Detection of Open Wounds on the Skin

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Abstract —Fast and accurate detection of open wounds is essential for effective medical treatment and prevention of infection. On this occasion, the author presents a system that can assist Computer Vision in detecting wounds on the skin surface from sample images using simple segmentation and machine learning. By partitioning the image into several segments, the image can be separated into foreground and background based on the similarity of the existing pixels. The Wound Detection System that we propose is classified as a Mid-Level Process, starting from the Input Image, followed by segmentation based on the similarity of red pixels, then classifying it using SVM, and ends with the output "This Image Does Have Open Wounds" or "This Image Doesn't Have Open Wounds". This system has also been tested with a variety of different images, both on images of skin wounds and those that are not, meaning that the majority of these images are red.

Keywords — Digital Image Processing, Kernel, Otsu Thresholding, Support Vector Machine, Wound Detection

I. Introduction

The skin is the arrangement of the five human senses which is the largest organ that makes up the human body which is the outermost surface of the body. The function of the skin is to regulate body temperature, protect internal organs, and cover the entire body surface. Numerous problems may occur on human skin, one of which is often experienced in wounds, both of mild, moderate, or severe severity.

Wounds are divided into two types: open and closed wounds. An open wound is a condition in which the skin tissue is damaged by a sharp object, shot, or hard impact with a blunt object that causes abrasions, cuts, or lacerations. While a closed wound is damage to skin tissue caused by blunt trauma. In this case, the patient's skin is intact as well as bruises, dislocations, and wounds to the muscles.

Digital image processing is a sub-field of computer science that discusses the use of computer algorithms to process images in digital form. Digital image processing itself aims to improve the quality of digital images and make it easier for us as humans to retrieve information from the digital image in question. There are many steps and techniques in performing digital image processing which will later be reviewed to detect open skin wounds.

Nowadays, the prevalence of technology and its shifting trends have shown people's tendency to send more messages to each other in the form of digital images. In this project, we are inspired to bring convenience and help more people by applying digital image processing techniques in real-life applications. Hence, we proposed to build a model that can detect the presence of open wounds.

II. Datasets

The dataset that was used in this project was obtained from Kaggle. In total, we use 1000 images, which consist of 500 wound images and 500 non-wounded images. Those images were stored in png, jpeg, and jpg formats. Among those images, 800 of them were plotted as training data, 100 images as validation data, and the rest as testing data. Moreover, the proportion between wounded and non-wounded images was equal in validation and testing data.

III. Methodologies

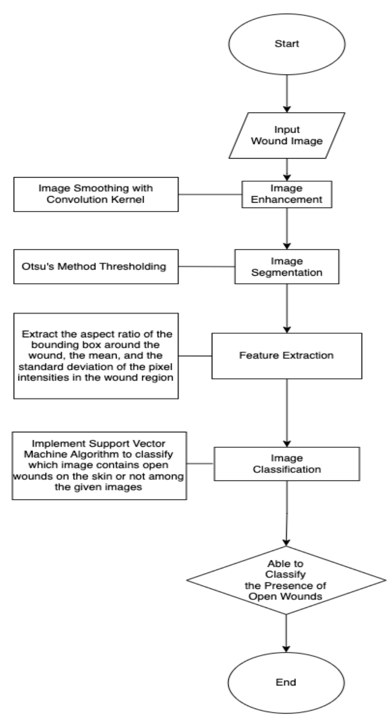


Figure 1: Flowchart Diagram

The primary method used in detecting wounds in images is segmentation. After inputting the image, the first step that the image will go through is image enhancement. Here we will use a convolution layer to blur the image. Then, we will proceed with the image segmentation based on the similarity of the red color (sore) and skin color. The next step is looking for the range of each pre-segmented pixel. The output image will be "This Image Does Have Open Wounds" if the range is more than 0.15 and will be "This Image Doesn't Have Open Wounds" otherwise. The prior flowchart diagram is the architecture of the Wound Detection System that we designed.

a. Python Library

In doing so we use a library that makes it easy for image processing. The libraries used are

1. OpenCV

   This library is used for image reading, changing the color channel of the desired image.

2. cv2_imshow (from google.collab.patches)

   This library is useful for displaying images that will be processed or that have been processed.

3. NumPy

   This library has the utility to perform various operations on arrays such as creating an array containing certain values, creating kernels, performing array padding, creating histograms from datasets, calculating the cumulative number of values in the dataset for weight and mean in the Otsu Method, and getting the largest value from an array.

b. Image Pre-Processing

Convolution is an important mathematical operator for many operations in image processing. Convolution provides a way to combine two arrays, usually for different array sizes in the same dimension, resulting in a third array with the same dimensions.

