SKIN TUMOR IDENTIFICATION BY USING BACK PROPAGATION AND AUTO-ENCODER NEURAL NETWORK

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES

OF

NEAR EAST UNIVERSITY

By

WALED ARHOMA ALI RAHOMA

In Partial Fulfillment of the Requirements for the Degree of Master of Science
in
Electrical and Electronics Engineering

NICOSIA, 2017

Waled Arhoma Ali Rahoma

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree of master of science in Electrical and Electronics Engineering

Examining Committee in Charge:

I hereby declare that, all the information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name :

Signature :

Date:

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To my family and parents….

ABSTRACT

The malignancy of the skin is the most popularly well-known kind of tumor. There are 3.5 million new cases every year, analyzed in more than two million individuals in the United States alone. It has been demonstrated that the diagnosis part of dermoscopy may really bring down the indicative accuracy due to unpracticed or even exhausted dermatologists. Machine learning can be a key part in the therapeutic medicine field for easy, fast, and accurate diagnosis of diseases. Therefore, there is a need for machine learning systems or so called intelligent systems that takes on the unpracticed dermatologists' job. This thesis is to present an intelligent skin tumor classification system approach based on both image processing techniques and artificial intelligence tools such as neural networks and deep learning. The motivation behind this study is to investigate the highest performance and accuracy in such medical classification application of Back-propagation neural and Auto-encoder neural network. A performance based comparison between traditional and deep neural network was presented. Different techniques are implemented in the system for the accurate processing of skin tumor images which leads to an accurate segmentation of the skin tumor in an image. Discrete wavelets transform was one of the techniques used to extract important image features before being fed to the neural network. Same processed images were fed to an Auto-encoder to evaluate the performance against the conventional network. Both networks were trained and tested using the available database. The accuracy, training time and error were calculated. Experimentally, it was discovered that a deep neural network: auto-encoder outperforms the BPNN in terms of accuracy, training time, and minimum error reached. Results shows that Haar wavelet transform was effective in segmenting skin tumor and extracting features that distinguish the tumor malignancy.

Keywords: Malignancy; machine learning; classification system; back-propagation neural Classifier; auto-encoder neural network

ÖZET

Cilt malignitesi, Amerika'da en çok bilinen tümör türüdür. ABD'de tek başına iki milyondan fazla kişi analiz edildiğinde her yıl 3.5 milyon yeni vaka olduğu görülüyor. Dermoskopinin tanı bölümünün, deneyimsiz veya hatta bitkin dermatologlar nedeniyle gösterge doğruluğunu gerçekten düşürebileceği gösterilmiştir. Makine öğrenimi, hastalıkların kolay, hızlı ve doğru teşhisi için terapötik tıp alanında önemli bir rol oynayabilir. Dolayısıyla, deneyimsiz dermatologların yerini alması için makine öğrenme sistemleri ya da akıllı sistem denilen sistemlere ihtiyaç duyulmaktadır. Bu tez, hem görüntü işleme tekniklerine hem de sinir ağları ve derin öğrenme gibi yapay zeka araçlarına dayalı akıllı bir deri tümörü sınıflandırma sistemi yaklaşımı sunmak için hazırlanmıştır. Bu çalışmanın arkasındaki motivasyon, geri yayılım nöral sınıflandırıcı ve derin sinir ağı gibi oto-kodlayıcı tıbbi sınıflandırma uygulamalarında en iyi performansı ve doğruluğu araştırmaktır. Bu tezde, geleneksel ve derin sinir ağı arasındaki performansa dayalı bir karşılaştırma sunulmuştur. Sistemdeki cilt tümörü görüntülerinin doğru işlenmesi için bir görüntüde cilt tümörünün doğru bölünmesine yol açan farklı teknikler uygulanmaktadır. Ayrık dalgacık dönüşümü, görüntüdeki ilgi bölgesini oluşturan özellikleri ayıklamak için kullanılan tekniklerden biri olmuştur. Görüntüler, bir geri yayılım ağına beslenen model ortalamaları kullanılarak yeniden ölçeklendirilmiştir. İşlenmiş aynı görüntüler, geleneksel ağa karşı performansı değerlendirmek için bir Otomatik Kodlayıcıya beslenmiştir. Her iki ağ da mevcut veritabanı görüntüleri kullanılarak eğitilmiş ve test edilmiştir ve doğruluk, eğitim süresi, hata hesaplanmıştır. Deneysel olarak, derin bir sinir ağı: otomatik kodlayıcı, doğruluk, eğitim süresi ve ulaşılan minimum hata açısından BPNN'den daha iyi performans gösterdiği keşfedilmiştir. Bu aynı zamanda, Haar dalgacık dönüşümünün, cilt tümörünün bölünmesinde ve tümör malignitesini ayıran özellikler çıkarmada iyi ve etkili olduğunu göstermektedir.

Anahtar kelimeler: Malignite; makine öğrenimi; sınıflandırma sistemi; geri yayılım nöral sınıflandırıcı; derin sinir ağları

TABLE OF CONTENTS

ACKNOWLEDGEMENT ii
ABSTRACT iv
ÖZET v
TABLE OF CONTENTS vi
LIST OF TABLES ix
LIST OF FIGURES xi
LIST OF SYMBOLS xiii

CHAPTER 1: INTRODUCTION 1
1.1 Overview 1
1.2 Proposed Work 2
1.3 Contributions of Thesis 2
1.4 Objectives of the Thesis 2
1.5 Thesis Overview 3

CHAPTER 2: ARTIFICIAL NEURAL NETWORK AND RELATED STUDIES ... 4
2.1 Related studies on Skin Cancer Classifications 4
2.1.1 Back Propagation neural network for skin cancer classifications 4
2.1.2 Deep learning in skin cancer classification 6
2.2 Overview 6
2.3 Architecture of ANN 7
2.3.1 Different types of activation functions 8
2.3.1.1 Sigmoid functions 9
2.4 Neural Network Structure 10
2.4.1 Single layer feed-forward 10
2.4.2 Multi-layer feed-forward 11
2.4.3 Recurrent network 11
2.5 Training of ANN 12
2.5.1 Supervised training 12
2.5.2 Unsupervised training 12

2.6 Back Propagation Neural Network 13
2.7 Deep Neural Network 14
2.7.1 Auto-encoder neural network 16

CHAPTER 3: SKIN CANCER IMAGES ANALYSIS AND PROCESSING 18
3.1 Introduction 18
3.2 The Proposed Methodology 18
3.3 Part 1: 20
3.3.1 Image processing phase 20
3.3.1.1 RGB to grayscale conversion 20
3.3.1.2 Image filtering using median filter 21
3.3.1.3 Extract background 22
3.3.1.4 Image addition 22
3.3.1.5 Image adjustment 23
3.3.1.6 Discrete Haar wavelets 24
3.3.1.7 Inverse discrete wavelets transform 25
3.3.1.8 Size reduction using pattern averaging 26
3.3.2 Classification phase 27
3.3.2.1 Data description 27
3.3.2.2 Back propagation neural network training 28
3.3.2.3 Training Auto-encoder network 32
3.4 Part 2: 35
3.4.1 Back-propagation neural network training without image processing 35
3.4.2 Training Auto-encoder network without image processing 38

CHAPTER 4: RESULTS, DISCUSSION AND COMPARSION.................................. 40
4.1 Results 40
4.2 Results Comparison 41
4.3 Results Discussion 42

CHAPTER 5: CONCLUSION AND FUTURE WORK 44
5.1 Conclusions 44

5.2 Recommendations and Future Work 44

REFERENCES... 45

LIST OF TABLES

Table 3.1:	Training ANN with different parameters...	29
Table 3.2:	BPNN parameters setting	30
Table 3.3:	Output classes coding	30
Table 3.4:	Auto-encoder input parameters during per-training and fine-tuning	34
Table 3.5:	BPNN parameters without image processing	36
Table 3.6:	Auto-encoder input parameters during pre-training and fine-tuning without image processing	38
Table 4.1:	Classification rate	41
Table 4.2:	BPNN versus Auto-encoder networks performance comparison	42
Table 4.3:	Results comparison with related works	43

LIST OF FIGURES

Figure 2.1:	Architecture of artificial neuron network	7
Figure 2.2:	Various types of activation functions	9
Figure 2.3:	Sigmoid activation function, logarithmic	10
Figure 2.4:	Tangent sigmoid activation function	10
Figure 2.5:	Typical multi-layer feed-forward	11
Figure 2.6:	Typical Recurrent Network	12
Figure 2.7:	Back propagation architecture	13
Figure 2.8:	A deep neural network	15
Figure 2.9:	Auto-encoder	17
Figure 3.1:	Flowchart of the proposed algorithm	19
Figure 3.2:	RGB to gray scale conversion	21
Figure 3.3:	Image filtering using median filter	21
Figure 3.4:	Background extraction	22
Figure 3.5:	Image addition	23
Figure 3.6:	Image adjustment	24
Figure 3.7:	Haar Wavelets transform	25
Figure 3.8:	Reconstructed image using inverse wavelet transform	26
Figure 3.9:	Rescaled image using pattern averaging	27
Figure 3.10:	BPNN architecture for the proposed network	28
Figure 3.11:	BPNN Training time and Iterations number	31
Figure 3.12:	MSE curve of the trained network of BPNN	31
Figure 3.13:	Actual versus target output	32
Figure 3.14:	Auto-Encoder architecture for the proposed network	33
Figure 3.15:	Learning curve and time during pre-training of the auto-encoder	34
Figure 3.16:	Learning curve and time of training for network during Fine-tuning	35
Figure 3.17:	BPNN training time and Iterations number	36
Figure 3.18:	MSE curve of the trained network of BPNN without image processing	37
Figure 3.19:	Actual versus target output	37
Figure 3.20:	Learning curve and time during pre-training of the auto-encoder	39

Figure 3.21: Learning curve and time during fine-tuning of the auto-encoder 39

LIST OF SYMBOLS USED

AE	Auto-encoder
ANN	Artificial Neural Network
BPNN	Back Propagation neural network
MSE	Mean Square Error
RGB	Red, Grey, Blue
SEC	Second

CHAPTER 1
INTRODUCTION

1.1 Overview

Skin malignancy is the most widely recognized, and the most common kind of tumor. Including melanoma, basal cell carcinoma, and squamous cell carcinoma, there are 3.5 million new cases every year, analyzed in more than two million individuals in the United States alone. These are more new cases every year than the total number of bosom, prostate, lung and colon malignancies, 20% of Americans will create skin disease in their lifetimes (Donaldson & Coldiron, 2011).

In a human body, skin is the biggest organ. It covers the bones, muscles and all the other parts of the body. Skin elements in the human body have more noteworthy significance in light of the fact that; a little change in its working may affect other parts and organsin the human body. Skin is presented to external surroundings. Consequently illnesses and contamination happen more to skin. In this way, we need to give a more noteworthy consideration regarding skin disease. The spot on skin which is wounded is known as an injury zone. Skin injuries are the principal clinical indications of illness, for example, Melanoma, chickenpox, and so forth. These days, medical field rely more on Computer-Aided Diagnosis System (CAD). Early discovery of skin illness is more intricate to the unpracticed dermatologist. By fusing computerized image processing for skin malignancy identification, the determination is conceivable without direct physical contact with skin (Ekwueme et al., 2011). Hence, creating CAD system is becoming a valuable territory in the medicinal field. Machine learning assumes a key part in the therapeutic field for the mechanization of numerous procedures. Dermoscopy may really bring down the indicative reliability in the hands of dermatologists. Therefore, there is a need for machine learning systems that take this job instead of dermatologists.

