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Improved Edge Detection using Morphological Operation to Segmentation of Fingernail Images

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ABSTRACT Accurate segmentation of fingernail images is essential for biomedical applications like dermatological diagnostics and nail disease assessments. This study compares traditional methods (Sobel and Canny edge detectors) with an improved method using adaptive thresholding and morphological closing for fingernail image segmentation. The methodology includes data collection, preprocessing, edge detection, segmentation, and evaluation. A dataset of 500 fingernail images (free of nail polish) was captured using a digital camera. Preprocessing involves grayscale conversion to simplify analysis and Gaussian smoothing to reduce noise while preserving key features. For segmentation, thresholding and K-means clustering isolate the fingernail from the background. Evaluation combines qualitative and quantitative analyses. Qualitative results demonstrate that the improved method consistently outperforms traditional techniques under diverse conditions. Quantitative evaluation, based on accuracy, recall, F1 score, and Intersection over Union (IoU), further supports these findings. The Sobel method achieves 0.80 accuracy, 0.77 recall, 0.87 F1 score, and 0.77 IoU. The Canny method achieves 0.82 accuracy, 0.78 recall, 0.88 F1 score, and 0.78 IoU. In contrast, the improved method achieves 0.97 accuracy, 0.98 recall, 0.99 F1 score, and 0.98 IoU. The results clearly show that the improved method, using adaptive thresholding and morphological closing, provides superior segmentation performance. Additionally, the approach remains computationally efficient, making it suitable for real-time applications in medical diagnostics.

INDEX TERMS edge detection, segmentation image, morphological operation, sobel, canny

I. INTRODUCTION

Segmentation of nail images is essential for some dermatological evaluations, where the detection of abnormalities is important for the diagnosis and treatment of disease. The structural complexity of the nail makes accurate imaging important in the evaluation of systemic diseases, nutritional deficiencies, and dermatological conditions that are assessed through nail involvement. Nail color, texture, and shape are just some of the ways in which disease can be recognized or identified [1][2]. A healthy person has pink nails. Normal nails are smooth and uniform in color. However, Any other factor that altered the development and form of the nail is considered abnormal [3][4]. White nails indicate malnutrition such as iron deficiency and poor circulation. Reddish-purple nails indicate a disordered digestive system due to excessive consumption of sugar, pharmaceuticals, fruits and juices. White spots on the nails indicate high sugar content and zinc deficiency caused by digestion [5][6]. However, the segmentation process is often complicated by factors such as image noise, variable lighting and complex nail textures, making reliable segmentation a difficult task [7][8].

Edge detection is a fundamental method in image processing, used to identify important boundaries and features in images. Traditional edge detection algorithms, including Sobel, Prewitt, and Canny, have been widely used due to their simplicity and effectiveness. For example, the Canny edge detector is known for its ability to generate sharp edges while reducing noise; however, it still struggles in the presence of complex backgrounds and different nail textures, resulting in suboptimal segmentation results [9][10]. These limitations highlight the need for improved edge detection techniques that are tailored to the unique characteristics of nail images.

Recent advances in image processing have led to more sophisticated segmentation methods. Techniques such as adaptive thresholding, morphological operations, and clustering algorithms have shown great promise in improving segmentation accuracy in biomedical images [11][12]. Result of research [13] show that improved method aim to accurately processing complex medical images. The method using histogram equalization and clustering analysis to refines segmentation accuracy. Based on previous research, adaptive thresholding and morphological operations can be used as improved edge detection in this research.

Therefore, this study examines methods to improve the edge detection performance for finger nail segmentation in this research area. To further improve the ability to separate nail features from the background, we combine classical edge detection techniques with the power of morphological operation. The results of this study will focus on academic research and practical applications in dermatology, facilitating advance diagnostic tools.

The primary aim of this research is to improve traditional edge detection methods by integrating morphological operations, thereby enhancing boundary detection in fingernail images and effectively addressing challenges such as noise, lighting variations, and background interference. Additionally, the study seeks to achieve accurate fingernail segmentation by isolating the nail region with high precision and minimizing artifacts under diverse imaging conditions. Another objective is to optimize the segmentation process by combining adaptive thresholding, morphological operations, and clustering techniques, such as K-means, to ensure computational efficiency and scalability. Ultimately, the research aims to support practical applications of the proposed method in both biomedical imaging such as nail disease diagnosis including nail art and enhancement preparations.

The structure of this paper is as follows: Section II presents a literature review based on edge detection. Section III presents the research methodology applied, and Section IV presents the results. Section V presents the detailed analysis while Section VI concludes by summarizing the main ideas as well as implications for future research.

II. PREVIOUS RESEARCHS

Additional research on the same research area was conducted by Javed et al. in 2020. It used several standard edge detectors available in OpenCV, to improve the visibility of skin lesions in dermoscopy images, including Canny and Sobel. This research also showed how edge detection plays an important role in improving diagnostic accuracy due to segmentation of skin lesions [15].

