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ARTICLE

FEED FORWARD WITH BACK PROPAGATION (FFBP) CLASSIFICATION FOR FINDMELANOCYTES IN THE SKIN EPIDERMIS AREA

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ABSTRACT

One of the most modern assessments of medical research is dermatology that concerned with the skin diseasestreatment and diagnosis.Skin disease detection process develops one of the keyissues in image processing operation and the necessary skin image classification system required for early detection of skin diseases.However in skin diseases finding process has one of the major problemswhich is analyzing the melanocytes in the skin epidermis area due the reason is the melanocytes are very similar to keratinocytes.Thus, in this paper proposes an efficient a melanocytesdiagnosis system using image processing operation. The texture analysis of skin histopathological images such as Asymmetry, Border Irregularity, Color, Diameter, Evolving(ABCDE) is used for image feature extraction process with the help of Gray Level Co-ocurrence Matrix (GLCM). Before done the feature exaction process the noises are removed by using Gaussian Filter and Dull Razorfilter then segmentation is done with the help ofEdge-Based Technique and finally, classification is done by using FeedForward with Back Propagation (FFBP) pixel-wise classification using supervised learning rule such as Delta learning rule.The FFBP classifier that uses a feature space derived from texture analysis values. The experimental results shows that the effectiveness of proposed system to enhance the melanocytesrecognition with higher accuracy as well as accuratelyidentifiedmelanocytes area.

KEY WORDS
Skin Diseases, Texture Analysis, Edge-Based Technique, ABCDE feature extraction, Feed Forward with Back Propagation (FFBP),Gaussian Filter, Delta learning rule and Dull Razor filter,Gray Level Co-ocurrence Matrix (GLCM).

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INTRODUCTION

Skin cancer is one of the most malignant and frequent sort of skin cancer and most aggressive types of skin cancer is melanoma [1]. The early detection of melanoma is vital to reduce this cancer mortality [2] [3]. Different kinds of techniques are used to dynamically diagnosis the melanoma and different kinds of authors are presented their proposed techniques in different ways. One of the emerging technique is confocal microscopy this technique can give pathological examination and initial diagnosis process and a cellular level view of the disease is processed by using the histopathology sides.

Basically the skin anatomy has two fundamental layers such as dermis (the inner layer) and epidermis (the outer layer). Typically the outer layer such as epidermis is made up of round cells named basal cells, scale-like cells name squamous cells, and flat. The epidermis comprisesmelanocytes which are in lower part of skin. The melanocytes are noting but pigment cell that are found in the produce melanin and epidermis, the pigment which provides the skin its real color. When the skin is showed to the sun, high pigments are produced by the melanocytes which cause the skin to darken or bronzed is direct to cause melanoma which is can be of Malignant or Benign. The melanoma canceris cause by abnormal growths of melanocyte which spreads or invades to other parts of body with abnormal control.The melanoma is divided into AcralLentiginousMelanoma, Lentigomalignant Melanoma,Nodular Melanoma andSuperficial Spreading Melanoma. Thus, to minimize the death rate essential to diagnose at this early stage. Thus, in this paper proposes an efficient a melanocytes diagnosis system using image processing operation. The texture analysis of skin histopathological images such as Asymmetry, Border Irregularity, Color, Diameter, Evolving(ABCDE) is used for image feature extraction process with the help of Gray Level Co-ocurrence Matrix (GLCM). Before done the feature exaction process the noises are removed by using Gaussian Filter and Dull Razor filter then segmentation is done with the help of Edge-Based Technique and finally, classification is done by using FeedForward with Back Propagation (FFBP) pixel-wise classification using supervised learning rule such as Delta learning rule. The FFBP classifier that uses a feature space derived from texture analysis values.

