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RESEARCH-ARTICLE

Enhancing Early Oral Disease Detection Through Custom Multispectral Light-Emitting Diode Imaging: A Noninvasive Digital Approach for Remote Dental Diagnostics

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Abstract

Oral health remains a critical yet often neglected aspect of general well-being, with a significant percentage of the global population lacking access to early-stage dental diagnostics. In India, approximately 67% (924 million) of the population have never visited a dentist, and 87% (1.2 billion) seek dental care only when symptoms become severe. Compared to a global survey, 27% (2.2 billion) of the world's population visit a dentist only once a year. Current dental screening methods rely on in-clinic examinations, which can be costly and inaccessible to many. Advancements in digital imaging and sensor technology offer promising opportunities to enhance early detection and preventive care through noninvasive and cost-effective approaches. Oral conditions such as dental caries (54%—750 million), gingivitis (51%—708 million), and periodontitis (50%—700 million)—if diagnosed in the early stages, can be managed without disease progression using various preventive methods. This study proposes

a custom-built multispectral light-emitting diode (LED) prototype system combined with a mobile camera for the early detection of oral conditions. The research explores the feasibility of this device in imaging and diagnosing various dental diseases, including caries, plaque, calculus, and oral lesions, using image processing techniques in MATLAB. A dataset of 1000 clinical images sourced from private clinics was analyzed using expert diagnoses and algorithmic classification, achieving a diagnostic accuracy of up to 90%. The results demonstrate that multispectral LED imaging enhances disease visualization compared to standard white-light images, facilitating improved detection and classification of dental conditions. The findings suggest that this novel LED-based imaging system could serve as a viable tool for at-home dental screenings, reducing the burden on clinical facilities and promoting proactive oral healthcare. The research also highlights the potential integration of artificial intelligence (AI) for automated diagnosis, paving the way for scalable, technology-driven solutions in preventive dentistry.

Issue Section: Special Papers
Keywords: oral health, early detection, image-based diagnosis, digital health, telehealth, dental screening device, artificial intelligence
Topics: Diseases, Imaging, Light-emitting diodes, Matlab, Wavelength, Visualization, Fluorescence

1 Introduction

Oral health is a fundamental aspect of overall well-being, yet access to timely and effective dental care remains a major global challenge, particularly in low- and middle-income countries [1]. According to recent surveys [2], a large segment of the population does not seek dental care until symptoms become severe. In India, 67% of people have never visited a dentist, and 87% seek treatment only when experiencing pain or discomfort [2]. This lack of early intervention contributes to the progression of preventable oral diseases such as dental caries, gingivitis, and periodontitis, leading to complex and costly treatments [1,3].

Recent technological advancements have transformed healthcare by integrating photographic data with computing technologies. The miniaturization of high-magnification cameras, combined with improvements in imaging sensors and algorithms, has opened new possibilities to improve medical screening and diagnosis [4]. While most modern imaging devices are designed for consumer photography, customized imaging systems can be developed to cater to specialized medical applications. Designing such a system involves carefully selecting and integrating hardware and software components, including lighting, filters, optics, sensors, and image processing algorithms [5,6]. Typically, a physical prototype is developed to assess the performance and effectiveness of the system.

In oral healthcare, innovative technologies are continuously being developed to improve diagnostic efficiency and treatment outcomes [7]. These advanced techniques are generally noninvasive, user-friendly, and beneficial to both patients and clinicians [7]. One of the most

important tools in modern dental diagnostics is the intra-oral camera (IOC). An IOC system typically consists of a camera with an integrated light source, a display unit, and a processing system [8]. These cameras offer a range of advanced features, including macromode for magnification, curing lights for composite restorations, light-emitting diode (LED) illumination, real-time video and photo capture, and fluorescence imaging for detecting various stages of caries, plaque, and gum inflammation [9].

