CPGS Kalaburagi, Karnataka, India
Email:drshubhangipatil1972@gmail.com
[2]Department of Electronics and Communication, Vishveshwarayya Technological University CPGS Kalaburagi, Karnataka, India
Email:baswaraj_gadgay@vtu.ac.in
[3]Department of Computer Science, Vishveshwarayya Technological University CPGS Kalaburagi, Karnataka, India
Email: bhagyashreesangavi@gmail.com

DOI: https://doi.org/10.57030/ijesrt.13.5.1.2024

ABSTRACT

As more tissues are harmed, wounds progress. Measurements of wound's surface area are taken at regular intervals to determine wound's progress toward healing. Measuring this method is time consuming, and routine evaluation is laborious. In general, wound healing may be broken down into two categories: contact & noncontact. Goal of this job is to make a reliable evaluation of wound's progress toward recovery.Taking pictures of the wound is first step in making a proper diagnosis. Pre-processing the wound picture to decrease noise by using effective filters and effective de-noising algorithms, & then segmenting wound region from wound image. Classifying wound pictures requires efficient classifiers. Chronic wounds are a major problem for many individuals.It's a huge issue in healthcare all throughout the globe. Treatments for chronic wounds involve routine examinations of wound's appearance and shape. This assessment frequently occurs via qualitative observation & manual wound measures. Many groups of scientists are now working on methods to evaluate the clinical progress of chronic wounds. The purpose of this research is to examine how imaging techniques may be used to treat chronic wounds. Research on the use of imaging techniques for chronic wounds is discussed. We evaluate their practicability, accuracy, & dependability. Planimetric approaches, volumetric methods, & tissue categorization make up remaining methods

KEYWORDS: Wounds, Tissues, Segment, Imaging Technology, planimetric techniques, volumetric Technique

1. INTRODUCTION

Performing a precise and exhaustive wound evaluation is crucial for providing the best wound care possible.First, it helps doctors calculate how long a wound will take to heal and what kind of therapy is necessary, & second, it provides a valid outcome measure which may be utilized to evaluate efficacy of wound treatment program. Extent of wound is an important factor that must be considered throughout evaluation process [5]. Wound depth [3], surface area [6],[7], width and length [8] & volume[9] are only few of the measures that were established and verified to assess wound size. Both of these approaches have been compared. Although there are advantages and disadvantages to each technique, it is generally accepted that methods that estimate wound surface area as opposed to wound depth or volume are most accurate & reliable[8, 10–13]. While stereophotographic decisions might be most accurate way to determine wound surface area, alternative techniques, such as tracing wound on a sheet of transparent acetate or using product of wound's width and length, have been found to be just as accurate and convenient[12-15]. Assessment of wound bioburden and wound severity are additional factors in determining wound healing [5].Wound exudate alongside necrotic tissue type, necrotic tissue quantity, necrotic tissue features, granulation tissue, and periulcer skin vitality must all be evaluated[16]. Several evaluation tools, such as PSST [12-13], PUSH Tool[10], wound recovery tool (SWHT)[21], the Sessing Scale[22], & wound healing scale (WHS)[13], have been created to evaluate various aspects of wound healing. In chronic pressure ulcers, a minimum of 2 of these scales having sufficiently publicly available data to be deemed legitimate and trustworthy indicators of wound healing, according to recent evaluations of these wound state measuring instruments. [14],[15]. All of those wound evaluation techniques & scales rely on qualified healthcare provider making a quick, on-the-spot evaluation of wound bed, edge, & periulcer skin, afterwards assigning number to wound which most accurately reflects their findings. Except for the WHS, all of the existing wound assessment devices were created with pressure ulcers in mind. Chronic vascular leg ulcers, such as those caused by diabetes, venous disease, or arterial disease, are unsightly yet surprisingly common. Seventy-five percent of home healthcare organizations in USA surveyed in a recent poll said they photograph wounds as part of their documentation process. The incorporation of wound images to record wound state is also recommended by several sources which explain how to conduct a wound assessment. There are several benefits to photographing wounds, like fact that physician need never touch wound themselves. When an ulcer is photographed, its size and the tissue type in wound bed may be determined. Hughes claims that a health care provider may learn more from an image than from subjective account, that might be misunderstood. It has been shown that photographic evidence assisted a patient in securing financial compensation for medical expenses. New automated & computerized methods were created to aid doctor in chronic wound documentation by capturing and analyzing photographic pictures of wound. In addition, digital photographs of wounds may be utilized to electronically transfer information regarding the healing state to a distant location, where a wound care specialist can be consulted. Telemedicine has been utilized to improve the quality of treatment for patients with chronic wounds who live in areas without easy access to large medical facilities.It was shown in a study of 32 doctors that they could make fundamental wound care judgments including whether or not patient needed further testing only by looking at a picture of the wound on a computer. Although pictures of wounds are often used for documentation purposes, it remains unclear whether or not they can be utilized to accurately evaluate wound's progress. This study's goal is to determine how to measure wound healing progress with precision.The first step in making a proper diagnosis of a wound is taking pictures of it. PWAT is only one of several methods available for gathering high-quality pictures of wounds. Since venous, pressure, diabetic, including arterial ulcers each have their own unique features, it is vital to establish the PWAT's validity and reliability for evaluating cosmetic status of chronic pressure & leg ulcers caused by vascular insufficiency. The wound pictures must be classified, which requires efficient classifiers. In this category of classifiers, WIAC are one option.

