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Analysis of Non-Melanoma Skin Lesions Using Curve Let based Texture Analysis on Probabilistic Neural Network Classifier

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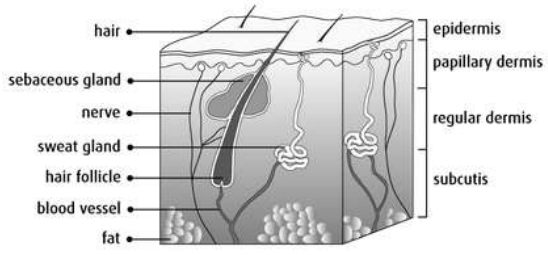
ABSTRACT:-

This paper presents a Curvelet Transform -based texture analysis method for classification of non-melanoma skin lesion classification. We are applying tree-structured on wavelet transform and subband analysis on Curvelet Transform on gray scale image analysis on wavelet and curvelet coefficients. In our proposed method Feature extraction and a 8 subband stages on feature selection method, based on entropy and correlation, were applied to a train set of images. The resultant feature subsets were then fed into neural network classifiers on 3 stages of Normal;Disease Effected 30-50% and Disease Effected above 50% and comparision measurement analysis on DWT /DCT Using* Probabiliste Neural Network *Classifier based accuracy improvement.

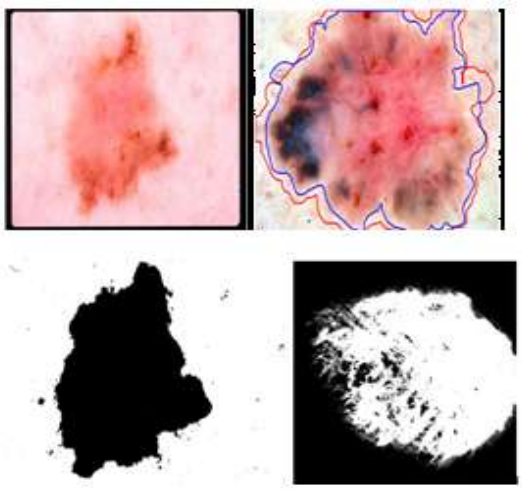
Keywords: - Melanoma skin lesion, DCT, DWT, Feature extraction, PNN, Accuracy.

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[7],[8].



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[3].



A computer aided diagnosis of melanoma generally comprises four components; image acquisition, border detection, feature extraction, and classification on DWT features and DCT Features the latter two are the main focus of this paper.

Literature Survey

Literature survey is the most important step in software development process. Before developing the tool it is necessary to determine the time factor, economy and company strength. Once these things are satisfied, then next step is to determine which operating system and language can be used for developing the tool. Once the programmers start building the tool the programmers need lot of external support. This support can be obtained from senior programmers, from book or from websites. Before building the system the above considerations are taken into account for developing the proposed system[4],[5],[6].

An improved Internet-based melanoma screening system with dermatologist-like tumor area extraction algorithm

In this paper, we describe an automatic system for inspection of pigmented skin lesions and melanoma diagnosis, which supports images of skin lesions acquired using a conventional (consumer level) digital camera. More importantly, our system includes a decision support component, which combines the outcome of the image classification with context knowledge such as skin type, age, gender, and affected body part. This allows the estimation of the personal risk of melanoma, so as to add confidence to the classification. We found that our system classified images with an accuracy of 86%, with a sensitivity of 94%, and specificity of 68%. The addition of context knowledge was indeed able to point to images that were erroneously classified as benign, albeit not to all of them.

A Comparative Study of Efficient Initialization Methods for the K-Means Clustering Algorithm

K-means is undoubtedly the most widely used partitional clustering algorithm. Unfortunately, due to its gradient descent nature, this algorithm is highly sensitive to the initial placement of the cluster centers. Numerous initial ization methods have been proposed to address this problem. In this paper, we first present an overview of these methods with an emphasis on their computational efficiency. We then compare eight commonly used linear time complexity initialization methods on a large and diverse collection of data sets using various performance criteria. Finally, we analyze the experimental results using non-parametric statistical tests and provide recommendations for practitioners. We demonstrate that popular initialization methods often perform poorly and that there are in fact strong alternatives to these methods.

An ICA-based method for the segmentation of pigmented skin lesions in macroscopic images.

Segmentation is an important step in computer-aided diagnostic systems for pigmented skin lesions, since that a good definition of the lesion area and its boundary at the image is very important to distinguish benign from malignant cases. In this paper a new skin lesion segmentation method is proposed. This method uses Independent Component Analysis to locate skin lesions in the image, and this location information is further refined by a Level-set segmentation method. Our method was evaluated in 141 images and achieved an average segmentation error of 16.55%, lower than the results for comparable state-of-the-art methods proposed in literature.

