Assessment and Analysis on Color Image Classification Techniques of Dermatological Ulcers

C. Dhaniya Briskillal, B.E., (M.E), K. Madhan Kumar, M.E., (Ph.D)

Abstract -- With the implementation of color image processing methods, the image of dermatological ulcers are analyzed in order to detect the affected area of the skin. The detection of classification rate focus on the application of feature extraction method that segment, classify and analyze the tissue composition of skin lesions or ulcers. Indexing of skin ulcer images was performed based on the statistical texture features derived from the RGB color components. This literature assesses the high level methodology for dermatological ulcer image classifier. The classifiers analyzed here are used for labeling the images by the dermatologist used in training and testing of the classifier. The classification performance rate, coverage area of the affected skin is analyzed based on the choice of different algorithms. Classifier uses the algorithm to perform attribute or feature selection that generates the candidate subsets of attributes and evaluate them by using the training and testing schemes, thus creating the computed values of corrected classified image rate up to 90% and assessed coverage area of affected skin up to 0.82.

Index Terms: Dermatological ulcers, Classification rate, Feature extraction, Classifiers. Texture features

I INTRODUCTION

Ulcers are usually caused by deficit in blood circulation and can be associated with arterial or venous insufficiency, diabetics, vascular diseases, tumors, infection and certain specific skin conditions explained in [17]. With the widespread use of digital cameras, freehand wound imaging for skin ulcers has become common practice in a clinical settings but still a demand arises for practical tool for accurate wound healing assessment describes in [3]. The healing process of an ulcer can be divided into three phases such as Inflammation, tissue formation and remodeling formulated in [10].

During the healing process the skin can change to a transient phase of necrosis. The appearance of a wound, lesion or ulcer provides important clues that can help with the diagnosis, determination of severity and the prognosis of healing provided in [2].

The major objective of this study is to evaluate several classification techniques of a feature or attribute extraction and selection to determine which color and texture features. The tissue composition of each lesions are classified independently by an expert dermatologist based on the color composition by different types given below:

- Granulation (Red)
- Fibrin (Yellow)
- Necrotic (Black)
- Hyperkeratosis Or Callous (White) &
- Mixed Tissue Composition

In the feature extraction and selection method, set of features extracted with large amount of data sets. In the process of classification among the different types of skin ulcers, the extracted features should be evaluated to determine which are more relevant to the solution of the problem given in [13]. Suitable algorithm is chosen for the classifier to perform feature selection methods that generates candidate subsets of attributes and this process is repeated with each candidate set until the stopping criterion is reached.

Cross validation is used to estimate the accuracy of the given set of attributes that are module in [5]. Cross validation is a sampling method that randomly divides the samples into r mutually exclusive partition or folds of approximately equal in size of n/r samples where n is the total number of available number of samples. The classifier is trained with the r-1 induced folds of samples and the classification rule or methodology is tested on the remaining fold. This process is repeated r times, so that each fold is used once as the test test given in the system.
The general system design describes the above processing unit is module in a block diagram given below in Fig.1

![Block Diagram](image)

**Fig 1. General system design for color image classification**

The section I describe the general system of the color image classification system with the basics of different types of ulcers with the suitable preprocessing and feature extraction method. The section II defines the color image classifiers that are used to classify the segmented image and reproduce the classification rates. The section III defines the various types of methodology used in the classification methods that improves the performance of classification rate. The section IV explains the overall performance metrics of the classification rate. Finally section V concludes with the best performance of classification method.

### III COLOR IMAGE CLASSIFIERS

Different classifiers chosen to run the algorithm are analyzed and describes based on the Fig.2

![Classifier Diagram](image)

**Fig.2 Types of Color Image Classifiers**

- In [9], the KNN classifier finds the k-nearest neighbors of the samples to be classified by using a distance metric (usually the Euclidean distance) between the attributes of the sample to be classified and the attributes of all the available samples with known classification.

- In [7], Wound Image Analysis classifier is used to classify the wounds based on the color description of various colors involves in analyzing the severity of the wound. WIAC framework is used efficiently to forecast the healing process of a wound effectively which uses the non-contact method of analyzing the status of the wound.

- In [6], the Naive Bayes or Bayesian classifier calculates the probability of a sampling belonging to each of the predetermined classes. This probability value is used to generate a model with a decision rule that provides a response to indicate the class with a higher probability.