RELATED WORK

Author [4] proposes a method named as Human skin detection method. For this the skin image preprocessing and smoothing approaches are combined and skin image's RGB mean values that combine to 2-D histograms and GAUSSIAN method. This approach is makes use of automatic detection of color skin medical image. The experimental result shows that the Gaussian method obtains the promising result in over human skin detection.

Author [5] proposes a system for skin melanoma analyzing by using histopathological image. In epidermis area finding the melanocytes in epidermis is a significant process and difficult process also. Thus, author proposes a novel technique for detection of the melanocytes in epidermis area. The proposed technique based on radial line scanning, this process is used for estimated the halo region and from all the keratinocytes has to detect melanocytes is this process by using nuclei approach. Experimental evaluation based on 40 different histopathological images it comprises 341 melanocytes and the experimental results are showing a superior performance.

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Melanoma is sort of dangerous skin disease; it can be diagnosed only in its early stage but using normal conventional dermatological approach is difficult one. Thus, author [6] proposes an image processing approach by using an efficient segmentation algorithm named a radial search method to obtain the true of lesion region in dermosocpy skin images. The thresholding method is applied in segmentation process and finds the edge using radial search process. The radial search approach is called as semiautomatic method and it's requires the manual initialization to start the process. Finally the three types of features are extracted from the segmented image such as border, color and asymmetry.
Author [7] proposes method for recognizing human skin diseases by using automated system based on texture analysis. The spatial distributions of hemoglobin and melanin in human skin are divided by independent component. The texture features are obtained from Gray Level Run Length Matrices. Finally, the classification process is done by using Minimum Distance Classifier. The experimental result are using DERMNET database which contain 350 images and recognition rate show the promising results in term of classification.

Author [8] presents a novel approach for skin cancer analysis and detection from the cancer affected image. The image enhancement and denoising process by using Wavelet Transformation and the Asymmetry, Border irregularity, Color, Diameter (ACBD) rules are used for histogram analysis. Finally, the classification process is done by using Fuzzy inference system. The pixel color is used for determine the final decision of skin cancer type, decision may be two stages like malignant stage and begin stage of skin cancer.

Skin image classification

This section provides anoverview of the proposed method for identifying the melanoma skin cancer with the help of differentiating the melanocytes and keratinocytes. The step by step process of the proposed approach is presented in [Fig.1].

