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CHRONIC WOUND AREA SEGMENTATION AND CLASSIFICATION

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Abstract: Identification and treatment of chronic wounds (CWs) are considered economic and social challenges, especially with respect to bedridden and elderly persons. CWs do not follow a predictive course of healing within a particular period. Their treatment and management costs are very high. Also,CWs decrease quality of life for patients, which cause severe pain and discomfort. The process of chronic wound healing is very complex and time consuming. Quantification of wound size plays a vital role for clinical wound treatment as the physical dimension of a wound is an important clue for wound assessment. The current techniques for wound area measurement are the ruler method and tracing which is mainly based on visual inspection, thus are not very accurate as well as time- consuming.. A computerized wound measurement system can provide a more accurate measurement, reduce bias and errors due to fatigue and can potentially reduce clinical workload .Here a efficient method for wound area segmentation based on ANN with color and texture Feature . The framework was trained and tested using 358 RGB images from Medetec wound database .Here we also proposed a simple but efficient method for wound area segmentation The satisfactory results obtained by this system make it a promising tool to assist in the field of clinical wound evaluation and suggest treatment .

***IndexTerms*-ANN,ColorFeature,ChronicWound.**

I.INTRODUCTION

Wound can be defined as the breakage of normal skin tissue due to violence, accident, or surgery.Based on the time needed for healing, wounds can be classified into two types: acute wound and chronic wound. As defined by the Centers for Medicare and Medicaid Services, chronic wounds are wounds that takes more than 30 days to heal. The current clinical techniques for wound measurement are the ruler method and tracing based method which requires much human involvement and these methods

mainly based on visual inspection . They are also subject to intra and inter-reader variability. In the tracing method, a square marked transparent foil placed on the wound and the wound boundary is marked using a pen. The wound area is measured by summing the square area which belongs to the traced wound boundary. Its accuracy is limited due to less contribution of squares which are located on the border of the wound A wound can be defined as deterioration and injury in the regular anatomical structure and function of the patient's skin. They emerge from various pathological operations that can start either externally or internally in any human organ. Wounds are divided into two main categories depending on healing time, which are acute and chronic wounds . Acute wounds (AWs) emerge as a loss of skin tissue during a surgery or accident, which naturally are repaired in a short time with a systematic healing process. However, chronic wounds (CWs) do not follow a systematic healing process and take longer to heal than AWs. In most clinical practices, wound assessment is primarily based on visual inspection by a dermatologist, which is subjective, time-consuming, and potentially error-prone. Therefore, a computer-aided diagnosis (CAD) system is in demand to process and analyze color images of CW. Such a CAD system can be utilized to segment and classify different wound tissues and present an objective, accurate assessment for various types of CWs Implementing a non-invasive, automatic wound diagnosis and monitoring system has great significance . CAD systems can provide a cost-effective and quantitive solution for precise observation for wound healing state Furthermore, accurate diagnosis and monitoring of the CWs are crucial for providing effective treatment. The CAD systems can be used to monitor the wound healing by segmenting various tissues and tracking the changes in tissues present in the wound, or its surrounding areas, over time. From this perspective, CW assessment could be based on the analysis of significant regions within different tissue types, each having homogeneous color and texture features.

II. LITERATURE SURVEY

Various research works has been done based on chronic wound processing and analysis for different disease diagnosis.

The CW diagnosis and monitoring are considered an active research area in the medical image analysis eld. There are many research groups that are working in different wound types. For example, Veredas et al. [1] introduced a wound area detection system based on statistical color models. They created color histogram models based on the k-means cluster-ing approach for four various wound tissue types, which are granulation, slough, necrosis, and periphery tissues. From a Bayesian perspective, they utilized back- projections of color pixels on the generated histogram models to calculate an estimation of the posterior probability of a pixel to belong to the four tissue classes. The resulting probabilistic model had been complemented with topological models of tissue distribution. Then, Gaussian and morphological filters are used as noise reduction techniques. Finally, they applied the region growing technique with thresholding approaches to get the final region of interest (ROI) of the wound and healing

areas. In this paper, the authors only presented a tissue classification system for PU images based on identifying three wound tissues in addition to the periphery tissues.

