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ANN BASED COMPUTER AIDED DIAGNOSIS AND CLASSIFICATION OF SKIN CANCERS

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ABSTRACT

This paper presents a Computer based early skin cancer detection system that involves preprocessing of noise removal and gray scale conversion, segmentation, feature extraction, and classification. The preprocessing step employs Median filter for removing thin hairs and other noises. The segmentation process extracts the suspicious region from the normal skin. The paper identifies 29 features that represent the unique features of skin images, and designs an ANN classifier based on the evaluated features to classify the skin images into malignant and benign. It discusses the results of sample skin images and compares them with those of existing methods with a view of exhibiting the superior performance of the proposed method.

Keywords: denoising, segmentation, artificial neural network.

1. INTRODUCTION

Skin cancer is one of the most dangerous skin diseases and seen in all the regions of the world regardless of age, gender and race. Skin cancers can be classified into benign and malignant melanoma. The appearance of benign looks like moles, while malignant melanoma is asymmetrical and irregular, and featured with colour variation. Among them, malignant melanoma is the deadliest form of skin cancer as it can spread out to all parts of the body through lymphatic system or blood [1]. Early diagnosis of melanoma helps in reducing the morbidity and cost of therapy. Statistics indicate that the patient will make a complete recovery in 90–95% of cases, if the melanoma is surgically removed when its thickness is less than 1 mm. However, when it grows beyond 1 mm, the prognosis is less effective and the mortality rate increases to around 10–15% for each millimetre that the cancer has grown. This is the precise reason of why it is vital for early detection [2].

The ABCD rule is a well recognized guidelines used for classification of dermatological images to benign or malignant [3, 4]. ABCD stands for the following features: A (asymmetry), B (border), C (colour), D (Diameter or Differential structures) [5]. The accuracy of diagnosis is highly dependent upon physician's expertise due to the subjective nature of examination. Recently, several computer aided diagnosis (CAD) have been developed to aid dermatologists in early diagnosis of skin cancers [6-11]. CAD could increase diagnostic accuracy for dermatologists and enable storing of images with diagnostic information for further investigations or creation of new methods of diagnosis. They can improve the speed of skin cancer diagnosis which works according to the disease symptoms.

The focus of this paper is to develop an artificial neural network (ANN) based CAD for classifying the dermoscopic skin lesions into benign or malignant melanoma. The paper comprises four sections. The first section provides the introduction, the second section suggests the proposed CAD, the third section discusses the results and the forth section concludes.

2. PROPOSED CAD

The proposed CAD comprises preprocessing, segmentation, feature extraction and classification. Denoising is the one of the most important preprocessing step, as the images contain noises and artifacts such as air bubbles and thin hairs around the lesion. Median filter is used for denoising in the developed model. Segmentation removes the healthy skin from the image and finds the suspicious region of interest [9, 10]. After segmentation, the output is a binary image. Segmentation is accomplished by scanning the whole image pixel by pixel and labelling each pixel as object or background.

There are some unique features for the cancerous images. After segmentation, the important features of image data are extracted from the segmented image. The extracted features are the representatives of skin lesions and can distinguish between Malignant and Benign. In the proposed model, 29 features are extracted. Of the set of 29 features, 5 describes basic shape such as area, perimeter, greatest diameter, shortest diameter and average diameter, 1 characterizes asymmetry, 5 characterizes border irregularity, 7 characterizes colour and 11 characterizes texture. The texture features include energy, contrast, homogeneity, correlation, variance, rms, standard deviation, mean, entropy, kurtosis and skewness, which are calculated using gray level co-occurrence matrix [12-14].

Classifier is used for classifying malignant melanoma from other skin diseases. Based on the computational simplicity ANN based classifier [15, 16] is used. The proposed classifier uses a feed forward multilayer ANN, which possesses an input layer, a hidden layer and an output layer. The structure of the ANN classifier is shown in Figure-1. There are 29 neurons in the input layer to receive the extracted features of the input image and a neuron in the output layer to produce the binary output that represents benign or malignant, while the hidden layer comprises 60 neurons. Tangent hyperbolic and linear activation functions are chosen for the hidden layer neurons and output neurons respectively. The hidden and output layer nodes adjust the weights

depending on the error in classification. Back propagation (BP) algorithm is used for training. In BP the signal flows in forward direction, but the error is back propagated and weights are updated to reduce error. In BP, weights are initialized randomly at the beginning of training. There will be a desired output, for which the training is done. During forward pass of the signal, according to the initial weights and activation function used, the network gives an output, which is compared with desired output. If both are not same, an error occurs. During reverse pass, the error is back-propagated and weights of hidden and output layers are adjusted. The training process continues until error becomes sufficiently low. The network is trained with known training data set comprising extracted features and target. After training, network can perform classification of new skin images. The collected data set comprising the input (X) and the target (Y) vectors can be represented as

$$\{X \leftrightarrow Y\} = \{f_1,\ f_2,\ f_3 \cdots\cdots,\ f_{29} \leftrightarrow Class\} \quad (1)$$