2. RELATED WORK

Automatic Color and Size Evaluation of Wound Tissue using AI Image Acuity Correction Images captured at different times and places with Smartphone2023 may be compared using this method, despite differences in illumination, focal length, & camera sensor. Next, we created deep learning models, & best-performing algorithm segmented wound areas, epithelialization areas, granulation tissue, & necrotic tissue with mean IOU values of 0.6964, 0.3957, 0.6421, & 0.1552, correspondingly.[23] While this method was successful in segmenting wound as well as granulation tissue, it was less reliable when it came to epithelialization & necrotic tissue. The performance of algorithm was enhanced by use of calibration chart, which assists in calibrating colors & scales. This method may allow for a comprehensive evaluation of wound, that would aid doctors in personalizing care.

While several techniques were suggested to improve the quality of semantic labeling as a whole, very few take rare-class items into account.[24] Using three methods, this paper presents a deep semantic labeling system that gives priority to underrepresented groups. To begin, a unique coarse-to-fine superpixel representation is created, wherein fine superpixels are used for uncommon classes and coarse superpixels are used for background regions. By using this novel dual representation, form features may be easily included in combined local and global CNN models. Secondly, during CNN feature learning from re-balanced training data, shape information is explicitly incorporated for both common & uncommon classes.

Computerized image processing allows for a precise early detection of burns as well as pressure ulcers. Utilizing color imaging system, this research presents a careful examination of various approaches.Using porcine animal simulator for wound development, [1] also developed approach for measuring histology data. When moment of damage can be determined, calibrated color differences amongst wounded & uninjured skin may be used to reliably categorize severity of wounds. Within 30 minutes after injury application, this color analysis allowed for statistically meaningful distinction between mild, moderate, and severe injuries.

Recent years have seen a rise in studies examining the feasibility of employing digital image processing to monitor wound progression and grade its severity. Multiple chances for non-invasive wound assessment exist in clinical as well as non-clinical environments thanks to introduction of mobile devices with significant functionality and processing capacities. Current imaging technologies allow for the collection of quantitative data about the size, structure, & color features of wounds via the use of objective and trustworthy approaches.[2] These fast algorithms for analyzing images aid in identifying the characteristics of injuries & tracking their recovery. The aim of this study is to promote connection among computer health and science by providing a thorough analysis of papers which tackle topic of wound size measuring using image processing methods.

