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Skin Cancer Detection Using MATLAB

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ABSTRACT: Human Cancer is one of the most dangerous disease which is mainly caused by genetic instability of multiple molecular alterations. Among many forms of human cancer, skin cancer is the most common one. To identify skin cancer at an early stage we will study and analyze them through various techniques named as segmentation and feature extraction. Here, we focus malignant melanoma skin cancer, (due to the high concentration of Melanoma- Hier we offer our skin, in the dermis layer of the skin) detection. In this, We used our ABCD rule dermoscopy technology for malignant melanoma skin cancer detection. In this system different step for melanoma skin lesion characterization i.e, first the Image Acquisition Technique, pre-processing, segmentation, define feature for skin Feature Selection determines lesion characterization, classification methods. In the Feature extraction by digital image processing method includes, symmetry detection, Border Detection, color, and diameter detection and also we used LBP for extract the texture based features. Here we proposed the Back Propagation Neural Network to classify the benign or malignant stage.

I. INTRODUCTION

A collection of abnormal cells in our body is name as cancer. In humans cancer can start anywhere in the body and spread into the surrounding tissues which is made up of trillions of cells. Normally, human cell grow and divide to form new cells according to the requirement of the body and it vary person to person. When cancer starts to develop in the body the process of reconstruction of new cell stops and the cell becomes more and more abnormal and a new cell form which is not required. That extra cell grows without stopping and called as tumors. Cancerous tumors are malignant. This means that they can grow and spread into nearby tissues. In short diseases in which abnormal cells divide uncontrollably and destroy body tissue resulting tumors The skin is the largest organ of the body. The skin protects us from microbes and from the other harmful materials.

Skin has three layers:

- **Epidermis-** the outer most layer of the skin and creates our skin tone.
- **Dermis –** it is beneath the epidermis and contains tough connective tissue and sweat glands.
- **Hypodermis** – made up of fat and connective tissue.

Most often skin cancer develops on skin exposed to the sun but it can also occur on areas which is not sun exposed. There are three types of skin cancer-basel cell cancer, squamous cell cancer and melanoma tumors.

- **Basel cell**-it starts in bassel layer of the skin. It occurs on the face.
- **Souamous cell** – it begins in squamous cell and mostly found in dark people.
- **Melanoma-** it begins in melocytes layer and occur at mouth and eyes.

The first two are not so common and do not spread quickly but the third skin cancer spread very quickly over the body. If it is not found in early stages, it is found to be more dangerous.

II. LITERATURE SURVEY

Vascular segmentation through the use of image processing tools provides significant information that allows for the accurate diagnosis, categorization, registration, and visualization of vascular disease. Currently, in the assessment of Abdominal Aortic Aneurysms (AAA), radiologists manually segment different regions on interest on each medical image to create a full volume of the abdominal aorta. Such manual segmentation is a time consuming task, prone to errors and a subjective approach especially when non-contrast enhanced images are present. In this paper, we introduce an automatic system to segment the aortic lumen in non-contrast enhanced CT scans and PC-MR images using digital image processing algorithms where image enhancement, denoising, edge detection, and regional growing algorithms are utilized. The output of this work forms the basis for a future reliable inner and outer wall segmentation of the AAA.

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This paper presents a method for automated delineation of the outer aneurysm boundary in multiple MR sequences. The method is inspired by the Active Shape Model (ASM) framework as proposed by Cootes and Taylor.5 ASMs consist of a landmark based shape model, linear models of gray value appearance around the landmarks, and an iterative optimization scheme. Both the shape model and the boundary appearance model are derived from segmented example images. The components of the original ASM scheme are modified to enable AAA segmentation. The landmark based shape model, called Point Distribution Model (PDM), is adapted to better describe tubular objects if the training set is small. A non-linear gray value model is proposed which can deal with the highly variable boundary appearance of AAA and exploits information of different MR images. The shape parameters are more robustly estimated using dynamic programming regularization6 and a weighted fit. To increase segmentation speed and robustness, a multi-resolution approach is used.

