Investigation on Image Based Diagnostic Approach for Throat Related Symptom Through Feature Extraction Using MATLAB

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ABSTRACT

Early diagnosis and treatment of these symptoms are essential to prevent complications and ensure a prompt recovery. Traditional throat examinations can also be distressing for young children, delaying care-seeking and complicating clinical assessment. The aim of this paper is to investigate image detection analysis of image-based diagnostic approach for pediatric throat symptoms using MATLAB-based image analysis, offering a child-friendly screening tool. Regions of Interest (ROI) marking and feature extraction are used to analyze images of children's throats, captured using widely available endoscopic cameras and transferred to MATLAB software for processing. The analysis pipeline measures contrast, RGB (Red, Green, and Blue) channel intensities, and overall image quality to determine suitability for further diagnostic analysis. Red and white ROIs are then marked to highlight throat conditions such as redness and swelling, and feature extraction techniques including edge detection and circle detection. Hence, abnormal patterns such as inflamed tonsils have been identified. Real images of children's throat aged three to ten years old are compared with virtual healthy throat images representing infected cases to evaluate performance analysis. Results show that both the red and white ROIs were accurately detected, enabling targeted examination of specific throat regions. Image captured by smartphone and endoscopic hardware other than specialized clinical equipment provide significance result to throat symptom screening, supporting non-specialist healthcare workers and reducing the burden of invasive examinations on young patients. The findings suggest that accessible image-based diagnostic tools can extend basic throat-screening capability to underserved pediatric populations while easing the diagnostic process for physicians.

Keywords: Throat, Regions of Interest (ROI), Feature Extraction, Image Detection

INTRODUCTION

Timely diagnosis of throat infections in children is often constrained not by clinical complexity but by access: specialist otolaryngology equipment, trained ENT physicians, and dedicated pediatric clinics are frequently concentrated in urban centers, leaving children in rural or resource-limited communities with delayed or informal diagnosis [18]. This access gap is compounded by the invasive nature of many traditional throat examinations, which can cause distress in young children and further discourage timely care-seeking [5]. Low-cost, smartphone-based diagnostic tools have been proposed as a means of narrowing this gap across a range of pediatric conditions, from ear disorders to vision screening, by shifting diagnostic capability away from specialized equipment and toward widely available consumer hardware [15]. This paper extends that approach to pediatric throat symptoms, evaluating whether a common smartphone-attached endoscopic camera combined with MATLAB-based image analysis can support accessible, non-invasive throat screening for children.

Throat infections are a significant health concern in children aged 1-10 years, often leading to discomfort and numerous healthcare visits. These infections are caused by various pathogens, including viruses, bacteria, and fungi, each presenting with distinct symptoms and throat findings. Common throat-related diseases in children include viral pharyngitis, strep throat, infectious mononucleosis, hand, foot, and mouth disease, croup, whooping cough, laryngitis, and tonsillitis [3]. These conditions manifest through symptoms such as sore throat, coughing, hoarseness, difficulty swallowing, and swollen glands, often accompanied by fever. Viral pharyngitis typically reveals redness and swollen tonsils, sometimes with white patches. Strep throat, caused by Streptococcus bacteria, is characterized by red, swollen tonsils with white patches or streaks of pus. Infectious mononucleosis, often caused by the Epstein-Barr virus, leads to swollen lymph nodes and is marked by red, swollen tonsils with a white or yellow coating and petechiae on the palate. Hand, foot, and mouth disease, commonly resulting from Coxsackievirus, presents with small red spots or ulcers in the throat and mouth [12].

Advanced techniques in medical imaging and analysis are increasingly being applied to the diagnosis of throat infections in children. By analyzing the color intensity and specific features of throat images, such as the presence and pattern of redness, swelling, and white patches, it is possible to enhance the accuracy of diagnoses and monitor the progression of diseases. Studies have shown that color analysis can be an effective tool in identifying the severity and type of throat infection. This is particularly relevant given that clinical prediction rules based on visual inspection and symptoms alone, such as the Centor score, have well-documented accuracy limitations [1]. For instance, [11] demonstrated that machine learning algorithms using color intensity metrics could differentiate between viral and bacterial infections with high accuracy. Other studies have explored the use of digital imaging and spectral analysis to identify characteristic features of various throat infections. For example, [20] utilized hyperspectral imaging to detect specific color patterns associated with different pathogens, enhancing the precision of diagnostic tools used in pediatric care. The integration of these advanced imaging techniques with clinical evaluations could significantly improve the early detection and management of throat infections in children, reducing the burden of these common ailments.

