SIGNATURE RECOGNITION BASED ON NEURAL NETWORK

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

By
SALMIN MOHAMED

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

NICOSIA, 2016

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Salmin Mohamed: Signature Recognition Based on Neural Network

Approval of Director of Graduate
School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

Director

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

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Name, last name:

Signature:

Date:

To my family…

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ABSTRACT

With the progress of new innovation, the technology security frameworks are being supplanted by a great deal more propelled methods to identify a person. These procedures are called biometrics, which include checking a person's organic attributes, for example, face, retina, unique finger impression, iris, voice, signature and so forth. Formally, biometrics alludes to the ID of people by their attributes or traits. In this thesis we propose a human signature recognition system based canny edge detection and pattern averaging and backpropagation neural network system, that has the capability of determining the human handwritten signatures of presented signature images of different individuals with different scales, illuminations and different signature writing style of same signature image. In addition, this thesis proposes a simple, easy, and fast processing approach to extracting an average of useful features from a signature image using a technique called pattern averaging. This technique plays an important role in reducing the processing and training time and also in improving the recognition rate of the neural network. The experimental results show that the trained back propagation neural network is capable of recognizing human handwritten signatures regardless of scale, illumination, and difference is writing style of the signatures.

Keywords: Biometricsc; Edge detection; Handwritten signatures; Illumination; Neural network; Pattern averaging; Scale

ÖZET

Yeni yeniliğin ilerlemesi ile birlikte, bir kişiyi tanımlamak için teknoloji güvenlik çerçeveleri çok daha fazla öne çıkarılmış yöntemlerle değiştiriliyor. Bu prosedürlere biyometri denir; kişinin organik özelliklerini, örneğin yüz, retina, benzersiz parmak izlenimi, iris, ses, imza ve benzeri faktörleri kontrol etmeyi içerir. Resmi olarak, biyometri, kişilerin özelliklerine veya özelliklerine göre Kimliğini belirtir. Bu tezde, sunumun insan el yazısı imzalarını belirleme yeteneğine sahip olan bir insan imza tanıma sistemi temelli kanot kenar algılama ve model ortalaması ve geri yayılım nöral ağ sistemi önerilmektedir. Farklı ölçekler, aydınlatmalar ve aynı imza görüntüsünün farklı imza yazı stiline sahip farklı kişilerin imza görüntüleri. Buna ek olarak, bu tez, desen ortalamaları adı verilen bir teknik kullanarak imza imajından ortalama faydalı özelliklerin çıkartılması için basit, kolay ve hızlı bir işleme yaklaşımı önermektedir. Bu teknik işlem ve eğitim süresinin azaltılmasında ve ayrıca sinir ağı tanıma oranının arttırılmasında önemli bir rol oynamaktadır. Deneysel sonuçlar, eğitilmiş geri yayılım nöral ağının insan el yazısı imzaları ölçekten, aydınlatmadan bağımsız olarak algılayabildiğini ve imzaların yazı stilindeki farklılığın farklı olduğunu göstermektedir.

Anahtar Kelimeler: Biyometri; Kenar algılama; Desen ortalamaları; Sinir ağı; El yazısı imzalar; Ölçek; Aydınlatma

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ANNs: Artificial Neural Networks

BPNN: Back Propagation Neural Network

CT: Computed Tomography

LOG: Laplacian of Gaussian

RGB: Red Green Blue Colours

SVRS: Signature Recognition Verification Service

SVM: Support Vector Machine

CHAPTER 1
INTRODUCTION

People recognize each other as indicated by their different attributes for a very long time. We recognize others by their face when we meet them and by their voice at this very moment to them. Character check (verification) in computer frameworks has been generally in view of something that one has (key, attractive or chip card) or one knows (PIN, secret key). Things like keys or cards, be that as it may, have a tendency to get stolen or lost and passwords are frequently overlooked or unveiled. To accomplish more solid check or distinguishing proof we ought to utilize something that truly portrays the given individual. Biometrics offer robotized techniques for character check or recognizable proof on the guideline of quantifiable physiological or behavioral qualities, for example, a signature or a voice test. These qualities ought to not be duplicable, but rather it is lamentably regularly conceivable to make a duplicate that is recognized by the biometric framework as an intelligent system example.

Signature validation innovation utilizes the dynamic investigation of a signature to confirm a man. The innovation depends on measuring speed, weight furthermore, point utilized by the individual when a signature is created. This innovation utilizes the person's manually written signature as a premise for validation of substances and information. An electronic drawing tablet and stylus are utilized to record the heading, speed and facilitates of a manually written signature. There is no encryption or message privacy offered yet with signature progression, however more present day cases utilize one-way hash capacities to encode the signature progression and information and annex it to the archive being agreed upon.

The progress of intelligent systems that uses neural systems is interesting and recently it has attracted more scientists into studying the potential uses of such systems in the signature recognition applications. The learning technique of a neural network is mimicked from the human brain one which relies on the features extracted from a seen image that retrieves the brain memory and generalizes the whole scene or image.

The same concept is to be used in this thesis. The features that can represent the signature and distinguish it are to be fed into a neural network that learns them through its backpropagation learning algorithm that will assure the generalization capability of the network when testing.

To extract the right features the images have to be processed using some image processing techniques that end up with a segmented signature. The images undergo a filtering process first in order to remove the noise of the image since images are acquired by a camera. Then, a threshold was specified using Ostu's threshold in which pixels over this threshold are converted to 1 or white and those below it are converted to 0 or black. The images are then segmented using Canny edge detection that detects the edges of signatures and consider only those edges instead of considering the whole image which makes the training of the network tougher.

The last phase here is the feature extraction phase in which the pattern averaging technique is used. This technique is a size reduction technique using averaging of the image pixels. Hence, averaging of the image pixels reduces the size of the image by considering only the important features or pixels of the image which facilitates the training phase and reduces the number of input neurons of the network.

Thus, the proposed signature recognition system is an investigation of the use of back propagation neural network and pattern averaging technique in recognizing the human handwritten signatures. The experimental results show that such a simple, easy, and fast processing system is capable of generalizing the modified, shift translated, illuminated, noisy, and shape updated handwritten images.

1.1 Aims of the Study

The aim of this work is to investigate the use of intelligent classifiers such as back propagation neural network combined with the feature extraction algorithm: pattern averaging in recognizing handwritten signatures collected from the Near East university students. Such a hard task can be a tough classification task for a backpropagation neural network due to the artifacts that n image can have. For the same individual, the signature image may be different. Moreover, the illumination and image translation can make it hard for the network to converge. Therefore, the aim of this thesis is to implement an intelligent that can't be affected by these artifacts. This is achieved by developing a network that is capable of recognizing signatures of regardless of illumination, translations and the small changes in signatures.

1.2 The important of the Study

This thesis presents a human signature recognition system based canny edge detection and pattern averaging and backpropagation neural network system, that has the capability of determining the human handwritten signatures of presented signature images of different individuals with different scales, illuminations and different signature writing style of same signature image. In addition, this thesis proposes a simple, easy, and fast processing approach to extracting an average of useful features from a signature image using a technique called pattern averaging. This technique plays an important role in reducing the processing and training time and also in improving the recognition rate of the neural network.

1.3 Limitation of the Study

The limitation of the thesis is as follows:

- The system in this study is work on computer with matlab software (R2015).

1.4 Overview of the Study

The thesis is structures as follows:

Chapter 1 is an introduction about the thesis. In this chapter, a goal of the presented work is stated. In addition, the aims, the contributions, and motivations, and contributions of the research are discussed. The structure overview of the thesis is also presented.

Chapter 2 is a general explanation about the image processing. An introduction of the image processing is first presented. Then, we explain the image processing techniques and methods used in the medical field. We attempt to explain the used image processing methods of the proposed system in details.

Chapter 3 is an explanation the artificial neural network systems where the concept and the various networks such as radial basis, recurrent and backpropagation neural network are explained.

Chapter 4 discusses the proposed system methodology, materials and methods are presented. The system flowchart and algorithm is presented in this chapter. Moreover, the methods used in order to come up with such system are discussed as well as the created database used in training and testing the proposed system.

Chapter 5 discusses the image processing techniques used in the proposed system in order to segment the signature images. as well as, it shows a samples of segmented and averages images.

Chapter 6 discusses the classification stage of the developed system. It shows the learning and also testing phases of the system. The learning results are discussed in this chapter as well as the performance of the network in the testing stage.

Chapter 7 is the last chapter and its shows the results comparison of the proposed human signature recognition system based pattern averaging and backpropagation neural network are presented, discussed and compared with previously proposed systems of the same goal are explained.

1.5 Literature Review

Signature is an exceptional instance of handwriting which incorporates exceptional characters and twists. Numerous signatures can be unintelligible. They are a sort of aesthetic handwriting objects. Be that as it may, a signature can be taken care of as a picture, and consequently, it can be recognized utilizing computer vision and counterfeit neural system methods. Signature recognition and confirmation includes two isolated be that as it may, firmly related errands: one of them is distinguishing proof of the signature proprietor, and the other is the choice about whether the signature is real or produced. Likewise, depending on the need, signature recognition and confirmation issue is put into two noteworthy classes: (i) online signature recognition and confirmation frameworks (SRVS) and (ii) disconnected SRVS. Online SRVS requires some unique fringe units for measuring hand speed and weight on the human hand when it makes the signature (Brault & Plamondon, 1993). Then again, all disconnected SRVS frameworks depends on picture handling and highlight extraction strategies.

In the last two decades, in parallel with the advancement in the sensor technology, some successful online SRVS are developed (Parizeau & Plamondon, 1990) (Lee et al., 1996). There are also many studies in the area of offline SRVS category (Xuhang et al., 2001) (Yuan el al., 2001) (Ismail & Samia, 2000). These studies are generally based on ANN (Baltzakis & Papamorkos, 2001) ((Xuhang et al., 2001) analysis of the geometry and topology of the signature (Droughord, 1996), and its statistical properties (Han & Sethi, 1996)

Recently, researchers attempted to investigate the use of artificial systems in signature recognition and verification applications. The intelligent systems such as support vector machine and artificial network attracted the scientists due to their efficiency in learning and extraction the features of signature images. in addition to their capability of recognizing images exposed to scale, rotation, and illumination variations.

Radial Basis Function Network was used as an intelligent classifier for the signature recognition by the authors in (Chadha et al., 2013). This work used Discreet Cosine Transform as a feature extraction technique in order to extract the useful features of a human handwritten signature. The authors tested their system with some rotated, scaled, and illuminated images in order to make it robust and effective. The recognition rate of this system was somehow low (80%).

Another work proposed by (Oz, 2005) which investigated the use of neural network in the recognition and verification of handwritten signatures. In their research, they proposed an off-line signature recognition and verification system that is based on a moment invariant method. The systems comprises of two neural networks that are used for signature recognition, and for verification (i.e. for detecting counterfeit). The authors tested their system and the system showed good performance of 91%.

CHAPTER TWO
IMAGE PROCESSING

2.1 Introduction

In parallel with space applications, digital image processing strategies started in the late 1960s and mid-1970s to be utilized as a part of restorative imaging, remote Earth assets perceptions, and astronomy. The innovation in the mid-1970s of modernized hub tomography (CAT), additionally called automated tomography (CT) for short, is a standout amongst the most essential occasions in the use of image processing in restorative judgment. Automated hub tomography is a procedure in which a ring of identifiers surrounds an article (or quiet) and a X-beam source, concentric with the indicator ring, turns about the object. The X-beams go through the item and are gathered at the inverse end by the relating identifiers in the ring. As the source turns, this technique is repeated. Tomography comprises of calculations that utilize the sensed information to develop a picture that speaks to a "cut" through the item. Movement of the item in a bearing opposite to the ring of identifiers delivers an arrangement of such cuts, which constitute a three-dimensional (3-D) version of within the article. Tomography was concocted freely by Sir Godfrey N. Hounsfield and Professor Allan M. Cormack, who imparted the 1979 Nobel Prize in Medicine for their creation. It is intriguing to note that X-beams were found in 1895 by Wilhelm Conrad Roentgen, for which he got the 1901 Nobel Prize for Physics. These two creations, about 100 years separated, prompted a percentage of the most dynamic application ranges of image processing today (Gonzalez & Woods, 2004).

Medical image analysis is shifting from the visual analysis of planar images to the computerized quantitative analysis of volumetric images. It is important to have high performance computing power to handle the extra computation necessary for volumetric images (Warfield et al., 1998).

2.2 Principles of Image Processing

In the wake of changing over picture data into a cluster of numbers, the picture can be controlled, prepared, and showed by PC. PC transforming is utilized for picture upgrade, rebuilding, division, portrayal, distinguishment, and coding, remaking, change.

The general electronic picture changing system may be separated into three sections: The information device (or digitizer), the mechanized processor, and the yield contraption (Stefanescu et al., 2004).

The digitizer changes more than a perpetual tone and spatially persevering sparkle spread f [x, y] to a discrete bunch (the propelled picture) fq[n, m], where n, m, besides fq are numbers.

- The modernized processor chips away at the propelled picture fq[n, m] to make an alternate mechanized picture gq[k, c], where k, c, and gq are numbers. The yield picture may be identified with in another heading system, in this way the use of various records k and c.

- The picture showcase changes over the propelled yield picture gq[k, c] afresh into a ceaseless tone moreover spatially steady picture g [x, y] for audit. It should be recognized that a couple of structures may not oblige a showcase (e.g., in machine vision and fake insight applications); the yield may be a touch of information. For example, a modernized imaging system that was expected to answer the request, Is there confirmation of a ruinous tumor in this x-bar picture ideally would have two possible yields (YES or NO), , i.e., a singular bit of information.

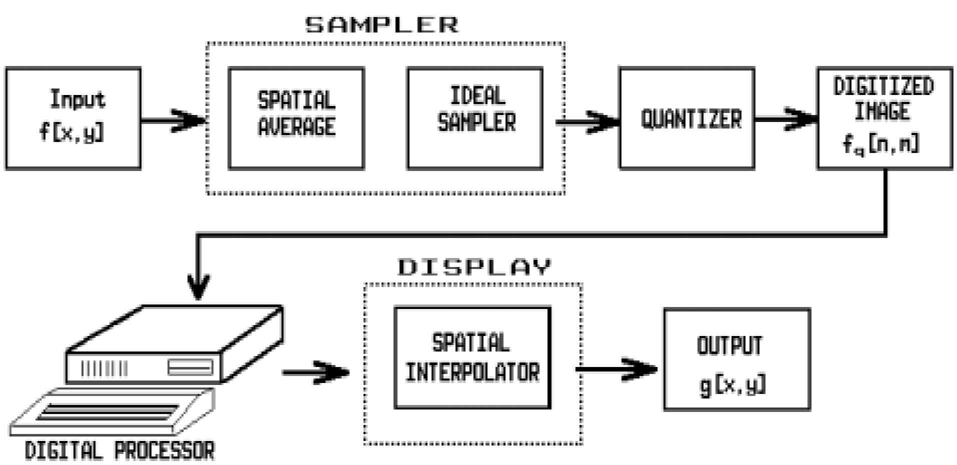

Figure 1: Digital image processing (Andrew, 2008)

2.3 Image Analysis Strategies

Image analysis involves the conversion of features and objects in image data into quantitative information about these measured features and attributes. Microscopy images in biology are often complex, noisy, artifact-laden and consequently require multiple image processing steps for the extraction of meaningful quantitative information (Gonzalez & Woods, 2001). An outline of a general strategy for image analysis is presented below:

1) The starting point in image analysis typically involves a digital image acquired using a CCD camera. Raw microscopy images obtained on digital CCD cameras are subject to various imperfections of the image acquisition setup, such as noise at low light levels, uneven illumination, defective pixels, etc… We often need to first process the image to correct for such defects and also to enhance the contrast to accentuate features of interest in the image for subsequent analysis. In section II, we introduce various image transformation and spatial filtering techniques that can be used for this purpose (Milan et al., 1998).