The generated input-target data are split into two partitions: the first one is the training data, which is used to train the network and the second, the testing/validation data, is used to assess how well the network is generalized.

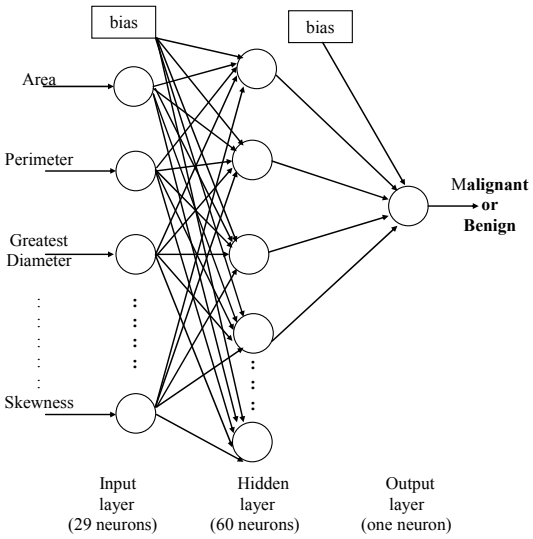


Figure-1. Structure of ANN classifier.

3. RESULTS AND DISCUSSIONS

The proposed CAD tool has been built using 180 skin images, comprising both benign and malignant skin lesions [17, 18]. Two sample dermoscopic images comprising a benign and a malignant image, presented in Table-1, are considered in analysing and discussing the results. The converted gray scale and the median filtered sample images are shown in Table-2. It can be seen from the images that the median filtering is very effective in reducing thin hairs and other noises. The suspicious regions of the preprocesed skin images are segmented and the segmented portions are marked on the RGB images and presented in Table-3. After segmentation, the 29 features are extracted and given in Table 4 for the sample images.

Table-1. Sample skin lesions.

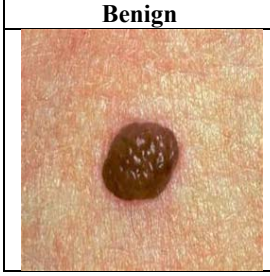
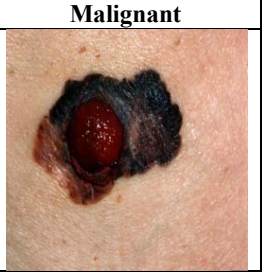
Benign	Malignant
	

Table-2. Preprocessed sample skin lesions.

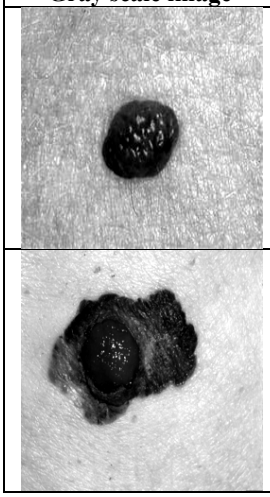
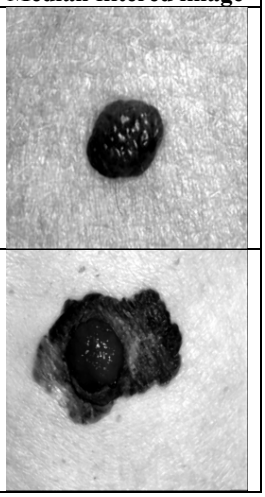
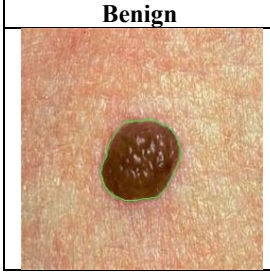
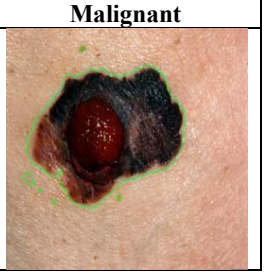
Gray scale image	Median filtered image
	

Table-3. Segmented skin lesions.

