EDGE DETECTION OF MAMMOGRAPHY IMAGE USING IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

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Prepared as
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Mohamed Al TAWIL

ABSTRACT

M. Sc. Thesis

EDGE DETECTION OF MAMMOGRAPHY IMAGE USING IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

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Image processing plays a pivotal role in various domains, including computer vision, medical imaging, and robotics. With the continuous evolution of image processing technologies, driven by advancements in computer vision and machine learning, opportunities arise for enhancing our ability to analyze and interpret digital images. This study introduces edmABC, an approach to edge detection specifically tailored for mammography image analysis. Inspired by the foraging behavior of honeybees, we adopt the Artificial Bee Colony (ABC) algorithm to identify and highlight boundaries within mammography images. Our objective is to improve edge detection in images, which is crucial to help the doctor with subsequent medical analysis and diagnosis.

The ABC algorithm was employed to explore the image space and select potential edge points based on fitness values. This approach synergizes local search, information sharing, and exploration, enhancing edge position accuracy. We introduced opposition-based learning and chaotic systems in population initialization. Additionally, grayscale values and statistical estimation were extracted to support solution evaluation.

Our proposed edmABC method demonstrates superior performance compared to standard edge detection techniques and prior research. The adaptation of the bee algorithm, coupled with grayscale values and statistical estimation, showcases excellent results.

This study presents edmABC as a promising solution for improving mammography image analysis. By leveraging the ABC algorithm and incorporating grayscale values and statistical estimation, our research contributes to the field's growing body of knowledge. The potential impact on medical diagnostics and the broader society underscores the significance of this study.

Key Words **:** ABC, Artificial bee colony algorithm, Edge detection, Breast cancer, Mammography, Statistical estimation, Gray gradient, Chaotic systems, Opposition-based learning.

Science Code **:** 92418

ÖZET

Yüksek Lisans Tezi

MAMMOGRAFİ GÖRÜNTÜSÜNÜN GELİŞTİRİLMİŞ YAPAY ARI KOLONİSİ ALGORİTMASI KULLANILARAK KENAR TESPİTİ

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Görüntü işleme, bilgisayarla görme, tıbbi görüntüleme ve robotik dahil olmak üzere çeşitli alanlarda önemli bir rol oynar. Görüntü işleme teknolojilerinin bilgisayarlı görme ve makine öğrenimindeki gelişmelerin yönlendirdiği sürekli gelişimiyle birlikte, dijital görüntüleri analiz etme ve yorumlama yeteneğimizi geliştirme fırsatları ortaya çıkıyor. Bu çalışma, özellikle mamografi görüntü analizi için uyarlanmış bir kenar algılama yaklaşımı olan edmABC'yi tanıtmaktadır. Bal arılarının yiyecek arama davranışlarından ilham alarak, mamografi görüntülerindeki sınırları belirlemek ve vurgulamak için Yapay Arı Kolonisi (ABC) algoritmasını benimsiyoruz. Amacımız, doktora daha sonraki tıbbi analiz ve teşhislerde yardımcı olmak için çok önemli olan görüntülerde kenar algılamayı iyileştirmektir.

Görüntü uzayını araştırmak ve uygunluk değerlerine göre potansiyel kenar noktalarını seçmek için ABC algoritması kullanıldı. Bu yaklaşım, yerel aramayı, bilgi paylaşımını ve keşfi sinerjilendirerek uç konum doğruluğunu artırır. Popülasyonun başlatılmasında karşıtlık temelli öğrenme ve kaotik sistemleri tanıttık. Ek olarak, çözüm değerlendirmesini desteklemek için gri tonlamalı değerler ve istatistiksel tahminler çıkarıldı.

Önerilen edmABC yöntemimiz, standart kenar algılama teknikleri ve önceki araştırmalarla karşılaştırıldığında üstün performans göstermektedir. Arı algoritmasının uyarlanması, gri tonlamalı değerler ve istatistiksel tahminle birleştiğinde mükemmel sonuçlar ortaya koyuyor.

Bu çalışma, edmABC'yi mamografi görüntü analizini geliştirmek için umut verici bir çözüm olarak sunmaktadır. ABC algoritmasından yararlanarak ve gri tonlamalı değerleri ve istatistiksel tahminleri birleştirerek araştırmamız, alanın artan bilgi birikimine katkıda bulunuyor. Tıbbi teşhis ve daha geniş toplum üzerindeki potansiyel etkisi bu çalışmanın önemini vurgulamaktadır.

Anahtar Sözcükler : ABC, Artificial bee colony algorithm, Edge detection, Breast cancer, Mammography, Statistical estimation, Gray gradient, Chaotic systems, Opposition-based learning.

Bilim Kodu **:** 92418

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“CONTENTS

Page

Page

Page

LIST OF FIGURES

Page

Page

LIST OF TABLES

Page

PART 1

INTRODUCTION

1.1. INTRODUCTION

Digital image processing is one of the most impressive technological areas of our time. The spread of digital technology and its rapid development has made it possible for us to deal with images differently. Using modern technologies in information science, artificial intelligence, and computer vision applications, we can now improve the quality of images, analyze them, and interpret their content in ways that were not possible in the past.

The field of digital image processing is an essential part of many modern applications in our daily and industrial lives. It contributes to the development of medical and forensic diagnostics and improves the performance of security and surveillance systems. It also plays a vital role in developing advanced technologies such as artificial intelligence, deep learning, and mobile robots. There are several uses for digital image processing, including picture augmentation, restoration, compression, and pattern detection. Image processing has been employed in a variety of disciplines, including security, robotics, agriculture, oil exploration, military and civilian enterprises, and remote sensing applications. [1]

In the world of healthcare and medicine, the fight against breast cancer remains one of the most critical health challenges we face. Breast cancer is the most common type of cancer in women, but it also affects men. Providing early care and diagnosis of breast cancer is vital to increase the chances of survival and improve the quality of life for patients. Hence, the importance of using mammography image processing technology plays a pivotal role in improving diagnosis and providing adequate health care. Breast cancer happens when cells in the breast reproduce and develop abnormally, resulting in a lump or tumor. It has the potential to move to the lymph nodes or harm other organs, such as the lungs.

More women have died from breast cancer than any other infectious disease, including malaria, in history. In developing nations, it is the main reason why women get cancer and pass away. In contrast, it is regarded as the second most common cancer-related cause of death for women in affluent nations (after lung cancer). It is one of the four cancers that affect women worldwide most frequently, along with lung, breast, bowel (including anus), stomach, and prostate. Breast cancer is a severe disease afflicting human, and the symptoms resulting from this disease in the treatment phase may continue for an extended period of life. This disease results in various symptoms, both physical and psychological. It may generate breast pain, breast swelling, or armpit swelling, leading to feelings of anxiety, depression, fear, and uncertainty. The psychological effects of breast cancer may continue even after treatment is complete.

The post-treatment health consequences of this condition demonstrated variability based on age and duration since diagnosis and treatment. Nevertheless, breast cancer survivors experienced notable increases in specific health issues, including coughing, respiratory and urinary tract infections, fatigue, sleep disturbances, osteoporosis, and lymphedema. Notably, osteoporosis and chest-related symptoms have been linked to hormonal therapy, while chemotherapy has been associated with respiratory and skin infections. Lymphedema and skin infections have also been observed with axillary dissection [2]. Early detection is essential for successful breast cancer treatment. Women are advised to perform regular self-examinations of the breasts and to have regular mammograms as recommended by their health care provider, as these regular examinations may help detect cancer and take treatment measures that help improve outcomes.

At the beginning of this chapter, the motivation is presented, followed by a statement of the problem, then the research questions, objectives, scope, and contributions. Finally, the organization of the thesis.

1.2. MOTIVATION

The motive behind using the bee colony algorithm to detect the edges of mammographic images is to take advantage of the collective intelligence and exploration capabilities inspired by the behavior of bee colonies to find images with better resolution.

Artificial bee colony optimization is also a strong move against noisy or complex images, as it considers multiple solutions and can adapt to different edge characteristics. By applying them, we can automate the process of tuning parameters and finding thresholds that produce accurate edge maps of the mammography image. The algorithm explores the parameter space using multiple bees, represents different potential solutions, and iteratively refines the solutions based on the suitability or quality measure.

While the motive behind using mammograms to detect the edges is to help doctors in the early detection and diagnosis of breast cancer. When edges are detected, minute lesions or calcifications that may have been difficult to detect on an original mammogram can become more apparent, helping clinicians visualize the shape and size of suspicious areas and leading to the identification and characterization of potential lesions.

1.3. PROBLEM STATEMENT

Despite the importance of early detection of breast cancer and the role of mammography images in this context, improving the accuracy of diagnosis and analysis of mammography images remains a significant challenge. Mammography is widely used to screen and diagnose breast cancer. However, mammography images contain rich and complex information and need advanced analysis tools to accurately extract vital information due to the diversity of tissue structures and noise [3]. Edge detection techniques can help doctors extract critical structural information, such as tumor boundaries, microcalcifications, and architectural abnormalities in mammograms, making these images easier to interpret and directing doctors toward appropriate areas for further analysis [4].

Interpreting mammographic breast images poses a challenge. According to the National Cancer Institute in the United States, 10-30 percent of breast masses are not visible to radiologists. Masses and microcalcifications, tiny particles, serve as indicators and manifestations of cancer in mammographic breast images. Consequently, diagnosing these manifestations accurately becomes difficult [5]. Previous studies have shown that breast cancer screening among populations helps reduce breast cancer mortality by 40-63 percent. Therefore, Techniques are urgently needed to enhance the contrast of mammographic images for digital image processing [6].

In medical image processing, poor image quality is critical in distorting diagnostic procedures, necessitating the need to employ image enhancement techniques. These techniques constitute a fundamental step before conducting examinations or inspections. Noise reduction and various filtering methods are fundamental aspects of enhancing digital images[7]. Furthermore, various forms of noise are added to images during sensing by instruments due to system conditions, such as changes in lighting or inadequate illumination, contributing to increased signal noise [8].

Despite the numerous methods used for mammographic image edge detection, a definitive mechanistic for distinguishing between cancerous and non-cancerous cells using edge detection and deep learning methods has yet to be established [2]. Therefore, this research asks how to improve the efficiency of edge detection in image mammography using the artificial bee algorithm, which contributes to providing tangible improvements in the field of early detection of breast cancer and improving the chances of survival and quality of life of women with this disease.

1.4. RESEARCH QUESTIONS

This study aims to explore and understand the effect of the bee algorithm in detecting the edges of suspicious areas in mammography images. When using the artificial bee algorithm in edge detection of mammography images, the following research questions were asked:

- How to detect the edges of mammogram images more accurately?
- How to increase the efficiency for the algorithm in finding better solutions?
- How to find the optimal solution to the presented problem?
- How to obtain the optimal solution for the bee algorithm swiftly?

1.5. RESEARCH OBJECTIVES

This new research fills the gap in developing an expert system to detect suspicious areas in the breast to differentiate between healthy tissue and tumors based on digital image processing technology for mammogram images. From this point of view, the theoretical foundations and current research in edge detection and bee algorithm techniques were studied.

The research objectives in this thesis revolve around establishing a method based on improving the artificial bee colony algorithm and testing this method through mammogram experiments. The research objectives of this study are:

- Applying noise processing technique over artificial bee colony algorithm to increase the detection level for the edges.
- Finding a better initial solution for artificial bee colony algorithm by increasing the discovery of multiple solutions using the opposition-based learning method and chaotic systems.
- Improving the function that calculates the fit of detected pixels to resist the noise by implementing a statistical estimate integrated with the gray pixel value for better estimation of the practical edge feature.
- Enhancing the efficiency of the artificial bee colony algorithm to further improve the performance and reduce the time complexity by choosing the most impactful alternatives solutions and selectively eliminating detected solutions with the lowest edge detection impact that do not contribute significantly to the edge detection task within the algorithm.

Relevant business ideas, theoretical thinking in the field, and incremental improvement of models through testing drive the design process forward. We chose this methodology because it has yet to happen much in the field. This research may lead to new models and, at the very least, provide further insight into detecting suspicious areas in mammographic images.

1.6. SCOPE OF THE RESEARCH

This study focuses on using a bee algorithm to detect edges in mammography images based on its focus on binary data. The search scope is defined as follows:

- A collection of nine mammography images from the Kaggle database will be used. This image is two-dimensional, with a size of 1024 x 1024 pixels.
- The bee algorithm will be used for edge detection, and an algorithm will be applied based on the new primitive configuration of the bee colony using an opposition-based learning method, chaotic systems. Moreover, the fit value evaluation will be based on the pixel's grey gradient value and statistical estimation.
- Improve the search for solutions by eliminating solutions that do not fit our approach. A broad search area may cause the algorithm to continue to run within specific values that do not change. In this way, the unwanted values in our approach are replaced by new values in each iteration of the algorithm's work. This causes the solutions to remain within the accepted ones, leading to better results.
- The global evaluation criteria MSE, RMSE, and PSNR will be used to evaluate and measure the performance of the bee algorithm in edge detection, such as accuracy and error rate.
- While the performance of the bee algorithm in edge detection will be compared with the performance of the Canny, Sobel, and Prewitt algorithms.

Various noise types, such as Salt & Pepper, Gaussian, Spotkle, and Poisson, significantly impact the mammography picture. Dealing with imbalanced data is another crucial challenge.

1.7. RESEARCH CONTRIBUTIONS

The main contribution of this work is the development of a bee colony algorithm to improve the edge detection process of mammography images. The development relied on changing the suitability function by merging the pixel's grey gradient value and statistical estimation. This method was not used before with the artificial bee algorithm to improve the algorithm's work.

In addition, the search for solutions will be improved by eliminating solutions that do not fit our approach. An extensive search area may cause the algorithm to continue running within specific values that do not change. With this method, the unwanted values in our approach are replaced with new values in each iteration of the algorithm's work, which results in the solutions staying within the accepted ones, which leads to better results.

1.8. ORGANIZATION OF THE THESIS

The structure of this thesis is outlined as follows:

- The first part introduces the study's background, outlines the research objectives, and highlights innovative aspects.
- The second part provides a comprehensive overview of existing methodologies within the field, including an explanation of the algorithms employed in this thesis.
- In the third part, the proposed methodology is detailed, accompanied by an elaborate description of the tools employed in the study.
- The fourth part is the evaluation of the proposed methodology.
- The fifth part compares the proposed methods against other methodologies and works, along with an inter-comparison.

- The sixth part concludes the thesis and outlines prospects for future research.

PART 2

LITERATURE REVIEW

2.1. INTRODUCTION

Edge detection of a digital image is essential in image pre-processing and computer vision. The main idea for edge detection is to identify sudden changes in the intensity values of pixels. Several edge detection techniques have different strengths and weaknesses, and these methods are suitable for different types of images and applications. Each edge detection technique has advantages and disadvantages in various fields. In this chapter, first, concepts and definitions of image processing techniques for edge detection are presented. The artificial bee algorithms are described in the second part of this chapter. Finally, part of the work done in this field is also presented in the literature of this study.

2.2. EDGE DETECTION

Computer image analysis and processing have the goal of enhancing images to exhibit distinct features that facilitate their interpretation and recognition by both humans and machines. Among these features, image edges play a pivotal role in image analysis and processing. Consequently, the procedure of 'edge detection' becomes imperative to extract these significant edges from images.

Edge detection is the most popular and widely used technique for processing and segmenting digital images, which identifies sharp stops in the image by capturing discontinuities in intensity values between image pixels and classifies edges accordingly [9]. An edge is the boundary between two regions that have relatively distinct gray-level characteristics. During the edge detection process, the image is divided into parts, and important objects and information in the image are detected. Edge detection can also be used to improve the appearance of a blurry image [10,11].

Additionally, edge detection serves to streamline image data and minimize the data volume requiring processing. Consequently, the formulation of a proficient edge detection technique becomes imperative [12]. This concept is illustrated in Figure 2.1, which outlines the image's edge detection process.

Figure 2. 1. Edge detection[11]

The detection of edges depends on two features in intensity, namely, the lack of continuity that depends on sudden changes in the image and the similarity on which the detection of edges depends on the similarity of regions in the image according to previously defined criteria [13].

Reducing the amount of significant data during image processing is necessary. So many researchers in this field have worked to solve this problem. Edge detection scanning has been performed using various computer methods based on different techniques [14].

While numerous edge detection operators are available, the aim now is to achieve superior outcomes compared to the existing system [15]. electing the contrast between the primary object and the background should be determined by considering the grayscale intensity. A subtle discrepancy of one point could be adequate in cases of high density. However, for lower-density situations, a more substantial differentiation between the object and the background becomes necessary [16,17].

Several edge detection methods exist, including classical or gradient-based edge detectors (first derivative), optimum edge detectors, and zero-crossing intercepts (second derivative). Typically, the local maxima or minima of the first derivative and zero crossings of the second derivative reveal spots along an edge [18]. The primary objective of each edge detector is to mitigate false positives while ensuring the detected edges closely align with actual edges. Edge detection is beneficial in pinpointing regions of interest, thereby simplifying the complexity of image processing [19,20].

At the moment, the edge detection method filters the picture's edge points by the points of the extreme image, producing a fuzzy edge image and a low average intensity value [21,22]. There are three basic steps used in edge detection (image smoothing - edge point detection - edge localization) [23].

2.2.1. Traditional Edge Detection Methods

There are different edge detection techniques, but most work by calculating the image's gradient, which is the rate of change of pixel values across an image. The gradient's magnitude indicates the edge's strength, and the gradient's direction provides information about the direction of the edge.

2.2.1.1. Canny Operator

In 1986, John Canny created the Canny edge detection technique. Image edge detection is a common task in computer vision and image processing. In order to reduce noise and improve edges, the image is first smoothed using a Gaussian filter by the Canny method. Next, it calculates the gradient amount and direction at each pixel in the image[24]. Next, a non-maximal funnel is applied to reduce edges and retain only the strongest ones. Finally, it applies a hysteresis threshold to determine which remaining edges should be kept as actual edges.

The Canny algorithm is known for its effective edge detection, reducing noise, and producing thin, accurate edge lines. It is often used as a pre-processing step for other computer vision tasks such as object recognition, tracking, and segmentation. [25,26]

2.2.1.2. Sobel Operator

Sobel is an edge detection algorithm used in computer vision and image processing to identify edges in an image. It calculates the image intensity gradient at each pixel using two convolution filters - one for horizontal edges and one for vertical edges. The Sobel operator works by transforming the image using Sobel's horizontal and vertical filters separately[27]. The horizontal filter detects changes in the intensity of the image in the x direction. In contrast, the vertical filter detects changes in the intensity of the image in the y direction. These filters are usually three-by-three arrays of values that weigh each adjacent pixel differently, with the central pixel having the highest weight. [28]

After transforming the image with both filters, the gradient size and direction can be calculated for each pixel according to $Eq.$ 2.1 and $Eq.$ 2.2 formulas:

$$I_{i,j} = \sqrt{Gx^2 + Gy^2} \tag{2.1}$$

$$direction = \tan^{-1}(Gy/Gx) \tag{2.2}$$

Where Gx and Gy are the gradients in the x and y directions, respectively, according to $Eq.$ 2.3 and $Eq.$ 2.4.

$$Gx = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} * orginal\ image \tag{2.3}$$

$$Gy = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * orginal\ image \tag{2.4}$$

The Sobel operator is a relatively simple and efficient edge detection algorithm that can be used as a building block for more complex image processing tasks. However, it may not be as accurate as other edge detection algorithms, such as the Canny algorithm, in certain situations where there is much noise, or the edges are very thin.

2.2.1.3. Roberts Operator

Roberts edge detection is a simple and commonly used algorithm for edge detection in image processing. It was developed by Lawrence Roberts in the late 1960s and is based on calculating an image density gradient at each pixel using a 2x2 mask. The mask consists of two kernels, one for detecting edges with a direction of 45 degrees and the other for detecting edges with a direction of 45 degrees. [29,30]

The Roberts operator is defined with $Eq. 2.5$ and $Eq. 2.6$:

$$I_{i,j} = \sqrt{Gx^2 + Gy^2} \tag{2.5}$$

$$direction = \tan^{-1}(Gy/Gx) \tag{2.6}$$

Where Gx and Gy are the gradients in the x and y directions, respectively, according to $Eq. 2.7$ and $Eq. 2.8$.

$$Gx = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} * orginal\ image \tag{2.7}$$

$$Gy = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} * orginal\ image \tag{2.8}$$

To apply the Roberts Edge Detection algorithm, this kernel is wrapped with the image to produce two scalable images. Then the gradient size image is obtained by taking the square root of the sum of the squares of the two gradient images. The resulting image shows the edges in the original image as white lines on a black background. The Roberts edge detection algorithm is fast and easy to implement but can produce noisy results, especially at high image noise levels. Therefore, it is often used as a pre-processing step for other, more complex edge detection algorithms.

