INTELLIGENT KNEE RHEUMATOID ARTHRITIS IDENTIFICATION SYSTEM BASED ON IMAGE PROCESSING AND NEURAL CLASSIFICATION

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are original to this work.

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To my Mum…

ABSTRACT

Rheumatoid arthritis can be defined as a chronic inflammatory disorder which affects the joints by harming body tissues. Therefore, there is a need for effective system analysis for the identification and detection of knee rheumatoid arthritis especially in its developmental or pre-diagnosis stages. This thesis is performed to develop an intelligent system for the recognition and classification of Rheumatoid Arthritis of the knee using image processing techniques and back propagation neural network. The system comprises of two main phases. The image processing phase is the first phase in which the images are processed using image processing techniques. These techniques include RGB to grayscale conversion, rescaling, median filtering, background extracting, image subtracting, image segmentation, canny edge detection and feature extraction using pattern averaging to rescale the image. Using pattern averaging enables the preserving of important features such as the distance between the femoral and tibia bones and some bone spurs. The second phase is such that the extracted features are then used as inputs for the neural network, which classifies the x-ray knee images as normal or abnormal (arthritic). Classification is carried out based on the back propagation learning algorithm, which involves the training of the network with 150 normal and abnormal x-ray knee images. The system was tested on the same number of images as the testing set and the experimental results showed that a recognition rate of 94.5% and 91.5% respectively, and the images have been correctly classified using the initial size of 256*256 and another size of 32*32

Keywords**:** Rheumatoid arthritis, intelligent system, segmentation**,** canny edge detection, pattern averaging, femoral, tibial, neural network**,** back propagation

ÖZET

Romatoid artrit, vücudun dokularına zarar vererek eklemleri etkileyen kronik bir enflamatuar bozukluk olarak tanımlanabilir. Bu nedenle, özellikle kendi gelişimsel ya da ön-teşhis aşamasında diz romatoid artrit tanımlanması ve saptanması için etkili bir analiz sistemine ihtiyaç vardır. Bu araştırma görüntü işleme teknikleri ve geri yayılım yapay sinir ağları kullanılarak diz Romatoid artrit sınıflandırılması maksatlı, akıllı bir sistem geliştirmek için hazırlanmıştır. Sistem iki ana aşamadan oluşmaktadır. Birinci aşama görüntü işleme aşamasıdır. RGB den gray-scale dönüşümü, yeniden boyutlandırma, medyan filtreleme, arka plan görüntüden çıkarılması, parçanın görüntüden çıkarılması, görüntüyü parçalara ayırma, canny kenar algılama ve ortalama modele göre yeniden boyutlandırma, özellik çıkartma bölümlerinden oluşur, Femoral ve tibia kemiği arasındaki önemli özelliklere ve son aşamada kemik çıkıntılarını işlemede yardımcı olmuştur. İkinci aşamada, özellik vektörleri yapay sinir ağları için giriş olarak kullanılmıştır. Burdaki Yapay sinir ağlarının amacı, x-ray diz görüntülerinden normal ve abnormal (artiritik) olarak, geri yayılım öğrenme algoritması kullaranarak 150 örnek yardımıyla sınıflandırmaktır. Sistem ağ öğrenme ile aynı sayıda 256x256 boyutundaki görüntülerle test edilip deneysel sonuçlar %94.5 tanımlama seviyesi sırasıyla %91.5 ve %91.5 olarak sonuç vermiştir.

***Anahtar Kelimeler*:** Rheumatoid arthritis, akıllı sistem, segmentasyon, canny tepe algılanması, şekil ortalama, femoral, tibial, yapay ağ, geri yayılım

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LIST OF ABBREVIATIONS

AAM:	Active Appearance Models
ANN:	Artificial Neural Network
BPNN:	Back Propagation Neural Network
DMARD:	Disease Modifying Anti-Rheumatic Drugs
MLP:	Multi-Layer Perception
MRI:	Magnetic Resonance Imaging
MSE:	Mean Square Error
NSAID:	Non Steroidal Anti-Inflammatory Drugs
OA:	Osteoarthritis
RA:	Rheumatoid Arthritis
RGB:	Red, Green, Blue

CHAPTER 1
INTRODUCTION AND AIM OF THESIS

1.1 Introduction

Rheumatoid arthritis (RA) can be defined as a complex inflammatory auto-immune disease which is associated with considerable disability, morbidity, and mortality. Early identification of patients with the aggressive, destructive disease is important, for prognostic and also therapeutic reasons. Another definition for the rheumatoid arthritis is a chronic inflammatory disorder which may affect the joints of the fingers, knee and hands and this causes swelling, stiffness and pain. The actuators for the onset of RA are only theorized, but it is expected that a genetic liability to the disorder, several viruses and bacteria (e.g. Epstein Barr-Virus and Mycobacterium tuberculosis; (Stehling et al.,2010), disruption of the immunological tolerance as well as the psychological condition by further weakening the immune system of people concerned may play a main role (Vignon , 1995). Since the main causes of RA are still unknown, cures or treatments have not been discovered till today. All treatments and therapies are present nowadays are only to reduce symptoms and delay the progress of the disease (Newman, 1995).

RA has many signs and symptoms that can be detected in an image including:

- Tender, warm, swollen joints
- Morning stiffness that may last for hours
- Firm bumps of rheumatoid nodules under the skin (tissue)

Rheumatoid arthritis (RA) or joint inflammation can be characterized as a complex incendiary auto-immune infection, which is connected with impressive disability, horribleness, and mortality (Navarro-Cano et al., 2003). Early distinguishing proof of patients with forceful dangerous infection is vital, for prognostic furthermore remedial reasons. An alternate definition for the rheumatoid joint pain is a ceaseless incendiary issue which may influence the joints of the fingers, knee and hands and this leads to swelling, firmness and agony.

Osteoarthritis (abbreviated as OA) is a chronic disease. The American College of Rheumatology defines OA as "a heterogeneous set of conditions that lead to joint signs and symptoms that are readily associated with the defective veracity of the articular cartilage, in addition to relative changes noticeable in the underlying bone of the joint boundaries". The defective integrity is characterized by the formation of lesion, fissures and cracks on the cartilage surface that eventually leads to severe abnormal exposure of the subchondral bone.

RA is most usually a consequence of maturing ligament. Maturing ligament logically gets to be stiffer and more powerless against wear and tear. Extreme RA can result in the ligament to destroy essentially totally with the goal that neighboring joint bones rub together with one another. This alluded to as "bone on bone" joint infection. As indicated by the studies by the World Health Organization, around 80% of the populace beyond 65 years old have radiographic confirmation of OA (Shamir et a1., 2009). RA can be result in any of joint in the body like spines, hips, fingers tingle, and however, it is more normal and serious in the knee.

Maturing is the real hazard component of osteoarthritis in the capacity of ligament to mend, diminishes as an individual gets more seasoned. Different variables are harmful, anatomical joint irregularities, heredity, high bone mineral thickness, joint hyper portability, stoutness, muscle shortcoming, and abuse or under utilization of the joints. Ladies who are 55 and more seasoned are more probable than men to create RA. Indications of osteoarthritis incorporate joint agony with movement, night torment, morning solidness, constrained movement, joint aggravation, clamor from the knee, and deformation. The early rheumatoid joint inflammation tends to influence the smaller joints first, in especially the joints that connect the fingers to hands and toes with feet.

The extent that the sickness creates, indications frequently spread to the wrists, knees, lower legs, and elbows. The signs and side effects of Rheumatoid joint pain may fluctuate in seriousness and advancement and may additionally travel every which way. Over the long run, rheumatoid joint inflammation may cause joints to distort and move out of its place (Stehling et.al., 2010).

The narrowed distance between the femoral and tibial bones, cartilage loss, and bone spurs are the basic signs of that disease. In our identification system, we focus on extracting these features using some image processing techniques, in order then to be fed into a neural network, which has the ability of classification after convergence of learning using many normal and arthritic knee images.

1.2 Contributions of the proposed work

This thesis is a contribution to the international Rheumatoid Arthritis diagnosis and early detection researches around the world using imaging and computer-aid techniques. This thesis is a part of the ongoing research for detecting and diagnosing Rheumatoid Arthritis, which aims to reduce the rate of occurrence of the disease and detect it in its earlier stages in order to treat it prior to its growth and development. However, this thesis provides different and additional methods and techniques to reach the desired purpose which is to classify it into three main classes: Normal (no RA) or abnormal (arthritic knee). This is done using two main phases: image processing and neural network through which the images are processed then classified using neural network.

1.3 Aim of thesis

RA is a dangerous and chronic disease that should be analyzed and detected in its early stages. Thus, the aim of this thesis is to develop a new approach for the identification of rheumatoid arthritis through knee image processing techniques and neural network classifier. Thus, any supplied knee image must be classified either normal or abnormal. The proposed system uses knees images obtained from a created database comprised of 150 images for training and 150 images for testing phase. These images had a varying size of 256*256 and 32*32 for training the network.

The image processing techniques used facilitates the diagnosis of that disease by analyzing and pointing out the rheumatoid arthritis signs and symptoms through extracting the useful and needed features or patterns such as the distance between the femoral and tibial bones, joint damage, bone widening and stiffening. Moreover, the developed system helps the doctors to accurately classify the RA knee X-ray images since it is designed to stimulate the human visual inspection that is based on visualizing some related features and signs of RA.

1.4 Thesis overview

The rest of this thesis is divided into 6 chapters, which are structured as follows.

Chapter 1 is an introduction about the thesis. In this chapter we define our thesis; we set the aims, the contributions, and motivations. In addition, the structure of the thesis is discussed.

Chapter 2 introduces the Rheumatoid arthritis in several aspects including the anatomy of knee, the disease nature and definition, in addition to the causes and symptoms of the disease. Moreover, the screening methods and techniques of the Rheumatoid Arthritis are described and illustrated in this chapter, as well as the diagnosis methods.

Chapter 3 is a detailed explanation about the first phase of our proposed system, in which the image processing phase is discussed. In this chapter, we explain the image processing phase using graphs, figures, and flowcharts in order to explain our new developed intelligent system for the identification of Rheumatoid arthritis. The image processing techniques used in the designed system are discussed in details in this chapter.

Chapter 4 discusses the classification phase of the proposed system. This phase is based on an artificial neural network classifier. In this chapter, we define neural network and explain its concepts, in addition to the back propagation learning algorithm that is used in our system and the reasons we used it. In this chapter, the training results of the system using tables, figures and curves such as the learning curves are provided. The system performance and the experimental results are also discussed in this chapter through tables and figures.

Finally**,** results comparison of the proposed identification system with previously proposed systems for the same aim which is the identification or detection of RA using image processing and neural classifier was explained in **chapter 5**. Conclusion and recommendation were highlighted in **chapter 6**.

CHAPTER 2

RHEUMATOID ARTHRITIS: ANATOMY, SIGNS, AND SCREENING METHODS

2.1 Medical background

This disease starts with the inflammation of the synovial membrane of the joints, in particularly in the small ones of the fingers and feet and is mostly bilateral. The inflammatory cells, if in inappropriately large amount, destroy body tissue. The synovial fluid accumulates and the joints swell in time and thicken into an abnormal tissue called pannus. Over time the pannus erodes the joint of cartilage and, scar tissue may be formed. Then, this scar tissue can rigidify where with the joints get immobilized and deformed. The surrounding structures of the inflammatory joints, as tendons heaths, bursas and origins of muscles are often involved supporting joint deformations as well. These strains are generally irreversible (Marieb et al., 2006). In seldom cases the vertebral column, vasculatures and several organs as skin, heart and lungs are also inflamed by RA. The disease gets diagnosed by several methods: ultrasound and MRI (magnetic resonance imaging) Rheumatoid Arthritis which detects inflammation marks in the joints and the surrounding structures; radiograph and MRI which detects meanderings in cartilage and bones (Stehling et al., 2010).

Rheumatoid Arthritis has been found to be among older generation of humans reaching the age of 40 and very prevalent amongst old individuals clocking the age of 70. The severity of this disease has been over time overlooked but more in recent years attention has been drawn to this disease. In this chapter, we attempt to explain the risk of having such disease through providing some of its symptoms and signs. Thus, we point out the importance of such identification system and the urgent need of it.

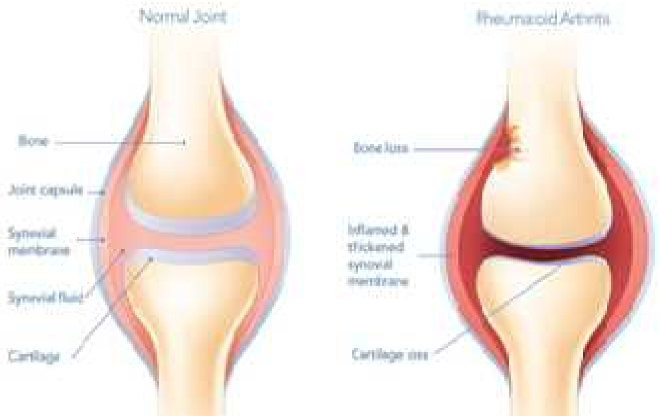

Figure 2.1: Normal and arthritic joints

Bones give backing to the body and help in its movement, the place where two or more bones meet is known as a joint. Joints may be immoveable, somewhat moveable or openly moveable. A synovial layer encompasses moveable joints. Inside the film synovial liquid greases up and feeds joint tissue, for example, cartilage. Articular cartilage is an extreme tricky covering of the closures of the bones which permits smooth joint movement. Joints give the body flexibility, precision of development and help in supporting the heaviness of the body.