By focusing on the detection of color intensity and feature extraction from throat images, this research aims to develop more reliable and non-invasive diagnostic methods. Such advancements hold the potential to improve patient outcomes through quicker diagnosis, targeted treatments, and better monitoring of disease progression. Related smartphone-camera-based approaches have applied deep learning networks directly to throat images for automated pharyngitis screening [19], though such approaches typically require large, annotated datasets and substantial computational resources compared to classical image-processing pipelines. In this paper, an image detection method is proposed for pediatric cases that utilizes RGB color extraction to create Regions of Interest (ROIs), feature extraction to identify any abnormalities, and tonsil detection, all performed using MATLAB.

METHOD AND METHODOLOGY

Most of these diseases share common symptoms such as red spots, swollen tonsils, and ulcer patterns. A common endoscopic camera was used for symptom detection. Test subjects include children and a virtual dataset of throat images. The analysis includes quality performance, contrast, and RGB extraction. Red and white Regions of Interest (ROIs) will be marked to highlight related symptoms, similar to the feature extraction process. Both sets of images will be analyzed using the same methods and compared for their performance.

Figure 1 is an endoscopic image capture of healthy throat (Real) as no sign of related symptoms meanwhile Figure 2 is a strep throat (Virtual) from internet data set of strep throats that has redness.

Figure 1 : Healthy Throat

Figure 2 : Strep Throat

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Data Collection

A total of 20 children, aged 3-10, and 20 virtual throat images from internet datasets were collected. Subjects included both genders, and only healthy throats were captured using real-time events. Therefore, virtual throat images focused on unhealthy throats. Using an endoscopic camera attached to smartphones, throat images were obtained [2]. The captured images have a resolution of 720p (1280x720 pixels) and a field of view typically ranging from 60 to 70 degrees. Meanwhile, the virtual datasets varied in quality. Images were processed using MATLAB simulations [8].

