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Detection of melanoma skin cancer with fine-tuned weight parameters and features using Radial Basis function Network

Mr. Sreedhar Burada[1*], Dr.Asha K H[2], Dr. M. Sunil Kumar[3]

[1]Research Scholar, Computer Science and Engineering, Don Bosco Institute of Technology, Bengaluru, Karnataka, India
Visvesvaraya Technological University, Belagavi, Karnataka, 560074, India. sreedharburada1@gmail.com

[2]Associate Professor, Computer Science and Engineering, Don Bosco Institute of Technology, Bengaluru, Karnataka, India
asha.kh06@gmail.com

[3]Professor, Computer Science and Engineering, School of Computing, Mohan Babu University (erstwhile Sree Vidyanikethan Engineering Colloge), Tirupati Andhra Pradesh, India
sunilmalchi1@gmail.com

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Abstract:
Melanoma Skin cancer is one of the dangerous cancer as well as widespread disease. Worldwide there is 53% melanoma cancer cases, and mortality rate is also increased in the further coming decades. Detection of skin cancer at the early stages, we can help the human beings form the death rate. To detect cancer at early stage we need to require a computer aided diagnosis mechanism which may help to the dermatologists for accelerating their diagnosis. Here, we propose a computer aided mechanism for detecting melanoma skin cancer with the weights are fine-tuned and extracted the features from the skin cancer image, and we develop the model by using radial basis network. The proposed model initially manages the converting color images to gray scale images by applying the median filter. The main objective of this filter is to reduce the image noise and other unrelated objects from the image. To classify the melanoma skin cancer we have to apply different phases like preprocessing, segmentation, feature extraction and classification. Here, we used PH2 data set for the proposed model and it generate specificity as 86.54%, accuracy as 88.99%, and sensitivity as 91.65%. The results and performance of the model is discussed in the result phase.

Keywords: *Melanoma, Dermatology, Median Filter, Radial Basis Function Network, Segmentation, Feature set.*

1. Introduction:

The skin cancer cases especially melanoma skin cancer cases are increased steadily throughout the world since last few decades. Because of changing in the environment, global warming, and sun directly explore on the population. [2] According to the American skin cancer society statistics there has been 53 percentage of mortality rate increased from the past decades. Melanoma skin cancer is one of the part of different skin cancer, it roots are from melanocytes, which is epidermis of the skin. It shows like tumor on skin which is cancer. The tumor is cancer which has some characteristics.

The experienced dermatologists can by observing the tumor and analyze the cancer characteristics. ABCDE rule, 7 segment point analyze are the some of the characteristics to represent the tumor has a skin cancer [1]. Based on the characteristics dermatologists may analyze the whether the tumor is melanoma skin cancer or not. Based on the experience of the dermatologists can diagnosis the skin cancer, but it is always not possible to diagnosis in a

proper way because some times without biopsies even experienced dermatologists cannot predict the type the cancer. If the biopsies results are negative the cost will increase and also it will take time to diagnosis. So solve all these challenges we need a computer aided mechanism is required to detect the proper skin cancer especially melanoma at the early stage. Also this model needs to reduce the mortality rate and treatment cost [3].
To satisfy the above mentioned challenging, we need an accurate disease detector with a reliable data set. [4] This model helps the young dermatologists and clinical assistance. Detection of disease at early stage, many researchers are used different application areas such as Machine Learning (ML), Deep Learning (DL), Computer Vision algorithms. The dermosopy images are classified based on the ABCDE rule which is a standard and well organized form for the skin cancer medical image. ABCDE rule having many features such as A (Asymmetry), B (Border), C (Color), D (Diameter), and E (Evolve). Many researchers are working under this basic characteristics and extracted the features, work on those features and developed different computer aided mechanisms [6].
Image Processing, Machine Learning, and Computer Vision are used in multiple number of applications such as image preprocessing, segmentation, classification and pattern recognition [22]. In current era, many deep learning technologies are to prefer to detect the various features in a skin cancer image. A vast study has been proposed on the Convolutional Neural Network (CNN) to detect the skin cancer on the huge number of cancer image data set. According to these studies, different skin cancer diseases has been classified. Apart from that CNN here, we proposed a Radial Bases Function Network (RBFN) model for classifying the input images [9]. The study has been focus on various image features such as shape, color, texture, length and width are vary from different types of skin cancer [5]. This paper aims on how to build a computer aided diagnosis system with support of radial basis function network to classify the melanoma and non-melanoma skin cancer. Here, the first phase portraits introduction about the proposed methodology, second phase portraits the literature review, third phase illustrates proposed architecture, Forth phase describes the feature extraction, Sixth phase illustrates proposed model results, and seventh phase describes the conclusion and feature work.