Joint pain is any issue that influences joints; it can result in torment and aggravation. Rheumatoid Arthritis is the second most basic kind of arthritis; the joints most ordinarily influenced are in the wrists, hands, knees, ankles and feet. It commonly happens at the same joint on both sides of the body. It can likewise influence different organs in the body, for example, the eyes, skin, heart, lungs, kidneys, nervous framework and digestive tract. Rheumatoid joint inflammation is an auto-safe disorder; this implies the body assaults itself by error. In Rheumatoid joint pain the invulnerable framework assaults joints and organ tissues. The white platelets of the safe framework move into the joint, they discharge chemicals called cytokines which assault the phones of the synovial film. These chemicals cause synovial cell to discharge other ruinous substances, they additionally cause the synovial layer to develop new vessels and structure a thickened territory called a pannus. After some time as the pannus develops it attacks and demolishes zones of cartilage and bone inside the joint. Aggravation causes liquid to develop in the joint making the joint swell, eventually without treatment the joint space river and Ankylosis can happen. Ankylosis is combination or becoming together of bones in the joints. This outcome in the loss of the capacity to move the joint. There is no cure for Rheumatoid Arthritis, however specialists ordinarily endorse different blends of medications that when joined together can decrease irritation and torment and ease off joint damage, these incorporate:

1) NSAIDs (non steroidal anti-inflammatory drugs)
2) Steroids
3) Standard DMARDs (disease modifying anti-rheumatic drugs)
4) Biologic DMARDs

Rheumatoid Arthritis treatment that can increasemuscle quality and help keep joints nimble incorporate;

- Physical treatment
- Occupational treatment
- Low effect exercise

For extreme Rheumatoid Arthritis that has not been helped by other treatment,a specialist may prescribe a surgical system. Case in point a joint substitution technique otherwise called an Arthroplasty perhaps suggested. For joints that are hard to supplant, joint combination otherwise called Arthrodesis perhaps suggested. Amid this methodology the joint is uprooted and the bones are melded with bone joining. An alternate surgical strategy for extreme Rheumatoid joint inflammation is a Synovectomy,during this methodology the synovial layer encompassing the joint is evacuated. At times a ligament joint may need to be supplanted with a simulated artificial joint.

2.2 Understanding joints

A joint is a joiner where two bones meet. The joints allow movement and flexibility of various parts of the body. The development of the bones is brought on by muscles which pull on tendons that are appended to the bone. Cartilage covers the end of bones. Between the cartilages of two bones that form a joint there is a small amount of thick fluid called synovial fluid. This lubricates the joint, which allows smooth movement between the bones without disruption. The synovium is the tissue that surrounds a joint and houses the joint capsule, cartilage and synovial fluid and the joint. Synovial fluid is made by cells of the synovium. The outer part of the synovium is called the capsule present in the synovial membrane. This is tough, gives the joint stability, and stops the bones from moving out of place. Surrounding ligaments and muscles also help to give support and rigidity to the joints (Vignon , 1995).

2.3 Rheumatoid Arthritis of the knee

Rheumatoid arthritis (RA) of knee is a dangerous type of inflammatory arthritis that affects 1.3 million Americans (WebMD, 2014). In 75% of cases, RA affects women. RA can affect people of any age, even very young children. Unlike osteoarthritis (OA), the "wear-and-tear" arthritis, RA is a chronic autoimmune disease in which the immune system attacks the joints. RA usually occurs in a symmetrical pattern, affecting the hands, knees, ankles, feet, hips, elbows, and shoulders. RA causes severe joint swelling, joint pain, stiffness, and deformity. It also affects other tissues and organs such as the heart, skin, and lungs. RA can also cause fever, fatigue, weight loss, and flu-like symptoms. Getting dressed, tying shoelaces, or walking to the car may be painful with knee arthritis. But with early and aggressive medical treatment, most cases of knee RA can be managed (Souza et al., 2010). Figure 2.2 illustrates a typical normal joint structure showing the bone, tendon, cartilage and some muscle tissue.

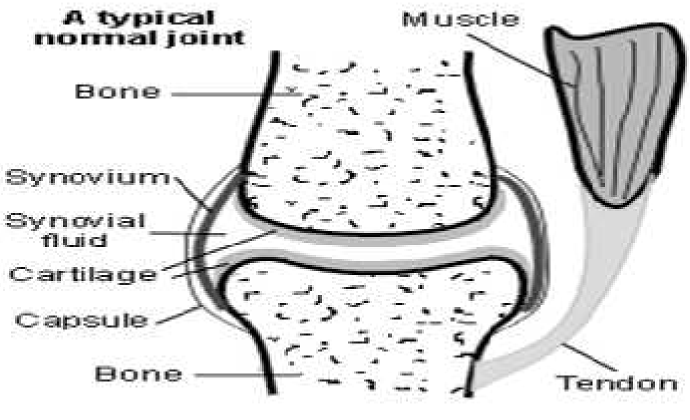

Figure 2.2: Joint structure

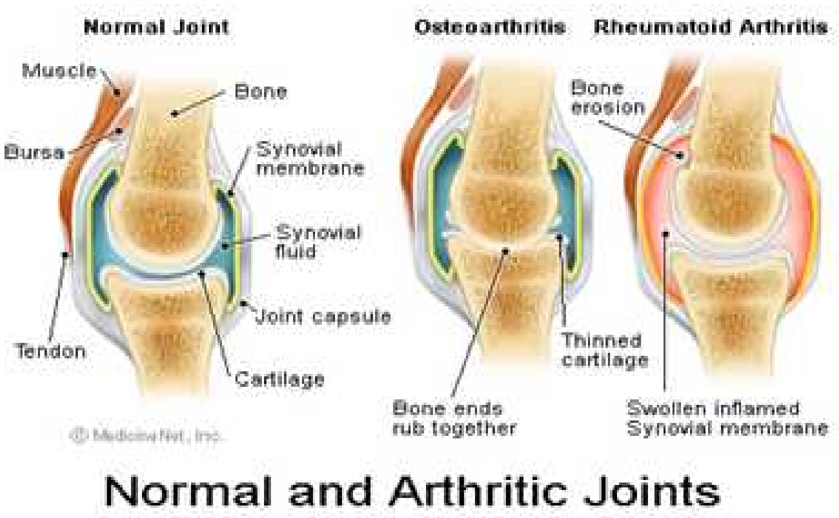

Figure 2.3: Normal and arthritic Knee

Rheumatoid joint pain (RA) reasons agony, swelling, solidness, and loss of capacity in the joints. The illness normally influences the joints, especially in the wrist and the fingers. Likewise, different parts of the body other than the joints can be influenced. Since there is no demonstrated cure for RA accessible yet, current medicines chiefly concentrate on torment easing, irritation decrease, and backing off or halting joint harm. So as to anticipate irreversible joint harm, early discovery of RA is crucial. For a successful therapeutic treatment, it is imperative that the disease can be observed nearly. Joint harm appraisal under control radiographs is an often utilized technique for checking the movement of RA (Gasson et al., 2000).

To come up with such a system, there should be a review of the previous related work. Many researchers have proposed related systems for the analysis of RA. Each system proposes a different algorithm and methods, however; the goal is one: the analysis of RA images for the purpose of accurate diagnosis.

Leung (2007) proposed a system based on longitudinal imaging, which is an effective tool for clinical studies and patient management based on visual inspection and image analysis. The author used two different methods for analyzing changes in a bone, segmentation and thresholding algorithm. In another study provided by Arpita Mittal , Arpita (2013), a system for the analysis of MRI RA images was proposed. The system is based on some morphological image processing techniques for the purpose of image enhancement. The author used techniques such as image dilation, erosion, image opening, and histogram equalization for image clarity. A study of the analysis of Rheumatoid Arthritis through image processing was proposed by Arpita Mittal and Sanjay Kumar Dubey (Mittal et al., 2012). In their papers, they used three different algorithms for the analysis of RA. Each algorithm consists of some image processing techniques. The first algorithm or method focuses on the image enhancements and acquirement techniques such as Gaussian filtering, image cropping in order to show the space between the two bones. The second method is as simple as the first since it is based on the image intensity adjustment techniques along with Gamma correction, that are applied to the analysis point of view of the knee image of old person having Rheumatoid arthritis. Using this method, the authors stated that the difference between two images can be analyzed by the histogram equalization. The third method provided in that work was the convolution using median filtering, which helps to preserve edges in order then to be detected using edge detection techniques.

2.4 Other areas of Rheumatoid Arthritis

Rheumatoid joint pain is an immune system ailment, an issue in which the body assaults its own particular sound cells and tissues. When somebody has rheumatoid joint inflammation, the layers around his or her joints get to be kindled and discharge catalysts that cause the encompassing ligament and issue that needs to be addressed away. In extreme cases, different tissues and body organs likewise can be influenced (Washington University Orthopedics, 2013).

Figure 2.4: RA of the hip (Washington University Orthopedics, 2013)

2.4.1 Rheumatoid Arthritis of the hip

Rheumatoid arthritis is a systemic issue, that is, it influences your whole body and not simply the hip joint. The irritation is identified with an insusceptible framework reaction instead of wear and tear.

The hip joint, in the same way as different joints in the body, is secured by an extraordinary container that totally encompasses the joint. This container has a unique covering (the synovial coating) and is loaded with oil (joint liquid) that helps the joint move easily. Rheumatoid joint pain normally causes a swelling of the synovial coating. This result in agony and swelling, yet in the end, rheumatoid joint pain can result in the bone and ligament of the joint itself to decay (Washington University Orthopedics, 2013).

2.5 RA symptoms and signs

Rheumatoid arthritis (RA) tends to start slowly with some minor symptoms that may come and go, and develop over a period of weeks or months. Symptoms of this chronic disease may vary from person to person and can change from possibly day to day. Attacks in disease activity are called flare-ups**,** while inactive periods are called remission **(**Patient.co.uk, 2014)**.**

- **Rheumatoid Arthritic knee symptoms and signs**

With knee RA, you may feel the following:

- Pain
- Swelling, inflammation
- Stiffness
- Warmth around the knee joints
- Fatigue

- **Other symptoms and signs**

These are some known other symptoms of RA which occur outside of the joints. A variety of symptoms may occur. The reason for some of these is not completely understood **(**Patient.co.uk, 2014)

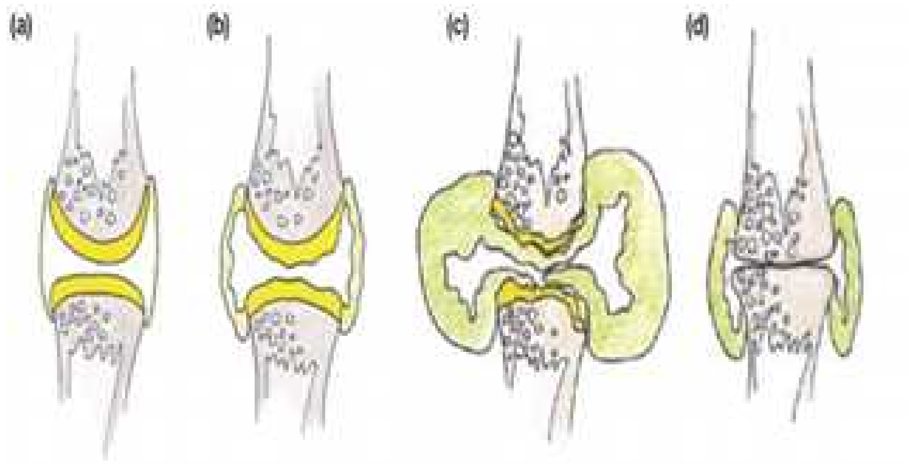

Figure 2.5: Rheumatoid arthritis stages representation (Arpita, 2013)

- Small painless lumps or knobs (nodules) grow in about 1 in 4 cases. These usually happen on the skin over the elbows and forearms, however typically does no damage.
- Inflammation around tendons may happen. This is due to the tissue that covers the tendons are similar to the synovium around the joints.
- Anaemia and tiredness are very common (Patient.co.uk, 2014).
- A fever, feeling unwell, weight reduction, and muscle throbbing painfulness now and again happen

Figure 2.5 illustrates a representation of stages in rheumatoid arthritis (RA). (a) Illustrative depiction of a synovial joint. The ligament surface of the joint is indicated in yellow, with the capsule of the joint being laid out by a thin greenish line representing normal synovium; (b) early RA. The synovium is thickened and has an unpredictable and nodular appearance. Likewise take note of that the surface of the joint exhibits slight inconsistency of the hyaline cartilage because of the arrival of proteolytic proteins; (c) advanced RA. Gross hypertrophy of the synovium is currently evident and the synovium has relocated over the hyaline cartilage surface. The ligament is appallingly sporadic and radically reduced, and now and again may be completely stripped, with deterioration and interruption of fundamental bone.; (d) end-stage worn out RA. Synovial hypertrophy has relapsed. Notwithstanding, the ordinary joint structures have been severely harmed, and superimposed osteoarthritis has been created. Here the ligament has been totally pulverized.

2.6 Screening methods for RA

The ultrasound, magnetic resonance imaging, and X-ray can help detect rheumatoid arthritis early and monitor the response to treatment. These three imaging techniques can differ in the accuracy and efficiency of RA detection.

