



Skin Cancer Detection using Artificial Neural Network

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Abstract: Skin Cancer is most prevalent cancer in the light-skinned population and it is generally caused by exposure to ultraviolet light. In this paper, an automatic skin cancer classification system is developed and the relationship of skin cancer image across the neural network are studied with different types of pre-processing. The collected image is fed into the system and image pre-processing is used for noise removal. Images are segmented using thresholding. There is a certain feature unique in the skin cancer region; these features are extracted using feature extraction techniques. Multilevel 2-D wavelet decomposition is used for feature extraction techniques. These features are given to the input nodes of the neural network. Backpropagation neural network and radial basis neural network are used for classification purposes, which categorize the given images into cancerous or non-cancerous.

Keywords: Skin cancer; Segmentation; thresholding; 2D Wavelet transform; BPN network; RBF network.

I. INTRODUCTION

Skin cancer is increasing in different countries, especially in Australia [5]. Skin cancer is the uncontrolled growth of abnormal skin cells. Skin cancer diseases are very dangerous, particularly when not treated at an early stage. Skin cancer is the most common of all cancer types. In skin cancer, the number of cases has been going up over the past few years. Many skin cancers are caused by much exposure to ultraviolet (UV) rays [6].

Most of this exposure comes from the sun and man-made sources [6]. The three most common types are:

Melanoma: Melanoma begins in melanocytes. On any skin surface, melanoma can occur. Melanoma is rare in dark-skinned people. It is found on skin on the head, on the neck, between the shoulders, on lower legs, on palms of the hands, on the soles of feet or under the finger nails [6].

Basal Cell Skin Cancer: Basal cell skin cancer begins in the basal cell layer of the skin. It is usually found in places that have been in the sun [6]. Basal cell skin cancer is the most common type of cancer in fair-skinned people.

Squamous Cell Skin Cancer: Squamous cell skin cancer begins in squamous cells. Squamous cell skin cancer is the most common type of skin cancer in dark-skinned people and is usually found in places that are not in the sun, such as the legs or feet [6].

II. LITERATURE REVIEW

Image processing techniques provide an efficient tool to classify cancer from the images. In the recent years, neural networks are also used to detect cancer to obtain proficient results. Different authors have used different ways to combine these technologies to achieve better conclusions. Various works have been done in the detection of skin cancer using image processing and combination of neural networks. Some of them are discussed. Azadeh et al. [5] have carried out a survey in which skin cancer is detected. This describes the automatic detection of skin cancer, which can help to increase the accuracy and also review the techniques used in recent years, for the early detection of skin cancer. This

describes the different steps of the process: image acquisition, image pre-processing, feature extraction, and classification.

Sonali et al. [6] have implemented a simple algorithm for the detection of skin cancer and also for finding shape and infected areas. This describes the different steps of the process: in the first step, pre-processing is done using a median filter, and in the second step, segmentation is done using two methods, thresholding and fuzzy c-means. In the third step, feature extraction is done by Gray Level Co-occurrence Matrix (GLCM) and contour signature. Ho Tak Lau et al. [7] have described an automatic skin cancer classification system and the relationship of skin cancer images using different types of neural networks and different types of pre-processing. This describes that the image is acquired and different image processing procedures are used to enhance the image properties and then useful information is extracted from the image and passed to the classification system for training and testing. Abdul et al. [8] have recommended a technique in which early detection of skin cancer is done using an Artificial Neural Network. The diagnosing methodology uses image processing techniques and Artificial Intelligence. This describes that the dermoscopy image of skin cancer is taken and it is subjected to various pre-processing steps for noise removal and image enhancement. Then, image segmentation is done using thresholding.

Features are extracted using feature extraction techniques: 2D wavelet transform. And Backpropagation Neural Network is used for classification purposes. Liu Jianli et al. [9] have carried out a survey in which skin cancer is segmented by a genetic neural network. The segmentation speed of the genetic neural network is much higher as compared with the standard BP neural network. The skin cancer images segmented by a genetic neural network have continuous edges and clear contours, which can be used in the quantitative analysis and identification of skin cancer. Mariam A. Sheha et al. [10] have designed an automated method for melanoma diagnosis applied on a set of dermoscopy images. Features extracted are based on Gray Level Co-occurrence Matrix (GLCM) and Using Multilayer Perceptron Classifier (MLP) to classify between Melanocytic Nevi and Malignant melanoma. MLP classifier was proposed with two different techniques in training and testing process: Automatic MLP

and Traditional MLP. Texture analysis is a useful method for discrimination of melanocytic skin tumours with high accuracy. Sigurdur et al.[11] have design skin cancer classification based on in vitro Raman spectroscopy is approached using a nonlinear neural network classifier.

