LUNG LESION SEGMENTATION USING GAUSSIAN FILTER AND DISCRETE WAVELET TRANSFORM

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

By
ALI SIDI ABUBAKER HESRI

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

Electrical and Electronics Engineering

NICOSIA, 2017

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

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ABSTRACT

Lung cancer is the growth of a tumor, referred to as a nodule that arises from cells covering the airways of the respiratory arrangement. The effectively detection of lung cancer at premature stages enables any cure options, and reduce risk of insidious surgery and increased continued existence rate. Recently, image processing techniques are extensively used in different medical areas for lung tumor image improvement in early detection and cure stages. This is due to the importance of the time factor of discovering the abnormality issues in target images. The developed system is mainly an algorithm combining different image processing techniques such as filtering, erosion, discrete wavelets transform, and thresholding. However, the main aim of this work is to investigate the effectiveness of different filters along with different types of discrete wavelets toward an accurate segmentation of a lung tumor in a CT image. The experimental results of the developed system show that the use of Gaussian filter with the Haar wavelets is superior for such segmentation task. The experimental results of the proposed system show its efficient ability of segmenting the lung tumor with high precision where the accuracy is the highest 96% when Guassian filter and Haar wavelets are used. It can be seen that the use of median filter with Haar wavelets lead to less effectiveness in segmenting the tumor where the accuracy is 89%.

Keywords: Lung cancer; image processing; Gaussian filter; median filter; segmentation; discrete wavelet transform

ÖZET

Akciğer kanseri, solunum düzenlemesinin hava yollarını kaplayan hücrelerden kaynaklanan bir nodul olarak adlandırılan bir tümörün büyümesidir. Akciğer kanserinin prematüre aşamalardaetkin bir şekilde tespit edilmesi, herhangi bir tedavi seçeneğine olanak sağlar;tehlikeli cerrahi vehastalığın artan varlığını devam ettirme oranı riskini azaltır. Son zamanlarda, görüntüleme teknikleri erken teşhis ve tedavi aşamalarında akciğer tümörü görüntülemesinin iyileştirilmesi için farklı tıbbi alanlarda yaygın olarak kullanılmaktadır. Bu, hedef görüntülerde anormallik sorunlarının keşfedilmesi zamanı faktörünün öneminden kaynaklanmaktadır. Geliştirilen sistem esas olarak; filtreleme, erozyon, ayrık dalgacık dönüşümü ve eşikleme gibi farklı görüntü işleme teknikleri birleştiren bir algoritmadır.Bununla birlikte, bu çalışmanın temel amacı, farklı filtrelerin farklı dalgacık türleri ile birlikte, BT görüntüsündeki bir akciğer tümörünün doğru segmentasyonuna yönelik etkinliklerini araştırmaktır.Geliştirilen sistemin deneysel sonuçları, Gauss filtresi ile Haar dalgacıklarının kullanılmasının segmentasyon görevi için üstün kalitede olduğunu göstermektedir.Önerilen sistemin deneysel sonuçları; Guassian filtresi ve Haar dalgacıkları kullanıldığı zaman doğruluğun en yüksek %96 olduğu yüksek hassasiyet ile akciğer tümörünün segmentasyonunu etkin bir şekilde yapabilme yeteneğini gösterir. Haar dalgacıkları ile medyan filtresinin kullanımının, doğruluğun %89 olduğu hallerde tümörün segmentlere ayrılmasında daha az etkinliğeyol açtığı görülebilir.

Anahtar Kelimeler: Akciğer kanseri; görüntüleme; Gauss filtresi; Medyan filtre; segmentasyon; ayrık dalgacık dönüşümü

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Lung cancer is thought to be the fundamental driver of cancer death around the world, and in its initial stages it is hard to identify in light of the fact that lone in the propelled organize side effects show up bringing about the death rate to be the most astounding among every single other sort of cancer (Beigelman-Aubry et al., 2007). In the event that lung knobs can be distinguished precisely at an early stage, the patient's survival rate can be expanded by a noteworthy rate. The rank request of cancers for both guys and females among Jordanians in 2008 demonstrated that there were 356 instances of lung cancer representing (7.7%) of all recently analyzed cancer cases in 2008 (Armato and Sensakovic, 2004). Lung cancer influenced 297 (13.1 %) guys and 59 (2.5%) females with a male to female proportion of 5:1 which Lung cancer positioned second among guys and tenth among females (Armato and Sensakovic, 2004). In the cutting edge time of mechanized completely robotized pattern of living, the field of computerized symptomatic frameworks plays an essential and key part.

The humankind pace of lung cancer is the most extreme among every single other kind of cancer. Lung cancer is one of the grimmest cancers on the planet, with the littlest proceeded with presence rate after the judgment, with a moderate yet beyond any doubt increment in the quantity of passings consistently. There have been a ton of ways to deal with lessen the dead brought on by the ailment. One approach is to develop new techniques for untimely identification so medicines will be exceptionally productive. Mechanized demonstrative framework plans in Medical Image Processing are one such field where various frameworks are proposed and still numerous more under applied outline due dangerous development of the innovation today (Sluimer et al., 2006).

The way toward doling out a mark to each pixel in a picture to such an extent that pixels with a similar name share certain visual qualities is known as Image segmentation.

Writing has an extensive variety of segmentation strategies utilized as a part of lung cancer conclusion. Picture processing has wide extension in medicinal picture processing for diagnosing the Lung cancer (Beigelman-Aubry et al., 2007). The reason for this paper is to audit related work on programmed conclusion of lung cancer and rundown different segmentation and characterization methods for discovery of lung nodules. The detection of lung cancer should be possible in various routes, for example, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), X-rays and sputum cytology. Every one of these techniques devours a considerable measure of benefits. In 2012, there were approximately 226,160 new instances of lung cancer and 160,340 related passings. Lung cancer is one of the commonest cancers in the created world, and people with this grave sickness must arrangement with the mortal impacts as well as with the psychosocial viewpoints. Proceeded with presence from lung cancer is straightforwardly identified with its development at its noteworthy time. Among various sorts of cancer the lung cancer is the most savage and best take after to its precise finding is the assurance of the current phase of the sickness. Therapeutic images are an exceptional mean for controlling the valuable activity. There are numerous therapeutic imaging systems which are utilized to perceive the sickness or influenced part inside our body. Cancer is one of the fundamental reasons for death for similarly men and ladies. The early acknowledgment of cancer can mind in curing the illness totally. So the need of procedures for recognizing the nearness of cancer knob in early stage is expanding these days Lung cancer is an infection that happens in light of undesirable development in tissues of the lung. Uncontrolled development recognized effectively at early stages, goes before with numerous treatment alternatives, which decreases danger of obtrusive surgery and expanded survival rate. Conceivable medications incorporate surgery, chemotherapy, and radiotherapy. Survival relies on upon stage, general wellbeing, and different components, however general just 14% of individuals who are determined to have lung cancer can survive five years after their finding. Some of the time couple of therapeutic images are not clear to see and recognize the phase of ailment precisely. Lung cancer a great deal spreads toward the focal point of the trunk since the common stream of lymph out of the lungs is toward the focal point of the trunk. With respect to the stages, when all is said in done there are four phases of lung cancer; I through IV. Organizing depends on tumor measurement and tumor and lymph hub position. Directly, CT are said to be more useful than plain trunk X-ray in distinguishing and diagnosing the lung cancer. An expected 85 percent of lung cancer cases in guys and 75 percent in females are brought about by cigarette smoking. Target of this review is to recognize lung cancer utilizing image processing methods. CT examined lung images of cancer patients are obtained from different healing facilities. Utilizing image processing methods like preprocessing and highlight extraction, area of interest is isolated. Building up the algorithm, features like area, limit, intensity and entropy are computed from every one of the images. The requirement values acquired from these features are contrasted and the standard qualities proposed by a doctor. From the tumors are characterized into two sorts. They are

- Benign tumor
- Malignant tumor

Benign tumors are non cancerous. They have a propensity to grow slowly and stay in one place, not spreading into other parts of the body. Benign tumors usually stay non-cancerous, except in very rare cases. Malignant tumors are cancerous. Cancer can commence in any one of the trillions of cells in our body frequently in our body new cells will generate and old cells or damaged cell will die whenever it needs. When cancer occurs, this cyclical process will be affected. Unusual growth of new cells and survival of old or injured cells will occur. The performance helps to illustrate the location of the cancer, size of the tumor and if it has increase. Knowing the stage, doctors can proficient to identify the probability of continued existence and also it helps to plan the best cure. The development of medical images acquisition techniques, in particular computerized tomography (CT), which may furnish more detailed information about the human body, has increased the capability and fidelity in the diagnosing of many diseases. On the other hand, the dimensions of these images are becoming bigger and bigger, increasing the need for computer vision techniques that can make interpretation easier.

1.1 The Aim of Thesis

The thesis aims is to investigate the use of different types of filters such as Gaussian and median filter in addition to the use of different types of wavelets transform the select the best for reaching the desired target which is segmenting the lung tumor accurately. The different techniques used in each system and different results obtained from each system are then to be shown and compared with each other to investigate the best techniques for performing such segmentation task.

1.2 Literature Review

The authors in (K. Punithavathy et al., 2015) recommended a methodology for programmed lung cancer detection in PET/CT images. For pre-processing, differentiate level versatile histogram evening out (CLAHE) procedure is utilized alongside Wiener filtering. Morphological shutting and opening operations are performed for accurate extraction of lung ROI. Highlight classification is done utilizing fluffy grouping method. FCM is basic, unsupervised and delicate bunching method and it holds more data of the image contrasted with hard grouping method.

The upside of their method is that the Morphological operations encourage exact lung ROI extraction and lessen the investigate space and the surface examination yielded number of critical surface features. These features filled in as contribution to the FCM classifier helps in accurate recognition of the lung cancer. Aftereffects of the proposed methodology are proficient with a general exactness of 92.67%.

In another work proposed in (A. Amutha et al., 2013) offered a level set-dynamic form demonstrate with limit work for lung tumor finding and segmentation. Dynamic form model is skillful to locate the exact limit of the tumor, whose vitality relies on upon its spatial situating and shape changes. Adjacent to with dynamic form demonstrating, arrange set conditions are consolidated for the progression of fragment uniformity measure characterized over the given classification.

The methods have dynamic form displaying alongside level set algorithm to conform the execution. The lung image is denoised by Kernel Based Non-Local Neighborhood denoising method by various denoising capacities, for example, exponential capacity portion, cosine work part, level bit, Gaussian, Turkey-bi-weight and wave piece capacity, and after that handled with the best bit work. Qualities of images, for example, differentiate; vitality, entropy, difference and homogeneity are viewed as that clears a path for proper classification comes about.

The order of lung image is made by the talented neural network in view of Bayes Classification known as Multivariate Multinomial Distributed Bayes Classification which classifies the image under standard and bizarre stages. The fundamental preferred standpoint of the framework is that it defines Level arrange conditions in a manner that the oppression of dynamic form on slope is limited. Another favorable position is that the executed segmentation algorithm holds the properties of both level set and dynamic form methods. Additionally the course of action of two segmentation methods to a great degree lessens the calculation time and inner vitality, and furthermore revises segmentation vitality. The area of mass limits is all around identified and saved by the framework, autonomous of angle. Besides the methodology can likewise segment the lung field with pathology of variation structures all the more accurately.

Dimililer.K et al., proposed method that is intelligent lung tumor detection system on CT images by using backpropagation neural network, the system was tested on 30 images with tumor and 30 images with non-tumor in the end system proposed has given accuracy 88% overall, where 25 out of 30 with tumor and 28 out of 30 with non-tumor as well as 26 out of 30 with tumor and 28 out of 30 with non-tumor in training phase with system performance overall 90%.

A. Tariq et al., (A. Tariq et al., 2013) proposed PC helped finding (CAD) framework for computerized detection of pneumonic lung nodules in registered tomography (CT) images. The framework executed median filter for denoising and inclination mean and difference based method for expulsion of foundation. The limit segmentation is done on the premise of ideal thresholding. Sobel angle administrator in the level and vertical bearings is executed for edge detection. Features extraction is accomplished for features, for example, area, vitality, unpredictability, entropy, mean and standard deviation.

For course of action reason, the component vector is encouraged to a half breed classifier in light of neural network and fluffy known as 'nuero fluffy classifier'. It contains two sub-networks i.e. fluffy self-arranging network and Multi-Layer Perceptron (MLP) in a fell manner. In NFC the component vector is given as contribution to fluffy layer to produce pre-classification vector which is given to MLP for classification of test. The aftereffect of framework is accurate and powerful which additionally encourages the detection of little nodules alongside the created one which prompt to early finding of lung cancer.

Noises ordinarily exhibit in images are Gaussian, uniform, or salt and pepper circulation. Another trademark noise is a spot noise, which is multiplicative in nature. There are customarily two sorts of filters in image processing to be specific linear and non-linear filters. Linear filters are utilized when there is uniform dissemination of noise in image. On account of irregular measure of noise called salt and pepper noise, linear filters are perfect. Henceforth non linear filters are utilized for noise evacuation in such cases.

In the survey done by T. Kondo et al., (T. Kondo et al., 2012) the districts of the lung cancer were seen and extracted by design by using the reevaluated GMDH-sort neural network. Multi-discoverer push CT (MDCT) images of the lung are used as a part of the survey. In the recognition method, the upgraded GMDH-sort neural network is created to see the lung areas and after that the locale of the lung cancer are extracted.

In this method the overhauled GMDH-sort neural network algorithm utilizing the learning base for the therapeutic image. Conclusion was proposed and it was connected to the restorative image determination of the lung cancer and the consequences of the overhauled GMDH-sort neural network were contrasted and those of the anticipated sigmoid function neural network prepared utilizing the back proliferation algorithm. The reexamined GMDH-sort neural network design appropriate the independence of the restorative images is composed utilizing the information base for the therapeutic image conclusion. Moreover, the neural network engineering is chosen from three sorts of neural network designs, for example, the sigmoid function neural network, the outspread premise function (RBF) neural network and the polynomial neural network utilizing the learning base system.

In GMDH-sort neural network basic parameters, for example, the quantity of layers, the quantity of neurons in concealed layers and valuable information factors are consequently chosen to limit forecast mistake standard characterized as PSS. On account of the ordinary neural network, we get a wide range of yield images for different auxiliary parameters of the neural network and numerous iterative counts of the back engendering are required for different basic parameters so as to discover more accurate neural network engineering. It was uncovered that the modified GMDH-sort neural network algorithm was accurate and a valuable method for the medicinal image detection of the lung cancer.

CHAPTER 2

MEDICAL INFORMATION BACKROUND

This chapter discusses a brief and general introduction of cancer and classifications of cancer, in additional background of lung. The discussion will continue through about lung cancer and the stages of lung cancer. Finally it will present brief information about classification of cellular and radiological classification.

2.1 Cancer

Cancer can be defined as accumulation of related infections. In a wide range of growth, a portion of the body's cells start to partition without ceasing and spread into encompassing tissues.

Cancer can begin anyplace in the human body, which is comprised of trillions of cells. Typically, human cells develop and gap to shape new cells as the body needs them. At the point when cells develop old or get to be distinctly harmed, they kick the bucket, and new cells have their spot.

At the point when disease grows, nonetheless, this methodical procedure separates. As cells turn out to be increasingly strange, old or harmed cells survive when they ought to kick the bucket, and new cells frame when they are not required. These additional phones can partition without ceasing and may frame developments called tumors.

Numerous diseases frame strong tumors, which are masses of tissue. Diseases of the blood, for example, leukemia, for the most part don't frame strong tumors.

Harmful tumors are threatening, which implies they can spread into, or attack, close-by tissues. Also, as these tumors develop, some disease cells can sever and go to far off spots in the body through the blood or the lymph framework and shape new tumors a long way from the first tumor.

Dissimilar to threatening tumors, benevolent tumors don't spread into, or attack, adjacent tissues. Kind tumors can at times be very substantial, be that as it may. Whenever evacuated, they as a rule don't become back, though threatening tumors some of the time do. Not at all like most kindhearted tumors somewhere else in the body, can benevolent cerebrum tumors be life debilitating.

Cancer is a disease in which cells acquire genetic alterations and divide without control. Dangerous tumors are more quickly developing than benevolent tumors and can spread and demolish neighboring tissue. Cells of threatening tumors can sever from the fundamental (essential) tumors and spread to different parts of the body through a procedure known as metastasis. After attacking sound tissue at the new site they proceed to partition and develop. These auxiliary destinations are known as metastases and the condition is alluded to as metastatic Cancer (Shah et al., 2005).