2. Literature review

Hameed et al. [4] proposed a new approach for combination of Convolutional Neural Network (CNN) and Support Vector Machines (SVM) for classifying the melanoma skin cancer. The integrated algorithm was effectively evaluated and compared to the other methods such as genetic algorithms, artificial neural networks, SVM. They achieve 3% greater accuracy result than these methods.
Ganster, Harald, et al. [5] proposed a system to enhance the early recognition of malignant melanoma by developing the computerized analysis of images which are acquired from Epiluminescence microscopy (ELM). Initially they prepare a set of binary mask of the skin lesion by applying several segmentation algorithms. They proposed a statistical feature subset selection methods to extracts the set of image features like shape, radiometrics, local and global parameters. For classification they proposed a KNN Classifier, which classifies 87% of sensitivity with the 92% of specificity.
Mahbod, Amirreza, et al. [8] proposed a complete automated computerized method to classify the skin lesion from the skin cancer images. Their main idea is ensemble the convolutional neural network for intra architecture and inter architecture. Their proposed model represents the different feature abstraction level. Their model performs 87.3% for melanoma classification and 95.5% for seborrheic keratosis classification. The proposed model average accuracy is 87.7%.
Li, Genghui, et al [10] proposed a three level radial basis function which can assists the optimization algorithm for optimizing their methodology. The proposed method explores three functionalities i) Global Exploration ii) Sub region search iii) Local Exploitation. Their methodology compared to the ten CEC2015 computationally expensive problems.
Mohakud and Das, et al [11] proposed an adaptive Convolutional Neural Network in the year 2022. Using this model it was identifying the type of the skin cancer. He proposed a GWO algorithm for optimization of the CNN parameters. After evaluating his proposed algorithm to other’s algorithm, it efficiency is better. The accuracy of the proposed algorithm is 98.33%, which was greater than 4% and 1% of PSO and GA methods respectively.
Fabian and Friedhelm [18] introduce a novel approach for the Radial Basis Function network architecture. They include multiple radial basis function layered and improved their efficiency. For implementing such structure initially they have taken the k-means clusters and estimate the covariance. With the use of Mahalanobis distance to speedup the convolution calculation. Their results are greatly put effort on the radial basis function network

compare to the traditional CNN model.

3. Proposed CAD using Radial Basis Network:

To getting the high accuracy level in detecting the melanoma skin cancer, the proposed method is implemented and evaluated in different phases. This model helps the dermatologists for clear understand the cancer image lesion and easily can diagnosis. The proposed model of the radial basis network is illustrate in the Fig 1. The architecture contains the preprocessing phase, segmentation phase, feature extraction phase, classification phase.

