CLASSIFICATION OF SEGMENTED CHEST X-RAY IMAGES USING NEURAL NETWORK

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

By
SEPIDEH ROSTAMI

In Partial Fulfillment of the Requirements for the Degree of Master of Science in Biomedical Engineering

NICOSIA, 2018

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree of Masters of Science in Biomedical Engineering

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

Name, Last name:

Signature:

Date:

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To my parents...

ABSTRACT

Chest X-ray images are non-invasive medical scans showing the chest region, results are probably taken by patients in typical clinics, hence, the manual inspection and classification of such images is painstakingly tedious and liable to error from the human in charge of the process.

This research focuses on developing an intelligent and automated system that is capable of identifying the different segmented chest X-radiographs representing organs like heart, lungs, clavicles etc.

The designed systems were trained and tested on processed and segmented images collected from a public medical database. Supervised and Unsupervised learning algorithms for back propagation (BPNN) and competitive neural networks (CNN) were considered for the classification task.

Rescaled image size of 64×64 and 128×128 pixels were used for training and validation of the designed networks. BPNN trained on the 64×64 pixels input images outperformed the BPNN trained on the 128×128 pixels. CNN were trained and tested for the same classification task, and it showed that image size of 64×64 pixels outperformed those of 128×128 pixels.

Keywords: Chest X-ray; segmented images; image classification; back propagation neural network; competitive neural network

ÖZET

Göğüs röntgen radyografisi görüntüleri göğüs bölgesini gösteren non-invazif tıbbi taramalardır, sonuçlar muhtemelen tipik kliniklerdeki hastalar tarafından alınır, bu nedenle bu tür görüntülerin elle muayene edilmesi ve sınıflandırılması zahmetlidir ve sorumlu kişiden gelen hataya neden olabilir. Bu araştırma, kalp, akciğerler, klaviküller vb. göğüs organlarını temsil eden farklı segmente radyografları tanımlayabilen akıllı ve otomatik bir sistemi geliştirmeye odaklanmaktadır. Göğüs radyogramlarının sınıflandırılması için geri yayılım ve sinir ağlarının tasarımı, eğitimi ve testi yapılmıştır. Bu çalışmada, sınıflandırma görevi için geri yayılım ve sinir ağları için denetimli ve denetimsiz öğrenme algoritmaları geliştirilmiştir. Ayrıca sınıflandırma problemi için hem denetlenen hem de denetlenmeyen öğrenme algoritmaları kullanılmıştır; geri yayılım, bölümlü ve etiketli görüntüler kullanılarak eğitilmiştir. Ağların öğrenme parametrelerini değiştirerek çeşitli deneyler gerçekleştirdik. Eğitim için 64 × 64 ve 128 × 128 piksel giriş görüntüleri kullanılmış ve 64 × 64 piksel giriş görüntüleri üzerinde eğitilmiş geri yayılım ağları, 128 × 128 piksel üzerinde eğitilmiş geri yayılım ağlarından daha iyi performans göstermiştir. Rekabetçi sinir ağları aynı sınıflandırma görevi için de tasarlanmış, eğitilmiş ve test edilmiştir. Deneysel olarak, ağların aynı sınıflandırma görevinde doğruluk, eğitim süresi ve erişilen hata bakımından farklı davrandıkları görüldü.

Anahtar Kelimeler: Akciğer grafisi; segmentli resimler; resim sınıflandırması; geri yayılım sinir ağı; rekabetçi sinir ağı

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LIST OF ABBREVIATIONS

2D:	Two Dimensional
ANN:	Artificial Neural Network
APD:	Avalanche Photo Diodes
BPNN:	Back Propagation Neural Network
CNN:	Competitive Neural Network
HRR:	Highest Recognition Rate
MADALINE:	Multiple Adaptive Linear Elements
MSE:	Mean Square Error
TP:	Total Potential

CHAPTER 1
INTRODUCTION

Radiology is an area of medicine that is laden with the responsibility of using safe and novel imaging technologies such as electromagnetic radiation which are beyond the visible light spectrum for medical diagnosis and treatment. The most common radiation used in medical imaging being X-ray.

Chest X-ray radiography 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 of it is absorbed by the object being scanned also, depending on the composition and density of the particular object. The rays that make it pass the object being scanned are captured on a photographic plate positioned at a suitable distance behind the object (Herrmann, Hoffman, Peterson, and Woodward, 2012).

Hence, radiography images are typically used to examine sensitive human body parts that cannot or do not want to open up for diagnosis. this technique has been used by Medical experts for decades to analyze fractures or abnormalities of body parts such as the teeth, chest, skull, etc.

In this thesis, we consider the use of X-ray radiography for chest scans, which is a very sensitive and important area in view of the body region involved. Generally, a medic may arrange a patient for chest radiography for symptoms such as chest pain, persistent cough, breathing difficulty, and coughing up blood relating to diseases which include pulmonary tuberculosis, lung cancer (Badie et al., 2012). The images collected from these scans can make known many things about the captured organs such as the condition of the lungs, if cancer is present, or air or fluid is being trapped in areas around it. Also, the shape and size of the heart can be monitored accordingly (which is related to congestive heart failure); the blood vessels can be examined for anomalies. Furthermore, fractures can also be seen in such scans, and changes that can occur after surgery operations. It is also being used to check the position of implants in the body such as heart pacemakers, chest tubes, and catheters. Chest images of such patients are taken, and archived for examination by a medical expert.

Furthermore, it has been observed that at times, the segmentation of chest images is required in order for medics to be able to provide a more thorough scrutiny and rigorous examination of such images for anomalies.The regions segmented from such images include the heart, the left clavicle, right clavicle, left lung, and the right lung. Also, has it can be imagined that several thousands of chest X-rays are probably taken by patients in typical clinics, hence, the manual inspection and classification of such images is painstakingly tedious and liable to error from the human in charge of the process.

Instead, we propose an artificial neural network based intelligent system that is capable of accepting the described images or their features, and hence output the classes of the chest X-ray segments contained in the images. The capability of neural networks to learn and recognized patterns, especially their geometric descriptions has been leveraged on in this work for classification (Basu, Bhattacharyya, and Kim, 2010). Neural Networks have been used in several complex tasks such as data mining, optical character recognition, decision support systems, image compression, encryption and decryption systems, face and voice recognition.

The capability of artificial neural networks to use and combine simple learning rules to master different complex tasks is very motivating, and has sufficed on lots of challenging pattern recognition problems.

The designed systems are trained on processed and segmented images collected from a public medical database. In this work, both supervised and unsupervised learning algorithms for backpropagation and competitive neural networks have been considered for the classification task.

For supervised learning (using backpropagation neural network), it is of course required to label all training data for learning, which is a very tedious, costly, and manually intensive process. Alternatively, for an unsupervised learning (using the competitive), the process of training data labelling is not required, hence saves time, cost, and the amount of manual input required.

The aim of this thesis is to design an automatic system that has the capability to recognize the segmented chest X-ray radiographs, and therefore after training, can be deployed for use in clinical environments. This will relieve human operators who are typically required to achieve such a task manually.

1.1 Contributions of Research

1. Design of an intelligent classification system for segmented chest X-ray radiographs based on artificial neural networks, which will alleviate manual efforts required from human operators and minimize sorting errors.
2. Investigate the sufficiency of both supervised and unsupervised learning algorithms in the classification task.
3. Suggest an optimum image size for which the trained networks gave better response or performance on the achieved recognition rates.

1.2 Scope of Research

The research conducted in this thesis includes the designed, training, and testing of backpropagation and competitive neural networks for the classification of the segmented chest X-ray radiographs. Also, an entropy based algorithm is proposed to augment the intelligent classification system decisions. Furthermore, by heuristic training, we establish the optimum size of image pixels which is most suitable for the learning task. The original images of size 1024×1024, but were minimally processed and compressed to 64×64 pixels and 32×32 pixels in order to determine with which image size will the trained networks achieve higher classification accuracies.

1.3 Thesis Overview

In the remaining chapters of this thesis, the methods and techniques used to realize the objectives of this thesis are described.

Chapter two gives a brief literature of the X-ray radiography, image processing and segmentation techniques, and relevant features extraction works. Also, supervised and unsupervised learning algorithms are introduced, artificial neural networks and their capability to learn are discussed, featuring backpropagation and competitive neural networks.

Chapter three presents the image processing and feature extraction work carried out in this thesis, the particular network for the neural network classifies are given with the training parameters.

Chapter four contains the simulation results of the different networks trained for the classification task, and an extensive discussion of results relating to the build of the learning algorithms implemented.

In chapter five, the thesis is concluded as a summary of the research scope, important findings, challenges encountered during the research, and appropriate recommendations for future work.

