A Method for Human Burn Diagnosis Using Machine Learning and SLIC Superpixels Based Segmentation

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Abstract

The burn is a global health issue. The treatment of burn is performed by a burn surgeon. Burn region color is used to categorize burn types by a burn surgeon. Due to the lack of resources in many places burn patient dies. In such a situation a computer-based diagnosis system is very helpful. The severity of the burn is based on the depth and size of the burn region. The burn severity analysis can be accurately done by using the CIELab image as it contains all spectrums of colors. In the proposed work, the CIELab image is segmented using SLIC (Simple Linear Iterative Clustering) superpixel segmentation algorithm to form the same color pixels clusters. These clusters are used to diagnosis the severity of a burn. The severity of a burn is measured by the value of kurtosis. A high kurtosis value implies a larger depth and a small value implies a smaller depth. Based on the depth of burn, grafting or non-grafting is suggested by a burn surgeon. We observed depth of the burn is high in full-thickness burn compared to the deep dermal and the superficial dermal burn. The proposed method can correctly identify full-thickness burn and most of the deep dermal burn image. The open-access standard data set BURNS BIP-US DATABASE is used for training and testing of the proposed model on SVM (Support Vector Machine). The proposed model can classify with an accuracy of 89.16% and F1-score 90%. The achieved accuracy of the model is better than 79% of multidimensional scaling (MDS) in previous work.

Index Term: SLIC, Superpixels, Burn, Segmentation, Classification, Graft, SVM.

1. Introduction

The human body is covered with skin. It regulates fluid and temperature in our body. Skin anatomy is complex and many structure layers are available in the skin. The human skin burn injury is caused due to heat, radiation, electricity, radioactivity, or chemicals. Thermal burns
destroy cells and other tissue of the skin. The burn is a global health issue [1] and the fourth significant cause of unintended injury death [2].

According to WHO (World Health Organization), approximately 1.8 million people die due to the burn injury. The medical costs for burn injury by countries are very high. If the impact of burns on the skin is high, then the patient can lose control. So it is necessary to give the first treatment to the patient as soon as possible. The primary therapy is performed depending on the burned part's intensity and severity. Burn region, depth, and place are key considerations in determining burn severity. An important component of the skin is the epidermis and dermis. The dermis is the dense inner layer, whereas, the epidermis is known as the outer thicker portion of the skin. The three kinds of burns are SD (superficial dermal) burn, DD (deep dermal) burn, and FT (full-thickness) burn, and it is essential to create the distinction between these three kinds of burns [3] [4]. The exterior skin or epidermis is affected by superficial dermal burns. It appears red, painful, and dry to the impacted portion. It may have blisters as well. The skin's dermis layers are affected by deep dermal burns. The portion of the burn seems blistered, red, and painful. FT burns kill the dermis and epidermis as well as the subcutaneous tissue. The impacted portion of the burn appears white, black, or charred.

The important part of the present research is labeling such items so that they can be properly handled. Also, the images of skin burn are improved for proper treatment for expert assessments [2]. The purpose of the research is to identify and classify burn based on color characteristics. The color characteristic such as color, intensity, and hue of burn region is used to classify SD, DD and FT burn. The healing time of these burns varies; SD burn heals after two weeks with proper treatment. DD and FT damaged the inner layer of the skin. If the depth of burn is high grafting is done by a burn surgeon. Therefore, it is essential to determine burn depth correctly. Incorrect diagnosis may lead to an increase in health risk [3, 4,5]. Due to complicated skin layer burn classification is difficult and 64 -76% accurate diagnosis performed by burn surgeon [2].

The burn identification and classification system have been developed in the past. The burn depth identification proposed by Rangayyan et al. [7] has used pixels wise feature extraction approach, due to which the burn depth identification result of the classifier is not optimal. In the present study, the SLIC superpixels segmentation algorithm is applied to form a cluster of similar region burns. Instead of all pixels, we calculated features from segmented regions to trained our model. We also calculated the kurtosis value from the segmented region to see the pattern of depth on the burn. The observed pattern confirmed that the kurtosis value is high in the FT burn. Based on the value of kurtosis the graft and non-graft are predicted by the SVM classifier. The proposed method better estimate the depth of the burn region as compared to state-of-the-art methods. This research will help burn surgeons to perform grafting if required in DD and FT burn.

