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**Early Diagnosis of Endometrium Cancer Using Image Processing
Techniques**

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﴿يَرْفَعُ اللَّهُ الَّذِينَ آمَنُوا مِنْكُمْ وَالَّذِينَ أَوْتُوا الْعِلْمَ دَرَجَاتٍ﴾

الصَّدَقَةُ
الْعَظِيمَ

"سورة المجادلة الآية 11"

Dedication

This thesis is dedicated to my father and the soul of my mother, my husband, and my children, the five pillars of my life. Without you, my life would fall apart. I am not sure where life's path will take me, but walking alongside you has given me strength of character. Father, you mean the world to me; I could not do it without your love, support, and appreciation. I will never forget how you always told me to "aim for the stars," I think I have found my first one. Mother, you are the only person on the planet who brings me happiness and unconditional love. You have given me so much; I appreciate your belief in me and your generosity.

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I would like to forward my special thanks to the National Cancer Institute -Sabratha. I would like to extend my appreciation and thanks to the radiologist,

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Abstract

According to GLOBOCAN 2020 estimates of cancer incidence and mortality, Endometrium cancer is the second leading cause of mortality in women after Breast cancer. However, it is also one of the treatable cancers if detected early. Radiologists read uterine ultrasound images manually, which most of the time, is a relatively difficult and confusing procedure that causes them to make mistakes. The focus of this research was to look at the possibilities of detecting and classifying Endometrium cancer using image-processing techniques. The study used filtering techniques to enhance the image enhancement process and used fuzzy logic to enhance edge detection of the field of interest. To improve the image detection process, the quality of the input ultrasound image was first improved during the pre-processing stage by removing noise using a median filter. Edges were then detected using fuzzy logic. Two techniques were then used to obtain the region of interest for the ultrasound image of the uterus, which is the endometrium region. The first technique is k-means, and the second is automatic thresholding. The researcher used two methods to evaluate the experiment. The first one involved measuring the quality of the resulting image using quality assessment equations which are Peak Signal to Noise, Mean square Errors, and Ratio Mean Absolute Errors. The second method involved conducting a questionnaire to evaluate the perceived quality of the processed image after three stages: edge detection, applying the k-means technique, and using automatic thresholding. The researcher also sought the expertise of doctors from the Department of Obstetrics and Gynecology at the National Cancer Institute in Sabratha to determine the best image that clearly shows the uterine lining. The results of the automatic thresholding technique were well-received by nine out of ten doctors. Based on this, recommendations were made to improve the experiment. These included using a large database to test the success of this experiment and utilizing other features that doctors rely on to detect cancer, such as the thickness of the uterine lining and the widening of the uterine cavity. This would aid in early detection and ultimately save patients' lives.

الملخص باللغة العربية

وفقاً لتقديرات GLOBOCAN لعام 2020 بشأن الإصابة بالسرطان والوفيات الناجمة عنه، يعتبر سرطان بطانة الرحم ثالثي أكثر أنواع السرطان شيوعاً بين النساء بعد سرطان الثدي. ومع ذلك، فهو أيضاً أحد أنواع السرطان القابلة للعلاج إذا تم اكتشافها مبكراً. يقوم أخصائيو الأشعة بقراءة صور الموجات فوق الصوتية للرحم يدوياً، وهو إجراء صعب نسبياً ومرتكب في معظم الأوقات، مما يؤدي إلى ارتکابهم الأخطاء. ركز هذا البحث على دراسة إمكانية اكتشاف وتصنيف سرطان بطانة الرحم باستخدام تقنيات معالجة الصور.

استخدمت الدراسة تقنيات التصفية لتحسين عملية تحسين الصورة واستخدمت المنطق الضبابي لتحسين اكتشاف حواف منطقة الاهتمام.

لتحسين عملية اكتشاف الصور، تم تحسين جوده صوره الموجات فوق الصوتية المدخله اولاً اثناء مرحله المعالجه المسبقه عن طريق ازاله التشويش باستخدام المرشح الوسيط . ومن تم اكتشاف الحواف باستخدام المنطق الضبابي. وبعد ذلك يتم استخدام تقنيتان الاولى k-means والثانية العتبة التلقائيه للحصول على منطقه الاهتمام لصوره الموجات فوق الصوتيه للرحم وهي منطقه بطانه الرحم.

استخدم الباحث طريقتين لتقدير التجربة. تضمنت الطريقة الأولى قياس جودة الصورة الناتجة باستخدام معدلات تقييم الجودة وهي نسبة الإشارة إلى الضوضاء ونسبة الخطأ المتوسط المربع ونسبة المتوسط المطلق للخطأ. تضمنت الطريقة الثانية إجراء استبيان لتقدير الجودة المتصرورة للصورة المعالجة بعد ثلاث مراحل: اكتشاف الحواف، وتطبيق تقنية k-means واستخدام العتبة التلقائية. كما طلب الباحث من الأطباء المتخصصين في قسم التوليد وأمراض النساء في المعهد الوطني للسرطان في صبراته تحديد أفضل صورة تظهر بطانة الرحم بشكل واضح. تم استقبال نتائج تقنية العتبة التلقائية بشكل جيد من قبل تسعه من أصل عشرة أطباء والعشر ذكر بان الصوره الناتجه من تقنيه k-means السابقة لتقدير العتبه التلقائيه كافية وواضحة .

وبناءً على ذلك، تم تقديم توصيات لتحسين التجربة. تضمنت هذه التوصيات استخدام قاعدة بيانات كبيرة لاختبار نجاح هذه التجربة والاستفادة من الميزات الأخرى التي يعتمد عليها الأطباء لاكتشاف السرطان، مثل سمك بطانة الرحم واتساع تجويف الرحم. وهذا من شأنه المساعدة في الكشف المبكر وإنقاذ حياة المرضى في النهاية

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List of Abbreviations

Adaptive histogram equalization	AHE
Computer Aided Diagnostic	CAD
Contrast limited adaptive histogram equalization	CLARE
Computerized tomography	CT
Dice similarity coefficient	DSC
Global histogram equalization	GHE
Harsdorf distance	HD
Histogram equalization	HE
Hormone replacement therapy	HRT
Hereditary nonpolyposis colorectal cancer	HNPCC
Local histogram equalization	LHE
Mean Absolute Error	MAE
Matrix LABoratory	MATLAB
Magnetic resonance imaging	MRI
Region of interest	ROI
Mean square error	MSE
National Cancer Institute	NCI
Probability density function	PDF
Peak signal-to-noise ratio	PSNR
Speckle-reducing anisotropic diffusion	SRAD
Transvaginal ultrasonography	TVUS
Ultrasound	US
World Health Organization	WHO

CHAPTER ONE:

Introduction

1.1 Background

Image processing is an important field in modern science and engineering. The processing of digital images can be divided into various classes including image enhancement, image restoration, and image analysis [1]. Medical image processing has grown dramatically

and becoming an interdisciplinary research field that draws expertise from applied mathematics, computer sciences, engineering, telecommunication, statistics, physics, biology, and medicine. Medical imaging is a technique and procedure that provides visual representations of a body's internal organs or tissues for clinical study and medical intervention [2]. Therefore, it is widely applied to support physicians in establishing a diagnosis. Studying medical images depends mainly on the visual interpretation of the radiologists. However, this consumes time, besides; it is usually subjective as it varies according to the experience of the radiologists. Due to the aforementioned considerations, using image processing techniques become a necessity, to facilitate analyzing and processing different medical image modalities like Magnetic resonance imaging(MRI), Computerized tomography (CT), and ultrasound.

Cancer is a disease in which the body's cells proliferate uncontrollably. Cancer is always named after the part of the body where it first appears, even if it later spreads to other parts of the body. Uterine cancer occurs when cancer begins in the uterus. The uterus is a pear-shaped organ located in a woman's pelvic cavity (the area below the stomach and in between the hip bones) [3]. Uterine cancer also named endometrium cancer, which is one of the most common malignant gynecological cancers that prove to be a serious threat to women's health. It is, however, largely preventable, and the treatment is dependent on the severity of the condition and the availability of local resources at the time of diagnosis [1-4]. This research describes an effort to apply image-processing techniques to uterine ultrasound images in terms of improving their quality and helping radiologists in both the screening and diagnosis phases, for detecting Endometrial Cancer [4]. In women with possible gynecologic problems, ultrasound is often one of the first tests used to examine the uterus, ovaries, and fallopian tubes [5]. Ultrasound uses sound waves to take images of the inside of the body. Image processing techniques, especially image enhancement techniques,

have been widely used to improve ultrasound image quality. Algorithms such as histogram equalization, median filters, gamma correction, Gaussian filters, and morphological filters have been widely used. In this thesis, the acquired ultrasound images as can be seen in chapter four are filtered using a median filter and then segmented to obtain Region of Interest (ROI) [6].

1.2 Thesis motivation

The use of imaging technologies in the health care field will be critical for facilitating diagnostic tasks and enhancing the efficiency of medical professionals. In endometrium cancer, patients in the early stages have a 91% 5-year survival chance. By contrast, patients in advanced stages have only a 20% survival chance [7]. Therefore, early diagnosis of endometrial cancer is very important to reduce the mortality rate of women, hence developing a high-performance image processing system for uterine ultrasound image segmentation, detection, and classification of endometrium cancer is very important. It will help radiologists as well as physicians to perform the best treatment because at the early stage, the cancer is small and treatable. Our motivation is to achieve the aforementioned requirements for a good uterine ultrasound image segmentation.

1.3 Problem statements

Since the actual cause of endometrium cancer is unknown, the methods of prevention are not yet established. Recognizing the signs of endometrium cancer at an early stage would play a significant role in motivating doctors to apply accurate treatment procedures and save women's lives. It has been reported that ultrasound images are the most popular and simple method of detecting endometrium cancer in its early stages. Radiologists can predict the accuracy of an ultrasound image with greater than 90% accuracy. Nonetheless, radiologists may miss 10% to 15% of endometrium cancer cases [8-9]. Therefore, accurate diagnosis of endometrium cancer is critical for successful therapy. However, the ultrasound image itself has some limitations, such as low resolution, low contrast, speckle noise, and blurry edges between various organs, so it is more difficult for a radiologist to read and interpret an ultrasound image. In addition, ultrasound diagnosis is heavily dependent on a doctor's personal experience. This reality is compounded by the fact that reading an ultrasound image is tedious, hard work, which can lead to fatigue and burn out, which, in turn, can ultimately lead to an increased rate of misdiagnosis and missed diagnosis.

Therefore, using digital image processing techniques to deal with ultrasound imaging and applying these techniques to uterine cancer detection is of critical importance. In general, a good segmentation technique should give accurate results in a reasonable time.

1.4 Objectives

The proposed framework of this thesis is made up of several image-processing techniques. Those techniques aim to reduce errors in the interpretation of uterine ultrasound images. Which can be used to help doctors to establish the right diagnosis.

1.4.1 General objective

The general objective of this study is to design endometrium cancer detection using image-processing techniques to assist radiologists and physicians in their treatment and diagnosis. This study will formulate the following general objectives:

- To review some important previous related works on endometrium cancer detection and classification for select suitable techniques.
- To study symptoms and important features of endometrial cancer that radiologists are looking for detection of uterine ultrasound images.

1.4.2 Specific objectives

This study formulates the following specific objectives.

- To improve the quality of uterine ultrasound images by denoising based on image processing filters.
- To select and use suitable methods for image preprocessing, segmentation, feature extraction, and classification.
- To differentiate between normal and abnormal endometrial shape.
- To implement the proposed techniques using MATLAB tools.

1.5 Methodology

This study was experimental research, to improve image quality by removing noise using image processing filters. The purpose was also to select the appropriate methods for image segmentation and feature extraction. This proposed approach was implemented using the Matlab toolbox to test the algorithm and obtain results. The final shape of the uterine lining was extracted, and a questionnaire was conducted

with ten doctors. The results showed that the automatic thresholding method was preferred by the doctors.

The researcher in this section will explain the research strategy, research method, research approach, data collection, data analysis, ethical considerations, and research limitations.

Research strategy

The research strategy is an overall plan for conducting a research study, the flow diagram in Figure 1.1 shows the strategy and actions taken to achieve this thesis objective until reaches its conclusion point.

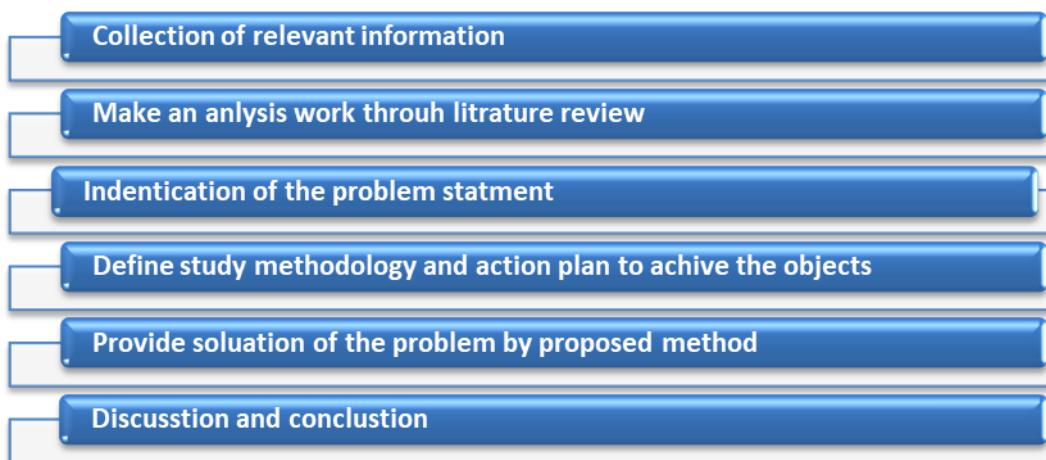


Figure 1.1 Representation of research plan and actions

1 Data Collection

Both descriptive and experimental methods are used in this study. The researcher used books, magazines, research papers, articles, theses, and the internet for data collection. All of the research material gathered has been organized for later analysis. The researcher discussed the topic and material that was collected with the supervisor

2 Literature review

To accomplish the objectives of this study, literature on the current development of image analysis related to endometrium cancer detection and classification was reviewed. Different image analysis techniques and tools were used on endometrium cancer. In addition, variety and important identifications were

selected for analysis. These image analysis techniques were selected based on the performance they had on the current related works.

3-Identification of the problem

The results of the analysis and discussion led to the formulation of a problem statement.

4-Proposed method to solve the problem

The following steps are to find a suitable solution for the identified problem statement. Therefore, a proposed work produces better and more efficient results.

5-Implementation of the proposed method

For the implementation of the proposed method, this thesis used the Matlab toolbox to test the algorithm and obtain results.

6-Discussion and conclusion

The researcher conducted a final brief discussion of the entire study and described its recommendations in this step. The researcher also discussed the efficiency and improved performance of the proposed work. For future work researchers, future research was mentioned.

For the experimentation of the proposed detection and classification model, some tools and application development environments are required for image processing, image analysis, and classification. Hence, MATLAB R2021a on the windows platform is used for image processing and analysis of uterine ultrasound images.

The study has the following limitation:

1-All materials for this research were between the duration of 2020 to 2022.

2-Limited number of images was used for the experiment.

1.6 Layout of the thesis

The remaining chapters of this thesis describe the works undertaken in the study.

- **Chapter 1:** In this chapter background of the research, research motivation, objectives, and the structure of the thesis were presented. In addition, the introduction of the thesis, aims, and significance of the thesis are discussed.
- **Chapter 2:** This chapter provides a general overview of the types and characteristics of endometrial cancer. It also reviews related research works that have been conducted in the field of medical image processing.

- **Chapter 3:** The researcher was given a brief overview of spatial domain filters used for image restoration in this chapter. Image edge enhancement and, image segmentation were also discussed.
- **Chapter 4:** Describe the methodology and implementation for a solved problem which was stated in chapter one. The simulation program for both noise removal filters and edge enhancement, image segmentation was discussed.
- **Chapter 5:** Investigate the findings and results which was experimented with in chapter 4, for each type of image filtering technique, edge detection, and image segmentation
- **Chapter 6:** The chapter, concluded the thesis report. This also includes recommendations and future research based on the findings of this thesis.

CHAPTER TWO: THEORETICAL BACKGROUND AND RELATED WORKS

This chapter aims to describe the theories leading to the detection of uterine abnormality. It is divided into two parts, part one is the theoretical background which aims to represent the importance of gynecology cancer studies and gives some essential information on the uterine anatomical structure and diseases, demonstrates different kinds of endometrial cancer,^r and early detection of this cancer which aid to effective treatment of the disease. The related work in part two will cover the fundamentals of image processing methods relating: to ultrasound image filtering, image edge enhancement, and segmentation. To perform the reviews, books, journals, websites, and internet resources were used to learn more about gynecological cancers, medical imaging,^g, and image processing techniques.

2.1 Gynecological cancers

Endometrium cancer is typically a fatal disease with high mortality [4], unlike the experience of the Western world where endometrial cancer is considerably treatable and with lower mortality. Endometrium cancer is a heterogeneous disease, that contains numerous distinct entities that have different biological features and clinical behavior including certain histological types. It can be categorized in several methods, including: based on its clinical features, its expression of tumor markers, and its histology type [10-11].

2.1.1 Anatomy of the pelvis and reproductive organs

The women's reproductive system is made up of external and internal organs [12]. The external organs lie in an area called the [vulva](#), and they include the labia, the [clitoris](#), and the [vaginal](#) opening. The internal reproductive organs can be found within the pelvic cavity, and they include the ovaries, which produce the called oocytes, as well as hormones such as estrogen and progesterone; the [uterine tubes](#), which carry the fertilized oocyte to the uterine cavity; the uterus, which houses the growing fetus during pregnancy; and the vagina, which is involved both in intercourse and fetal delivery, the uterine tubes, which carry the fertilized oocyte to the uterine cavity; the uterus, which houses the growing fetus during pregnancy; and the vagina, The normal anatomy of the pelvis and reproductive organs was shown in the figures below Figures 2.1. [13].

