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Development and modification Sobel edge detection in tuberculosis X-ray images

Retno Devita[1], Iskandar Fitri[2], Yuhandri[2], Finny Fitry Yani[3,4]
[1]Department of Computer System, Faculty of Computer Science, Universitas Putra Indonesia YPTK, Padang, Indonesia
[2]Department of Information Technology Doctor, Faculty Computer Science, Universitas Putra Indonesia YPTK, Padang, Indonesia
[3]Departement of Child Health, Faculty of Medicine, Universitas Andalas/Dr. M. Djamil General Hospital, Padang, Indonesia
[4]Departement of Pediatric, Faculty of Medicine, Universitas Andalas/Dr. M. Djamil General Hospital, Padang, Indonesia

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ABSTRACT

Tuberculosis (TB), a major global health threat caused by mycobacterium tuberculosis, claims lives across all age groups, underscoring the urgent need for accurate diagnostic methods. Traditional TB diagnosis using X-ray images faces challenges in detection accuracy, highlighting a critical problem in medical imaging. Addressing this, our study investigates the use of image processing techniques-specifically, a dataset of 112 TB X-ray images-employing pre-processing, segmentation, edge detection, and feature extraction methods. Central to our method is the adoption of a modified Sobel edge detection technique, named modification and extended magnitude gradient (MEMG), designed to enhance TB identification from X-ray images. The effectiveness of MEMG is rigorously evaluated against the gray-level co-occurrence matrix (GLCM) parameters, contrast, and correlation, where it demonstrably surpasses the standard Sobel detection, amplifying the contrast value by over 50% and achieving a correlation value nearing 1. Consequently, the MEMG method significantly improves the clarity and detail of TB-related anomalies in X-ray images, facilitating more precise TB detection. This study concludes that leveraging the MEMG technique in TB diagnosis presents a substantial advancement over conventional methods, promising a more reliable tool for combating this global health menace.

Corresponding Author:

Retno Devita
Department of Computer System, Computer Science Faculty, Universitas Putra Indonesia YPTK
Padang, West Sumatera, Indonesia
Email: retno_devita@upiyptk.ac.id

1. INTRODUCTION

Tuberculosis (TB) stands out as a primary contributor to mortality caused by infectious agents, exerting its impact on the respiratory system and posing a sustained threat to the global human population [1], [2]. According to the World Health Organization (WHO), tuberculosis ranks as a significant menace, following closely behind HIV/AIDS in terms of its severity [3]. The causative agent of tuberculosis is the bacterium Mycobacterium tuberculosis [4], [5]. Tragically, many children succumbing to TB do not receive a diagnosis or access TB treatment [6]. The susceptibility to tuberculosis development is markedly elevated in children, with an untreated progression rate ranging from 30% to 40%, surpassing that observed in adults. Furthermore, children may manifest nonspecific symptoms resembling those of other common childhood diseases [7]. Image processing is a methodology employed for the manipulation of images in two dimensions, characterized by operations designed to correct, analyze, or modify images. This technique finds extensive applications across diverse fields, including education, medicine, industry, agriculture, geology, marine sciences, and more. In the medical domain, image processing plays a pivotal role, particularly aiding medical teams in diagnosing various diseases through technologies such as X-ray, CT scans, and magnetic resonance imaging (MRI) [8], [9]. Tuberculosis is one such disease benefitting from advancements in X-ray technology, empowering medical professionals in the accurate diagnosis of the ailment [10].