Another paper by Kumar et al. in 2022 was incorporated to illustrate the segmentation of fingernail images for the diagnosis of nail health problems. To extract fingernails from the images, the researchers applied an adaptive thresholding technique accompanied by morphological operations. According to the study, it was found that accurate segmentation of fingernail images can help in the diagnosis of nail diseases [16]. In 2022, Yunhong et al. studied different edge detection methods in medical applications, such as skin and fingernail images. In their work, they were able to compare the results between conventional and state-of-the-art approaches such as deep learning. They showed that although deep learning models provide better segmentation results, classical techniques such as Canny and Laplacian can still be used for faster evaluation in clinical settings [17]. In 2016, Kalra et al. studied the integration of edge detection techniques with deep learning algorithms for nail image segmentation. It showed that their method can differentiate multiple nail diseases and their study may be useful for dermatologists in diagnosis [18]. A review by Anas et al. in 2019 reviewed the state-of-the-art edge detection methods for all motor imaging modalities. The research discussed in detail how these techniques, such as the modified approaches of Canny and Sobel, improve the segmentation of important structures involved in the generation of medical images such as nail structures, which are of great value in diagnosis and therefore treatment planning [19]. This feature extraction from nail images was performed by Jailingeswari et al. In 2026, where they used an edge detection algorithm. Their work showed that the features extracted from the contours can be used to assess the condition of the nail and predict diseases that may develop later. The researchers mentioned performing image preprocessing as an essential step to improve the edge detection capability in their method [20].

III. METHODS

This section describes the dataset used in research, and steps in research. The method consist of data preprocessing steps such as grayscale conversion, Gaussian filter, and contrast adjustment, edge detection techniques such as traditional methods and improved methods, and segmentation approach using thresholding and k-means clustering. Traditional methods consist of sobel operator and canny edge detector. Improved methods consist of canny edge detector incorporating adaptive thresholding and morphological operations. FIGURE 1 shows the flowchart of this study.

A. DATA COLLECTION

The data used in this study consists of high-resolution images of human fingernails collected from individuals of different ages, and genders. The process of collecting fingernail images was conducted with the respondents' consent by signing an ethics document. The data is taken using digital image Canon Lumix. The images are taken under controlled lighting conditions to eliminate the influence of other factors.

However, during data acquisition, it cannot be assumed that the lighting conditions are consistent across all images. The data also shows differences in the shape, size, and texture of fingernails. These variations are important to evaluate the stability and performance of the proposed method under different conditions. For inclusion criteria, Fingernail must be free of nail polish. The amount of data used in this study is 500 images. FIGURE 2 illustrates the data from the study described above.

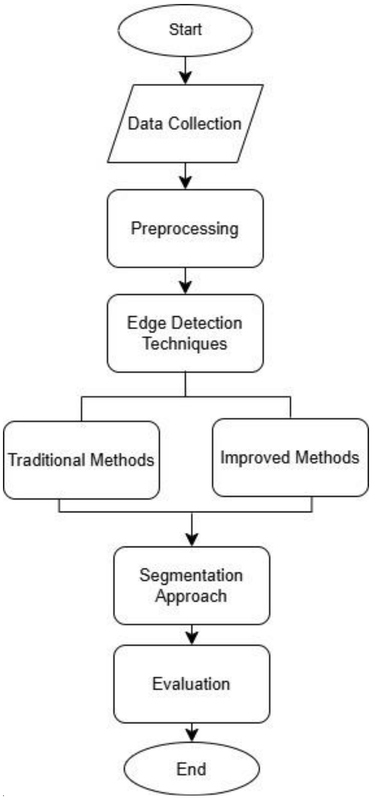


FIGURE 1. **Flowchart of research**

FIGURE 2. **Data of research**

B. PREPROCESSING

Preprocessing is generally a common process in which data is enhanced to improve image quality and remove noise [21]. The steps are grayscaling, application of a Gaussian filter, and the final step is contrast stretching. By including grayscale conversion, each image is converted to grayscale to avoid complications during the process [22]. This process involves mapping a color image in RGB space, for example, to a single-band grayscale image, although by reducing the color information, the process retains luminance information. Equation of grayscaling process can be used two equations such in Eq. (1) [23] and Eq. (2) [23]. It is because each human being has different sensitivity in color. Eq. 2 [23] also called the luminosity method where weighs red, green and blue according to their wavelengths.

$$Grayscale = \frac{(R+G+B)}{3} \tag{1}$$

$$Grayscale = 0.299\,R + 0.587G + 0.114\,B \tag{2}$$

with R is value of red, G is value of green and B is value of blue.

Conversion to grayscale is particularly beneficial in biomedical image analysis because color information is generally irrelevant when it comes to texture recognition: the edge of a fingernail is clearly visible even without color contrast, while differences in brightness are essential to reveal edge differences. This may be necessary to prepare edge detection algorithms, as these algorithms perform well in operations with brightness versus color gradients [23]. Third, grayscale conversion improves noise removal in the preprocessing stage, as color noise that interferes with the visualization of important image features is removed. The nail segmentation task proposed here by converting the image to grayscale avoids the need to perform edge detection on color, which would be much slower in the process and less efficient [24].

