FUZZY NEURAL NETWORKS FOR IDENTIFICATION OF BREAST CANCER USING IMAGES' SHAPE AND TEXTURE FEATURES

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
ABEDELKADER HELWAN

In Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Biomedical Engineering

NICOSIA, 2018

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Approval of Director of Graduate School of Applied Sciences

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Signature:

Date:

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To my parents...

ABSTRACT

Breast cancer is one of the major medical images diagnosis dilemmas. The rise of artificial intelligence and fuzzy logic (FL) motivated researchers to overcome this problem in order to find a method that can help in identifying the breast cancer. In this thesis, we propose the integration of fuzzy logic and neural network (NN) for the identification of breast cancer X-ray images. The three phases taken to come up with this design are: image pre-processing, features extraction, and finally features classification stages. The classification stage is a fuzzy neural network (FNN) that aims to classify those extracted features in one of the two classes: a benign tumour or a malignant tumour. The breast images used in the system design are obtained from the Digital Database for Screening Mammography (DDSM). The operations used to detect and extract the tumours from the images are thresholding, filtering, adjustments, Canny edge detection, and some morphological operations such as image opening. After the image pre-processing the texture features are extracted from the segmented tumours using the Gray-Level Co-Occurrence Matrix (GLCM). However, the shape features are also extracted directly from the images. Both types of features are combined and fed into the FNN to be classified. The extracted shape features are asymmetry, shape and roundness. The texture features selected to be used are the mean, entropy, standard deviation, and uniformity. Once the feature extraction is achieved, the extracted features are classified by a fuzzy neural network designed with a different number of rules.

Experimentally, the designed FNN was tested using breast images and a different number of rules in order to find the optimum number of rules that gives the highest identification rate. The system was capable of achieving a high identification rate of 97.5% and 0.269 error rate using 36 rules. This performance is considered as good compared to other related works and it may prove that selected texture and shape features can be enough for distinguishing the malignancy of breast tumour in order to the learning capability of the fuzzy neural network design employed in this thesis

Keywords: Malignancy; breast cancer; texture and shape feature; fuzzy neural system; GLCM

ÖZET

Meme kanseri hala büyük medikal görüntü teşhis ikileminde. Yapay zeka ve bulanık mantık araştırmacılarının bu problemi aşması, bu kanseri teşhis etmede yardımcı olabilecek bir yöntem bulmak için bu problemin üstesinden gelmek. Bu tez çalışmasında, meme kanseri röntgen görüntülerinin tanımlanmasında yardımcı olan bulanık mantık ve sinir ağının entegrasyonunu öneriyoruz.

Bu tasarımla ortaya çıkan aşamalar şunlardır: görüntü ön işleme, özütleme özellikleri ve son olarak FNN kullanarak sınıflandırma özellikleri. Sınıflandırma aşaması, bu çıkarılmış özellikleri iki sınıftan birinde sınıflandırmayı amaçlayan bulanık bir sinir ağıdır: iyi huylu tümör veya malign tümör. Tasarlanan sistemin eğitiminde kullanılan veriler DDSM'den elde edilir. Tümör aret eşikleme, filtreleme, ayarlama, kanlı kenar algılama ve görüntü açılışı gibi bazı morfolojik işlemleri tespit etmek ve çıkarmak için kullanılan veri işlemleri. Doku özellikleri Gray-Level Co-Occurrence Matrix (GLCM) kullanılarak segmentlenmiş tümörlerden çıkarılır. Bununla birlikte, şekil özellikleri doğrudan görüntülerden çıkarılır. Ek olarak, her iki özellik de birleştirilir ve sınıflandırılacak FNN'ye beslenir. Asimetri, şekil ve yuvarlaklık, görüntülerden ayıklanacak şeklin özellikleridir. Bununla birlikte, kullanılacak olan doku özellikleri ortalama, entropi, standart sapma ve tekdüzeliktir. Öznitelik çıkarıldıktan sonra, çıkarılan özellikler farklı sayıda kural ile tasarlanmış bir bulanık sinir ağı ile sınıflandırılır.

Deneysel olarak, tasarlanan FNN, en yüksek tanımlama oranıyla biten en uygun kural sayısını bulmak için farklı görüntüler ve farklı sayıda kural kullanılarak test edilmiştir. Sistem, 36 kuralla yüksek bir% 97,5 ve% 0,69 hata oranına ulaşma kapasitesine sahipti. Bu performans iyi olarak kabul edilir ve bu tezde kullanılan bulanık sinir ağı tasarımının öğrenme kabiliyetine göre seçili doku ve şekil özelliklerinin meme tümörünün malignitesini ayırt etmek için yeterli olabileceğini kanıtlayabilir.

Anahtar Kelimeler: Malignite; meme kanseri; doku ve şekil özelliği; bulanık sinir sistemi; GLCM

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LIST OF ABBREVIATIONS

ANN:	Artificial Neural Network
NN:	Neural Network
FL:	Fuzzy Logic
FNN:	Fuzzy Neural Network
BPNN:	Back Propagation neural network
MSE:	Mean Square Error
SEC:	Second
SVM:	Support Vector Machine
MIN:	Minutes
KNN:	K-Nearest Neighbor
F-KNN:	Fuzzy-K-Nearest Neighbor
F-KNNE:	Fuzzy-K-Nearest Neighbor Equality
CNN:	Convolutional Neural Networks
DCNN:	Deep Convolutional Neural Networks
ANFIS:	Adaptive neuro fuzzy inference system
DDSM:	Digital Database for Screening Mammography
TSK:	Takagi-Sugeno-Kang
MFIS:	Mamdani Fuzzy Inference System
MISO:	Multi-Input Single-Output Structure
MIMO:	Multi-Input Multi-Output Structure

CHAPTER 1
INTRODUCTION

1.1 Introduction

Mammography is an area of medicine that is laden with the responsibility of using safe and novel imaging technologies such as electromagnetic radiation which is beyond the visible light spectrum for medical diagnosis and treatment. The most common radiation used in medical breast imaging being mammography (Dheghan and Defzooli, 2011). Breast radiography or mammography images are non-invasive medical scans showing the chest region, non-visible electromagnetic radiations are usually used in these radiography scans. The radiations used are able to penetrate through opaque objects, while some it is absorbed by the object being scanned also, depending on the composition and density of the particular object. The rays that make it past the object being scanned are captured on a photographic plate positioned at a suitable distance behind the object (Lucchini and Vecchia, 2003).

Hence, mammograms are typically used to examine sensitive women's breasts that cannot or do not want to open up for diagnosis. Medical experts have used this technique for several decades to explore for nodules that may be found in breasts, which can be cancerous.

The breast cancer is the most common types of cancer distributed among women (Dheghan and Defzooli, 2011). Breast cancer is dangerous and needs to be detected at an early stage in order to prevent its growth, to treat and to reduce the percentage of deaths caused (Lucchini and Vecchia, 2003). Different imaging techniques are used for the screening of breast cancer. Mammography is one of the most common screening techniques for the breast cancer. This is a specific type of radiography that uses low radiation levels (Anders and Lenovalli, 1994). The mammography produces breast images called mammograms in order to diagnose and detect the presence of intruders or abnormal structures in the breast.

Recently various systems have been developed using soft computing methodologies for pattern classification in order to increase the recognition rate (or accuracy) (Anders and

Lenovalli, 1994; Lucchini and Vecchia, 2003; Dheghan and Defzooli, 2011). The designed breast cancer identification system includes image pre-processing, feature extraction and classification stages. Recognition accuracy of the system depends on the accurate extraction of features and classification accuracy. Classification systems can help in increasing the accuracy and minimizing possible errors. One of the efficient soft computing methodologies used for pattern recognition problems is fuzzy logic and neural networks. The use of fuzzy logic allows the reduction of complexity of the data and handling uncertainty and impression. Neural networks have nonlinear mapping and self-learning characteristics, that increases the accuracy of the model. The combination of fuzzy logic and neural networks allows us to develop a system with fast learning capability that can accurately describe pattern classification systems. In this thesis, these methodologies are combined to construct fuzzy neural networks to solve pattern identification problem.

The researches and studies considered in the literature are mostly designed for special cases and most of them use neuro-fuzzy system that uses multi-input single-output structure. These systems are based on Mamdani type of rues. Sometimes the considered problems have multiple inputs and multiple outputs. Because Adaptive neuro fuzzy inference system (ANFIS) has multi-input single output structure, the solution of such kind of problems become difficult. In this thesis, multi-input multi-output fuzzy neural structure based on Takagi-Sugeno-Kang (TSK) type rule is proposed for the classification of breast tumours and for the improvement of the recognition rate of the system.

The detection and diagnosis of breast cancer in its earlier stages allows treating it prior to its growth. The accurate detection and classification of breast tumours will help to reduce the rate of occurrence of that disease. Thus, the aim of this thesis is the design of a breast cancer identification system. The design of the system mainly relies on the extraction of texture and shape features of the breast images. The challenge is to extract the right characteristics that may differentiate the benign and malignant breast tumours. Therefore, we use different image processing techniques and artificial intelligence elements to extract shapes and texture features of images for accurate classification of diseases. The proposed system is based on different image processing techniques such as image filtering using median filters, image adjustment, image thresholding, and some morphological techniques (erosion).

1.2 Significance of Thesis

It is seen that fuzzy neural networks (FNN) are efficient tools in specific fields and for some applications such as control, prediction etc.. Nevertheless, fuzzy neural networks have few applications in medicine and in particularly, medical images classification and diagnosis. Thus, in this thesis, a multi-input multi-output system is developed. A fuzzy neural network is designed based on the Type-2 TSK neuro-fuzzy system. The FNN was designed so that it can be trained to classify breast tumors in two classes. The novelty of this work is the design of a specific and unique FNN for the classification of medical images in two. Moreover, another aim and significance of this work is the use of seven shape and texture features that is believed they can distinguish the breast cancer malignancy. Both, the proposed features extraction methodology and the design of a robust FNN system were the novelties of this work which was eventually validated through the good accuracy the network achieved when classifying the malignancy of breast tumor.

1.3 Thesis Overview

The thesis includes the following sections for the accomplishing the design of the breast cancer identification system

Chapter 1 is an introduction of the work and thesis.

Chapter 2 is a detailed review of the usage image processing and softcomputing techniques for medical applications. Discussions of some related research works that are presented to solve the breast cancer problem on using elements of sofcomputing are presented.

Chapter 3 discusses the basics of methodologies used for the design of breast cancer identification system. The introduction to NN, fuzzy systems and its reasoning mechanism and also the integration of fuzzy logic and neural networks in system design are described.

Chapter 4 presents the proposed image analysis system design where all used processing techniques are explained. The used image processing algorithms, in particularly GLCM method, extraction of shape and texture features of images are discussed.

Chapter 5 presents the proposed Fuzzy neural network system designed for the classification of breast cancer classification. Also, this chapter explains the architecture of the proposed FNN system. Moreover, this chapter discusses the fuzzy neural network performance evaluation in addition to the results compared with other related works. The conclusion is also presented in this chapter.

CHAPTER 2
REVIEW OF IMAGE PROCESSING AND SOFCOMPUTING TECHNIQUES USED IN MEDICAL DIAGNOSIS

2.1 Review of Image Processing Techniques for Medical Images Diagnosis

Many different methods have been applied for the detection of breast cancer using image processing techniques. Image processing has been extensively used in various areas in medicine. Those areas include medical image diagnosis, segmentation, enhancement etc… image segmentation is needed in this field as it helps in detecting or contouring regions of interest in some images where specific objects should be segmented.

Segmentation is a partitioning of an image so that a particular region is extracted or segmented. However, this cannot be easily achieved, as it depends on some properties of the image or the region that should be detected such as edges, shapes, textures, intensities etc..

Over the past decades, different and many algorithm were developed for segmentation purposes in medical images (Fu and Mui, 1981) (Pal and Pal, 1993) (Koshana, 1994) (Lucchese and Mitra, 2001). Those approaches are all based on different properties of images. those properties can be the points, regions edges, objects or regions etc..

- ***Algorithms based on the points properties***

This algorithm is based on detecting a point in a homogeneous part of the image. This is achieved by analyzing some properties of the point such as colour, brightness, intensity and other characteristics. The drawback of this algorithm is the difficulties in selecting the important and useful features in images that have many homogenous segments of similar point characteristics. Many researches have used these approaches for segmenting medical images (Sharma et al., 2010)(Withey and Koles, 2007)(Zhang and Wang, 2000).

- ***Algorithms based on the edge detection***

This algorithm is very popular for segmentation, in particularly, in medical field where a certain region segment in the image needs to be extracted (Aroquiaraj and Thangavel, 2013) (Wu et al., 2015) (Sahakyan and Sarukhanyan, 2015). Edges in an image are the changes and discontinuities in intensities of the image pixels. Hence, this approach works mainly on the images which have brightness or intensity changes on its region edges. Thus, detecting these intensity changes can lead to segmentation of the region edges which for an object in an image.

ISO - intensity contours were used in the work proposed in (Padayachee et al., 2007) for the identification of the breast edges. In this work, some image processing techniques are used to detect and identify the object of interest "breast tumour" in the image. This is achieved using thresholding in which a single graylevel is selected by the analysis of the graylevel distribution in the image histogram. This allows the segmentation of the mammogram into the background and breast tissue in which the region of interest can be easily extracted. The work proposed in (Rederic et al., 2000) presented the breast cancer detection using thresholding and tracking. The presented techniques are used to identify the breast border. The authors in (Rederic et al., 2000) provides an explanation of asymmetries in digitized mammograms in addition to proposing an enhancement method for the asymmetries.

Researchers have used various algorithms for segmenting the breast tumorous cells in histological images. The authors in (Erezsky et al., 2015) reviewed different segmentation algorithms such as K-means, Watershed, and texture segmentation. These 3 techniques were applied to breast cell images and the signal to ration for each technique was calculated. Moreover, the authors proposed their own technique for breast cells segmentation which is based on detecting the properties of point connections. Moreover, the authors claimed that their proposed method yielded better segmentation results and lesser signal to noise ration compared to other discussed techniques.

Another breast cancer cell segmentation and contouring algorithm is proposed in (Mouelhi et al., 2011). In their work, an algorithm for segmenting the breast cancer cells is based on watershed and concave vertex graph as a next stage since the segmentation here occurs on many stages. At first, the malignant cells are detected using the geodesic active contour. Then high concavity points are taken from the cell contours to be then used for selecting the clustered cell regions only. Secondly, the touching cells regions are first segmented using watershed technique and then a concave vertex graph is constructed. This shows the inner edges and concave points which helps in separating cells regions. Finally, the authors of this work showed that their algorithm is very accurate in breast cancer cells segmentation without losing geometrical features.

An algorithm for the tumour cells detection breast cells microscopic images is proposed in (Phukpattaranont and Boonyaphiphat, 2006). The algorithm is comprised of two processing stages. The first one is the segmentation of breast cells using watershed mathematical process. Second, the breast cells are extracted or described using Fourier transform descriptors and the principal components analysis is performed to classify cells into normal or cancerous cells.

Moreover, authors in (Vahadane and Sethi, 2013) improved the watershed segmentation algorithm to detect breast cancer cells in histological images using nuclear segmentation. Their algorithm is based on many image processing techniques such as image enhancements and Ostu's thresholding in addition to the fast radial symmetry transform (FRST) for the nuclei extraction and foreground seeds generation.

Gaussian smoothing is first used to remove the high-frequency noise and the blurred nuclei segmentation. Then, background markers are used based on the image information to reduce the over-segmentation. FRST is also used to extract nuclei and to form foreground seeds. Finally, post-processing takes place by using erosion and dilation which results in segmenting the cell nuclei.

2.2 Review of Soft Computing Techniques for Medical Images Diagnosis

The breast cancer is the most common types of cancer distributed among women (Dheghan and Defzooli, 2011). Breast cancer is dangerous and needs to be detected at an early stage in order to prevent its growth; to treat it and to reduce the percentage of deaths caused (Lucchini and Vecchia, 2003). Image processing techniques are widely used for the screening of breast cancer. Mammography that uses a specific type of radiography at low radiation levels (Anders and Lenovalli, 1994) is one of them. Mammography produces breast images called mammograms in order to diagnose and detect the presence of intruders or abnormal structures in the breast. For this purpose different methodologies have been used.

In (Xiong and Jing, 2009), the masses in breast cancer images are identified by utilizing Twin Support Vector Machine (TW-SVM). Their proposed system was assessed by a data set of 100 mammograms obtained from the Digital Database for Screening Mammography (DDSM). The outcomes provided by the authors in (Xiong and Jing, 2009) demonstrated that the sensitivity of 89.7% with 0.31 false positive are obtained for every image. In the further examination, the authors in (Xiong and Jing, 2009) showed that their proposed CAD framework was able to achieve 94% sensitivity for identifying malignant masses in the test sets. On the other hands, the identification rate of benign tumours was much lower, only 78%.