Figure 3 : Endoscopic Camera attach to Smartphone

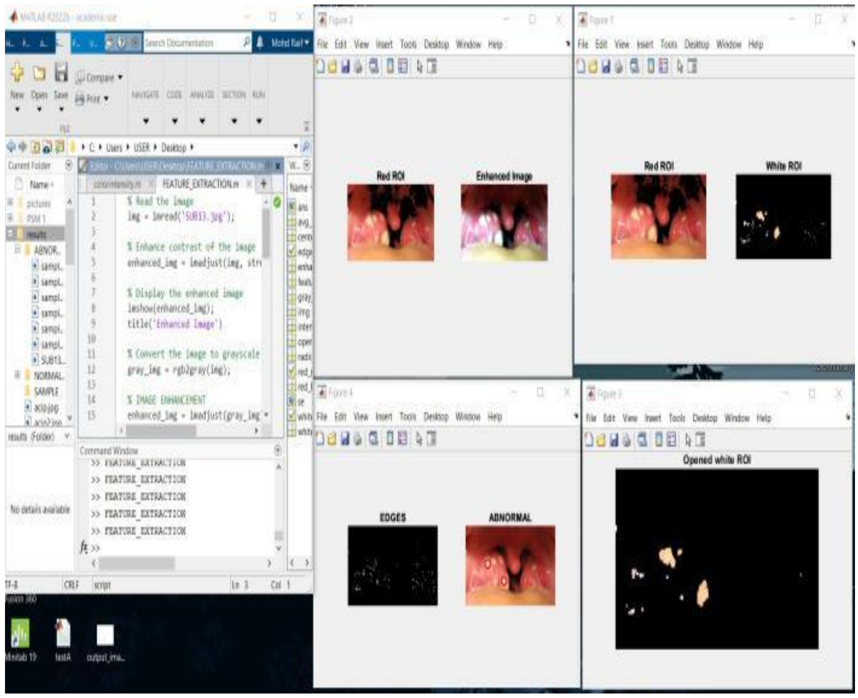

Figure 4 : MATLAB Simulations

Approach

After the images have been acquired, they need to be pre-processed to prepare them for analysis. One way to do this is by converting the images to grayscale format using a function in MATLAB. This reduces the number of dimensions in the image, making the analysis process faster. Secondly, extracting color intensity histograms captures the distribution of pixel intensities across different color channels before proceeding to feature extraction. This step helps identify the red and white Regions of Interest (ROIs) by undergoing RGB color extraction. The ROIs aim to highlight areas of infection or symptoms so that abnormalities can be detected and pointed out. During feature extraction, the throat images will undergo several steps of code to identify any abnormalities in the throat.

Grayscale Format

The first step in the image processing. MATLAB successfully converts the image to grayscale format using standard image processing techniques, such as intensity averaging or color channel separation, without losing important details or introducing artifacts. Calculated average grayscale intensity and its distribution of pixel intensities are shown in Figure 