A Gaussian filter is used to remove noise from the image while retaining the important features needed for edge detection. This step is common in image smoothing and is known to be quite effective in removing noise while still conveying important image features. It works by comparing the image with a Gaussian function, which can be described by a bell curve. The bell curve is shown in FIGURE 3. This method is particularly useful because it reduces HF noise and any unwanted components without significantly distorting the structure [25]. Equation of Gaussian filter is shown in Eq. (3) [25].

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{x^2}{2\sigma^2}} \tag{3}$$

Where σ is the standard deviation of the distribution. The distribution is assumed to have a mean of 0.

The main advantage of Gaussian filtering is that it can efficiently combine neighboring pixels with a set of weighted average functions that exclusively reflect the relative distances of those pixels to the central pixel. The central pixels contribute more to the output pixel value than the distant pixels, allowing for smoothing [26]. However, the choice of σ for the Gaussian filter is more important because it controls the amount of image smoothing that needs to be performed. A small σ will preserve more image features while smoothing less noise, while a large σ will provide more smoothing, which will help eliminate large fluctuations in noise that reduce detail [27]. Number of σ in this research is 2 because this number giving the best smooth and image feature in image still visible.

Contrast stretching is a typical preprocessing step in the field of image processing, in which the pixel intensity distribution in an image is adjusted to improve the visibility of its features. With increased contrast, the authors found that important structures became more distinct from the image background, contributing to better image analysis and interpretation [28]. Equation is used in contrast stretching is shown in Eq. (4) [28].

$$o(i,j) = \frac{u(i,j)-c}{d-c}\ (L-1) \tag{4}$$

o(i,j) and *u(i,j)* are respectively are pixels after and before transformation in coordinates (*i,j*). *c* and *d* respectively represent the maximum and minimum values of the pixels in the image. *L* represents the maximum grayscale value. If the pixel value is smaller than 0 then the value of L will be 0 and if it is greater than (L-1) then the value of L will be (L-1).

Histogram equalization is a simple method commonly used to improve the contrast of nail images. Histogram equalization is performed by redistributing the image intensities and making the histogram equal across the entire image [25]. Redistribution of the initial histogram is carried out by mapping each pixel value in the initial histogram into a new pixel value using Eq. (5) [25].

$$n(g) = \max(0, round[(L-1) * \frac{c(g)}{N}] - 1 \tag{5}$$

where *n(g)* is the new pixel value, *N* represents the number of pixels in the image, *g* represents the initial gray level value whose value is 1.. L-1, *L* represents the maximum gray level value. while *c(g)* states the number of pixels that have a value equal to g or less which is systematically expressed in Eq. (6) [25].

$$c(g) = \sum_{i=1}^{g} h(i), g = 1,2, \dots, L-1 \tag{6}$$

with *h(i)* is the initial histogram.

C. EDGE DETECTION

To accurately segment the desired region area, an appropriate edge detection technique must be used to delineate the region of interest, which is the nail. For comparison purposes in this study, the traditional edge detector and the improved edge detector were examined. The traditional methods include two of the most common traditional methods for edge detection, i.e., the Sobel operator and the Canny edge detector. The Sobel operator is a discrete differential operator used to estimate the gradient of the intensity function of the image in question. It works with two 3x3 convolution filters to detect vertical and horizontal edges. This method emphasizes regions of high spatial frequency which helps to identify edges in the image [25]. The Sobel operator is characterized by low computational complexity, which is why it can be used in real-time processing [29]. The matrix is used in sobel operator is shown in Eq. (7) [29] and Eq. (8) [29].

$$G_x = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{7}$$

$$G_y = \begin{bmatrix} -1 & 0 & 1 \\ 2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{8}$$

The canny edge detector is essentially a combination of four steps including scaling, non-maximum suppression, and delay thresholding steps. The first step involves computing the gradient amplitude and direction, to enable edge detection [24]. Non-maximum suppression goes one step further and smooths the edge response to refine the detected edges to a line width of one pixel. Last but not least, delay thresholding uses two thresholds to decide which pixels belong to a strong edge and which pixels belong to a weak edge connected to the strong edge while leaving out the noise [27]. Compared to Sobel's method, this method involves noise reduction and edge linking. However, it can still be difficult to tell them apart when the features are fine, such as the appearance of fingernails.

In improved method with adaptive thresholding and morphological operations on the edges involved in the detection process. Adaptive thresholding is a process in which the threshold value is modified based on the local features of the image, unlike fixed thresholding which remains unchanged regardless of the image [30]. Adaptive thresholding involves capturing edges and features in regions. Equation in thresholding is shown in Eq. (9) [30].

$$g(x,y) = \begin{cases} 1, & if\ f(x,y) \geq T \\ 0, & if\ f(x,y) < T \end{cases} \tag{9}$$

where *g(x,y)* is binary image from grayscale image *f(x,y)* and T is threshold value. In this research using number T is 0.5.