For decades, X-ray imaging have been enabled to help detect rheumatoid arthritis (RA) and to monitor and check for the development of bone damage. Later, a new technology started to be used along with X-ray which is the magnetic resonance imaging techniques (MRI), and ultrasound which can show early, non-bony signs of RA that are invisible on X-ray. In this thesis we decided to use X-ray rheumatoid arthritic knee images instead of MRI and ultrasounds.

2.6.1 RA X-ray imaging principles

X-ray imaging is an electromagnetic imaging in which an X-ray beam produced by an X-ray tube passes through the body. In the body, some parts of the energy of the X-ray beam are absorbed. This process is called attenuation of the X-ray beam. On the other side of the body, detectors or films capture the attenuated X-rays, resulting in a clinical image after passing through a digital computerized system (Physical Principles of Medical Imaging Online, 2012).

In conventional x-ray imaging the radiographic film is covered by a filter which decreases the amount of scattered x-rays which can cause a chemical reaction. When treated, areas exposed to ionizing radiation will appear darker on the film as a result of the silver atoms radiography, one 2D image is produced.

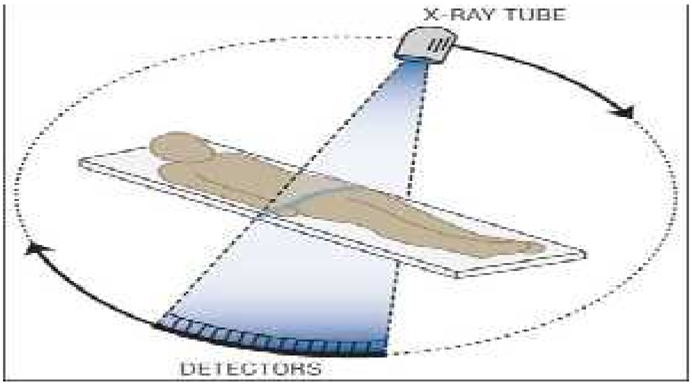

Figure 2.6: Normal vs. arthritic knee using x-ray imaging (Physical Principles of Medical Imaging Online, 2012)

Cootes and other researchers Cootes et al. (2001) investigated the possibilities of automating the assessment of joint damage in hand radiographs. Basically, the goal of their work is to design an algorithm called a robust segmentation algorithm for the hand skeleton, which is basically based on active appearance models (AAM).

Figure 2.7: Conventional X-ray imaging of knee (Heatlthline, 2014)

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CHAPTER 3

RA FEATURES EXTRACTION USING IMAGE PROCESSING

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3.1 Image processing

The general digital image processing system can be divided into three components: the input device (or digitizer), the digital processor, and the output device (image display) (Gonzalez and Woods, 2002).

1. Digitizing converts continuous tone and continuous spatial distribution of brightness and [x, y] to a separate group (digital image) FQ [n, m], where n, m, and FQ integers.

2. Digital processor works on digital image FQ [n, m] to generate an image GQ new digital [k, c], where k, c, and GQ integers. The image may be output represented in different coordinate system, and therefore the use of different indicators as c

3. Display image converts digital output (GQ) [k, c] back to a continuous tone and spatially continuous image g [x, y] for display. It should be noted that some systems may not require the display (for example, in machine vision and artificial intelligence applications); output may be a piece of information. Ideally will have two possible outcomes (YES or NO),for example, a single bit of information (Gonzalez and Woods, 2002).

- **Pixel**

Pixel is the littlest component of a picture. Each pixel compare to any one worth. In a 8-bit dark scale picture, the estimation of the pixel somewhere around 0 and 255. The estimation of a pixel anytime compare to the force of the light photons striking by then. Every pixel store a quality corresponding to the light force at that specific area.

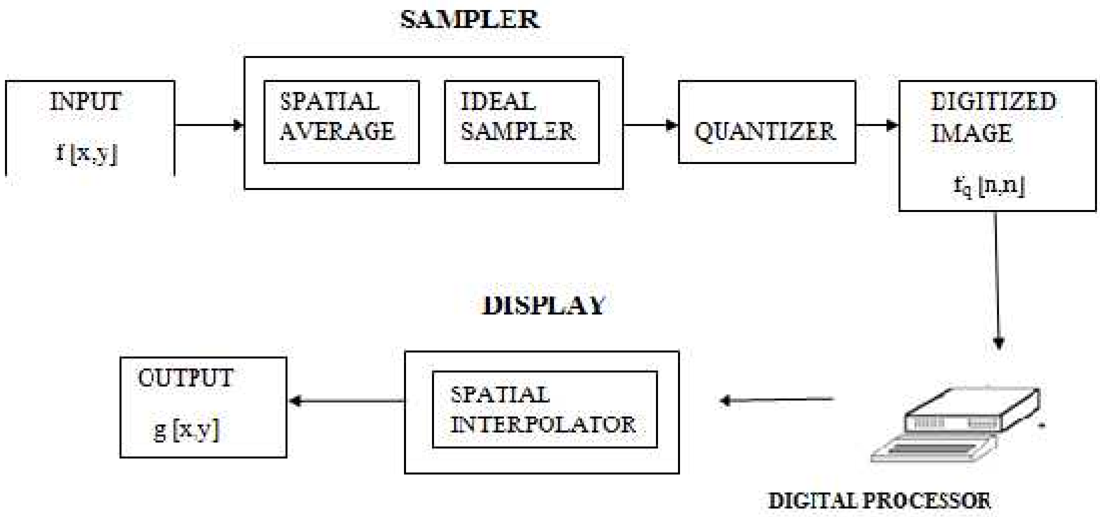


Figure 3.1: Digitization process of image

- **Calculation of total number of pixels**

. We have characterize an image as a two dimensional sign or framework. At that point all things considered the quantity of PEL would be equivalent to the quantity of lines increase with number of segments. This can be numerically spoken to as underneath: Total number of pixels = number of columns (X) number of sections Or we can say that the quantity of (x,y) direction sets make up the aggregate number of pixels. We will look in more detail in the instructional exercise of picture sorts , that how would we ascertain the pixels in a shading picture

- **Gray level**

The estimation of the pixel anytime signifies the force of picture at that area , and that is otherwise called dark level.

We will see in more insight about the estimation of the pixels in the picture stockpiling and bits per pixel instructional exercise, however for the time being we will simply take a gander at the idea of the stand out pixel value

PIXEL VALUE. (0)

As it has as of now been characterize in the first place , that every pixel can have stand out quality and every worth signifies the force of light by then of the picture.

We will now take a gander at an extremely one of a kind esteem 0. The worth 0 methods nonappearance of light. It implies that 0 signifies dim, and it further implies that at whatever point a pixel has an estimation of 0, it implies by then , dark shading would be shaped

3.2 The proposed methodology

The proposed system consists of two main phases which are the processing phase and the classification phase in which the image is classified as normal or abnormal (arthritic knee). In the image processing phase the images 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 such as distance between the tibial and femoral bones and bone spurs. At the end of this phase, the images are ready to be fed to the new phase which is the neural network in which they are classified as normal or abnormal.

Image processing techniques used:

1. Read RGB images

2. Convert to grayscale

3. Smooth images using median filters

4. Segment images using a canny edge detection technique

5. Clear unwanted components in the images

6. Extract important features using pattern averaging

Classification Phase

- Classify images using neural network

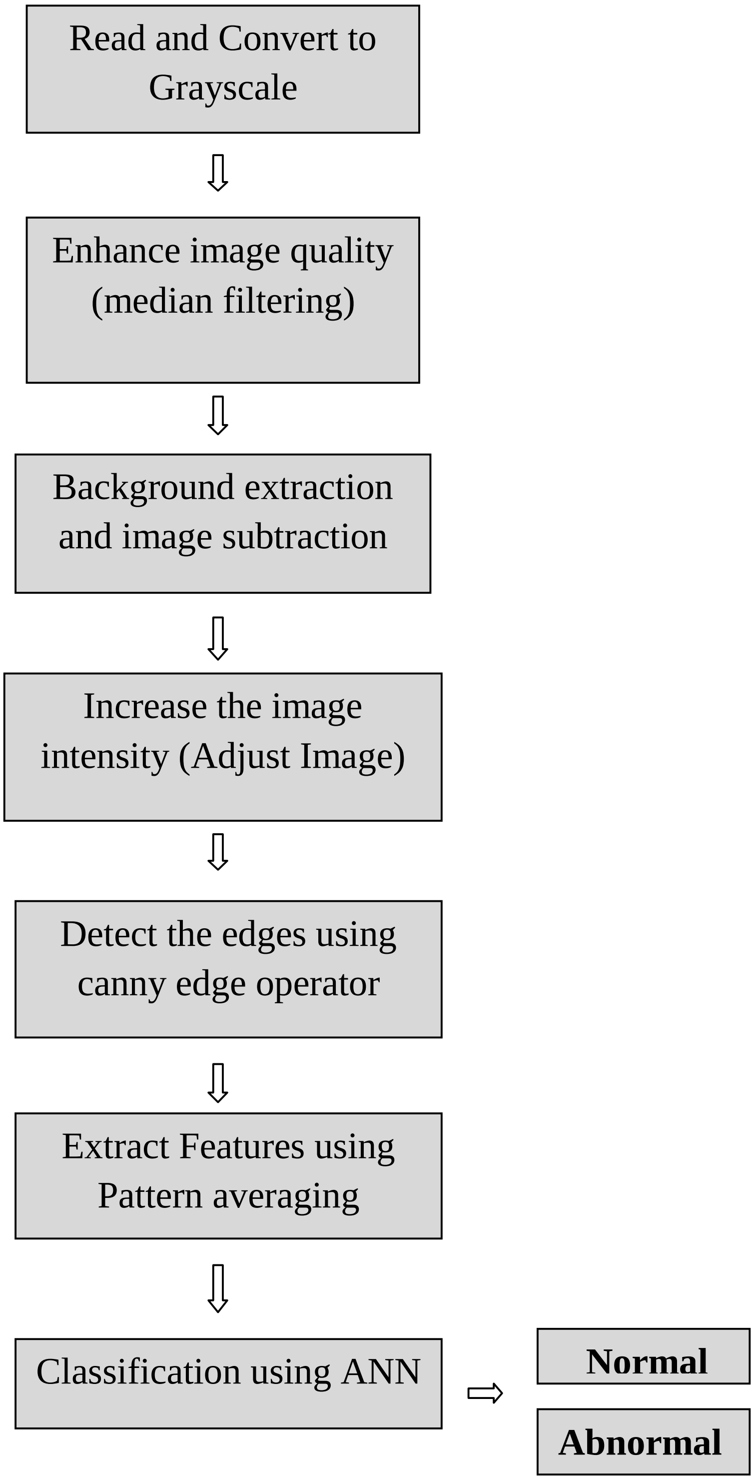


Figure 3.2: Flowchart of the presented algorithm

Figure 3.2 represents a flowchart that illustrates our proposed system for the identification of Rheumatoid Arthritis.

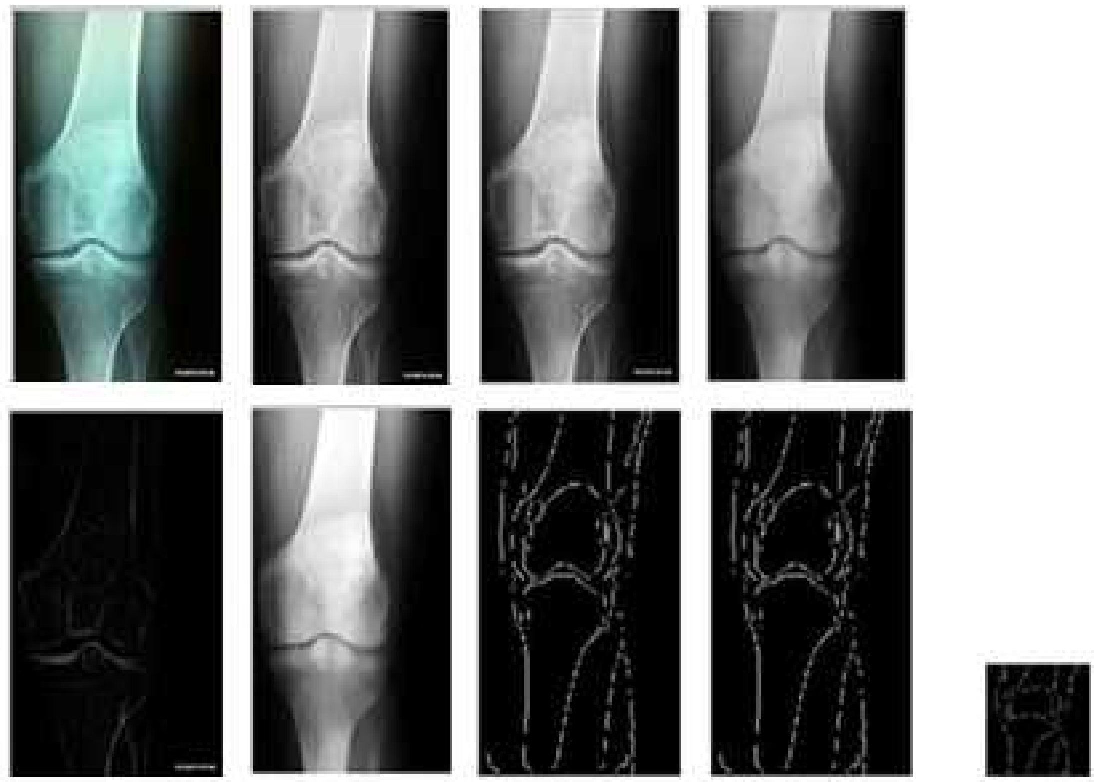


Figure 3.3: The proposed system algorithm for normal knee

Figure 3.3 shows a normal knee image that undergoes all the system processes in order finally to be segmented. Figure 3.4 shows an abnormal image that was processed using our algorithm in order to detect its edges and extract some useful features.

