

## **A SYSTEMATIC LITERATURE REVIEW: PERFORMANCE COMPARISON OF EDGE DETECTION OPERATORS IN MEDICAL IMAGES**

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### **ABSTRACT**

*Medical images play a crucial role in the diagnosis of diseases. To make the diagnosis more accurate, the image should usually be enhanced first using image processing methods such as segmentation and edge detection stages. However, the complexity and noise that may arise in these images pose challenges in edge detection. Therefore, to portray the characteristics of edge detection operators, this research presents a systematic literature review of the performance of various edge detection operators in medical images, focusing on literature published between 2019 and 2023. After the selection process, 41 papers out of the initial 112 collected papers were chosen for further review. The study evaluates edge detection operators e.g., Canny, Sobel, Prewitt, Roberts, and Laplacian of Gaussian (LOG) on medical images such as X-rays, MRI, CT scans, ultrasound, Pap smears, and others. In the analysis, the accuracy, computational time, and response to noise of each operator are compared. The results indicate that despite longer computational times, Canny emerges as the most accurate operator, especially in Pap smear and CT scan images. The LOG operator offers high accuracy in MRI images with more efficient computational time. Evaluation of operator reliability against noise confirms the superiority of Canny. Furthermore, the future potential of edge detection in medical services is also reviewed. For instance, Canny, known for accurate and noise-resistant edges, enhances detection in complex CT-Scan and X-ray images. Meanwhile, LOG, handling artifacts with lower computational time, improves edge clarity in medical images. Potential applications include enhanced diagnosis, efficient patient monitoring, and improved image clarity in future medical services.*

**Keywords:** diagnostic accuracy, edge detection operators, image processing, systematic literature review.

### **I. INTRODUCTION**

**N**OWDAYS, science and technology have seen significant advancements, especially in the field of medicine, which are essential for improving the efficiency of medical care, particularly in disease diagnosis [1]. Many doctors rely on medical imaging, including MRI, CT scans, and ultrasounds, for essential tasks such as studying anatomical structures and planning medical procedures [2]. While these imaging technologies are fundamental, their complexity and the presence of noise demand effective solutions. Digital image processing has emerged as a vital response to these challenges [3].

Digital image processing is a process and technology that has successfully enhanced the quality and identification of an image. This process is used to enrich information contained within the image [2]. To identify the dimensions and contours of objects in the image, accurate image processing methods involve segmentation and edge detection stages [4]. Image segmentation aims to separate objects in the image from the background, while edge detection is used to identify the edges of objects [5].

Edge detection is a crucial image analysis feature, widely applied by researchers in medical image analysis [6]. There are various methods for edge detection referred to as operators [7]. The first group, known as first-order edge detection, utilizes first-order derivatives, with operators like Roberts, Prewitt, and Sobel falling into this category. The second group, known as second-order edge detection, involves second-order derivatives and includes methods like Canny and Laplacian of Gaussian (LOG) [8].

The importance of image segmentation and edge detection techniques in the medical context is

significant, especially in diagnosing various diseases and identifying the location of pathologies, thereby facilitating more accurate and rapid decision-making [2]. In this context, including the sensitivity and specificity percentages of each medical tool can provide a more detailed overview of their effectiveness in disease detection.

Although several edge detection operators have been proposed, a careful evaluation is needed to determine which operator is most effective in the context of diagnosing diseases through medical images. Therefore, this research aims to conduct a systematic review of recent edge detection operators in medical images from 2019 to 2023, to understand the strengths and weaknesses of each operator and provide a better insight into the recent developments in this domain. In carrying out this research, we categorize the reviewed journals into five main categories: edge detection using Canny, Sobel, Prewitt, Roberts, and Laplacian of Gaussian (LOG) operators. The study evaluates and compares their performance using metrics such as accuracy to assess how well the model can measure data accurately [1], Mean Squared Error (MSE) to quantify the error between the original and reconstructed images [5], Peak Signal-to-Noise Ratio (PSNR) to measure the similarity between two images [4], and Computation to help assess how fast or slow an edge detection algorithm can operate [7], among others. This comprehensive evaluation is imperative for assessing the reliability and computational efficiency of these operators in the context of medical image analysis. The explicit goal is to identify the best edge detection operator for accurately detecting diseases using medical images, with the results guiding future choices for effective operators in various medical image contexts.

Before delving further into various edge detection operators in medical image processing, it would be highly beneficial to examine the related research and work that has been conducted in this domain. Previous studies provide valuable context regarding the development of digital image processing technology in diagnosing diseases through medical imaging. Therefore, the next section provides a brief overview of related work as a foundation for understanding the broader research framework.

## II. RELATED WORK

In the Systematic Literature Review by Dawood [9], various conventional edge detection operators are evaluated for their role in image recognition. The assessment includes authors, datasets, methodologies, parameters, and operator performance. A common challenge in all methods is low accuracy, particularly in handling noise and extended computation times. Despite longer computation times, the Canny operator and its enhanced version stand out for providing superior accuracy, even in noisy conditions, compared to other conventional operators.

Agrawal and Bhogal [10] conducted a Systematic Literature Review on conventional edge detection operators used in dental imaging for identifying dental diseases, specifically in X-ray images. Their review discusses the types of dental diseases, their causes, treatments, and includes examples of diagnostic images. It also addresses the challenges of identifying dental diseases from X-ray images. Although the review compares the outcomes of different edge detection operators, it does not assess their performance results or determine the most effective operator. The conclusion drawn is that conventional edge detection operators remain effective in detecting dental diseases across various types of dental X-ray images.

In the Systematic Literature Review paper by Kumari et al. [11], a comparison of selected reference papers was made regarding the performance of various conventional edge detection operators on different images. The evaluation includes authors/researchers, research titles, techniques and operators used, and results. The conclusion was that the Canny operator had the best results with a low error rate but requires a long computation time. The Sobel operator provided coarser edge detection results, while the Prewitt operator excelled in faster computation time but with low accuracy.

Another review paper by Tariq et al. [12] assessed quality evaluation methods to gauge the performance of edge detection operators on digital images from 17 selected reference papers. The advantages and disadvantages of each method were discussed. The results indicated that the most common and widely used method for evaluating the performance of edge detection operators was visual inspection. The researchers also recommended using an appropriate quality assessment method, such as accuracy, speed, stability, and reliability, along with at least three test images.

Our research employs a Systematic Literature Review to evaluate the performance of conventional edge detection operators used in various medical imaging techniques, such as RGB imaging, X-rays,