2. Related Work
A medical image diagnosis is a challenging task. The diagnosis of the burn image is performed by an expert surgeon. The color of the burn region is used to identify the burn types. The image processing and machine learning approaches are very popular to help a burn surgeon. Several works have been performed to classify burn. Bade et al. [2] have used a deep learning approach to identify a burn. The approach was based on the characteristic of a whole patch and pixel-wise features. This approach is expensive in terms of calculation and prone to noise. It is therefore not possible for their classifier to produce optimal performance. King et al. [5] have identified constructive wavelengths to allow the automatic identification of burns and tuning the automated classification system. It also looks forward to future porcine fire studies. The knowledge base is considered a strong base to map essential tests.

The ROC (Receiver Operating Characteristic) model result is helpful for the diagnosis of burn. Li et al. [6] introduce multi-spectral imaging (MSI) to identify a burn injury. The work allows a burn surgeon to identify tissue for surgery on a burn region. The approach improved the reliability of the identification of the burn model significantly. Rangaraju et al. [7] have suggested a clinical technique for grafting and the degree of a burn. Changes in the original skin structure and stress on the body make it possible to produce densely packed tissue in the skin. Their method classifies burn types based on coagulation (clotting). The collation ratio of 0.65 is considered as FT burn, whereas the collation ratio of 0.35-0.65 is considered as DD burn. The SD burn collation ratio is below 0.35. Sabeena and Kumar have used SVM [8] to accurately define burns and their segmentation. Having an effective burning and intervention system is the main idea behind their work. The pre-processing and segmentation technique can segment the burn region. The system classification accuracy is not optimal. Suvarna and Niranjan[9], have compared the classifiers SVM, TM(Template Matching ), and k-NN(k-Nearest Neighbours) on the burn image. The study suggests SVM classification accuracy is better than TM and k-NN but they have not collected the facts and features of burn image. Therefore, classification accuracy is less, and further, it can be improved. Acha et al. [10] have used a technique to find the depth of the burn. They have segmented the image and features were extracted from concerned objects to calculate the depth of the burn.

A machine learning technique Fuzzy-ARTMAP neural network classifier has been used to classify burn. The ARTMAP is considered a family of Adaptive Resonance Theory (ART)-based neural network architectures. It is fast and capable of stable, interactive, supervised or unsupervised learning, classification, and prediction. The ART unmonitored network map area and non-linear machines determine the extent of the burn. Tran et al. [11] has used CNN (Convolution Neural Network) to classify burn and identify the depth of the burn. This analysis helps doctors to identify burn depth and take a decision for treatment.

In Hong-yan Li's paper [12], the degree of skin burns is determined by the mean of the standard deviation of the color map also the histogram and percentage of burned areas. The skin burns assessment template is constructed by measuring distributed and weighted values. The researchers have also set a threshold that can distinguish the various types of burns. Yadav et al.
[22] developed a feature extraction model to classify the burn into two types. Type one requires grafting and others don't require graft. By diving data set into two classes. They suggested superficial-dermal burn doesn’t require grafting but in deep-dermal and full-thickness burn may require grafting. They have used SVM to classify burn and automated system classification accuracy was 82%. Cirillo et al.[23] proposed a comparative study to segment the burn image. They used tensor flow to segment the color burn image. They have also compared different segmentation techniques like PCA (Principal Component Analysis), ICA (independent component analysis), Tucker, JSEG, and SLIC on CIELab color images. The authors suggested SLIC superpixel is accurate and gives better segmentation accuracy.

Concerning the burn identification, features of a burn region are important. These features are used to differentiate a burned image and a healthy image. The best-selected feature makes the system more reliable and an error probability is less. The doctors determine the depth of the burn by the color of a burn region. The first step to designing a computer-based system is the identification of color from a burn region. The burn surgeon also categorizes burn based on the color value of the burn region. In the present work, the texture and color of the burn region are considered to identify the burn. The color of all spectrums is available in CIELab image and the color spectrum is also beyond human perception. This is the reason to choose the CIELab image for burn identification and classification. The present study focuses to develop a computer-based automated model to determine the depth of the burn and classify them into graft and non-graft.

