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MACHINE LEARNING TECHNIQUES IN SKIN TUMOR IDENTIFICATION

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ABSTRACT

Recently, artificial intelligence started to invade medicine in its entire fields: diagnosis and therapy. Artificial intelligence can be a key part in the diagnostic medicine field for easy, fast, and accurate diagnosis of diseases. Thus, machine learning systems or so called intelligent systems that takes on the unpracticed physicians' job are in urgent need. In this paper, we present the use of two different intelligent systems for the skin tumor classification system. The approach is based on both image processing techniques and artificial intelligence tools such as backpropagation and Radial basis function neural networks. The main aim of this study is to investigate the best performance and accuracy in such medical classification application between the both used networks. Moreover, in this work we propose a simple image processing algorithm for segmenting the skin tumor from images using simple and fast techniques such as Gaussian filtering and image opening. Upon processing and rescaling the images are fed to both networks to be trained and tested and accuracy, training time, and error were calculated. Experimentally, both networks succeeded in generalizing the correct classification results of the unseen skin tumor images but with different rates, accuracies, and errors. As a result, it was found that a radial basis function network outperforms the backpropagation network in terms of accuracy, training time, and minimum square error achieved.

Keywords: skin tumor, benign, malignant, Malignancy; machine learning; classification system; backpropagation neural network, Gaussian filtering, and image opening, radial basis function network.

Literature Review

Significant development has been remarked recently in tumor classification as researchers investigated the different types of tumor classification using different techniques. The recent and related work has shown that the classification of skin cancer images can be achieved through supervised learning techniques such as artificial neural networks (back propagation neural network) (Ercal et al., 1994) and fuzzy systems (Salah et al., 2011) together with image processing and feature extraction techniques.

The other supervised learning classification techniques were also used for such applications such as k-nearest neighbors (k-NN) which is used to collect pixels that have similarities in each image feature (Daubechies, 1992), (Hiremath, 2006) and this may be effectively used to classify the skin tumor images as normal or abnormal.

Thus, by analyzing the state of art of the work related to skin tumor classification, it is noticeable that image processing combined with intelligent learning or machine learning systems become the best choice for early detection and classification of the skin tumor. This can be due to the financial issues since the intelligent and image processing systems are not expensive and also due to the accuracy that they provide for either detecting or classifying skin tumor (Ercal et al., 1994) (Aswim et al., 2014) (Sumithra et al., 2015) (Esteva et al., 2013).

Project paper Description

Skin Cancer or so called melanoma is the tumor that affects the skin. Skin growth may show up as dangerous or kind structure. It is a serious and may be life-threatening cancer.

This paper is to classify the 2 types of skin tumor: Melanoma and not melanoma (Benign and malignant). The system will be comprised of two phases: image processing and classification phase. In the image processing phase the skin tumor images will be processed in order to segment the tumor and make the images ready for the next phase. The next phase is the classification of images using back propagation and Radial basis function networks into "Melanoma" or "Nonmelanoma".

Aims of paper

The main aim of this paper is to investigate the Radial basis function in skin tumor classification and compare the obtained results such as accuracy, training time, and error reached with those of the backpropagation neural network. We aim in the processing phase of the system to propose a simple approach for the segmentation and feature extraction of the skin tumor images using simple image processing techniques such as image opening and rescaling using pattern averaging. Furthermore, a comparison between the two types of networks is used to show the efficiency of each one in classifying the skin tumor malignancy.

BPNN AND RBFN TRAINING

We discuss the classification phase of the suggested system. It discusses the neural network, concept, principles, and the used learning algorithm as well. The paper also shows the training stage of the system, by showing the classification rate and by listing the input parameters values used for creating the network. Moreover, this paper discusses the performance of the neural classifier by calculating the testing and the overall accuracy of the system.

1.1 Artificial Neural Network

Artificial neural network can be defined as a system consists of interconnected simple computational units called neurons or cells. It is an attempt to mimic the structure and function of the brain. A neural network is based on the ability to perform calculations in the hope that we can reproduce some of the flexibility and power of the human brain by artificial means (Zurada, 1992).

The associated neurons are connected by links, and every link has all its numerical weight associated with it. Weights are the primary means of long-term memory in Artificial Neural Networks. The von Neumann's computer model is obviously faster and more accurate in computing but its lacks flexibility, and noise tolerance; it cannot always deal with incomplete data (Negnevitsky, 2005). The most important is the inability to raise the level of performance over time from experience. i.e. incapable of learning.