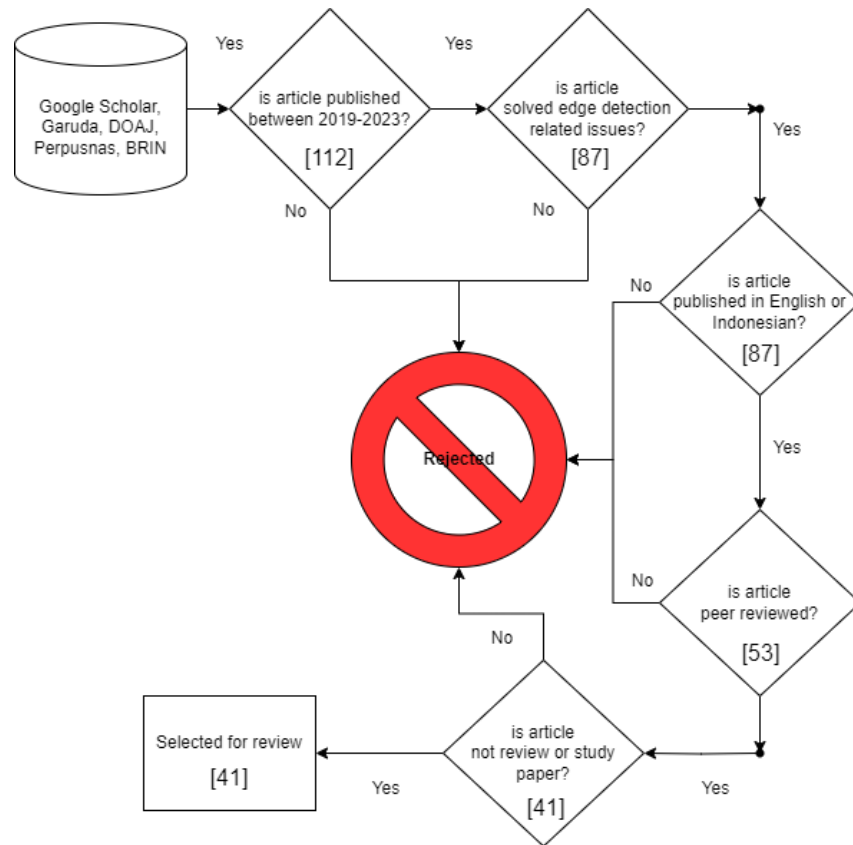


Figure 1. Paper Selection Method

radiographs, CT scans, ultrasounds, and MRI, with a specific focus on human organs. The objective is to identify knowledge gaps and to recommend the most effective edge detection methods for medical imaging. The study uses evaluation metrics including accuracy, computation time, SNR/PSNR, entropy, and MSE. By examining a range of medical images and objects, this research aims to provide comprehensive evaluation results, facilitating informed decision-making in medical image processing. This sets the foundation for developing advanced and adaptive edge detection technologies for diverse medical applications.

### III. RESEARCH METHOD

Our research method is based on the Systematic Literature Review (SLR) mechanism as described by Terence and Purushotaman [13]. The selection process for papers involved querying scholarly databases including IEEE Xplore, Elsevier, Springer, SAGE, John Wiley, Inderscience, Taylor & Francis, Sensors, Scopus, and Google Scholar. We selected papers based on specific criteria: publications from 2011 to 2019, research applying IoT techniques to address agricultural issues, and studies featuring real-time implementation data. Following this initial selection, the papers were further reviewed. This SLR approach ensures a rigorous and comprehensive examination of the literature, confirming the relevance and adherence of selected papers to predefined criteria. Figure 1 depicts the diagram of our paper selection process, as adapted from [13].

#### A. Review Objective and Research Questions

In the context of the research objectives, the following research questions are considered:

- 1) Question 1: How does the performance of edge detection operators compare in terms of accuracy on different medical images?
- 2) Question 2: Is there a significant difference in the computation time required by various edge detection operators on medical images?
- 3) Question 3: Are there specific factors that influence the strengths or weaknesses of each method in detecting object edges?

- 4) Question 4: How do edge detection operators compare in terms of reliability in dealing with noise or disturbances in medical images, as indicated by SNR, PSNR, Entropy, and MSE values?
- 5) Question 5: What is the potential application of edge detection in medical services in future cases?

#### *B. Search Strategy*

A careful search strategy was developed after establishing the goals and research questions to thoroughly examine all relevant empirical data related to the purpose of this research. This technique includes specifying the search area for articles taken from electronic databases such as Google Scholar, Garuda, DOAJ, Perpustakaan, and BRIN. The discovered articles were subsequently subjected to two different applications of inclusion and exclusion criteria.

#### *C. Search Criteria*

The explanation of the paper selection method is outlined below, considering the appropriateness and variation of key terms. For this purpose, the following keyword list is determined:

("Medical Image") OR ("Biomedical Image") OR ("CT Scan Image") OR ("X-Ray Image") OR ("USG Image") OR ("Radiograph Image") OR ("MRI Image") OR ("Dental Image") OR ("Fracture Image") OR ("Disease Detection") OR ("Disease Analysis") OR ("Comparative Analysis") AND ("Edge Detection Methods").

Inclusion (I) criteria for paper selection were: (I.1) Papers published between 2019 and 2023; (I.2) Papers written in either Indonesian or English; (I.3) Research published in peer-reviewed journals; and (I.4) Papers that discuss and apply conventional edge detection operators to diagnose diseases in medical images.

Exclusion (E) criteria were applied as follows: (E.1) Papers not written in Indonesian or English; (E.2) Papers that did not undergo the peer-review process; and (E.3) Papers categorized as reviews or theoretical studies.

#### *D. Data Collection and Selection*

We searched the selected electronic databases using a predefined search strategy to identify relevant studies. The initial search yielded 112 papers. Applying the inclusion and exclusion criteria, all identified studies met the exclusion criteria as well as inclusion criteria I.1, I.2, and I.4. However, most of these papers were excluded because they did not satisfy inclusion criterion I.3, which requires that the papers be published in peer-reviewed journals. After applying all the selection criteria, a total of 41 papers were chosen for further review. These selected papers will be thoroughly analyzed, discussed, and categorized based on the type of conventional edge detection operators they investigate.

#### *E. Methodological Quality Assessment*

Papers selected for this systematic review were methodologically assessed to determine their suitability for inclusion and their potential to broaden the research scope. This assessment was based on four criteria: (C.1) clarity of the research aim; (C.2) adequacy of the research context; (C.3) clarity of the findings; and (C.4) value of the research based on its findings. Approximately 85% of the studies met these criteria satisfactorily.

### **IV. FINDINGS**

#### *A. Edge Detection in Medical Images Using the Canny Operator*

John F. Canny developed the Canny operator in 1986 with the aim of creating an optimal edge detection method. This approach maximizes the signal-to-noise ratio to identify specific edges. It should be noted that the Canny operator requires higher computation compared to other edge detection operators [9]. The Canny Edge Detection Operator essentially identifies edges that have the highest intensity changes in an image [13]. There are several criteria for the optimal edge detection that can be fulfilled by the Canny operator: (1) Good detection (detection criterion); (2) Accurate localization (localization criterion); (3) Clear response (response criterion) [14]. The Canny algorithm uses a 3x3 neighborhood area consisting of eight directions to interpolate the gradient magnitude along the gradient direction [15]. The Canny operator has a low error rate, and the pixel distance found in Canny edge

detection is very short, providing a single response and edge [16]. The advantage of the Canny operator lies in its ability to reduce noise before edge calculation, resulting in more edges [17].

In a study by Bade et al., it was proven that the enhanced Canny operator easily detects edges in various X-ray images of COVID-19 by combining improved local contrast morphology, as evidenced by better accuracy, MSE, sensitivity, and specificity compared to other conventional edge detection operators [16].

Fendriani et al. analyzed the comparison of filter variations for the Canny edge detection operator on 6 CT-scan medical images in an effort to detect lung cancer. Evaluation metrics such as computation time, Mean Square Error (MSE), and Peak Signal to Noise (PSNR) were employed to determine the best filter that can be applied to the Canny operator to reduce noise and improve image quality. The median filter emerged as the best filter with the lowest MSE and highest PSNR values [18].

Harmaya et al. found that the Canny operator is the best edge detection operator for four types of RGB images of dental caries compared to other edge detection operators, achieving the highest accuracy [19].

Riana et al. conducted experiments on 2000 Pap Smear images to detect cervical cancer at an early stage using the Canny operator, which achieved an accuracy of 97.66% [20].

Widiyanto et al. detected lung cancer in X-ray, CT-scan, and Mammography medical images using a quantum-based Canny edge detection operator. The implementation results showed that the proposed operator has better PSNR values and the lowest MSE compared to other operators such as Sobel, Robert, and Prewitt [21].