3. The Proposed Model

The burn types have been discussed in the literature [15, 16]. The methods can differentiate burn into full-thickness, deep-dermal, and superficial-dermal. However, most of the existing methods lack in consistency and are failed to classify burn as graft and non-graft based on the depth of the burn. This creates a need to develop an automated and robust system, which has good classification accuracy and can segment a burn into graft and non-graft.

The treatment of burn is performed after the diagnosis of the burn region. The severity of burn determination is very complicated. The expert surgeon uses color properties of burn skin to determine the severity of the burn. Grafting is generally performed on the full-thickness burn and deep-dermal burn. Superficial burn heals after some days, so grafting not require.

To complete this goal, the suggested threefold solution is as follow:

(i) Identify Physical characteristics of burn.

(ii) Develop a mathematical model to extract features.

(iii) Classify burn based on features extracted from the mathematical model.

The burn image is loaded to an automated system and resized to 100x100 pixel sizes to extract the HOG feature. After, that it is converted to the CIELab color image. The three channels L*,
a*, and b* are separated from the burn image. These channels are used to extract features for training and classification of the burn wound.

In the present study the channel L*, a*, and b* are selected for feature extraction. The value of L*, a* and b* varies from positive to negative represented by {black, white}, {red, green} and {yellow, blue} respectively. It is very difficult to select the correct color to differentiate burns. So mean of color features is one choice to calculate from burn images.

The mean cluster colors value of channel L* and a* are calculated and used as a feature for burn types classification. The variance of superpixel is calculated to find ROI (Region of Interest). The skewness and kurtosis are calculated from channel a* to find color intensity on the burn region. The entropy of CIELab image used to check the randomness of colors present in the image. Chroma calculated from the superpixel segmented channels a* and b* is used to differentiate SD, DD and FT burn. Color sensitivity is provided by hue calculated from the superpixel segmented channel. The depth of burn is measured by the value of the kurtosis. High values specify more burn depth and low value specify less burn depth. SD burn heals after few days so no grafting requires but grafting technique is required when the severity of the burn is very high especially in DD and FT burn.

![Figure1. The proposed burn classification model.](image)

### 3.1 The CIELab Image

First, the input image is converted into a CIELab image. Three coordinates are extracted from the CIELab image. The proposed approach utilizes CIELab color coordinates and is capable of expanding the RGB gamut due to the property of perceptual uniformity.
Commission on illumination has recommended the CIELab color model as one the complete model for color perception. The CIELab gives chromatic and luminance by using L*, a*, and b* coordinates. The value of L*=0 represent black and L*=100 represent the white color of an image. The value of a*=-127 represents green and a* = +128 represent red. The value of b*=-127 represents blue and b* = +128 represents yellow. The color intensity of CIELab is uniform and is very close to human perception. This is one reason to choose CIELab color image analysis in this study.

3.2 The SLIC superpixels segmentation

Superpixels based segmentation is performed on the CIELab image. It makes clusters of superpixels based on color similarity and the vicinity of the region. The image size affects the spatial distance in the XY plane of the CIELab image and maximum color pixel distance between two colors. So to cluster pixels in the image, spatial distance is normalized and new distance based on the size of superpixels is calculated. The size of superpixels plays a vital to classify burn types. After the several experiments superpixel size set to 80.

SLIC Superpixels Algorithm

Input: CIELab Image (L_img)

Output: Mean of L*, a*, and b* Channel.

Step1: Find Label matrix L and Set number of superpixels N=80

Step2: Convert cluster region of L into 1xn cell array.

step3: Calculate the number of rows(r) in channel a* and number of column(c) in b*
step4: Calculate data matrix (data) of size N filled with zero.