2.2.1.4. Prewitt Operator

The Prewitt operator is an edge detection filter widely used in image processing. It was developed by Judith Prewitt in 1970 and is based on calculating the image intensity gradient at each pixel using a three-by-three mask [31].

The Prewitt trigger consists of two kernels, one for edge detection in the horizontal direction and one for edge detection in the vertical direction, according to $Eq.\,2.9$ and $Eq.\,2.10$ formulas:

$$I_{i,j} = \sqrt{Gx^2 + Gy^2} \tag{2.9}$$

$$direction = \tan^{-1}(Gy/Gx) \tag{2.10}$$

Where Gx and Gy are the gradients in the x and y directions, respectively, according to $Eq.\,2.11$ and $Eq.\,2.12$.

$$Gx = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} * orginal\ image \tag{2.11}$$

$$Gy = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * orginal\ image \tag{2.12}$$

To apply the Prewitt operator, this core is wrapped with the image to produce two scalable images. Then the gradient size image is obtained by taking the square root of the sum of the squares of the two gradient images. The resulting image shows the edges in the original image as white lines on a black background [31,32]. The Prewitt actuator is more potent than the Roberts actuator and can detect edges more accurately. However, it is still prone to image noise, and thus, it is often used in combination with other edge detection algorithms to get better results.

2.2.1.5. Laplacian Operator

The Laplacian operator is a second-order differential operator commonly used in image processing for edge detection and sharpening. It calculates the Laplacian image density at each pixel using a 3x3 or 5x5 mask and has two types, positive and negative. [33]. The Laplacian operator is defined for positive $Eq.$ 2.13 and for negative $Eq.$ 2.14:

$$I_{i,j} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} * orginal\ image \tag{2.13}$$

$$I_{i,j} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} * orginal\ image \tag{2.14}$$

To apply the Laplacian factor, the core is wrapped with the image to produce a Laplacian image. The Laplacian image shows the edges in the original image as zero crosses, where the intensity changes from dark to light or vice versa. The Laplacian operator is sensitive to noise in the image and can produce false edges. To reduce the effect of noise, the Laplacian of Gaussian (LoG) operator is often used, which first applies a Gaussian smoothing filter to the image to reduce noise and then applies the Laplacian operator [33,34]. The Laplacian operator is also commonly used in image sharpening, in which a Laplacian image is added back to the original image to enhance its fine edges and details. The Laplacian operator is a powerful tool for edge detection and image sharpening. However, it requires fine-tuning its parameters to avoid false detections and to obtain the best results.

Table 2.1 shows the advantages and limitations of traditional edge detection methods. The table discusses some water characteristics and limitations for each method, enabling beneficiaries to estimate the extent to which each method meets their requirements and objectives.

Table 2. 1. Advantages and limitations of edge detection methods

Edge Detector	Method	Advantages	Limitations

Canny	Gaussian Based	1. Improved signal-to-noise. 2. Good for noisy photos 3. Sensitive to noisy pixels. 4. Careful.	1. Difficult, complex, and slow.
Sobel	Gradient Based	1. Plain and simple. 2. Edge direction detection.	1. Great sensitivity to noise. 2. Inaccurate. 3. Unreliability.
Roberts	Gradient Based	1. Plain and simple. 2. Edge direction detection.	1. Great sensitivity to noise. 2. Inaccurate. 3. Unreliability.
Prewitt	Gradient Based	1. Plain and simple. 2. Edge direction detection.	1. Great sensitivity to noise. 2. Inaccurate. 3. Unreliability.
LoG	Gradient Based	1. The properties are fixed. 2. the characteristics are fixed in all directions. 3. It is possible to test a wide area around the pixel.	1. The angle curves are not accurate, and the function of the gray density level is different. 2. High sensitivity to noise, as the size of the edges deteriorates as the noise increases.

2.3. MEDICAL IMAGE

Medical images are pictures of tissues, organs, and structures inside a patient's body using irradiation techniques, magnetic field use, or optical imaging. These images are used for diagnostic and therapeutic follow-up purposes [35,36].

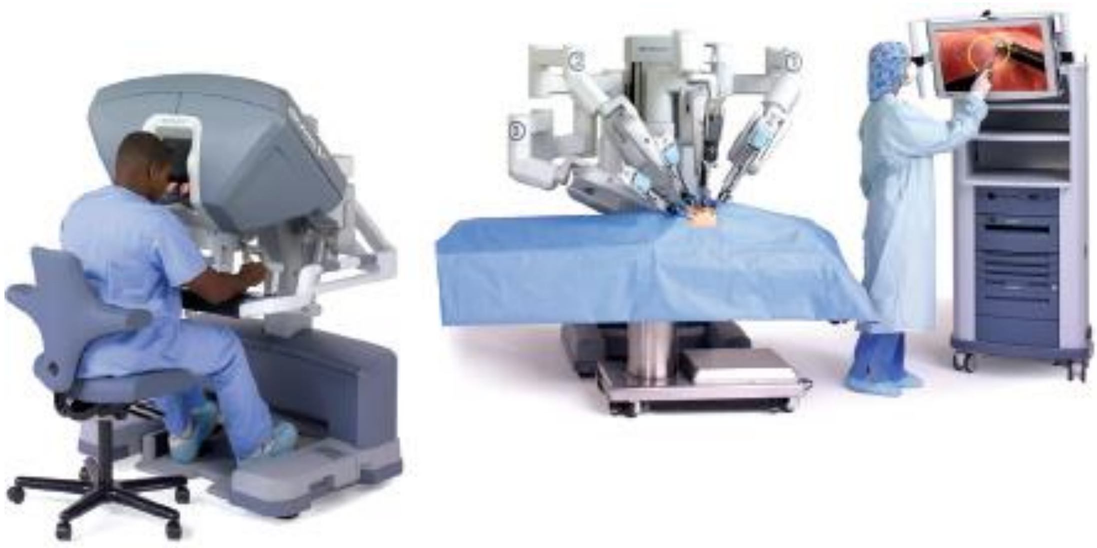


Figure 2. 2. Using image processing technique for Computer-assisted surgeries [35].

Figure 2. 2 shows the da Vinci system used in urological tumors such as prostatectomy. This system allowed for three-dimensional vision, which helped improve the quality of work.

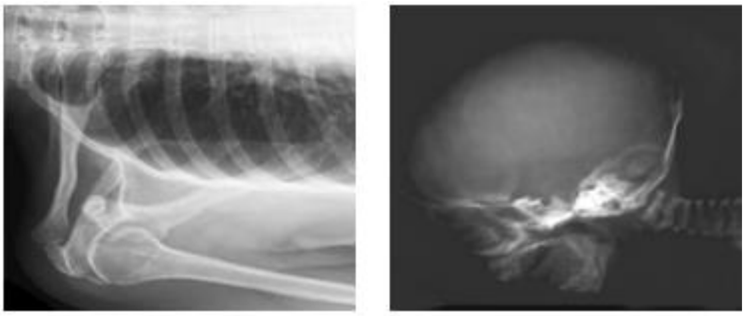
2.3.1. Medical Image Processing

Medical image processing is a set of techniques and tools used to analyze and improve medical images, such as radiographs, CT scans, magnetic resonance imaging (MRI), and other images used in medical diagnosis. This treatment aims to improve image quality, tissue contrast, identify delicate structures, and assist doctors in diagnosing cases and making treatment decisions more accurately [37,38].

2.3.2. Types Of Medical Images

There are several common types of medical images used in medical image processing:

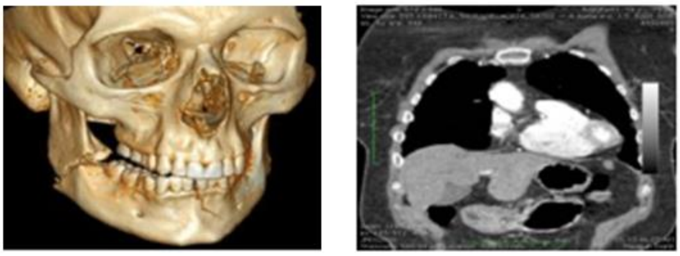
X-rays: The medical image is generated using X-rays that pass through the body and are recorded on sensitive films or on digital devices. This imaging is used in several medical fields, as it is used for imaging skeletal structures such as bones, teeth, and the chest and for diagnosing and screening breast tissue and others [39]. Figure 2. 3 shows some images of X-ray.



Shoulder Image Head Image

Figure 2. 3. X-ray image [39]

CT scans: This technique relies on X-rays to obtain detailed cross-sectional images. It is used to create 3D cross-sectional images of organs and structures in the body, such as hands, hips, renal tract, elbow, spines, sinus, dental, wrist, knee, cervical, facial bones, shoulder, brain, ankle, and foot [39,40] Figure 2. 4 shows some images of CT scans.



3D CT scans 2D CT scans

Figure 2. 14. CT scans image [39]

Magnetic resonance imaging (MRI): Organs and tissues are visualized in three dimensions using magnetic fields and radio frequencies. This method produces detailed, high-resolution images and is regarded as safe. It is used to check tumors and cysts, disorders of the liver and abdominal organs, abnormalities of the brain and spinal cord, and to plan surgery. [39,41]. Figure 2. 5 shows some images of MRI.

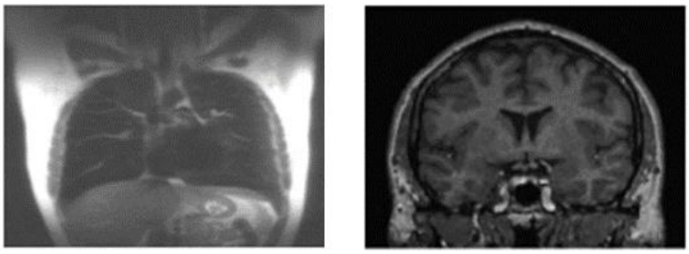


Figure 2. 15. MRI images [39]

Ultrasound: is used to create pictures of the organs and tissues inside the body. Usually used in imaging the fetus and soft organs such as the liver, kidneys, heart, and glands in the neck [39,42]. Figure 2. 6 shows some images of Ultrasound.

Figure 2. 16. Ultrasound image [39]

Optical imaging: It relies on optical systems to improve the vision of tissues and organs. It is used in medical research, surgery, hemodynamics examination, tumor detection, brain imaging, breast cancer scanning, bone health scanning, teeth, gums, and jaw scanning [39].

2.3.3. Mammogram

Mammograms are a standard test used to detect tumors and abnormal changes in the breast. Mammogram examination is one of the most important means that help in the early diagnosis of breast cancer and increases the chances of recovery if the cancer is detected in its early stages[43]. It is performed by using X-rays to take a picture of the breast. Figure 2. 7 shows some images of Mammograms. Mammograms have two main types:

Screening Mammogram: It is performed when no symptoms or signs of disease appear and as part of a regular breast examination for women. Each breast is photographed at least from different angles to detect abnormal changes.

Diagnostic mammogram: It is performed when there is an abnormal change in the breast, whether by detecting prior pathology or responding to abnormal findings on a conventional mammogram. Diagnostic mammograms can include imaging from additional angles and careful analysis of suspicious changes.

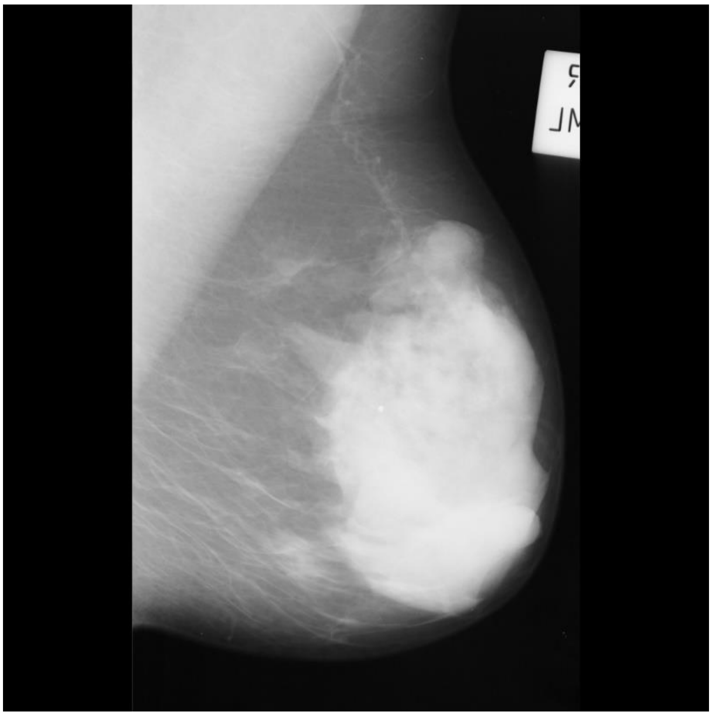


Figure 2. 17. Mammogram [92].

2.4. ARTIFICIAL BEE COLONY ALGORITHM

The ABC algorithm was introduced by Karaboga in 2005 and is one of the most popular swarm algorithms used in random optimization [44]. This algorithm draws inspiration from the foraging behavior of honeybees, presenting a metaheuristic optimization approach. It operates as a population-based method, with bees symbolizing candidate solutions or resolutions for an optimization predicament. The algorithm encompasses three distinct bee categories: the employed, onlooker, and scout bees [45]. The employed bees engage in the quest for potential food sources, which mirror possible solutions, and then share their findings with onlooker bees. These onlooker bees subsequently select food sources to exploit, guided by their quality, which is assessed through an objective function. Meanwhile, scout bees venture into uncharted territory, conducting random searches across the exploration space.

The artificial bee colony algorithm is widely used in various subjects [46,47]. This remarkably adaptable and robust optimization algorithm holds applicability across diverse domains, spanning from medical applications to satellite imagery analysis. Its application is straightforward, and its utility extends broadly due to its ability to seek out local solutions swiftly and access global solutions efficiently[48,49]. Notably advantageous, this algorithm boasts a reduced number of control parameters compared to alternative optimization techniques. Furthermore, it adeptly manages random cost objective functions and facilitates hybridization. Nevertheless, it's important to acknowledge certain drawbacks of the ABC algorithm, such as its limitation in yielding optimal solutions for specific scenarios and the challenge of connecting these solutions to a local optima value [50].

The ABC algorithm commences by generating an initial population that's randomly distributed across the landscape, representing the positions of potential food sources (denoted as a and b in Figure 2.8). The value attributed to each food source (a and b) is contingent on various factors. The optimization challenge and the quantity of nectar tied to a food source correlate with the similarity value linked to its sweetness. In this algorithm, there exist two categories of inactive foraging bees: scouts (S in Figure 2.8) and observers (R in Figure 2.8).

A working bee that carries information about each food source and its potential yield is assigned to it. With a certain likelihood, these employed bees will impart this knowledge. The number of food sources available is mirrored by the population of bees that are active. After foraging, the bees return to the hive and place the collected nectar in the allocated food area. Three possibilities exist for the amount of nectar still present in an active bee's mouth (shown in Figure 2.8 as UF, EF1, and EF2). With the help of this orchestration, the bees can develop a very advantageous solution proportionate to the complexity of complex optimization problems [51]. Initially, all bees function as researchers without any preexisting knowledge. After a phase of random food source exploration, scout bees can transition into any of the roles based on the utility of the targeted food sources.

Once the initialization step is complete, an objective function determines whether these candidates offer a workable solution (measured by nectar quantity). Food sources, employed foragers (EF), and unemployed foragers (UF), including observers and scouts, are the three main elements this function primarily leans on to achieve the best outcome. This cycle also includes recruiting and letting go of food sources.

Candidate solutions undergo development through diverse ABC processes based on the values of this objective function. However, in cases where the fitness function (nectar intake) fails to be optimized after reaching the maximum cycle count, the associated food source is considered abandoned. Subsequently, it is substituted with a fresh, randomly selected food source location. [52,53].

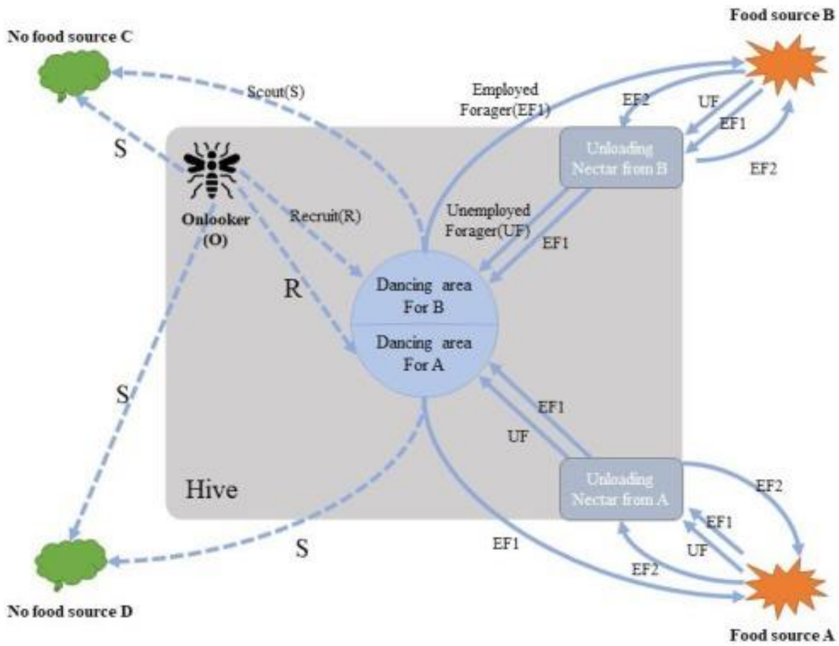


Figure 2. 18. The behaviour of honey bees foraging for nectar [52].

It has achieved considerable success in effectively addressing diverse optimization challenges across various domains. Since its inception in 2009, the ABC algorithm has found successful applications in an array of problems spanning signal processing, image analysis, and video processing [54,55].

However, like any other optimization algorithm, the performance of ABC depends on various factors, such as the characteristics of the problem, the parameters of the algorithm, and the quality of the initial solutions. Therefore, fine-tuning and adapting the algorithm is crucial to achieving good results.

2.4.1. Features Of The Artificial Bee Algorithm

- Population-based approach: The ABC maintains a population of candidate solutions, called bees, which are initially randomly generated.
- Solution representation: The solutions are represented as vectors of real numbers, where each element corresponds to a decision variable in the optimization problem.
- Search process: The ABC consists of three types of bees: employed, onlooker, and scout bees. Employed bees search locally around their current solution, while onlooker bees choose solutions based on the quality of nearby employed bees. Scout bees search randomly in the solution space to discover new solutions.
- Solution evaluation: Each solution's quality is assessed using an objective function that converts its solution vector into a scalar quality value.
- Fitness calculation: According to each solution's objective function value, each one's fitness is determined and utilized to direct the search process in the direction of better solutions.
- Local search: The ABC employs a local search strategy that helps refine the solutions the employed bees find.
- Parameter tuning: The number of bees, the size of the neighborhood used by employed bees and observer bees, and the likelihood that a scout bee would find a new solution are just a few variables the ABC can be set for to maximize performance [44,55].

2.4.2. Artificial Bee Colony Algorithm Steps

ABC is an iterative process on the same principle as other population algorithms, iteratively searching for optimal solutions in the problem space. Figure 2.9 and flowchart (Figure 2.10) show the steps of the algorithm and the process of moving from one step to another. In the beginning, a group of bees is initialized with random solutions. Employed bees evaluate their solutions, create new ones, and, if better, replace them.