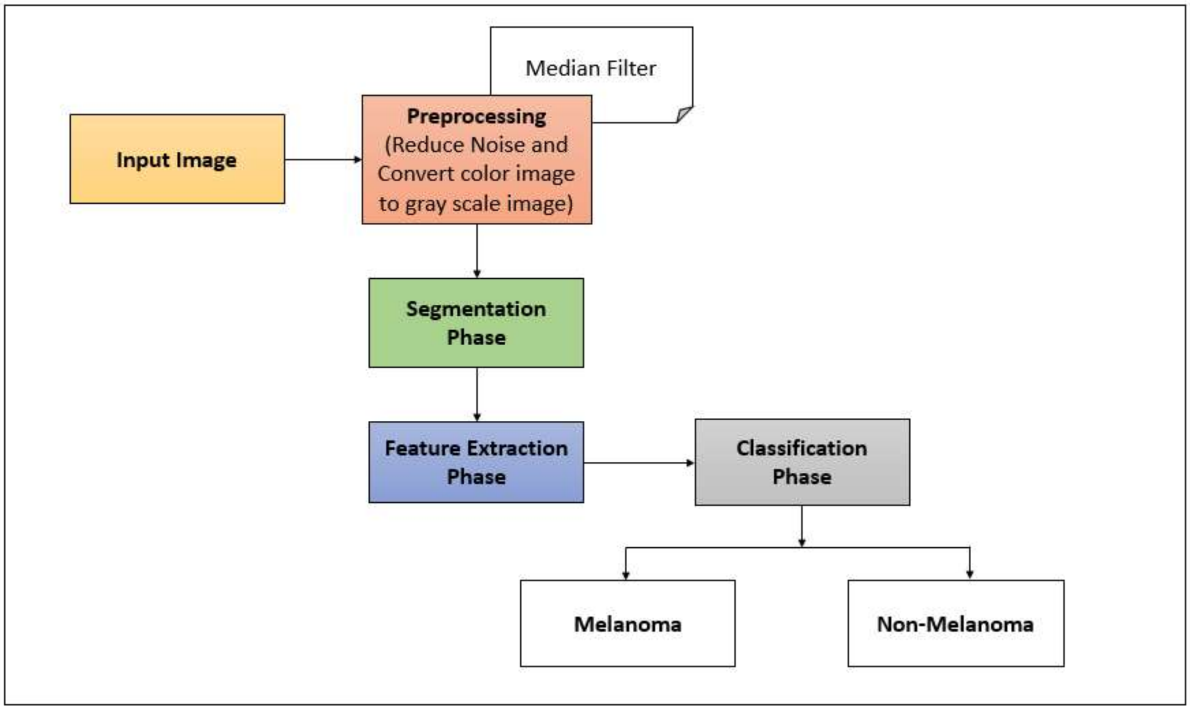


Fig 1: Architecture for the proposed model of computer aided diagnosis mechanism using RBFN

Ir ome unrelated art image to gray color images by using median filter. Generally noise of the image will commonly effect in the result of detecting melanoma skin classification. So, before we need to process the next segmentation phase we have to remove the noise for getting better accuracy result. For this, here, we are using median filter. Filter generally can be classified in to two categories i) Linear Filter and ii) Non Linear Filter. Linear filters are used, if the noise of the image is distributed uniformly. Generally these linear filters are time idle and not suitable for the image of noise is distributed unevenly, most of the medical images noise is distributed unevenly, and so, linear filter for the medical image is not the best choice. To resolve this we used in our paper is nonlinear filter, these filters are support for the removing the noise randomly. Pepper and salt images are comes under nonlinear filter.

[12] The segmentation phase is extracts the known image segment by using the region of interest. The Fuzzy C-Means clustering algorithm can be used to segment the image, preparing it for classification. [13] FCM is a best segmentation technique among all other traditional segmentation techniques. It will give a best accurate result when compare to the other segmentation techniques. FCM is an unsupervised learning algorithm. In this paper we are going to perform segmentation by using fuzzy C-Means clustering technique. Because of assigning the data points to the multiple clusters along with varying the degree of membership, FCM clustering is most effective way to handle the image noise and ambiguity in the image segmentation. FCM segmentation is especially suitable for the medical images because pixel boundaries are not well defined, where the transitions between region of interest and surrounding tissues can be ambiguous. [15] In our earlier work we proposed a hybrid mechanism for classifying the skin cancer image by applying the Fuzzy C-Means clustering algorithm and tuning the weights with the help of differential evaluation based convolutional neural network. After that we are focus on weights of the given input image for fine tuning the hyper parameter of an image and also improved on Fuzzy C-Means

clustering to segment the input image [16, 17].