2.2 Classification of Cancer

• Carcinoma – An ailment that rises up out of the epithelial cells (the covering of cells that secures or encases organs). Carcinomas may assault the enveloping tissues and organs and metastasis to the lymph center points and diverse locales of the body. The most broadly perceived sorts of development in this social occasion are chest, prostate, lung and colon tumor, our study in this classification of cancer.

• Sarcoma – A kind of debilitating tumor of the bone or fragile tissue (fat, muscle, veins, nerves and other connective tissues that support and envelop organs). The most generally perceived sorts of sarcoma are leiomyosarcoma, liposarcoma and osteosarcoma

• Lymphoma – Lymphoma is a harm of the lymphatic system, which runs all through the body, and can in this way happen wherever. The two essential structures are non-Hodgkin's which begins with uncontrolled advancement of the - white platelets - lymphocytes - of the sheltered system) and Hodgkin's lymphoma in which cells of the lymph center points get the opportunity to be unmistakably dangerous.

• Leukemia - Leukemia is a malady of the white platelets and bone marrow, the tissue that structures platelets (Uppaluri et al., 1997).

2.3 Lung Background

The lung is a respiratory organ and it is the major organ of the respiratory system within which gas transfer occurs. Oxygen is delivered to the vascular system such that it can be transported to the cells and carbon dioxide, a by-product of cell metabolism, is removed. At total lung capacity the average human lung volume is 4-5 liters, of this volume approximately 10 percent is tissue, 10 percent is blood and 80 percent is air. The lungs are divided into sections, or lobes. The correct human lung has three flaps, right upper projection (RUL), right center projection (RML) and right lower flap (RLL). The littler left lung has two flaps, left upper projection (LUL) and left lower projection (LLL).The aviation routes comprise of a leading bit, which transports gasses all through the lung, and the respiratory locale in which gas trade happens.The conducting zone incorporates the trachea, the bronchi, the bronchioles and the terminal bronchioles. The respiratory zone contains the acini, which includes the respiratory bronchioles, the alveolar ducts and the alveoli. There are approximately 480 million alveoli in an adult human lung, which are arranged in clusters to form alveolar sacs. The tissue content of the lung includes the walls of the circulatory vessels, conducting airways and the acini. The characteristics and cellular composition of these lung components varies widely. The large conducting airways are thick, multi-layer walls containing a mucosa, smooth muscle and cartilage. As the airways decrease in size, less cartilage is present. The terminal acini units consist of the respiratory bronchioles and alveoli, as shown in. The respiratory bronchiole walls still contain smooth muscle and cuboidal epithelium, but unlike the conducting bronchioles no cartilage is present. The alveolar walls are composed of an endothelium lining of the capillaries, an epithelium lining the airspaces and an interstitial layer containing connective tissue fibers. The epithelium of the alveoli is made up of type I pneumocytes and type II pneumocytes (secretory cells). The type I pneumocytes provide a large surface area for gas exchange while the alveolar type II pneumocytes are responsible for the synthesis, storage and secretion of phosopholipid rich surfactant (Franklin, 2000).

2.4 Lung Cancer

Cell division of typical lung tissue is important to hold the structure and usefulness of the organ. Ordinary cells experience controlled moves amongst resting and partitioning states. Presentation to tobacco smoke, overabundance radiation and other natural cancer-causing agents alongside hereditary components can bring about threatening change (carcinogenesis) of typical cells. Dangerous or malignant cells develop and partition free of the necessities and constraints of the body, keeping away from the resting state run of the mill of ordinary cells. These harmful cells can travel by means of the blood stream to different parts of the body where they keep on growing as metastases. (Uppaluri et al., 1997).

2.4.1 Lung Cancer Staging

Lung cancer staging is a method by which the extent of disease is classified. This process is important in identifying appropriate treatment approaches and determining prognoses. All available factors, including clinical factors (physical exam, imaging and laboratory findings) and pathological finding are used to determine the stages. The methods for staging differ based on cellular classification. This staging system takes into account the extent of the tumor (T), the level of regional lymph node involvement (N) and the presence of metastases (M) (Tanoue, 2008):

• Primary tumor (T)

TX: Positive malignant cytology finding with no observable lesion

Tis: Carcinoma in situ

T1: Diameter of 3 cm or smaller, is surrounded by lung or visceral pleura, and is without invasion more proximal than the lobar bronchus

T2: Diameter greater than 3 cm and/or has extension to the visceral pleura, atelectasis, obstructive pneumonitis that extends to the hilar region but does not involve the whole lung or tumor of a main bronchus more than 2 cm distal from the carina

T3: A tumor of any size that straightforwardly attacks any of the accompanying: trunk divider stomach, meditational pleura, parietal pericardium; or, related atelectasis or obstructive pneumonitis of the whole lung or, tumor in the fundamental bronchus under 2 cm distal to the carina however without association of the carina

T4: any size's tumor that attacks anyone of the accompanying: mediastinum, heart, awesome vessels, trachea, throat, vertebral body, carina; or, separate tumor knobs in a similar flap; or, tumor with a threatening pleural emanation (Minna, 2005);

- Stage 0: TisN0M0
- Stage IA: T1N0M0, 5 year survival rate of 60-80%
- Stage IB: T2N0M0, 5 year survival rate of 50-60% 10
- Stage IIA: T1N1M0, 5 year survival rate of 40-50%
- Stage IIB: T2N1M0 or T3N0M0, 5 year survival rate of 25-40%
- Stage IIIA: T3N1M0 or T (1-3) N2M0, 5 year survival rate of 10-35%
- Stage IIIB: T4N (0-3) M0 or T (1-4) N3M0, 5 year survival rate of 5%
- Stage IV: T(1-4)N(0-3)M1, 5 year survival rate less than 5%

Due to the aggressive nature of small cell lung cancers (SCLC), the majority of diagnosed patients also have metastases and hence a simple two stage classification (limited versus extensive) is typically favored over the detailed TNM staging used for NSCLC. Limited stage SCLC is assigned for small tumors which are confined to the chest (including mediastinum and supraclavicular node) with no pleural effusion [mountain 1997]. Limited SCLC stage is associated with a 2 year survival rate of 20%. Extensive stage SCLC is assigned for an occurrence of distant metastases and/or for any tumor too expensive to be incorporated into the limited stage. The prognosis for extensive stage SCLC is a 2 year survival rate of 5% (Dollinger et al., 2001).

2.4.2 Cellular Classification

There are two main histological groups of lung cancer; small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). Small cell lung cancer is an aggressive cancer that accounts for around 15% of all lung cancers. SCLC's are derived from a common neuroendocrine precursor cell within the airways and is often fast growing and metastasize easily. Approximately 85% of all lung cancers are NSCLC, of which there are three sub-types. These subtypes are grouped together under NSCLC due to their similarity in treatment and prognosis. NSCLC's are derived from a common precursor epithelial cell that may be poorly differentiated or differentiated into; squamous cell carcinoma, large cell carcinoma or adenocarcinoma, Squamous cell carcinomas typically arise in the bronchial epithelium and are typically centrally located and comprise about 30% of all lung cancers. Large cell carcinomas account for about 10% of all lung cancers and show no evidence of squamous or glandular maturation and typically present in the mid to peripheral regions of the lung. Adenocarcinomas are the most common type of NSCLC comprising of approximately 40% of all lung cancers and are the primary focus for this lung nodule study. Adenocarcinomas arise from the glandular cells located in the epithelium lining of the bronchi and are typically peripherally located, often near the pleural surface. Adenocarcinomas were sub typed by Noguchi into 7 pathological sub-types A-F. These sub-types, A to F, are associated with progressively poorer prognoses in terms of long term survival: A. Confined bronchioalveolar carcinoma (LBAC) B. LBAC with foci of given way alveolar structures C. LBAC with foci of dynamic fibroblastic multiplication D. Inadequately separated adenocarcinoma E. Tubular adenocarcinoma F. Papillary adenocarcinoma with compressive and damaging development The World Health Organization (WHO) redesigned the rundown of neurotic sub-sorts of adenocarcinoma in 2004 as:

1. Adenocarcinoma with mixed subtypes

2. Acinar adenocarcinoma

3. Papillary adenocarcinoma

4. Bronchioalveolar carcinoma (BAC) – nonmucinous, mucinous or intermediate

5. Solid adenocarcinoma with mucin production the difficulty with attempts to categorize the pathological sub-types of adenocarcinoma is that most lung adenocarcinomas are histopathplogically heterogeneous and contain multiple sub-types. As a further

complication adenocarcinoma nodules sometimes present containing squamous cell or even NSCLC components. In addition, categorization is based on pathologist's classification of nodule content from histopathology data, which examines only small sub samples of tissue.

2.4.3 Radiological Classification

A solitary pulmonary nodule is defined as a discrete area of pulmonary opacity appearing on chest x-ray or MDCT. Opaque lesions less than three centimeters are defined as nodules while a larger lesion is referred to as a mass. Solitary pulmonary nodules may be cancerous or non-cancerous (usually a granuloma). With increasing biopsies being performed due to the early detection of lung cancer through MDCT screening, the MDCT appearances have been described with nodule classifications of solid, non-solid (also sometimes referred to as pure ground glass opacities – GGO) and part solid (sometimes referred to as GGO with a solid central component) being associated somewhat with histological subtypes (Tsuchiya, 2005).

2.5 Summary

This chapter presented a brief and general introduction of cancer and classifications of cancer, in additional background of lung. Moreover, the discussion was continuing through about lung cancer and the stages of lung cancer. It also presented a brief introduction about classification of cellular and radiological classification.

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CHAPTER 3

IMAGE PROCESSING TECHNIQUES

This chapter discusses a brief and general introduction of the image processing, since the proposed system is based completely on image processing techniques and methods. It briefly presents the history of image processing and how it has developed through years. Moreover, this chapter explains the main image processing techniques that are used in each image analysis system such as image enhancement and image filtering. It also discusses some applications of image processing in medicine and explains the image fusion.

3.1 Digital Image Processing

Image processing is a technique to play out a couple of operations on a picture, with a particular true objective to get an enhanced picture or to think some supportive information from it. It is a kind of banner handling in which data is a picture and yield may be picture or qualities/highlights related with that picture. Nowadays, picture preparing is among rapidly creating headways. It outlines focus investigate zone inside planning and programming building disciplines too. Image processing fundamentally incorporates the accompanying three stages:

- Importing the image by means of image securing devices;
- Analyzing and controlling the image;
- Output in which result can be adjusted image or report that depends on image investigation.

There are two sorts of strategies utilized for image processing to be specific, simple and computerized image processing. Simple image processing can be utilized for the printed copies like printouts and photos. Image examiners utilize different essentials of understanding while utilizing these visual systems. Computerized image processing systems help in control of the advanced images by utilizing PCs. The three general stages that a wide range of information need to experience while utilizing advanced system are pre-processing, upgrade, and show, data extraction. The name computerized image processing as a rule alludes to giving out of a two-dimensional picture through an advanced PC (Armato & Sensakovic, 2004). In a more extensive foundation, it infers advanced processing of some two-dimensional figures. An advanced image is an accumulation of genuine numbers spoke to by a limited number of bits. The guideline favorable position of Digital Image Processing techniques is its adaptability, repeatability and the preservation of unique information accuracy.

Figure 3.1: The first picture of the moon by a U.S. spacecraft (Gonzalez & woods, 2004)

The analysis of medical images 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).

3.2 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.

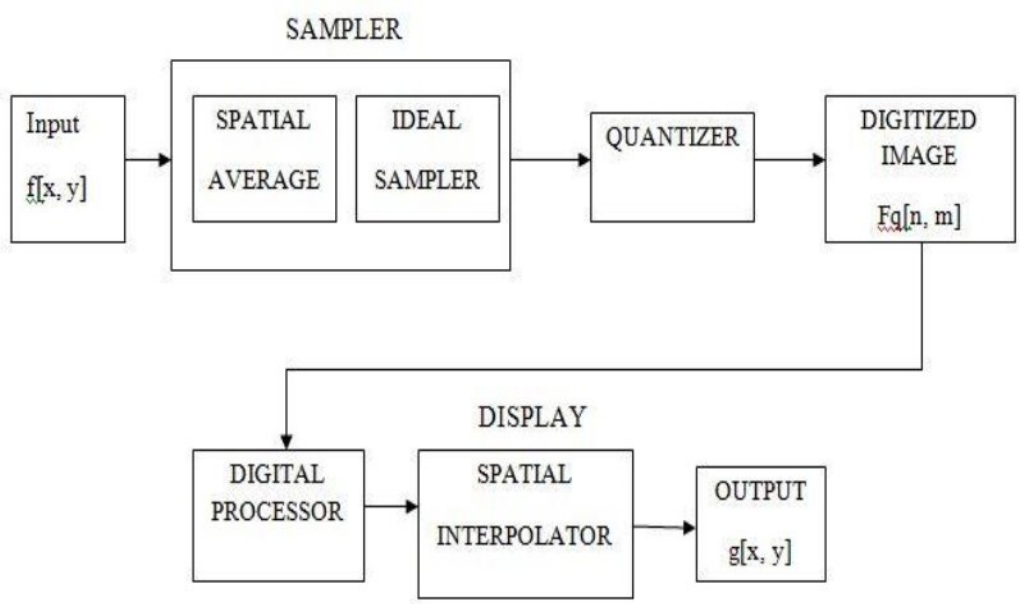


Figure 3.2: Digital image processing (Andrew, 2008)

3.3 Medical Image Analysis

Biological pictures contain an abundance of items and examples, which may pass on data about basic system in science. Investigate at the accompanying microscopy pictures:

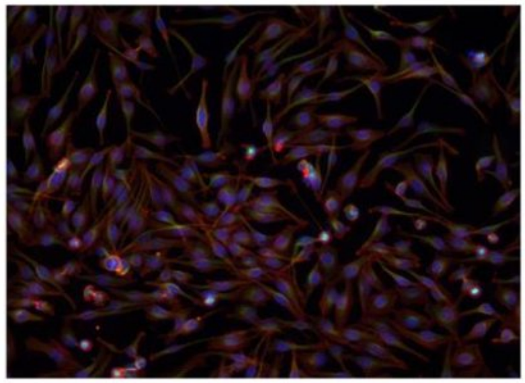


Figure 3.3: Tissue-culture cells (Gonzalez & Woods, 2001).

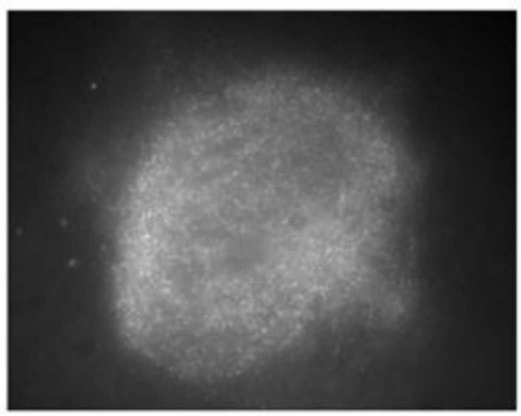


Figure 3.4: Speckled spindle (Gonzalez & Woods, 2001).

Image processing and examination gives a way to extricate and evaluate protests and examples in image information and acquire answers to important organic inquiries. It offers two focal points over conventional more manual techniques for investigation: 1) Human vision, while exceedingly touchy, can be effortlessly one-sided by pre-considered ideas of articles and ideas; robotized image examination gives an impartial way to deal with separating data from image information and testing speculations. 2) Once an image-examination routine is conceived, it can be connected to an expansive number of microscopy images, encouraging the gathering of a lot of information for measurable investigation (Milan et al., 1998).

3.3.1 Image analysis strategies

Image examination includes the change of components and questions in image information into quantitative data about these deliberate elements and traits. Microscopy images in science are frequently mind boggling, loud, relic loaded and therefore require various image processing ventures for the extraction of important quantitative data (Gonzalez and Woods, 2001). A blueprint of a general procedure for image examination is exhibited beneath:

1) The beginning stage in image examination commonly includes an advanced image gained utilizing a CCD camera. Crude microscopy images acquired on computerized CCD cameras are liable to different blemishes of the image securing setup, for example, clamor at low light levels, uneven brightening, damaged pixels, and so forth… We regularly need to first process the image to adjust for such deformities and furthermore to upgrade the complexity to emphasize components of enthusiasm for the image for consequent examination. In segment II, we present different image change and spatial sifting methods that can be utilized for this reason (Milan et al., 1998).

2) Having adjusted antiquities and improved differentiation in the images, we can apply different computational strategies to concentrate components and examples from the images. In the accompanying segment, we portray different instruments of morphological image processing and image division that can be utilized for this reason.

3) After organic imperative elements have been fragmented from images, we can then get quantitative data from these components and articles. MATLAB gives an arrangement of apparatuses that can be utilized to quantify the properties of areas; the lattice representation of images in MATLAB likewise considers simple control of information and figuring of amounts from microscopy images (Fan et al., 2002).