Morphological closing also known as morphological operation is a middle operation between dilation and morphological erosion used to fill the evenly spaced gaps in the detected edges and thus to obtain good edge continuity without the risk of false detection in regions with high noise. Equation in erosion is shown in Eq. (10) [31]. Eq. (10) [31] states that input coordinates *[m,n]* for each image pixel value is reduced by the value of the structuring elements (SE) at the corresponding coordinates of the image being processed and the resulting pixel value is the minimum value of each subtraction. Structuring elements in this research using disk SE with size 5 x 5.

$$E_G(A,B) = \max_{[j,k]\in B}\{a[m+j, n+k] - b[j,k]\} \tag{10}$$

Dilation establishes more general boundaries of objects while erosion does the opposite by adding details to the edges of the object. Equation of dilation is shown in Eq. (11) [31]. Eq. (11) [31] states that the input coordinates *[m,n]* for each structuring element (SE) are added together with the pixel value at the corresponding coordinate of the image being processed and the resulting pixel value is the maximum value of each addition.

$$D_G(A,B) = \max_{[j,k]\in B}\{a[m-j, n-k] + b[j,k]\} \tag{11}$$

Morphological closing is a combination of dilation followed by erosion, which is useful for closing any small gaps initially detected in the edge map using traditional techniques. This operation has been shown to improve edge continuity and thus provide more accurate segmentation in noisy and otherwise irregular images [31].

D. SEGMENTATION APPROACH

Once edges are detected, the object of interest, in this case the fingernail, is segmented from the background and other non-tissue regions. Two types of segmentation are used: global thresholding and k-means clustering. Global thresholding is one of the simplest and at the same time the most powerful image segmentation techniques. It works by converting a grayscale image to binary where pixels are labeled as either object or background based on a threshold intensity [25]. K-means clustering is a powerful and popular unsupervised machine learning technique that divides an image into k clusters, based on pixel intensity values. Using an iterative approach, the algorithm classifies pixels into specific groups to minimize the expected variance within each group, so that similar intensity values are grouped together [32]. The number of k is used in this research is 2. It means that pixel intensity values will be divided into two categories or clusters based on specific patterns or similarities. Each group will initially have two randomly assigned centroids. Each pixel will be assigned to the nearest cluster based on distance (e.g., Euclidean distance). The algorithm iteratively updates the centroids' positions until the changes in cluster positions stop or meet a predefined condition. It also facilitates unsupervised learning techniques to segment fingernails from the background and other parts of the image. Equation is used in k-means clustering is shown in Eq. (12) [32].

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{12}$$

where J is objective function, k is number of clusters, n is number of cases, xi states case i, cj is centroid for cluster j.

E. EVALUATION

In this study, the evaluation of the segmentation method is carried out through qualitative analysis and quantitative analysis. The qualitative analysis were conducted to visually assess the quality of the segmented fingernail images. One of the primary aspects of qualitative analysis is comparing the segmented fingernail images produced by the improved edge detection and morphological operations with those generated by baseline methods. For instance, the study could include comparisons against traditional methods like the Canny or Sobel edge detectors without morphological refinements. Images are evaluated for the clarity of edges, smoothness of boundaries, and removal of irrelevant artifacts. High-quality visual results demonstrate the algorithm's ability to isolate the nail region accurately under various conditions, such as uneven lighting or complex backgrounds.
For the quantitative analysis uses confusion matrix. This matrix acts as an important evaluation tool for the proposed method. A confusion matrix is typically associated with classification problems, as it evaluates the performance of a classification model by comparing predicted and actual labels. The confusion matrix be used to assess k-means clustering results by comparing the cluster assignments to known class labels, In the confusion matrix, there are false negative (FN), false positive (FP), true negative (TN) and true positive (TP) identified in the table, the matrix table can be seen in TABLE 1 [33]. By using a confusion matrix, it can calculate various evaluation matrices such as accuracy, and recall. The following is the calculation formula [30][31].

TABLE 1
Confusion Matrix

Actual Class	Predicted Class	
	Class = Yes	Class = No
Class = Yes	True Positive (TP)	False Negative (FN)
Class = No	False Positive (FP)	True Negative (TN)

1.Accuracy
Accuracy is the number of correct data comparisons to the total number of data. Accuracy can be calculated in Eq. (13) as follows.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{13}$$

2. Recall
Recall is used to show the percentage of positive data classes that are successfully predicted correctly from all positive class data, which is calculated using in Eq. (14) as follows.

$$Recall = \frac{TP}{TP+FN} \tag{14}$$

3.Precision
Precision is used to measure how large the proportion of positive classes that are successfully predicted correctly from all positive classes, which is calculated using the Eq.(15) as follows.

$$Precision = \frac{TP}{FP+TP} \tag{15}$$

4. F1-Score
F1-Score is an evaluation metric that reflects the balance between Precision and Recall. F1-Score can be calculated in Eq. (16) as follows.