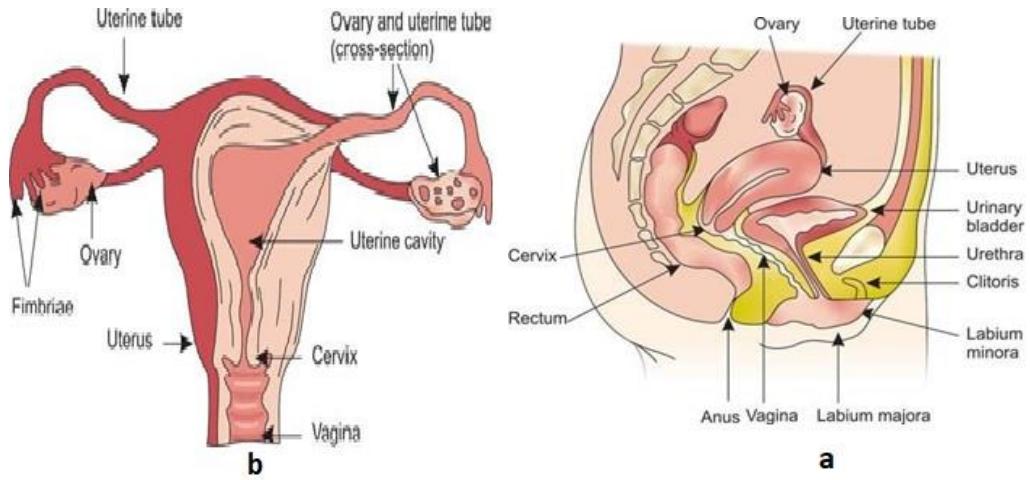


Figure (2.1) Female reproductive organs(a)The female pelvis
(b)Expanded view of the female reproductive organs

2.1.2 Uterine cancer

Uterine cancer, also known as endometrial cancer arising from the innermost layer of the uterus, the endometrium, is called endometrial carcinoma. endometrial carcinoma is the most common type of gynecological cancer in females in developed countries and, if left without treatment, has high morbidity and mortality rates. To reduce the high morbidity and mortality associated with this condition, it must be promptly diagnosed and treated at the right time. The endometrium, which lines the uterus and womb, is where the majority of uterine cancers develop. In these cases, the term "endometrial cancer" is frequently used [14].

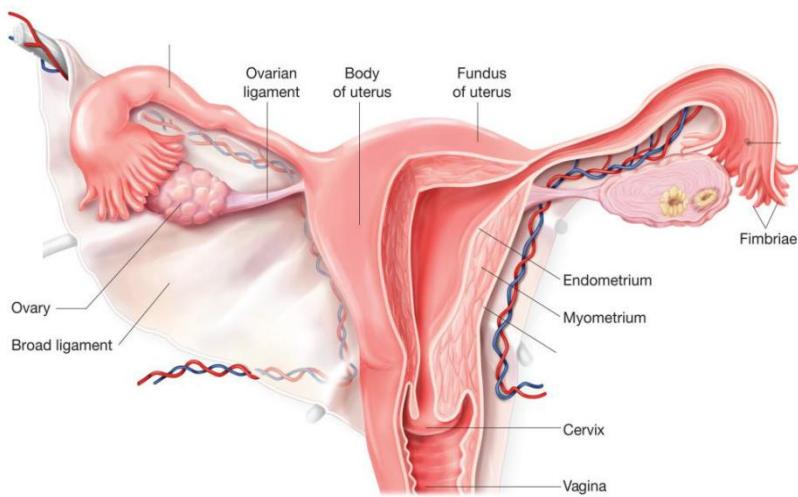


Figure (2.2) Uterine anatomy

2.1.3 Endometrium Cancer Epidemiology

Endometrial carcinoma is among the more common (the fourth most common) cancers in women in developed countries. Every year around 570,000 females develop uterine cancer world-wide alone, out of which more than 90% are of endometrial origin. It is commonly diagnosed in the seventh decade, with the mean age being 61 years [15]. In Africa, where endometrium cancer may often present at an earlier age of the female and can progress more aggressively, little is known about pathways and triggers for females to take action based on their recognition of their symptoms. Diagnostic delays of 3-6 months are associated with advanced-stage endometrium cancer, where treatment is most ineffective, and while system-related barriers to care account for a portion of that delay in access, women's attitudes and lack of awareness of endometrium cancer symptoms also account for a stalled initiation of action and lower survival rates. Detection and treatment of cancer at an early stage improves the prospects for long-term survival [16].

2.1.4 Symptoms of uterine cancer

The most common symptoms of uterine cancer are abnormal vaginal bleeding, especially in women who have stopped having periods (post-menopausal women) [17].

Abnormal bleeding can be:

- Vaginal bleeding after the menopause.
- Bleeding that is unusually heavy or happens between periods.
- Vaginal discharge, this can range from pink and watery to dark and foul smelling.

Because of postmenopausal or irregular vaginal bleeding, 9 out of 10 uterine cancers (90 percent) are detected. This is why Uterine cancer is frequently detected at an early stage.

2.1.5 Risk factors of uterine cancer

The following factors appear to increase women's chances of developing uterine cancer:

- **Age:** It is more common in women between the ages of 50 and 64 after menopause. It can, however, happen to females before they reach menopause.

- **Overweight:** Female being overweight increases the risk of Uterine cancer in women.
- **Hormone replacement therapy (HRT):** Females' risk of uterine cancer is increased if they take estrogen-only HRT for a long time after menopause.

Family history: A faulty gene can be inherited in a small number of families, causing a condition known as Lynch Syndrome (hereditary nonpolyposis colorectal cancer or HNPCC). This increases the risk of developing cancers such as uterine, bowel, and ovarian cancer.

- **No pregnancies:** If a female has never had children or has never been pregnant, her risk of uterine cancer is slightly increased.
- **Polycystic Ovaries:** Females with polycystic ovaries have a slightly higher risk.
- **Menstrual history:** Females risk is slightly increased if they started their periods early in their life and/or went through menopause later.

Having a risk factor does not guarantee that a female will develop Uterine cancer. Being aware of these, on the other hand, may help in making important lifestyle changes that could prevent Uterine cancer or, in the case of family history, prompt referral to the genetic screening service system.

2.1.6 Diagnosis of uterine cancer

Certain tests will be carried out when a male is present to confirm the diagnosis and then to assess if cancer has spread from the womb. These tests include:

1-Transvaginal Ultrasound: A small probe is gently inserted into a women's vagina to perform a transvaginal ultrasound.

2-Hysteroscopy: A hysteroscope is a thin tube with a light at the end that is passed through the female vaginal canal and into the womb. This allows the doctor to take tissue samples which is called a biopsy from inside the womb.

3-Biopsy: During hysteroscopy or with the use of a soft fine plastic device called a Pipelle, the doctor can take small amounts of tissue samples from the female womb. To determine if cancer cells are present, biopsies are sent to a histopathology laboratory and examined under a microscope.

4 **CT Scan:** This is often a scan to assess the female chest, abdomen, and pelvis.

It is performed in the X-Ray radiology department and involves passing through a circular

5 MRI Scan: This procedure is a very useful scan to assess the muscle layer of the womb and also the lymph nodes involved in the pelvis

2.1.7 Types of uterine (Womb) Cancer

There are two main kinds of uterine cancer: endometrial cancer and sarcoma of the womb.

1. **Endometrial cancer:** Endometrial cancer is the most common type of womb cancer. It accounts for 95% of all cases. The term ‘endometrium’ refers to the lining of the womb. The most common type of endometrial cancer is called adenocarcinoma. Other less common types are endometrial cancers include:
 - a. Clear cell carcinoma
 - b. Serous carcinoma
 - c. Carcinosarcoma, also referred to as MMMT is a mix of carcinoma and sarcoma.
2. **Sarcoma of the womb.** This cancer affects the muscle layers of the womb rather than the lining. The most common type is called leiomyosarcoma. It is far less common than endometrial cancer.

2.1.8 Staging of Uterine (Womb) Cancer

The tests and scans used to diagnose a female's cancer will reveal the size of the tumor and whether it has spread (the stage). However, until the female has had a surgical procedure, the doctor may not be able to tell her the exact stage. For uterine cancer most doctors apply the FIGO Staging system:

Stage 1: The cancer is only within the womb. Surgery is the main treatment but some females need radiotherapy if the cancer is within the outer half of the muscle layer of the womb. Chemotherapy may be useful to prevent recurrence in certain types of cancer such as serous carcinoma.

Stage 2: The cancer has grown down into the cervix (neck of the womb). Treatment is surgery and radiotherapy.

Stage 3: This stage means the cancer has spread outside the womb, but is still within the pelvis. It may involve the lymph nodes. Treatment is often a combination of surgery, radiotherapy, and, chemotherapy.

Stage 4: In this stage, the cancer has spread to other female body organs such as the bladder or bowel (Stage 4A), or more distant organs such as the liver or lungs

(Stage 4B). The main treatments are often a combination of chemotherapy, radiotherapy, and possibly surgery [18].

2.2 Ultrasound imaging

Sonography procedure plays a very important role in the detection of gynecological cancers and is used widely with clinical examinations but also for first-line imaging to give an accurate indication for more sophisticated diagnostic techniques or more invasive endoscopic procedures. It has been used for endometrial cancer detection in recent years because of the advantages of ultrasound (US) imaging such as no-radiation, sensitivity to dense endometrial, low false positive rate, portable, and cheap cost. Due to the nature of US imaging, the images always suffer from poor quality caused by speckle noise, low contrast, blurred edge, and shadow effect. It takes considerable effort for radiologists to extract the contours of lesions and the manual extraction is not reproducible.

2.2.1 Transvaginal ultrasonography

Transvaginal ultrasonography (TVUS) the first-line diagnostic tool for identifying uterine cavities, is also low-cost and the most convenient tool for the detection and diagnosis of uterine lesions. It produces high-resolution images of the uterus and endometrium because of the proximity of vaginal transducers to the uterus [18]. The use of TVUS for uterine imaging provides useful information, such as uterine and endometrial length and thickness, endometrial texture, and uterine position (e.g., flexion, versions), allowing identification of abnormalities. TVUS is also recommended for screening endometrium-related diseases. Figure 2.3 below illustrates image samples from female patients with normal endometria, endometrial cancer, and endometrial polyps [19].

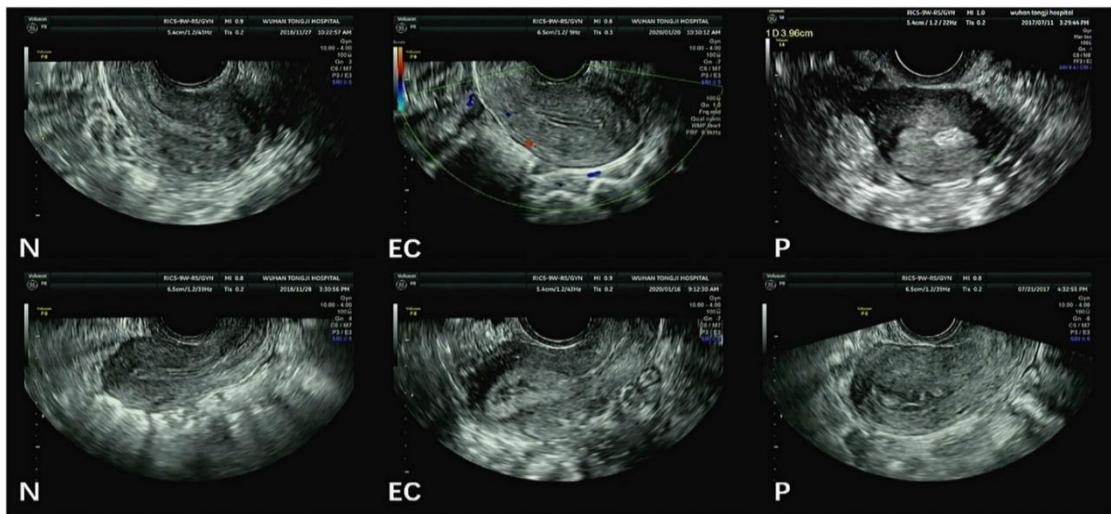


Figure (2.3) TVUS images : N - normal endometrium, EC - endometrial cancer, P - endometrial polyps.

Nowadays, ultrasound imaging is a very important diagnosis procedure in medical image analysis. It is important to segment out the cavities, different types of tissues, and organs in the ultrasound image for effective and correct diagnosis.

2.3 Related Works

To achieve the goals of this study, the literature on recent issues in image analysis techniques related to endometrium cancer detection and classification was reviewed. These reviews help us to evaluate different image analysis techniques.

3.2.1 Noise removal

The most common problem with the ultrasonic diagnosis procedure is speckle noise generated from the non-homogenous structure of the tissue. Speckle noise is a specific form of noise that degrades fine details and edge definitions in ultrasound images. There are several techniques have been proposed to reduce speckle noise from the ultrasound images. Several studies have been conducted to solve the speckle noise problem in ultrasound images.

(**Thakur et al., 2005**), in this section, only two methods are considered to conduct a comparative study of different noise reduction methods based on wavelet filters according to different threshold values applied to ultrasound images. The raw image is converted into a multi-scale wavelet field and the wavelet coefficients are

processed in a soft-threshold method. The denoised image is the output image obtained from the inverse wavelet transform of the threshold coefficients using the Donoho method. It has been observed that these noise reduction methods are effective in the sense that they preserve edge detail along with noise suppression[20].

Damodaram, et al., 2012), used one of the very important denoised techniques to improve diagnostic information form ultrasound, the Wiener filtering technique was used to remove speckle noise from ultrasonic images of the liver. The search results of the algorithm were very useful for denoising [21].

3.2.1 Image segmentation

This literature survey concludes that there are many different techniques to perform image segmentation.

Ji and Shi (2011) analyzed the weakness of a watershed segment method and proposed a new water flow image segmentation method based on morphological gradient reconstruction. In the proposed technique, morphological opening and closing operations are used to rearrange a gradient image, maintain important additions to details and noise of regional contours, and avoid the common water flow separation phenomenon. It also overcomes the contour positioning of the region derived from traditional morphological opening and closing operations for the original image. Their simulations show that in terms of visual effects or eliminating too much segmentation, the position and contour of the area of noise and other properties[22].

Rawat and Gupta (2018) proposed a technique that combines fuzzy C means and Darwinian particle swarm optimization (PSO). Among fuzzy-based clustering algorithms, the FCM algorithm is the most popular, but it can have a locally optimal solution because of a random centroid onset. To overcome such problems, they recommended optimization algorithms, such as PSO or other evolutionary algorithms. With the proposed method, lesion parts from different medical images can be segmented, and multiple images can be obtained with high accuracy by using FCM–Darwinian PSO to detect the outer lines of images. The search results of the method are evaluated by various parameters, such as sensitivity, specification, Jaccard index, and dice coefficient[23].

Saravanan and Sathiamoorthy (2018) developed a computerized segmentation technique based on active contours without outline techniques for an

effective PCOS classification of 3D ultrasound images. In this technique, the location and size of follicles are calculated automatically by combining information from local and global conditions under new probabilistic conditions. Then, the identified follicles are segmented via database-guide graphical cutting segmentation. Thereafter, a clustered marginal space learning method is used to identify the detected objects effectively. The proposed system is evaluated using 501 ovarian volumes consisting of a woman's left or right ovary with 8,108 available follicles. Their approach is the first to identify and segment ovarian follicles in a 3D ultrasound volume automatically (Saravanan and Sathiamoorthy 2018) [24].

2.3.2 Endometrial cancer detection

(**Snehal N. Patil et al., 2012**) were discovered a model for CAD system helps doctors as well as radiologists to identify suspicious nodules of cancers and thus increases its sensitivity, specificity, accuracy & efficiency of the diagnosis. The CAD Systems are beneficial to detect cancerous nodules. Thus, the process was implemented accordingly and the work under Module 3 is in progress.

(**Mrs. Snehal R. Shinde et al., 2019**) were explored system of Endometrial Cancer Diagnosis using CAD systems is useful to improve the present methods of diagnosis to obtain an accuracy of 87.5%. In addition, the proposed system proves to be the best in analyzing the stage at which the cancer has spread as well as its features such as area and radius. Computer-Aided Diagnostic (CAD) Systems thus are truly beneficial to detect cancerous nodules.

(**Xue Wang et al., 2022**) were conducted in another very important study. In this study, 85 cases of three-dimensional transvaginal ultrasound (3D TVUS) images were collected retrospectively, including 75 cases of endometrial adhesion and 10 cases of non-adhesion. Firstly, the uterine ultrasound images were filtered by block-matching 3D filtering and speckle-reducing anisotropic diffusion (SRAD). These two types of filtered images were combined with the original image to construct a three-channel image. Then, the augmented images were sent to 3D U-Net to realize endometrium segmentation. The performance of the segmentation models was evaluated using the Dice similarity coefficient (DSC), Jaccard, sensitivity, and 95th percentile Harsdorf distance (HD95). Finally, the medial axis transform was used to extract the endometrial centerline, based on which the endometrial thickness could be automatically measured. **The study concludes** the endometrium segmentation method

proposed in this paper achieved 90.83% in Dice, 83.35% in Jaccard, 90.85% in sensitivity, and 12.75 mm in HD95 in the testing set. Taking the doctor's manual measurement as the gold standard, 94.20% of the automatic endometrial thickness measurements based on the segmentation results were within the allowable error range of clinical diagnosis[26].

CHAPTER THREE : Digital Image Processing Techniques

This chapter aims to undertake a review of digital image processing. This chapter discussed Image processing techniques used in this work; this will cover the fundamentals of three image-processing methods: image filtering, image edge detection, and image segmentation.

3.1 Fundamentals of digital image processing

Image processing is a method to perform some operations on digital images, to get an enhanced output image, or to extract some useful information from the raw image. It is a sort of signal processing where the input is a raw digital image and the output could be an image with new features or characteristics associated with it. Recently, image processing has been among the rapidly growing technologies. It forms core research areas within engineering, computer science, and medical imaging disciplines. Digital image processing includes the following three steps:

- Importing the image using image acquisition tools.
- Analyzing and manipulating the input image.
- Output in which the result can be altered image or report based on image analysis.

There are two kinds of methods used for image processing namely, analog and digital image processing. Analog image processing is used for hard copies such as printouts and photographs. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of images have to undergo while using digital techniques are pre-processing, enhancement, and information extraction [27].