Schnorrenberg (1996) has suggested that a computer-aided system that can estimate the malignancy probability of mammography lesion can assist the radiologists to decide patient management while improving the diagnostic accuracy. And since, various classifiers such as linear discriminants, rule-based methods, and artificial intelligence (AI) are being investigated for building systems that can classify mass lesions in mammography by merging computer-extracted image features.

Andre et al., (2002) proposed a Kohonen's self-organizing map (SOM) which extracts and digitize the features from the mammograms. The whole system is ultimately based on artificial neural networks (ANN) where it offers segmented image data from SOM as an input to the MLP network for the diagnosis task. The performance of the system was not so good compared to the other state-of-the-art systems present, with only 60% of the cases were classified correctly, however, the results obtained in this study indicate that the use of SOM to digitize mammograms is possible with an attempt to improve and optimize the system.

The systems based on soft computing elements are being developed in order to increase the recognition rate (or accuracy) of pattern classification (Dehghan and Dezfooli, 2011; Padayachee et al., 2007; Helwan and Abiyev, 2015). The breast cancer identification system includes image pre-processing, feature extraction and classification stages. Recognition accuracy of the system depends on the accurate extraction of features and classification accuracy. Classification systems can help in increasing the accuracy and minimizing possible errors. One of efficient soft computing methodologies used for pattern recognition problems are fuzzy logic and neural networks. The use of fuzzy logic allows the reduction of complexity of the data and handling uncertainty and impression. Neural networks have nonlinear mapping and self-learning characteristics, that increases the accuracy of the model. The combination of fuzzy logic and neural networks allows us to develop a system with fast learning capability that can accurately describe pattern classification systems. In this thesis, these methodologies are combined to construct fuzzy neural networks to solve pattern identification problem.

Fuzzy logic and FCM clustering plays an important role in medicine. Fuzzy technology is now frequently used in bioinformatics also. There are numerous medical studies which show fuzzy logic application from past 15 years (Dev et al. 2014). In ref (Pham & Prince 1999) a fully automated algorithm for obtaining fuzzy segmentations of images that are corrupted with intensity in homogeneities. Adaptive fuzzy c-means (AFCM) with deformable algorithms are used for the reconstruction of the cerebral cortex from brain MRI. Covariance characteristics are the added features to AFCM when compared with FCM. Breast Density is also an important risk factor for developing breast cancer.

FCM is used to segment basic body tissue, chest wall and fibrogladular tissue in a study by Ke Nie et al., (2008) Cheng et.al, in his study proposed a novel fuzzy neural network approach which resulted in lesser false positive rate per mammogram when compared with true positive value (Cheng & Cui 2004). Fuzzy enhanced mammogram (FEM) image segmentation methods are proposed. Diagnosis of abnormal masses from mammogram using fuzzy rules and classification is done by Support Vector Machine (SVM) in ref (Rao & Govardhan , 2015). There were two methods which were introduced in which overall Correct Detection Ratio (CDR) for FEM1 was 87% and for FEM2 it was 77%. The FEM1 method is very fast and accurate for the diagnosis of abnormal tumors. In (Gohariyan et al., 2017) combination of MRI and mammogram images are used to separate the abnormal glands using FCM and Artificial Networks algorithms such as affine transformation, Gabor filter, neural network. The proposed technique obtained 98.14% accuracy. From ref (Wu et al. 2013) we observe that fully automated segmentation algorithm atlas aided FCM is implemented on breast MR images to quantify the fibroglandular tissue content. This automated segmentation is compared to average of 2 reader's manual segmentation. The proposed method proves to be more stable and efficient. Atlas-FCM outperforms the commonly used two-cluster FCM alone.

Moreover, in the literature, the integration of neural and fuzzy structures are proposed for solving various feature extraction and classification problems (Wang et al., 2016; Al-Betar, 2014). In (Wang et al., 2016) adaptive neuro-fuzzy inference system (ANFIS) is applied for images' feature extraction. The reference (Al-Betar, 2014) ANFIS structure is used for solving cervical cancer recognition. The authors in (Ahmed et al., 2016) use neuro-fuzzy system for Crohn's disease classification. In (Samanta et al., 2014) Haralick features, in (Ghosh et al., 2015) grid color movement features are used for glaucoma classification**.** Backpropagation neural networks are used for the classification purpose. In (Dey et al., 2015), genetic algorithm is applied for the design of multi-input and single- output neuro-fuzzy system. Well known ANFIS (adaptive neuro-fuzzy inference system) structure is used for optimizing the chiller loading (Lu et al., 2015).

2.3 Problem Statement

The above-considered systems are designed for special cases and most of them use a neuro-fuzzy system that uses a multi-input single-output structure (MISO). These systems are based on Mamdani type of rues. Sometimes the considered problems have multiple inputs and multiple outputs. Because ANFIS has multi-input single output structure, the solution of such kind of problems become difficult. In this thesis, multi-input multi-output fuzzy neural structure based on Takagi-Sugeno-Kang (TSK) type rule is proposed for the classification of breast tumours and for the improvement of recognition rate of the system.

The detection and diagnosis of breast cancer in its earlier stages allows treating it prior to its growth. The accurate detection and classification of breast tumours will help to reduce the rate of occurrence of that disease. Thus, the design of a breast cancer identification system is considered in this thesis.

To solve the diagnosis of BC the following steps have been taken:

- Extracting the basic texture and shape features of the breast images: The challenge is to extract the right characteristics that may differentiate the benign and malignant breast tumours. Therefore, in this work, we attempt to extract seven shapes and texture features that we believe they distinguish both tumours. The proposed system is based on different image processing techniques such as image filtering using median filters, image adjustment, image thresholding, and some morphological techniques (erosion). The shape and texture features are then extracted and used for classification purpose.

- Designing the architecture of FNN for classification of breast images.

- Training the FNN model for classification breast cancer.

- Simulating the model and evaluating its performance in terms of accuracy, error, and time.

CHAPTER 3
MATERIAL AND METHODS

3.1 Overview

This chapter describes the materials and methods used in this thesis. The basics of neural networks, their structures, and learning algorithms are all discussed. Moreover, the basics of the fuzzy systems, its main blocks are given. In addition, the integration of fuzzy logic and neural network which is the heart of this work is presented.

3.2 Biological Neuron

The nature of human brain structure is complex and precise, and these properties allow the brain to have the capability of performing various difficult assignments. The human brain contains a lot of neurons, and each neuron is linked with the thousands of other neurons. The essential anatomic and effective part in the human brain is a nerve cell, the nerve cell is also known by (nervous system) or neuron. The neuron can be defined as an extension of the normal cell with an axon and dendrites. Moreover, the biological neuron composed of dendrites, soma, axon, and the weight or synapse. Figure 3.1 shows the components of the biological neuron. As shown in the figure that the nucleus is located in the middle of the soma. The soma generates input through gathering all the arriving signals. Also from the figure, it can be seen that dendrites are directly related to the cell body (Soma). The function of dendrites is to receive signals from other neurons and transmit it to the soma. The output path to other neurons is represented by the axon which is branching into main and secondary branches to link the dendrites and next neuron's soma. There are structures known as synapses at the end of each branch of the axon. These synapses can be referred as the connection points between two different neurons. The synapses connections can be inhibitory or excitatory. These synapses transmit the signals between neurons in two directions. These signals are electrochemically transmitted in the junction points. The potential in the synapses changes based on the chemical materials being transmitted between the neurons. The potential effects soma and causes its activation if the received signals by dendrites are strong sufficient to flame the neuron. Moreover, if the received signals by dendrites are strong sufficient to flame the neuron, then the neuron will transmit another signal by the axon to nearby neurons in the same process. The signal is going also to be received by the connected dendrites, so can fire next neurons (Xiao, 1996). In other words, the neurons collect signals from other neurons through fine structures known as dendrites and these neurons can be activated or deactivated based on the received electrochemical signals. For instance, when the sum passes a threshold or certain value, then the neuron will fire (activated) and the signal goes along to the neighbouring neurons through the axon which splits into thousands of branches known as synapses. But in the case that the sum is less than the activation value, then no neuron be fired and this results in deactivated neurons (Haykin, 2009; Du and Swamy, 2013; Kriesel, 2007; Xiao, 1996); Fausett, 1994).

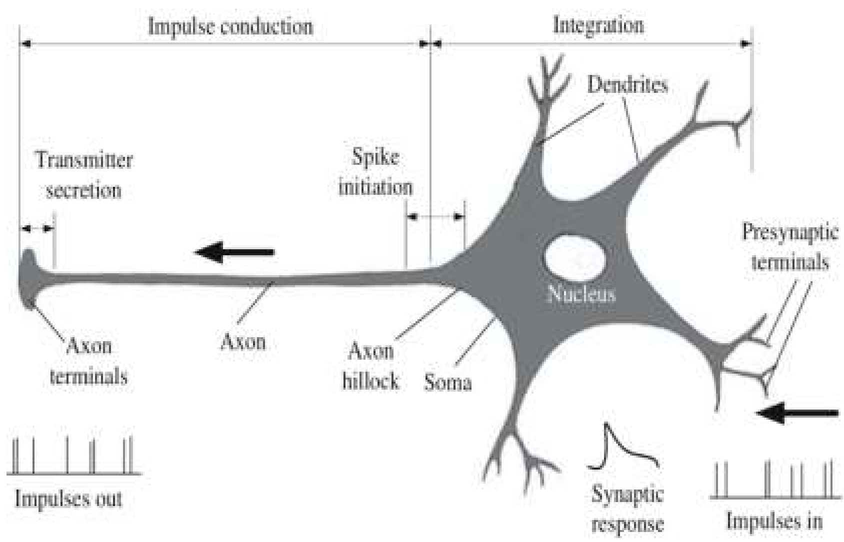


Figure 3.1: Architecture of human biological neuron (Du and Swamy, 2013)

3.3 Neural Network Structures

Artificial Neural Networks (ANNs) can be defined as a data processing model which tries to imitate the way of human biological brain works. There are many nodes (neurons) that linked or connected with each other through lines (weight) in ANNs; these neurons work with each other to find solution for specific tasks. The processes of neural networks (NN) consist of two steps; the first step is training or learning of neural network through use of data (examples) which can be carried out by using learning algorithm. Whereas, the second step is recalling; this step means testing the trained network for new given data (examples). However, the structure, properties of neurons and training methods are factors that affects classification of neural networks or specify the type of neural network. The most common types of neural network are listed below (Haykin, 2009; Du and Swamy, 2013; Kriesel, 2007; Tino et al., 2015; Gurney, 1997).

There are different NN structures. Feed-Forward Neural Networks (FFNNs): Multilayer perceptron, Radial basis function network, Recurrent neural network, Hopfield network, and Boltzmann machine.

Feed-Forward Neural Networks are the most commonly used type of neural networks. FFNNs consist of three types of layers (inputs layer, hidden layer and output layer). The structure of FFNNs is sorted by the type of layers, such as the first layer is input layer and last layer is the output layer, whereas the middle layers (located between input and output layer) can be called as hidden layers, which can be one or more layers. Moreover, in FFNs, the neurons are connected to the following layer neurons by one-direction lines (weights). In other words, there is no feed-back connection in FFNN and the neurons of the same layer are not connected with each other. The most common types of Feed-Forward neural networks are listed below (Haykin, 2009; Du and Swamy, 2013; Kriesel, 2007; Tino et al., 2015; Gurney, 1997).

The nodes in the inputs layer represents the input parameters thus the number of units in inputs layer depend on the number of inputs parameters. The nodes in output layer denotes to the output parameter. The number of hidden layer neurons can be identified experimentally (trial and error). The amount of layers and neurons of hidden influences the performance of a neural network. The neurons or nodes in hidden layer receive and send signals. In the output layer, the output of neuron can be generated through employing transfer or activation function to the weighted sum, the weighted sum can be calculated by multiplying the input by its related weight (w), Thereafter, the results are added to each other in order to form sum. Mathematically, the neuron output (y) of hidden layer can be written as following:

$$Y = F\left(\sum_{i=1}^{J1} x_{i,j}\, w_{i,j} + \theta\right) \tag{1}$$

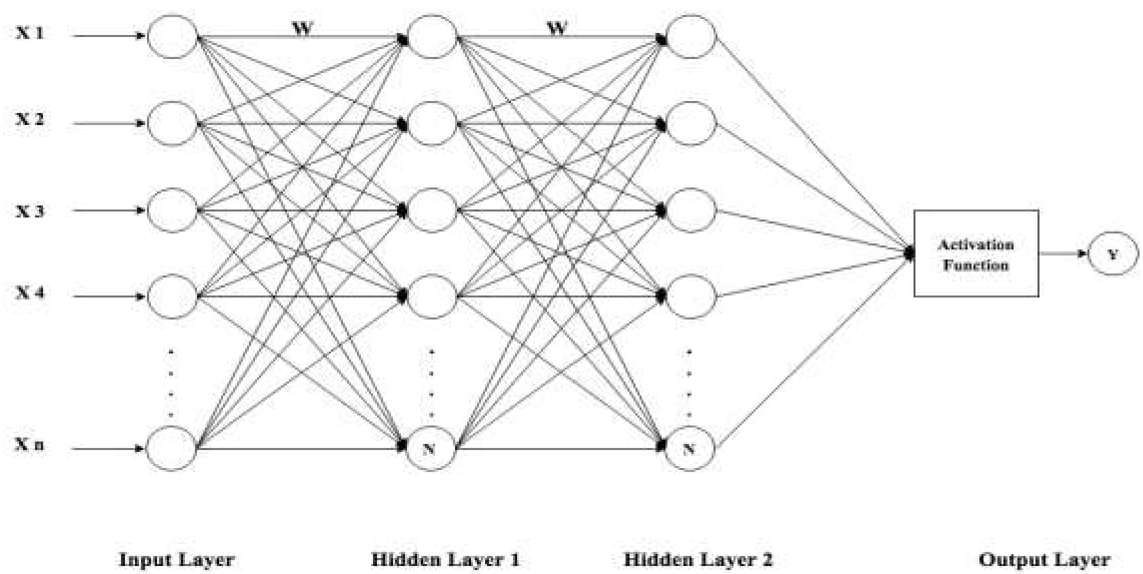


Figure 3.2: Multilayer perceptron (MLP)

The main parts of Multilayer perceptron are layers, weights, and activation functions. Each part has an important role in MLP. As shown in figure 3.2 there is three various type of layers (input layer, hidden layer & output layer). These layers are fully connected forward through lines (weights) which allows the information to be passed between layers. Generally, the Input layer is usually placed at the beginning (considered as the first layer) of the network. This layer consists of a number of nodes and these nodes represent the number of inputs parameters. Moreover, the input layer has no transfer function but, it allows to the information of inputs to be transferred to the hidden layer. Whereas, the hidden layers usually located between the input and output layers, and connected to them through lines (weights). Moreover, the weights start to be modified or updated constantly at hidden layers. The hidden layers are known as processing layers which consist of a number of neurons and the number these neurons can be defined experimentally. The last layer is known as an output layer, which provides the final output of the all network, thus can be considered as processing layer. Figure 3.2 indicated to MLP with two hidden layers, the input layer is fed by inputs parameters. While the first hidden layer is fed by the output of the input layer and the second hidden layer is fed by the output of the first hidden layer. Moreover, the input of the output layer is fed by the output of the second hidden layer, whereas the output of the output layer is used to form the output of the network.

The connection lines between layers are called as weights. These lines play an important role in determining the output in neural networks. In the beginning, the weight in the neural networks is set at random, and then this weight begins to be updated in order to get more accurate results. However, this update can be done through many iterations (epoch) (Haykin, 2009; Du and Swamy, 2013; Kriesel, 2007; Tino et al., 2015; Shalev-Shwartz; Ben-David, 2014).

On the other hand, the purpose of using activation or transfer functions in most of the neural networks is to provide a boundary for the output of nodes. Furthermore, the format of inputs data can be influenced by the type of transfer function, in another word, defining the type of transfer function can indicate how inputs data must be formatted or arranged. Neural network can have various types of transfer functions.

3.4 Learning of NN Backpropagation Algorithm

As previously mentioned, neural networks (NN) process involves training (learning) and generalization or recalling. The learning or training of neural network is represented by reducing the cost function and can be carried out through locating the optimum weight (w) and sometimes, the parameters of another network. This process is also known as the learning algorithm. Back-propagation algorithm is considering as the most commonly used algorithm for training Multilayer Perceptron. The training in neural networks can be carried out by epochs. An epoch can be defined as a full cycle when whole the examples in training are given to the network and are processed using the learning algorithm only once. When training of neural network is completed, the network starts to perform a complex relationship and possesses the capability for recalling (Haykin, 2009; Du and Swamy, 2013; Kriesel, 2007; Tino et al., 2015; Shwartz and David, 2014). There are three different types of methods of learning:

1. Supervised learning - This type of learning is known as learning with a teacher. In this learning, the neural network is provided by target output values in order to modify the parameters of the network through straightforward manner (finding the differences between the desired values and the predicted values). (Haykin, 2009; Du and Swamy, 2013), (Kriesel, 2007; Shwartz and David, 2014; Maillard and Gueriot, 1997).
2. Unsupervised Learning - In non-supervised learning, the neural networks are only provided with inputs data, where real outputs values are not given to the networks. The networks must be able to find a relationship between information from the inputs data. In other words, the training algorithm must be able to find appropriate subsets of samples of a training set. (Haykin, 2009; Du and Swamy, 2013; Kriesel, 2007; Shwartz and David, 2014; Maillard and Gueriot, 1997).
3. Reinforcement learning- This kind of learning can be referred to as a special status of supervised learning, where the accurate desirable value of output is unknown. In supervised learning, the instructor provides the only reaction about success or failure of a result.