Benign	Malignant
	

After feature extraction, the skin lesions are categorized as negative-class, comprising benign lesions and positive-class with malignant melanomas. The target value for negative-class is set to be 0.1 and positive-class as 0.9, which are required for generating database for training and validating the proposed classifier. The database is therefore divided into training and testing datasets, each possessing both benign and malignant classes. In order to obtain satisfactory results, 80% of total

dermoscopic images are considered as training set and the remaining images as testing set.

Table-4. Extracted features of sample skin lesions.

	Benign	Malignant
Area	5.4500e+03	1.6269e+04
Perimeter	2.8645e+02	5.5514e+02
GD	9.2238e+01	1.6643e+02
SD	7.5558e+01	1.2752e+02
Diameter	8.3302e+01	1.4392e+02
AsyIndx	1.3158e-01	1.5459e-01
CI	1.1981e+00	1.5074e+00
IrA	5.2560e-02	3.4123e-02
IrB	3.1055e+00	3.3356e+00
IrC	6.8556e-01	1.0179e+00
IrD	1.6680e+01	3.8914e+01
Colour Count	0.0000e+00	7.4340e+03
	0.0000e+00	0.0000e+00
	0.0000e+00	0.0000e+00
	2.7700e+02	6.0600e+02
	4.7840e+03	5.4680e+03
	0.0000e+00	0.0000e+00
Colour Score	2.0000e+00	3.0000e+00
Energy	3.2582e-01	2.1970e-01
Contrast	2.8416e-01	2.4170e-01
Homogeneity	8.6313e-01	8.8996e-01
Correlation	8.7505e-01	9.7375e-01
Variance	1.3596e-02	5.1993e-02
RMS	8.0630e-01	7.2744e-01
Standard Deviation	1.2899e-01	2.6611e-01
Mean	7.9719e-01	6.8471e-01
Entropy	6.3189e+00	7.0464e+00
Kurtosis	8.2067e+00	3.0622e+00
Skewness	-2.2655e+0	-1.2765e+0

When classification is done, results could have an error rate, either fails to identify an abnormality, or identify an abnormality that is not present. A confusion matrix, containing information about actual and predicted classifications, is usually formed to visualize the performance of the classifier. In addition, the common quantitative performance measures, such as, accuracy, sensitivity and specificity, are used in this paper. They are computed by

$$Accuracy == \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

$$Sensitivity == \frac{TP}{(TP + FN)} \quad (3)$$

$$Specificity == \frac{TN}{(TN + FP)} \quad (4)$$

The confusion matrix, obtained from the results of the test images, of the developed classifier is shown in Table-5. The calculated performance metrics are compared with those of the classifiers in the existing publications [19-23] with view of exhibiting the superior performance of the proposed classifier.

Table-5. Confusion matrix.

	Predicted class	
	Benign	**Malignant**
Benign	20	2
Malignant	0	14

Comparing the results of the proposed classifier with the existing methods, it is very clear that the proposed classifier is able to achieve 94.44% of accuracy, 100% of sensitivity and 90.91% of specificity, which are much higher than those of the existing methods. It is very clear from the above discussions that the PAC perform better in view of classifying the skin lesions into malignant and benign.

Table-6. Comparison of performances with existing methods.

Ref.	No. of selected features	Classifier	Accuracy (%)	Sens. (%)	Spec. (%)
[19]	13	LDA		100	85
[20]	18	SVM RBF kernel		93.3	92.3
[21]	21	K-NN		87	92
[22]	2	Logistic regression		91.3	91
[23]	13	LDA		88	81
Prop. CAD	29	ANN	94.44	100.00	90.91

4. CONCLUSIONS

A computer based early skin cancer detection system has been suggested. It has employed preprocessing of noise removal and gray scale conversion, segmentation, feature extraction and classification. Median filter has been applied in removing thin hairs and other noises. The suspicious region has been extracted from the normal skin by the process of segmentation. 29 features representing the characteristics of skin images have been identified and evaluated. Based on the evaluated features, ANN classifier has been designed to classify the skin images into malignant and benign. The comparison of the performances such as accuracy, sensitivity and specificity has exhibited the superior performance of the proposed CAD.

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