- In [1], the ANN classifier is an interconnected group of nodes that is capable of machine learning as well as pattern recognition. It consist of set of adaptive weights i.e.) numerical parameters that are tuned by learning algorithm.

- In [17], MLP classifier consists of a set of nodes that constitute the input layer, one or more intermediate or hidden layers of computational nodes and output layer. The set of measurements to be classified is provided to the input layer and propagates forward through the hidden layer towards the output layer creating the computed value for classification.
II METHODOLOGY

This section describes the analysis of different image classification methods with suitable algorithms to predict the best extent classification rate of a classifier discussed below:

A. ROUND-ROBIN CLASSIFICATION

This method describes the color image classification and diagnosis of four major groups of prostate cancer such as stroma, benign prostatic hyperplasia, prostatic intra-epithelial neoplasia and prostatic carcinoma. To overcome the high dimensionality of multiclass system, a novel round robin tabu search algorithm is used to segment image sample of four major class of prostate cancer with classification performance of about 91.9%. Since the classifier uses different features for each binary classifier, the results increases for classification accuracy but the time elapsed for the execution process. Table 1 describes the comparison of the multiclass method and Round robin classification of the system that results lower computational time with the round robin classifier than the multiclass imagery method.

<table>
<thead>
<tr>
<th></th>
<th>M (msec)</th>
<th>C (msec)</th>
<th>T (msec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multi-class</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dataset1</td>
<td>48.2</td>
<td>0.11</td>
<td>48.31</td>
</tr>
<tr>
<td>Dataset2</td>
<td>65.3</td>
<td>0.06</td>
<td>65.36</td>
</tr>
<tr>
<td>Round Robin</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dataset1</td>
<td>74.0</td>
<td>0.49</td>
<td>74.49</td>
</tr>
<tr>
<td>Dataset2</td>
<td>109.34</td>
<td>0.14</td>
<td>109.48</td>
</tr>
</tbody>
</table>

M: measuring features cost, DR: data reduction, C: classification, T: total time.

Table.1 Computation Time Comparison

In round-robin algorithm, simple voting scheme is used to predict the highest priority class among the four major classes of prostate cancer. The samples are correctly classified by the nearest neighbor classifier because different feature are used for each binary classifier and results in the increase of classification accuracy. Once the Tabu search find the best subset of features, an Nearest Neighbor classifier are used to determine the class of new subset but the cost of measuring feature is increased because more features are required in Round Robin approach. Neighbors are calculated using a squared Euclidean distance defined as

\[ d(x, y) = \sum_{i=1}^{n} (x_i - y_i)^2 \]

where \( x \) and \( y \) are two input vectors and \( n \) is the number of features.

From the table it is inferred that the execution time using RR classifier such as 74.49msec for Dataset1and 109.48msec for Dataset2 are higher than the Multicast classifier such as 48.31msec for Dataset1 and 65.36 for Dataset2 for classification process.

B. MLP BASED WRAPPER ALGORITHM

This methodology describes the color images of the skin ulcers that are detected and classified using the MLP classifier. First the database images are collected and each images are independently and manually segmented into two regions, describes the lesion and the background by an each region attributes to RGB color components and convert it to the HSI component. The wrapper algorithm is used to specify the type of ulcers where this algorithm generates the candidate subsets of attributes and evaluates them by using HSI images. This process is repeated with each candidate set until the stopping criterion is reached.

Fig.3 Analysis of texture in color imaging system.

In preprocessing, each images are independently and manually segmented into two regions represents the lesion and background. The noise is reduced by feature extraction method. Wrapper algorithm uses the cross validation that is used to estimate the accuracy of the learning scheme for a given set of attributes. The wrapper algorithm uses the MLP classifier that consists of a set of nodes that constitute the input layer, one or more hidden layer or output layer. The set of measurements to be classified is provided to the input layer and propagates forward through the output layer created a computed value for the classification up to 73.8%.

C. COLOR PIXEL CLASSIFICATION

The color pixel classification approach describes the color representation prediction, color quantization and classification algorithm. Skin segmentation based on color pixel classification is not affected by the color space but the segmentation performance is degraded by the chrominance channels used in the classification. Increase in histogram size will increase the performance of segmentation. To overcome all the difficulties, Bayesian classifier with the Histogram technique is used. Color pixel classification using
Bayesian classifier is used to determine and differentiate the skin color and non-skin color. The Bayesian classifier with the histogram technique provides higher classification rates compared to other classifiers. The Bayesian classifier with the histogram technique is feasible for the skin color pixel classification problem because the feature vector has a low dimension.