Step5: for each I=1 to N

Calculate, matrix L*=I{L}

b*=I{L}+r*c

a*= I{L}+2*r*c

Find data{1,1}=mean(L_img(L*))
data{1,2}=mean(L_img(b*))
data{1,3}=mean(L_img(a*))

The SLIC Superpixels segmentation of superpixels size 80, 200 and 300 have been shown in figure1. After several experiments on data set superpixels size set to 80 in feature extraction model.

| SD Image | DD Image | FT Image |
|----------|----------|----------|
| ![Image](a) | ![Image](b) | ![Image](c) |
| ![Image](d) | ![Image](e) | ![Image](f) |
| ![Image](g) | ![Image](h) | ![Image](i) |
Figure 3. In the figure 3. (a) is SD burn image and 3(d),3(g), 3(j) are corresponding superpixel image of size N=80, 200 and 300 respectively, 3(b) is DD burn image and 3(e),3(h), 3(k) are corresponding superpixel image of size N=80, 200 and 300 respectively, 3(c) is FT burn image and 3(f),3(i), 3(l) are corresponding superpixel image of size N=80, 200 and 300 respectively.

3.3 Feature Extraction

The burn may occur in any part of the body. The severity of the burn affected region determines the degree of burn. Texture, color, and shape of burned skin are different than healthy skin. The shape of the burned part can be identified by the HOG (Histogram of Oriented Gradients). The local shape information is also extracted by the HOG feature. The color plays a vital role in differentiating burns.

The burn injury parts have different colors near the burn region. The color of superficial-dermal, deep-dermal, and the full-thickness burn is Red / Pale-pink, Blotchy-red / white, and white/brown/black (charred) /deep-red respectively. The classification of burn injury is performed based on human color perception idea into SD, DD, and FT by an expert surgeon.

The CIELab color space contains all colors spectrum. It also contains colors spectrum beyond our perception. The colors of three L* coordinate a*and b* are different. The color values of these coordinates are used to identify burn. Since the intensity of the pixels of colors region is different, so the image is segmented using [24] superpixels segmentation algorithm to form a cluster of the same pixels color region. The mean value of the segmented region is calculated so that the intensity of color gives more saturated value. Based on the mean value of the core fragment and the periphery segment can be differentiated. The lower mean value indicates the periphery, whereas a high mean value indicates the core fragment.

The feature extraction model is shown in figure 4. The training and classification of the proposed model are performed with feature vector {Hog, Standard deviation, Hue, Chroma, Entropy, Kurtosis, Variance, and Skewness}. The feature selection is difficult from the burn, because two burn types may contain the same color pixels value. Therefore, the CIELab image is segmented.
to form a cluster of the same color region. The experiment confirms that an optimal selection of features improves the accuracy of the proposed model.

The CIELab color is device independent and contains an infinite number of colors of an image. It also contains all color bands. So, it is rational to convert RGB (Red, Blue Green) image into the CIELab image. The coordinates $L^*$, $a^*$, and $b^*$ of an image contain all color information of the burn region.

The Superpixel segmentation is performed on CIELab image and the mean value of similar cluster region pixels are calculated from color coordinates $a^*$ and $b^*$, so that color intensity of burn region remains uniform. The chroma is used to specify the colorfulness of the burn region. The hue gives brilliance and saturation. The color pixels values of the burn region are different due to different wavelengths of pixels value constituting hue. The value of saturated hue doesn’t contain white color. First mean of superpixels segmented channel $a^*$ and $b^*$ is calculated after that hue is calculated by the following equation.

$$
Hue = a \tan \left( \frac{seg_{b^*}}{seg_{a^*}} \right)
$$

(1)

Where, $seg_{b^*}$ and $seg_{a^*}$ is mean value of superpixel segmented channel $b^*$ and $a^*$.

The burn region severity of superficial-dermal, deep-dermal, and full-thickness burn is different due to color purity of the affected region is different. In the proposed approach chroma is used to find color purity of the burn region and it is given by the formula

$$
C = \sqrt{seg_{a^*}^2 + seg_{b^*}^2}
$$

(2)

The intensity of burn region pixels plays an important role in the classification of burn. The variance of the label matrix is used to provide a variation of color intensity in the image.

$$
Var = \frac{1}{N} \sum_{i=1}^{N} |L_i - \mu|^2
$$

(3)

Where $L$=superpixel label matrix and $\mu$ is mean of superpixels.

$$
\mu = \frac{1}{N} \sum_{i=1}^{N} L_i
$$

(8)

Estimating the severity of the burn is an important task. The surgeon performs the grafting of the burn region by examining the depth of the burn. In the proposed work the skewness of channel $a^*$ is used to calculate the peakedness of the burn region pixels, which give the depth of the burn. The skewness of channel $a^*$ is used to find the shape and size of the burn region.