Sobel edge detection which is used to improve edge detection in MRI images of brain tumors [11]. The data used is an available online dataset. The algorithm used is 8-directional and still uses a 3x3 kernel. MRI raw images require noise filtering by applying 8-Sobel edge detection, can reduce speckle noise and irregular tumor classification accuracy. The most common method for image segmentation based on sharp intensity changes is edge detection. Sobel, Robert, Canny, Prewitt, and laplacian of Gaussian (LoG) are some of them. Edge detection approaches were examined for fracture detection studies. This research aims to study, analyze and compare the techniques of Sobel, Canny, and Prewitt in identifying fractures. According to the analysis, the resulting findings were satisfactory, and the accuracy of the method was 87 percent [12]. Improving image intensity and complete reference-based image quality measurement. In edge detection, angle-based image quality measurements use the Sobel, Prewitt, Roberts, Canny and LOG operators. The proposed research is selecting the best image with enhancement techniques and image quality measures among all (described) for feature extraction [13]. Simulating the fixed threshold method and the adaptive threshold method of image segmentation, and concluded that the fixed threshold method can be applied to images with clear targets and backgrounds, and the adaptive threshold method can be applied to images with an uneven distribution of light and dark [14].

X-ray remains an effective and crucial diagnostic method for identifying changes in human body components, especially with the advent of digital image acquisition techniques. X-ray machines are a cost-effective option in regional hospitals, making them accessible to patients. One primary application of this technology is in diagnosing tuberculosis. While TB diagnosis in adults is generally straightforward, in children, it poses challenges. The X-ray results in children often appear vague or less clear, making it difficult to distinguish between damaged and normal lung areas. Consequently, diagnosing TB in children via X-ray technology requires extra caution and meticulous assessment. Sobel edge detection methods with existing magnitude gradients. The outcomes with the existing magnitude gradient proved inconclusive, as indicated by the low peak signal to noise ratio (PSNR) value. Subsequent research aimed to enhance Sobel edge detection by focusing on the magnitude gradient to produce clearer images. The results, reflected in the parameter values of processed gray-level co-occurrence matrix (GLCM), namely contrast and correlation, exhibited higher values than Sobel before development. The resulting image at a higher value serves as a more sensitive and specific diagnostic tool for pediatric pulmonary TB, aiming to increase diagnostic accuracy and ensure timely treatment. This research was carried out with the development of edge detection techniques for identifying childhood tuberculosis in X-ray images.

2. METHOD

This research introduces a novel approach to edge detection, incorporating distinct stages such as data input, pre-processing, segmentation, edge detection, and feature extraction. Figure 1 shows the research framework of this research.

2.1. Input image

The initial phase of the research involves image input. The images under analysis originate from the GE OPTIMA XR220 AMX X-ray machine at the M. Djamil Padang Central General Hospital. The resultant X-ray images are presented in grayscale, portraying patients examined for tuberculosis with radiological findings represented in a black and white format. These X-ray images, stored in *.jpg format files, serve as the basis for the identification of individuals afflicted with either tuberculosis or non-tuberculosis conditions.

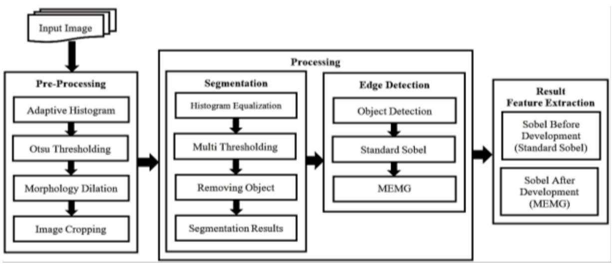


Figure 1. Research framework

2.2. Pre-processing

The pre-processing stage encompasses a series of procedural steps or techniques designed to refine and cleanse raw data, rendering it suitable for subsequent analysis or modelling [15]. The primary objective of data pre-processing is to enhance image quality, eliminate noise, and ready the data for subsequent analytical stages. This ensures that the data is primed for utilization, facilitating the generation of accurate results. The pre-processing stage in this research is adaptive histogram then Otsu thresholding after that morphology dilation finally image cropping.

2.2.1. Adaptive histogram

Adaptive Histogram is an image processing technique employed to enhance the contrast and quality of an image by optimizing the distribution of pixel intensities within it [16]. This technique distinguishes itself from conventional histogram equalization, where the entire image is considered as a single unit, and a global histogram is applied. In adaptive histograms, the image undergoes segmentation into smaller blocks, and the histogram is computed and adjusted locally for each individual block.