There is the normal knee processed images with the absence of the arthritic features and bone spurs, useful features are detected by the canny operator to further establish the intrinsic characteristics of the normal functioning human knee. The different stages in the proposed system algorithm for rheumatoid arthritis in a normal knee operated with the different processing operations are shown above in Figure 3.3.

Figure 3.4: The proposed algorithm for an abnormal knee image

3.4 Image database

In general, databases that are used in developing knee images rely on X-ray images taken by conventional X-ray diagnostic machines. The produced images of this machine are examined by a doctor or physician who makes the final decision based on some visible features seen in the image. However, our new approach to Rheumatoid Arthritis intelligent identification is based on artificial intelligence using image processing and intelligent classifier which models the human visual recognition who is normally able to identify the Rheumatoid Arthritis according to some morphological features such as the narrowed distance between bones and some bone spurs. The normal and abnormal images were collected from a medical center in the author's hometown in Nigeria, Africa, for RA of the knee diagnosis. The images were obtained all in size 256*256 owing to the fact that some of these imaging technologies in the medical facility in Nigeria were not fully developed as of the time they were collected. The collected images were rotated incrementally by 15 degrees to finally get 6 images including the original one. The total number of images are 300. Among them, 200 are normal and 100 abnormal images (arthritic knees). Table 3.1 shows the number of normal and abnormal images.

Table 3.1: Total number of images

	Number of Normal Images	Number of Abnormal Images	Total Number of Images
Training set	50	100	150
Testing set	50	100	150
Total	100	200	300

The rotation of images is aimed to increase the number of images because of the unavailability of an online database of RA knee images. Rotation also aims to test the trained system's rotational invariance capability. The obtained original and rotated color images were then converted from true color to gray level, in preparation for the feature extraction phase.

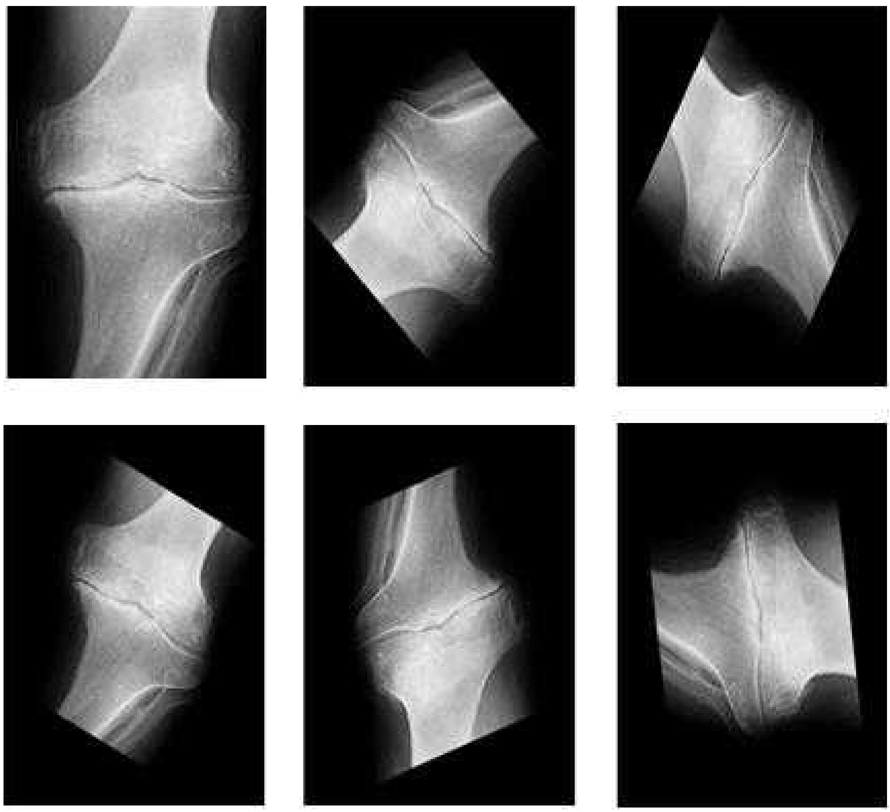


Figure 3.5: RA knee image rotated to 15 degrees incrementally

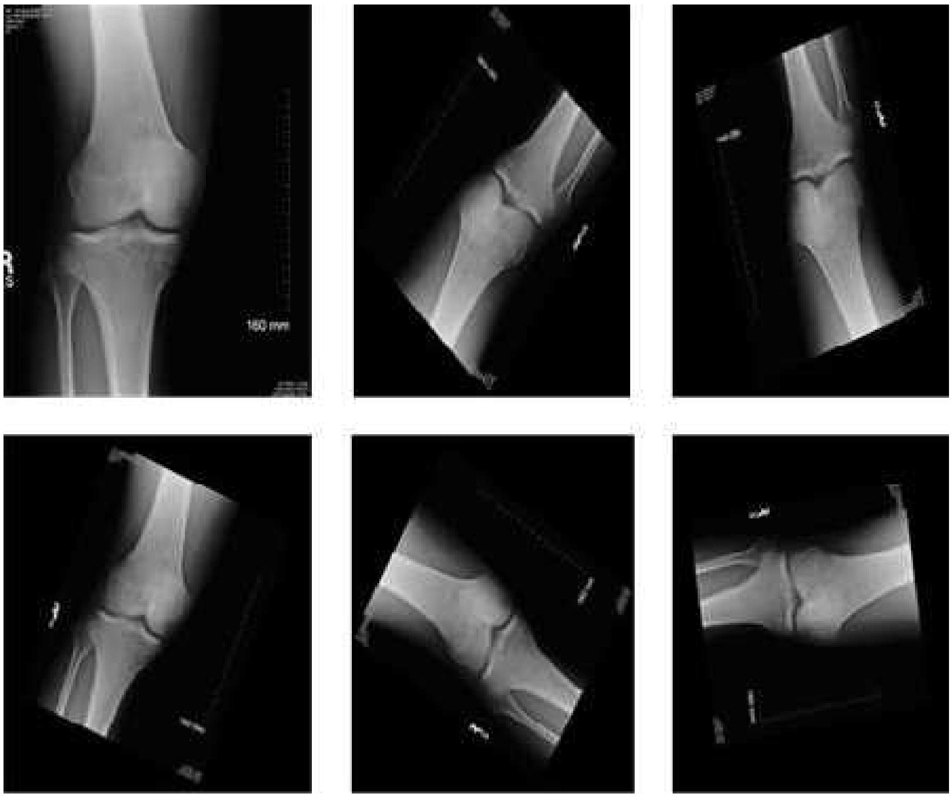


Figure 3.6: Normal knee image rotated to 15 degree incrementally to produce 6 images including the original one

3.4 Image processing techniques

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.

3.4.1 RGB to grayscale conversion

The pictures were initially changed over from RGB to grayscale in which this change is done utilizing the radiance system. This strategy is a more refined rendition of the normal system. It likewise midpoints the estimations of the picture framework, yet it shapes a weighted normal to record for human recognition since people are more delicate to green than different hues, accordingly; green is weighted most vigorously. The equation for luminosity is

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

(a) RGB image (b) Grayscale converted image

Figure 3.7: RGB to 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 and not averagely (Church et al., 2008). Grayscale conversion is done in order to make the algorithm faster, RGB images are in true colour and they tend to slow down the the algorithm.

Figure 3.7 illustrates the conversion of an abnormal knee RGB image into a grayscale image using luminosity method.

3.4.2 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 linear filters. It is mostly based on the averaging technique of the input image or the middle (median) value technique(Church et al., 2008).

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 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 (Helwan, 2014).in other words,The median filter goes through each element of the image and replace each pixel with the median of its neighboring pixels which are located in a square neighborhood (kernel) around the evaluated pixel. Median Filtering smoothes the data while keeping the small and sharp details.

What impact does this have on the limit values? There are different methodologies that have distinctive properties that may be favored specifically circumstances:

-Avoid handling the limits, with or without editing the sign or picture limit a while later.

-Fetching sections from different places in the sign. With pictures for instance, sections from the far even or vertical limit may be chosen.

-Shrinking the window close to the limits, so that each window is full.

Figure below 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 (Church et al., 2008).

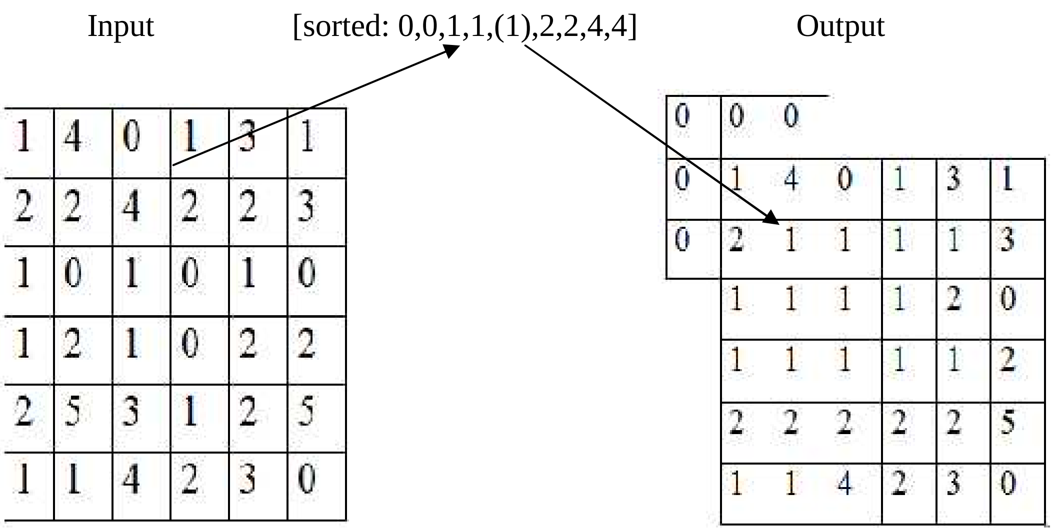


Figure 3.8: Median filter working principles

(a) Original grayscale image (b) Median filtered image

Figure 3.9: Image smoothing using median filter

3.4.3 Background forming

Morphology technique can be defined as a group of image preparing operations that procedure pictures in light of shapes. These morphological operations are taking into account applying an organizing component to a data picture so as to make a yield picture of the same size. In such operation, the estimation of every pixel in the yield picture is taking into account a correlation of the relating pixel in the data picture with its neighbors. This is finished by picking the size and state of the area. At that point, we can build up a morphological operation that is touchy to particular shapes in the data picture (Gonzalez and Woods, 2004).

The structure component is a network comprises of 0's and 1's, where the 1's are known as the neighbors. The estimation of every pixel in the yield picture is situated by correlation of the comparing pixel in the data picture with its neighbors. It has many shapes according to its application. In our case, or system, the “disk” structure element with a “radius” of 20 is used to extract the background of the image (Helwan, 2014).

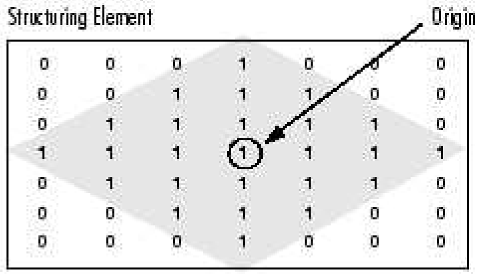


Figure 1: Structure element

The most well-known and fundamental morphological operations are enlargement and disintegration. Enlargement is to add pixels to the limits of items in a picture, while disintegration is to uproot pixels on article limits. The quantity of pixels that are included or even expelled from the structure in a picture relies on upon the size and state of the organizing component that is utilized to process that picture. In these morphological operations (widening and disintegration), the state of any given pixel in the yield picture can be controlled by applying a principle to the contemplated pixel and its neighbors in the information picture (Gonzalez and Woods, 2004).

Dilation operation is used to remove or add a pixel at object boundarybased on the shape and radius of its corresponding structuring element. During dilation, the value of the output pixel is the maximum value of all the pixels in the input pixel of the set neighborhood (Radha and Lakshman, 2013).

Erosion can be considered as a dual to dilation; it can be defined as dilation by set complementation and vice versa. Thus, to erode an image we should dilate the complement of it, while dilating an image can be accomplished by eroding the complement of the image. In other words, we can say that the dilation can be used to expand foreground of the image and shrinks its background, while erosion is used to shrink the image foreground and expands its background (Radha and Lakshman, 2013).

The extraction of background is achieved using a morphological technique called image opening. This technique can be defined as erosion followed by dilation using the same structure element for the two morphological operations. In this technique the objects that cannot completely contain the structuring element are removed in order then for the background to be to extracted (Beham, et al., 2012).

Figure 3.11 illustrates the background extraction operation of a normal knee X-ray image.

(a) Original filtered image (b) Extracted background

Figure 3.11: Background extraction

3.4.4 Subtracting images

Image subtraction is a basic tool for the analysis, processing, and interpreting of medical images. It is used in a wide range of circumstances and fields in particularly in the medical field to help in detecting tumors (Gonzalez and Woods, 2004).