Ziqi Xu et al. conducted edge detection research experiments on brain CT-scan medical images by comparing various conventional edge detection operators, adding the Otsu segmentation algorithm, and performing double threshold detection. The research results showed that the modified Canny operator is the best in edge detection, indicated by better entropy, MSE, and computation time values [22].

Bhawna Dhruv et al. modified various conventional edge detection operators by applying the Ant Colony Optimization (ACO) algorithm to obtain better results in detecting pancreatic cancer. It can be concluded that the ACO-based Canny operator is the best, with the highest entropy values, proving its ability to accommodate more information [23].

Stefanus Kieu Tao Hwa et al. used the CEED Canny edge detection operator and ensemble feature variations to detect TB in lung X-ray images. The results showed that the operator used can improve the accuracy, sensitivity, and specificity compared to previous research [24].

TABLE 1  
 PERFORMANCE ANALYSIS OF THE CANNY OPERATOR

| Author         | Images Type                 | Object   | Preferred Operator    | Accuracy (%) | Computation (s) | SNR/PSNR      | Entropy       | MSE          |
|----------------|-----------------------------|----------|-----------------------|--------------|-----------------|---------------|---------------|--------------|
| [16]           | X-ray                       | Lungs    | CEED Canny            | 93.69        | 1.322           | 16.874        | -             | 122          |
| [18]           | CT-Scan                     | Lungs    | Canny + Median Filter | -            | 1.213           | 32.390        | -             | 382.1        |
| [19]           | RGB                         | Teeth    | Canny                 | 85           | 0.884           | -             | 80.761        | -            |
| [20]           | Pap Smear                   | Cervix   | Canny                 | 97.66        | 0.946           | 15.337        | 75.131        | -            |
| [21]           | X-ray, CT-Scan, Mammography | Lungs    | Quantum Canny         | 90.12        | 1.510           | 64.935        | 90.172        | 260          |
| [22]           | CT-Scan                     | Brain    | Canny + Otsu          | 87.66        | 1.501           | 67.424        | 78.913        | 327.9        |
| [23]           | CT-Scan                     | Pancreas | Canny + ACO           | 83.98        | 0.874           | 43.641        | 73.070        | -            |
| [24]           | X-ray                       | Lungs    | CEED Canny            | 93.59        | 1.312           | 16.773        | 88.976        | 274.1        |
| [25]           | RGB                         | Skin     | Canny                 | 88.60        | 0.935           | -             | 80.231        | 179.6        |
| <b>Average</b> |                             |          |                       | <b>80.03</b> | <b>1.663</b>    | <b>28.600</b> | <b>63.030</b> | <b>171.7</b> |

TABLE 2  
 ANALYSIS OF CANNY OPERATOR FUTURE POTENTIAL

| Author | Images Type                 | Object   | Preferred Operator    | Future Potential                                                                                        |
|--------|-----------------------------|----------|-----------------------|---------------------------------------------------------------------------------------------------------|
| [16]   | X-ray                       | Lungs    | CEED Canny            | The combination of CEED techniques and the application of Gaussian filters can enhance accuracy results |
| [18]   | CT-Scan                     | Lungs    | Canny + Median Filter | The application of a Median Filter significantly reduces noise in the image                             |
| [19]   | RGB                         | Teeth    | Canny                 | -                                                                                                       |
| [20]   | Pap Smear                   | Cervix   | Canny                 | Integration with Thresholding techniques can assist in detection performance                            |
| [21]   | X-ray, CT-Scan, Mammography | Lungs    | Quantum Canny         | Integration with Quantum methods can determine gradient magnitudes, enhancing performance               |
| [22]   | CT-Scan                     | Brain    | Canny + Otsu          | Integration with the Otsu algorithm can improve edge detection capabilities                             |
| [23]   | CT-Scan                     | Pancreas | Canny + ACO           | -                                                                                                       |
| [24]   | X-ray                       | Lungs    | CEED Canny            | The integration of CEED techniques can enhance accuracy results                                         |
| [25]   | RGB                         | Skin     | Canny                 | -                                                                                                       |

Zulhelmi et al. detected RGB images of skin diseases using the proposed Canny edge detection operator. Adjustments to the edge and comparison processes were applied for accurate skin disease detection. The proposed Canny operator achieved a better score at the sixth threshold [25].

The comparative performance analysis and future potential of the Canny edge detection operator in each review paper can be seen in Tables 1 and 2, respectively. Table 1 demonstrates the diversity in medical image processing approaches, highlighting the prevalent use of the Canny operator for edge detection in objects like Lungs, Teeth, and Skin. Notably, research [16], [20], [21], and [24] achieve high accuracy, around 90%, with the Canny operator. Some studies, such as [18], [22], and [23], adopt more intricate approaches by combining the Canny operator with various algorithms and filtering techniques like Median Filter, Otsu, and ACO, resulting in diverse outcomes. Computational time is a crucial factor, with [23] achieving the lowest time at 0.874 seconds, while [21] and [22] showing higher times around 1.510 and 1.501 seconds. Additional metrics like PSNR, entropy, and MSE offer insights into image reconstruction quality. Despite the overall accuracy of 80.03%, selecting the right image processing method remains complex, necessitating consideration of contextual factors like parameters and dataset characteristics used in each study.

Table 2 reveals the significant potential of the Canny operator in medical image analysis, as demonstrated by various studies. Notable examples include the use of CEED techniques in enhancing edge detection accuracy in X-ray lung images [16], and the successful integration of Canny with a Median Filter for noise reduction and improved image quality in CT-Scan lung images [18]. Other studies highlight the potential benefits of combining Canny with different methods, such as Thresholding techniques in cervical Pap Smear images [20], and Quantum Canny in X-ray, CT-Scan, and mammography lung images [21]. These findings underscore the ongoing relevance of the Canny operator, with optimization through innovative techniques showing promise for increased accuracy and performance in future medical image analysis.

#### *B. Edge Detection in Medical Images Using the Sobel Operator*

The Sobel operator is an evolution of the zero-buffer HPF filter, adopting the principles of Gaussian and Laplacian as functions to generate the HPF function [26]. The Sobel operator is a tool that minimizes interpolation and is more responsive to diagonal lines than vertical or horizontal lines. The Sobel operator operates using a 3x3 pixel-sized kernel [5]. Both kernels are combined to measure the absolute value of the overall and individual gradients [27]. The advantage of this Sobel method lies in its ability to reduce noise before performing edge detection calculations [28].

Aditya et al. used Sobel and Prewitt operators to detect fractures in adults based on 10 X-ray medical images. The preprocessing steps included binarization, noise removal, thinning, cropping, and resizing. The evaluation criteria included accuracy, MSE, PSNR, and entropy, and the results showed that the Sobel operator performed the best [1].

Chakrapani et al. conducted real-time edge detection on various VLSI architecture images using the Prewitt operator. Evaluations included frequency, image size, computation time, and others. The conclusion stated that combining the Sobel operator with other techniques produces more optimal performance [3]. Nanda et al. conducted research on detecting benign tumors (FAM) in breast ultrasound images using the Sobel operator. After segmentation, the ultrasound images were converted to binary images, and image cropping was performed. The results showed that the Sobel operator was effective in determining the edges of FAM objects, even though it formed rough edge lines [5].

Utari et al. recognized fetal shapes in six ultrasound images from Trimesters 1-2 using the Sobel operator. Image preprocessing was done using Mean and Median filtering. The results showed that the Sobel operator reduced noise before edge detection calculations [27]. Arimbi and Sofi utilized the Sobel operator and median filter to detect edges of the spine in CT-scan medical images. The research successfully identified anchor points with edge detection [29].

