# Classification of Skin Cancers using Radial basis Function Network

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## ABSTRACT
This paper suggests a model for classifying skin lesions into benign and malignant melanoma using radial basis function network (RBFN). The model initially converts the color image into gray image and then applies Median filter for removing thin hairs and other noises. It then segments the cancerous region through segmentation and then extracts features that represent the characteristics of the skin lesion. The RBFN then processes the computed features and classifies the skin lesion either as a benign or a malignant. The paper discusses with intermediate results on sample skin images and exhibits the elegant performance of the suggested model.

## General Terms
image processing, classification

## Keywords
denoising, segmentation, radial basis function network.

## 1. INTRODUCTION
The occurrence of skin cancer in all regions of the world has risen steadily over the last few decades due to changes in the pattern of sun exposure of the population. Skin cancer is very common and accounts for over 20% of all cancer registrations. It can be classified into Malignant Melanoma and Benign. Malignant melanoma is an aggressive type of cancer, which originates from melanocytes located in the epidermis of the skin. Although skin cancers are the most common cancers, they account for only 2% of all cancer deaths and of those malignant melanoma is responsible for over 80%. Early diagnosis of melanoma helps in reducing the morbidity and the cost of therapy [1, 2].

The ABCD rule is a well-recognized standard used for classification of dermatological images to benign or malignant [3, 4]. ABCD stands for the following features: A (asymmetry), B (border), C (color), and D (Diameter or Differential structures) [5-7]. Even for experienced dermatologists, it may be difficult to make correct diagnosis because many symptoms look very similar to each other, although they are caused by different diseases. The dermatologists therefore need computer aided diagnostic tools (CADT) that analyze the details such as color, size, density of the skin changes, shape, etc and offer suggestions for effective diagnosis.

Several CADTs have been suggested in the literature [8-13]. Such tools could increase diagnostic accuracy 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. Although there are many computer aided diagnostic tools, there seems to be a lot of room for further improvement.

This paper aims to build a CADT using radial basis function network 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 CADT (PC), the third section discusses the results and the forth section concludes.

## 2. PROPOSED CADT
The proposed CADT is explained by a block diagram of Fig.1, which comprises preprocessing, segmentation, feature extraction and classification. The preprocessing converts the color image into gray scale image, and removes the noises and other artifacts, while the segmentation extracts the cancerous region from the skin background. The CADT is built with 29 features comprising 5 basic shape, 1 asymmetry, 5 border irregularity, 7 color and 11 texture features. The 18 features representing basic shape and color features are evaluated for all the segmented skin images. The remaining 11 texture features, represented by Eqs. 3.23-3.33 are computed with four different number of gray levels of 8, 16, 32 and 64 and also with four different angles of 0, 45, 90 and 135 for representing offsets [0 1], [-1 1], [-1 0] and [-1 1] respectively. The total number of texture features equals 176 ($=11\times16$), which are then reduced to ($11\times16$) vector by principal component analysis. The classifier processes the features and classifies whether the lesion belongs to benign or malignant.

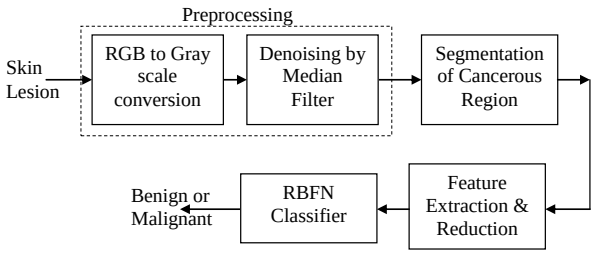



**Fig. 1 Block diagram of proposed CADT**

The proposed classifier uses a RBFN [16-18], which possesses two fully connected layers namely, hidden and output layers as shown in Fig. 2.Unlike the well known feed-forward artificial neural network, which is based on computing a nonlinear function of the scalar product of the input and weight vectors, the design of RBF network is viewed as a curve-fitting problem in a high-dimensional space. The training searches for the best fit to the training data in a multidimensional search space, which may be represented by a network of radial basis functions. The input nodes are

directly linked to the hidden layer neurons and the output of the $j-th$ hidden neuron can be written in the form of a non-linear Gaussian distribution function as

$$O_j(h) = \exp\left\{ \frac{\| X - C_j \|^2}{\sigma_j^{\,2}} \right\} \quad (1)$$

Each neuron in the output layer has a linear transfer function that sums the weighted outputs of all hidden neurons connected to that output neuron. The output $O_k(o)$ of $k-th$ neuron is

$$O_k(o) = \sum_{j=1}^{nh} W_{kj} O_j(h) \quad (2)$$

The key features of this configuration are the simple mathematical representations and lowered computational effort. The network is trained with known training data set comprising extracted features and target.

