CLASSIFICATION OF MALIGNANT MELANOMA AND BENIGN SKIN LESION BY USING BACK PROPAGATION NEURAL NETWORK AND ABCD RULE

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Abstract : Human Cancer is one among the most unsafe and disastrous illnesses which is for the most crucial part brought about by hereditary or insecurity of various sub-atomic modifications. Among many types of human disease, skin tumour or cancer is the most widely recognized one. To recognize skin tumour at an early stage we will think and break down it through different methods named as segmentation and feature extraction in those stages. Here, we center on basically threatening melanoma skin disease, (because of the high grouping of Melanoma we offer our skin, in the dermis layer of the skin) location. In this, We utilized our ABCD rule govern dermoscopy innovation for harmful melanoma skin malignancy location and then rectify. In this framework distinctive parts for melanoma skin injury i.e, to begin with, the Image Acquisition Technique, pre-processing, segmentation is being characterized a component for skin Feature Selection decides sore, grouping strategies. In the Feature extraction by advanced picture preparing technique inhibits, Asymmetry recognition, Border Detection, Colour, and Diameter detection and furthermore we will be using in LBP. For extracting the texture based features. Here we proposed the Backward Propagation Neural Network method .

IndexTerms - video surveillance, DWT, morphological erosion, dilation, Frame differencing.

I. INTRODUCTION

The event of skin disease in all around the world and Has risen consistently in the zone of the most recent images of decades because of changes in the pattern of presentation of the popular faces. Skin Cancer is exceptionally normal and records for more than 30% of all growth enrollments. It can be classified into Malignant Melanoma and Benign. Malignant Melanoma is a huge kind of malignancy, which begins from melanocytes situated in the epidermis layer of the skin. In spite of the fact that skin diseases are the most common tumors, they represent just 3% of all cancer deaths and of those threatening melanoma is responsible of more than 70%. Early conclusion of melanoma helps in diminishing the bleakness and the cost of treatment in the project.

CLASSIFICATION OF SKIN CANCER

Melanoma skin disease is the most hazardous type cancer chiefly found in light-cleaned place. It can be lethal if not treated at early stage. We as a whole know well that early identification and treatment of skin disease can lessen the mortality and of patients. In this way, to distinguish skin growth at early stage Digital images is being taken into consideration as a standout amongst the best weapon which is utilized to recognize and group skin-tumor. It is non-intrusive in vivo strategy, helps the clinician check up in melanoma recognition in its initial stage. This additionally added picture of dermoscopy, and add up to body photography, indicative framework and reflectance microscopy. PC innovation assumed a crucial part in medicinal field. This fills in as a medicinal choice bolster broadly spread and that is unavoidable over an extensive variety of therapy region, for example, gastroenterology, malignancy investigate, ailments, mind tumors brain tumors and so on.

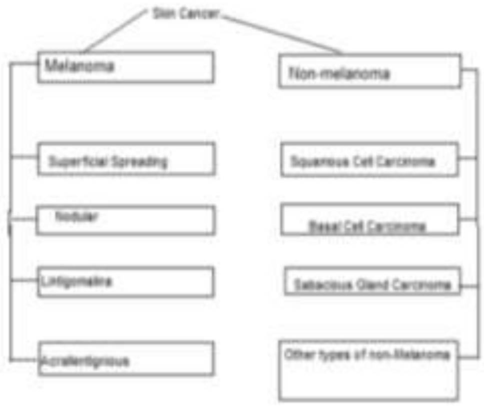
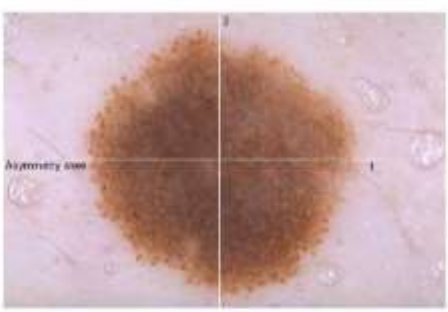


Fig 1: Classification of skin cancer

II. Literature Survey

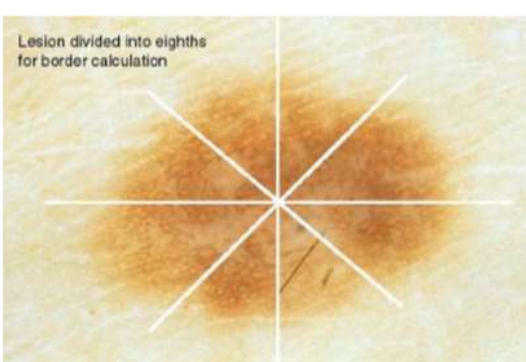
ABCD Rule: ABCD score can be computed when the 'Asymmetry, Border, Colors, and Dermoscopic structures criteria are surveyed semiquantitatively. To yield an aggregate dermoscopyscore(TDS) each of the criteria is increased by a given weight variable. A benevolent melenocytic injury is demonstrated by the TDS values under 4.75, values in the vicinity of 4.8 and 5.45 or more noteworthy are profoundly suggestive of melanoma.