One of well-known and widely supervised learning algorithm the Backpropagation algorithm. It is delta rule generalization which also referred as Least Mean Squares Algorithm (LMS). This algorithm aims to reduce the cost function analogous to the mean square error among the real and predicted output values through using gradient- descent method. In Back propagation algorithm, at the begin of first epoch, the input layer in the network is fed by the input pattern and then the output is produced. The error (the difference between target and actual value) propagates to backward and thus a blocked-loop hold system is formed. The gradient-descent algorithm is used to modify the weights. The activation function plays important role in allowing to back-propagation rule to be applied. The error can be calculated by using mean square error MSE equation.

$$E = \frac{1}{M}\sum_{z=1}^{M} E_z = \frac{1}{2M}\sum_{z=1}^{M} \|Yz\ -'Yz\|^2 \tag{2}$$

$$E_z\ = \frac{1}{2}\|Yz - 'Yz\|^2 \quad = \ \frac{1}{2}\ e_z^T\ e_z \tag{3}$$

$$e_z = Yz{-}'Yz \tag{4}$$

The Error (E) is reduced by employing gradient-descent which allows to the weights to be adjusted. This can be done using below equation.

$$\Delta_z\, \boldsymbol{W} = -n\frac{\partial E_z}{\partial W} \tag{5}$$

η is referred to rate of learning and represents our step size which ranged between (0-1) and this can be chosen manually. W is representing the parameters of networks such as weights and bias. Furthermore, equation (6) referred back-propagation algorithm. Moreover, the algorithm can be better through involve using of (μ) momentum factor which analyze and the provide status for convergence (Haykin, 2009; Du and Swamy, 2013; Kriesel, 2007; Xiao, 1996; Tino et al., 2015; Shwartz and David, 2014).

$$\Delta_z(t)\, \boldsymbol{W} = -n\frac{\partial E_z}{\partial W} + \mu\Delta W(t-1) \tag{6}$$

Figure 3.3: Effects of learning rate and momentum parameters on weight updating (Du and Swamy, 2013)

3.5 Fuzzy Logic

The concept of Fuzzy Logic (FL) was conceived at the beginning of the 70s by Lotfi Zadeh, a professor at the University of California at Berkley, and presented not as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership (Zadeh, 1965). Professor Zadeh reasoned that people do not require precise, numerical information input, and yet they are capable of highly adaptive control. If feedback controllers could be programmed to accept noisy, imprecise input, they would be much more effective and perhaps easier to implement (Zadeh, 1965).

In this context, FL is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. FL provides a simple way to arrive at a definite conclusion based on vague, ambiguous, imprecise, noisy, or missing input information. FL's approach to control problems mimics how a person would make decisions, only much faster.

FL incorporates a simple, rule-based IF X AND Y THEN Z approach to a solving control problem rather than attempting to model a system mathematically. The FL model is empirically-based, relying on an operator's experience rather than their technical understanding of the system. For example, rather than dealing with temperature control in terms such as "SP =500F", "T <1000F", or "210C <TEMP <220C", terms like "IF (process is too cool) AND (process is getting colder) THEN (add heat to the process)" or "IF (process is too hot) AND (process is heating rapidly) THEN (cool the process quickly)" are used. These terms are imprecise and yet very descriptive of what must actually happen. Consider what you do in the shower if the temperature is too cold: you will make the water comfortable very quickly with little trouble. FL is capable of mimicking this type of behavior but at very high rate (Babuska, 1998).

3.6 Fuzzy Reasoning

FL offers several unique features that make it a particularly good choice for many control problems (Bobuska, 1998; Drobics, 2003).

1) It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth control function despite a wide range of input variations.

2) Since the FL controller processes user-defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules.

3) FL is not limited to a few feedback inputs and one or two control outputs, nor is it necessary to measure or compute rate-of-change parameters in order for it to be implemented. Any

sensor data that provides some indication of a system's actions and reactions is sufficient. This allows the sensors to be inexpensive and imprecise thus keeping the overall system cost and complexity low.

4) Because of the rule-based operation, any reasonable number of inputs can be processed (1-8 or more) and numerous outputs (1-4 or more) generated.

5) FL can control nonlinear systems that would be difficult or impossible to model mathematically.

The concept of graded membership in fuzzy sets was introduced by Zadeh (1965). This notion of graded membership was introduced in order to provide a mathematical precision to information arising from our cognitive process. The theory of fuzzy sets provides a mechanism for representing linguistic constructs such as 'many', 'low', 'medium', 'often', 'few'. In general, the fuzzy logic provides an inference structure that enables approximate human reasoning capabilities (Gupta and Rao, 1994). On the contrary, the traditional binary set theory describes crisp events, events that either do or do not occur. It uses probability theory to explain if an event will occur, measuring the chance with which a given event is expected to occur. The theory of fuzzy logic is based upon the notion of relative graded membership and so are the functions of mentation and cognitive processes. Thus, the utility of fuzzy sets lies in their ability to model uncertain or ambiguous data so often encountered in real life.

Fuzzy logic provides a methodology for representing and implementing our knowledge about how best to control a process. **A** fuzzy system is a static nonlinear mapping between its inputs and outputs (i.e., it is not a dynamic system). It is assumed that the fuzzy system has inputs $u_i \in U_i$ where i = 1, 2, . . . , n and outputs $y_i \in Y_i$ where i = 1, 2, . . ., m. A block diagram of a fuzzy system is shown in Figure 1. The fuzzy system is composed of the following four elements:

1.A rule-base basically consists of a set of If-Then rules and contains a fuzzy logic quantification of the expert's linguistic description of the considered problem.

2. Fuzzy inference mechanism ("inference engine") emulates the expert's decision making in interpreting and applying knowledge.

3. A *fuzzification* converts inputs into inforııation that the inference mechanism can easily use to activate and apply rules.

4. A defuzzification converts the conclusions of the inference mechanism into actual inputs

The inputs and outputs are "crisp"-that is, they are real numbers, not fuzzy sets. The fuzzification block converts the crisp inputs to fuzzy sets, the inference mechanism uses the fuzzy rules in the rule-base to produce fuzzy conclusions (e.g., the implied fuzzy sets), and the defuzzification block converts these fuzzy conclusions into the crisp outputs.

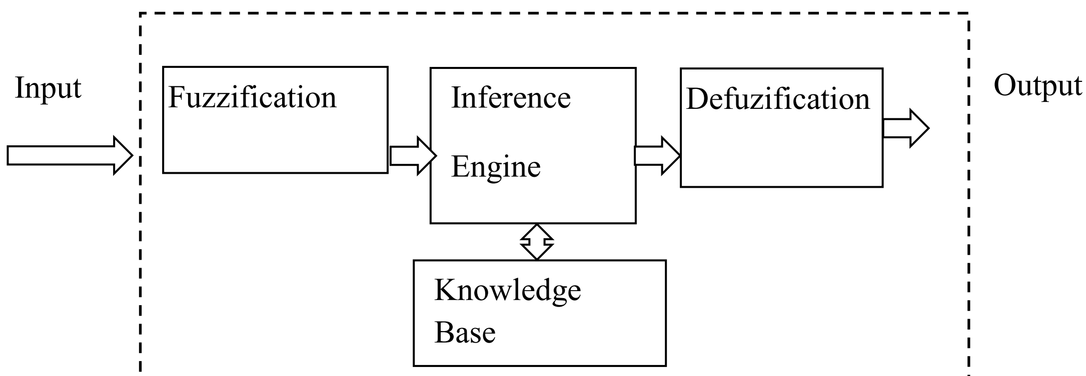


Figure 3.4: Fuzzy system

The basic problem in fuzzy system design is the development of a knowledge base. In the literature, different approaches are purposed for the development of an appropriate knowledge base. One of the widely used approaches is the use of neural networks.

3.7 Integration of Fuzzy logic and Neural Networks

Neural network structures can deal with imprecise data and ill-defined activities. However, the subjective phenomena such as reasoning and perceptions are often regarded beyond the domain of conventional neural network theory. It is interesting to note that fuzzy logic is another powerful tool for modelling uncertainties associated with human cognition, thinking and perception. In fact, the neural network approach fuses well with fuzzy logic (Gupta, 1992; Cohen and Hudson, 1990; Yamakawa and Tomoda, 1989) and some research endeavours have given birth to the field of 'fuzzy neural networks' or 'fuzzy neural systems'. Paradigms based upon this integration are believed to have considerable potential in the areas of expert systems, medical diagnosis, control systems, pattern recognition and system modelling. Two possible models of fuzzy neural systems are schematically shown in Figures 3.5. The computational process envisioned for fuzzy-neural systems is as follows. It starts with the development of a 'fuzzy neuron' based on the understanding of biological neuronal morphologies, followed by learning mechanisms. This leads to the following three steps in a fuzzy-neural computational process: (i) development of fuzzy neural models motivated by biological neurons, (ii) models of synaptic connections which incorporates 'fuzziness' into neural network, and (iii) development of learning algorithms (that is, the method of adjusting the synaptic weights). Based upon the computational process involved in a fuzzy-neural system, one may broadly classify the fuzzy neural structures as feedforward (static) and feedback (dynamic), Figure 9. In a feedforward (static) architecture, the neuron responds instantaneously to the fuzzy inputs because of the absence of dynamic elements in the structure (Cohen and Hudson, 1990). The neural mathematical operations in a feedforward network can be performed either by fuzzy arithmetic or fuzzy logic operations. As was mentioned in the preceding section, the function of a non-fuzzy neuron can be modeled as

$$y(t) = \varphi[\sum_{i=0}^{n} w_i x_i] \tag{7}$$

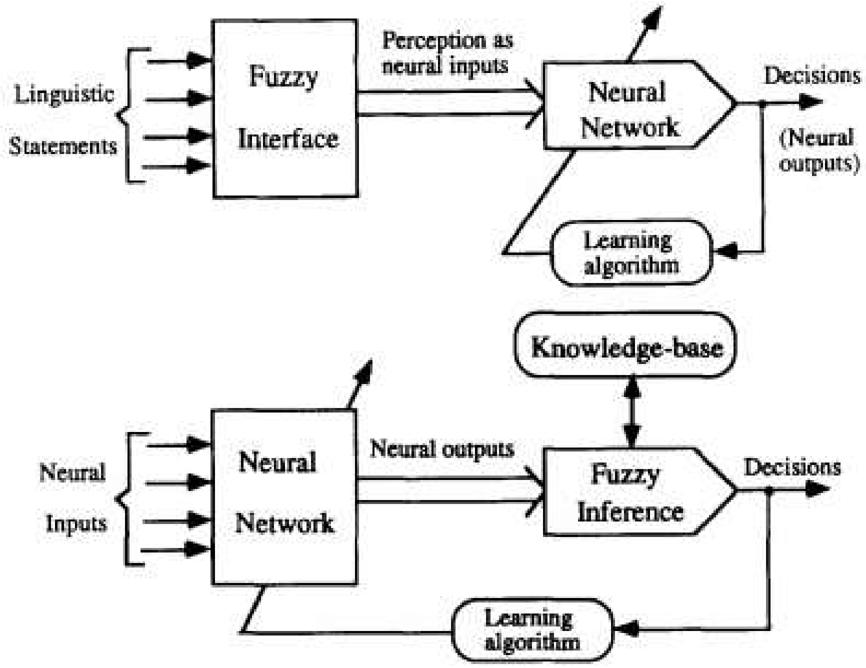


Figure 3.5: Fuzzy neural network general architecture (Gupta and Rao, 1994)

3.7.1 Learning scheme: adapting the knowledge base

The weighting and spatiotemporal aggregation operations performed by the synapses and soma, respectively, provide a similarity measure between the input vector X(t) (new neural information) and the synaptic weight vector W(t) (accumulated knowledge base). When a new input pattern that is significantly different from the previously learned patterns is presented to the neural network, the similarity between this input and the existing knowledge base is small. As the neural network learns this new pattern, by changing the strength of the synaptic weights, the distance between the new information and accumulated knowledge decreases (Yamakawa and Tomoda, 1989).

In other words, the purpose of learning is to make W(t) very similar to a given pattern X(t). Most of the neural network structures undergo a 'learning' procedure during which the synaptic weights (connection strengths) are adapted. Algorithms for varying these connection strengths such that learning ensues are called 'learning rules'. The target of learning rules relies on the applications. For instance, the goal in design characterization from test data is to classify and foresee effectively on new data, while the goal in control applications is to rough nonlinear capacities, and additionally to influence obscure frameworks to take after the coveted reaction. In characterization and functional estimation issues, each cycle of introduction of all cases is normally alluded to as a 'learning age'. Be that as it may, there has been no speculation with respect to how a neural system can be adjusted.

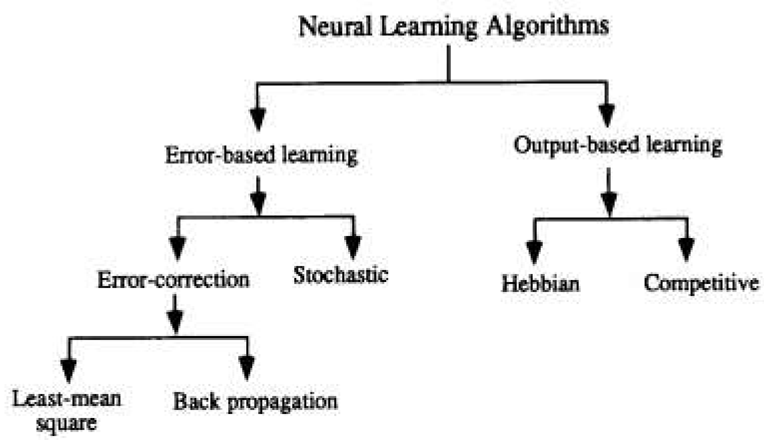


Figure 3.6: A flow diagram of learning algorithms employed in different neural structures to adapt the synaptic weights (Gupta and Rao, 1994)

A flow chart delineating the diverse learning calculations ordinarily utilized for the adjustment of synaptic weights is appeared in Figure 3.6. As appeared in this figure, learning calculations might be comprehensively arranged as 'error-based (managed)' and 'yield based (unsupervised)'. Error-based (otherwise called administered) learning calculations utilize an outer reference signal (instructor) and produce an error signal by contrasting the reference and the obtained reaction (Gupta, 1990). In view of error signal, neural system changes its synaptic associations with enhance the framework execution. In this learning plan, it is accepted that the coveted answer is known apriori. The error-based learning methodology is schematically appeared in Figure 3.7.

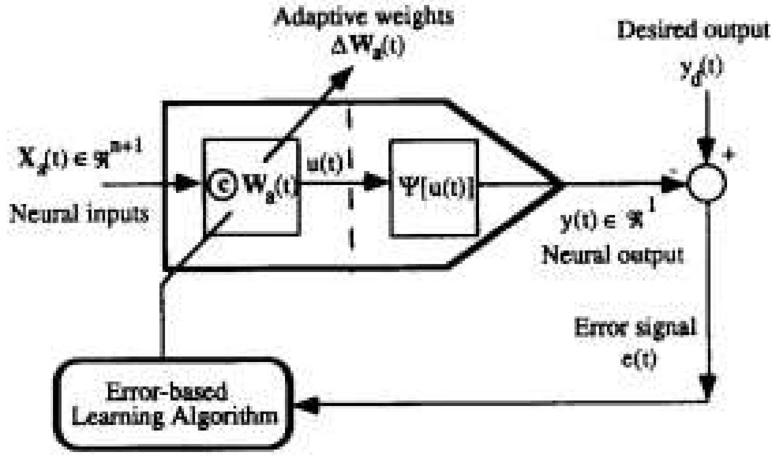


Figure 3.7: An error-based learning scheme where the learning process is guided by the error signal e(t) (Gupta and Rao, 1994)

CHAPTER 4

DESIGN OF FNN FOR MEDICAL IMAGE PROCESSING AD DIAGNOSIS

4.1 Overview

This chapter discusses the structure of the system used for the diagnosis of breast cancer. The design stages of the diagnostic system are described, the image preprocessing, feature extraction and classification are presented. The image processing phase is the first phase in this work in which images are processed in order to extract the shape and texture features using different algorithms. The algorithms used in image processing stages are presented.