$$F1 - Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall} \tag{16}$$

4. IoU
IoU (Intersection over Union) is the most commonly used measure for comparing the similarity between two arbitrary shapes. IoU encodes the shape properties of the objects being compared, such as the width, height, and position of two bounding boxes, into region properties, and then calculates a normalized measure that focuses on their areas (or volumes). IoU can be calculated in Eq. (17) until Eq. (19) as follows [34].

$$Intersection = TP \tag{17}$$
$$Union = TP + FP + FN \tag{18}$$
$$IoU = \frac{Intersection}{Union} = \frac{TP}{TP + FP + FN} \tag{19}$$

IV. RESULTS

A. QUALITATIVE ANALYSIS

Based on the method described in Section III, we implemented the fingernail image segmentation for fingernail image. The image segmentation system is developed using Matlab equipped with Image Processing Toolbox. The image is formatted as Joint Photographic Experts Group (jpg) file. Result of experiments is shown in FIGURE 3. When the system was executed, original image as input image in system that shown in FIGURE 3(a). The input image goes through preprocessing stages including cropping nail area (FIGURE 3(b)), grayscale image (FIGURE 3(c)), gaussian smoothed image (FIGURE 3(d)), and contrast adjusted image (FIGURE 3€). After that, the input image undergoes three different processes. The first process is sobel edge detection which will be followed by the k-means clustering process shown in FIGURE 3(f) and FIGURE 3(g). The second process is canny edge detection and k-means clustering shown in FIGURE 3(h) and FIGURE 3(i). The third process is adaptive thresholding, morphological closing and k-means clustering respectively shown in FIGURE 3(j), FIGURE 3(k) and FIGURE 3(l). Based on the results, especially the k-means clustering results, namely FIGURE 3(g), FIGURE 3(j) and FIGURE 3(l) shows that FIGURE 3(l) which include in improved method give the best image segmentation results.

B. QUANTITATIVE ANALYSIS

The other evaluation is done in this research is quantitative analysis. Evaluation based on quantitative analysis using confusion matrix. There are three confusion matrix is shown in FIGURE 4(a) for sobel method, FIGURE 4(b) for canny method and FIGURE 4(c) for improved method. Based on confusion matrix, the evaluation metrics such as accuracy, recall, F1 score, and Intersection over Union (IoU) can be identified. These evaluation metrics are commonly used to assess the effectiveness of segmentation algorithms. These metrics were calculated for both traditional and improved methods to highlight the performance gain achieved through the proposed improvements. The results are summarized in TABLE 2, which shows a comparison of the traditional edge detection methods (Sobel and Canny) versus the improved method in terms of segmentation accuracy.

Overall, the improved method outperformed both Sobel and Canny edge detectors across all metrics. In particular, the Intersection over Union (IoU), which measures the overlap between the predicted segmentation and the ground truth, demonstrating the accuracy of the improved edge detection and segmentation approach.

V. DISSCUSSIONS

Based on results of qualitative analysis, Integrating morphological operations with improved edge detection techniques represents a significant advance in fingernail image segmentation. Edge detection serves as the basis for identifying boundaries in images, but its effectiveness is often challenged by noise, uneven illumination, and complex backgrounds. Morphological operations, mathematical tools based on image shape, address these limitations by refining detected edges and improving image structure. By combining these techniques, researchers achieve more accurate and robust segmentation, especially in medical imaging applications such as fingernail analysis.

TABLE 2
Performance Comparison of Edge Detection and Segmentation Methods

Method	Accuracy	Precision	Recall	F1 score	IoU
Sobel	0.73	0.72	0.77	0.74	0.59
Canny	0.86	0.85	0.87	0.86	0.76
Improved	0.97	0.95	1.00	0.97	0.95

Morphological operations, including dilation and erosion improve segmentation by addressing specific shortcomings of edge detection algorithms. Dilation can fill small gaps in detected contours, ensuring boundary continuity, while erosion removes small artifacts and noise. This sequential application is particularly effective for nail images, where segmentation requires separating the nail region from irregular textures and skin shading.

One of the main advantages of combining edge detection and morphology is its ability to adapt to different imaging conditions is shown in FIGURE 3. Fingernail images often have problems such as inconsistent lighting, different hand poses, and different skin tones. While edge detection identifies potential boundaries, it can also capture irrelevant details such as skin folds or background elements.

Morphological operations refine these results by emphasizing relevant structures and removing irrelevant ones. This combined approach ensures that the segmented output is both accurate and visually interpretable, making it suitable for downstream applications such as disease diagnosis or aesthetic analysis.

A detailed explanation of the method shows its potential to bridge the gap between traditional segmentation methods and modern requirements for accuracy and automation. While edge detection provides a fundamental layer of analysis morphological operations add adaptability and precision to the process, mimicking human attention to detail. This is especially important in biomedical contexts, where accurate nail segmentation can help diagnose conditions such as onychomycosis or psoriasis. Additionally, the combination reduces computational complexity compared to purely deep learning-based methods, making it a viable option for resource-constrained environments. According to FIGURE 4(a), the confusion matrix shows poor performance with low accuracy and high error rates.