2.2.2. Otsu thresholding

Otsu Thresholding, also known as the Otsu Method, is an image processing technique that determines an optimal threshold for separating images into two classes based on pixel intensity levels [17]. By analyzing the image intensity histogram, it aims to automatically distinguish between foreground and background, minimizing intensity variance within each class. The goal is to maximize dissimilarity between classes, enhancing object-background separation.

2.2.3. Morphology dilation

Dilation is a fundamental operation in image processing, employed within the domain of image morphology [18]. The primary objective of this operation is to augment or magnify the object area within the image, thereby addressing small gaps within the object. Dilation finds application in various contexts, encompassing tasks such as noise elimination, amalgamation of distinct objects, and augmentation of object dimensions.

2.2.4. Image cropping

Image cropping, a fundamental aspect of image processing, involves selecting and removing specific segments from the original composition to emphasize key areas or objects. By isolating pertinent segments, it eliminates non-essential regions, streamlining content and enhancing clarity and impact. This process directs viewer focus and improves the image's relevance and engagement for the audience.

2.3. Processing

In the field of image processing research, the processing stage emerges as a critical juncture, marking the point where a plethora of techniques, algorithms, and operations are meticulously applied to manipulate, enhance, or meticulously extract pivotal information from digital images. This crucial phase demands the sophisticated application of advanced computational methods designed to deeply scrutinize and thoughtfully modify the rich visual content encapsulated within these images. Within the scope of this particular research endeavor, the processing stage methodically unfolds through two distinct and carefully orchestrated phases: segmentation processing and edge detection processing.

2.3.1. Segmentation

Image segmentation is the intricate process of disassembling or categorizing based on the intrinsic characteristics of pixels within an image. This segmentation can manifest as the isolation of the foreground from the background or the amalgamation of pixel regions predicated on similarities in color or shape. The primary objective of segmentation lies in streamlining image analysis by concentrating on specific areas or objects. The image segmentation process consists of four stages: histogram equalization, multi-thresholding, removing objects, and segmentation results.

A. Histogram equalization

Histogram equalization is a crucial image processing technique, enhancing contrast by adjusting pixel intensity distribution. It transforms pixel values to achieve a more uniform cumulative distribution function (CDF), balancing dark and light areas for improved visual clarity and detail. By redistributing pixel intensities, it unveils hidden details, enriching the image's depth and detail, especially in areas with poor contrast.

B. Multi thresholding

Multi-thresholding is an image segmentation method wherein pixels within the image are classified into multiple classes or groups utilizing more than one threshold value [19]. The primary objective of multi-thresholding is to categorize pixels into more than two groups based on their intensity levels. This approach proves beneficial when the image contains more than two types of objects or structures characterized by distinct intensity levels. During this stage, the image undergoes conversion into a binary representation through the application of multiple thresholds, facilitating the classification of pixels into various segments based on the respective thresholds employed.

C. Removing object

In this crucial phase of digital image processing, operations craft a new image that's the inverse of the original. Using a circular structural element with an 8-pixel radius, it expertly removes objects touching or near the image boundary. This refines the composition, enhancing focus on central subjects, streamlining content, and improving overall aesthetic quality. The process ensures primary elements are highlighted without interference from bordering objects, enhancing clarity and functional quality [20].

D. Segmentation results

The segmentation result, emerging from the prior process, encapsulates the precise delineation of analogous entities within the image. In this specific study, the focus was sharpened towards the accurate identification of pneumonia-related anomalies within pediatric chest X-ray images. This targeted segmentation aims to isolate and highlight the pneumonia-affected areas, providing a clearer, more defined visual representation that aids in the diagnostic accuracy and understanding of the condition's impact on children's pulmonary health.

2.3.2. Edge detection

The edge detection stage is a crucial process that generates edges from image objects, aiming to enhance the details of blurry images resulting from errors or the image acquisition process. Sobel edge detection is a common method for identifying edges in images [21]-[25]. The Sobel operator yields a high response in areas where sharp changes in image intensity occur, indicating the presence of edges or boundaries between objects in the image. The stages executed in the edge detection process in this research include object detection, Sobel standard, and morphological edge-mapping gradients (MEMG).

