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Classification and Segmentation of Non-Melanoma Skin Lesions Using Curvelet Based Texture Analysis

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ABSTRACT:

This paper presents a curvelet based texture analysis for segmentation and classification of non-melanoma skin lesion. Classification and Segmentation of Skin Lesions Using Texture Analysis and wavelet based texture analysis is done. The features are entropy, convolution, contrast, energy and correlation are calculated for input image. The resultant features compared with the database images. Then the image is classified. After lesion detection image is segmented. In our proposed method we are applying curvelet Transform on gray scale image. 8 subband stages features extracted they are entropy, convolution, contrast, energy and correlation. We have a train set of 15images in our database. The resultant feature subsets were then fed into probabilistic neural network classifier on 3 stages. The stages are Normal, Disease Effected 30% and Disease Effected above 50%. Then image is segmented using fuzzy logic cluster method. Parameters are Accuracy, sensitivity. specificity of three methods calculated. Results are compared with existing methods. Our proposed method have good result in accuracy.

Keywords:

Curvelet transform, GLCM, Fuzzy logic clustering, PNN

INTRODUCTION:

Non-melanoma skin cancer is a malignant tumour that starts in cells of the skin. Malignant means that it can spread, or metastasize, to other parts of the body. The skin is the body's largest organ. It covers your whole body and protects it from injury, infection and ultraviolet (UV) light from the sun. The skin helps control your body temperature and gets rid of waste materials through the sweat glands. It also makes vitamin D and stores water and fat. The skin has 2 main layers.

The top layer, on the surface of the body, is called the epidermis. The dermis is below the epidermis. It has nerves, blood vessels, sweat glands, oil (sebaceous) glands and hair follicles. The epidermis is made up of 3 types of cells: Squamous cells are thin flat cells on the surface of the skin. Basal cells are round cells that lie under the squamous cells. Melanocytes are found in between the basal cells. They make melanin, which gives your skin and eyes their colour.

Cells in the skin sometimes change and no longer grow or behave normally. These changes may lead to non-cancerous, or benign, tumours such as dermatofibromas, epidermal cysts or moles (also called nevi). Changes to cells in the skin can also cause cancer. Different types of skin cells cause different types of skin cancers. When skin cancer starts in squamous cells or basal cells, it is called non-melanoma skin cancer. When cancer starts in melanocytes, it is called melanoma.

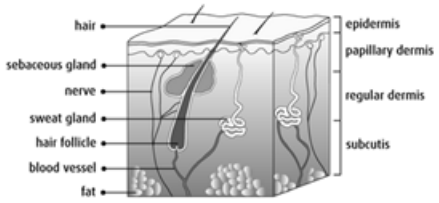

Fig: Normal skin lesions and main components.

A computer aided diagnosis of melanoma generally comprises four components; image acquisition, border detection, feature extraction, and classification based on without using Discrete wavelet transform next one based on Discrete wavelet transform feature extraction and discrete curvelet transform feature extraction.

1.Classification and Segmentation of Non-Melanoma Skin Lesions Using Texture Analysis.

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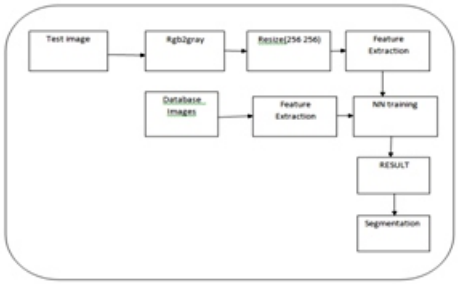
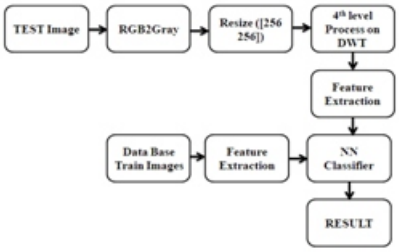


Block Diagram of Classification and Segmentation of Non-Melanoma Skin Lesions Using Texture Analysis.

The test image is converted to gray image features are extracted. These features are fed to the probabilistic neural network classifier[3][4]. Classifier compares these features with the database image features and gives the result. Here we get three types of result one is skin not effected, skin lesion 30% effected and skin lesion 50% effected. Then segmentation using clustering method.