Hani et al. [2] developed a system that detects the beginning of a PU healing by using the hemoglobin content as a marker. They applied the principal component analysis (PCA) technique to whiten the data. They used independent component analysis (ICA) technique to extract gray level hemoglobin from PU images. Then, they implemented a k-means clustering technique to segment detected regions of granulation tissue. In this paper, the authors did provide an effective measure for the healing process for PUs. They detected and segmented the granulation tissue and ignored the other tissue types..

Wang et al. [3] proposed a wound analysis system that run on Android smartphones. They applied the accelerated mean-shift algorithm to segment wound images. The healing status is assessed based on the red-yellow-black color evaluation model. They detected the foot outline by finding the largest connected component in the segmented image. In this paper, the authors did not compute a score for the healing status of the wound.

Seixas et al. [4] implemented a segmentation approach for skin wound images. Their system is based on proposing an approach to a seed for the region growing segmentation technique. Also, they utilized the energy of each color channel for the RGB images to enhance the range of the possible values for each tissue type. The main concern of this article was to nd a good seed for the wound segmentation technique. The authors did not present any results of the evaluation of their proposed segmentation method. Wang et al. [5] proposed a deep learning technique to segment and analyze the area of the wounds automatically. They proposed a deep convolutional neural network (CNN) to segment the wound area. Also, CNN is used to extract the signicant features to detect infection via support vector machines (SVM) technique and predicted the healing pro-cess via Gaussian process (GP) regression. In this paper, the authors did not compute a score for the healing status of the wound.

III.METHODOLOGY

The methods proposed are applied in the system through two procedures. During the training procedure, chronic wound images in the database are segmented by different methods with their corresponding optimized parameters .During the operation procedure, the wound region in any new wound image will be automatically recognized and evaluated by the trained system based on feature vectors of segmented image.