Onlooker bees select used bee solutions based on fitness and generate new solutions. Scout bees replace solutions that do not improve. Bees share solution information to explore the search space. Here are the steps of the ABC algorithm:

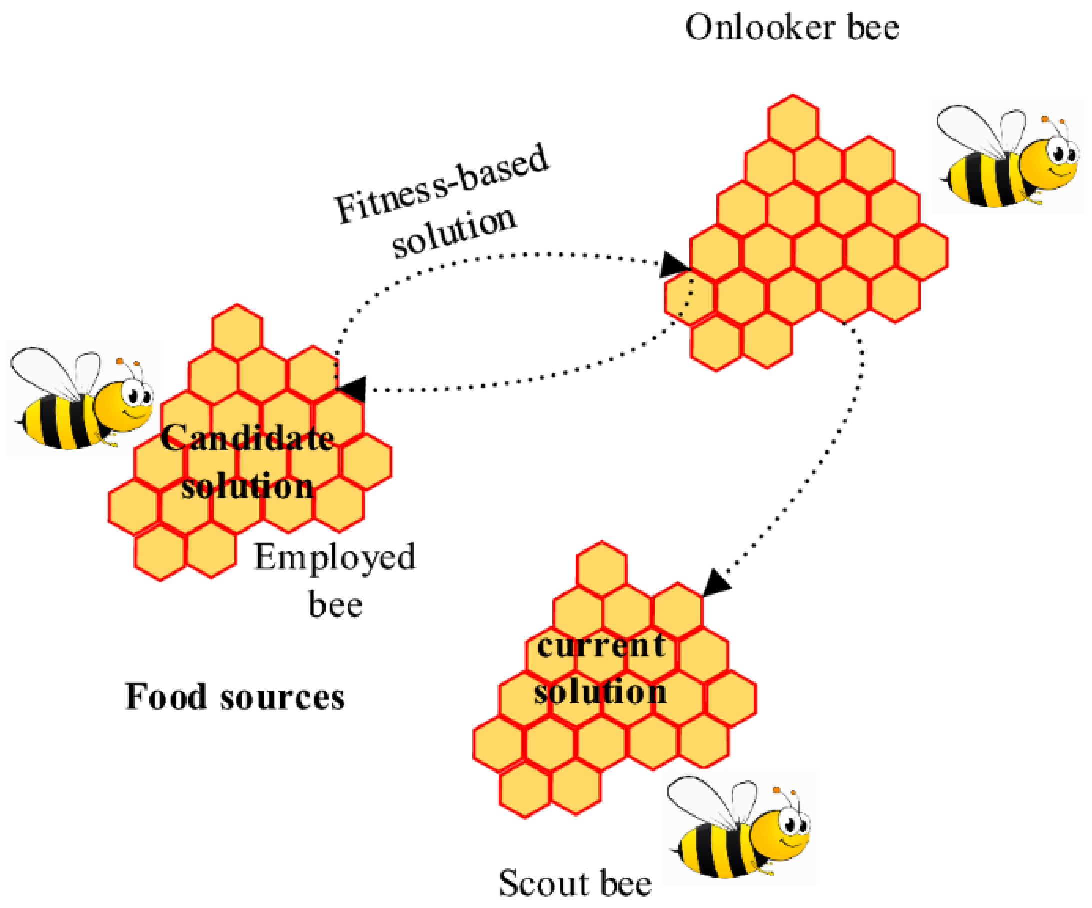


Figure 2. 19 Artificial bee colony algorithm.

2.4.2.1. Initialization Of The Population

Initialization of the population is the first step of the bee steps. It is vital in the results and other bee steps work[56]. At this stage, a community of employed bees is randomly generated within the search space by creating food sources with a few SN dimensions of n dimensions randomly, according to $Eq. 2.15$.

$$x_{i,j} = x_{min,j} + rand(0,1)\left(x_{max,j} - x_{min,j}\right) \quad (2.15)$$

Where $i = 1, 2, 3, \dots, SN,\ j = 1, 2, 3, \dots, n, x_{min,j}\ and\ x_{max,j}$ respectively, are the lower and upper boundaries of the j dimension. According to the SN number of employed bees, these sources are distributed at random.

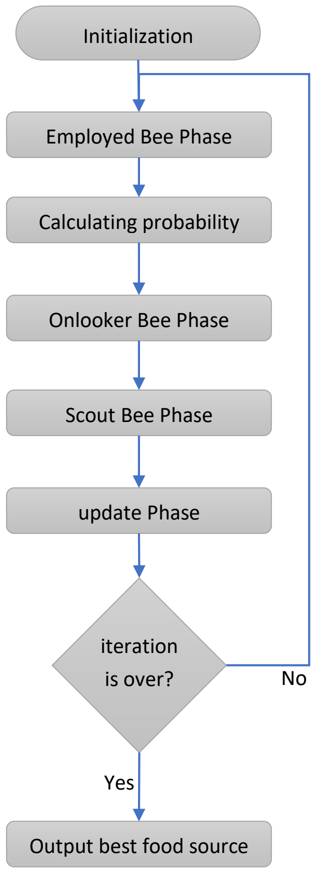


Figure 2. 20 Flowchat artificial bee colony algorithm steps

2.4.2.2. Employed Bee.

This marks the second stage of the bee's progression and constitutes the initial step of the iteration process. In this phase, for each employed bee, a fresh food source denoted as $v_{i,j}$ is generated in proximity to its current location through the equation $Eq. 2.16$. Subsequently, the viability of this new solution is assessed. If the novel source proves superior to the existing one, the bee adopts the newly discovered source; otherwise, it maintains its current choice. This selection process employs a pragmatic decision-making approach between the current and prospective solutions.

$$v_{i,j} = x_{i,j} + \emptyset_{i,j}(x_{i,j} - x_{k,j}) \tag{2.16}$$

Where $i = 1, 2, 3, \ldots, SN,\ j = 1, 2, 3, \ldots, n\ and\ k$ is a random number that must differ from i, $\emptyset_{i,j}$ is a random number in the range $[-1,1]$.

2.4.2.3. Calculating Probability

Subsequent to the employed bees' completion of gathering data regarding the newfound sources, they disseminate this information within an area referred to as the "dance zone" to the onlooker bees. Subsequently, the onlooker bees evaluate these sources and engage in a probabilistic process to choose the most suitable source. This probabilistic selection hinges on the fitness values associated with the solutions present within the population. The selection mechanism predicated on fitness could encompass methods such as roulette wheel, rank-based ranking, global random sampling, tournament selection, or other analogous approaches.

$$p_i = f_i / \sum_{j=1}^{SN} f_i \tag{2.17}$$

Where f_i is the fitness value of the solution i.

In basic ABC, a roulette wheel selection scheme is used where each chip is proportional in size to a fitness value according $to\ Eq. 2.17$.

2.4.2.4. Onlooker Bee Phase

Onlooker bees select employed bee solutions based on their fitness value. The probability of an onlooker bee choosing an employed bee solution is proportional to its fitness value according to its probability value pi. Then a new solution is generated, and the fit is evaluated using an equation $Eq. 2.16$. If the new solution is better than the current one, the onlooker bees save the new solution. Otherwise, they will keep the existing one.

2.4.2.5. Scout Bee Phase

Should the food source denoted as Xi not exhibit improvement over a specified number of iterations (defined as a limit), it is inferred that this particular source has been abandoned. Consequently, the employed bee responsible for this source transitions into a scout bee, responsible for generating novel food sources. The process entails generating a fresh food source in a random manner within the confines of the search space, as stipulated by the equation $Eq. 2.15$.

2.4.2.6. Update Phase

At this point, the best food source among the sources is chosen, contrasted with the best food source picked in the previous iteration. Updates are made to the most excellent food source if a new one proves superior. If not, the preceding food source is still the best option. Ultimately, we have the best food source obtained within the algorithm after iteration.

2.5. RESEARCH BACKGROUND

This section will comprehensively review some of the relevant works on edge detection by standard methods and the bee algorithm. In the end, Table 2.2 presents the advantages and limitations of some literature reviews.

Beant Kaur and Anil Garg [57] presented a new technique based on mathematical morphology for edge detection, a theory and technique for processing and analyzing geometric structures. Mathematical morphology was developed for binary images. It was then used in the grayscale image and its functions, so mathematical morphology helps improve the image and detect its edges. In this science, the parameters are closed and opened using expansion and erosion. When the parameters are opened, the image erodes and expands when closed[58]. He used this method to detect the edges of a remote sensing image, and these images are generally very noisy. The results were good, as it was considered that the use of mathematical morphology in detecting edges is more efficient than other traditional methods after comparing it with methods that use a mask in addition to Canny and Laplacian.

While Preeti Topno and Govind Murmu [59] used an average filter to reduce the noise in the edges of the image resulting from the edges detection for different operators, the noise is considered one of the problems in the image. One of the types of noise that this research addresses is salt and pepper noise. Roberts, Sobel, Prewitt, and Canny have been used to edge detection and then used the median filter, which is a non-linear filter that reduces noise and preserves edge properties to improve and reduce noise [60]. The results showed that the Canny algorithm for edge detection is the best among the other methods. However, it contains a disadvantage, which is the high cost of the computational process.

Chino et al. [61] discussed a mixed strategy between the integrated canny edge detector with binary filtering and PCA to edge detection of the color image. The two sequential and parallel approaches were used and compared to detect the weak and complex edges in the image with a complex background, which showed that the parallel strategy shows gains in performance by 68%. Various metrics, such as PSNR, are used to measure the accuracy of edge detection.

The canny method was improved and used in edge detection in the research of CAI-XIA DENG, GUI-BIN WANG, and XIN-RUI YANG [62]. The canny method was improved by replacing the Gaussian filter with the morphological filter that handles the noise in the image. The results were good, as noise such as salt and pepper noise were removed well, edge accuracy was improved, and objective evaluation and visual impact were better than other methods. The soft computing method has been studied in [63] Research for edge detection and image segmentation. This method has been used based on fuzzy logic, genetic algorithm, and neural networks. The results showed the quality of these methods in edge detection and image segmentation.

Liying Yuan, Xue Xu [64] method for edge detection, which depends on the combination of the Canny operator smoothing algorithm and local edge detection algorithm where the whole edge can be obtained by global edge detection using a smooth adaptive filter based on Canny operator, showed that the edge of the canny operator is complete and more prosperous than the Sobel operator, has no false edge and has intense noise canceling ability. In the research [65], a comparison was made between different edge detection techniques and digital image processing using complex images, and the methods of optimal edge detection, Sobel operator, Prewitt operator, and LoG, were compared. The results were that the canny operator performs better in images containing noise and complex images than the other methods.

In the research [66], the edge detection operators on the images were compared using the MATLAB program. The outage severity levels are the foundation for the Roberts, Sobel, Prewitt, Kirsch, Robinson Marr Hildreth, sLoG, and Canny techniques. According to the findings, the edges produced by the Marr-Hildreth, LoG, and Canny edge detectors are nearly identical. In paper [67], the relationship between pixel gradient and edge membership scores generated from the size of the gradients associated with each pixel was changed using a simple parametric model based on the trigonometric function in conventional approaches. The results showed improved edge detection.

Using deep learning, researchers have proposed many and varied ways to edge detection in recent years due to the need for an accurate and suitable method for detecting all types of images, including coding methods, network reconstruction, and others. In the paper [68], the researcher demonstrated how deep learning is applied in a wide range of edge detection by summarizing each method's benefits and structure. In order to increase detection accuracy, the complexity of the algorithm, network, and training is sacrificed. The research [69] presented a way to edge detection and digital segment image through computing approaches based on different techniques.

To edge detection of digital images without pre-processing, a method based on the Convolutional Neural Network (CNN) was used. It better integrates the information of multiple levels into the feature map and generates Hybrid Convolutional Features (HCF) to edge detection of the image more powerfully and accurately [70]. To extract better, more accurate, and reliable results for edge detection. The research presented [71] a method for edge detection based on the fuzzy rule, and the method contains specific fuzzy rules and an organic function that affects the decision rules in edge and non-edge regions. The results were good and better compared to other methods.

When studies related to the ABC algorithm are investigated, it is seen that there is only a limited body of research focused on the ability linkage analysis of ABC on the problem of edge detection in digital images. Anan Banharnsakun [72] presented a method based on the artificial bee algorithm for edge detection by discovering the optimal edge filter and then applying this filter to detect edges by improving the threshold value. The experimental results were good. This algorithm worked well in detecting edges and gave high accuracy.

The standard implementation of the artificial bee colony algorithm must be modified to incorporate Selçuk Aslan's [73] two methods for generating candidates based on combining abandoned food sources and the bee colony's final food sources. To do so, one must change the solution pool procedure. The first approach was using food sources after the algorithm to generate solutions using the best food sources discovered by ABC. In contrast, the second method relied on increasing the set of solutions in the first method by adding the neglected solutions. The results conducted on authentic images showed that these methods improved the ability of the bee algorithm to extract edges and reduced the error compared with the genetic algorithm and the bacterial search optimization algorithm.

In a new approach using the bee algorithm, the bee algorithm was developed by adding memory to the solutions that were neglected, and this memory works to save information about the preference values that appeared for the solution during the search process. This approach was used in complex and noisy images to discover individual circles and multiple circular shapes. The results are promising, outperforming the GA and BFOA algorithms in speed and accuracy [74].

For the images containing colors, Mourad Moussa [75] presented a new method based on combining the artificial bee algorithm with the Otsu multi-level thresholding method. Otsu was used to evaluate the bee algorithm and choose the best solutions. In this study, RGB, YCbCr, and Lab chromaticity levels were relied upon, and the results compared with the ant algorithm showed the superiority of this method, in addition to reducing implementation time, which leads to faster implementation.

Om Prakash Verma [76] presented a new method using an improved derivative technique with an artificial bee colony algorithm to improve the edge detection process. An improved derivative technique was used to calculate the fit function of edge pixels, and then the most suitable pixels were selected by implementing an algorithm Artificial bee colony. The results showed the method's superiority over most of the methods used by edge detection in noisy and complex images. They reduced the thick and double edges in the final image.

A. Kumar [77] presented presented a new approach to modifying the artificial bee colony (MABC) algorithm by adding different objective functions to find the optimal multi-level thresholds. He used the anarchic system and routine of opposition-based learning to prepare the population. The results showed a comparison with the algorithms ABC, PSO, and GA that the proposed algorithm is better in accuracy and computational value and contains fewer control parameters. However, the computational value was more complex than theirs in the multi-level threshold.

Multiclass segmentation of synthetic aperture radar (SAR) images was performed by a modified bee colony (I-ABC) algorithm that optimizes the 2D entropy of the fit function of the I-ABC algorithm and computes global threshold values. A neuromorphic set (NS) and a co-occurrence matrix extract the features from the image and then optimize using the bee colony algorithm (I-ABC). The image subset T and I are generated using the co-occurrence matrix. The best threshold is discovered in the employed, onlooker, and scout stage. The results showed that this algorithm improves the segmentation accuracy and speed and reduces the noise on the edges of the [78,79] object. In the paper [53], a method was presented to discover the airplanes present at the airports (UCAVs) in the complex environment by using the artificial bee colony algorithm and the salinity-based visual attention hybrid model that is used to detect the prominent areas, after the discovery of the prominent areas, the bee algorithm is used to discover the edges of these areas. The results showed the effectiveness of this approach in detecting the edges of the aircraft images in a noisy environment.

The discovery of fire areas is of great importance in saving lives, so the research [80] presented an approach based on the artificial bee colony algorithm and the two-dimensional Otsu and Canny, and this assembly aimed to detect the fire in the packet carrier[81]. Otsu 2D to calculate the fitness function, and then the edges are detected using the canny algorithm. The results showed the method's effectiveness in detecting fire on the conveyor belt in a noisy environment with less expense and high efficiency compared to the traditional methods.

A bee colony algorithm without a masked operator or any derivative process in the edge detection process was used. To define a new source, he presented a unique formula with eight adjacent pixels per pixel and used the pixel value as nectar for a bee. The results showed that the flag bee algorithm could be used to edge detection [82,83]. In paper [54], an artificial bee colony algorithm is optimized for extracting information from grayscale aerial images by classifying abandoned pixels as forbidden pixels, which results in not checking all pixels in the image. The results showed that the bee algorithm is good at detecting the edges of the aerial images.

It is often produced through calcium leakage into dead breast cells or secretions associated with many breast diseases, such as pathological calcification. A paper [84,85] compared the watershed method for identifying cancer cells and edge detection by canny edge detection to determine the amount of calcium. In breast cells to identify cancer in mammogram images. The results showed that the watershed method detected calcium clusters by color, while the canny edge detected secondary cells.

A new algorithm is proposed to detect mammogram calcification based on the Kirsch factor and the Markov model, where the edges are extracted using the Kirsch factor. Then these edges are linked using the Markov model to determine the calcifications. Experiments have shown the effectiveness of this method in extracting microcalcification groups and that it is superior to the canny method.[86,87]

In the research [88], the Sobel edge detection method was used as a previous stage of the contour model to solve the problem of creating initial contour points manually by users of the active contour model. To conduct the experiments, 160 Mini-MIAS mammograms were used, and the results showed the quality of this method in solving such problems, as the segmentation accuracy was 92.5% with a sensitivity of 93% and a specificity of 85%.

Table 2. 2. Advantages and limitations of some literature reviews

Paper	Method	Advantages	Limitations
[57]	Mathematical morphology	Direct geometric interpretation simplicity	Efficiency computational cost is high
[59]	average filter with Roberts, Sobel, Prewitt, and Canny	Low noise effect	Efficiency computational cost is high
[61]	Canny with binary filtering and PCA	1- The ability to remove noise. 2- Detect edges in complex background 3- Detect edges in color images	1- It takes a lot of time to implement. 2- Efficiency computational cost is high.
[62]	Use Open-Close filter instead of Gaussian filter	1- Low noise effect. 2- Preserves sharp edges and details.	It takes a lot of time to implement.
[63]	Soft Computing	using soft computing approach based on the Fuzzy logic, Genetic Algorithm and Neural Network.	1- It takes a lot of time to implement. 2- Noise effect.

[64]	Canny with local edge detection algorithm	1- More precise edges 2- Little effect on noise	It takes a lot of time to implement.
[68]	Deep Learning	More precise edges	sacrifices the complexity of an algorithm, network, and training.
[70]	CNN	1- Edge detection without preprocessing. 2- Sharper edges.	It takes a lot of time to implement.
[71]	Fuzzy-Rule	1- use YCbCr image. 2- Sharper edges.	Efficiency computational cost is high.
[72]	ABC	More precise edges	1- Efficiency computational cost is high. 2- It takes a lot of time to implement.
[73]	ABC	More precise edges	Combine abandoned food sources with food sources obtained in the final colony
[74]	ABC	Sharpness in edges and speed in complex images.	Depending on the previously processed solutions.
[75]	ABC	1- The algorithm works on color images in the YCbCr color space 2- Good edge accuracy. 3- Efficiency in operation.	Not good when working on color space LAB and HSL images.
[76]	ABC and improved derivative technique	1- Work with complex images 2- low iterations.	Produces a thick edge
[77]	ABC	1- Works well with corners. 2- works in complex images.	Fitness evaluation is used twice per cycle, while in other algorithms once.
[53]	saliency-based visual attention and artificial bee colony (ABC) algorithm	Detect edges in complex images.	lose some information.

[80]	2D-Dimensional Otsu, Canny edge detection, and Artificial Bee Colony algorithm	Sharpness in edges and speed in complex images.	It takes a lot of time to implement.
[82]	ABC	Use ABC and don’t use any method or mask with ABC	2,500 cycles of repetition for the small image
[54]	ABC	Sharpness in edges and speed in complex images.	iterations is very large
[86]	Kirsch edge operation	Good in noise image	Don't work with a complex image
[88]	Contour model with Sobel	More precise edges	Time Complexity is high

2.6. SUMMARY:

Edge detection is vital for accurate image interpretation, especially in areas of medical imaging such as breast cancer diagnosis. Given the complexities of mammography, this chapter explores the evolution of edge detection techniques and highlights the recent interest in metaphysical algorithms such as ABC. This chapter presents concepts and definitions of edge detection and standard methods. Next, the concepts and working principles of the artificial bee colony algorithm are described. Finally, part of the previous work done in this field was expressed. In the forthcoming chapter, we will delve into the detailed explanation of the proposed method, elucidating the tools employed within this study in a comprehensive manner.