In addition to negatively impacting patients' mental and physical well-being, wounds can add significantly to expense of treatment. Meanwhile, there's is scarcity of doctors in certain regions, and wound diagnosis based only on a clinical examination might be inaccurate at times. In order to properly diagnose, treat, and care for a wound, accurate wound analysis is essential. Rapid advancements in deep learning have made it the most popular method for analyzing wound images in fields of computer vision and medical imaging.[3] recent studies have focused on using deep learning to various aspects of wound picture processing. Before diving into the preprocessing techniques used in wound image analysis, it's a good idea to familiarize yourself with the publically accessible datasets from different studies. Wounds of all kinds are studied, along with models utilized for classification, identification, & segmentation in deep learning..

The effects of chronic wounds upon quality of life are devastating. They may worsen fast & need constant attention while they recover. By quantitatively measuring key aspects associated to healing, image-based wound analysis allows for objective assessment of wound's progress. Wound pictures may be difficult to segment robustly due to the wide variety of wound forms and imaging settings. introduce Detect-and-Segmentation (DS), wound -generating deep learning method.[4] great capacity for generalization. Here, we put our strategy to the test on a dataset of diabetic foot ulcers and compared the results to those obtained using an image-based segmentation technique. We compared the results obtained using the DS method to those obtained using a standard method on four further independent data sets, which included a wider range of wound kinds and anatomical locations. Diabetic foot ulcer dataset saw a significant increase in correlation (MCC) from 0.29 (full picture) to 0.85 (DS). The average MCC rose from 0.17 to 0.85 when the DS was applied to unrelated data. In addition, the DS allowed segmentation models to be trained with as much as 90% fewer inputs without degrading segmentation performance.

3. PROPOSED SYSTEM

An interactive wound-healing evaluation tool is goal of suggested system. This is accomplished in an interactive fashion with aid of operator's inputs. This guarantees that measurements account for the various factors while offering reliable results. Segmentation is a useful tool for locating wounds and identifying their borders. Filtering & denoising methods may be used in the pre-processing step to improve the quality of wound picture. A wound's healing progress may be monitored by observing its appearance after treatment using transparent layers.

4. METHODOLOGY

WIAC (Wound Image Analysis Classifier)

Algorithm:

- Pick a wound picture from the wound image library we compiled from free sources.
- Utilizing reliable segmentation method, isolate wound from wound photo.
- Applying filtering and de-noising methods to wound picture will help enhance quality of segmented wound.
- Reduce the color saturation of the wound by overlaying translucent layers of segmental wound forms after picture has been preprocessed.
- To see the wound healed, repeat step 4 many times.
- Tag segmented picture of wound with one of 3 labels depending upon severity: 0, 1, or 2.
- Healing state of a wound may be assessed by converting segmented pictures from higher to a reduced severity level.

SVM Algorithm Pseudo Code;

Candidate SV= {closest apir from opposite classes}
While there are violating points do
Find a violator
Candidate SV=U candidate SV
S
Violator
If any $\alpha_{<0}$ due to addition of c to S then
Candidate SV=candidate SV\p
Repeat till all such points are pruned
End if
End while

K-Nearest Neighbour (KNN) algoritm:
Let (X_i, C_i) where i = 1, 2……., n be data points. X_i denotes feature values & C_i denotes labels for X_i for each i.
Assuming the number of classes as 'c'
$c_i \in \{1, 2, 3, \ldots\ldots, c\}$ for all values of i

Let x be a label-unknown point, & suppose we want to determine its label category utilizing k-nearest-neighbor techniques.
KNN Algorithm Pseudocode:

1. Calculate "d (x, x_i)" i =1, 2 **n**; where **d** denotes the Euclidean distance between the points.
2. Arrange the calculated **n** Euclidean distances in non-decreasing order.
3. Let **k** be a +ve integer, take the first **k** distances from this sorted list.
4. Find those **k**-points corresponding to these **k**-distances.
5. Let $\mathbf{k_i}$ denotes the number of points belonging to the i^{th} class among **k** points i.e. $k \geq 0$
6. If $k_i > k_j \ \forall \ i \neq j$ then put x in class i.