Here is an outline of the process:

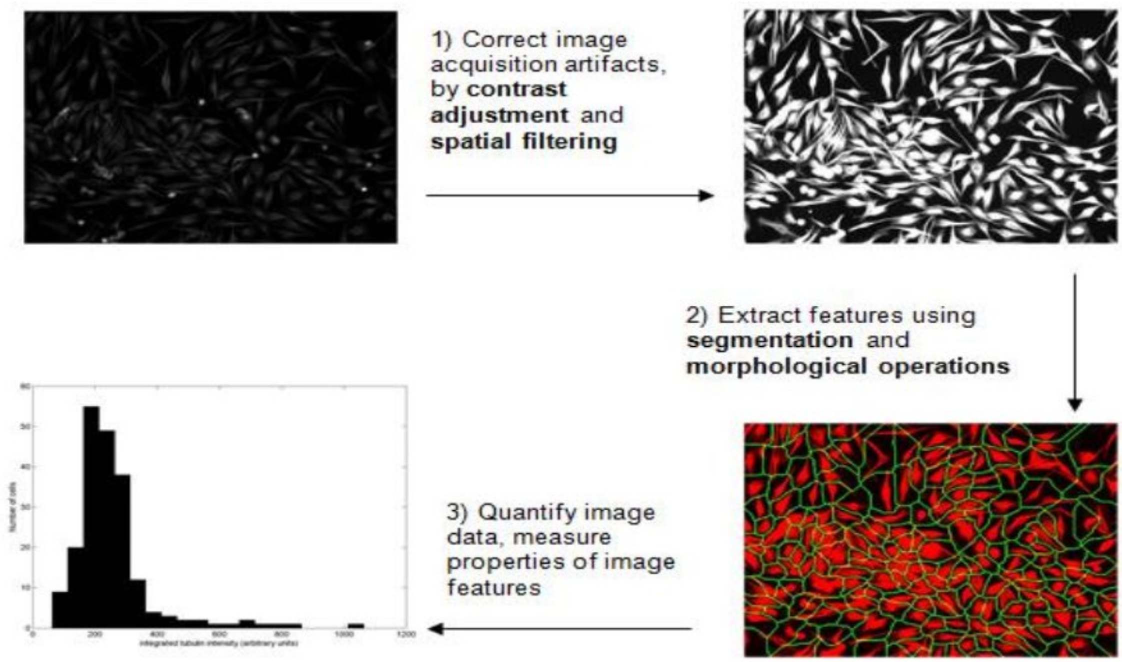


Figure 3.5: The process of image analysis

3.4 Image Enhancements

This procedure is basically improving the interpretability or impression of information in pictures for human watchers and giving `better' commitment for other robotized picture handling frameworks. The focal focus of picture change is to modify credits of a picture to make it more fitting for a given task and a specific observer. Amid this methodology, at least one characteristics of the picture are changed. The choice of attributes and the way they are adjusted are specific to a given undertaking. Furthermore, passerby specific components, for instance, the human visual structure and the observer experience, will introduce a great deal of subjectivity into the choice of picture overhaul systems (Fan et al., 2002).

There exist various methodologies that can redesign an automated picture without demolishing it. The redesign strategies can exhaustively be divided into the going with two arrangements:

1. Spatial Domain Methods

2. Recurrence Domain Methods

In spatial space techniques, we particularly deal with the picture pixels. The pixel qualities are controlled to fulfill fancied update. In repeat range techniques, the picture is at first moved into repeat space. It infers that, the Fourier Transform of the picture is enrolled first. All the change operations are performed on the Fourier change of the picture and subsequently the Inverse Fourier change is performed to get the resultant picture. These overhaul operations are performed with a particular true objective to change the picture splendor, differentiate or the scattering of the diminish levels.As a result the pixel esteem (intensities) of the yield image will be altered by change capacity connected on the info values (Gonzalez & woods, 2001).

Image enhancement basically implies, changing an image f into image g utilizing T. (Where T is the change. The estimations of pixels in images f and g are meant by r and s, separately. As said, the pixel values r and s are connected by the expression,

$$s = T(r) \tag{3.1}$$

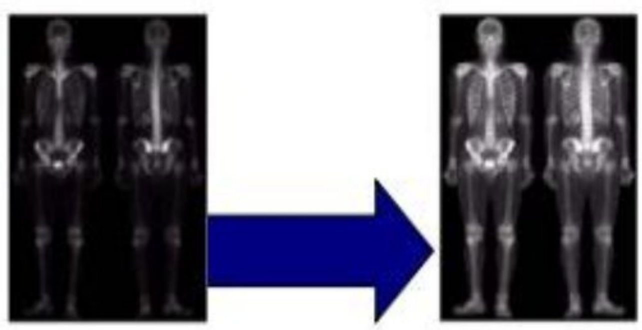


Figure 3.6: Example of image enhancement (Fan et al., 2002)

3.4.1 Contrast adjustments

Regularly, images have a low element reach and a large number of its components are hard to see. We will introduce diverse power changes that will enhance the presence of the images. Enhancing the presence of an image does not only serve a tasteful part –

frequently, it can enhance the execution of image division calculations and highlight acknowledgment.

Amid the adjustment of contrast, the power estimation of every pixel in the crude image is changed utilizing an exchange capacity to shape a complexity balanced image. The most well-known exchange capacity is the gamma contrast change:

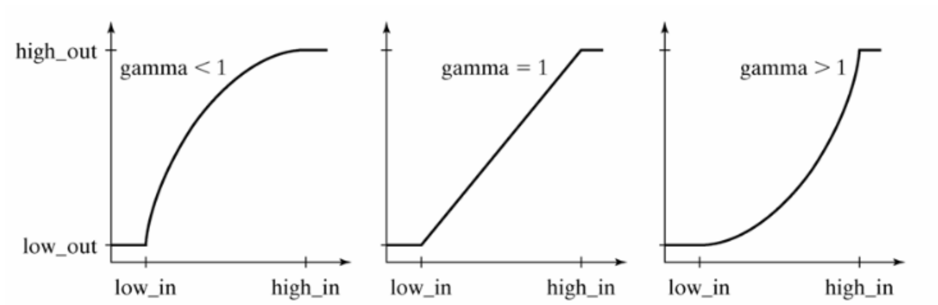


Figure 3.7: Gamma correction (Gonzalez & woods, 2001)

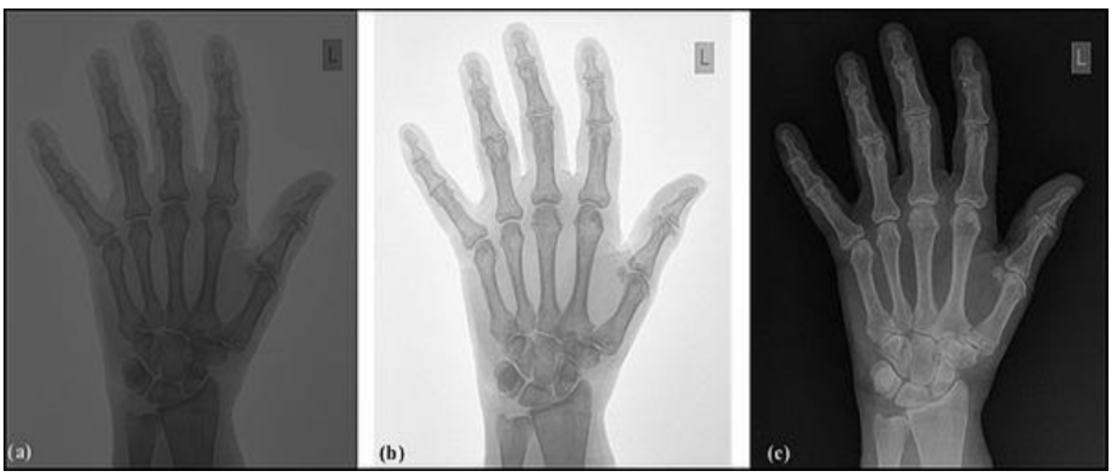


Figure 3.8: Examples of contrast enhancement applied to a radiograph of the wrist

The figure above shows an example of an x-ray wrist image where (a) is the unprocessed image, (b) is the adjusted one and (c) is the inverted grayscale image.

3.5 Image Compression

There are a few distinctive courses in which image records can be packed. For Internet utilize, the two most normal compacted realistic image configurations are the JPEG arrange and the GIF design. The JPEG technique is all the more regularly utilized for photos, while the GIF strategy is generally utilized for line workmanship and different images in which geometric shapes are moderately basic. For the reasons of finite save capacity and limited bandwidths the majority of images need compression before transmitting or save (Dimililer, 2013).

Different methods for image compression incorporate the utilization of fractals and wavelets. These techniques have not increased far reaching acknowledgment for use on the Internet as of this composition. Be that as it may, both strategies offer guarantee since they offer higher compression proportions than the JPEG or GIF techniques for a few sorts of images. Another new technique that may in time supplant the GIF configuration is the PNG organize.

A content record or program can be packed without the presentation of blunders, yet just up to a specific degree. This is called lossless compression. Past this point, mistakes are presented. In content and program documents, it is critical that compression be lossless in light of the fact that a solitary blunder can genuinely harm the importance of a content record, or cause a program not to run. In image compression, a little misfortune in quality is normally not perceptible. There is no "basic point" up to which compression works splendidly, however past which it gets to be distinctly unthinkable. At the point when there is some resistance for misfortune, the compression variable can be more noteworthy than it can when there is no misfortune resilience. Therefore, realistic images can be packed more than content records or projects

Figure 3.9: Image compression

While obviously images coded by lossless systems don't contrast in any detail from the first images, lossy images may vary on account of lost points of interest or in light of ancient rarities included the compression procedure (for example JPEG "blackness" antiquities). In the illustrations appeared, the images are appeared after edge upgrade, differentiate extending ('windowing') and up scanning (1024*1024) for enhanced deceivability of little structures (counting the "blackness" curios). The left image is uncompressed, and moderately high information compression elements have been chosen for the two different images (CR= 12 and CR= 24).

3.6 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 greyscale of multivariate values and form a connected region,
- Neighboring pixels which are in different categories have dissimilar values.

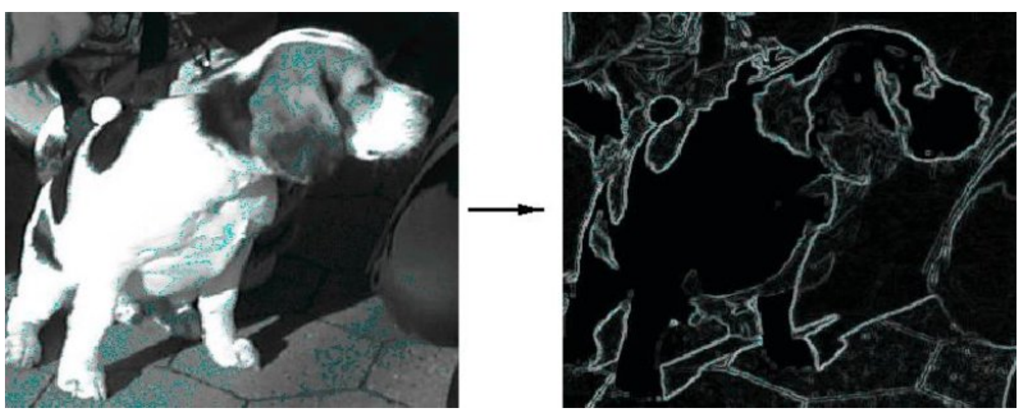


Figure 3.10: Edge based segmentation (Saif et al., 2012)

3.6.1 Canny operators

The Canny edge detector is widely used in computer vision to locate sharp intensity changes and to find object boundaries in an image. 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 (Haitham, 2004). Canny operator has been used for such algorithm with regard to the following criteria (Saif et al., 2012):

Its magnitude value can be obtained using the following formula:

$$|G| = |G_x| + |G_y| \tag{3.2}$$

$$|G| = \sqrt{G_x^2 + G_y^2} \tag{3.3}$$

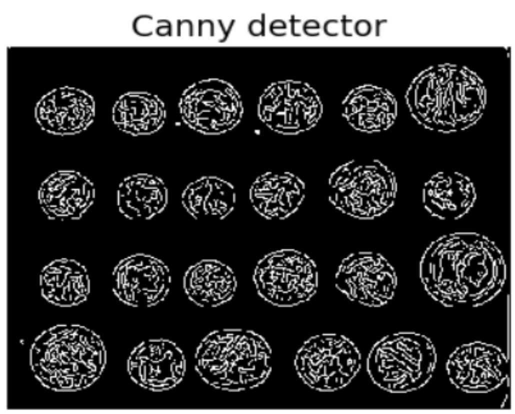


Figure 3.11: Canny edge detection (Saif et al., 2012)

3.7 Image Processing Applications

The field of digital image has rapidly expanded in the recent years. The usefulness of this technology is clear in many different disciplines and areas (Andrew, 2008).

The fields of image processing are:

- Robotics
- Medical imaging
- Machine vision
- Digital camera images

3.7.1 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:

1. Segmentation - automated methods that create patient-specific models of relevant anatomy from images;
2. Registration - automated methods that align multiple data sets with each other;
3. Visualization - the technological environment in which image-guided procedures can be displayed;

Imaging development in Medicine made the authorities to see within parts of the body for basic assurance. It moreover helped pros to make keyhole surgeries for going to within parts without genuinely opening unreasonably of the body. CT scanner, Ultrasound and Magnetic Resonance Imaging expected control x-ray imaging by making the authorities to look at the body is the inconspicuous third estimation. With the CT scanner, inside the body can be revealed with straight imposition and the undesirable domains can be recognized without realizing either uneasiness or torment to the patient. X-beam snatches signals from the body is appealing particles swinging to its alluring tune and with the help of its extreme PC, changes over scanner data into revealing pictures of internal organs. Picture handling procedures delivered for separating remote detecting data might be modified to analyze the yields of remedial imaging structures to get best inclination to separate signs of the patients with no trouble (Rao, 2004).

3.7.2 Computerized image processing requirements for medical applications

• Interfacing Analog yields of sensors for example, magnifying lens, endoscopes, ultrasound and so forth, to digitizers and thusly to Computerized Image Processing frameworks (Fan et al., 2002).

- Image upgrades.
- Changing thickness element scope of B/W images.
- Color redress in shading images.
- Manipulating of hues inside an image.
- Contour discovery.
- Area estimations of the cells of a biomedical picture.
- Display of picture line profile.
- Restoration of images.
- Smoothing of images.
- Registration of different images.
- Construction of 3-D images from 2-D images.
- Generation of negative images.
- Zooming of images.
- Pseudo shading.
- Point to point estimations.
- Getting help impact.

3.8 Summary

This chapter presented a brief explanation of the history of image processing. In addition, it provided some applications of the image processing, in particularly, in medicine. It also presents some useful and important image processing techniques and explained them and focused on their use in medicine and biomedical engineering fields.

CHAPTER 4

METHODOLOGY

This chapter discusses about methodology that proposed in the study, first of all discussion will be about block diagram of the system proposed then explains for each methods, first step it briefly presents the two types of filters: Gaussian filter and median filter. Moreover, different types of discrete wavelet transform and explaining each type of them. In additional the chapter discusses image adjustment, erosion technique, thresldding and finally image subtract technique.

4.1 Methodology Proposed

The developed system is to segment the lung tumor in CT images. Various techniques to process images and reach that goal are used. The images first were filtered to reduce the noise found in them and to increase their intensity pixels. In later stages, the enhanced images undergo wavelets transform techniques to extract 4 different output images that represent the horizontal, vertical, approximation, and the diagonal images. These 4 images are then summed to the reconstructed image which is the image inverse wavelet image. This summation helps in defining the tumor separately from other parts of the image. Erosion was also used to shrink the images and separate each part from the others which later helps in segmenting the tumor. Thresholding was also used; however, here the threshold was set to be maximum or ‘1’. This threshold selection allows the binarization of the image, by keeping the tumor and the clavicles as foreground objects or ‘1s’, while the others were considered as background objects or ‘0s’. The smallest connected components that represent the tumor are then removed from the image to haveanother image which has only the lung image without the tumor. The two images are then subtracted which yields to a segmentation of the lung tumor in a tumor lung image.

The thesis aims is to investigate the use of different types of filters such as Gaussian and median filter in addition to the use of different types of wavelets transform the select the best for reaching the desired target which is segmenting the lung tumor accurately. The different techniques used in each system and different results obtained from each system are then to be shown and compared with each other to investigate the best techniques for performing such segmentation task.

The figure below shows the flowchart of the developed lung tumor segmentation system. As can be seen, the system consists of three different stages. At first, the images are enhanced using some filters and adjustment techniques. The second stage is to use discrete wavelets transform where the four output images will be extracted. In this stage the 4 wavelets are summed to the reconstructed image. The last stage is when the summed image is eroded, tresholded and then the subtraction operation takes place so that the tumor is segmented.