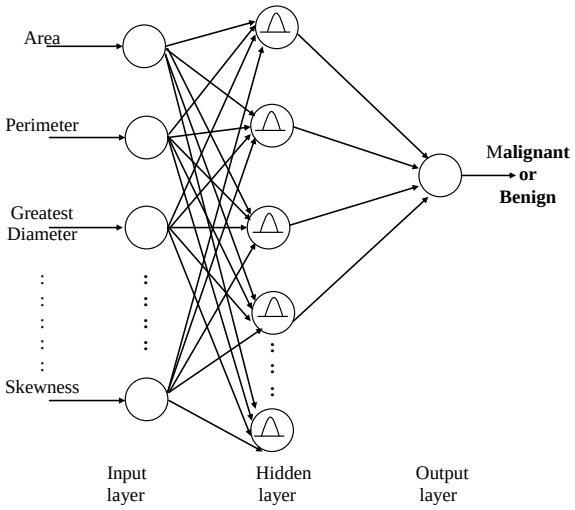



**Fig. 2 Structure of RBFN classifier**

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

$$\{X \leftrightarrow Y\} = \{f_1,\ f_2,\ f_3 \cdots\cdots,\ f_{29} \leftrightarrow Class\} \quad (3)$$

## 3. RESULTS AND DISCUSSIONS

The benign and malignant skin lesions have been taken from [19, 20] in tailoring the proposed CADT (PC). The detailed results of a benign and a malignant skin lesions have been presented and discussed in this section. Table 1 contains these two sample images while Table 2 displays the converted gray scale and the median filtered sample images. It is seen from the tables that the thin hairs and other noises are effectively removed by the median filter. Table 3 shows the edge markings, obtained by the segmentation process, of the cancerous region. The 11 reduced texture features along with 18 shape and color features, are evaluated for all the skin lesions in both negative and positive classes. Table 4 lists all the evaluated features of the sample benign and malignant skin lesions.

The training and testing data sets are created by considering the extracted features as input vectors and assigning a value of 0.1 for benign and 0.9 for malignant for target vector. Usually 80% of input data set is considered as training data set and the remainder as testing data set. After training, the RBFN classifier is ready for classification and its results could have an error rate, either fails to identify an abnormality, or identifies an abnormality that is not present. A confusion matrix, containing information about actual and predicted classifications, is usually formed to study the performance of the classifier. Besides the common quantitative performance measures, such as, accuracy, sensitivity and specificity, are calculated in this paper by the following equations.

$$Accuracy = = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (4)$$

$$Sensitivity = = \frac{TP}{(TP + FN)} \quad (5)$$

$$Specificity = = \frac{TN}{(TN + FP)} \quad (6)$$

**Table 1 Sample dermoscopic images**

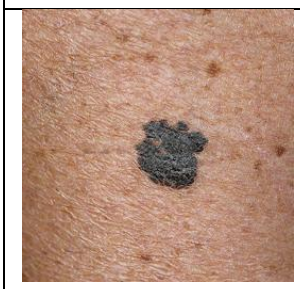
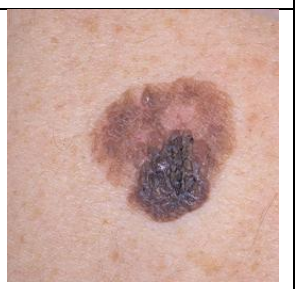
| Benign | Malignant |
|---|---|
|  |  |

**Table 2 Preprocessed sample dermoscopic images**

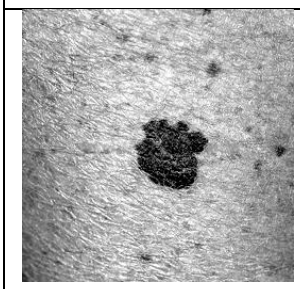
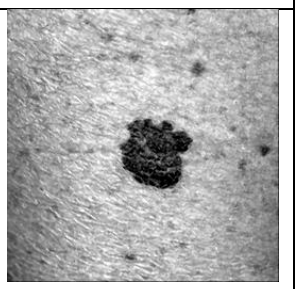
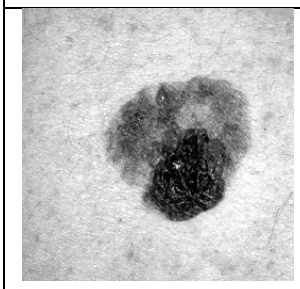
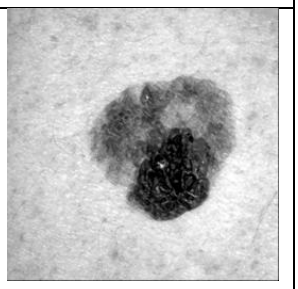
| Gray Scale Image | Median Filtered Image |
|---|---|
|  |  |
|  |  |