RF(Random Forest) Algorithm;
One kind of supervised classification technique is the random forest algorithm. This technique, as its name implies, generates a forest consisting of many individual trees.
In general, a forest's appearance is strengthened by the presence of more trees. The same holds true with the random forest classifier, where an increased number of trees yields better overall performance.
RF(Random Forest) Pseudocode for creation
1) Choose "k" features at random from a pool of "m" features.
2) Given that k > m
3) Find optimal node "d" split point amongst provided "k" characteristics.
4) Create offspring nodes from parent node utilizing optimal split.

5) For an additional "l" nodes, repeat steps 1-3.
6) Create a forest by doing steps 1–4 "n" times. This will yield "n" trees.

The first step of the random forest method is to choose "k" features at random from a pool of "m" features. You can see that we are randomly sampling features and data by looking at the picture.
The next step is to use best split strategy with the randomly chosen "k" characteristics to locate the root node.
The following step involves determining the daughter nodes through the same best split method. We'll finish first three steps and then construct the tree, placing the objective at tip.
Finally, steps 1–4 are repeated to generate a "n" number of trees at random. The random forest is made up of these artificial trees.

Random forest forecast pseudocode:
Utilize following pseudocode to make predictions utilizing trained random forest method.
Predicts result (target) based on the test characteristics using rules of set of randomly generated decision trees.
Vote exceeds for every forecasted objective should be calculated.
Final prediction from random forest method may be thought of as high-voted predicted target.
Test features must be processed according to rules for every randomly generated tree in order for trained random forest algorithm to provide a prediction.

5. SYSTEM ARCHITECTURE

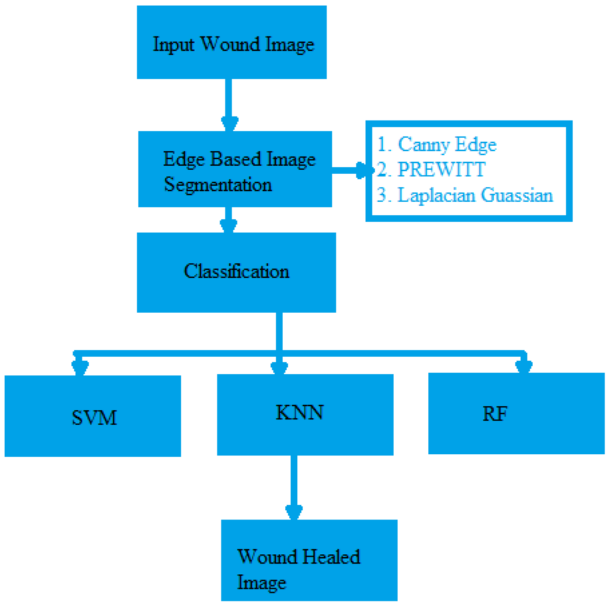


Figure 1: System Architecture

The utilization of this module involves conversion of image to grayscale & removal of noise. This process is achieved by employing algorithm that partitions image in distinct regions or parts, specifically for reason of wound assessment. Additionally, such module provides the capability to extract edges of image.