Image processing is the first step in developing an intelligent system for such application: skin tumor diagnosis and classification. The skin tumor images are usually in need of enhancement to remove noise, adjustment to brighten them, and segmentation to detect and extract features. Here is the primary role of image processing in this kind of medical of applications: segmentation of tumor in order to extract the important features that would be enough to distinguish the tumor malignancy and fed into the intelligent system for classification purposes.

After processing, the next step takes place which is the classification or recognition using intelligent approaches such as neural network, fuzzy logic, k-nearest neighbor (Negnevitsky, 2005) etc… each approach has its own properties, structure, architecture, and training or learning techniques, etc.. Thus each one of these intelligent systems may perform differently.

1.2 Proposed Work

The proposed work implements the artificial neural network technologies in the classification and recognition of skin cancer tumor. Two types of supervised learning neural networks will be implemented and tested in this work; these are the back propagation neural network and the deep learning neural network. Different image processing techniques like image filtering and back ground extraction will be used to enhance the efficiency of the neural networks. These techniques are implemented for the classification of skin tumor.

1.3 Contributions of Thesis

- This thesis develops a comparative study of skin tumor classification using back-propagation neural network and deep network: auto-encoder.
- Moreover, within the work we propose a simple approach for segmenting the skin tumor and extracting its features using Haar wavelet transform.
- Within the work, we show the usefulness of wavelet transform as feature extractor of the skin tumor images.
- Also, within this work we show the advantages of a deep network over a traditional one (BPNN) in terms of accuracy, performance, training time, etc.

1.4 Objectives of the Thesis

This thesis' main aim is to investigate the deep learning in skin tumor classification and compare the results with those which were conventionally obtained using back propagation neural network. In the image processing part we aim to propose an Approach for the segmentation and feature extraction of the skin tumor images using Haar wavelet transform and pattern averaging for the size reduction. Moreover, in this thesis, we compare the Auto-encoder neural network and BPNN performances and parameters as well as the overall performance with the work listed in the literature.

1.5 Thesis Overview

The thesis is divided into 5 chapters, which are divided as follows.

Chapter 1 is an introduction about the thesis. In this chapter, a definition of the thesis is presented; we set the aims, contributions, and motivations. In addition, the overview of the thesis is given.

Chapter 2 is a detailed and general explanation about the artificial neural network. We explain the types of ANN that will be used in this thesis.

Chapter 3 discusses the proposed system methodology, materials and methods. The system flowchart is also presented to give details about the process of image processing and classification phases.

Chapter 4 shows the results, discussions and comparisons of the Back propagation neural network versus the Auto-encoder in terms of input-output parameters and experimental performance. The proposed skin tumor classification system performance is discussed and compared with previously proposed systems for the same purpose.

Chapter 5 presents the conclusion and future work.

CHAPTER 2
ARTIFICIAL NEURAL NETWORK AND RELATED STUDIES

2.1 Related studies on Skin Cancer Classifications

Significant development has been remarked recently in cancer classifications as researchers investigated the different types of cancer classification using different techniques. Different previous work has stated that the classification of skin cancer images can be achieved through supervised learning techniques such as Back-propagation (Ercal et al., 1994) and Fuzzy Systems (Salah et al., 2011) in artificial neural networks with image processing techniques.

Thus, by analyzing the related studies of skin cancer classifications, it is noticeable that image processing combined with intelligent learning or machine learning systems have become the best choice for early detection and classification of skin cancer. This is mainly due to different reasons that make the use of artificial intelligence more advantageous for medical images classification applications. Artificial intelligence is a low cost classification mean with high classification and recognition accuracy (Ercalet al., 1994; Aswin et al., 2014; Sumithra et al., 2015; Esteva et al., 2013).

Different skin cancer detection and recognition techniques were proposed recently in scientific communities. Most of the proposed techniques investigate the image processing algorithms combined with artificial neural networks for classification and recognition purposes. There was a variation in the methods used in image processing and neural networking. For example, using different segmentation techniques, different feature extraction methods and different neural networking classifier. Some of them are discussed in the proceeding sob-sections.

2.1.1 Back Propagation Neural Network for skin cancer classifications

(Jaleel et al., 2013) performed another study in 2013.In this study Dermoscopic images were gathered from some hospitals and internet websites. They were then undergone Median Filtering. The resulted images from the filtering were segmented by threshold segmentation. Extraction of images features was carried out using Gray Level Co-occurrence Matrix (GLCM). The features that were extracted using this method are:

Correlation, Contrast, Homogeneity, Mean and Energy. This process was established using MATLAB. The accumulated Features were entered as inputs to artificial neural network. The function of activation used is log sigmoid; it produces an output of either 0 or 1. The non-cancerous cases are represented as 0 and the cancerous cases are represented as 1. From the 50 images that were selected for classification, 27 images were classified by the ANN based classifier as cancerous and 23 were classified as non-cancerous samples. A comparison between the actual results and the output obtained from the neural network system showed that 9 cases were misclassified by the latter. This determines that this methodology has an accuracy of 82%.

Another study investigated by (Choudhar et al, 2014), used a neural network system for skin cancer detection. There were different stages for this detection; these stages involve Dermoscopic images collection.90 images were used for training and testing of the neural network. 30 images were randomly selected for testing the network. The methodology proposed in this study started by removing hair and noises using simple median filter. Maximum Entropy Thresholding topology was used for the segmentation of filtered images. Gray Level Co-occurrence Matrix (GLCM) algorithm was then implemented for the extraction of images features. The extracted features using this method include Mean, Kurtosis, Skewness, Contrast, Homogeneity, Standard Deviation, and Energy. Finally, a classification process based on Back Propagation Neural Network (BPNN) was implemented in this work. From the collected testing data, 6 cases were classified as noncancerous and 20 cases were classified as cancerous. In total, 4 images out of the 30 test images were not classified correctly. This Methodology has got 86.66% accuracy.

A study was conducted by (Achakanalli et al., 2014) in which, database was collected from Internet and dermatology. The images in this database were undergone a filtering using median filtering. The resulted images were segmented using the Threshold Segmentation. Then, Gray Level Co-occurrence Matrix (GLCM) was used as the statistical Feature Extraction technique. The resulted Features extracted from GLCM which are Energy, Correlation, Contrast, Mean, Skewness, Homogeneity and Kurtosis, were represented as inputs to the artificial neural network. As it was mentioned earlier, it produces an output of either 0 or 1. The non-cancerous cases are represented as 0 and the cancerous or malignant melanoma cases are represented as 1. From the 60 images that were selected for classification, 38 images were classified as cancerous and 22 were classified as non-cancerous cases. Another comparison between the actual results and the output obtained from this system showed that 9 cases were misclassified by the latter. The Accuracy of this proposed method is 90 %.

(Fassihi et al., 2011) conducted a study entitled Melanoma Diagnosis by the Use of Wavelet Analysis based on Morphological Operators. To extract image features, they employ alternative constants of wavelet decomposition. Melanoma classification is executed by using the mean and variance of wavelet coefficients as the input data of neural network. Out of 91 images, 71 as melanoma and the other 20 as non-melanoma. 73 images were entered as the input data of the neural network for training and testing and 18 images as validation. The resulted accuracy between melanoma lesions and non-melanoma was 90%.

2.1.2 Deep learning in skin cancer classification

Deep learning was recently used in classifying skin cancer disease and showed a great effectiveness in distinguishing the malignancy of the cancer. (Esteva et al., 2013) a convolution neural network was used as a deep network classifier that learns the skin tumor features extracted using wavelet transform and attempt to make a decision about the skin tumor malignancy. The deep network used in their paper was trained using many cancerous and non-cancerous images and the accuracy obtained was 90%.

Another research was conducted by (Liao, 2013) the investigation of deep learning to Universal Skin Disease Classification. The author used a deep convolution neural network for this classification task. The images were not segmented in this work; they were directly fed into the network. The network was trained using 23,000 images collected from different websites including Google as the author stated. This deep learning system for skin disease classification was capable of achieving 91% accuracy after testing it.

2.2 Overview

Artificial neural network is a computing system built up by a number of highly linked processing information and elements by creating a response to the dynamics of the external input case (Caudil, 1987). The following section is a brief overview of the architecture, training rules and selection of ANN models.

"ADALINE" and "MADALINE" are models which were developed by Bernard Widrow and Marcian Hoff of Stanford in 1959. These models were named from the use of Multiple Adaptive Linear Elements. ADALINE was upgraded for the recognition of binary patterns.

Basically, it had the ability of predicting the next bit if it was reading streaming bits for example from a phone line. MADALINE on the other hand was the initial neural network utilized to a real world problem, employing a filter adaptation which terminates echoes of phone lines (Widrow & Hoff, 1962).

Nine years later, Widrow & Hoff upgraded a learning procedure, which tests the value before adjusting it by the weight (i.e. Zero or One) based on the rule:

$$\Delta W = (pre - weight\ line\ value) * \left(error/(number\ of\ inputs)\right) \qquad (2.1)$$

Where Δw is the weight change (Abdi et al., 1996).

The basic idea to this is that while there is a big error in an active perceptron, the weight values will be distributed by this one perceptron since it can adjust and distribute these values across the network, or at least to adjacent perceptrons. If the line before the weight is Zero, an error will still be resulted when establishing this rule, even though this will correct itself eventually. The error will be eliminated once it is conserved to be distributed to the weights in the network.

2.3 Architecture of ANN

The processing of information in human brain is done through billions of neurons (nerve cells) that form a network. Electrical pulses are generated and exchanged between neural cells. Computer algorithms that imitate these structures of biological are properly called artificial neural networks (Birdi et al., 2013).

Figure 2.1 shows the architecture of artificial neuron network, and the relationship between both the inputs and output expressed in equations.

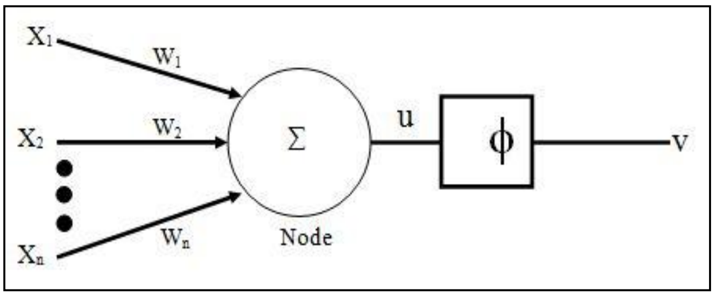


Figure 2.1: Architecture of artificial neuron network (Rojas, 1996)

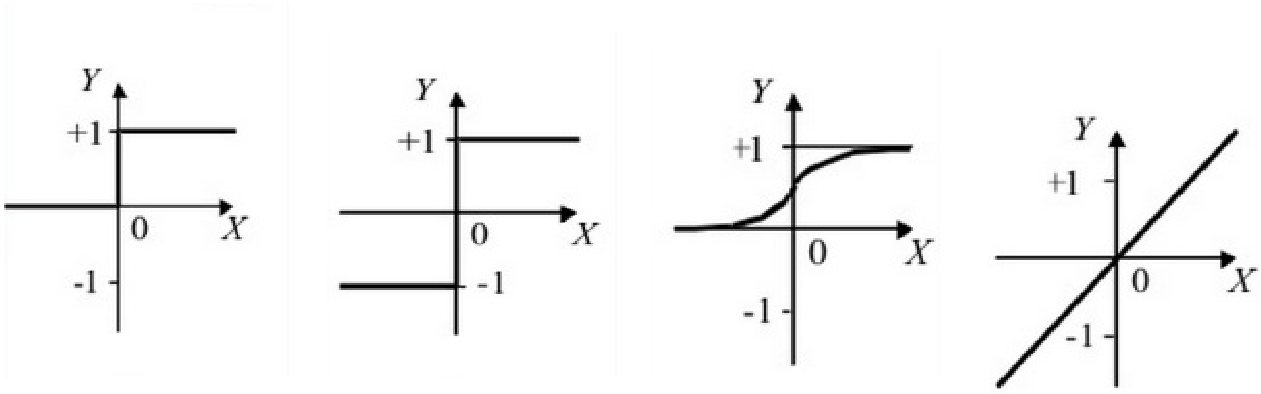
$$u = \sum_{1}^{j} w_{ij} x_j \tag{2.2}$$

$$v = \Phi(u) \tag{2.3}$$

Where, i is the neuron or node, j is the inputs index, w_{ij} is the weight interconnection from input j to neuron, x_1, x_2, ….., x_n, represents the inputs to the neuron, w_1, w_2,…., w_n, are the compatible weights to the neurons, ϕ is the activation function that can be used to introduce nonlinearity to the relationship between the inputs and output, u is the total potential and v represents the network output. Note, there are many functions that are utilized as activation functions or transfer functions; the most prevalent functions in neural networks are Gaussian, log-sigmoid, linear, binary step, tan-sigmoid, etc.