Ghozali and Sumarti analyzed edge detection in X-ray images of COVID-19 using the Sobel operator. The steps included converting the original image to grayscale, filtering with high-pass filtering, segmenting the image using thresholding, and sharpening with edge detection using the Sobel operator. The results provided edge detection information about COVID-19-infected areas using the Sobel operator [30].

TABLE 3  
 PERFORMANCE ANALYSIS OF THE SOBEL OPERATOR

| Author         | Images Type | Object              | Preferred Operator    | Accuracy (%) | Computation (s) | SNR/PSNR      | Entropy       | MSE          |
|----------------|-------------|---------------------|-----------------------|--------------|-----------------|---------------|---------------|--------------|
| [1]            | X-ray       | Shoulder, Hand, Leg | Sobel                 | 80.43        | 0.721           | 16.014        | -             | -4           |
| [3]            | VLSI        | -                   | Sobel                 | -            | 1.280           | 4.702         | -             | 671          |
| [5]            | Ultrasound  | Breast              | Sobel                 | 71.69        | 0.704           | -             | 80.341        | 512.6        |
| [27]           | Ultrasound  | Fetus               | Sobel + Median Filter | 89.66        | 0.768           | 35.743        | 84.876        | 102.7        |
| [29]           | CT-Scan     | Spine               | Sobel + Median Filter | -            | 0.842           | 24.829        | 86.772        | -            |
| [30]           | Rontgen     | Lungs               | Sobel                 | 69.98        | 0.610           | 1.331         | -             | -            |
| [31]           | Ultrasound  | Fetus               | Sobel + Median Filter | 85.34        | -               | -             | 83.754        | 263.6        |
| [32]           | RGB         | Erythrocyte         | Sobel                 | 76.90        | 0.718           | 3.447         | -             | 653.5        |
| [33]           | MRI         | Brain               | Sobel+8 direction     | -            | 2.777           | 10.235        | 76.630        | 361          |
| <b>Average</b> |             |                     |                       | <b>52.66</b> | <b>0.935</b>    | <b>10.700</b> | <b>45.819</b> | <b>282.5</b> |

TABLE 4  
 ANALYSIS OF SOBEL OPERATOR FUTURE POTENTIAL

| Author | Images Type | Object              | Preferred Operator    | Future Potential                                                                                            |
|--------|-------------|---------------------|-----------------------|-------------------------------------------------------------------------------------------------------------|
| [1]    | X-ray       | Shoulder, Hand, Leg | Sobel                 | The use of a 3x3 matrix can enhance performance                                                             |
| [3]    | VLSI        | -                   | Sobel                 | Integration with FPGA can save computational time                                                           |
| [5]    | Ultrasound  | Breast              | Sobel                 | -                                                                                                           |
| [27]   | Ultrasound  | Fetus               | Sobel + Median Filter | The application of High Pass Filtering (HPF) using Median Filter can eliminate noise in the image           |
| [29]   | CT-Scan     | Spine               | Sobel + Median Filter | The application of HPF using Median Filter can eliminate noise in the image                                 |
| [30]   | Rontgen     | Lungs               | Sobel                 | The combination of Thresholding and HPF can aid in edge detection processes                                 |
| [31]   | Ultrasound  | Fetus               | Sobel + Median Filter | The application of High Pass Filtering (HPF) using a Median Filter can eliminate noise in the image         |
| [32]   | RGB         | Erythrocyte         | Sobel                 | -                                                                                                           |
| [33]   | MRI         | Brain               | Sobel+8 direction     | Integration with the 8-direction algorithm can detect edges in all directions, providing better performance |

Utari identified fetal images in relation to maternal nutritional intake using the Sobel and Kirsch operators. Image filtering was also performed, and the evaluation compared the performance of both operators. The results showed that the Sobel operator had quite good performance [31].

Suppa and Supratman analyzed malaria in red blood cells in RGB images using the Sobel operator. Image cropping and preprocessing processes were conducted. The evaluation displayed an accuracy of 76.9% for 26 input data [32].

Ajai et al. conducted a comparative analysis of various conventional edge detection operators in detecting brain tumor diseases in MRI images. The analysis covered data acquisition, image preprocessing, filtering, and the application of edge detection operators. The evaluation showed that the Sobel operator with 8 directional templates was the best compared to other operators [33].

The performance and future potential comparative analysis of the Sobel edge detection operator in each review paper can be seen in Tables 3 and 4, respectively. Table 3 highlights the performance analysis of the Sobel operator across diverse image types. Notably, the Sobel operator's accuracy ranges from 69.98% in X-ray Lungs images to 89.66% in Ultrasound Fetus images. Computational time varies from 0.610 seconds in X-ray Lungs to 2.777 seconds in MRI Brain images, emphasizing the impact of operator choice and additional parameters like the Median Filter on computational performance. The Sobel operator is commonly applied to bones in X-ray images and fetal development in Ultrasound images. Overall averages show an accuracy of 52.66%, computational time of 0.935 seconds, SNR/PSNR of 10.700, entropy of 45.819, and MSE of 282.5, providing insights into the Sobel operator's performance in this research context despite variations in image types and parameter settings.

Table 4 provides intriguing insights into the potential of the Sobel operator in various medical image applications. Some significant findings include the optimization of the 3x3 matrix in X-ray bone images [1], the integration of Sobel with FPGA in VLSI images to save computational time [3], and the use of Median Filter as a High Pass Filter (HPF) in ultrasonography images to address noise issues [27], [29], [31]. The combination of thresholding and HPF has also proven effective in X-ray lung images [32]. Additionally, integrating Sobel with an eight-direction algorithm enhances edge detection performance in MRI brain images [33]. These findings suggest opportunities for further research to enhance the accuracy and applicability of the Sobel operator in the context of future medical images.

*C. Edge Detection in Medical Images Using the Prewitt Operator*

The Prewitt method was proposed by Prewitt in 1966 [34]. The Prewitt operator adopts the principles of the Laplacian function, known as a function to generate the HPF, to expedite computations by avoiding the processing of zero-valued regions [35]. The constant value of the Prewitt operator is 1 [36]. The Prewitt operator is a discrete differentiation operator used to calculate the estimated intensity gradient function in an image [37]. Edges in the image are measured by estimating the gradient in eight directions using a 3x3 or larger convolution mask. The mask with the largest gradient module is selected, and the average derivatives in the x and y directions are calculated to reduce noise, considering pixel values around the point where the edge size is to be measured [7].

Ghosh et al. compared the Sobel and Prewitt operators in detecting lung cancer in various X-ray medical images using a Wiener filter to eliminate existing noise. Evaluation was done by displaying the confusion matrix and other metrics, and the results showed that the Prewitt operator performed the best [6].

Vilimek et al. analyzed a comparison and quantitative assessment of various edge detection operators in identifying various medical images such as CT-Scan and MRI using dynamic noise effects. Evaluation was carried out by calculating correlation values, MSE, and others, with the Prewitt operator being the best [7].

Rizki et al. selected the best edge detection operator to analyze pregnancy ultrasound images by converting the original image to a binary image. Several operators were compared, including Roberts, Sobel, and Prewitt. One evaluation was done by displaying the amount of white pixels in the binary image in pixels. The results showed that the Prewitt operator was the best in detecting pregnancy ultrasound images [38].

Panda et al. detected bone fracture symptoms in X-ray images using various edge detection operators such as Canny, Sobel, and Prewitt. Image enhancement was done using a Gaussian filter to eliminate noise. Evaluation was carried out by comparing accuracy, MSE, entropy, computation time, and others, and the results indicated that the Prewitt operator was the best [39].

Karthick et al. compared the Prewitt and LOG operators to detect lung X-ray images using a Gaussian filter. One evaluation was done by comparing the PSNR values, and it was found that the Prewitt operator had a higher PSNR value and was the best operator [40].