6. RESULTS AND DISCUSSION

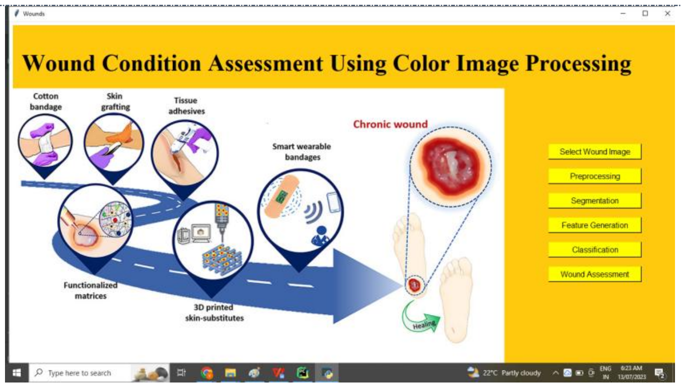


Figure2 : Menu

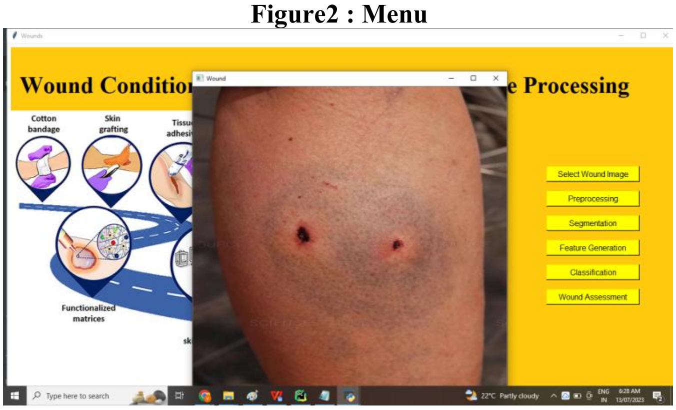


Figure 3: Input image

Inputting the image using this module initially

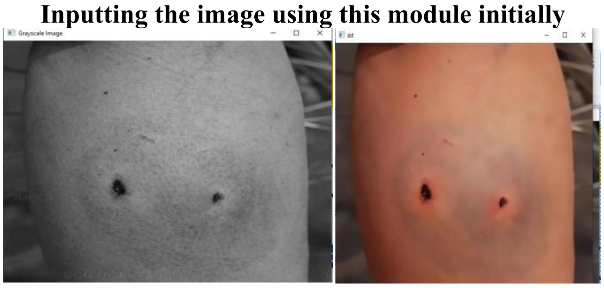


Figure 4: Pre-processing

Grayscale Image and De-noised Image
Converts color picture to gray scale & eliminates disturbance from an image using denoised algorithm

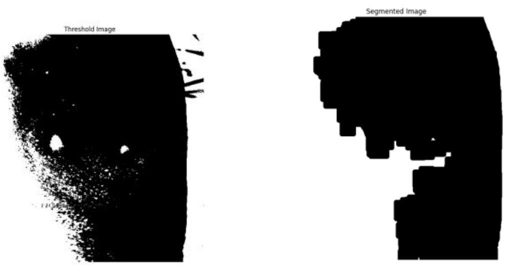
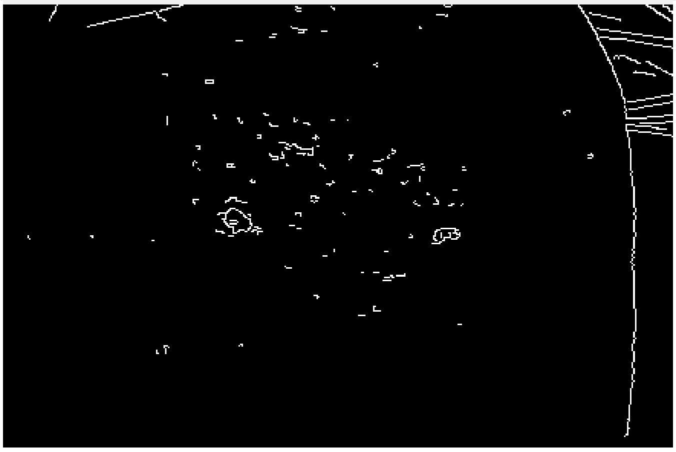


Figure 5:Segmentation

to partition the wound image into multiple wound parts or regions, for wound assessment purpose



Figre 6 : Feature Extraction

Gives the edges of an image

SlNo	WoundAssesement	Tests
1	Cause of Wound	Itching
2	Duration	2 Weeks
3	State of wound	Small
4	Current State of Health of patient	Normal
5	Color, amt,consistency	Black,small,medium

Table 1: Wound assessment Result

7. CONCLUSION

The next step of this research is to create WIAC for accurate monitoring of wound recovery. Creating a robust classifier for quantifying the wound-healing process. Images of wounds are labeled according to their severity using classifiers. Color image processing methods such as categorization, filtration, denoising, & transparent overlay were employed to provide a useful tool for analyzing the wound-healing process. Helping a doctor diagnose condition of wound noninvasively by detecting cells in picture of wound & estimating how healthy those cells are. This instrument makes it simple to evaluate wound deterioration. Tool's efficacy may be determined by comparing pictures it uncovers with database of actual wound images.