2.3.1 Different types of activation functions

An artificial neural network process is to sum up the associated weight's product and the signal of the input to produce an output or activation function. The activation function is considered the identity function for the input. The neuron gets the same type of activation function in any particular layer. Non- linear activation functions are applied in almost all cases. The activation diverse functions types which are used in a neural network are step function, sign function, identity function and sigmoid functions as it can be seen in Figure 2.2.



(a) Step function (b) Sign function (c) Sigmoid function (d)Identity function

Figure 2.2: Various types of activation functions (Birdi, 2013)

2.3.1.1 Sigmoid functions

Sometimes S shaped functions called sigmoid functions are used as activation functions which are found useful. Logistic and hyperbolic tangent functions are commonly used sigmoid functions. The sigmoid functions are extensively used in back propagation neural networks because it reduces the burden of complication involved during training phase. The sigmoid function has a continuous range of value from 0 to 1. The equation below shows the sigmoid activation function representation and how the output value calculated.

$$y(x) = \frac{1}{(1 + \exp^{-ax})} \tag{2.4}$$

Figure 2.3 demonstrates sigmoid activation function.

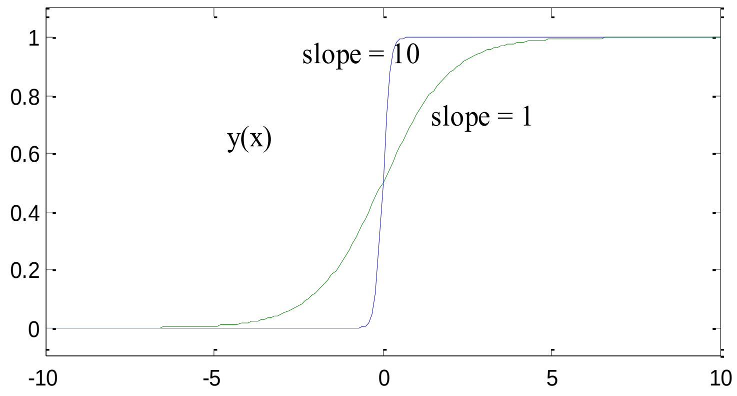


Figure 2.3: Sigmoid activation function, logarithmic

Figure 2.4 presents tangent sigmoid activation function.

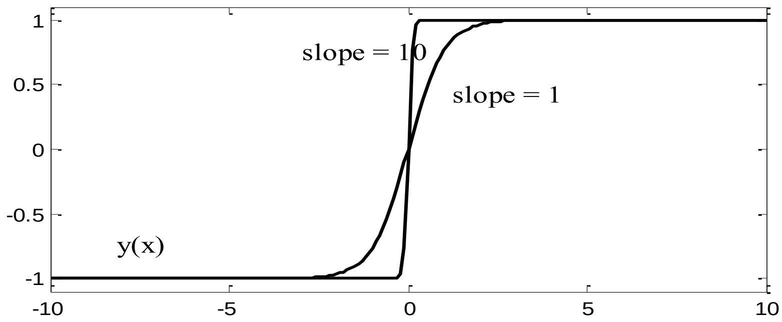


Figure 2.4: Tangent sigmoid activation function

The sigmoid activation function rang is between 0 and 1, but in some cases the range that used in this function is between -1 to 1, where it is called tangent sigmoid function.

2.4 Neural Network Structure

Generally, there are three fundamentally different classes of networks, which are based on network architecture: single layer feed forward, multi-layer feed forward, and recurrent network (Haykin, 1994).

2.4.1 Single layer feed-forward

A single layer feed-forward network has a single layer of artificial neurons, and it processes input signals in a forward directional manner (Cha et al., 2011).

2.4.2 Multi-layer feed-forward

The multi-layer feed-forward is development of the single layer network. It is implemented for much more difficult and complicated problems that can't be solved by single layer structures. It is composed mainly of three important parts which are: input layer of neurons, one or more hidden neurons layers and an output neurons layer as illustrated in Figure 2.5. The hidden layer gives the network its power and allows it to extract extra features from the input (Cha et al., 2011).

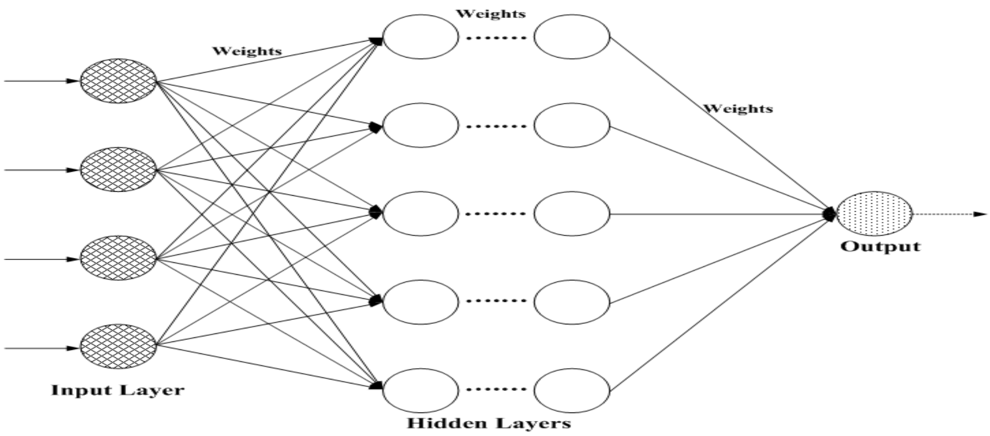


Figure 2.5: Typical multi-layer feed-forward architecture (Cha et al., 2011)

2.3.3 Recurrent network

A recurrent network has similarities to a feed-forward neural network, but it differs by having at least one feedback loop. These feedback connections propagate the outputs of some nodes or the network back to the inputs layers or nodes to perform repeated computations (Cha et al., 2011). Figure 2.6 shows recurrent neural network architecture.

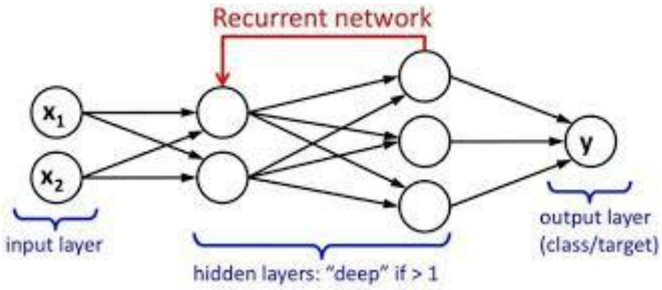


Figure 2.6: Typical Recurrent Network (Cha et al., 2011)

2.5 Training of ANN

An ANN has to be flexible and adaptive such that it produces the desired outputs in response to the training set of inputs. This study adopted the back propagation as a network training for all models, BPNNis nowadays a common network architecture (Rumelhart et al., 2013). Algorithms are training in a supervised style by BPNN. The input and output are used to train a network until the network can reach the minimum error (Haykin, 1994). This method is used for most of our ANN models. In general, the networks trained with four algorithms and all achieved satisfactory results.

Furthermore, these training algorithms can be divided into two categories, such as supervised and unsupervised training.

2.5.1 Supervised training

In the supervised training, comparison between actual outputs and desired output of an ANN, therefore it attempts that desired solutions are known for the training data sets. This reduce error with the passing time by adjusting the weights input until acceptable network accuracy is reached. Most representative supervised training algorithms use the Back-propagation algorithm, which has been used since (McClelland et al., 1986).

2.5.2 Unsupervised training

In contrast, unsupervised training does not require a correct desired data set. In fact, the fundamental in the data or the links between the patterns in the data is exposed and organized into categories. This is especially useful when solutions are unknown (Cha et al., 2011).

2.6 Back Propagation 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.

The feed forward, Back-propagation architecture was presented by the early of 1970’s by several independent sources(Rumelhart et al., 2013). At the present time, this interactive developed algorithm of Back-propagation has become popular, valuable, and easy learning even for complex models, such as multi-layered networks. The greatest strength of ANN is in its dealing with nonlinear solutions to indefinite problems. The professional back-propagation network has an input layer, an output layer, and at least one hidden layer. As shown in Figure 2.7.

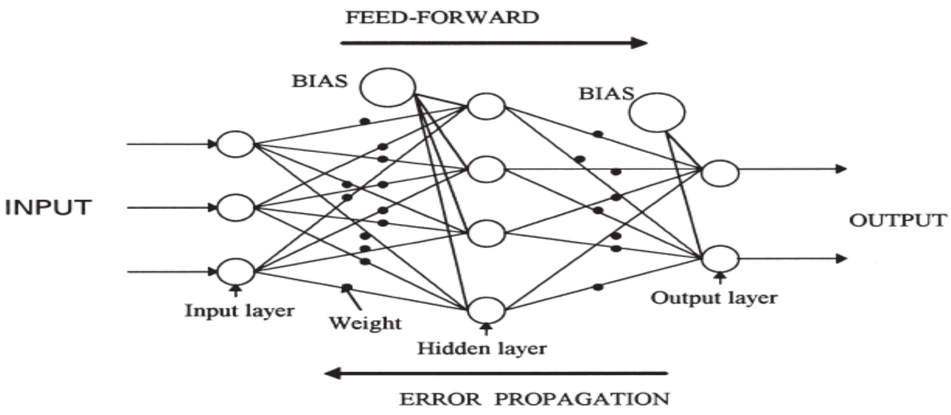


Figure 2.7: Back propagation architecture (Rojas, 2013)

BP algorithm is one of the most popular ANN algorithms. Rojas, (2013) claimed that BP algorithm could be packed up to four major steps. Once the weights chosen randomly, compute of necessary corrections are done by back propagation algorithm. The algorithm can be expressed in the following four steps:

- Computation of feed-forward
- Back propagation to the output layer
- Propagation to the hidden layer
- Weight updates

While the function error value may become small enough, the algorithm is stopped. It considers being the basic formula for BP algorithm. With the variations proposed by other scientistsdefinition seems to be fairly accurate and simple to follow. The last step, weight updates is happening throughout the algorithm (Demuth & Beale, 2002; Rojas, 2013).

There are three essential parameters controlling of a back propagation network.

- **Mean squared error**

Mean Squared Error (MSE is mainly based on the idea of decreasing the error between the desired output of the process and the actual output.

- **Learning rate and momentum factor**

These two parameters are effecting to the learning ability of the artificial neural network.

- Learning rate factor (η) is used to control the speed of learning to the network. It represents the step size of weight adjustment at each iteration.

- Momentum factor (α) is another important factor that affects the learning process of a neural network. It determines and attenuates the speed at which the neural network learning is done. It is very useful in making the neural network avoid getting caught in local energy minima. It could also smooth out the error path by stopping the hard variations in weight values.

