Diagnosis and Detection of Automatic Skin Burn Area Color Images Identification of Burn Area Depth in Color Images

B.Sabeena[1] , Dr. P.Rajkumar[2]
[1]PG Scholar & CSE & Info Institute of Engineering
Associate professor & CSE & Info Institute of Engineering

***ABSTRACT** :---Skin image is in that the burned skin and non- burned images has to be classified. It is a deadly form of burning. Skin burn may appear as malignant or benign form. Skin cancer at its early stages can be cured. But when it is not recognized at its early stages, it begins to spread to other parts of the body and can be deadly. Benign Melanoma is simply appearance of moles on skin. A normal mole is usually an evenly colored brown, tan, or black spot on the skin. It can be either flat or raised. Skin burns are the deadly form of cancers in humans. If skin burns is detected at early stages, it can be cured completely. So an early detection of skin cancer can save the patients. Skin burns are of two types- Benign and Malignant Melanoma. Benign melanoma is not a deadly condition, but malignant melanoma is a deadly form. Both resemble same in appearance at the initial stages. Only an expert dermatologist can classify which one is benign and which one is malignant. The SVM based Classification methodology uses Image processing techniques. Main advantage of this computer based SVM classification is that patient does not need to go to hospitals and undergo various painful diagnosing techniques like Biopsy.*

***Keywords:**--* Skin lesion, Melanoma, Features detection ,Classification, Segmentation,

I. INTRODUCTION

This chapter gives you an introduction about the skin burn identification and its segmentation results analysis. The main idea behind this project is to improve burn or affected process by datasets features and classification based of done.

Digital image processing is one of most important area of research and has opened new research prospects in this field. Digital image processing refers to processing digital image by means of digital computer. Image processing is a very profound key that can change the outlook of many designs and proposals. Fundamental steps in digital image processing are image acquisition, image enhancement, image restoration, color image processing, compression, image segmentation and recognition. Image segmentation has become a very important task in today's scenario. An importance of segmentation is, segmentation is generally the first stage in any attempt to analyze or interpret an image automatically.

A segmentation is the partitioning of a digital image into multiple regions (sets of pixels), according to some homogeneity criterion. The problem of segmentation is a well-studied one in literature and there are a wide variety of approaches that are used. Different approaches are suited to different types of images and the quality of output of a particular algorithm is difficult to measure quantitatively due to the fact that there may be much correct segmentation for a single image. Image segmentation denotes a process by which a raw input image is partitioned into non overlapping regions such that each region is homogeneous and the union of any two adjacent regions is heterogeneous. A segmented image is considered to be the highest domain-independent abstraction of an input image. Image segmentation is an important processing step in many image, video and computer vision applications. Extensive research has been done in creating many different approaches and algorithms for image segmentation, but it is still difficult to assess whether one algorithm produces more accurate segmentations as to be determined.

Over the past decade, the field of image analysis research has undergone a rapid evolution. Image processing Now-a-days have varied applications in the fields of medical imaging, whether meteorology, computer vision, digital photography, microscopy etc. Super-Resolution Imaging consolidates key recent research contributions from eminent scholars and practitioners in this area and serves as a starting point for exploration into the state of the art in the field. Recent advances in camera sensor technology have led to an increasingly larger number of pixels being crammed into ever-smaller spaces. This has resulted in an overall decline in the visual quality of recorded content, necessitating improvement of images through the use of post-processing. This paper particularly features on developing suitable method for rapid and efficient way to perform hardware implementation for some of Basic crucial image processing algorithms that can be used in simple application specific devices. Image quality can be enhanced by some of basic morphological and intensity image transforms such as controlling its illumination, contrast stretching, thresholding similarly some applications needs image segmentation via edge detection, boundary extraction, image negatives or extraction of positive from image negatives , image subtraction etc. these algorithms are focused in this paper. This paper aims at Developing algorithmic models in MATLAB. Creating workspace in MATLAB to process image pixels in the form of multidimensional image signals for input and output images opto acoustic tomography has demonstrated optical contrast imaging through entire small animals or human tissues in high resolution. Implementations in the sub-10 MHz ultrasonic region can achieve penetration depths of several centimeters with resolutions ranging in the few hundreds of micrometers. This performance enables structural and functional optical imaging of tissues at several millimeters to centimeters depth.

In this study, we propose a new automated skin lesion segmentation method via image-wise supervised learning (ISL) and multi-scale superpixel based.The novelty of our algorithm when compared to previous studies is as follows: (1) we propose an image-wise supervised learning approach to initialize seeds via a probabilistic map between the skin lesion and the background. This initialization improves the capacity for to segment the lesion area, whereas traditional methods usually require to propagate from user defined or predefined seeds; and we propose a novel multi-scale Super pixel computer based SVM classification based model with a parallel propagation. Such features are extracted using Gray Level Co-occurrence Matrix (GLCM) method. These features are given as the input nodes to the. SVM is used for classification purpose. It classifies the given data set into burned or non-burned. Original K-means algorithm choose k points as initial clustering centers, different points may obtain different solutions. In order to diminish the sensitivity of initial point choice, we employ a mediod, which is the most centrally located object in a cluster, to obtain better initial centers.