The classification framework is probabilistic and highly automated. The framework includes a feature extraction for Raman spectra and a fully adaptive and robust feed forward neural network classifier. Classification rules learned by the neural network may be extracted. Nilkamal et al. [12] have described the past and present technologies for skin cancer detections along with their relevant tools. This design new approach for Skin Cancer detection and analysis from given photograph of patient's cancer affected area, which can be used to automate the diagnosis and therapeutic treatment of skin cancer. The proposed scheme is using Wavelet Transformation for image improvement, de noising and Histogram Analysis whereas ABCD rule with good diagnostic accuracy worldwide is used in diagnostic system as a base and finally Fuzzy Inference System for Final decision of skin type based on the pixel color severity for final decision of Benign or Malignant Skin Cancer.

Mahmoud et al. [13] have describe two hybrid techniques for the classification of the skin images to predict it if exists. The proposed hybrid techniques consist of three stages, namely, feature extraction, dimensionality reduction, and classification. In the first stage, we have obtained the features related with images using discrete wavelet transformation. In the second stage, the features of skin images have been reduced using principle component analysis to the more essential features. In the classification stage, two classifiers based on supervised machine learning have been developed. The first classifier based on feed forward back-propagation artificial neural network and the second classifier based on k-nearest neighbour. Maryam et al.[14] have describe Irregular streaks are important clues for Melanoma diagnosis using dermoscopy images.

This extends our previous algorithm to identify the absence or presence of streaks in a skin lesions, by further analyzing the appearance of detected streak lines, and performing a three-way classification for streaks, *Absent*, *Regular*, and *Irregular*, in a pigmented skin lesion. The directional pattern of detected lines is analyzed to extract their orientation features in order to detect the underlying pattern. The method uses a graphical representation to model the geometric pattern of valid streaks and the distribution and coverage of the structure. Robert Amelard et al.[15] have describe High-level intuitive features (HLIF) that measure border irregularity of skin lesion images obtained with standard cameras are presented. Existing feature sets have defined many low-level unintuitive features. Incorporating HLIFs into a set of low-level features gives more semantic meaning to the feature set, and allows the system to provide intuitive rationale for the classification decision. Promising experimental results show that adding a small set of HLIFs to the large state-of-the-art low-level skin lesion feature set increases sensitivity, specificity, and accuracy, while decreasing the cross-validation error.

Xiaojing Yuan et al. [16] developed a decision support system for early skin cancer detection that relies on analysis of the pigmentation characteristics of a skin lesion, detected using cross polarization imaging, and the increased vasculature associated with malignant lesions that is

detected using transillumination imaging. Current system uses size difference based on lesion physiology and achieves great overall accuracy. This explore texture information, one of the criteria dermatologists use in the diagnosis of skin cancer, but has been found very difficult to utilize in an automatic manner. The overarching goal is to improve the overall decision support capability of the DSS. The objective is to use texture information ONLY to classify the benign and malignancy of the skin lesion. A three-layer mechanism that inherent to the support vector machine (SVM) methodology is employed to improve the generalization error rate and the computational efficiency.

M. J. Ogorzalek et al. [17] computer-assisted techniques and image processing methods can be used for image filtering and for feature extraction and pattern recognition in the selected images. Apart from standard approaches based on geometrical features and color/pattern analysis we propose to enhance the computer-aided diagnostic tools by adding non-standard image decompositions and applying classification techniques based on statistical learning and model ensembling. Ensembles of classifiers based on the extended feature set show improved performance figures suggesting that the proposed approach could be used as powerful tool assisting medical diagnosis. Maglogiannis et al. [18] have review the state of the art in systems by first presenting the installation, the visual features used for skin lesion classification, and the methods for defining them.

Then, describe how to extract these features through digital image processing methods, i.e., segmentation, border detection, and color and texture processing, and we present the most prominent techniques for skin lesion classification. The describe the statistics and the results of the most important implementations that exist in the literature, while it compares the performance of several classifiers on the specific skin lesion diagnostic problem and discusses the corresponding findings.

III. METHODOLOGY

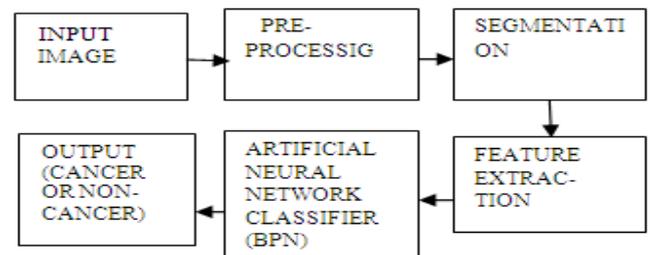


Figure1: block diagram representation

Skin cancer detection consists following steps:

- a. **Image Acquisition:** In first step images are acquired.
- b. **Image Preprocessing:** In second step pre-processing is done using median filter. Median filter is used to remove unwanted hair, bubbles and noise from the images [6]. The skin cancer image usually contains fine hair, noise and bubbles[5]. These are not the cancer factor so these are removing using median filter[6].
- c. **Segmentation:** In third step segmentation done using thresholding[7]. Thresholding is the technique for established boundaries in image that contain solid object resting on a contrasting background[6].
- d. **Feature Extraction:** In fourth step features are

extracting using feature extraction technique[7]. In feature extraction technique useful information are extract from segmented image. Feature extraction is done using multilevel 2-D wavelet decomposition[8].