The Bayesian decision rule for minimum cost is a well-established technique in statistical pattern classification. Using this decision rule, a color pixel $x$ is considered as a skin pixel if

$$\frac{\rho(X|\text{skin})}{\rho(X|\text{nonskin})} \geq \tau$$

Where $\rho(X|\text{skin})$ and $\rho(X|\text{nonskin})$ are the respective class-conditional pdfs of skin and nonskin colors and $\tau$ is a threshold. The theoretical value of $\tau$ that minimizes the total classification cost depends on the a priori probabilities of skin and nonskin and various classification costs; however, in practice $\tau$ is often determined empirically. The class-conditional pdfs can be estimated using histogram or parametric density estimation techniques.

The Bayesian classifier with this histogram technique used for the skin color pixel segmentation will provide a classification rate of 89.84% and the correct detection rate ranges up to 91%. Although this technique provides good coverage of all different skin types, it lacks of available pdf of datasets. Skin color pixel luminance is discarded due to the different lighting variation which made more complexity in computational time. Increase in histogram size leads to the finer Pdf estimation to attain the high accuracy in classification rate.

**D. CLUSTERING TECHNIQUE**

This technique describes the k-means clustering algorithm followed by the Artificial Neural Network classifier that is used for the skin ulcer detection at an early stage. Since skin ulcers are caused due to the increase in the UV radiation, if detected earlier all forms of skin cancers are curable. Thus this paper depends on the basis of classifying skin lesion at an early stage.

**E. WIAC ALGORITHM**

This WIAC algorithm describes the status of the wound healing assessment that measures the area covered by the wound. WIAC is an efficient classifiers that are used to classify the wound images. The purpose of this paper is to accurately access the healing status of the wound that...
captures the wounded images by the use of tools like photographic wound assessment tool to predict the different types of wounds such as pressure, diabetic and arterial ulcers. After acquiring the required image of wound, it leads to the segmentation process that segments the wounded area from that of unwounded area and pre-processing is done to reduce the noise using efficient filtering and denoising techniques.

**Fig.7. Flowchart of Wound Image Analysis Classifier**

**WLAC Algorithm Steps:**

- Select a wound image from wound database acquired from open source wound images.
- Segment the wound from the wound image using an efficient segmentation technique.
- Improve the quality of the segmented wound from the wound image by using filtering.
- Denoising techniques.
- After preprocessing of segmented wound image overlay transparent layers of segmented wound shapes to reduce the intensity of colors in the wound.
- Repeat step4 various times to get healed image of the wound.
- Classify the segmented wound image into three labels based on severity level 0,1,2.
- Conversion of segmented wound images from higher severity level to lower severity take place.
- Level leads to analyzing the healing status of the wound.

WAIC algorithm provides the conversion of segmented wound images from higher severity level to lower severity level that leads to analyze the healing status of wound images. The classification time during execution ranges higher than other classifier. The percentage of classification accuracy range with a value of 63.8% due to the usage of photographic wound assessment tool used in detection of grade, number and location of wound that will not be indexed properly.

**F. Log Polar Fourier Transform**

An integrated computer based system for the characterization of skin digital images was described by the image acquisition arrangement designed for capturing skin images, under reproducible conditions. This system processes the captured images and performs unsupervised image segmentation and image registration utilizing an efficient algorithm based on the log-polar Fourier transform of the images by means of the ANN classifier. Cross talking between neighboring pixels is a factor that contributes to noise. Noise can be eliminated through appropriate filtering such as morphological filtering to preserve the edge information or median filtering to assist the color identification. The human skin consists of irregular surface, scatters incident light in irregular directions and burying diagnostic information. To avoid such problems the appropriate lighting geometry, light reflections reduction and software corrections also applied to the image during the acquisition.

![Flowchart of Wound Image Analysis Classifier](image_url)

![Generic feed-forward neural network used for classification](image_url)
The function is very important while using different features for each class such as ANN. The classification rate of order of 90% for Grade 1 when compared to Grade 2 and Grade 3 since Grade 1 refers to simplify the top most layer of the skin.