2) Having corrected artifacts and enhanced contrast in the images, we can apply various computational techniques to extract features and patterns from the images. In the following section, we describe various tools of morphological image processing and image segmentation that can be used for this purpose.

3) After biological important features have been segmented from images, we can then derive quantitative information from these features and objects. MATLAB provides a set of tools that can be used to measure the properties of regions; the matrix representation of images in MATLAB also allows for easy manipulation of data and calculation of quantities from microscopy images (Fan et al., 2002).

Here is an outline of the process:

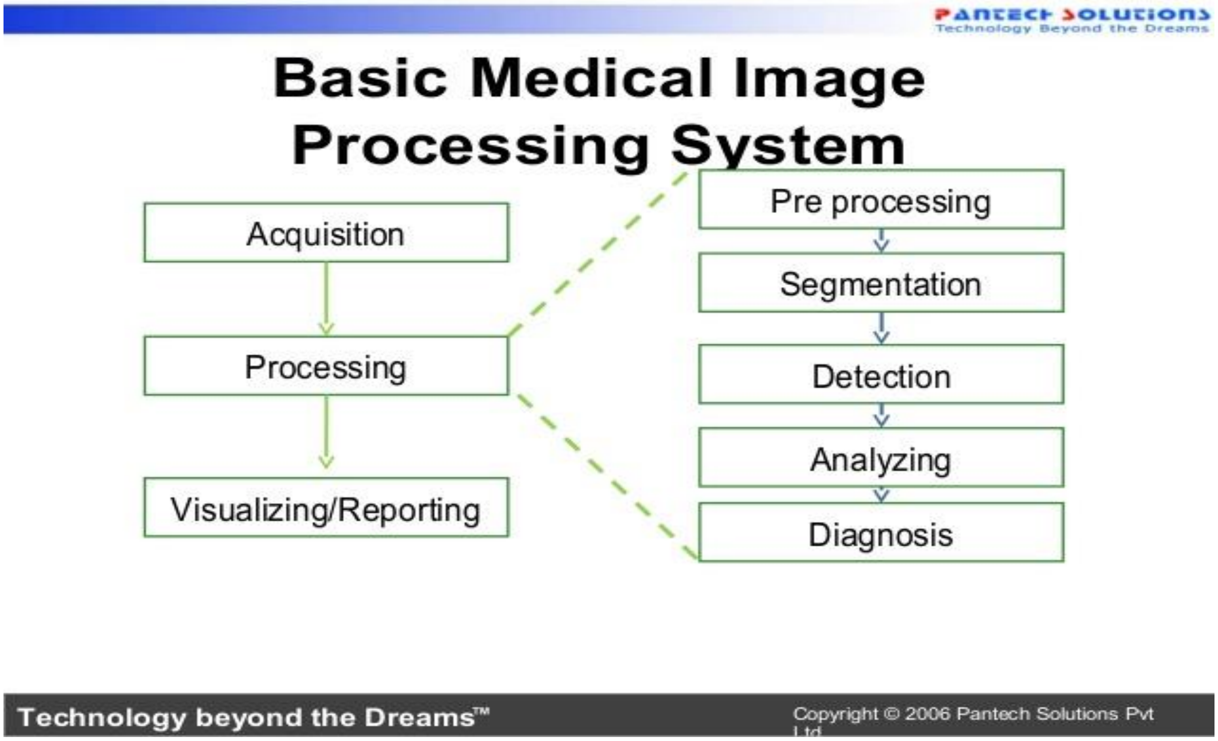

Figure 2: Image analysis process

2.4 Image Enhancements

Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task. Moreover, observer-specific factors, such as the human visual system and the observer's experience, will introduce a great deal of subjectivity into the choice of image enhancement methods (Fan et al., 2002).

There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided in to the following two categories:

1. Spatial Domain Methods

2. Frequency Domain Methods

In spatial domain techniques, we directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values (Gonzalez & Woods, 2001).

Image enhancement simply means, transforming an image f into image g using T. (Where T is the transformation. The values of pixels in images f and g are denoted by r and s, respectively. As said, the pixel values r and s are related by the expression,

$$s = T(r) \tag{1}$$

Where T is a transformation that maps a pixel value r into a pixel value s. The results of this transformation are mapped into the grey scale range as we are dealing here only with grey scale digital images.

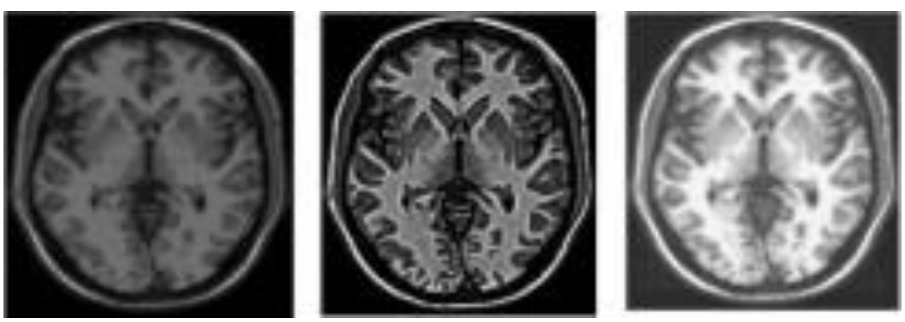

Figure 3: Example of image enhancement (Fan et al., 2002)

2.5 Contrast Adjustments

Often, images have a low dynamic range and many of its features are difficult to see. We will present different intensity transformations that will improve the appearance of the images. Improving the appearance of an image does not merely serve an aesthetic role – often, it can help improve the performance of image segmentation algorithms and feature recognition.

During contrast adjustment, the intensity value of each pixel in the raw image is transformed using a transfer function to form a contrast-adjusted image. The most common transfer function is the gamma contrast adjustment:

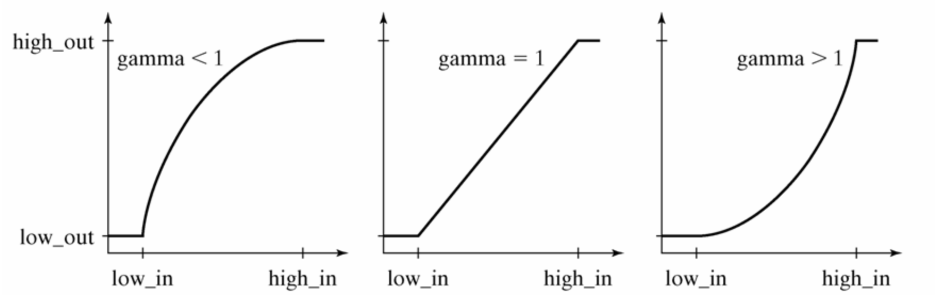

Figure 4: Gamma correction (Gonzalez & Woods, 2001)

Here low in and low high give the low and high grayscale intensity values for the contrast adjustment, and gamma gives the exponent for the transfer function.

2.6 Data Compression and Data Redundancy

Data compression is defined as the process of encoding data using a representation that reduces the overall size of data. This reduction is possible when the original dataset contains some type of redundancy. Digital image compression is a field that studies methods for reducing the total number of bits required to represent an image. This can be achieved by eliminating various types of redundancy that exist in the pixel values. In general, three basic redundancies exist in digital images that follow. Psycho-visual Redundancy: It is a redundancy corresponding to different sensitivities to all image signals by human eyes. Therefore, eliminating some less relative important information in our visual processing may be acceptable.

Inter-pixel Redundancy: It is a redundancy corresponding to statistical dependencies among pixels, especially between neighboring pixels.

Coding Redundancy: The uncompressed image usually is coded with each pixel by a fixed length. For example, an image with 256 gray scales is represented by an array of 8-bit integers. Using some variable length code schemes such as Huffman coding and arithmetic coding may produce compression. There are different methods to deal with different kinds of aforementioned redundancies. As a result, an image compressor often uses a multi-step algorithm to reduce these redundancies.

2.6.1 Compression Methods

During the past two decades, various compression methods have been developed to address major challenges faced by digital imaging (Wallace, 1991).

These compression methods can be classified broadly into lossy or lossless compression. Lossy compression can achieve a high compression ratio, 50:1 or higher, since it allows some acceptable degradation. Yet it cannot completely recover the original data. On the other hand, lossless compression can completely recover the original data but this reduces the compression ratio to around 2:1. In medical applications, lossless compression has been a requirement because it facilitates accurate diagnosis due to no degradation on the original image. Furthermore, there exist several legal and regulatory issues that favor lossless compression in medical applications.

- Lossy Compression Methods

Generally most lossy compressors (Figure 6) are three-step algorithms, each of which is in accordance with three kinds of redundancy mentioned above.

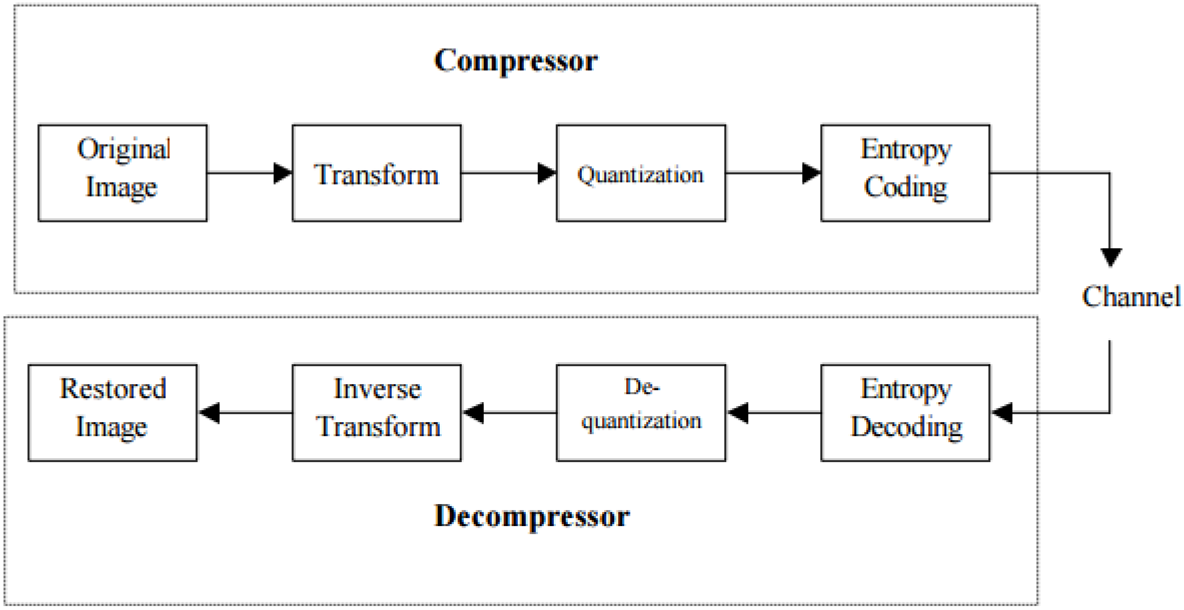

Figure 5: Lossy compression (Wallace, 1991)

The first stage is a transform to eliminate the inter-pixel redundancy to pack information efficiently. Then a quantizer is applied to remove psycho-visual redundancy to represent the packed information with as few bits as possible. The quantized bits are then efficiently encoded to get more compression from the coding redundancy.

- Lossless Compression Methods:

Lossless compressors (Fig.6) are usually two-step algorithms. The first step transforms the original image to some other format in which the inter-pixel redundancy is reduced. The second step uses an entropy encoder to remove the coding redundancy. The lossless decompressor is a perfect inverse process of the lossless compressor.

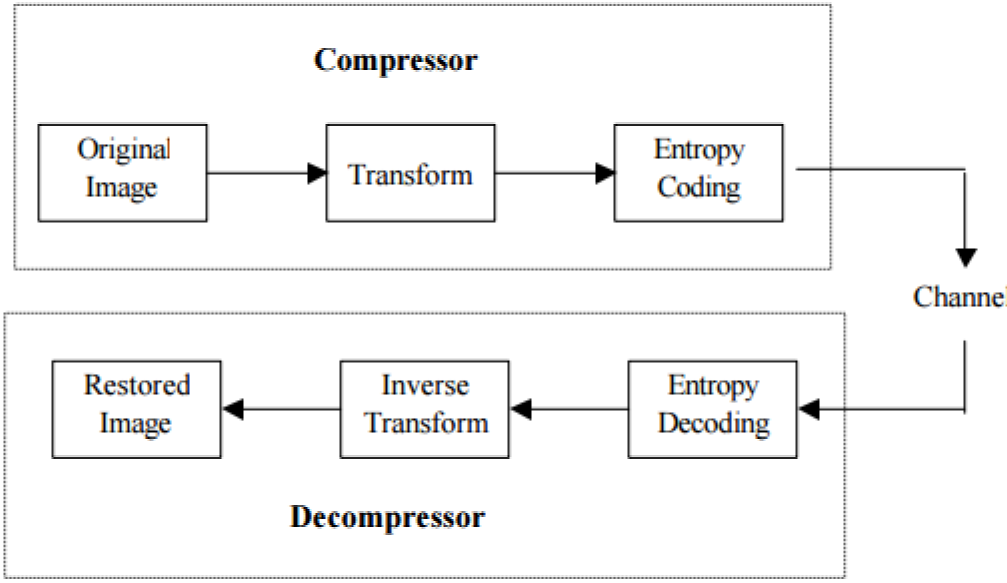

Figure 6: Lossless compression (Wallace, 1991)

2.7 Image Segmentation

Image segmentation is the division of an image into regions or categories, which correspond to different objects or parts of objects. Every pixel in an image is allocated to one of a number of these categories. A good segmentation is typically one in which:

• Pixels in the same category have similar grayscale of multivariate values and form a connected region,

• Neighboring pixels which are in different categories have dissimilar values.

Figure 7: Edge based segmentation (Saif et al., 2012)

2.8 Edge Detection

Edges are boundaries between different textures. Edge also can be defined as discontinuities in image intensity from one pixel to another. The edges for an image are always the important characteristics that offer an indication for a higher frequency. Detection of edges for an image may help for image segmentation, data compression, and also help for well matching, such as image reconstruction and so on.

There are many methods to make edge detection. The most common method for edge detection is to calculate the differentiation of an image. The first-order derivatives in an image are computed using the gradient, and the second-order derivatives are obtained using the Laplacian. Another method for edge detection uses Hilbert Transform.