This paper focuses on custom-built multispectral LEDs incorporated into an IOC system to develop a prototype capable of imaging and quantifying fluorescence within the oral cavity. Fluorescent emissions from teeth play a critical role in diagnosing oral conditions through photographic analysis [10]. Ambient LED lighting improves fluorescence and phosphorescence in teeth, helping to investigate clinically oral health issues. Capturing oral images using LED lights with specific wavelengths allows the identification of various clinical characteristics [11]. The optical properties of dental hard tissues have been applied in various clinical practices and require further exploration using advanced optical techniques. Optical imaging in dentistry is vital for the early detection of oral diseases, enabling minimally invasive treatments and effective functional and aesthetic restoration of tissues [12]. These methods utilize the principles of light scattering, absorption, and fluorescence, employing both LED and traditional light sources [10]. The common principle underlying these techniques is that the optical spectrum of a tissue reflects its biochemical composition and structure, providing valuable diagnostic insights for tissue characterization [12]. The motivation for developing this system comes from the observation that tissue autofluorescence can help differentiate between healthy and abnormal conditions, such as normal versus cancerous tissue, healthy versus carious teeth, normal tooth color versus abnormal tooth color, and healthy versus diseased gingiva. This insight has inspired the creation of various imaging systems for noninvasive, in vivo measurement of tissue autofluorescence. Given the weak autofluorescence signal compared to that of reflected light, specialized components are required to effectively separate fluorescent photons from reflected ones. Simulations of the imaging system allow us to test different LED wavelength combinations to excite tissue fluorophores and quantify their emitted photons. These simulations are validated by comparing the prototype's predictions with actual measurements from a system designed to induce fluorescence in the oral cavity. Soft-prototyping tools have been shown to be reliable in guiding future design refinements and improving imaging systems.

The objective of simulating fluorescence imaging in the oral cavity is to aid in developing systems that provide clinicians with precise diagnostic and quantitative information to detect dental diseases [10,12]. Early detection and accurate clinical staging of the presence, activity, and severity of a disease are critical for effective treatment strategies. Developing technologies for early disease detection offers significant health and economic benefits, enabling timely preventive care and lowering treatment costs [7].

More recently, numerous innovative technologies have emerged to support clinicians and practitioners in diagnosing and managing oral conditions, such as the detection of dental caries and oral cancer, the quantification of dental plaque, and the identification of other oral diseases [8,11]. These advancements have also encouraged the use of photography as an educational tool, for maintaining medicolegal records, and for supporting clinical diagnoses. Collectively, these technologies have transformed the way diseases are diagnosed and managed, promoting more conservative and effective treatment approaches [13]. Traditional dental diagnostics primarily rely on in-clinic visual inspections and radiographic imaging performed by trained professionals. While these methods are effective, they are often inaccessible due to financial constraints, geographical barriers, and a shortage of dental professionals, particularly in rural areas [14]. Additionally, many individuals remain unaware of the importance of routine oral examinations, further delaying diagnosis and treatment [2]. Despite advancements in medical imaging technology, early detection of dental diseases remains a challenge due to several factors like many populations, especially in remote regions, lack access to affordable and convenient dental diagnostic tools, conventional diagnostic equipment and procedures can be expensive, deterring individuals from seeking regular check-ups, while telehealth has improved healthcare accessibility, reliable and cost-effective at-home solutions for oral health assessment are still lacking [15]. Current diagnostic techniques often require specialized training, making them impractical for self-assessment or remote screening [1].

This study aims to improve oral health diagnostics by developing a multispectral LED-based imaging system capable of enhancing disease visualization. Improved imaging can help field-level personnel reliably identify disease features and may also enable artificial intelligence (AI)-driven auto-identification of dental conditions. By allowing individuals to capture images at home and either self-identify issues or have them assessed remotely, this technology has the potential to facilitate early detection, promote preventive care, and enable population-wide mass screening efforts.

2 Background

Dental diseases, including dental caries, periodontal disease, and dental fluorosis, are becoming more prevalent. Recent oral health surveys reveal that an alarming 94% of the population experiences some form of dental problem [2]. However, many dental problems are preventable, and serious complications can be avoided through regular monitoring of oral health [16,17]. In addition, monitoring the condition of periodontal tissues, gingiva, and oral mucosa can provide valuable information on a patient's overall health, helping in the management of cardiovascular and cerebrovascular diseases, diabetes, AIDS, and some other medical conditions [17].

2.1 Visible Light Spectrum.

Visible light is a segment of the electromagnetic spectrum, consisting of specific wavelengths that the human visual system can perceive. This range spans approximately 380 to 750 nanometers (nm) [18]. A multispectral image comprises multiple grayscale images, each representing a specific wavelength or band of wavelengths within the electromagnetic spectrum. Unlike standard red, green, blue (RGB) images, multispectral imaging extends beyond the visible spectrum, covering ranges from ultraviolet to near-infrared. As a result, multispectral imaging captures more detailed information than RGB images, providing enhanced insights that are not visible to the human eye [19].