A. Asymmetry For surveying asymmetry, the melanocytic sore is separated by two 90º axes that were situated to deliver the most minimal conceivable asymmetry score. On the off chance that both dermocopically indicate topsy-turvy forms with respect to shape, hues and dermoscopic structures, the asymmetry score is 2. On the off chance the score is 1 when there is asymmetry on one pivot just.



B. Border The lesion is divided into eighths, and the shade example pigment pattern is evaluated. Inside each one-eighth section, a sharp, unexpected cut-off of shade i.e., at the fringe gets a score 1. Conversely, a steady, ill defined cut-off inside the fragment gets the score of 0. In this way, the maximum score of border is 8, and the minimum score is 0.

The lesion is divided into eighths, and the pigment pattern is accessed . Within each one-eighth segment, a sharp, abrupt cutoff of pigment pattern at the periphery receives a score of 1. In contrast, a gradual, indistinct cut-off within the segment receives a score 0. Thus, the maximum border score shows 8, and the minimum score shows 0.



C. Color There are six different colors which are counted in determining the color score: white, red, light brown, dark brown, blue, gray, and black. For each color, add +1 to the score and white should be counted only if the area is lighter than the adjacent skin. The maximum color score shows 6, and the minimum score shows 1.

Dermoscopic structures:

There are few structural features to evaluate the dermoscopic structures : network, structureless (or homogeneous) areas, branched streaks, dots, and globules. The presence of any feature results in a score +1 Structureless areas must be larger than 10% of the lesion to be considered present. Branched streaks and dots can be counted only when more than two are clearly visible. The presence of a single globule is sufficient for lesion to be considered positive for globules. One of the most popular Neural Network(NN) algorithms is back propagation algorithm. BP algorithm could be divided into four main steps. After choosing the weights of the network randomly, the back propagation algorithm can be used to compute the necessary corrections.

The algorithm is decomposed in the following four steps:

Feed-forward computation
Back propagation to the output layer
Back propagation to the hidden layer
Weight updates

This is most unpleasant and essential equation for BP calculation. There are some varieties which are proposed by other researcher yet Rojas definition appears to be very precise and simple to take after. The last stride and weight updates is going on all through the calculation.

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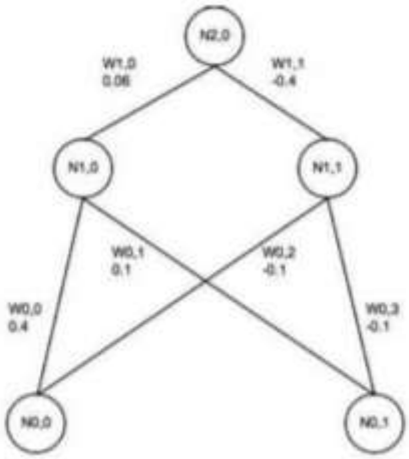


Pattern Data for AND:

n0,0	n0,0	Output n2,0
1	1	1
1	0	0
0	1	0
0	0	0

β = Learning rate = 0.45
α = Momentum term = 0.9
f(x) = 1.0 / (1.0 + exp (-x))

NN shown on above figure has two hubs (N0,0 and N0,1) in info layer, two hubs in shrouded layer (N1,0 and N1,1) and one hub in yield layer (N2,0). Input layer hubs are associated with concealed layer hubs with weights (W0,1-W0,4), Concealed layer hubs are associated with yield layer hubs with weights (W1,0and W1,1). The qualities that are given to weights are taken haphazardly and will be changed amid BP cycles. Table with info hub values and fancied yield with learning rate and energy are additionally shown in figure 5. There is sigmoid capacity equation $f(x) = 1.0/(1.0 + \exp(-x))$. Demonstrated are figurings for this straight forward system (computation for instance set 1 will be appeared (input estimations of 1 and 1 with yield esteem 1). In NN preparing, all illustration sets are figured yet rationale behind estimation is the same.