3.1.1 Digital image

A digital image is a numerical representation of a two-dimensional image, i.e., it is a discrete function. Discrete points known as pixels are used to describe the digital image, the pixels are arranged in a grid and each pixel has its position, represented by the space coordinates, and color. The color is discretized as well, with values that range from (0 to 255). In the case of digital grayscale images, a pixel with the value 0 represents a black pixel, the pixel with the value 255 represents a white

pixel, the RGB color model, which is a triplet of red, green, and blue color intensity values, can be used to represent colored images [27].

3.1.2 Coordination system of the digital image

An image with size $M \times N$ (column x row) is represented by as image matrix (I). Each pixel was referred to by the row and column in which they are located and the coordinate of origin is on the upper left of the image ($u = 0$ and $v = 0$). Therefore, the maximum column and maximum row are $M-1$ and $N-1$ respectively. Figure 3.1 shows the coordination of any type of digital image [27].

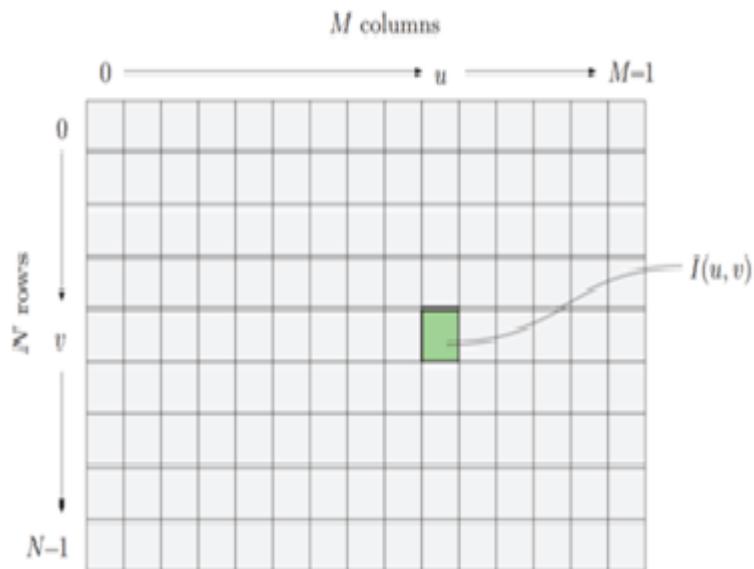


Figure (3.1) Digital image coordination

3.2 Image restoration and reconstruction

Image restoration is the process of restoring the degraded or corrupted image to its original form. It is an objective process. A restoration effort to reconstruct a degraded image using prior knowledge of the degradation phenomenon. These methods are based on modeling the degradation and then applying the inverse process to recover the original image. Image restoration techniques are based on mathematical or probabilistic image processing models. In contrast, enhancement is based on human subjective preferences for what constitutes a "good" enhancement result. Image Restoration refers to a class of methods aimed at removing or reducing degradations that occurred during the acquisition of the digital image. Image restoration is the initial step of image processing. Noise is added to the image while sending an image

from one place to another via satellites, wireless networks, or during the image acquisition process [28].

3.2.1 Image degradation Model

Image restoration is a process of recovering an image that has been degraded by some knowledge function H and additive noise $\eta(i,j)$. The degradation process operates on a degradation function that operates on an input image with an additive noise term. The input image is represented by using the notation $f(i,j)$, noise term can be represented as $\eta(i,j)$. These two terms when combined give the result as $g(i,j)$. If we are given $g(i,j)$, some knowledge about the degradation function H or J , and some knowledge about the additive noise term $\eta(i,j)$, the objective of restoration is to obtain an estimate $f(i,j)$ of the original image. We want the estimate to be as close as possible to the original image. The more we know about h and η , the closer $f(i,j)$ will be to $f(i,j)$. The model of degradation can be expressed mathematically as [29].

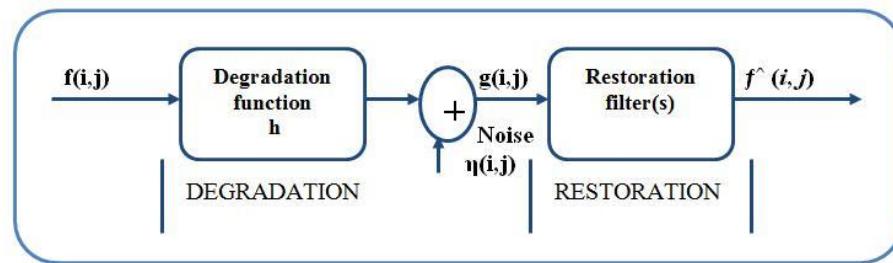


Figure (3.2) Model of image degradation and restoration

3.2.2 Noise in digital images

Digital image noise is a random variation of brightness or color information in images and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information. Image distortion is the most pleasurable problem in image processing. Image distorted due to various types of noise such as Gaussian noise, Poisson noise, Speckle noise, Salt and Pepper noise and many more are fundamental noise types in the case of digital images.

2.2.3 Types of noise

Image noise is any degradation in the image signal caused by external disturbance. If the digital image was being sent electronically from one station to another via satellite or wireless transmission or through networked cables, we may expect errors to occur in the image signal. These errors will appear on the output image in different ways depending on the type of disturbance in the signals. Usually, we know what type of errors to expect and the type of noise on the image; hence, we investigate some of the standard noise for eliminating or reducing noise in ultrasound images. Image noise is classified as Amplifier noise (Gaussian noise), Salt-and-pepper noise (Impulse noise), Shot noise, Quantization noise (uniform noise), Film grain, on-isotropic noise, Speckle noise (Multiplicative noise), and Periodic noise.

a. Gaussian noise (Multiplicative Noise)

Gaussian Noise, also known as Gaussian distribution, is a statistical noise with a probability density function (PDF) equal to the normal distribution. To generate this noise, a random Gaussian function was added to the image function. Because it occurs in amplifiers or detectors, it is also known as electronic noise. Thermal vibration of atoms and the discrete nature of radiation from warm objects are the sources. In telecommunications and computer networking, communication channels can be affected by wideband Gaussian noise coming from many natural sources, such as the thermal vibrations of atoms in conductors, shot noise, black body radiation from the earth and other warm objects, and celestial sources such as the Sun. In general, Gaussian noise disturbs the gray values in digital images. As a result, the Gaussian noise model is essentially designed and defined by its PDF or normalized histogram concerning ray value. This is stated as:

$$P(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad 3.1$$

Where (x) is the gray level, (μ) is the mean and (σ) is the standard deviation and (σ^2 is the variance). Approximately 70% of its pixel values are in the range $[(x - \mu), (x + \mu)]$. Figure 3.2 shown Gaussian noise.

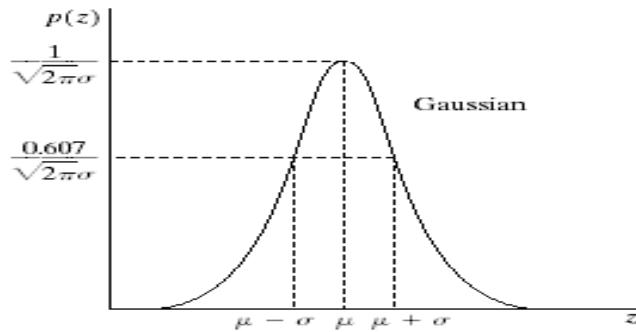


Figure (3.3) Gaussian distribution

The shape of the normalized histogram is almost the same in the spectral domain. In the digital image process, sing Gaussian noise can be reduced using a spatial filter, Figure 3.3 shows the uterine ultrasound image effected by Gaussian noise.

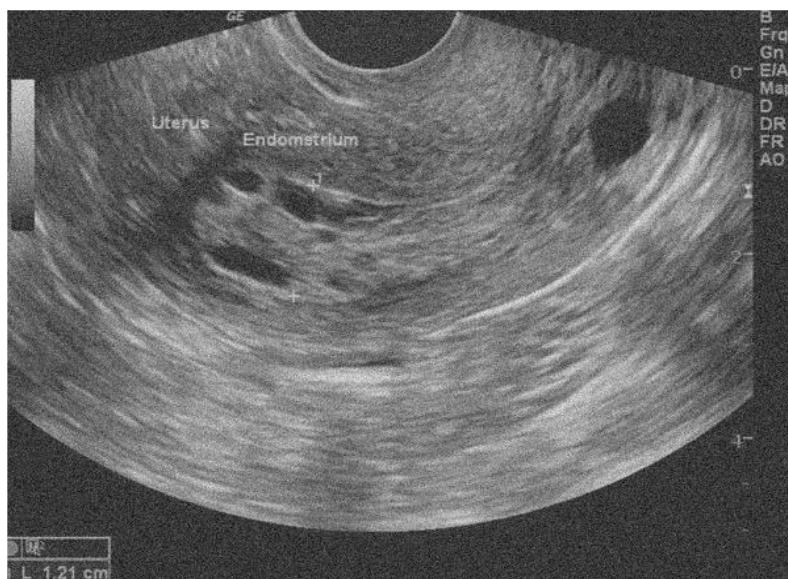


Figure (3.4) Uterine ultrasound image with Gaussian Noise

b. Salt-and-pepper noise

This type of noise called Salt-and-pepper noise is a type of noise usually seen on digital images. It is also known as impulse noise. This type of noise can be caused by sharp and sudden disturbances in the image signal. It presents itself as sparsely occurring white and black pixels. This is also called data drop noise because statistically, it drops the original data values. This noise is also referred to as salt and pepper noise. However, the image is not fully corrupted by salt and pepper noise instead some pixel values are changed in the image. However in the noisy image,

there is a possibility that some neighbors do not change. An effective noise reduction method for this type of noise is a median filter or a morphological filter. For reducing either salt noise or pepper noise, but not both, a contra-harmonic mean filter can be effective.

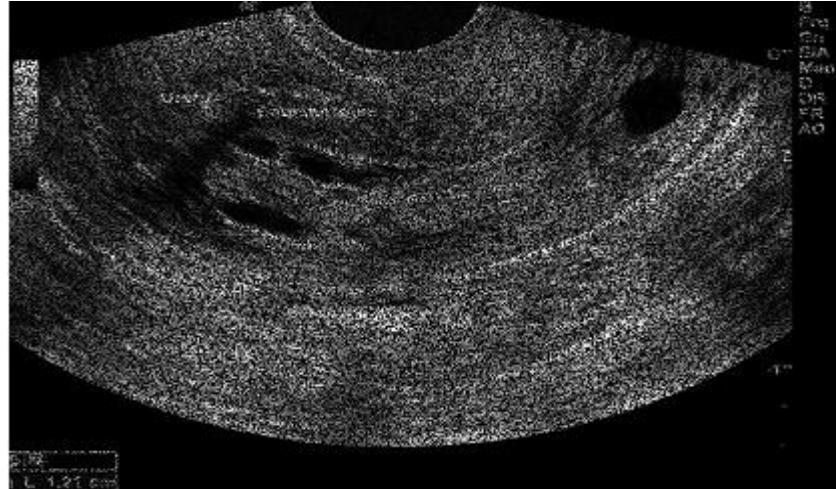


Figure (3.5) Ultrasound image with Salt & Pepper Noise

The PDF of impulse noise is given by:

$$3.2 \quad p(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases}$$

If $b > a$ gray level b will appear as a light dot; If either P_a or P_b is zero, the impulse is called unipolar. If neither probability is zero (bipolar), and especially if they are approximately equal: salt and pepper noise.

c. Speckle Noise

Speckle noise is a multiplicative noise; it degrades images such as synthetic aperture radar (SAR) images, ultrasound medical images, tomography images, etc. It is non-uniform noise that makes images grainier. Speckle noise may be defined as a correlated signal and it is modeled as a multiplicative noise in contrast to additive Gaussian and impulse noise [30].

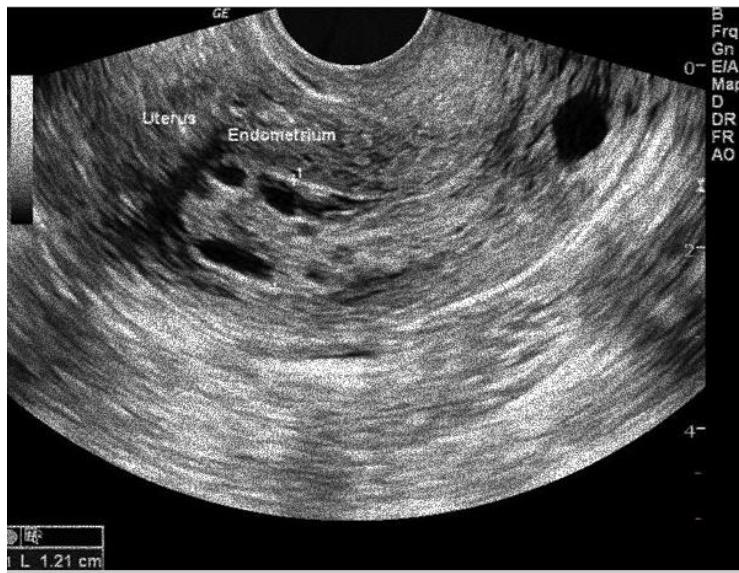


Figure (3.6) Uterine ultrasound image with Speckle Noise

3.2.4 Digital Image restoration

Image restoration is used to carry out several useful tasks in digital image processing [28]. One of the very important tasks is noise removal using image filtering which is a technique for modifying or enhancing an image when a filter is used to reduce the amount of unwanted noise in the ultrasound image. A filter usually operates on a neighborhood of pixels in an image. In the spatial domain, image filtering is done by convolving the raw image with the filter function to obtain the filtered image, where the convolution takes place over the neighborhood of each input pixel [28]. A mean filter and a median filter are both types of filters that can be used for noise removal. Whereas the mean filter is a good example of a linear filter, the median filter is an example of a nonlinear filter.

3.2.5 Spatial domain Filtering

The filtering in the image processing spatial domain demands a filter mask (it is also referred to red as kernel or convolution filter). The filter mask is a matrix of odd usual size, which is applied directly to the original image. The mask is centered on each pixel of the raw image. For each position of the mask, the pixel values of the image are multiplied by the corresponding values of the mask. The products of these multiplications are then added and the value of the central pixel of the original image is replaced by the sum. This must be repeated for every pixel in the image. Linear filter is a filter that operates the pixel value in the support region linearly. The support

region is specified by the ‘**filter matrix**’ and is represented as $H(i,j)$. The size of H is called the ‘filter region’ and the filter matrix has its own coordinate system, i is column index and j is row index. The center of it is the origin location and it is called the ‘hot spot’.

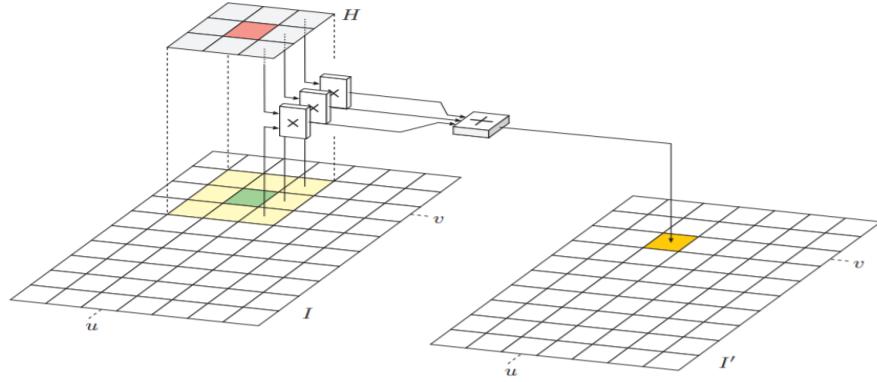


Figure (3.7) Demonstrate liner filter work

Applying the filter

To apply the filter to the image, we follow these steps.

- Move the filter matrix over the image I and H (0,0) must go along with the current image position (u,v)
- Multiply each filter coefficient $H(i,j)$ with the corresponding image element $I(u+i, v+j)$
- Average all results from the previous step and it is the result for the current location $I(u,v)$

All steps can be described as equation below

$$I' = I \sum_{i=-1}^{i=1} \sum_{j=-1}^{j=1} I(u + i, v + j) \cdot H(i, j) \quad 3.3$$

When the only degradation present in an image is noise, i.e. The following techniques can be used to reduce the noise effect:

a. Mean Filter:

Mean filter is one of the techniques, which is used to reduce noise of the images. This is a local averaging operation and it is a one of the simplest linear filter. The value of each pixel is replaced by the average of all the values in the local neighborhood. Let S_{xy} represents the set of coordinates in the sub image of size $m*n$ centered at point (x,y) . The arithmetic mean filter computes the average value of the

corrupted image $g(x,y)$ in the area defined by S_{xy} . The value of the restored image f at any point (x,y) is the arithmetic mean computed using the pixels in the region defined by S_{xy} . can be obtained by,

$$\hat{f}(x,y) = \frac{1}{mn} \sum_{(s,t) \in S_{xy}} g(s,t) \quad 3.4$$

Where S is a neighborhood of (x,y) and $n*m$ is the number of pixels in S . This operation can be using a convolution mask in which all coefficients have value $1/mn$. A mean filter smoothes local variations in the image Noise is reduced because of blurring. For every pixel in the image, the pixel value is replaced by the mean value of its neighboring pixels with a weight. This will result in a smoothing effect in the image

b. Median filter

The median filter is a non-linear spatial digital filtering technique, often used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise (but see the discussion below), also having applications in signal processing. Nonlinear spatial filters can easily be devised that operate through exactly the same basic mechanism as we described above for the linear case. The kernel mask slides over the image in the same way as the linear case, the only difference being that the filtered value will be the result of some nonlinear operation on the neighborhood pixels. In this thesis, the median filter will be used as a popular example of a nonlinear filter. It used the middle value in the neighborhood of the target pixel. The median filter overcomes one of the limitations of the mean filter, which is its inability to reduce impulsive noise. The median filters are also useful in preserve in the edges of an image while reducing the image noise. The mathematical formulation for the median filter is given as follows:

$$\hat{f}(x,y) = median_{(s,t) \in S_{xy}} \{g(s,t)\} \quad 3.5$$

Figure 3.8 illustrates an example calculation and show how the median filter work

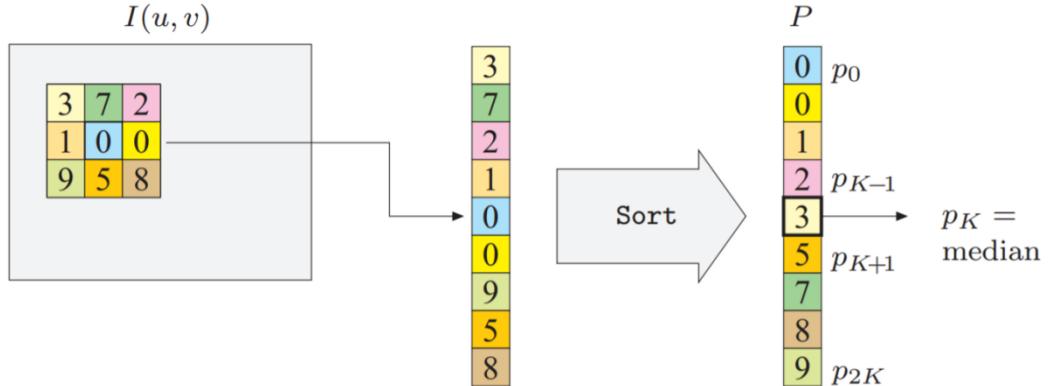


Figure (3.8) Demonstrate median filter work

The median is calculated by first sorting all the pixel values from the surrounding neighborhood (3,7,2,1,0,0,9,5,8) into numerical order(0,0,1,2,3,5,7,8,9) and then replacing the pixel being considered with the middle pixel value (3). (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used) [31].