PART 3

RESEARCH METHODOLOGY

3.1. INTRODUCTION

The significance of image processing and its relevance to mammography images has been elucidated in preceding chapters, alongside an exploration of prominent edge detection techniques. Through a comprehensive review of these methodologies and a discernment of prevailing research gaps, a fresh paradigm for the edge detection of mammographic images (edmABC) is postulated. As a result, this chapter delineates a holistic research blueprint. Subsequently, the tools harnessed in this study—ranging from image segmentation and anticipated region extraction utilizing the artificial bee algorithm to the intricate realm of edge detection—are meticulously expounded upon. Finally, the mechanism for appraising the efficacy of the proposed methodology is explained.

3.2. APPLIED TOOLS

To execute the envisaged approach, Visual Studio Code was employed as the development environment. Conforming to the requisites of the study, the implementation was orchestrated through the Python programming language. Python, an elevated programming language, stands as one of the most pervasive and esteemed languages globally. Crafted in the latter part of the 1980s by Guido van Rossum, Python boasts versatility, user-friendliness, and an open-source essence, rendering it ubiquitous across domains like web applications, software engineering, data science, and machine learning (ML). Python's allure lies in its efficiency, accessible learning curve, intrinsic error detection mechanisms, and cross-platform compatibility. The language is freely accessible, seamlessly integrates with diverse systems, and expedites development cycles. Python accommodates both object-oriented and procedural paradigms, flaunts an extensive standard library, and enjoys compatibility with most operating systems. With Python, the realm of large-scale program development transcends the constraints of shell code or batch files, gaining augmented structure and robust support. Conversely, Python surpasses C in terms of error-checking capabilities. Being a supremely high-level language, Python encompasses advanced types like adaptable arrays and dictionaries. Furthermore, owing to its extensive type of system, Python possesses the capacity to address more intricate challenges compared to languages such as Awk or Perl. However, the intricacies of Python are at least as straightforward as those of the languages. The language also has a large set of basic packages that can be used as the basis for your programs. Python is an interpreted language, which saves much time during the development process because there is no need to do compilation and binding. The interpreter can be used interactively, which makes it easier to deal with the properties provided by the language, to write programs for training or testing, or to test a function during the development process of a program, in addition to the possibility of using the interpreter as a calculator. The experiment was carried out on a core i7 eighth laptop ASUS with Hard SSD, 8 CPU, 12.0 GB of RAM, windows 11 pro-64-bit operating system using the Python programming language, OpenCV library was used to read the image, and NumPy to deal with arrays. At the same time, the calculations were performed without the use of offices.

3.3. OUTLINE OF THE THESIS

In general, basic step-by-step procedures are needed for evaluating, recognizing, and extracting the desired qualities and the vital details and information of any image from its raw images. Our research also focuses on edge extraction and picture preprocessing. This edmABC involves three steps from the source image to edge image extraction. A flowchart with the steps will help understand the process in Figure 3.1.

The first step involves entering the image 1024*1024 into the methodology and converting it into a two-dimensional matrix to gray. Then, in the second step, the input image is processed to reduce the noise in the image. This is done by merging the grayscale values and the statistical differences values. The process of extracting the grayscale values from the image depends on taking the most significant differences between the pixels adjacent to the pixel to be calculated, while Extracting the statistical difference values of the image by making the pixel to be calculated the center of a circle, applying the laws of statistical differences (we will explain them later) on the pixels contained in the circle, and finally applying the artificial bee algorithm to the image to discover the edges.

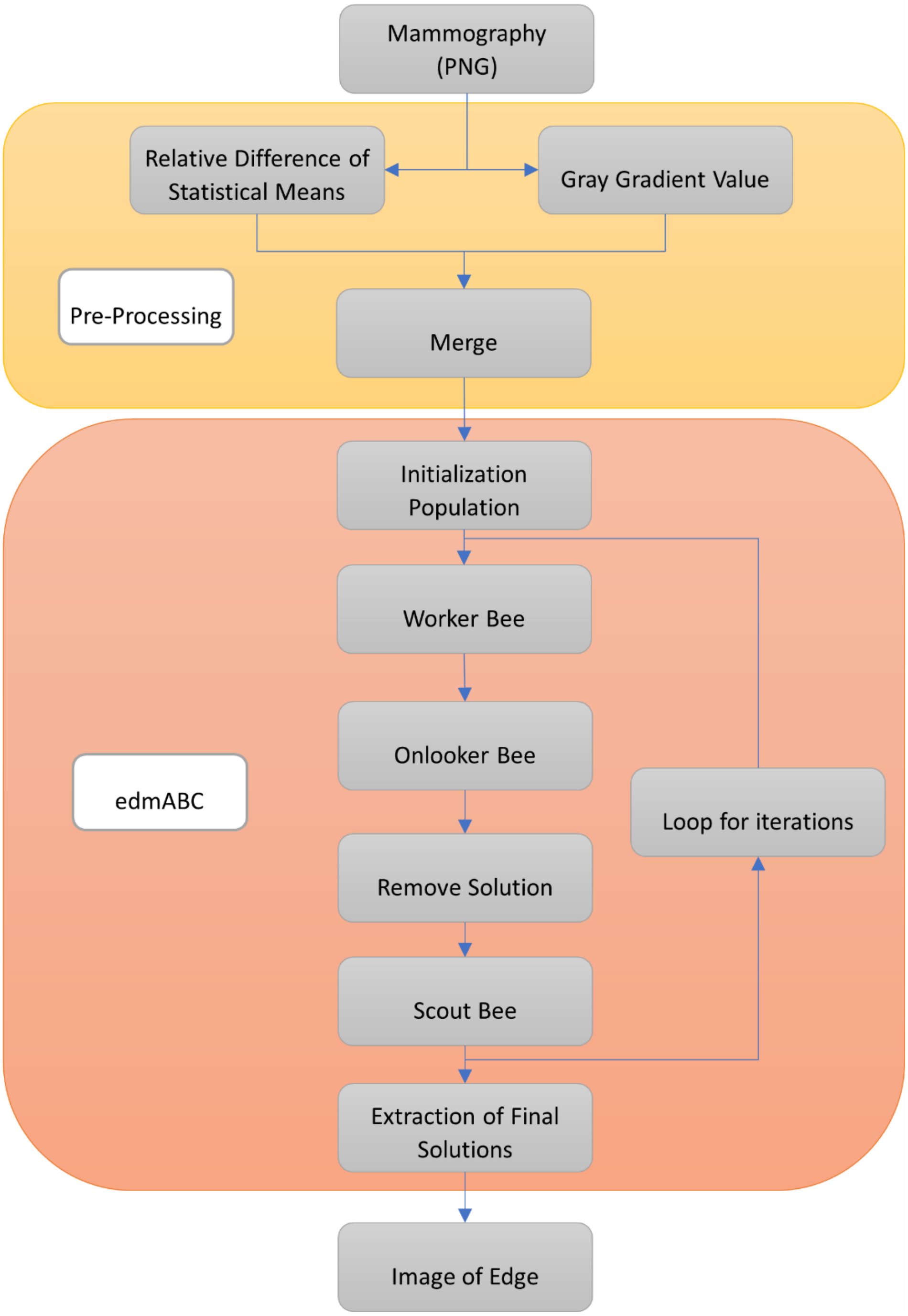


Figure 3. 1. Flowchart for edmABC

3.4. PRE-PROCESSING

Noise in mammographic images can arise from various sources, including X-ray quantum noise. Reducing noise in mammographic images is critical because it can affect interpretation accuracy and the ability to detect abnormalities. Therefore, noise must be reduced as much as possible before applying the bee algorithm for edge detection. In image processing, many methods and filter algorithms help remove noise from the image. However, in our approach, we will use a new method to merge the gray gradient value of the pixel with statistical difference values to remove noise from the image.

3.4.1. Gray Gradient Value Of Pixel

The gray gradient value of a pixel is essential in image processing tasks such as edge detection, as it helps define boundaries and transitions between different areas. The grayscale value of a pixel indicates the magnitude of the change in the intensity of the grayscale at the location of that pixel. In other words, it measures how different the intensity of a pixel is in relation to neighboring pixels. It indicates the slope or rate of change in grayscale values and provides information about local intensity variations in an image [89].

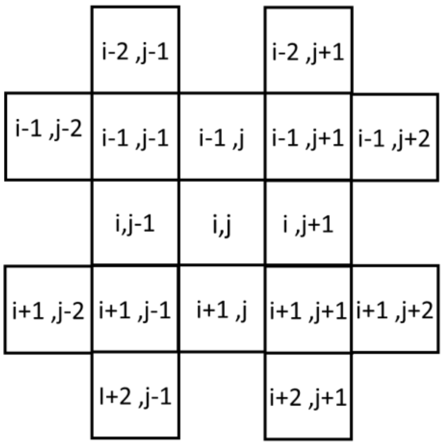


Figure 3. 2. 16 pixels of gray gradient value [89]

$$I(i,j) = max \begin{Bmatrix} |I(i,j-1) - I(i,j+1)| \\ |I(i-1,j) - I(i+1,j)| \\ |I(i-1,j+1) - I(i+1,j-1)| \\ |I(i-1,j-1) - I(i+1,j+1)| \\ |I(i-2,j-1) - I(i+2,j+1)| \\ |I(i-2,j+1) - I(i+2,j-1)| \\ |I(i-1,j-2) - I(i+1,j+2)| \\ |I(i-1,j+2) - I(i+1,j-2)| \end{Bmatrix} \quad (3.1)$$

The gradient value is calculated by determining the difference in grayscale intensity between a pixel and its adjacent pixels. Various techniques can be used to calculate the gradient. We will use $Eq.$ 3.1 to calculate the gradient value in our method. Figure 3.2 shows the pixels that we will use in the calculation.

3.4.2. Statistical Estimation

Statistical estimation helps to determine which pixels are on the edge, so the higher the value of the statistical differences, the greater the probability of the pixel falling on the edge and the lower the probability that it is not on the edge. In this section, we will use the method used in the research [90], which used statistical estimation with the artificial ant algorithm for edge detection. The results were good, so we will use this method in our thesis according to the flowchart Figure 3.4, which shows the workflow of the method and how to extract the statistical estimation values.

In the beginning, the pixels adjacent to the pixel are determined circularly according to R, so the pixel to be calculated is the circle's center. Divided this circle into two parts (D1 and D2) according to the direction θ. As mentioned earlier, a difference in the attributes between D1 and D2 determines whether the pixel is an edge. Figure 3.3 shows how to divide circularity into D1, D2, the value of R, and how to determine the angle of rotation, where i is the center of the circle and the pixel being calculated.

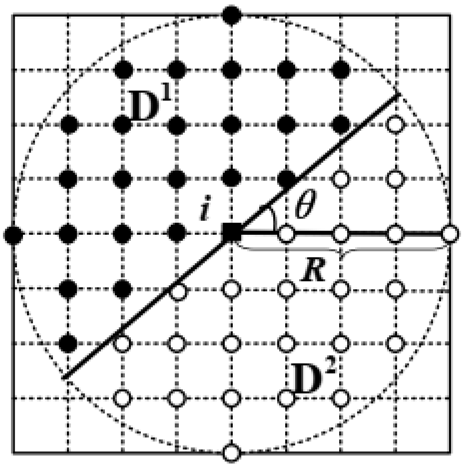


Figure 3. 23. The pixel i centered R-radius circular neighbourhood is divided into two regions according to orientation: D1 (the region with dots) and D2 (the region with circles) [89].

There are four values of θ which are determined by $Eq.$ 3.2. Since the value of θ is different, so are the values of (D1 and D2), where D1, D2 each have four different values.

$$\Delta\theta = \pi/4 \tag{3.2}$$

$$\theta_n = n\Delta\theta \tag{3.3}$$

From the above, $\theta_n = 0, \pi/4, \pi/2, 3\pi/4$

According to $Eq.$ 3.3, the statistical theory is applied in calculating the pixel samples in the two areas (D1, D2) according to the values of θ, which is an average of the pixel values in each area.

$$E_{\theta_n}^{k} = \frac{\sum_{x,y} f(x,y)}{N_{x,y\ \in D}} \tag{3.4}$$

Where $k = 1,2; n = 0,1,2,3$. The x and y values refer to the coordinates of a pixel, while $f(x, y)$ refers to the gray value of that pixel. N indicates the number of pixels in each section of the circle computed according to $Eq.$ 3.5 , where r = R are the values of the radius of the circle.

$$N_D = (r - 1) * \big((2 * r) - 1\big) + 1 \qquad (3.5)$$

After the values of D1 and D2 are calculated according to θ, four values are generated for each area, then $Eq. 3.6$ is used to calculate the difference between the two areas and extract four values that represent the differences between the two areas according to the θ values so where the higher the value of ΔE, the greater the probability of divergence between D1 and D2, and the more likely that pixels will fall on the edge.

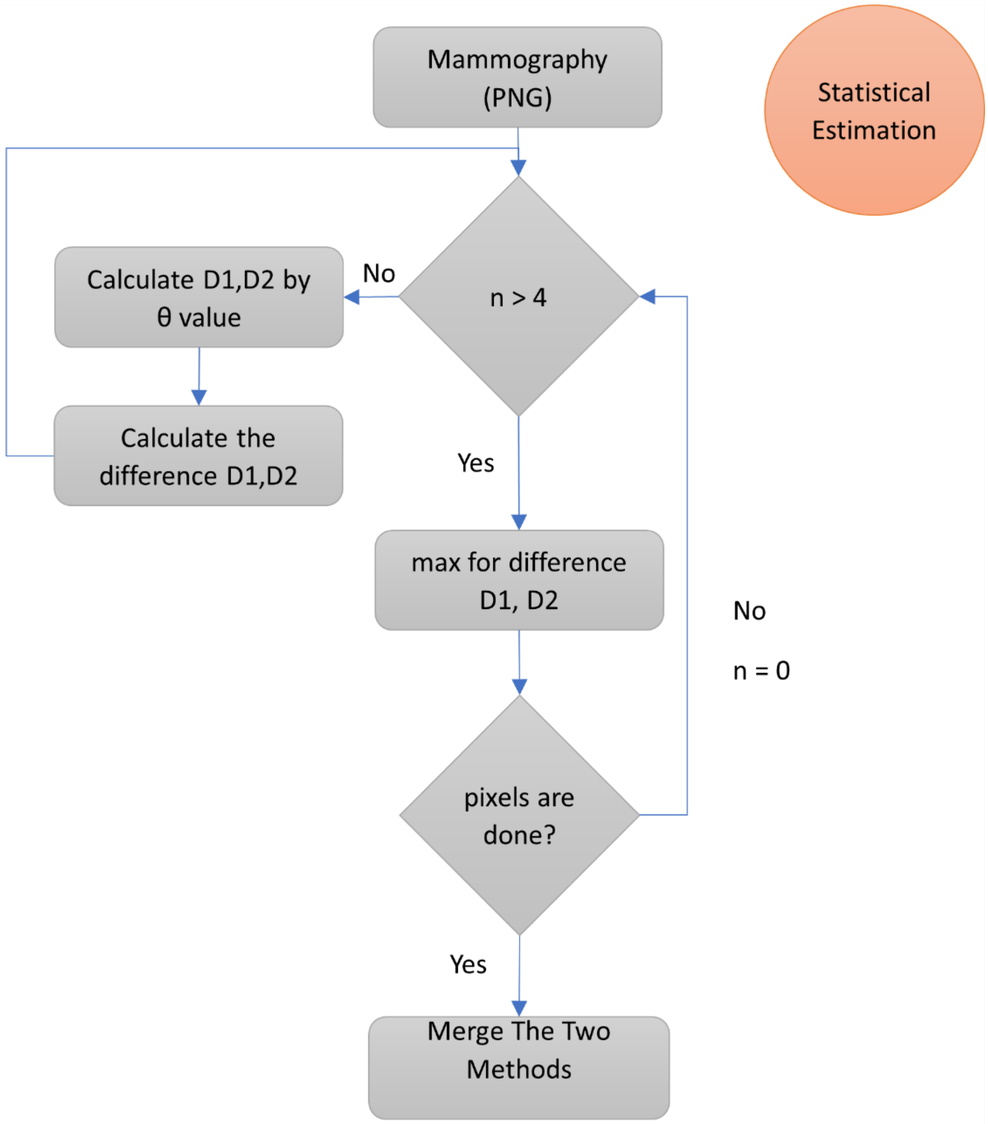


Figure 3. 24. Flowchart for statistical estimation.

In the end, the value of the pixel that represents the center of the circle is calculated (ΔE) through $Eq.$ 4.7, by taking the largest value among the difference's values.

$$\Delta E_{\theta_n} = \begin{cases} 0 & , E_{\theta_n}^1 + E_{\theta_n}^2 = 0 \\ \dfrac{2\left|E_{\theta_n}^1 - E_{\theta_n}^2\right|}{E_{\theta_n}^1 + E_{\theta_n}^2} & , E_{\theta_n}^1 + E_{\theta_n}^2 \neq 0 \end{cases} \quad (3.6)$$

$$\Delta E = \begin{cases} 0 & , \quad max\ (E_{\theta_n}^1) < 20 \quad max\ (E_{\theta_n}^2) < 20 \\ max(\Delta E_{\theta_n}), & else \end{cases} \quad (3.7)$$

A threshold has been added to the values of the differences, which is 20, so if the value between the differences is less than the threshold value, 0 is assigned to the pixel to avoid using it in detecting edges through bees.

3.4.2. Merging Gradient Values with Statistical Estimation

In contrast to statistical estimation, which has a solid ability to suppress noise but may result in some edge loss, gradient values are simple to produce but are susceptible to noise. Given the preceding, the grayscale and statistical estimation values were mixed by $Eq.$ 4.8 The algorithm's fitness function for an artificial bee will use this value.

$$F_{i,j} = a * \frac{\Delta I_{ij}}{\Delta I_{max}} + b * \Delta E_{ij} \quad (4.8)$$

Where a and b are weighting factors, I_{max} is the maximum gradient value.

3.5. IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

After removing noise from the image, the edge detection phase of the mammography image begins using the improved artificial bee colony algorithm. This section will present the steps of the improved artificial bee colony algorithm and the methods used to improve it in each step of the algorithm. First, the locations of pixels whose value is more significant than zero are extracted, and these locations are saved within a two-dimensional matrix. We will call the matrix a non-zero matrix (NZMatrix). This matrix will have a significant role and benefit in speeding up the algorithm. In this step, the input of the algorithm is three parameters, the radial image in the form of a two-dimensional matrix, a matrix containing the pixel location whose value is more significant than zero (NZMatrix), and the image (F) that resulted from the process of merging gradient values with statistical estimation.

3.5.1. Initialization Population

As mentioned in the previous section, the initialization process is a critical step in the optimization process, as it determines the starting point for the search and can significantly impact the algorithm's performance in terms of convergence speed and the quality of the final solution. So, the opposition-based learning method and chaotic systems were used to generate the initial population that Wei-feng Gao, San-yang Liu used in his paper "A modified artificial bee colony algorithm," published in 2012 [91].

The initialization was based on this method by integrating opposition-based learning with chaotic systems to generate initial solutions. The flowchart Figure 3.5 shows how to work in this step where the opposition-based learning and the chaotic systems methods are implemented. Then they are combined and extract the initial solutions for the bee colony.

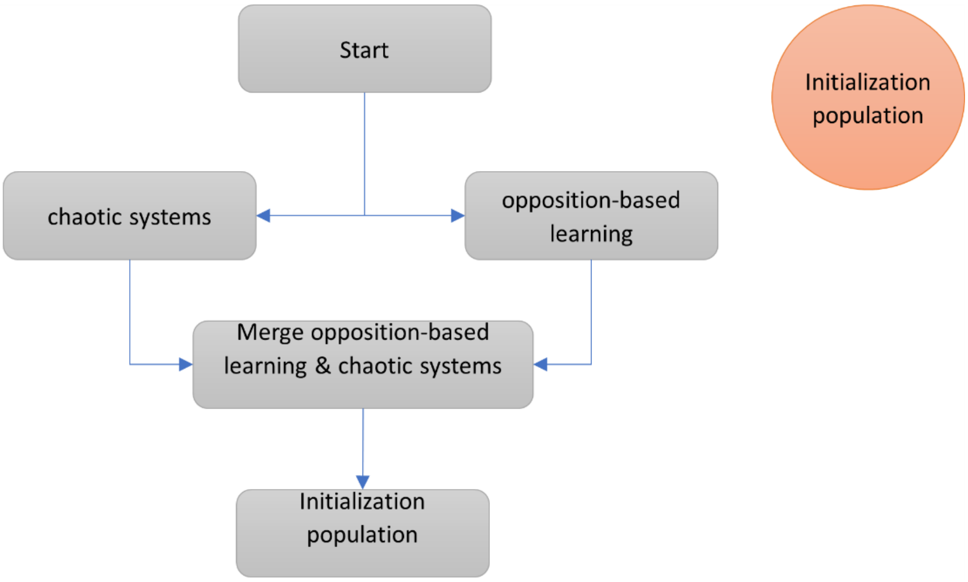


Figure 3. 25. Flowchart Initialization Population

The process of chaotic systems was done using a sinusoidal iterator according to $Eq. 3.9$, where the work of the sinusoidal function is repeated according to the specified iterations K, then using $Eq. 3.10$ to generate the value of the chaotic systems, the work is iterated for all bees in the colony SN.

$$ch_{k+1} = \sin \pi ch_k \tag{3.9}$$

Where $ch_k \in (0,1), k = 1,2, \dots, K$, K is the number of iterations

$$X_{i,j} = x_{min,j} + ch_{k,j}\left(x_{max,j} - x_{min,j}\right) \tag{3.10}$$

Where $x_{max,j}$, $x_{min,and\ j}$ are the upper and lower value of the pixels, respectively.