III. System Analysis

(a) Local binary patterns

(LBP System Analysis) is a straightforward and exceptionally profitable surface administrator which names the photo of a picture by thresholding the area of every images and consider it as the outcome as a paired numbers in the image Because of its discriminative energy and effortlessness. LBP surface level has turned into a prominent approach in various applications. It can be viewed as a binding together way to deal with the automation dissimilar facts and basic models of surface investigation. Maybe the most essential property of the LBP administrator in certified applications and its power to monotonic low scale changes brought on, for instance, by brightening varieties. Another crucial property is its computational effortlessness, which makes it easy to break down pictures in testing and continue with the other settings.

(b)FNN classifier

The classifier is presented on the classifier is presented on the basis of the modification of the typical four-layer forward FNN. The analysis layer is introduced so that it becomes a five-layer network, the architecture of which is shown in fig 1. Its input-output relations among layers and the corresponding symbols are described as follows: Input layer: nxp neurons, each relates to Input xji,j= 1,2.. . n,i= 1,2.. .p, the whole input bi} is a two dimension matrix . Received data + WVD PCA Analysis layer: h Xp neurons, the output of FNN output each is f g i ,g = 1,2.. .h ,i= 1,2.. . p The classifier is presented on the basis of the modification of the typical four-layer forward FNN. The analysis layer is introduced so that it becomes a five-layer network, the architecture of which is shown in fig 1. Its input-output relations among layers and the corresponding symbols are described as follows: Input layer: nxp neurons, each relates to inputxji,j= 1,2.. . n,i= 1,2.. .p, the whole input b,;i} is a two-dimension matrix . Received data + WVD PCA Analysis layer: h Xpneurons, the output of FNN output each is f g i ,g = 1,2.. .h ,i= 1,2.. . p Inference layer: multiplying inference rule is used ,namely μk = π μki

(C) KNN classifier

We have utilized k-closest neighbor approach as a classifier in this work. A protest is grouped by a larger part vote of its neighbors, with the question being doled out to the class which is most normal among its k closest neighbors. The inspiration for this classifier is that examples which are near each other in the element space are probably going to have a place with a similar example class. The neighbors are taken from an arrangement of tests for which the right characterization is known. It is regular to utilize the Euclidean separation, however other separation measures, for example, the City square, Cosine separations could be utilized. In this work we have utilized three diverse separation measures , City piece and Cosine remove measure to concentrate the impact on the arrangements.

IV. Proposed system

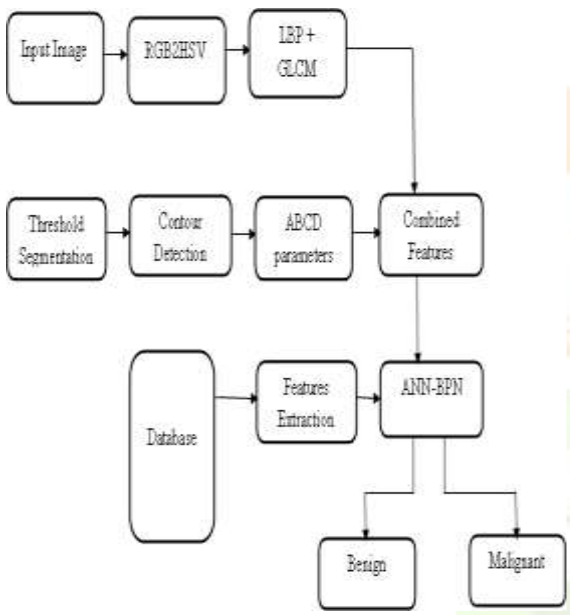


Fig 2: Block Diagram of Proposed System

Local ternary pattern

Local ternary patterns (LTP) are an extension of Local binary patterns (LBP). It does not threshold the pixels into 0 and 1, rather it uses a threshold constant to threshold pixels into three values. Considering k as the threshold constant, c as the value of the center pixel, a neighboring pixel p, the result of threshold will be:

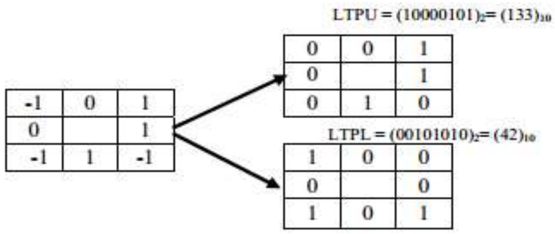
$$\begin{cases} 1, & \text{if } p > c + k \\ 0, & \text{if } p > c - k \text{ and } p < c + k \\ -1 & \text{if } p < c - k \end{cases}$$

In this way, every threshold pixel has one of the three values. Neighboring pixels are combined after thresholding into a ternary pattern. Computing a histogram of these ternary values will result in a large range, so that the ternary pattern is split into two binary patterns.