1.1.1 Multi-layer percepton (MLP)

In medical decision to make a variety of neural networks are used for decision accuracy. MLPs are the simplest and commonly used programs built a neural network because of structural litheness, and the capabilities and availability of a good representative, with a large number of programming algorithms (Narasingarao et al., 2009). MLPs are feeding forward neural networks and global approximators, programmed with an algorithm publishing standard background. Supervised by the networks so that they require required to be trained to respond. They are able to convert the input data required to respond, so used widely for pattern classification. With one or two hidden layers, they can bring almost any map inputs and outputs.

Overall, the MLP consists of three layers: the input layer, and production layer and the intermediate layer or hidden.

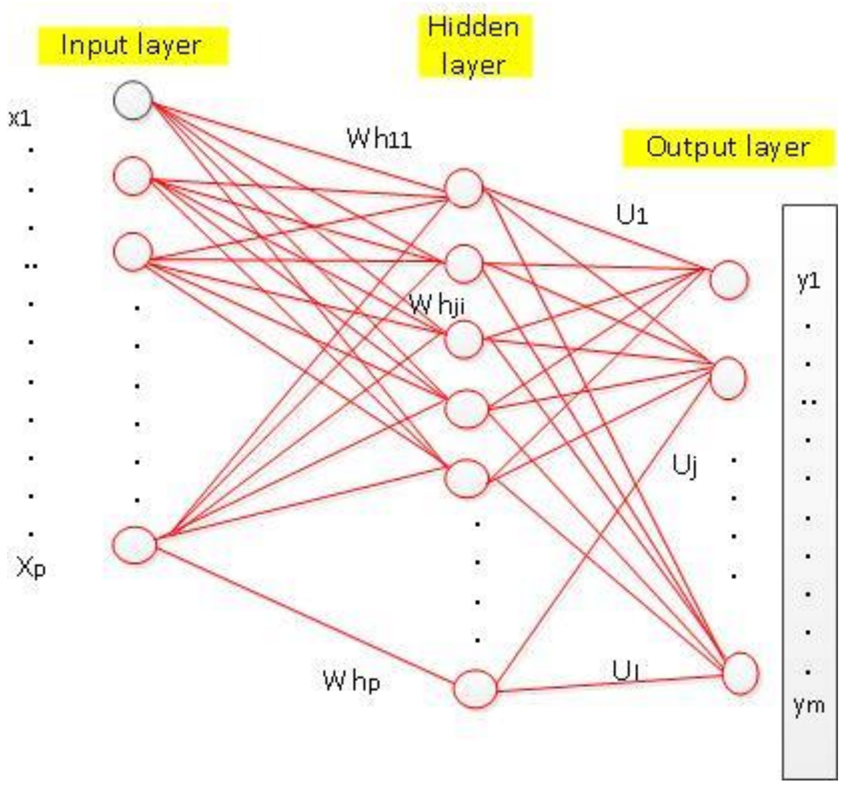


Figure1.1 Structure of MLP Feedforward network (Baxt, 1995)

As the figure shows, this network has the input layer with three neurons, in the middle, and one hidden layer with three neurons and the output layer to the right with two neurons. There neuron in input layer each variable predicted (Q1, Q ...P). In the case of N categorical variables, N -1 neurons are used to represent categories N variable (Baxt, 1995).
The net calculation of input and output of the j hidden layer neurons are as follows:

$$net = \sum_{t=1}^{N+1} w_{ji} x_i \qquad 1.1$$

$$Y_i = f(net_j^h) \qquad 1.2$$

1.2 Radial Basis Function Network

The operation of radial basis function networks is somewhat different from the back propagation neural networks. Especially, the weights update in the hidden layer. The output layer of a RBFN can be seen as that of a BPNN with linear activation functions.
Cover's theorem establishes that pattern separability increases when such patterns are projected nonlinearly onto a higher dimensional space (Strumiłło and Kamiński, 2003) Radial basis functions serve as input transformation basis when expanded into the hidden layer feature space. The hidden neurons in a RBFN provides these functions. Hence, it follows from cover's theorem that large number of neurons in the hidden layer should encourage pattern separability. The output layer consists of neurons which combine linearly the bases computed in the hidden layer.
If we consider a two category classification problem (classes P and Q), with input vector patterns, x, hidden weights, w, and basis function, Ψ, then we can write that

$$x \in P, \quad \text{if } w^T.\psi(x) > 0 \qquad 1.3$$

$$x \in Q, \quad \text{if } w^T.\psi(x) < 0 \qquad 1.4$$

while, the separation hyperplane is given as Equation

$$w^T.\psi(x)=0 \qquad 1.5$$

Considering Equations1.4,1.5 , the probability of separability tends toward 1 when the basis function, Ψ, is nonlinear; and the dimension of hidden space is greater that that of the input space.