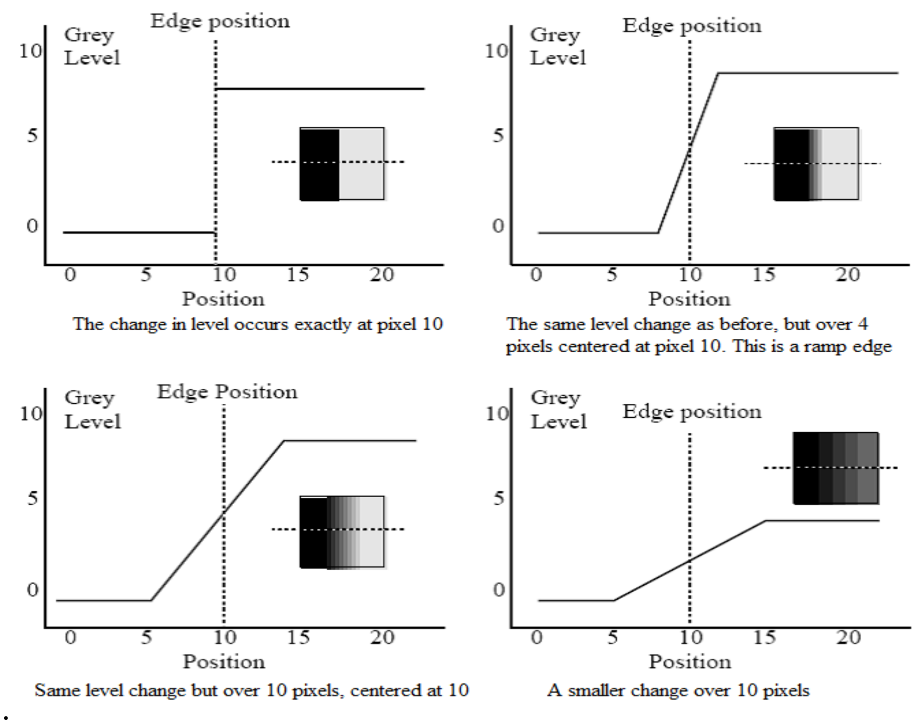

Figure 8: Step Edges

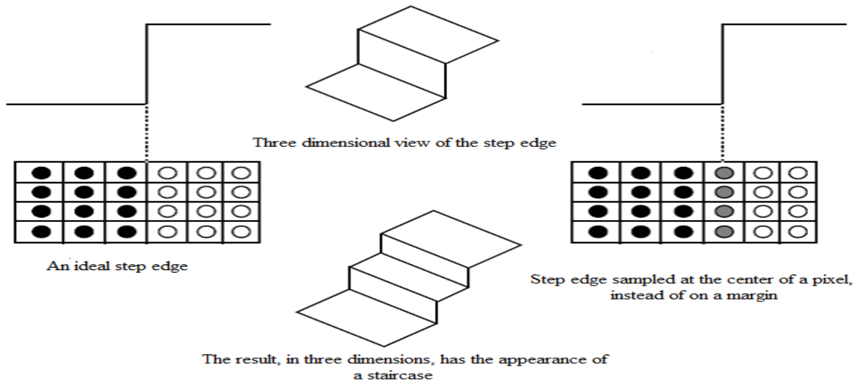

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Figure 9: The effect of sampling on a step edge

2.8.1 Fist-Order Derivative Edge Detection

Fist-Order Derivative Edge Detection:

$$\nabla \mathbf{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}. \tag{2.1}$$

An important quantity in edge detection is the magnitude of this vector, denoted ∇f, Where

$$\nabla f = |\nabla \mathbf{f}| = \sqrt{G_x^2 + G_y^2}\ . \tag{2.2}$$

Another important quantity is the direction of the gradient vector. That is,

$$\text{angle of } \nabla \mathbf{f} = \tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{2.3}$$

Computation of the gradient of an image is based on obtaining the partial derivatives of $\partial f/\partial x$ and $\partial f/\partial y$ at every pixel location. Let the 3×3 area shown in Fig. 14 represent the gray levels in a neighborhood of an image. One of the simplest ways to implement a first-order partial derivative at point $z5$ is to use the following Roberts cross-gradient operators:

$$G_x = (z_9 - z_5) \tag{2.4}$$

and

$$G_y = (z_8 - z_6) \quad (2.5)$$

These derivatives can be implemented for an entire image by using the masks shown below with the procedure of convolution.

Another approach using masks of size 3×3 shown below which is given by

$$G_x = (z_7 + z_8 + z_9) - (z_1 + z_2 + z_3) \quad (2.6)$$

and

$$G_y = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7) \quad (2.7)$$

a slight variation of these two equations uses a weight of 2 in the center coefficient:

$$G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \quad (2.8)$$

$$G_y = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7) \quad (2.9)$$

A weight value of 2 is used to achieve some smoothing by giving more importance to the center point. The following table called the Sobel operators, is used to implement these two equations.

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

0	0	0
0	–1	0
0	0	1

0	0	0
0	0	–1
0	1	0

The Roberts operators.

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

The Prewitt operators.

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

The Sobel operators.

1. Second-Order Derivative Edge Detection

The Laplacian of a 2-D function $f\,(x, y)$ is a second-order derivative defined as

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \tag{2.10}$$

There are two digital approximations to the Laplacian for a 3×3 region:

$$\nabla^2 f = 4z_5 - (z_2 + z_4 + z_6 + z_8) \tag{2.11}$$

$$\nabla^2 f = 8z_5 - (z_1 + z_2 + z_3 + z_4 + z_6 + z_7 + z_8 + z_9) \tag{2.12}$$

Masks for implementing these two equations are shown in Fig. 10.

0	−1	0
−1	4	−1
0	−1	0

(a)

−1	−1	−1
−1	8	−1
−1	−1	−1

(b)

Figure 10: Two kind of 3×3 Laplacian mask

The Laplacian is usually combined with smoothing as a precursor to finding edges via zero-crossings. The 2-D Gaussian function

$$h(x,y) = -e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2.13}$$

where σ is the standard deviation, blurs the image with the degree of blurring being determined by the value of σ. The Laplacian of *h* is

$$\nabla^2 h(x,y) = -\left[\frac{x^2+y^2-2\sigma^2}{\sigma^4}\right] e^{-\frac{r^2}{2\sigma^2}} \tag{2.14}$$

This function is commonly referred to as the Laplacian of Gaussian (LOG).

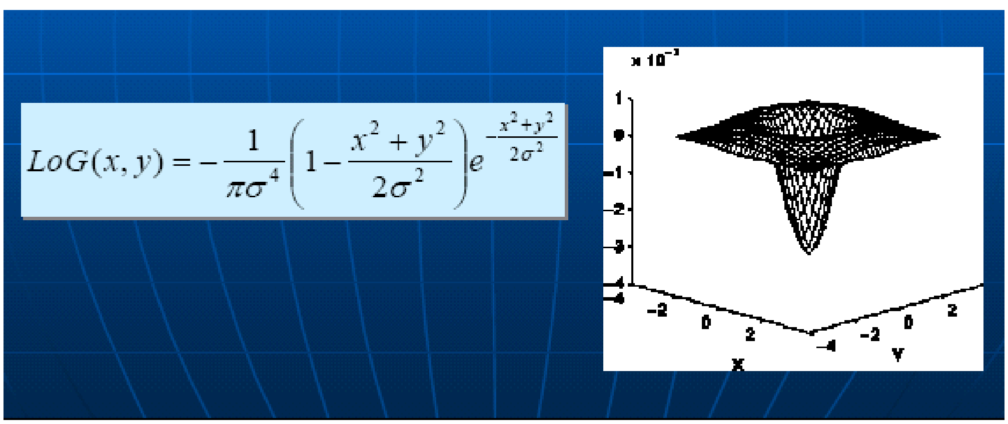

Figure 11: Dimension coordinate of Laplacian of Gaussian (LOG)

After calculating the two-dimensional second-order derivative of an image, we find the value of a point which is greater than a specified threshold and one of its neighbors is less than the negative of the threshold. The property of this point is called zero-crossing and we can denote it as an edge point.

We note two additional properties of the second derivative around an edge: (1) It produces two values for every edge in an image (an undesirable feature); and (2) an imaginary straight line joining the extreme positive and negative values of the second derivative would cross zero near the midpoint of the edge. This zero-crossing property of the second derivative is quite useful for locating the centers of thick edges.

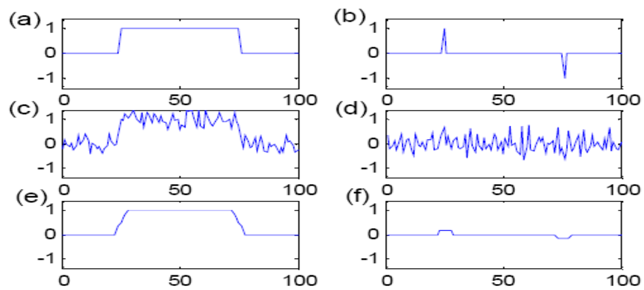

Figure 12: The results of differentiation of using the ramp edges

2.9 Medical Image Processing

Restorative imaging has been experiencing an insurgency in the previous decade with the coming of quicker, more precise, and less obtrusive gadgets. This has driven the requirement for relating programming improvement which thusly has given a noteworthy catalyst to new calculations in sign and picture transforming (Stefanescu et al., 2004).

In particular, in therapeutic imaging we have four key issues:

- **Segmentation:** Automated methods that create patient-specific models of relevant anatomy from images;
- **Registration:** Automated methods that align multiple data sets with each other;
- **Visualization:** The technological environment in which image-guided procedures can be displayed;

Imaging innovation in Medicine made the specialists to see the inside parts of the body for simple determination. It likewise helped specialists to make keyhole surgeries for coming to the inside parts without truly opening excessively of the body. CT Scanner, Ultrasound and Magnetic Resonance Imaging assumed control x-beam imaging by making the specialists to take a gander at the body's subtle third measurement. With the CT Scanner, body's inside can be uncovered with straight forwardness and the unhealthy territories can be distinguished without bringing about either uneasiness or torment to the patient. X-ray grabs signals from the body's attractive particles turning to its attractive tune and with the assistance of its intense PC, changes over scanner information into uncovering pictures of inward organs. Image processing strategies produced for breaking down remote sensing information may be altered to dissect the yields of therapeutic imaging frameworks to get best preference to break down indications of the patients without any difficulty (Rao & Rao, 2004).

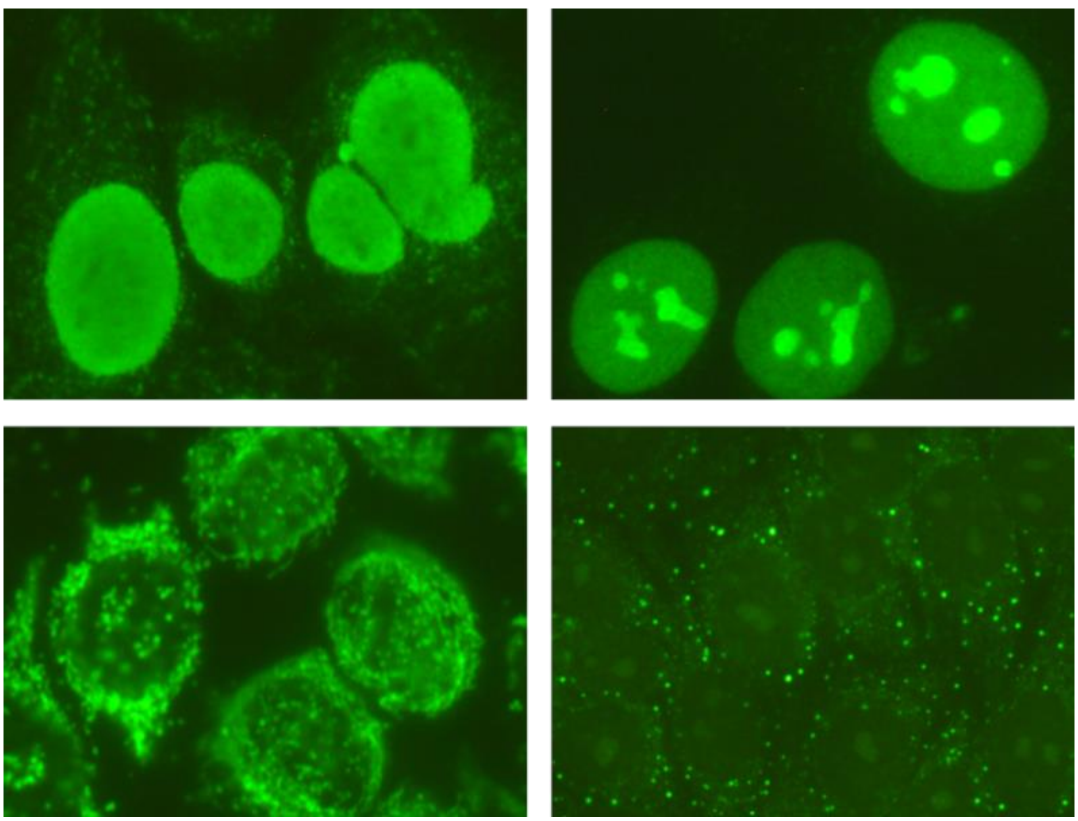

Figure 13: Medical image processing

CHAPTER THREE
ARTIFICIAL NEURAL NETWORKS

3.1 Introduction

Artificial neural networks (ANNs) are the simple simulation of the structure and the function of the biological brain. The complex and accurate structure of the brain makes it able to do hard different simultaneous tasks using a very huge number of biological neurons connected together in grids. A first wave of interest in neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational tasks (Krose & Smagt, 1996). At that time, Von Neumann and Turing discussed interesting aspects of statistical and robust nature of brain-like information processing. But it was only in 1950s that actual hardware implementations of such networks began to be produced (Fyfe, 1996). ANNs are used widely nowadays in different branches of science. It is used for medical purposes like in (Abiyev & Altunkaya, 2008) and (Abiyev & Akkaya, 2016). Used for image processing for different purposes like (Khashman & Dimililer, 2007). It is also invested in power and power quality applications and active power filters (Valiviita, 1998) and (Sallam & Khafaga, 2002). In (Yuhong & Weihua, 2010) a survey on the application of the ANNs in forecasting financial market prices, financial crises, and stock prediction was presented.

The different mentioned applications of neural networks imply firstly the learning of the ANNs to do defined tasks. One of the most common methods of teaching ANNs to perform given tasks is the back propagation algorithm. It is based on a multi-stage dynamic system optimization method proposed by Arthur E. Bryson and Yu-Chi Ho in 1969 (Ho, 1969). In 1974, it was applied in the context of ANNs through the works of Paul Werbos, David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams, and it became famous and led to a renaissance in the field of artificial neural networks.

3.2 Analogy to the Human Brain

The artificial neural network is an imitation of the function of the human biological brain. It's using the structure and the function of brain. The human brain is composed of billions of interconnected neurons. Each one of these neurons is said to be connected to more than 10000 neighbor neurons. Figure (3.1) shows a small snip portion of the human brain where the yellow blotches are the body of the neural cells (soma). The connecting lines are the dendrites and axons that connect between the (Shen & Wang, 2012). The dendrites receive the electrochemical signals from the other cells and transmit it to the body of the cell. If the signals received are powerful enough to fire the neuron; the neuron will transmit another signal through the axon to the neighbor neurons in the same way. The signal are going also to be received by the connected dendrites and can fire next neurons.

3.3 Artificial Neural Networks

Artificial neural networks are a structure that has inspired its origins from the human thinking center or the brain. This structure has been inspired and developed to build a mechanism that can solve difficult problems in the science. Most of the structures of neural networks are similar to the biological brain in the need for training before being able to do a required task (Kaki, 2009). Similar to the principle of the human neuron, neural network computes the sum of all its inputs. If that sum is more than a determined level, the correspondent output can then be activated. Otherwise, the output is not passed to the activation function. Figure 3.4 presents the main structure of the artificial neural network where we can see the inputs and weights in addition to the summation function and the activation function. The output function is the output of the neuron in this structure. The input of the activation function is given by:

$$TP = \sum x_n \omega_n \tag{3.1}$$

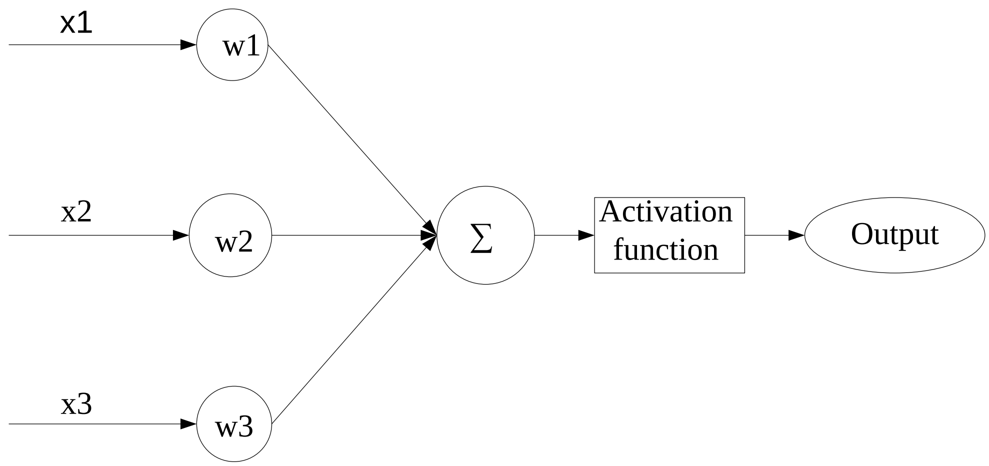

Figure 14: Basic structure of artificial neural network

3.3.1 Structure of ANN

The structure of ANNs consists mainly of three aspects in addition to the learning method. These aspects are the layers, weights, and activation functions. Each one of these three parts play a very important rule in the function of the ANN. The learning function is the algorithm that relates these three parts together and ensures the correct function of the network.