Histograms are concatenated to generate a descriptor and double the size of LBP.

This paper proposes the navel method for extraction of features by using the Local Ternary Pattern (LTP) and signed bit multiplication, which uses a central pixel for feature computation. The extracted features of this project are main component of the initial set of learning images (training set).Once the features of test images are extracted, the image is classified by comparing the feature vector with other train vectors in database using ANN classifier.

Splitting LTP into two LBP channels



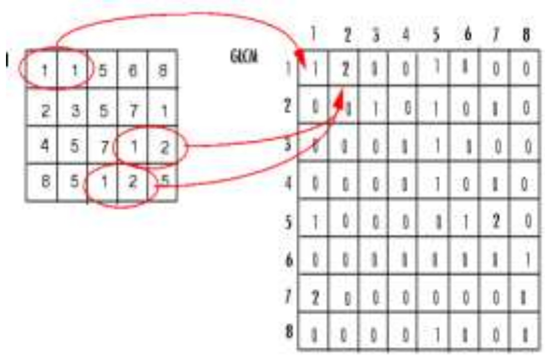
V. Proposed Methodologies

Gray-Level Co-Occurrence Matrix:

GLCM is created by using the `graycomatrix` function. The `graycomatrix` function creates a gray-level co-occurrence matrix (GLCM) 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*. It is bydefault that the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but we can specify other spatial relationships between the two pixels. Each element (*i*,*j*) in the resultant `GLCM` is 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 processing required to calculate a GLCM for the full dynamic range of an image is prohibitive, `graycomatrix` scales the input image. It is by default that `graycomatrix` uses the scaling to reduce the number of intensity values in gray scale image from 256 to 8. The number of gray levels determines the size of the GLCM. For controlling the number of gray levels in the GLCM and the scaling of intensity values by using the `Num Levels` and the `Gray Limits` parameters of the `graycomatrix` function, see the `graycomatrix` reference page for more information.

The gray-level co-occurrence matrix reveals certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along with the diagonal, the texture is coarse with respect to the specified offset. To illustrate, the following figure shows how `graycomatrix` calculates the first three values in a GLCM. At the output GLCM, element (1,1) contains the value `1` because there is only one instance in the input image where two horizontally adjacent pixels have the values `1` and `1`, respectively.

`GLCM(1,2)` contains the value `2` as there are two instances where two horizontally adjacent pixels have the values `1` and `2`. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3 are present. `Graycomatrix` continues the processing of input image, scanning the image for other pixel pairs (*i*,*j*) and recording the sums in the corresponding elements of the GLCM.



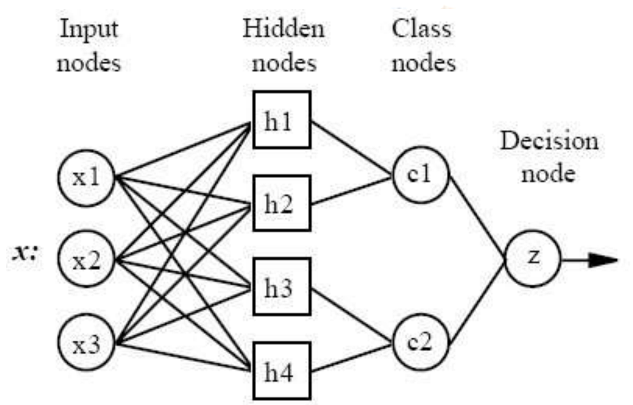
To create multiple GLCMs, specify an array of offsets to the `graycomatrix` function. These offsets define pixel relationships of varying direction and distance. For example, you can define an array of offsets that specify four directions (horizontal, vertical, and two diagonals) and four distances. In this case, the input image is represented by 16 GLCMs. When you calculate statistics from these GLCMs, you can take the average.

You specify these offsets as a *p*-by-2 array of integers. Each row in the array has a two-element vector, `[row_offset, col_offset]`, that specifies one offset. `Row_offset` is the number of rows between the pixel of interest and its neighbour. `Col_offset` is the number of columns between the pixel of interest and its neighbour. This example creates an offset that specifies four directions and 4 distances for each direction. After you create the GLCMs, you can derive several statistics from them using the `graycoprops` function. These statistics provide information about the texture of an image.Statistic such a as Contras, Correlation, Energy, Homogeneity gives information about image.