Existing Method:-

Multi-Level Discrete Wavelet Transform

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image.

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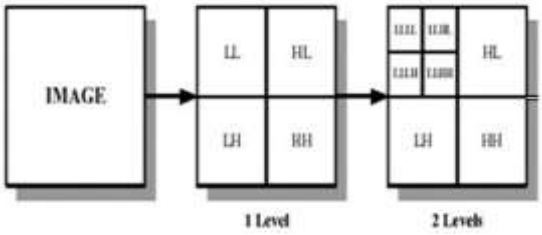
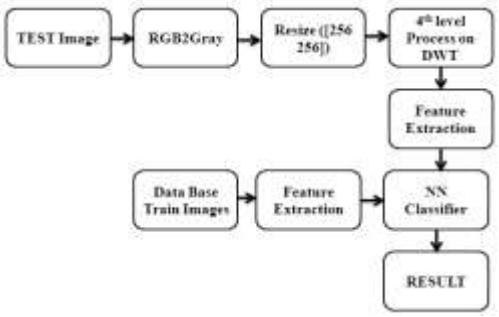
The DWT decomposes an input image into four components labeled as LL, HL, LH and HH [9]. The first letter corresponds to applying either a low pass frequency operation or high pass frequency operation to the rows, and the second letter refers to the filter applied to the columns. The lowest resolution level LL consists of the approximation part of the original image. The remaining three resolution levels consist of the detail parts and give the vertical high (LH), horizontal high (HL) and high (HH) frequencies. Figure 3 shows three-level wavelet decomposition of an image[9].



Wavelet-based texture analysis in Non Melonoma Skin Images

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



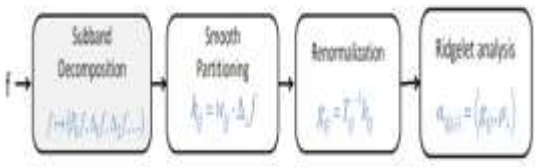
These visual characteristics can be captured through texture analysis. Wavelet-based texture analysis provides a multiresolution analytical platform which enable us to characterize a signal (an image) in multiple spatial/frequency spaces. The multi-scale characteristics of wavelet can be very useful 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 [8], (2) Tree-structured wavelet analysis which provides low, middle and high frequency decomposition which is done by decomposing both approximate and detail coefficients as shown in Figure. 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.

Proposed Method:

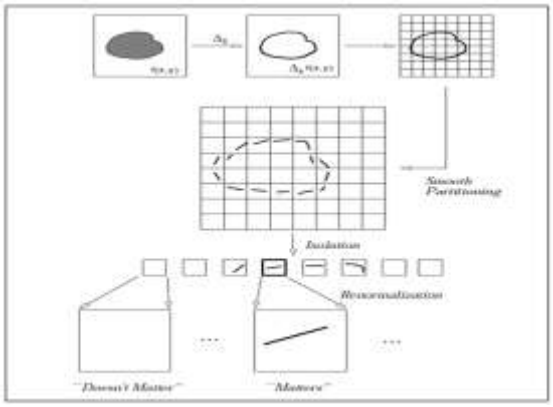
Discrete Curve let Transform:-

The curve let transform is a very young signal analyzing method with good potential. It is recognized as a milestone on image processing and other applications. Hoping that this tutorial can help you realized what curve let transform is.



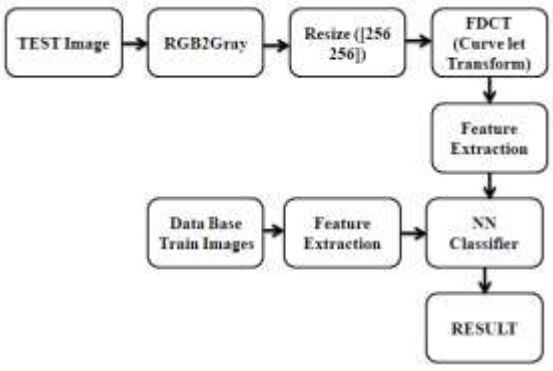
The ridgelet transform is optimal at representing straight-line singularities. Unfortunately, global straight-line

singularities are rarely observed in ral applications. To analyze local line or curve singularities, a natural idea is to consider a partition of the image, and then to apply the ridgelet transform to the obtained sub-images. This block ridgelet-based transform, which is named curvelet transform.