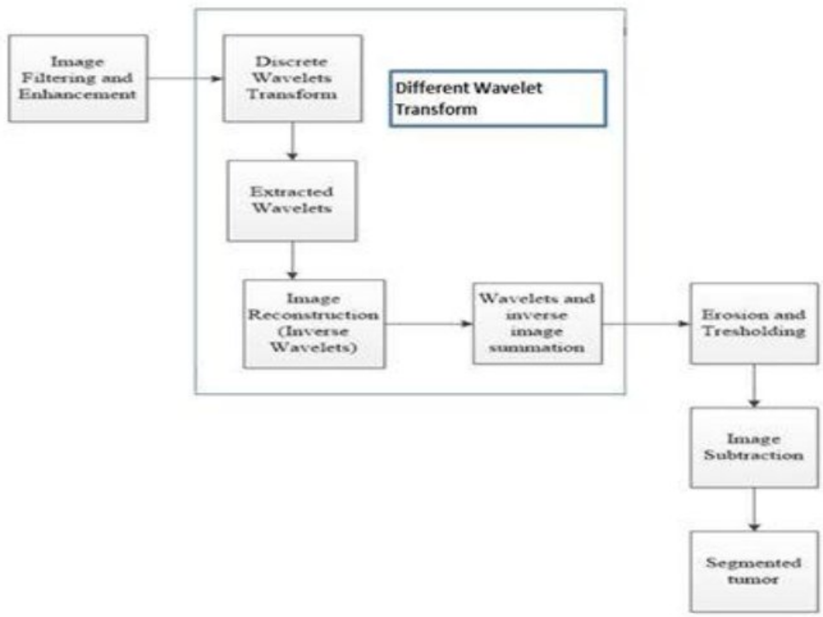


Figure 4.1: Proposed system flowchart

As can be seen in Figure 4.1 the developed segmentation system consists of different techniques that eventually lead to the lung tumor segmentation. For this purpose two types of filters are used in addition to many types of wavelets transform as well. The results of each version of the system are different and they will be discussed in next chapters.

4.1.1 Image Filtering

Image smoothing is a main and first step in an image processing system in which the image is filtered to clear its edges and enhance its quality by removing the noise inside it. Smoothing, is an image processing technique used in order to reduce the noise in an image to produce less pixilated 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 (Eng&Malek, 2001).

To do this, two types of filters were used in the developed system: median filter and the Gaussian filter.

4.1.1.1 Median filter

Median filter is a windowed filter of non-linear process that is used to smooth image that may contain kind of noisy elements. The filter is considered as a low-pass one. The basic concept of this type of filter is that it replaces a pixel by the median value of window of selected pixels. Below is an example of the median filter (Yujin, 2006).

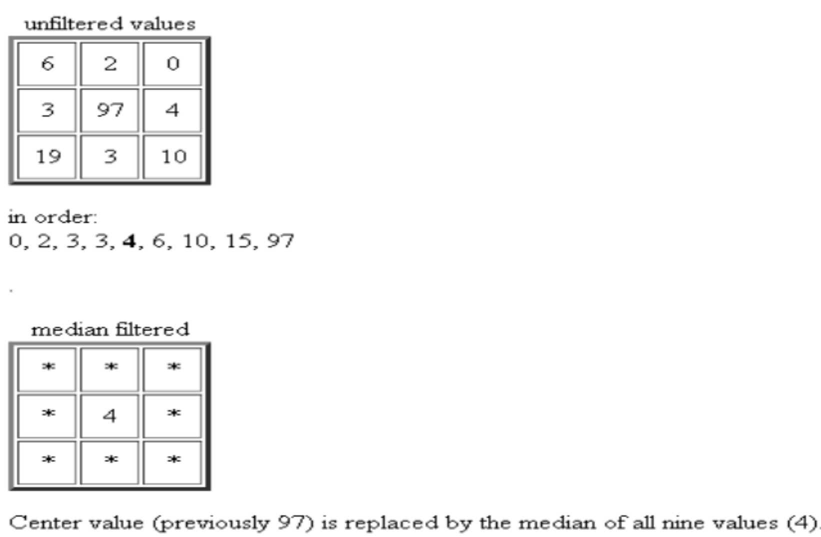


Figure 4.2: Median filtering basic ideas

This filter is utilized to lessen indiscreet commotion or the salt-and pepper noise in an image with protecting the helpful components and image edges. Middle filtering is a straight procedure in which the yield of the being prepared pixel is found by computing the middle of a window of pixels that encompasses that contemplated pixel (Eng&Malek, 2001). 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) of 10*10 pixels around the evaluated pixel.

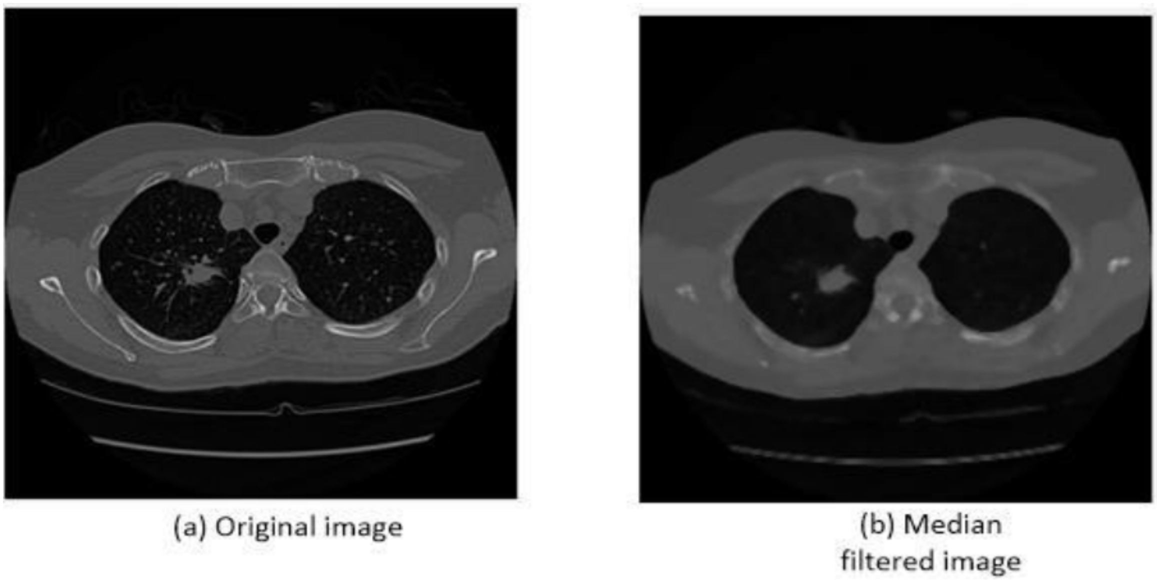


Figure 4.3: Median filtering

4.1.1.2 Gaussian filter

The Gaussian smoothing operator is a 2-D convolution administrator that is utilized to `blur' pictures and evacuate detail and noise. In this sense it is like the mean filter, yet it utilizes an alternate window or kernel that speaks to the state of a Gaussian (`bell-molded') shaped. This kernel has some exceptional properties which are itemized underneath (Calder bank et al., 2000).

The Gaussian distribution in 1-D is as follows:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}} \tag{4.1}$$

Where σ stands for the standard deviation of the distribution. The distribution has also a mean of zero (*i.e.* it is centered on the line x=0). The following figure represents the distribution of 1-D Gaussian.

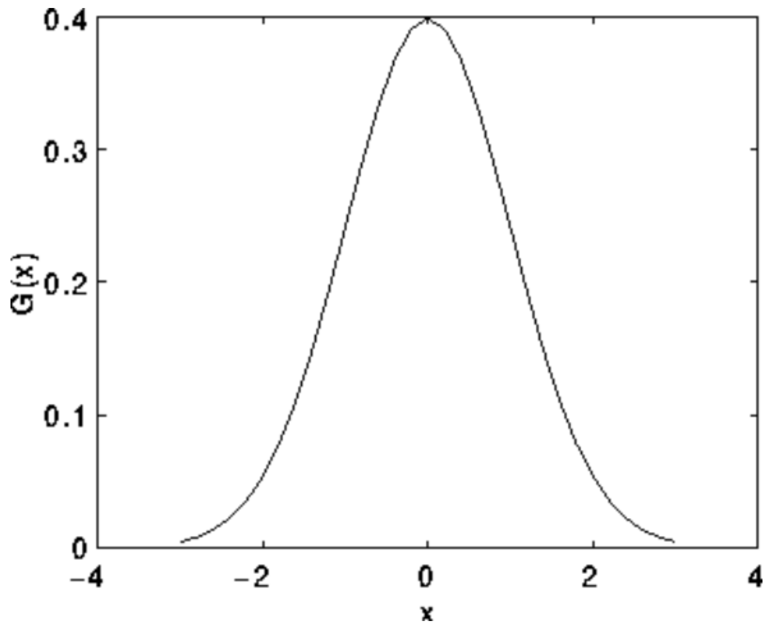


Figure 4.4: Distribution of 1-D Gaussian

In 2-D, an isotropic (*i.e.* circularly symmetric) Gaussian has the form:

$$G(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4.2}$$

This distribution is shown in Figure 4.5.

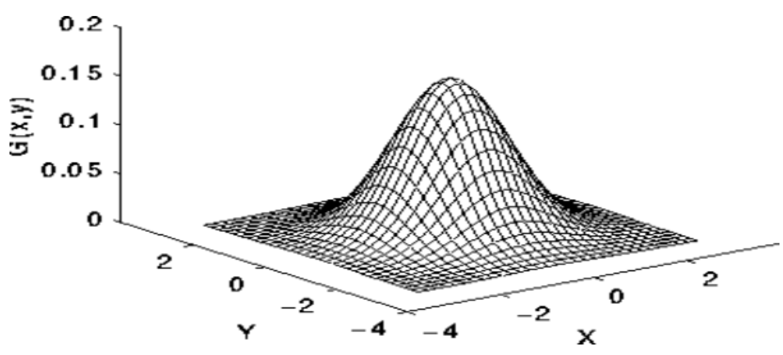


Figure 4.5: Distribution of 2-D Gaussian

The likelihood of Gaussian smoothing is to use this 2-D assignment as a `point-spread' limit, and this is proficient by convolution. Since the image is secured as a social affair of discrete pixels we need to convey a discrete figure to the Gaussian limit before we can play out the convolution. On a basic level, the Gaussian dissemination is non-zero all over, which would require an interminably endless convolution parcel, however for all intents and purposes it is effectively zero more than around three standard deviations from the mean, in this manner we can truncate the piece now. Figure 4.5 exhibits a sensible entire number valued convolution bit that approximates a Gaussian with of 1.0. It is not clear how to pick the values of the cover to infer a Gaussian. One could use the value of the Gaussian at the point of convergence of a pixel in the cover, however this is not correct in light of the fact that the value of the Gaussian vacillates non-straightly over the pixel. We consolidated the value of the Gaussian over the whole pixel (by summing the Gaussian at 0.001 enlargements). The integrals are not numbers: we rescaled the show so that the corners had the value 1. Finally, the 273 is the aggregate of the significant number of values in the cover.

$$\frac{1}{273}\begin{array}{|c|c|c|c|c|}\hline 1 & 4 & 7 & 4 & 1 \\ \hline 4 & 16 & 26 & 16 & 4 \\ \hline 7 & 26 & 41 & 26 & 7 \\ \hline 4 & 16 & 26 & 16 & 4 \\ \hline 1 & 4 & 7 & 4 & 1 \\ \hline \end{array}$$

Figure 4.6: Discrete approximation to Gaussian functions with σ=1.0

The Figure 4.7 shows the Gaussian filtered image of standard deviation =0.8 (b) and standard deviation = 4 (c)

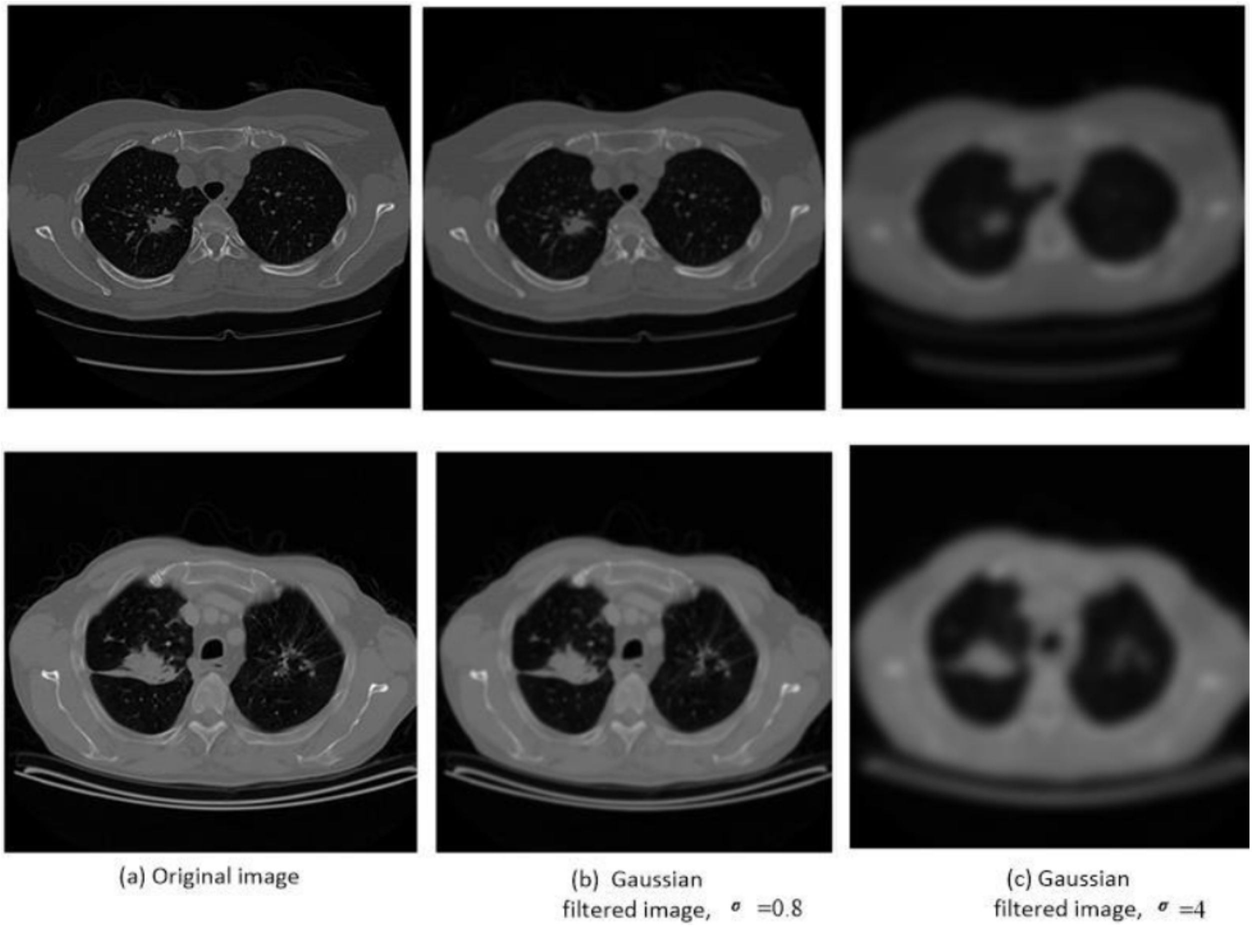


Figure 4.7: Gaussian filtering

As seen in the figure above, the Gaussian filter is good when standard deviation is high since it blurring all parts which allows to the removal of the unwanted parts such as clavicles and small elements inside the lungs. However, applying high standard deviation is not always good for this segmentation task because the high blurring effect may also blur and the remove the tumor which is the region of interest which will lead to a low accuracy system. Therefore, the standard was selected to be 0.8 which showed good results discussed in the results discussion section.

