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Analysis and Classification of Diabetic Foot Ulcer Using Kernel Graph Cut Method

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Abstract:*Diabetic foot ulcer is the complication of diabetic mellitus (DM) by increase of glucose in the blood results in nerve injury, by preprocessing technique the image suppresses unwanted distortion or enhances some image feature. Several techniques is used where segmentation is considered as one of the major step in medical image processing which divides a digital image into multiple regions to analyze and distinguish into different objects. First the image is classified by Support Vector Machines (SVM), K-Nearest Neighbor (K-NN) classifier and wound image analysis classifier (WIAC) are trained for classifying various set of wound images by their own set of features. The output of each classifier is an overlaid on segmented wound image, which measures the Further, the segmentation is done by Kernel Graph Cut segmentation process the redefinition of the contours of the wound image carried over, thus the wound determined is segmented, which measures the severity level of the wound for every texture covering on the segmented wound image.*
Keywords: *Kernel Graph Segmentation, KNN, SVM, WIAC*

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I. Introduction:

Generally, it is common that human being is affected by wounds. The wound is resulted due to injury out of cut or burn etc., and most of the time occurs accidentally. The formation of the wound is generally due to the dead tissue which gets formed at the location where injury occurs. Hence it becomes inevitable to devise a method to heal the wound at the earliest and for achieving this it is required to assess the wound based on its type and the severity level. The present work finds different techniques to capture the image of the wound, for performing the wound assessment. The wound assessment is carried out after filtering the wound image by removing the air bubbles and hair around the wound in order to clean and segment the wound image to estimate the healing time required. A detailed case study on the formation of a wound and stages involved in the healing process of the same along with the types of tissues and its color intensity has been discussed by eminent personalities in the past. Various techniques involved in the analyzation and healing status of wounds by using color image processing. One such techniques, is novel classifier which classifies the wound based on the severity and applying overlay segmentation to reduce the severity and changing the severity level as classified labels. The wound healing status is monitored by analyzing and classifying the wound based on its severity level, the process of converting unhealthy tissues into healthy tissues are called as wound healing process has to be taken up. Considering the tissue classification as the fundamental criteria, the assessment of the wound healing process is performed; wound healing process undergoes various phases and mostly depends on several factors like age, gender, and health conditions etc., of the patient. By assessing wound healing process, it is always possible to estimate the efficacy of the drug to be administrated to the patient under medication. A new classifier Wound Image Analysis Classifier (WIAC) is developed which classifies the wound as superficial, deep dermal and full thickness based on the severity of the wound. This classifier classifies them into any one of the severity level as '0' or '1' or '2'. A novel classifier which uses transparent overlay as drug and it is applied on the segmented wound classifies the wound based on its severity level as metric. Different segmentation techniques were used to analyze and choose the best segmented image based on the quality, area, size and shape of the wound. Classifier classifies the wound based on various characteristic features like intensity of the various colors present in wound image. A linear model (classifier) which distinguishes background and cellular local patches known as patch classifier is part of the segmentation algorithm in the wound image analysis classifier techniques. Second level classification of cellular regions which are tagged as background by the patch classifier is carried out by an additional classifier trained on spatial clusters of local patches (regions). When a wound image is under test, a grid of textures is overlaid on it. The severity level of the segmented wound is produced by each texture is assigned to the overlay classifier and further the regions marked as background are further classified by the regions classifier. By applying the Kernel Graph Cut segmentation process the redefinition of the contours of the wound image are carried out. Support Vector Machines (SVM), K-Nearest Neighbor (K-NN) classifier and WIAC are trained for classifying various set of wound images by their own set of features. The output of each classifier is an overlap score for every transparent overlay overlaid on segmented wound image, which measures the severity level of the wound for every texture covering on the segmented wound image while classifying the wound. As defined by the linear model the overlap score of any given overlay is termed as the Euclidian distance of its feature-vector represented in the hyper plane. The three overlap scores for each overlay, one from each classifier, are further fed as a vector, into an additional training session that calculates the final classification, which is used to put weights on the output of the three classifiers to achieve the final classification known as classification stacking.

Project Management:

The two classifiers classify the acute and chronic wounds were further classified as pressure, ulcer, and diabetic. The major classification is internal and external wounds, the changes involved in chronic wounds which must be digitized frequently to analyze the changes and extracting the classifier decision based on classifying labels. In the next section a new classifier called SVM and its sub classifier like Multiclass SVM have been implemented to analyze the wound healing process and segmentation is carried further on kernel based segmentation to segment the wound depth and the effects.

Classification On Segmented Image:

The segmented wound images are partitioned into a grid of non-overlapping textures of 20*20 pixels. An expert visual inspection is carried out to mark the wound images and their corresponding pixel wise cell-background baseline markings are used as input for the training set. From each overlay, either sets of features or combination of features are extracted each one describing the texture's statistics to be used for separating wound textures, background textures, as follows:

a. Wound Image and overlay gray-level mean and standard deviation.
b. Histogram of Gray level overlaying.
c. Histogram of overlays gradient intensity, a measure for the amount of details in the overlay.
d. The spatial smoothness of the overlays is the only difference which can be observed between each pixel intensity and its neighbors surrounding pixel.
e. The features of a broader area surrounding the texture, including mean and standard deviation of gray-level, gradient intensity and smoothness, as well as gray-level histogram are concatenated.
f. The following listed analyses were performed to evaluate the contribution of each feature set to estimate the performance of the overall patch classifier.
g. Each of the feature vectors were evaluated separately in comparison to the combined overlay classifier i.e., using a single feature vector and the corresponding classifiers (SVM, K-NN, WIAC) as the overlay classifier on every data set. The results obtained using the intensity histogram were inferior and other feature sets were significantly marginal.