For data points $\{x^i, y^j\}$; where x are input vectors of dimensionality i, and y are target vectors of dimensionality j. It follows from the discussions above (probability of separability) that for m hidden neurons or bases, the relation in Equation should hold.

$$1 \le i \le m \qquad 1.6$$

Generally, hidden neurons are centered on the training data using some criteria or schemes. Common schemes include random selection of data points, orthogonal least squares, clustering, etc. Hidden neuron activations can be computed with Equation using the Gaussian function.

$$\psi_k(x)=\exp\left(\frac{\|x-x_k\|}{2\sigma_k^2}\right) \qquad 1.7$$

where, x_k and σ_k are the center and width (spread constant) of the Gaussian basis function, respectively. However, it is possible to use some other non-linear basis functions (Garg et al., 2008).

Assume that the function relating y to x is r(x); then it is the aim to compute r(x) as given in next Equation 1.8.

$$r_j(x)=\sum_{k=0}^{m} w_{jk}\psi_k(x) \qquad 1.8$$

Function r(x) can then be minimized using the mean square error function as shown in next Equation 1.9.

$$E=\frac{1}{2}\sum_p\sum_j(y_j^p-r_j(x^p))^2 \qquad 1.9$$

where, p is the particular input vector pattern.

The Euclidean distance between x and x_k is minimized during training of the network. When $x=x_k$, the Gaussian function output,Ψ(x), is maximum; and tends toward 0 when $\|x-x_k\|\to\infty$.

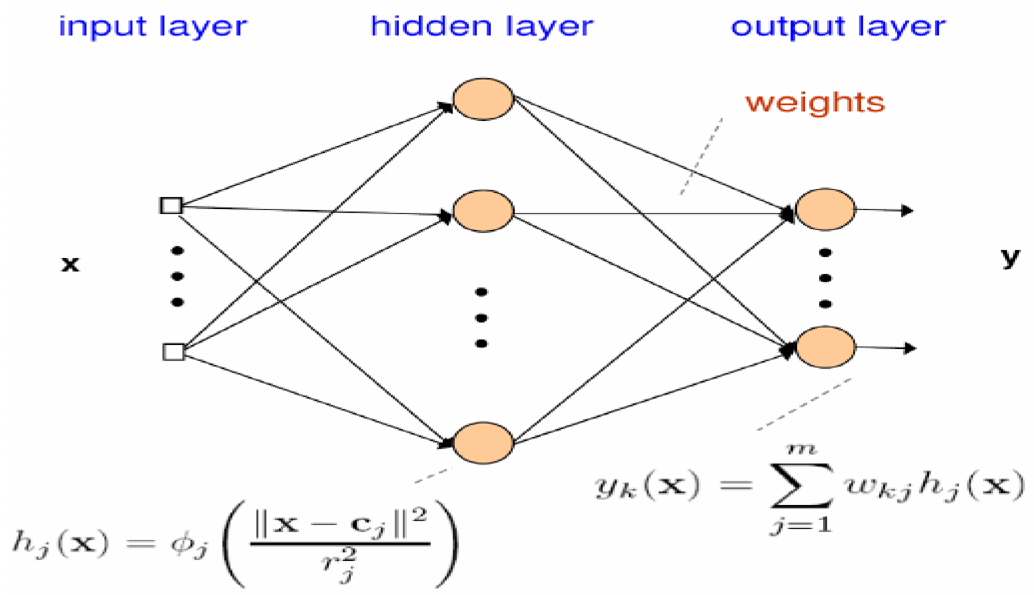
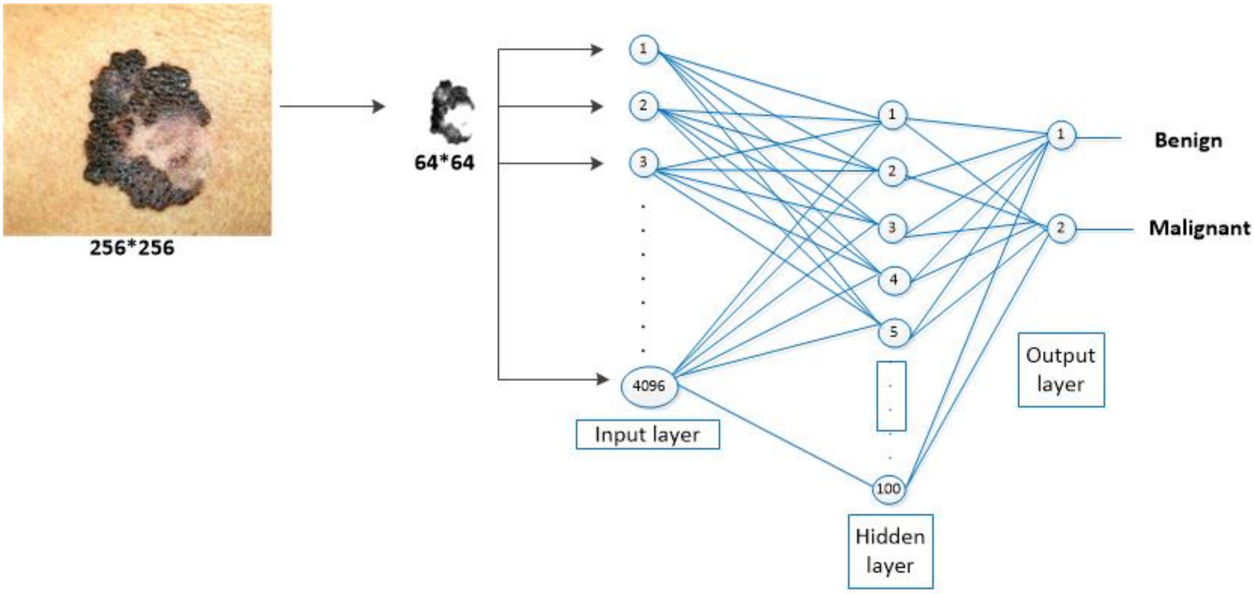