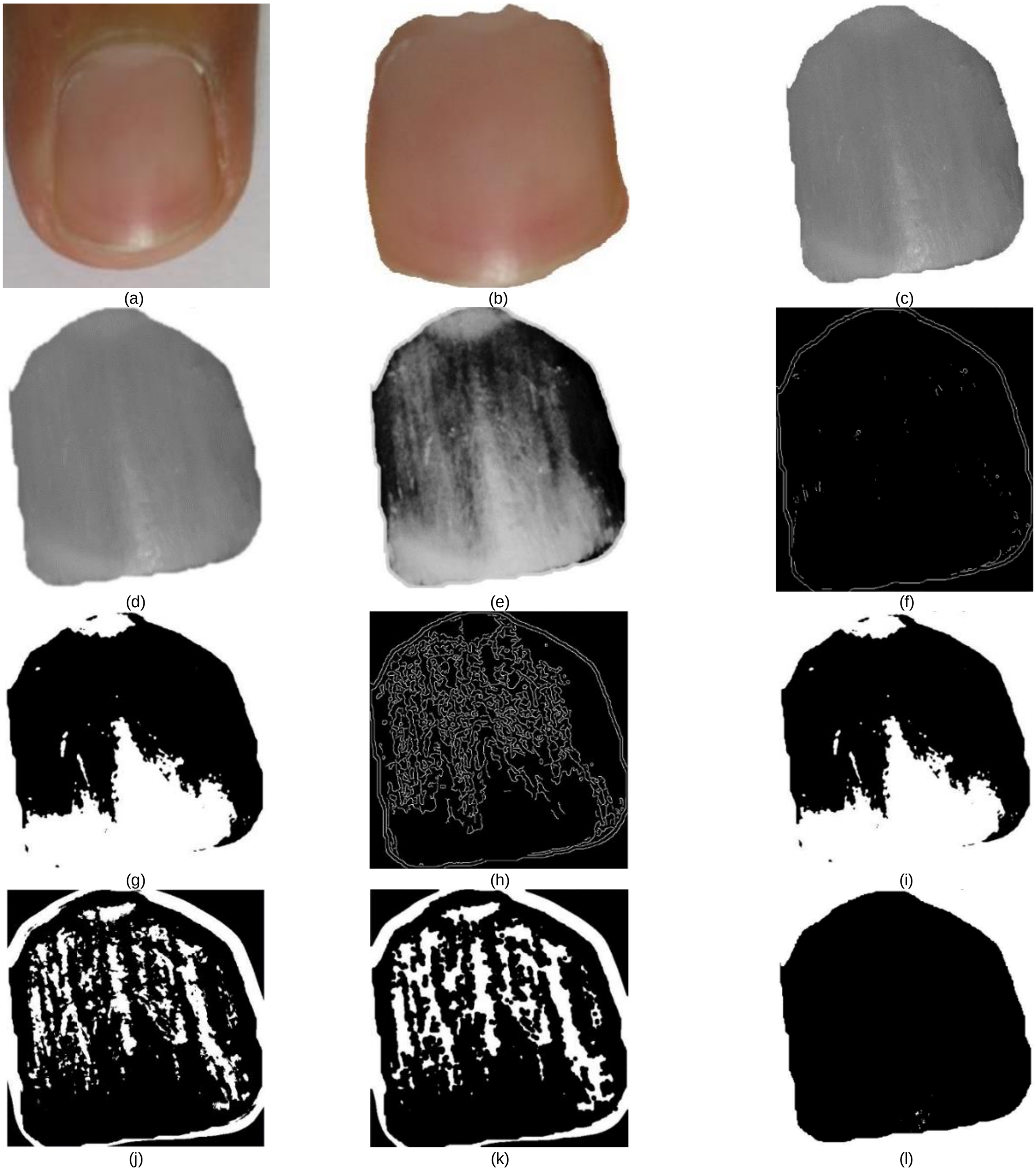
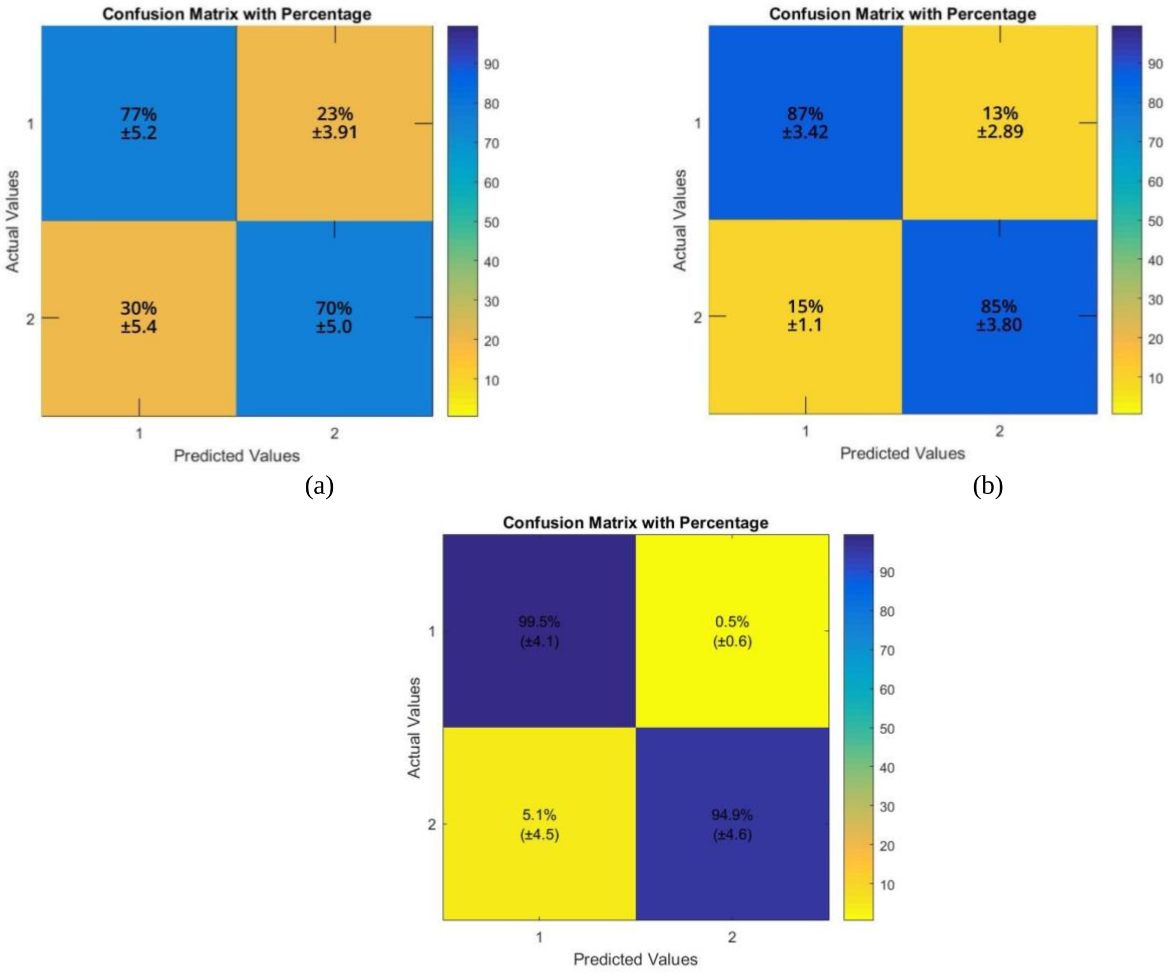