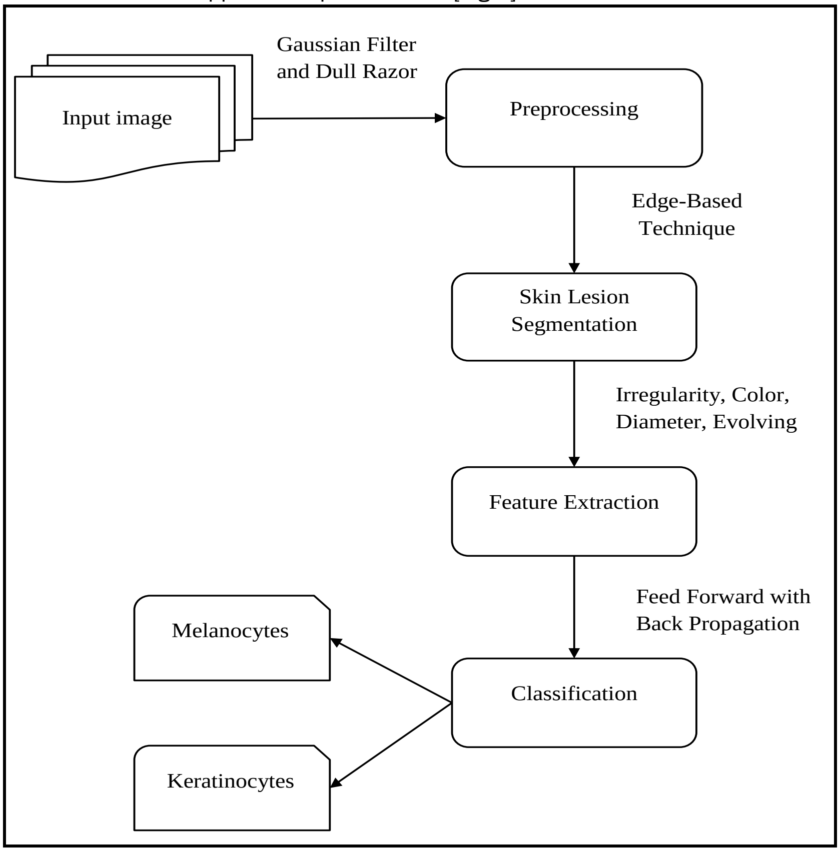

Fig. 1: Skin image classification.

Preprocessing

The main objective of pre-processing is to improve the given image quality and remove unwanted noise and effects from the image which is contain three different kinds of processes [9].First stage in the skin cancer detection system is the skin image. The skin image is in digital format is given as input to the system. Next stage is preprocessing which includes denoising and hairs removal.

In this work useGaussian Filter and Dull Razor filter for noise removing and hair removing operation. After preprocessing the image is directed to the segmentation process which is used to separates the normal skin from suspicious lesion [10] [11]. There are some specific features used to differentiate the melanocytes and keratinocytes part in the skin image. Asymmetry, Border Irregularity, Color, Diameter, Evolving (ABCDE) based feature extraction process is done here.

Hair removal

The Dull Razor filter is used for hair removal operation in givencolor image whichreplaced the hair pixels by neighboring pixels is process is as follows.

Dull razor algorithm

Input

Skin images with hair.

Output

Skin images without hair.

The images obtained in RGB color format with 256*512 sizes. The RGB images are changed into gray color image utilizing the following transformation

$$Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B(4.1) \qquad (1)$$

In preprocessing stage the average filter is used, average filter is a low pass filter and is considerably easy for de-noising the images. The function of average filter is computed as

$$g(x, y) = 1/M \sum (x, y) \epsilon S \, f(x, y) \qquad (2)$$

Where S denotes neighborhood of pixel (x,y) and M denotes the number of pixels in neighborhood S.

Step 1: It recognizes the dark hair locations by a formalized gray-scale morphological closing operation. Closing operation simply defined as dilation after erosion process utilizing the same structuring element for both process. The main input of this process is a given image is to be a structuring element and closed. The process of a graylevel dilation followed by graylevel erosion is defined as Graylevel closing.

$$f \cdot b = (f \oplus b) \ominus b \qquad (3)$$

Step 2:The about equation is used to differentiate the hair pixels shapes as long and thin structure, and substitutes the verified pixels by a bilinear interpolation.[Fig. 2] shows the effects of filling in closing gaps and holes which describe as closing operation.

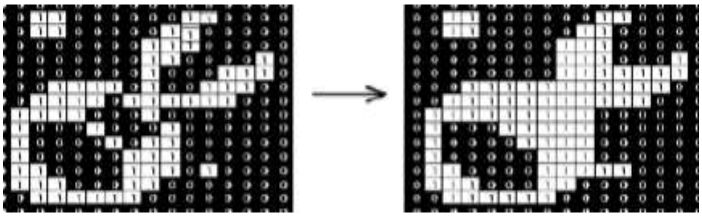

Fig. 2: Closing operation.

Step 3:After that star the smoothesoperation forreplaced hair pixels with an adaptive median filter is defined as follows

$$f_{(i,j)}^{(n)} = \int_{(i,j)}^{(n-1)} if |X_n^{(n-1)} - m_{ij}^{(n-1)}| < T \qquad (4)$$

Where, T is defined as pre-defined threshold value. The impulse detection process senses the noise even at great exploitation level setting which means here use the flag matrix value as 1 wherever noise occurs.FinalDull Razor Filter operation results is shown in [Fig. 3].