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

Mustafa Seçil and other researchers used this technique in their proposed system In orde to study The role of dynamic subtraction MRI in detection of hepatocellular carcinoma (Seçil et. al., 2008). They found that subtraction is a basic automatic method that is normally accessible in most MRI frameworks. The utilization of subtraction of element difference improved arrangement encourages the discovery of HCC in disarranged building design of cirrhotic livers.

$$R\ i,j\ =\ O\ i,j\ -\ B(i,j) \tag{3.2}$$

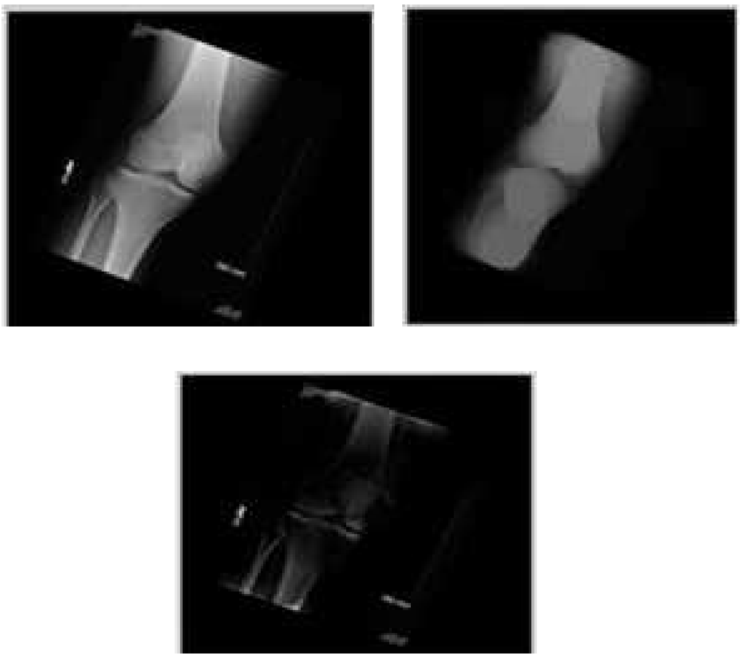


Figure 3.12: Image subtraction

O and B represent the original and background image respectively. O(i,j) and B(i,j) represent the elements values of the original and background images matrices in which the number of elements of both matrices which must be equal. Figure 19 shows the subtraction of two images which result in an output image.

3.4.5 Gamma correction in medical imaging

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 and 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 (Aggarwal et al., 2013).

(a) Subtracted image (b) Adjusted image

Figure 3.13: Image adjustment

Figure 3.13 represents the adjustment of an image and its effects in enhancing the image contrast.

$$S = T(r) \tag{3.3}$$

$$V_{out} = AV_{in}^{\gamma} \tag{3.4}$$

In our case we selected the four parameters and gamma values in a way to obtain the best quality and contrast image.

Figure 3.13 shows 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.

3.4.6 Canny edge 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 thresholding, 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 and 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 (Helwan, 2004). Canny operator has been used for such algorithm with regard to the following criteria (Saif et al., 2012):

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

The steps of canny algorithm in order to segment an image into many regions are as follows:

1. Smoothing: it means blurring an image in order to remove noise and it is done by convolving the image with the Gaussian filter.

2. Finding gradients: Since the edges must be marked where the gradients of the image has large magnitudes, we have to find the gradient of the image by feeding the smoothed image through a convolution operation with the derivative of the Gaussian filtering both the vertical and horizontal directions.

Its magnitude value can be obtained using the following formula:

$$|G| = |G_x| + |G_y| \tag{3.5}$$

$$|G| = \sqrt{G^2{}_x + Gy^2} \tag{3.6}$$

where G_x and G_y are the gradient values computed by using canny mask in x and y direction respectively and edge direction can be computed using the formula.

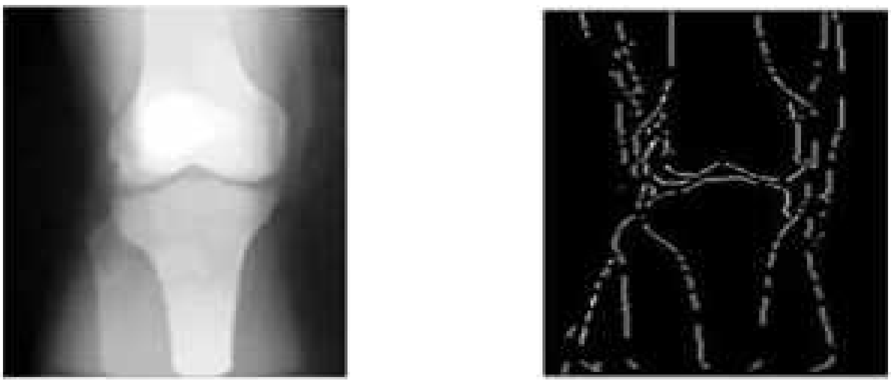
3. Non-maximum suppression: this technique is to find the local maxima in the direction of the gradient, and suppress al others, in order to minimize the false edges.

4. Perform double thresholding: in this stage, the potential or strong edges are determined by thresholding, therefore, instead of using a single static threshold value for the entire image, the Canny algorithm provided what is called hysteresis thresholding, in which two threshold values are used. These two threshold levels are T1 or high threshold and T2 or the low threshold, where T1>T2. Pixel values above the T1 value are immediately classified as edges.

5. Final edge tracking by hysteresis: this is the final stage, in which the final edges are tracked by suppressing all edges that are not connected to a very strong edge (Saif et al., 2012).

These are high threshold and low threshold. The pixel having the quality more prominent than high threshold is situated as an edge pixel and the pixel having the worth more noteworthy than the low limit and is having a way to the edge pixel is safeguarded though pixel having slope esteem more noteworthy than low edge and is not associated with edge is stifled.

Figure 3.14 illustrates segmentation of a background image using canny edge detection.



(a) Background image (b) Segmented image using canny operators

Figure 3.14: Canny edge detection

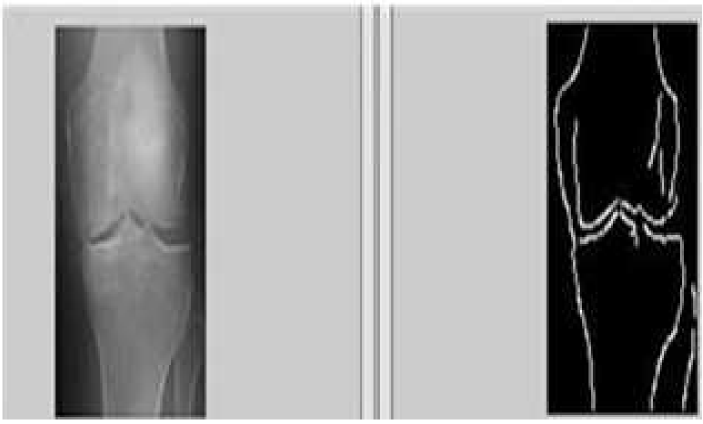


Figure 3.15: Canny edge detection

Figure 3.15 illustrates segmentation of a background image using canny edge detection. By analyzing and visualizing these two segmented images, we can notice that the segmentation result is better when segmenting the background image not the subtracted one, since the edged are clearer. Thus, our proposed system uses the both methods, means that the system provides two options regarding the input image to be segmented, either background or the subtracted image.

Advantages of using canny operators:

- It provides good noise immunity.
- It detects the true edges or intensity discontinuities.
- It smoothens edges
- It is in a completely different class from Sobel and Laplacian. It is much smarter and accurate since it includes a bunch of post processing whereas Sobel and Laplacian are simply high pass filter outputs followed by linear binary thresholding (Saif et al., 2012).

3.4.7 Clear unwanted components

After segmenting, the images are cleaned in which some unuseful components are removed. This function is an image processing technique used in order to remove or clean the image from the unneeded components. A certain value is set and all connected components that have pixel values higher than that value are removed. After applying this method the image gets well segmented and only the needed regions stay appeared.

This technique has been used by many authors in order to remove some unwanted components in an image specifically when working with medical images. A. Helwan created a system for the iris tumor detection using image processing techniques (Helwan, 2014).

One of the techniques used in that system is the removal of the unwanted components to obtain a clear edge detected image.

Figure 3.16 shows the result of applying such technique in removing unneeded components of a normal knee segmented image. it is clear that the segmented image has some unuseful details such as some internal edges represent the inner bone edges which are not needed since our concerns is to segment the extremes edges of the knee in order to visualize the distance between the femoral and tibial bones. Using this method, these unneeded details are removed, so the edges are clearer and the image is segmented accurately.

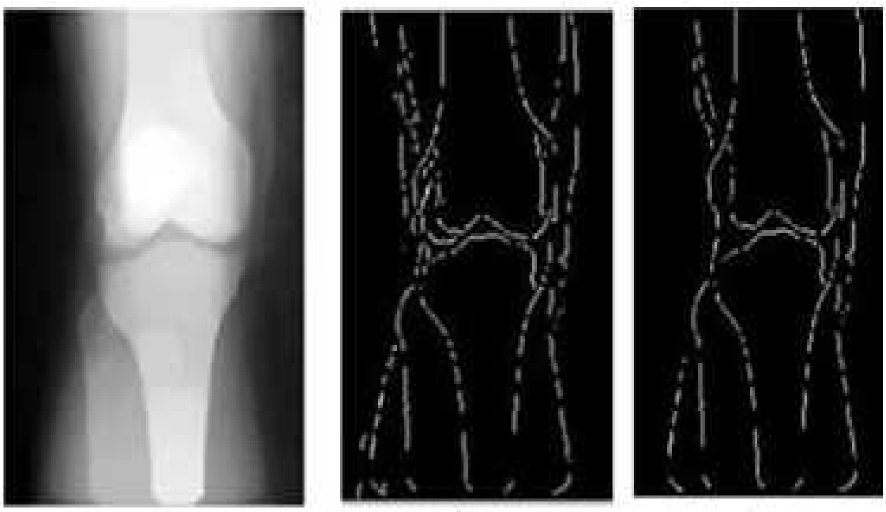


Figure 3.16: Clear unwanted components from the segmented image

3.5 Feature extraction 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 pattern selecting a window of 8*8 segments and are averaged. Therefore, each studied pixel is then the average of the 64 neighbor's pixels in the selected window. Thus, we come up with a rescaled image with the same features and properties of the original one for the purpose of fast processing and easy computing.

An intelligent blood cell identification system was developed by Adnan Khashman (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.

In Figure 3.17 an example of a processed rescaled image with pattern averaging is shown.

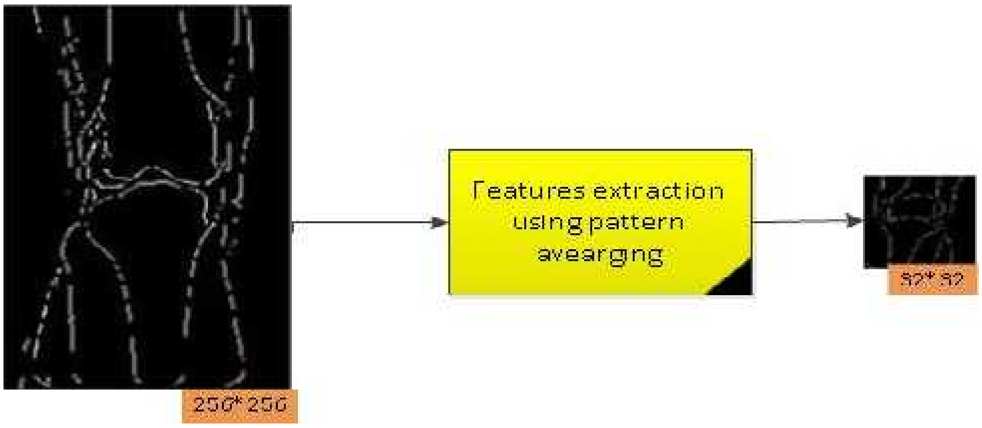


Figure 3.17: Feature extraction using pattern averaging, input image 256*256, output image 32*32 bitmap

CHAPTER 4
NEURAL NETWORK CLASSIFICATION

4.1 Artificial neural network

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

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

4.1.1 Multi-layer perception (MLP)

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

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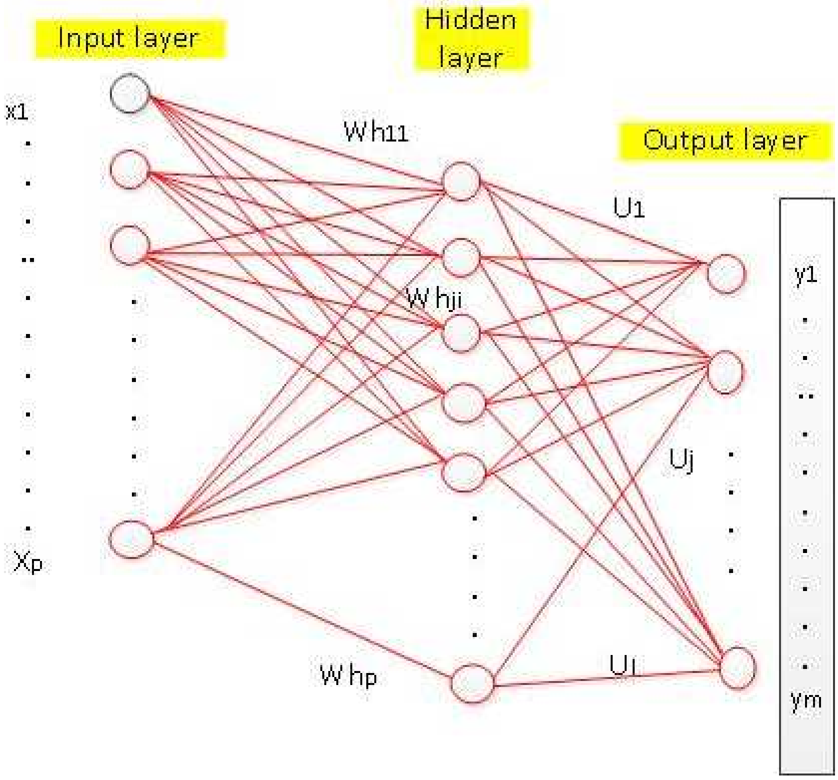

Figure 4.1: Structure of MLP feedforward network

Figure 4.1 shows that in this network has the input layer with three neurons, in the middle, and one hidden layer with three neurons and the output layer to the right with two neurons. There neuron in input layer each variable predicted (Q1, Q ...P). In the case of N categorical variables, N -1 neurons are used to represent categories N variable (Baxt, 1995).