3.3 Image preprocessing

Image preprocessing refers to the initial processing of the raw image. The captured digital ultrasound images are transferred into a computer. These Digital images though displayed on the screen as pictures, are digits, which are readable by the computer system, and are converted to tiny dots or pixels (image elements) representing real objects. In some cases, preprocessing is done to enhance the image quality by containing undesired distortions referred to as noise or by the enhancement of important features of interest

3.3.1 Ultrasound image contrast enhancement based on histogram equalization

Ultrasound images are extremely important in diagnose and treatment of patients. It shows different human body parts and tissues. A better ultrasound image is required for doctors to make accurate diagnoses and treatments [32]. Due to the complexity of ultrasound images, various types of tissues, and anatomical structures involved, image enhancement techniques are needed for improving the visibility and detectability of the region of interest. Contrast enhancement techniques are widely used in various medical image-processing applications [19]. Among these techniques, histogram equalization (HE), global histogram equalization (GHE), local histogram

equalization (LHE) also named adaptive histogram equalization (AHE), and contrast limited adaptive histogram equalization (CLAHE) [27]. The histogram of any digital image can be computed by the following discrete function with intensity levels in the range $[0, L-1]$. $\mathbf{H}(\mathbf{r}_k) = \mathbf{n}_k$

3.6

where \mathbf{r}_k is the k^{th} intensity value and \mathbf{n}_k is the number of pixels in the image with intensity \mathbf{r}_k . The normalized histogram is calculated using the following probability density function (PDF) [33].

3.4 Image segmentation techniques

The majority of image segmentation algorithms are classified into three categories: boundary-based segmentation, region-based segmentation, and hybrid-based segmentation [34]. The first method splits an image using discontinuity by recognizing lines, edges, and isolated points based on abrupt changes in local attributes, The regions' boundaries are then determined. The second technique uses the homogeneity of spatially dense information such as texture, intensity, and color to create the segmentation result. The third technique is a hybrid of boundary-based and region-based segmentation. Existing segmentation methods typically separate objects from the background only, require prior knowledge of the data, and require user-specified input parameters, which may result in under- or over-segmentation. As a result, advancements in current techniques will allow for better image classification. Despite the extensive amount of research on the subject of image segmentation and the wide range of techniques applied, segmentation can be accomplished using different methods such as thresholding, edge-based segmentation, region-based segmentation, and energy-based segmentation. As a result, the following subsections start by discussing thresholding-based segmentation before moving on to the other three categories.

3.4.1 Thresholding-based image segmentation technique

One of the best segmentation methods is the thresholding-based technique because of its simplest steps on image segmentation related to image space regions (the characteristics of the image). This technique determines a proper threshold (grey-level intensity value T), then divides the digital image pixels (of the binary image) into several classes by separating the foreground objects (with intensity greater than the threshold value) into one class and the background (with intensity less than the

threshold value) into another class. The basic thresholding procedure can be summarized as follows:

$$I_{\text{segmentation}}(x,y) = \begin{cases} 1, & \text{if } I(x,y) > T \\ 0, & \text{if } I(x,y) \leq T \end{cases} \quad 3.7$$

where $I_{\text{segmentation}}(x,y)$ denotes the segmented binary image with two different groups of binary grey outputs: "1" representing foreground object regions and "0" for the black background, $I(x, y)$ is the original gray-scale image, and T represents the gray value threshold defined at the valley peak point from the histogram representation. There are various types of thresholding techniques [33].

(a) Global (e.g. Otsu) where, only one threshold value is defined for the whole image based on the histogram statistics of the image.

(b) Local (e.g. simple statistical thresholding, 2-D entropy-based thresholding, histogram-transformation thresholding, etc.), the threshold value is derived from the local image properties (e.g. local average grey value of the image).

(c) Dynamic or adaptive (e.g. watershed and interpolatory thresholding), if the threshold values are calculated separately from each pixel or group of pixels in the image using a sliding kernel window over the input image.

The main issues related to this technique are the choice of the threshold value that gives only two different classes (e.g., foreground and background) which cannot be used in multi-channel images. Another critical problem of thresholding is the manual selection of the threshold values and the kernel window size which tends to be difficult, time consuming and computationally expensive when the number of sub-image regions increases. Moreover, thresholding does not consider the spatial characteristics of the image, which tend to be sensitive to noise and grey level intensity inhomogeneity, and this will also corrupt the histogram of the image, making the partition very hard. As an improvement for the above limitations, multilevel thresholding (segmenting the image into multiple classes) and automatic threshold selection algorithms are proposed. However, these improvements fail when there is limited difference in intensity distribution between the foreground objects and background due to gray level intensity overlapping.

3.4.2 Edge-based image segmentation technique

Edge detection methods are very common and widely used techniques in digital medical image processing. This technique based on detecting edges or the

boundaries between two or more different areas in ultrasound image based on the grey-scale properties and discontinuities. These techniques are usually used as a preprocessing of another segmentation approach [34]. However, these methods are unsuccessful when applied to images that are edgeless and very noisy [34]. Especially ultrasound images affected by speckle noise, where there is not much difference between foreground and background. As a partial solution to this, a post-processing stage of edges and boundaries tracking, linking or grouping is proposed as a linking and line detection algorithm [35].

This solution is considered computationally intensive and not very efficient. The most traditional algorithms used in image edge detection are Sobel, Prewitt, Laplacian, and Canny operators [35]. Segmentation in this category is accomplished by identifying the edges in the image on the gradient of the image with the goal of producing the object boundaries. Objects are identified using this method by using edges as criteria. It is commonly used to recognize objects including the first order derivative/gradient operator, the second derivative operator, and the optimal edge detector.

1. Gradient operator which involves first order derivatives responds whenever there is discontinuity in intensity level. It has a leading edge that is positive and a following edge that is negative, such as Prewitt, Roberts and Sobel operators to detect edges by finding the magnitude in its first derivative [34].
2. Second Derivative Operator when the darker side is positive, and the lighter side is negative. It is particularly sensitive to the noise in an image. But it is very useful for extracting some secondary information, such as Laplacian operator.
3. Optimal Edge Detector as canny edge detector can produce continuous edges, single-pixel thick, noise-resistant. It can also detect strong and weak edges [34].

Several factors contribute to the shortcomings of the edge-based segment. The first factor is that the technique fails to produce the object's boundary. The reason for this is that it allows for missing and disjointed edges between the area of interest and the background. The edges produced by this technique were disjoint in the majority of cases. The second factor is its sensitivity to noise. As a result, the edge frequently failed to achieve correct segmentation in noisy images. The third factor is its sensitivity to edge expansion between critical regions. These problems occur when

images have a high spatial resolution and complex geometric shapes. As a result, the edges between regions are poorly defined, resulting in over or under segmentation.

3.4.3 Region-based image segmentation technique

Region based segmentation techniques split images into segments regions that are similar based on a group of predefined similarity criteria such as intensity and edges information [35]. There are two common techniques used in this method; region growing and region splitting. This category includes the growing, splitting, merging, and clustering of regions.

1. Region-growing techniques

Region Growing is a method in which a pre-defined criteria is used to group the entire image into sub-regions. However, this method suffers from the following drawbacks: sensitivity to noise, holes or discontinuity in the extracted region and high computational complexity [35]

A Region-growing technique is considered as a pixel-based segmentation method, which first selects initial pixel points usually called seeds and selected manually representing well-defined image regions and then grow them to classify the all of the image pixels into sub or larger regions based on some predefined rules. In particular, these rules define the growth mechanism and examine areas homogeneity after each growth stage, e.g., checking grey level histogram values, color and edges in the image.

2. Region Splitting and Merging techniques

Region-splitting and merging technique is the opposite concept of region-growing method. Region Splitting and Merging partitioned image into set of separated sub-regions. Next, a merging and/or splitting operation is performed on each sub-region according to a given criteria for segmentation. This method suffers from complexity and high-compositionality.

These methods are also unpopular due to a number of constraints. The first is more computationally complex than other techniques, requiring more computational time and memory. The second limitation is that it is not suitable for images with shadows or shading due to difficulties in extracting geometric information. Because region-based segmentation has limitations, the segmentation process should pay attention to those limitations in order to deliver more precise and reliable methods.

3.4.4 Clustering – based techniques

Clustering is the process of organizing data into groups called clusters; each cluster contains data that is more similar to one another than to others. Clustering is used in a variety of fields, including medicine, geography, and agriculture. Clusters are formed based on the variation of properties such as size, color, and texture. There are two types of clusters considered: hierarchical, in which data is organized into a tree data structure, with the root representing the entire database and the internal nodes representing the cluster. The second type is partitioning, which divides pixels into k clusters. The K-means algorithm is used to divide image pixels into k clusters, where k is a completely positive number. MacQueen's K-means algorithm, which has been used for image segmentation in several applications.

CHAPTER FOUR: EXPERIMENTATION OF ENDOMETRIAL CANCER DETECTION

This chapter describes the implementation of enhancement and segmentation of the endometrium region from the uterine ultrasound image, which was discussed in detail in chapter two. The proposed method of this thesis has five components, image acquisition, image preprocessing, image segmentation, feature extraction, and classification. Image acquisition is the process of recording images. Uterine ultrasound images were taken from the National Cancer Institute - Sabratha Hospital.

4.1 Development environments

The development of a full-fledged segmentation system of Endometrium cancer detection by integrating image analysis techniques is an expensive task. Starting from image acquisition, we need a high-quality digital ultrasound machine, and also a well-established and controlled environment to take the images. In addition to this, image-processing techniques are resource-intensive tasks. They need powerful computers with high processing speed, larger memory, and hard disk space. The system uses the image processing stages were illustrated in Figure (4.1).

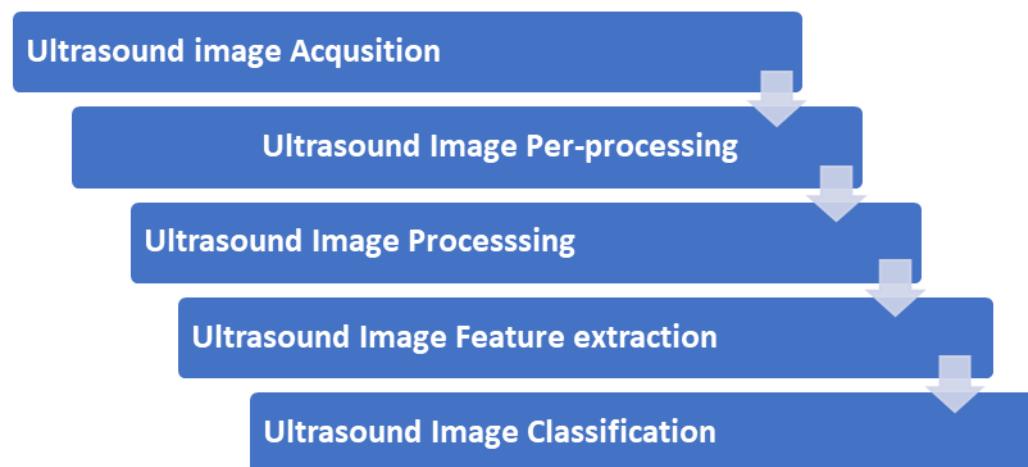


Figure (4.1) Image processing stages

4.2. Proposed methodology

Uterine ultrasound images captured were transferred into a computer and converted to digital images. Digital images, though displayed on the screen as pictures, were digits, that were readable by the computer and were converted to tiny dots or pixels (picture elements) representing real objects. Image preprocessing was done to improve the

quality by suppressing undesired distortions referred to as noise or by enhancement of the important features of interest. For endometrium cancer detection, the Uterine ultrasound images were collected in the first stage, after the image acquisition stage, preprocessing will be taken place. The next stage will be image enhancement in which in the output image the finer details will be clearer than the original image, after that the image will be segmented to extract the endometrium region. Figure (4.2) shows the flowchart that demonstrates the main algorithm criteria of the thesis methodology.

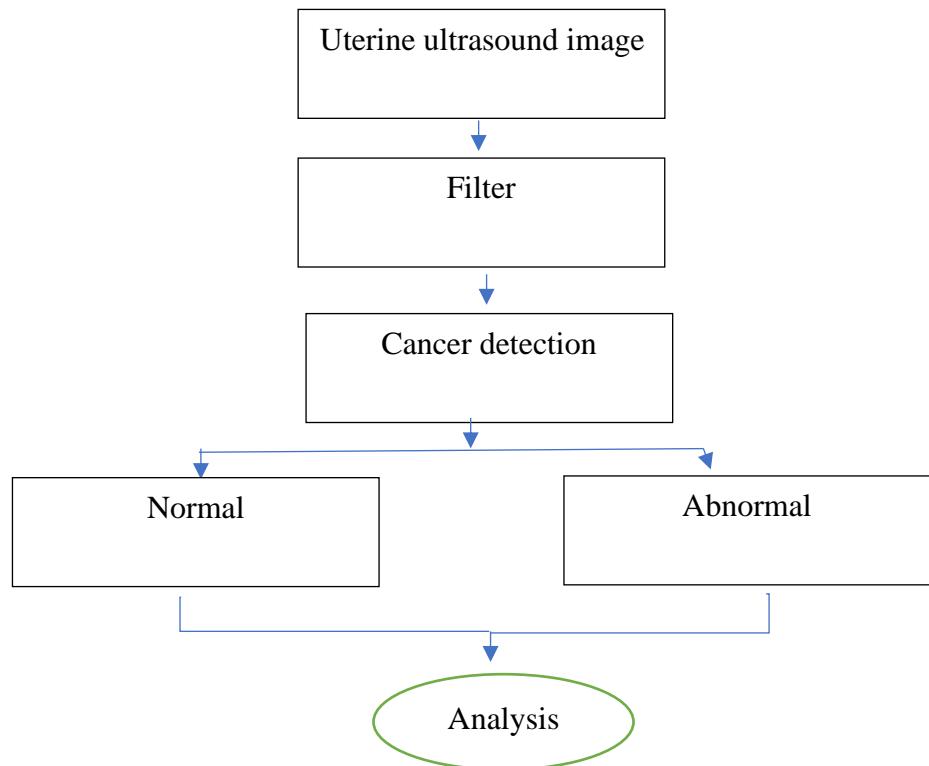


Figure (4.2) Flowchart represents the proposed methodology of the thesis algorithm

4.3 Phase 1: Acquisition of ultrasound image from the folder

In this work, we have used MATLAB R2021a which is a multi-paradigm numerical computing proprietary programming language environment developed by MathWorks. It can be used to display, edit, process, and analyze many formats and types of images. MATLAB is a powerful tool to analyze and process images. It can read and load a sequence of images, which are stored in one folder one by one, it, can also enhance the quality of each image, remove noises, and change the image to a binary image for feature extraction purposes. Figure (4.3) shows an experiment using MATLAB

software, which has been performed using an ultrasound uterine image, scanned from the National Cancer Institute database.