CHAPTER 2
LITERATURE REVIEW

In this chapter, a brief review of radiography, its application in medical imaging, and diagnosis is presented. Also, the applied approach to the classification of the segmented images, pattern recognition, is introduced. Furthermore, background on related image processing and feature extraction techniques as are considered in this thesis are discussed sufficiently. Artificial neural networks, the backbone of machine learning, and which has also been used extensively in this work for the classification phase are introduced; including the particular algorithms for the supervised and unsupervised learning.

2.1 Related Works

The segmentation of chest X-ray using convolutional neural network was described by (Cernazanu and Holban, 2012). In their work, they introduced image segmentation into bone tissue and non-bone tissue. The aim of their work was to develop an automatic or an intelligent segmentation system for chest X-rays. The system was established to have the capability to segment bone tissues from the rest of the image.

They were able to achieve the aim of the research by using a convolutional neural network, which was tasked with examining raw image pixels and hence classifying them into “bone tissue” or “non-bone tissue”. The convolutional neural networks were trained on the image patches collected from the chest X-ray images.

It was recorded in their work , that the automatic segmentation of chest X-rays using the convolutional neural networks, and approaches suggested in their research produced plausible performance.

In another recent research, “lung Cancer Classification using Image Processing”, presented the application of some image processing techniques in the classification of patients chest X-rays into whether cancer is present or not (benign or malignant). This work ,it was shown that by extracting some geometric features that are essential to the classification of the images such area, perimeter, diameter, and irregularity; an automatic classification system was developed.

Furthermore, in the same research, texture features were considered for a parallel comparison of results on the classification accuracy. The texture features used in the work are average gray level, standard deviation, smoothness, third moment, uniformity, and entropy. The BPNN was used as the classifier, and an accuracy of 83% was recorded in the work (Patil and Kuchanur, 2012).

In this thesis the classification of chest X-ray radiographs into five classes has been achieved using artificial neural networks. The five classes are the heart, left lung, right lung, left clavicle, and right clavicle. Back propagation neural network (BPNN), which relies on a supervised learning algorithm was used to train the network on the images collected for the research.

Furthermore, competitive neural network, which relies on an unsupervised learning algorithm was also designed for the same classification task as described above. Since, the competitive neural network uses an unsupervised learning algorithm, therefore the need to label training data is eliminated. Hence, it can be said that the competitive neural network requires lesser overhead in cost for labelling the training data, lesser time to manipulate data, and implementation hardware, since such networks have no hidden layers.

2.2 Pattern Recognition

Pattern recognition is method of developing systems that have the capability to classify patterns; while patterns can be seen as a collection of descriptive attributes that distinguishes one pattern or object from the other. It is the study of how machines perceive their environment, and therefore capable of making logical decisions through learning or experience. During the development of pattern recognition systems, we are interested in the manner in which patterns are modelled and hence knowledge represented in such systems. Several advances in machine vision have helped revamp the field of pattern recognition by suggesting novel and more sophisticated approaches to representing knowledge in recognition systems; building on more appreciable understanding of pattern recognition as achieved in the human visual processing.

A typical pattern recognition as the following important phases for the realization of its purpose for decision making or identification.

- **Data acquisition**: This is the stage in which the data relevant to the recognition task are collected.
- **Pre-processing**: It is at this stage that the data received in the data acquisition stage is manipulated into a form suitable for the next phase of the system. Also, noise is removed in this stage, and pattern segmentation may be carried out.

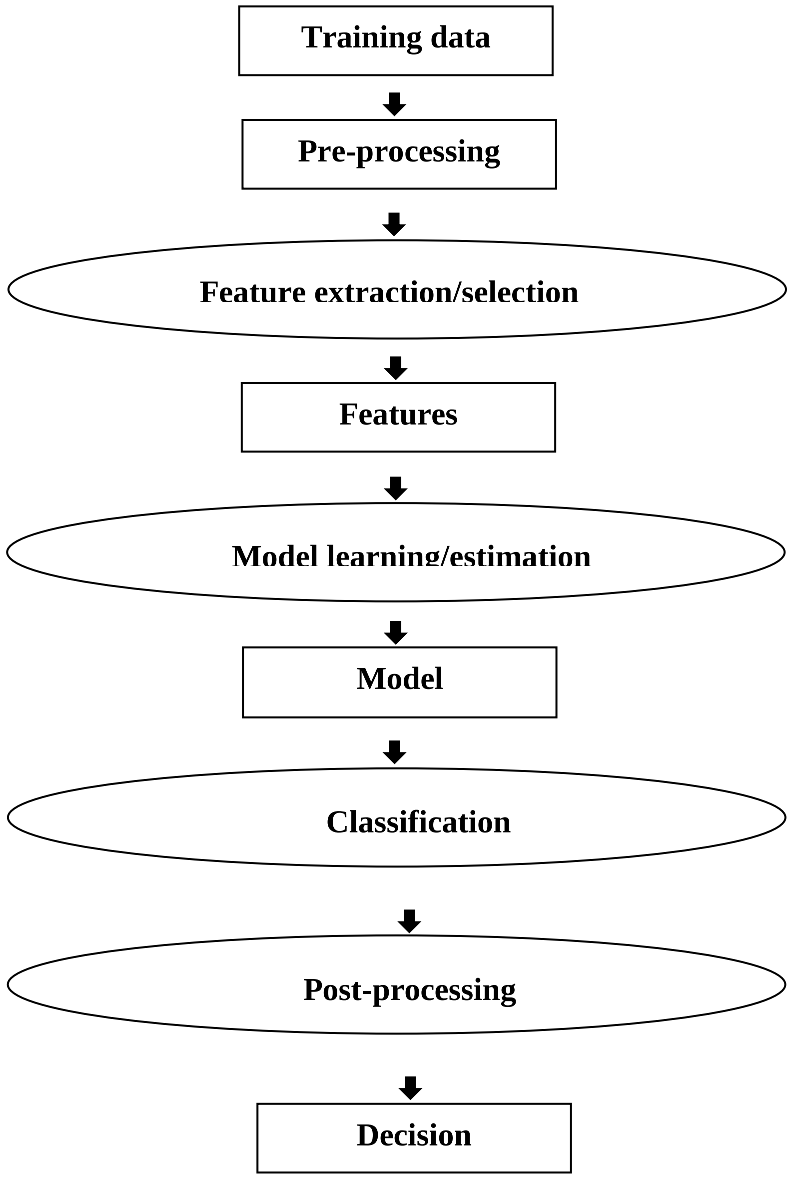

Figure 2.1: Typical pattern recognition system

- **Feature extraction/selection**: This stage is where the system designer determines which features are significant and therefore important to the learning of the classification task.
- **Features**: The attributes which describe the patterns.
- **Model learning/ estimation**: This is the phase where the appropriate model for the recognition problem is determined based on the nature of the application. The selected model learns the mapping of pattern features to their corresponding classes.
- **Model**: This is the particular selected model for learning the problem, the model is tuned using the features extracted from the preceding phase.
- **Classification**: This is the phase where the developed model is simulated with patterns for decision making. The performance parameters used for accessing such models include recognition rate, specificity, accuracy, and achieved mean squared error (MSE).
- **Post-processing**: The outputs of the model are sometimes required to be processed into a form suitable for the decision making phase stage. Confidence in decision can be evaluated at this stage, and performance augmentation may be achieved.
- **Decision**: This is the stage in which the system supplies the identification predicted by the developed model.

There exist several approaches to the problem of pattern recognition such as syntactic analysis, statistical analysis, template matching, and machine learning using artificial neural networks.

Syntactic approach uses a set of feature or attribute descriptors to define a pattern, common feature descriptors include horizontal and vertical strokes, term stroke analysis; more compact descriptors such as curves, edges, junctions, corners, etc., which is termed geometric features analysis. Generally, job of the system designer is to craft such rules that distinguishes one pattern or object from another. The designer is meant to explore attribute descriptors which are unique to identify each pattern, and where there seems to a conflict of identification rules which leeds to have same geometric feature descriptors save that one is the inverted form of the other, the system designer is meant to explore other techniques of resolving such issues.

Statistical pattern analysis uses probability theory and decision to infer the suitable model for the recognition tasks.

Template pattern matching uses the technique of collecting perfect or standard examples for each distinct pattern or object considered in the recognition task. It is with these perfect examples that the test patterns are compared. It is usually the work of the system designer to craft the techniques with which pattern variations or dissimilarities from the templates are measured, and hence determine decision boundaries as to accept or reject a pattern being a member of a particular class. Euclidean distance is a common used function to measure the distance between two vectors in n-dimensional space.

Template matching can either be considered as global or local depending on the approach and aim for which the recognition system is designed. In global template matching, the whole pattern for recognition is used to compare the whole perfect example pattern; whereas in local template matching, a region of the pattern for classification is used to compare a corresponding region in the perfect template.