Discarding the intensity histogram feature set and training a overlay classifier based on the remaining feature sets resulted with inferior performance compared to the classifier that was trained using all feature sets. After the classification of local overlays, an additional classification of each spatially-connected component of the background textures is performed to decide whether it is actually a part of the background or not. The task of global regional classification is performed by a trained additional classifier event. The original image and the overlay map are used to extract the following features from a segmented wound image such as the region's size (number of pixels), a histogram based on the original image intensities and another based on the textures overlap scores. The following are the steps followed in any classifier:

a. First step of this classifier is to pick a wound from wound database.
b. Various segmentation techniques are applied to segment the wound from the wound image and selecting the best wound image by considering various factors like quality, area of the wound etc.,
c. The quality of the wound is improved by preprocessing the segmented wound image using filtering / denoising techniques.
d. The severity level ‘0’ or ‘1’ or ‘2’ is determined by classifying the filtered, denoised, segmented wound images into various levels.
e. The three most efficient classifiers namely SVM, K-NN, WIAC are used in the classification of the wound images.

f. After getting the severity level from various classifiers individually the transparent overlay technology is applied to transform the high severity level to low severity level and to extract the healed wound image.

Outline Of Wiac:

The present thesis focuses on automation of wound monitoring remotely by uploading wound images and making it available to the doctors and get treatment for the wound by analysing the status of the wound using automation methods of various image processing techniques. In this report different filtering, segmenting, clustering and classifying techniques have been applied effectively to analyze and classify the wound for obtaining wound healing assessment. An efficient classifier called 'WIAC' has been developed which uses segmentation and classification, filtering method as a denoising element and applying iteratively transformation overlay technique using image overlap for efficient tracking of wound healing status. This research which is divided into various chapters like denoising of wound images based on color, segmenting the region of interest of a wound image, classifying the wound based on severity level which can be computed by extracting intensity of the color of a wound. The subsequent section gives a brief explanation regarding various techniques involved in filtering, segmenting, classifying. The sections that are subsequently placed details the steps involved in the process of image database collection.

Fig 1.1: Deep wound with high severity level

Kernel Graph Cut Segmentation:

Unsupervised Wound Image Segmentation", an unsupervised segmentation technique has been applied for identification of region of interest in the wound images by removing unwanted regions of the wounds and to filter the edges of the wound, Gabor filtering technique is incorporated. In the study there are two methods namely Gabor Filters and Kernel Graph Cut are adopted for segmenting wound image. The various textures in the wound image are used for the segmentation of the image in the Gabor Filter method which entails the generation of a large number of two dimensional Gabor Filters called a Filter Bank to filter the concerned image. Once the filtration of the image under consideration is performed the process of feature extraction is assured. The optimized value of features extracted from the image under consideration enhances the performance of the clustering and segmentation of image processing. The second method adapts the multi region graph cut in a Kernel induced space uses a variety of features such as color, intensity, pixel relationships, texture vectors and spatial location of pixels for the segmentation of the wound image. This method involves in minimization of a function containing the original data term which allusions the wound image data transformed by means of a Kernel function. The two consecutive optimization algorithms repeated are Graph cut and iterative fixed point calculations for revising the parameters of the region.

II. Discussion And Comparison:

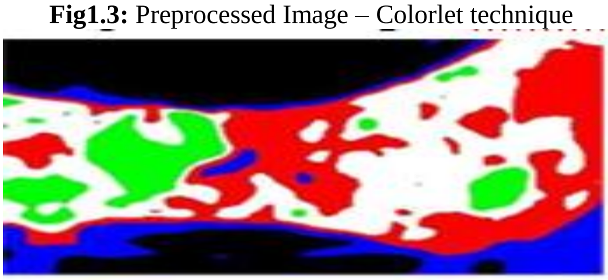
The proposed method which undergoes various phases like preprocessing, segmentation and classification has been implemented by taking a wound and undergoes median filtering technique which removes the hair depicted in figure 1.2

Figure 1.2: Original Image

Preprocessing Using Colorlet:

Colorlet transformation technique was employed on the figure 7.2 to the air bubbles and segmented wound leg on and around the wound and the result is as depicted.

Fig1.3: Preprocessed Image – Colorlet technique



III. Conclusion:

A unified framework for wound segmentation and wound condition analysis; with our proposed deep learning approaches to train various FCNs that can automatically detect and segment the DFU and surrounding skin area with a high degree of accuracy. These frameworks will be useful for segmenting the other skin lesions such as moles and freckles, spotting marks pimples, other wound pathologies classification, infections like chicken pox or shingles. This work also lays the foundations for technology that may transform the detection and treatment of DFU. This work has been done to achieve future targets that include: 1) to determine the various pathologies of DFU as multi-class classification and segmentation; 2) developing the automatic annotator that can automatically delineate and classify the DFU and related pathology; 3) developing various user-friendly system tools including mobile applications for DFU recognition and segmentation.

IV. Future Work:

In future made on two classifiers namely K-NN and Fuzzy in classifying the wound by pressure, ulcer and chronic wounds. These two classifiers classify the acute and chronic wounds were further classified as pressure, ulcer, and diabetic. The major classification is internal and external wounds, the changes involved in chronic wounds which must be digitized frequently to analyze the changes and extracting the classifier decision based on classifying labels. The classifying labels decide which type of wound rather than severity level. After classifying the type of the wound based on the tissue classification the assessment of wound healing process is studied in the subsequent chapters. In the next section a new classifier called SVM and its sub classifier like Multiclass SVM have been implemented to analyze the wound healing process based on the presence of various tissues like granulation, slough, necrosis and healthy skin.

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