2.7 Deep Neural Network

Deep Learning is a new and advanced filed of Machine Learning. It has been developed and improved in order to move the moving Machine Learning to be closer its main and original goal Artificial Intelligence.

Deep Learning is called “deep” due to its structure of the neural networks. Earlier, neural networks used to have two layers deep because it was not computationally feasible to build larger networks. Nowadays, a neural network with more than 10 layers and even more layers are being initiated and built. These types of networks are called deep neural networks. Figure 2.8 shows architecture of a deep neural network. It shows that the network consists of many layers which make it deep (Deng, 2014).

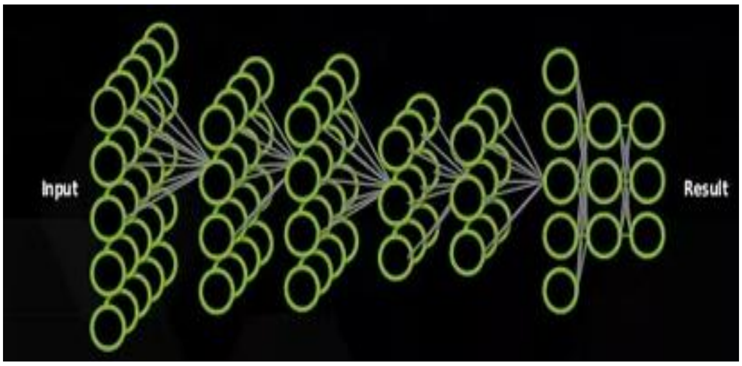


Figure 2.8: A deep neural network (Deng, 2014)

In conventional networks like Back-propagation neural network, the extraction of features is done manually using some mathematical engineering algorithms before feeding images to network. However, deep learning the networks are automatically extracting features through their big number of layers instead of manual extraction of features using different algorithms. For example; if we have an image as an input for a network. For conventional networks the features should be computed like distribution of colors, image histograms, edge detection, etc., however, for deep neural networks, the raw images should be fed directly into the deep network which has the capability to handling images, and extracting features through its different layers and also through its learning techniques which will be discussed later. Recently, the deep networks are being applied to all kinds of other available datasets like raw text, numbers etc. This helps artificial intelligence scientist to improve architecture of deep learning paradigms and algorithms to be close enough to artificial intelligence.

2.7.1 Auto-encoder neural network

There are different types of deep networks such as Auto-encoder, Stacked Auto-encoder, Deep belief network etc. In this thesis only an Auto-encoder was used; although the training technique is the same for the different types of the deep networks.

Auto-encoders (AE) are mainly multilayer feed forward networks with a small difference in the way of initializing weights. Here, the weights are initialized using a generative learning algorithm, which means that the network doesn't have to be deterministic of outputs classes since it uses unsupervised learning techniques in its primary training phases. This helps in providing good initiated weights for the network (Erhan et al., 2010).

An auto-encoder is a feed forward neural network that is trained first to learning the inputs features unsupervisely; in other words outputs are the same as inputs, no output labeling. This Training technique helps this network to learn the underlying features of the training data or images that are importantly needed for the construction of same image at the output layer. This learning technique is called "Pre-training" and it is the same step in training a deep network. The outputs are the input themselves since it is unsupervised learning. During pre-training the input-hidden layer weights are saved as well as the hidden-output layer activations. These saved weights are then used in the second training phase which is called fine-tuning. This learning technique is a supervised learning technique where the input data are labeled and the Back-propagation learning technique is used for training the network. However, the input weights should be equal to the input weights that were saved before during the pre-training; and the hidden-output weights can be initiated randomly.

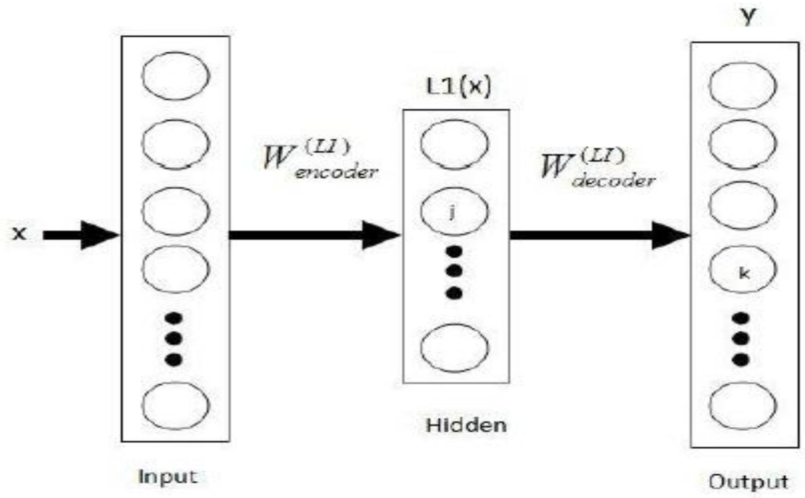


Figure 2.9: Auto-encoder (Erhan et al., 2010)

Figure 2.9 shows an auto-encoder which is composed of two main parts: the encoder, and decoder. The input-hidden layer makes the encoder part where the input data are fed and the features are extracted. The decoder part is the hidden-output layer where the extracted features are received for reconstruction of the input image.

CHAPTER 3
SKIN CANCER IMAGES ANALYSIS AND PROCESSING

3.1 Introduction

In this chapter, the first phase of our suggested system; image processing phase is discussed. Therefore, we introduce the image processing as tools and concept. Then we discuss the proposed system through flowcharts and Figures that show the processes and algorithms used in order to come up with an accurate analysis of skin tumor. The second phase is the classification phase which employs Artificial Neural Network, both Back-propagation and Auto-encoder neural network.

3.2 The Proposed Methodology

The proposed system consists of two parts; in the part one many techniques are used in processing of images such as conversion to grayscale, filtering using Median Filter, and features extraction using Haar wavelet transform. These techniques are done in order to enhance the quality of images and to extract the important features such as internal and external edges of the tumor and eliminate the other parts. At the end of this phase, the images are ready to be fed to the classification phaseas normal or abnormal (melanoma or non-melanoma)which will be done by using ANN intelligence system, both Back Propagation and Auto-encoder neural network. In the second part the original images converted to grayscale and its size reduced to 50*50, these images were fed to the ANN to assess the performance of the classification process without implementing any image processing techniques.

The proposed method explained in Figure 3.1 First, images are converted to grayscale then undergone some image enhancement techniques such as Median Filtering, image adjustment. Moreover, Haar wavelet transform is then applied to get 4 different sub-bands which are added to the reconstructed image. The result of this addition operation is then rescaled using pattern averaging technique which reduces the size of images with preserving the important features. Finally, the rescaled image is fed into the neural network to be classified as melanoma and non-melanoma skin tumor.

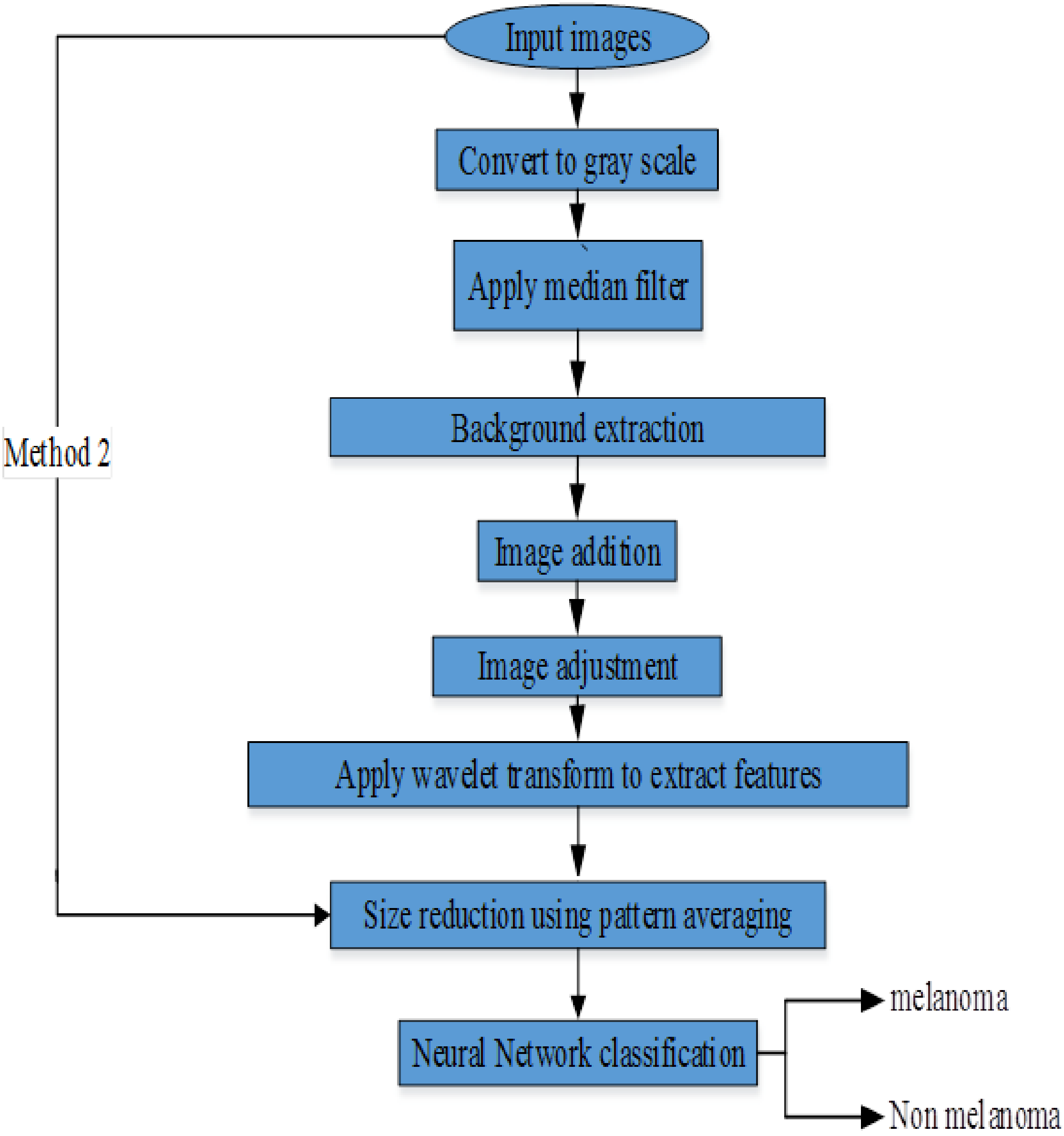


Figure 3.1: Flowchart of the proposed algorithm

3.3 Part 1:

3.3.1 Image processing phase

The images were enhanced for adequate identification through a series of image processing methods. These methods constitute the adequacy of the system in the processing phase.

- Image processing techniques used:
    1. RGB to grayscale conversion.
    2. Filter images using Median Filters.
    3. Extract background.
    4. Add background to original image.
    5. Image adjustment.
    6. Extract image features using Haar wavelet transform.
    7. Reconstruct the image using inverse wavelet transform.
    8. Reduce size of images using pattern averaging.

3.3.1.1 RGB to grayscale conversion

The images were first converted to grayscale in which the conversion is done using the luminosity method. Using this method, the grayscale image is clearer since the colors are weighted according to their contribution in the RGB image (Church et. al, 2008).The formula for luminosity is:

$$0.21R + 0.72G + 0.07B \tag{3.1}$$

Figure 3.2 illustrates the conversion of skin tumor image into a grayscale image using luminosity method.