A. Object detection

Object detection is the systematic procedure of discerning and spatially localizing distinct entities within a given image [26]-[29]. The principal aim is to proficiently identify and outline the spatial extents of objects of interest, rendering it an indispensable component within the realms of computer vision and image analysis. The object detection methodology employed in this research entails the utilization of standard Sobel operators and the MEMG technique.

B. Standard Sobel

The Sobel edge detection process encompasses convolution, gradient magnitude computation, determination of edge direction (based on gradient magnitude), and subsequent edge selection [30]. The Sobel operator individually applies to the original image during the convolution step, resulting in two distinct partial derivative images, one capturing horizontal changes and the other vertical ones. Through gradient magnitude analysis, we compute the edge magnitude, pixel-by-pixel, using these two partial derivative images:

$$M = \sqrt{Gx^2 + Gy^2} \tag{1}$$

Information: Gx = horizontal edge gradient, Gy = vertical edge gradient.

Within the edge direction analysis (gradient direction), the calculation involves determining the edge direction through the arctangent of the ratio of the vertical gradient (Gy) to the horizontal gradient (Gx). This computation yields information regarding the direction of the maximal intensity change at each pixel. We then select edges based on elevated magnitudes and edge directions that indicate significant changes in image intensity.

C. MEMG

MEMG stands for modification and extended magnitude gradient. In the developmental phase of Sobel edge detection applied to X-ray images of pediatric pulmonary tuberculosis, a 5x5 kernel matrix is employed. This choice is predicated on its ability to yield a more intricate and detailed image during the edge detection process.

$$Mx = \begin{bmatrix} 1 & 2 & 1 & 2 & 1 \\ 1 & 1 & 2 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & -2 & -1 & -1 \\ -1 & -2 & -1 & -2 & -1 \end{bmatrix} \text{My} = \begin{bmatrix} 1 & 1 & 0 & -1 & -1 \\ 2 & 1 & 0 & -1 & -2 \\ 1 & 2 & 0 & -2 & -1 \\ 2 & 1 & 0 & -1 & -2 \\ 1 & 1 & 0 & -1 & -1 \end{bmatrix}$$

The development of Sobel detection is named MEMG with the magnitude gradient equation formed:

$$MEMG = (Gx * Gy) + \sqrt{Gx^2 + Gy^2} \quad (2)$$

Information: Gx = horizontal edge gradient, Gy = vertical edge gradient.

2.4. Result: feature extraction

The feature extraction stage is crucial, revealing an image's intrinsic attributes like texture, shape, and color. GLCM method is employed, focusing on parameters like contrast, correlation, energy, and homogeneity. Image conversion to double: edge detection results undergo conversion to double precision for GLCM processing. GLCM: extracts texture-based features from X-ray images using contrast, correlation, energy, and homogeneity. Contrast measures intensity differences, correlation gauges pixel pair linearity, energy assesses intensity pair concentration in the matrix, and homogeneity measures intensity variation uniformity.

2.4.1. Sobel before development (standard Sobel)

The Sobel standard, a methodology steeped in historical significance and known for its pioneering role in edge detection, derives its outcomes from the application of the Sobel standard formula. Although it marks a foundational development in image processing, the Sobel standard's performance reveals notable constraints, especially regarding the precision of its results. Using X-ray images of children's chests to detect tuberculosis in pediatric cases highlights these limitations. The inherent restrictions of the Sobel standard, in terms of accuracy, underscore the need for advanced or modified techniques to better address the nuanced requirements of medical diagnostics in young patients.

2.4.2. Sobel after development (MEMG)

The post-development Sobel iteration marks a pivotal advancement in edge detection, leveraging an enhanced version of the original Sobel method. Termed the Sobel standard, this precursor laid the groundwork for the more refined MEMG technique. MEMG's implementation showcases a remarkable leap in performance, outstripping the conventional Sobel standard by delivering more precise and clearer edge detection outcomes. This evolution underscores the continuous quest for improving image processing techniques for more accurate identification processes.