5 . The results display the grayscale image, average grayscale intensity, and pixel distribution. The average intensity provides an overall measure of the brightness level, indicating how light or dark the image is on average. The pixel intensity distribution reveals the spread and concentration of pixel values, offering insights into the contrast and distribution of details in the image. These processes are helpful for identifying specific patterns or abnormalities in the image.

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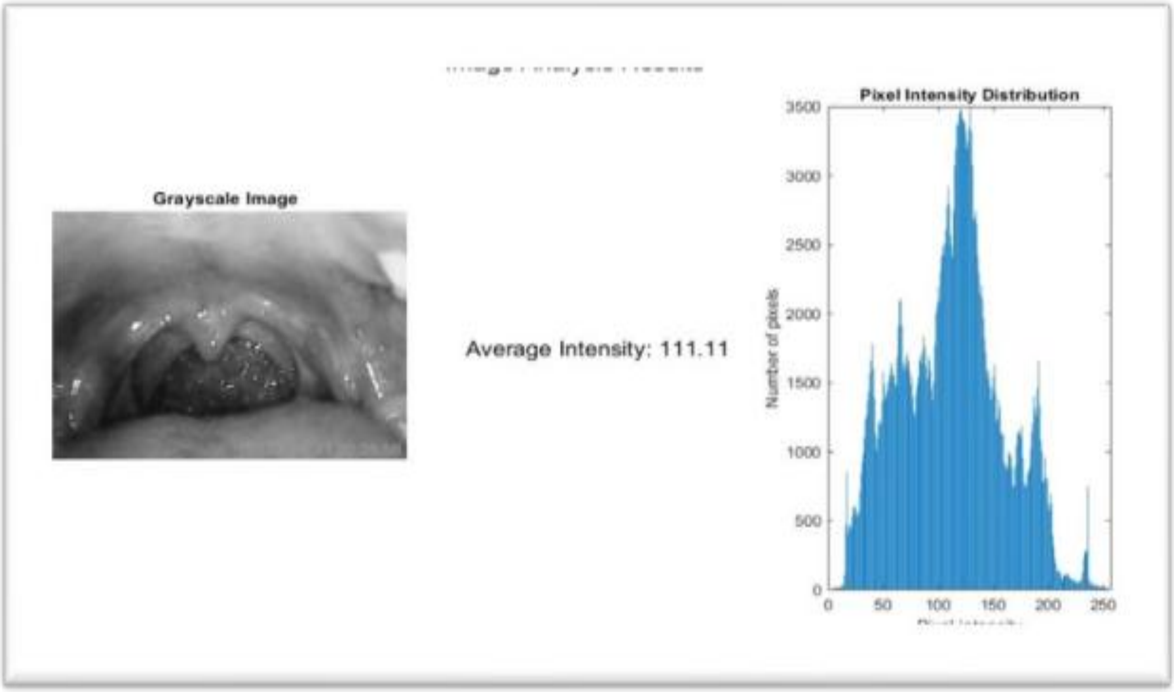

Figure 5: Calculated average grayscale and distribution of pixel intensity

Image Enhance and Colour Extraction (ROIs)

This step involves extracting colour intensity histograms to capture the distribution of pixel intensities across different colour channels. This process provides valuable insights into the color characteristics of the throat image, enhancing the understanding of the visual information present and potentially aiding in the detection and assessment of abnormalities or changes. By highlighting these Regions of Interest (ROIs), the analysis becomes more focused, reducing computational complexity and enabling targeted analysis of potential abnormalities. Figure 6 shows the results of the process.