4.1.2 Adjusting image intensities

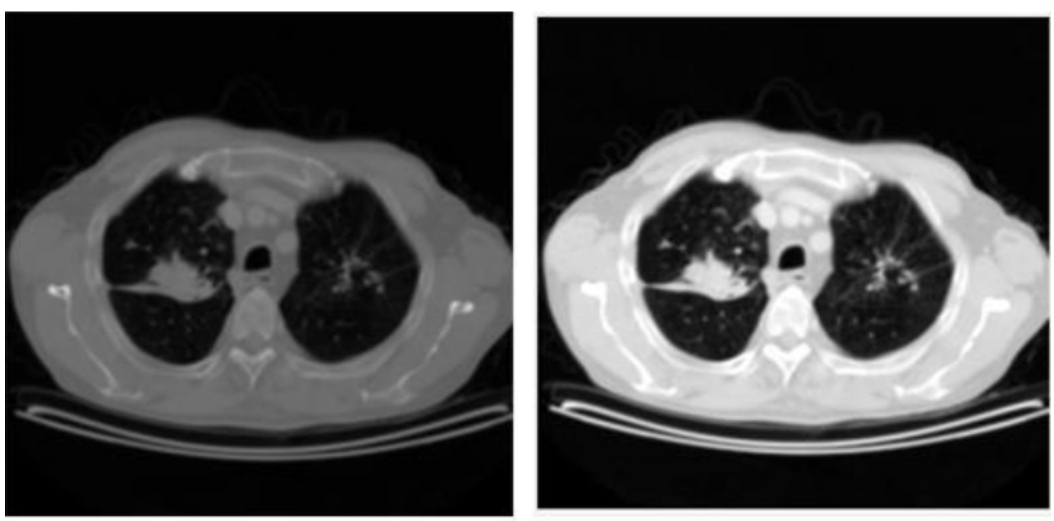
An image needs adjustments when there are no sharp contrasts in the middle of highly contrasting. Brightness alludes to the general daintiness or obscurity of an image (Kim, 1997).

With the end goal of increasing the image intensity and upgrade its quality, the images experience what is called image adjustment. This image processing technique intends to improve the quality and brightness of the image by expanding the intensity of its pixels.

This is achieved by changing the contrast or splendor of an image. In this strategy, pixel values beneath a predetermined value are shown as dark, pixel values over a predefined value are shown as white, and pixel values in the middle of these two values are shown as shades of dim. The outcome is a direct mapping of a subset of pixel values to the whole scope of grays, from dark to white, delivering an image of higher contrast.

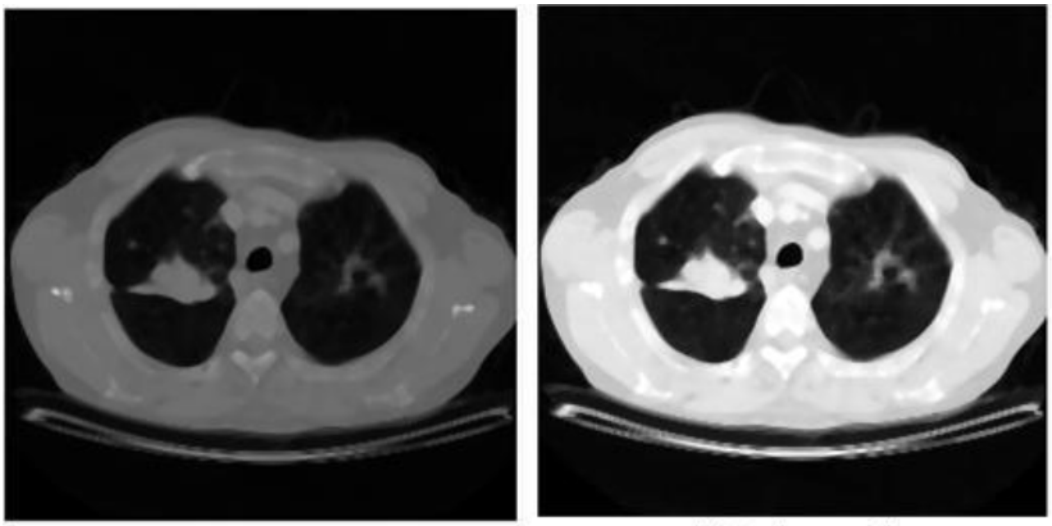
In short, image adjustment is to map the intensity values in grayscale image I to new values in J such that 1% of data is saturated at low and high intensities of I. This increases the contrast of the output image J.

The figures underneath illustrates the conformity of an image and its belongings in improving the image contrast.



(a) Gaussian filetered image (b) Adjusted image

Figure 4.8: Gaussian versus adjusted image



(a) Median filtered image (b) Adjusted image

Figure 4.9: Median versus adjusted image

Figure 4.8 and Figure 4.9 above shows the adjustment of the median and Gaussian filter where the intensity was mapped to a new range of intensities. It can be seen that this technique is good in separating the tumor from other parts which makes it easier to be segmented in later stages. Moreover, this technique enhances the resolution of the image since the image pixels are brighter and clearer after applying it.

4.1.3 Wavelet transform

The wavelet transform resembles the Fourier transform (or impressively more to the windowed Fourier transform) with an absolutely remarkable authenticity work. The essential qualification is this: Fourier transforms separate the flag into sine and cosines, i.e. the capacities confined in Fourier space; in inverse the wavelet transform uses works that are constrained as a piece of both the genuine and Fourier space. Overall, the wavelet transform can be delineated by the going with condition (Haar, 1990):

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^{*}_{(a,b)}(x)\, \mathrm{d}x \tag{4.3}$$

Where the * represent the complex conjugate symbol, while the function ψ can represent some function that can be selected arbitrarily.

As it is watched, the Wavelet transform is in all actuality an endless course of action of various transforms, dependent upon the legitimacy work used for its computation. This is the guideline reason, why we can hear the expression "wavelet transform" in through and through various conditions and applications. There are also various courses how to sort the sorts of the wavelet transforms. Here we exhibit only the division in light of the wavelet orthogonality. We can use orthogonal wavelets for discrete wavelet transform headway and non-orthogonal wavelets for nonstop wavelet transform change.

4.1.3.1 Discrete wavelet transform

The discrete wavelet transform (DWT) is a utilization of the wavelet transform using a discrete course of action of the wavelet scales and interpretations agreeing to some described guidelines. All things considered, this transform separates the banner into generally orthogonal course of action of wavelets, which is the essential difference from the consistent wavelet transform (CWT), or its execution for the discrete time game plan now and again called discrete-time constant wavelet transform (DT-CWT) (Daubechies, 1998).

The wavelet can be worked from a scaling capacity which portrays its scaling properties. The control that the scaling capacities must be orthogonal to its discrete interpretations proposes some numerical conditions on them which are said everywhere, e.g. the enlargement equation.

$$\emptyset(x) = \sum_{k=-\infty}^{\infty} ak\emptyset(Sx - k) \tag{4.4}$$

Where S is a scaling factor which is usually selected to be 2.

$$\int_{-\infty}^{\infty} \phi(x)\, \phi(x + l)\, \mathrm{d}x = \delta_{0,l} \tag{4.5}$$

Three types of discrete wavelets were used in this thesis which aims to investigate the best method for this segmentation application.

- **Haar Wavelets**

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

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

This property can, be that as it may, be leverage for the examination of signs with sudden moves, for example, observing of hardware disappointment in machines.

The Haar wavelet's mother wavelet function $\psi(t)$ can be depicted as

$$\psi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2} \\ -1 & \frac{1}{2} \le t < 1 \\ 0 & otherwise \end{cases} \tag{4.6}$$

Its scaling function $\phi(t)$ can be described as

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases} \tag{4.7}$$

- **Inverse discrete wavelet transform**

The Haar transform y_n of an n-input function x_n is

$$y_n = H_n x_n \tag{4.8}$$

The Haar transform matrix is real and orthogonal. Thus, the inverse Haar transform can be derived by the following equations (Sonka et al., 1999).

$$H = H^{*}, H^{-1} = H^{T}, \text{i.e. } HH^{T} = I \tag{4.9}$$

Where I is the identity matrix. For example, when n = 4

$$H_4^T H_4 = \frac{1}{2}\begin{bmatrix} 1 & 1 & \sqrt{2} & 0 \\ 1 & 1 & -\sqrt{2} & 0 \\ 1 & -1 & 0 & \sqrt{2} \\ 1 & -1 & 0 & -\sqrt{2} \end{bmatrix} \cdot \frac{1}{2}\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ \sqrt{2} & -\sqrt{2} & 0 & 0 \\ 0 & 0 & \sqrt{2} & -\sqrt{2} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.10}$$

Thus, the inverse Haar transform is

$$x_n = H^T y_n \tag{4.11}$$

The Figure 4.10 shows the Haar discrete wavelet transform when using the median filter. The figure shows the four extracted wavelets: Approximation, Vertical detail V1, Horizontal detail H1, and Diagonal detail D1.

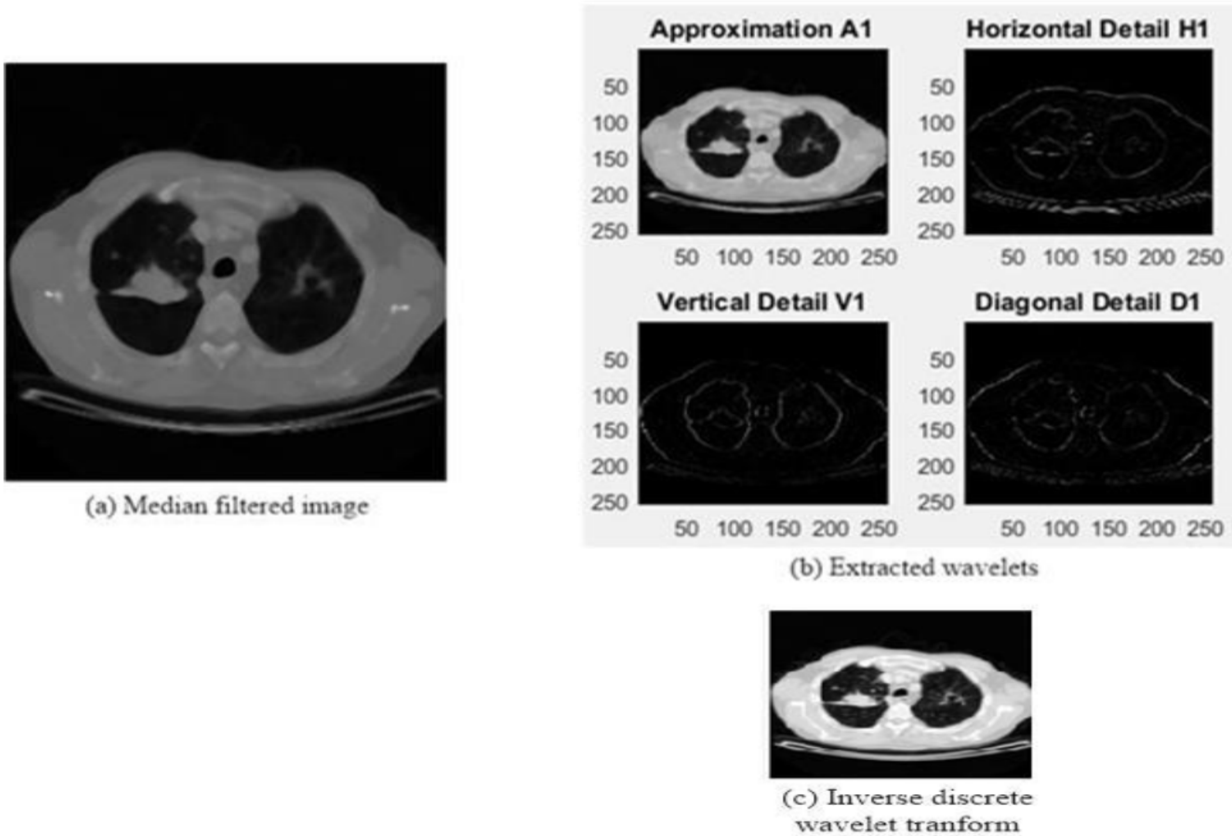
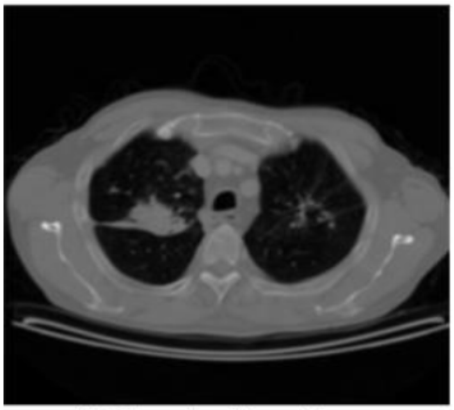
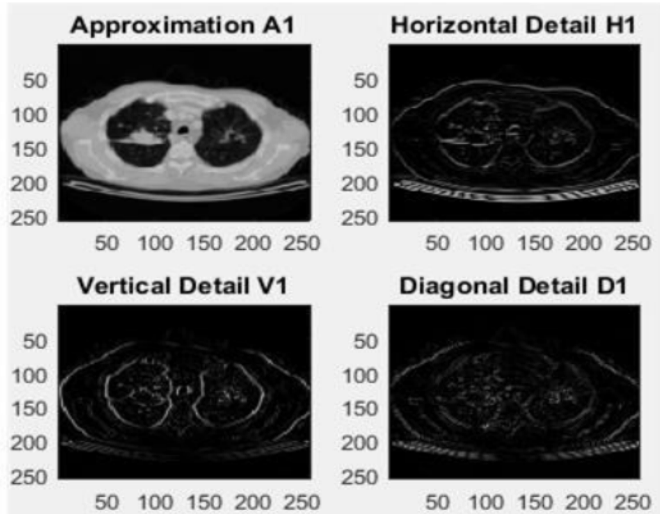


Figure 4.10: Haar discrete wavelet of median filtered image

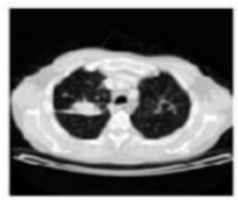
Figure 4.11 shows the use of Haar discrete wavelet transform; however, here the filter that was used is the Gaussian filter. It can be easily seen that the 4 wavelets are different when using Gaussian filter than median filter.



(a) Gaussian filtered image



(b) Extracted wavelets



(c) Inverse discrete wavelet tranform

Figure 4.11: Haar wavelet transform with Gaussian filter

- **Biorthogonal discrete wavelets**

Biorthogonal wavelets highlight a couple of scaling functions and related scaling channels — one for examination and one for union.

There is likewise a couple of wavelets and related wavelet channels — one for investigation and one for union (Strang, 1998).

The investigation and union wavelets can have diverse quantities of vanishing minutes and consistency properties. You can utilize the wavelet with the more noteworthy number of vanishing minutes for examination bringing about a meager representation, while you utilize the smoother wavelet for recreation.

Figure 4.12 shows the Biorthogonal discrete wavelet transform when it was used with Gaussian filter. It also shows the inverse Biorthogonal discrete wavelet transform image.

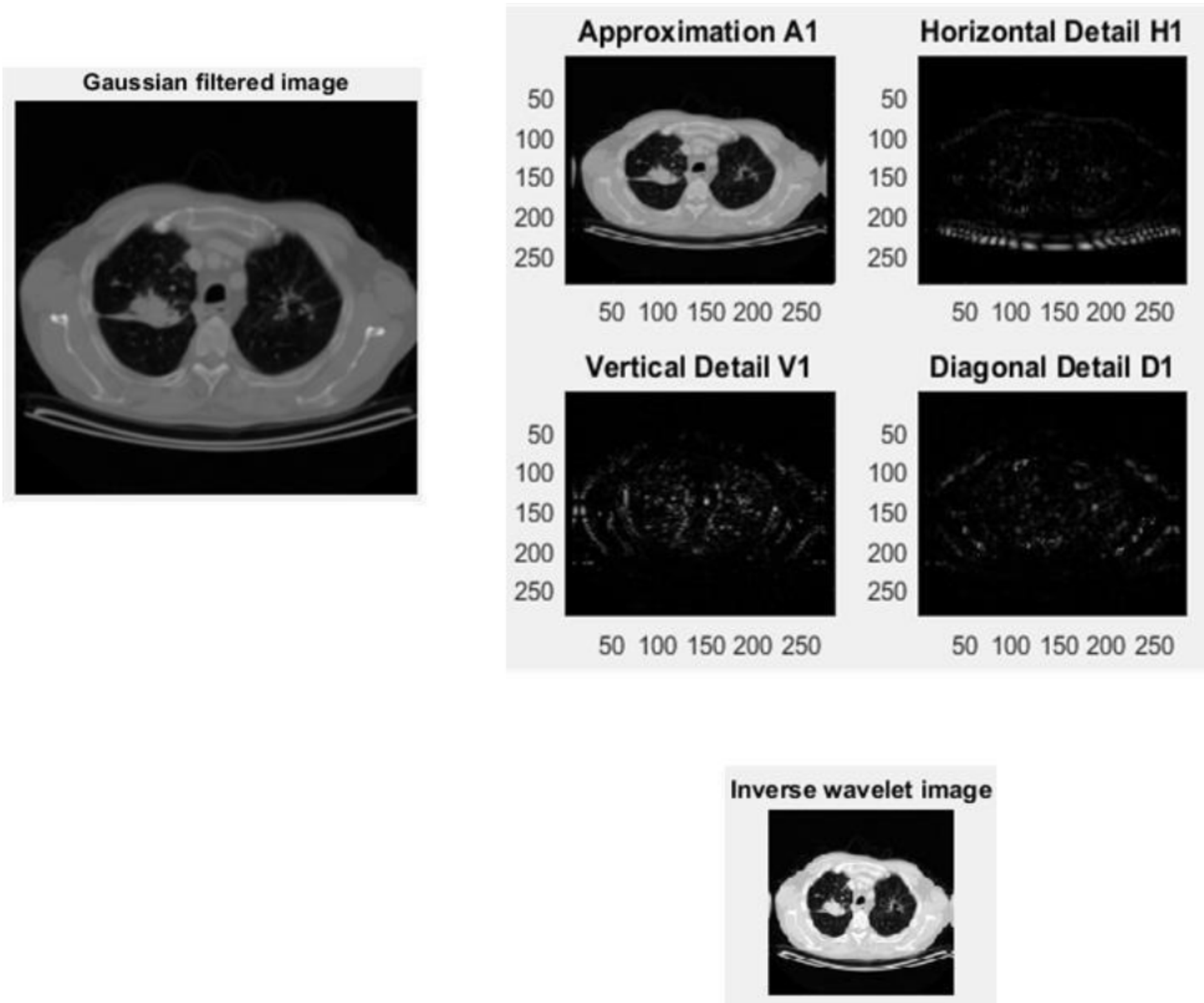


Figure 4.12: Biorthogonal discrete wavelet transform with Gaussian filter

Figure 4.13 shows the Biorthogonal discrete wavelet transform when it was used with median filter. It also shows the inverse Biorthogonal discrete wavelet transform image. It is clear that the wavelets are different when using different filters.