Figure1.2 Radial Basis Function Network (Deng, 2014)

1.3 The Classification Phase

1.3.1Backpropagation neural network training

During this phase, skin tumor images are classified into benign or malignant using a supervised neural network. We used a backpropagation neural network due to its simplicity and the sufficient number of images. We used 180 images, 93 are malignant and 87 are benign. The system was trained on 100 images; 50 for benign tumors and 50 for malignant tumor images. The input layer of the BPNN network consists of 4096 neurons since each image is rescaled to 64*64 bitmap using pattern averaging. The hidden layer consists of 100 neurons, while the output layer has 2 neurons since we have only 2 output classes: benign and malignant.
Figuer1.3 shows the neural network topology of our proposed identification system for the BPNN.
Table1.1 represents the total number of images collected from the database. In addition it shows the number of images used in both training and testing phases of the system.
Table1.2 represents the input parameters setting of the system that were used in training the system. The network ran for 5000 maximum iterations with a learning rate of 0.3, a momentum rate of 0.7 and a minimum error of 0.001 since it is a medical application. Table1.3 shows the output classes of the identification system it shows that the system has 2 classes: benign and malignant; each with its numerical coding.



Output layer

Figure1.3 BPNN topology for the proposed network

Table1.1: Total Number of images

	Number of normal images	Number of melanoma images	Total Number of non-melanoma Images
	180	93	87
Training set	100	50	50
Testing set	80	43	37

Table1.2: ANN Parameters Setting

Parameters	Value
Number of neurons in input layer	4096
Number of neurons in output layer	2
Number of neurons in hidden layer	100
Iterations number	5000
Maximum epochs	5000
Learning rate	0.3
Momentum rate	0.7
Error	0.001
Activation Function	Sigmoid
Training time	1 min 35 s

The network was simulated and trained on Matlab software and tools. We used two different sets of 100 images; the first set is for the benign tumor images and it contains 50 images, the second set is for the malignant tumor images and it contains 50 images. Figure1.4 is the training results of the two sets (learning curve) for the BPNN.