Upadhyay and Tanwar employed edge detection techniques on X-ray-based images of bone fractures using various edge detection operators such as Canny, Sobel, and Prewitt. The research aimed to find the best operator, and after evaluation, it was determined that the Prewitt operator was the best in the conducted study [41].

Niam and Qirom detected fractured bones in 10 CT-Scan images of the tibia using the Prewitt edge detection operator. Image preprocessing was done by cropping and resizing the image, and an accuracy of 80% was obtained [42].

Bhargavi and Sivasakthiselvan compiled a report on brain tumor detection from MRI images using the Prewitt operator and filtering techniques. The Prewitt operator was combined with a GUI framework, HPF, and mathematical simulation models. The results showed that the technique used was more effective and efficient [43].

The comparative performance analysis and future potential of the Prewitt edge detection operator in each review paper can be seen in Tables 5 and 6, respectively. Table 5 analyzes the performance of the Prewitt operator across diverse medical images, considering accuracy, computation time, prevalent objects, image types, and other parameters. Variations in results among different studies are observed. Notably, the accuracy varies with the use of Prewitt and additional filters. For example, studies combining Prewitt and Gaussian or High Pass Filters achieved accuracies ranging from 62% to 88.73%. Computation time also differs, with the fastest at 0.845 seconds for CT-Scan and MRI and the longest at 1.642 seconds for X-ray bone images. Bones are the most tested objects, especially in X-ray and CT-Scan studies. X-ray images are the most frequently used, followed by CT-Scan and MRI. Despite an average accuracy of 67.64%, a computation time of 0.819 seconds, and a PSNR of 15.312, the Prewitt operator's overall performance in medical image analysis is deemed insufficient. This may be influenced by preprocessing methods and the specific types of additional filters used, highlighting the need for tailored selection based on the characteristics of the medical images under examination.



TABLE 5  
 PERFORMANCE ANALYSIS OF THE PREWITT OPERATOR

| Author         | Images Type  | Object | Preferred Operator        | Accuracy (%) | Computation (s) | SNR/PSNR      | Entropy       | MSE          |
|----------------|--------------|--------|---------------------------|--------------|-----------------|---------------|---------------|--------------|
| [6]            | X-ray        | Lungs  | Prewitt + Weiner Filter   | 62           | -               | 5.334         | -             | 759.6        |
| [7]            | CT-Scan, MRI | Liver  | Prewitt + Gaussian Filter | 85.02        | 0.845           | 14.976        | 84.880        | 433          |
| [38]           | Ultrasound   | Fetus  | Prewitt                   | 70.72        | 0.873           | 12.385        | 80.341        | 512.6        |
| [39]           | X-ray        | Bone   | Prewitt + Gaussian Filter | 87           | 0.935           | -             | -             | 315.7        |
| [40]           | X-ray        | Lungs  | Prewitt + Gaussian Filter | -            | 0.987           | 39.800        | 96.542        | 375          |
| [41]           | X-ray        | Bone   | Prewitt                   | 67.69        | 1.642           | 9.984         | 76.833        | -            |
| [42]           | CT-Scan      | Tibia  | Prewitt                   | 80           | 1.271           | -             | 74.213        | -            |
| [43]           | MRI          | Brain  | Prewitt + HPF + GUI       | 88.73        | -               | 40.021        | -             | 312.3        |
| <b>Average</b> |              |        |                           | <b>67.64</b> | <b>0.819</b>    | <b>15.312</b> | <b>51.601</b> | <b>338.5</b> |

TABLE 6  
 ANALYSIS OF THE FUTURE POTENTIAL OF THE PREWITT OPERATOR

| Author | Images Type  | Object | Preferred Operator        | Future Potential                                                                            |
|--------|--------------|--------|---------------------------|---------------------------------------------------------------------------------------------|
| [6]    | X-ray        | Lungs  | Prewitt + Weiner Filter   | Integrating with the Weiner Filter can enhance image quality                                |
| [7]    | CT-Scan, MRI | Liver  | Prewitt + Gaussian Filter | Applying HPF using Gaussian Filter can eliminate noise in the image                         |
| [38]   | Ultrasound   | Fetus  | Prewitt                   | -                                                                                           |
| [39]   | X-ray        | Bone   | Prewitt + Gaussian Filter | Applying HPF using Gaussian Filter can eliminate noise in the image                         |
| [40]   | X-ray        | Lungs  | Prewitt + Gaussian Filter | Applying HPF using Gaussian Filter can eliminate noise in the image                         |
| [41]   | X-ray        | Bone   | Prewitt                   | -                                                                                           |
| [42]   | CT-Scan      | Tibia  | Prewitt                   | -                                                                                           |
| [43]   | MRI          | Brain  | Prewitt + HPF + GUI       | Using HPF and GUI helps eliminate noise and adjust parameters without updating the software |

Table 6 summarizes the analysis of the Prewitt operator's potential in various medical image applications. Noteworthy findings include the use of Prewitt with Weiner Filter to enhance chest X-ray image quality [6]. Additionally, applying Prewitt with Gaussian Filter on liver and artery CT-Scan and MRI images effectively eliminates noise [7]. The study indicates diverse usage of Prewitt, including without additional filters in fetal ultrasound [38] and with Gaussian Filter in X-ray images of bones and lungs [39][40]. For CT-Scan images of the shinbone, Prewitt without additional filters is considered adequate [42]. Overall, integrating Prewitt with specific filters like Weiner and Gaussian holds potential for improving image quality in certain medical applications, with strategy adjustments depending on the image type and observed object. These findings lay the groundwork for future research aiming to optimize and adapt the Prewitt operator in medical images, enhancing its accuracy and applicability across various medical situations.

#### D. Edge Detection in Medical Images Using the Roberts Operator

The Roberts edge detection operator is a type of edge detection operator that employs a local difference operator and relies on two matrix templates when the image is viewed as a pixel matrix [44]. The Robert edge detection method is based on differentials in the horizontal and vertical directions, which are combined through a binary conversion process. The binary conversion function is used to equalize the distribution of black and white colors in the image [45]. The small size of the filter becomes an advantage of this method because it allows for very fast computations. However, a drawback of this method is its susceptibility to noise due to its small size [46]. In addition, the Robert operator reacts poorly to edges unless the edges are very sharp [47].

Husni and Adrial analyzed the comparison of conventional edge detection operators in detecting lung cancer in 5 types of CT-Simulator medical images. Contrast enhancement was performed on the images first to minimize disturbances in the images. It was found that the Roberts operator was the best operator with the lowest MSE and highest PSNR values [4].

Khairudin et al. conducted research to analyze the quality of edge detection operators on 2D lung images by first converting them to grayscale images. The evaluation stage was also discussed, and the results showed that the Roberts operator was one of the operators capable of edge detection [17].

Wei et al. applied various edge detection operators to diagnose lung diseases using various X-ray images. The compared edge detection operators included Canny, Prewitt, Sobel, Roberts, and LOG. The final results indicated that the Roberts operator performed well in the study [44].