**Table 3 Segmented skin lesions of sample images**

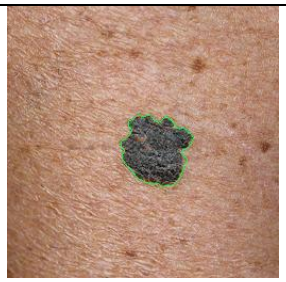
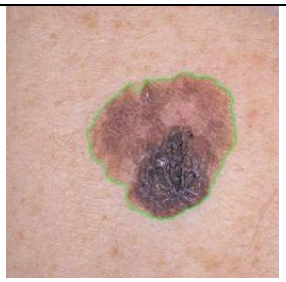
| Benign | Malignant |
|---|---|
|  |  |

**Table 4 Extracted features of sample images**

| | **Benign** | **Malignant** |
|---|---|---|
| Area | 3.2000e+03 | 1.3557e+04 |
| Perimeter | 2.4694e+02 | 1.3690e+03 |
| GD | 6.7129e+01 | 1.3909e+02 |
| SD | 6.2453e+01 | 1.2701e+02 |
| Diameter | 6.3831e+01 | 1.3138e+02 |
| AsyIndx | 1.1588e-01 | 1.0671e-01 |
| CI | 1.5164e+00 | 1.1000e+01 |
| IrA | 7.7168e-02 | 1.0098e-01 |
| IrB | 3.6785e+00 | 9.8421e+00 |
| IrC | 2.7544e-01 | 9.3643e-01 |
| IrD | 4.6763e+00 | 1.2084e+01 |
| Colour Count | 2.8400e+02 | 2.1000e+01 |
| | 0.0000e+00 | 2.0000e+00 |
| | 0.0000e+00 | 0.0000e+00 |
| | 5.4000e+01 | 2.9690e+03 |
| | 1.5040e+03 | 1.3450e+03 |
| | 0.0000e+00 | 0.0000e+00 |
| Color Score | 2.0000e+00 | 2.0000e+00 |
| Energy | 2.2591e-01 | 4.3649e-01 |
| Contrast | 3.4531e-01 | 1.8209e-01 |
| Homogeneity | 8.3816e-01 | 9.1227e-01 |
| Correlation | 7.9220e-01 | 8.9493e-01 |
| Variance | 9.7871e-03 | 1.0085e-02 |
| RMS | 7.1127e-01 | 7.9274e-01 |
| Standard Deviation | 1.0724e-01 | 1.1543e-01 |
| Mean | 7.0420e-01 | 7.8580e-01 |
| Entropy | 6.4097e+00 | 6.1937e+00 |
| Kurtosis | 1.0234e+01 | 8.0192e+00 |
| Skewness | -2.2512e+0 | -2.2136e+0 |

**Table 5 Confusion matrix**

| | Predicted Class | |
|---|---|---|
| | Benign | Malignant |
| Benign | 19 | 3 |
| Malignant | 1 | 13 |

Table 5 shows the confusion matrix formed from the results of the test images, while Table 6 compares the performance metrics of the proposed classifier with those of the existing models of [24,30,39,47,47]. The analysis of these tables clearly indicates the superior performance of the proposed classifier through achieving 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 PACT performs better in view of classifying the skin lesions into malignant or benign.

**Table 6 Comparison of Performances with existing methods**

| *Ref.* | *No. of selected features* | *Classifier* | *Accuracy (%)* | *Sens. (%)* | *Spec. (%)* |
|---|---|---|---|---|---|
| [24] | | ANN | | 67.5 | 80.5 |
| [30] | 2 | Decision tree | | 69.4 | 89.9 |
| [39] | 6 | K-NN | | 70.2 | 76.5 |
| | | Bayesian | | 85.1 | 76.5 |
| [47] | 11 | QDA | | 67.5 | 62.8 |
| | 3 | ANN | | 86 | 70 |
| [49] | 200 | SVM Polynomial kernel | 70 | | |
| **PC** | **29** | **RBFN** | **88.89** | **92.86** | **86.36** |

# 4. CONCLUSIONS

A RBFN based classifier has been proposed for assisting the dermatologists in diagnosing skin cancer. The model has been built to eliminate artifacts such a thin hair and noises, segment the cancerous region, extract features that represent the characteristics of malignant and benign skin lesions and classify the lesion into benign or malignant. The detailed results on two sample images, one belongs to benign and another to malignant, have clearly exhibited the superior performances of the proposed CADT in terms of accuracy, sensitivity and specificity. The performance of the CADT can be further improved by considering the statistical features through wavelet transform.

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