Table1.3 : Output classes coding

Output Classes	Coding
Benign tumor	[1 0]
Malignant tumor	[0 1]

The figure1.6 shows the training taken to train the network as well as the minimum square error reached during the training of the backpropagation neural network. This figure1.7 represents the regression plot of the desired output (dotted line) and the actual output. As the actual output is far from the target as the error is increased. In this figure, it is remarked that the target and the actual output are very close which means that the error is minimized and the network well trained for BPNN (training ratio: 100%). Figure 1.5 shows the learning curve of the developed network.

```
methods:

       adapt: Learn while in continuous use
   configure: Configure inputs & outputs
      gensim: Generate Simulink model
        init: Initialize weights & biases
     perform: Calculate performance
         sim: Evaluate network outputs given inputs
       train: Train network with examples
        view: View diagram
 unconfigure: Unconfigure inputs & outputs

train recognition rate is 100
```

Figure1.4 : Snapshot of the neural network training program

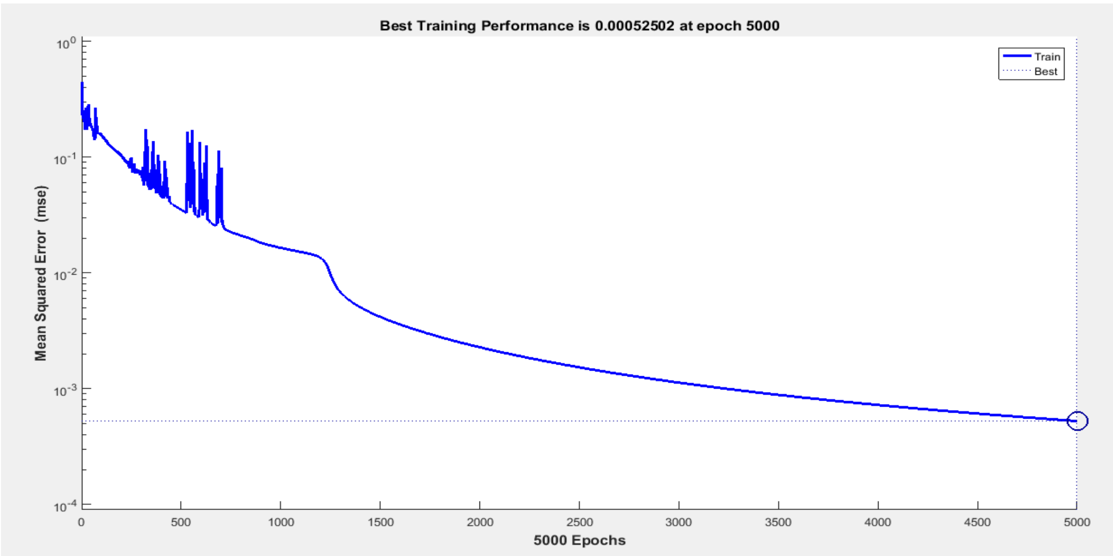


Figure1.5 : Variation of the MSE with the iteration number of BPNN

Epoch:	0	5000 iterations	5000
Time:		0:01:35	
Performance:	0.449	0.000525	0.00
Gradient:	1.18	0.000855	1.00e-05
Validation Checks:	0	0	6