The depth of the burn region pixel distribution is calculated as
Where $A^*$ is channel $a^*$ pixels value and $s$ is the standard deviation.

The shape and size of the burn region is defined by the skewness of channel $a^*$

$$skewness = \frac{1}{N} \sum_{i=1}^{N} (A_i^* - \bar{A}^*)^3$$

(6)

Where $A^*$ is channel $a^*$ pixels value and $s$ is the standard deviation.

The feature extraction model is shown in Figure 3.

![Feature Extraction Model Diagram]

**Figure 4.** Feature Selection Model.

### 3.4.1. Mathematical SVM Model

The data for training is a set of points (vectors) $x_i$, along with their categories $y_i$. The data set is defined as

$$\{(x_i, y_i) \mid x_i \in \mathbb{R}^d, y_i \in \{-1, 1\}\}_{i=1}^n$$

(7)

The hyperplane $\alpha$ is defined as $\alpha = w \cdot x + b$
We compute $\alpha$ with each training data set. The minimum value $\alpha$ is calculated as

$$A = \min_{i=1...n} |w_i x + b|$$

(8)

The hyperplanes with maximum value $A_i$ are given by $h = \max_{i=1...n} \{H_i | A_i\}$

Where $H(x_i) = \{+1, w_i x + b \geq 0\}$

(9)

$$H(x_i) = \{-1, w_i x + b < 0\}$$

(10)

The point on or above hyperplane of burn image is considered as 1. The point below burn image hyperplane considered as -1.

3.4.2. Training Using SVM

The features are calculated from SLIC superpixels segmented channels. It is vital to select the correct feature to classify burn and separate them into grafting and non-grafting. The classification accuracy of the proposed system is dependent on features used for training and classification of the burn image.

The training data set contains 20 burn images and they are labeled into two class graft and non-graft. The grafting technique may require DD and FT burn but in SD burn, grafting is not performed by the burn surgeon. The feature vector $\{\text{Hog, Standard deviation, Hue, Chroma, Entropy, Kurtosis, Variance, and Skewness}\}$ is feed to SVM for training.

4. Results

4.1. Data Set:

This database belongs to the Biomedical Image Processing (BIP) Group from the Signal Theory and Communications Department (University of Seville, SPAIN) and Virgendiel Rocio Hospital (Seville, SPAIN) and the data set is open to use for research [20].

4.2 Performance Analysis

The proposed model has been implemented in MATLAB 16a with an i-7 processor and 8 GB RAM. A burn diagnosis can be correctly performed by selection of correct color pixels values. We first analysed the intensity of color in the burn. For this we calculated skewness values in the training and testing dataset of a* channel. As the red color pixel value is present in the a* channel. The skewness value of the channel a* is shown in figure 5 and figure 6 for training and testing dataset. Figure 5 having $x_j$ images, where $j=1$ to 20. For $j=1$ to 9 it is superficial-dermal burn image, $j=10$ to 14 it is deep-dermal burn image and $j=15$ to 20 full-thickness burn. It can be included by looking at the trend line that the intensity of the red pixel is highest in superficial-dermal burn image and it slightly decreases in a deep-dermal and full-thickness burn. A similar
trend can be seen in the test image dataset of 74 images as in figure6. In the present study for training and classification channel, a* skewness has been chosen as one of the features.