Image Convolution is a technique for smoothing an image or clarifying an image by replacing a pixel value with a number of pixel values that are appropriate or close to the original pixel. However, with the convolution, the size of the image remains the same and does not change.

Convolution has 2 functions f(x) and g(x) which are defined as follows:

$$h(x) = f(x) * g(x) = \int_{-\infty}^{\infty} f(a) \cdot g(x-a) da$$

In this case, the * signifies the convolution operator, and variable **'a'** is the auxiliary variable.

Here we use the Convolution function to blur the images, in order to smoothen them as they experience noise disturbance on the 3x3 kernel matrix. As a result, it will be easier to partition the image into several parts during the segmentation process.

Before proceeding into the segmentation process, we will also visualize the intensity histogram. An intensity histogram is a graphical representation of the distribution of intensity values in an image. It is a plot of the number of pixels with a given intensity value, and it is calculated by summing the pixel intensities of the image. For this visualization, we will pick one random image from the training datasets.

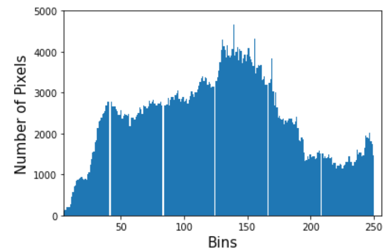


Figure 2: Intensity Histogram

As could be seen in the above figure, the horizontal axis represents the graph of pixel intensity in a contiguous flattened array fashion while the y-axis depicts the number of pixels of the image itself.

c. Segmentation

Image segmentation is a method of partitioning digital images into subgroups known as segments. Usually, the splitting or grouping process is based on the characteristics of the pixels in the image. Image segmentation can be the separation of the foreground from the background or the grouping of pixel areas based on similarities in color or shape. This process helps to reduce the complexity of the image when it is further processed. By separating it into segments, image analysis can be easier, faster, and more efficient. The segmentation algorithm is based on one of the two basic properties of discontinuity and similarity of intensity values. The first category is partitioning images based on sudden changes in intensity, such as edges in images. The second category is based on dividing images into similar regions according to predefined criteria. The Histogram Threshold approach is included in this category.

c.1 Otsu Method Thresholding

Thresholding is one of the methods that is widely used for image segmentation. This method is useful in distinguishing the foreground from the background. By selecting an adequate 'T' threshold value, the gray-level image can be converted into a binary image. The binary image must contain all the important information about the position and shape of the desired (foreground) object. The advantage of getting the first binary images is to reduce data complexity and simplify the process of recognition and classification.

Based on the pixel, the Thresholding technique is divided into 3 kinds namely: Basic, Adaptive, and Range. Otsu thresholding is one example of an adaptive threshold method that segments images into two classes.

The Otsu method works with a search technique for the distribution of the intensity values of the images used, the weight values are searched based on the two classes, the average calculation of the two classes, the total of the average value, and the search for the Between Class Variance value.

c.2 Check On Segmented Image

After the image is segmented, the first check will be carried out on the number of red pixels with predetermined red, green, and blue threshold values. The threshold value is determined by observing the pixel value intervals in images that contain open wounds.

If a segmented pixel has a red value that exceeds the red threshold value, a blue color value that is less than the "blue color threshold value", and a green color value that is less than the "green color threshold value", it will be entered into the variable number which holds the number of pixels that are considered a color. Red is a component of an open wound. If not, then no addition will be made to the variable amount.

If the variable number compared to all the pixels being checked has a percentage that is more than 1%, a second check will be carried out. If the comparison results are less than 1%, then the image is declared to have no open wounds.

At the last checking, the values that will become threshold values will be reassigned, namely the red threshold value, the upper green threshold value, the lower green threshold value, the upper blue threshold value, and the lower blue threshold value. These values are used to calculate the skin area around the wound.

If a pixel has a red value that exceeds the red threshold value, a blue color value that is more than the upper blue color threshold value, or a green color value that is more than the lower green color threshold value, it will be entered into the number variable which holds the number of pixels that considered the area of skin around a wound that is a component of an open wound. If not, no addition will be made to the variable amount.

If the variable comparison of the number of skin colors around the red color which is assumed to be a wound with all the pixels being checked has a percentage of more than 15%, the image will be declared to have an open wound. If not, then the image will be declared as having no open wounds.

d. Feature Extraction

Feature extraction is the process of extracting relevant features from the wounded images that will be used as inputs to a machine-learning model for wounded image detection. In general, the features can be derived from the pre-processed and segmented images using techniques such as edge detection, texture analysis, and color histogram.