- e. **Artificial Neural Network Classifier:** In fifth step these information is used in classification system for training and testing[3]. Classification done by using back propagation neural network and radial basic neural network.
- f. **Output:** In last step data set of cancerous and non-cancerous are found.

IV. IMAGE PROCESSING ALGORITHMS

Pre-processing is to perform image processing on original image [5]. The various phases include Conversion to Gray image and Noise Reduction. Pre-processing used to referring to remove the unwanted feature on skin [7].

In first step converts the true color image RGB to the gray scale intensity image by using a function called `rgb2gray ()`.

In second step noise are remove using median filter. Median filter are used to preserve the amplitude and location of edges. Median filter reduces the variance of the intensities in the image that means median filter smoothers the image by utilizing the median of the neighbourhood [6].



Figure 2. Original image



Figure3. RGB to gray scale image

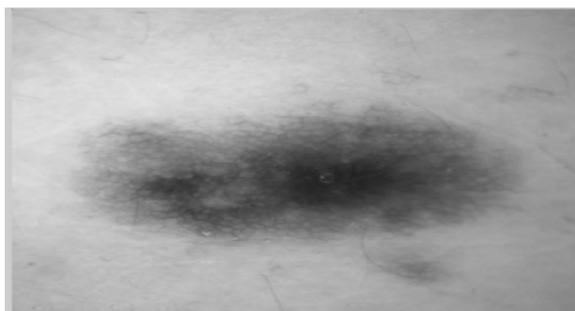


Figure4. Pre-processed image

Figure4 show image pre-processing by using median

filter.

V. AREA OF INTEREST SEGMENTATION

Region of interest (ROI) is extract by segmentation. Segmentation is done using thresholding [7]. The aim of segmentation process is to divide the image into homogenous, self-consistent regions. Segmentation is the process of partition the image into the group of pixels which are homogenous with respect to some criterion [6].

Thresholding technique produces segments having pixels with similar intensities. Usually the cancer remains in image after segmentation. Thresholding is a technique for established a boundaries in image that contain solid objects resting on contrasting background [6]. Segmentation converts any image into a series of Black text written on a White background. Thresholding is a simplest method of image segmentation. From gray scale image, thresholding can be used to create binary image. Thresholding can be used to separate light and dark region [8]. Image thresholding classifies pixel into two categories:-

Those to which some property measured from the image fall below the threshold, and those at which the property equal and exceeds a threshold.



Figure 5. Thresholding segmentation

In the skin cancer image, cancer is clearly seen by using median filter. Thus we can divide segmentation image into two parts object and background part.

VI. WAVELET TRANSFORM

Wavelet transforms have become one of the most important and powerful tool of signal representation. wavelet transforms are based on small waves, called wavelets[23]. The two-dimensional wavelet transforms are slightly different to one-dimensional ones. One can easily extend it by simply multiply the one-dimensional scaling and wavelet functions. The maximum level to apply the wavelet transform depends on how many data points contain in a data set, since there is a down-sampling by 2 operation from one level to the next one[28]. Wavelet transform in two dimensions is used in image processing. We should select our “mother wavelet” for better approximate and capture the transient spikes of the original signal. “Mother wavelet” will not only determine how well we estimate the original signal, but also, it will affect the frequency spectrum of the denoised signal. We are using 8 mother wavelet such as Haar, Sym4, Syn7, Db1, Db10, Bior1.3, Bior5.5, Coif3.

VII. FEATURE EXTRACTION

Important feature of image data are extract from the segmented image[2]. The extracted feature should be detailed enough classified. Multilevel 2-D wavelet transform is used for feature extraction[3]. Two dimension wavelets are a natural extension from the single dimension case. 2-D wavelet can be defined as the outer product of one dimension wavelets. Outer product work in a similar way to inner products, however inner products take two vectors and combine to form a scalar, outer product work the other way, extrapolating a matrix from two vectors. Two level of decomposition are used. At each level of decomposition, the wavelet of primary image is divided into an approximate and three detailed image which show the basic information and vertical, horizontal and diagonal details, respectively[4]. The Feature extracted using the wavelet transform are: Mean, Maximum, Minimum, Median, Standard deviation and Variance.