The net calculation of input and output of the j hidden layer neurons are as follows:

$$net = \sum_{t=1}^{N+1} w_{ji} x_i \quad (4.1)$$

$$Y_i = f(net_j^h) \quad (4.2)$$

4.1.2 Backpropagation neural network algorithm

ANN is basically developed to solve data mining applications. It is an adaptive learning technique in which it has a different and specific learning methodology; the learning by examples. Therefore; some complex tasks can be handled using neural networks such as prediction, recognition, and classification (Rojas, 1996). Various learning and training algorithms can be used to train the network. One of the most publicly used algorithms is the backpropagation algorithm. In order to produce the desired output, the input weights should be adjusted and the correction-error should be reduced. The most popular used learning algorithm for updating the weights and correcting the learning error is the backpropagation algorithm. Backpropagation is a learning technique for the feedforward multilayer neural networks. It has two passes through the different layers; the forward pass and the backward pass. In the forward pass the weights are summed and then combined in the output layer. In the backward pass the weights are correct. The actual output is subtracted from the desired one in order to produce the error. The error is then propagated back to all previous layers in order to update the weights and get the desired output (Al-Milli, 2013).

There are elements that combine to form the topology for a back propagation neural network. The equations that describe the network training and operation can be divided into two categories. First, the feed-forward calculations. These are used in both training mode and in the operation of the trained neural network. Second, the error back propagation calculations. These are applied only during training. But before we present the two categories of calculations, another important element must be described. This is the activation function that the algorithm will be based upon.

I) Activation Function:

An artificial neuron, is the fundamental building block in a back propagation network. The input to the neuron is obtained as the weighted sum given by equation (4.3)

$$net = \sum_{i=I}^{n} Oi\, Wi \qquad (4.3)$$

For this thesis the activation function is in sigmoid form. The simplicity of the derivative of the sigmoid (logistic) function justifies it s popularity and use as an activation function in training algorithms. Sigmoid function creates non-linearity in the network and is computationally easy to perform. With a sigmoid activation function, the output of the neuron is given by equation (4.4) and equation (4.5).

$$Out = F\ net \qquad (4.4)$$

$$F\ net = \frac{1}{(1 + (\exp(-net)} \qquad (4.5)$$

The derivative of sigmoid function can be defined as follows;

$$\frac{\partial F(net)}{\partial net} = \frac{\exp(-net)}{(1+\exp(-net)^2}$$

$$=(\frac{i}{1+\exp(-net)})$$

$$=(\frac{\exp(-net)}{1+\exp(-net)})$$

$$=out=(1-out)$$

$$=F(net)[1-F(net)] \quad (4.6)$$

II) Feed Forward Calculations:

This is the simple three layer back propagation model. Each neuron is represented by a circle and each interconnection, with its associated weight, by an arrow. Normalisation of the input data prior to training is necessary. The values of the input data into the input layer must be in the range (0 - 1). The stages of the feed forward calculations can be described according to the layers. The suffixes i ,h and j can be used to describe the input, hidden and output layer respectively.

a) Input layer (i); The output of each input layer neuron is exactly equal to the normalised input.

$$\textit{Input-Layer Output}_i = O_i = I_i \quad (4.7)$$

b) Hidden Layer(h); The signal presented to a neuron in the hidden layer can be equated to the sum of all the outputs of the input layer neurons multiplied by the their associated connection weights, as in equation (4.8). The output of a hidden layer is usually calculated using sigmoid function

$$\textit{Hidden-Layer Input}_h = I\,h = \sum_i W\text{?}iOi \quad (4.8)$$

$$\textit{Hidden Layer Output}_h = O_h = \frac{1}{1(\exp)(-\mathbf{I}\,\mathbf{h})} \quad (4.9)$$

c) Output Layer; The signal presented to a neuron in the output layer is equal to the sum of all the outputs of the hidden layer neurons multiplied by the their associated connection weights plus the bias weights at each neuron, as in equation (5.0).

Output Layer Input $_j = I_j = \sum_h Wj?O?$ (5.0)

The Output layer is also calculated using Sigmoid function.

Output Layer Output $_j = O_j = \frac{1}{1+\exp(-Ij)}$ (5.1)

The set of calculations that has been described so far in the feed forward calculations, can be carried out during the training phase as well as during the testing / running phase.

III) Error Back Propagation Calculations;

The error back propagation calculations are applied only during the training of the neural network. Vital elements in these calculations are described next. These include, the error signal, some essential parameters and weight adjustment.

a) Signal Error. During the network training, the feed forward output state calculation is combined with backward error propagation and weight adjustment calculations that represent the network's learning. Central to the concept of training a neural network is the definition of network error. The aim of the training process is to minimise this error over all training patterns. The output of a neuron in the output layer is a function of its input, or Oj = f(Ij). The first derivative of this function, f '(Ij) is an important element in error back propagation. For output layer neurons, a quantity called the error signal is represented by Δj,which is defined in equation 5.2 below,

$$\Delta j = f'(Ij)\,(Tj - Oj)$$

$$= (Tj - Oj)Oj\,(1 - Oj) \qquad (5.2)$$

This error value is propagated back and appropriate weight adjustments are performed. This is done by accumulating the Δ's for each neuron for the entire training set, add them, and propagate back the error based on the grand total Δ. This is called batch (epoch) training.

a) Essential Parameters;

There are two essential parameters that do affect the learning capability of the neural network. First, the learning coefficient η which defines the learning 'power' of a neural network. Second, the momentum factor a which defines the speed at which the neural network learns. This can be adjusted to a certain value in order to prevent the neural network from getting caught in what is called local energy minima. Both rates can have a value between 0 and 1

4.2 System recognition: classification phase

During this phase, the x-ray images of knee are classified into normal or abnormal using a supervised neural network. We used twobackpropagation neural networks due to its simplicity and the sufficient number of images. We used 300 images, 100 are normal and 200 are abnormal (arthritic knees). The system was trained on 300 images; 100 for normal knees and 200 for abnormal knee images. The input layer of the BPNN1 network consists of 1024 neurons since each image is rescaled to 32*32 bitmap using pattern averaging. The hidden layer consists of 40 neurons, while the output layer has 2 neurons since we have only 2 output classes: normal and abnormal. Also there is an additional BPNN2 whıich comprises of 65,536 neurons, in this case we consider just the original unresized images of size 256*256 without pattern averaging for training the network.

Figure 4 shows the neural network topology of our proposed identification system for the BPNN1 and BPNN2.

Table 2 represents the input parameters setting of the system Table 2 shows all the parameters used when training the network. The network ran for 5000 maximum iterations with a learning rate of 0.001, a momentum rate of 0.4 and a minimum error of 0.001 since it is a medical application.

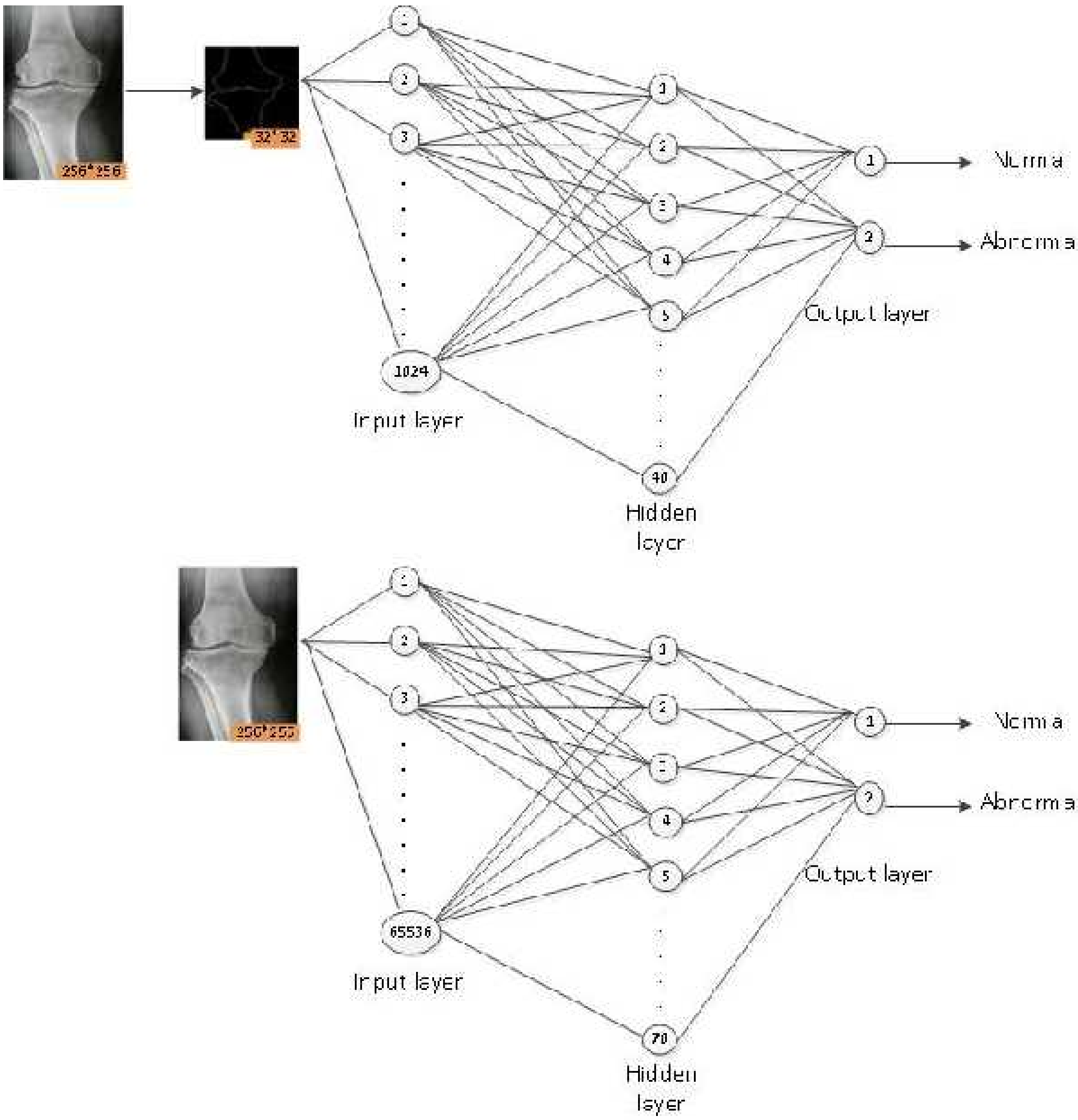

Figure 4.2: BPNN architecture for BPNN1 and BPNN2

Table 4.1: BPNN Parameters Setting

Parameters	**Value(BPNN1)**	**Value(BPNN2)**
Number of neurons in input layer	1024	65,536
Number of neurons in output layer	2	2
Number of neurons in hidden layer	40	70
Maximum Iteration number	5000	5000
Learning rate	0.001	0.001
Momentum rate	0.4	0.4
Error	0.001	0.001
Activation Function	Sigmoid	Sigmoid
Training Time	1min:39sec*	40min:35sec*

4.3. System Training

The network was simulated and trained on Matlab software and tools. We used two different sets; the first set is for the normal images and it contains 200 images, the second set is for the abnormal images and it contains 100 records. In training the system, we consider two different networks, the first which is the processing results with size 32*32, and the second the untouched and unresized processing results which have the original size of 256*256. In doing so we want to establish that there is a probability of obtaining different or higher results after the feature extraction or one without any form of extracted features. Owing to the largeness in the size of BPNN2 it can be noted that it will take more time to train than our averaged BPNN2. The training time recorded for BPNN1 which derived the best results is 1minute 39 seconds while the training time recorded for BPNN2 which derived adequate results was recorded at 40 minutes 35 seconds.

*Intel® Celeron® CPU B830 @ 1.80 GHz RAM: 2.00GB 32-bit Operating System

The following is the training results of the two sets (learning curve) for both BPNN1 and BPNN 2.