FIGURE 3. **Results of Processing (a) Original Image (b) Cropping area nail in image (c) Grayscale image (d) Gaussian smoothed image (e) Contrast Adjusted Image (f) Sobel Edge Detected Image (g) K-means clustering after Sobel Edge Detection (h) Canny Edge Detected Image (i) K-means clustering after Canny Edge Detection (j) Adaptive Thresholded image (k) Morphologically Closed image (l) K-means Clustered image after Morphologically closed image**



(a) (b) (c)

FIGURE 4. Confusion Matrix with Percentage (a) Sobel Method (b) Canny Method (c) Improved Method

It demonstrated in True Positive is 77% ± 5.2 makes the accuracy has significantly decreased compared to the other method. True Negative is 70% ± 5.0 were correctly classified indicating improved performance. False Positive is 23% ± 3.91 included relatively high. The error rate is even higher showing the method struggles to differentiate class. FIGURE 4(b) has moderate performance with decreased misclassification rates compared to the first matrix. True Positive is 87% ± 3.42 included high, the accuracy has increased compared to the first matrix. True Negative is 85% ± 3.80 has the accuracy also increased compared to the first model. False Positive is 13% ± 2.89 indicates the error is significantly lower than in the first matrix. False Negative is 15% ± 1.1 indicates the error rate has also decreased. FIGURE 4(c) moderates very high accuracy for
both classes with minimal misclassification rates. This method is ideal for appliccations requiring high precision and low error rates such as medical diagnosis. True Positive is 99.5 % ± 4.1 indicates almost all correctly classified showing very high accuracy. True Negative is 94.9% ± 4.6 were show most correctly classified. False Positive is 0.5% ± 0.6 show the proportion of class 1 samples misclassified as class 2 is extremely small. False Negative is 5.1% ± 4.5 show the error rate is slightly higher but still within acceptable limits.
Based on result of quantitative analysis in TABLE 2, The Sobel method provides moderate performance, but its accuracy and IoU are lower compared to other methods. The canny method improves over Sobel, achieving slightly higher accuracy, recall, F1 score and IoU. The improved method significantly outperforms both Sobel and Canny methods across all metrics. It achieves the highest accuracy, recall, F1 score, and IoU, indicating excellent edge detection and segmentation performance. According to quantitative analysis, The improved method delivers superior results compared to Sobel and Canny methods. With 0.97 accuracy, 0.98 recall and 0.98 IoU, it demonstrates enhanced precision, better overlap with ground truth, and fewer missed edges or segments. This results is the highlights the effectiveness of the new method in edge detection and segmentation tasks.