2.Classification and Segmentation of Non-Melanoma Skin Lesions Using Wavelet Based Texture Analysis.

In clinical diagnostic approaches (e.g. ABCD rule of dermos copy and pattern analysis) dermatologists look into the visual differences within the lesion and also changes in the appearance of the lesion over the time.

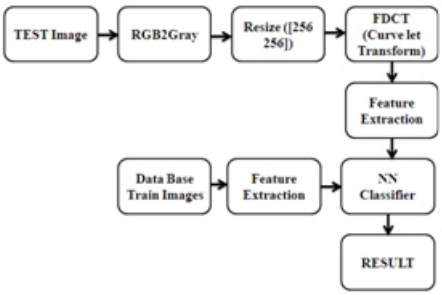


Block Diagram of Classification and Segmentation of Non-Melanoma Skin Lesions Using wavelet transform Texture Analysis.

These visual characteristics can be captured through texture analysis. Wavelet-based texture analysis[1] provides a multiresolution analytical platform which enable us to characterize a signal (an image) in multiple spatial/frequency spaces. The multi-scale characteristics of wavelet can be very useful since dermoscopy images are taken under different circumstances such as various image acquisition set up (lighting, optical zooming, etc) and versatile skin colors on disease effected analysis.The 2D wavelet transform has been widely applied in image processing applications. There exists two wavelet structure; (1) Pyramid-structured wavelet transform which decomposes a signal into a set of frequency channels with narrower bandwidths in lower frequency channels, useful for signals which their important information lies in low frequency components, (2) Tree-structured wavelet analysis which provides low, middle and high frequency decomposition which is done by decomposing both approximate and detail. In dermoscopy image analysis, the lower frequency components reveal information about the general properties (shape) of the lesion, which is clinically important, and the higher frequency decomposition provides information about the textural detail and internal patterns of the lesion which is also significant in the diagnosis. Thus the decomposition of all frequency channels are useful in this application. Therefore, the tree-structured wavelet analysis can be more informative for classification of skin lesions.

Classification and Segmentation Of Non-Melanoma Skin Lesions Using Curvelet Based Texture Analysis.

Actually the ridgelet transform is the core spirite of the curvelet transform. An anisotropic geometric wavelet transform, named ridgelet transform, was proposed by Candes and Donoho.



Block Diagram of Classification and Segmentation of Non-Melanoma Skin Lesions Using curvelet transform Texture Analysis.

The ridgelet transform is optimal at representing straight-line singularities. Unfortunately, global straight-line singularities are rarely observed. To analyze local line or curve singularities, a natural idea is to consider a partition of the image, and then apply the ridgelet transform to the obtained sub-images.

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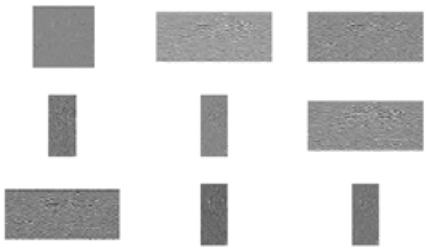

Fig: Decomposition of Curvelet transform

The effort on edge enhancement has been focused mostly on improving the visual perception of images that are not clarity because of so many sub bands. Noise removal and preservation of useful information are important aspects of image enhancement. A wide variety of methods have been proposed to solve the edge preserving and noise removal problem for more improvement. Curve Lets are also playing a most role in many image-processing applications. The curve let transform can be decomposed with four steps: (1) Sub band Decomposition (2) Smooth Partitioning (3) Renormalization (4) Ridge let Analysis. By inversing the step sequence with mathematic revising, it is able to reconstruct the original signal which is called inverse curvelet transform.

GLCM Features Extraction Process on DWT/ DCT:

A Co-occurrence matrix (CCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right(horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i,j) in the resultant CCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. The number of gray levels in the image determines the size of the CCM. We can use multiple levels of wavelet transforms to concentrate data energy in the lowest sampled bands. Specifically, the LL sub band transformed again to form LL2, HL2, LH2, and HH2 sub bands, producing a two-level wavelet transform. An (R-1) level wavelet decomposition is associated with R resolution levels numbered from 0 to (R-1), with 0 and (R-1) corresponding to the coarsest and finest resolutions. At first the co-occurrence matrix is constructed, based on the orientation and distance between image pixels.