Back propagation networks (BPN):

Back Propagation (BPN) and General Regression Neural Networks (GRNN) both have similar architectures, but there is only a fundamental difference: Probabilistic network performs classification where the target variable is categorical, on the other hand, general regression neural networks perform regression but the target variable is continuous. If we select a BPN/GRNN network, based on the type of target variable, DTREG will automatically select the correct type of network.

Architecture of a BPN:



All BPN networks have four layers:

1. **Input layer** —For each predictor variable, there is one neuron in the input layer. In the case of categorical variables, *N*-1 neurons are used where *N* is the number of categories. The input neurons (or processing before the input layer) defines the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then provide the values to each of the neurons in the hidden layer.
2. **Hidden layer** — This layer comprises of one neuron for each case in the training data set. The neuron stores the values of predictor variables for the case along with the target value. When presented with the *x* vector of input values from the input layer, a hidden neuron applies the RBF kernel function using the sigma value(s) and computes the Euclidean distance of the test case from the neuron's center point .Finally, the resulting value is passed to the neurons in the pattern layer.
3. **Pattern layer / Summation layer** — The next layer in the network is different for both the BPN networks and GRNN networks. There is only one pattern neuron for each category of the target variable for BPN networks. The actual target category of training case is being 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 which they represent (hence, it is a weighted vote for that category). There are only two neurons in the pattern layer For GRNN networks. One neuron is the denominator summation unit while the other is the numerator summation unit. The denominator summation unit adds up the weight values which is coming from each of the hidden neurons. For each hidden neuron, the numerator summation unit adds up the weight values which is multiplied by the actual target value.
4. For GRNN networks, the decision layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value

BACK PROPAGATION ALGORITHM

Consider a network with a single real input x and network function F. The derivative F'(x) is computed in two phases:

Feed-forward: the input x is fed into the network. The primitive functions at the nodes and their derivatives are evaluated at each node. The derivatives are stored.

Back propagation: . The result is transmitted to the left of the unit. The result collected at the input unit is the derivative of the network function with respect to x.The constant 1 is fed into the output unit and the networkis run backwards. Incoming information to a node is added and the result is multiplied by the value stored in the left part of the unit.

Decision layer — The decision layer is different for both BPN and GRNN networks. For BPN networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer and which is used for the largest vote to predict the target category.

A. ***Background Change Detection*** processes the system images in grayscale. Pre-processing involves the modeling of the predetermined background. The median function will be used to model the background. Subtraction process uses wavelets to process succeeding frames. Wavelets are actually grouped into families like Mexican Hat wavelets, Morlet wavelets, Daubechies wavelet and Haar wavelets. Most of these wavelets group have a number of characteristics in common. For object detection, Wavelet coefficients of the current frames will be obtained using the same family of the wavelet. A difference matrix stores the difference between the current frame coefficient and modeled background coefficients. The difference matrix will then be passed to the next block which is the object detection process. It will be responsible for obtaining the foreground from the result of subtraction process and then thresholding can be done . After applying this concept, if the element value of the difference matrix is greater than a specified threshold then it will be considered as part of the foreground as it denotes that there exists a change from the modeled background.

For object classification the basic AND operation functions by outputting a value of 1 only if all of its inputs are equivalent to 1. Applying this concept, given two consecutive foreground images containing only the moving and stationary objects both having a pixel value of 255 , a value of 255 will only be outputted if and only ifthe pixel value in the previous and current frame are bothequivalent to 255 .