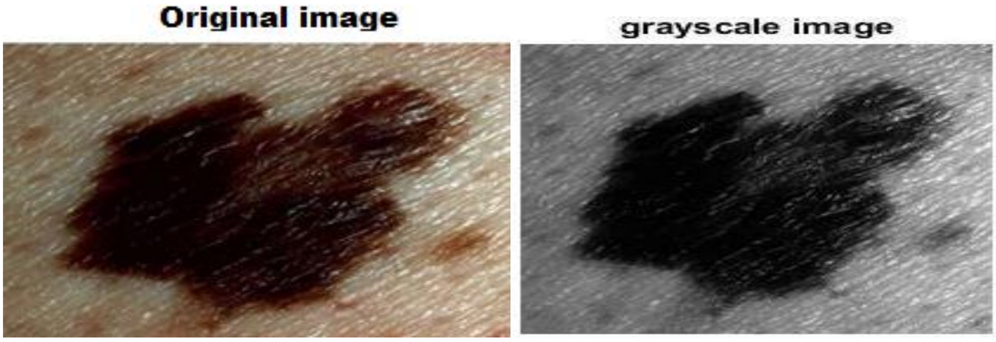


Figure 3.2: RGB to grayscale conversion, Source (https://uwaterloo.ca/vision-image processing-lab/research-demos/skin-cancer-detection)

3.3.1.2 Image filtering using median filter

Filtering is technique used to reduce the noise in an image to produce less pixilated and clearer. The most common type of filters ismedian filter which belongs to the non-linear filters. This filter is used to reduce impulsivenoise in an image and keeping the needed features and image edges (E.Kaveri et al,2016) as shown in Figure 3.3.

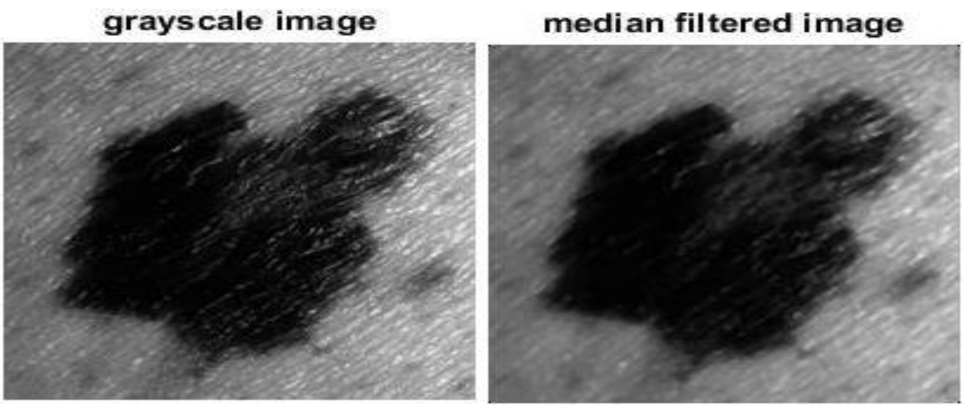


Figure 3.3: Image filtering using median filter

3.3.1.3 Extract background

The extraction of background is achieved using a morphological technique called image opening. The most common and basic morphological operations are dilation and erosion. Dilation is to add pixels to the boundaries of objects in an image, while erosion is to remove pixels on object boundaries. The number of pixels that are added or even removed from the structure in an image depends on the size and shape of the structuring element that is used to process that image. In these morphological operations (dilation and erosion), the condition of any given pixel in the output image can be determined by applying a rule to the studied pixel and its neighbors in the input image (Gonzalez &Woods, 2004).
Figure 3.4 illustrates the background extraction operation of a skin tumor image.

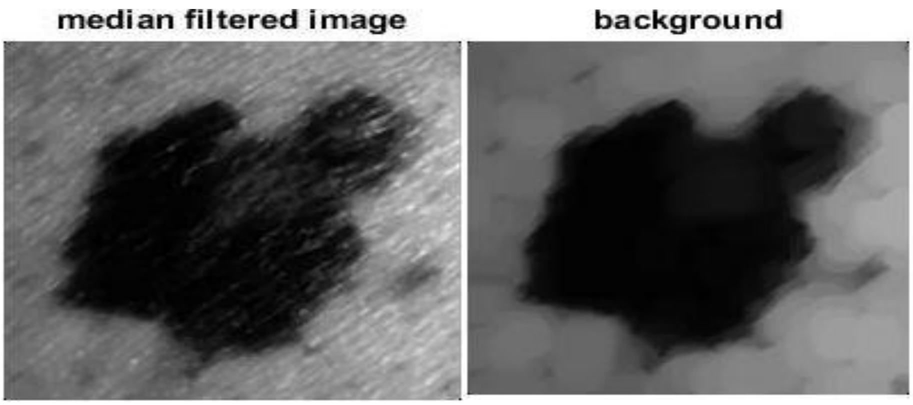


Figure 3.4: Background extraction

3.3.1.4 Image addition

The images addition is done using a pixel addition operator that takes two images as input and produces as one image as output, in which its pixel values are simply the pixel values of the first image plus the pixel values of the second image (Gonzalez and Woods, 2004).

$$R(i,j) = O(i,j) + B(i,j) \tag{4.2}$$

O and B represent the original and background image respectively. O (i,j) and B (i,j) represent the elements values of the original and background images matrices in which the number of elements of both matrices which must be equal. Figure 3.5 shows the addition of two images which result in an output image.

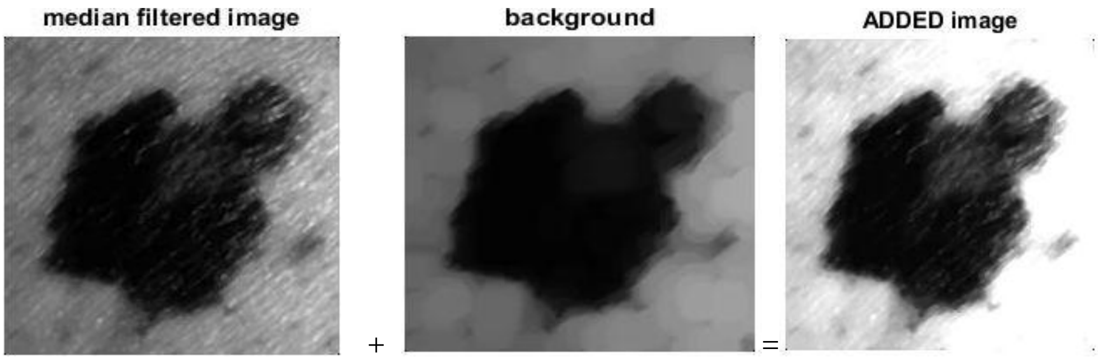


Figure 3.5: Image addition

3.3.1.5 Image adjustment

For the purpose of increasing the image intensity and enhance its quality, the images undergo intensity adjustment. This image processing technique that aims to enhance the contrast of the image by increasing the intensity of its pixels. During this operation, the intensity value of each pixel in the input image is transformed using a transfer function to form a contrast-adjusted image (Gonzalez and Woods, 2004).

Gamma correction technique was used for enhancement and preserving brightness level of the images. Their proposed technique is that the weighted average of the histogram leveled, gamma corrected and the first picture are consolidated to acquire the upgraded processed image. The proposed calculation accomplish contrast enhancement as well as preserve the brightness level of images (Aggarwal et al., 2013).The Figure 3.6 represents the adjustment of an image and its effects in enhancing the image contrast.

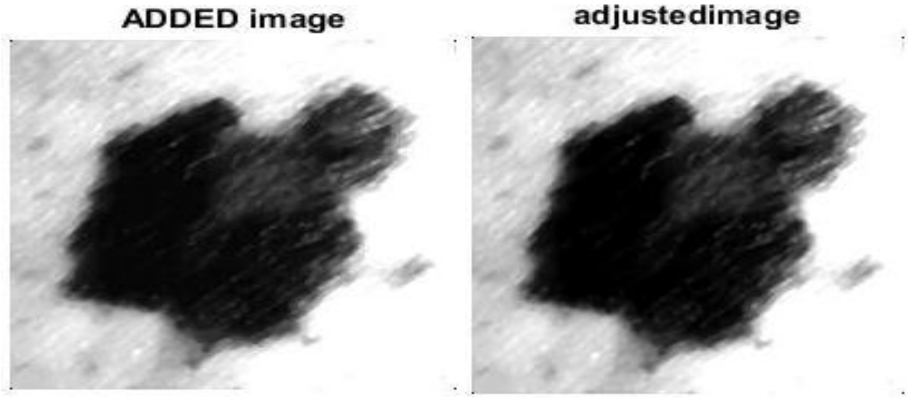


Figure 3.6: Image adjustment

3.3.1.6 Discrete Haar wavelets

Haar functions are utilized since 1910. They were presented by Hungarian mathematician Alfred Haar. These days, a few meanings of the Haar functions and a few adjustments were distributed and utilized. One of the best alterations, which were presented, is the lifting plan (Davis et al., 1998). These transforms have been connected, for example, to phantom methods for multiple esteemed rationale, picture coding, edge extraction, and so forth. In the course of recent years, an assortment of effective and refined wavelet–based plans for imagecompression, as talked about later, were created and executed.

The Haar wavelet is likewise the easiest conceivable wavelet. The specialized drawback of the Haar wavelet is that it is not continuous, and subsequently not differentiable.

The Figure 3.7 shows the application of discrete Haar wavelets on the adjusted skin tumor image. It shows the four extracted sub-bands: vertical, horizontal, diagonal and approximation sub-bands. It can be seen that the tumor edges were accurately segmented and extracted in the different sub-bands.

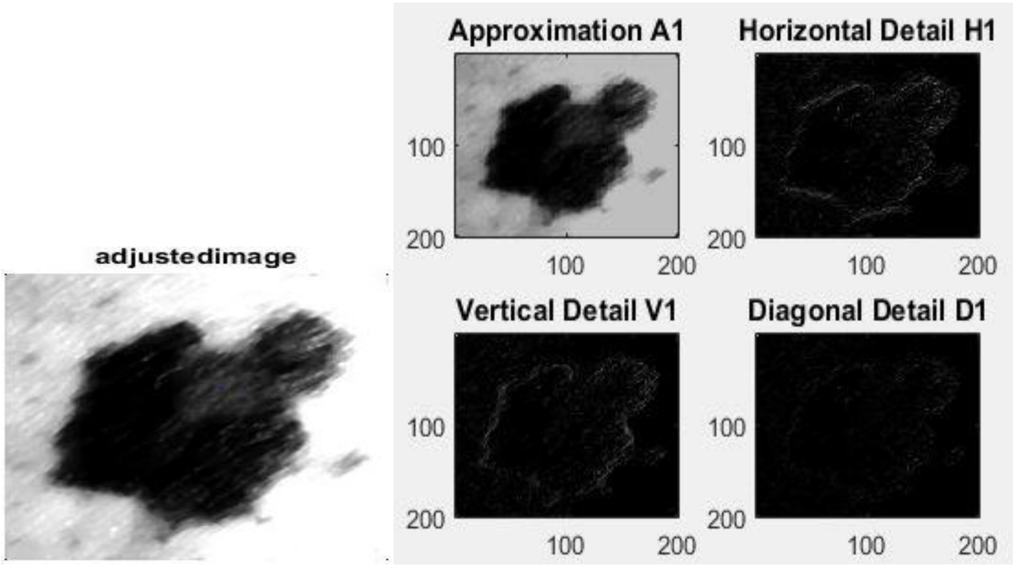


Figure 3.7: Haar Wavelets transform

The use of wavelet transform is important to remove unnecessary details of the image and extract the useful features out of the images. As it is clear from Figure 3.7, the image was divided into four sub bands. Each one of the resulting images contains different frequency spectrum and details. This lead to the possibility of reducing the visual details that neither are nor needed for computer based processing.

3.3.1.7 Inverse discrete wavelets transform

The Figure 3.8 shows the reconstructed skin tumor image after applying the Haar wavelets transform. This is done by finding the inverse Haar transform.