Artificial neural networks, on the other hand, are considered intelligent pattern recognition systems due to their ability is to learn from examples known as training. These systems have sufficed in lots of pattern recognition systems; the ease with which same learning algorithms can be applied to various recognition tasks is motivating.

In this approach, the designer is allowed to focus on determining features to be extracted for learning by the designed systems, rather than expending a huge amount of time, resources, and labour in understanding the whole details of the application domain; instead, the system learns relevant features that distinguish one pattern from the other.

2.3 Image Processing

An image can be considered as a visual perception of a collection of pixels; where, a pixel can be seen as the intensity value at a particular coordinate in an image. Generally, pixels are described in 2D, such as f(x,y).

The pixel values can vary in an image depending on the number gray levels used in the image. The range of pixels can be expressed as 0 to 2^m, for an image with gray level of m. Image processing is essential on computer vision, as image data can be suitably conditioned before machine learning.

2.3.1 Image feature extraction and manipulation operations

In pattern recognition and machine learning field the most important aspect is to offers and apply various techniques to operate such as image data, feature extraction, image enhancement, and image segmentation are called image processing technique. While techniques such as Image manipulation technique involve image sampling for up-scale or down-scale images, and changing it to gray images such as (black / white).

in image processing the method that describes some characteristics on obtained images and features of interest ,that usually vary for different problems are called Feature Extraction. Those types of features are basically numerical parameters in which describes a few important aspects of specify images. Feature extraction methods such as corners, edge detection and points, there are many more important methods used to minimize unnecessary information in specific images.

Filters are special essence that work on having predefined pixel values to achieve specific feature extraction applying on image of interest. Types of filters that is used in feature extraction are as follows ,the Canny filter, Sobel filter, Hough filter, etc.

- S.E.D (Sobel Edge Dectection)

To perform a 2D spactial computations, sobel operators are needed to reinforce edges and transition present in the source image. Therefore, Sobel filter is suitable for the edge detection in image processing. Furthermore, by using a convolution of an image by performing the Sobel filter in both directions ,such as x-direction and y-direction, you achieve the edge detection . Sobel filters are build to have the highest answer to edges running on rows plus cloumns in the image; thus description of the Sobel filters are given in the figure next page .

-1	0	+1
-2	0	+2
-1	0	+1

(a) G_x

+1	2	+1
0	0	0
-1	-2	-1

(b) G_y

Figure 2.2: “Sobel operator (“Edge detection”, 2017)”

G_y & G_x represent the horizontal and vertical edges of sobel edges. Equation 2.1 is used to acquire the magnitude of absolute graduate at each filter computes them either in row or column orientation.

$$|G| = \sqrt{G_x^2 + G_y^2} \quad (2.1)$$

For computing the absolute gradient in much faster way we use equation 2.2.

“$|G| = |G_x| + |G_y|$” (2.2)

- C.E.D “(Canny edge detection)”

In order to achieve optimal detection result, an algorithm or multi stage process is obtained from edge detection. Therfore, they are obtained in the following ways:

1. In first stage noise has been removed from the image by using Source imaging process.
2. To estimate the highlight regions in the spacify image with high first derivatives, an edge detection filter is applied such as sobel.
3. A non-maximal suppression process is applied where all the edges are tracked by algorithm and pixels are sets against the ridges to zero, therefore, thin lines in the image earlier is used to dictate computed edges.
4. Edge tracking algorithm can be contemplated to disply hysteresis in which it demoralizes intermittent of any noise edges into parts during ridge tracking; indeed it is commanded by T1 and T2 threshold values (T2 is less than T1). T1 is the beginning of tracking, constantly in both axes ,till the ridges height get less or below T2.

The Canny edge detection algorithm is more functional and effectual .therefore; it gives more desirable output than the Sobel detection technique does.
as you can see in Figure 2.3 which define the outcome of using Sobel and Canny detection algorithms which shows in bellow image (a).

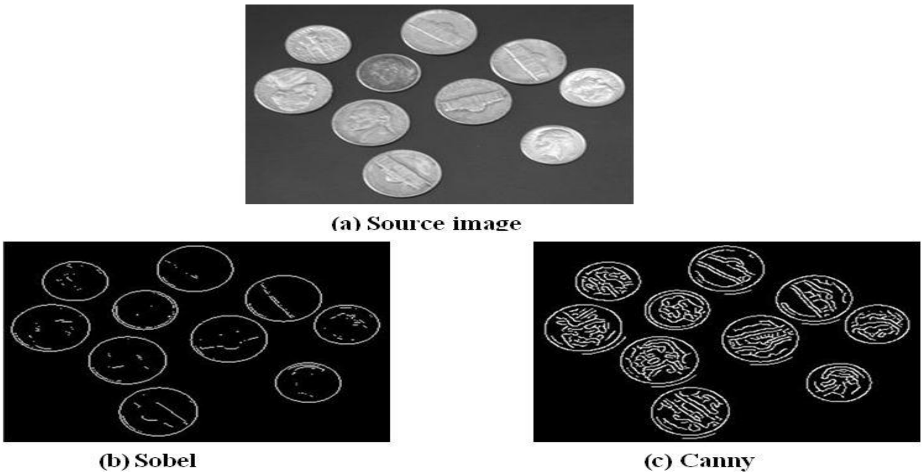

Figure 2.3: Canny and Sobel edge detections ("Edge detection", 2017)

It can be seen in the figure above that the after applying the two edge detection techniques discussed, the Canny detection algorithm produced a much better result than the Sobel detection or filter.
Image enhancement suffices in situations where there is a need to improve image quality, the image characteristics are manipulated such that an improved image is obtained on the considered image property. Some common image enhancement operations include contrast balance, mask mode radiography (obtained by image subtraction), histogram equalization, image denoising, image sharpening, etc.
process of Image segmentation involves in separating out a region or some areas of an specific image that need to be processed. In image processing, this outcome is very useful whereby a section of an image or the whole image is segmented fro the background. The highlighted regions are referred to as the foreground. This important technique that is used in image segmentation is known as image thresholding.

Image thresholding can either be local or global. Local image thresholding requires that not the whole image is considered for the segmentation operation; while, global thresholding uses the whole image during segmentation.

Image thresholding can be achieved using the equation provided below.

$$g_{out}(u,v) = 0, \quad if\ g_{in}(u,v) < T \qquad (2.3)$$

$$g_{out}(u,v) = 1, \quad if\ g_{in}(u,v) \geq T \qquad (2.4)$$

where, $g_{in}(u,v)$ is the considered thresholded pixel, $g_{out}(u,v)$ is the result of the thresholding, and T is the pixel used for the thresholding operation.

2.4 Artificial Neural Network (ANN)

Mc Cullouch and Pitts (1934) published a paper proposing the working principle of neurons. They use electrical circuits to simulate a simple neural network, so that they can explain the manner in which brain neuron works.

The organization of behavior was written by Donald Hebb in (1949), this study shows the ability of neural pathways to be strengthened whenever they are used. This idea essentially showcase the pattern of human learning. The link between two nerves is heightened, he agued if the fire as the same time.

ADALINE and MADALINE were developed in 1959 by Hoff and Widrow. The name stood for an acronym meaning Multiple Adaptive Linear Elements. Recognition of binary patterns was the main reason ADALINE was developed, it could predict a proceeding bit while reading streaming bits from a phone line. MADALINE happens to be the pioneer neural network employed to real world problem, it erase errors on phone lines by means of an adaptive filter. Although this system has been in existence for years, it is still commercially available.

A learning procedure that evaluates value prior to weight adjust (0 or 1) was developed in 1962 by widrow and Hoff. It is given by the following canon:

$$\Delta W = (\text{pre - weight line value}) * (\text{error} / (\text{number of inputs})) \qquad (2.5)$$

Δw = (the weight change).

The rationale behind this is that single active perceptron can possess a big error, the weight value can be adjusted to disseminate it across the network, or to neighbouring perceptrons.

An error weight still exist by applying this rule if the line next to the weight is 0, despite automatically fixing itself eventually. The error can be erased if it is conserved for the purpose of distributing it completely to all of the weight.

An artificial neural network is reffered to simplifying system that interconnects computational units called neurons or perceptrons; in which they tend to mimic the brain anatomy and physiology.

The ability of a neural network at performing computations relies on the hope of incorporating artificial methods to emulate certain power and adaptability of the human brain.

Links having numerical weights connects several the neurons. In ANNs, the basic means of long-term memory are weights.

An Artificial Neural Network (ANN) simply refers to a statistical model which attempts to mimic the formation of biological neural networks and and how they function. These computational units are termed artificial neurons and serve as the basis of all neural networks.