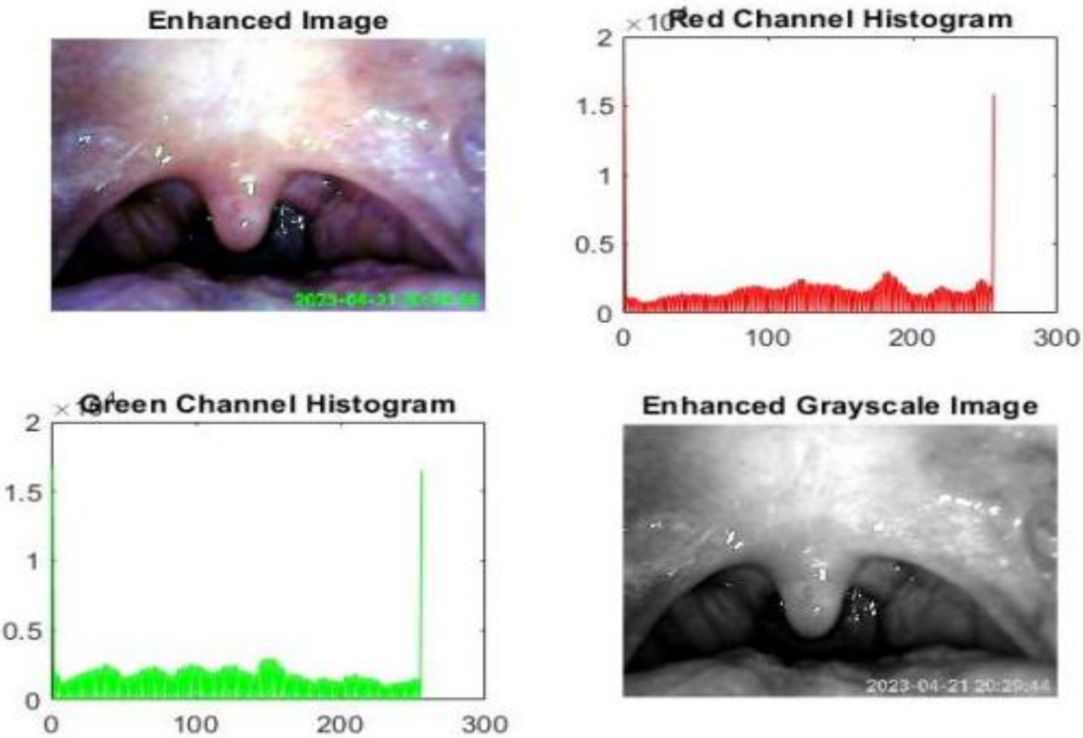

Figure 6 : Enhance images and Channel Histogram

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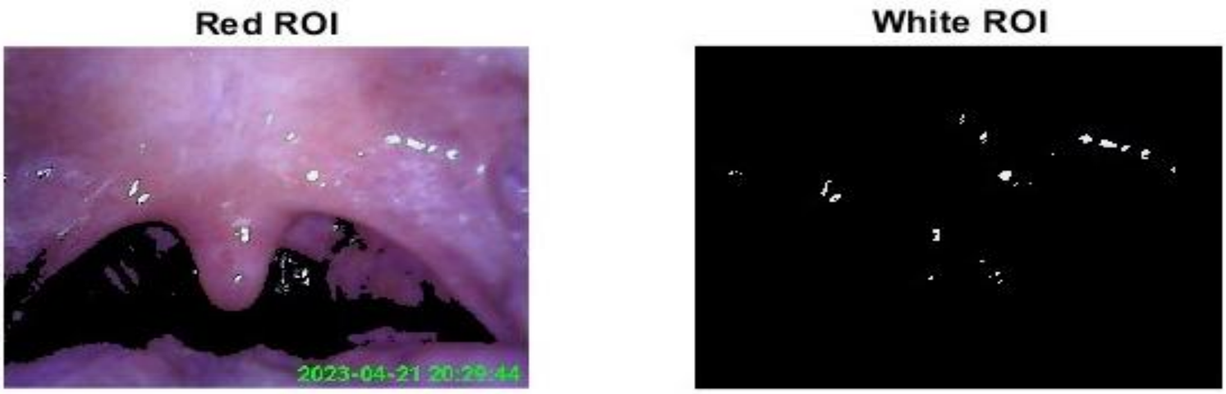

Figure 7 : ROIs Red and White results.

Performance of image segmentation based on intensity thresholds. It first creates a binary mask (red_mask) by comparing the grayscale image (gray_img) with a threshold value of for example 50. Pixels with intensities greater than 50 are set to 1, indicating potential regions of interest for red objects. Similarly, a higher threshold value of 200 is used to create a binary mask (white_mask) for potential white objects. The masks are then applied to the original image (img) using element-wise multiplication to isolate the regions of interest. The resulting red and white regions of interest in Figure 7 retain the pixels from the original image that passed the respective intensity thresholds. Using the [1 1 3] value in the repmat function replicates the binary mask along the third dimension, representing the RGB channels of the image. This ensures that the resulting ROI has the same size and channel information as the original image.

In Figure 8, it is evident why the red ROI is larger than the white ROI. The pixels in the red ROI have higher intensity values within the image, resulting in a larger, clearer ROI plot. This is also because, as shown in Figure 9 of the code, the red ROI is plotted when pixel intensities are above 50. In contrast, the white ROI only includes pixels with intensities above 200, resulting in fewer pixels and gaps in the plot. Consequently, this affects the results as shown in Figure 10 (White ROI).