The below algorithm illustrate the Fuzzy C Means clustering algorithm.

Step 1: Initialize the parameter are number of clusters (C), Fuzziness parameter (m), Membership matrix (U) – The dimensions of this matrix is C x N, where, N is the number of data points (i.e., pixels). For each element in the matrix U_{ij} is represent the degree of membership of the pixel 'j' to cluster 'i'. Set a threshold € to determine when the algorithm should stop.

Step 2: Calculate the centroid of a cluster.

For each cluster i, calculate the centroid C_i based on the membership matrix U. The centroid represents the center of a cluster in the feature space.

$$C_i = \frac{\text{Weighted sum of all data points}}{\text{Normalizes the weights}}$$

Where, weights are the membership degrees raised to the power of m.

Step 3: Update membership matrix. Update the membership degree u_{ij} for each data point x_i and cluster j.

Step 4: Convergence Checking. We have to determine the change in the membership matrix U or Centroids C is below the given threshold, otherwise go to the step 2 and repeat the process.

[8] The extraction of feature phase helps to construct the computer aided diagnosis system. Here we are extracted features from the segmented images. In our paper we proposed that 29 features are extracted. Out of 29 features 5 features were comprised for basic shape, 1 feature for asymmetry, 5 features for border irregularity of the segmented image, 7 features for the color notation of the segmented image, the reset 11 features are for the texture features. [18] The below table 1 describes the number of features and its name of the feature.

Feature Name	**No. of Features extracted from segmented image.**
Basic Shape	5
Asymmetry	1
Border Irregularity	5
Color	7
Texture	11

The last phase of the proposed work is classification phase, which describes that the devise features are helps to classify the input skin cancer image whether it is melanoma or non-melanoma. For classify the input image we proposed a model called as RBFN (Radial Bases Function Network) [10]. The proposed model RBFN works on the nonlinear transformation over input image vectors. The main objective of the radial bases function is convert the non-linear separable things into linear separable things. [11] For doing such conversion the RBFN works to increase the dimensionality of the feature vectors. For increasing the dimensionality of the feature vector can be easily convert nonlinear to linear transformation, if it will convert to linear transformation the classification of the melanoma skin cancer will be make easy. Suppose we did not convert the higher dimension to lower dimension, it is very difficult to classify the input segment image because many problems like curve fitting problems and edge detecting problems. Because of this reason we proposed the RBFN to transform the nonlinear to linear and increase the dimensionality of the feature vector. The below Fig. 2 represent the complete architecture of the RBFN. It is a fully connected layer. The model is the combination of input layer, number of hidden layer and output layer. RBFN used for the viewing the curve fitting problems in high dimensional space [14].