3.3.2 Layers

ANN is constructed by creating connections between different layers to each other. Information is being passed between the layers through the synaptic weights. In a standard structure of ANN there are three different types of layers (Mena, 2012):

- **Input layer:** The input layer is the first one in a neural network. Its rule is the transmission of input information to the other layers. An input layer doesn't process the information; it can be considered as the sensors in biological system. It can also be called non processing layers.
- **Output layer:** The last layer in the neural network whose output is the output of the whole network. In contrary to the input layer, the output layer is a processing layer.
- **Hidden layers:** This is the main part of the network. It consists of one or more of processing layers. They are connecting the input layers to the output layers. Hidden

layers are the main processing layers where the weights are being updated continuously. Each one of the hidden layers connects between two hidden layers or one hidden and input or output layer.

Figure 3.5 presents the layers of the neural network and the connections between the layers. As shown in the figure, the inputs are fed to the input layer. The output of the input layer is fed to the hidden layers. The output obtained from the hidden layers is fed to the output layer that generates the output of the network.

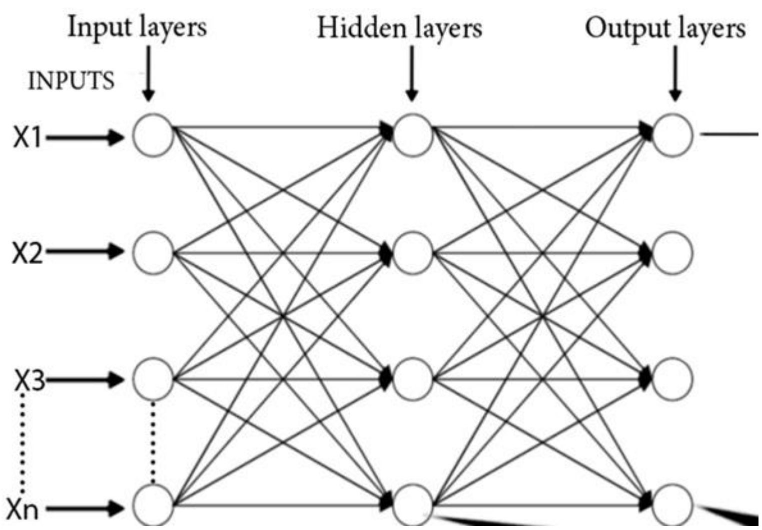

Figure 15: Layers structure in ANNs

3.3.3 Weights

The weights in an ANN represent the memory of that network in which all information is stocked. The values of the weights are updated continuously during the training of the network until the desired output is reached. The memory or weights are then stored to be used in future. After learning the values of these weights are used as the memory of network (Roberts, 2015).

3.3.4 Activation functions or transfer functions

When the inputs are fed to the layers through the associated weights and finding the sum of them, an activation or transfer function is used to determine whether the output is to be activated or not. Or in some activation functions, the function is used to determine how much the processed input will share in constructing the total output of the network. Activation functions are very important in neural networks because they can decide whether the input to the neuron is enough to be passed to the next layer or not (Mena, 2012). There are many types of activation functions in artificial neural networks:

3.3.4.1 Linear activation functions or ramp

In this type of the activation function, the output is varies linearly when the input is small (Yuhong & Weihua, 2010). If the input is large, the absolute output is limited by 1 as shown in figure 3.6. The function of this transfer function is defined by:

$$o(TP) = \begin{cases} -1 & TP \leq -1 \\ TP & -1 \leq TP \leq 1 \\ 1 & 1 \leq TP \end{cases} \tag{3.2}$$

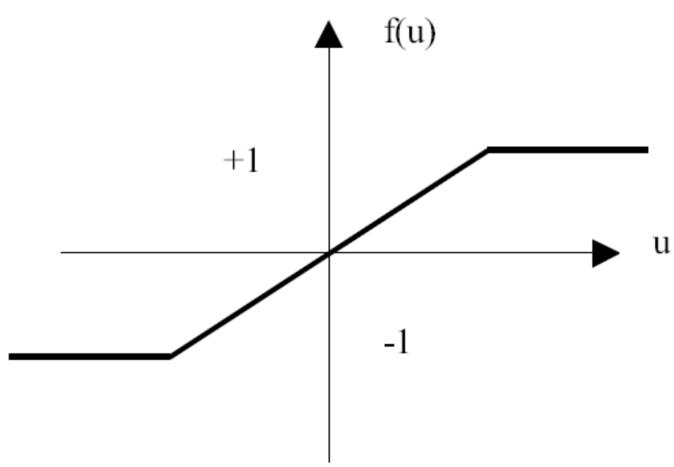

Figure 16: Ramp activation function

3.3.4.2 Threshold function (Hard activation function)

In the threshold function the output is zero if the summed input is less than certain value of threshold, and 1 if the summed input is greater than threshold. This way the output is oscillating between two values (Yuhong & Weihua, 2010). It can be either activated or deactivated like in figure 3.7. The function of the hard function is defined by:

$$o(TP) = \begin{cases} 0, & TP < \theta \\ 1, & TP > \theta \end{cases} \tag{3.3}$$

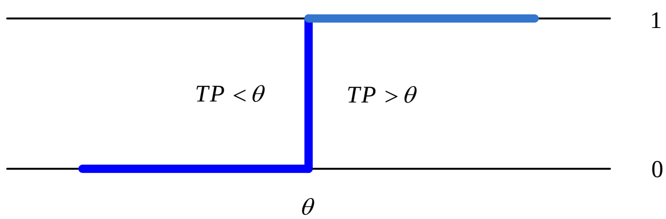

Figure 17: Hard activation function

3.3.4.3 Sigmoid function

This function can range between 0 and 1, but in some cases it can be useful to range it between -1 and 1. The logarithmic sigmoid and hyperbolic tangent is of the most common sigmoid functions. These two functions are the most used in the back propagation because they are differentiable. The formulas of these two functions in addition to the curves are presented in figure 3.8. The slope of the curves can be varied based on the application for which it is used (Kaki, 2009).

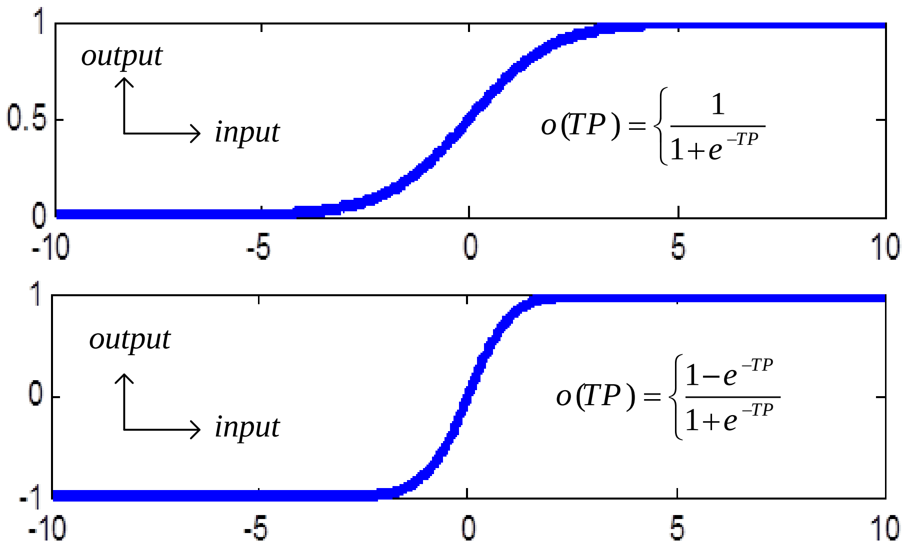

Figure 18: Logarithmic and hyper tangential sigmoid activation functions

In the back propagation algorithms, the log-sig and tan-sig functions are the most used (Kaki, 2009). The main advantage of these two functions is the fact that they can be easily differentiated. The derivative of the logarithmic sigmoid is given by:

$$\frac{d}{dt}o(\theta) = o(\theta) * (1 - o(\theta)) \tag{3.4}$$

3.3.5 Classification of ANNs

ANNs can be classified based on different aspects; these are the flow of information, function or task, and the training method. The flow of information can be either from input layer toward hidden and output layers. It can also flow from next layer to the previous layer. According the function, neural networks are used to accomplish many different tasks. These tasks can be categorized into four main categories:

- **Classification:** Where an object is assigned to a group of known categories.
- **Association:** Linking objects to more précised categories.
- **Optimization:** Where the task is to find the best solution for a case or problem.

3.3.6 Training methods of ANNs

Generally, the training of a network is an attempt to lead the network to converge toward desired output or outputs. two main learning methods are used in teaching the networks. These are the supervised and the unsupervised learning method.

- **Supervised learning:** The ANN is provided by input data and desired target for this data. The network then updates its weights according to a defined algorithm rule until it converges to a minimum error or reaches a maximum number of iterations. A very important example of the supervised learning method is the error back propagation method.
- **Unsupervised learning:** In this method, the input data is provided to the network which in turn modifies its weights according to defined conditions.

3.3.7 Back propagation algorithm

The back propagation training algorithm uses a feed forward process, a back propagation updating method, and supervised learning topology. This algorithm was the reason of neural networks development in the 80s of the last century. Back propagation is a general purpose learning algorithm. Although it is very efficient, it is costly in terms of processing requirements for learning. A back propagation network with a given hidden layer of elements can simulate any function to any degree of accuracy (Gupta, 2006).

The back propagation algorithm is still as simple as it was in its first days. That is due to its simple principle and efficient algorithm. The input set of training data is presented at the first layer of the network, the input layer passes this data to the next layer where the processing of data happens. The results after being passed through the activation functions are then passed to the output layers. The result of the whole network is being then compared with a desired output. The error is used to make a one update of the weights preparing for a next iteration. After the adjustment of the weights, the inputs are passed again to the input, hidden, and output layers and a new error is calculated in a second iteration and vice versa.

The mentioned process continues until achieving an acceptable level of the error so that the network can be considered has learned. Figure 19 presents the structure of the network with layers and back propagation process.

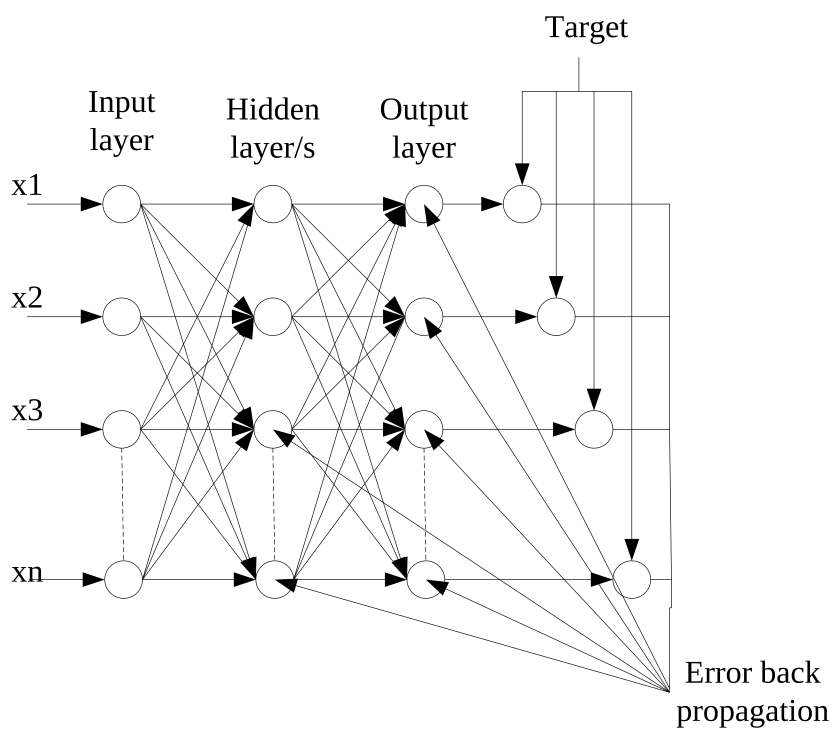

Figure 19: Structure of ANN and error back propagation (Haykin, 2000)

There are two essential parameters controlling the training of a back propagation network. The learning rate is used to control the speed of learning. It decides whether a great adjustment of weights will be done at each iteration or just small adjustments. It is important to mention here that a high learning rate is not advised because it can cause the network to memorize things instead of learning. A reasonable value of learning rate can do the job perfectly. Another parameter is the momentum factor which is used to control the oscillation of error in some local minimums. It is very important to avoid some kinds of falling into fake minimums and ensure the continuity of training (Gupta, 2006).

3.4.7.1 Modelling of back propagation algorithm

The back propagation is an algorithm that uses the theory of error minimization and gradient descent to find the least squared error. Finding the least squared error imposes the calculation of gradient of the error for each iteration. As a result, the error function must be continuous derivable function (Haykin, 2000). These conditions lead to the use of continuous derivable activation functions as they are the precedents of error calculation. In most of cases, the tangent or logarithmic sigmoid functions are used. The sigmoid function is defined by:

$$o(x) = \frac{1}{1+e^{-ax}} \tag{3.5}$$

Where the variable a is a constant controlling the slope of function. Where the derivative of the sigmoid function is given by:

$$o^{\backslash}(x) = f(x)(1-f(x)) \tag{3.6}$$

The equations describing the training of the network can be divided into two categories:

- **Feed forward calculations:** Used in both training and test of the network.
- **Error back propagation:** Used in training only.

In the feed forward process, the output or total potential can be given by:

$$TP = \sum x_n \omega_n + b_n \tag{3.7}$$

Where, x_n is the input vector, w_n is the weight matrix, and b_n is the bias values vector. The total potential obtained in each layer must be passed by an activation function. The activation function can be either linear or non-linear function (Zurada, 1992). An example of a linear function that is mostly used in neural networks is the sigmoid function given in equation (2.5). Another example is the tangent sigmoid given by:

$$o(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3.8}$$

It is important to notice that this function is also continuous and derivable. The derivative of this function is given by:

$$o^{\backslash}(x) = 1 - \frac{(e^{x} - e^{-x})^2}{(e^{x} + e^{-x})^2} \tag{3.9}$$

The output of the last activation function is the actual output of the neural network. This output is then compared with the goal of training to generate the error signal. The error signal is actually defined by equation (3.10). the goal of the training of neural network is always to minimize that error.

$$E = \sum (T - o)^2 \tag{3.10}$$

Where, T signifies the target output. An error function is then defined based on the value of E such that:

$$\Delta_j = (T_j - o_j) o_j (1 - o_j) \tag{3.11}$$

This value is propagated back to the network using the next equations to update the weights and biases of the different layers. The weights are then updated using the next equation:

$$\omega_{jhnew} = \omega_{jhold} + \eta \Delta_j o_h + \alpha(\delta \omega_{jhold}) \tag{3.12}$$

Concerning the hidden layers, their weights are updated using the error update defined by:

$$\Delta_h = o_h (1 - o_h) \sum \omega_{jh} \Delta_j \tag{3.13}$$

The new weights values are then given by:

$$\omega_{hinew} = \omega_{hiold} + \mu \Delta_h o_i + \alpha(\delta \omega_{hiold}) \tag{3.14}$$

The values of α and η are the well known momentum factor and learning rate. At the end of weights update, a new feed forward iteration is done again. The error is being calculated at each iteration until it arrives an accepted error value.

3.3.8 Applications of artificial neural networks

ANNs are used in different fields of science in many applications these days. In some applications they are still in the research mode. The neural network technology is a promising field for the near future. In this part of our work, different fields of application of ANN will be discussed. The neural networks are used mainly in pattern recognition, pattern association, function approximation, control systems, beam forming, and memory (Hykin, 1999).