2.2 Multispectral Light-Emitting Diode.

Fluorescence detection, a noncontact and nondestructive probing method, has gained considerable attention due to its high sensitivity and specificity.

2.2.1 Use Cases and Concepts Behind Each Wavelength.

- 360–450 nm

The principle involves illuminating oral tissues with ultraviolet and blue light as excitation sources. These light beams penetrate the tissue, where they are absorbed by fluorophore molecules. In response, the fluorophores emit fluorescence at specific longer wavelengths, typically within the *green*, *yellow*, or *red* spectrum. The exact excitation and emission wavelengths used vary depending on the equipment or commercial product in use [11].

- 405-nm wavelength

The cariogenic bacteria *Streptococcus mutans* produce specific metabolites known as porphyrins. The intensity of the fluorescent signal increases with the thickness of the bacterial film. Detecting caries near amalgam restorations can be challenging, as the emitted light tends to reflect off the restoration, leading to inaccurate or false results [20].

- 405-nm wavelength SIROInspect (Sirona)

When healthy dental tissue is exposed to light at around 405 nm, it emits a green fluorescence. In contrast, carious areas appear red due to the presence of porphyrin compounds, which are produced during the degradation of hard dental tissue by cariogenic bacteria [21].

- 450 nm (Soprolife)

Areas emitting green fluorescence indicate healthy dental tissue, whereas red fluorescence signals the presence of carious lesions. However, red fluorescence can also result from deep dentinal caries or false signals caused by organic deposits. To confirm the cause, the red fluorescent area should be cleaned with sodium bicarbonate. If the red fluorescence is due to organic deposits on the surface, it will disappear after cleaning [20].

- 655 nm wavelength (Diagnodent)

Green fluorescence indicates healthy dental tissue, while red fluorescence suggests the presence of carious lesions. However, red fluorescence can also indicate deep dentin caries or false positives from organic deposits. To verify the source, the area showing red fluorescence should be cleaned with sodium bicarbonate. If the red signal originates from organic surface deposits, it will disappear after cleaning [20].

- 440 and 680 nm (SOPROCARE)

The presence of dental plaque helps differentiate between healthy and diseased gingival tissues [20].

3 Literature Review

A number of studies proposed advanced imaging and detection technologies. For example, a novel method was introduced in Ref. [22] for tooth detection and dental issue classification using panoramic radiographs. To achieve accurate results, their approach involved collecting images from three different dental clinics and annotating them at the pixel level to highlight 14 distinct dental conditions. The annotated data were augmented through various operations, and an AI approach based on a convolutional neural network (CNN) on a semantic segmentation model was trained on these images. These operations included annotating at the pixel level to delineate different dental issues, applying semantic segmentation using CNN to classify different regions of the X-ray images, binarizing segmented images using multiple thresholds to facilitate identification of individual teeth and dental issues, and using erosion and dilation morphological operations to refine the segmentation and separate connected objects such as adjacent teeth. Moreover, a labeling algorithm was applied to identify individual teeth or groups of teeth based on the refined segmentation. Bounding boxes were generated for each detected instance, and a refinement algorithm was applied to eliminate inconsistencies in the segmented regions. Depending on the scenario, each tooth or group of teeth was numbered, and a detailed report was prepared listing the identified dental problems for each case to assist healthcare professionals in diagnosis [22]. In the same realm, a spectral film scanner was developed by Shrestha et al. [23] that utilized multiplexed LED illumination to digitize film images in color accurately. Simulations demonstrated the effectiveness of the multiplexed LED system, and experimental results confirmed that the scanner could produce precise color images using a relatively small number of LEDs. However, the study also revealed that increasing the number of LEDs raises noise levels, which negatively affects the scanner's performance beyond a certain threshold [23].