Pertiwi identified 22 X-ray images of lungs in patients with COVID-19 using various edge detection operators. The stages in the research included image input, converting the image to grayscale, contrast

TABLE 7  
 PERFORMANCE ANALYSIS OF THE ROBERTS OPERATOR

| Author         | Images Type    | Object                  | Preferred Operator      | Accuracy (%) | Computation (s) | SNR/PSNR      | Entropy       | MSE          |
|----------------|----------------|-------------------------|-------------------------|--------------|-----------------|---------------|---------------|--------------|
| [4]            | CT-Simulator   | Lungs                   | Roberts                 | 68.33        | -               | 24.312        | 81.754        | 372.8        |
| [17]           | RGB            | Lungs                   | None                    | 64.88        | 0.658           | 20.073        | 78.775        | 489          |
| [44]           | X-ray          | Lungs                   | Roberts                 | 70.12        | 0.615           | -             | 86.883        | -            |
| [48]           | X-ray          | Lungs                   | None                    | 13           | -               | 53.766        | -             | 275          |
| [49]           | MRI            | Brain, Foot bone, Spine | Roberts + ANN           | -            | 4.730           | 9.520         | -             | 558          |
| [50]           | MRI            | Bone                    | Roberts + Median Filter | 58.77        | 2.413           | -             | 62.126        | 785.6        |
| [51]           | MRI            | Brain, Bone, Liver      | None                    | -            | 0.782           | 10.231        | 40.954        | 836.2        |
| [52]           | CT-Scan, X-ray | Brain, Chest            | None                    | 60.25        | 1.033           | 17.945        | -             | 693.9        |
| <b>Average</b> |                |                         |                         | <b>41.91</b> | <b>1.279</b>    | <b>16.981</b> | <b>43.811</b> | <b>495.7</b> |

TABLE 8  
 ANALYSIS OF ROBERTS OPERATOR FUTURE POTENTIAL

| Author | Images Type    | Object                  | Preferred Operator      | Future Potential                                                                                                |
|--------|----------------|-------------------------|-------------------------|-----------------------------------------------------------------------------------------------------------------|
| [4]    | CT-Simulator   | Lungs                   | Roberts                 | Improved contrast in the image can reduce artifacts                                                             |
| [17]   | RGB            | Lungs                   | None                    | -                                                                                                               |
| [44]   | X-ray          | Lungs                   | Roberts                 | -                                                                                                               |
| [48]   | X-ray          | Lungs                   | None                    | -                                                                                                               |
| [49]   | MRI            | Brain, Foot bone, Spine | Roberts + ANN           | Applying ANN Algorithm can result in better edge recognition, clearer images, and computational time efficiency |
| [50]   | MRI            | Bone                    | Roberts + Median Filter | Applying HPF using Median Filter can eliminate noise in the image                                               |
| [51]   | MRI            | Brain, Bone, Liver      | None                    | -                                                                                                               |
| [52]   | CT-Scan, X-ray | Brain, Chest            | None                    | -                                                                                                               |

enhancement using intensity adjustment and masking processes, converting the image to a binary form, and edge detection processing using various operators. The conclusion was that the Roberts operator could perform edge detection on X-ray images [48].

Shao et al. applied various edge detection operators to MRI images by combining the Artificial Neural Network (ANN) algorithm to achieve optimal performance. The research adopted a method based on the characteristics of horizontal, vertical, and diagonal differences, then performed a comparative analysis of different operators from the perspective of frequency domain and speed domain. The results showed that the Roberts operator could produce better performance compared to the Sobel operator [49].

Karthicsonia and Vanitha conducted edge detection segmentation on MRI images with Osteosarcoma as the object. The research used Median, Wiener, and Gaussian filters. The edge detection operators used included Roberts, Prewitt, Sobel, Canny, and LOG. It was concluded that the Roberts operator is sensitive to noise but performs better when combined with a Median filter [50].

Mahdi et al. compared various edge detection operators on MRI images of the brain, bones, and liver. Operators such as Sobel, Prewitt, Roberts, and Canny were compared. The results showed that the performance of the Roberts operator was not quite satisfactory [51].

Na'am et al. applied filtering techniques in CT-Scan and X-ray medical images using the Multiple Morphological Gradient (MMG) method for edge detection. The research results showed an increase in confidence in the diagnosis of objects in medical images [52].

The comparative performance analysis and future potential of the Roberts edge detection operator in each review paper can be seen in Tables 7 and 8, respectively. Table 7 presents an analysis of the Roberts operator's performance on various medical images, focusing on accuracy, computation time, tested objects, and image types. Results vary across studies, with accuracy ranging from 13% to 70.12%. Computation time also varies, with the highest at 4.730 seconds and the lowest at 0.615 seconds. The tested objects include Lungs, Brain, Ankle Bones, Spine, and Liver, with Lungs and bones dominating. X-ray and MRI are the most frequently used image types, with a focus on X-ray Lung images in several studies. The overall average accuracy of 41.91% and computation time of 1.279 seconds suggest that the Roberts operator's performance is not yet satisfactory. The selection of the operator should be tailored to the specific characteristics of the tested medical image types, and the application of preprocessing methods, such as additional filters, can significantly impact performance results.

Table 8 provides insights into the potential of the Roberts operator in various medical image contexts. In CT-Simulator lung images, it enhances contrast and reduces artifacts [4]. When combined with the Neural Network Algorithm (ANN) in MRI brain, ankle bones, and spine images, the Roberts operator

improves edge recognition, produces clearer images, and enhances computational efficiency [49]. Additionally, in MRI bone images, combining the Roberts operator with a Median Filter effectively eliminates noise [50]. Overall, the Roberts operator shows significant potential, particularly in contrast improvement and edge recognition, emphasizing the importance of considering specific contexts and image types in its application within the field of medical imaging.

#### *E. Edge Detection in Medical Images Using the Laplacian of Gaussian (LOG) Operator*

The Laplacian of Gaussian is one of the edge detection operators developed from the second derivative [53]. The Laplacian of Gaussian (LOG) operator, also known as the Marr and Hildreth operator, combines Gaussian filtering with Laplacian for edge and noise detection, proving useful in identifying edges at various image scales and focus levels. It focuses on areas where sharp intensity changes occur in the image, ranging from blurry to sharp and abrupt changes [37]. This is due to the use of the Gaussian function, which smoothens the image and reduces noise in the image. Consequently, the operator reduces the number of falsely detected edges [54]. The Laplacian of Gaussian method uses a single 5x5 kernel [55].

Ahmed Naseir compared conventional edge detection operators in the segmentation process of medical X-ray image edges. The observed objects included various bones in the human body such as the shoulder bone, spine, and knee bone. The evaluation resulted in the LOG operator being the best in the study [2].

Hasiholan applied the LOG operator to detect edges in RGB images of Atherosclerosis disease using MATLAB programming. The operator captures edges from all directions, producing sharper edges. The research showed that the LOG operator has quite good capabilities in detecting Atherosclerosis disease [8].

Malarvizhi and Balamurugan analyzed various variations of edge detection operators applied to MRI images with the object of cervical herniated spinal bones. The comparative operators included Canny, Sobel, Prewitt, Roberts, ZC, and LOG. The evaluation, using MSE and PSNR values among others, revealed that the LOG operator was the best [37].

Ganesan conducted research to find blood vessels in retinal images, aiming to understand various diseases such as retinopathy and other eye diseases. The study utilized edge detection operators including Canny, Robert, Sobel, Prewitt, and LOG. The results showed that the LOG operator was the best among the operators [56].

Mwawado et al. segmented RGB images of diabetic patients' legs using various edge detection operators. Preprocessing involved resizing the image and converting it to double and grayscale types. The evaluation, comparing edge detection images, MSE, PSNR, computation time, and others, concluded that the LOG operator was the best in detecting diabetes-related wounds [57].

Hutagalung also detected edges in RGB images of Hemochromatosis disease using the LOG operator, aiming to assist in detecting Hemochromatosis disease and aiding in the healing process. Before segmentation, a Gaussian filter was applied to the image to remove noise. The LOG operator demonstrated good performance [58].

Makandar et al. analyzed and compared edge detection results on medical images with lung objects to detect diseases using various conventional edge detection operators. Data preprocessing involved converting RGB images to grayscale and adjusting images to the same size and resolution. The results showed that the best PSNR and MSE values were obtained with the Canny operator [59].