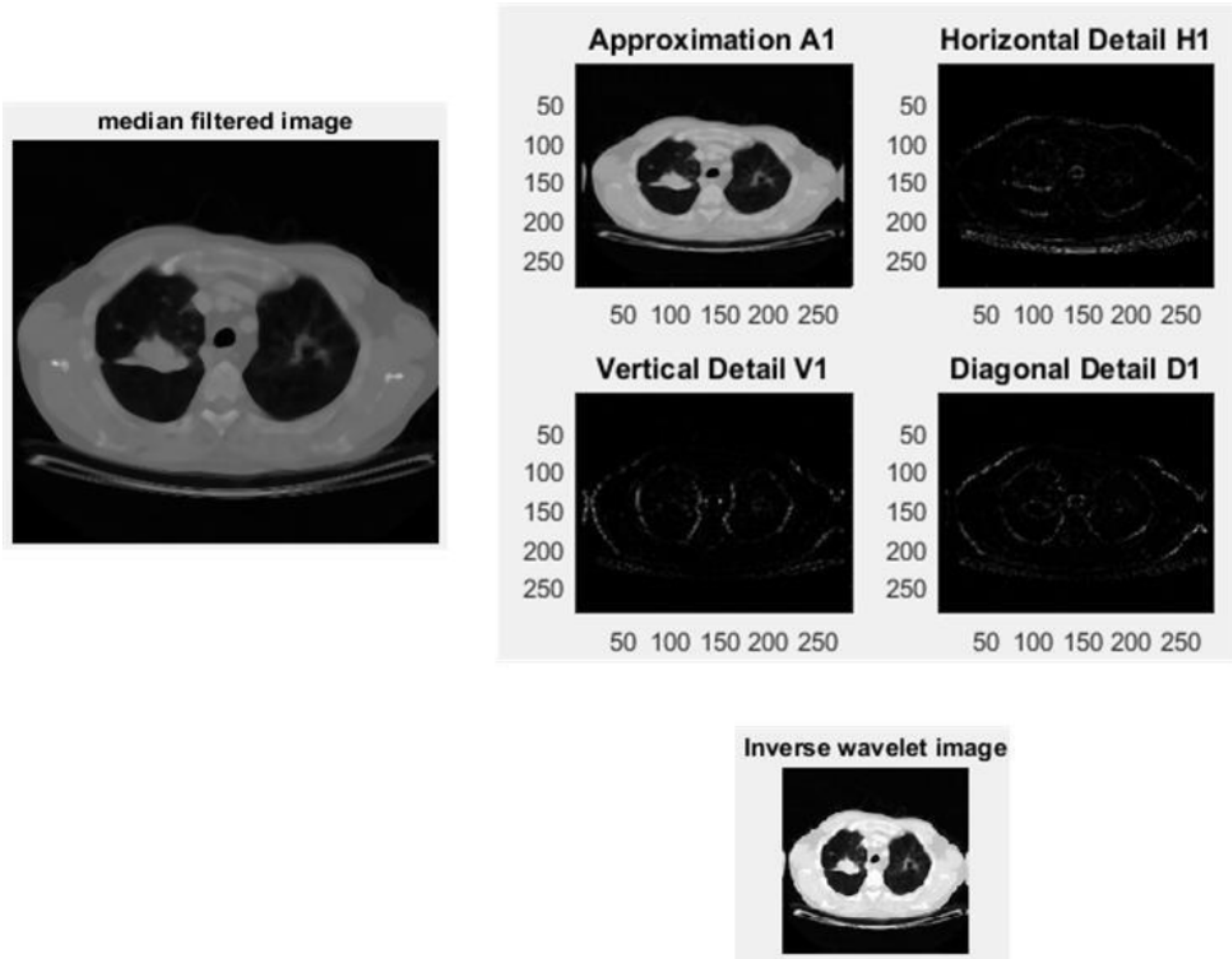


Figure 4.13: Biorthogonal discrete wavelet transform with median filter

- **Daubechies wavelets**

The DbN wavelets are the Daubechies' extremal stage wavelets. N alludes to the quantity of vanishing moments. These filters are additionally alluded to in the writing by the quantity of channel taps, which is 2N (Davis, 2000).

4.1.4 Images Summations

After getting the 4 different wavelets from the image, the image is reconstructed using the inverse discrete wavelets transform. Then, these images are summed together to obtain a clearer and enhanced image where the tumor is well defined and separated from the other parts of the image. This addition operation helps to segment the tumor in later stages (Wang et al., 1999).

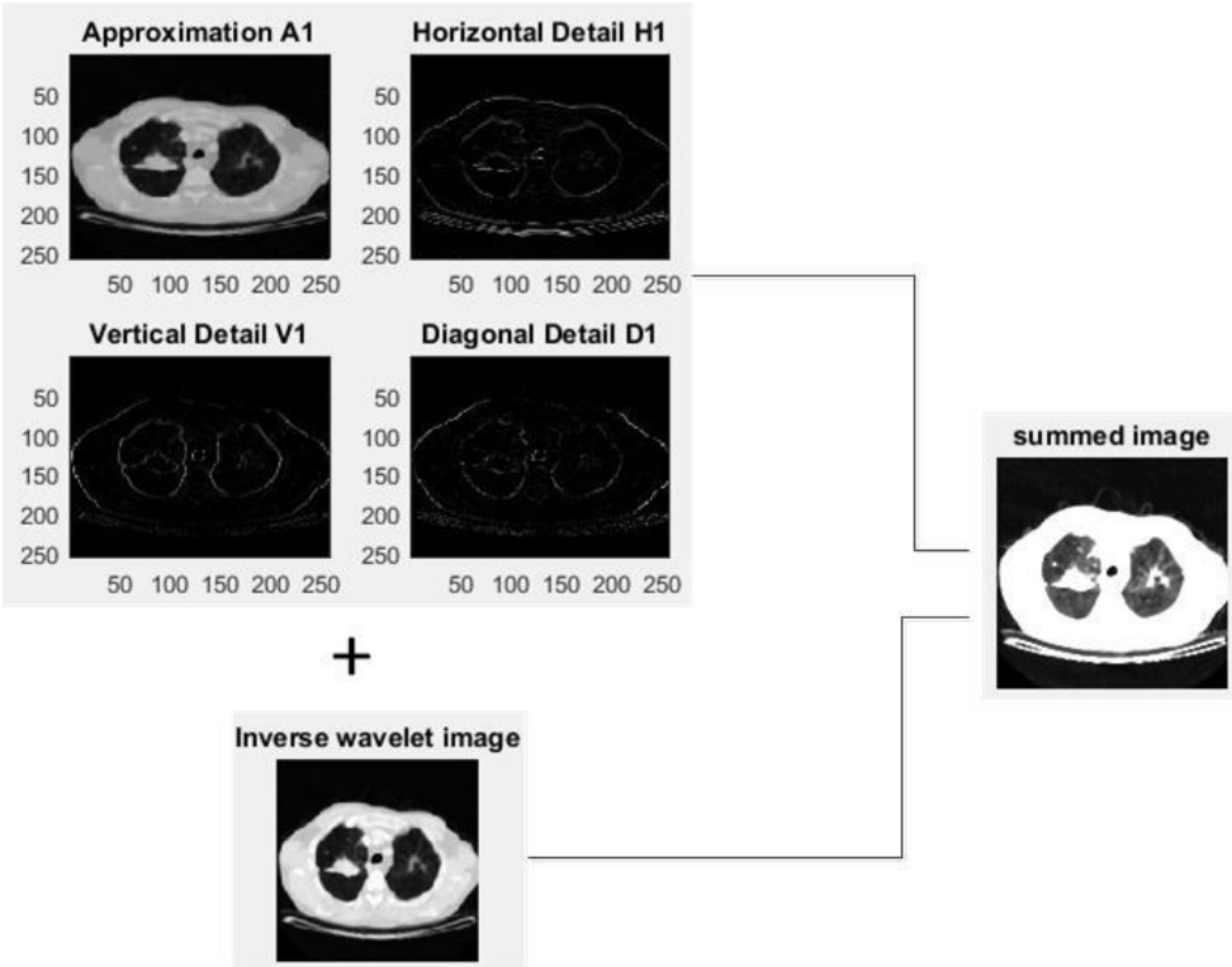


Figure 4.14: Summation of Haar wavelets and reconstructed image. The filter used here is the median filter

Figure 4.14 shows the addition operation of the 4 extracted wavelets with their corresponding inverse wavelet image. In Figure 4.14 the median filter is used. Figure 4.15 shows the same process but the filter that was used here is the Gaussian filter.

Figures 4.16, 4.17, and 4.18 also show the summation of the 4 extracted wavelets with their corresponding inverse wavelet image in addition to the result image. In Figure 4.16 the median filter and ‘db7’ wavelets are used. Figure 4.18 shows the same process but the ‘Bior 3.5 ‘wavelets are used here. In Figure 4.17, ‘Bior 3.7’ wavelets are used.

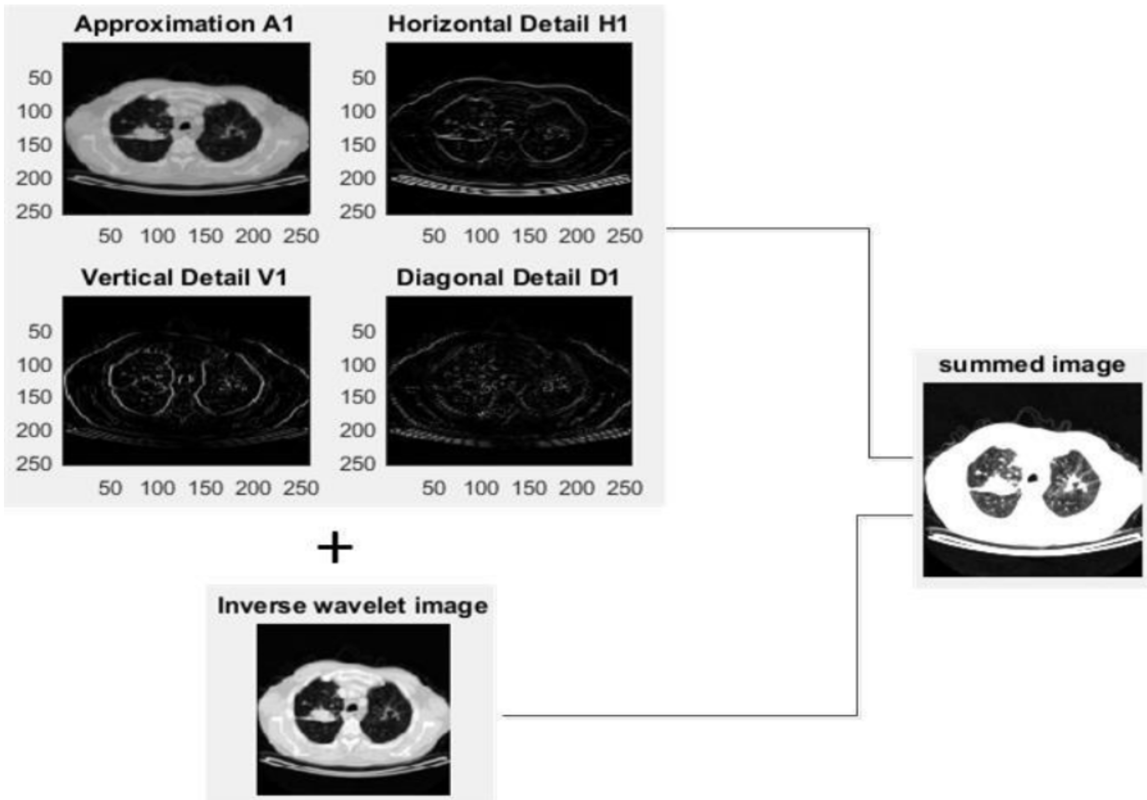


Figure 4.15: Summation of Haar wavelets and reconstructed image. The filter used here is the Gaussian filter

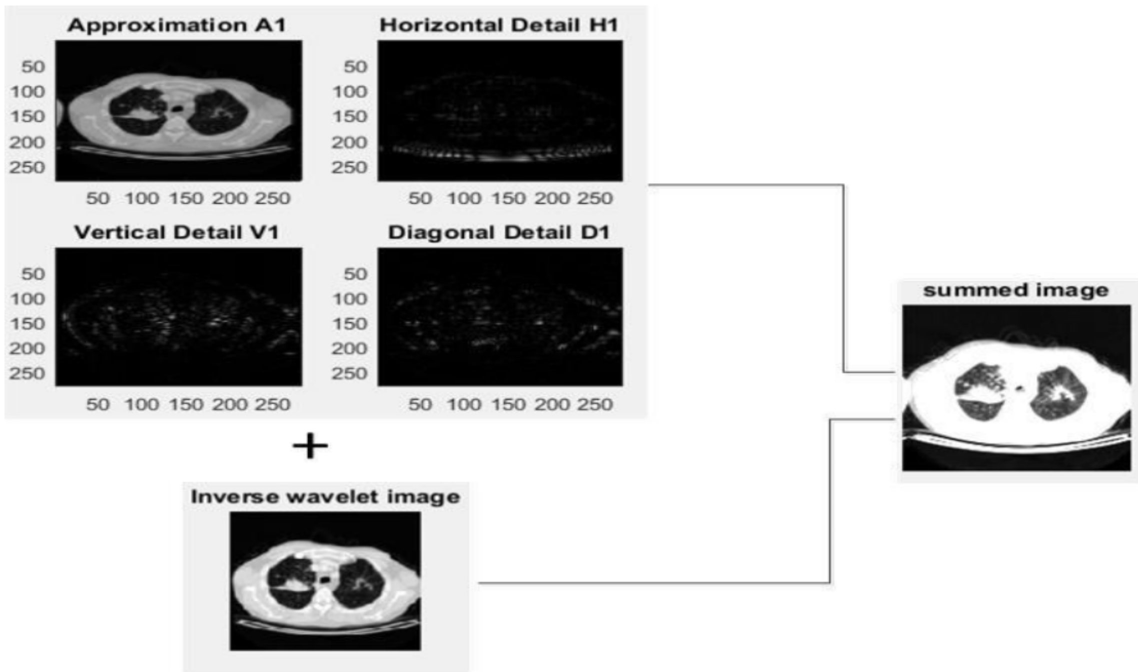


Figure 4.16: Summation of ‘db7’wavelets and reconstructed image. The filter used here is the median filter