Mean:-

$$\hat{f}(x, y) = \frac{1}{mn} \sum_{(s,t) \in S_{xy}} g(s, t) \quad (1)$$

Maximum:-

$$\hat{f}(x, y) = \max_{(s,t) \in S_{xy}} \{g(s, t)\} \quad (2)$$

Minimum:-

$$\hat{f}(x, y) = \min_{(s,t) \in S_{xy}} \{g(s, t)\} \quad (3)$$

Median:-

$$\hat{f}(x, y) = \text{median}\{g(s, t)\}_{(s,t) \in S_{xy}} \quad (4)$$

If total number of n is odd number than the formula of median is

$$\text{Median} = \left(\frac{n+1}{2}\right)^{\text{th}} \text{ term} \quad (5)$$

If total number of n is even than the formula of median is

Median=

$$\frac{\left(\frac{n}{2}\right)^{\text{th}} \text{ term} + \left(\frac{n}{2} + 1\right)^{\text{th}} \text{ term}}{2} \quad (6)$$

Variance:-

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x - \bar{x})^2 \quad (7)$$

Standard deviation:-

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x - \bar{x})^2} \quad (8)$$

n: is the symbol for the number of data.

x: is correspond to the observed value.

s: is sample data.

$g(s, t)$: is the original image pixel,

$\hat{f}(x, y)$: is the resulting noisy pixel

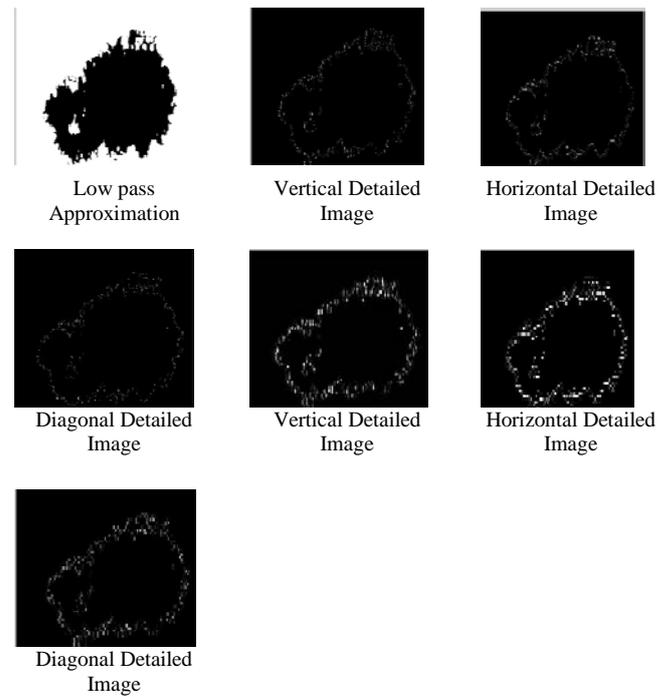


Figure 6. Feature extraction

VIII. ARTIFICIAL NEURAL NETWORKS

An Artificial Neuron is basically an engineering approach of biological neuron. A Neural Network is a massively parallel distributed processor made up of simple processing units which have natural propensity for storing experiential knowledge and making it available for use. It resembles to brain in two aspects. First, Knowledge is acquired by the Network from its environment through a learning process. Second, Interneuron connection strength is used to store acquired knowledge[3].

In Neural Network, each node perform some simple computation and each connection conveys a signal from one node to another labelled by a number called “connection strength”.

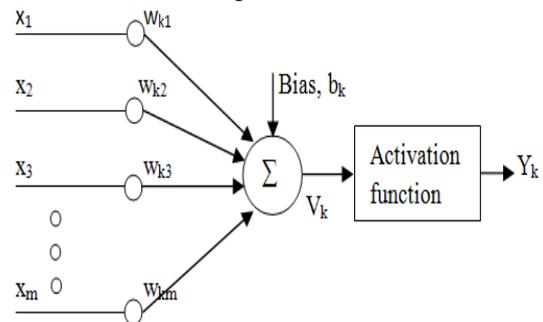


Figure 7. simple neuron

Linear Combination U_k ,

$$U_k = \sum W_{kj} * X_j \quad (9)$$

Induced Local Field V_k ,

$$V_k = U_k + b_k \quad (10)$$

Activation function defines the value of output Y_k ,

$$Y_k = \phi(V_k) \tag{11}$$

There are different type activation function in neural network such as, Threshold Activation Function, Piecewise Linear Activation Function, Sigmoid Activation Function, Signum Activation Function etc. Learning is a process by which free parameters of a Neural Networks are adapted through a process of simulation by the environment in which the network is embedded. Once the system begins to learn containing some initial weight values, as the learning process increase weight values keeps on changing and provide the final output at end [24].

IX. BACKPROPOGATION ALGORITHM

Back-propagation neural network is one of the most common neural network structures, as it is simple and effective. Back-propagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer function. The hidden and output layer nodes adjust the weights value depend on the error in classification. The modification of the weights is according to the gradient of the error curve, which point in the direction to the local minimum. BNN is benefit on prediction and classification but processing speed is slower compared to other learning algorithms[3].