II. EXISTING SYSTEM

A. GMM FEATURE EXTRACTION

GMM: weighted average of Gaussians Mixture Models

- Each Gaussian has its own mean and covariance matrix that has to be estimated separately
- Unlike in the case with just one Gaussian, you do not know which training sample contributes to which Gaussian and hence the existing formulas for mean and covariance matrix are not applicable.

Disadvantages discussed here it as,

- Complexity is more for classification.
- More time consuming.
- Namely sensitivity, less accuracy and border error are occurred.
- To perform prompt correct evaluation of skin burn depth in order to make the appropriate choice of treatment as difficult one.

Adaptive Gaussian Mixture Models (GMM) have been one of the most popular and successful approaches to perform foreground segmentation on multimodal background scenes. However, the good accuracy of the GMM algorithm comes at a high computational cost.

III.PROPOSEDSYSTEM

A. GLCM-FEATURE EXTRACTION

A gray level co-occurrence matrix (GLCM) to extract second order statistical texture features for motion estimation of images. The four features energy, correlation, contrast, homogeneity are to be calculated. Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Hara lick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images.

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, θ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (θ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, θ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 2.1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbour). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixel).

CONTRAST:

Contrast is a measure of the extent to which an object is distinguishable from its background. It represents the local variations present in an image, and calculates the intensity contrast between a pixel and its neighbour Contrast calculated from the image as per the following equation.

$$C=\sum_{i,j=0}^{n-1}(i,j)^2 P(i,j)$$

Where, n denotes the number of pixels in the image and P (i, j) is the cell denoted by the row and column of the image.

ENERGY:

Energy represents the **orderliness of** a mammographic image. Energy is generally given by the mean squared value of a signal. Energy calculated from the image as per the following equation.

$$E=\sum_{i,j=0}^{n-1} P(i,j)^2$$

CORRELATION

Correlation is a measure of **gray tone linear-dependencies** in the image, in particular, the direction under investigation is the same as vector displacement. High correlation values (close to 1) imply a linear relationship between the gray levels of pixel pairs. Thus, GLCM correlation is uncorrelated with GLCM energy and entropy, i.e., to pixel pairs repetitions. Correlation reaches it maximum regardless of pixel pair occurrence, as high correlation can be measured either in low or in high energy situations

$$\text{Correlation} = \frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} i \cdot j \cdot P_{ij} - \mu_x \cdot \mu_y}{\sigma_x \cdot \sigma_y}$$

HOMOGENEITY

Homogeneity parameter also known as **inverse difference moment measures** image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. Homogeneity is a measure that takes high values for low contrast images.

$$\text{Homogeneity} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{1}{1+(i-j)^2}\cdot Pij$$

B. SVM –CLASSIFICATION

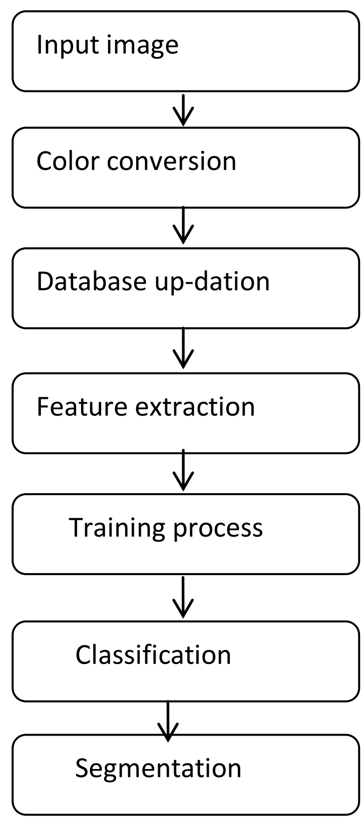
In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

C. K MEANS-SEGMENTATION

Original K-means algorithm choose k points as initial clustering centers, different points may obtain different solutions. In order to diminish the sensitivity of initial point choice, we employ a mediod, which is the most centrally located object in a cluster, to obtain better initial centers. The demand of stochastic sampling is naturally bias the sample to nearly represent the original dataset, that is to say, samples drawn from dataset can't cause distortion and can reflect original data's distribution. Comparing two solutions generated by clustering sample drawn from the original dataset and itself using K-means respectively, the location of clustering centroid of these two are almost similar. So, the sample-based method is applicable to refine initial conditions . In order to lessen the influence of sample on choosing initial starting points, following procedures are employed. First, drawing multiple sub-samples (say J) from original dataset (the size of each sub-sample is not more than the capability of the memory, and the sum for the size of J sub-samples is as close as possible to the size of original dataset) . Second, use K-means for each sub-sample and producing a group of mediods respectively. Finally, comparing J solutions and choosing one group having minimal value of square-error function as the refined initial points. Advantages of proposed systems are discussed below.