In this case, after we have segmented the image, we can extract features from the wound region. These features will be used as input to the SVM classifier. In specific, for a particular image in the datasets, we will extract the aspect ratio of the bounding box around the wound, the mean, and the standard deviation of the pixel intensities in the wound region.

e. Classifications

From the results of the Feature Extraction, we will implement a Support Vector Machine apart from k-nearest neighbors to classify which image contains open wounds on the skin or not among the given images in the validation dataset.

Support Vector Machine (SVM) can be used for wounded image detection by training an SVM model on a dataset of wounded and non-wounded images. The images in the dataset are first pre-processed and segmented to extract the features, such as the area ratio, color ratio, and shape ratio. These features are then used as inputs to the SVM model, which is trained to classify the images as wounded or non-wounded. Once the SVM model is trained, it can be used to predict the class of a newly wounded image by extracting the features and feeding them into the model. SVM is a powerful algorithm that can handle high-dimensional and imbalanced datasets, making it well-suited for wounded image detection.

k-nearest Neighbors (k-NN) is a non-parametric and instance-based machine learning algorithm that can be used for wounded image detection. k-NN works by finding the k-nearest neighbors of a new wounded image and using their classes to predict the class of the new image. In the context of wounded image detection, k-NN would first be trained on a dataset of wounded and non-wounded images. The images in the dataset are pre-processed and segmented to extract the features, such as the area ratio, color ratio, and shape ratio. These features are then used as the inputs to the k-NN model, which is trained to classify the images as wounded or non-wounded.

Once the k-NN model is trained, it can be used to predict the class of a new wounded image by extracting the features and finding the k-nearest neighbors in the training dataset. The class of the new image is then predicted based on the majority class of the k-nearest neighbors. k-NN is a simple and effective algorithm that can be used for wounded image detection.

IV. Performance Metrics

In this project, we use F1-Score and accuracy as the performance metrics. The score of the performance metrics that have been obtained will be used to determine whether the methods and algorithms that have been used are reliable to detect wounds-related images. There are three methods used in this project, namely Support Vector Machine and k-nearest neighbors (using Manhattan and Euclidean as the distance metrics).

Implementing those methods to predict the validation data performs as depicted in the table below:

Prediction	F1 Score	Accuracy
Support Vector Machine	0.6969	0.7
KNN Manhattan	0.45	0.5
KNN Euclidean	0.58	0.6

Table 1: Performance Metrics

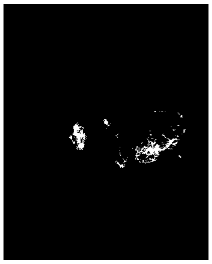
Hence, we may eventually deduce that SVM is the best method that could be used to predict wound-related images compared with k-nearest neighbors since it produces better results in terms of accuracy and F1-Score.

V. Results

The results of detecting skin wounds on skin images with open wounds can be seen in Figure 1 below.

(a)

(b)



(c)

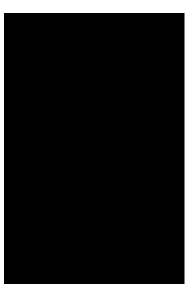
(d)

Figure 4: (a) Image of Skin with an Open Wound; (b) Image after Segmentation using the Otsu Method; (c) Image after Color Feature Extraction and Detection Results; (d) Image Classification

Then, the results of the detection of skin wounds in the skin image can be seen in Figure 2 below.

(a)

(b)



(c)

(d)

Figure 5: (a) Image of Skin without Open Wound; (b) Image after Segmentation using the Otsu Method; (c) Image after Color Feature Extraction and Detection Results; (d) Image Classification

VI. Conclusion

From the results obtained, it can be deduced that wound detection can be done by simple segmentation and using SVM. Namely, by comparing the characteristics of red pixels and skin color pixels, it has provided us with good results when comparing images with open wounds and those without open wounds. Furthermore, even in poor-quality images, we have proved that our model can detect the presence of open wounds with the help of the machine learning algorithm.

VII. Limitation

Here, the image dataset used is in the form of wounds on the skin and random images with red objects. So when segmented, the characteristics of the wound will be detected, particularly red pixels surrounded by skin color pixels. This method has limitations when the detected image is a skin image which includes objects that are not wounds but have a red color and are quite large in size. The non-wounded image will be detected as an image containing an open wound. This is caused by the feature extraction method that we use is limited to extracting color features in segmented images.

VIII. Suggestions

Based on the limitations described above, the next suggestion for development is the need to find out a method for detecting wounds with segmentation and feature extraction that does not only rely on skin color and the color of the object in the middle of the skin image. This can be done by utilizing feature extraction based on shape, line, edge, and using deep learning for the classification so that this design system can be applied to Computer Vision in real time. Furthermore, the implementation of Deep Learning methods such as Convolutional Neural Networks (CNN) during the classification of the image might improve the score of the performance metrics.

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