4.2 Structure of the Breast Cancer Diagnostic System

The detection and diagnosis of breast cancer in its earlier stages allows treating it prior to its growth. The accurate detection and classification of breast tumours will help to reduce the rate of occurrence of that disease. Thus, the design of a breast cancer identification system is considered in this thesis. The design of the system mainly relies on the extraction of texture and shape features of the breast images. The challenge is to extract the right characteristics that may differentiate the benign and malignant breast tumours. Therefore, in this work, we attempt to extract shape and texture features that we believe they distinguish both tumours. Therefore, we use different image processing techniques and artificial intelligence elements to achieve this goal. The proposed system is based on different image processing techniques such as image filtering using median filters, image adjustment, image thresholding, and some morphological techniques (erosion). The shape and texture features are then extracted and used for classification purpose.

Figure 4.1 represents the general structure of the proposed breast cancer identification system. As shown, the system includes three basic blocks: image pre-processing, feature extraction and classification. In image pre-processing stage the segmentation and detection of the object of interest are performed. The object of interest is the cancer region on the breast images. The breast images after preprocessing are entered to the feature extraction unit. Here the texture and shape features of images are extracted. These features are fed into FNN based classifier for classification of images.

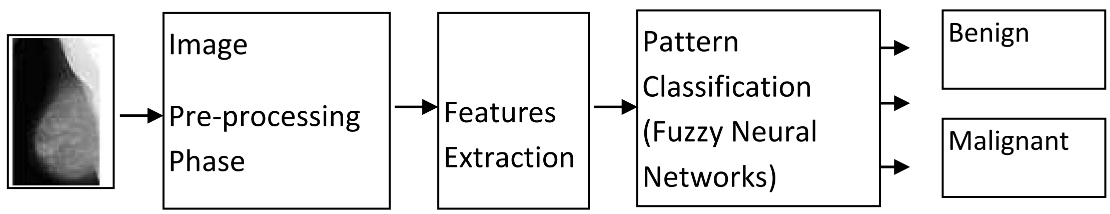


Figure 4.1: The structure of the proposed system

Figure 4.2 shows the flowchart of the identification system. As seen, noises are first removed from images using median filters and image adjustment, that is used to smooth the region of interest (tumor) of the image. After enhancement, the tumor is segmented and extracted using morphological operations; erosion and image opening. Once the tumor is extracted, the feature extraction process starts. First, the texture features are extracted by applying the GLCM algorithm on the image, and then shape features are extracted. After the extraction of the texture and shape features, they are fed into a fuzzy neural network that learns to classify those features into benign or malignant tumors.

4.3 Data Set

The images are taken from The Digital Database for Screening Mammography (Heath et al., 2001) and then converted into grayscale using the luminosity method. The converted images are represented by two-dimensional matrices. These images are filtered using median filtering so the noises are removed. After filtering, the obtained images are adjusted in order to increase their pixel intensities so that the region of interest (tumour) can be clearer and brighter. The images undergo threshold computing for the purpose of segmenting the region of interest (tumour) located in the breast. We also used some morphological techniques such as erosion in order to extract the region of interest. The 7 texture and shape features are extracted from the region of the interest and used for the classification of images.

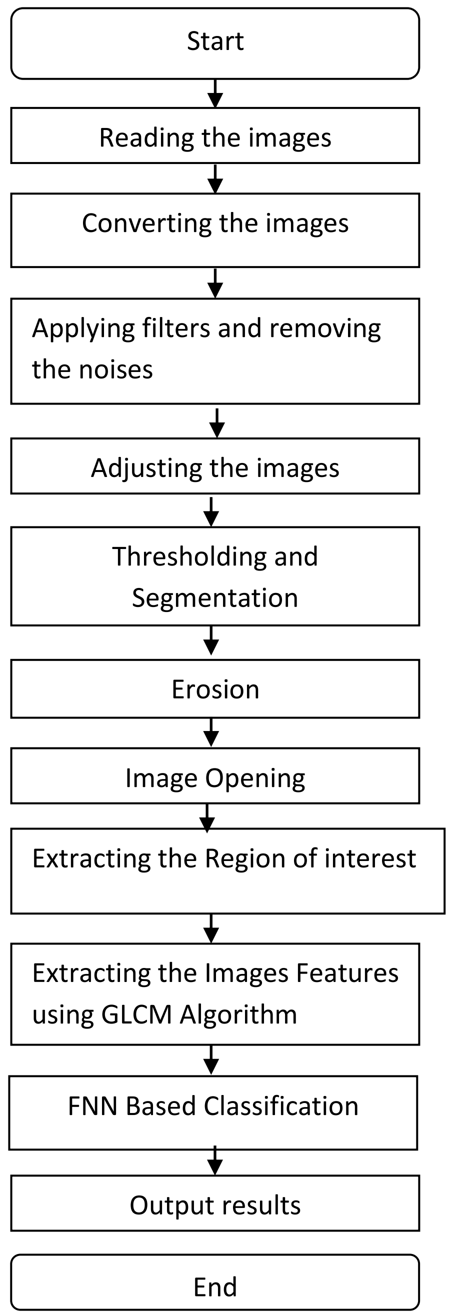


Figure 4.2: Flowchart of the proposed identification system

The Gray Level Co-occurrence Method GLCM method (Zhu and Zhang, 2010) is applied for extraction of the texture features of the images. The extracted texture and shape features are fed into the FNN. FNN uses the input features and classifies them into benign or malignant classes. Figures 4 and 5 show the image analysis and processing of benign and malignant breast tumour images respectively. The image processing operations are explained below.

Figure 4.2 shows the flowchart of the proposed work. As seen, noises are first removed from images using median filters and image adjustment, which is used to smooth the region of interest (tumor) of the image. After enhancement, the tumor is segmented and extracted using morphological operations; erosion and image opening. Once the tumor is extracted, the feature extraction process starts. First, the texture features are extracted by applying the GLCM algorithm on the image, and then shape features are extracted. After the extraction of the texture and shape features, they are fed into a fuzzy neural network that learns to classify those features into benign or malignant tumors.

Figure 4.3 shows a sample of the breast mammograms found in the used database, which are then used to train and test the proposed fuzzy neural network

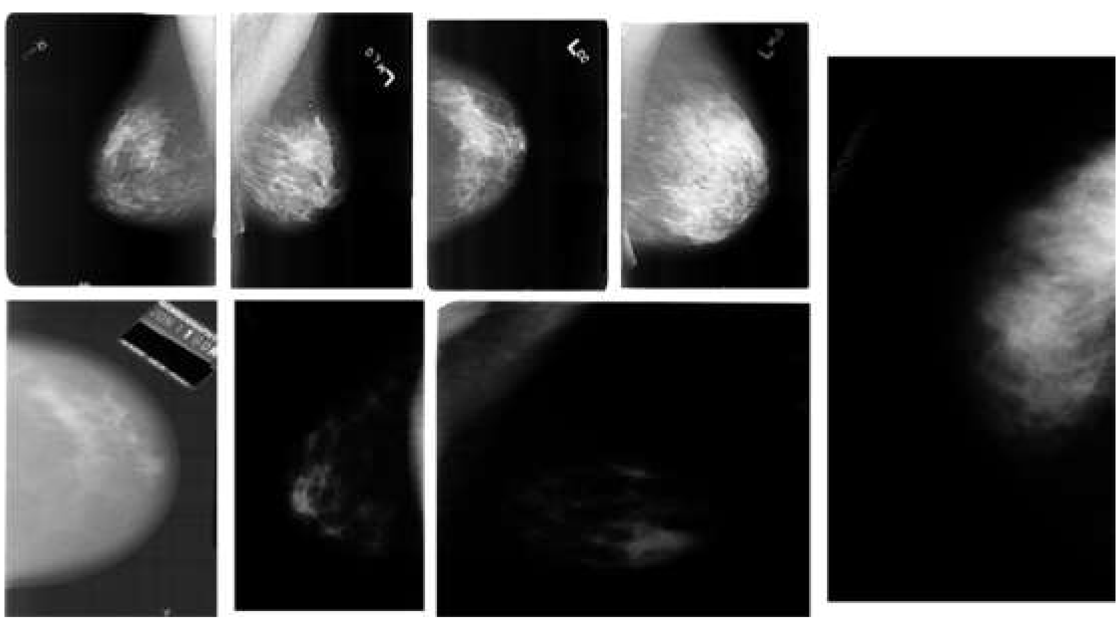


Figure 4.3: Samples of the database breast images

4.4 Image Analysis and Processing

Analytically, comparative results between cancers show that lung cancer is the highest killer followed by breast cancer. As demonstrated in (Tripathi et al., 2014), breast cancer is mostly found in a woman. Lesion as classified into two categories; malignant and benign is actually the cause of this dangerous illness. Among these two categories, benign is removable and unlikely to reoccur and hence termed; harmless lesion. While malignant in other hand is termed cancerous cell having high potential to grow and spread to other parts of the body (Dudea et al., 2013). High number of patients diagnosed with breast cancer does not notice its presence and probably died before getting proper medication. Therefore, to reduce the number of death resulting from breast cancer, early detection is necessary for proper treatment.

Breast cells cancer segmentation in microscopic images is a tedious job, in particularly when it comes to detecting whether the cells are with a tumor or not. This is usually due to the similarity and between both types of tumorous and healthy cells. Doctor's diagnosis decisions, like segmentation, are usually based on some visual inspections in which they check or depend on the size, colour, and texture of the cells. Those decisions may be affected by fatigue, stress, and less experience that humans may have. Thus, there is a need for an automated and computerized diagnosis system that helps in segmenting and detecting the cells with tumours in a breast microscopic image. These kinds of systems are lesser time consuming, not costly and may be more accurate since they are not affected by the aforementioned human factors.

Thus, in this thesis, we ought to propose a new image processing based algorithm for the segmentation of breast tumours found in the X-ray breast images. The algorithm does a good enhancing and filtering of the images as they may have some noises; then it starts the features extraction process where the regions of interest are put under spot. Lastly, the cancer cells are segmented. Experimentally, the system was validated on some breast cell images and it shows a good performance in segmenting the breast cancer.

Figure 4.4 shows a breast tumour (Benign) mammogram that undergoes all the image processing methods used in this work which ends up in segmenting the tumorous part of the image.

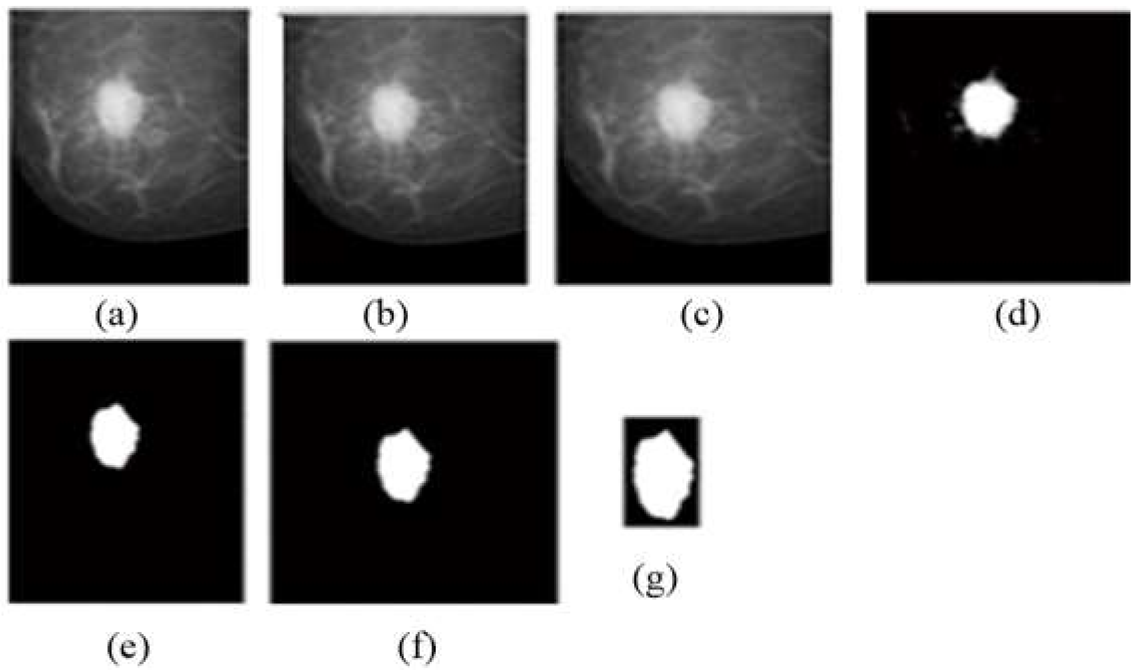


Figure 4.4: Benign tumour breast image undergoes the proposed system algorithm: (a) Original RGB abnormal breast image, (b) Grayscale image, (c) Filtered image using median filter, (d)Adjusted image, (e) tresholded image, (f) Eroded image, (g) Extracted tumor.

As seen in Figure 4.5 the breast image has to be processed and analyzed before it finally gets segmented. The image undergoes first some enhancement techniques in order to be cleared of some salt and pepper noise which may affect the final segmentation of the breast tumour. Hence, median filtering and adjustment of the images are employed. Secondly, breast tumour was segmented by first thresholding the image and then eroding it using image erosion. At last, texture and shape features are extracted using Gray Level Co-occurrence Matrix.

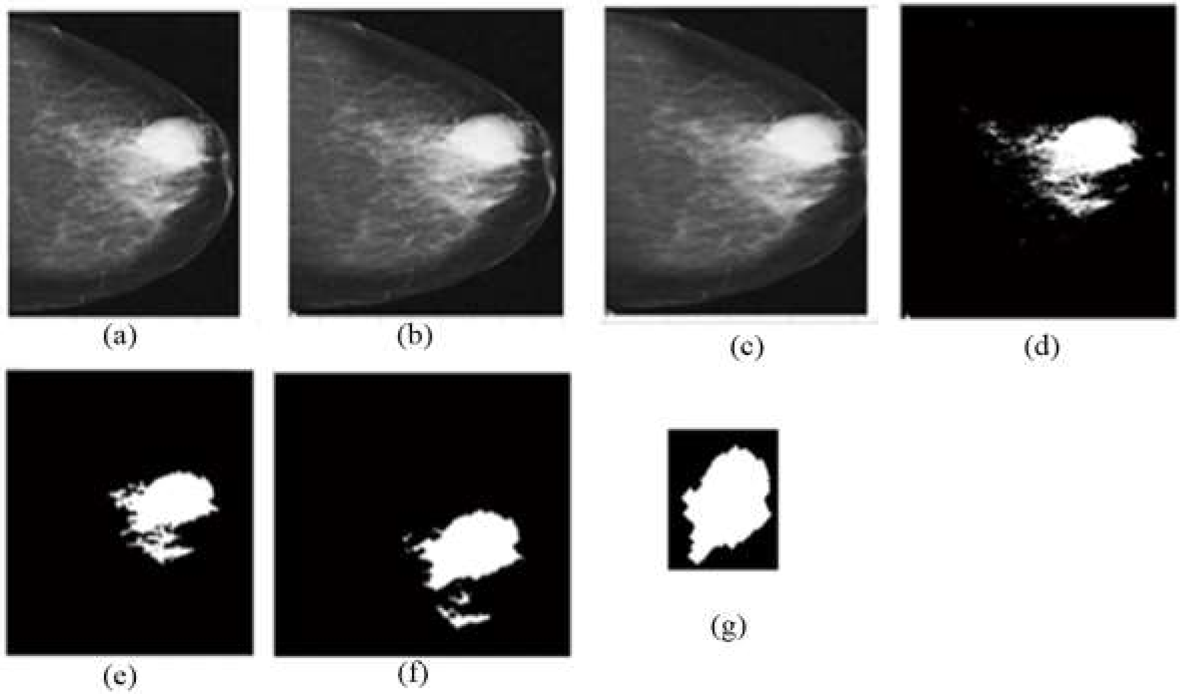


Figure 4.5: Malignant tumour breast image undergoes the proposed system algorithm: (a) Original RGB abnormal breast image, (b) Grayscale image, (c) Filtered image using median filter, (d)Adjusted image, (e) tresholded image, (f) Eroded image, (g) Extracted tumor.

4.4.1 Grayscale conversion

Images are first converted to grayscale using luminosity method. This technique relies on the contribution of each color of the three RGB colours. This results in a bright grayscale image as the three different colors of the RGB image are weighted according to their contribution in the image not averagely (Gonzales and Woods, 2006) (Fig. 4.6.b). This method is a more sophisticated version of the average method. It also averages the values of the image matrix, but it forms a weighted average to account for human perception since humans are more sensitive to green than other colors, therefore; green is weighted most heavily. This is shown in equation (8)

$$0.21R + 0.72G + 0.07B \tag{8}$$

where R is the red color, G is the green, and B is the blue.