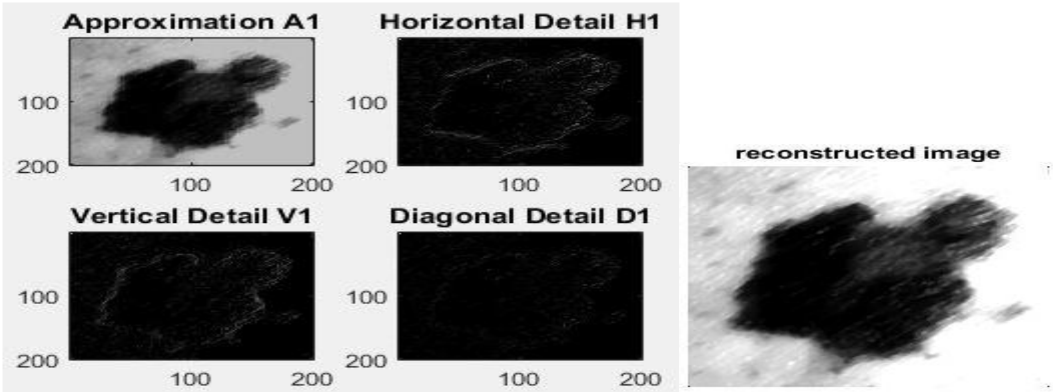
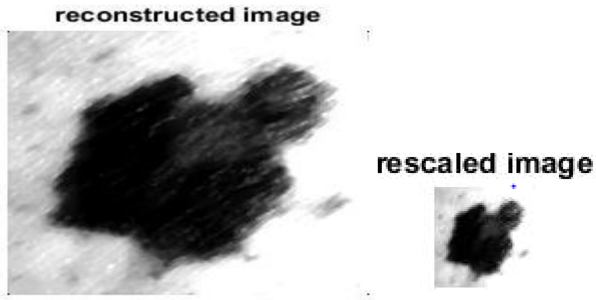


Figure 3.8: Reconstructed image using inverse wavelet transform

3.3.1.8 Size reduction using pattern averaging

Pattern averaging is used to take the average feature from an image which represents same features but with smaller size comparing to the original image. (Khashman, 2009).In order to be fed the images to the neural network the size should be reduced. We used patter averaging to reduce the size of images while keeping the useful and needed features which extracted by the previously used methods.

This technique is defined as the averaging of the defined segments of the image by selecting a window of 4*4 segments that are averaged. Therefore, each studied pixel is then the average of the 16 neighbor's pixels in the selected window. Thus, we come up with a rescaled image with the same features and properties of the original one for the purposes of fast processing and easy computing. As shown in Figure 3.9.



(Image size 200*200) (Image size 50*50)

Figure 3.9: Rescaled image using pattern averaging

The resized images at this stage of the work are converted to one dimensional vector. This conversion is required for the neural network training and can't be avoided. The one dimensional image vector isto be fed to theartificialneural network, (Back-propagation and Auto-encoder neural network). The input size of the neural network is 2500 elements while its output is a vector of two elements that signify whether the image is melanoma or non- melanoma.

3.3.2 Classification Phase

During this phase, skin tumor images are classified into benign or malignant using a supervised neural network by Back Propagation and Auto-encoder neural network.

3.3.2.1 Data Description

180 digital dermoscopicimages were used in this thesis (i.e., using a dermoscopy to capture animage) 87 are benign (Non melanoma) and 93 are malignant (melanoma) i.e. 100 images for training (50 melanoma and 50 non-melanoma images) and 80 images for testing (43 melanoma and 37 non-melanoma images). This data set will be used for both BPNN and Auto-encoder.

3.3.2.2 Back propagation neural network training

Because each image is rescaled to (50*50) pixels using pattern averaging, input layer of the BPNN network consists of 2500 pixels. The hidden layer consists of three layers (50, 50,100) neurons and output layer has two neurons since there is only 2 output classes: melanoma and non-melanoma.

Figure 3.10 shows the architecture of neural network of our proposed system for the BPNN.

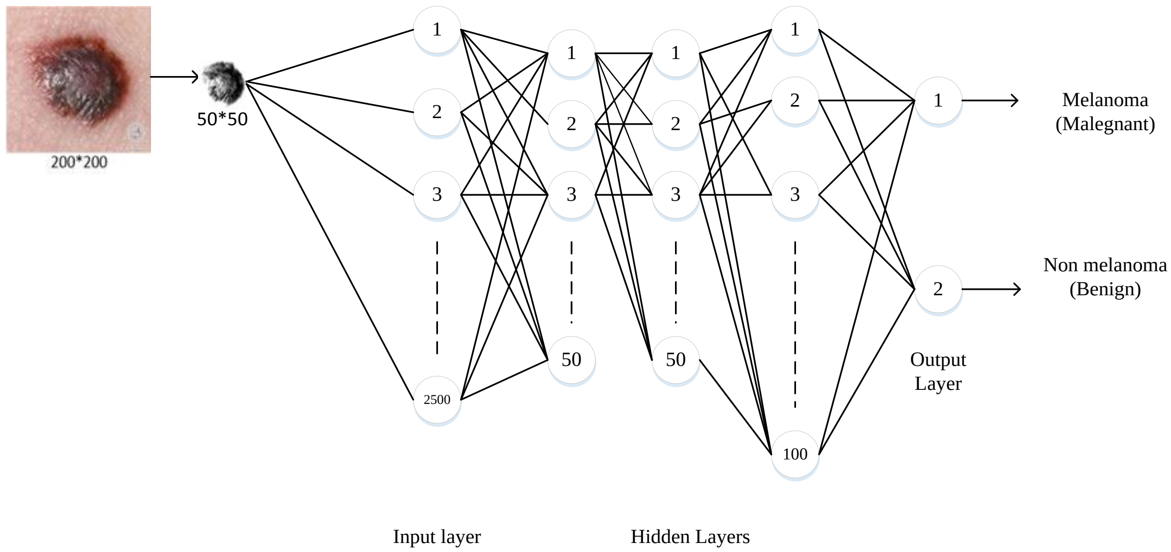


Figure 3.10: BPNN architecture for the proposed network

Table 3.1 below presents the different parameters for which training was carried out. Results of the training and test of these parameters are also presented. In this table, the hidden layers started from one small hidden and were increased gradually. The results of the table show that the training and test accuracies are varying with the variation of training parameters. It was found that the use of one layer with higher number of neurons reduces the efficiency of training while increasing the training time. The use of multiple hidden layers that contain less number of neurons gives better performance and ensures faster convergence of the network. After many experiments it was found that the use of three hidden layers gives best performance in the least time.

Table 3.1: Training ANN with different parameters

Hidden layers	**Learning rate**	**Momentum rate**	**Training accuracy**	**Test accuracy**
20	0.3	0.6	85%	70%
40	0.1	0.4	85%	73%
100	0.5	0.1	88%	72%
300	0.1	0.2	80%	65%
[50, 50]	0.2	0.8	92%	80%
[50, 100]	0.1	0.2	92%	80%
[100, 100]	0.4	0.7	93%	81%
[50 50 50]	0.2	0.8	94%	80%
[50 50 80]	0.1	0.9	93%	83%
[50 50 100]	0.2	1	99%	89%

Table 3.2 represents the input parameters that were used in the system training. The network ran for 3502 maximum iterations with a momentum rate of 1, a learning rate of 0.2, and a minimum error of 0.000096.

Table 3.2: Training network Parameters for BPNN

Parameters	Value
Number of neurons in input layers	2500
Number of neurons in hidden layers	50, 50, 100
Number of neurons in output layers	2
Iterations number	3502
Learning rate	0.2
Momentum rate	1
Error	0.0000996
Activation	Sigmoid
Training time	59 sec

Table 3.3 shows the output classes of the identification system it shows that the system has 2 classes: benign and malignant; each with its numerical coding.

Table 3.3: Output classes coding

Output Classes	Coding
Benign tumor(Non-Melanoma)	[1 0]
Malignant tumor (Melanoma)	[0 1]

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.
Figure 3.11shows the training results of BPNN.

Figure 3.11: BPNN Training time and Iterations number

The Figure 3.12 shows the training of the network as well as the minimum square error reached during the training of the Back Propagation neural network.

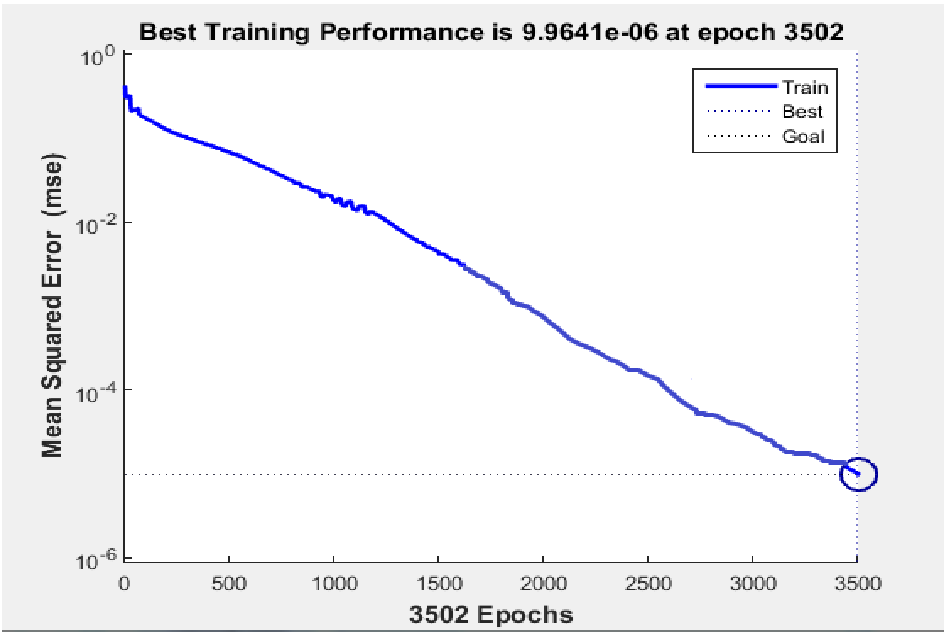


Figure 3.12: MSE curve of the trained network of BPNN

Figure 3.13 explain the regression plot of the desired output and the actual output. Because the actual output is far from the target the error is increased. This Figure represent that the target and the actual output are very close which means that the error is minimized and the network is well trained for BPNN (training ratio: 99%).

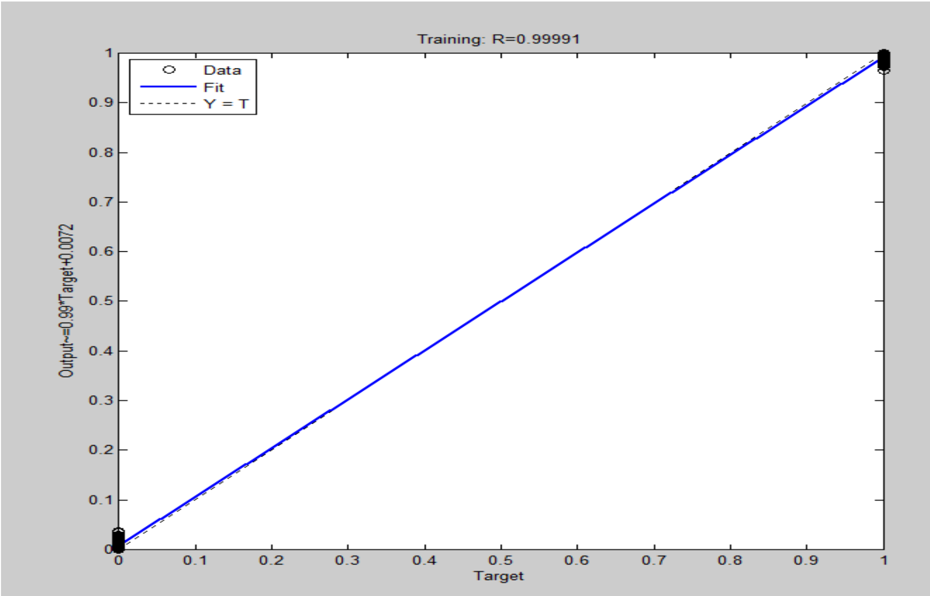


Figure 3.13: Actual versus target output

3.3.2.3 Training Auto-encoder network

As previously discussed the training of an auto-encoder consists of two consecutive stages. The first one is the pre-training; an unsupervised learning where outputs are the same as inputs. During pre-training the networks learns to extract the needed features that will be used to construct the image at the output layer. This learning is due to its two parts: encoder and decoder. During this training technique the input-hidden weights were saved in order to be used then as input weights for the network when fine-tuning.