- **Pattern association:** It is a brain like distributed memory that learns by association. Auto association is a process where the neural network is supposed to store a set of vectors by presenting them to the network. In a hetero association structure, a set of inputs is being associated with an arbitrary set of outputs. The hetero association is supervised learning process.
- **Pattern recognition:** Pattern recognition is a simple task done by humans in their everyday life with merely no effort. Simply, we can recognize the smell of some food that we have tasted before easily. Familiar persons can be recognized even if they are aged or their expressions have been changed since last time we saw. Pattern recognition is known as a process by which a received signal can be assigned to a prescribed number of categories (Hykin, 1999). Although pattern recognition task are very easy for humans, they are very difficult to be carried out using traditional computers. The neural networks have presented an excellent approach for carrying out pattern recognition tasks using computing machines.

A well trained network can easily recognize and classify a pattern or group of patterns to classes. Face recognition, fingerprint recognition, voice recognition, iris recognition and many other applications are examples of pattern recognition.

- **Function approximation:** Interpolation and function approximation has been a very important field of numerical mathematics. It is very to determine the function describing the relation between discrete variables. Related set of input output numerical association can be modeled using linear or non linear functions. Neural networks can be used to describe the relation between input and output variables of the set. Neural networks can approximate function in two different ways:

- **System identification:** figure 20 shows the scheme of system identification task. If we have an unknown system that we need to model, a neural network can be associated with the system. The input output relationship of the system can then be modeled by the neural network during the training. The weights of the neural networks are updated until it will produce the same output of the system if subjected to the same input.

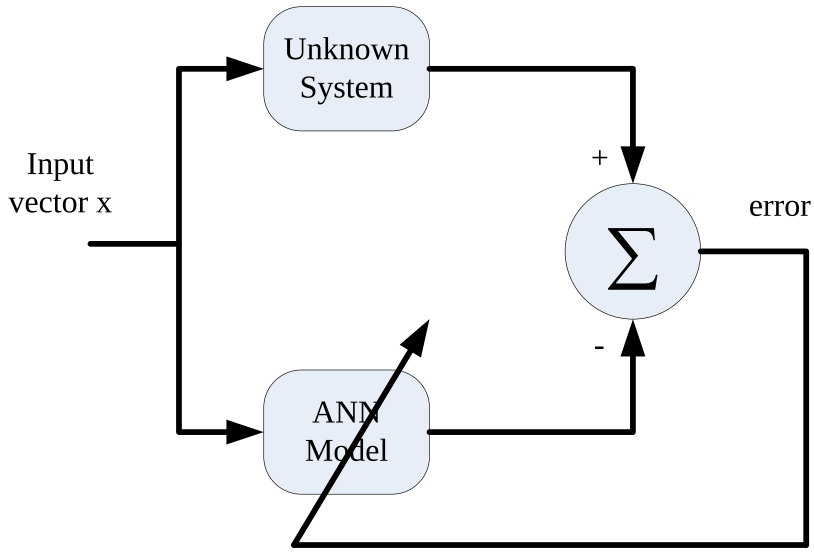

Figure 20: System identification using neural networks (Haykin, 1999)

- **Control:** The control of processes is another learning task neural networks can do. The brain is evidence that a distributed neural network can be used in the systems control. If we consider a feed-back process like the one shown in figure 21, the system is using a unity feed-back to control the process. The plant output is fed back to the control that compares output with the desired output. A neural network controller can be used to generate the appropriate control of the plant.

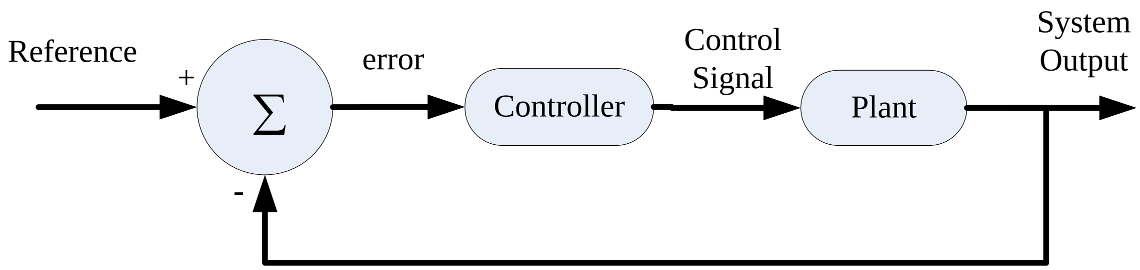

Figure 21: The use of ANN for control processes (Haykin, 2000)

3.3.9 Summary

This chapter discussed the theory of Artificial Neural Network. A brief historical review of ANNs and there development was presented at the beginning of the chapter. Different structures of artificial neural networks and their elements were presented. A detailed functional and structural comparison between the artificial neural networks and human neural network was discussed.

The supervised and non-supervised learning methods of ANNs were also presented. Due to its efficiency and ability to perform different tasks, the back propagation algorithm was also discussed and presented. At the end of the chapter, the main different applications of the neural networks were presented and discussed briefly.

CHAPTER 4
THE PROPOSED METHODOLOGY

4.1 Signature Recognition in Image Processing

the fact that the signature is generally utilized as a method for individual check stresses the requirement for an programmed check framework on account of the lamentable symptom of being effectively manhandled by the individuals who might fake the identification or aim of a person. Signature is an uncommon instance of penmanship which incorporates uncommon characters and twists. Numerous signatures can be incoherent. They are a sort of creative penmanship objects. Nonetheless, a signature can be taken care of as a picture, and subsequently, it can be perceived utilizing PC vision and simulated neural system methods.

4.2 The Proposed Methodology

The proposed system is a signature recognition intelligent system based on a backpropagation neural network. The purpose of this research is to evaluate the effectiveness of a backpropagation neural network in recognizing different signatures and to compare the obtained results with those in the literature review. The developed framework consists of two main phases which are the processing phase and the classification phase in which the image is classified as many signatures. In the image processing phase the signatures are processed using many techniques such as conversion to grayscale, filtering using median filter, and segmentation using canny edge detection. These techniques are done in order to enhance the quality of images and to extract the important features in such a way to take only the signature and ignoring the other features and parts of the image. At the end of this phase, the images should be fed to the new phase which is the neural network in which they are classified as different signatures for different individuals.

The two main phases of the proposed signature recognition system are illustrated in figure 22.

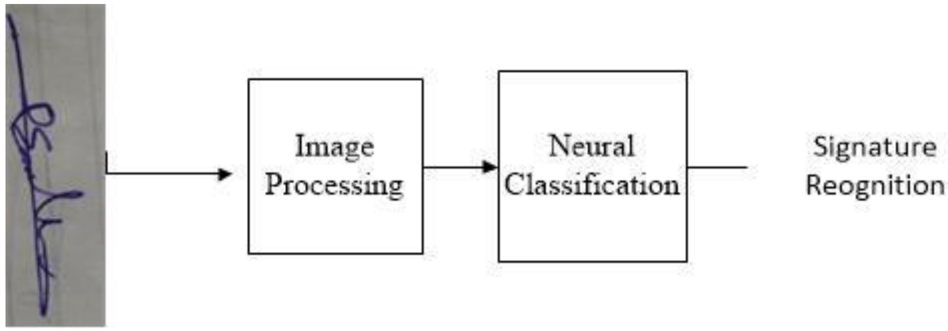

Figure 22: Phases of the developed recognition system

These following are the image processing techniques and the classification methods used in our proposed system for the intelligent recognition of human handwritten signatures.

- Read RGB images
- Convert to grayscale
- Image size rescaling to 256*256 pixels for the purpose of faster processing
- Adjustment of the image in order to increase the pixels intensity
- Threshold the images
- Segment the signatures using a canny edge detection technique
- Clear unwanted components in the images
- Rescale the image size again to 64*64 pixels using pattern averaging
- Feed the images into a backpropagation neural network
- Train the neural network
- Test the neural network

The analysis and processing of the signature image take place first in the system so that a free-noise, and segmented signature is extracted from the original image. The later stages are the feature extraction and neural classification phases in which the size of images is reduced with preserving their features using pattern averaging technique. Once the image size is reduced, they are fed into a backpropagation neural network respectively with their targets.

Figure 23 represents a flowchart that illustrates our proposed system for the identification of handwritten signature. Figure 24 shows a handwritten signature image from our database that undergoes all the system processes in order finally to be segmented.

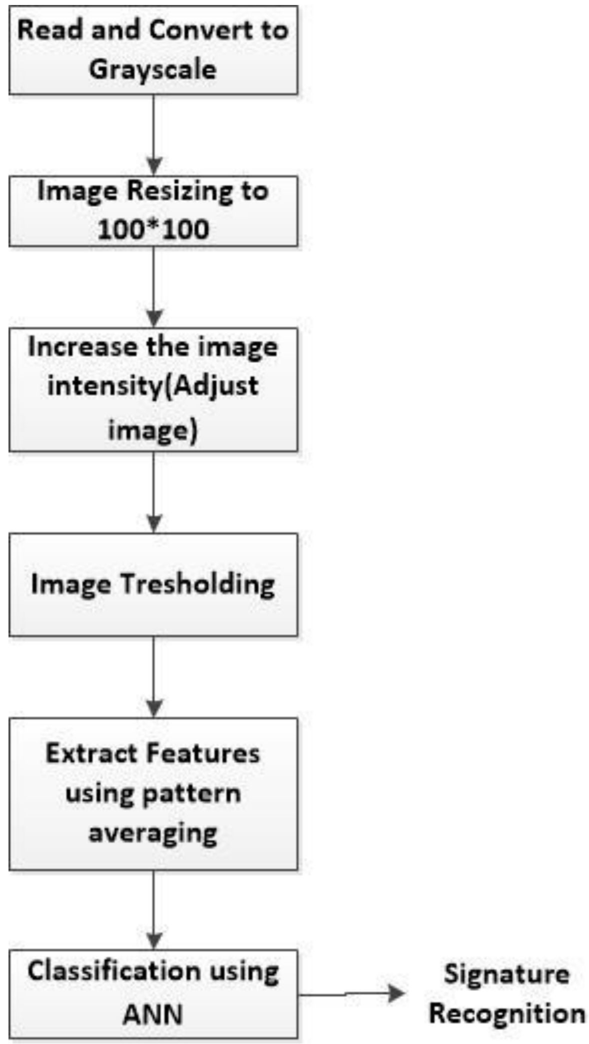

Figure 23: Flowchart of the developed framework

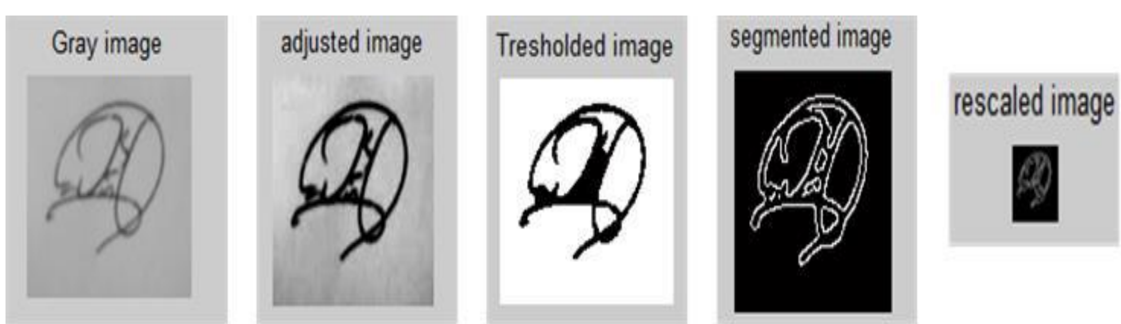

Figure 24: One signature image processed using the developed image processing system

4.3 Pre-Processing Phase

4.3.1 Image Acquisition

Image acquisition is the first phase which is the image processing phase. However, image acquisition and database preparation can be considered as pre-processing phase. Images can be acquired using several ways depending on the application. Image acquisition refers to the process of capturing images by camera and converting the images into a manageable entity (Moeslund 2012). Catching the images utilizing camera required certain condition that must be put under thought, in light of the fact that if the images are not caught tastefully then the required undertaking that is required to be carry on the images may not be accomplished enough. Light should be permitted into the scene where the image will be caught. Enlightenment can be a wellspring of vitality, for example, daylight or light, in this examination work, daylight is utilized as the wellspring of vitality expected to fall on the images of signatures to permit catching. Additionally, the position of the camera to the image must be set with a specific end goal to permit all out catching of the images. Commotion must be dodged in the images amid catching; clamor is an arbitrary variety of the power. This can be maintained a strategic distance from by prohibiting the thought about article from falling the images to be caught.

4.3.2 System Database

The signature images were collected from the students of the Near East University during one of the lectures. As mentioned before, the images were captured by cameras, and then were transferred into computer for cropping and adjustments purposes. The images were all resized to 256*256 pixels for fast processing purposes. The total number of images is 100 images. Among them, 60 are for training and 40 for testing phase. Table 4 shows the number of signature images in the database.

In order to improve the effectiveness of the network, some students were asked to sign more than one time so that the network has all the required properties such as rotation-invariance and Scale invariance aims to make the intelligent system more robust in determining the image of signature that can be placed at different angles (Khashman 2012).

Moreover, the purpose of asking students to sign more than one time is to use the other signatures for testing phases in order to evaluate the effectiveness of the design designed signature recognition system.

Figure 25: Sample of the images in the created database

4.4 Summary

This chapter showed the proposed methodology that the developed system is based on. It showed the first phase of the work which is the collection of data and preparation of the database that will be used for training and testing the system in later stages.

CHAPTER 5
IMAGE PROCESSING PHASE

5.1 Introduction

Image analysis involves the conversion of features and objects in image data into quantitative information about these measured features and attributes. The proposed signature recognition system is based on the processing of the signature images in order to extract the only needs features that can distinguish human signatures so that it can be easy for the neural network to classify them into different signatures. Such image processing involves many techniques. The images are first converted to grayscale since they were acquired using a camera (Figure 26.a). The noise is later on reduced using medical filter; a non-linear filter used to remove noise with preserving the edges of the image. The intensities of the pixels of the image are then mapped into a new range of intensities which results in a better image in which the signature is being darker (Figure 26.b) however; the other part is getting white. After increasing the intensities of the pixels in the image; tresholding takes place. This is a technique is a non-linear operation that converts a gray-scale image into a binary image where the two levels are assigned to pixels that are below or above a certain threshold (Figure 26.c).By applying this technique the image edges get smoothed and clear, therefore, this makes it easy to be detected. For the detection of edges "Canny operators" are used (Figure 26.d).

Finally the image is rescaled with preserving the important features using pattern averaging technique (Figure 26.e).