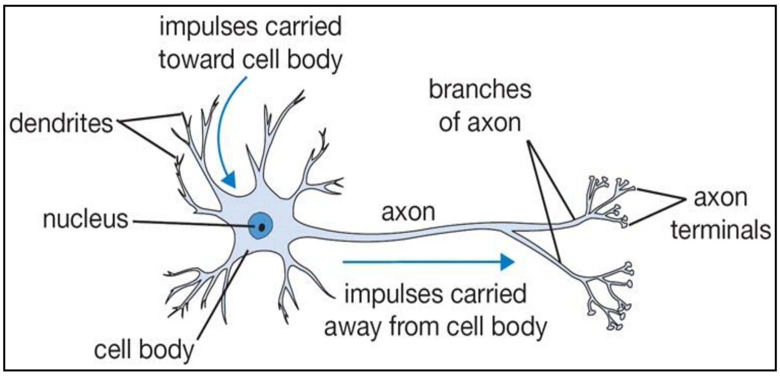

Figure 2.4: Biological neuron ("CNN for Visual Recognition", 2018)

ANN was explained in Graupe book as a computational method which grossly simulate the neurons of biological supreme nervous system.

The central neurons receive data as inputs, and after produce an output. Summation of the weighted inputs represents the total potential.

Central Neurons will fire only when the total potential exceeds a certain threshold, but if it is less that thresthold, then and it will not be activated.

ANN simulate the structure and functions of the brain; they have features that are somewhat the same as those seen in biological neurons. It also tries to model the information processing potentiality of nervous systems.

The neurons of the artificial system mimicks the input of dendrites on the biological neurons in which receives the stimulus for outcome process, in biological neurons ;node corresponds to the cell body, a place where information computation is carried out, the weights that correlates to the synaptic weights, the output coincides with axons where the total potential (TP) is supplied after processing.

In below it shows the artificial neuron , plus equations below identify the connection between the inputs and the output.

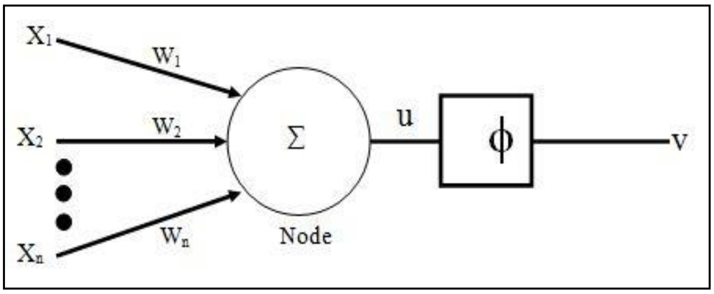

Figure 2.5: "The artificial neuron"

inputs are represented with x_1, x_2, ….., x_n, and weights with w_1, w_2,…., w_n, , total potential by u, activation Is given by ϕ, output of the network is represented by v. It is worthy of knowing that several operations are used as activation functions; example of the most available action in neural networks are Gaussian, log-sigmoid, Signum, tan-sigmoid, linear, etc.

2.4.1 Supervised and unsupervised learning

The phase of building knowledge into neural networks is called learning or training. The three basic types of learning paradigms are:

Supervised learning: The input and desired output examples are given to the system concurrently. Generally, this network is meant to reduce cost function. A complied error is observed between the actual outputs and the desired outputs.

Training data includes both the input and the desired results.

- For some examples the correct results (targets) are known and are given in input to the model during the learning process.
- These methods are usually fast and accurate.
- Have to be able to generalize: give the correct results when new data are given in input without knowing a priori the target.

Error per training pattern = desired output - actual output

Accumulated error= ∑(error of training patterns)

Unsupervised learning: only input examples are given with the exception of the desired output, the network is meant to ascertain patterns between the input attributes with regards to certain parameters and thus group the examples.

• The model is not provided with the correct results during the training.
• Can be used to cluster the input data in classes on the basis of their statistical properties only.
• Cluster significance and labeling.
• The labeling can be carried out even if the labels are only available for a small number of objects representative of the desired classes.

2.4.2 Supervised learning rules

- Perceptron learning rule

There are several different models of supervised learning that have been implemented in artificial neural networks.

$$T.P = \sum_{i=1}^{m} w_{ji} x_i \tag{2.6}$$

$$\begin{aligned} &If\ T.P \geq \theta, \quad then\, y = 1 \\ &else\ T.P < \theta,\ then\, y = 0 \end{aligned} \tag{2.7}$$

Where T.P is known as the total potential of the neuron, Θ is the threshold value, w_{ji} is the weight connection from input x_i to neuron j, m is the number of inputs, and y is the output of the neuron. If the total potential is greater than or equal to the threshold value, then the neuron fires; if otherwise, then the neuron does not fire.

2.4.3 Back propagation neural network (BPNN)

The layer neural network used as feed forward; which works on supervised learning algorithm. Taking into consideration, learning is achieved through this way. i.e. errors collected at the output layer will feeded back to the network for weights adjustment and create new weights accordingly. These networks employ the delta learning law described in above for learning algorithms, the only disparity, is that BPNN can be widened.
BPNN depends on feeding back error values collected at the output of the network in order to upgrade the interconnected weights between layers of the network.

backward pass occurs only during training. i.e. during simulation almost all links will be proceeding in the forward direction. Back propagation algorithm is build on gradient descent optimization method.

The pseudo code algorithm used for Back propagation neural network is given below.

- select the initial weights arbitrary
- when there is a very large error

  -For individual single training pattern (outlined in a random order)

- the outputs error should be evaluated
- compute error signals for pre-output layers using the output error
- weight adjustments should be evaluated using error signal
- adjustments of weights should be tried

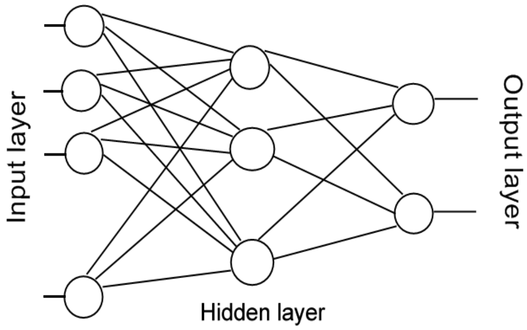

Figure 2.6: "Back propagation neural network (BPNN)"

- each input parameter value should be employed to each input node
- identity function should be used to operate Input nodes

2.4.4 Learning parameters for the back propagation algorithm

Learning rate

The learning rate is a very important parameter in supervised learning, it is used to control how fast the network learns the training examples. The value of this parameter varies between 0 to 1. Learning rate determines the step size with which network weights are updated during training. If the value set for the learning rate is too high, the network runs a high risk of only memorizing the training data, as learning is completed in fewer epochs (possible that the network weights have not been properly tuned to the examples); a situation referred to as over-fitting. If the value set for the learning rate is too low, then the network runs a risk of not insufficient learning of the training data by the time the set number of maximum epochs is reached. It there follows that using a value that is too small for the learning rate makes the learning much slower, and the network may not converge to the set MSE goal before training is stopped. Generally, the suitable value for the learning rate is determined heuristically (through a trial and error method). Low values are usually preferred.

- **Momentum rate**

The momentum parameter is often optional for supervised learning, its sole purpose is to help reduce the possibility of the network getting trapped in a poor local minimum during training. Its value also ranges between 0 to 1. The momentum rate parameter can be seen as kind of inertia being introduced into the network. It helps push the learning past poor local minima during network training; and also dampens oscillations that may occur during learning, hence the learning curve is usually smoother compared to when the momentum rate parameter is not used in the learning algorithm.

- **Goal of cost function (MSE)**

Generally, for any supervised learning algorithm, since a cost function relating the deviation of the actual response of the network from the desired is to be minimized, it then follows that there should be a specified value for the goal of the cost function being minimized.

When the network reaches this specified value for the MSE goal, the training of the network is stopped.

- **Maximum epochs**

Since neural networks learn by examples, the forward pass of an example from the input and the back pass of the computed error constitute what is referred to as an epoch. This process is repeated for each training example till all the examples have been propagated through the network; after which the process repeats in such manner, while the set value for the MSE goal is monitored. When training neural networks, it is very important to specify the maximum number of iterations allowed in the training. This has the effect of not allowing the network to continue training indefinitely in a situation where the learning has not converged to the set MSE goal, hence is used as an important stopping criterion in training.

- **Number of hidden neurons**

For the back propagation neural network and most other networks, the network is made of at least three layers, input layer, hidden layer, and output layer.

The input layer is where the training examples are supplied to the network, the hidden layer learns the features represent in the input, and the output layer allows the actual output of the network to be obtained. Also, the input layer neurons are non-processing, they basically serve to supply the input features to the network.

The output layer in a supervised learning, allows the computation of the error between the desired output and actual output of the network; and therefore back propagation of errors into the network for weights adjustment or tuning.

The hidden layer is very important, considering that it is where the main knowledge representation of the features present in the training examples is achieved. Hence, it is very crucial that a suitable number of neurons are used at the input layer of neural networks to ensure proper learning of a task.