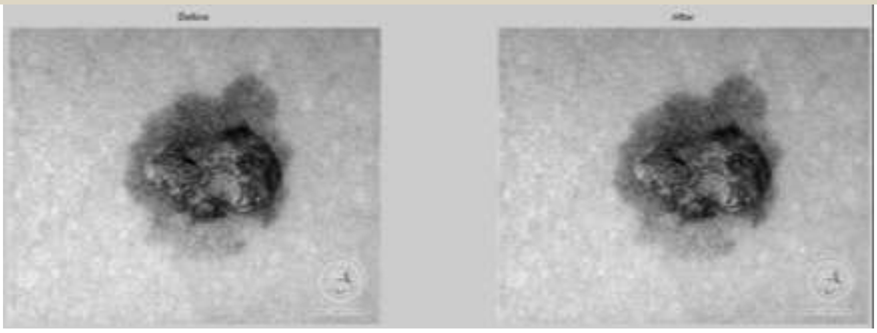

Fig. 3: Dull razor filter.

Gaussian filter

Assume the Gaussian parameters are Kis signified as the number of distributions, ω_(i,t)is a weight associated to the i^thstandard deviationΣ_(i,t) values with Gaussian at time t and mean μ_(i,t) , η is signified as a density function of Gaussian probability is formulatedby using follows equation

$$\eta\ (X_t,\mu,\Sigma) = \frac{1}{(2\Pi)^{n/2}|\Sigma|^{1/2}} e^{-1\frac{1}{2}(X_t-\mu)\Sigma^{-1}(X_t-\mu)} \quad (5)$$

Assume that the skin image RGB color features of are independent and it have the some identical differences. Thus, the closing operationmatrix is defined asfollows

$$\Sigma_{i,t} = \sigma_{i,t}^2 I \quad (6)$$

At the end of this process got noise removed skin image is as shown in [Fig. 4].

Fig. 4: Before and after gaussian filter.

Edge-based technique

After the preprocessing work segmentation process start with the help ofEdge-Based Technique which is segmented based on specific edge regions by finding the edge pixels and which is connect by using contours[12]. Basically, the boundaries are characterize by edge, the edge is gratefully helpful in process with boundaries and regions and as an edge point is transition given gray level skin image which is liked with a point [13]. Typically, the edges happened on the boundary between two different kinds of regions. Here have to consider the gradient point in the edge direction which is pixel's intensity is increases rapidly. The image gradient is defined as follows

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right] \quad (7)$$

The edge strength is provided by the gradient magnitude

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \quad (8)$$

The gradient direction is computed by using following equation

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$$\theta = tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right) \quad (9)$$

Asymmetry, border irregularity, color, diameter (ACBD)

There are some identical features that differentiatemelanocytes and keratinocytesfor finding benign melanoma or malignant melanoma which task is used to find the featuresvector. Here, use three sorts of feature such as texture,shape and color with the help of Asymmetry, Border irregularity, Color, Diameter (ACBD) usingGray Level Co-ocurrence Matrix (GLCM).

Table 1: GLCM structure properties

Contrast	$\sum_{r=1,c=1}^{row,col} (i-j)^2 P_{i,j}$
Correlation	$\frac{1}{\sigma i.\sigma j} \sum_{r=1,c=1}^{row,col} (i-\mu i)(j-\mu j) P_{i,j}$
Homogeniety	$\frac{1}{(1+(i-j))} \sum_{r=1,c=1}^{row,col} P_{i,j}$
Energy	$\sum_{r=1,c=1}^{row,col} P^2{}_{i,j}$

The GLCM structure properties are shown in [Table 1] which is characterize the texture in terms of skin physical variation.

Asymmetry is one of the significant features for understanding the correct shape with the help of symmetry, which is very helpful in pattern analysis.In case, the shape is totally symmetrical means which ratio is defined as 1. As these asymmetries areincreases means the ratio is closer to 0. Asymmetry Index is defined by using following equation

$$AI = \frac{\Delta A}{A} X100 \quad (10)$$

Where, A is defined as the area of the whole given skin Image. ΔA is defined as the region difference between lesion area and total image.