3. RESULTS AND DISCUSSION

In this subsection, we meticulously outline the results achieved at every procedural milestone, proceeding to a thorough discussion on the insights drawn from the outcomes previously detailed. The spectrum of research outcomes presented here includes a series of images that have undergone various stages of transformation. This sequence begins with the original input images, advances through stages of pre-processing where images are prepared for analysis, progresses to the core processing phase where significant manipulations are applied, and culminates in the presentation of the final result images.

3.1. Input image result

The input image employed in this research serves as the primary dataset for comprehensive data analysis. Within the context of this investigation, the designated input image pertains to an X-ray representation of a pediatric thoracic cavity. This X-ray imagery serves as a detailed visualization of the child's chest condition, forming the basis for subsequent tuberculosis detection analyses. Table 1 presents a set of 8 samples featuring X-ray images of children's chests, utilized as pivotal components within the scope of this research.

Table 1 meticulously displays 8 chest X-ray images of pediatric patients from a hospital setting, forming the foundation of our research on pediatric chest conditions. Each image contains vital anatomical details, crucial for our tuberculosis detection system's development. Integrating these images into our system initiates a series of analyses, focusing on feature extraction for accurate tuberculosis identification. The dataset's diversity enhances the robustness of our investigation into pediatric chest pathologies, demanding meticulous image processing.

Table 1. Input image (X-ray image children's chests of patient)

Patient 1	Patient 2	Patient 3	Patient 4	Patient 5	Patient 6	Patient 7	Patient 8
							

3.2. Pre-processing result

The pre-processing outcomes in this study follow a sequence: adaptive histogram, Otsu thresholding, morphological dilation, and cropping. Each refines input data for pediatric tuberculosis detection via X-ray imaging. Adaptive histogram enhances contrast, Otsu thresholding optimally segments images, morphological dilation accentuates features, and cropping ensures focused analysis. These processes meticulously prepare data for subsequent analytical stages.

3.2.1. Adaptive histogram result

The initial pre-processing begins with the adaptive histogram technique, refining chest X-ray images for clarity and detail. These results, documented in Table 2 "Adaptive Histogram" column, form a foundational step in our approach to pediatric tuberculosis detection. They enhance input data quality for comprehensive analysis in subsequent stages.

3.2.2. Otsu thresholding result

The outcomes of the second pre-processing stage stem from the Otsu thresholding technique. Subsequent to the successful execution of the adaptive histogram preprocess, the Otsu thresholding preprocess results are attained. A depiction of these results is presented in Table 2 under the designated "Otsu Thresholding" column. This sequential pre-processing operation further refines the input data, contributing to the overarching objective of enhancing the quality and interpretability of chest X-ray images for subsequent analyses in the pursuit of pediatric tuberculosis detection.

3.2.3. Morphology dilation result

The outcomes of the dilation morphology pre-processing represent the third sequential stage of pre-processing within this research endeavor. This outcome is derived subsequent to the implementation of Otsu thresholding as part of the pre-processing procedure. The specific findings associated with dilation morphology are meticulously tabulated in Table 2 under the designated column heading "Dilation Morphology," providing a comprehensive visualization of the morphological changes induced by this process.

3.2.4. Image cropping result

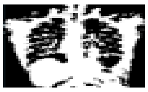
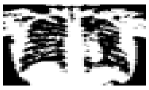
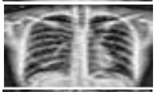
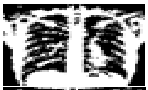
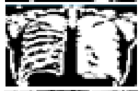
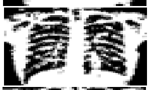
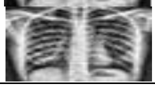
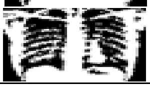
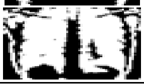
Image cropping constitutes the conclusive and fourth pre-processing stage in this research investigation. The outcomes of the image cropping pre-process, which were acquired subsequent to the dilation morphology pre-processing, are meticulously documented. The detailed results pertaining to the image cropping pre-process are systematically presented in Table 2, elucidating the specific alterations and enhancements achieved through this stage, and are cataloged under the designated column heading "Image Cropping" for comprehensive examination and reference.