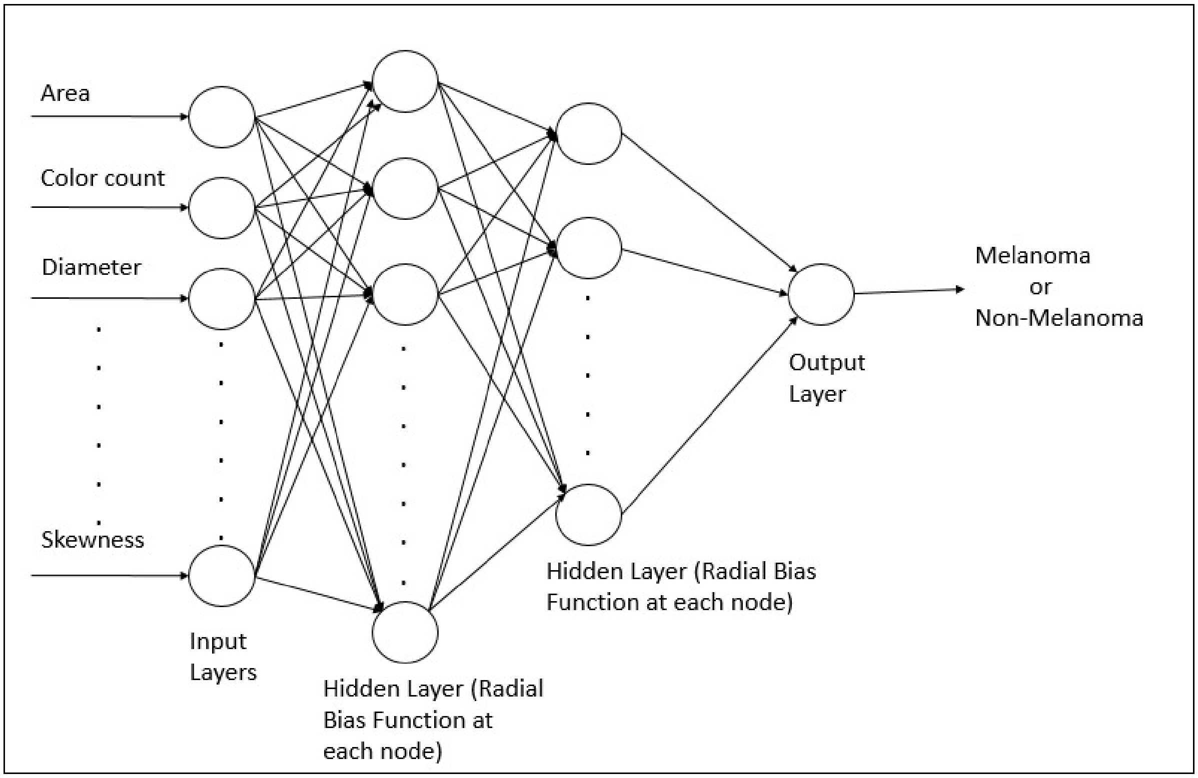


Fig 2. Architecture of Radial Basis Function Network.

The training phase consistently aims to find the optimal fit to the training data within a higher-dimensional search space [19]. The 21 devised features serve as inputs to 21 neurons, with each neuron's output being directly mapped to the hidden layer, forming what is known as a Radial Basis Function Network [21]. The output layer nodes perform a linear combination of the outputs from the hidden layer nodes. The classification is solely carried out in the output layer, which uses a linear classifier. In the hidden layer, only the radial basis function is applied, producing output values between 0 and 1. This process transforms the input feature vector, which is a skin cancer image, into a hidden space [20]. The main objective of training the hidden layer is to determine the appropriate center for each node, which plays a crucial role in how effectively the network can learn to represent the underlying patterns in the data. By optimizing these centers, the model can enhance its ability to distinguish between different classes, ultimately improving classification accuracy. This process involves adjusting the parameters through techniques such as back propagation, allowing the network to better capture the nuances of the input features and their relationships. The output of the k^{th} hidden neuron is represented as a nonlinear Gaussian distribution function [25], which can be expressed as,

$$H_k(f) = e^{\frac{-(f-C_k)^2}{2*S_k^2}} \quad \text{-------------------------------------- (1)}$$

Where, $H_k(f)$ is the output of the k^{th} hidden neuron, f is the input feature vector, C_k is the center of Gaussian function for the k^{th} neuron, and S_k is the standard deviation, which controls the width of Gaussian function.

Each neuron in the output layer performs a linear transformation by summing the weighted outputs of all hidden neurons connected to it.

$$output\ (Y_k) = \sum_{k=1}^{N} w_k * H_k(f) \quad \text{-- (2)}$$

The proposed model is trained with the PH^2 data set, collected from kaggle dataset repositories. Here, we are trying to extract the features from the data set and map these feature to the target function which is mention in the equation number 1 and equation number 2. [7] Once the training is completed at the hidden layer along with weights are fine-tuned, the proposed network can be ready for the classification of the skin cancer [23, 24]. The target out is the classification of the skin cancer image.