Figure5. Skewness value pattern in training image

Figure6. Skewness value pattern in test image

The another analysis was to find disordeness of pixel in the burn region. For this we calculated entropy of the burn. In the figure 7 and figure 8 we can observed that the entropy value is high in SD burn and gradually decreases in DD and FT burn. In the Figure 7 having $x_j$ images, where $j=1$ to 20. For $j=1$ to 9 it is superficial-dermal burn image, $j=10$ to 14 it is deep-dermal burn image and $j=15$ to 20 full-thickness burn taken from training dataset.
The accuracy of the proposed model is comparatively high than other state-of-the-art approaches. The superpixels segmented image features perform better in training and classification of burn image.

**5. Discussion**

The burn identification and classification are performed based on the color and texture of the burn image [1]. The present study uses SLIC superpixels based segmentation to form a cluster of the same color region and performed better than a pixel-wise approach [14]. The features are selected region wise to perform training and classification.

Sabeena and Kumar [8] have used SVM for burn identification and classification. The authors also classified burn into two class one, which requires graft and others which does not require graft. The feature selection of the burn region is a difficult task. The correct feature selection
improves the training and classification accuracy. In SVM based classification of burn, image accuracy is better than other classifiers [9],[14]. The crucial part of burn identification and classification is to calculate the severity of the burn region. Based on the severity of burn region depth grafting is suggested by burn surgeon. The depth of burn is measured by the value of kurtosis. The value of kurtosis is higher in full-thickness burn and gradually decreases in the deep-dermal and superficial-dermal burn. The previous study [10] has used kurtosis value to measure the depth of burn but the present approach provides better accuracy by classifying all the full-thickness burn. The correct identification of burn severity can help the surgeon to take more appropriate decisions to perform grafting on the burn region [11].

Table1 illustrate the comparison of the proposed superpixel based approach and the previous work of authors [22] and the MDS approach. The accuracy of training data is 100% compared to previous work 98% [22]. The accuracy of the test data set is more than 89% which is better than 82.43% and 79% of the MDS approach [18]. The F1-score is also very high more than 90% compared to other approaches.

The training and test phase features are calculated from superpixel segmented channels. Superpixel segmentation allows forming a cluster of the same color region in five-dimensional spaces. The blister present in training and test data set is identified by HOG features. HOG feature is used to identify the shape of an object. The size of the image also plays a major role while calculating the HOG feature. After several experiments, the burn image is resized to 100x100pixels, the window: size is set to 3x3 and the histogram bin is set to 6. The blisters are present in the superficial dermal burn, which arises due to burning on the skin. The authors have also identified blisters present in training and test data by selecting the HOG features. The pixel color of superficial-dermal, deep-dermal burn, and full-thickness burn is different. Most of the pixels in superficial-dermal burns are red. Deep-dermal pixels are blotchy red/white. Full-thickness burn pixels are white /black. The superpixel segmented channel L contains information of black (L*=0) and white (L*=-100) color pixels. So the variance of channel L is calculated. To check the distribution of red pixels in the image, the standard deviation of channel a* is calculated. It is a very good indicator to measure symmetrical data distribution in the burn image. Colorfulness plays an important role in identifying the color of the burned skin. Hue provides the colorfulness which is extracted by segmented channels a* and b*. The purity of color measurement required to differentiate color variation in a burn image. Chroma of the segmented image is used to provide purity of the color in the burn image.

5.1. The burn depth analysis

The kurtosis is used to measure the severity of burn depth. The high kurtosis value indicates the high severity of the burn depth. Based on the depth of the burn, the grafting is performed by the surgeon. In the proposed model, the value of kurtosis is smaller in SD burn and high in DD and FT burn. In training data set Aj image, where j=1 to 20. The value of j=1 to 9 are of a superficial- dermal image having low kurtosis value indicates low burn depth, the value of j=10 to 14 are of
deep-dermal burn having moderate kurtosis value and the value of \( j = 15 \) to 20 are of full-thickness burn having high kurtosis value, indicates high burn depth, shown in figure 9.

\[ \begin{align*}
\text{Figure 9. The value of Kurtosis in training data set}
\end{align*} \]

The behavior of kurtosis value is similar in the test image data set containing 74 images. The pattern of kurtosis of the test data set is shown in figure 10.

\[ \begin{align*}
\text{Figure 10. The value of Kurtosis in test data set}
\end{align*} \]