If the number of hidden neurons is too few, then the network may not have enough power to accommodate the feature representation present in the training examples; a situation also referred to as low degree of freedom.

Conversely, if the number of neurons used is too many, then the network develops a far more complex model to the training examples than is required, the network has too much representation power, such that it may begin to model features that too peculiar to the training examples, hence the network is likely to over-fit. A situation also referred to as too high degree of learning freedom.

It is therefore desirable that the number of neurons used in the hidden layer should not be too few or too many. Generally, during training, the number of suitable hidden neurons is determined through a trial and error approach.

Activation function:

Activation functions are used to squash the output of artificial neurons to within a certain range of values. It is conceived that the output of neurons should not be infinite. The weighted sum of the inputs to a neuron is computed, the value referred to as the total potential, which is then passed through an activation function.

Common activation functions used in neural networks include the Signum, linear, Log-Sigmoid, and the Tan-Signoid.

During the design of neural networks, the type of application determines the activation function to be used in each layer of the network. The layer that is so application specific is the output layer. The type of activation used in the output layer depends on the range or type of values expected at the output.

For real values problems such as regression tasks, the linear activation function is used, for classification tasks, output values are generally integers, hence the Log-Sigmoid or Tan-Sigmoid can be used.

2.4.5 Competitive neural network (CNN)

An unsupervised learning algorithm is used during training process in Competitive neural networks. Therefore, there is no choosen target outputs as it is attained in the supervised learning algorithms. let's consider having fixed targets that a network is expected to gain from, the system works another algorithm to investigate the highlights introduce in the information, in this manner taking in the ability to amass input patterns with comparative highlights or traits into one class. The CNN depends basically on the Hebbian learning principle, the difference of being in focused adapting, all neurons need to challenge among themselves to begin the capacity and get enacted, and just a single neuron is let go whenever or actuated, as connected to Hebbian realizing where in excess of one neuron can be initiated or terminated whenever. These systems utilize a "winner takes-all" learning guideline. In a specific order just weights associated with the winner neuron are refreshed in a specific epoch, while different weights are not upgraded. In this way the new neuron gets its associated weights refreshed as it were. In this learning procedure has the reap impact of more upgrading the association amongst inputs and comparing champ neurons amid learning process

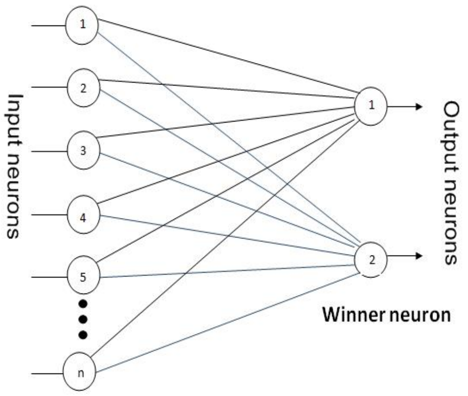

Figure 2.7: Competitive neural network

2.5 Summary

This chapter opens with a brief description of some the works that have been done in this area. Such works include the classification of chest X-rays to ascertain the presence or absence of cancer; segmentation of the chest X-rays using neural networks, etc.

This chapter introduced pattern recognition systems, techniques, and approaches such syntactic analysis, geometric feature analysis, and template matching.

Brief review of basic image processing operations and algorithms as it is contained in the scope of this thesis were presented. Feature extraction techniques such as Sobel and Canny edge detections, image enhancement, and image segmentation were discussed.

Furthermore, artificial neural networks were thoroughly discussed as it is related to this work, their capability to learn was explored. Supervised and unsupervised learning algorithms were introduced.

Back propagation neural network and learning algorithm were presented, with essential equations used to update the network weights.

Competitive learning, an unsupervised learning algorithm, was discussed. Its distinction from another unsupervised learning algorithm, Hebbian learning, was established. Then it was shown that the competitive neural network relies on the "winner-takes-all" learning rule, where only the winner neuron gets its connected weights updated, while other neurons weights are not updated. The crucial equations to updating the weights of the network were also supplied therein.

CHAPTER THREE

DATA PROCESSING AND NEURAL NETWORKS

3.1 Overview

This chapter describes the data processing operations used to achieve the aims of this thesis; image rescaling, and some feature extraction works are presented also. The images have been rescaled to 64 × 64 and 128 × 128 pixels, so that a comparative analysis can be made after the networks have been trained. Furthermore, the different neural networks, back propagation neural network and competitive neural network, used for learning the classification task are sufficiently described.

3.2 Data Processing

The original images used in this thesis are of size 1024 × 1024 and in unit 8 MATLAB data format. These images are processed as in the sequence described below.

- Sobel edge detection operation applied.
- Median filtering with a mask size of 2 × 2 to smoothen out the edges.
- Dilation of images.
- Entropy of images.
- Rescaling of images.

The stages for the overall classification system is given below.

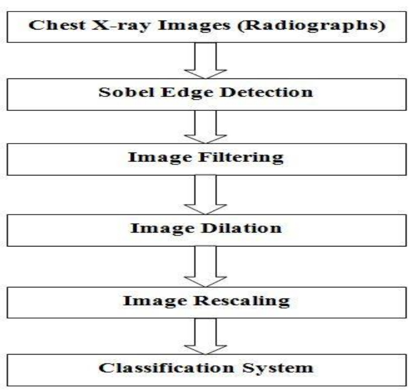

Figure 3.1: Stages for the proposed classification system

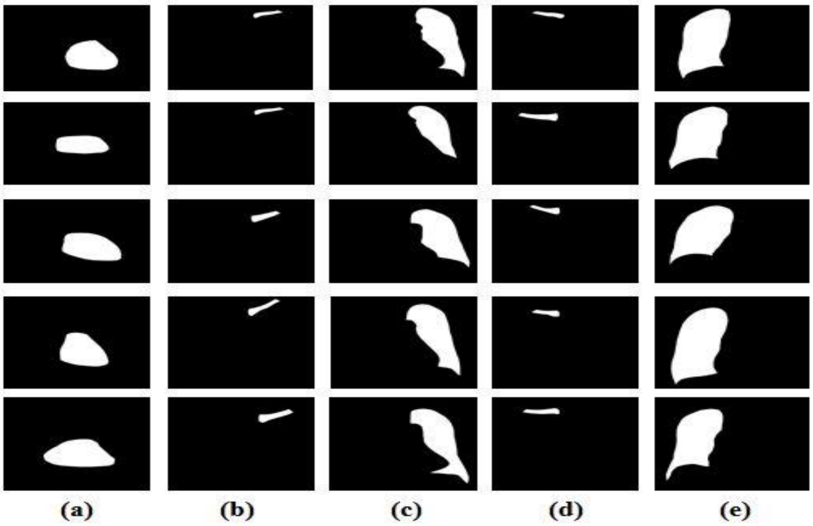

Figure 3.2: Segmented chest X-ray radiographs
(a) heart, (b) left clavicle, (c) left lung, (d) right clavicle, (e) right lung

The figure above (Figure 3.2) shows the segmented chest X-rays with (a) being the heart, (b) being the left clavicle, (c) being the left lung, (d) being the right clavicle, and (e) being the right lung.

3.2.1 Feature extraction

In this phase, simple edge detection techniques described in chapter two, will be applied to the collected images. This approach aims to highlight only the pattern edges contained in the images on which the designed neural networks will be trained, rather than using the whole images. This approach reduces computation requirements for the classification task, since only pattern edges are used instead of the whole images.

- Sobel edge detection and filtering

The Sobel edge detection algorithm was applied to the images as described earlier in chapter two, and then a median filter of size 2×2 applied to the images, the results of this processing stage are shown in the figure next page .