The other technological trend was fluorescence-based technologies. Fluorescence imaging has emerged as a particularly promising approach for noninvasive oral disease detection. Singh et al. [24] demonstrated that multispectral fluorescence imaging offers an objective way to

visualize dental abnormalities and assess the extent of bacterial infection. Since carious, calculus, and healthy teeth exhibit distinct fluorescence properties, the technique allowed for the clear delineation of affected areas within a tooth. The study attributed the reduced total fluorescence in abnormal samples primarily to enamel surface damage. Additionally, the researchers highlighted significant differences in the intensity ratios of porphyrin bands across healthy, carious, and calculus samples, supporting the potential of multispectral fluorescence imaging for large-scale in vivo studies aimed at validating its diagnostic effectiveness [24]. In a similar trend, a light-induced fluorescence (LIF) device was developed by Kim et al. [8] for visually detecting dental plaques, using a mobile app that delivers deep learning-based oral hygiene analysis. The device enabled users to assess their oral hygiene by checking in a mirror, while the app encouraged consistent hygiene management by providing time-series analysis results. The authors also proposed future plans to introduce LIF-based medical devices tailored for underserved populations, such as the elderly, individuals with low socioeconomic status, and those in rural areas. These plans included utilizing edge computing and creating affordable devices as smartphone accessories [8].

Fluorescence applications advanced further by Vetchaporn et al. [11], which demonstrated that an intra-oral camera with fluorescence capabilities could offer the combined benefits of traditional intra-oral cameras and conventional fluorescence devices. This made it an effective tool for screening dysplasia in oral potentially malignant disorders through teledentistry. Their study found that combining autofluorescence with white light LED examination enhanced the accuracy and reliability of detecting dysplasia compared to using autofluorescence alone. The results from optical fluorescence imaging were interpreted alongside the patient's clinical signs and symptoms. While a standard intra-oral camera cannot evaluate dysplastic characteristics of lesions, the addition of fluorescence aids makes it a more effective tool for identifying dysplasia in oral potentially malignant disorders [11]. Similarly, Pretty et al. [25] described a fluorescence imaging device to capture digital images of anterior teeth, accompanied by software to objectively measure the area and severity of fluorosis. The study included a convenience sample of 26 participants with varying degrees of fluorosis, as assessed by Thylstrup-Fejerskov (TF) index scores from 0 to 3. Each participant's upper left central incisor was evaluated using the TF index, photographed with a standard digital camera, and imaged with the fluorescence device. The TF index was subsequently applied to visually assess both digital photographs and fluorescence images, showing a strong correlation between TF scores and fluorescence data (Kendall's tau = 0.862). This indicates that fluorescence imaging provides a reliable, objective, and potentially blinded method for the longitudinal monitoring of enamel fluorosis in vivo [25].

The integration of AI with dental imaging has contributed to revolutionizing diagnostic capabilities. Al Kheraif et al. [26] proposed using 2D dental imaging combined with deep learning through CNNs to detect dental diseases. They collected approximately 1500 2D X-ray

images using an X-ray camera, creating a dataset split into 800 images for training and 700 for testing. The image pixels were analyzed to ensure quality, and affected areas were segmented by drawing scribble lines to identify different regions. The system efficiently analyzed the images, focusing on abnormal or disease-related features. The model evaluation demonstrated promising performance, achieving a precision of 97.07% [26]. Yauney et al. [27] demonstrated the effectiveness of two classifiers in accurately predicting the location of dental plaque in white-light dental images beyond random chance. Their fully trained and validated CNN, developed using both fluorescent biomarker images and expert-labeled data, can process standard white-light intra-oral images to identify plaque pixels with high sensitivity and specificity, eliminating the need for specialized devices or expert involvement. They also suggested that this approach could be extended to detect other conditions, such as oral cancer and early periodontal disease, and could be applied to nonoral fields where diagnostic biomarker imaging supports expert knowledge [27]. You et al. [28] introduced a novel AI model designed to detect dental plaque on primary teeth. The model achieved clinically acceptable performance levels, matching the diagnostic accuracy of an experienced pediatric dentist. These results highlight the potential of utilizing similar AI technologies to support children in improving their oral health [28]. Moriyama et al. [29] proposed a MapReduce-inspired model for estimating pocket depth, which conducts parallel extraction of pocket regions during the mapping phase and aggregates multidirectional information in the reducing phase. Their experiments revealed a weak correlation between pocket depth and the visual appearance of pockets, making it challenging to accurately diagnose moderate periodontitis using only oral images. However, the model demonstrated potential for effectively screening patients with severe periodontal disease. Additionally, the proposed system can serve as a home-based self-check tool, providing visual analysis comparable to that of a dentist [29].