The skin segmentation is tending to have irregular borders with notchesand sharp edges.Melanocytes area tends to have smooth borders. In case the shape is fullysymmetrical which ratio is defined as 1, otherwise the ratio iscloser to 0. The Irregularity index is defined as a perimeter (P) and function of area (A) is defined as follows

$$IR = \frac{4\pi A}{P^2} \quad (11)$$

Basically color features are defined as standard derivation, skewness and mean and these features are obtained by utilizing Color Moment (CM) descriptor

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{iJ} \quad (12)$$

$$\sigma_i = \left(\frac{1}{N}\sum_{J=1}^{N}(f_{iJ}-\mu_i)^2\right)^{\frac{1}{2}} \quad (13)$$

$$\gamma_i = \left(\frac{1}{N}\sum_{J=1}^{N}(f_{iJ}-\mu_i)^3\right)^{\frac{1}{3}} \quad (14)$$

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Where f_{ij} is the color value of the i^th color component of the j^{th}image pixel and N is the total number of pixels in the image. γ_i, σ_i, $\mu_i (i = 1,2,3)$defined as the skewness, standard deviation and meanof each channel of given image respectively.

Feed forward with back propagation

In this work the Feed Forward with Back Propagation (FFBP) is train withDelta learning rule using 3X3 to 5 X5 input images. The FFBP has one input and output layers, here the hidden layer's nodes were stared from as a template which means is similar to any kind of image processing operation for example sobel templates or kirsch. Here the templates are examined by using the Taylor series coefficients. From this results can found the sharp edges with trained data. In this FFBP process the hidden layers of a network receives the signals from given input layer over a connection links which is weighted, performs the transmits and computation results as message to the output layer which are connected with the help of connection link weight $W_{11}, W_{12}, \dots W_{vm}$. The network indent layer is as an output layer or another input layer in its place it acts as output or input layer depends on the processing situation. TheFFBP is shown in [Fig. 5]

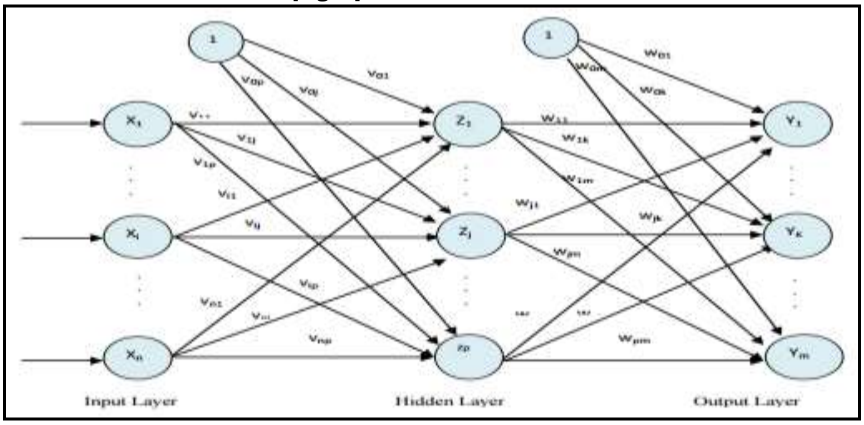

Fig. 5: Feed forward with back propagation.