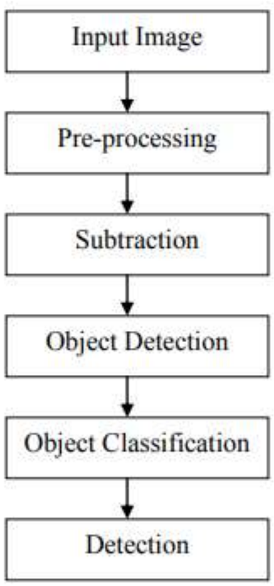


Fig 2. System Block Diagram

II. PROPOSED SYSTEM

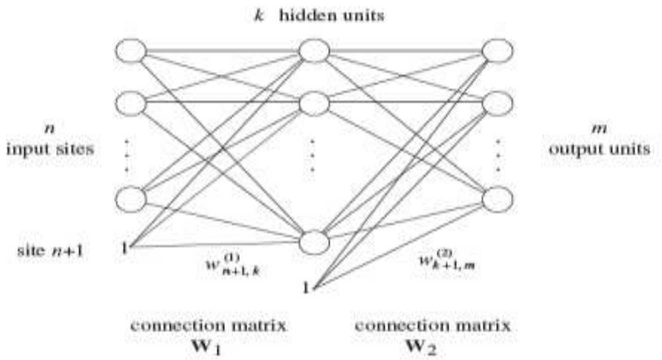
With- in-depth study of background modeling and subtraction, the paper proposes the methodology of Daubechies wavelet decomposition using object detection which effectively solves the problem of sensitive illumination change which leads to more background noises. It focuses on the time-consuming processes.The main motivation behind performing this tasks in the wavelet domain is the noise resilience nature of wavelet domain, as the lower frequency sub-band of the wavelet transform has the capability of a low-pass filter. The other motivation is that the high-frequency sub-bands of wavelet transform represent the edge information, that provides a strong cue to handle images occlusion problems.Background subtraction is based on effective moving object detection using Daubechies wavelet transform, frame differencing and background updates which work on the better result which lacked due to the varying light conditions, shadows, and other occlusions. In this paper, a simple and effective unimodal approach of background subtraction by exploiting the low sub-band characteristics of the object image in the wavelet domain is used. The Daubechies complex wavelet transform is used because it is approximately shift-invariant and has better directionality information with respect to DWT(Discrete Wavelet Transform).

STEPS OF THE ALGORITHM

The back propagation algorithm is used to compute the necessary corrections, after choosing the weights of the network randomly. The algorithm is stopped when the value of the error function has become. Sufficiently smallThe algorithm can be decomposed in the following four steps:

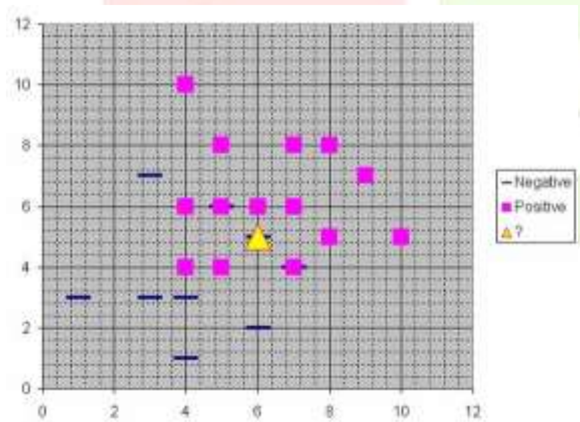
i) Feed-forward computation
ii) Back propagation to the output layer
iii) Back propagation to the hidden layer
iv) Weight updates

. The following figure is the notation for three layered network,



How BPN network work:

The basic idea is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables.Although the implementation is very different, back propagation networks are conceptually similar to *K-Nearest Neighbor* (k-NN) models. The basic idea is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables. Consider this figure:



Now, suppose we are trying to predict the value of a new case represented by the triangle with predictor values *x*=6, *y*=5.1. Should we predict the target as positive or negative? Assume that each case in the training set has two predictor variables, *x* and *y*. The cases are plotted using their *x*,*y* coordinates as shown in the figure. Also assume that the target variable has two categories, *positive* which is denoted by a square and *negative* which is denoted by a dash. The nearest neighbor classification performed for this example depends on how many neighboring points are considered. If 1-NN is used and only the closest point is considered, then clearly the new point should be classified as negative since it is on top of a known negative point. On the other hand, if 9-NN classification is used and the closest 9 points are considered, then the effect of the surrounding 8 positive points may overbalance the close negative point. Notice that the triangle is position almost exactly on top of a dash representing a negative value. But that dash is in a fairly unusual position compared to the other dashes which are clustered below the squares and left of center. So it could be that the underlying negative value is an odd case.

The further some other point is from the new point, the less influence it has.

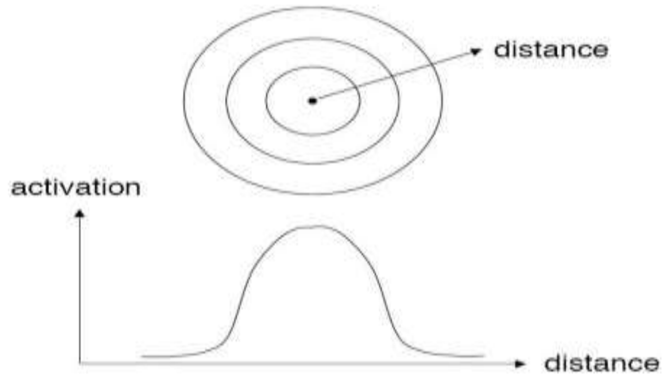


Fig. 3 Architecture of proposed system

Advantages and disadvantages of BPN networks:

- BPN networks generate accurate predicted target probability scores.
- BPN networks approach Bayes optimal classification.
- BPN/GRNN networks are slower than multilayer perceptron networks at classifying new cases.
- BPN/GRNN networks require more memory space to store the model.
- It is usually much faster to train a BPN/GRNN network than a multilayer Perceptron network.
- BPN/GRNN networks often are more accurate than multilayer perceptron networks.
- BPN/GRNN networks are relatively insensitive to outliers (wild points).