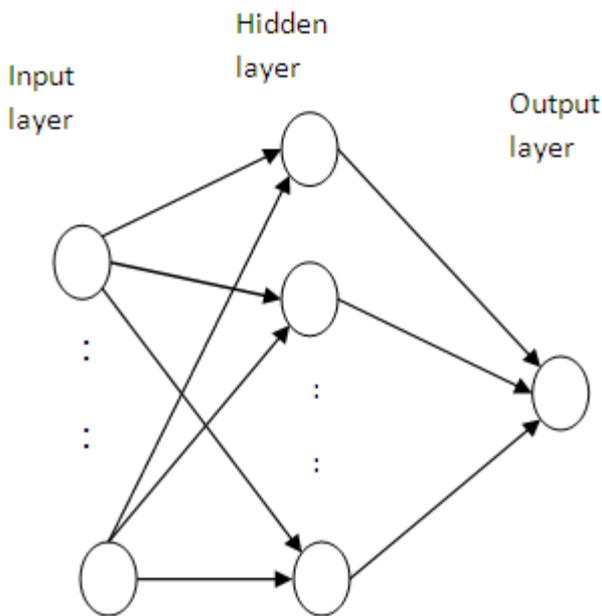


Figure8: A feed-forward neural network

In first step weight initialized by set all the weight and node threshold to some small random variable. In second step calculation of activation done.

Input Unit: - The Activation Level of the input unit is determined by the instances presented to the Network

Hidden unit and Output unit: - The Activation Level O_j of Hidden unit and Output Unit are determined by:

$$O_j = F[\sum W_{ji} * O_i - \theta_j] \tag{12}$$

Where W_{ji} – weight from input

O_j to unit j,

θ_j – Node threshold at unit j,

F – Activation Function.

In third step weight training done

Start at output unit and work backward to the hidden layer recursively adjust the weight by

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji} \tag{13}$$

The weight change is computed by:

$$\Delta W_{ji} = \eta \delta_j O_i \tag{14}$$

Where η = learning rate,

δ_j = error gradient

The error gradient is given as follows at Output Unit

$$\delta_j = O_j(1 - O_j)(T_j - O_j) \tag{15}$$

And for Hidden Unit

$$\delta_j = O_j(1 - O_j) \sum \delta_k W_{kj} \tag{16}$$

Where T_j = Target Value,

O_j = Actual Output Value,

δ_k = Error Gradient at unit k

to which a connection point at unit j.

In step four Repeat Iterations until convergence

X. EXPERIMENTAL RESULT

In this proposed system, a feed forward multilayer network is used. Back propagation algorithm used for training. There must be input layer, at least one hidden layer and output layer. The hidden layer and output layer nodes adjust the weights value depending on the error in classification. In BPN the signal flow will be in feed forward direction, but the error is back propagated and weights are update to reduce the error. Database image are taken from the medicinenet.com. In this paper we are taking a database of 100 images. In which 50 are cancerous and 50 are non-cancerous. In this case we are taking a 42×100 input, hidden layer of 20 neuron and 1 output layer. Neural network pattern reorganization technique is used for find the accuracy of training, validation and testing. Database is dividing into a three set: 50 images for training, 30 images for validation and 20 images for testing.

Comparing different wavelet, eight different wavelets are used in this paper followed by some classification test to compare them and find out the best results.

Table1. Classification test with different wavelet

Wavelet	training	Validation	testing	Total
Sym4	94%	85%	73.3%	86%
Sym7	98%	85%	76.7%	89%
Db1	100%	95%	76.7%	92%
Db10	100%	90%	80%	92%
Bior3.1	100%	90%	70%	89%
Bior5.5	98%	80%	73.7%	87%
Coif3	94%	90%	83.3%	90%
Haar	100%	96.7%	75%	94%

$$\text{Accuracy} = \frac{c}{n} \times 100 \tag{17}$$

c= total no of correct attempt.

n= total no of attempt.

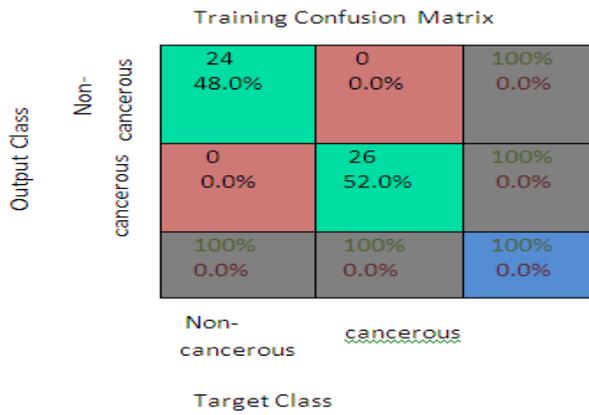


Figure9. Training confusion matrix for haar wavelet.