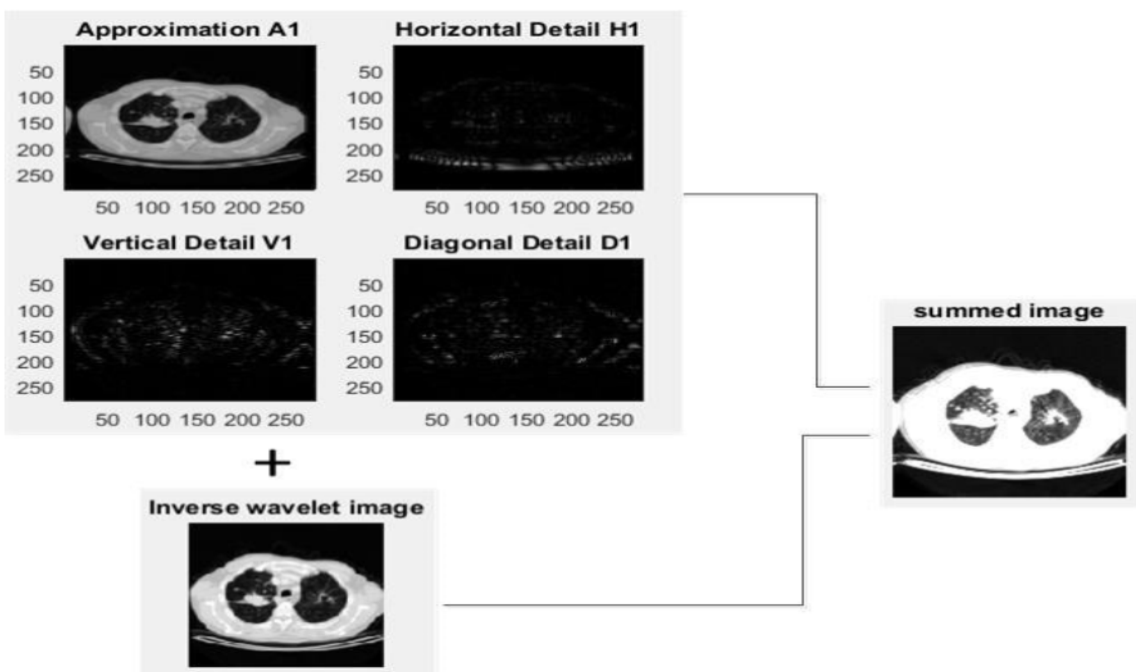


Figure 4.17: Summation of ‘Bior 3.7’ wavelets and reconstructed image. The filter used here is the median filter

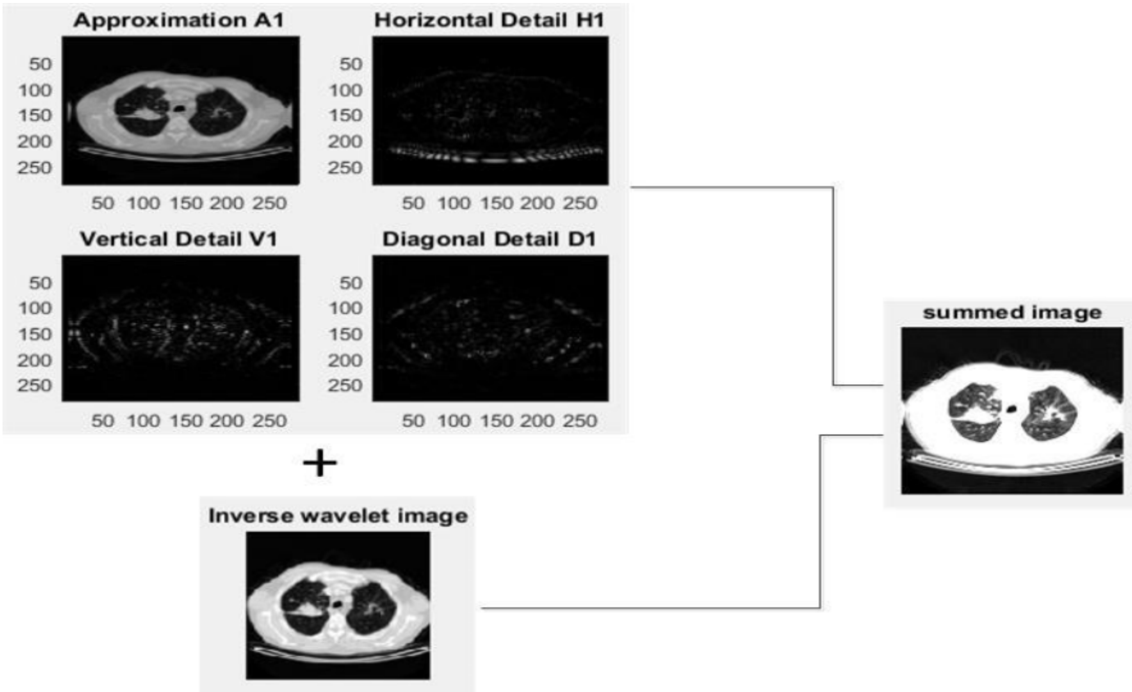


Figure 4.18: Summation of 'Bior 3.5' wavelets and reconstructed image. The filter used here is the median filter

4.1.5 Erosion

Morphology technique can be defined as a group of image processing operations that process images based on shapes. These morphological operations depend on applying an organizing component to an input image with a specific end goal to make a yield image of a similar size. In such operation, the value of every pixel in the yield image depends on an examination of the relating pixel in the input image 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 input image (Lim et al., 1990).

The structure component is a matrix comprises of 0's and 1's, the place the 1's are known as the neighbors. The value of every pixel in the yield image is set by a correlation of the comparing pixel in the information image with its neighbors. It has many shapes as per 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.

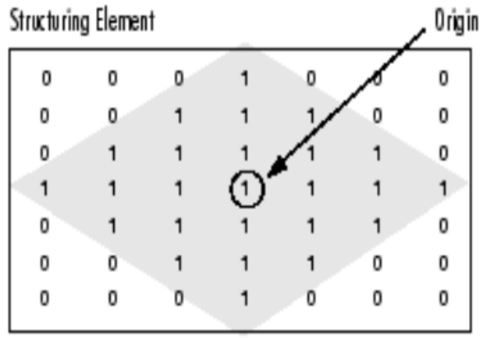


Figure 4.19: Structure element (Gonzalez & Woods, 2004)

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

Figure 4.20: Image erosion of the summed image

Figure 4.20 shows the summed image after applying erosion. It can be seen that the eroded image is much more effective because the different parts in the image are well defined and separated which allows easy and effective and thresholding in the next stage. It is remarkable that the pixels of the eroded image are increased and brightened in addition to that the small components, which are not needed, are almost removed.

4.1.6 Threshoding

Thresholding is the detachment of district of images into two areas. One district compares to the frontal area locale, in which it contains the articles that we are keen on. The other area is the foundation, compares to the unneeded items. This gives division of the image in view of the image distinctive powers and force discontinuities in the closer view and foundation locales. The contribution of this technique is generally a grayscale or shading image, while the yield is a double image speaking to the division. The dark pixels allude to foundation and white pixels allude to frontal area. The division is accomplished by a solitary parameter known as the force edge (Sezgin, 2004). This is set by examining the histogram of the image which speaks to the force disseminations of the image. Amid Thresholding, every pixel is contrasted with that edge value. On the off chance that the pixel value is more prominent than that edge, then this pixel is considered as frontal area pixel (white). In the event that the pixel value is lower than that limit value, then the pixel is considered as foundation pixel (black)(Gonzalez and Woods, 2002). Figure 4.21 illustrates a breast cancer image that undergoes Thresholding.

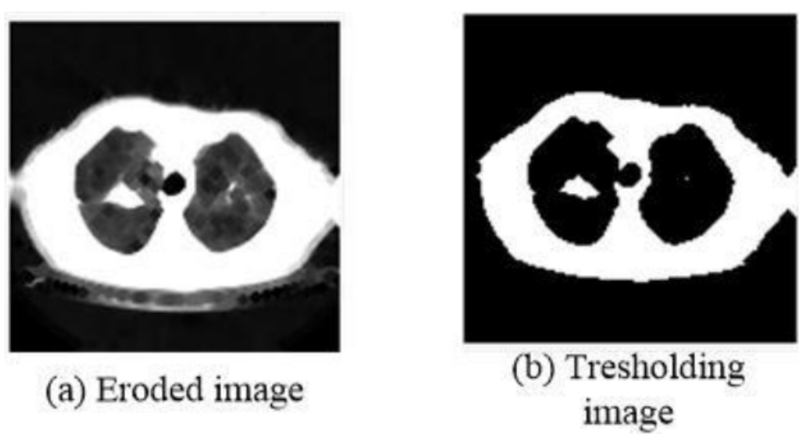


Figure 4.21: Image thresholding

4.1.7 Image subtraction

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 (Seçil et al., 2004).

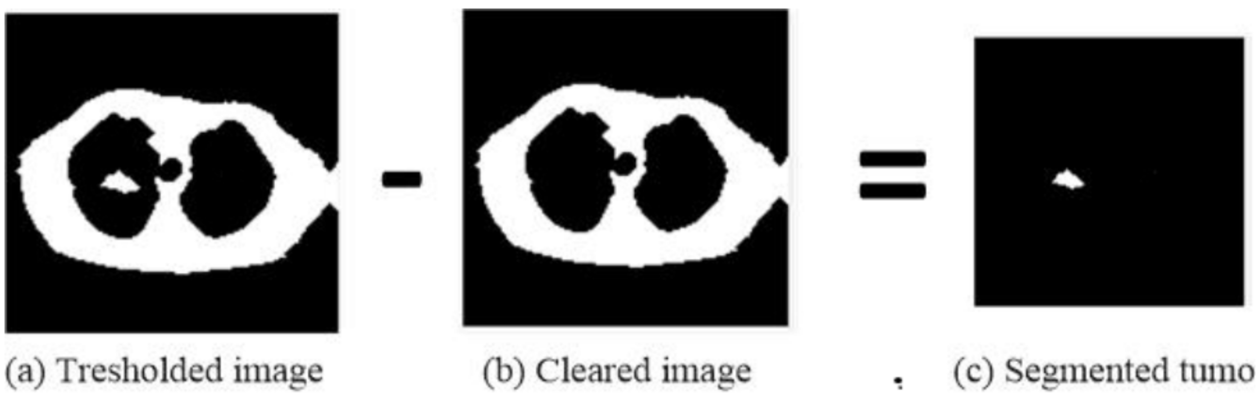


Figure 4.22: Image subtraction

4.2 Summary

This chapter presented a brief explanation of block diagram of system proposed. In addition, it provided explanation for each method was used in the study for example: filtering, discrete wavelet transform, image adjustment, erosion, thresholding techniques. Finally it presented a brief discussion about image subtract technique.

Median and Gaussian filters are both used in this work for comparison purposes. The comparison is which one of these two filters help better in denoising and separating the tumor from the other parts of the image. The one the does these tasks perfectly is found to lead to a better segmentation. The median filter was found to remove noise from images but it doesn't smooth the edges. Moreover, this filter doesn't perform well in separating the tumor from the other objects in the image. In contrast, the Gaussian filter was found to remove noise in addition to smooth edges because of its blurring effects which helps in segmenting each object in the images by separating them. This is achieved by blurring the image that helps in removing the small objects connected to the tumor. As a result, the good effects provided by the Gaussian filter helps in accurate segmentation of the tumor after processing it.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 System Performance

This thesis is to develop an image processing system for the segmentation of the lung tumor in CT images. Different versions of the same system approach were developed to eventually investigate the best one that results in the highest accuracy and efficiency in segmenting the lung tumor. The median and Gaussian filters were used along with different types of discrete wavelets transform. Changing the types of filters so in the wavelets type's yields to different accuracy and segmentation results. The developed system was tested on 70 images. Among them, 50 are lung images with tumor, and 20 are non-tumor images. The same images were used for testing the different versions of the developed system in order to investigate the effectiveness of each.

For each version of the developed system the accuracy of the tumor and non-tumor lungs were calculated. Then the total accuracy was calculated. The accuracy was defined as the number of the correctly segmented tumors divided by the total number of images.

$$ACC=P/N$$

Where P is the number correctly segmented images, and N is the total number of images.

Table 5.1: Gaussian filter and Haar wavelets

Dataset	**Filter type**	**Discrete Wavelets transform type**	**Correctly segmented images**	**Total Recognition**
Abnormal images (50)	Gaussian Filter	Haar wavelets	46/50	92%
Normal images (20)			20/20	100%
System	**96%**			

performance	

Table 5.2: Median filter and Haar wavelets

Dataset	Filter type	Discrete Wavelets transform type	Correctly segmented images	Total Recognition
Abnormal images (50)	Median Filter	Haar wavelets	39/50	78%
Normal images (20)			20/20	100%
System performance	**89%**			

Table 5.3: Gaussian filter and Biorthogonal 3.7 wavelets

Dataset	Filter type	Discrete Wavelets transform type	Correctly segmented images	Total Recognition
Abnormal images (50)	Gaussian Filter	Biorthogonal wavelets (Bior 3.7)	43/50	86%
Normal images (20)			20/20	100%
System performance	**93%**			

Table 5.4: Median filter and Biorthogonal 3.7 wavelets

Dataset	**Filter type**	**Discrete Wavelets transform type**	**Correctly segmented images**	**Total Recognition**
Abnormal images (50)	Median Filter	Biorthogonal wavelets (Bior 3.7)	44/50	88%
Normal images (20)			20/20	100%
System performance	**94%**			

Table 5.5: Median filter and Biorthogonal 3.5 wavelets

Dataset	**Filter type**	**Discrete Wavelets transform type**	**Correctly segmented images**	**Total Recognition**
Abnormal images (50)	Median Filter	Biorthogonal wavelets (Bior 3.5)	42/50	84%
Normal images (20)			20/20	100%
System performance	**92%**			

Table 5.6: Median filter and Db7 wavelets

Dataset	Filter type	Discrete Wavelets transform type	Correctly segmented images	Total Recognition
Abnormal images (50)	Median Filter	Db7 wavelets	38/50	76%
Normal images (20)			17/20	85%
System performance	**80.5%**			

Table 5.7: Median filter and Db4 wavelets

Dataset	Filter type	Discrete Wavelets transform type	Correctly segmented images	Total Recognition
Abnormal images (50)	Median Filter	Db4 wavelets	41/50	82%
Normal images (20)			18/20	90%
System performance	**91%**			

The tables above show the accuracies of the system developed. Table 5.1 shows the accuracy of the system when the Gaussian filters and Haar wavelets type is used. Table 5.2 shows the accuracy of the system when the Median filter and Haar wavelets type is used. The table 3 shows the Bior 3.7 wavelets along with the median filter. Table 5.4 shows the same wavelets type but within the Gaussian filter. In addition, the table 5.5 and 5.6 show the median filter and Gaussian filter with the Bior 3.5. The table 5.7 shows the use of median filter together with the Db7 wavelets.

The above tables show that the change of filters and also types of discrete wavelets transform has an effect on the accuracy of the segmentation of the tumor.

The table below representing image characteristic for the values of brightness and contrast also, the table contains abnormal image as well as normal image. In additional, the values were selected the minimum and maximum values which are obtained from system.

Table 5.8: Image characteristic

Database	Brightness	Contrast
Abnormal images(50)	0.0828 – 0.258	0.6549 - 1
Normal images(20)	0.1081 – 0.2309	0.851 - 1

5.2 Results Discussion

The developed system is mainly an algorithm combining different image processing techniques such as filtering, erosion, discrete wavelets transform, and thresholding. However, the main aim of this work is to investigate the effectiveness of different filters along with different types of discrete wavelets toward an accurate segmentation of a lung tumor in a CT image.

The experimental results of the developed system show that the use of Gaussian filter with the Haar wavelets is the best for such segmentation task. This is shows in table 5.1 where the accuracy is the highest 96%. It can be seen that the use of median filter with Haar wavelets lead to less effectiveness in segmenting the tumor where the accuracy is 89% shown in table 5.2. The table 5.3 shows the use of Gaussian filter along with the Biorthogonal wavelets (Bior 3.7). This table shows a 93% accuracy which is good but still less than the results shows in table 5.1 where Haar wavelets and Gaussian filter are used. The median filter was then used with the Biorthogonal wavelets (Bior 3.7), but the results were different here. The accuracy was 94% which is higher than the previous one where the Gaussian filter is used. This shows that Gaussian is not always good for getting higher accuracy. It depends on the type of wavelets transform used also.

A different type of Biorthogonal wavelets was used (Bior 3.5) in table 5.5 with the median filter and the accuracy was 92% which is less than the Bior 3.7 accuracy although the same filter was used.

Moreover, the Db7 wavelets type was also used to test the developed system in table 5.6. The median filter was used along with Db7 and the results were the least 80.5%. This is due to the weak extraction of the 4 wavelets from the image which allows to distortion of the image; leads to the removal or harshness of many important parts of the image including the tumor. This makes it hard to be segmented since there may be no tumor structure at all.

In contrast, the median filter was also used with the Db4 wavelets transform in table 5.7 and it showed good segmentation results of 91% which is better than the results of table 6 where the Db7 is used.