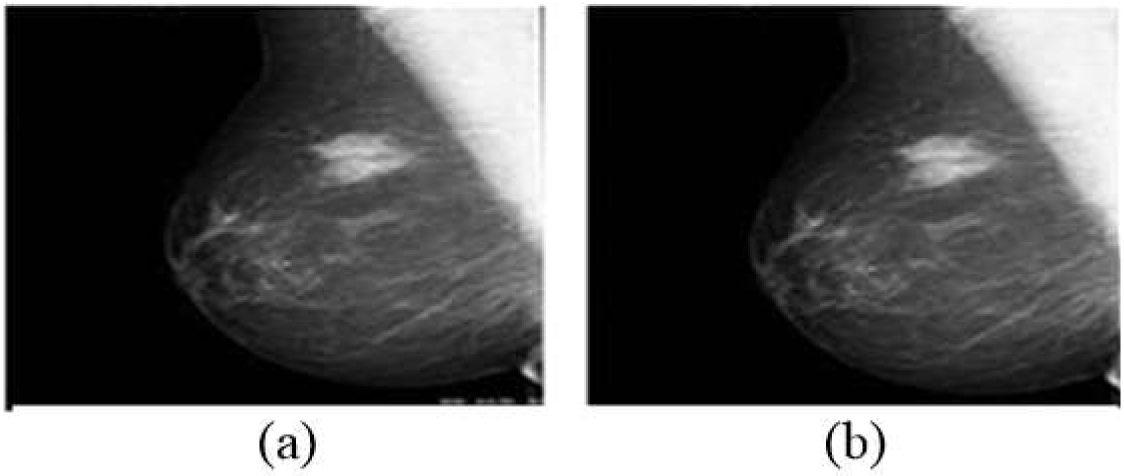


Figure 4.6: Grayscale conversion: (a) RGB image, (b) Grayscale image

4.4.2 Median filtering

Filtering is always used in medical image applications for de-noising and smoothing purposes. Different types of filters can be used depending on the application and type of noise needed to be reduced (Gonzales and Woods, 2006). In this work, a median filter is used to remove salt-and-pepper noise, in addition, to preserve the useful features while smoothing the image edges. The median filter is good as it has a good noise suppressing power, as well as a good computational efficiency. It is a non-linear filter in which the value of the processed pixel is obtained by calculating the median of a window of pixels that surrounds the processed pixel (Wang and Zhang, 1999). Under this median operation, this filter becomes more applicable for suppressing noise and deleting the fine details in the input image. The median filter is less sensitive than the mean to extreme values, and these extreme values are more effectively removed. The median filter helps in rejecting certain types of noise, in particular, “shot” or impulse noise in which some individual pixels have extreme values.

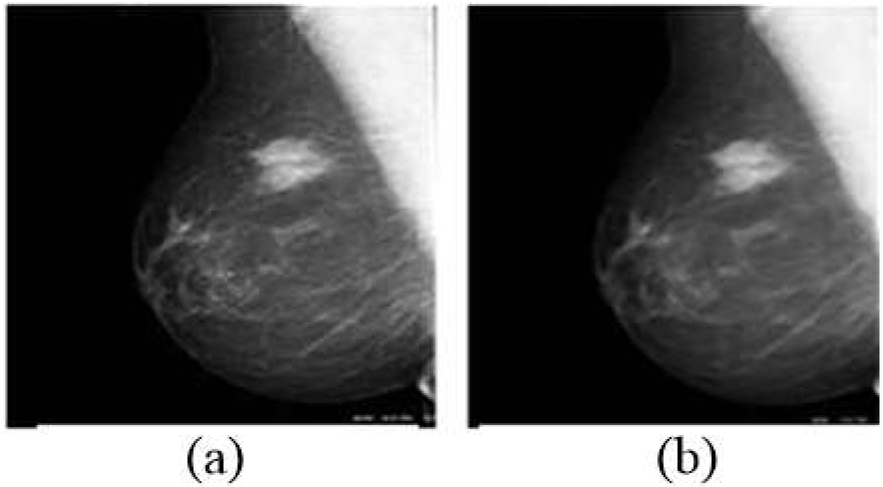


Figure 4.7: Image filtering: (a) Grayscale image, (b) Filtered image

4.4.3 Image adjusting

Here, the intensities of the input image's pixels are mapped into a new range of intensities (Wang and Zhang, 1999). This is implemented by setting the low and high input intensity values that should be mapped in addition to the scale over which they should be mapped (Fig. 4.8).

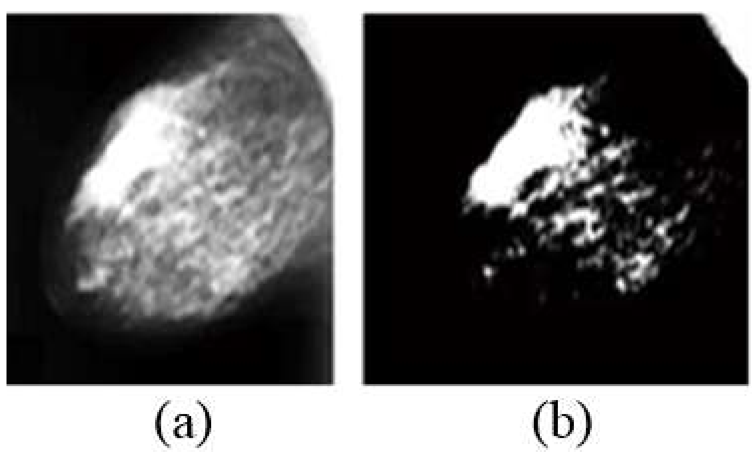


Figure 4.8: Image adjusting: (a) original image, (b) adjusted image

4.4.4 Thresholding

This technique provides the division of the image in the foreground and background regions based on the different intensities and intensity discontinuities of the image (Boujelben et al., 2012; Mokri et al., 2012). This technique reads a grayscale or colour image as an input and outputs a binary image i.e. the threshold image. The black pixels in the output image showing the background and white pixels refer to the foreground. The segmentation is achieved by a single parameter known as the intensity threshold. The selection of this threshold value was achieved using the Otsu's thresholding method, which relies on the grey level distribution in the histogram of the image in order to select a threshold value (Figure 4.9). Hence, the threshold was selected as 0.42 which provides a good separation of a tumour and other areas. Pixels of intensity values higher than the selected threshold value are considered as foreground pixel (white). Pixels of intensities value lower than the threshold value are considered as background pixels (black).

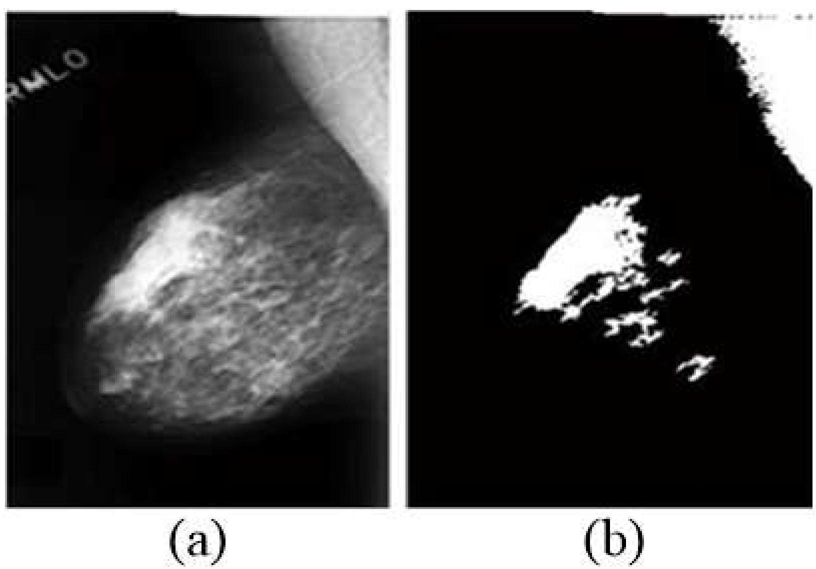


Figure 4.9: Thresholding: (a) Original image, (b) Tresholded image

4.4.5 Morphological techniques

These procedures can be characterized as an arrangement of operations that analyse the images based on their shapes (Mokri et al., 2012). These operations are connected by choosing a structuring element for an input image, bringing about a yield image of a similar size. The structure element is a matrix consisting of 0's and 1's, in which the 1's are called the neighbours. The values of every pixel in the yield image are set by a correlation of the relating pixel in the input image with its neighbours. Structure element has many shapes. Here, the "disk" structure element with a "range" of 15 is utilized. The most widely recognized morphological operations are dilation and erosion. The last is utilized to shrivel the objects in a binary image. After erosion, the primary pixels that remain are those that fit largely with the structuring elements. Figure 4.10 shows the result of erosion of an image with a "disk" structure element of "radius" 15.

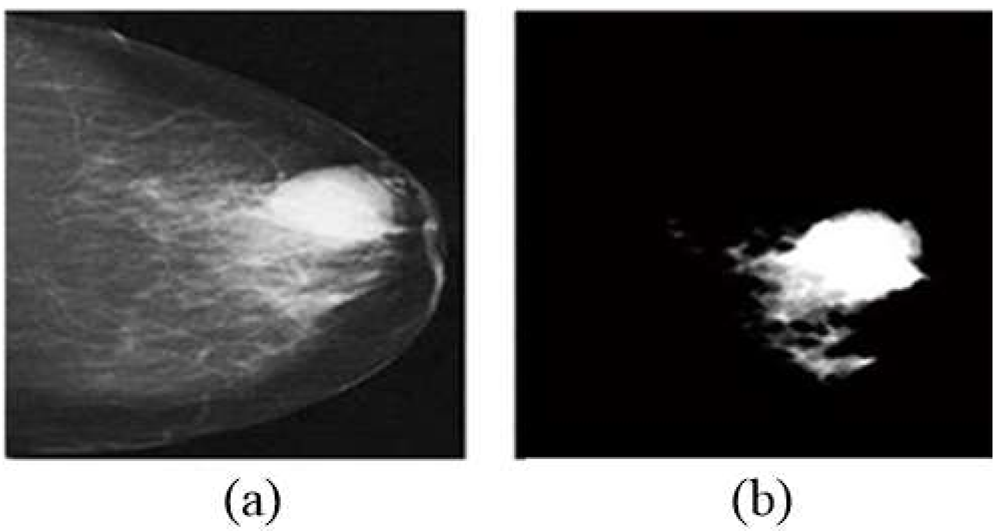


Figure 4.10: Image Erosion: (a) original image, (b) Eroded image

4.4.6 Features extraction

In this phase, the texture and shape features of the image are extracted in order to discriminate the malignancy of the breast tumours. Since the two distinct classes (benign and malignant tumours) vary in intensities and shapes, those two sorts of features ought to be extricated from the segmented region of interest (ROI) with the end goal of acquiring precise classification results. A GLCM is first created from the segmented ROI; which is a grey level co-occurrence matrix that describes the composition of an image by calculating how frequently a pair of pixels with particular qualities and in a tagged spatial relationship occurs (Honeycutt and Plotnick, 2008). The texture features are then extracted from the GLCM; nonetheless, the shape elements are extricated specifically from the segmented tumour (Haralick, 1973).

Table 4.1 depicts the list of features extracted from the images.

Table 4.1: Extracted Texture and Shape Features

Features	Feature number
Roundness	1
Uniformity	2
Asymmetry	3
Compactness	4
Entropy	5
Standard deviation	6
Mean	7

4.4.6.1 Texture features

Recently, the texture features of the segmented area have been utilized broadly by numerous scientists as a part of the field of advanced mammography (Honeycutt and Plotnick, 2008). These features can be derived specifically from the pixels estimations of the segmented ROI as indicated by a particular recipe for each feature, or can be computed by implication as well as a histogram of the segmented ROI. The following are the formulas of the features extracted from the segmented ROI of the two image classes (Clausi and Zhao, 2002): benign and malignant breast tumours.

- Mean (average): it is the average intensity of the image. Concerning mammograms, a denser tissue has a higher average of intensity.

$$\mu = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i,j) \tag{9}$$

where p(i,j) represents the pixel's value at the point (i,j), in an ROI of size M×N.

- Standard deviation: it can be defined as a measure of the average contrast, according to the irregularity of the texture.

$$\sigma = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (p(i,j) - \mu)^2} \tag{10}$$

where p(i,j) is the pixel's value at the specific point (i,j), and in a ROI of size M×N. μ is the average intensity.

- Entropy: it is defined as a disorder. In the case of texture analysis, it is a measure of spatial disorder or randomness in image.

$$h = -\sum_{k=0}^{L-1} \mathrm{Pr}_k (\log_2 \mathrm{Pr}_k) \tag{11}$$

where P_{rk} represents the probability of the k-th grey level, and L is the total number of the available grey levels in a ROI of size M×N.

- Uniformity: it is denoted as U and it is a texture measure based on the histogram of the segmented ROI.

$$U = \sum_{k=0}^{L-1} \mathrm{Pr}_k^2 \tag{12}$$

where P_{rk} represents the probability of the k-th grey level. Since the P_{rk} values are ranged from (0 to 1) and their sum equals 1, U is maximum when the numbers of pixels in all grey levels are equal, resulting in all the grey levels to be equal probable and their distribution to be uniform and decreases otherwise.

4.4.6.2 Shape features

The shape has a vital role in distinguishing the two different classes of breast tumour. The benign breast tumour is usually a circular and symmetric shape. However, the malignant breast tumour has a random and asymmetric shape (Clausi and Zhao, 2002).

- Roundness: it is the graylevel variation in a graylevel co-occurrence matrix.

$$R = \frac{4A\pi}{P^2} \tag{13}$$

where A is the area of the segmented region of interest and P is its perimeter. If the Roundness is greater than 0.90 then, the object is circular in shape.

- Asymmetry: it is used to evaluate whether the intensity levels tend to the dark side or light around the mean.

$$A = \sqrt{(x_{ij} - \mu)^2 \, p(x_{ij})} \tag{14}$$

where x_{ij} is pixel value at the point *(i,j),* and μ is the mean. The $p(x_{ij})$ is the probability of occurrence of that pixel value.

- Shape or Compactness: Since the shape of the segmented ROI is one of the important features that distinguish the benign and malignant tumours, shape features are extracted from each ROI prior to classification.

$$C = \frac{P^2}{4\pi A} \quad (15)$$

where P is the perimeter, A is the area of the segmented ROI in pixels. The 4π factor is added to the denominator such that the compactness of a complete circle is 1.

4.5 Design of Fuzzy Neural Network for Breast Cancer Classification

4.5.1 Proposed FNN

In this thesis, we proposed a fuzzy neural network for the classification of breast cancer using extracted shape and texture features of the breast tumour. Fuzzy logic proposed by L. A. Zadeh (Zadeh, 1996) resembles human reasoning process. They are widely used to solve different problems, such as control, classification, prediction, identification etc. Fuzzy logic is an easy and convenient approach for mapping an input space to an output space. This is done by the if-then rules that have an antecedent and consequent parts. The antecedent part includes input variables. The consequent part includes output variables of the system. Mapping inputs to their corresponding outputs is a basic function of pattern recognition system where the inputs can be the patterns and outputs are the classes. In a fuzzy rule base, the values of variables are basically described by fuzzy values or linguistic terms. Each fuzzy value is characterised by a membership function. Membership functions allow us to quantify linguistic term. The design of fuzzy system includes the precise construction of antecedent and consequent parts of the rules.

One of the effective technologies for construction of the if-then rules is the use of neural networks. The NNs have such characteristic as self-learning and generalisation abilities, nonlinear mapping, the parallelism of computation and vitality. The self-learning characteristics allow the increase of the accuracy of the neural networks based model. Fuzzy logic allows to reduce the complexity of the data and to handle uncertainty and imprecision. The combination of fuzzy logic and neural networks allows us to design a system with fast learning capability that can describe nonlinear systems characterized with uncertainties. Here, these two methodologies are combined to construct fuzzy neural networks and solve pattern classification problem

The previously considered neuro-fuzzy systems in the literature are mainly designed for special cases and most of them use neuro-fuzzy system based on multi-input single-output structure. These systems are based on Mamdani type of rues (Mamdani and Assilian, 1997). Sometimes the considered problems have multiple inputs and multiple outputs. Because ANFIS has multi-input single output structure, the solution of such kind of problems become difficult. In this thesis, multi-input multi-output fuzzy neural structure based on Takagi-Sugeno-Kang (TSK) type rule is proposed for the classification of breast tumours and for the improvement of recognition rate of the system (Takagi and Sugeno, 1985).

The extracted shape and texture features are inputs of the FNN based classifier. The classifier based on the above features classifies the images into the benign or malignant tumour. The fuzzy neural networks (FNN) realize the fuzzy reasoning process through the structure of neural networks. The design of FNN includes the generation of the proper rule base that has IF-THEN form. Here, it is necessary to determine the accurate definition of the premise and consequent part of fuzzy IF-THEN rules for the classification system through the training capability of the neural network (Jang et al., 1997; Abiyev and Abizade, 2016). This is obtained through evaluation of the error response of the designed classification system. Mamdani (Mamdani and Assilian, 1997) and Takagi-Sugeno-Kanag (TSK) (Takagi and Sugeno, 1985) type fuzzy rules are basically used for designing the fuzzy systems. In the thesis the second type- TSK fuzzy rules are used for system design. TSK fuzzy rules include fuzzy antecedent and crisp consequent parts. These fuzzy systems based on TSK rules approximate nonlinear systems with linear ones and have the following form.