Results:

The proposed model extracts the 29 features such as image perimeter, area, color, Skewness, etc. These feature are helps the proposed model for the skin cancer classification. Based on these features the proposed model RBFN can effectively classifies the skin cancer lesions. [26] Here, we used PH^2 data set, which is available for the all researchers from the kaggle data source repositories. Table 1 describes the sample input images of melanoma and non-melanoma, gray scale images which used as the filtering technique in the preprocessing the data. Before performing the preprocessing we have collected all skin cancer image as normalization and later apply the filtering techniques. Here, we are applied a median filter for removing noise and unwanted artifacts from the images. The sample Median filtering image is represents in the fourth row of the below table and the last row shows the melanoma segmented and non- melanoma segmented images. It is observe by using the median filter images that contain thin hair and other unwanted artifacts are clearly removed. During the implementation of the median filter we applied the hair removal algorithm for removing such unwanted artifacts. The last row represent the segmented images it clearly shows the edge detection for the melanoma skin cancer classification. Here, we extracted 29 features among these 11 features are marked as the texture feature and 18 features are marked as the color, shape and Skewness of the image. These features are helps in both the direction positive and negative for the classification process.

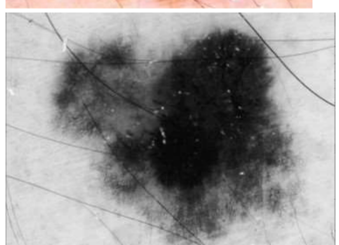
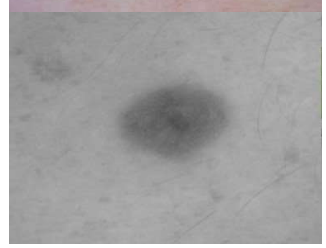
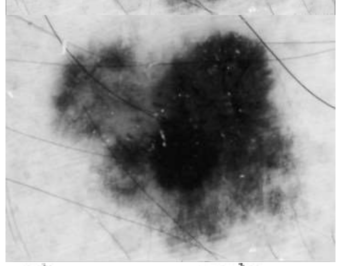
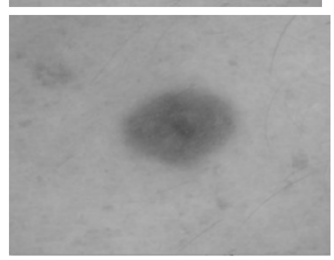
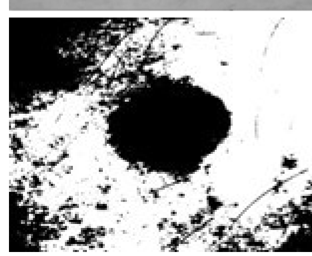
Name of the Skin cancer	Melanoma	Non-Melanoma
Input Image		
Gray Scale Image		
Median Filter Image		
Segmented Images		

Table 1: Sample Input Image, Gray Scale Image, Median Filter and Segmented Images

We used here PH2 data set for getting the classification of skin cancer. The used data set is openly available for the all the researchers. From this data repositories we consider 180 skin cancer images for classification purpose. The proposed methodology can use the 180 skin cancer image data set from that 130 images are the melanoma type of skin cancer images and 50 images are the non-melanoma type of the skin cancer images. The above experimental is done by using the python with the supporting of pycharm. After training the Radial Biases Function Network, the model is ready for the classification skin cancer images. The below Fig. 3 show the Confusion Matrix of classification of the skin cancer images.

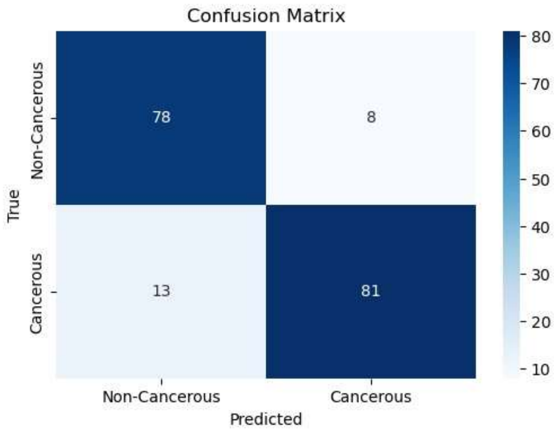


Fig 3. Confusion Matrix

The objective of the confusion matrix is classification of the cancerous and non-cancerous skin cancer. The matrix generally consider for the measuring the classification purpose here we used Radial Basis Function Network. The quantitative metrics of the confusion matrix such as specificity, accuracy and sensitivity are calculated by the following equation.