G.BACK PROPOGATION ALGORITHM

This paper describes the detection of skin burn and classification of images using Artificial Neural Network classifier. The images are collected from various database centre and it is preprocessed by enhancing the lab color space and then various pattern analysis such as ANN classifier is applied on the collected skin burn images to predict the classification rate for three types of grade such as Grade 1 represents the superficial burn caused due to skin burn heals within 5 to 7 days. Grade 2 represents the partial thickness burn that leaves scars on the affected area. Grade 3 represents the full thickness burns that are totally destroying the epidermis layer of the skin. These proposed systems are more useful at the remote location where the medical experts are not available. During the accidents as the patients gets admitted to the hospital or while being transported to ambulance, the medical personnel attending the patient can send burn images immediately through online camera to the specialist.

Feature selection is very important while classifying the skin burn image into different grades. Initially the image is re-sized to 90*90 pixels, and then Red, Green and Blue (RGB) space is converted to L*a*b* color space. Lab color space has 3 coordinates, one luminous and two chrominance V1 and V2. Luminous component is used for contrast enhancement. After contrast enhancement of the image, the V1 and V2 chrominance planes of the L*a*b* color space is selected for feature extraction using the coefficient of Discrete Cosine Transform (DCT) function is chosen to train classifiers. The two dimensional DCT equation is given below, where \( X(k_1,k_2) \) is the DCT an \( x(n_1,n_2) \) is the image.

\[
X(k_1,k_2) = \frac{4}{N^2} \sum_{n_1=1}^{N-1} \sum_{n_2=1}^{N-1} x(n_1,n_2) \cos\left(\frac{\pi(2n_1+1)k_1}{2N_1}\right) \cos\left(\frac{\pi(2n_2+1)k_2}{2N_2}\right)
\]

Where \( k=1, 2, 3, \ldots \ldots \ldots, N \)

Fig.9. Flow Chart for Training ANN With Burn Images Using BPA

The ANN classifier is used with the Back Propagation Algorithm to segment the severity of the skin burn wounds. Fig.8 describes the Back Propagation Algorithm that convert the collected database into a required format to extract the features from the color information. Finally by using Artificial Neural Network classifier, it will display the grades of burns and provide the reduction of classification time without any complex algorithm. It predicts the classification rate of order of 90% for Grade-1, 75% for Grade-2 and 82.5% for Grade-3. It provides high classification rate for Grade-1 when compared to Grade-2 and Grade-3 since Grade-1 refers to simplify the top most layer of the skin.

III OVERALL PERFORMANCE

This section describes the overall performance of the classification rate of different classifier analyzed in the above sections. Fig.9 shows the classification rate of different classifier. The MLP classifier described in[17] will provide a classification rate of 73.8% whereas KNN classifier described in [9] uses different features for each binary classifiers, the results increases for classification accuracy with the computed value of 91.9%.
The ANN classifier assessed in [1] describes the skin ulcer detection at an early stage with the use of the k-means clustering algorithm. The Bayesian classifier analyzed in [6] describes the color pixel classification used with the histogram technique provides the classification rate of 89.84% but it increases the computational time. By using the histogram technique, color space favours over other colors, that overlap between skin and nonskin types. Increase in histogram size leads to finer pdf estimation but requires greater memory storage.

The WIAC classifier described in [7] used to predict the status of wound healing assessment. The percentage of classification accuracy range with a value of 63.8%. From the above analysis graph in Fig.10, it is infer that KNN provide the best classification rate among all the classifier but the computational complexity increases will further affects the classification accuracy. The MLP classifier used with the wrapper algorithm provide the reduced computational time which will improve the classification accuracy to the better extend.

IV CONCLUSION

The generation and estimation of tissue composition provides key information for monitoring the response to treatment of patients with dermatological ulcers. This processing system may serve as a diagnostic adjunct for medical professionals for the confirmation of a diagnosis of dermatological ulcer as well as for the training of new dermatologists. Various classifiers analyzed in this paper will provide the implementation of more accurate, faster and more reliable classification system. Six different algorithms are used for image segmentation along with different classifiers provides the better extent of classification rate. Out of the five classifiers tested, KNN classifier provided the best overall performance with the classifier rate value ranges of 91.9%.

The results from this survey are promising for the future that an objective analysis of color image classification of skin ulcers using proposed method with the SVM classifier can overcome some of the limitation of visual analysis, storage requirements and lead to the development of improved optimization for the treatment and monitoring of skin ulcers with the high percentages of corrected classification rate.

REFERENCE

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