If x_1 is A_{1j} and x_2 is A_{2j} and … and x_m is A_{mj} Then $y_j = b_j + \sum_{i=1}^{m} a_{ij} x_i$ (16)

Here, x_i and y_j are input and output signals of the system respectively, $i=1,...,m$ is the number of input signals, $j=1...r$ is number of rules. A_{ij} are input fuzzy sets, b_j and a_{ij} are coefficients.

The structure of fuzzy neural networks used for classification of breast cancer images is based on TSK type fuzzy rules and is given in Figure 4.11. The FNN includes six layers. In the first layer, the x_i *(i=1,…,m)* input signals are distributed. The second layer includes membership functions that describe the linguistic terms. Here, for each input signal entering the system, the membership degree to which input value belongs to a fuzzy set is calculated. In the thesis, the Gaussian membership function is used to describe linguistic terms (Abiyev and Kaynak, 2008; Abiyev, 2011; Abiyev, 2011).

$$\mu 1_j(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}}, \quad i=1..m, \; j=1..r \qquad (17)$$

where *m* is a number of input signals, *r* is a number of fuzzy rules (hidden neurons in the third layer). c_{ij} and σ_{ij} are centre and width of the Gaussian membership functions respectively. $\mu 1_j(x_i)$ is membership function of *i*-th input variable for *j*-th term (Abiyev, 2011).

The third layer is a rule layer. Here, number of nodes is equal to the number of rules. Here, $R_1, R_2, \ldots, R_r$ represents the rules. The output signals of this layer are calculated using t-norm min (AND) operation.

$$\mu_j(x) = \prod_i \mu 1_j(x_i), \quad i=1,..,m, \; j=1,\ldots,r \qquad (18)$$

where Π is the min operation.

These $\mu_j(x)$ signals are input signals for the fifth layer. Fourth layer is a consequent layer. It includes n linear systems. Here, the values of rules output are determined.

$$y1_j = b_j + \sum_{i=1}^{m} a_{ij} x_i \qquad (19)$$

In the fifth layer, the output signals of the third layer are multiplied by the output signals of the fourth layer. The output of j-th node is calculated as

$$y_j = \mu_j(x)y1_j \tag{20}$$

In the sixth layer, the output signals of FNN are determined as

$$u_k = \frac{\sum_{j=1}^{r} w_{jk} y_j}{\sum_{j=1}^{r} \mu_j(x)} \tag{21}$$

Here, u_k are the output signals of FNN, ($k=1,..,n$). After calculating the output signal, the training of the parameters of the network starts.

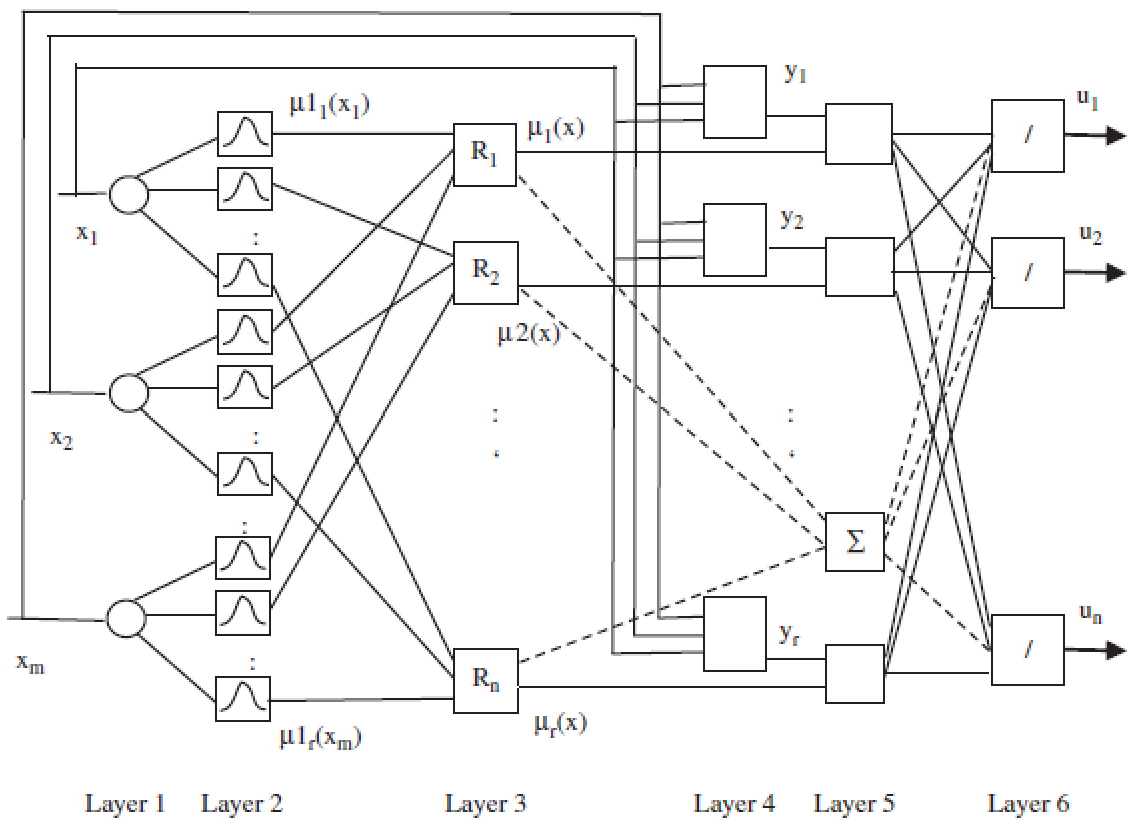


Figure 4.11: FNN based identifier structure

4.5.2 Parameter learning

Initially, the parameters of the FNN are generated randomly. These parameters are the membership functions of the fuzzy rules in the second layer of Fig. 6 and the parameters of the linear functions of in fourth and fifth layers. To design FNN model, the training of the parameters of the membership functions $c_{ij}(t)$ and $\sigma_{ij}(t)$ (i=1,..,m, j=1,..,r) in the premise part and parameter values of the $w_{jk}(t)$, $a_{ij}(t)$, $b_j(t)$ (i=1,..,m, j=1,..,r, k=1,..,n) in consequent part is carried out. In the thesis, fuzzy clustering and gradient algorithms are applied for the update of the parameters of FNN (Abiyev et al., 2016). Fuzzy c-means clustering is applied to find parameters of the antecedent part that is parameters of the membership functions. After clustering, the training of parameters is performed using gradient descent learning algorithm with adaptive learning rate. The use of adaptive learning rate speeds up the learning and guarantees the convergence. In addition, the momentum is used to speed-up the learning processes additionally.

During learning on the output of the network, the value of error cost function is calculated.

$$E = \frac{1}{2}\sum_{k=1}^{n}(u_k^d - u_k)^2 \tag{22}$$

Here, n is the number of output signals of the network, u_k^d and u_k are desired and current output values of the network (k=1,..,n) respectively. The parameters w_{jk}, a_{ij}, b_j, (i=1,..,m, j=1,..,r, k=1,..,n) of network and parameters of membership function c_{ij} and σ_{ij} (i=1,..,m, j=1,..,r) of FNN structure are adjusted using the following formulas.

$$w_{jk}(t+1) = w_{jk}(t) - \gamma \frac{\partial E}{\partial w_{jk}} + \lambda(w_{jk}(t) - w_{jk}(t-1));$$
$$a_{ij}(t+1) = a_{ij}(t) - \gamma \frac{\partial E}{\partial a_{ij}} + \lambda(a_{ij}(t) - a_{ij}(t-1));$$
$$b_j(t+1) = b_j(t) - \gamma \frac{\partial E}{\partial b_j} + \lambda(b_j(t) - b_j(t-1));$$
$$c_{ij}(t+1) = c_{ij}(t) - \gamma \frac{\partial E}{\partial c_{ij}} + \lambda(c_{ij}(t) - c_{ij}(t-1));$$
$$\sigma_{ij}(t+1) = \sigma_{ij}(t) - \gamma \frac{\partial E}{\partial \sigma_{ij}} + \lambda(\sigma_{ij}(t) - \sigma_{ij}(t-1));$$
$$i = 1,..,m;\ j = 1,..,r; k = 1,..,n. \tag{23}$$

Here, m is the number of input signals (input neurons) and r is the number of fuzzy rules (hidden neurons), γ is the learning rate, λ is the momentum,

The derivatives in (16) are computed as

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial u_k}\frac{\partial u_k}{\partial w_{jk}} = (u_k(t) - u_k^d(t)) \cdot y1_j \Big/ \sum_{j=1}^{n} \mu_j ,$$
$$\frac{\partial E}{\partial a_{ij}} = \frac{\partial E}{\partial u_k}\frac{\partial u_k}{\partial y1_j}\frac{\partial y1_j}{\partial y_j}\frac{\partial y_j}{\partial a_{ij}} =$$
$$\sum_k (u_k(t) - u_k^d(t)) \cdot w_{kj}\mu_j x_i \Big/ \sum_{j=1}^{n} \mu_j ,$$
$$\frac{\partial E}{\partial b_j} = \frac{\partial E}{\partial u_k}\frac{\partial u_k}{\partial y1_j}\frac{\partial y1_j}{\partial y_j}\frac{\partial y_j}{\partial b_j} =$$
$$\sum_k (u_k(t) - u_k^d(t)) \cdot w_{kj}\mu_j \Big/ \sum_{j=1}^{n} \mu_j \ . \tag{24}$$

In (16) the derivatives are determined as

$$\frac{\partial E}{\partial c_{ij}} = \sum_k \frac{\partial \mathrm{E}}{\partial u_k} \frac{\partial u_k}{\partial \mu_j} \frac{\partial \mu_j}{\partial c_{ij}} \tag{25}$$

$$\frac{\partial E}{\partial \sigma_{ij}} = \sum_k \frac{\partial \mathrm{E}}{\partial u_k} \frac{\partial u_k}{\partial \mu_j} \frac{\partial \mu_j}{\partial \sigma_{ij}} \tag{26}$$

Here, i=1,..,m, j=1,..,r, k=1,..,n.

$$\frac{\partial E}{\partial u_k} = u_k(t) - u_k^d(t); \quad \frac{\partial u_k}{\partial \mu_j} = \frac{y_j - u_k}{\sum_{j=1}^{n} \mu_j}; \tag{27}$$

$$\frac{\partial \mu_j(x_i)}{\partial c_{ij}} = \mu_j(x_i)\frac{2(x_i - c_{ij})}{\sigma_{ij}^2};$$

$$\frac{\partial \mu_j(x_i)}{\partial \sigma_{ij}} = \mu_j(x_i)\frac{2(x_i - c_{ij})^2}{\sigma_{ij}^3} \tag{28}$$

Using equations (21-25), the derivatives in (20) are calculated and the correction of the parameters of FNN is carried out.

CHAPTER 5
SIMULATION

5.1 Simulation

The x-ray images of the breast tumours are used in this breast cancer image identification system. Hence, images are collected from the Digital Database for Screening Mammography (DDSM); a public breast image database available on the internet (Heath et al., 2001). The breast cancer images are used for the purpose of training and testing the designed FNN system. The images are of size 221*358 pixels. Table 5.1 shows the dataset description. In data pre-processing phase, these images are processed and rescaled to 250*250 pixels for fast and easy computing. The processed breast cancer images undergo the feature extraction in which the texture and shape features are extracted. These features are used for distinguishing the type of breast tumours, whether it is related to benign or malignant clusters. This is achieved by training the FNN system. This FNN system is fed by those features extracted from the images. The outputs of the FNN system are clusters related to malignant and benign tumours (Figure 5.1).

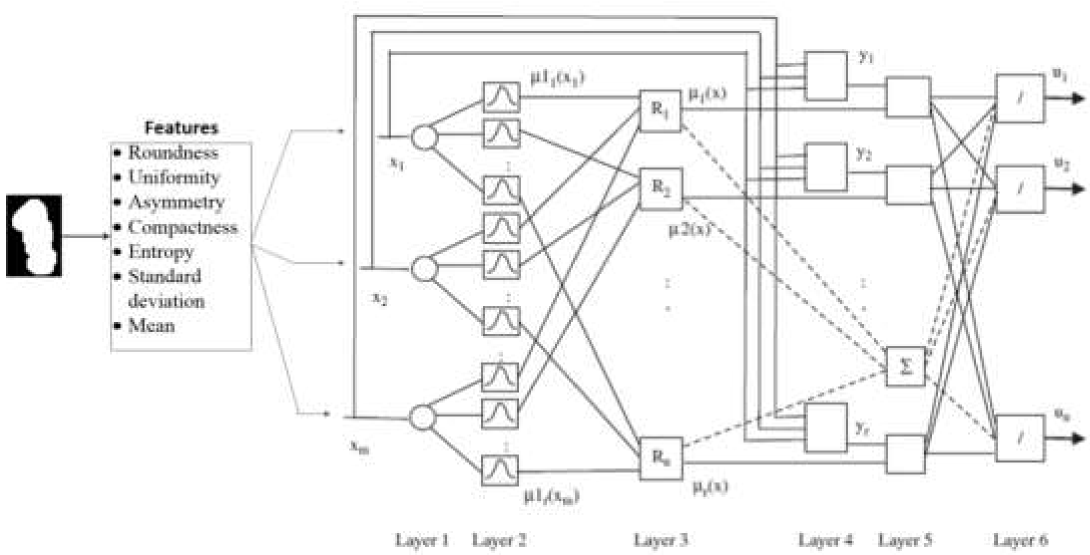


Figure 5.1: FNN designed for breast cancer classification

The structure of the FNN classification model is designed using 7 input- and 2 output neurons. If we use traditional neuro-fuzzy structure (for 7 inputs and 2 cluster centres, 2^7=128 rules should be generated. Here, using all possible combinations of inputs and cluster centres, the rules should be designed. Then the large number of rules will be designed. In contrast to these researches, in the thesis, the number of rules is selected according to the clustering results, equal to cluster centres.

Table 5.1: Dataset description

Data	Total number of images	Training	Testing
Number of images	400	200	200

5.2 FNN Training

At first the FNN based classifier shown in Figure 6.1 is trained using backpropagation algorithm and then is used for the classification of the breast images. The training of the network is implemented using 10 fold cross validation. In this approach, the original data set is randomly partitioned into 10 equal sized subsamples. Here, one subsample is retained as the validation data and used for testing the FNN model and the remaining 9 subsamples are used for training the model. During training, each of the 10 subsamples is used exactly once as the validation data. Therefore the cross-validation process is then repeated 10 times. All the 10 results from the folds are averaged in order to estimate the learning iteration.

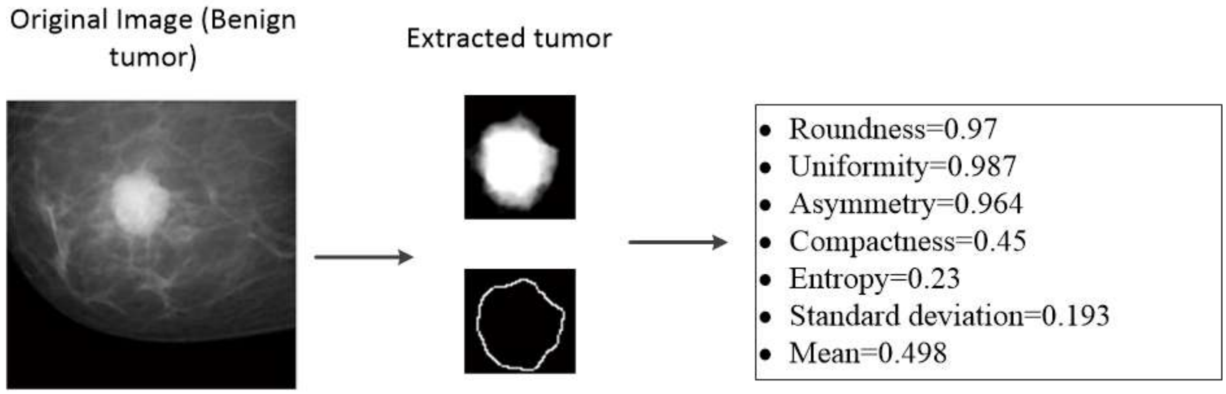
The number of inputs is seven and the number of outputs is two: one represents the benign tumour and one for the malignant cancer. During simulation different numbers of rules are used. The number of rules guarantees significant training while keeping the time expense to a minimum. After processing, the maximum and minimum values of each used feature for both classes are calculated and shown in Table 5.2.

Figure 5.2 shows the feature values of two example images of benign and malignant tumours.