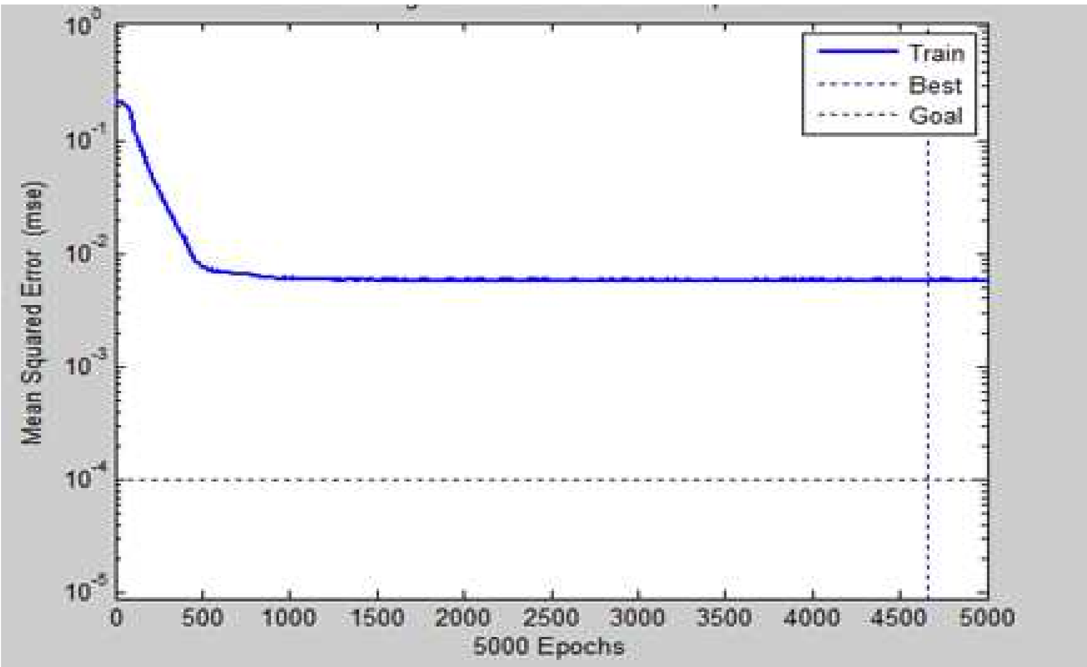

Figure 4.3: Variation of the MSE with the iteration number of BPNN1

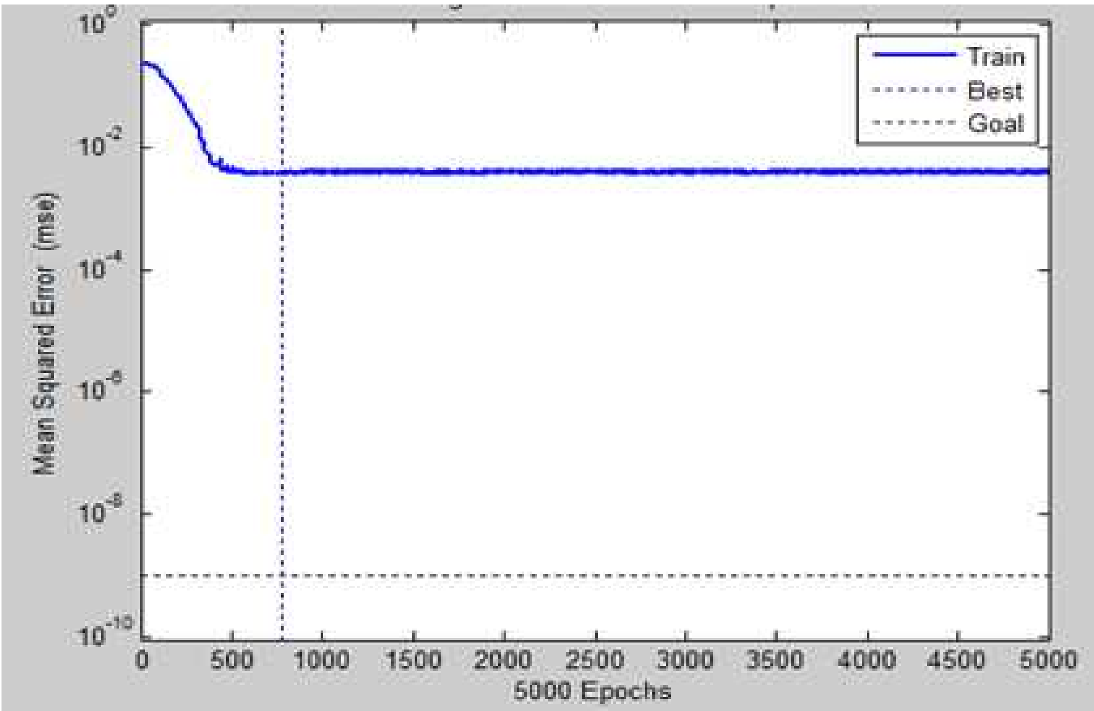

Figure 4.4: Learning curve of BPNN2

Figure 4.5 and Figure 4.6 represents the regression plot of the desired output (dotted line) and the actual output. As the actual output is far from the target as the error is increased. In this figure, it is noted that the target and the actual output are very close which means that the error is minimized and the network well trained for BPNN1,however for BPNN2 there is a slight but not significant decline in the network training (training ratio: 100% and 99%)

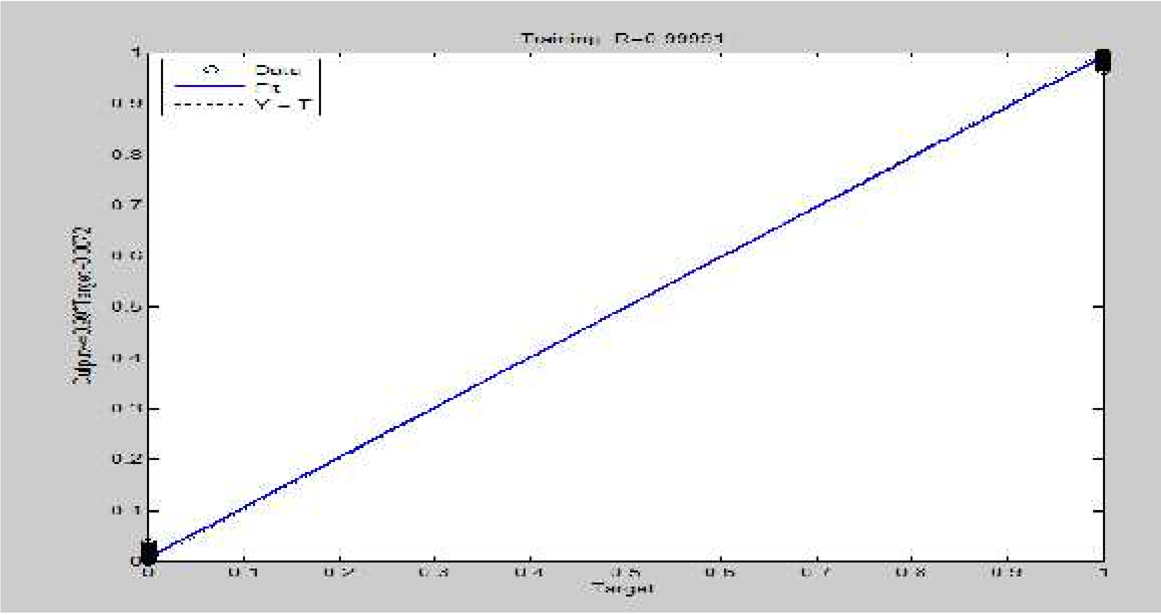

Figure 4.5: Actual versus target output

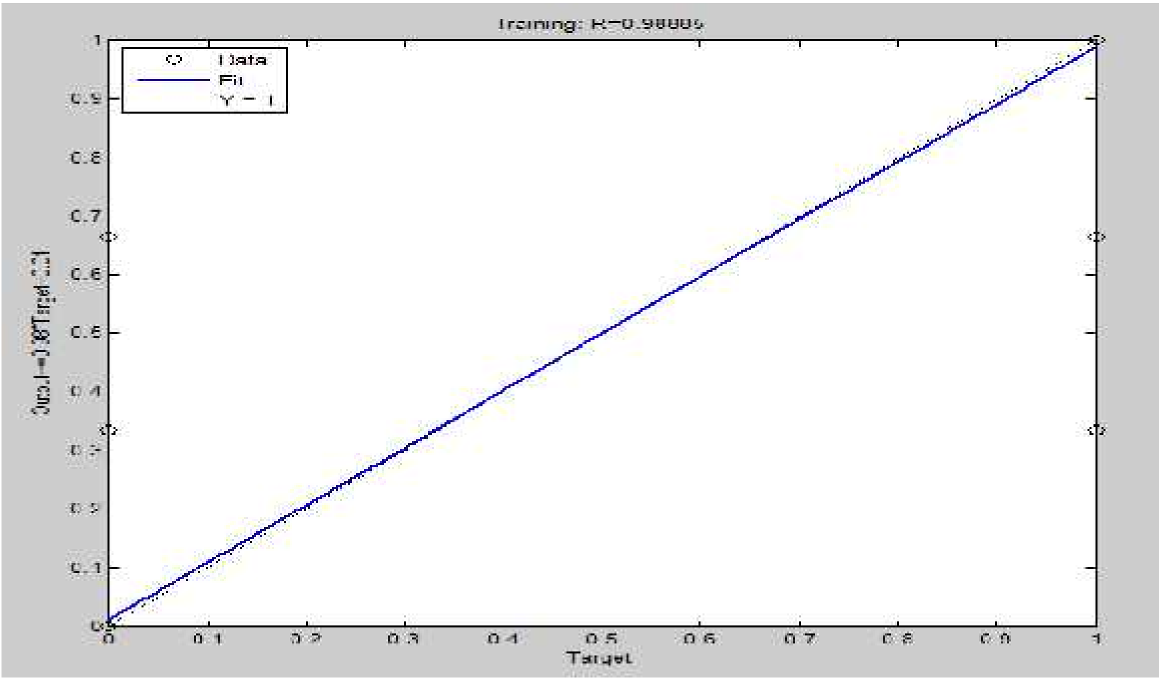

Figure 4.6: Regression plot of BPNN2

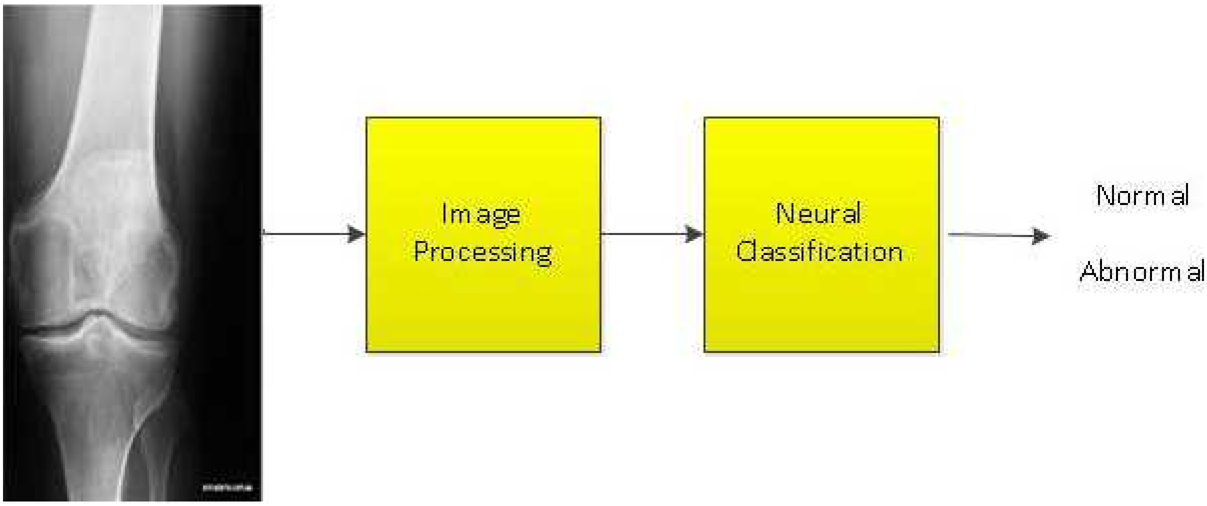

Figure 4.7: The Recognition system

Figure 4.7 represents a progressive passage of the intelligent system, the system can be said to be intelligent due to the fact that it is designed to replicate human intuition and produce results, that’s why the eventual results describe the accuracy of the recognition system in relative to human perception. The recognition system is built to produce clearer images for appropriate medical diagnosis and classify these images into their distinct classes.

CHAPTER 5

RESULTS, DISCUSSION AND COMPARISON

5.1 Simulation results

This thesis introduces an intelligent identification system established with image processing and neural classification. The images are processed in order to select the patterns of interests using image processing techniques. The images then bear sample averaging with a purpose to rescale them while retaining the extracted features.

Figure 4.7 in the previous chapter represents the different phases of our identification system which starts by processing the images in order to extract the region of interests, then we extract shape and texture features such as distance between the two bones. The features are then fed to a back propagation neural network that classifies the images unto normal and abnormal.

This identification system was tested using MATLAB software and tools .Matlab is an established technical computing language for scientists and engineers and also an educative platform for developing algorithms and highly used in programming and data functions. The system was tested using 300 images; 100 for normal and 200 for abnormal images. The result of both testing and training phases is included in Table 5.1.

Table 5.1 shows the recognition rate obtained in both training and testing phases of both BPNN1 and BPNN2. It also represents the number of images used in each set, as well as the overall identification rate obtained which is 94.5% and 91.5% respectively.