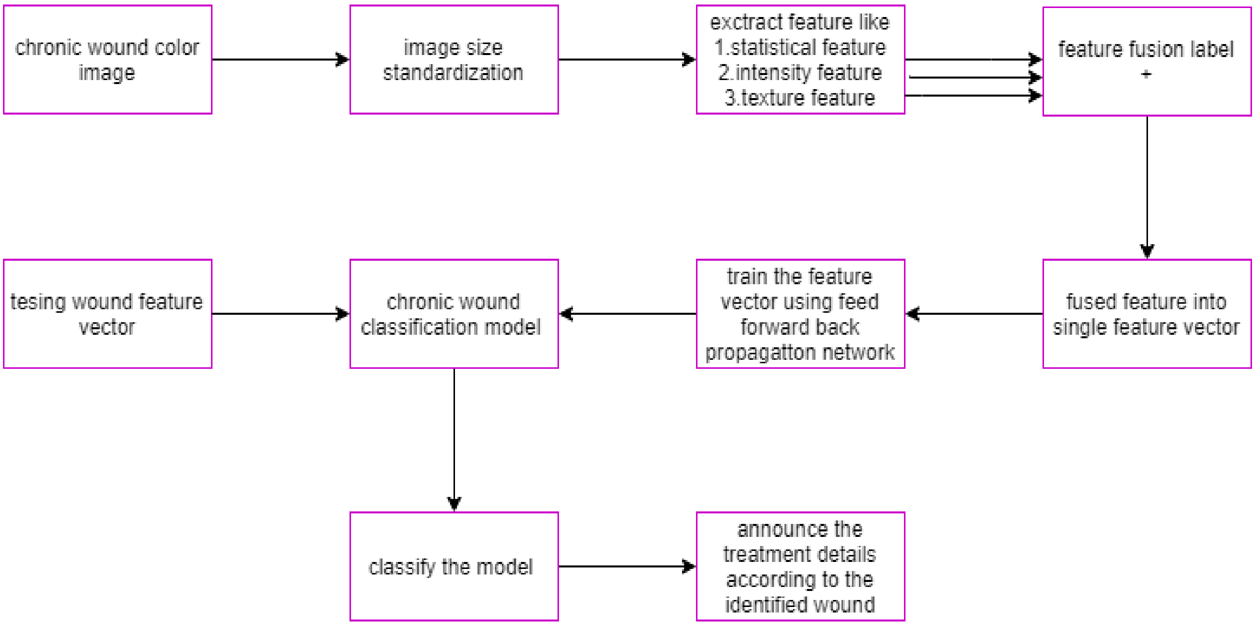
First of all we collected enough chronic wound image from Medetec wound data base, after the collection of images which are standardized for further steps of procedure .Feature extraction is Important ,it include 1.color feature,2.Texture Features,3.LBP feature. Almost 80 feature are collected ,Next step was develop Artifical Neural network for classification and detection of Cws.Made training feature data set & given label name to identify different wounds.After that saved the feature and label directory for ANN training.The developed ANN model is used for training and testing purpose.Here we used 12 types of wounds.which are classified and 12 types of these wound need different type of treatment.Which is also shown with each type of wound in output.which give a medical knowledge for patient We used 358 CW images to train and test our proposed frame- work from the Medetec wound database was used,. Initially we create a data set of different chronic wound like abdominal wound, burn and scalds hemangioma etc.here we used MATLAB 2019 .After we extracted different significant features to classify various tissue types from the contrast-enhanced CW colored images . The most significant information elicited from the processed images comprises color, texture(GLCM), LBP features. After all the feature extraction we gave this data to ANN.Here we contain training and testing set we got almost 80feature . Use FEED FORWARD BACKWARD NETWORK based on back propagation algorithm. ANN is made confusion matrix .Here 20 hidden layer ,and 1 output layer is used .There are many chronic wound which are pre processed before the feature extraction. After that we collected almost feature from images .That images gave to ANN for training and testing..12 typed of wound need different type of clinical treatment .in testing t ime which suggest treatment. Other than this 12 wound are marked as unknown..The treatment will announce in audio and text format.

In the case of CW area calculation first of all the RGB image of CW converted into YUV format..Then the using multithresh ostu's method CW is segmented INTO 3 format

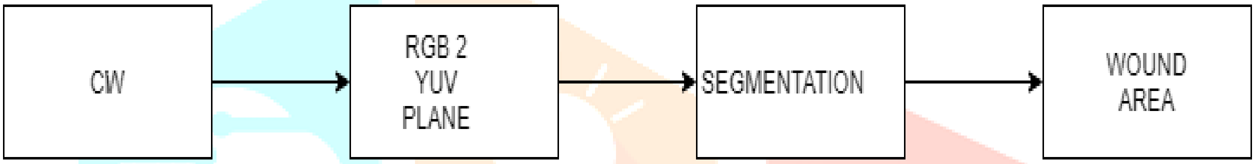
1.desired wound
2.background
3.intermediate

Those 3 segment is collected and we find out the area of CW and ratio to the total area.

3.1System architecture



3.1 block diagram for CW classification



3.2 block diagram for CW segmentation

3.2 PRE -PROCESSING

. All the chronic image should be standardized in the (224*224*3). It helps t he is an important step which ensures that each input parameter (pixel, in this case) has a similar data distribution.