Figure1.6: Training time and minimum square error reached

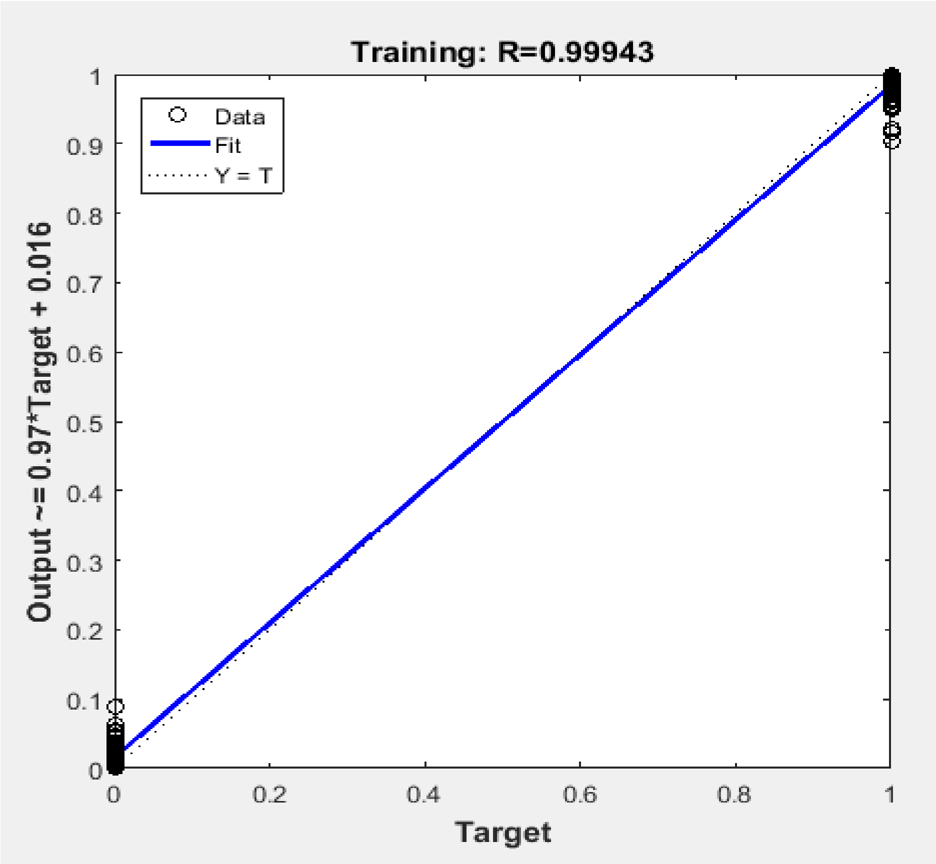


Figure1.7 : Actual versus target output

RBF network training

A radial basis function network is somehow different from the back propagation neural networks especially, in the way the weights in the hidden layer are updated. The output layer of a RBFN can be seen as that of a BPNN with linear activation functions [10].

The output of neuron units are calculated using k-means clustering similar algorithms, after which Gaussian function is applied to provide the unit final output. During training, the hidden layer neurons are centered usually randomly in space on subsets or all of the training patterns space (dimensionality is of the training pattern) [10]; after which the Euclidean distance between each neuron and training pattern vectors are calculated, then the radial basis function (also or referred to as a kernel) applied to calculated distances.

The radial basis function is so named because the radius distance is the argument to the function [12].

$$Weight = RBFN(distance) \qquad 1$$

Similarly, same data are used for the RBFN where 50 benign and 50 malignant skin tumor images are used for training the network. Table 1.4 shows the parameters values set during the training phase of this network.

As seen in Table1.4 ; the network is trained with 50 hidden neurons and spread constant of 0.5.

Table1.4 : RBFNs training parameters

Network parameter	RBFN
Number of training samples	50
Number hidden neurons	50

Spread constant	0.5
Iterations number	1000
Maximum epochs	50
Training time (secs)	10
Mean Square Error reached	0.0330

It is observed that RBFN with 50 hidden neurons and spread constant of 0.5 reached the lowest mean square error (MSE) (0.0098) in a very short time of 10 seconds. Moreover, this network was capable of reaching that low MSE with only 50 maximum epochs which is much smaller than that of BPNN. Moreover, it is observed that this network was able to learn and converge in a shorter time than that of BPNN. The learning curve for RBFN is shown in next Figure .