Gawad et al. optimized edge detection operators to detect brain tumor diseases based on MRI images using various training images and optimal edge images corresponding to the threshold technique. The optimized Canny operator outperformed other operators, with the best accuracy, MSE, and PSNR values [60].

The performance and future potential comparative analysis of the LOG edge detection operator in each reviewed paper can be seen in Tables 9 and 10, respectively. Table 9 analyzes the performance of the Laplacian of Gaussian (LOG) operator across various medical images, considering accuracy, computation time, tested objects, and image types. Notably, the LOG operator demonstrates high accuracy, with studies achieving 98.81% in MRI brain images [60] and 87.85% in X-ray bone images [2]. However, a study on CT-Scan lung images using LOG had a lower accuracy of 71.43% [59]. Computation time varies, with the longest at 1.237 seconds for eye images [56] and the fastest at 0.202 seconds for RGB foot images [57]. Tested objects include Bones, Blood Vessels, Eyes, Feet, Body Tissues, Lungs,

TABLE 9  
 PERFORMANCE ANALYSIS OF THE LAPLACIAN OF GAUSSIAN OPERATOR

| Author         | Images Type | Object          | Preferred Operator    | Accuracy (%) | Computation (s) | SNR/PSNR      | Entropy       | MSE          |
|----------------|-------------|-----------------|-----------------------|--------------|-----------------|---------------|---------------|--------------|
| [2]            | Rontgen     | Bone            | LOG                   | 87.85        | -               | 20.372        | 22.61         | 302.4        |
| [8]            | RGB         | Atherosclerosis | LOG + Gaussian Filter | -            | 0.979           | 28.661        | 96.725        | 537          |
| [37]           | MRI         | Spine           | LOG                   | 73.29        | 0.992           | 29.752        | 97.120        | 486.6        |
| [56]           | -           | Retinal         | LOG                   | 84.31        | 1.237           | 30.334        | 97.553        | -            |
| [57]           | RGB         | Leg             | LOG + Perona Malik    | 87.12        | 0.202           | 62.040        | -             | 375          |
| [58]           | RGB         | Bone            | LOG + Gaussian Filter | 87.93        | -               | -             | 86.55         | 219.2        |
| [59]           | CT-Scan     | Lungs           | LOG                   | 71.43        | 1.144           | 10.795        | -             | 545.7        |
| [60]           | MRI         | Brain           | LOG + Optimize        | 98.81        | 0.862           | 25.910        | -             | 166.7        |
| <b>Average</b> |             |                 |                       | <b>73.84</b> | <b>0.677</b>    | <b>25.983</b> | <b>50.070</b> | <b>329.1</b> |

TABLE 10  
 ANALYSIS OF THE LAPLACIAN OF GAUSSIAN OPERATOR FUTURE POTENTIAL

| Author | Images Type | Object          | Preferred Operator    | Future Potential                                                            |
|--------|-------------|-----------------|-----------------------|-----------------------------------------------------------------------------|
| [2]    | Rontgen     | Bone            | LOG                   | -                                                                           |
| [8]    | RGB         | Atherosclerosis | LOG + Gaussian Filter | Applying HPF using Gaussian Filter can eliminate noise in the image         |
| [37]   | MRI         | Spine           | LOG                   | Reducing distortion in the image can enhance image quality                  |
| [56]   | -           | Retinal         | LOG                   | -                                                                           |
| [57]   | RGB         | Leg             | LOG + Perona Malik    | Integration with the Perona Malik model produces more accurate edges        |
| [58]   | RGB         | Bone            | LOG + Gaussian Filter | Applying HPF using Gaussian Filter can eliminate noise in the image         |
| [59]   | CT-Scan     | Lungs           | LOG                   | -                                                                           |
| [60]   | MRI         | Brain           | LOG + Optimize        | Optimized edge detection method can help improve medical diagnosis accuracy |

and Brain, using MRI, X-ray, RGB, and CT-Scan images. Overall, the LOG operator performs well, with an average accuracy of 73.84% and computation time of 0.677 seconds. It is crucial to consider preprocessing methods and the types of additional filters used when selecting the operator and filter for specific medical image types.

Table 10 presents an analysis of the Laplacian of Gaussian (LOG) operator's potential in medical image processing. The integration of LOG with a Gaussian filter proves effective in improving image quality by reducing noise in RGB blood vessel images and eliminating distortion in MRI spine images. Combining LOG with the Perona Malik model enhances edge detection accuracy in RGB foot images. Additionally, the integration of LOG with a Gaussian filter in RGB body tissue images effectively eliminates noise, while in MRI brain images, LOG optimization with an edge detection method aims to enhance medical diagnosis accuracy. Overall, the findings emphasize the significant potential of the LOG operator in enhancing medical image quality when integrated with appropriate methods and filters tailored to specific image types and observed objects, providing a basis for future optimization in medical image applications.

## V. DISCUSSION

Based on the literature findings, the average accuracy comparison of conventional edge detection operators in medical images indicates that the Canny operator tends to provide the highest accuracy in detecting object edges, specifically at 80.03% as show in Figure 2 below. A study [20] found that Canny could recognize edges in Pap smear medical images with the highest accuracy in detecting cervical cancer among other studies, reaching 97.66%. This establishes the Canny operator as the edge detection operator with the highest accuracy in the first position. In the second position, the LOG operator achieved an average accuracy of 73.84%. Although the LOG operator's average accuracy is lower than that of the Canny operator, another study [60] found the highest LOG accuracy compared to other studies, reaching 98.81% using MRI medical images in detecting brain tumors. In the third position, the Prewitt operator had an average accuracy of 67.64%. Another study [43] achieved the highest accuracy using the Prewitt operator, reaching 88.73% with MRI medical images in detecting brain tumors. The Sobel operator took the fourth position with an average accuracy of 52.66%. Despite the Sobel operator's lower average accuracy compared to the Prewitt operator, a study [27] obtained the highest accuracy at 89.66% compared to other studies using the Sobel operator on ultrasound medical images to detect fetal shapes. The Roberts operator had the lowest average accuracy among all edge detection operators, specifically at 41.91%. However, a study [44] achieved the highest accuracy using the Roberts operator, reaching 70.12%. The final results indicate that, in terms of accuracy, the Canny and LOG operators