Neural Network is trained by utilized Delta Rules which is also named as Backpropagation Rule [14]. The back propagation network training process is includes three different kinds of process. Staring process is feed forward stage which has hidden node Z_j is obtain the input signals is defined as the $x_1, x_2, \dots, x_n$ from these input nodesX_i over the connection weights $v_{11}, v_{12} \dots v_{nv}$is used to calculates the final input as the product sum of the given input weights and signal which means $Z_{inj} = v_{0j} + \sum x_i v_{ij}$employs an activation function to generates the proper response and lastly sends these signals to the output node Y_k.
This process is similar to hidden node, each and every output nodes Y_k is obtainsthe signals $z_1, z_2, \dots z_v$ from the each and every hidden node Z_j over the $W_{11}, W_{12}, \dots, W_{vn}$compute the final input $y_{ink} = w_{0k} + \sum z_j w_{jk}$ e employs an activation function to yield the network output. An activation function which is utilized at both the output layerand hidden layer is a sigmoid function which means $f(x) = 1/(1 + exp(-x))$.

Once the response of the network is computed after that each and every output node compares its response with the given target function $t_k$to defined the related error. Depends on these error the factor $\delta_k$is defined as $\delta_x = (t_k - y_k) * f^1(y_{ink})$.The value $\delta_k$is utilized to distributed the error at $Y_k$which is return back to all the hidden nodes which are linked to Y_k. As same as factor δ_j is calculated as $\delta_j = \delta_{inj} * f^1(z_{inj})$ for each and every hidden node Z_j to transmit errors back to input layer.

When all the δ factors are propagated and defined to appropriate layers, after that the weights are simultaneously adjusted. The adjustment of the weight from the hidden node to output node is depends on the δ_k as $\Delta w_{jk} = \alpha\, \delta_k z_j$and δ_j as $\Delta v_{ij} = \alpha\, \delta_j x_i$. So, the new weights between hidden node and input node arev_$v_{0j}(new) = v_{0j}(old) + \Delta v_{0j}$ and$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$and the weights between output nodes and hidden nodes are $w_{0k}(new) = w_{0k}(old) + \Delta w_{0k}$, $w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$. This procedure is continued until attain the end condition. The end condition may be the number of epochs it has reached or reduce the Mean Square Error (MSE). The least MSE is calculated by using following equation

$$MSE = 0.5 \sum (t_k - y_k)^2 \qquad (15)$$

RESULTS AND DISCUSION

Evaluation of FFBPclassification was undertaken by comparing the epidermis and dermis regions with true epidermis regions.