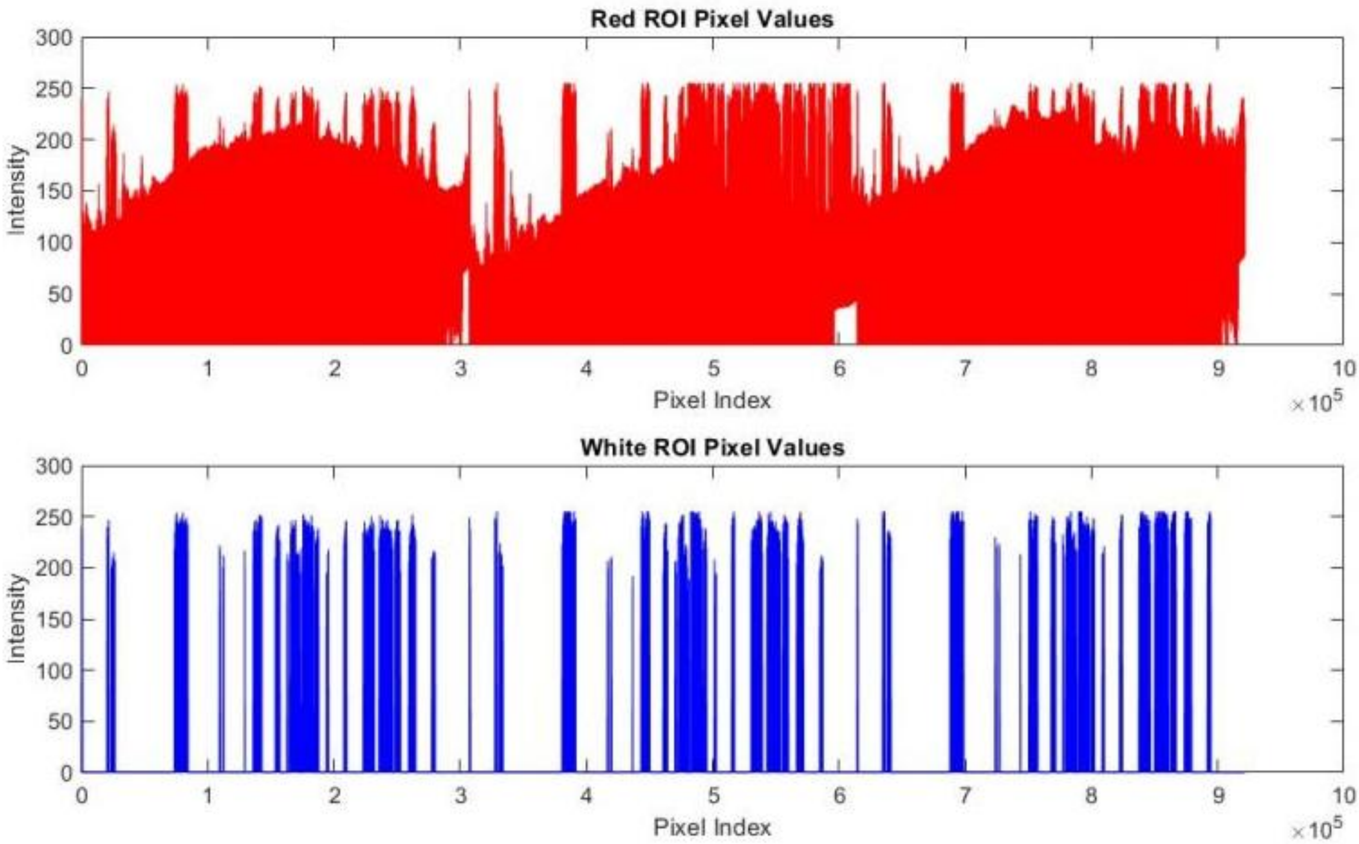

Figure 8: Red and White ROIs pixel values.

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Feature Extraction

The feature extraction process involves identifying distinctive features from the image that characterize and identify specific elements or patterns. In this project, abnormalities are identified using RGB data and ROI pixel values displayed in the image. Two feature extraction techniques are applied: edge detection and circle detection. The 'Canny' edge detection algorithm identifies edges in the white ROI mask, representing significant changes in intensity or color useful for identifying boundaries or regions of interest [4]. The resulting edges are shown in the first subplot of the figure. Usage of 'imfindcircles' function detects circular shapes within the white ROI mask using the Hough transform [6], with a specified radius example of range (10 to 50 pixels). Detected circles are represented by their center coordinates and radii. These circles are overlaid on the original image using the 'viscircles' function, displayed in the second subplot of the figure. Figure 9 shows result of the feature extraction techniques and image analysis, providing insights into edges and circular patterns within the white ROI. The edge detection aims to identify patterns such as streptococcal pharyngitis, while abnormal extraction targets the detection of tonsil forms or other foreign objects.

Figure 9 : Results for Edges and Abnormal

Figure 10 displays the histogram of edge intensity contrast and intensity characteristics. The circle radius histogram illustrates the size distribution of detected circles, while the circle count quantifies their number, assisting in object counting and assessing the density of circular elements. Consequently, this explains why the edge patterns appear random and inaccurate, influenced by reflected light that affects contrast intensity in the area. In contrast, abnormalities in circles tend to be more accurate when no foreign objects are detected. The low count and small radius of circles may be influenced by unclear image processing.