Table 2 displays outcomes from implemented pre-processing methods, detailing pediatric patients scrutinized and results of adaptive histogram, Otsu thresholding, dilation morphology, and image cropping preprocesses. Each column represents a step-in research progression, offering structured insights into pre-processing stages' impact on pediatric chest X-rays. This tabular format aids nuanced comprehension of the evolving research landscape, enriching scientific discourse in this domain.

3.3. Processing result

The processing result constitutes the outcome achieved subsequent to the execution of various processing stages, utilizing input image data derived from the ultimately pre-processed image. In this study, the selected input image originates from the previously cropped image. The pre-processing outcomes are further categorized into two distinct sub-stages, specifically the segmentation results and edge detection results. The detailed findings of these processing phases are comprehensively presented in Table 3, affording a structured examination of the outcomes obtained through segmentation and edge detection methodologies applied to the pre-processed image. This tabulated presentation serves to elucidate the nuanced advancements achieved in the course of the research endeavor.

Table 2. Pre-processing result

Patient	Adaptive histogram	Otsu thresholding	Morphology dilation	Image cropping
1				
2				
3				
4				
5				
6				
7				
8				

3.3.1. Segmentation result

The segmentation outcome is pivotal in this research, detailed in the dedicated section. It explains the successful execution of intricate segmentation procedures on pediatric chest X-rays, aiming to differentiate tuberculosis from non-tuberculosis images. Results include histogram equalization, multi thresholding, removing object, and segmentation, meticulously documented in Table 3. This systematic approach highlights the system's efficacy in discriminating between tuberculosis and non-tuberculosis cases in pediatric chest X-ray analysis.

3.3.2. Edge detection result

The edge detection outcome, the product of meticulous detection of image edges, is crucial in this research, particularly for identifying pneumonia, a tuberculosis indicator in pediatric cases. Results are categorized into object detection, standard Sobel, and MEMG methods, each offering varied approaches. These findings, detailed in Table 3, comprehensively showcase advancements in identifying tuberculosis-related manifestations in pediatric chest X-rays through edge detection techniques.

Table 3 provides a comprehensive display of the outcomes obtained at each stage of the meticulously executed process within this research study. The initial column enumerates the patient numbers associated with the children's chest X-ray image data acquisition. Subsequently, columns two through five delineate the results of distinct sub-process stages within the segmentation phase, namely histogram equalization result, multi-thresholding result, removing object result, and segmentation result itself. The ensuing columns, six through eight, present the outcomes of the edge detection phase, encompassing object detection, standard Sobel, and MEMG standards.

3.4. Feature extraction result

The feature extraction outcome stems from analyzing image features using MEMG edge detection. It quantifies characteristics like contrast, correlation, energy, and homogeneity. Comparative analysis between standard Sobel (Sobel before development) and MEMG (Sobel after development) results is facilitated. These findings are systematically documented in Table 4. Table 4 meticulously presents feature extraction outcomes from X-ray images, comparing contrast and correlation for Sobel before and after development. A preferable contrast range is 0 to high, while correlation ranges from -1 to 1. Results affirm the superiority of Sobel after development (MEMG), with higher contrast and correlation values. Energy and homogeneity values remain relatively unchanged.