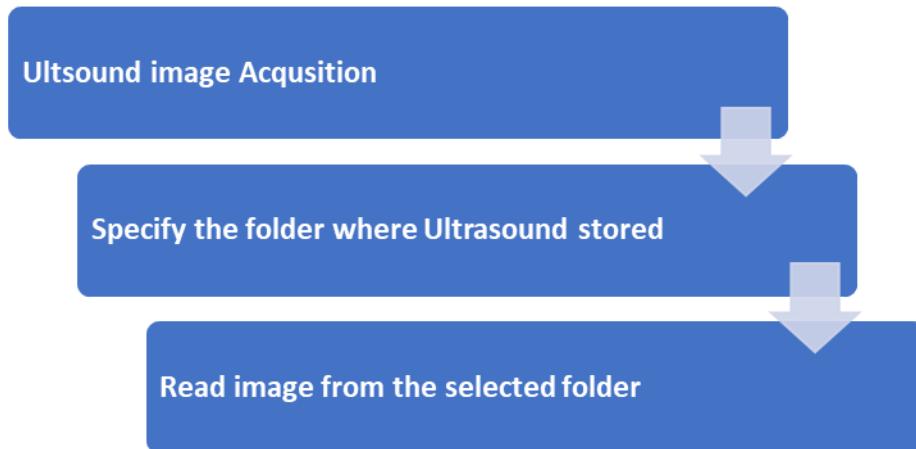


Figure (4.3) Block diagram of Image Acquisition

Step 1: Image acquisition

The ultrasound images captured were transferred into a computer and converted to digital images. Usually, the images that were obtained during image acquisition may not be suitable for identification and segmentation purposes because of certain factors, such as noise, lighting variations, poor resolutions of an image, and unwanted background. The MATLAB command for image acquisition provides the data path where the training images are present as below.

```
[filename,pathname]=uigetfile('*.*','Pick a MATLAB code file');  
filename=strcat(pathname,filename);
```

Step 2: Grayscale conversion

In the case of RGB images, the second step after loading the image from the stored folder was to convert the RGB image to grayscale. This conversion is done using the luminosity method, which relies on the contribution of each color of the three RGB colors. Using this method, the grayscale image is brighter since the colors are weighted according to their contribution in the RGB image not average. Figure (4.4) shows an experiment of converting to a grayscale image `rgb2gray` function can convert the true color into RGB to the grayscale intensity image

```
GrayUltrasoundImage=rgb2gray(UtrasoundImage);
```

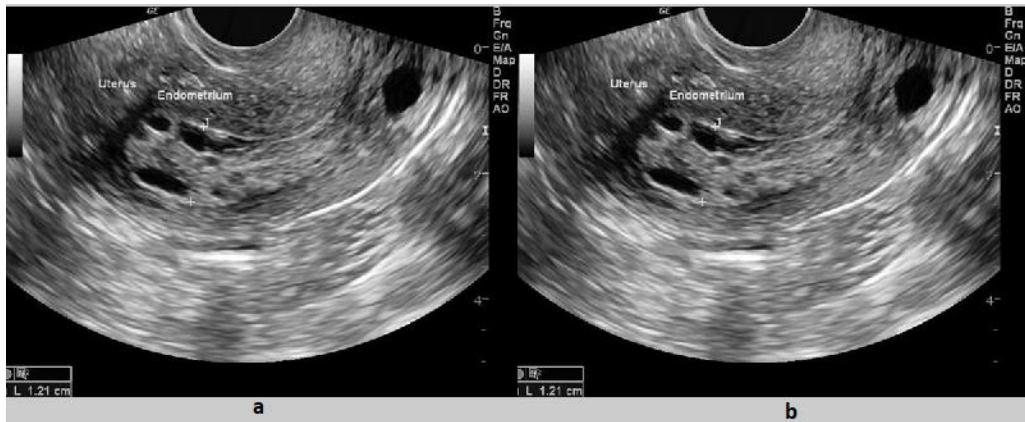


Figure (4.4) Experimental results for ultrasound image acquisition

(a) Original ultrasound image (b). Gray scale ultrasound image

4.4 Phase two: Image preprocessing and enhancement

The proposed method used a combination of image processing techniques using different techniques with high sensitivity for detecting endometrial cancer. Image processing techniques improve the detection of cancer by enhancing the quality of the images, therefore, the physicians diagnose properly. Moreover, using some techniques such as edge detection helps in detecting and segmenting the region of interest ROI, located in the uterine ultrasound image. The preprocessing step is of utmost importance, as it will help computation time and reduce processing. Preprocessing includes steps like background removal, image type conversion, unwanted artifacts, and label reeducation from the Ultrasound image.

4.4.1 Reduction of artifacts and separation of background

The reduction of these artifacts is a necessary step in improving ultrasound imaging, Existing artifacts (such as labels, wedges, and markers) cause failure of proper segmentation algorithms, in digital uterine ultrasound images artifacts and labels are the regions in Ultrasound images contain the brightest pixels. These regions must be removed before the detection of the region of interest so the segmentation techniques can be done efficiently. artifacts and labels located on the left or right top corner depending on the view of the image to eliminate the artifacts and an unwanted background (black pixels) in an ultrasound we have applied the following steps.

Step 1: Image binarization

Firstly, the grayscale image (Gray Ultrasound Image) was converted into a binary image by applying thresholding which is a low-level image processing method to separate and enhance the region of interest to provide an increased visual appearance of an image. This enhancement and separation were provided by dividing the image into two regions background (logical 1) and foreground (logical 0). Figure (4.5) shows an ultrasound image after being converted to a binary image.

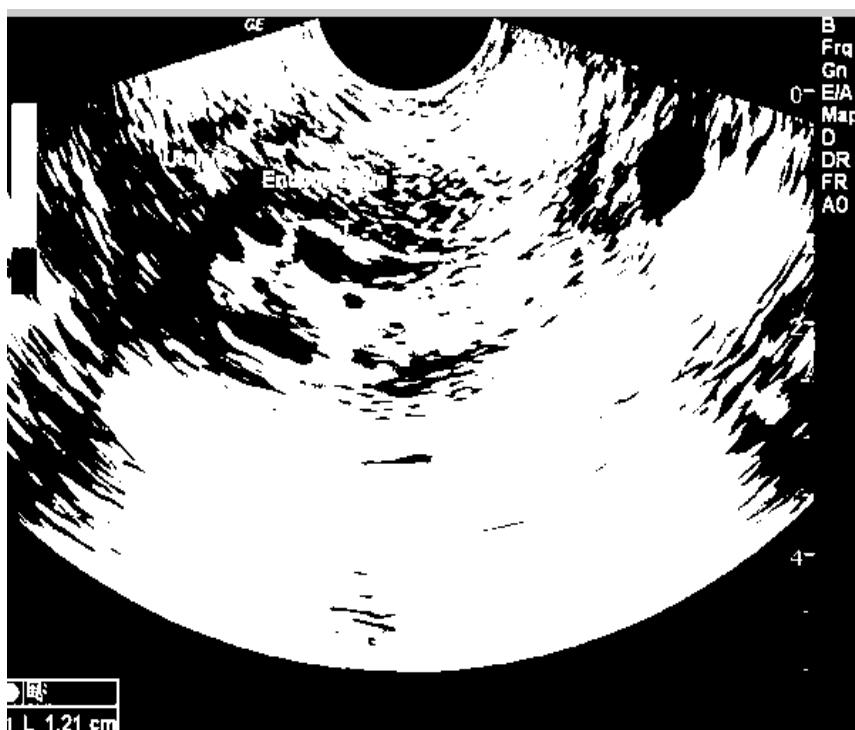


Figure (4.5) Experimental results for converting into a binary image

Step 2: Filling Holes

Filling the holes using the infill MATLAB function, after binarization we fill up the remaining holes present in the image by removing some lighting the unwanted things in the image removing the written part in the image Figure (4.6) displays both images to see if spots are removed `T=imcomplement(infill(complement(T), 'holes'));`

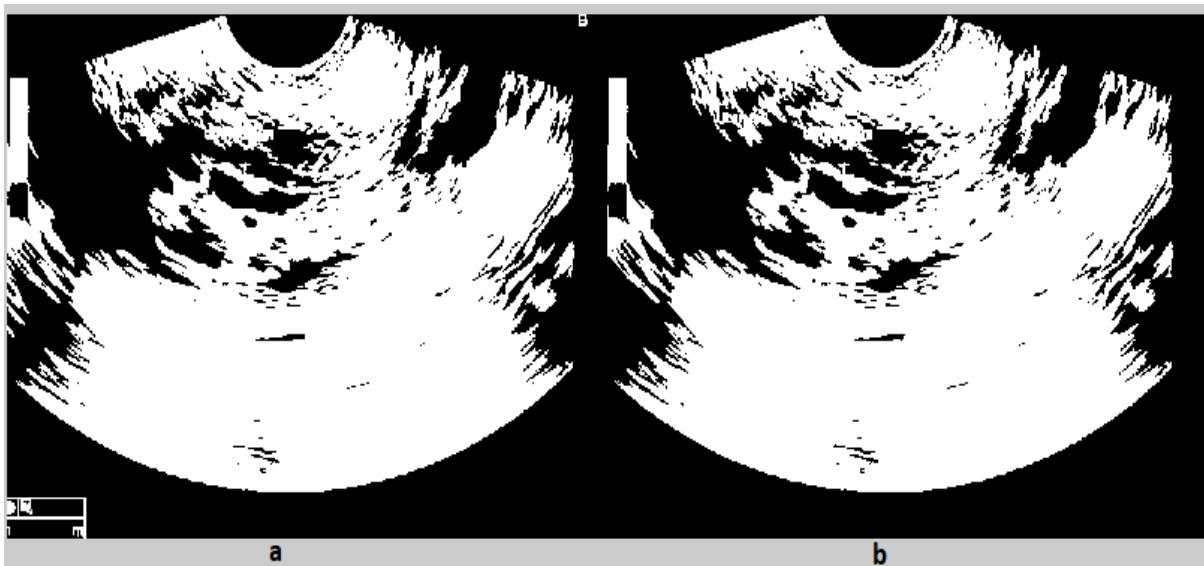


Figure (4.6) Artifacts and label removal: (a) Binary image (b) Image after filling holes

Next, we multiply the binary mask by the image for this report function used where the mask consists of the above image. Figure (4.7) shows the output grayscale image after repeating the binary image



Figure (4.7)Rempat ultrasound image

Step 3: Enhance the output image by contrast

Contrast within an ultrasound image is based on the brightness or darkness of a pixel about other pixels. Modifying the contrast among neighboring pixels can enhance the ability to extract information from the image operations such as noise removal and smoothing decrease contrast and make neighboring pixel values more similar, the

command that implements contrast processing is the imadjust. Using this, the contrast in an image can be enhanced or degraded if needed. Figure (4.8) shows the ultrasound image after contrast.



Figure (4.8) Enhanced output image by contrast

Step 4: Filtered image to remove noising

After artifacts and labels were removed and contrasted with the image, the next step was the image filtering technique the obtained output image went through the median filter using medfilt2 techniques. Figure 4.9 shows a filtered image

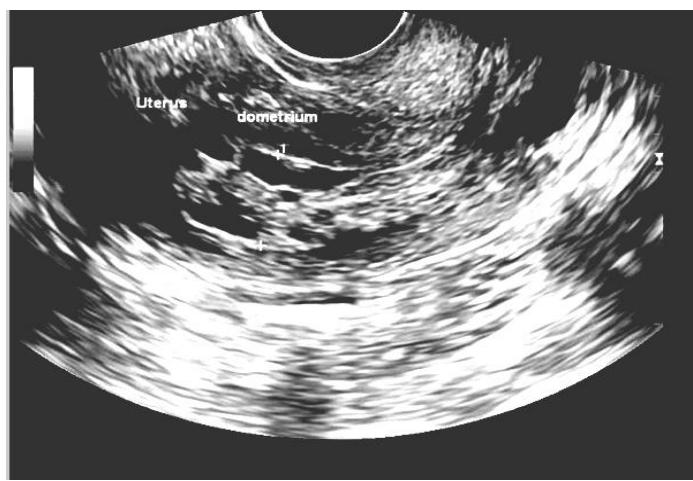


Figure (4.9) Filtered uterine ultrasound image

4.5 Phase three: Image edge detection by fuzzy logic

An edge detection algorithm for uterine ultrasound digital images is proposed in this thesis. Edge detection is one of the most important and most difficult tasks in image processing and analysis.

An edge is a boundary between two uniform regions. Edges can be detected by comparing the intensity of neighboring pixels. In image processing techniques, we can detect edges using filters including Sobel, canny, Prewitt, and many others. However, because uniform regions are not crisply defined, small intensity differences between two neighboring pixels do not always represent an edge. Instead, the intensity difference might represent a shading effect. The fuzzy logic method for edge detection in image processing allows to use of membership functions to define the degree to which a pixel belongs to an edge or a uniform region.

Step 1: Input grayscale image to fuzzy logic system

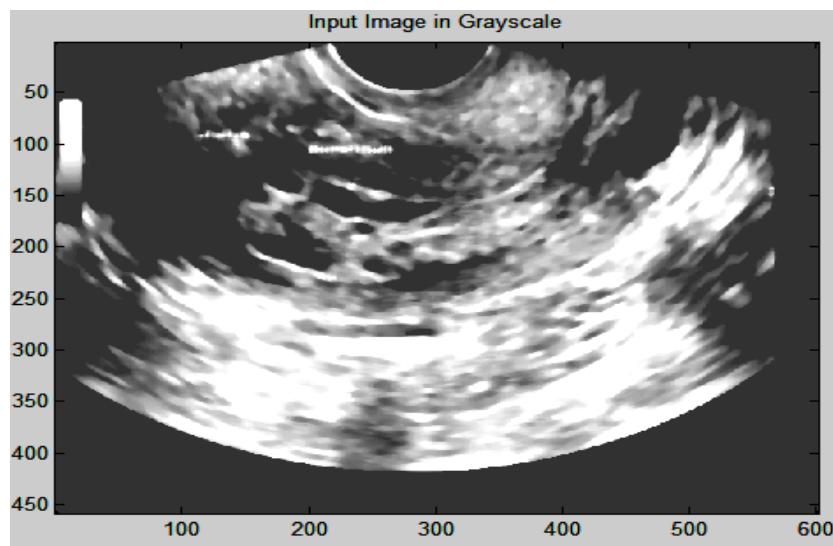


Figure (4.10) Input grayscale image to the fizzy system

Step 2: Convert the Image to Double-Precision

Convert input grayscale image into double precision. The evalfis function for evaluating fuzzy inference systems supports only single-precision and double-precision data. Therefore, convert Igray to a double array using the im2double function. $I = \text{im2double}(I\text{gray})$.

Step3: Obtain and plot Image Gradient

The fuzzy logic edge-detection algorithm for ultrasound images relies on the image gradient to locate breaks in uniform regions. Calculate the image gradient along the x-axis and y-axis. G_x and G_y are simple gradient filters. To obtain a matrix containing the x-axis gradients of I , we convolve I with G_x using the conv2 function. The gradient values are in the [-1 1] range. Similarly, to obtain the y-axis gradients of I , convolve I with G_y .

$$G_x = [-1 \ 1];$$

```

Gy = Gx';
Ix = conv2(I,Gx,'same');
Iy = conv2(I,Gy,'same');
Plot the image gradients.
figure; image(Ix,'CDataMapping','scaled'); colormap('gray'); title('Ix');
figure; image(Iy,'CDataMapping','scaled'); colormap('gray'); title('Iy');

```

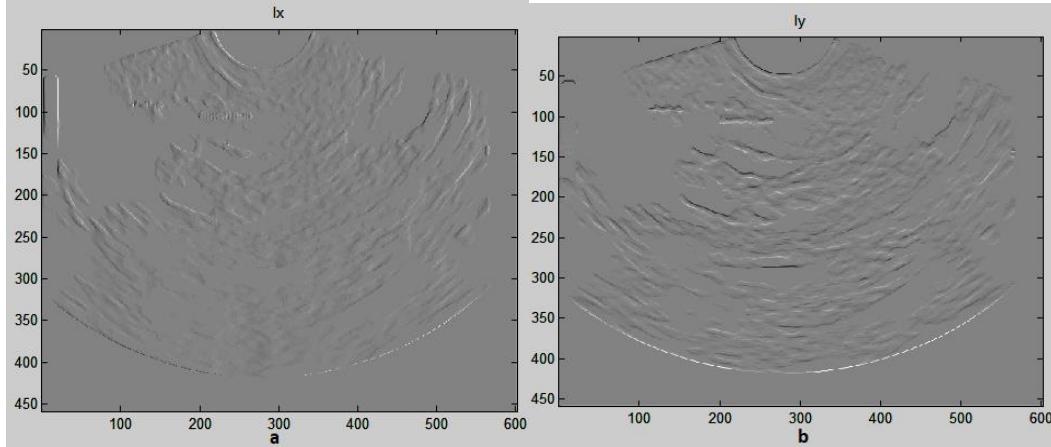


Figure (4.11) Obtain Image gradient (a). xl gradient (b) ly gradient

Step 4: Define Fuzzy Inference System (FIS) for Edge Detection

- Create a fuzzy inference system (FIS) for edge detection, edges

```
edges = mamfis('Name','edge detection');
```

- Specify the image gradients, Ix and Iy, as the inputs of edge FIS.

```
Edge FIS = addvar(edgeFIS,'input','Ix',[-1 1]);
```

```
Edge FIS = addvar(edgeFIS,'input','Iy',[-1 1]);
```

- Specify a zero-mean Gaussian membership function for each input. If the gradient value for a pixel is 0, then it belongs to the zero-membership function with a degree of 1.

```
sx = 0.1; sy = 0.1;
```

```
edge FIS = added(edge FIS, 'input',1, 'zero', 'gaussmf',[sx 0]);
```

```
edge FIS = addmf (edgeFIS,'input',2,'zero','gaussmf',[sy 0]);
```

sx and sy specify the standard deviation for the zero-membership function for the Ix and Iy inputs. To adjust the edge detector performance, you can change the values of sx and sy. Increasing the values makes the algorithm less sensitive to the edges in the image and decreases the intensity of the detected edge

- Specify the intensity of the edge-detected image as an output of

```
edgeFIS = addvar(edgeFIS,'output','Iout',[0 1]);
```

- Specify the triangular membership functions, white and black, for Iout.

$wa = 0.1; wb = 1; wc = 1;$

$ba = 0; bb = 0; bc = 0.7;$

```
edgeFIS = addmf(edgeFIS,'output',1,'white','trimf',[wa wb wc]);
```

```
edgeFIS = addmf(edgeFIS,'output',1,'black','trimf',[ba bb bc]);
```

As we can with sx and sy , we can change the values of wa , wb , wc , ba , bb , and bc to adjust the edge detector performance. The triplets specify the start, peak, and end of the triangles of the membership functions. These parameters influence the intensity of the detected edges.

- Plot the membership functions of the inputs and outputs of edge FIS.

Figure

```
subplot(2,2,1); plotmf(edgeFIS,'input',1); title('Ix');
subplot(2,2,2); plotmf(edgeFIS,'input',2); title('Iy');
subplot(2,2,[3 4]); plotmf(edgeFIS,'output',1); title('Iout')
```

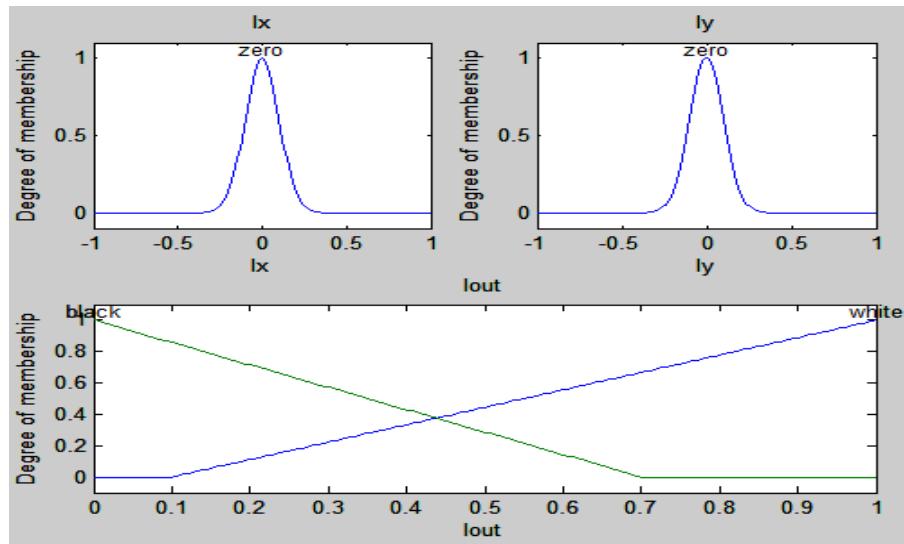


Figure (4.12) Inputs and output membership functions

- Specify FIS Rules

Add rules to make a pixel white if it belongs to a uniform region and black otherwise.