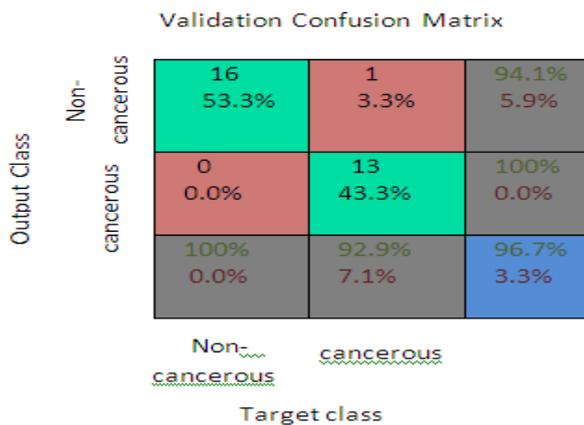


Figure10. validation confusion matrix for haar

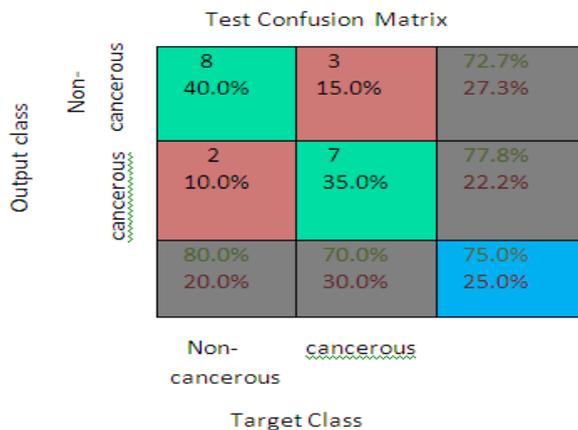


Figure11. Test confusion matrix for haar wavelet.

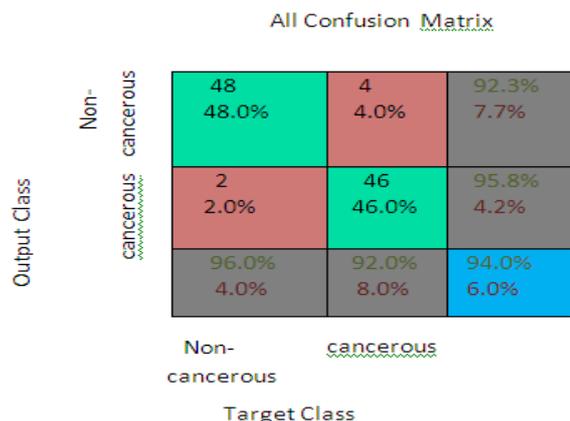


Figure12. All confusion matrix for haar wavelet

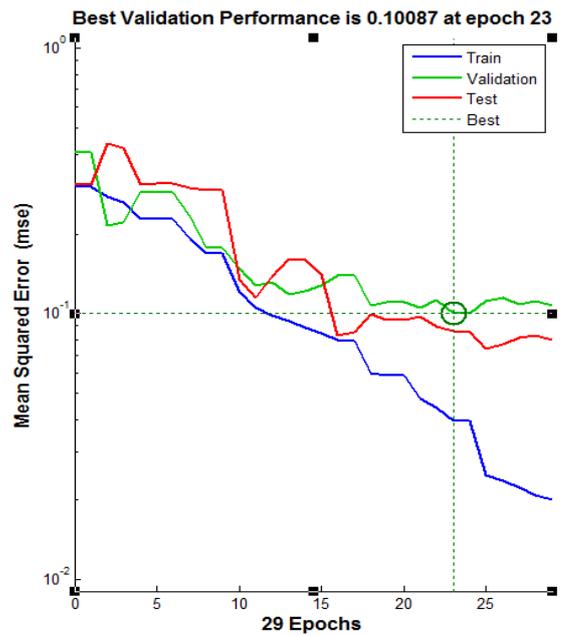


Figure. 13. Performance Plot for System

This figure does not indicate any major problems with the training. The validation and test curves are very similar. If the test curve had increased significantly before the validation curve increased, then it is possible that some over fitting might have occurred.

The below figure shows the error plot for the samples provided for testing, training and validation

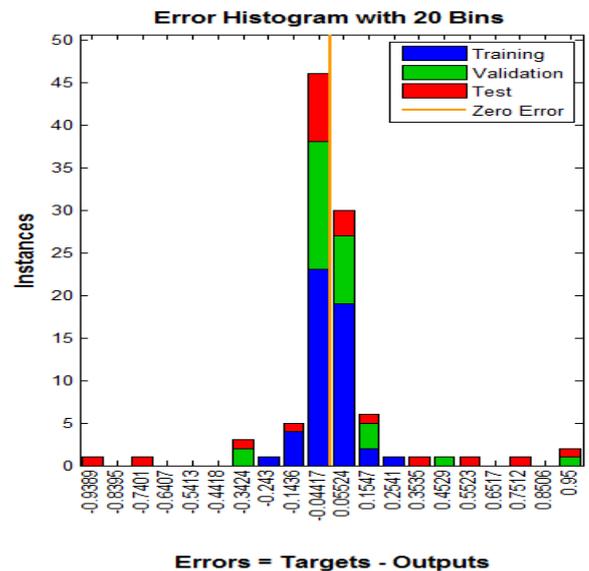


Figure. 14. Error Plot for the system

The blue bars represent training data, the green bars represent validation data, and the red bars represent testing data. The histogram can give you an indication of outliers, which are data points where the fit is significantly worse than the majority of data.