III. SYSTEM ANALYSIS

3.1 EXISTING METHOD

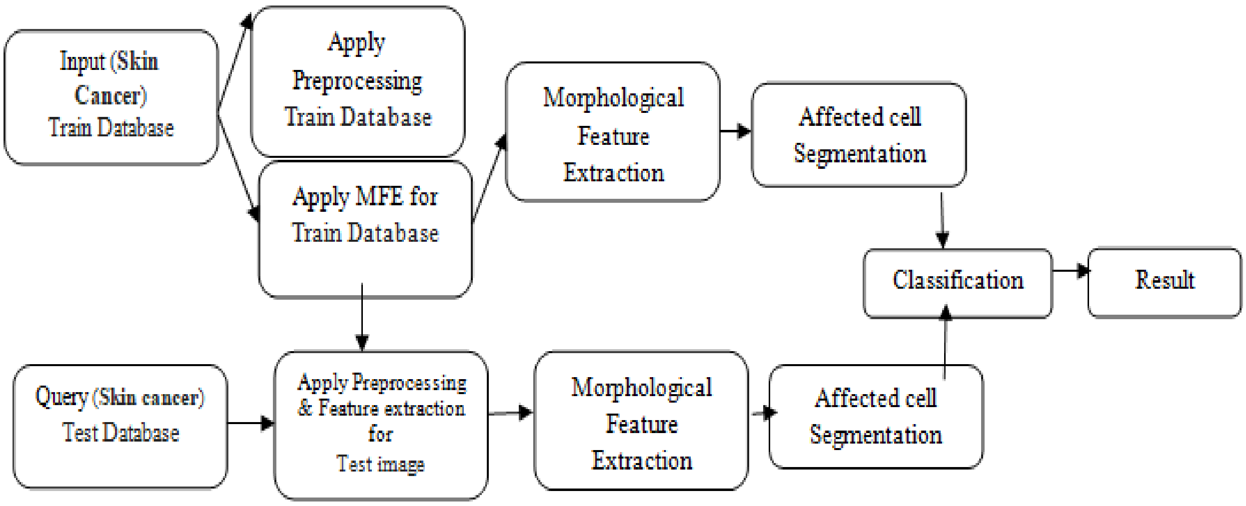
- Principal Component Analysis
- Local binary pattern and shape features
- KNN and FNN classifier

3.3 PROPOSED METHOD

Skin lesion classification for Computer Aided Diagnosis (CAD) system based on,

- Hybrid features involves color features and texture descriptors
- NN-Back Propagation Neural Network classifier
-

ARCHITECTURE DIAGRAM



IV. SYSTEM IMPLEMENTATION

4.1. Preprocessing

The purpose of image preprocessing is to eliminate unwanted noise present in the original input image and improve the quality of fine details present in it [2, 3]. This will make it informal for further processing of image in order to achieve the defined aim. The image preprocessing includes image enhancement, removal of noise and breast part extraction. Smoothing image pixel using averaging filter, Otsu technique to separate background from breast region, morphological operations, sharpening have been used for preprocessing on digital mammographic images.

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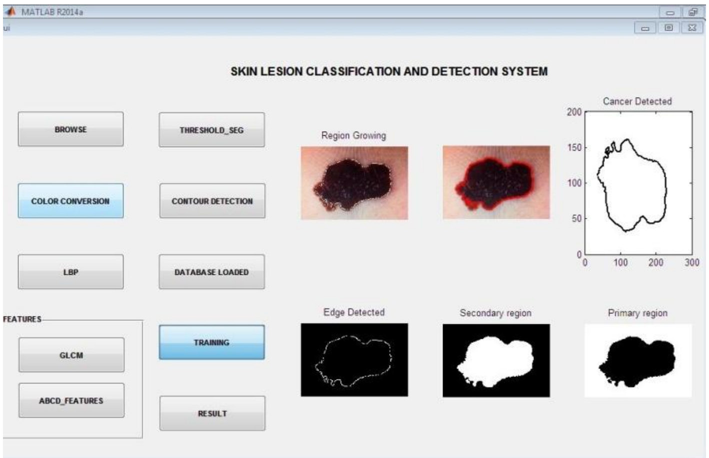
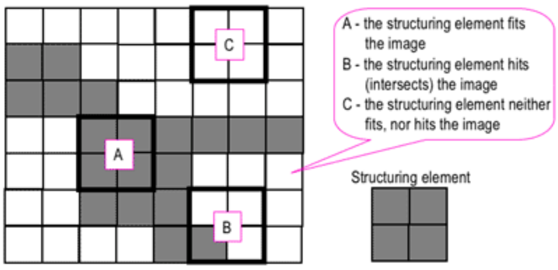


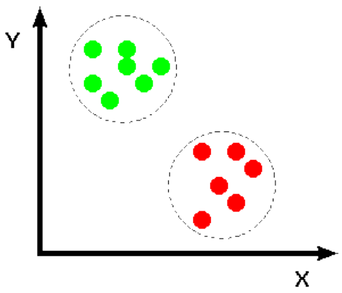
4.2. Calculate cell features in the input image

Feature extraction in image processing is a technique of redefining a large set of redundant data into a set of features of reduced dimension. Transforming the input data into the set of features is called feature extraction. Feature selection greatly influences the classifier performance; therefore, a correct choice of features is a very crucial step. In order to construct an effective feature set, several published articles were studied, and their feature selection methodology was observed. It was noted that certain features were widely used as they gave a good classification. We implemented these features onwhole images in our system. Those features were considered to boost the classifier performance.
Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood:



Probing of an image with a structuring element
(white and grey pixels have zero and non-zero values, respectively).

4.3 CLASSIFIED FEATURES



Common Names: Classification

Classification includes a broad range of decision-theoretic approaches to the identification of images (or parts thereof). All classification algorithms are based on the assumption that the image in question depicts one or more features (*e.g.*, geometric parts in the case of a manufacturing classification system, or spectral regions in the case of remote sensing, as shown in the examples below) and that each of these features belongs to one of several distinct and exclusive classes.