These advancements also have led to the introduction of integrated smart systems and mobile applications for dental care. Won et al. [30] developed a handheld, portable optical coherence tomography (OCT) system for imaging dental plaque and gingiva in a clinical setting. This study evaluated the system's versatility and practical use for assessing oral health. The handheld OCT probe was operated by trained dental hygienists, even without prior experience with OCT, demonstrating the system's user-friendliness. The results showed that the OCT system effectively visualized dental plaque at various locations, including the enamel surface, the junction between enamel and gingiva, and between adjacent teeth [30]. Liu et al. [31] proposed an intelligent dental Health-IoT iHome system that integrates smart hardware, deep learning, and mobile technology to enhance the accessibility of dental care and provide efficient home-based dental services. The system includes a trained model for detecting and classifying dental diseases, along with mobile applications designed for both patients and dentists. These apps offer features such as pre-examination, consultation, appointment scheduling, and evaluation, facilitating seamless interaction between patients and dental

professionals. During a one-month trial across ten private dental clinics, the AI algorithm demonstrated over 90% accuracy in recognizing seven dental diseases, significantly improving patient engagement and optimizing clinic resource utilization, proving its reliability in real-world settings [31]. Datta and Chaki [32] proposed a cost-effective technique for detecting dental caries compared to other methods. This approach utilizes visible light, making it safe for human use, and achieves over 93% accuracy in identifying caries lesions. However, it cannot detect individual teeth if the tooth is broken and only analyzes the surface of the enamel, without assessing the depth of the caries. In such cases, X-ray imaging can provide additional insights. The study suggests that future work could focus on developing a comprehensive solution by integrating RGB and other imaging modalities to accurately detect both the shape and depth of caries lesions [32]. Bhan et al. [33] proposed an image-processing-based approach in their research, developing an automated software tool to assist dentists and orthodontists in efficiently identifying caries in dental X-ray images. This tool aims to reduce the effort and time required by eliminating the need for professionals to meticulously examine every edge in the X-ray images, minimizing eye strain and enhancing diagnostic efficiency [33]. Duong et al. [34] developed an automated method for detecting and classifying dental caries lesions using smartphone color images, following the international caries detection and assessment system II. This research paved the way for the creation of an AI-powered mobile application that provides users with early warnings about their oral health, helping them seek timely treatment at dental clinics or hospitals. Additionally, the application supports dentists by streamlining clinical examinations, enabling quicker, more accurate, and unbiased diagnoses for each patient [34].

Based on the literature reviewed, our research aims to address key technological and clinical gaps in oral health assessment through:

1. Enhancing visualization and diagnosis of oral conditions in LED images compared to regular images.
2. Exploring the potential to automate the identification of oral conditions using MATLAB with LED images.

4 Methodology

This study employed a mixed-methods research approach [35], integrating qualitative and quantitative techniques to develop and evaluate the custom-built multispectral LED imaging system for oral disease detection. The research followed a review of current oral imaging limitations, and expert consultations helped define the research gap and inform the device's design. A custom-built LED imaging system was designed to improve oral disease visualization. Oral images were captured using both traditional white-light imaging and the LED system at private dental clinics. The quantitative component involved statistical comparisons between LED images, MATLAB-processed images, and expert-annotated regions.

The mixed-methods approach ensured that the research combined scientific rigor with practical evaluation, making the findings more robust and applicable for real-world use.

4.1 Ethical Considerations.

The study was reviewed and approved by the Institutional Ethics Committee (IEC) of the Indian Institute of Public Health—Hyderabad/Public Health Foundation of India. Following ethics approval, the research was conducted at two private dental clinics in Hyderabad, India, where oral images were collected. A formal data collection request letter was provided to the participating dental clinics, issued by the HI Rapid Lab at the Indian Institute of Public Health, Hyderabad. The letter stated that the study focused on Custom-Built Multispectral LED Imaging for Oral and Dermal Conditions as part of a master's thesis. It emphasized that the IEC had granted approval for the research and requested support in collecting oral image data with due consent. Additionally, the letter assured the clinics that all collected data would be de-identified, securely stored at the institution, and used solely for research purposes. Permissions were secured from the administrators of the participating clinics to conduct imaging procedures on-site. The research team expressed gratitude for the clinics' support in facilitating the data collection process.