We are using a multilevel decomposition. Comparing different level of decomposition, one to five level different decomposition are used in this paper followed by some classification test to compare them and find out the best results

Table2: Classification result with different level.

Level	Training	Validation	Testing	Total
First	90%	73.3%	95%	86%
Second	100%	96.7%	75%	94%
Third	96%	76.7%	85%	88%
Fourth	100%	93.3%	75%	93%
Fifth	98.0%	80.0%	80.0%	89%

XI. RADIAL BASIS FUNCTION NETWORKS

Radial basis function (RBF) networks a type of artificial neural network for application to problems of supervised learning. The two main advantages of this approach are keeping the mathematics simple and the computations relatively cheap. Radial Basis Function Networks (RBFN) consists of 3 layers an input layer, a hidden layer, an output layer [26].

The hidden units provide a set of functions that constitute an arbitrary basis for the input patterns. Hidden units are known as radial centres and represented by the vectors c_1, c_2, \dots, c_h .

It can be regarded as a special Multilayer Perceptron (MLP) because it combines the parametric statistical distribution model and nonparametric linear perceptron algorithm in serial sequence. In the kernel layer, it consists of a set of kernel basis functions called radial basis functions[27]. Radial basis functions are means to approximate multivariable functions by linear combinations of terms based on a single univariate function.

This is radialised so that in can be used in more than one dimension. They are usually applied to approximate functions or data which are only known at a finite number of points (or too difficult to evaluate otherwise), so that then evaluations of the approximating function can take place often and efficiently[26].

$$s(x) = \sum_{j=1}^m \lambda_j \phi(\|x - x_j\|), x \in R^n \quad (17)$$

x_j - are the data points,

x -is a free variable,

ϕ is a univariate, are scalar parameters.

In this paper we are taking a database of 100 images. In which 50 are cancerous and 50 are non-cancerous. 50 image are taken for training and 50 are taken for testing.

Comparing different wavelet, eight different wavelets are used in this paper followed by some classification test to compare them and find out the best results.

Table3. Classification test with different wavelet

Wavelet	Training	Testing	Total
Sym4	88%	90%	87%
Sym7	90%	90%	87%
Db1	84%	92%	88%
Db10	84%	86%	88%
Bior3.1	84%	90%	86%
Bior5.5	90%	90%	94%
Coif3	82%	92%	91%
Haar	84%	92%	88%

XII. RESULT

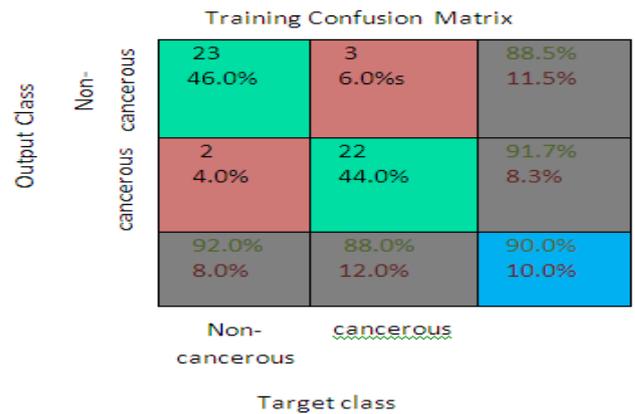


Figure15. Training confusion matrix for bior5.5 wavelet.