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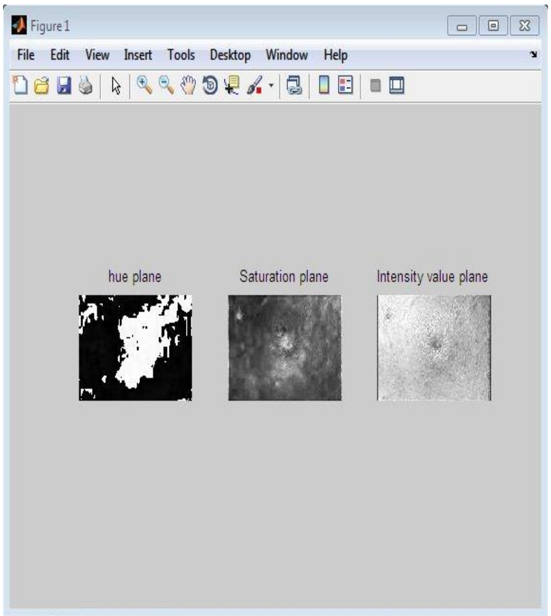
The classes may be specified *a priori* by an analyst (as in *supervised classification*) or automatically clustered (*i.e.* as in *unsupervised classification*) into sets of prototype classes, where the analyst merely specifies the number of desired categories. (Classification and *segmentation* have closely related objectives, as the former is another form of component labeling that can result in segmentation of various features in a scene.)

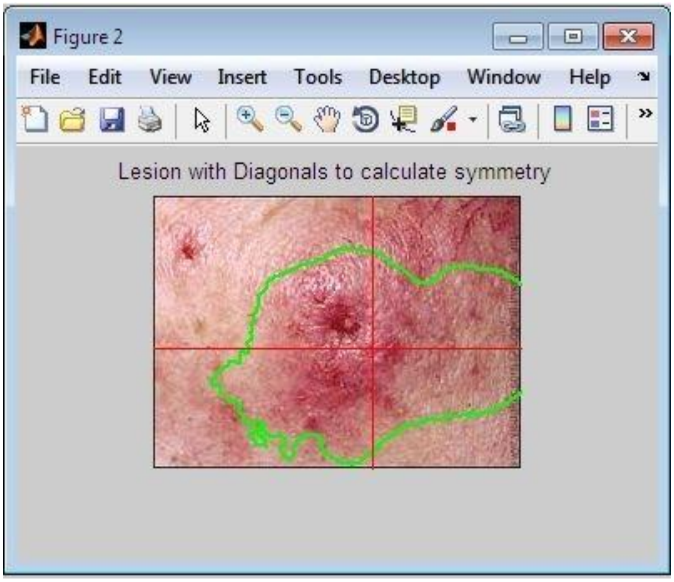


Process:

Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: *training* and *testing*. In the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, *i.e. training class*, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features.

4.4. CLASSIFICATION

This classification result gives the details about breast cancer and non cancer. To get the spitted part from the k means segmentation result. Above the result which is used to find the cancer and non cancer skin from this module.



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After extracting the pertinent feature, the final stage is to classify the attained data and assign it to a particular class. For this purpose, classifiers like Support Vector Machine, Decision tree, KNN are used.

V. RESULT AND DISCUSSION

5.1 PROBLEM IDENTIFICATION

This paper focuses upon the detection of a tumor in the breast from skin cancer images. By utilizing various image processing techniques such as segmentation, Binarization, thinning, triangulation and EDT, the demarcation of the tumor in the mri is obtained. The following results shows the output received after each step in the algorithm. For our proposed work 10 normal images and 20 tumor affected images are taken as input images and their features are extracted and the classification results are shown below.
This paper presents techniques that are required to achieve an automatic classification system to diagnosis the presence of the skin cancer from MRI.

Drawbacks

- Accuracy is low
- Cannot provide optimized cancer detect
- Segmentation process have some trouble

APPLICATION

- Skin cancer diagnosis support system in Health care fields

VI. CONCLUSION AND FUTURE ENHANCEMENT

In this paper, the various steps involved in automatic tumor detection were implemented. The proposed approach in this paper with images processed and classification proved via its performance such as Sensitivity is 100%, Specificity is 100% and its accuracy in classification is 99.66%. Our system gives the better performance when compared existing method, so it is very helpful to the medical people in detecting tumor in breast. Also these proposed algorithms can help rural people to find out the tumor occurrence in mammogram image in case of emergency situations. The purpose of this algorithm is to provide a useful advice to the end user, not to give a final decision concerning presence of cancerous changes in an image. Our system has potential of improving physician diagnostic performance.

6.1 FUTURE PERSPECTIVES

Future we are in corporating the above algorithm for genetic algorithm that mimics the evolution method within the nature could be a heuristic search technique to get the optimum answer in an exceeding immense solution. This work will incorporate on extraction of the clinical utility of mri image.

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