For fine-tuning the same number of images was used for training pre-trained auto-encoder. However, this requires supervised learning which means that the outputs were labeled and the number of output layer neurons is 2 because the number of output classes is 2: benign and malignant.

Figure 3.14 represent the architecture of neural network of our proposed system for the Auto-encoder.

Table 3.4 shows the input parameters of the system that were used in training the system for both stages: pre-training and fine-tuning. The network ran for 100 maximum iterations for pre-training and 200 for fine-tuning. The network reached a minimum square errorof 0.06 and a 100% recognition rate during pre-training in 17 seconds. However, the time was 9 seconds during the fine-tuning where network reached a minimum square error of 0.025 and 98% recognition rate.

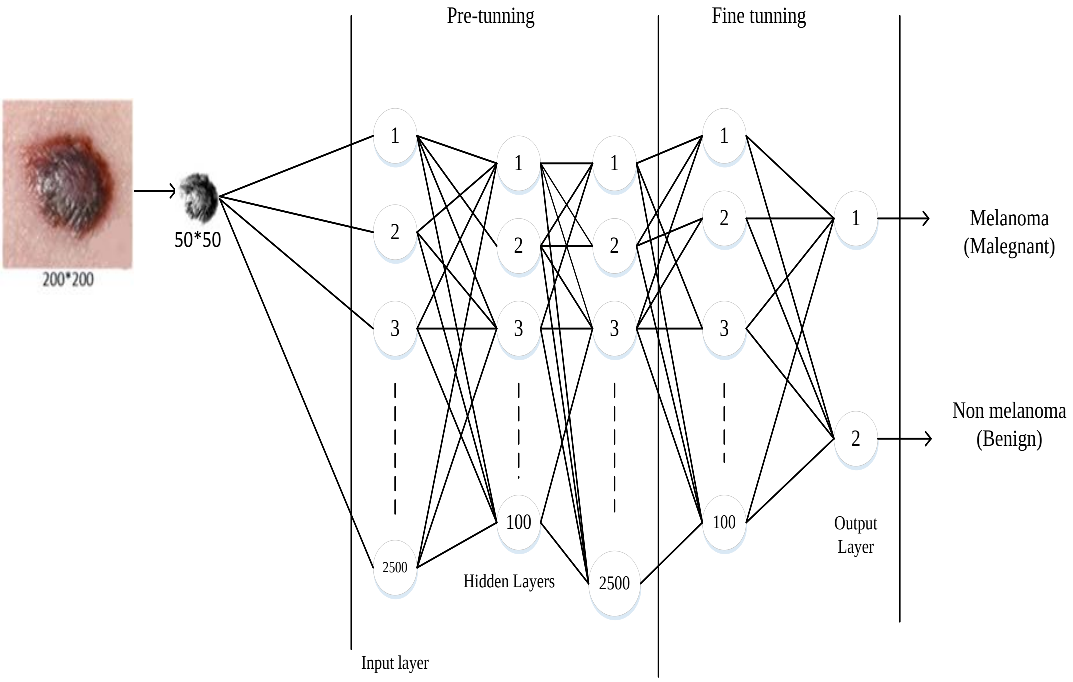


Figure 3.14: Auto-Encoder architecture for the proposed network

Table 3.4: Auto-encoder input parameters during pre-training and fine-tuning

Parameters	Value (Pre-training)	Value (Fine-tuning)
Number of neurons in input layers	2500	2500
Number of neurons in hidden layers	100	100
Number of neurons in output layers	2500	2
Iterations number	100	200
Learning rate	0.37	0.05
Momentum rate	0.6	0.45
Error	0.0682	0.0254
Activation Function	Sigmoid	Sigmoid
Time training	17 Sec	9 Sec

The Figure 3.15 shows the training curve, minimum error reached and training time for the auto-encoder during pre-training.

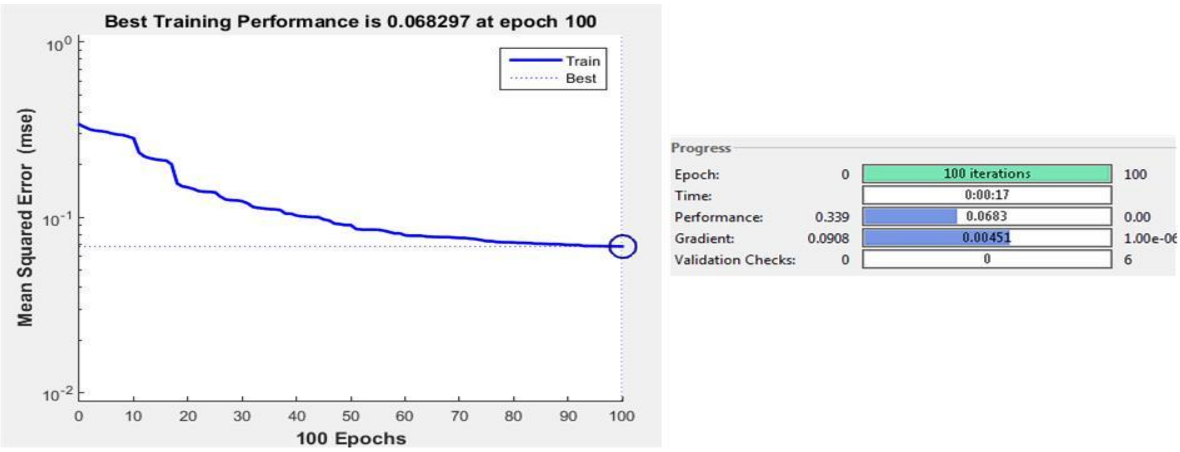


Figure 3.15: Learning curve and time during pre-training of the auto-encoder

Figure 3.16 shows the training curve, minimum error reached and training time for the Auto-encoder during fine-tuning. The Auto-encoder was first pre-trained well with a low error and low training time. This resulted in a high recognition rate of the auto-encoder in the fine-tuning stage with a very low error and very low training time.

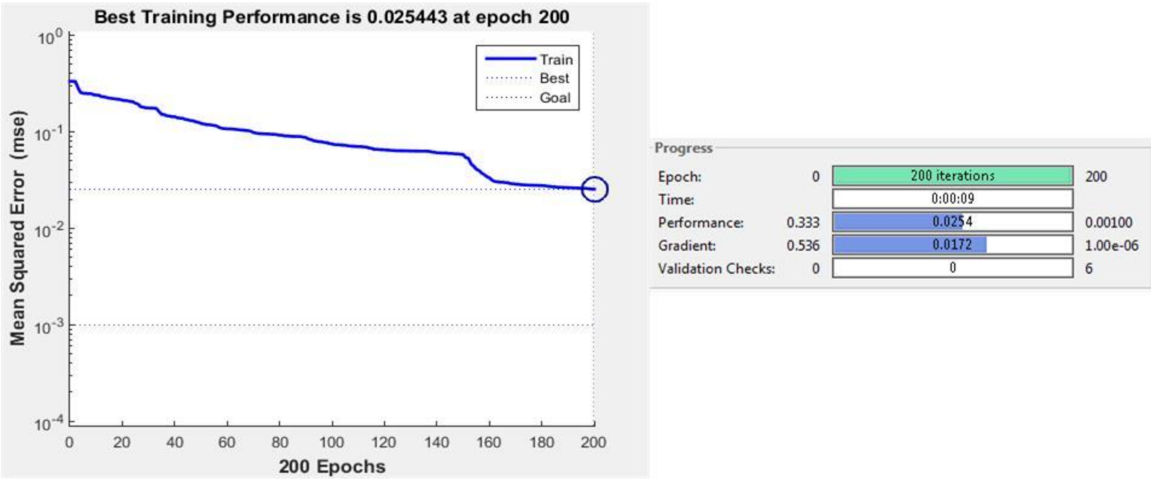


Figure 3.16: Learning curve and time of training for network during Fine-tuning

3.4 Part 2:

In this part the original images converted to grayscale and its size reduced to 50*50, these images were fed to the ANN to assess the performance of the classification process without implementing any image processing techniques.

3.4.1 Back-propagation neural network training without image processing

In this part, the ANN will be applied on the grayscale resized images 50*50 with the same parameters that used in the part 1.

Table 3.5: BPNN parameters without image processing

Parameters	Value
Number of neurons in input layers	2500
Number of neurons in hidden layers	50, 50, 100
Number of neurons in output layers	2
Iterations number	8740
Learning rate	0.2
Momentum rate	1
Error	0.0000979
Activation Function	Sigmoid
Training time	189 sec

Table 3.5 represents the input parameters that were used in the systemtraining. The network ran for 8740 maximum iterations with, a momentum rate of 1,a learning rate of 0.2, and MSR of 0.009 during 189 sec. Figure 3.17 present the training of BPNN. The Figure 3.18 shows the training of the network as well as the mean square error reached during the training of the Back Propagation neural network.

Figure 3.17: BPNN training time and Iterations number

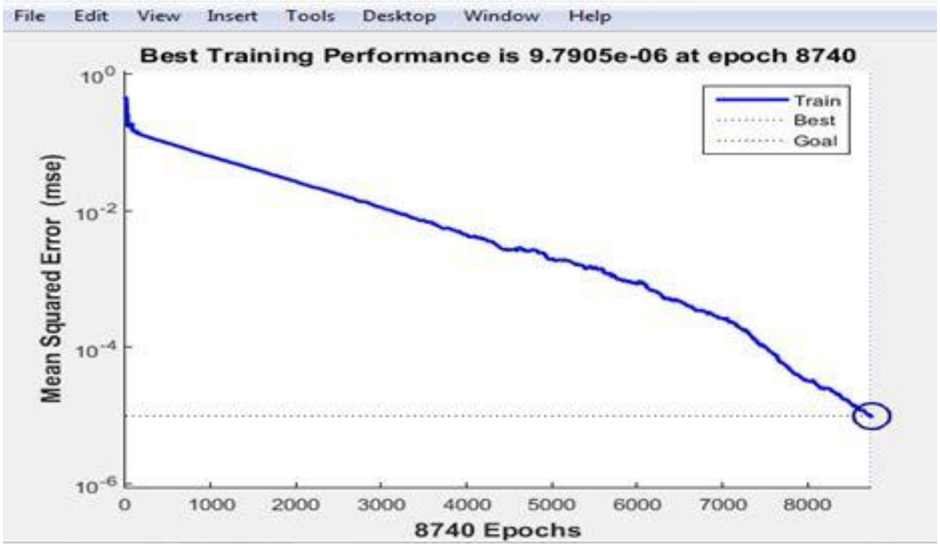


Figure 3.18: MSE curve of the trained network of BPNN without image processing

Figure 3.19 explains the regression plot of the desired output and the actual output. In this Figure, it is obvious that the target and the actual output are very close which means that the error is minimized and the network is well trained for BPNN (training rate: 99%).