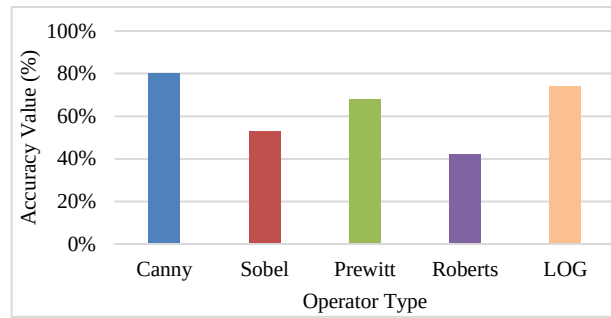


Figure 2. Visualizing the Accuracy Avg. of Edge Detection Operators

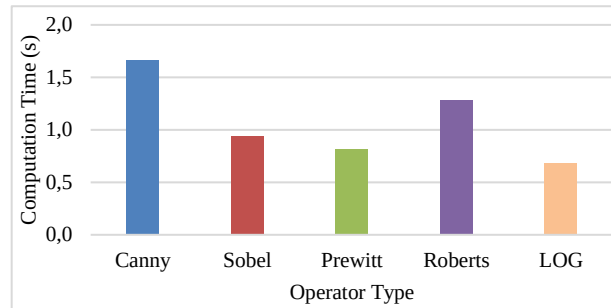


Figure 3. Visualizing the Computation Avg. of Edge Detection Operators

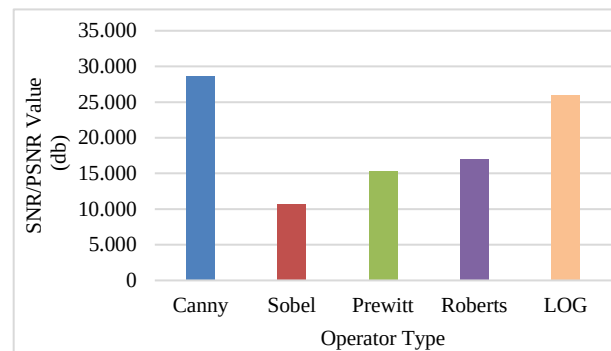


Figure 4. Visualizing the SNR.PSNR Avg. of Edge Detection Operators

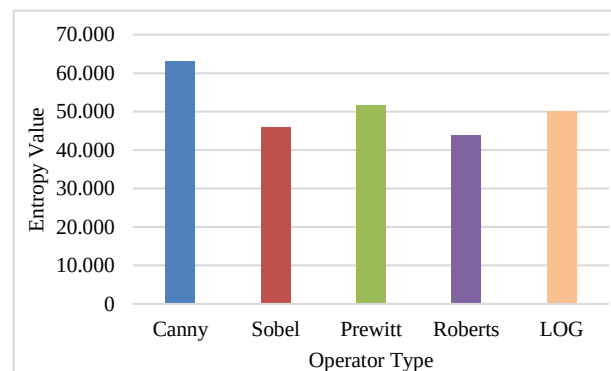


Figure 5. Visualizing the Entropy Avg. of Edge Detection Operators

perform quite well in edge detection in medical images, while other operators such as Prewitt, Sobel, and Roberts have lower and less effective performance in edge detection.

Regarding computational time aspects, the literature shows a significant variation among various edge detection operators. Although the Canny operator has high accuracy results, the average computational time obtained is longer at 1.663 seconds as show in Figure 3. The LOG operator has an average computational time value of 0.677 seconds. Next, the Prewitt operator has an average computational time value of 0.819 seconds. On the other hand, the Sobel operator has an average computational time value of 0.935 seconds. The Roberts operator has a value of 1.279 seconds. These results indicate that the LOG

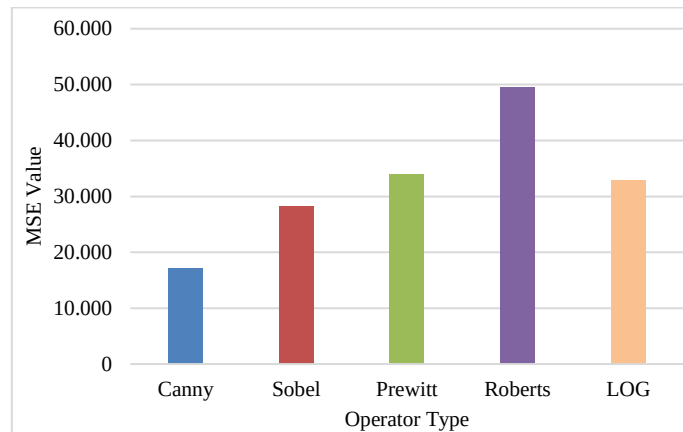


Figure 6. Visualizing the MSE Avg. of Edge Detection Operators

operator has the fastest computational time, while the Canny operator has the longest computational time.

Different image types require specific edge detection operators and techniques for optimal performance. For CT-Scan and X-ray images with complex contrast levels, the Canny operator proves effective when combined with techniques like CEED, Thresholding, and Filtering (Gaussian and Median filters for noise reduction). However, computational time can be a drawback. High-resolution ultrasound images benefit from the Sobel operator, especially with a 3x3 matrix and FPGA techniques to save computation time. The Prewitt operator is suitable for X-ray medical images with HPF techniques, but integration with Weiner Filter can pose challenges. The Roberts operator, commonly used for MRI and X-ray images, can achieve better results with the integration of ANN algorithms, compensating for its lower accuracy. RGB and MRI images are well-suited for the LOG operator, particularly with Gaussian Filter and Perona Malik techniques, along with optimizations for enhanced edge accuracy.

The evaluation of the reliability of edge detection operators against noise and interference is indicated by SNR/PSNR, Entropy, and MSE values as shown in Figure 4, 5 and 6. The higher the SNR/PSNR and Entropy values, and the smaller the MSE values obtained, the better the performance of each operator. According to the literature, the Canny operator has an average SNR/PSNR value of 28.600. The Entropy value is 63.030, and the MSE value is 171.7. The Sobel operator has average SNR/PSNR, Entropy, and MSE values of 10.700, 45.819, and 282.5, respectively. The Prewitt operator has an average SNR/PSNR value of 15.312. The average Entropy value is 51.601, and the average MSE value is 385.5. The Roberts operator has an average SNR/PSNR value of 16.981. The average Entropy value is 43.811, and the average MSE value is 495.7. Finally, the LOG operator has an average SNR/PSNR value of 25.983. The average Entropy value is 50.070, and the average MSE value is 329.1. Based on the obtained values, it can be concluded that the Canny operator is the one with the best performance in facing noise in medical images. Conversely, the Roberts operator has the lowest performance and is not effective enough in dealing with noise in images.

The potential applications of edge detection in future medical services indicate that edge detection plays a crucial role. Canny, with its ability to produce accurate and noise-resistant edges, can contribute to improving edge detection in medical images, making the diagnostic process more effective, especially in cases of CT-Scan and X-ray images with high complexity. LOG, with its capability to handle artifacts and lower computational time, can be used in medical contexts to enhance edge clarity in images that may be influenced by external factors. This is particularly important in ensuring information integrity when medical images are used in critical diagnostic procedures. Thus, the potential applications of edge detection with Canny and LOG operators can include enhancing diagnosis, efficient patient monitoring, and improving image clarity in future medical services. The selection of edge detection operators should be tailored to the specific needs of particular medical applications to maximize the contribution of this technology in enhancing healthcare quality.

## VI. CONCLUSION

Based on the discussion results, the Canny edge detection operator excels with the highest accuracy, particularly reaching 97.66% in Pap smear medical images and 80.03% overall. However, it is important

to note that although Canny demonstrates high accuracy, its computational time tends to be longer, reaching 1.633 seconds. On the contrary, the LOG operator emerges as a good choice with an accuracy of 98.81% in MRI medical images and more efficient computational time, i.e., 0.677 seconds. The use of Prewitt, Sobel, and Roberts operators, although discussed in some studies, shows lower accuracy, with Roberts being the edge detection operator with the lowest accuracy at 41.91%. Considering factors such as image type, resolution, and image processing techniques, Canny proves to be more suitable for complex images such as CT-Scan and X-ray. Evaluation of reliability against noise confirms the superiority of Canny with an SNR/PSNR value of 28.600, while Roberts demonstrates low performance. In the context of medical services, the Canny and LOG operators hold promise in significantly enhancing diagnosis, patient monitoring, and image clarity. However, the selection of edge detection operators needs to be tailored to the specific needs of medical applications for the optimal provision of healthcare services.

This discussion underscores the critical significance of the edge detection operator's success in medical applications. Specifically, the high accuracy of the Canny and LOG operators provides a robust foundation for improving diagnosis and patient monitoring. Despite Canny's longer computational time, its high accuracy adds significant value in the healthcare context.

As a direction for further development, it is recommended to conduct additional research on optimizing the computational time of the Canny operator. The integration of new technologies or more efficient algorithmic approaches may help minimize computational delays without compromising accuracy. Additionally, further research can explore the potential applications of edge detection operators, such as Canny and LOG, in specific medical scenarios or for the development of more complex systems in the healthcare domain.

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