While opposition-based learning was generated according to $Eq. 3.11$

$$OX_{i,j} = x_{max,j} + x_{min,j} - x_{i,j} \tag{3.11}$$

$$Q = \left\{X_{i,j} \cup OX_{i,j}\right\} \tag{3.12}$$

In the end, the opposition-based learning method and chaotic systems are combined according to $Eq. 3.12$, which produced values that will be primitive for bees, on which we will rely to discover edges.

3.5.2. Employed Bee

After preparing the artificial bee colony with primitive sites (solutions), the employed bee process begins. The employed bee process in our approach takes place in two steps:

3.5.2.1. Generating New Solution

This step creates a new solution for each employed bee by relying on the previous solution according to $Eq. 3.13$. Before moving to the evaluation step, the new solution is checked. Is it within the search space and not included in the list of explored solutions?

The research space in our thesis is the image's dimensions, so the solution does not have to be outside the research space. The solution is halved when the new solution is outside the search space. Then if the new solution is not in the list of detected solutions, it will go to step 2 (evaluation step). Whereas, if it is included in the list of detected solutions, this step will be repeated until a new solution bypasses the checking process or reaches a certain Iteration (W_GNS). When the Iteration is W_GNS, it will choose a new solution from the non-zero matrix that is generated initially (NZMatrix).

$$V_{i,j} = x_{i,j} + \emptyset_{i,j}(x_{i,j} - x_{k,j}) \qquad (3.13)$$

Where $k \in \{1,2, \dots, SN\}$ *and* $j \in \{1,2, \dots, n\}, k$ is a random number that must differ from i, $\emptyset_{i,j}$ is a random number in range $[-1,1]$.

The flowchart of Figure 3.6 illustrates the process of generating a new solution based on the old solution.

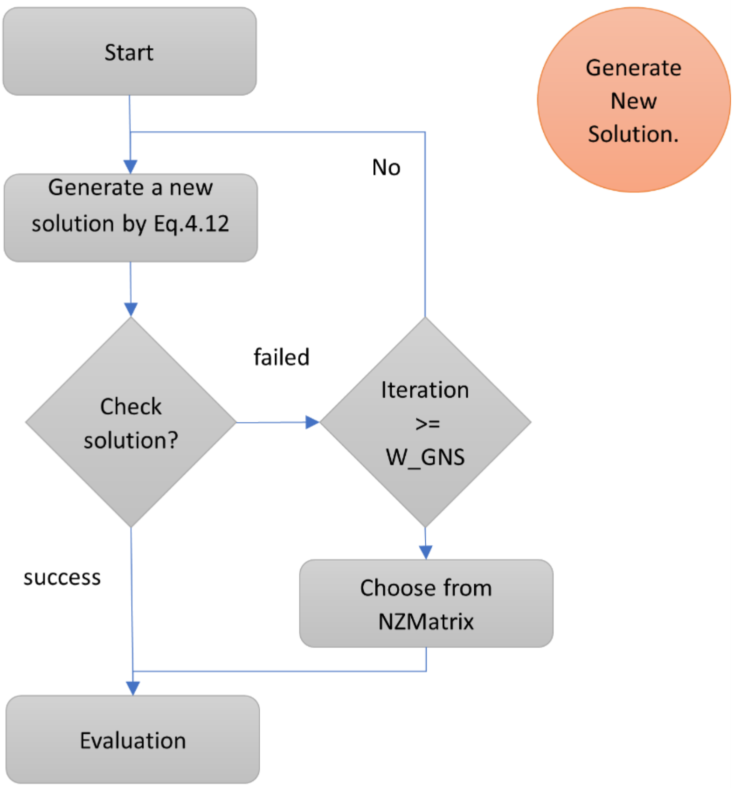


Figure 3. 26. Flowchart generating new solution

3.5.2.2. Evaluation

After generating the solution, the employed bee compares the suitability of the updated solution with the previous one. The evaluation was based on the values obtained from the pre-processing (F) of our methodology, where the pixel value was multiplied according to the new solution within the primary image with its corresponding value in F and compared this process with multiplying the pixel value according to the previous solution within the primary image. With its corresponding value in F, if the first value is greater than the second value, the old solution is replaced by the new one.

The generation and evaluation process are repeated for all employed bees, and when all bees are completed, they will move to the next step, which is the onlooker bee step.

3.5.3. Onlooker Bee

The onlooker bees gather information from the employed bees to decide about their foraging behavior and the quality of the solutions they have discovered. Based on this information, the onlooker bees decide which solutions to explore further. The employed bee process is in three steps. The flowchart of Figure 3.7 shows the three steps you go through to move to the next step.

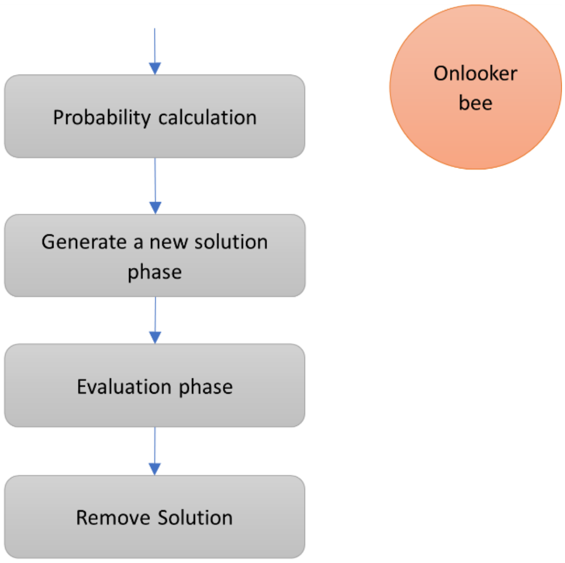


Figure 3. 27. Flowchart onlooker beee

3.5.3.1. Probability calculation

The onlooker bees calculate the probabilities of selecting each bee to determine the best solutions discovered in the employed bee stage. There are several ways to calculate the probability. Our approach used pixel values to generate the probability according to $Eq. 3.14$. The probability is calculated for all detected solutions, and a random number is generated to choose a solution according to the calculated probabilities.

$$p_i = {S_i}\Big/{\sum_{i=1}^{SN} S_i} \qquad (3.14)$$

Where S_i is the solution that was discovered.

3.5.3.2. Generate New Solution

After choosing the solution according to the calculated probabilities, a new solution is generated instead of the chosen one from the probabilistic solutions. The new solution is generated using $Eq. 3.15$, where the random solution from the discovered solutions is used. Before moving to the evaluation step, the new solution is checked as in the previous paragraph (3.5.2.1) in terms of whether the new solution is outside the search space or in the list of previously detected solutions.

$$V_{i,j} = Q_{i,j} + \emptyset_{i,j}\left(Q_{i,j} - R_{i,j}\right) \qquad (3.15)$$

Where $k \in \{1,2,\ldots,SN\}\ and\ j \in \{1,2,\ldots,n\}$, $Q_{i,j}$ is the chosen precautionary solution, $R_{i,j}$ is the random solution from the discovered solutions, $\emptyset_{i,j}$ is a random number in range $[-1,1]$.

3.5.3.3. Evaluation

After generating the solution in place of the chosen one from the probabilistic solutions, the onlooker bee compares the suitability of the updated solution with the previous one. The evaluation was based on the values obtained from the pre-processing (F) of our methodology, as in the previous paragraph (3.5.2.2).

3.5.4. Remove Solution

This new step does not exist in the essential bee algorithm step. This step aims to eliminate solutions that do not fit our approach. An extensive search area may cause the algorithm to continue working within specific values that stay the same, resulting in inaccurate and possibly erroneous results. So, by using this method, the undesirable values in our approach are replaced with new values, and this is done in each iteration of the bee algorithm, so the solutions will remain within the accepted solutions, which

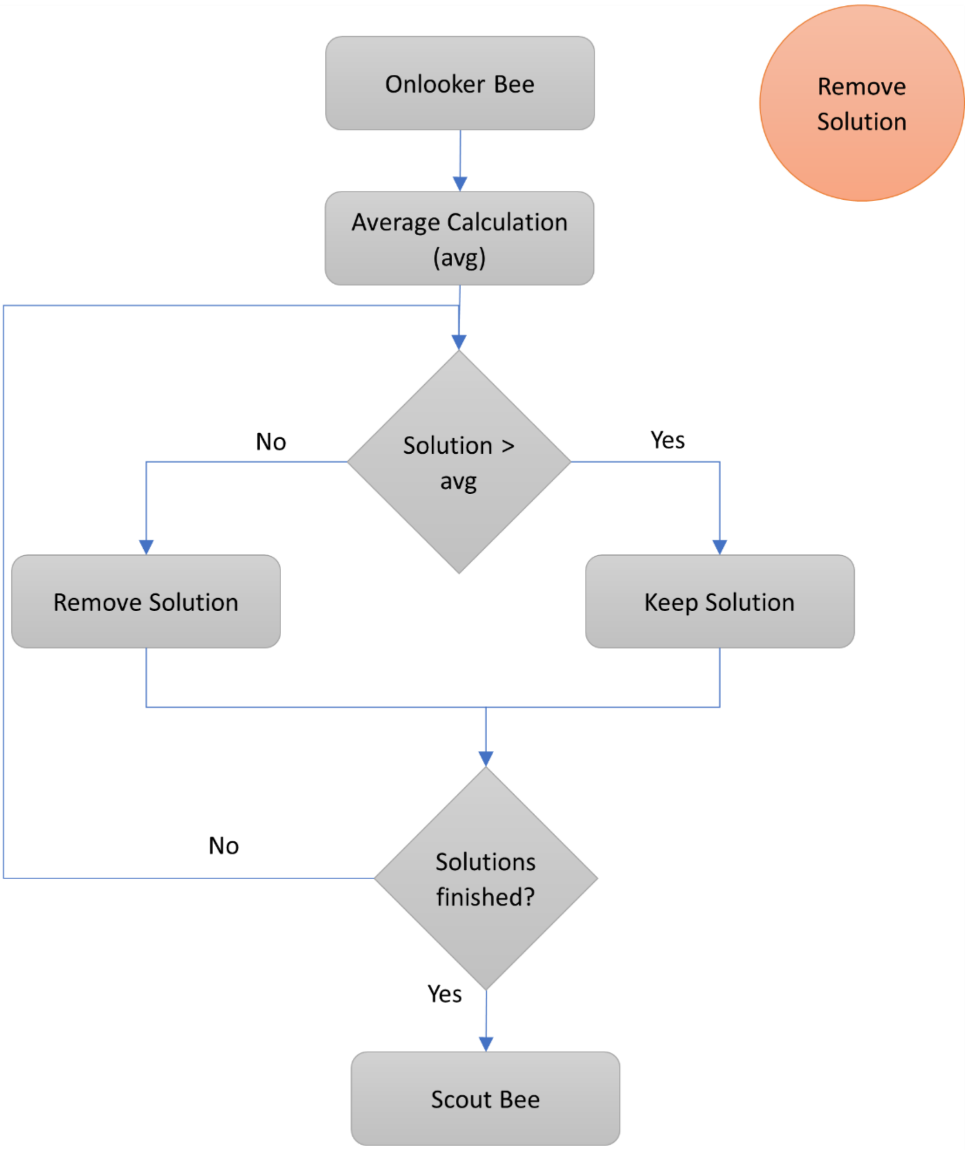


Figure 3. 28. Flowchart remove solution

leads to better results and edge accuracy. The flowchart of Figure 3.8 shows how this step works and how to eliminate undesirable values.

Undesirable solutions are selected by averaging all solutions and then comparing all solutions with the mean, according to $Eq. 3.16$. If the solution exceeds the average, it is kept. Otherwise, it is discarded.

$$Solution, avg \rightarrow \begin{cases} Solution > avg\ ;\ \ Keep\ the\ solution \\ Solution < avg\ ;\ \ Remove\ the\ solution \end{cases} \tag{3.16}$$

3.5.5. Scout Bee

In the beginning, solutions whose iteration exceeds the limit allowed within the algorithm are identified. Randomly generated solutions replace these solutions by integrating opposition-based learning with the chaotic systems previously used in the population initialization step. Before replacement, these solutions are examined to select the best among them and consider them edge pixels. The best solutions were chosen in the next step, "extracting final solutions".

3.5.6. Extraction Of Final Solutions

This is the edmABC's last step, meaning that its output will be the edges of the image. This step runs at the end of repeating the previous steps of the algorithm. Where the reasonable solutions are determined from the detected solutions whose repetition did not exceed the allowed repetition in the algorithm, it collects all the extracted solutions and converts them into an edged image.

When the iteration of the previous steps is completed, the solutions that did not recur are left, whose repetition did not exceed the allowed iteration in the algorithm, then process these solutions and choose the best among them. These solutions are checked by a threshold value that will determine if the pixel is an edge. The threshold is determined by several values that change according to the data change during the work according to $Eq. 3.17$:

$$fit = quantile(F, Q) * image.max \tag{3.17}$$

Where $quantile(F, Q)$ is the value of the last quartile of the output values of the second stage of the methodology (where the values were arranged ascendingly and a value that Q% was chosen, $image.max$ is the value of max intensity in the image.

The solution is compared to the fit value so that if the solution is more significant than this value, the solution is considered an edge. Otherwise, it is not considered an edge. In the end, the solutions chosen as the best solutions in each iteration are combined with those chosen as the best solutions in this step. Moreover, the formation of these solutions is an image that represents the edges of the original image.

3.6. SUMMARY

The detection of edges in mammographic images holds significant importance. Building upon previous research, this chapter introduces a novel approach to edge detection in mammographic images. Initially, the tools employed in implementing the edmABC are elucidated. Subsequently, the operation of the edmABC is outlined, followed by an explanation of the image pre-processing technique. The subsequent step involves edge detection within mammographic images using the modified bee algorithm. The fourth chapter will detail the outcomes and assessment of the proposed method.

PART 4

EXPERIMENT RESULT AND DISCUSSION

4.1. INTRODUCTION

This paper introduces a novel approach employing a bee colony algorithm for the purpose of edge detection in mammography images. The preceding section clearly delineated the outlined research methodology. This chapter is devoted to outlining the utilized dataset as well as the evaluation methodology. Subsequently, the outcomes derived from the tests conducted on the proposed method are presented. The proposed technique demonstrates a capacity to accurately discern edges in accordance with the expectations inherent in edge detection methodologies, as well as the characteristics of the employed dataset.

4.2. DATASET

Kaggle is an online website that provides developers, scientists, and researchers with a platform to access a wide range of data sets, challenges, and competitions in diverse fields. Kaggle is a popular destination for sharing, discovering, analyzing, and using data in research, machine learning, and artificial intelligence. Kaggle has thousands of different sets of data, covering a variety of fields such as medicine, economics, science, technology, education, and more. You can use Kaggle data for various projects and research, develop and test machine learning models, improve your data analysis and programming skills, and develop predictive models.

In this research, images from MIAS data from Kaggle Dataset [92] were used (Figure 4. 1), widely used among researchers, as the number of downloads reached 12020. The image format is PGM. It was converted to PNG format using the Python programming language to process it. These images are horizontal grayscale images of the breast. The size of all images is 1024 pixels by 1024 pixels.

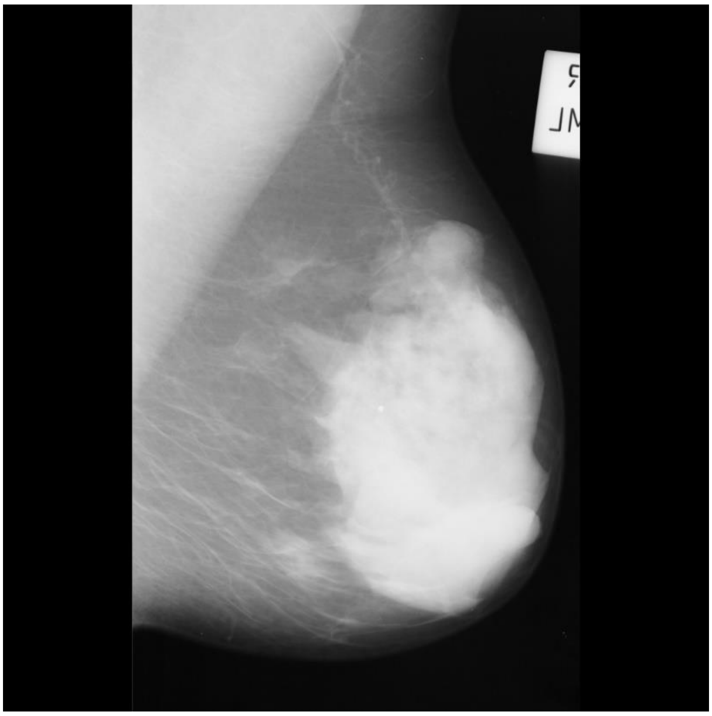


Figure 4. 1. Mammography [92].

4.3. EVALUATION AND RESULTS OF METHOD

In this part, nine mammogram images were used to compare the performance of edge detection techniques with the edmABC algorithm. Previous research on edge detection of a mammogram image showed that testing the algorithm on five images is sufficient. In this research, nine images were used. This image has been used in several scientific studies. Then, the efficiency of the edmABC is evaluated based on the previous research and information available for the data set.

The work started by extracting the gray gradient values by taking the highest value of the differences between pixels adjacent to the pixel. We moved on to calculating the statistical differences values for each pixel, then merging the gradient values with the statistical differences, and finally, the bee algorithm. To extract the gradient values, the pixels that we will work on were determined by 16 pixels distributed in the vicinity of the pixel to be calculated. In contrast, in the statistical differences, we will work on the pixels defined as a circle with a radius of 4 pixels. In the bee algorithm, the number of bees (SN=300) for all images, Dimensions n = 2 and limit = 75, W_GNS = 5, Q=0.80 while the number of iterations was calculated according to $Eq.$ 4.1.

$$fit = 10 * \sqrt{L};\;\; L\ is\ the\ length\ of\ the\ non-zero\ matrix \qquad (4.1)$$

The experiment was carried out on a core i7 eighth laptop ASUS with Hard SSD, 8 CPU, 12.0 GB of RAM, windows 11 pro-64-bit operating system using the Python programming language, OpenCV library was used to read the image, and NumPy to deal with arrays. At the same time, the calculations were performed without the use of offices.

4.3.1. Evaluation

Evaluation is an essential aspect of any research endeavor, serving as a yardstick against which the effectiveness and validity of methodologies, algorithms, and systems are measured. It provides a structured approach for evaluating proposed solutions' overall performance, efficiency, and quality, enabling researchers to draw meaningful conclusions and make informed decisions. Our study focused on edge detection using a synthetic bee colony algorithm for mammograms. The evaluation process is pivotal in measuring the algorithm's accuracy, robustness, and suitability for real-world applications. This chapter delves into the methodology used for evaluation, the data set used, and the metrics used to determine performance and present the results obtained. By rigorously evaluating the results, we aim to ascertain the algorithm's effectiveness in enhancing edge detection in mammography and contribute to a broader understanding of its potential implications and applications.

4.3.1.1. Performance Measures

Performance metrics are metrics or indicators used to evaluate an algorithm's effectiveness, efficiency, success, and quality of results. In this research, the most widely used edge detection method is used to evaluate the proposed method. Some of these methods are MSE, RMSE, and PSNR.