A pixel is in a uniform region when the image gradient is zero in both directions. If either direction has a nonzero gradient, then the pixel is on an edge

$r1 = \text{"If } Ix \text{ is zero and } Iy \text{ is zero then } Iout \text{ is white"};$

$r2 = \text{"If } Ix \text{ is not zero or } Iy \text{ is not zero then } Iout \text{ is black"};$

```
edgeFIS = addRule(edgeFIS,[r1 r2]); edgeFIS.Rules
```

Step 5: Evaluate FIS

```
Ieval = zeros(size(I));% Preallocate the output matrix  
for ii = 1:size(I,1)  
Ieval(ii,:) = evalfis([(Ix(ii,:));(Iy(ii,:))]',edgeFIS);  
End
```

Step 6: Plot Results

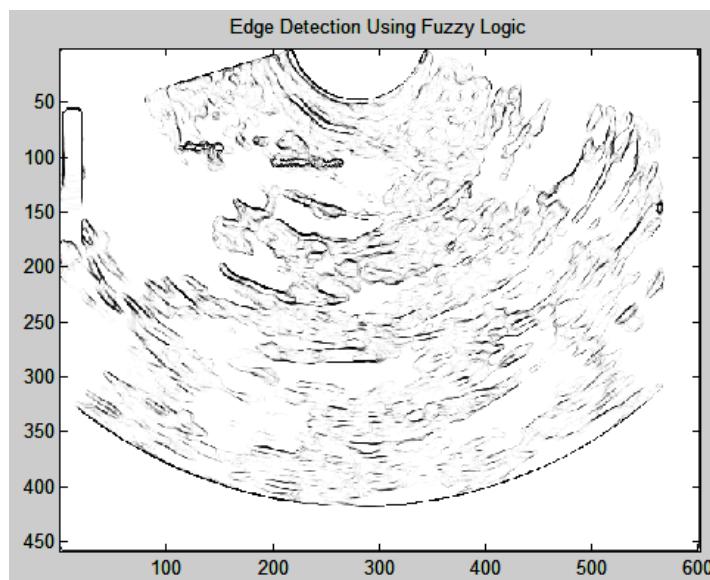


Figure (4.13) Edge detection using fuzzy logic

4.6 Phase four: Uterine ultrasound image segmentation

Image segmentation is the technique of partitioning or pixel classification, which aims to segment objects or regions from the background. The segmentation process of the uterine ultrasound image is to extract the endometrial region after input image use, the main interest of the image segmentation stage is to divide the uterine ultrasound image into regions and separate the area or region of interest (ROI) and isolate the endometrial region from a uterine ultrasound image,

4.6.1 First approach K-means clustering technique

Clustering is the technique where the same type of objects is grouped. These groups are called clusters. Objects of one cluster must have different characteristics than the objects of another cluster. There are several algorithms to accomplish the task of clustering. One of these algorithms is the K-means clustering algorithm. Now, these clustering techniques can be used for image segmentation as different pixels of an image have different characteristics and based on those characteristics the pixels can

be grouped into several clusters. These clusters of pixels can be viewed as different segments of the image.

Step 1: Prepare the output image from fuzzy logic for k mean

Convert image obtained from fuzzy logic technique to binary image using MATLAB function `I2=im2bw (Ieval, 0.7)`; by replacing all pixels in the input image with luminance greater than level with the value 1 (white) and replacing all other pixels with the value 0 (black). This range is relative to the signal levels possible for the image's class. Therefore, a level value of 0.7 corresponds to an intensity value halfway between the minimum and maximum values of the class. The next step, `h=fspecial('unsharp')` returns a 3-by-3 unsharp contrast enhancement filter. Figure 4.14 shows binary binary-enhanced image, which will be the input image for k-means clustering.



Ad

Figure (4.14) Input binary image to k means

Step 2: K means segmentation

This thesis focuses on segmenting the exact location of the endometrium region from uterine ultrasound images the proposed method used a k-means clustering algorithm to automatically segment the endometrium regions. K- means which is an unsupervised algorithm utilized for the detachment of the area of interest of the image which is the endometrium region from its experience is called K- means grouping. It isolates the given ultrasound image or information into a K number of bunches or gatherings relying upon the application. This calculation has two stages. Right off the

at K centroids are browsed each bunch and in the following stage, the calculation computes the separation between the centroids and takes each highlight the closest centroid in the groups. The algorithm can be summarized as follows:

1. Initialize the number of cluster k and randomly define k cluster centers
2. Assign each data point to the closest cluster center
3. Recalculate the cluster centers using current cluster memberships
4. Repeat the process until convergence or squared error criterion satisfies a minimum threshold value

The quality of final clustering highly depends on the random selection of initial cluster centers, which is the major limitation of k-means clustering. As shown in Figure 4.15

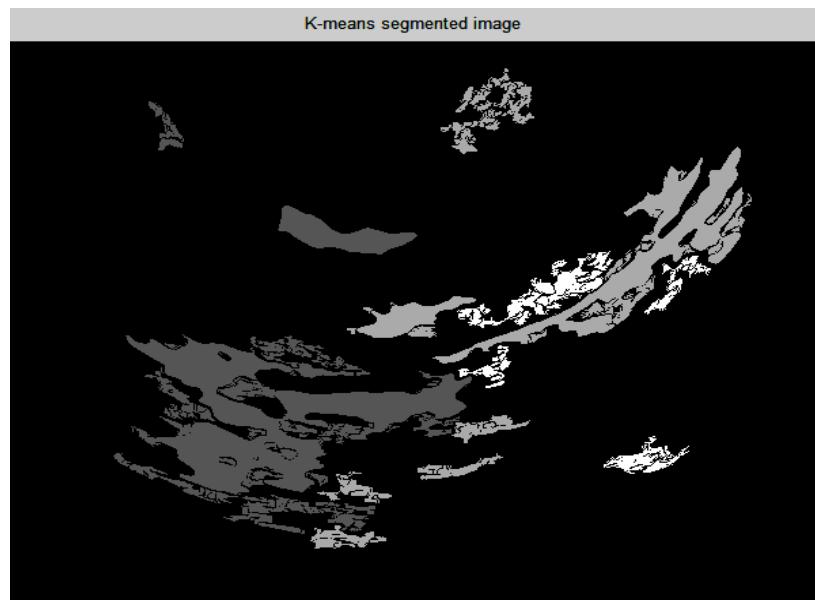


Figure (4.15) Endometrium Segmentation Using K-Means Clustering from Ultrasound Image of uterine ultrasound

Step 3: Draw boundary on the regions at the ultrasound image

Detection of edges in an image is an important step towards understanding image features. Since edges often occur at image locations representing object boundaries, edge detection is extensively used in image segmentation when images are divided into areas corresponding to different objects. The edge-detecting method performed in this proposed system was the Sobel method, followed by the Boundary tracing technique. Firstly, Sobel Edge Detection after K-means segmentation results, obtained ultrasound image was subjected to one of edge detection operators. Sobel was applied to obtain image edges that occur on the boundary between two different regions in an

image and they are classified as a derivative-like gradient-based where a gradient of consecutive pixels is taken in x and y directions, this operation is called kernel operation. In Sobel, two 3x3 convolution masks are applied to each pixel, and the result is treated as a vector representing the edge through the current pixel. And its results are shown in Figure (4.13)



Figure (4.16) Edge detection experimental results by Sobel

This method was chosen because it can produce a boundary edge more detailed because of the capacity of smoothing effect on the random noises of an image. Secondly, We applied Boundary Tracing techniques for tracing of detected edge which was done using a neighborhood contour tracing algorithm. Results of the Sobel Edge detector consisting of a connected curve are given as input and output is a set with coordinates of cells (pixels) that lie on the curve. Once the pixels that lie on the edge (points having pixel intensity 1) around the object are detected, they are joined to form a closed contour as shown in Figure (4.14).

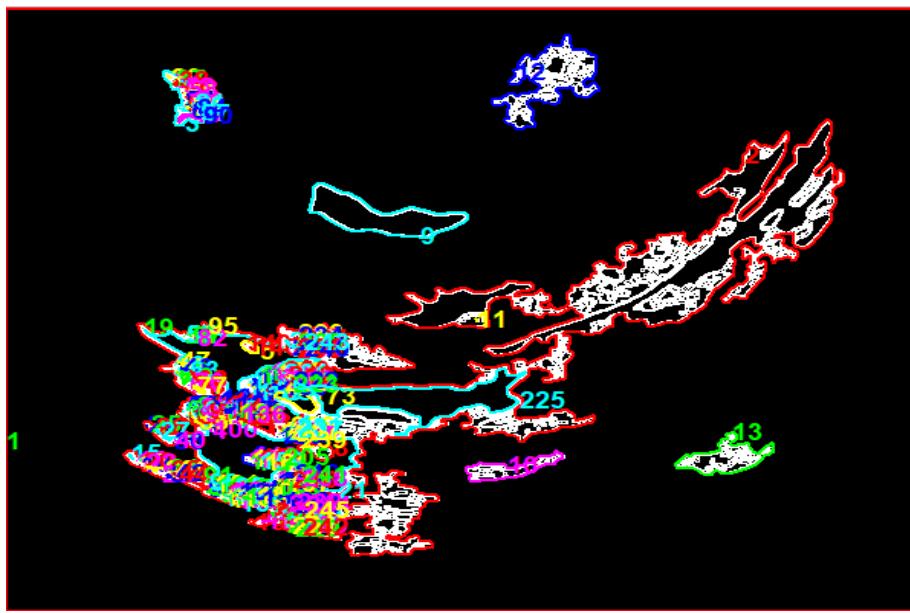


Figure (4.17) The boundaries of the different regions identified by Boundary Tracing

4.6.2 Second approach Automatic thresholding segmentation technique

Thresholding is a very popular operation for image processing applications, which are object detection, object-based coding, object tracking, and clinical or tissue identification. Segmentation is the technology and the process of separating a specific target, which is the endometrium region from a specific area, which is the uterine ultrasound image. This thesis is based on threshold segmentation. The basic principle of threshold segmentation is to divide image pixels into several categories by setting different characteristic thresholds. Ultrasound image segmentation based on Thresholding, in the binary image the foreground pixels (bright pixels) were marked 1, and background pixels (black pixels) were marked 0 but the background markers should not be too close to the edges of the objects that were to be segmented. In this case, the binary image of the filled operation was determined by the connectivity called the infill (image filling) built-in function. While infill was applied to the image the connectivity of the background was specified. In the MATLAB steps that were used to segment ultrasound images, the endometrium region was separated from the background in binary image segmentation.

Step 1: Resize the enhanced ultrasound image, using the imresize function

Resize the enhanced image using the imresize function. This function resizes images by increasing or decreasing their pixels. we resize an image two times of size 300-by-300, This function creates more pixels using the pixel values already present in the

neighborhood. MATLAB command $target\ Image = imresize(Ultrasound\ Image, [300\ 300]);$

Step 2: Apply median filter to remove the noise

The median filter removes noise from the image while protecting the edges. This filter is especially effective in ultrasound noise removal. A median filter which is a nonlinear operation is applied to an image by using the neighbors of a pixel. The median filter takes the median value instead of the averaging or weighted average of pixels in the mask. The operation is made by selecting the mask size which is generally a 7×7 -pixel group and then putting the all-pixel values in order. After that, the median value is found and the processing pixel is replaced with the median value [6].

MATLAB command $b = medfilt2(b, [7\ 7]);$

Step 3: Apply Thresholding to the image

Convert grayscale image to binary (0s and 1s), Binarization is based on a rough thresholding. The output binary image has values of 0 (black) for all pixels in the input image with luminance less than the threshold level and 1 (white) for all other pixels. The output image has only two intensity levels (values 0 and 1). The output image is a binary image.

$c = im2bw(b, graythresh(b));$

Step 4: Foreground and background as a marker

In the binary image, the foreground pixels (bright pixels) were marked 1 and the background pixels (black pixels) were marked 0 but the background markers should not be too close to the edges of the objects that were to be segmented. In this case, the binary image of the filled operation was determined by the connectivity called the infill (image filling) built-in function. While `imfill` was applied to the image the connectivity of the background

Step 5: Clear borders of objects or lighter structures.

Using `imclearborder(im)` is the simplest case of binary images, this function removes objects that touch the image borders. $Ic = imclearborder(MM, 8);$ suppresses structures that are lighter than their surroundings and that are connected to the image border. Ic can be an intensity or binary image. The output image is intensity or binary, respectively. The default connectivity is 8 for two dimensions and 26 for three

dimensions. Figure (4.15) shows the experimental results of the obtained image after applying the above steps.



Figure (4.18) Output image after applying a median filter, median filter, and border clearness by clear border

Step 6: Apply Binary area open; remove small objects

Applying $e = \text{bwareaopen } Ic==1,1000;$; MATLAB function to remove from a binary image all connected components (objects) that have fewer than 1000 pixels, producing another binary image. Figure (4.15) shows the resulting image from this MATLAB function

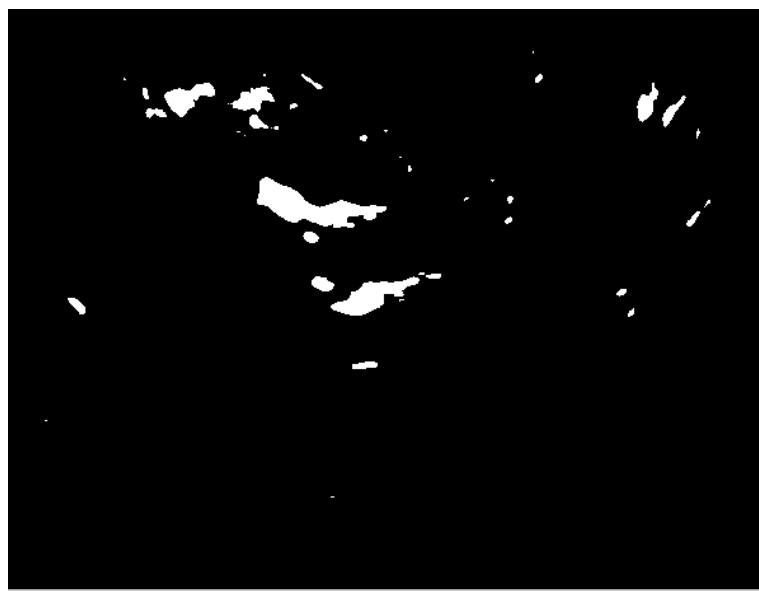


Figure (4.19) Remove small objects

Step 7: Image segmentation result

In Figure (4.16) which was the result of the segmentation process, we display the original enhanced image with the segmented endometrium region.

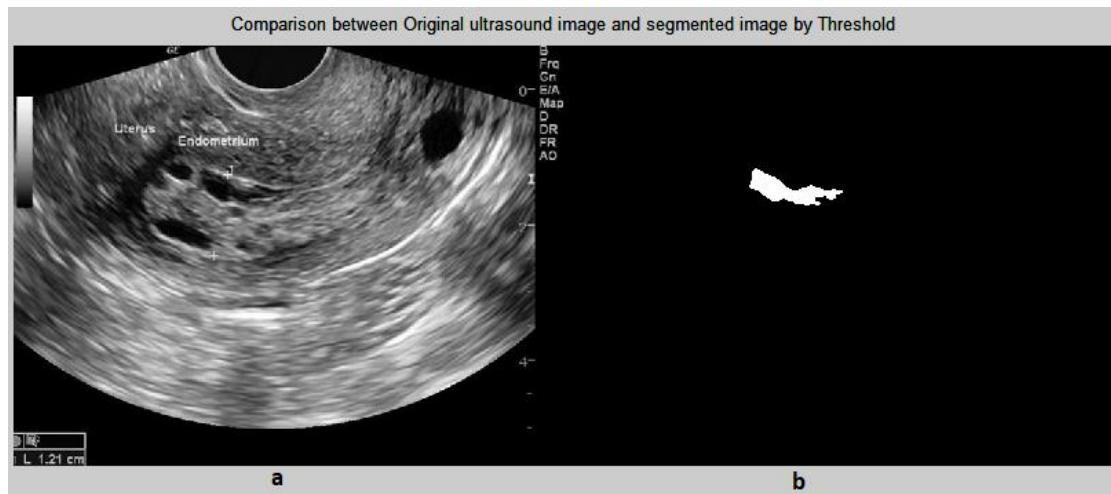


Figure (4.20) Comparison between Original ultrasound image and segmented image

Step 8: Create a contour and plot the endometrium region

Apply `imcontour (I,n)` draws a contour plot of the intensity image I, automatically setting up the axes so their orientation and aspect ratio match the image. n is the number of equally spaced contour levels in the plot; if you omit the argument, the number of levels and the values of the levels are chosen automatically. Figure (4.17) shows the result of the shape of the endometrium.