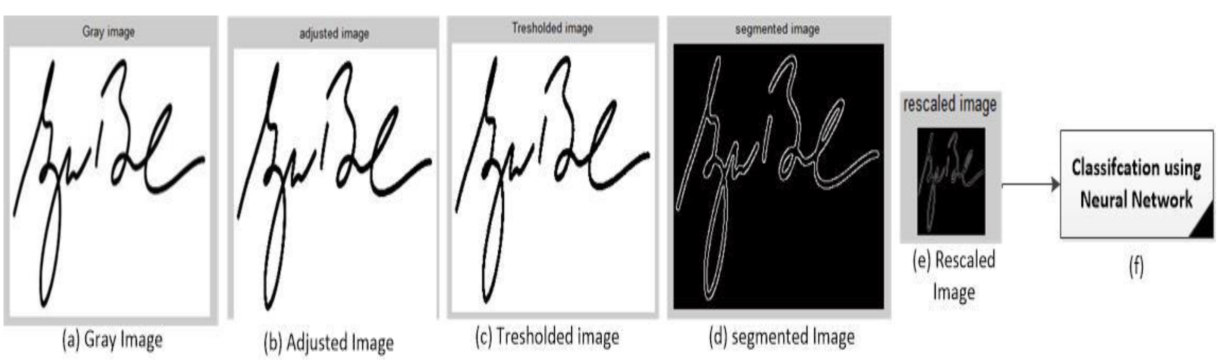

Figure 26: The proposed framework

5.2 Signature Images Processing

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

5.2.1 RGB to grayscale conversion

The images were first converted from RGB to grayscale in which this conversion is done using the luminosity method (Figure 27). 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. The formula for luminosity is

$$0.21\ R + 0.72\ G + 0.07\ B$$

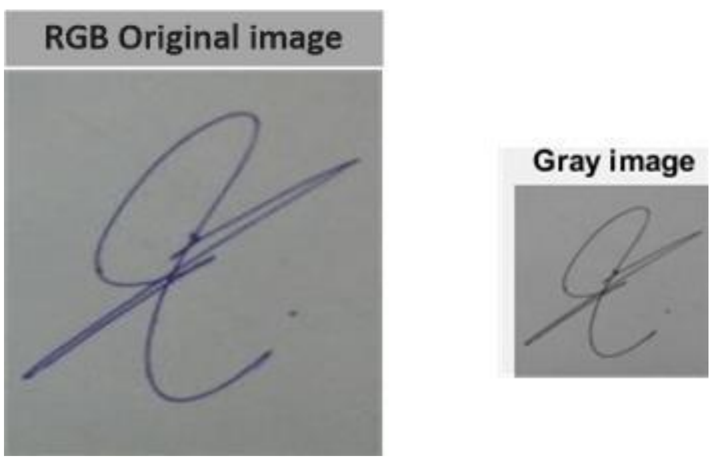

Figure 27: Grayscale conversion

which relies on the contribution of each color of the three RGB colors. Using this method, the grayscale image is brighter since the colors are weighted according to their contribution in the RGB image not averagely (James Church et al., 2005).

Figure 28 illustrates the conversion of a signature image from our database into a grayscale image using luminosity method.

5.2.2 Image smoothing using median filtering

Smoothing, so called blurring, is an image processing technique used in order to reduce the noise in an image to produce less pixelated and clearer image. Most smoothing techniques are based on low pass non-linear filters. It is mostly based on the averaging technique of the input image or the middle (median) value technique (James Church et al., 2005).

To perform a smoothing operation we will apply a filter to our image. The most common type of filters is the linear filters such as median filter which is used in our proposed system. This filter is used to reduce impulsive noise or the salt-and pepper in an image with preserving the useful features and image edges. Median filtering is a non-linear process in which the output of the being processed pixel is found by calculating the median of a window of pixels that surrounds that studied pixel. In other words, the median filter goes through each element of the image and replaces each pixel with the median of its neighboring pixels which are located in a square neighborhood (kernel) around the evaluated pixel.

- Fetching entries from other places in the signal. With images for example, entries from the far horizontal or vertical boundary might be selected.
- Shrinking the window near the boundaries, so that every window is full.

Figure 28 illustrates an example of a median filter and its mechanism to reduce the noise in an image by setting a kernel or window that goes through the whole matrix and find an output for the processed pixel by calculate the median of the pixels in the window (James Church et al., 2004).

Figure 29 shows the input image after applying the median filter.

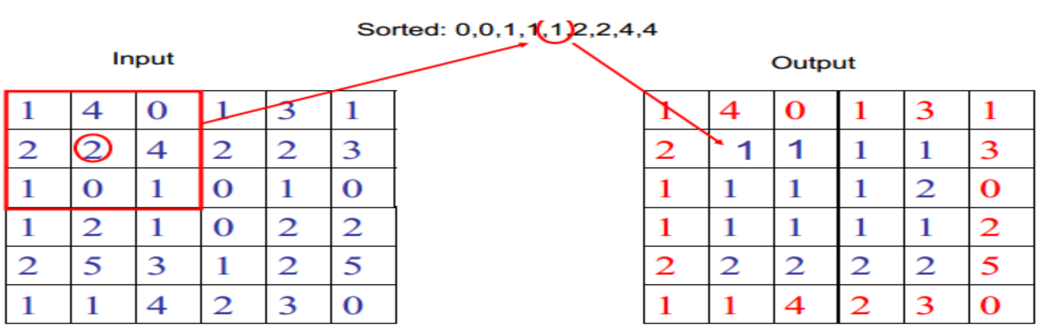

Figure 28: Median filter process

Figure 29: The input signature image after applying median filter

5.2.3 Adjustment of image intensities

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

Ankit Aggarwal, R.S. Chauhan and Kamaljeet Kaur developed a system for the adaptive image enhancement technique preserving brightness level using gamma correction. Their proposed technique is that the weighted average of the histogram leveled, gamma corrected and the first picture are consolidated to acquire the upgraded processed image .The proposed calculation accomplish contrast enhancement as well as preserve the brightness level of images (Ankit Aggarwal et al., 2013).

The figure below represents the adjustment of an image and its effects in enhancing the image contrast.

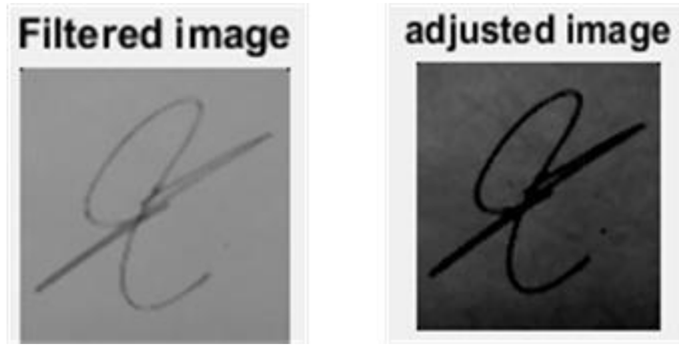

Figure 30: Adjusted image intensities

It can be seen that the signature is clearer and getting extracted after applying this technique. We can notice from the above image that the image adjustment operation has a great effect in enhancing the contrast and brightness of the image, so it is clearer and its features are more bright and shown. This helps in detecting the edges and features of the image in the next process

5.2.4 Thresholding

Thresholding is the separation of region of images into two regions. One region corresponds to the foreground region, in which it contains the objects that we are interested in. The other region is the background, corresponds to the unneeded objects. This provides segmentation of the image based on the image different intensities and intensity discontinuities in the foreground and background regions. The input of this method is usually a grayscale or color image, while the output is a binary image representing the segmentation. The black pixels refer to background and white pixels refer to foreground. The segmentation is achieved by a single parameter known as the intensity threshold. This is set by analyzing the histogram of the image which represents the intensity distributions of the image. During Thresholding, each pixel is compared to that threshold value. If the pixel value is greater than that threshold, then this pixel is considered as foreground pixel (white). If the pixel value is lower than that threshold value, then the pixel is considered as background pixel (black) (Gonzalez & Woods, 2002).

Figure 31 illustrates a signature image that undergoes thresholding of 0.42 as threshold value.

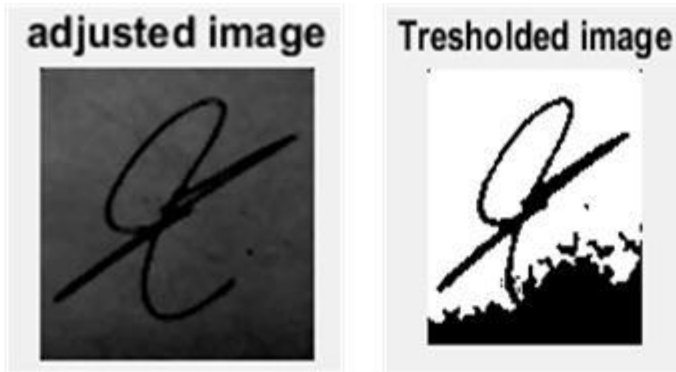

Figure 31: Thresholding of the adjusted image

5.2.5 Canny edged based segmentation

Segmentation can be defined as grouping of the image parts into many regions. The goal of such image processing operation is to represent some meaningful and needed areas of the image, such as tumors, faces etc…

In other words, the segmentation is the grouping of interesting regions of the image into foreground regions of interest and background regions to be ignored using some techniques such as tresholding, which is done by setting a threshold value. Thus, the pixel values that are lower than the threshold are considered as 0's (black or background), while the pixel values higher than the threshold are considered as 1's (white or foreground) (Shapiro & Stockman, 2004).

Pixel edges are associated with some intensity changes or discontinuities; therefore, edge detection is the process of identifying such sharp intensity contrasts (i.e., discontinuities) in an image. Classical edge detection operators Sobel and Prewitt uses 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one for horizontal changes, and one for vertical. In this proposed system, we detected edges using canny operators. This technique is the most common used method for detecting edges and segmenting the image. The Canny edge detector is considered as one of the best currently used edge detectors since it provides good noise immunity and detects the true edges or intensity discontinuities while preserving a minimum error. Canny operator has been used for such algorithm with regard to the following criteria (Jamil & Saif , 2012):

- To maximize the signal-to-noise ratio of the gradient.
- To ensure that the detected edge is localized as accurately as possible.
- To minimize multiple responses to a single edge.

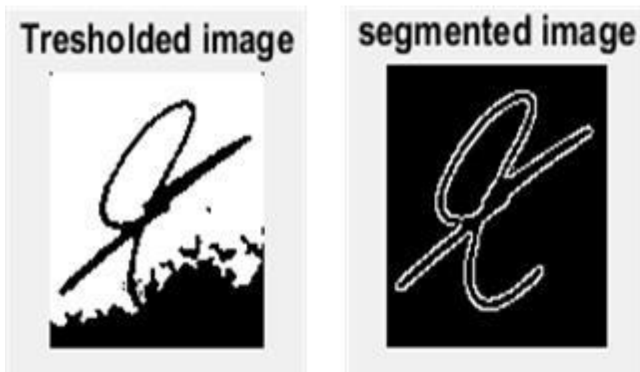

Figure 32: Segmented signature using Canny edge detection

5.2.6 Features extraction and rescaling using pattern averaging

After the segmentation process using the canny edge detection, the images size should be reduced in order to be fed to the neural network. To reduce the size of images while keeping the useful and needed features extracted by the previously used methods, we used patter averaging. This technique is defined as the averaging of the defined segments of the image by selecting a window 4*4 segments that are averaged. Therefore, each studied pixel is then the average of the 16 neighbor's pixels in the selected window. Thus, we come up with a rescaled image of size 64*64 pixels with the same features and properties of the original one for the purposes of fast processing and easy computing.

An intelligent blood cell identification system was developed by Adnan Khashman (Adnan Khashman, 2008) for the identification of the three blood cells. The authors used pattern averaging to reduce the size of the blood cell images while preserving the needed features.

Below in Figure 33 is shown some of processed rescaled images.

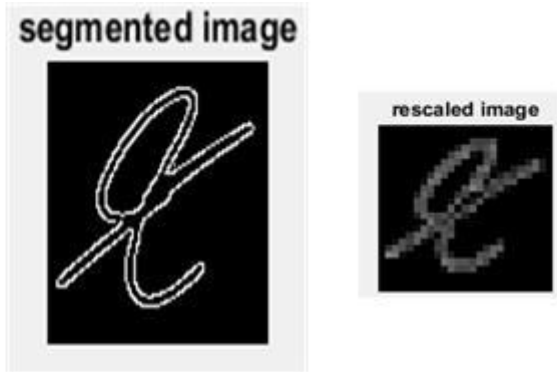

Figure 33: Rescaled image using pattern averaging

5.3 Segmented Signatures

At the end of this image processing phase the images are saved all in a file. This was meant to evaluate the effectiveness of the system and to assure that all images were correctly segmented and rescaled.

Figure 34 below shows a sample of the segmented signatures processed using the developed system.

Figure 35 shows a sample of the rescaled processed images using the proposed system.

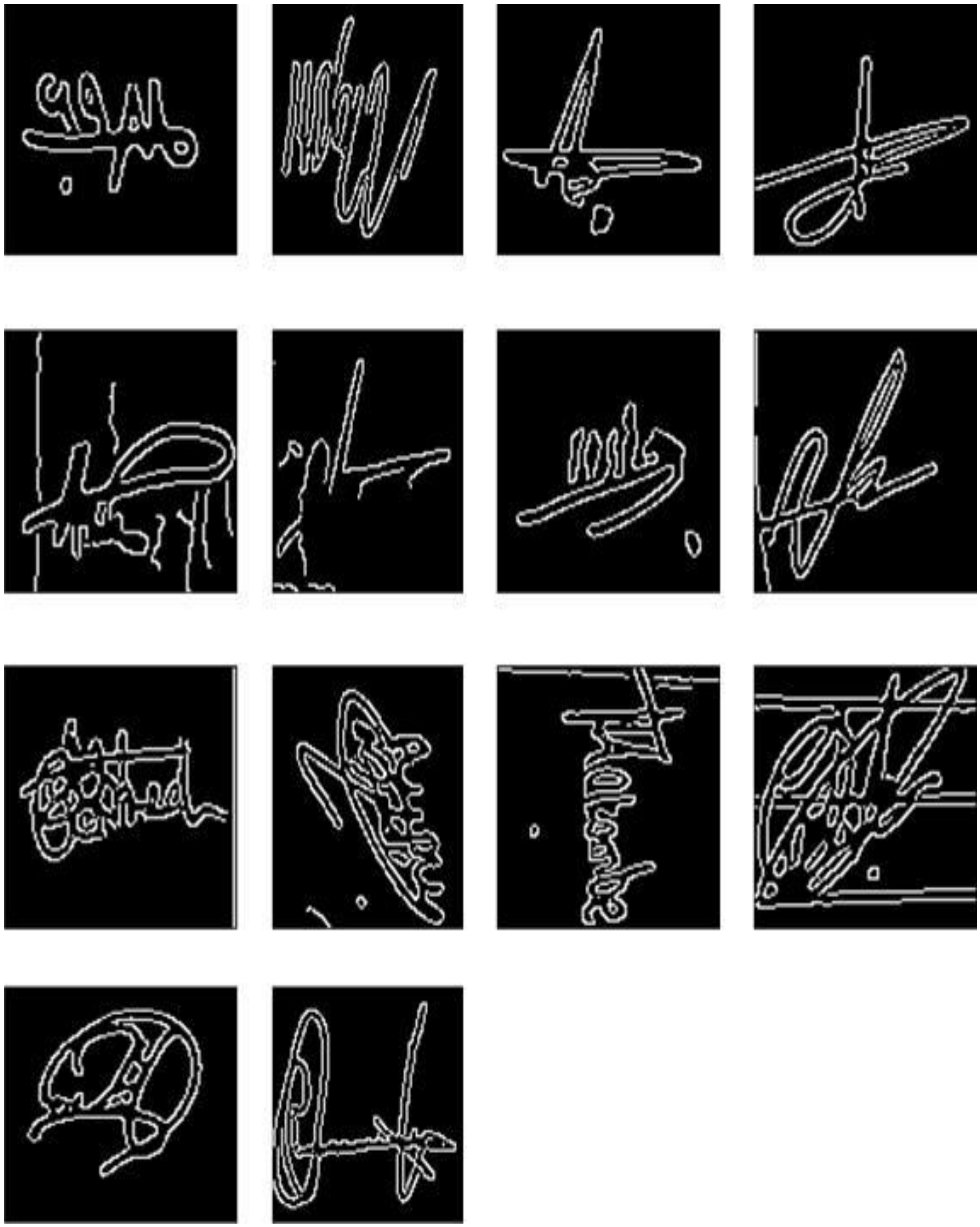

Figure 34: Sample of the processed and segmented signature image using the proposed system

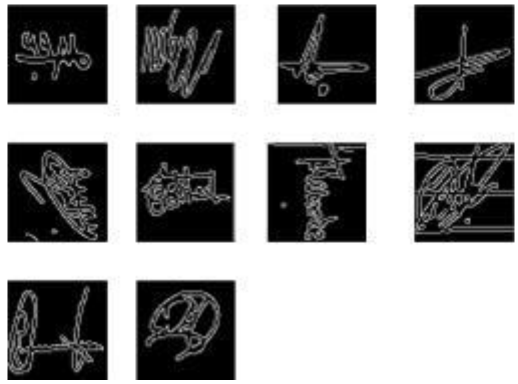

Figure 35: Sample of the rescaled signatures processed using the proposed system

5.4 Summary

This chapter presented the phase one of the developed intelligent signature recognition system. It discussed each technique used in details by explaining and giving figure of images processed using the designed system.