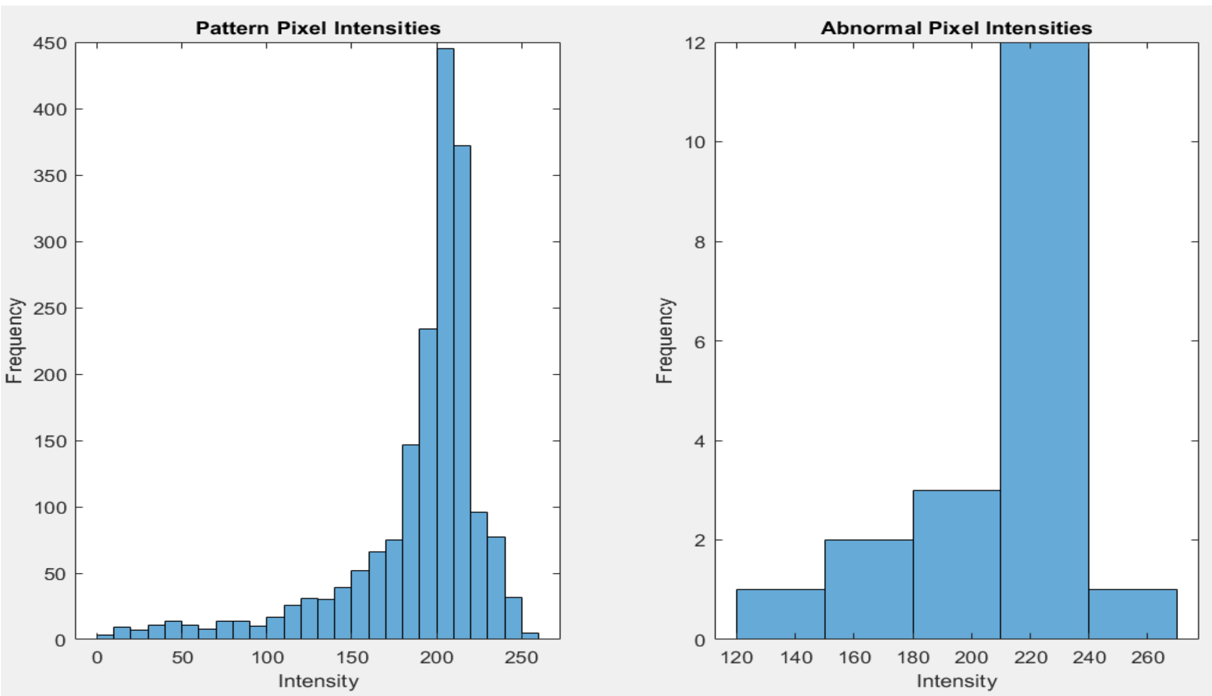

Figure 10 : Edge Intensity histogram contrast and Intensity characteristics

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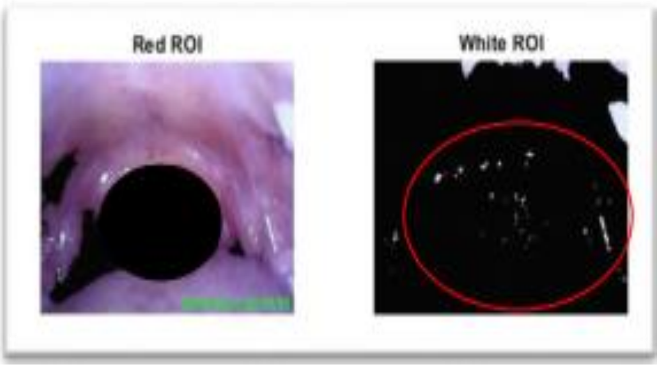
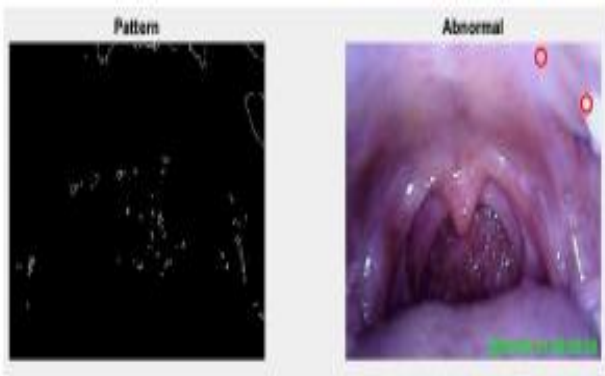
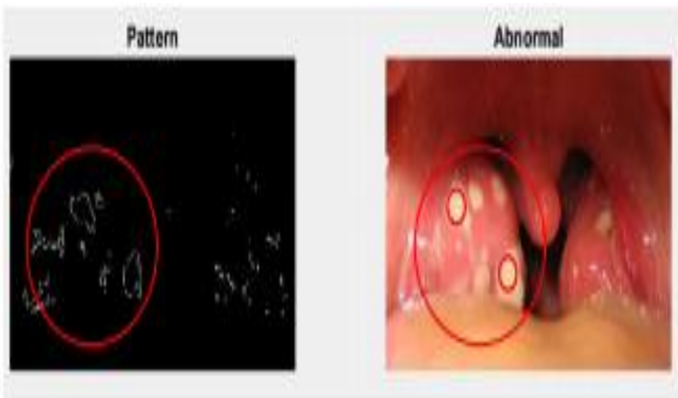
RESULTS