Curvelet-based texture analysis in Non Melonoma Skin Images

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.



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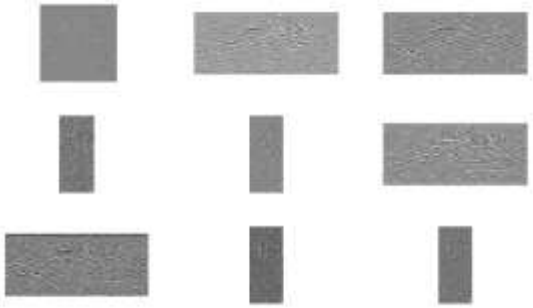


The effort on edge enhancement has been focused mostly on improving the visual perception of images that are not clarity because of so many sub bands. Noise removal and preservation of useful information are important aspects of image enhancement. A wide variety of methods have been proposed to solve 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 decomposition of an image is performed by applying their performance was very slow; hence, researchers developed a new version which is easier to use and understand. In this new method, the use of the ridge let transform as a pre-processing step of curve let was discarded, thus reducing the amount of redundancy in the transform and increasing the speed considerably The first part of the tutorial reviews the motivation of " Why Curve let Proposed " and briefly reminds the history of tiling in time frequency space. Followed, the curve let transform structure is shown. 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 curve let transform. There are some simulation experiments be shown for those three application respectively with comparison of wavelet transform and curve let 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. At first the co-occurrence matrix is constructed, based on the orientation and distance between image pixels. For example; with an 8 grey-level image representation and a vector *t* that considers only one neighbor, we would find;

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=∑∑p(x, y) ^2 P(x, y) is the GLC M

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.

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.

Contrast I=∑∑(x-y)^2 p(x,y)

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

H = ∑∑ (p(x , y)/(1 + [x-y]))

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

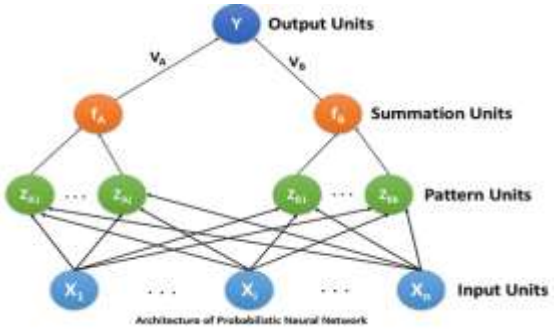
S=∑∑p(x, y) log p (x, y)

Correlation Coefficient: Measures the joint probability occurrence of the specified pixel pairs.

C=∑∑((x- μx)(y-μy)p(x , y)/$\sigma_x\sigma_y$))

Probabiliste Neural Networks

The network 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[1],[2].



Input layer

Each neuron in the input layer represents a predictor variable. In categorical variables, *N-1* neurons are used when there are *N* number of categories. It standardizes the range of the values by subtracting the median and dividing by the interquartile range. Then the input neurons feed the values to each of the neurons in the hidden layer.

Pattern layer

This layer contains one neuron for each case in the training data set. It stores the values of the predictor variables for the case along with the target value. A hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma values.

Summation layer

For PNN networks there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's

category. The pattern neurons add the values for the class they represent.

Output layer

The output layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category[3].

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)

	DWT(Wavelet)	DCT (Curve Let)
Normal	69.2308	90
30-50% Skin Disease Effected	69.2308	90
Above 50% Skin Disease Effected	69.2308	90

Table:1 Comparision between DWT and DCT on Accuracy Analysis

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

Specificity =Tp/(Tp+Fn)

	DWT(Wavelet)	DCT (Curve Let)
Normal	60	100
30-50% Skin Disease Effected	60	100
Above 50% Skin Disease Effected	60	100

Table:2 Comparision between DWT and DCT on Specificity Analysis

Fig: Skin Lesion Image Classification Disease Effected on 50% Effected

Fig: Skin Lesion Image Classification Disease Effected on 30% Effected

Fig: Skin Lesion Image Classification Disease Not Effected

CONCLUSION:-

This project implemented an Skin Disease effected on Non melenomaskin cancer image classification using texture features and it will be classified effectively based on neural network. Here, probabilistic neural network was used for classification based on unsupervised leaning using wavelet and curvelet statistical features and target vectors. The clustering was estimated from smoothing details of images accurately for effective skin disease effected part on segmentation. In addition with, the statistical features are

extracted from co-occurrence matrix of detailed coefficients of segmented images. These features are useful to train a neural network for an automatic classification process. Finally this system is very useful to skin leasion classification on different stages on multiple image analysis

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