CHAPTER 6
NETWORK TRAINING AND PERFORMANCE

6.1 Introduction

This chapter describes the collection of the images that is used in both training and testing this work, as well as the backpropagation neural network design, training, and testing which are implemented to evaluate the aim of this research, and the simulation of the developed system to show its effectiveness in recognizing the human signatures.

It is the aim to develop an artificial vision system that can perform the task of recognizing signatures in images. In this work, considering challenges such as object illumination, scale, translation, simple differences in signature, etc. which make the recognition a complex problem for such an open recognition problem, we resolve to implement an intelligent system which can somewhat graciously cope with the aforementioned recognition constraints. A back propagation neural network (BPNN) has been used in this work as an intelligent classifier to perform this recognition task.

This research is achieved in two phases. First is the human signatures processing phase by segmenting the signatures in an image and rescaling it to fit the designed neural network. The second phase is the recognition of signatures from images using the back propagation neural network. The second phase involves training and testing of the network by many signature images collected from a classroom in the Near East University. The flowchart for the system is shown in Figure 36; and both phases are briefly described below.

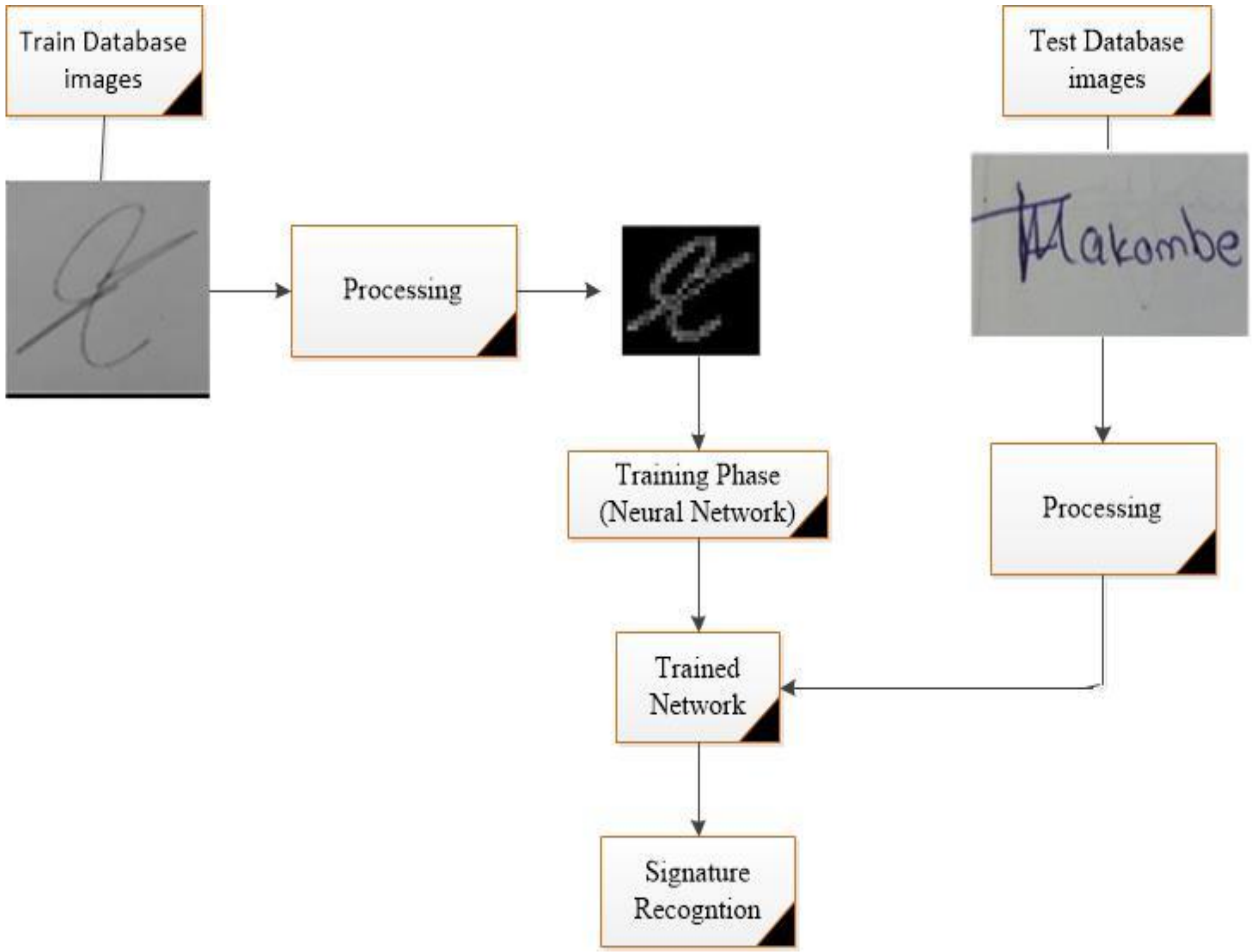

Figure 36: Training and testing phases of the developed signature recognition system

The figure above shows the flowchart of the proposed intelligent signature recognition system using backpropagation neural network. The images are used to train the backpropagation network through their features which are extracted pattern averaging after the signature is segmented using tresholding and canny edge detection techniques. After training and convergence, the testing images are used then for testing the neural network after they pass through the segmentation and rescaling phase.

6.2 Backpropagation Neural Network Classification

In this phase, a back propagation neural network is trained to recognize human signatures in an image. In order to achieve this binary classification task, training data is collected to have many and different signature images. As previously discussed some signatures were written more than one time in order to increase the efficiency of the system and to use the others for training. In this project, all training and testing data are collected from the students classroom. Since, the actual Samples of positive and negative examples collected from the internet are shown below in Figure 37.

Figure 37: Sample of training images

A back propagation neural network is trained on the collected sample signature images. These one or more of each signature were used for training the back propagation neural network (BPNN). All images are converted to from color to grayscale, filtered, segmented using tresholding and canny edge detection, and finally rescaled to 64*64 (4096 pixels)using pattern averaging for fast processing and preserving features. The whole data is divided into training and testing data. The testing data allows the observation of performance of the trained BPNN on unseen or new data. It is very desirable that trained ANNs can perform well on unseen data. Note that unseen data means same data used for training but written as a second or third time by students which causes a change in the image. This change may be either scale translation, or simple differences in signature. This leads to a robust system capable of recognizing signatures in different shift translations and different hand writings.

6.2.1 System training

The network was simulated and trained on Matlab software and tools. A backpropagation algorithm was used as a learning method due to its simplicity and the sufficient number of images. The database contains 100 images. 60% of the mages were used for training and 40% for testing.

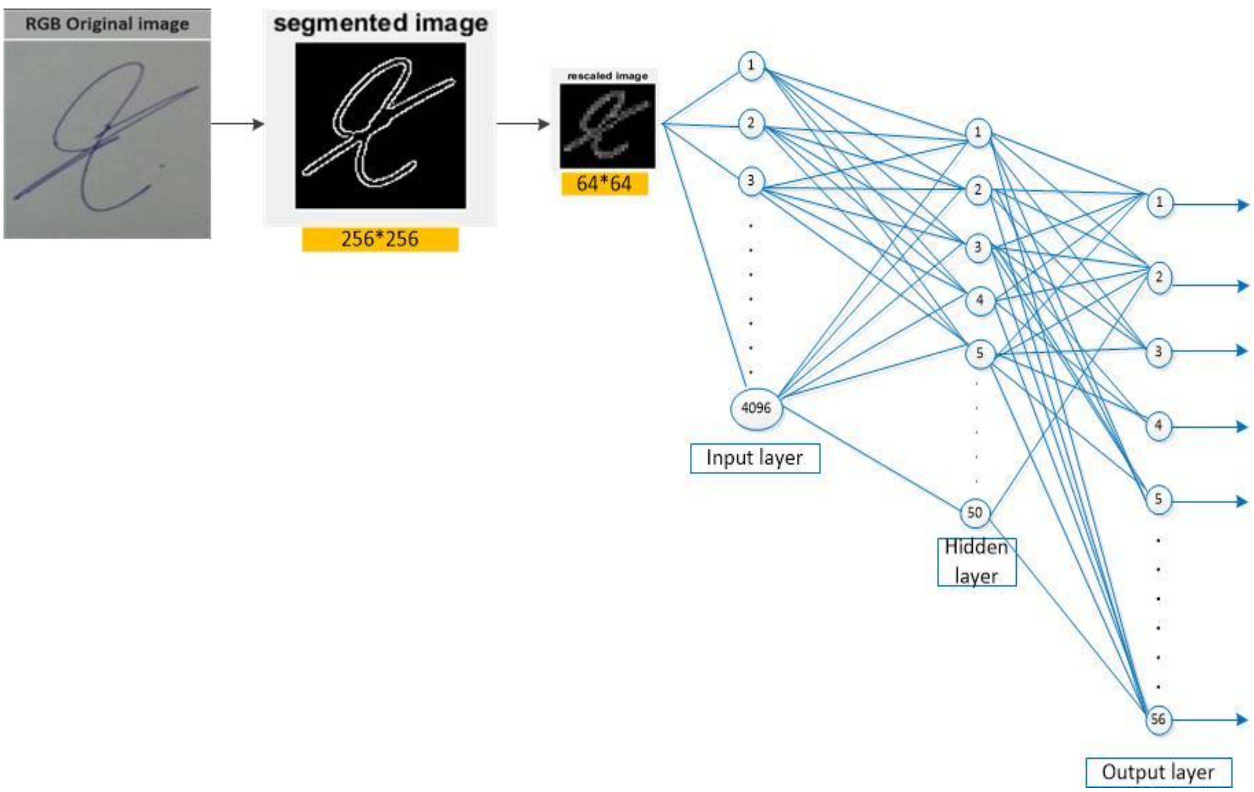

Figure 38:BPNN1 with 50 neurons

The figure above illustrates the neural network architecture proposed for the signature recognition task. The input layer of the BPNN network consists of 4096 neurons since each image is rescaled to 64*64 bitmap using pattern averaging. The hidden layer consists of 50 neurons, while the output layer has 56 neurons since we have only 56 different signatures classes. The figure 39 shows the network when 20 hidden neurons are used.

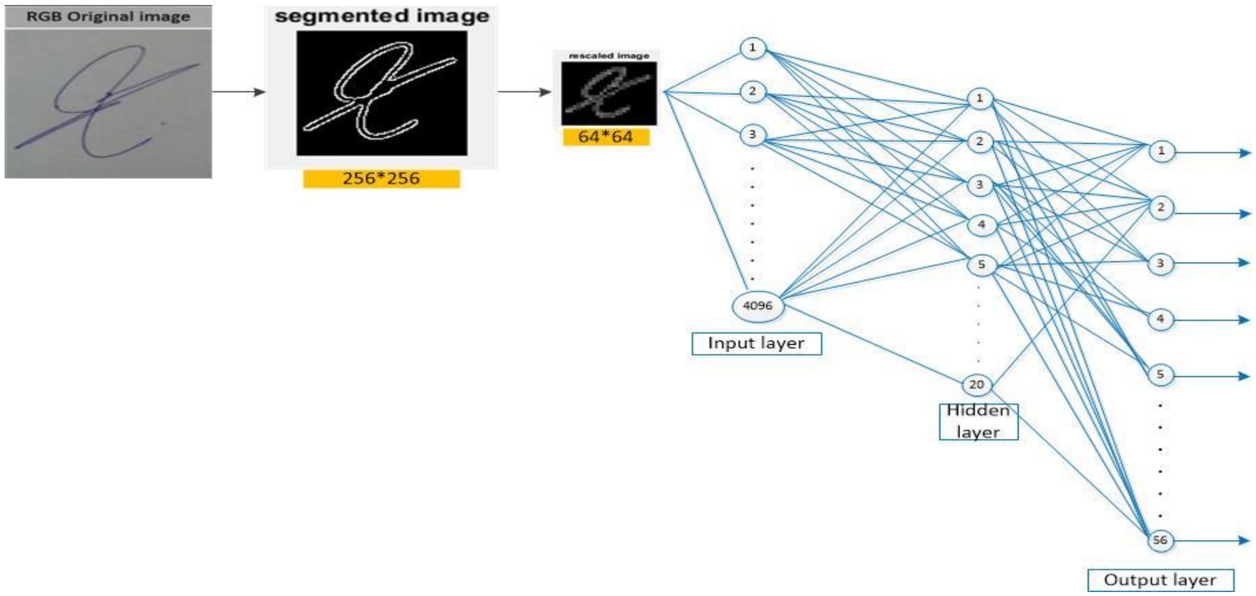

Figure 39: BPNN2 with 20 hidden neurons

Table 1 represents the input parameters used when training the network. It can be seen that the network ran for 7000 maximum iterations with a learning rate of 0.05, a momentum rate of 0.37 and a minimum error of 0.001.

Table 1: Training input parameters of the network

Parameters	BPNN1	BPNN2
Number of neurons in input layer	4096	4096
Number of neurons in output layer	56	56
Number of neurons in hidden layer	50	20
Maximum Iteration number	1000	1000
Learning rate	0.05	0.05
Momentum rate	0.37	0.37
Error	0.001	0.001
Activation Function	Sigmoid	Sigmoid

The following is the training results of the two sets (learning curve) for the developed BPNN1. It shows that the error is decreasing while the number of iteration is increasing. It can be seen that the network converges at epoch 199 with a mean square error of 0.001 using Gradient Descent with momentum. The network finally converged and reached a minimum error 0.0011 at epoch 199 with 97% as a recognition rate in the training phase. Figure 40 shows the learning curve of the BPNN2 where 20 hidden neurons are used. Figure 41 shows the learning curve of the BPNN2 where 20 hidden neurons are used. Figure 42 shows the error between the actual and target outputs. It can be seen that the trained network reached a good local minimum since the actual and target output are almost overlapped.