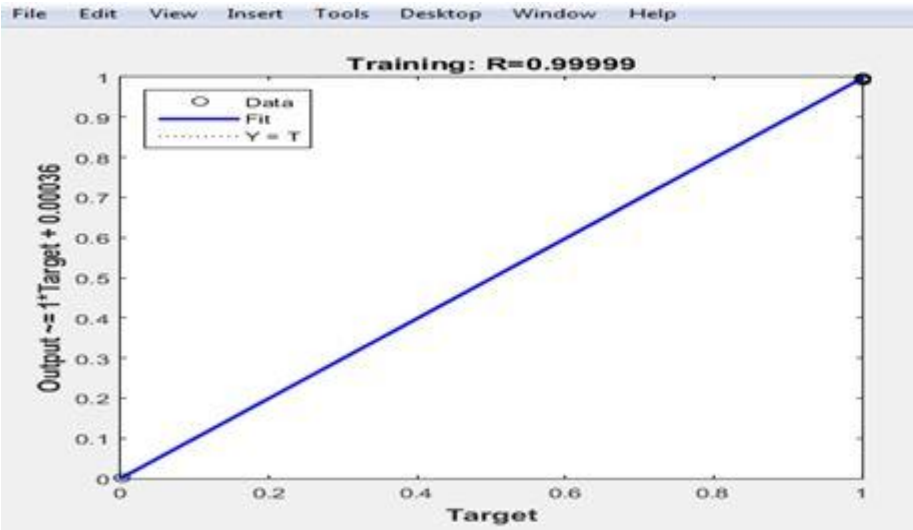


Figure 3.19: Actual versus target output

3.4.2 Training Auto-encoder network without image processing

Table 3.6 shows the input parameters that were used in training the system for both stages: pre-training and fine-tuning. The network ran for 200 maximum iterations for pre-training and 200 for fine-tuning. The network reached a minimum square error of 0.0238 and a 99% recognition rate during pre-training in 35sec. However, the time was 9 sec during the fine-tuning where network reached a minimum square error of 0.0417 and 98% recognition rate.

Table 3.6: Auto-encoder input parameters during pre-training and fine-tuning without image processing

Parameters	Value (Pre-training)	Value (Fine-tuning)
Number of neurons in input layers	2500	2500
Number of neurons in hidden layers	100	100
Number of neurons in output layers	2500	2
Iterations number	200	200
Learning rate	0.37	0.05
Momentum rate	0.6	0.45
Error	0.0283	0.0417
Activation Function	Sigmoid	Sigmoid
Time training	35 sec	9 sec

Figure 3.20 shows the training curve, minimum error reached and training time for the auto-encoder during pre-training.

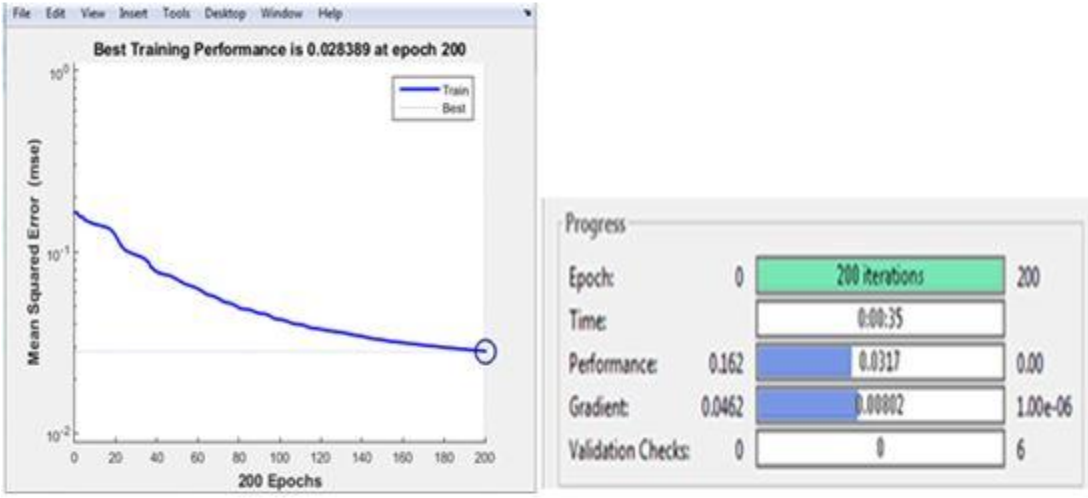


Figure 3.20: Learning curve and time during pre-training of the auto-encoder

Figure 3.21 shows the training curve, minimum error reached and training time for the auto-encoder during fine-tuning.

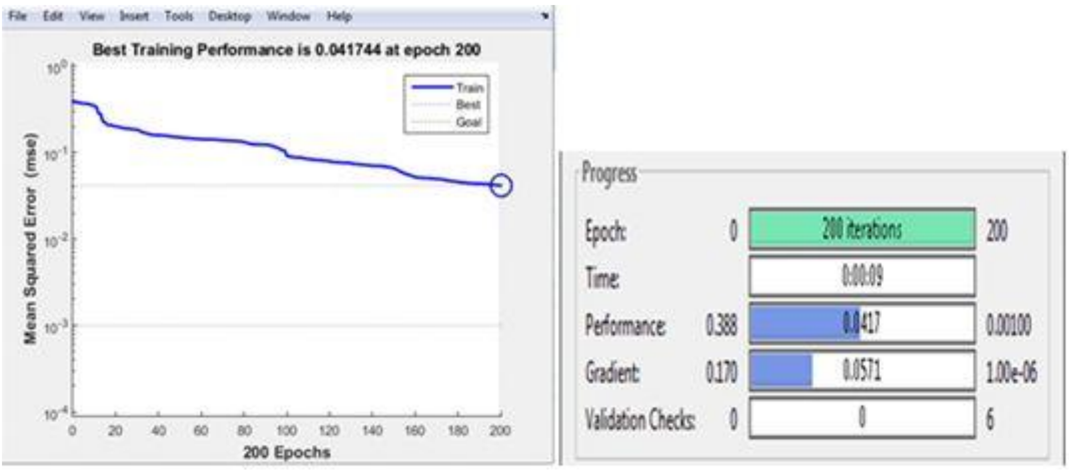


Figure 3.21: Learning curve and time during fine-tuning of the auto-encoder

CHAPTER 4
RESULTS, DISCUSSION AND COMPARSION

In this chapter, the results of classification of skin tumor based on the proposed system will be discussed and presented in more details. Comparison of the obtained accuracy and identification rates is going to be carried out in the core of this chapter. Over more, comparison with previous studies will also be carried out to verify the capability of our work and the possibilities of obtaining better results in future work.

4.1 Results

The proposed methodology in chapter 3 is used to train the network for skin tumor classification. As mentioned in that chapter, theimage processing techniques are used in order to extract the features of interests. Then, the images size rescaled using pattern average withkeeping the extracted features in order to lower the processing and computing time. Finally, the extracted skin tumor images are fed to the network to be used as training examples for the networks.

Same images were fed into networks but without processing. This aimed to check the difference in accuracy of the system and to find out whether the image processing techniques improved the efficiency of the system or not. As a result, it was found that excluding image processing techniques didn't help the network to learn the exact features that distinguish the benign and malignant skin tumors. The accuracy of the system with and without image processing explained in Table 4.1.

Table 4.1: Classification rate

Tumor images type	Image sets	Number of images	Recognition rate of BPNN	BPNN without processing	Recogniti on rate of AE	AE without processing
Melanoma (93)	Training set	50	98%	100%	98%	98%
	Testing set	43	78%	58%	95%	80%
Non-Melanoma (87)	Training set	50	100%	98%	99%	99%
	Testing set	37	80%	59%	94%	78%
System performance	Both sets	180	**89%**	**81%**	**96%**	**88%**

Table 4.1 shows the recognition rate ofboth training and testingfor both BPNN and Auto-encoder. It also represents the number of images used in each set and the overall performance rate obtained which is 89% for the Back Propagation neural network and 96% for the Auto-Encoder neural network with image processing. Moreover, it represent identification rate obtained without image processing which is 81% for the BPNNand 88% for the Auto-encoder.

4.2 Results Comparison

The experimental results show that the Auto-Encoder neural network is capable of offering better performance than the BPNN based system under similar conditions. The performance of the auto encoder based system reached the limit of 96% overall in training and testing in a short time of 26 seconds. The obtained MSE for this case was about 0.025. It is valuable to note out that the networks were retrained many times before achieving an optimum result for all parameters. Table 4.2 shows Comparison between the two implemented networks results.

Table 4.2: BPNN versus Auto-encoder networks performance comparison

Networks	performance rate	Training time	MSE
BPNN	89%	59 sec	0.000096
Auto-encoder	96%	26 sec	0.0254

4.3 Results Discussion

As it was previously mentioned in this thesis, many researchers have been working on the topic of image classification of skin tumor. Each study has its own method and proposition. The main purpose of the different techniques is to extract the interested features of the image. These features are then provided to the neural network to classify the images. In our research we used Haar wavelet transform to extract the tumor from an image. The important features of the tumor were then rescaled based on an averaging algorithm to obtain a proper size of the image. In the same field, a small part of these studies were applied for the automatic disease identification. It can be considered as a new idea in the identification of skin diseases. Another thing which makes this method special that it uses many different techniques such as image processing, back propagation neural network and Auto-encoder neural network. For better results and discussion on the performance of the system, table 4.3present comparisons between our study and some other related studies.

Table 4.3: Results comparison with related works

Paper Title	Authors	Methods used	Train/Test data	Recogni-tion Rate
Diagnosis and detection of skin cancer using artificial intelligence	(Jaleel, et al., 2013)	Image processing and Neural Network (BPNN)	50 images 27/23	82%
Artificial neural network for skin cancer detection	(SarikaChoudhari,et al, 2014)	Feature extraction using GLCM and classification using (BPNN)	90 images 60/30	86.6%
Melanoma diagnosis by the use of wavelet analysis based on morphological operators	(NimaFassihi, et al, 2011)	coefficients of wavelet decomposition and (BPNN)	91 images 71/20	90%
A Deep learning approach to universal skin disease classification	(Haofu Liao 2013)	Deep convolutional neural network	2300	91%
Deep networks for early stage skin disease and skin cancer classification	(Esteva et al., 2003)	Wavelets and convolutional neural network	NA	90%
Proposed system	Waled&Sertan	Haar Wavelets and neural network (BPNN)	180 100/80	89% (BPNN) and 96% auto-encoder

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion

The implementation of artificial neural networks based on back propagation and deep learning training algorithms for skin tumor recognition was proposed in this work. Different image processing techniques were applied prior to the implementation of artificial neural networks to improve the quality of recognition. The experimental analysis shows that the Auto-Encoder neural network was stronger in performing the classification tasking terms of performance and time efficiency with and without image processing. The accuracy obtained using the Auto-encoder learning was about 96% in 26 seconds with image processing and 88% in 44 seconds without the use of special image processing techniques. The BPNN has shown less performance of approximately 89% in 59 seconds with image processing and 81% in 189 seconds without image processing. Finally it can be stated that Auto-encoder neural networks is faster, more accurate, and more efficient than a conventional Back Propagation neural network in classifying skin tumor.

5.2 Recommendations and Future Work

For future work many techniques for enhancing the detection, segmentation and classification of the skin tumor can be recommended:

- Using other techniques than wavelet transforms such as Discrete Cosine Transform which may give better segmentation results of the skin tumor. This may lead to a better classification rate using the neural networks.
- Using different image enhancement techniques for the pre-processing phase.

Finally, for more advanced researches, a better deep learning network can be used such as Deep Belief networks or Convolution Neural network in order to classify the tumor as benign or malignant accurately. These classifiers can extract the features of skin tumor due to their many hidden layers.

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