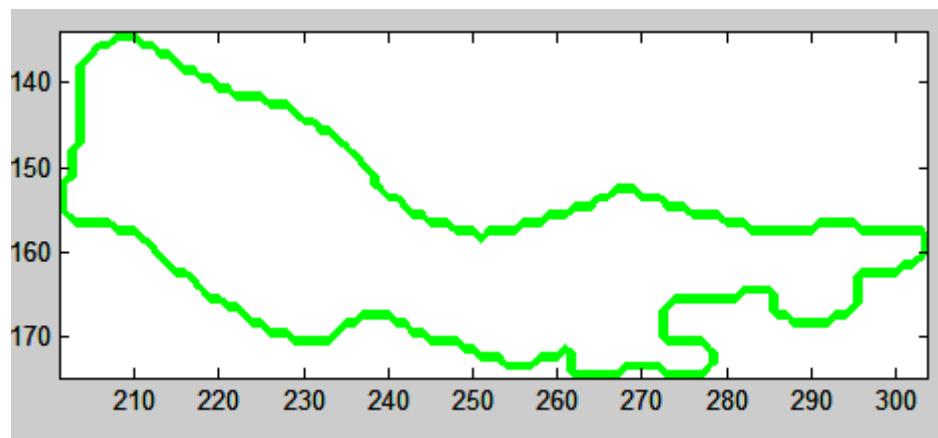


Figure (4.21) Detection of segmented endometrium region by contour

4.7 Image Segmentation Evaluation

To judge the importance of uterine ultrasound image segmentation techniques, it is required a suitable image segmentation measure that should provide quantitative

evidence of whether the image is segmented well, and also an indicator of how much it is segmented, the quality of segmented images must be evaluated to see the results of processed images using image segmentation techniques.

In this thesis the quality of an image is examined by objective evaluation as well as subjective evaluation, we used two famous methods, the first method was objective measurement by using the mathematical equations to measure the quality of segmented images in which the mathematical averages are used in determining the difference between the original image and the improved image and determining the percentage of difference.

The second method was human visual inspection, which is an evaluation made by a radiologist who has experience in reading and analysis of uterine ultrasound images, the resulting endometrial shapes were presented to several radiologists alongside the original image. The radiologists were asked using a designed questionnaire by the searcher to comment upon the accuracy of the enhanced image and segmentation resulting in the given shape and site of a mass an image is said to be enhanced if it allows the viewer to better perceive the desirable information in the image.

4.7.1 Objective Evaluation Performance Measurement

The quality of the segmented image was measured by peak signal-to-noise ratio (PSNR). This parameter is a close estimation of the human impression of reproduction quality. The higher the PSNR better the picture quality. PSNR is the assessment standard of the recreated picture quality PSNR (Peak Signal Noise Ratio) is a common parameter used as an indicator in comparing the similarity of the two images (raw image and processing image). Detailed results of PSNR value are shown in Table 4.1. This table defined that only some ultrasounds have better visualization, the PSNR values wg the following equation [34].

$$MSE = \frac{1}{mn} \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} (I(i,j) - R(i,j))^2 \quad 4.1$$

Where I is the raw image R is the processed image, m, n number of pixels in two directions x,y for the image

$$PSNR = 20 \cdot \log 10 \left(\frac{\text{MAX}_I}{\sqrt{MSE}} \right) \quad 4.2$$

Where MAXI is the maximum possible value of the image.

Table (4.1) Performance Measurement

Grade	Edge detection	K means clustering	Thresholding
PSNR	44.23158	43.2544	33.7371

4.7.2 Subjective Evaluation Performance Measurement

The radiologists were asked to evaluate the original images and the resultant images and a questionnaire was designed to reflect their judgments, this questionnaire was designed to measure the degree of satisfaction that each radiologist has with the used images. Five specialists were involved in evaluating the cases and filling out the questionnaire for each case of images. The original and the other one is the processed one. The Radiologists were asked to make a comparison between the original and the processed images. The comparison is based on the characteristics of image quality the results of the questionnaire were converted to the following table (4.2) which shows the percentage of satisfaction for ten specialists.

Table (4.2) Satisfaction percentages of image

Grade	Edge detection	K means clustering	Thresholding
Poor	0	0	0
Good	7	1	0
Excellent	3	9	10
Percentage	70% Good	99% Excellent	100% Excellent

Almost similar satisfaction percentages were obtained for image Segmentation by k means clustering and Thresholding algorithms.

CHAPTER FIVE: RESULTS

In the previous chapter, the description of the methodology used to implement endometrial detection has been discussed. This chapter explains our experimental results on uterine ultrasound images for segment endometrial region, enhancement techniques are used to improve the interpretability or perception of information in images for human viewers or to provide enhanced input for other automated image processing techniques. The results in this thesis indicate that the proposed approach makes a better segmentation to detect endometrium cancer.

5.1 Results of Image Pre-processing Removal of Ultrasound Noise

The following figures show that, for an identical impulse noise density, the image quality of a de-noised image improves with increasing image size. For restoring a Gaussian noisy image, the Median Filter produces the best results Figure 5.1

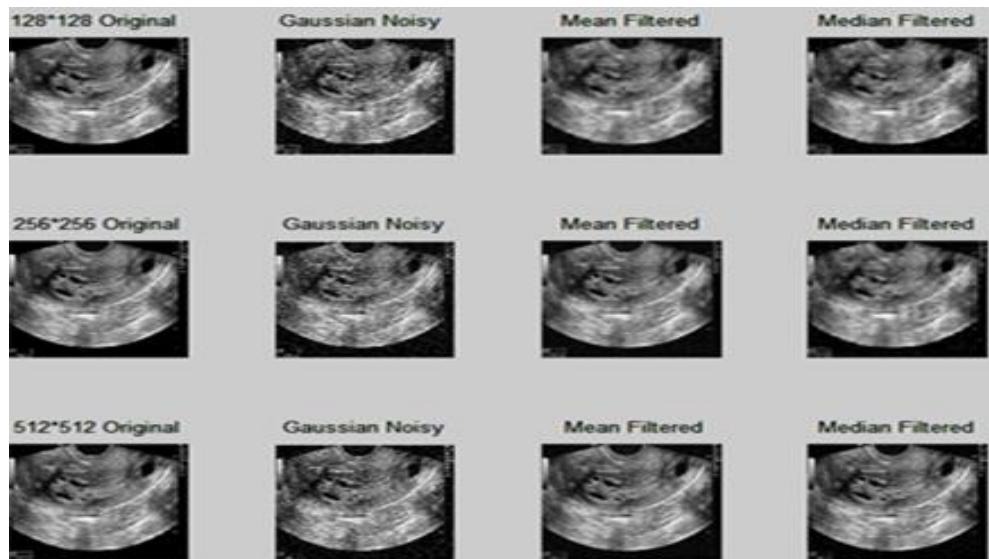


Figure (5.1) Results of removed Gaussian Noise effect

5.1.1 Ultrasound Image Slat & Pepper Noise Effect

According to the figure below, the image Quality of a de-noised image improves with image size for a constant impulse noise density. Filtering with the Median Filter obtained the best results for a salt and pepper noisy image, as shown in Figure (5.2.).

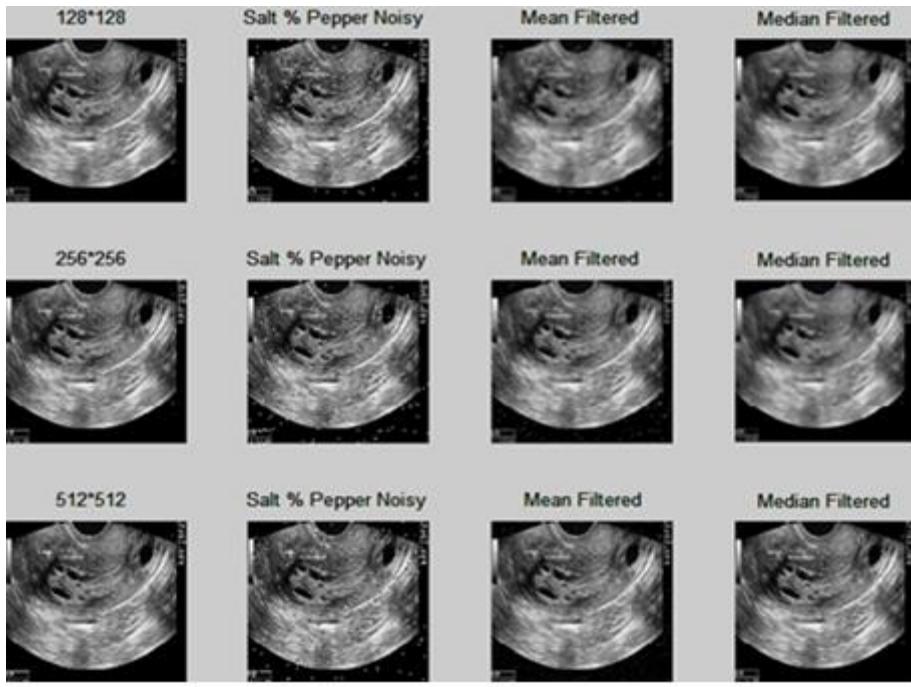


Figure (5.2) Results of removed Slat & Pepper Noise Effect

5.1.2 Ultrasound Image Speckle Noise Effect

According to the figure below, the image quality of a de-noised image increases with image size for a constant impulse noise density. For speckle noise images, the median Filter produces the best results. as shown in Figure (5.3).

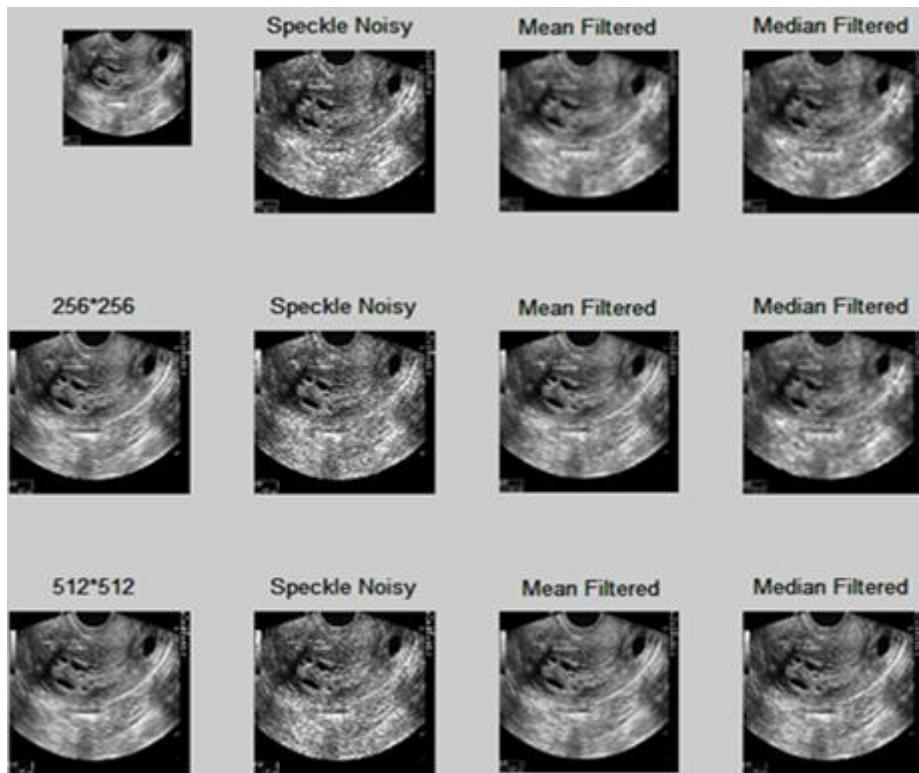


Figure (5.3) Results of removed speckle Noise Effect

5.1.3 Peak Signal Noise Ratio (PSNR), Mean Absolute Error (MAE), and Mean Square Error (MSE)

Image quality measurement is critical in many image-processing applications. In recent years, considerable effort has been focused on developing objective image quality measurements. MSE and PSNR are fundamental, simple to implement, and have low computational complexities. However, these procedures do not provide satisfactory results.

MSE and PSNR are suitable image similarity measures only when the images differ by essentially increasing a specific type of distortion. Comparing restoration results requires a measure of image quality.

- Mean Squared Error (MSN)

Mean squared error (MSE) is one of the mathematically based metrics. It calculates the cumulative squared error between the original image and the distorted image.

$$\text{MSE} \text{ is given as } MS = \frac{1}{MN} \sum_{y=0}^{M-1} \sum_{x=0}^{N-1} [E(x, y)]^2$$

5.1

where x and y indicate the pixel position, and M and N are the image width and height.

- Peak Signal-to-Noise Ratio (PSNR)

The peak signal-to-noise ratio (PSNR) is a measure of the peak error between the compressed image and the original image. PSNR is given as

$$PSNR = 20 \cdot \log 10 \left(\frac{\text{MAX}_I}{\sqrt{MSE}} \right) \quad 5.2$$

Where MAXI is the maximum possible value of the image. The higher the PSNR, the better the quality of the reproduction. PSNR has usually been used to measure the quality of compressed or distorted images

- Mean of Absolute value of Errors (MAE)

Mean of the Square of Errors and MAE is the Mean of the Absolute value of Errors. Here, errors are the differences between the predicted values (values predicted by our regression model) and the actual values of a variable. They are calculated as follows:

$$MAE = \sum_1^n \frac{|(y_i - y_p)|}{n} \quad 5.3$$

Where y_i actual value y_p predicated value, n number of observation

The table below shows the overall PSNR, MAE, and MSE values for different image sizes. PSNR is the most important measurement, followed by MSE and MAE.

Table (5.1) Ultrasound image size 128x128 PSNR, MAE, and MSE

Ultrasound image size 128x128									
Filter type	Gaussian			Salt & Pepper			Speckle		
	PSNR	MSE	MAE	PSNR	MSE	MAE	PSNR	MSE	MAE
Mean	80.5	23335	155	80.3	24332	156	80.44	24336	156
Median	79.2	94516	255	86.92	94516	254	80.10	94516	254

Table (5.2) Ultrasound image size 256x256 PSNR, MAE, and MSE

Ultrasound image size 256x256									
Filter type	Gaussian			Salt & Pepper			Speckle		
	PSNR	MSE	MAE	PSNR	MSE	MAE	PSNR	MSE	MAE
Mean	80.6	24334	154	80.4	24336	156	80.45	24334	155
Median	79.7	94515	254	86.98	94516	254	80.12	94515	252

Table (5.3) Ultrasound image size 512x512 PSNR, MAE, and MSE

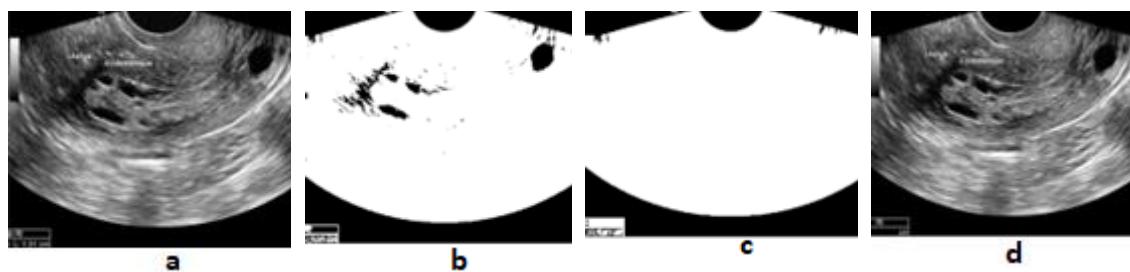
Ultrasound image size 512x512									
Filter type	Gaussian			Salt & Pepper			Speckle		
	PSNR	MSE	MAE	PSNR	MSE	MAE	PSNR	MSE	MAE
Mean	80.45	24333	153	80.1	24336	156	80.46	24332	153
Median	79.9	94514	253	86.99	94516	254	80.14	94514	251

Peak signal-to-noise ratio (PSNR) was employed with priority to illustrate the quantitative quality of the reconstructed image for various methods. On increasing image size with constant impulse noise density, PSNR increases, and MSE and MAE decrease. This is because the ratio of image size to noise density increases with an increase in image size and constant noise, therefore the output image is recovered. In ultrasound grey scale Image with three noises (Gaussian, Salt & Pepper and Speckle De-noised all noisy images by (Mean and Median) filters and concluded from the results that Following de-noising, the median filter performed better than the Mean Filter for all Speckle and Gaussian noise, The performance of the Median filter after de-noising for all Salt & Pepper noise is better than Mean filter The image quality of

de-noised image increases with the increase in image size for a constant impulse noise density.

5.2 Results of artifact and label removed from ultrasound image

Figure 5.4 shows operations applied on uterine ultrasound image to limit the processing in uterine ultrasound image for segmenting the endometrial region, we need to remove unwanted parts of the image, in four steps, the first step was converting grayscale image to binary image, as in Figure (5.4. a), So, the white region at the binary image could shrink by erosion or expand by dilation operation Automatic thresholding Segmentation was performed based on gray level intensities of the image. The uterine ultrasound image was converted to a gray-level image, which was used to enhance the foreground (or bright) ultrasound as shown in Figure 5.4 (a and b) below. An automatic thresholding function was applied to binarize the grayscale images. Filling the holes using morphological operators could binarize the image with the ultrasound image having a pixel intensity of one and a background of zero.