4.3.1.1.1. Mean Squared Error (MSE)

The mean squared error (MSE) is a common metric for calculating the average squared difference between original picture pixel values and processed or reconstructed image pixel values. The total fidelity or quality of the reconstructed image is quantified using this metric. MSE is calculated according to $Eq. 4.2$.

$$MSE = \frac{1}{N} * \sum \left(I_{i,j} - R_{i,j}\right)^2 \tag{4.2}$$

Where N is the total number of pixels in the image, $I_{i,j}$ represents the pixel value of the corresponding pixel in the original image, and $R_{i,j}$ represents the pixel value of the corresponding pixel in the edge image.

A smaller MSE indicates a higher similarity between the original and reconstructed images, whereas a larger MSE indicates greater dissimilarity or more significant reconstruction errors.

4.3.1.1.2. Root Mean Squared Error (RMSE)

The root mean squared error (RMSE) can also be used to evaluate the quality of reconstructed or processed images. It provides a measure of the average pixel-wise difference between the original and reconstructed images, considering the errors' magnitude and spatial distribution. RMSE is calculated according to $Eq. 4.3$.

$$RMSE = \sqrt{\frac{1}{N} * \sum \left(I_{i,j} - R_{i,j}\right)^2} \tag{4.3}$$

A smaller RMSE indicates higher similarity and a larger RMSE indicates greater dissimilarity or more significant reconstruction errors.

4.3.1.1.3. Peak Signal-To-Noise Ratio (PSNR)

PSNR stands for Peak Signal-to-Noise Ratio and is another commonly used metric to evaluate the quality of reconstructed or processed images. It quantitatively measures the fidelity or similarity between the original and reconstructed images by considering the error and the maximum possible signal power. The PSNR is calculated based on the mean squared error (MSE), according to $Eq.$ 4.4.

$$PSNR = (20 * \log_{10} I_{MAX}) - (10 * \log_{10} I_{MSE}) \qquad (4.4)$$

I_{MAX} represents the image's maximum possible pixel value, and MSE is the mean squared error.

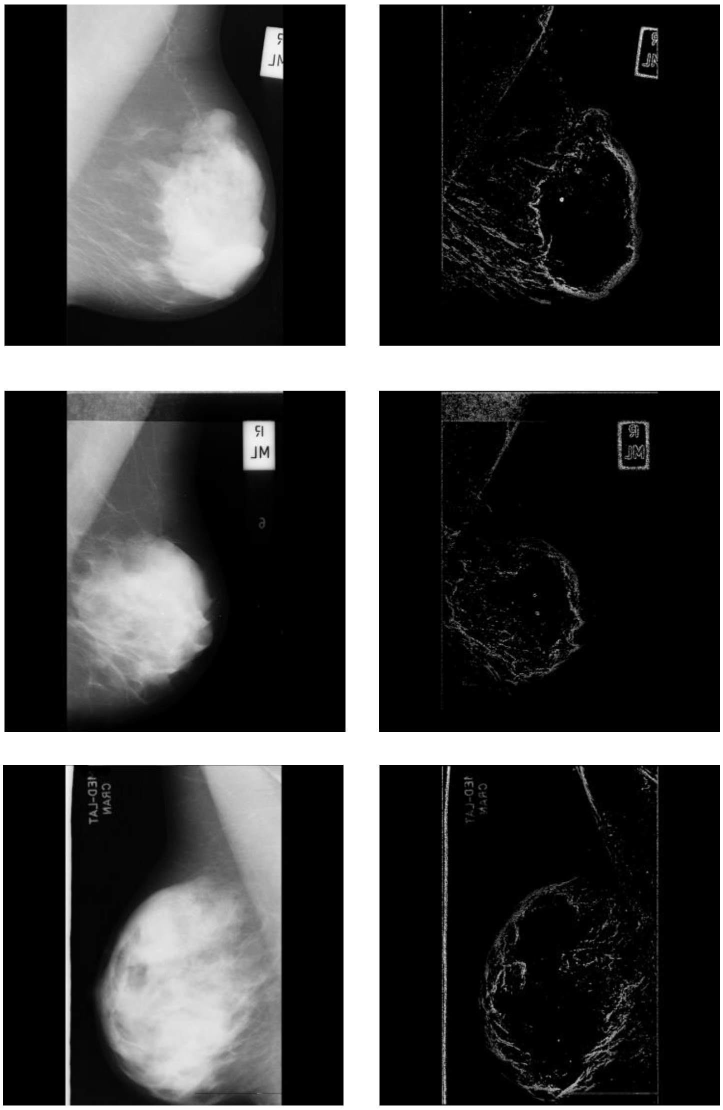
The higher the PSNR value, the higher the image quality or similarity between the original and reconstructed images. A higher PSNR indicates lower distortion or noise in the reconstructed image compared to the original image.

4.3.2. Result

The final set of solutions discovered by the edmABC consists of the food sources found from the beginning until the completion of the maximum number of cycles specified by selecting the best solutions in each cycle. For the ABC algorithm in edmABC, the best solutions were determined by relying on the extracted values in the work of the algorithm mentioned in the previous part. In this section, the original image is displayed along with the edge detection image in the suggested manner.

4.3.2.1. Image

This section presents the image resulting from extracting the edges of the mammography images using edmABC, as it presents the original image and the image resulting from detecting the edges. By juxtaposing the acquired edge images with the untreated originals Figure 4.2, Figure 4.3, and Figure 4.4, we conclude that the proposed method is good at detecting edges as we can see the edges. Where a is the original image and b is the edgmABC image.



mdb320.png

mdb002.png

mdb067.png

a b

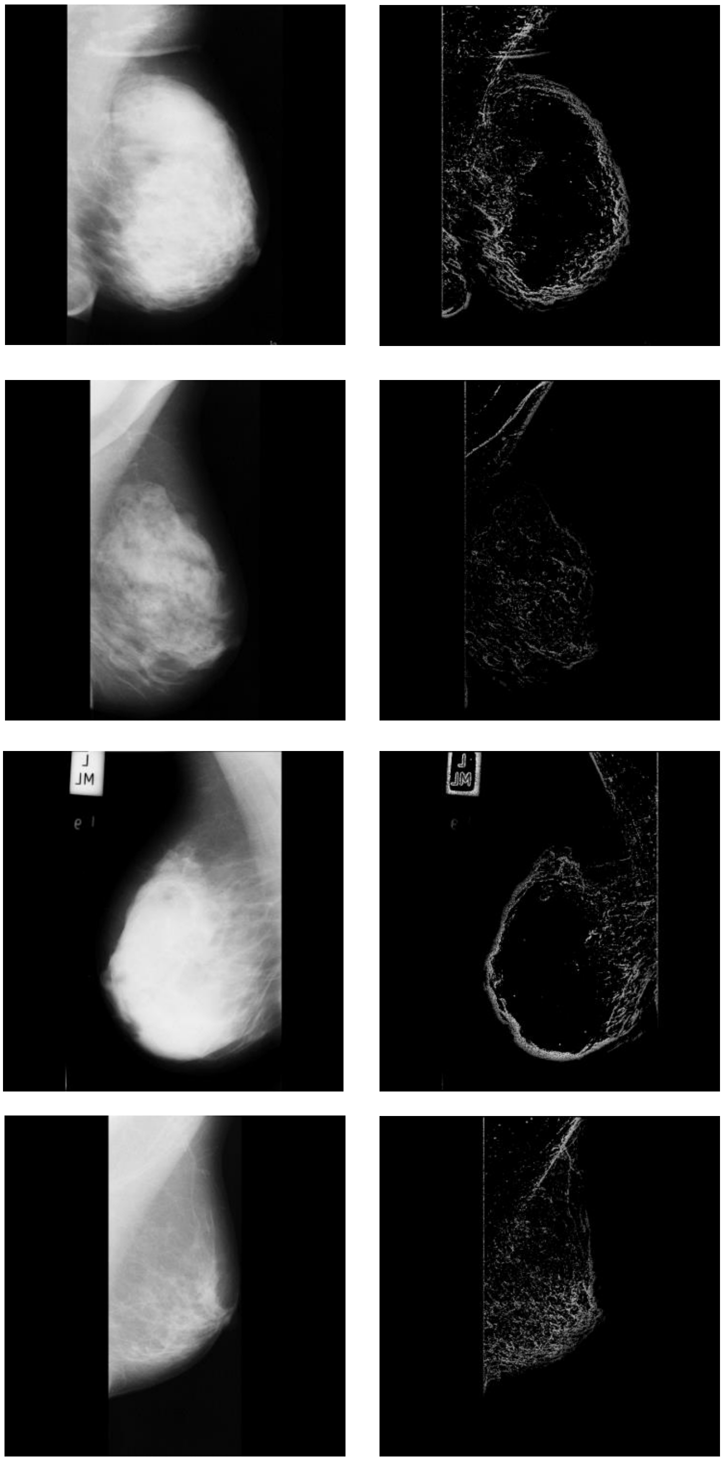
Figure 4. 2. Edge detection by edmABC, a is original image, b is edge detection edmABC.

mdb240.png

mdb286.png

mdb171.png

mdb192.png

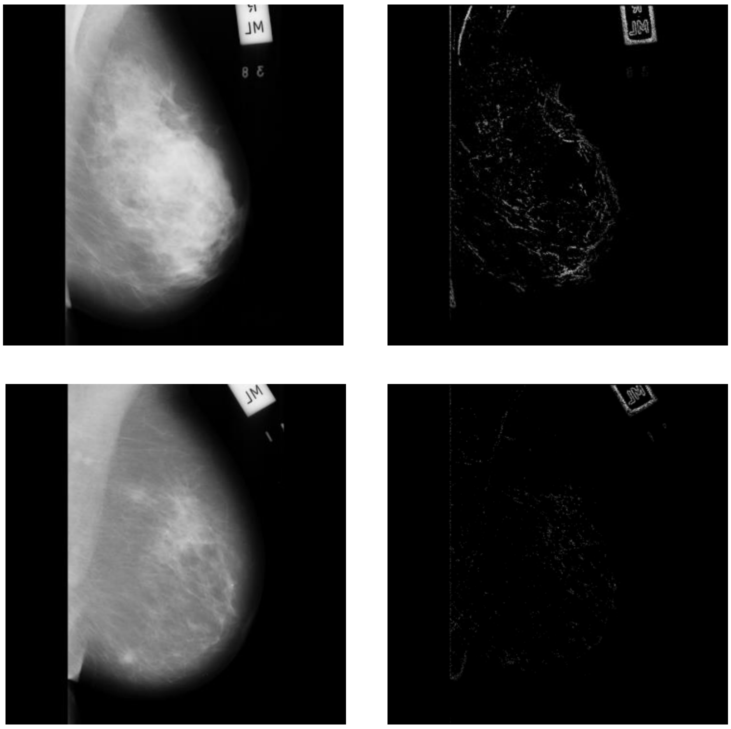


a b

Figure 4. 3. Edge detection by edmABC a is original image, b is edge detection edmABC.

mdb194.png

mdb206.png



a b

Figure 4. 4. Edge detection by edmABC, a is original image, b is edge detection edmABC.

4.3.2.2. PSNR, MSR And RMSR For Images

In this section, MSE, RMSE, and PSNR were used as performance measures to assess the effectiveness and quality of the results for the edmABC. MSE provides a quantitative measure of the processed image's quality. At the same time, RMSE represents the average size of the differences between the pixel values in the original image and the resulting image. A technique called PSNR can be used to assess how much edge detection techniques have reduced the quality of an image. It offers an excellent yardstick to gauge how closely the modified image resembles the original.

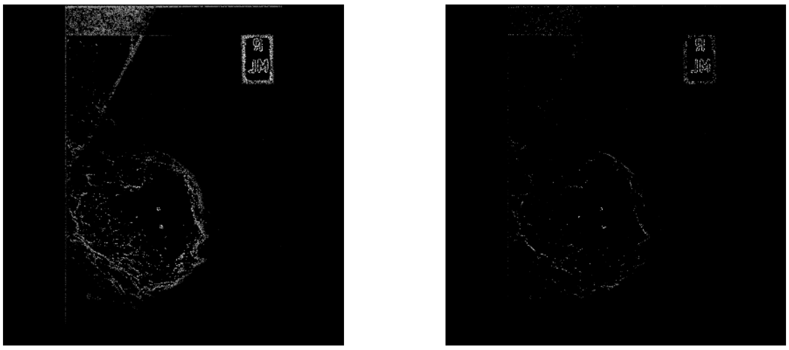
Table 4.1 shows the average evaluation values for the nine images used in our edmABC method, where the edges of the nine images were detected 30 times using our method. The results show that the MSE, RMSE, and PSNR values are good, and the detection of edges by the edmABC gives good results.

Table 4. 1. MSE, RMSE, and PSNR average evaluation for edmABC.

Times	MSE	RMSE	PSNR
1	9558.372	96.858	8.491
2	9558.765	96.859	8.491
3	9559.529	96.864	8.491
4	9560.158	96.867	8.490
5	9560.087	96.867	8.490
6	9558.932	96.861	8.491
7	9559.849	96.866	8.490
8	9559.222	96.863	8.491
9	9557.803	96.855	8.491
10	9560.045	96.866	8.490
11	9558.286	96.857	8.491
12	9558.195	96.858	8.491
13	9556.067	96.845	8.492
14	9559.133	96.863	8.491
15	9558.377	96.859	8.491
16	9559.084	96.861	8.491
17	9558.493	96.858	8.491
18	9559.616	96.863	8.491
19	9558.868	96.860	8.491
20	9560.838	96.872	8.490
21	9559.140	96.862	8.491
22	9559.060	96.861	8.491
23	9559.881	96.866	8.490
24	9559.369	96.862	8.491
25	9559.008	96.862	8.491
26	9558.206	96.855	8.491
27	9559.726	96.865	8.490
28	9558.624	96.860	8.491
29	9558.790	96.860	8.491
30	9559.252	96.862	8.491

4.3.2.3. The Effect Of Opposition-Based Learning Method And Chaotic Systems On The Proposed Method

The proposed approach demonstrates that utilizing opposition-based learning with chaotic systems yields superior outcomes compared to initializing the population with random generation. As illustrated in Figure 4.7 (a), representing the utilization of opposition-based learning with chaotic systems, the resulting edges are notably more precise and favorable than those in Figure 4.7 (b), which represents the utilization of random values. This is attributed to adopting opposition-based learning with chaotic systems, which injects greater diversity into the bee colony's domain.

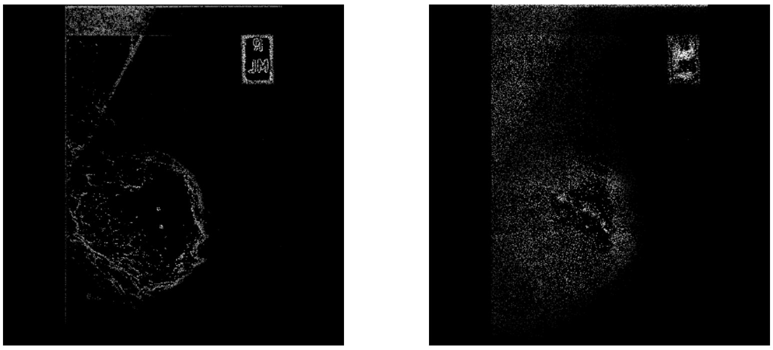


a b

Figure 4. 5. Effect of opposition-based learning method and chaotic systems

4.3.2.4. The Effect Of Gradient Values And Statistical Estimation On The Proposed Method

Results of the study demonstrate that employing gradient values alongside statistical estimation to compute suitability scores for identified solutions yields superior outcomes compared to conventional approaches. As illustrated in Figure 4.8 (a), which depicts the utilization of gradient values with statistical estimation, the edges are notably sharper and more accurate in contrast to Figure 4.8 (b), representing the use of the traditional method, where edges appear blurred. This enhancement can be attributed to employing grayscale values with statistical variance, effectively eliminating image noise, and concentrating efforts on pixels with a higher probability of constituting an edge.

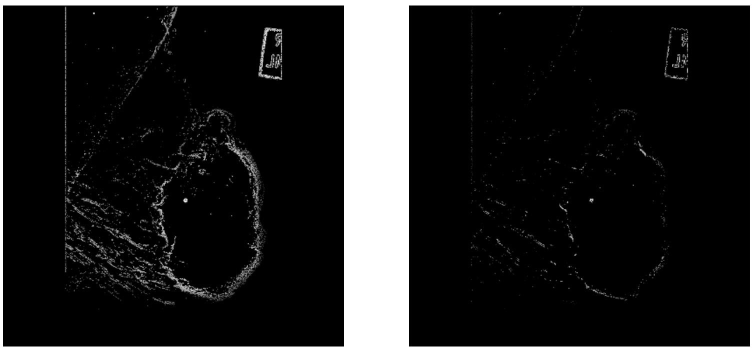


a b

Figure 4. 6. Effect of gradient values and statistical estimation

4.3.2.5. The Effect Of Discarding Insignificant Solutions For Edge Detection On The Proposed Method

The findings reveal that selectively eliminating identified solutions that make minimal contributions to the edge detection process within the algorithm yields superior and more precise edges compared to edge detection procedures that retain these solutions. Illustrated in Figure 4.9 (a), the solution elimination approach showcases finer edges, while Figure 4.9 (b) exhibits edges with reduced clarity. This outcome arises from the strategic removal of inconsequential solutions, which facilitates the prioritization of more significant alternatives.



a b

Figure 4. 7. Effect of discarding insignificant solutions for edge detection

4.4. PERFORMANCE EVALUATION:

In image analysis, edge detection methods are crucial in enhancing image interpretation. Notably, the Prewitt, Canny, and Sobel edge detection techniques have gained widespread recognition for their proficiency in delineating edges and boundaries within images. In this section, we undertake a comprehensive comparative evaluation by juxtaposing our novel edge detection method against these established methodologies. The outcomes of this comparison have the potential to enrich the discourse surrounding edge detection techniques, shedding light on the capabilities of the Artificial Bee Colony algorithm and its implications for image analysis. This analysis not only advances our comprehension of edge detection methodologies but also underscores the significance of innovative approaches in enhancing the precision and utility of medical image interpretation, thus benefiting the realms of clinical diagnosis and decision-making.

4.4.1. Image:

This section shows the visual results of the images used in the edge detection process using the edmABC and standard methods. The visible results are strong transitions in brightness, color, or texture between different areas in an image. Using the edmABC for edge detection, exceptional visual results that are significantly superior to what can be achieved using standard methods have been achieved. The outstanding performance of the proposed algorithm is characterized by its accuracy and high efficiency in identifying and distinguishing edges in images. The visual results of detection using this algorithm show a clear superiority in identifying sharp margins and changes in visual data, which enhances the quality of image analysis and understanding.

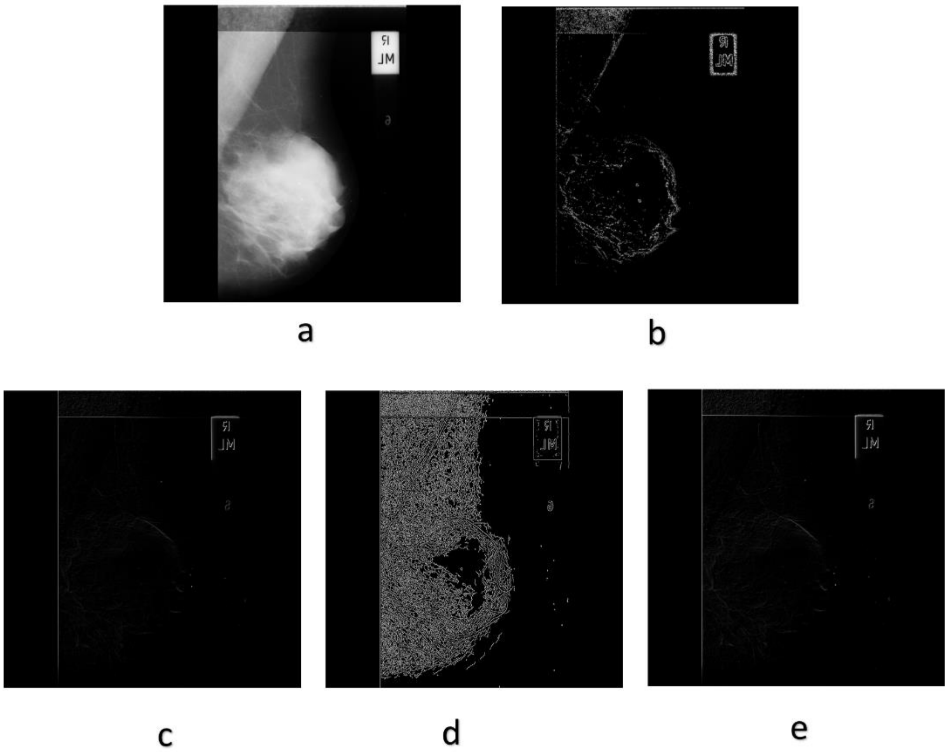


Figure 4. 8. Edge detection for mdb02.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

The benefits of this algorithm can be further demonstrated by comparing the visual results of the discovery between the edmABC and the standard methods. The edmABC improves the frequency of detection and discrimination processes, leading to better decision-making processes and automatic image analysis. In short, it can be said with confidence that the visual results of edge detection using the edmABC stand out as a superior state-of-the-art technique characterized by accuracy, efficiency, and the ability to deal with multiple challenges in image analysis and visual vision.