3.3 FEATURE EXTRACTION OF CW I M A G E

Chronic wound feature is an important and widely used visual feature in image processing and analysis which plays an important role in the human visual perception mechanism. Image color is invariant with respect to the size of image, translation and rotation of image. The different methods used to extract color feature from image are histogram method, statistical method, and color model. The number of pixel of given color is calculated in color histogram method. In the color model method, mdm color is represented by the single point where in the color space every color has its color coordinates. RGB model, CMY model, HSV model these are some majorly used color models . The statistical model is the one used in syetem-1 to extract color feature. The statistical methods classified as a first order (one pixel), second order (pair of pixels) and higher order (three or more pixels) statistics. First order histogram statistics are mean, variance, skewness and kurtosis . Color moment have the highest precision to extract color featur A gray level co-occurrence matrix (GLCM) is most commonly used method for texture analysis in which various textural features extracted from a gray level co-occurrence matrix.Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Here in feature extraction method almost total 80 type feature are collected fromCW.which are fused to form a new model.Which are collected to give FEED forward backpropagation network for training and testing.

3.4 CLASSIFICATION

The classification algorithm contains two phases: training phase and testing phase. In the training phase, training instances is constructed whereas in testing phase; label is assigned to an unlabeled test instance. Artificial Neural Network (ANN) consists three layers of neurons - input, output and hidden where information is constantly "fed forward" from one layer to the next. Network is attuned until the network output matches the target (based on the comparison of the output and the target.

3.5 SEGMENTATION

Thresholding algorithm that is used to separate the pixels of an input image into several different classes, each one obtained according to the intensity of the gray levels within the image .By using this algorithm found ot correct CW area.and calculate the ratio.

After particular factor is priced. Fama and McBeth(1973)develop a two pass methodology in which the beta of each asset with respect to a factor is estimated in a first pass time series regression and estimated betas are then used in second pass cross

IV. RESULTS AND DISCUSSION

This paper implements an image processing method, trying to segment different chronic wound and find out the features of the input images using feature extraction methods. We used 358 CW images to train and test our proposed frame-work from Medetec wound database was used .The images are fetched and classified into 12 groups .The images are classified into 12 wound group and one unknown .The total accuracy of this project is 98.%.The final out put is suggest the better treatment for each disease. 80% of image are trained.and got feature from each image and fused image into a feature vector, while we testing it classify the model result to anyone 12 chronic wound or unknown.

	Label	Count
1	Abdomina ...	11
2	Burn and S...	19
3	Epidermoly...	5
4	Extravasati...	20
5	Foot wound...	48
6	Hemangioma	6
7	Infected an...	31
8	Malignant ...	9
9	Meningoco...	24
10	Orthopedic ...	49
11	Pressure ul...	84
12	Venous leg ...	79