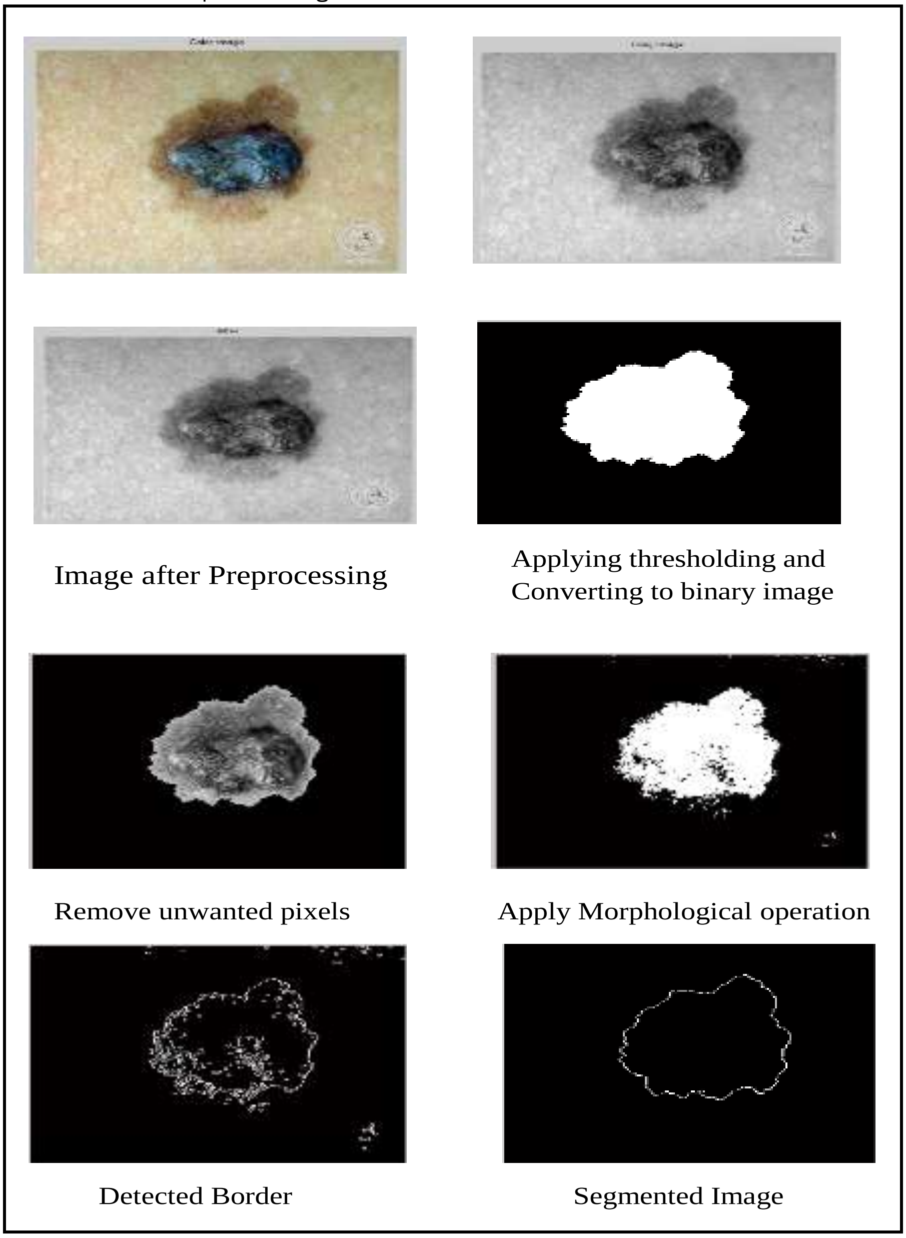

Fig. 6: Implemented results.

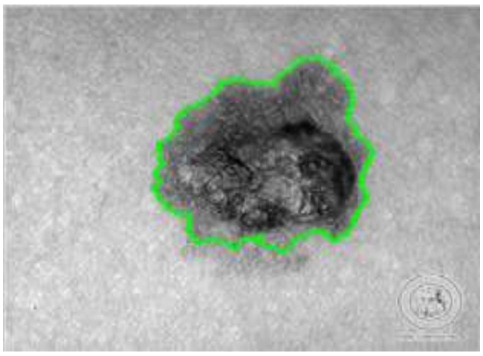

Fig. 7: Final segmented image.

The implemented results are shown in [Fig. 6] and final segmented image is presented in [Fig. 7].

Database

In this proposed work, collected the skin disease image from the websites [15] [16] and [17], which contain approximately 20 images which are separated into different types of classes. In the database, the images are in .JPEG format. In the preprocessing stage, the images are treated as 300 X 300 dimensions. Additionally, the images are collected in different types of backgrounds.

Performance metrics

The total number of pixels in each skin biopsy image was utilized to define the True Negative (TN), True Positive (TP), False Negative (FN) and False Positive (FP) fractions.Correspondingly, the different fractions can be considered as follows:

$$FN = (imageArea - A_s) \cap A_w \qquad (16)$$

$$FP = A_s \cap (imageArea - A_w) \qquad (17)$$

$$TP = A_s \cap A_w \qquad (18)$$

$$TN = (imageArea - A_s) \cap (imageArea - A_w) \qquad (19)$$

These fractions were utilized as the percentage specificity, sensitivityand accuracy of the automated segmentation.

$$specificity = \frac{TN}{(TN + FP)} X100 \qquad (20)$$

$$Sensitivity = \frac{TP}{(TP + FN)} X100 \qquad (21)$$

$$Overall\ Accuracy = \frac{(TP + TN)}{(TP + FP + FN + TN)} \qquad (22)$$

The accuracy measurement measures thepercentage of biopsy skin image pixels correctly classified as epidermis andnon-epidermis.