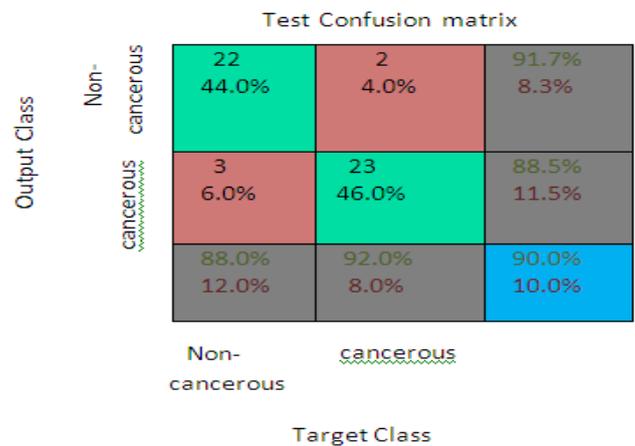


Figure16. Test confusion matrix for bior5.5 wavelet

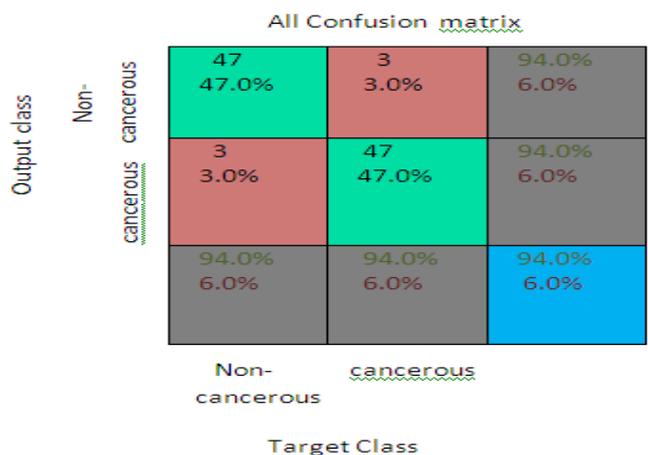


Figure17. All confusion matrix for bior5.5 wavelet.

We are using a multilevel decomposition. Comparing different level of decomposition, one to five level different decomposition are used in this paper followed by some classification test to compare them and find out the best results.

Table4: Classification result with different level.

Level	Training	Testing	Total
First	92%	88%	84%
Second	90%	90%	94%
Third	90%	90%	87%
Fourth	84%	84%	86%
Fifth	88.0%	88.0%	87%

XIII. CLASSIFICATION RESULT

In this paper we are constructed two types of neural network back propagation neural network (BPNN) and radial basis function neural network (RBFNN) , both achieved good results. BPNN based network can reach very high results, but the RBFNN based network has good generalization ability. So the BPNN based network can be used as simulation of the process for exploring new algorithms. Feed forward back-propagation neural network or back propagation neural network is a simple and effective model of ANN. It contains three layers, which are input, hidden, and output layers. Its structure is multilayer and has a learning process. Radial basis function neural network (RBFNN) is one of the efficient artificial networks. These types of the networks are mostly used for function approximation. Unlike BPNN, in the structure of RBFNN, there is only one hidden layer that makes computation time very less. Radial Basis Function Neural Network (RBFNN) is a type of multilayer network[27]. It is different from BPNN in its training algorithm. The basic RBFNN structure consists of three layers. These are an input layer, a kernel (hidden) layer, and an output layer. RBFNN can overcome some of the limitations of BPNN because it can use a single hidden layer for modelling any nonlinear function. Therefore, it is able to train data faster than BPNN. While RBFNN has simpler architecture, it still maintains its powerful mapping capability

XIV. CONCLUSION

Skin cancer is the most dangerous diseases, so early detection of this diseases is necessary. But the detection of skin cancer is most difficult task. From the literature review many techniques are used for the detection of lung cancer but some limitations also exists. Our proposed method follows an approach in which first step is feature extraction, and then these features are used to train and test the neural network. Wavelet transform is used to extract the feature of images. From the results, the proposed technique successfully detects the Skin cancer from images. Our proposed method gives 92% accuracy with BPNN and 88% accuracy with RBFNN using a haar wavelet. If it is detected correctly in early stages then it increase the key of survival. In future this technique can be used in the detection of type of skin cancer in cancerous images.

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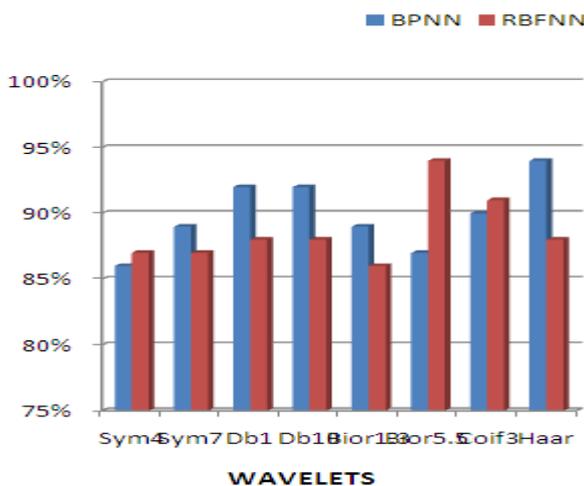


Figure18: comparison between RBFNN and BPNN using a multiple wavelet.

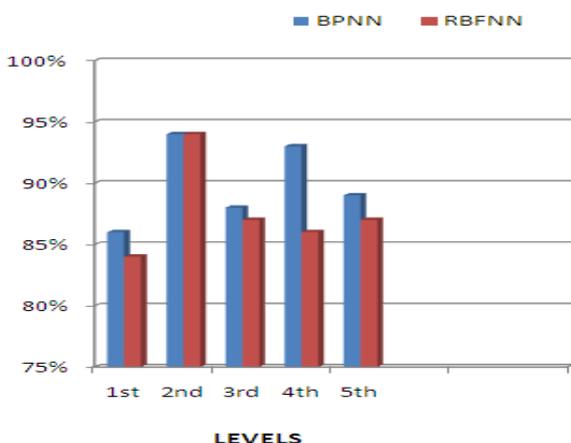


Figure18: comparison between RBFNN and BPNN using a multiple level.

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