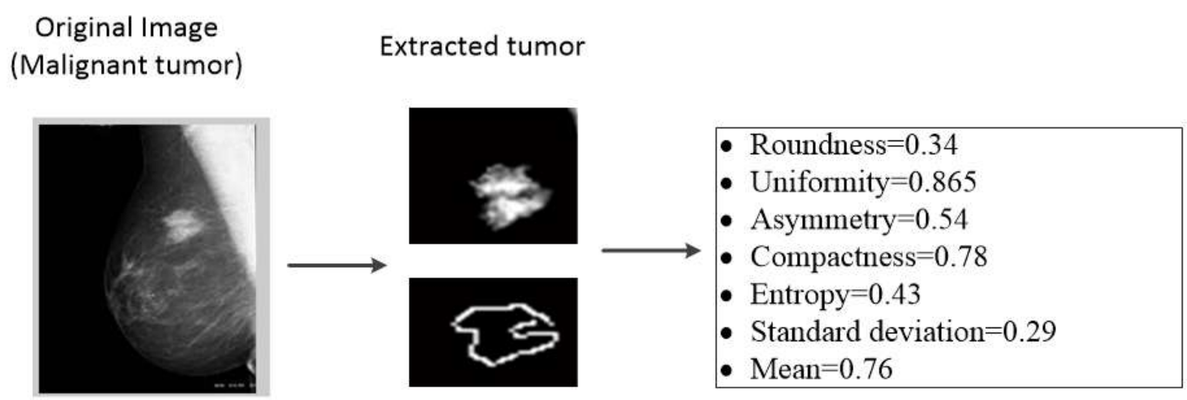
Table 5.2: Intervals of ROI extracted feature

Extracted features	**Benign**	**Malignant**
Roundness	0.85-0.99	0.25-0.84
Uniformity	0.98-1	0.81-0.89
Asymmetry	0.90-0.99	0.2-0.89
Compactness	0.2-0.7	0.72-1
Entropy	0.0503-0.304	0.347-0.593
Standard deviation	0.040565-0.238626	0.232185-0.439165
Mean	0.46-0.54	0.556-9

During this learning stage, initial arbitrary values of weights are randomly initialized to values between 0 and 1. The learning rate and the momentum rate were set through different investigations keeping in mind the end goal; to attain the required minimum error value. Therefore, the learning rate and the momentum coefficient are set as 0.01 and 0.65 correspondingly. A minimum error is taken as 0.001. The training of the FNN based classifier is performed using gradient descent learning algorithm.



(a) Benign Tumor features values



(b) Malignant Tumor features values

Figure 5.2: Features values of benign and malignant tumors

200 breast cancer images obtained from the DDSM are used for training the FNN system. Among them, 100 images are benign tumour and 100 are malignant tumour (cancerous). The training is continued for 5000 epochs. The 10 fold cross validation is used here. Figure 5.3 shows the plot of RMSE values. It is seen that the system learned well as the error seemed to decrease after each epoch. The network has reached an RMSE error of 0.22837, which is good enough for this phase. Moreover, it should be noted that the time taken for the FNN system to learn and achieve the minimum square error is 20 seconds as seen in table 5.3.

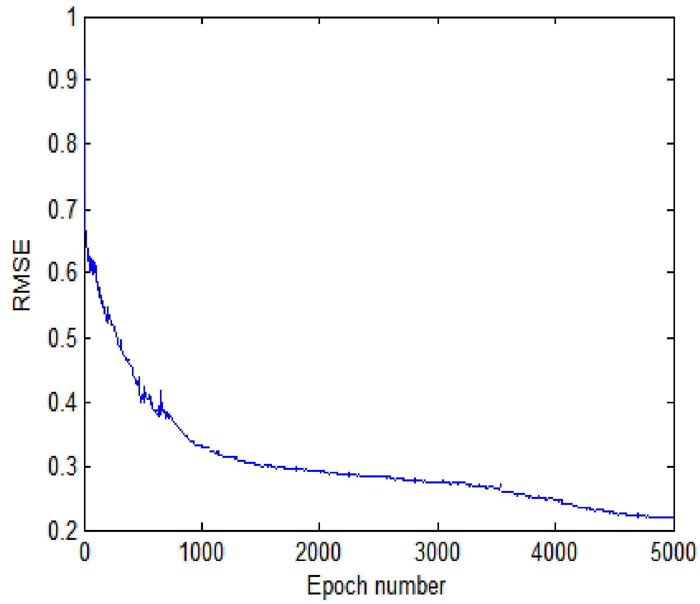


Figure 5.3: Learning curve of FNN

Table 5.3: FNN Computation cost and accuracy

Model	Training time	Maximum Iterations	Error reached	Training accuracy
FNN	20 secs	5000	0.22837	100%

5.3 FNN Performance Evaluation

The FNN system was tested on a dataset of 200 mammograms; 100 for benign, and 100 for malignant tumours. The simulation has been done using a different number of rules as shown in Table 5.4. The second and third columns of the table show the value of errors obtained for training and evaluation data sets. The fourth column of the table contains the values of errors obtained when test data are used. The fifth column represents the percentage of images that were accurately recognized by the fuzzy neural networks during testing.

Table 5.4: Simulation Results

Number of Rules	Training error	Evaluation error	Test error	Accuracy
16	0.366811	0.438844	0.428461	84.5
28	0.287870	0.389205	0.401062	91.0
36	0.228371	0.280195	0.269012	97.5

Table 5.5 represents the total classification rate of the designed breast cancer identification system. Note that the identification rate shows the capability of the trained network to generalize, i.e., to identify or classify the correct diagnosis while tested with unseen data. This classification rate is defined as the total number of correctly classified images of the two classes divided by the total number of images. The table shows the FNN system's training and testing classification rate of each set and class of data.

Table 5.5: Breast cancer identification results

Breast image types	Number of images	Identification rate	
Benign tumour	100	95/100	94%
Malignant tumour	100	100/100	100%
Total identification rate	200	195/200	97.5.%

The experimental results of the developed breast cancer identification system show that the accuracy of the system seems to change proportionally to the change of rules. Thus, an accuracy of 84.5% was obtained where 16 rules are used. In addition, the training, validation, and testing errors were quite high. It is observed that this accuracy starts to increase and errors start to decrease when more rules are used (28 and 36). Hence, using 36 rules results in a high accuracy of 97.5% and low minimum error during training, validation, and testing.

Overall, it can be concluded that the FNN system successfully classified the two classes consistently with the clinical data or images. The FNN system was capable of achieving a better performance in identifying the correct diagnosis of the unknown images.

5.4 Results of Comparison of FNN and Backpropagation Neural Network for Breast Cancer Classification

In a previous study, we proposed a simple backprpagatiuon neural network for the classification of breast cancer in mammograms as seen in Figure 5.4. The network was trained using gradient descent and same database was used for training and testing this network. Similarly, same shape and texture features are extracted from the processed mammograms and used in that study.

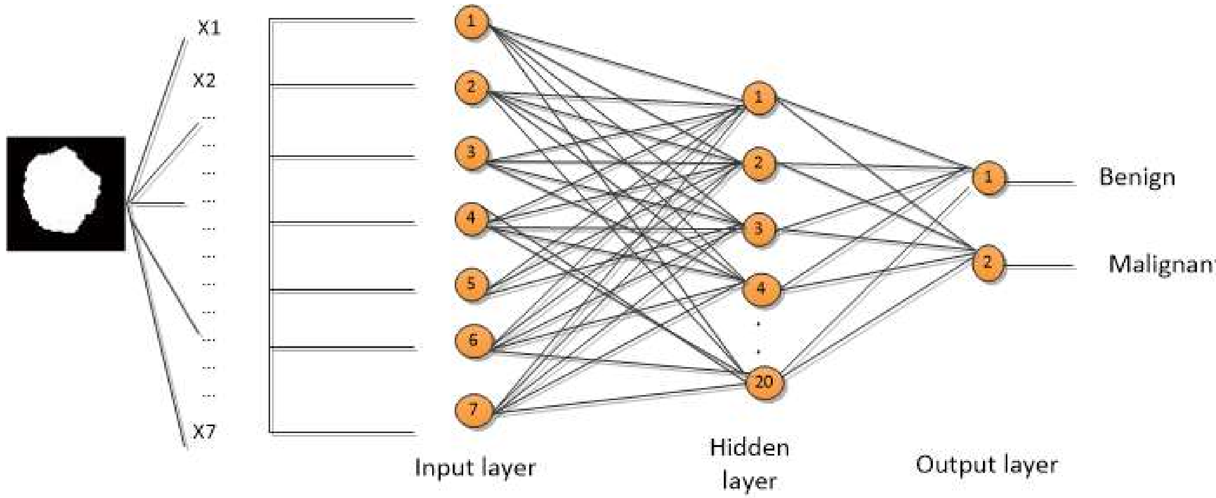


Figure 5.4: Learning curve of FNN

Table 5.6 shows the training parameters of the BPNN that was trained on 400 breast images with benign and malignant tumours.

Table 5.6: BPNN learning parameters

Parameters	Value
Number of neurons in input layer	7
Number of neurons in output layer	2
Number of neurons in hidden layer	20
Iteration number	5000
Learning rate	0.001
Momentum rate	0.5
Error	0.001

Training time (sec)	300
Activation Function	Sigmoid

Figure 5.5 shows the learning curve of the BPNN.

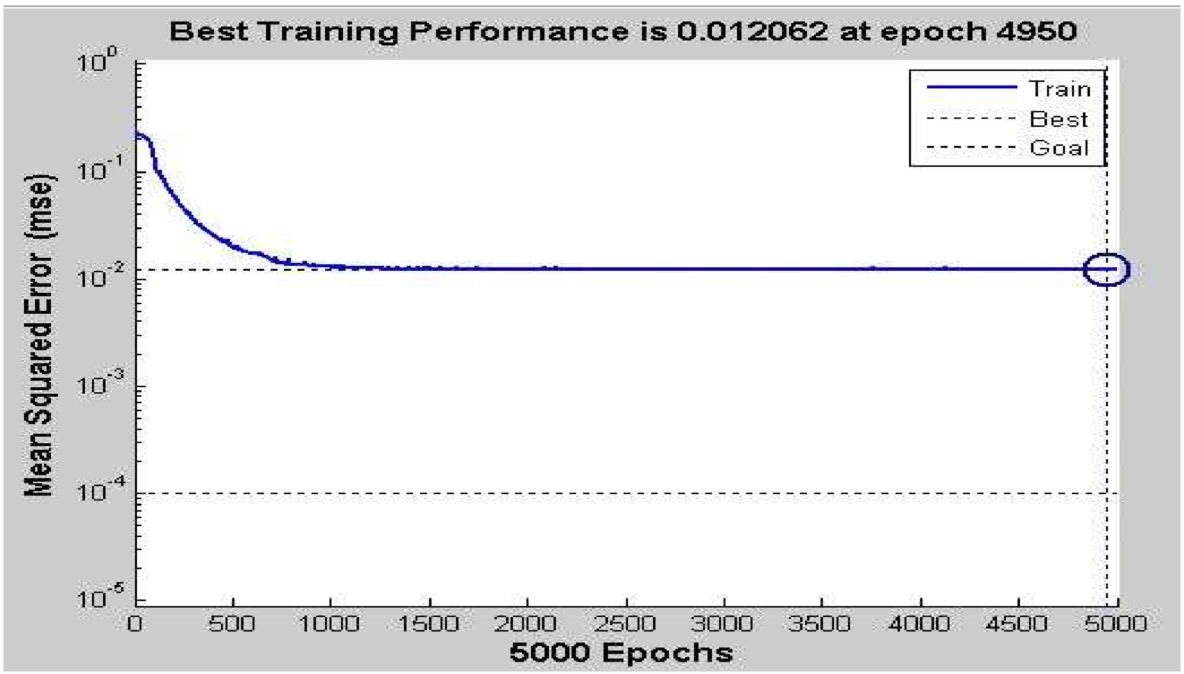


Figure 5.5: BPNN learning curve

As seen in Figure 5.4 the backpropagation neural network that was trained to classify the breast tumor images was capable of achieving a mean square error of 0.01206 at epoch 4950. It is important to mention that this error was reached in only 300 seconds.

On the other hand, table 5.7 shows a comparison of the FNN and BPNN performances in terms of accuracy, error reached, training time and number of maximum iterations required for the models to converge. It can be seen that the FNN achieved a better generalization capability where it achieved an accuracy of 97.5% which is higher than that achieved by BPNN (92%).

Table 5.7: Comparison of FNN and BPNN in breast cancer classification

Breast image types	Number of images	Identification rate	Iterations	Error reached (MSE)	Training time (secs)
BPNN	600	92%	4950	0.0120	300
FNN	400	97.5%	5000	0.2283	20

A comparison of the developed networks employed in this work with some earlier works is shown in Table 5.8. Firstly, it is seen that the employed pre-trained CNNs achieved high recognition rates compared to other deep networks and Fuzzy neural networks, which is obviously due to their powerful efficiency in learning the important features from input images through its rules. The fuzzy neural networks (FNN) employed within this work achieved higher accuracies than other earlier work that used a convolutional neural network (CNN), which was built from scratch (Nawaz et al., 2018). Furthermore, it is important to note that the networks gained a better generalization capability compared to those other fuzzy and nearest neighbors equality based networks used for breast cancer classification such as K-nearest neighbor (KNN) (Aroquiaraj and Thangavel, 2014), fuzzy K-nearest neighbor (F-KNN) (Aroquiaraj and Thangavel, 2014),, and fuzzy K-nearest neighbor equality (F-KNNE) (Aroquiaraj and Thangavel, 2014), although some of these networks and algorithms were trained on a larger number of images.

Note that some works haven't provided explicitly achieved errors and number of data used for train and test are considered for comparison. Hence, the comparison was carried out in terms of accuracy and the dataset used. Our results can show that applying Fuzzy neural networks to the problem of breast cancer diseases classification is promising, in a way that similar or confusing diseases can be recognized and correctly classified with good recognition rates.

Table 5.8: Comparison with earlier works

	Method used	Dataset used	Accuracy
(Nawaz et al., 2018)	CNN	DDSM (Heath et al., 2001)	94%
(Aroquiaraj and Thangavel, 2014)	KNN	DDSM (Heath et al., 2001)	91.25%
(Aroquiaraj and Thangavel, 2014)	F-KNN	DDSM (Heath et al., 2001)	93.4%
(Aroquiaraj and Thangavel, 2014)	F-KNNE	DDSM (Heath et al., 2001)	96.5%
Our Method	BPNN	DDSM (Heath et al., 2001)	92%
Our Method	FNN	DDSM (Heath et al., 2001)	97.5%

CHAPTER 6

CONCLUSIONS

The design of the fuzzy neural networks for breast cancer identification system is presented. The motivation behind this work is the deficiency of using Fuzzy neural system in medical image processing and intelligent based researches especially breast cancer identification. The state of the art of breast cancer identification using sofcomputing techniques has been presented. The image processing techniques are used for the acquisition of the image features that is for the segmentation of the tumour area and then obtaining its important features. Seven features that represent the texture and shape characteristics of the tumour are extracted. In the second stage, these features are fed into FNN based classifier. The network is trained using gradient descent learning algorithm. The training process is implemented using 10 fold cross validation. After convergence, the fuzzy neural network is used for classifying the breast images “mammograms” in order to distinguish the benign and malignant breast tumours. In the testing stage, the recognition rate was obtained as 97.5%. In conclusion, it was observed that using more rules results in obtaining better accuracy of the system in accurately classifying unseen images. Furthermore, it wa1s found that the classification of breast tumour using the extracted texture and shape features has a great effect in increasing the generalization capability of the fuzzy-neural system.

The seven selected shape and texture features showed good results in distinguishing the malignancy of the tumour. However, for future suggestions, more features can be used to accurately define the type of breast tumour that helps the FNN to achieve a better generalization capability when tested on unseen images.