RESULTS

Table 2: Skin features

Asymmetry	Border irregularity	Color	Diameter
5.5223	0.4857	1.0722	0.5506
5.5365	0.4674	1.0718	0.5726
3.5239	0.7705	1.080	0.6175
2.562	0.7212	1.0371	0.8526

[Table 2] shows the skin features values in term of ABCD features, various skin structures are analysis in the this technique and the classification results shows the proposed method an effective tool in identifying skin diseases.

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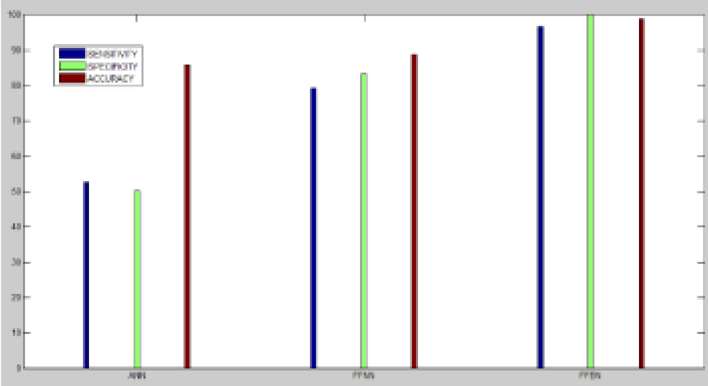

Fig. 8: Comparison of classification algorithms.

[Fig. 8] shows the different types of algorithms are compared in terms of performance metrics such as sensitivity, specificity and Accuracy. The proposed method shows the promising result to compare with other existing algorithms.

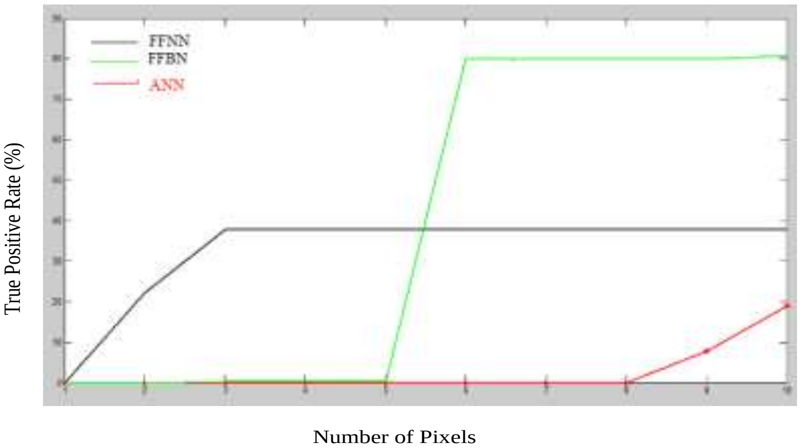

Fig. 9: True positive rate (TPR).

[Fig. 9] shows the comparison results of existing FFNN, ANN and proposed FFBP algorithm in terms of TRP. The proposed method shows promising results to compare with their existing algorithm because of very poor performance in differenced the melanocytes from the keratinocytes by the utilizing the biopsy skin image.

CONCLUSION

This paper successfully proposes an efficient a melanocytes diagnosis system using image processing operation. The texture analysis of skin histopathological images such as ABCDE is used for image feature extraction process with the help of GLCM. Before done the feature exaction process the noises are removed by using Gaussian Filter and Dull Razor filter then segmentation is done with the help of Edge-Based Technique and finally, classification is done by using FFBP pixel-wise classification using supervised learning rule such as Delta learning rule. The experimental results shows that the between classification results when compared with other existing classification algorithms.

CONFLICT OF INTEREST
None
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None
FINANCIAL DISCLOSURE
None

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