Entropy:

Hence, for each texture feature, we obtain a co-occurrence matrix. These co-occurrence matrices represent the spatial distribution and the dependence of the grey levels within a local area. Each (i,j) th entry in the matrices, represents the probability of going from one pixel with a grey level of 'i' to another with a grey level of 'j' under a predefined distance and angle. From these matrices, sets of statistical measures are computed, called feature vectors.

Energy:

It is a gray-scale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture..

$$E=\sum\sum p(x, y)\ ^2\ P(x, y) \text{ is the GLC M}$$

Contrast:

Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth.

$$\text{Contrast I}=\sum\sum(x-y)^2\ p(x,y)$$

Entropy:

It measures image texture randomness, when the space co-occurrence matrix for all values is equal, it achieved the minimum value.

$$S=\sum\sum p(x, y) \log p\ (x, y)$$

Correlation Coefficient:

Measures the joint probability occurrence of the specified pixel pairs.

$$C=\sum\sum((x- \mu x)(y-\mu y)p(x , y)/\sigma x\sigma y))$$

Homogeneity:

Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

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$$H = \sum\sum (p(x , y)/(1 + [x-y])))$$

Probabiliste Neural Networks classifies input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers: the Input Layer, Radial Basis Layer and the Competitive layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix.

These distances are scaled by Radial Basis Function nonlinearly. Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.After image classification image is segmented using fuzzy logic cluster method.

RESULT Analysis:

Accuracy:

Accuracy is also used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. That is, the accuracy is the proportion of true results (both true positives and true negatives) among the total number of cases examined. To make the context clear by the semantics, it is often referred to as the "rand accuracy. It is a parameter of the test.

$$Acc=(Tp+Tn)/(Tp+Tn+Fp+Fn)$$

Specificity:

In medical diagnosis, test sensitivity is the ability of a test to correctly identify those with the disease (true positive rate), whereas tests specificity is the ability of the test to correctly identify those without the disease (true negative rate).

$$Specificity= Tn/(Tn+ Fp)$$

Sensitivity:

sensitivity is the ability of a test to correctly identify those with the disease (true positive rate)

$$Sensitivity=Tp/(Tp+Fn)$$

Parameter	Existing method1	Existing method2	Proposed method
Accuracy	50%	90.01%	99.44%
Specificity	50%	89.65%	99.57%
Sensitivity	50%	94.51%	98.82%

Table : Comparison of sensitivity, specificity, accuracy of existing and proposed method.

Fig: Skin Lesion Image Classification Disease 50% Effected

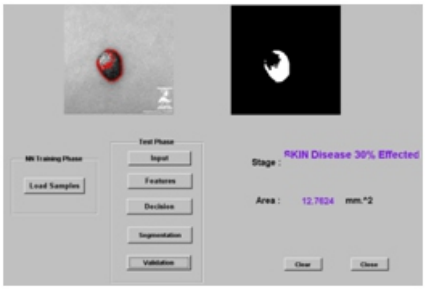

Fig: Skin Lesion Image Classification Disease 30% Effected

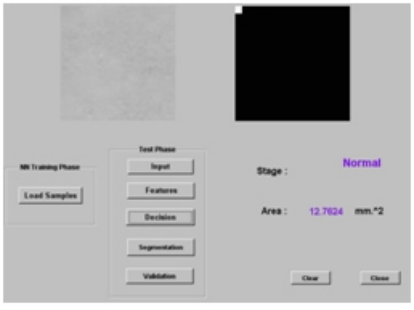

Fig: Skin Lesion Image Classification Disease Not Effected

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CONCLUSION:

This project is implemented on Non melanoma Skin lesions. The image classification is done using texture features. The texture features are energy, contrast, correlation, entropy and homogeneity. After extraction of features image is classified. Here, probabilistic neural network was used for classification. The classifications are normal, 30% effected and 50% effected. If the lesion is detected then segmentation is done. For segmentation fuzzy logic clusteringis used. The parameters are analyzed for 3 methods. Proposed method have high accuracy. Finally this method is very useful to classify skin lesion on different stages.

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