- The resulting analysis was performed to evaluate the application of IR thermal imaging methods in skin burn depth estimation.
- Image segmentation that are highly efficient approaches.
- The segmentation technique developed here both captures certain perceptually important non-local image characteristics

BLOCK DIAGRAM



Here it as the query input is given in the form of affected images for an segmented outputs for an detection process.then second we have to go Here, the process of converting an RGB to Gray has to be done. The original given image is to be taken, the RGB components has to be converted to gray components. Third, this block defines that the given image is to be compared with the database images, this operation is to be going to processed for an finding a affected areas in an given query image. In Features characterizes the shape of the skin burn representation purposes, the effected parts should be segmentation process, the features are extracted here. In segmentation processes, the purposes of segmenting the images has been successfully segmented by extracted features based of done.Then this process is for an classification of an given query images, that as the given image has should be skin burned or skin normal, that has to be classified. Here for an classification, the SVM algorithm is to be used of done. The classification is in that the skin has to be classified by the SVM used of that the skin as normal or burned, is that the comparisons are to be done.

IV. CONCLUSION AND FUTURE SCOPE

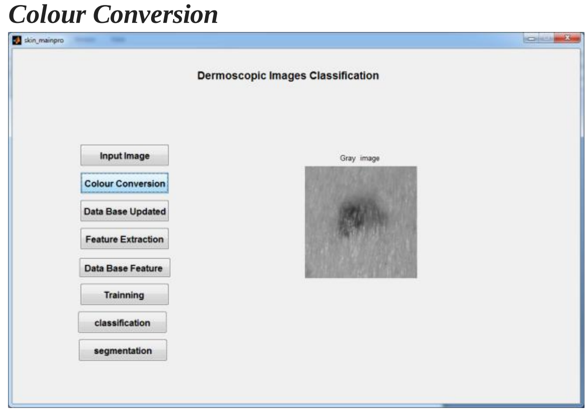
In previous methods, Performance degradation is due to miss-classification of burn wounds Examination of the classifier results shows, that the performance of the classifier has improved from feature extraction of GLCM and further to SVM method.. It has been noticed that even doctors having difference of opinion while classifying burn images. This is to be accepted, when a diverse database like ours is constructed from images belonging to people of different race, gender and age under differing ambient light. Very few papers, as cited in reference are available on this work, reporting results of those are on very specific and local database of images obtained under controlled conditions. Filter models have provided good performance with the resource utilized. And also the filter designed here is reconfigurable. It can be used for various image processing applications.

Thus, development of automated characterization systems for skins for clinical use mostly for diagnosis of malignant melanoma preoccupies several R&D laboratories and medical teams. The most remarkable features of such systems have been surveyed in this paper. These systems employ a variety of methods for the image acquisition and preprocessing, and feature definition and extraction, as well as skin classification from the extracted features. Further more operations on future works depends on better accuracy measures