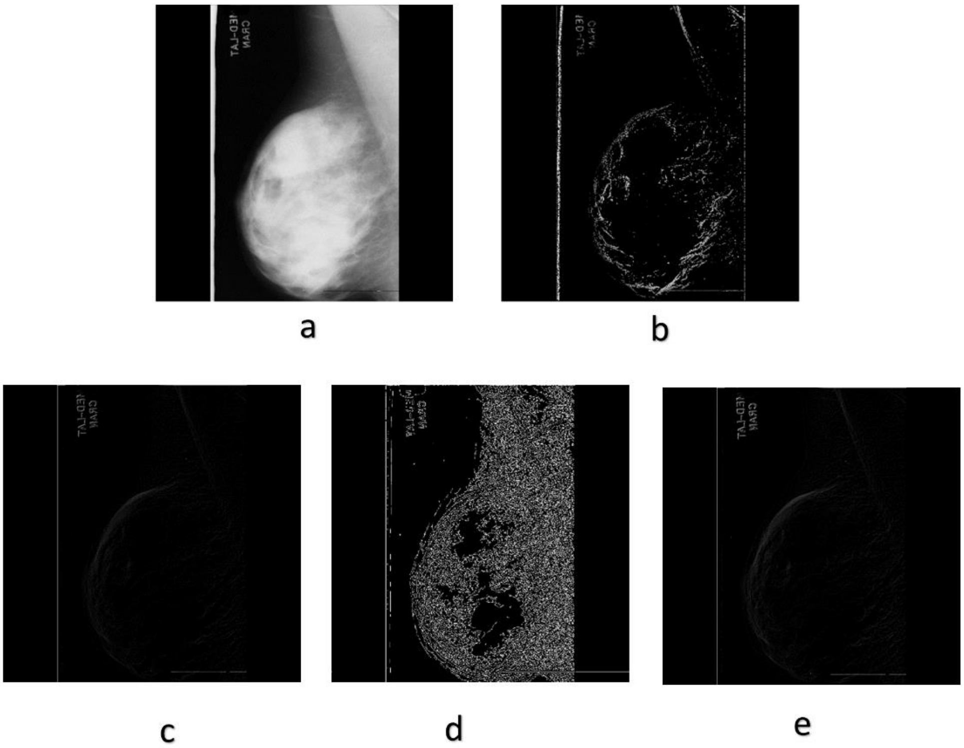


Figure 4. 10. Edge detection for mdb067.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

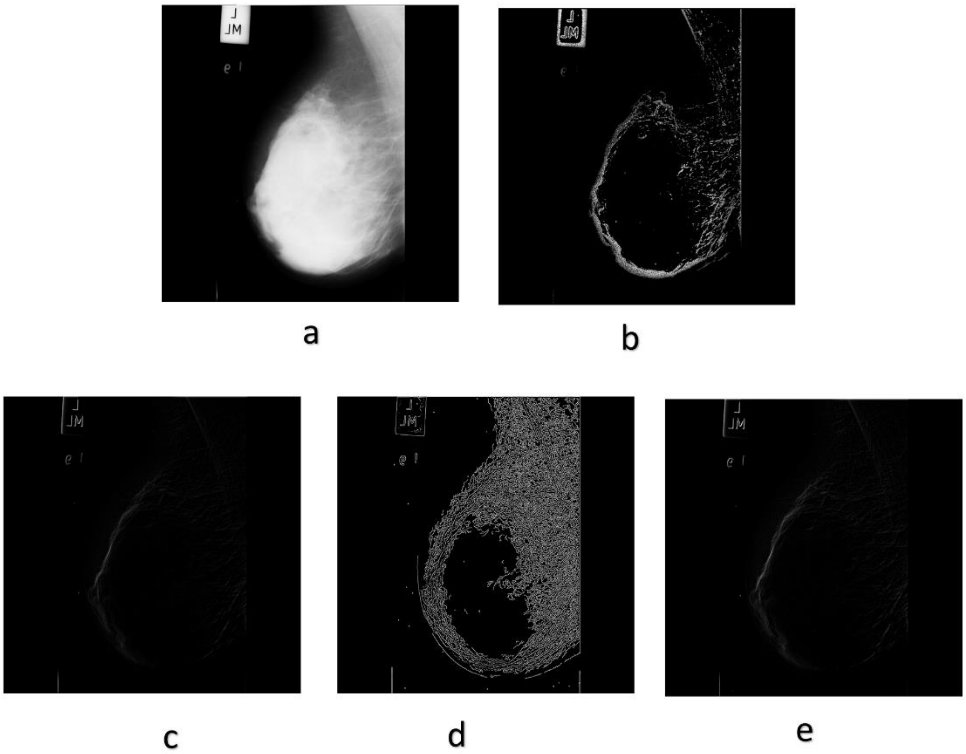


Figure 4. 9. Edge detection for mdb171.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

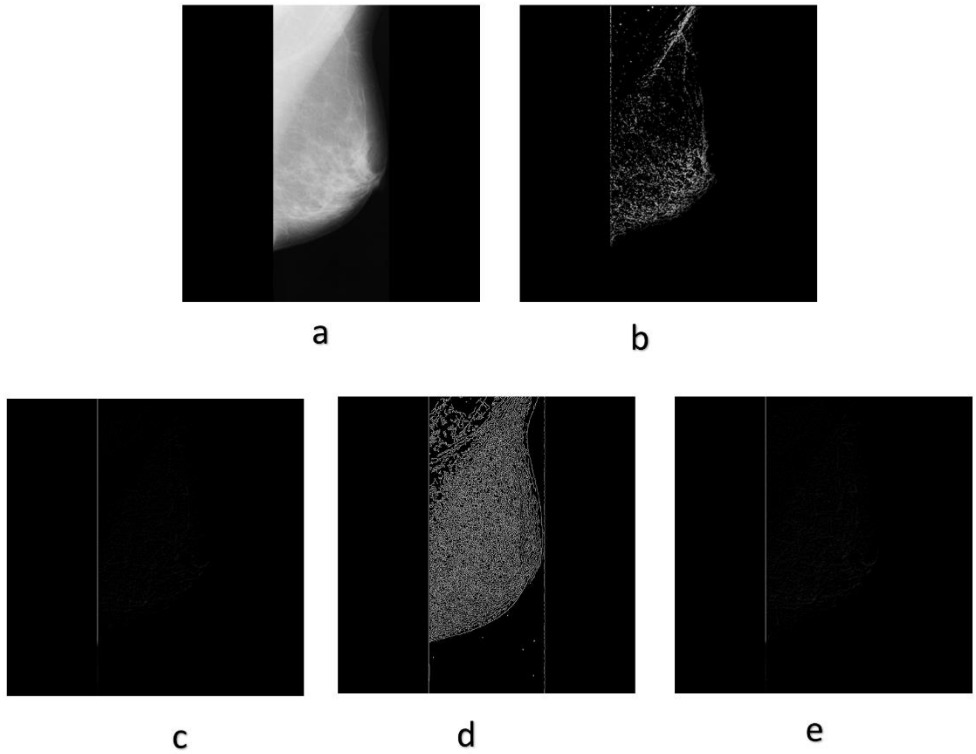


Figure 4. 11. Edge detection for mdb192.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

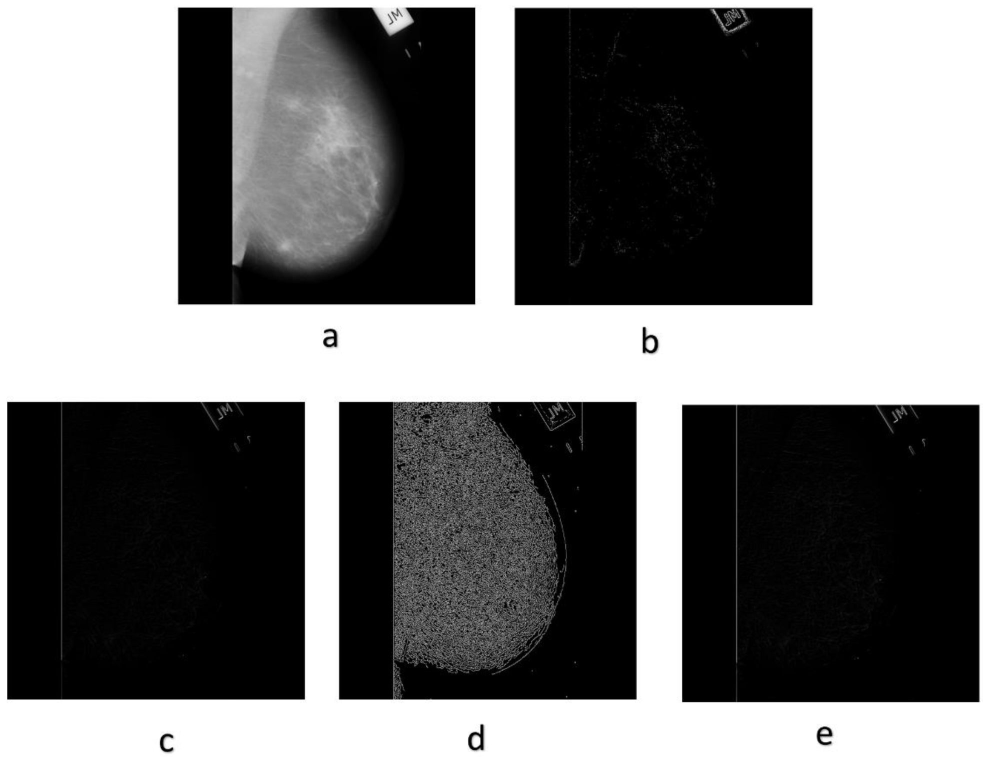


Figure 4. 12. Edge detection for mdb206.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

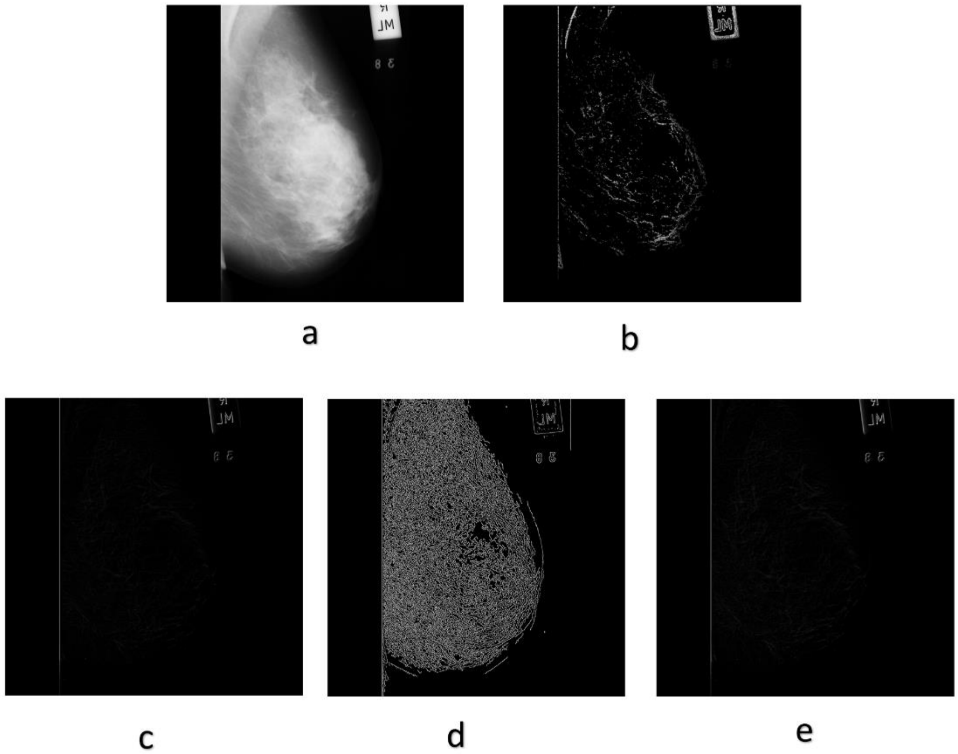


Figure 4. 13. Edge detection for mdb194.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

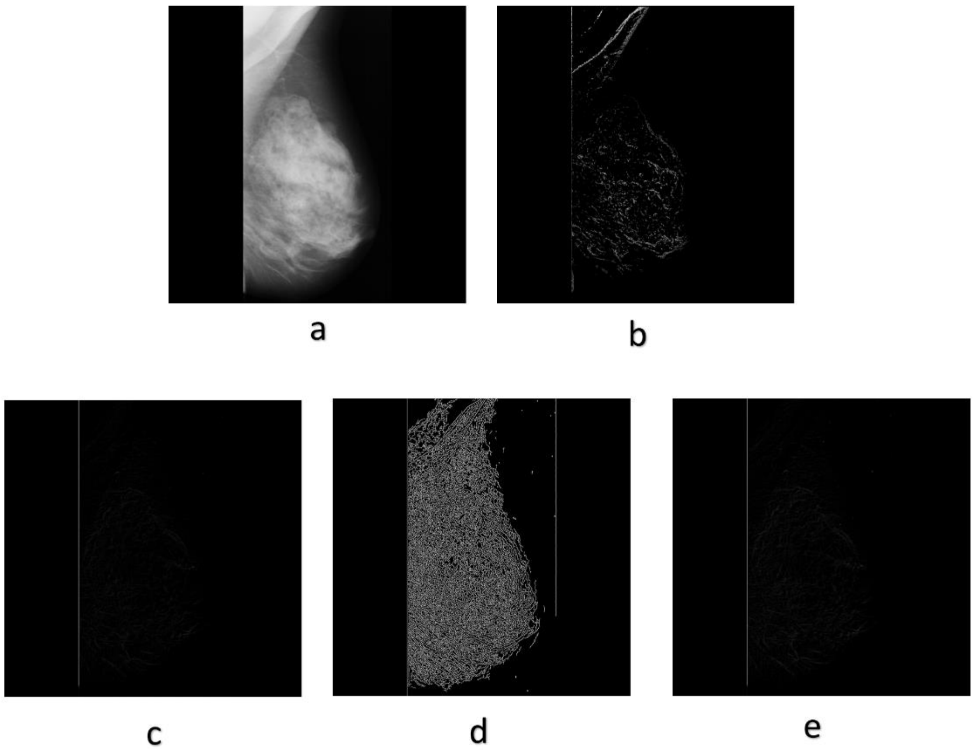


Figure 4. 14. Edge detection for mdb286.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

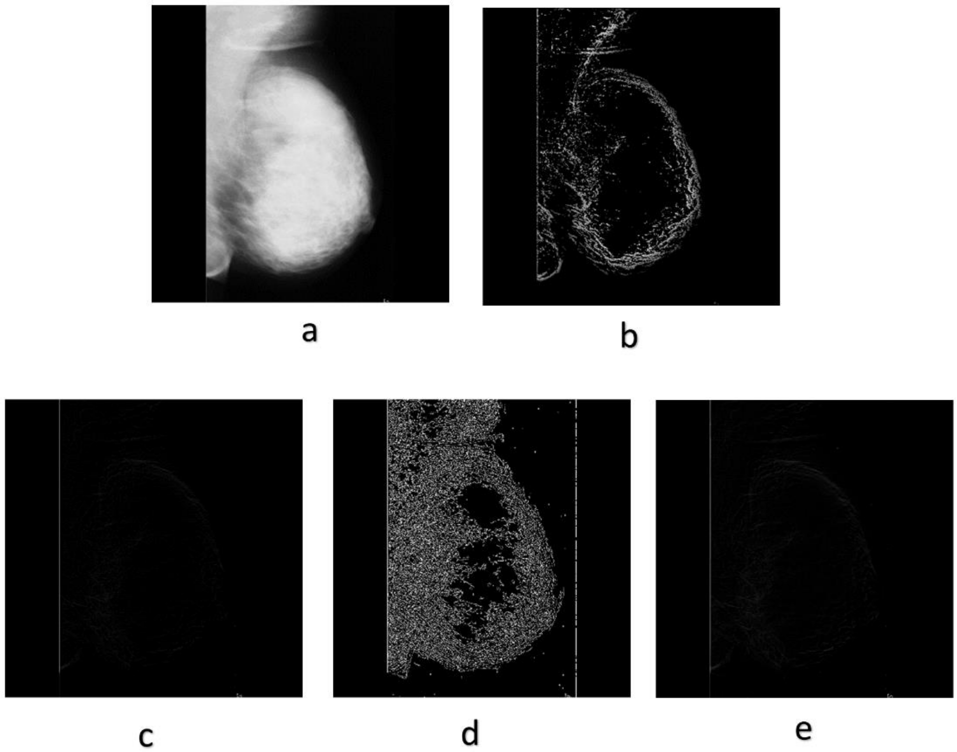


Figure 4. 16. Edge detection for mdb240.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

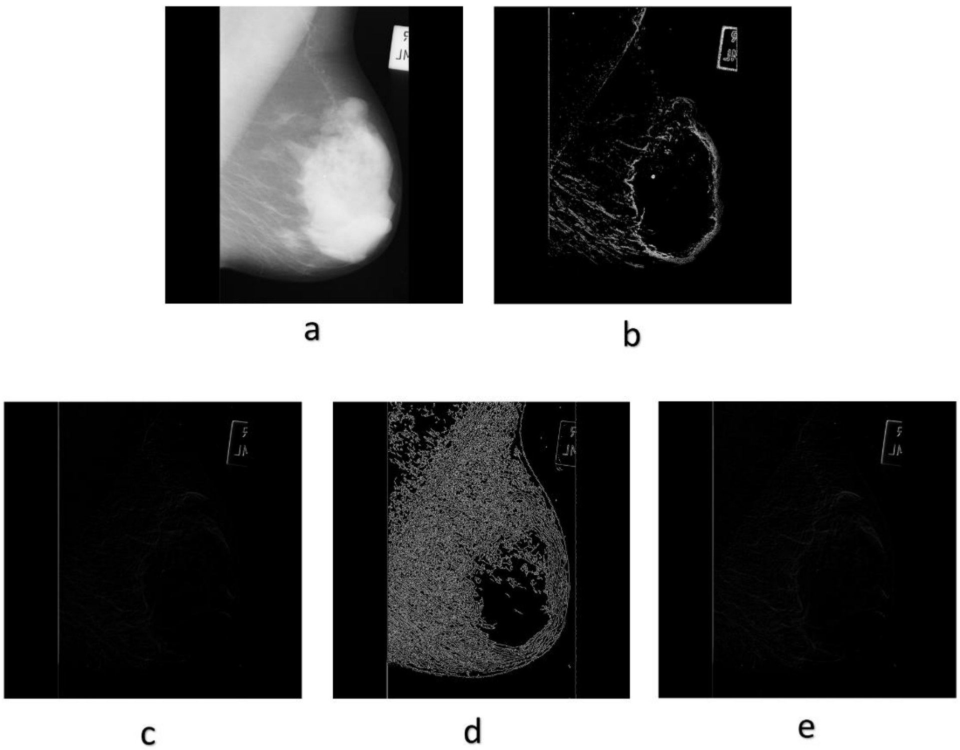


Figure 4. 15. Edge detection for mdb320.png image, a: original, b: edmABC, c: Prewitt, d: Canny, e: Sobel.