REFERENCES

1. Wound status evaluation using color image processing, G L Hansen [1], E M Sparrow, J Y Kokate, K J Leland, P A Iaizzo, 1997,
2. A Systematic Investigation of Models for Color Image Processing in Wound Size Estimation, Filipe Ferreira, 2021,
3. A Survey of Wound Image Analysis Using Deep Learning: Classification, Detection, and Segmentation, RUYI ZHANG1 , DINGCHENG TIAN 1 , DECHAO XU1 , WEI QIAN1,2 , AND YUDONG YAO,2021
4. Detect-and-segment: A deep learning approach to automate wound image segmentation panelGaetano Scebba [a], Jia Zhang [a], Sabrina Catanzaro [b], Carina Mihai [c], Oliver Distler [c], Martin Berli [d] , Walter Karlen ,2022,
5. Kerstein MD: The scientific basis of healing. Adv Wound Care 1997; 10(3):30-36
6. Kane D: Chronic wound healing and chronic wound management, in Krasner D, Rodeheaver GT, Sibbald RG. (eds): Chronic Wound Care: A Clinical Source Book for Healthcare Professionals, Third Edition. Wayne, PA, Health Management Publications, 2001,pp 7-17.
7. B. Coulomb, P. Saiag, E. Bell, F. Breitburd, C. Lebreton, M. Heslan, and L. Dubertret, “A new method for studying epidermalization in vitro,” Brit. J. Dermatol., vol. 114, pp. 91–101, 1986.

8. MacLeod J (ed): Davidson's Principles and Practice of Medicine, Thirteenth Edition. Edinburgh UK, 1981, pp 590-592.
9. J. R. Mekkes and W. Westerhof, "Image processing in the study of wound healing," Clin. Dermatology, vol. 13, no. 4, pp. 401-407, 1995.
10. Thomas A. Krouskop, Robert Baker, Michael S. Wilson, "A noncontact wound measurement system",Journal of Rehabilitation Research and Development, Vol. 39 No. 3, Pages 337-346,2002.
11. William Paul Berriss, Stephen John Sangwine, "Automatic Quantitative Analysis of Healing Skin Wounds using Colour Digital Image Processing",World Wide Wounds ,Edition 1.1,1997.
12. Herbin M, Bon FX, Venot A, Jenlouis F, Dubertret ML. "Assessment of healing kinetics through true color image processing", IEEE Transactions on Medical Imaging, 12(1). p. 39-43, Mar 1993.
13. Thomas Gilman,"wound outcomes: the utility of surface measures",Lower Extremity wounds, 3(3),pp 125-132,2004.
14. P Plassmann, KG Harding, JM Melhuish, "Methods of Measuring Wound size - A Comparative Study", WOUNDS, vol.6, no.2, p.54-61, 1994.
15. Julien Mairal, Michael Elad, and Guillermo Sapiro, "Sparse Representation for Color Image Restoration" IEEE Transactions On Image Processing, Vol. 17,No. 1,January 2008.
16. Sylvie treuillent, Benjamin Albouy, and Yves Lucas "Three-Dimensional Assessment of Skin Wounds Using a Standard Digital Camera" IEEE Transactions On Medical Imaging, Vol. 28, No. 5, May 2009.
17. Hazem Wannous , Yves Lucas, and Sylvie Treuillet "Enhanced Assessment of the WoundHealing Process by Accurate Multiview Tissue Classification "IEEE Transactions On Medical Imaging, Vol. 30, No. 2, February 2011
18. Hazem Wannous a, Yves Lucas b, Sylvie Treuillet, "Efficient SVM classifier based on color and texture region features for wound tissue images", Medical Imaging 2008: Computer- Aided Diagnosis, Proc. of SPIE Vol. 6915, 69152T, (2008)
19. AI-Assisted Assessment of Wound Tissue with Automatic Color and Measurement Calibration on Images Taken with a Smartphone2023
20. Yu, L.; Fan, G. DrsNet: Dual-Resolution Semantic Segmentation with Rare Class-Oriented Superpixel Prior. *Multimed. Tools Appl.* **2021**, *80*, 1687–1706.