Removing unnecessary neurons

This causes the model to run slower than multilayer perceptron networks when using scoring to predict values for new rows. One of the disadvantages of BPN models compared to multilayer perceptron networks is that BPN models are large due to the fact that there is one neuron for each training row. DTREG provides an option to cause it remove unnecessary neurons from the model after the model has been constructed.

Removing unnecessary neurons has three benefits:

1. The size of the stored model is reduced.
2. The time required to apply the model during scoring is reduced.
3. Removing neurons often improves the accuracy of the model.

The neuron that causes the least increase in error (or possibly the largest reduction in error) is then removed from the model. The process is repeated with the remaining neurons until the stopping criterion is reached. The process of removing unnecessary neurons is an iterative process. Leave-one-out validation is used to measure the error of the model with each neuron removed. When unnecessary neurons are removed, the “Model Size” section of the analysis report shows how the error changes with different numbers of neurons. You can see a graphical chart of this by clicking Chart/Model size.

There are three criteria that can be selected to guide the removal of neurons:

1. Minimize error – If this option is selected, then DTREG removes neurons as long as the leave-one-out error remains constant or decreases. It stops when it finds a neuron whose removal would cause the error to increase above the minimum found.
2. Minimize neurons – If this option is selected, DTREG removes neurons until the leave-one-out error would exceed the error for the model with all neurons of neurons – If this option is selected, DTREG reduces the least significant neurons until only the specified number of neurons remain.

VI. Experimental Results

By Using Back Propagation Neural Network and ABCD Rule In this paper we analysis the malignant melanoma and Benign Skin Lesion first we taken input image.

The input image is given.

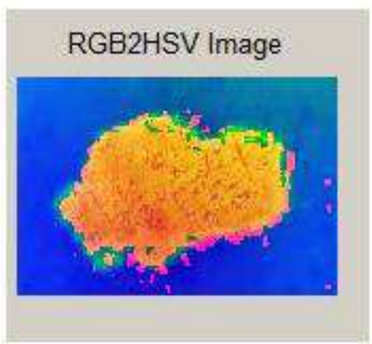


Fig.3:Input image

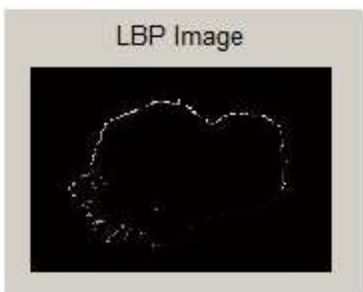


Fig 3: Colour Conversion Input image Fig.3 Represent the colour conversion of input image. After conversion of the input image is given into the LBP.

Fig.4: LBP applied input image After conversion of the input image is given into the LBP. Inthe next block we applying GLCM feature extraction it is completed is shows in fig 9.

Fig.4:GLCM features We applying.

Fig.4: LBP applied input image After conversion of the input image is given into the LBP. Inthe next block we applying GLCM feature extraction it is completed is shows in fig 9.

We are applying threshold to create the mask of the input images.It is present in fig 6.

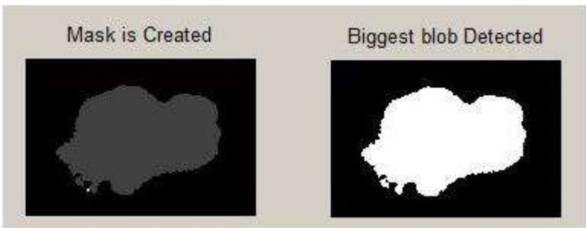
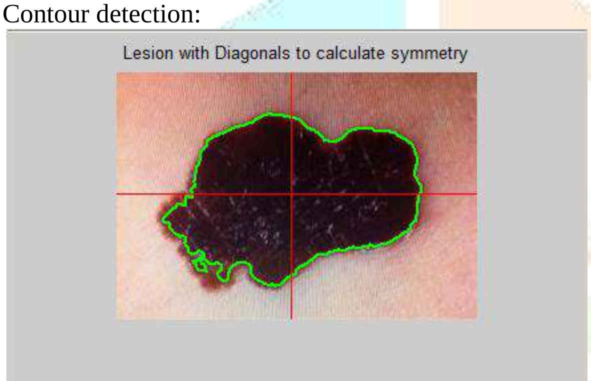
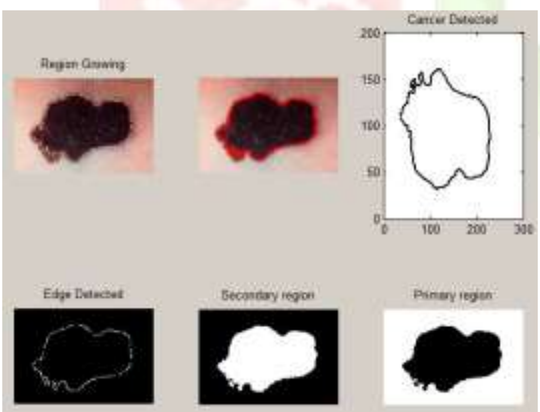