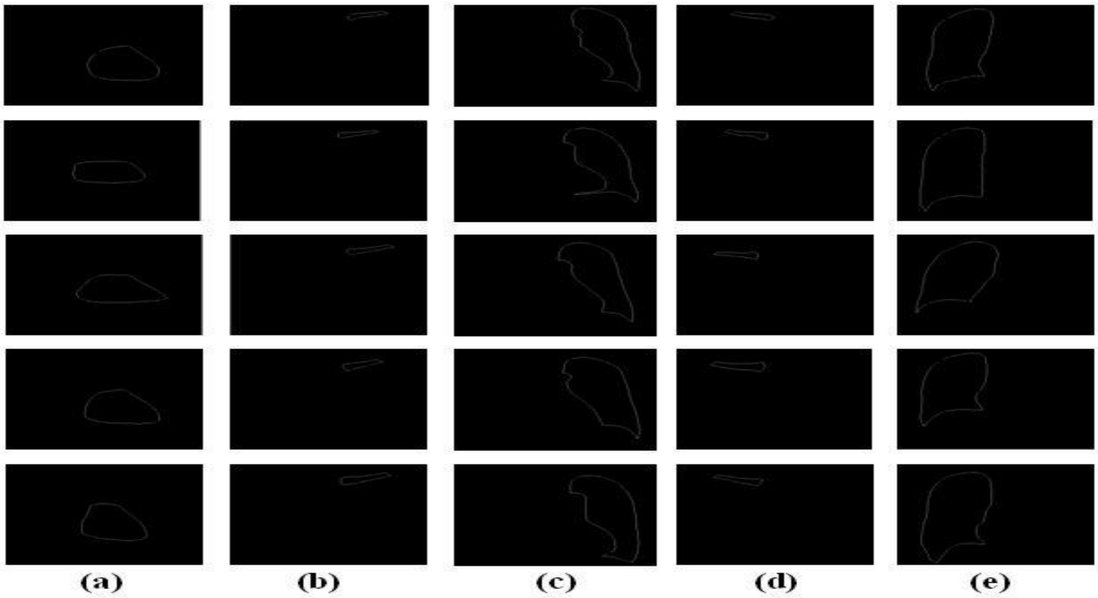

Figure 3.3: Edge detection for images using Sobel operation
(a) heart, (b) left clavicle, (c) left lung, (d) right clavicle, (e) right lung

- **Image dilation**

The images in figure 3.3 have edges that are weakly highlighted in the images, hence, the dilation operation has been used to reinforce the strength of the edges in the images. This has been seen to hence learning in many research works. Neighbour dilation operation of 3 pixels has been used, and the results can be seen in Figure 3.4, below.

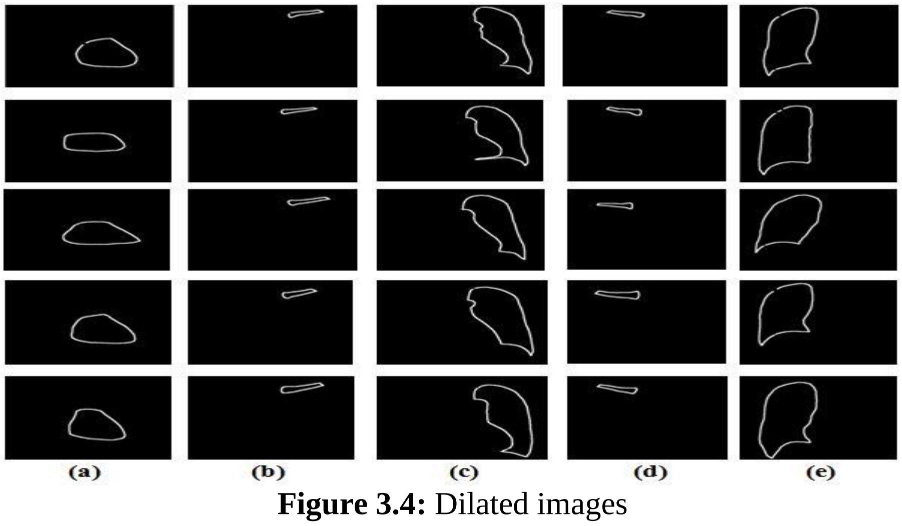

Figure 3.4: Dilated images
(a) heart, (b) left clavicle, (c) left lung, (d) right clavicle, (e) right lung

- **Image Entropy**

The entropy of an image is the measure of the degree of disorderliness of pixels in the image. This parameter can give crucial information about images of similar patterns. Hence, the consideration of the entropy parameter in this thesis, which has been proposed an augment to the training data for the designed networks.
The table showing the entropy values for images found in Figure 3.4 is shown below.

Table 3.1: Entropy values for the different image classes

Image class	**1**	**2**	**3**	**4**	**5**
Heart	0.1200	0.0858	0.0858	0.1013	0.0992
Left clavicle	0.0465	0.0619	0.0546	0.0499	0.0590
Left lung	0.1535	0.1604	0.1501	0.1541	0.1594
Right clavicle	0.0491	0.0660	0.0504	0.0619	0.0562
Right lung	0.1508	0.1620	0.1448	0.1433	0.1662

It can be seen that the entropy values for the same class of images have a range of values. e.g. the heart images have entropy values that are around 0.1. A close inspection will also show that the clavicle images (left and right) have entropy values centred around 0.05, while the lung images (left and right) have entropy values centred around 0.15.
From this observation, an entropy augmented classification learning is proposed in this work, in which the entropy values will be included in the training data for network learning. The performance of this approach will also be compared with the results obtained with entropy augmented training data.

- **Image resizing**

The processed images were downscaled to databases of size 64×64 and 128×128 pixels, such that the performance of the trained neural network could be accessed during the simulation phase.
For rescaling of images, technique of pattern averaging is used and the equation applied to attain this is given in formula 3.1.

“$Seg_i = (\sum P[x, y]) / D$ (3.1)”

“$D = (TP_x . TP_y) / S$ (3.2)”

where Seg indicates the segmented number, in equation P represent pixel value, and total number of pixels in each segment is represented by D; x and y pixel are denoted TP and overall segment number is denoted by S.

A window size of 16×16 and 8×8 was used to downscale the original images (1024×1024 pixels) to 64×64 pixels and 128×128 pixels respectively.

3.3 Back Propagation Neural Network (BPNN)

BPPN are very essential in problems related to pattern recognition and used a lot in solving them, and it has its roots from supervised learning algorithm. The fortunate training of BPPN is an interesting process (trial and error), in order to attain network parameters which produces very good result with least error.

thence, this thesis, certain experiments were operated such that eesentially crucial results can be attain. The learning specifications varied contain of number on hidden neurons, the learning rate, and momentum rate.

Here is the structure on the outline design of back propagation neural network for the 64×64 images is defined below in Figure 3.5.

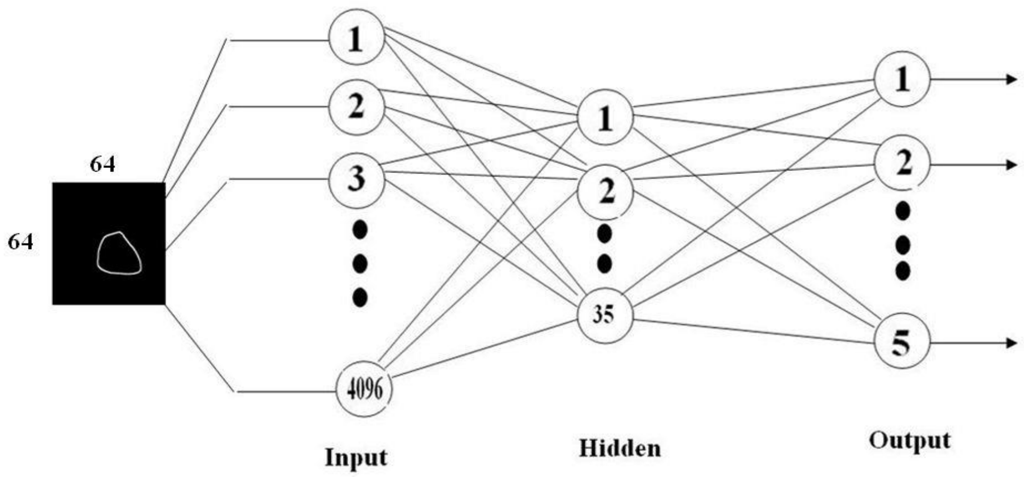

Figure 3.5: "Back propagation neural network"

As you can notice in the figure above, the number and amount of input neurons equal the total number of input image pixels. i.e. 64×64 input image pixels equals 4096 pixels (number of input neurons).

An image from the database representing the heart was applied in the figure to certainly show the design and application of the network.

3.3.1 Coding of netwotk outputs

sypervised learning algorithm are used for BPNN because it is critical for data to be defined in training process. In this thesis we used training methods that can categorize data into five categories plus helps to present the classification. It is the course intelligent classification system was developed for segmenting chest X-rays radiographs; the advanced system will be required to classify supplied images into one of the following classes: heart, left clavicle, left lung, right clavicle, and right lung.

The output coding of the designed back propagation networks as used in this thesis is described below.

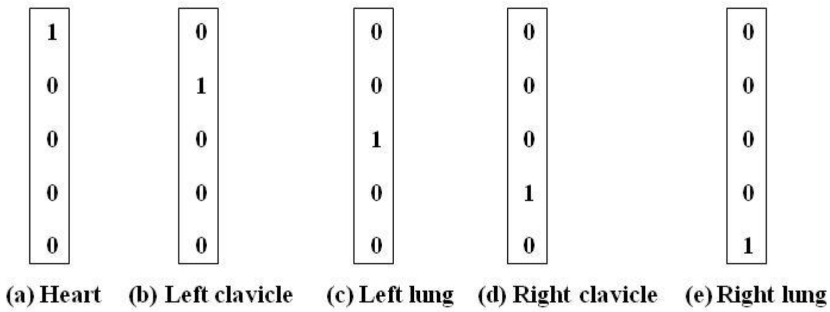

Figure 3.6: Output coding of back propagation network

It can be seen from the figure above that 5 neurons will be sufficient to code the corresponding classes of the input images as the output of the network.