It can be concluded that the enhanced edge detection using morphological operations for fingernail image segmentation represents a combination of classical image processing techniques and practical innovations adapted for real-world monitoring systems and mobile diagnostic tools, providing a scalable and cost-effective solution for fingernail analysis and efficiency. The adaptability of the method makes it a promising candidate for implementation in automated health. Qualitative analyses demonstrate the accuracy of the proposed edge detection and segmentation compared to traditional methods such as Sobel and Canny in the context of nail images.

Evaluation of the results shows an improvement in the segmentation accuracy as well as the visual quality of the segmented images. FIGURE 3(l) confirms the increasing accuracy of the improved method in identifying thin nail edges, especially when the images may have more complex backgrounds or low signal-to-noise ratios, such as due to different lighting conditions. Therefore, the effectiveness of the improved method can be largely attributed to the application of adaptive and morphological thresholding operations. Variable thresholding allows the image contrast to be divided into multiple parts that take into account the pixel intensities as well as the local brightness and contrast of the image, making the image less sensitive to changes in these regions. Operations like closing edges are smooth because small gaps are closed and noise is eliminated, resulting in more continuous edges. This happens as in similar studies, namely [35][36]. The researches states that combining edge detection with morphology operations (dilation and erosion) will produce better outcomes. These results apply to medical image segmentation, especially lung x-ray images.

In improved method, It is efficiency in edge detection and nail segmentation is one of its main advantages; it is also applicable to images of different sizes, different surfaces, and various backgrounds. The provided guidance also suggests that unlike other conventional methods that may not be able to handle complex issues such as incomplete edges or noise, this improved method can handle these complex issues with ease. Another important beneficial aspect is the trade-off between time complexity and accuracy. However, with the requirement of adaptive thresholding and morphological processing, the proposed method is not too time-consuming and only slightly increases the processing time [37].

However, there are also some limitations that need to be mentioned about the proposed method as follows: The proposed method has obvious advantages over the traditional method, but the following disadvantages should also be acknowledged: First, the method still depends on predefined values such as the kernel size for morphological operations and the number of clusters in the K-means algorithm. These parameters may need to be optimized depending on the dataset or imaging conditions, and these parameters may slightly hinder the feasibility of this method. Second, the current work specifically focuses on nail segmentation using the method proposed in this paper. It has not been rigorously tested on other types of biomedical images or on general image segmentation problems. Further experiments with more types of images are needed to see how flexible this approach is. Finally, although processing times are relatively fast, introducing more complex preprocessing operations or large data can also significantly increase the load, thus placing some limitations on real-time processing when needed.

The proposed method has some implication such as enhanced diagnostic accuracy, advancements in biomedical image analysis and foundation for machine learning applications. By improving edge detection and segmentation, identification of nail abnormalities which are indicators of systemic diseases or localized infections is more accurate. This improvement supports early diagnosis and targeted treatment. The application of morphological operations in fingernail image processing provides a novel approach for further research in medical imaging such as nail health and its correlation with systemic conditions. Hence that, accurate segmentation serves as a critical pre-processing step for machine learning models. This research can support the development of robust artificial intelligence systems for automated diagnosis, enhancing their training with higher-quality input data. This study also can be future advancements in medical image segmentation and diagnostics.

VI. CONCLUSION

In this paper, we presented a novel approach to edge detection and segmentation specifically designed for fingernail images. The approach involves six different steps, including data collection, preprocessing, edge detection technique, divided into traditional methods and improved methods, segmentation approach and evaluation. Traditional methods consist of Sobel and Canny edge detector. Meanwhile improved methods consist of adaptive thresholding with morphological operations. The evaluation was done by considering the qualitative analysis and quantitative analysis. The quanlitative analysis demonstrates that the improved method consistently outperforms existing techniques in segmenting fingernail images under diverse conditions. Furthermore, qualitative analysis of the segmented images highlights the method's ability to handle variations in fingernail shapes, textures, and lighting conditions, producing clean and continuous edges that are essential for accurate segmentation. Despite its improved performance, the method remains computationally efficient, making it suitable for real-time applications in medical diagnostics. According to quantitative analysis, The improved method delivers superior results compared to Sobel and Canny methods. With 0.97 accuracy, 0.98 recall and 0.98 IoU, it demonstrates enhanced precision, better overlap with ground truth, and fewer missed edges or segments. For enhancement the performance of fingernail images segmentation methods, future research should focus in various data and other method. Various data will enable give various result when implemented in method. Meanwhile, other method such as artificial intelligence could give the best result and method in segmentation fingernail images.

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