Figures (5-4) represent artifacts and labels removed from the ultrasound image

- (a) Pre-processed grayscale image
- (b) converting to binary image
- (c) filling holes
- (c) Output image without artifacts

5.3. Results of endometrial region edge detection

In this thesis, edge detection is used to specify the boundary of each region in uterine ultrasound images, in addition to announcing the presence of overlapped ultrasound objects. we used fuzzy techniques for image processing, and a common quality improvement technique of image processing was compared with each other in the uterine ultrasound images. According to Figure 5.5, uterine ultrasound image was visually improved after the implementation of algorithms inseparability of edges, details of images, and also resolution and contrast. MSE and PSNR values of the measured images are PSNR =64.9679, MSE=0.0207

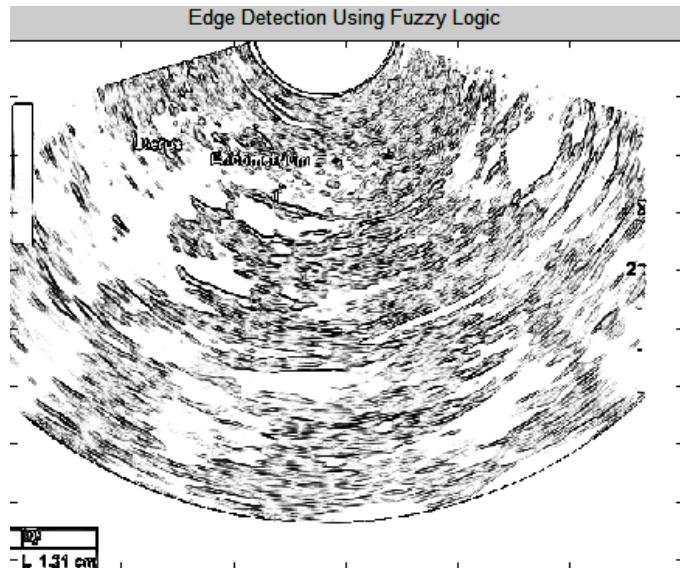


Figure (5-5) Results of uterine ultrasound Edge detection by fuzzy logic

In such uterine images, the surface of the endometrial appears brighter than the surrounding tissue, so with image contrast improvement using the mentioned methods, the endometrial will be brighter. Then, the endometrial surface can be easily separated from the uterine ultrasound image using the image segmentation methods. A fuzzy rule-based algorithm provides better edge detection and has an exhaustive set of fuzzy conditions which helps to extract the edges with a very high efficiency

5.4. Results of Endometrial region segmentation by k-means clustering

The ultimate aim of this thesis was to improve the diagnosis accuracy that helped radiologists make the right decision to detect cancer in the early stages. Segmentation is used for class quantification of uterine ultrasound images in which we can classify the shape of the endometrium. Here we can notice that K represents the clusters and classes that belong to each type of area, by applying K-means Clustering on the ultrasound image, the following results can be obtained. As can be seen from Figure 5.6, the use of this method for image segmentation, and performance shows that this method is effective and can be well recognized.

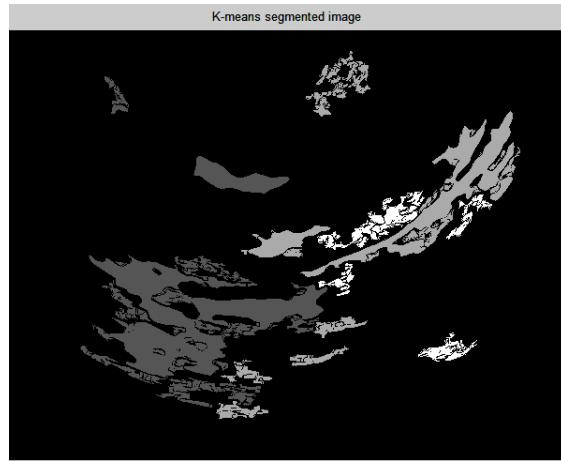


Figure (5-6) Illustrate the Endometrial region image after k-means segmentation

The resulting images obtained from image segmentation are more meaningful and can be analyzed easily to reach to some decisions. Thus, it can be said that the efficiency of image analysis mostly depends on the solidity of image segmentation.

5.4.1. Results of detected boundary for endometrial region

Figure (5.7) shows the Results of boundary detection. The experiment results showed that the proposed segmentation method for boundary has better robustness and higher the contour boundary is clear, especially the endometrium region number 9, and there are special signs between the boundaries.

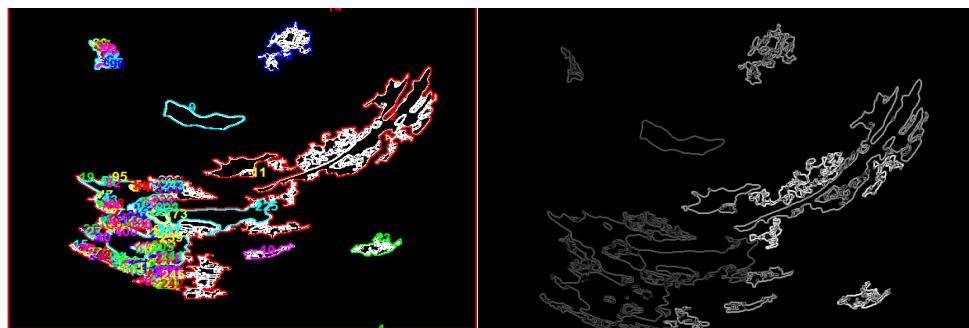


Figure (5-7) Illustrate gray detected boundary for the endometrial region

5.5 Automatic Thresholding Segmentation

Isolating the endometrium region from the background involves the following steps: first, the gray threshold is calculated and the gray image is converted to a binary image. The resulting binary image is enhanced and refined by removing small objects and filling the holes within the ultrasound. Next, the refined binary image is segmented into several objects with each object representing an endometrium or several overlapped objects.

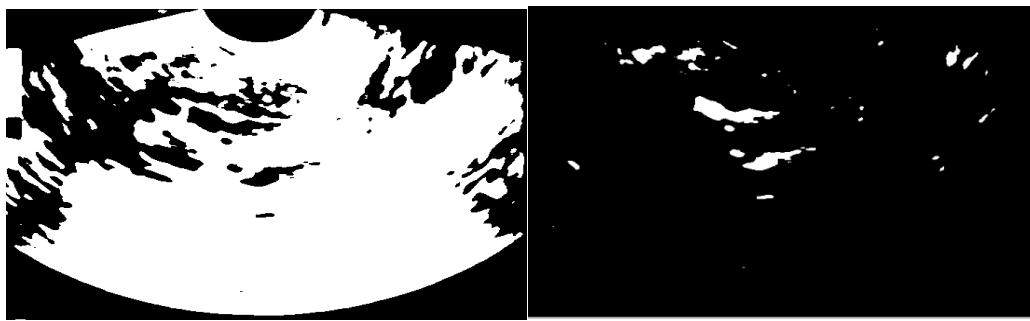


Figure (5-8) Segmented and traced the boundary of the binary normal endometrium shape

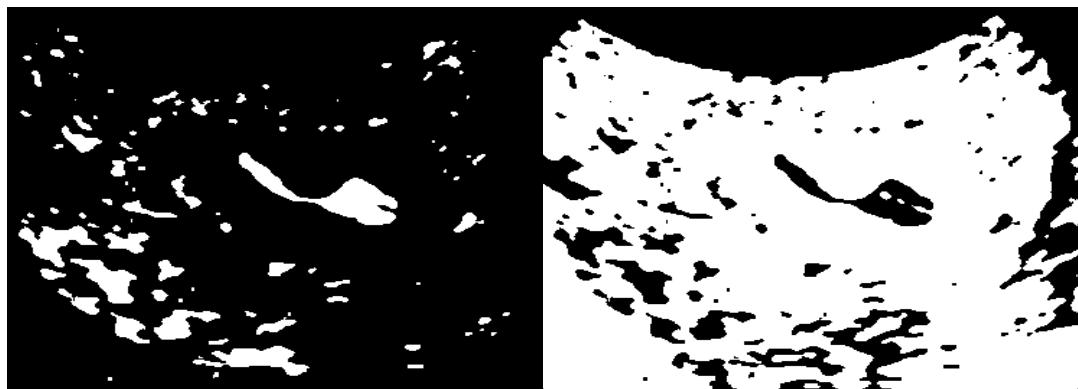


Figure (5-9) Segmented and traced the boundary of the abnormal endometrium shape

The result of endometrium detection is shown in Figure 5.8, which was benign or normal endometrium, and Figure 5.9, which was Malignant Endometrium or cancer endometrium

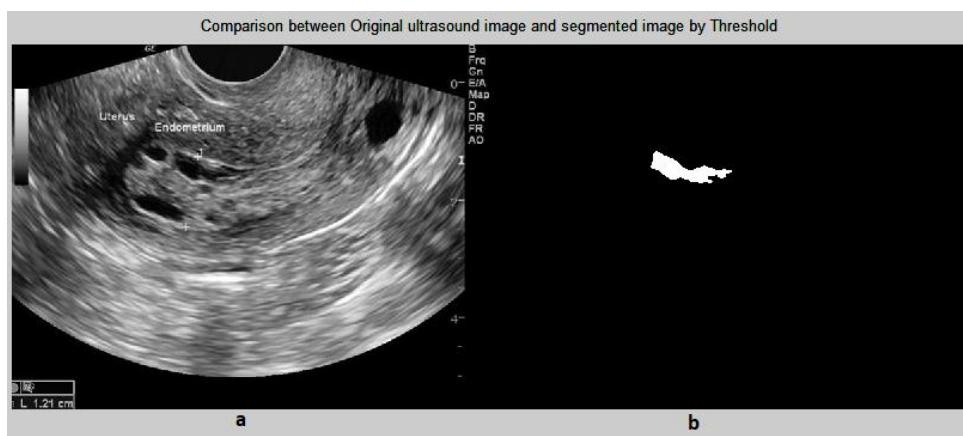


Figure (5-10) Segmented normal endometrium shape region
(a) Original Grayscale image (b) image with selected endometrium ROI

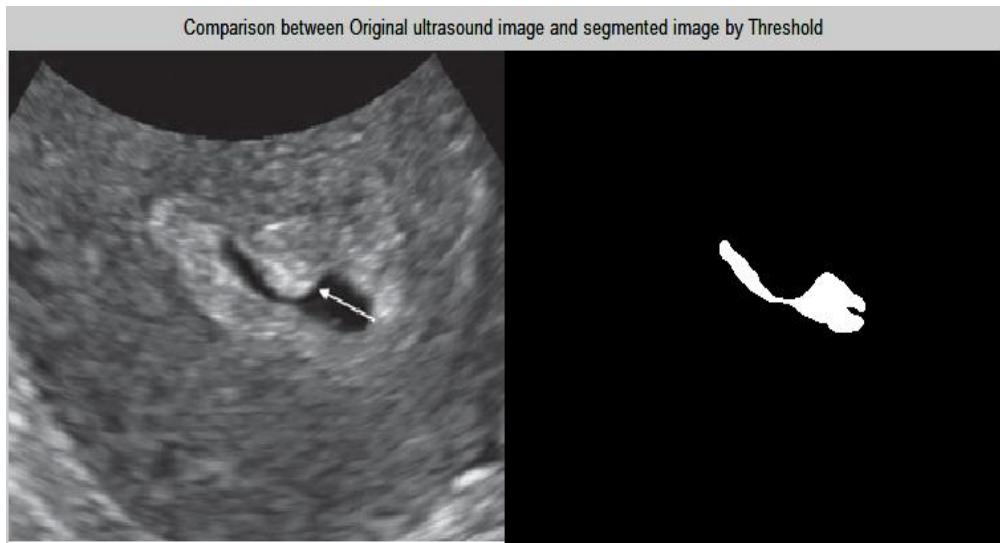


Figure (5-11) Segmentation of abnormal endometrium (a) Original Grayscale image (4) Original image with selected endometrium ROI

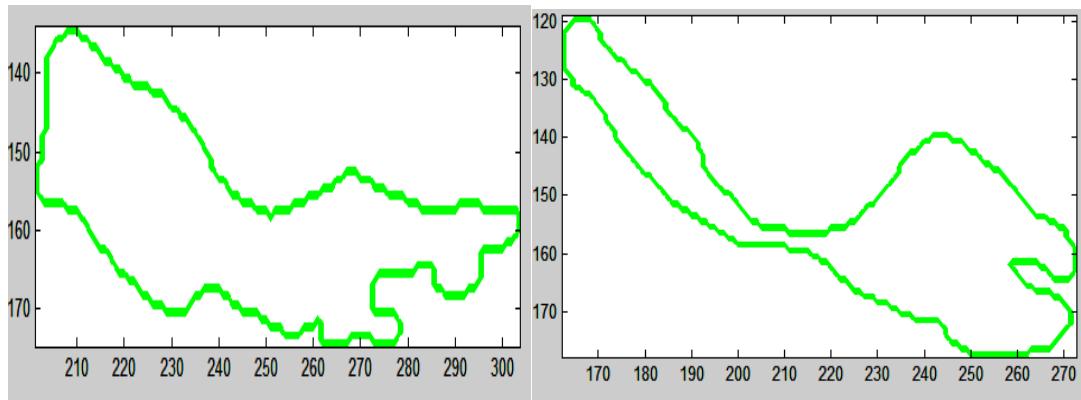


Figure (5-12) Segmentation of Endometrium ROI (a) Original Grayscale image (b) Malignant image with selected endometrium

Detection of endometrial shape in uterine ultrasound image was achieved by extracting the foreground objects. Separating an image into foreground and background is called Image Segmentation. Image segmentation is achieved by using the common properties of the pixels. In this work, intensity property of pixels is used in developing image segmentation algorithms.

Image segmentation algorithms generally are based on one of the two basic properties of intensity values: discontinuity and similarity. In the first criteria, the image is partitioned when there is an abrupt change in the intensities of neighboring pixels, such as edges in an image. In the second criteria, image is partitioned into

regions that are similar according to some predefined conditions. In this project we used the second criteria i.e., similarity in developing the Image Segmentation algorithms. It became easy for the doctor to classify the endometrial shape, as normal or abnormal. To test theses algorithm, we applied it to two images. From the results, we can say that the algorithm gave excellent results in the detection endometrial final shape.

CHAPTER SIX: CONCLUSION AND FUTURE WORK

6.1 Conclusion

As discussed in chapter one and chapter two, the exact cause of Endometrium cancer is unknown, the methods of preventing is not specified yet. Moreover, late detection and manual screening of Endometrium cancer are the main problems in getting decision of doctors to apply the methods of treatment and rescue the life of women. Especially, these missed diagnoses due to human error often have severe consequences. It is clear that image-processing systems are a desirable technology in health care industry. Hence, the researcher have proposed it to detect and classify an endometrial shape in uterine ultrasound images using edge detection, k means method and thresholding segmentation. A preprocessing method based on histogram equalization and median filtering was applied for image denoising and enhancement. As a result, there are also big challenges to combine this image processing system with manual detection system due to financial problem, lack of experts and screening modalities. Even if, to reduce mortality rates, Endometrium cancer detection shall be done using a image processing with combination of medical history, physical examination and manual uterine ultrasound imaging. Accurate diagnosis of endometrial cancer is critical since only localized cancer is treatable and curable, as opposed to metastasized cancer. As a result, the fundamental goal of this thesis is to improve endometrial cancer detection using ultrasound image processing. An action plan is devised and implemented to accomplish the aforementioned goals. The main objective of this study was to segment and classify the abnormal endometrial shape in uterine ultrasound image. The results of this study obtained by applying digital image processing technique to an original image in order to classify the shape of segmented endometrial. Using k-means and thresholding analysis to objectively segment the uterine and classify it into normal and abnormal. In general, image-processing using to detect endometrial shape offers a means to improve the efficiency of Ultrasound imaging and help radiologists and physicians to achieve higher diagnostic accuracy in which Endometrium cancer early detection reduce mortality rate and improve the survival rate of patients

6.2 Future perspectives

For effective endometrium cancer treatment, accurate uterine ultrasound image segmentation, detection and classification are an important task in medical diagnosis before the tumor grow and spreads. Transvaginal ultrasonography (TVUS) is the only broadly accepted and used diagnostic test for early Endometrium cancer detection. Besides identifying abnormalities of Endometrium cancer using Ultrasound imaging often requires the eye of a trained radiologist.

Therefore, image-processing techniques are increasing in importance in medical diagnosis because of their classification capability. So the introduction of image processing techniques functions as a decision tool by assisting radiologists for diagnosing cancer in the uterine ultrasound images easily but the purpose is not to replace the radiologist but to facilitate their day to day activities and to provide a second opinion and that become the prime interest of them. Using this image processing system, Endometrium cancer can be found early, it is likely to be small and Endometrium protecting treatment is possible. Hence, surgeons can remove the tumor and some surrounding tissue, followed by radiotherapy. To achieve the above objectives perfectly, the following future works are suggested for additional research and improvement on the current work:

- The work done in this thesis is extremely efficient. Even though, some improvements are always needed to accomplish our goals.
- Applying large local dataset images and test on this proposed work.
- Further establishment is needed to implement further algorithms using computer Aid diagnosis (CAD).

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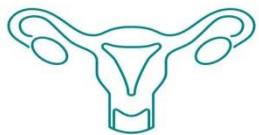
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Appendix
7.1 Questionnaires

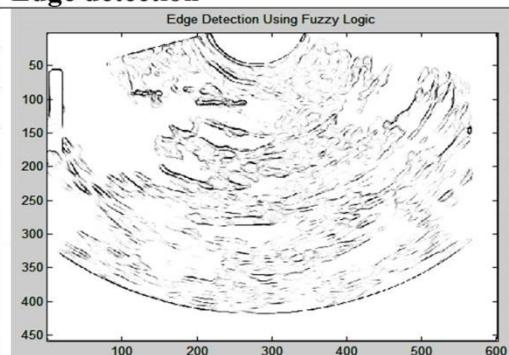


Questionnaire



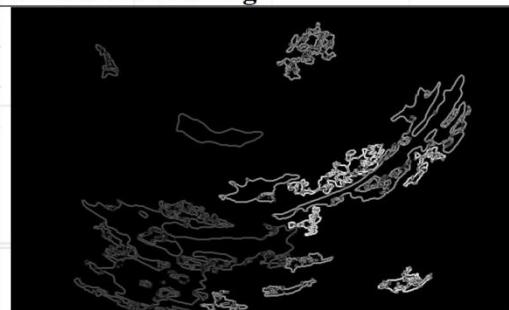
NAME:

Edge detection



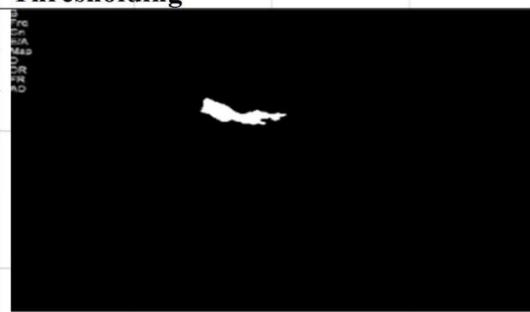
Poor	<input type="checkbox"/>
Good	<input checked="" type="checkbox"/>
Excellent	<input type="checkbox"/>

K means clustering



Poor	<input type="checkbox"/>
Good	<input checked="" type="checkbox"/>
Excellent	<input type="checkbox"/>

Thresholding



Poor	<input type="checkbox"/>
Good	<input type="checkbox"/>
Excellent	<input checked="" type="checkbox"/>