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APPENDICES

APPENDIX 1

BPNN SOURCE CODE

- **Image processing**

```
Close all
clear;
clc;
N=300;
saveData=zeros(7,300);
for k = 1:N
myFolder = 'D:\N.breast';
if ~isdir(myFolder)
errorMessage = sprintf('Error: The following folder does not exist:\n%s',
myFolder);
uiwait(warndlg(errorMessage));
return;
end
filePattern = fullfile(myFolder, '*.gif');
jpegFiles = dir(filePattern);
baseFileName = jpegFiles(k).name;
fullFileName = fullfile(myFolder, baseFileName)
fprintf(1, 'Now reading %s\n', fullFileName);
[I xmap] = imread('bebreast25.gif');
```

```
[I xmap] = imread(fullFileName);
f = ind2gray(I,xmap);
imshow(f); % Display image.
drawnow; % Force display to update immediately.
% Filteringgguding different filters******************
%%%%% average filter*************************
i= fspecial('average',[3 3]);
a=imfilter(f,i);
figure, imshow(a), title('average filtered image');
%pause
%****************************************************
%%%%% Median filter*************************
m=medfilt2(a);
figure, imshow(m), title('median filtered image'); %%% using median
filtering
%pause
%%%%% adjust filter*************************
im=imadjust(f,[0 1], [1 0]); %% image adjustement, gamma =1, by
default....get the negative image
figure, imshow(im), title('adjusted image');
51
%pause
g2=imadjust(f,[0.5 0.75], [1 1]); %% image adjustement, gamma =1, by
```

```
default..convert the intensities btw 0.5 and 0.75 to values btw 0 and 1.
% g3=im2uint8(mat2gray(log(1+double(f)))); %%%%%logarithmic intensity
transformations
figure, imshow(g2), title('adjusted image #2');
%figure, imhist(f)
%pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% treshold the image
level = graythresh(g2);
bw = im2bw(g2,level);
bw = bwareaopen(bw, 50);
figure, imshow(bw),title('treshold image');
%pause
% Canny
S5 = edge(bw, 'canny',0.3);
imshow(S5);title('Canny Edge Dectection [auto]');
size(S5);
%pause
ds = bwareaopen(S5,40); %# Remove small edge objects
imshow(ds); title('ds'); %# Plot the remaining edges
%pause
%%%%Morphology technique, image erosion to erase the unwanted components
se = strel('disk',5);
```

```
I4 = imerode(g2,se);

I5 = imopen(I4,se);

imshow(I4),title('eroded image [auto]');

%pause

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%ROI exxtraction

props = regionprops(I4);

[~,ind] = max([props.Area]);

imshow(I4 == ind);

pause

% %%%%%%%%%%%%%Features Detection....GLCM

[glcm] = graycomatrix(I4);

%stats = graycoprops(glcm,{'contrast','homogeneity','correlation','Energy'});

%%%%%Entropy

E = entropy(glcm);

%%%%%%%Standard Deviation

std = std2(glcm);

%%%%%%%Mean

mean = mean2(glcm);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

props = regionprops(I4, 'Area', 'Perimeter');

areas = [props.Area];

perims = [props.Perimeter];

Assym = [props.sym]
```

```
% computer circularities, and plot against areas
circularities = 4 * pi * areas ./ perims .^ 2; % Dongsheng's formula
plot(areas, circularities, 'ro')
52
%%%
Roundness = 4 * pi * areas ./ perims .^ 2; % Dongsheng's formula
compactness = (Perims .^ 2) ./ (4 * pi * area);
%tf=ischar(stats)
class(stats);
a=[ E; std ;mean];
b=[ Roundness compactness Assym];
c = num2cell(b);
Ninput=[a;c];
Format shortG
Ninput=cell2mat(Ninput)
Ninput
Close all
saveData(:,k)=Ninput;
% Ninput(:,k)=Ninput;
end
xlswrite('correctdata.xlsx', saveData,'sheet1');
closeall
```

- **Normalizing**

```
%M=normalizing(a,c)
X=xlsread('dataset.xlsx', 'sheet1');
nr = meshgrid(max(X),[1:size(X,1)]');
normdata=X./nr;
xlswrite('af.norm.xlsx', normdata,'sheet3');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% to excel file
filename = 'trainset.xlsx';
writetable(M,filename,'Sheet',1,'Range','A');
close all
```

- **Neural Network**

```
clearall
closeall
clc
PATTERNS = [];
dataset = xlsread('dataset2.xlsx','sheet4'); %database%%% inputs
PATTERNS = [dataset];
dis.out=xlsread('output.xlsx','sheet2'); %...outputs
% CREATING AND INITIATING THE NETWORK
net1=newff(PATTERNS,dis.out,20,{'logsig','logsig'},'traingdx');
net1 = init(net1);
net1.LW{2,1} = net1.LW{2,1}*0.01;
%net.b{2} = net.b{2}*0.01;
```

53

```
% TRAINING THE NETWORK
net1.trainParam.goal = 0.01; % Sum-squared error goal.
net1.trainParam.lr = 0.005; % Learning Rate.
%%0.007....................96.8%%
net1.trainParam.alpha = 0.27; %% 0.27
net.trainParam.show = 50; % Frequency of progress displays (in epochs).
net1.trainParam.epochs =10000;% Maximum number of epochs to train.
[net1,tr] = train(net1,PATTERNS,dis.out); % Normal, Benign, Malignant
actout.normal=sim(net1,PATTERNS);
actout.normal
```

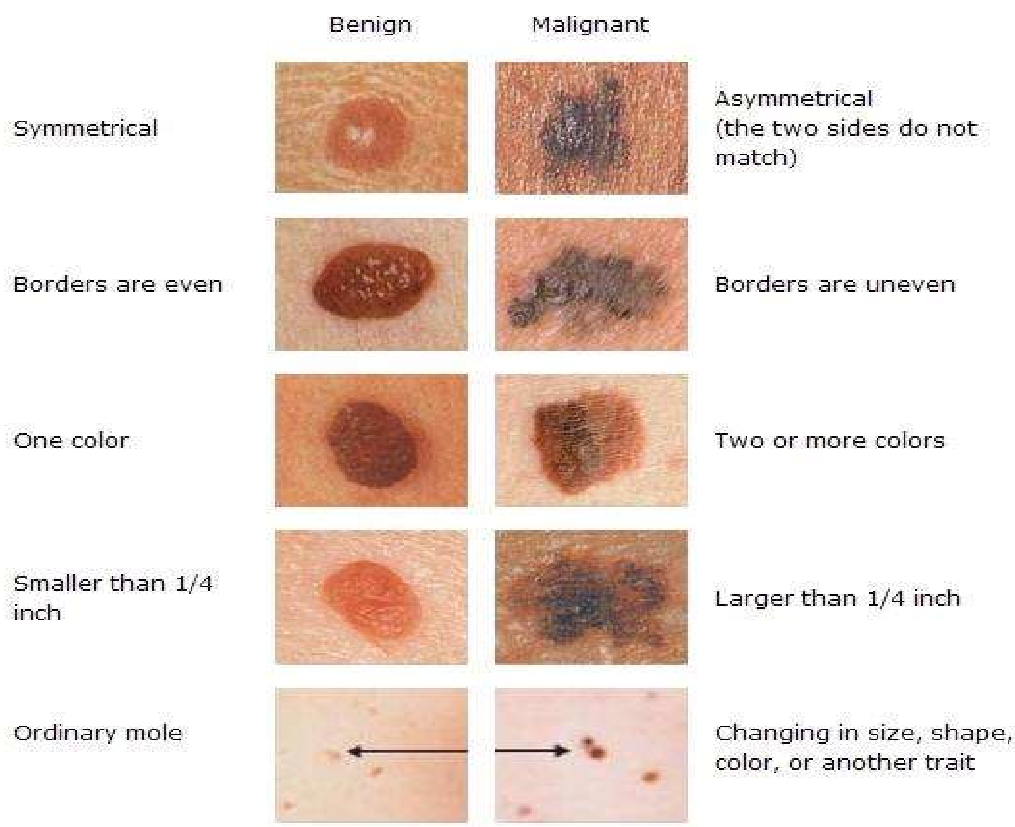
APPENDIX 2

FEATURES OF BENIGN AND MALIGNANT PROCESSED MAMMOGRAMS

Extracted features	Benign	Malignant
Roundness	0.85-0.99	0.25-0.84
Uniformity	0.98-1	0.81-0.89
Asymmetry	0.90-0.99	0.2-0.89
Compactness	0.2-0.7	0.71-1
Entropy	0.0503-0.304	0.317-0.593
Standard deviation	0.040565-0.238626	0.232185-0.439165
Mean	0.46-0.54	0.56-9

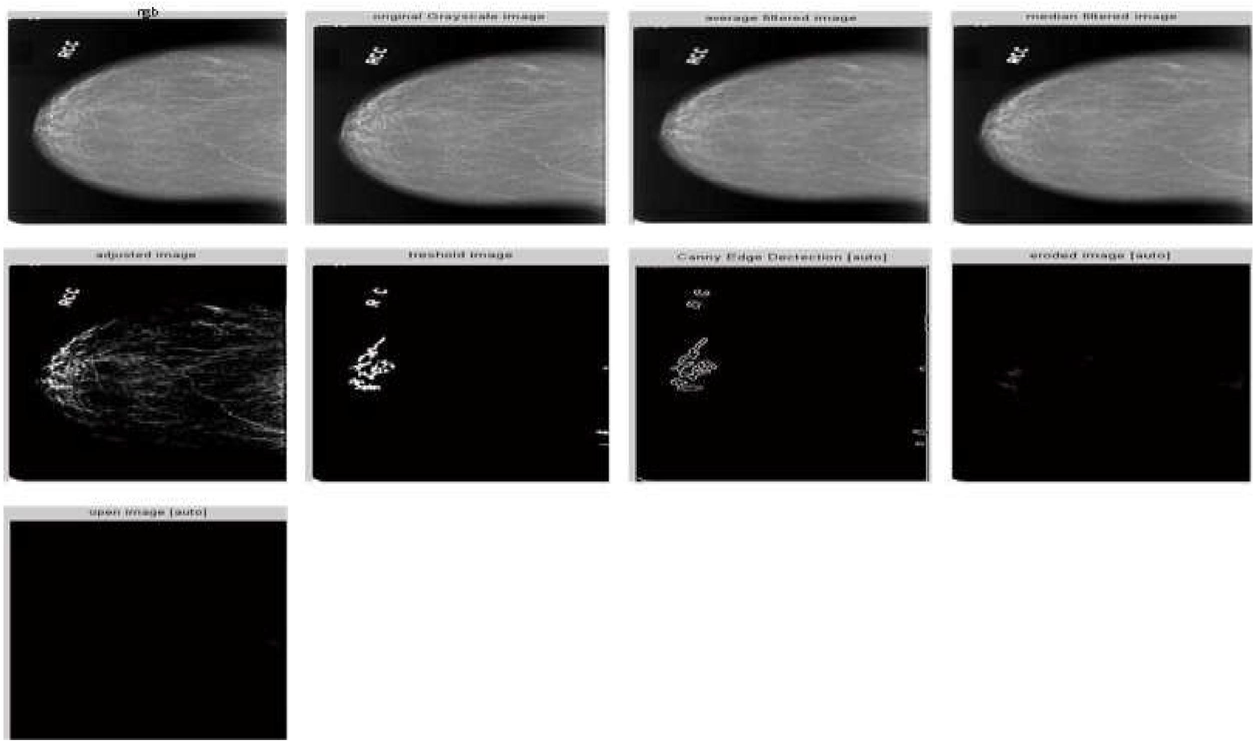
APPENDIX 3

SIGNIFICANT SHAPE AND TESTURE FEATURES

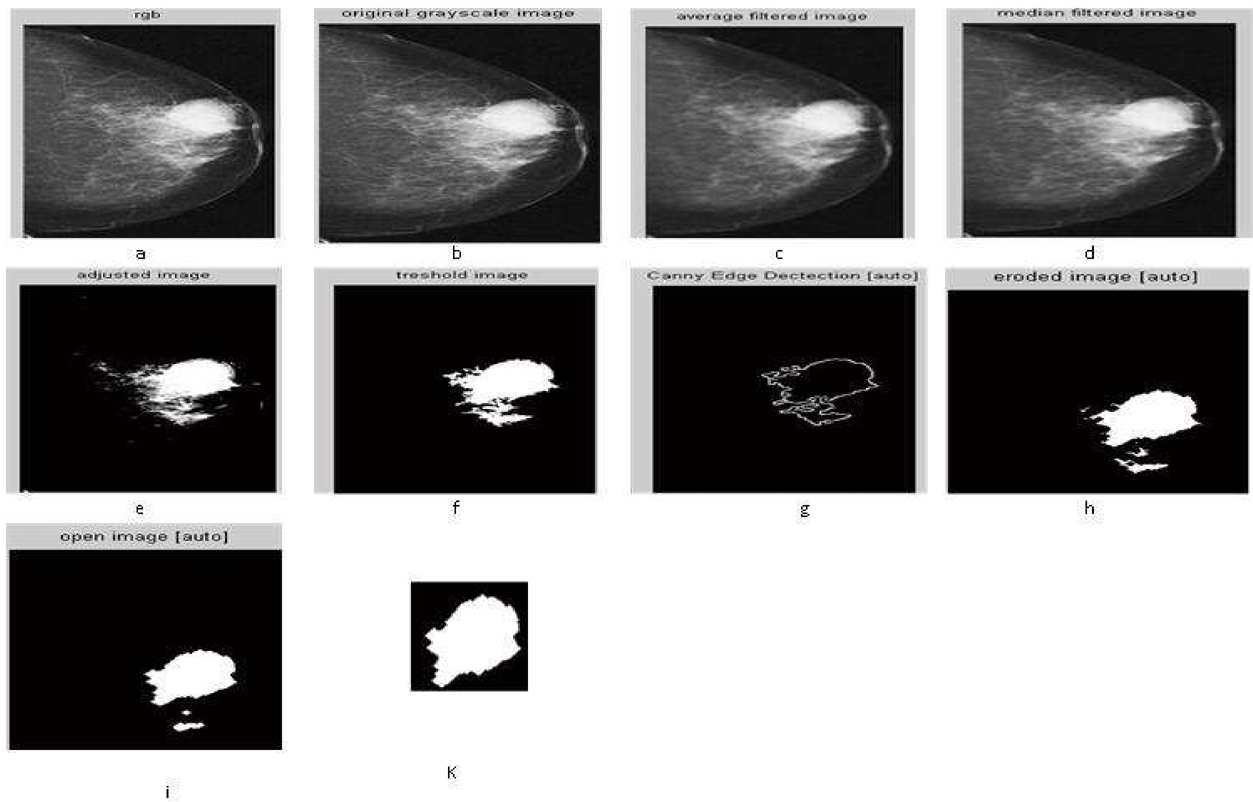


APPENDIX 4

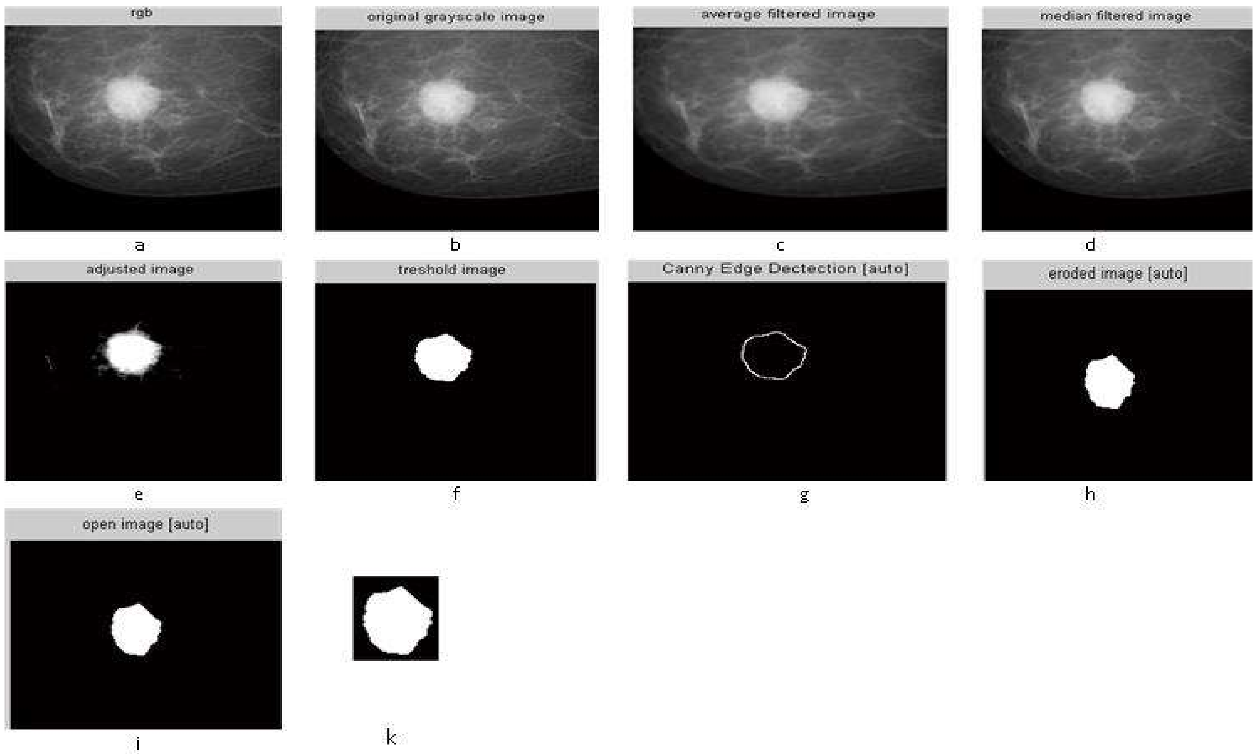
IMAGE ANALYSIS PHASE



Normal breast image undergoes all methods of our proposed system. (a) Original RGB normal breast image, (b) Grayscale image, (c) Filtered image using an average filter, (d) Filtered image using median filter, (e) Adjusted image, (f) Tresholded image, (g) segmented image using canny edge detection, (h) Eroded image, (i) Opened image



Breast Cancer image undergoes all methods of our proposed system. (a) Original RGB abnormal breast image, (b) Grayscale image, (c) Filtered image using average filter, (d) Filtered image using median filter, (e)Adjusted image, (f) tresholded image, (g) segmented image using canny edge detection, (h) Eroded image, (i) Opened image, (k) Extracted tumor.



Benign tumor breast image undergoes all methods of our proposed system. (a) Original RGB abnormal breast image, (b) Grayscale image, (c) Filtered image using average filter, (d) Filtered image using median filter, (e)Adjusted image, (f) tresholded image, (g) segmented image using canny edge detection, (h) Eroded image, (i) Opened image, (k) Extracted tumor.

APPENDIX 5

CURRICULUM VITAE