Table 5.1: Recognition rate

Knee images type	Image sets	Image Number	Recognition rate of BPNN1	Recognition rate of BPNN2
Normal (100)	Training set	50	100%	99%
	Testing set	50	96%	92%
Abnormal (200)	Training set	100	100%	99%
	Testing set	100	93%	91%
Normal &Abnormal	Both sets	300	94.5%	91.5%

5.2 Results discussion

In this thesis, an intelligent identification Rheumatoid arthritis system was designed. The system is based on both image processing and neural network classification. A big and enough number of images of normal and abnormal knee were collected from different centers of Rheumatoid arthritis diagnosis. These images were then rotated and used for training and testing the network. The network was finally able to distinguish between the two types of images: normal and abnormal, through the extracted features of each type which are the distance between the tidial and femoral bones and the bone spurs. These features are detected and then extracted during the image processing phase using pattern averaging.

5.3 Results comparison

As discussed previously in the literature review section, most of the researches that have been conducted on Rheumatoid arthritis were meant to diagnose or analyze it using some image processing techniques. A small number of works have been done on the intelligent identification of this disease. Thus, our work is a new approach for the identification of rheumatoid arthritis based image processing and intelligent classifier; neural network.

- An approach for removing heuristic elements from DOT images and a system for utilizing these components to analyze rheumatoid joint inflammation (RA) were presented by Ludguier D. Montejo et al (Montejo et al., 2013). Their designed system is for diagnosing Rheumatoid arthritis and not for classifying it as our proposed system. The system consists of two main stages. The first is the data pre-processing in which images are processed in order to prepare them for the next stage which is the feature extraction. The authors have calculated the accuracy of the system in diagnosing rheumatoid arthritis and it was 90%.
- An intelligent assistive method for for analysis of Rheumatoid joint inflammation utilizing histogram smoothing and highlight extraction of bone images was developed by SP. Chokkalingam and K. Komathy (Chokkalingam and Komathy, 2014). The authors used a combination of image processing techniques on bone scans, in order to accurately detect the occurrence probability of Rheumatoid arthritis (RA) . The image processing techniques used in that system are histogram smoothing, morphological operation, and edge detection by edge following algorithm and image subtraction for

the purpose of determining the presence of Rheumatoid arthritis in the best efficient and effective technique. After processing the images, a GLCM (Gray Level Co-occurrence matrix) was used in order to detect some bone features such as mean, median, energy, correlation, bone mineral density and etc… the features were stored and then used to train fed a neural network which has the capability of classifying Rheumatoid arthritis into normal and abnormal after convergence. The authors finally tested their system and the identification rate of their system was 91%.

- Bhavyashree k g, sheela rao. N. Worked on a system for the detection of arthritis using image processing techniques only. The system aimed to estimate the volume or thickness of cartilage since its importance in detecting Rheumatoid arthritis. The system used different techniques; the image is first processed with B-Splines creation then it is segmented. Then the edges are detected with canny and log edge operators. After segmentation, the distance between the edges is calculated in order to find cartilage thickness. The thickness is measured as the number of the pixels between edges. Then, depending on the thickness value between the femoral and tibial bones the decision is made about Rheumatoid arthritis. The authors set a threshold value in which the thickness is above, so the case is abnormal. However, if the thickness is below that threshold this means that the case is abnormal. This system was tested and the accuracy was 92%.

Table 5.2: Results comparison

Paper Title	Authors	Methods used	Recognition Rate
Computer-aided Analysis of Rheumatoid Joint Pain with optical tomography, Part 1: feature extraction	Ludguier D. Montejo et al	Image processing	93 %
Intelligent Assistive Methods for for Analysis of Rheumatoid Joint Inflammation utilizing histogram smoothing and highlighting extracted of Bone Images	Chokkalingam and K. Komathy	Image processing and neural network	91%
Determination and analysis of arthritis using digital image processing techniques	Bhavyashree k g, sheela rao. N	Image processing	90%
Proposed system Recognition	Preye David Tantua, Kamil Dimililer	Image processing and neural network of BPNN1 and BPNN2	94.5% and 91.5%

CHAPTER 6

CONCLUSION AND RECOMMENDATION

6.1 Conclusion

The motivation behind such system is that most of the previous related works are image analysis systems. Such systems uses a combination of image processing techniques in order to process images and then measure the distance between the tibial and femoral bones as an attest of diagnosing the disease. Thus, there is a need for an intelligent rheumatoid arthritis system that stimulates the human visual inspection who normally diagnose the rheumatoid arthritis depending on some features such as the narrowed distance between the tibial and femoral bones and also the bone spurs. In this thesis, a new approach for the intelligent identification of Rheumatoid arthritis was developed. This new approach is based on image processing and artificial neural network. The new approach in our system is that it stimulates the human visual inspection that usually identifies the Rheumatoid arthritis, according to some signs or features such as distance between the tibial and femoral bones, and bone spurs. During the feature extraction phase, we rescale the image using pattern averaging in order to preserve the previously mentioned useful features and feed them to the network.

A database was created by getting some X-ray normal and abnormal images from a medical facility in Abuja, Nigeria. The images were then rotated in order to get a large number of images for training and testing purposes. Moreover, rotating images aims to create a robust system that has the capability of capturing classification regardless of image orientation. After convergence, the network was tested and identification rate was satisfactory which proves that such system can be developed as a full computerized machine or embedded in a biomedical device. As a result, it should be noted that the recognition rate was not dependent on the size rather than on the extracted features which facilitates the learning ability of the neural network. This is proved in which the network was trained using different sizes (32*32 and 256*256) both opposite and varying sizes and the result showed (94.5% and 91.5%) a difference of 3.0 which is relatively good considering that this is a medical research

6.2 Recommendation

Furthermore future work to improve the relevance of this new system can be to increase the database; increase in database size can yield better results. Also, the limitation in the image resolution the database used in the thesis can be solved when using modern technologies in medical science that can produce optimum image resolution. Also, a test of this system on other neural network examples and algorithms such as Support vector machine, Competitive learning, and Radial basis function in order to compare the best results the produced optimum results is suggested. Lastly, using other different methods for extracting medical features such as K-nearest neighbor can prove as advancement to this model research area.

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APPENDICES

Appendix 1

SOURCE CODE

- Image processing phase of BPNN1

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% this code is meant to read all the rotated images in a for loop, and
then process the images; filter, rescale, segment,
%%and then extract some feature and write these features valus in an excel
%%file in oreder then to be read by another program file to train the
%%neural network
clear all
close all
clc

for k = 1: 100
myFolder = 'D:\RA.images\norm';
filePattern = fullfile(myFolder, '*.jpg');
jpegFiles = dir(filePattern);
  baseFileName = jpegFiles(k).name;
  fullFileName = fullfile(myFolder, baseFileName)
  fprintf(1, 'Now reading %s\n', fullFileName);
  d1 = im2double(imread(fullFileName));
imshow(d1);
pause

d1=rgb2gray(d1);                              %# Load the image, scale from
0 to 1
imshow(d1);
pause
I=d1;

%******************************************************************
m=medfilt2(I);
figure,  imshow(m),    title('median  filtered  image');  %%%  using  median
filtering
pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming
background = imopen(I,strel('disk',15));
figure,imshow(background);
title('background');
pause


%% subtract the original form the background

I2 = I - background;
figure, imshow(I2),title('substracted image');
pause
%% increase the image intensity
%I3=I2;
I3 = imadjust(background);
%I3 = imadjust(I2);

figure, imshow(I3), title('adjustedimage');
pause
```

```
%*************************************************************************

d1=I3;
%# Plot the original image
d = edge(d1,'canny',0.25);                            %# Perform Canny edge
detection..the value increases ...the edges points decreases
 imshow(d); title('canny edge detected image');        %# Plot the edges
>>>>>...note: 0.25...40 are goo for nra6
pause
 ds = bwareaopen(d,45);                          %# Remove small edge objects
....% the value increases ...the edges points decreases
 imshow(ds); title('cleaned image');    %# Plot the remaining edges
pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%pattern averaging

inputs = blkproc(ds, [6 6], @mean2);
imshow(inputs)
pause
size(inputs)
T=inputs(:,k)



end
%  sheet=1;
  xlswrite('bfnorm.xlsx',T,'sheet1');
%*******************************************8888
```

❖ Image processing phase of BPNN2

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% this code is meant to read all the rotated images in a for loop, and
then process the images; filter, rescale, segment,
%%and then extract some feature and write these features valus in an excel
%%file in oreder then to be read by another program file to train the
%%neural network
clear all
close all
clc

for k = 1: 100
myFolder = 'D:\RA.images\norm';
filePattern = fullfile(myFolder, '*.jpg');
jpegFiles = dir(filePattern);
  baseFileName = jpegFiles(k).name;
  fullFileName = fullfile(myFolder, baseFileName)
  fprintf(1, 'Now reading %s\n', fullFileName);
  d1 = im2double(imread(fullFileName));
imshow(d1);
pause
d1=rgb2gray(d1);                                   %# Load the image, scale from
0 to 1
imshow(d1);
pause
I=d1;

%*******************************************************************
m=medfilt2(I);
figure, imshow(m),   title('median filtered image'); %%% using median
filtering
```

```
pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming
background = imopen(I,strel('disk',15));
figure,imshow(background);
title('background');
pause


%% subtract the original form the background

I2 = I - background;
figure, imshow(I2),title('substracted image');
pause
%% increase the image intensity
%I3=I2;
I3 = imadjust(background);
%I3 = imadjust(I2);

figure, imshow(I3), title('adjustedimage');
pause
%************************************************************************

d1=I3;
%# Plot the original image
d = edge(d1,'canny',0.25);                          %# Perform Canny edge
detection..the value increases ...the edges points decreases
 imshow(d); title('canny edge detected image');          %# Plot the edges
>>>>>...note: 0.25...40 are goo for nra6
pause
 ds = bwareaopen(d,45);                         %# Remove small edge objects
....% the value increases ...the edges points decreases
 imshow(ds); title('cleaned image');     %# Plot the remaining edges
pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%pattern averaging

inputs = blkproc(ds, [8 8], @mean2);
imshow(inputs)
pause
size(inputs)
T=inputs(:,k)

end
%  sheet=1;
  xlswrite('bfnorm.xlsx',T,'sheet1');
%******************************************8888
```

- Rotating Images

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% this code is to read rgb x-ray images from a specific folder, then using
a for loop each image is
%rotated 5 times by 15 degree incrementally..so we get 6 images of each one
%including the original image..the rotated images are than saved in a
%specific folder created in the "D" directory.........................

folder = 'D:\nra';
% Rotate img by multiple angles

for k = 1: 11
myFolder = 'D:\RA.images\norm';
filePattern = fullfile(myFolder, '*.jpg');
jpegFiles = dir(filePattern);
  baseFileName = jpegFiles(k).name;
  fullFileName = fullfile(myFolder, baseFileName)
  fprintf(1, 'Now reading %s\n', fullFileName);
  img = im2double(imread(fullFileName))

for i=1:5
hrotate = vision.GeometricRotator;
hrotate.AngleSource = 'Input port';
% % Rotate img by multiple angles
%
rotimg = step(hrotate,img,i*85);
%   subplot(1,5,k);
  imshow(rotimg)
  pause
%   size(rotimg)
newimagename = [folder num2str(k) '.jpg'];
imwrite(rotimg,newimagename)
end
%imwrite(rotimg,newimagename)

end
```

Appendix 2

SOURCE CODE 2

- Neural Networks codes training of BPNN1

```
clear all
close all
clc

PATTERNS = [];
    dataset = xlsread('datasets.xlsx','sheet1');        %database%%% inputs

    PATTERNS = [dataset];


dis.out=xlsread('outputs.xlsx','sheet1');   %...Read outputs or targets
% CREATING AND INITIATING THE NETWORK
net1=newff(PATTERNS,dis.out,20,{'ogsig','logsig'},'traingdx');
net1 = init(net1);
net1.LW{2,1} = net1.LW{2,1}*0.01;

% TRAINING THE NETWORK
net1.trainParam.goal = 0.001; % Sum-squared error goal.
net1.trainParam.lr      =      0.001;            %      Learning      Rate.
%%0.007....................96.8%%
net1.trainParam.alpha = 0.27;                                 %% 0.27
net.trainParam.show = 50; % Frequency of progress displays (in epochs).
net1.trainParam.epochs =5000;% Maximum number of epochs to train.

[net1,tr] = train(net1,PATTERNS,dis.out);   %%%%%%%training......

    actout=sim(net1,PATTERNS);
    actout
```

- Neural Networks codes training of BPNN2

```
clear all
close all
clc
%photo_number = 140;
PATTERNS = [];
%PATTERNS=inp
    PATTERNS  =  xlsread('dataset.3.xlsx','sheet4');            %database%%%
inputs
Dis_output=xlsread('dataset.3.xlsx','sheet2');%...Read outputs or targets

%Dis_output =out;
[g,h]=size(PATTERNS);
[m,h]=size(Dis_output);

net = newff(minmax(PATTERNS),[40,2],{'logsig' 'logsig'},'traingdx');
```

```
net = init(net);
net.LW{2,1} = net.LW{2,1}*0.1;
net.b{2} = net.b{2}*0.1;

% TRAINING THE NETWORK

net.trainParam.goal = 0.000000001;
net.trainParam.show = 50;
net.trainParam.epochs = 5000;
net.trainParam.mc = 0.006;
net.trainParam.lr= 0.04;
[net,tr] = train(net,PATTERNS,Dis_output);

% for C=1:h

train1 = sim(net,PATTERNS)
```

- Testing phase

```
TEST_PATTERNS=xlsread('dataset1.xlsx','sheet2');
 [m,n]=size(TEST);

   testout =sim(net1,TEST);

    testout
```