Table 3. Processing result

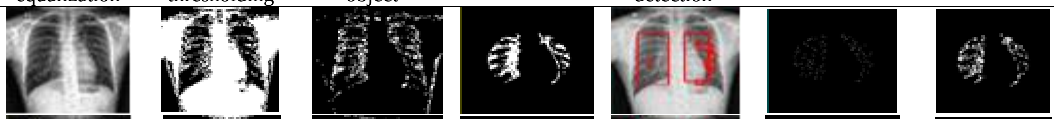
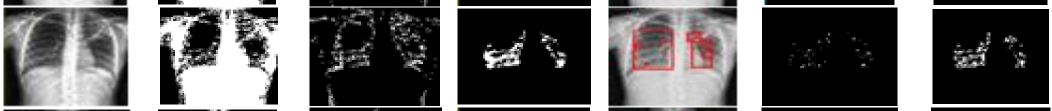
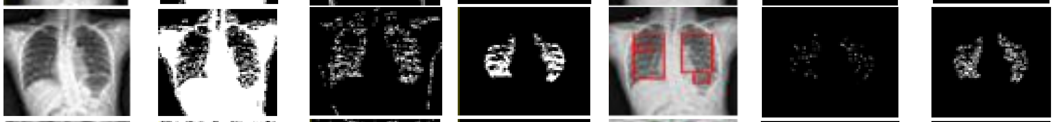
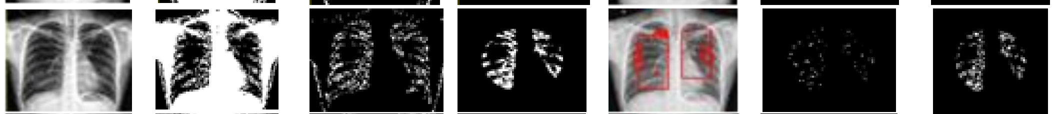
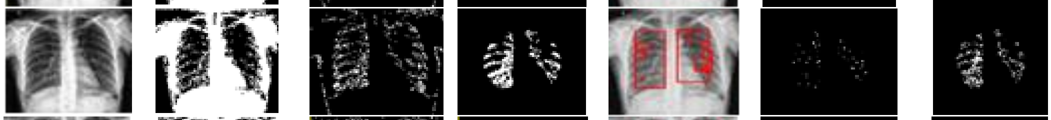
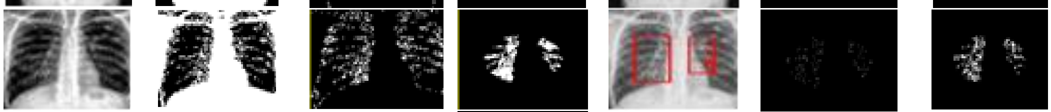
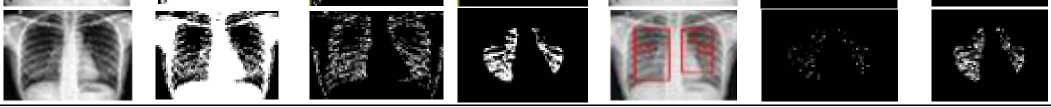
Patient	Segmentation result				Edge detection result		
	Histogram equalization	Multi thresholding	Removing object	Result	Object detection	Standard Sobel	MEMG
1							
2							
3							
4							
5							
6							
7							
8							

Table 4. Feature extraction result

Patient	Sobel before development (standard Sobel)				Sobel after development (MEMG)			
	Contrast	Correlation	Energy	Homogeneity	Contrast	Correlation	Energy	Homogeneity
1	0.27137	0.23731	0.98723	0.99515	0.95840	0.68202	0.91932	0.98289
2	0.22009	0.23975	0.98962	0.99607	0.74737	0.69738	0.93458	0.98665
3	0.30920	0.23656	0.98546	0.99448	1.07650	0.66891	0.91217	0.98078
4	0.21699	0.24587	0.98972	0.99613	0.68346	0.68903	0.94140	0.98780
5	0.30824	0.24251	0.98544	0.99450	1.07830	0.67894	0.90995	0.98075
6	0.31399	0.24258	0.98517	0.99439	0.96755	0.68420	0.91812	0.98272
7	0.25716	0.23286	0.98794	0.99541	1.00220	0.68255	0.91554	0.98210
8	0.30327	0.24269	0.98568	0.99458	1.10890	0.68264	0.90658	0.98020