4.4.2. Performance metrics

This section presents the results of the performance metrics of the images used in the edge detection process using the proposed and standard methods. The analysis using performance measures MSE, RMSE, and PSNR of mammogram images shows promising results indicating the superiority of the edmABC over standard methods in the edge detection process. These metrics clearly showed a clear progression in the performance of the edmABC compared to the currently approved methods.

The MSE (Mean Squared Error) measure results reflect fewer errors among the images processed with the edmABC, indicating a closer affinity between the reference images and those treated. This convergence is also evident in the RMSE (Root Mean Squared Error) metric, which significantly reduces error values and thus indicates a higher quality of processed images. In addition, the PSNR (Peak Signal-to-Noise Ratio) metric shows an apparent value increase when the edmABC is used. This indicates that the signal-to-noise ratio is significantly improved, which shows a significant improvement in the quality of the processed images.

Analysis using these three metrics shows that the edmABC outperforms standard methods in improving the quality and accuracy of edge detection in mammographic images. This indicates the possibility of improving and developing diagnostic methods using the proposed techniques and applying them in other areas of a similar nature to achieve better results and superior performance.

Table 4. 2. Result of MSE, RMSE and PSNR

		edmABC	Canny	Sobel	Prewitt
mdb002	MSE	7165.632259	7939.943998	7305.668502	7416.711027
	RMSE	84.65005765	89.1063634	85.47320341	86.12032877
	PSNR	9.578258445	9.132629216	9.494203989	9.428690027
mdb067	MSE	11777.25562	11848.00848	12104.9164	12255.69722
	RMSE	108.5230649	108.8485575	110.022345	110.7054525
	PSNR	7.420362595	7.394350045	7.301185663	7.247423379

mdb171	MSE	11153.67383	11848.20093	11618.55964	11747.65394
	RMSE	105.610955	108.8494416	107.7894227	108.3865948
	PSNR	7.656624209	7.394279501	7.479280692	7.431292161
mdb192	MSE	6595.896848	6572.124535	7095.788855	7178.285729
	RMSE	81.21512696	81.06864088	84.23650547	84.72476456
	PSNR	9.938065057	9.953745766	9.620796769	9.570596196
mdb194	MSE	9326.01356	9065.294703	9348.339098	9477.078362
	RMSE	96.57128745	95.21184119	96.68680933	97.35028692
	PSNR	8.433843183	8.556984337	8.423459034	8.364058892
mdb206	MSE	7889.631963	8029.305573	7552.572657	7678.038954
	RMSE	88.82360026	89.60639248	86.9055387	87.62441985
	PSNR	9.160236162	9.084023746	9.349854489	9.278300497
mdb240	MSE	12625.38936	12421.09788	13394.77859	13533.95597
	RMSE	112.3627579	111.4499793	115.7358138	116.3355318
	PSNR	7.118355806	7.189203769	6.861448215	6.816556017
mdb286	MSE	6165.251484	6590.337878	6138.814338	6237.387799
	RMSE	78.5191154	81.18089602	78.35058607	78.97713466
	PSNR	10.23129564	9.9417268	10.24995862	10.18077614
mdb320	MSE	13329.86065	13280.28813	13666.28617	13808.07862
	RMSE	115.4550157	115.2401325	116.9028921	117.5077811
	PSNR	6.882547516	6.878728631	6.774298502	6.729471099

Table 4.2. succinctly encapsulates the essence of our comparative evaluation between our proposed approach utilizing the Artificial Bee Colony algorithm and the traditional edge detection methods, namely Prewitt, Canny, and Sobel. This table provides a concise, yet comprehensive overview of the performance results attained by each method, enabling readers to swiftly gather insights into their respective strengths and limitations.

This tabular representation is an invaluable resource for understanding the distinctive attributes of each method. By juxtaposing the numerical outcomes, readers can readily identify patterns of excellence and limitations within the context of various evaluation metrics.

Our proposed method demonstrated superior performance in images such as mdb002, mdb067, mdb171, and mdb320. Meanwhile, in images like mdb192, mdb240, and mdb194, our approach closely approximated the performance of the Canny method, known for its prowess in these cases. In mdb286, our method closely approached the results achieved by the Sobel method, which is renowned for its effectiveness in this scenario. However, in the case of mdb206, the Prewitt and Sobel methods emerged as superior performers.

This table is a dynamic visual representation of our research outcomes, enabling readers to swiftly grasp the performance differentials and trends across various images. Through this comprehensive comparative analysis, we aim to foster a nuanced understanding of the capabilities and applicability of each method, contributing to the broader understanding of edge detection techniques in the domain of medical image analysis.

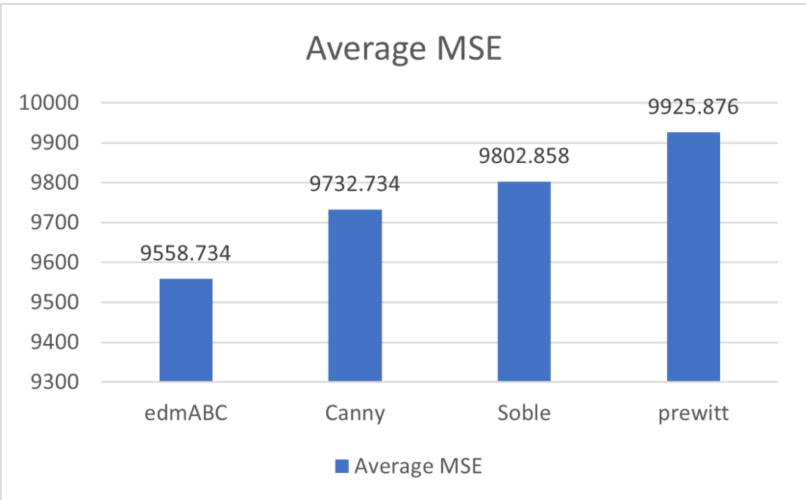


Figure 4. 17. Average of MSE

Upon computing the average values of Mean Squared Error (MSE) Figure 4.17, Root Mean Squared Error (RMSE) Figure 4.19, and Peak Signal-to-Noise Ratio (PSNR) Figure 4.18 from the image evaluation, as delineated in Table 1. Notably, the proposed method exhibited superior performance compared to the alternative techniques. This was evident through consistently favorable results, with a substantial margin of difference setting it apart from the other methods. The outcomes underscore the efficacy of our approach, highlighting its capability to yield substantial enhancements in image quality and accuracy across multiple evaluation metrics.

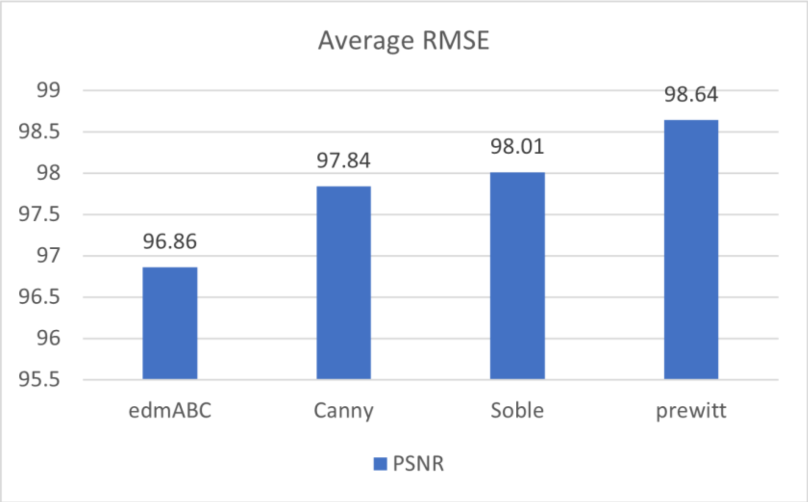


Figure 4. 18. Average of RMSE

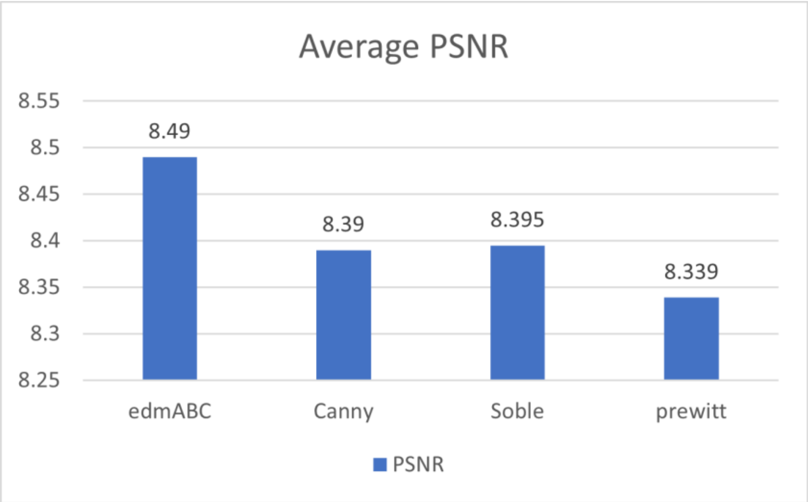


Figure 4. 19. Average of PSNR

4.5. FURTHER EVALUATION

This section focuses on how the results of the proposed method compare with those of other evaluated methods to develop edge detection techniques for mammograms. The results are compared with the comparison results by [19]. The algorithm was also compared to the road score Fuzzy Canny Edge Detector and Fuzzy Relative Pixel Edge Detector proposed by [93]. For this purpose, the images and performance measures used in these two papers were used.

In a recent research paper [19], a comparative study was conducted using four mammographic images, namely mdb194, mdb206, mdb192, and mdb286. The evaluation aimed to assess the performance of several edge detection methods, including Sobel, Canny, Prewitt, Log, and Roberts. The evaluation process utilized performance metrics such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). Both individual image comparisons and a collective analysis were undertaken, averaging the MSE and PSNR values across all images.

The findings indicated that the Canny edge detection method exhibited superior performance among the considered methods, as it consistently outperformed others. However, a noteworthy revelation emerged upon comparing our proposed method against the benchmark results from this research. Our proposed approach showcased enhanced results, surpassing even the performance of the previously esteemed Canny method. This promising outcome signifies that our proposed method has successfully transcended the performance threshold set by the Canny method, which was deemed optimal in the cited study.

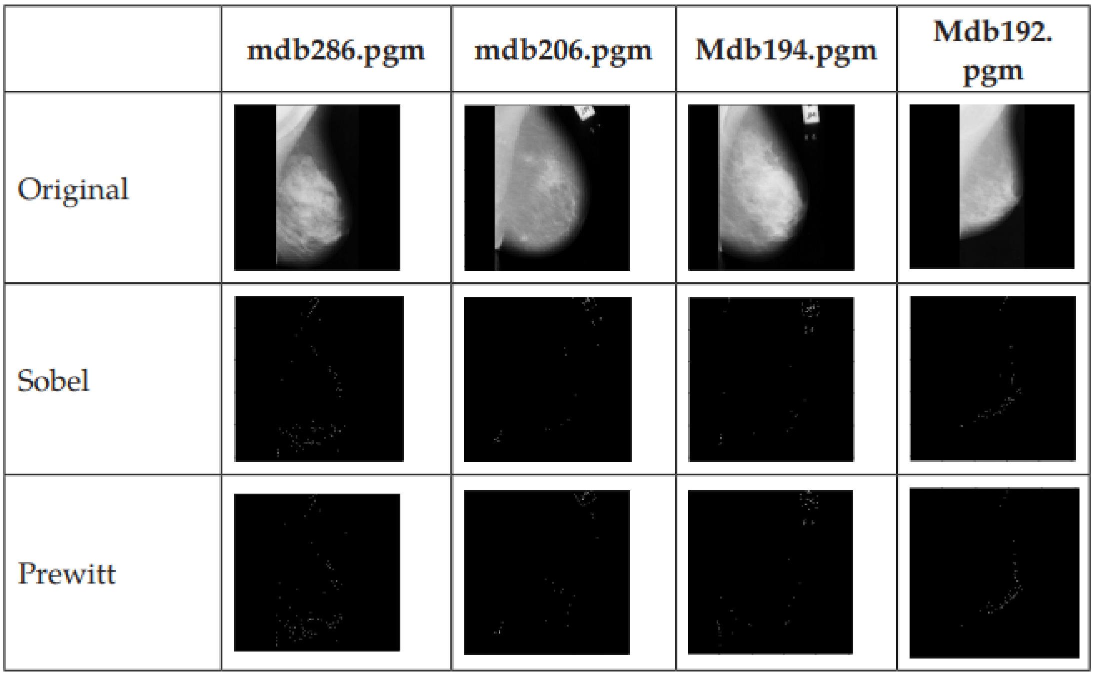


Figure 4. 20. Edge detection in paper [19]

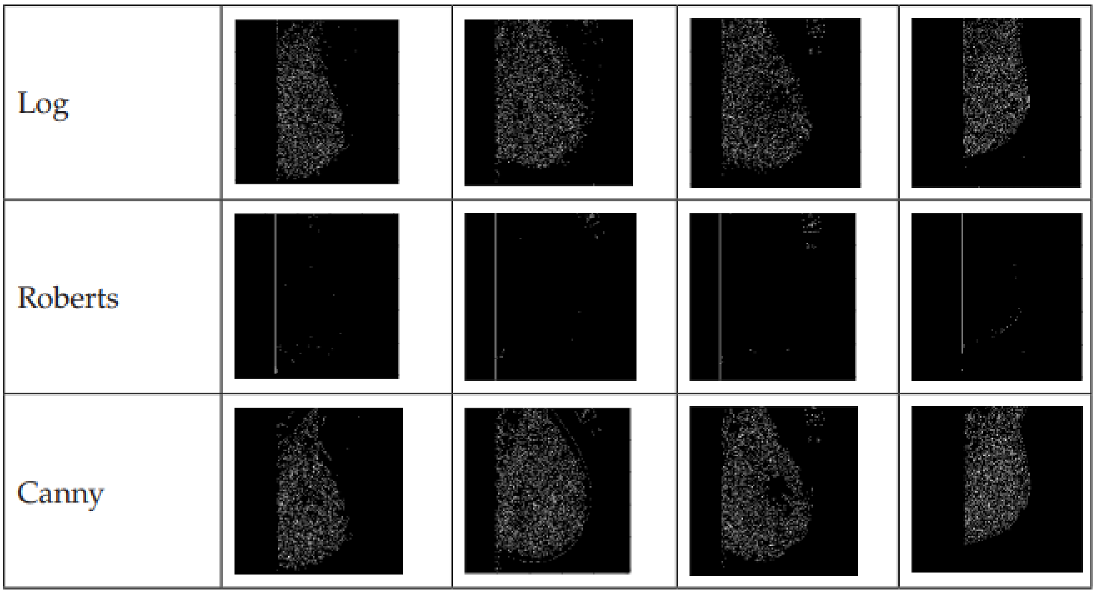


Figure 4. 21. Edge detection in paper [19]

In contrast to a prior research study [93], a comprehensive comparative investigation was conducted utilizing five radiographic breast images, namely mdb002, mdb067, mdb171, mdb240, and mdb320. The primary focus was on edge detection using Fuzzy, Fuzzy Canny, and Fuzzy Relative Pixel methods, with a subsequent juxtaposition of their outcomes against conventional edge detection techniques like Sobel, Canny, Prewitt, Log, and Roberts.

The outcome analysis involved a meticulous evaluation process employing performance metrics such as Root Mean Squared Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR). This evaluation was performed individually for each image and extended to encompass the collective assessment of RMSE and PSNR values across all images.

The results underscored the ascendancy of the Fuzzy edge detection method, consistently outperforming its counterparts. However, when we compared the outcomes of our proposed method against the benchmark study, a significant revelation emerged. Our proposed approach exhibited superior performance, surpassing the previously regarded optimal Fuzzy method.

A noteworthy distinction arises in the comparison, evident through the PSNR results. Notably, the average PSNR value for the Fuzzy method in the cited research was 8.11, whereas our findings yielded a value of 8.49. This observation aligns with the premise that higher PSNR values correspond to improved image quality. Consequently, our proposed method's ability to achieve a higher PSNR value underscores its potential to enhance image accuracy and interpretability, ultimately advancing edge detection techniques within mammographic image analysis.

4.6. SUMMARY

This part provides a comprehensive summary of the results obtained from evaluating our proposed edge detection method using a synthetic bee colony algorithm for mammograms. The evaluation process included a careful analysis of the edmABC performance in enhancing edge detection and its impact on the quality of image interpretation. Our study used a well-structured dataset of mammograms representing a variety of cases and conditions. The edmABC was applied to extract edge images and to emphasize borders and transitions within images. These carefully extracted edge images were then compared to the original radiographs. The performance of the edmABC has been evaluated against standard edge detection methods and previous research using the usual performance measures such as MSE, RMSE, and PSNR. These metrics were calculated for all images and averaged. The evaluation results showed that the proposed method outperformed the standard and previous research methods. The superiority of the proposed method was manifested in reducing the values of the mentioned scales, which indicates that it can extract the edges of the images more accurately and qualitatively. These results enhance the efficiency and feasibility of the edmABC and confirm its ability to improve edge detection processes in mammography images. In the next part, the research conclusions are reviewed, and suggestions are made for possible future work and development areas.

PART 5

CONCLUSION AND FUTURE WORK

5.1. INTRODUCTION

Detection of image edges is one of the primary and vital operations in image processing. It provides essential reference points for identifying and marking objects and structures of interest in the image. Going beyond the importance of mammograms, this study presented a new methodology for processing these images and improving their understanding. Accordingly, the first part of this research deals with drawing the study's objectives and defining its scope in detail. The second part identifies relevant previous work and the research based on it. At the same time, the third part is devoted to explaining the proposed approach to the research in the smallest detail, including a precise description of the implementation tools. Part Four presents the results of implementing the proposed approach, and a detailed analysis of its performance is presented. The fifth part compares the results of the proposed approach with the generally adopted edge detection methods and similar previous studies. This chapter also includes an explanation of the results of the research. In the last part, the research conclusions are reviewed, and suggestions are made for possible future work and development areas.

5.2. RESEARCH SUMMARY

This thesis focused on improving an effective method for detecting the edges of mammography images using the artificial bee algorithm. This goal was achieved through a comprehensive process that includes several specific steps. An artificial bee algorithm was applied to extract the edges of the mammography images, and this was achieved using an opposition-based learning method and chaotic systems to initialize the population, while grayscale values of pixels were combined with statistical estimation to calculate the fitness function. A standard data set was used to examine the method's effectiveness in recognizing the edges of mammographic pictures to evaluate the proposed method's value correctly. With well-known edge detection techniques such as Prewitt, Canny, Roberts, and Sobel, the results of the suggested method were compared. When the results were compared, it became clear that the suggested method performed better than the other methods and could extract the image's edges successfully. Additionally, the effectiveness of the suggested method was assessed by contrasting its findings with those of earlier studies, and it was discovered that in these situations, the proposed method likewise produced better results. The proposed method using a bee algorithm with grayscale estimation and statistics has proven excellent performance and represents a promising option in multiple related applications.

5.3. PROPOSAL FOR FUTURE RESEARCH

Based on the research and results achieved in this study, future research can be proposed that deals with developing and improving the proposed method for detecting the edges of mammography images. This future research could include the following aspects:

- Improving the artificial bee algorithm by experimenting with variables such as population size, number of cycles, and navigation methods. Other approaches to improve the edge detection process can also be studied.
- Expanding the search by using a more extensive and diverse set of mammography images. This may enhance the validation and sustainability of the proposed method in various scenarios.
- Improving the efficiency of the proposed method in terms of time and resources used. Parallel models can also be developed to speed up edge detection.
- Integration of advanced technologies with the proposed algorithm to improve performance. For example, deep learning techniques or neural networks can be tried to improve edge detection accuracy.

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RESUME

Mohamed AL TAWIL graduated from elementary and high school in the Syrian city of Aleppo. After that, in 2011, he started a bachelor's program in the Department of Communications Engineering at the University of Aleppo. One year later, he could not complete his studies at the university due to the situation in the country. In 2016, he re-enrolled in the bachelor's program in the Department of Informatics Engineering at Al-Sham Private University in northern Syria. He moved to Turkey and studied for a master’s degree in computer engineering at Karabük University in 2020. His goal is to complete his doctoral studies, Insha’Allah.