Fig.5:Threshold image

Contour detection:





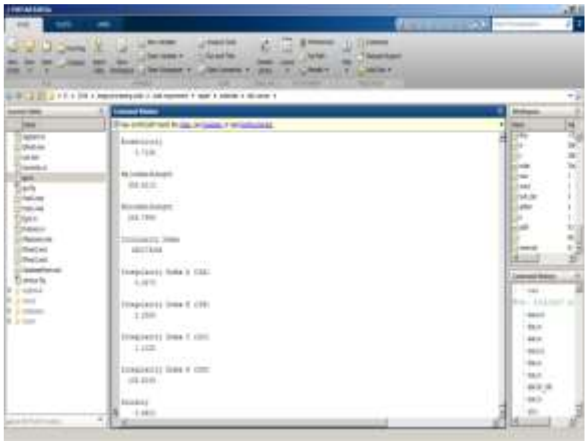
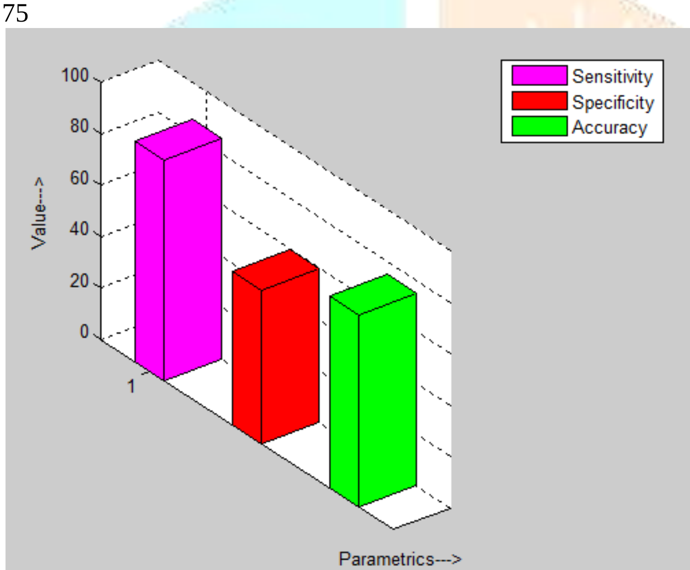


Fig.6: ABCD calculation

Finally we calculate the ABCD value calculated it shows in command window the values is given below, Irregularity index A(Ira): 0.0273

Irregularity index B (Ira):2.5305 Irregularity index C (Ira):1.1125 Irregularity index D (Ira):109.8154 Solidity: 0.6613 Bounding box: 0.5000, 0.5000, 271.0000, 186.0000 Centroid: 136.5471, 93.1910 Orientation: -1.7634 Sensitivity: 85.7143 Specificity: 60 Accuracy: 75



detected or not .if detected means fig.15 will shows otherwise the normal dialog box will showed .

VII. Conclusion

Skin disease is a standout amongst the most incessant sorts of malignancy around the world. Fundamentally, there are two sorts of skin tumour called threatening melanoma and non-melanoma. melanoma skin tumour (MSC) is the most unsafe type of disease basically found in light-cleaned populace. The point of our work is to recognize skin disease at an early stage with the assistance of two strategies i.e. highlight extraction and division. By and large, there are four phases named as-division, highlight extraction, obtaining and characterization. Among these division is a standout amongst the best strategies. It is ordered into three classifications i.e. thresholding, edge form based and district based. We will utilize thresholding technique to accomplish better outcome. This technique depends on otstu strategy which naturally distinguishes the picture. This technique gives better outcome a decent difference amongst sore and skin.

VIII. Refrences

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