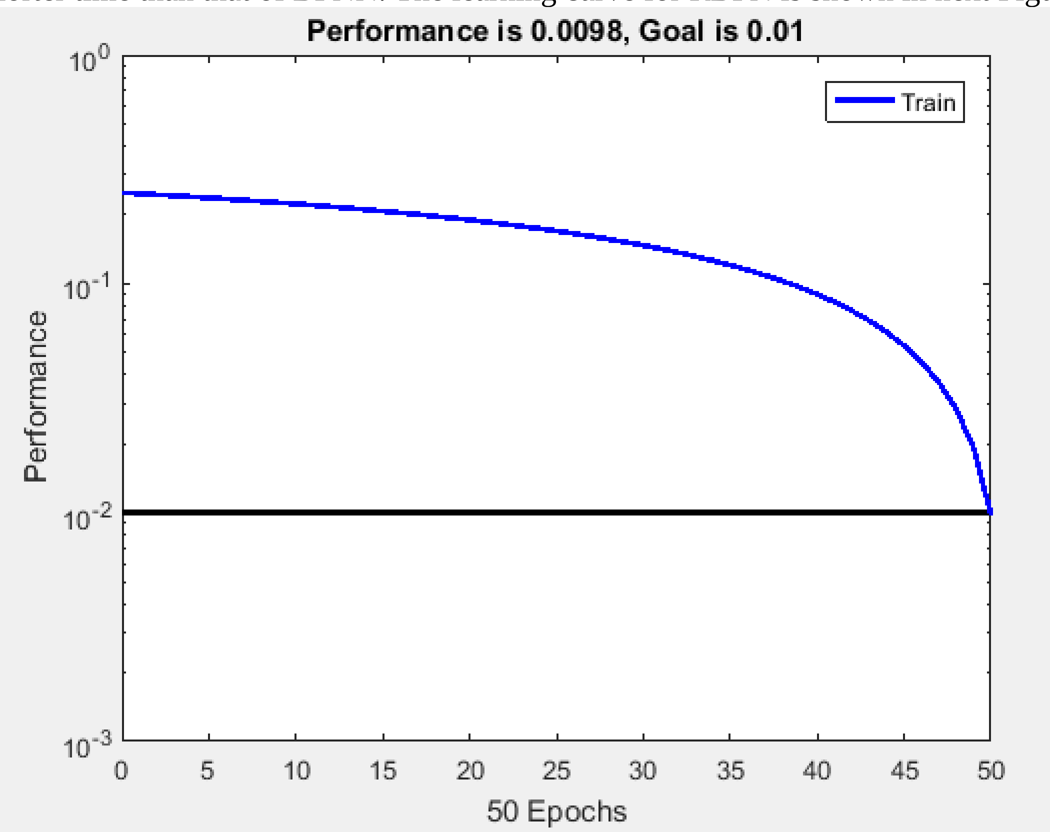


Figure1.8 : RBF network's learning curve

1.3 System Performance

This paper presents an intelligent identification system established image processing and neural classification. The system is to distinguish the malignancy of a skin tumor using many images. The images are processed in order to extract the patterns of interests using image processing techniques. The images then bear sample averaging with a purpose to rescale them while retaining the extracted features in order to lower the processing and computing time. The research is to investigate the use of a conventional network such as backpropagation network and the Radial basis function network in classifying the malignancy of skin tumor images to find out the more efficient, more accurate, and shorter in time one to be used.

This identification system was tested using MATLAB software and tools. It was tested using 80 images; 43 for melanoma and 37 for non-melanoma images. The result of both testing and training phases is included in the following table1.5.

Table1.5 : Classification rate

Tumor images type	Image sets	Number of images	Classification rate of BPNN	Classification rate of RBFN
Malignant (93)	Training set	50	100%	99%
	Testing set	43	63%	85%
Benign (87)	Training set	50	100%	97%
	Testing set	37	62.7%	82%
Benign &Malignant	Both sets	180	81%	90.75%

Table1.5 above shows the recognition rate obtained in both training and testing phases of BPNN. It also represents the number of images used in each set, as well as the overall identification rate obtained which is 81% for the backpropagation neural network and 95% for the Radial basis function network.
It can be noticed that the RBF network was more efficient in classifying the malignancy of the skin tumor images. Moreover, compared to BPNN the RBF network achieved higher classification rate with a smaller error and shorter training time than the BPNN.

RESULTS DISCUSSION AND COMPARISON

2.1 Results Discussion

In this paper, an intelligent identification of the skin tumor malignancy is developed. The system is based on both image processing and neural network classification. A good number of images of benign and malignant skin tumor images were obtained from a public database available on the internet. The paper motivation is to investigate the use of both BPNN and RBF network for the classification of skin tumor to check the effectiveness and accuracies.

Table2.1: BPNN versus RBFN results comparison

Parameters	BPNN	RBFN
Number of neurons in input layer	4096	4096
Number of neurons in output layer	2	2
Number of neurons in hidden layer	100	50
Iterations number	5000	1000
Maximum iterations reached	5000	50
Learning rate	0.3	0.3
Momentum rate	0.7	0.7
Mean Square Error reached	0.0330	0.0098
Training time	1 min 35 s	10 sec
Classification rate	81%	90.75%

After learning and convergence, the network was finally able to distinguish between the two types of images: benign and malignant, through the segmentation process using the processing techniques used and the extracted features using pattern averaging technique. However, big differences were found in accuracies, effectiveness, processing time, minimum error for both networks.

Table2.1 above shows the input parameters of both used network for the proposed application: classification of skin tumor malignancy. The difference in some parameters between BPNN and RBF network is due to the difference in network training algorithms and network structure itself. However, the point to be emphasized and compared here in table2.1 above is the training time. The time that was taken for the RBF network to reach a minimum error and high recognition rate was much lower than that of BPNN which shows the effectiveness and robustness of a RBF network.