Overall, it can be drawn that the Haar wavelets are the most effective type of discrete wavelets transform to extract the best 4 wavelets that keep actual shape of the tumor and help in separating it from the other parts of the image. Thus, the results were always better when Haar wavelets type was used. Moreover, the type of used filters also plays an important role in getting better accuracy. Thus, the Gaussian filter showed a better effectiveness in segmenting the tumor when used with wavelets transform compared to the median filter.

In addition, the Db7 showed an ineffective and weak performance in segmenting the lung tumor when it is used with the median filter.

5.3 Results Comparison

Many researchers have been done for the segmentation of lung tumor. Some of them are based on some image processing techniques such as wavelets and edge detection and threshodling. Other are mainly based on artificial intelligence but for the same purpose which is to segment the tumor.

Some authors in (Orozco et al., 2015) presented a supervised extraction of the region of interest to eliminate the shape differences among CT images. The authors used the Daubechies db1, db2, and db4 wavelet transforms computed with one and two levels of decomposition. After that, the computed the 19 features from each wavelet sub-band. Then, the sub-band and attribute selection is performed. As a result, 11 features are selected and combined in pairs as inputs to the support vector machine (SVM), which is used to distinguish CT images containing cancerous nodules from those not containing nodules. Their system was able of getting a high accuracy rate of 92%.

Another work for the segmentation of lung tumor was proposed by (Sharma et al., 2011). Their work was based on different image processing techniques such as Erosion, Median Filter, Dilation, Outlining, and Lung Border Extraction. These techniques were applied to the CT scan image in order to detect the lung region. Then the segmentation algorithm is applied in order to detect the cancer nodules from the extracted lung image. After segmentation, rule based technique is applied to classify the cancer nodules. Finally, a set of diagnosis rules are generated from the extracted features. Their system was able of getting a high accuracy rate of 80%.

5.4 Summary

This chapter discussed result that obtained from the study; there were 7 tables in these chapters. The result obtained was by used two types of filters and different types of discrete wavelet transforms. The best result was fund 96% when system used Gaussian filter and haar wavelet transform, finally the performance of system proposed compared with other performance of two system proposed previously and it fund the system proposed better than other two system performance.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Conclusion

This thesis proposed method describes a method for the segmentation lung tumor in CT scan images Thus it can be concluded that the proposed system performs fine and is robust against anatomical variations of the lungs. The thesis is to develop a system based on different image processing techniques that were significantly used in order to help in identifying the tumor area and prepare it for segmentation purposes. As mentioned in previous chapters, the 4 wavelets coefficients were obtained using Haar wavelets transform which showed potential separation of the tumor and the other parts of image. The summation of the 4 wavelets coefficients images with the reconstructed image using inverse wavelets transform also shows a great result since it margins the tumor. The final technique used to segment the tumor is to apply two tresholds on the same image. One is a high threshold that keeps the tumor and lungs in an image. However, the second threshold is set automatically and it helps in elimination the tumor from the image. The final segmented tumor is the subtraction of the two tresholding images.

During the experiment of testing the developed system, different discrete wavelet transforms were used with two types of filtering. After which, the Haar and Gaussian filtering with 96% accuracy was found to be the best.

In conclusion it can be stated that the combination of Guassian filter along with the Haar discrete wavelets transform in addition to the other image processing techniques such as thresholding and image erosion showed an efficient and accurate algorithm for segmenting the lung tumor in CT medical images.

6.2 Future Work

The result of this thesis can be upgraded further by increasing the size of the study including additional images also; it can be used algorithm of thesis to segmentation tumor in other types of cancer such as skin cancer, brain cancer, breast cancer and so on. Future research should consider about classification of cancer by using variations methods such as artificial neural network (ANN) such as Backpropagation networks and deep learning algorithms such as Auto-encoder and Deep Belief networks. Future work can pursue to classification stage of lung cancer.

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APPENDIX

SOURCE CODES

```
clc
clear
close all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%Abnormal Images
%%%%%%%%%%%Guassain Filter and Haar wavelets
N=50;
for k = 1:N
myFolder = 'D:\THESIS\last matlab code\Database\Tumors';
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));
%   figure, imshow(img)

% pause
%*****************************************************************
m = imgaussfilt(img,0.8);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%***********************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'Haar');
A1 = upcoef2('a',cA1,'Haar',1);
H1 = upcoef2('h',cH1,'Haar',1);
V1 = upcoef2('v',cV1,'Haar',1);
D1 = upcoef2('d',cD1,'Haar',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
```

```
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'Haar');  %The idwt2 command performs a single-level two-
dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('D:\THESIS\last matlab code\Database\Tumors', 'LT',num2str(k),'.jpg'));

end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%Normal Images
clc
clear
close all

N=20;
for k = 1:N
myFolder = 'D:\THESIS\last matlab code\Database\No Tumor';
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));
%   figure, imshow(img)

% pause
%**************************************************************************
% m=medfilt2(img);
m = imgaussfilt(img,0.8);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%*********************************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'Haar');
A1 = upcoef2('a',cA1,'Haar',1);
H1 = upcoef2('h',cH1,'Haar',1);
V1 = upcoef2('v',cV1,'Haar',1);
D1 = upcoef2('d',cD1,'Haar',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
```

```
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'Haar');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('D:\THESIS\last matlab code\Database\Tumors', 'NLT',num2str(k),'.jpg'));

end
```

```
clc
clear
close
all%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%% Abnormal Images
%%%%%%%%%%%%Median Filter and Haar wavelets

N=50;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-Tumors';
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));
%   figure, imshow(img)

% pause
%**************************************************************
 m=medfilt2(img, [5 5]);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%********************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'Haar');
A1 = upcoef2('a',cA1,'Haar',1);
H1 = upcoef2('h',cH1,'Haar',1);
V1 = upcoef2('v',cV1,'Haar',1);
D1 = upcoef2('d',cD1,'Haar',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
```

```
% title('Diagonal Detail D1')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'Haar');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'LT',num2str(k),'.jpg'));

end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%Normal Images
clc
clear
close all

N=20;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-NonTumor';
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));
%   figure, imshow(img)

% pause
%****************************************************************
 m=medfilt2(img, [5 5]);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);

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

%**********************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'Haar');
A1 = upcoef2('a',cA1,'Haar',1);
H1 = upcoef2('h',cH1,'Haar',1);
V1 = upcoef2('v',cV1,'Haar',1);
D1 = upcoef2('d',cD1,'Haar',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
% pause
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'Haar');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E = entropy(w) ;
fprintf('entropy of normal image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of normal image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of normal image is %f \n', contrast)
 varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of normal image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'NLT',num2str(k),'.jpg'));

end
```

```
clc
clear
close all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Abnormal Images
%%%%%%%%%%%Guassain Filter and Biorthogonal wavelets

N=50;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-Tumors';
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));
%   figure, imshow(img)

% pause
%*******************************************************************
m = imgaussfilt(img,0.8);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%*************************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.5');
A1 = upcoef2('a',cA1,'bior 3.5',1);
H1 = upcoef2('h',cH1,'bior 3.5',1);
V1 = upcoef2('v',cV1,'bior 3.5',1);
D1 = upcoef2('d',cD1,'bior 3.5',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
```

```
% title('Diagonal Detail D1')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.5');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'LT',num2str(k),'.jpg'));

end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%Normal Images
clc
clear
close all

N=20;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-NonTumor';
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));
%   figure, imshow(img)

% pause
%****************************************************************
m = imgaussfilt(img,0.8);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%**********************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.5');
A1 = upcoef2('a',cA1,'bior 3.5',1);
H1 = upcoef2('h',cH1,'bior 3.5',1);
V1 = upcoef2('v',cV1,'bior 3.5',1);
D1 = upcoef2('d',cD1,'bior 3.5',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
% pause
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.5');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E = entropy(w) ;
fprintf('entropy of normal image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of normal image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of normal image is %f \n', contrast)
 varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of normal image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'NLT',num2str(k),'.jpg'));

end
```

```
clc
clear
close all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Abnormal Images
 %%%%%%%%%%%Median Filter and Biothogonal wavelets

N=50;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-Tumors';
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));
%   figure, imshow(img)

% pause
%*************************************************************
 m=medfilt2(img);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%*******************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.5');
A1 = upcoef2('a',cA1,'bior 3.5',1);
H1 = upcoef2('h',cH1,'bior 3.5',1);
V1 = upcoef2('v',cV1,'bior 3.5',1);
D1 = upcoef2('d',cD1,'bior 3.5',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
```

```
% title('Diagonal Detail D1')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.5');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause

bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'LT',num2str(k),'.jpg'));

end
```

```
%%%%%%%%%%%%%%%%%%%%%%%Normal Images

clc
clear
close all

N=20;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-NonTumor';
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));
%   figure, imshow(img)

% pause
%******************************************************************
 m=medfilt2(img, [5 5]);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%************************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.5');
A1 = upcoef2('a',cA1,'bior 3.5',1);
H1 = upcoef2('h',cH1,'bior 3.5',1);
V1 = upcoef2('v',cV1,'bior 3.5',1);
D1 = upcoef2('d',cD1,'bior 3.5',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
```

```
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.5');  %The idwt2 command performs a single-level two-
dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E = entropy(w) ;
fprintf('entropy of normal image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of normal image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of normal image is %f \n', contrast)
 varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of normal image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'NLT',num2str(k),'.jpg'));

end
```

```
clc
clear
close all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Abnormal Images
%%%%%%%%%%%%%%Guassain Filter and Biorthogonal wavelets
N=50;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-Tumors';
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));
%   figure, imshow(img)

% pause
%***************************************************************
m = imgaussfilt(img,0.8);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%*******************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.7');
A1 = upcoef2('a',cA1,'bior 3.7',1);
H1 = upcoef2('h',cH1,'bior 3.7',1);
V1 = upcoef2('v',cV1,'bior 3.7',1);
D1 = upcoef2('d',cD1,'bior 3.7',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
```

```
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.7');  %The idwt2 command performs a single-level two-
dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'LT',num2str(k),'.jpg'));

end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%Normal Images

clc
clear
close all

N=20;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-NonTumor';
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));
%   figure, imshow(img)

% pause
%***************************************************************
m = imgaussfilt(img,0.8);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%*********************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.7');
A1 = upcoef2('a',cA1,'bior 3.7',1);
H1 = upcoef2('h',cH1,'bior 3.7',1);
V1 = upcoef2('v',cV1,'bior 3.7',1);
D1 = upcoef2('d',cD1,'bior 3.7',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
```

```
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.7');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E = entropy(w) ;
fprintf('entropy of normal image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of normal image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of normal image is %f \n', contrast)
 varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of normal image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'NLT',num2str(k),'.jpg'));

end
```

```
clc
clear
close all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Abnormal Images
%%%%%%%%%%%Median Filter and Biothogonal wavelets

N=50;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-Tumors';
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));
%   figure, imshow(img)

% pause
%************************************************************
 m=medfilt2(img);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%******************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.7');
A1 = upcoef2('a',cA1,'bior 3.7',1);
H1 = upcoef2('h',cH1,'bior 3.7',1);
V1 = upcoef2('v',cV1,'bior 3.7',1);
D1 = upcoef2('d',cD1,'bior 3.7',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
```

```
% title('Diagonal Detail D1')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.7');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause

bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'LT',num2str(k),'.jpg'));

end
```

```
 %%%%%%%%%%%%%%%%%%%%%%%Normal Images

clc
clear
close all

N=20;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-NonTumor';
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));
%   figure, imshow(img)

% pause
%******************************************************************
 m=medfilt2(img, [5 5]);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%************************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'bior 3.7');
A1 = upcoef2('a',cA1,'bior 3.7',1);
H1 = upcoef2('h',cH1,'bior 3.7',1);
V1 = upcoef2('v',cV1,'bior 3.7',1);
D1 = upcoef2('d',cD1,'bior 3.7',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
```

```
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior 3.7');  %The idwt2 command performs a single-level two-
dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E = entropy(w) ;
fprintf('entropy of normal image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of normal image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of normal image is %f \n', contrast)
 varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of normal image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'NLT',num2str(k),'.jpg'));

end
```

```
clc
clear
close all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Abnormal Images
%%%%%%%%%%%Median Filter and db7

N=50;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-Tumors';
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));
%   figure, imshow(img)

% pause
%*****************************************************************
 m=medfilt2(img);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%***********************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'db7');
A1 = upcoef2('a',cA1,'db7',1);
H1 = upcoef2('h',cH1,'db7',1);
V1 = upcoef2('v',cV1,'db7',1);
D1 = upcoef2('d',cD1,'db7',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
```

```
% title('Diagonal Detail D1')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'db7');  %The idwt2 command performs a single-level two-dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause

bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'LT',num2str(k),'.jpg'));

end
```

```
%%%%%%%%%%%%%%%%%%%%%%%Normal Images
clc
clear
close all

N=20;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-NonTumor';
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));
%   figure, imshow(img)

% pause
%*****************************************************************
 m=medfilt2(img, [5 5]);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%***********************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'db7');
A1 = upcoef2('a',cA1,'db7',1);
H1 = upcoef2('h',cH1,'db7',1);
V1 = upcoef2('v',cV1,'db7',1);
D1 = upcoef2('d',cD1,'db7',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
% pause
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'db7');  %The idwt2 command performs a single-level two-
dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E = entropy(w) ;
fprintf('entropy of normal image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of normal image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of normal image is %f \n', contrast)
 varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of normal image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'NLT',num2str(k),'.jpg'));

end
```

```
clc
clear
close all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Abnormal Images
%%%%%%%%%%%Median Filter and db4

N=50;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-Tumors';
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));
%   figure, imshow(img)

% pause
%******************************************************************
 m=medfilt2(img);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);


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

%************************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'db4');
A1 = upcoef2('a',cA1,'db4',1);
H1 = upcoef2('h',cH1,'db4',1);
V1 = upcoef2('v',cV1,'db4',1);
D1 = upcoef2('d',cD1,'db4',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
```

```
% title('Diagonal Detail D1')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'db4');  %The idwt2 command performs a single-level two-
dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause

bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E=entropy(w);
fprintf('entropy of tumor image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of tumor image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of tumor image is %f \n', contrast)
varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of tumor image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'LT',num2str(k),'.jpg'));

end
```

```
%%%%%%%%%%%%%%%%%%%%%%%Normal Images
clc
clear
close all

N=20;
for k = 1:N
myFolder = 'C:\Users\TOSHIBA\Documents\Lung-thesis Matlab code\Lung-NonTumor';
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));
%   figure, imshow(img)

% pause
%************************************************************
 m=medfilt2(img, [5 5]);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%background forming

I3 = imadjust(m);
%I3 = imadjust(I2);

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

%*******************************************************************
 d1=I3;
[cA1,cH1,cV1,cD1] = dwt2(d1,'db4');
A1 = upcoef2('a',cA1,'db4',1);
H1 = upcoef2('h',cH1,'db4',1);
V1 = upcoef2('v',cV1,'db4',1);
D1 = upcoef2('d',cD1,'db4',1);

% colormap(map);
% subplot(2,2,1); image(wcodemat(A1,192));
% title('Approximation A1')
% subplot(2,2,2); image(wcodemat(H1,192));
% title('Horizontal Detail H1')
% subplot(2,2,3); image(wcodemat(V1,192));
% title('Vertical Detail V1')
% subplot(2,2,4); image(wcodemat(D1,192));
% title('Diagonal Detail D1')
% pause
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%
Xsyn = idwt2(cA1,cH1,cV1,cD1,'db4');  %The idwt2 command performs a single-level two-
dimensional wavelet reconstruction with
%respect to either a particular wavelet
% imshow(Xsyn)
% pause
Xsyn=imresize(Xsyn,(size(cA1)));
% imshow(Xsyn) , title('reconstructed image')
% pause
q=Xsyn+cA1+cH1+cV1+cD1;
% figure, imshow(q), title('summed image')
% pause
se = strel('diamond',2);
b = imerode(q,se);
q=b;
level = 1;
bw = im2bw(q,level);
% figure, imshow(bw),title('treshold image1');
% pause
;
bw2 = bwareaopen(bw, 200);
% figure, imshow(bw2),title('treshold image2');
% pause
w=bw-bw2;
% imshow(w), title('segmented Tumor')
% pause
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%summantion of images wavelets
E = entropy(w) ;
fprintf('entropy of normal image is %f \n', E)
brightness = mean2(w);
fprintf('Brightness of normal image is %f \n', brightness)
contrast = max(w(:)) - min(w(:));
fprintf('contrast of normal image is %f \n', contrast)
 varianceofIntenisty =  mean(w(:));
fprintf('Tintenisty  of normal image is %f \n',varianceofIntenisty)
imwrite(w,strcat('C:\Users\TOSHIBA\Documents\lgtProj', 'NLT',num2str(k),'.jpg'));

end
```