5.2 Comparison of the Proposed method with Previous Works

The comparison of the work [22] and the MDS [18] is shown in table 1. The F1-score of the proposed superpixel segmentation based classification is 0.90, which is much higher than 0.85 of [22] and 0.73 of the MDS approach. It can also be observed from the table that false positive and false negative value of the proposed approach has been reduced from previous work [22]. The high accuracy rate is achieved in the experiment is due to the segmentation of the burn image. The SLIC superpixels segmentation algorithm forms clusters of similar color pixels region in the burn image. The SLIC superpixel segmented region is used to extract features for training and classification in the SVM classifier. During the experiment, it is found that the size of the superpixels segmentation affects training and classification. So it is very crucial to select the
correct size of superpixel for a system to perform classification better. In the present work, the superpixel size is set to 80. Apart from this, the HOG feature plays an important role in training and classification of burn image. HOG feature is used to identify the shape of the object. It calculates the gradient of the image and identifies the shape of the object. The training and test data both contain blister present in burn image. This is identified by the HOG feature. The size of histogram bins is important to select correctly. In the present approach, the window size is fixed to 3x3 and the number of histogram bins: set to 6.

The automated system can classify them. The confusion matrix of the test result is shown in table2. In the table, TP (True Positive), FP (False Positive), TN (True Negative), FN (False Negative) have been calculated based on graft and non-graft class. The size of 74 test image data set varying in size from 78kb to 3kb. Out of 74 test images, 33 are of superficial-dermal burn, 27 are of deep-dermal burn and 14 are of a full-thickness burn. The system can identify all the 14 full thickness.

| Proposed Super Pixel Method | Work[22] | MDS Approach |
|-----------------------------|----------|--------------|
| Accuracy                    | 89.19    | 82.43        | 79.73        |
| Precision                   | .88      | 0.82         | 0.73         |
| F1-Score                    | .90      | 0.85         | 0.83         |
| Recall                      | .93      | 0.88         | 0.97         |
| (TP)                        | 38       | 36           | 38           |
| (FP)                        | 5        | 8            | 14           |
| (FN)                        | 3        | 5            | 1            |
| (TN)                        | 28       | 25           | 21           |
| Sensitivity (S)             | 93       | 87.80        | 97.0         |
| Specificity (E)             | 84.85    | 83.33        | 60.0         |

Table1. The comparison of the work [22] and the MDS approach

In most cases, full-thickness burn and deep dermal burn require grafting. The superficial dermal burn heals after 14 days, so grafting is not needed.

The proposed approach segments the burn image into clusters of similar color pixels regions. After that features are from segmented regions to correctly classified human burn those require graft and non-graft. The proposed framework is also able to estimate the depth of burns. The depth of FT burn is higher, the DD burn depth is moderate and the depth of SD burn is lowest. The blisters present in the SD burn are taken care of by the HOG feature. The training and test image both contains blisters. The accuracy and F1-score of the proposed approach are much higher than previous work, which confirms the best features have been used to train and classify burn.

| Class            | Non-Graft | Graft |
|------------------|-----------|-------|
| Non-Graft        | 28        | 5     |
| Graft            | 3         | 38    |
Table 2. Confusion matrix of the proposed model

6. Conclusion
Image processing and machine learning are very popular and widely used for diagnosis biomedical imaging. The proposed approach has two modules, segmentation of the burn image, and feature extraction for classification. The segmentation of the burn wound image is performed by the SLIC superpixel algorithm. The SLIC superpixels segmentation divides the image into different regions to form the clusters of same-color pixels. The colors of superficial-dermal, deep-dermal, and full-thickness burn are different, so feature selected using this technique improve the classification rate. The color and texture features are identified from the burn wound region. The proposed method can estimate the depth of the burn and classify them into graft and non-graft. This will help a burn surgeon because in most of the full thickness burn grafting is performed. The accuracy of 89.19% and F1-score 0.9 is acceptable. The SLIC superpixel segmentation technique improved the accuracy of the presented automated system, compared to the previous work and available research literature. The accuracy of the research can be further improved by selecting other segmentation techniques and removing outliers. In future studies, we will try to apply other colors and texture features to classify burn wounds.

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