Experimentation of distinct number of learning rate, hidden neurons and momentum rates was carried out and analyzed at the time of training as shown in table 3.2

thus there are five categorization task classes and five output neurons.

Table 3.2: Parameters for training (64×64 input pixels)

Networks	BPPN1	BPNN2	BPNN3	BPNN4
Samples	620	**620**	620	620
Hidden neurons	20	**35**	45	60
Learning rate	0.010	**0.0045**	0.300	0.15
Momentum rate	0.040	**0.0072**	0.0504	0.0619
Activation function	Sigmoid	**Sigmoid**	Sigmoid	Sigmoid
Epochs	1000	**1000**	1256	1374
Training time (secs)	148	**156**	184	193
Mean Squared Error	0.0077	**0.0025**	0.0056	0.0096

The network with lowest achieved MSE is shown below in figure 3.7,As considering The learning curve for BPNN2.

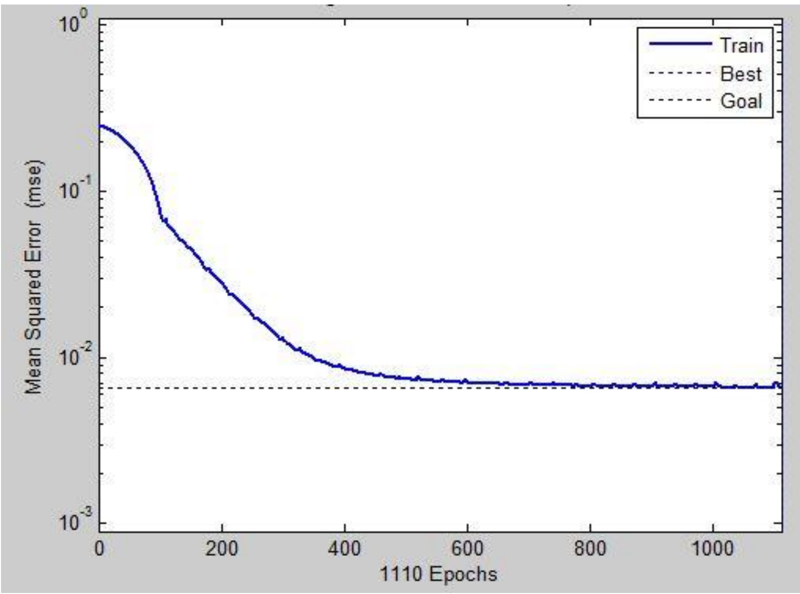

Figure 3.7: Learning curve for BPNN2

Furthermore, to investigate the effect of the input image sizes on learning, the training images were also rescaled to 128×128 pixels, and used to train the designed networks.

The training parameters for the networks are given below in table 3.3.

Table 3.3: Training parameters for back propagation networks (128×128 input pixels)

Networks	BPPN5	BPNN6	BPNN7	BPNN8
Samples for training	620	620	**620**	620
Neurons in the hidden layer	65	80	**100**	120
Rate of learning	0.020	0.0063	**0.005**	0.103
Rate of momentum	0.078	0.0070	**0.0048**	0.0632
Activation function	Sigmoid	Sigmoid	**Sigmoid**	Sigmoid
Epochs	1407	1500	**2000**	2102
Time for training (secs)	151	162	**196**	226
MSE	0.0099	0.0127	**0.0081**	0.0286

The different networks trained on 128×128 input image pixels can be seen in table 3.3 as BPNN5, BPNN6, BPNN7, and BPNN8.

3.4 Competitive Neural Network (CNN)

this study, an unsupervised learning algorithm using CNN was assigned, extracting the fact, that in such networks manual labelling of training data is not needed, therefore saves plentiful time and cost. The architecture used in this study is shown in figure 3.8.

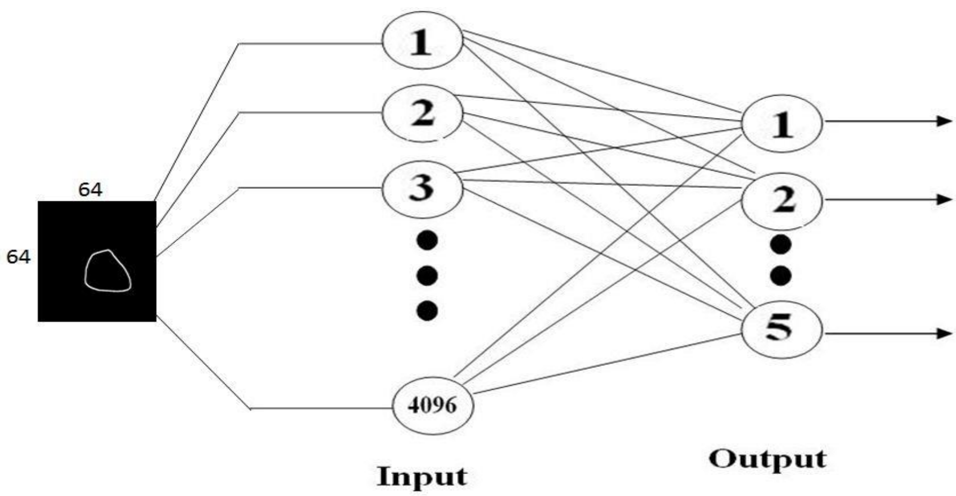

Figure 3.8: “Competitive neural network”

Table 3.4 shows the training parameters.

Table 3.4: Parameters for training (64×64 input pixels)

Networks	CNN1	CNN2	CNN3
Samples for training	**620**	620	620
Rate for learning	**0.0036**	0.05	0.1
Maximum Epochs	**100**	200	400
Training time (secs)	**92**	129	158

This was carried out for the back propagation networks, competitive networks were trained on 128×128 pixels images as input, such that the performance of the competitive learning can be compared with when 64×64 pixels images were used for training.

The table showing the different trained competitive networks is given below. i.e. table 3.5.

Table 3.5: Training parameters for competitive neural network (128×128 input pixels)

Networks	CNN4	CNN5	CNN6
Training samples	**620**	620	620
Learning rate	**0.0062**	0.07	0.31
Maximum Epochs	**100**	200	400
Training time (secs)	**97**	135	164

3.5 Summary

In this chapter, the different image processing schemes such as edge detection, filtering, image dilation, entropy and the technique of pattern averaging to rescale the images used are presented.

The rescaled images of size 64×64 pixels and 128×128 pixels were used to train the designed networks, so that the effect of image size of learning can be obtained.

Back propagation neural networks were designed, using various training parameters in order to determine the best network based on the achieved recognition rates during the testing phase.

Also, competitive neural networks known as CNN, rely on an unsupervised learning algorithm were designed and trained on the processed databases.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Overview

This chapter contains the simulation results of the trained neural networks described in chapter three. The back propagation network and competitive neural networks were simulated with the test data that were not part of the training data, and the recognition rates achieved are presented in the following sections.

Furthermore, extracted entropy values of images were considered as a method of augmenting the classification decision of the networks.

4.2 Neural Network Simulations

The designed back propagation neural networks and competitive networks testing using image pixels of sizes 64×64 and 128×128 were described in the below presented tables. The networks were simulated with the data that were not part of the training data. This has been done such the generalization power of the train networks can be obtained during testing.

It is very important that trained networks have the capability to suffice on classification problems for data of the same task with which they have not been trained, but are representations of the classification task. i.e. such networks performance should not collapse with a moderate degree of distortion in the test data.

Samples of images used for testing the networks are shown in Figure 4.1.

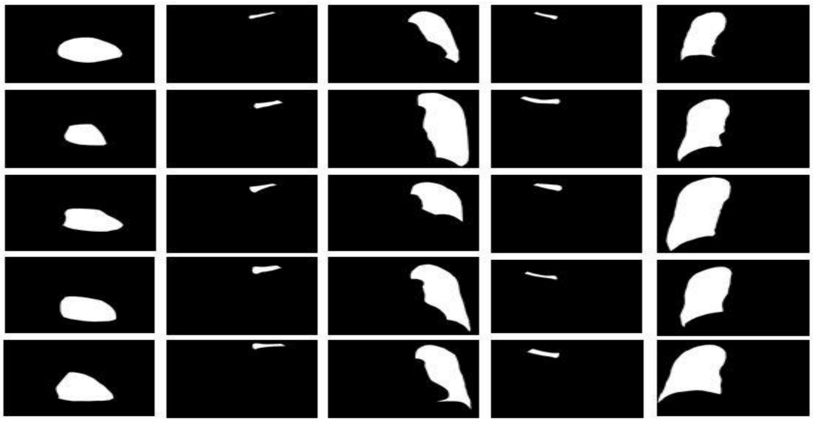

Figure 4.1: Samples images for network testing

4.2.1 Back propagation neural network

The simulation results of the back propagation networks as described in chapter three are given below in Table 4.1 and Table 4.2 . The training parameters were varied heuristically during the training process such that the network with best performance can be obtained; training parameters for the networks BPPN1, BPPN2, BPNN3, and BPNN4 can be seen in chapter 3, section 3.3 (Table 3.2).

shows the recognition rates of recognition acquired for the back propagation networks using 64×64 pixels is shown in Table 4.1.