Both test subjects were evaluated manually through side-by-side observation. This approach was chosen because the methods used aim to detect abnormalities, ROIs, and tonsils in throat images, all of which can be observed with the naked eye. Performance evaluation was conducted by comparing the results of Table 1 both images: Test Subject (a) and Infected Throat (b), which underwent feature extraction and tonsil detection methods. The purpose of this testing was to analyze the effectiveness of the image detection method on specific images containing all testing inputs, elucidating the working mechanism of the image analysis method.

Table 1 Test Subject Image Analysis (a),(b),(c) and Infection Throat Image Analysis (d) ,(e), (f)

Test Subject	Infection Throat
 (a)	 (d)
Red and White ROI	
 (b)	 (e)
Patterns and Abnormalites	
 (c)	 (f)

In both cases (a) and (b), the analysis yielded satisfactory results. The regions of interest (ROIs) were accurately identified, allowing focused examination of specific areas in both cases (b) and (e). However, edge and abnormality detection in case (c) was unsuccessful, whereas in case (f), the edges and abnormalities followed the tonsil pattern, thereby highlighting the abnormality. Conversely, analysis of the Infected Throat image in Table 1 (d) demonstrated smoother performance. Both the red and white ROIs were accurately detected, enabling targeted examination of specific throat regions. Edge and abnormality detection in the image was partially successful, showing the approximate area. This indicates the software's capability to identify potential issues or anomalies with slight accuracy.

DISCUSSIONS AND CONCLUSIONS

The quality of an image, including factors such as resolution and lighting conditions, significantly impacts the accuracy of tonsil detection. High-quality images with clear RGB information provide better input for image processing algorithms [7], consistent with RGB-based redness quantification approaches validated in other clinical imaging contexts [13]. Conversely, low-quality images may have degraded RGB information, making it more challenging to accurately detect tonsils and identify abnormalities or patterns [11,17].

The threshold value used in image processing algorithms is a critical parameter for accurate detection [9,14]. Careful selection of an appropriate threshold value is essential to avoid false positives and false negatives. A threshold set too low may include unnecessary regions, leading to false positives and vice versa. Adaptive thresholding techniques, which consider local image characteristics, show promise in improving ROIs detection accuracy [16].

Achieve better detection accuracy requires consideration of both the quality of the input image, particularly its RGB information [7], and the selection of an appropriate threshold value. Advances in adaptive thresholding techniques and ongoing research in medical imaging analysis contribute to developing more accurate detection algorithms.

In conclusion, to enhance the efficiency and effectiveness of software system, focus on improving image quality, determining precise threshold values, optimizing computational efficiency, and enhancing the user-friendly graphical interface. Addressing these areas will advance the system's capabilities, enabling accurate pediatric throat image analysis, efficient diagnosis, and facilitating ease of use for healthcare professionals.

Beyond the immediate technical findings, this work speaks to a broader accessibility challenge in pediatric care. Because the proposed method relies on commonly available smartphone and endoscopic hardware rather than specialized ENT equipment, it lowers the cost and technical barriers associated with throat symptom screening, potentially extending basic diagnostic support to non-specialist healthcare workers in rural or under-resourced clinics. Combined with ongoing improvements in image quality and threshold optimization, such tools align with broader digital health efforts to expand accessible, non-invasive diagnostic capability for children, particularly in settings where specialist pediatric otolaryngology care is scarce, consistent with reported gains in equitable access from telemedicine-based pediatric otolaryngology services [10,18].

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