$$\text{Accuracy} = \frac{(Summation\ of\ True\ Positive\ and\ True\ Negative)}{(Overall\ Summation\ of\ Tru\ Positive\ Negative\ and\ False\ Positive\ Negative)} \text{ -------------- (3)}$$

$$\text{Sensitivity} = \frac{(True\ Positive)}{(Sum\ of\ True\ Positive\ and\ False\ Negative)} \text{ -------------- (4)}$$

$$\text{Specificity} = \frac{(True\ Negative)}{(Sum\ of\ True\ Negative\ and\ False\ Positive)} \text{ --------------- (5)}$$

The below Fig. 4 represents the bar graph of the classification if the skin cancer image, also it shows the precision, recall and F1-score components to measure the classification of skin cancer. The measures are 86%, 91% and 88% of the non-cancerous skin cancer with respective to the precision, recall and F1-Score. And the measures are 91%, 86% and 89% of the cancerous skin cancer with respective to the precision, recall and F1-Score.

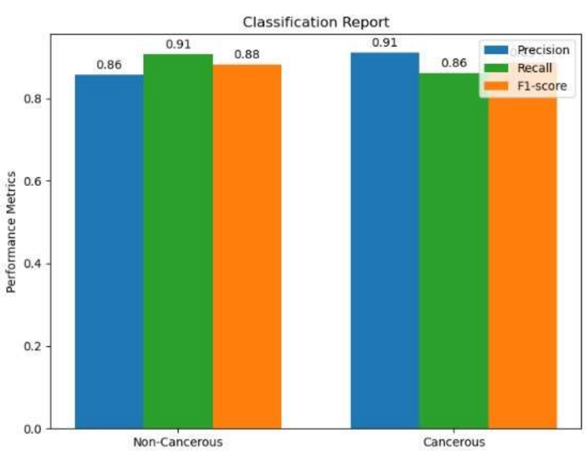


Fig 4: Bar Graph representation of classification

Comparison with existing model: The below table 2 describes existing work of their extractions features, classifiers report, accuracy, specificity and Sensitivity. From the table the precision and accuracy is achieved of the proposed methodology as Radial Bias Function Network. We Proposed 29 features are extracted from our proposed methodology is achieving 88.99% accuracy, 91.65% Sensitivity and 86.54% Specificity, which are higher than the existing methods.

Ref	No of Selected Features	Classifier Model or Algorithm used	Accuracy	Specificity	Sensitivity
[27] Abbas, Qaisar, et al	17	SRM: Statistical Region Merging DTEA: Dermatologist-like Tumor Extraction Algorithm RAC: Region-based Active Contour SDP: proposed Skin lesions border Detection using dynamic programming	-	82.28% 66.35% 79.13% 91.28%	21.46% 45.70% 38.80% 85.60%
[28] Alaa Ahmed Abbas, et al	-	PSNR – Peak Signal-to-Noise Ratio	96.26%	-	-
[29]	11	Deep learning-based method on U-Net Architecture, encoder to decoder	87.61%	-	-
[30]	21	K Nearest Neighboring Algorithm	73%	87%	92%
Proposed method	29	Radial Bases Function Network	91.65%	86.54%	88.99%

Conclusion:

A Radial Basis Function Network (RBFN)-based classifier has been developed to support dermatologists in diagnosing skin cancer by addressing challenges such as noise and hair artifacts in images. The model effectively segments cancerous areas, extracts distinguishing features of skin lesions, and classifies them into malignant melanoma or benign categories. Testing on two representative images—one malignant and one benign—demonstrated the diagnostic system's high accuracy, sensitivity, and specificity, highlighting its effectiveness. Enhancing the model by integrating statistical features using methods like k-means clustering, support vector machines (SVM), and wavelet transforms could further boost its performance.

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