4. CONCLUSION

This study introduces and evaluates a novel edge detection method, the MEMG, which utilizes magnitude gradients to significantly improve predictive accuracy for TB. The results of our experiment show that the MEMG method makes TB signs on X-rays clearer and more detailed, which is a big improvement over the standard Sobel method. In particular, MEMG raises contrast values by more than 50% and brings correlation values closer to unity, which means it can find TB-related problems with more accuracy. Critics may argue that the existing standard Sobel method suffices for TB detection. However, our findings highlight

MEMG's superior performance, particularly its ability to provide clearer, more detailed images, thus facilitating a more accurate TB diagnosis. This is crucial to improving TB detection rates and patient outcomes, reinforcing the necessity of adopting more sophisticated image processing techniques in medical diagnostics. Given the promising results of MEMG in enhancing TB diagnosis through X-ray imaging, further research should explore its application across other diseases and imaging techniques. Additionally, future studies could focus on refining the MEMG algorithm to optimize performance further and validate its effectiveness in larger, more diverse datasets. The adoption of advanced methods like MEMG in clinical settings could revolutionize TB diagnosis, offering a call to action for researchers and practitioners alike to embrace these technological advancements.

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BIOGRAPHIES OF AUTHORS

Retno Devita a tenured lecturer at Universitas Putra Indonesia YPTK Padang, specializing in the computer systems study program within the Faculty of Computer Science. She earned her undergraduate degree (S1) and Master's (S2) in the computer systems and informatics engineering study programs, respectively, at UPI YPTK Padang, West Sumatra, Indonesia. Currently, she is pursuing her doctoral education (S3) in the information technology study program at the same institution. Offering a diverse range of courses within the computer systems study program, including microcontrollers, artificial intelligence, science management, and digital engineering, she contributes significantly to the academic landscape. She can be contacted at email: retno_devita@upiyptk.ac.id.

Iskandar Fitri holds the esteemed position of Professor at Universitas Putra Indonesia YPTK Padang, serving as a lecturer in the information technology doctorate program within the Faculty of Computer Science. His academic journey includes completing his undergraduate education (S1) in the electronics engineering study program at Universitas Nasional, followed by Master's (S2) and Doctoral (S3) degrees in the electronics engineering study program at Universitas Indonesia. Presently, he is recognized as a professor specializing in the microwave field at UPI YPTK Padang. Offering a diverse array of courses in the information technology study program, such as microwaves, research methodology, and artificial intelligence. He can be contacted at email: if@upiyptk.ac.id.

Yuhandri holds the distinguished title of Professor at Universitas Putra Indonesia YPTK Padang, contributing as a lecturer in the information technology study program within the Faculty of Computer Science. He earned his undergraduate degree (S1) in the computer systems study program and completed his Master's (S2) in the informatics engineering study program at UPI YPTK Padang, West Sumatra, Indonesia. Additionally, he obtained his doctoral degree from Gunadharma University, Jakarta, Indonesia. Presently, Professor Yuhandri is recognized as a leading expert in the field of image processing at Universitas Putra Indonesia YPTK Padang. His pedagogical repertoire encompasses courses in the information technology study program, encompassing subjects like image processing, artificial intelligence, and computer networks. He can be contacted at email: yuyu@upiyptk.ac.id.

Finny Fitry Yani is a consultant of pediatric respirology since 2011. She works as academic and clinical staff at Department of Child Health, Faculty of Medicine Universitas Andalas and Dr. M. Djamil Hospital, Padang, Indonesia, and member of Indonesian Pediatrics College since 2004. She had several publications about childhood tuberculosis, pneumonia and asthma. She finished the Doctoral study at 2017, with doctoral research about vitamin D to prevent TB infection among children contact TB. Since 2010 active as Pediatric TB working groups National tuberculosis Program Health Ministry and 2017 as Executive Secretary in Indonesian TB research network. Since 2020 she is a member of Expert Committee National Tuberculosis Program of Health Ministry. She can be contacted at email: finny_fy@yahoo.com.