Fig4.1 CW classification

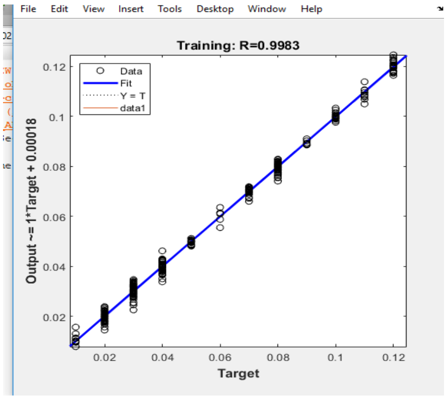


Fig4.2 Training analysis

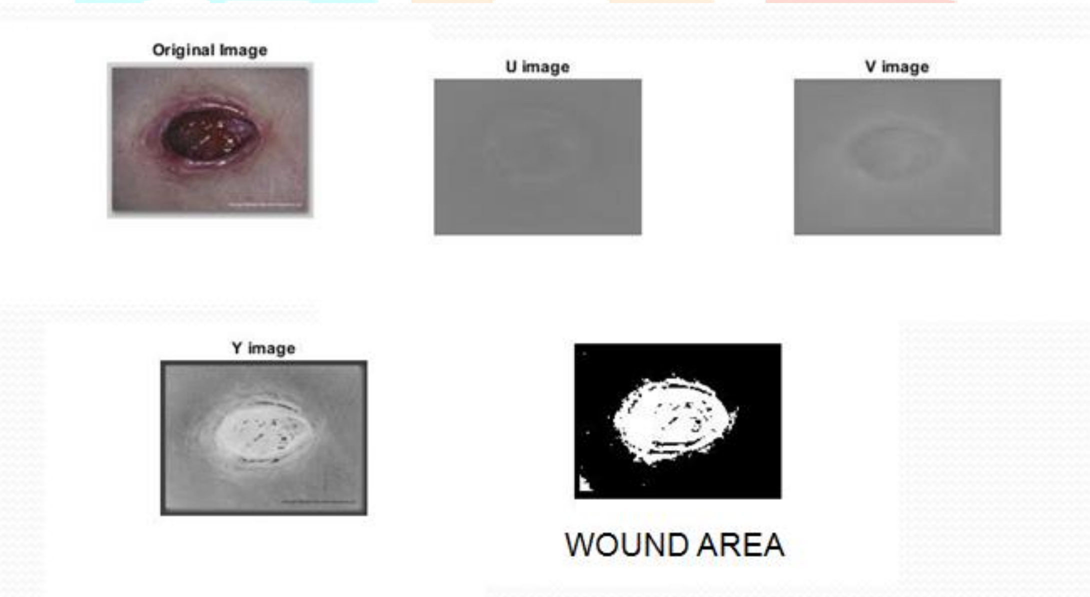


Fig 4.3 CW segmentation

4.1 performance analysis

Table 4.1: ANN performance analysis

class	accuracy	sensitivity	specificity	ERR	PRECISION	FPR	recall	F1-scope
1	99.481	0.14	0.020	0.51948	90.909	0.26738	200	90.909
2	99.059	0.02	0.007	0.94118	97.959	0.26738	400	96
3	99.345	98.795	99.467	0.44248	97.619	0.53333	200	98.204
4	99.558	100	99.467	0.44248	97.468	0.53333	100	98.718
5	99.746	95	100	0.25445	100	0	200	97.436
6	100	100	100	0	100	0	100	100
7	99.746	95.238	100	0.25381	100	0	200	97.561
8	99.762	100	99.733	0.23753	97.917	0.26738	100	98.947
9	100	100	100	0	100	0	100	100
10	99.753	96.875	100	0.24691	100	0	200	94.413
11	99.738	100	99.733	0.26178	88.889	0.26738	100	94.118
12	100	100	100	0	100	0	100	100

The performance analysis of the system was done using the statistical measures for Binary Classification like Sensitivity, Specificity and Accuracy. Sensitivity measures how well a particular test predicts one category from another. Specificity measures how well a particular test predicts the other category and Accuracy measures how well the test predicts both the categories. The equations are given below:

1. Accuracy = ((TP +TN)/(TP +TN +FN +FP)) 100
2. Sensitivity = (TP/(TP + FN)) 100
3. Specificity = (TN/(TN + FP)) 100
4. Error rate = ((FP +FN)/(TP +TN +FN +FP))100
5. Precision = (TP/(TP + FP)) 100
6. False positive rate = (FP/(TN + FP))
7. Recall = (TP/TP + FN) 100
8. F1_Score = (2 TP/(2 TP + FP + FN)) 100

Here,

True Positive(TP) - means the total number of diseased images correctly identified by the algorithm .
True Negative (TN)- means the total number of diseased images mistakenly identified by the algorithm.
False Positive(FP) - means the total number of diseased images correctly rejected by the algorithm.
False Negative(FN) - means the total number of diseased images mistakenly rejected by the algorithm.

V. CONCLUSION

We have proposed a automated wound area segmentation . The feature extraction for this method is very simple a computationally efficient. There is a one-time cost of training with a set of manually traced images; once trained, the system is fully automated. The satisfactory results of the identification system demonstrate that the proposed methods and implemented system are a promising way for automated clinical wound assessment, and the reduction of the human error and intensity guarantees the greater accuracy. The aound area calculation will give enough knowledge about of healing time.The Future works may include further optimization of the system based on these preliminary results. The better output accuracy better than any other previous methods

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