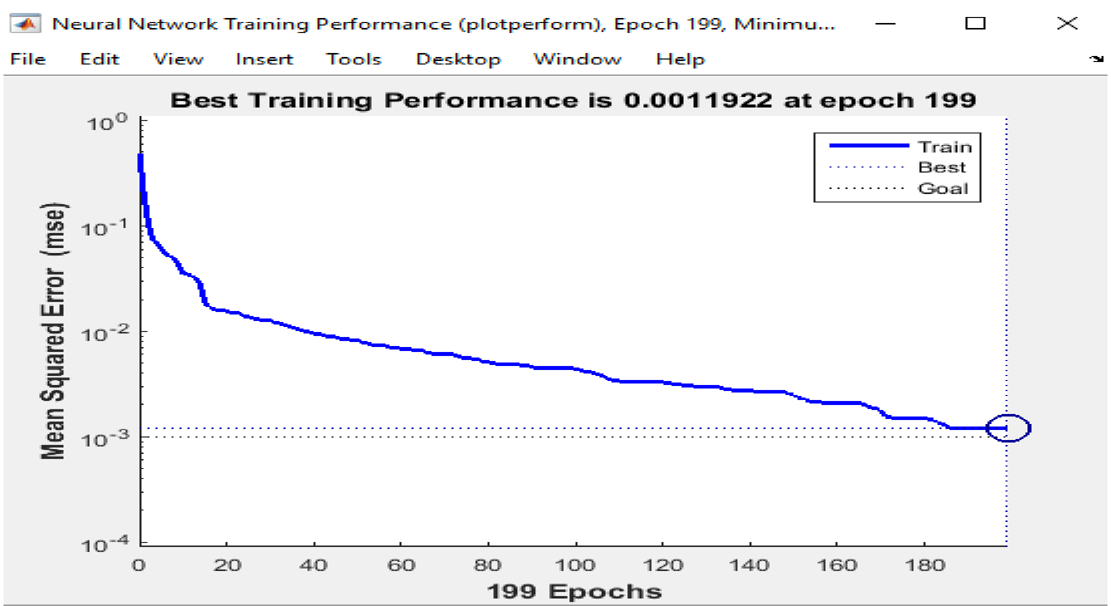

Figure 40: Learning curve of BPNN1

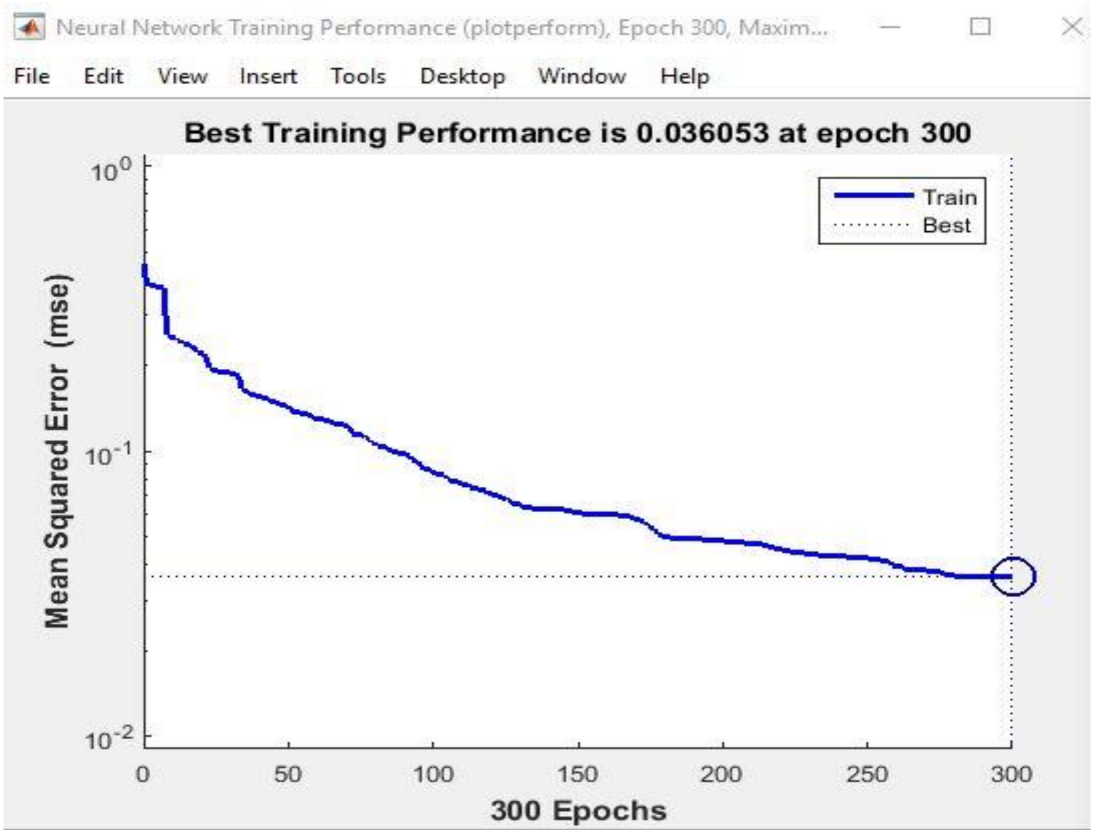

Figure 41: Learning curve of BPNN2

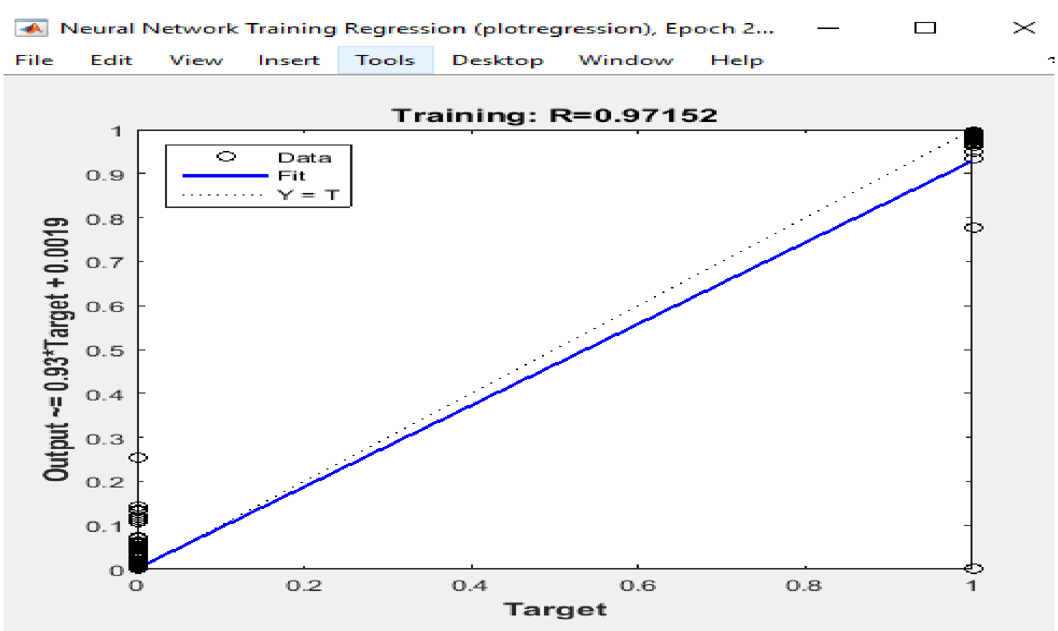

Figure 42: Neural network training recognition rate

6.2.2 System performance

After the convergence of the network, the testing phase takes place. In this phase we evaluate the ability of the proposed system to recognize some signatures that were seen before but with different shift translations, illuminations, and different handwritings. The system was tested on Matlab software (R2015). 40 different signature images were used in testing the developed and trained network.

The result of both testing and training phases is included in the following table2.

Table 2: Recognition rate of the developed system

Signature images type	Image sets	Number of image	Recognition rate of BPNN1	Recognition rate of BPNN2
100	Training set	60	97%	96%
	Testing set	40	87%	86%
All signature images	Both sets	100	92%	91%

The table 3 below shows the processing time of each image processing technique of our proposed system applied on signature images. It shows the time required for a signature to be segmented in an image of size 256*256.

Table 3: Total processing time required to process one image

Process phase	Processing Time
Image reading	0.048 s
Image conversion	0.020 s
Image resizing	0.030 s
Image adjusting	0.039 s
Image Tresholding	0.089 s
Total detection process of one image	0.4165

The table 4 below shows the processing time required for all image set to be processed, segmented, rescaled and fed into a neural network for training. This processing time also includes the neural network training time

Table 4: Total Processing and training time of all images

Process phase	**Processing Time**
Image processing of all images	1 min
Network training	2 mins
Total detection process and training of all images	3 mins

6.3 Summary

This chapter presented the methodology proposed in this thesis. It went through the two phases of the system where the images are processed and then classified. This chapter provided many examples of images processed using the developed system. Moreover, the chapter described the training and performance of the network by showing the training and testing recognition rates and processing times.

CHAPTER 7
RESULTS DISCUSION AND COMPARISON

7.1 Results Discussion

This thesis describes a challenging task in artificial intelligence, and also image processing. We prove that back propagation neural network (BPNN) can be employed to learn the robust recognition/classification of human handwritten signatures. The trained BPNN is then used in a non-overlapping sampling fashion to 'inspect' target images containing signatures for recognition. The developed system is tested and found to be very effective in the recognition of signatures after being segmented from images using image processing techniques. Also important is that the developed system is intelligent such that image scene conditions such shift translation and signature small differences only slightly affect the overall efficiency of the system.

One the most difficult challenges in this work were to obtain high recognition rate in the training phase. This is due to the fuzziness of the segmented images since they are signatures which may be sometimes very similar or have no much difference so that the network will learn. Therefore, this makes it difficult for the network to learn. Thus, our system is to segment the images first using image processing techniques such as Canny edge detection that is used to reduce the amount of data to be learnt by the network. In addition, to reduce the unneeded features of the image, pattern averaging technique was used to reduce image size and to extract the important features of the signatures.

7.2 Results Comparison

As mentioned in the literature review section, many studies were conducted for the purpose of recognizing signatures using intelligent systems. Each work was based on different image processing techniques. However, our proposed work suggested a new technique for the signature recognition which is to use the pattern averaging algorithm for the extraction of features from the signature image after it is segmented using tresholding and Canny edge detection algorithms. The developed system includes the use of backpropagation neural network as an intelligent classifier to learn the extracted features.

The table below shows the results comparison of our signature recognition system with some other systems that used different databases but same classifiers. It can be seen that the developed system performs well in the generalization phase since its accuracy is either equal or higher than the other proposed researches.

Table 6: Results comparison with other works

Paper Title	Authors	Methods used	Recognition Rate
Biometric Signature Processing & Recognition Using Radial Basis Function Network	Ankit Chadha, Neha Satam, and Vibha Wali (Chadha et., 2013)	Signature Processing and Radial Basis Function Network	80 %
Offline signature recognition using neural networks approach	Ali Karounia, Bassam Dayab, Samia Bahlakb	Geometric features extraction and neural network	92%
Signature Recognition and Verification with Artificial Neural Network Using Moment Invariant Method	Cemil Oz	Moment invariant method and ANN	91%
Signature Recognition System	Salmin Mohamed	Canny edge detection , Pattern averaging and Backpropagation neural network	92% (BPNN1) 91%(BPNN2)

7.3 Conclusion

Mark or signature is an exceptional instance of handwriting which incorporates extraordinary characters and twists. Numerous signatures can be ambiguous. They are a sort of masterful handwriting objects. However, a mark or signature can be taken care of as a picture, and consequently, it can be perceived utilizing computer vision and counterfeit neural system strategies.

The point of the thesis is to develop a system that is capable of reading images and using acquired experience (during training) to determine the human identity of a signature found in the image. It is important that the task of recognizing signatures is not one that is easily achieved in computer vision, as some critical image constraints such as object scale, translation, rotation, illumination, noise, and difference in signatures of the same individual, etc. make the task quite difficult. Thus, our system start by processing the images in order to remove noise first, and then segment the signature to make it easy for the network to learn since what is needed in the image is the signature only. Moreover, the system uses a very efficient feature extraction technique for the same purpose. This technique reduces the size of signature by taking only the important features to be fed into a backpropagation neural network.

In fact, our proposed signature recognition system is simple as compared to other proposed systems. However, the results obtained after testing it proved that it is more effective than the other related systems. This is due to effective technique of segmenting the signatures and also the extraction of features of the image which facilitates the learning stage of the neural network. Note that the feature extraction using pattern averaging also helped in distinguishing the human handwriting signatures used for training and testing the network.

Finally, it can be stated that a simple signature recognition system was developed in this thesis. Regardless of the simplicity of the system it is efficient enough to be compared to more complex and advanced related recognition systems. This is due to the effective image proceeding and feature extraction techniques used for segmenting and extracting the signatures.

7.4 Recommendations

Finally, a recommendation for future work is the exploration of support vector machine (SVM) for the recognition task. It is conceived that using SVM can help eliminate the classifier re-training as obtains in the BPNN; since SVM is a maximum margin classifier that always converge to the same local minima. However, it is noteworthy that working with SVM on data with high dimensionality can significantly raise required computational cost and time. Hence, future work should reveal some important trade-offs for using SVM as compared to BPNN.

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APPENDIX
SOURCE CODE

- **Image Processing**

%%%%%%%%%%%%%%%%%Processing one image

```
f=imread('s52.jpg');
f=rgb2gray(f);
f=imresize(f, [100 100]);
figure, imshow(f), title('Gray image');
pause
f=medfilt2(f, [3 3]);
figure, imshow(f), title('Filtered image');
pause
%f=imre   size(f, [256 256]);
g2=imadjust(f,[0.5 0.75], [0 1]);   .
figure,imshow(g2), title('adjusted image');
pause
%% treshold the image
level = graythresh(g2);
bw = im2bw(g2,level);
bw = bwareaopen(bw, 50);
figure,imshow(bw), title('Tresholded image');
pause
% Labeled the component(s), and plot the centroid on the original image
% Canny
S5 = edge(g2, 'canny', 0.25);
figure,imshow(S5), title('segmented image');
pause
m3=S5;
T = blkproc(m3, [4 4], @mean2);
figure,imshow(T), title('rescaled image');
pause
close all
```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%Train BPNN

```
clc;
clear;
close all;
PATTERNS = [];            %%%%%%%%%%%%%%%%%%%%%%%Training phase of 60 images
for k = 1:60
pic = strcat('C:\Users\TOSHIBA\Documents\MATLAB\signature recognition\train
data\s', num2str(k), '.jpg');
f = imread(pic);
f=rgb2gray(f);

f=imresize(f, [256 256]);
```

```
g2=imadjust(f,[0.5 0.75], [0 1]);   %% image adjustement, gamma =1, by
default..convert the intensities btw 0.5 and 0.75 to values btw 0 and 1.
% figure,imshow(g2), title('adjusted image');
% pause
%% treshold the image
level = graythresh(g2);
bw = im2bw(g2,level);
bw = bwareaopen(bw, 50);
% figure,imshow(bw), title('Tresholded image');
% pause
% Labeled the component(s), and plot the centroid on the original image
% Canny
S5 = edge(g2, 'canny', 0.25);
%figure,imshow(S5), title('segmented image');
%pause
m3=S5;
T = blkproc(m3, [4 4], @mean2);
% figure,imshow(T), title('rescaled image');
%pause
 imwrite(T,strcat('C:\Users\TOSHIBA\Documents\MATLAB\signature
recognition\Processed images', 'SegIMG',num2str(k),'.png'));
 v=T(:);
PATTERNS =[PATTERNS v];


end

TARGETS= xlsread('datasig.xlsx','sheet1');        %database


%%%%Training the neural network

net = newff(minmax(PATTERNS),[30 56],{'logsig','logsig'},'trainscg');

% TRAINING THE NETWORK
net.trainParam.lr = 0.03;  % Learning Rate.
net.trainParam.show = 300; % Frequency of progress displays (in epochs).
net.trainParam.epochs =500;% Maximum number of epochs to train.
net.trainParam.mc = 0.47 % Momentum Factor.
net.trainParam.goal = 0.001 % Momentum Factor.

target=[];

[net,tr] = train(net,PATTERNS,TARGETS);



%RECOGNITION RATE OF TRAIN DATA

%target max indices
[M,I_t]=max(TARGETS);% row vector
%dimensions of target matrix
[u,v]=size(TARGETS);
```

```
%actual output matrix sim_net

sim_net=sim(net,PATTERNS);
[N,I_sim_net]=max(sim_net);% row vector
%comparison of target and actual outputs
result = I_t==I_sim_net;% row vector
%sum of all elements,1s, to know how many corrects
corrects=sum(result);
%recognition rate,
w=double(corrects*100/v); %let recognition rate be w

fprintf('train recognition rate is %d\n',w);
%
%

% %RECOGNITION RATE OF TEST DATA
%
%target max indices
% [M,I_t]=max(test_target);% row vector
% %dimensions of target matrix
% [u,v]=size(test_target);
%
% %actual output matrix sim_net
%
% sim_net=sim(net,test_input);
% [N,I_sim_net]=max(sim_net);% row vector
% %comparison of target and actual outputs
% result = I_t==I_sim_net;% row vector
% %sum of all elements,1s, to know how many corrects
% corrects=sum(result);
% %recognition rate,
% w=double(corrects*100/v); %let recognition rate be w
%
%
%
% fprintf('test recognition rate is %d\n',w);


%close all
```