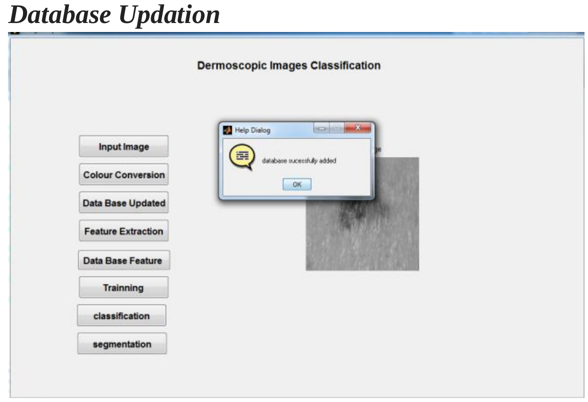
RESULTS

Input Image

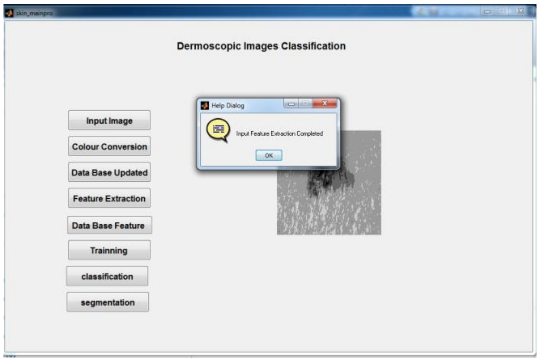
Colour Conversion



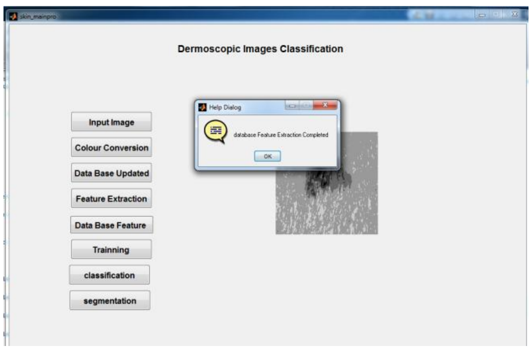
Database Updation



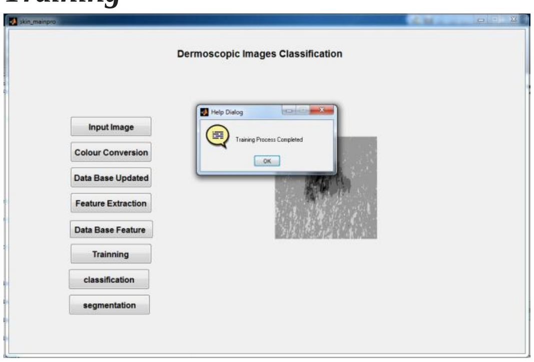
Input Faeture Extraction



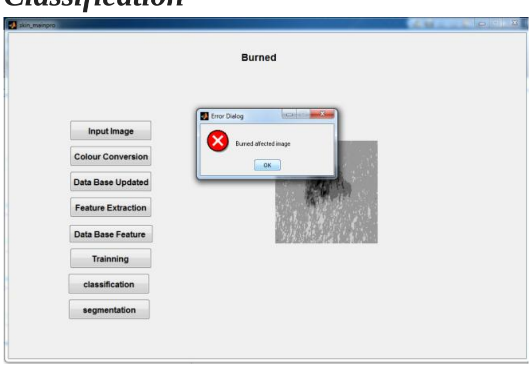
Database Feature Extraction



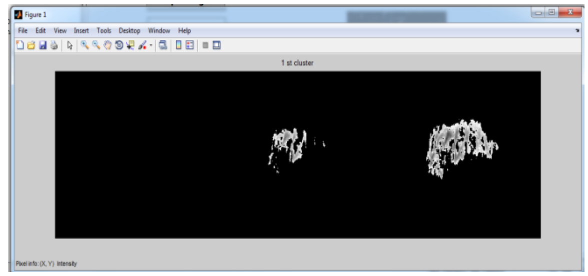
Training

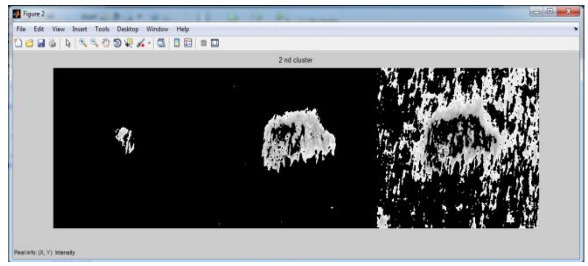


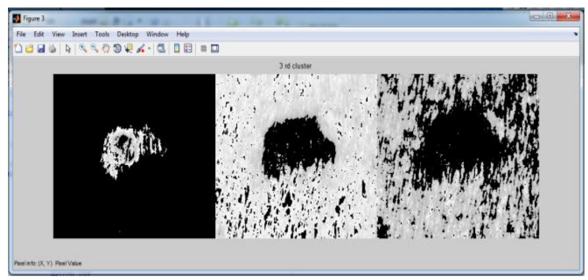
Classification

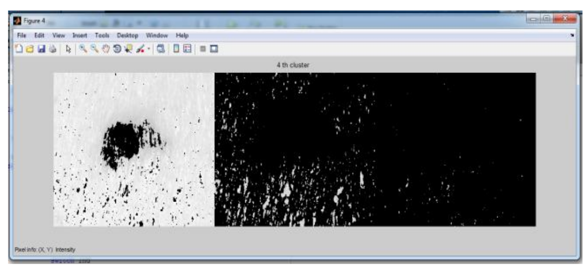


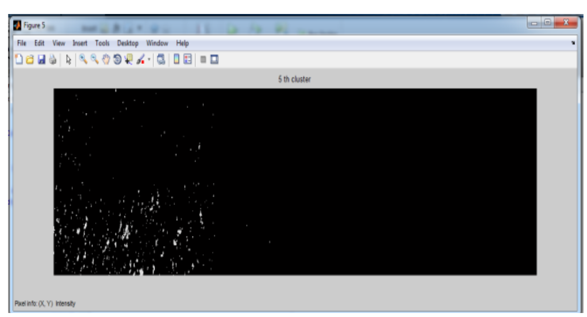
Segmentation











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