Table 4.1: Rates of recognition for validation and training data (64×64 pixels)

Models	Training data (620)	Validation data (350)
Number 1BPNN	92.73%	90.41%
Number 2 BPNN	**99.18%**	**98.56%**
Number 3 BPNN	96.32%	95.3%
Number 4 BPNN	98.9%	93.24%

The table indicate that however all the back propagation networks trained have motivating performance on both databases such as the training and test databases (i.e. none has a recognition rate that is less than 90%), BPNN2 or let’s say back propagation neural network BPNN 2 got the highest recognition rate on the training as well as test data by comparision to the other networks.

Furthermore, to determine the effects of the rescaling the training data, training data images of size 128×128 pixels also been used to test the trained back propagation networks as described in chapter three.

Table 4.2: Rates of recognition for validation and training data (128×128pixels)

Network models	Training data (620)	Validation data (350)
BPNN5	87.43%	85.27%
BPNN6	86. 85%	84.14%
BPNN7	**88.95%**	**86.43%**
BPNN8	88.49%	83.67%

Table 4.2 above shows the test results for the designed back propagation networks using 128×128 pixels as input image size.

It can be seen from the table that BPPN7 managed to have the highest recognition rates on for the test data and training data unlike BPNN5, BPNN6, and BPNN8.

4.2.2 Competitive neural network

we also used unsupervised learning algorithm to train competitive neural networks in this thesis for the same categorization task. Their training was very fast because they have no desired outputs, hence no back pass of error gradients for weights and error calculation.

The simulation results for CNN for number of maximum epochs and different learning is given in The tables (4.3 and 4.4).

The results of using 64×64 pixels input image size for training the networks is described in Table 4.4. The learning parameters and particular network architectures can be found in chapter three, section 3.4.

Table 4.3: Rates of recognition for validation and training data (64×64pixels)

Network models	Training data (620)	Validation data (350)
CNN1	83.19%	80.60%
CNN2	**85.20%**	**83.70%**
CNN3	86.77%	76.24%

The table above shows CNN2 has maximum recognition estimate on both testing and training. moreover, it also shows that CNN3 even with the highest training compared to

CNN2, is still low with respect to CNN2. i.e. comparing to CNN2 we can say that CNN3 has lower generalization power.

The table showing the simulation results for the trained competitive neural networks which were trained on input images of size 128×128 pixels is given below as Table 4.4.

Table 4.4: Rates of recognition for validation and training data (128×128pixels)

Network models	Training data (620)	Validation data (350)
CNN4	**81.35%**	**80.04%**
CNN5	79.93%	78.65%
CNN6	80.65%	78.97%

It can be seen from Table 4.4 that CNN4 has the best performance on both the test training data, compared to the other networks CNN5 and CNN6, trained on the same data.

4.3 Discussion of Results

In this thesis, two types of neural networks have been trained on the chest X-ray images, such that after learning, the networks will be capable to classify supplied images into a heart, left clavicle, left lung, right clavicle, and right lung.

The back propagation neural network uses a supervised learning scheme to achieve learning, hence, such networks experience more concise learning in that the corresponding desired outputs are also presented to the networks during learning. Hence, it can be expected that these networks achieve a better performance or recognition rate compared to the competitive networks which use an unsupervised learning algorithm.

It can be seen from Table 4.1 and Table 4.2 that all the networks (BPNN1, BPNN2, BPNN3, and BPNN4) trained on 64×64 pixels have higher recognition rates compared to the all the networks (BPNN5, BPNN6, BPNN7, and BPNN8) trained on input images of size 128×128 pixels. It can therefore be suggested that in the classification task considered in this thesis, input image size of 64×64 resulted in a better learning for the back propagation networks. This outcome has been suggested to be associated with more compact representation of the edge detected patterns in the images for image size of 64×64 pixels than 128×128 pixels.

Table 4.3 and Table 4.4, shows that competitive networks (CNN1, CNN2, and CNN3) trained on 64×64 pixels input image achieved higher recognition rates compared to the competitive networks (CNN4, CNN5, and CNN6) trained on 128×128 pixels input image.

In all, it can be observed that on the average, the back propagation networks achieved higher recognition rates compared to the competitive networks. This can be obviously attributed to the supervised learning approach on which back propagation networks are based.

The consideration behind the use of competitive networks in this thesis, is that they require no manual labelling of target or desired outputs as it obtains in the back propagation networks, hence, cost, manual input, and time for designing and training such networks are reduced. Also, since, competitive networks do not have hidden layers, there is a reduction in the size of hardware required if practical, real life dedicated hardware were to be implemented as such for the classification task described in this thesis.

4.4 Summary

In this chapter, the testing of the designed and trained neural networks for the classification of chest X-rays images into one of the following classes: heart, left clavicle, left lung, right clavicle, or the right lung, are presented. Back propagation neural networks were trained using various learning parameters such that the best network based on classification accuracy can be obtained. Also, the networks were trained using an input image size of 64×64 pixels and 128×128 pixels.

Furthermore, the designed and trained competitive neural networks were tested using the same input data as obtains in the back propagation networks. A few examinations were additionally completed for these systems utilizing distinctive learning parameters.

In both BPNN and CPNN, it was seen that 64×64 pixels input image present excellent result on the accomplished acknowledgment rates; and the average, the BPNN is better than the CNN on characterized recognition rates. Also, the CNN does not need manual labelling of training data as it was done for the BPNN, in this way, it can be as a compensation for the lower grouping exactness acquired from the systems.

CHAPTER 5
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, artificial neural network based intelligent systems for the classification of segmented chest X-ray radiographs (images). In many clinical situations, it is desirable that the chest X-ray radiographs be segmented into regions of interest for further and closer examination. In this manner, it is obviously easier to notice minor irregularities or anomalies that may not be obvious when the whole chest X-ray images are inspected, especially considering human error that may occur probably due to fatigue or repetition of the same inspection task for several working hours.

In this work, automatic classification systems were developed that can accept images of chest X-ray, and therefore produce the corresponding class to which the images belong. The classification task considered in this thesis requires that the developed system is capable to classify the segmented chest X-rays into one of the following chest regions: heart, left clavicle, left lung, right clavicle, or right lung.

Furthermore, both supervised and unsupervised learning algorithms were used for the classification problem; back propagation networks were trained using segmented and labelled images. Several experiments were performed by varying the learning parameters of the networks. Also, both input image size of 64×64 and 128×128 pixels were used for training, and it was observed the back propagation networks trained on the 64×64 pixels input images outperformed the back propagation networks trained on the 128×128 pixels input images.

Competitive neural networks were also designed, trained, and tested for the same classification task. It will be noted that the implementation of such networks requires no labelling of training data, hence, training required lesser manual input for labelling data.

Also, input images of size 64×64 pixels and 128×128 pixels were used to train and test the networks. An average recognition rate of 70% was obtained, which is of course lower than that of the back propagation networks; but considering the fact that competitive networks relies on unsupervised learning approach (the network must learn on its own features that separate one class from the others), and no labelling was required for training, the situation can be considered a tradeoff as to back propagation networks in which huge amount of time is required for labelling the training data.

In addition, such networks have no hidden layers, therefore, lesser network parameters deemed to optimized during training. i.e. fewer interconnections, weights, and computations required. Training takes lesser time too, which can be seen in Table 3.4 and Table 3.5.

5.2 Recommendation

It can be seen that the developed systems are not rotational invariant, that is, if the images are displaced angularly, the classification systems are expected to suffer a drastic drop in performances, hence, the development of intelligent systems that can cope with chest X-ray radiographs that are displaced through various angles. This is very crucial considering the importance of the classification task as described in this thesis.

Furthermore, it is suggested that other classification algorithms such as radial basis networks, k-means clustering can be considered for the classification task described in this thesis. Also, the use of multi-class support vector machine is highly suggested such that a better performance is obtained as compared to the results presented in this work. A Support vector machine is an optimum margin classifiers, hence, always converge to the optimum solution or decision hyperplane; and therefore do not suffer weight initialization problems as obtains in neural networks.

It is also suggested that feature extraction of some parameters that sufficiently describes the images can be considered for future work. The extracted features can be used to train the networks described in this thesis, rather than using the whole processed images as inputs.

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