Table 8 shows a performance comparison of both types of used networks: BPNN and RBF network. The experimental analysis of this table concludes that the RBF network was capable of performing the proposed application (classification of skin tumor malignancy) with a better accuracy (90.75%), less time (10 secs) and less minimum error (0.0098) than a BPNN.

Many challenges were faced during the training of the BPNN network. Since artificial neural network weights are usually randomly initialized at the start of training, it therefore follows that trained BPNN is not always guaranteed to converge to the global minimum or good local minima. Thus, the learning of benign and malignant images can be negatively affected; this therefore affects the classification phase, where the trained BPNN may incorrectly classify a tumor. Therefore, to solve this problem, the MATLAB program should be retrained for many runs till a testing recognition (relating to BPNN generalization capability) of greater than 80% is obtained. This greatly reduces the BPNN's probability of wrongly classifying a skin tumor image. In this project, the network was trained for many times until the training classification rate reaches 81% and above.

One more challenge we faced is that the neural network goes into "overfitting" which means that the network is well trained however; it is weak in the generalization capability. The best solution to solve such a problem is to force-stop the network before it overfits. This can be done using many techniques but since our data is divided into training and testing data only we have tried to solve this problem by increasing the number of iterations to 5000 instead of 10000. This solution was based on that the minimum square error was obtained at epoch 5000. Thus, the network is memorizing the data after this epoch which allows the "overfitting" to occur. Figure shows some testing results of the benign tumor image during the "overfitting" problem. It can be seen that the network has weak generalization capability since it is "overfitting".

2.2 Results Comparison

Many researches have been conducted for the classification of skin tumors and all were meant to diagnose or analyze it using some image processing techniques and some classifiers. Each research has its own techniques that meant to extract features from the original images in order to be fed into a neural network that classifies them into benign or malignant. Many researches used the Gray-Level Co-occurrence Matrix (GLCM) that extracts the texture features from the image. However, in the proposed research we extract the tumor using simple image processing techniques then rescale the segmented tumor with preserving the significant features using pattern averaging. Thus, our work is a new approach for the skin tumor malignancy identification based image processing and intelligent classifier; backpropagation neural network and Radial basis function network.

The table below shows the accuracy comparison between the proposed benign tumor identification system and some of the related works discussed in the literature review part. It shows that our system is more efficient and accurate than the other systems.

Table2.2 : Results comparison

Paper Title	Authors	Methods used	Train/Test data	Recognition Rate
Neural Network Diagnosis of Malignant Melanoma From Color Images	Fikret Ercal,et al (Fikret Ercal,et al, 1994)	Image processing and Neural Network	216 images 108/108	80%
Design and Evaluation of Neural Classifiers Application to Skin Lesion Classification	MadsI-Iintz-hladsen et al. (hladsen et al., 1995)	Gauss Newton optimization and neural network	160 images 120/40	66%
Hybrid Genetic Algorithm - Artificial Neural Network Classifier for Skin Cancer Detection	Aswin.R.B et al (Aswim et al., 2014)	Genetic Algorithm - Artificial Neural	NA	88%
Our Work	Assist. Prof. Dr. Kamil Dimililer & Maher	Image Processing, Pattern averaging and neural network	180 100/80	81% (BPNN) and 90.75% (RBFN)

2.3 Conclusion

This paper proposed an intelligent system for classifying the skin tumor images from the features derived from the image processing techniques used. Two types of neural networks were used for performing this task. Backpropagation neural networks and radial basis function network were selected for this classification task. A comparison between both types of these networks was made based on different parameters set during the training phase to evaluate the performance of each and to discover the network that performs better in this classification task. It was discovered that a Radial basis function network with less hidden layer performs better when trained and tested on unseen data. In addition, this network reached the least minimum square error in a shorter time than the other backpropagation networks. In other words, the backpropaagation network that reached the highest training recognition rate wasn't capable of achieving the highest recognition rate in the testing phase. This means that a network can be weak in generalization even if it performed well in the training phase. This is the reason why different networks were used.

As a result, it should be noted that the Radial basis function network outperformed the backpropagation network for classifying the skin tumor malignancy. This outperformance is in terms of accuracy, minimum error, maximum epochs and training time.

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