4.2 Data Collection Process.

A purposive sampling technique was employed to recruit 50 participants (16 males and 34 females) aged between 10 and 65 yrs old. Each participant underwent an oral imaging procedure, capturing 10 to 15 images from multiple angles, leading to a dataset of approximately 1000 to 1100 images. The imaging process involved capturing both standard white-light images using a mobile camera flash and multispectral LED-based images using the custom-built device. All images were taken in a controlled, darkened environment to minimize lighting variations. Special attention was given to ensure consistency in imaging conditions by using a cheek retractor to obtain clear views of the oral cavity (Table 1).

Table 1

Summary of dental data

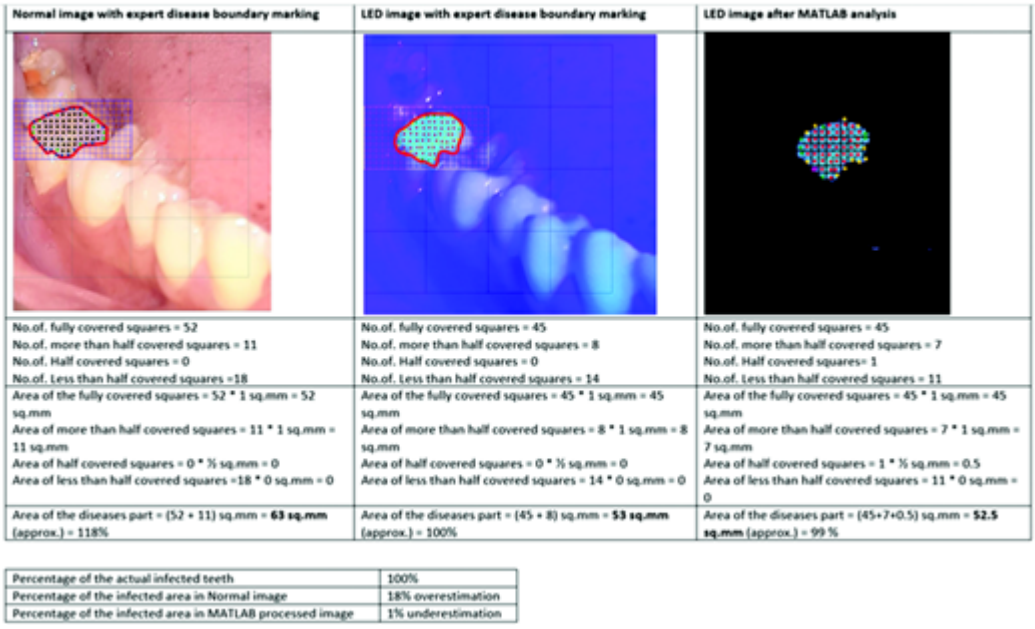
Condition	Subjects	Images
Normal dentition	3	45
Dental plaque	10	150
Dental calculus	10	150
Dental caries	13	180
Oral lesions	3	45
Teeth discolorations and stains	8	150

Condition	Subjects	Images
Attrition	10	200
Filling and artificial teeth	8	150

4.3 Image Preprocessing and Analysis Techniques.

The collected images underwent preprocessing to standardize brightness and contrast levels for consistent analysis. The MATLAB image processing tool was used to apply color thresholding and segmentation techniques, allowing the identification of diseased areas. A dentist manually annotated disease boundaries in images to serve as a reference for evaluation. The processed images were then analyzed using statistical methods to determine their accuracy in detecting oral diseases compared to traditional white-light images. To assess the effectiveness of the multispectral LED imaging system, three different image sources were compared: white-light images (standard mobile camera), multispectral LED images (custom-built device), and MATLAB-processed images. The primary evaluation metric was disease area detection accuracy, determined by comparing expert-annotated diseased regions with those detected in MATLAB-processed images as shown in Fig. 1. A grid counting (GC) method was used to quantify the diseased area, and correlation analysis (*r*-values) was performed to measure the relationship between LED-based and MATLAB-processed images. The results were analyzed to determine whether multispectral LED imaging provided enhanced disease visualization compared to traditional methods.

Fig. 1



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Analysis by comparing the diseased area values obtained by GC method from all the images (normal image, LED image, and MATLAB-processed image)

4.3.1 MATLAB Analysis—Color Threshold Analysis.

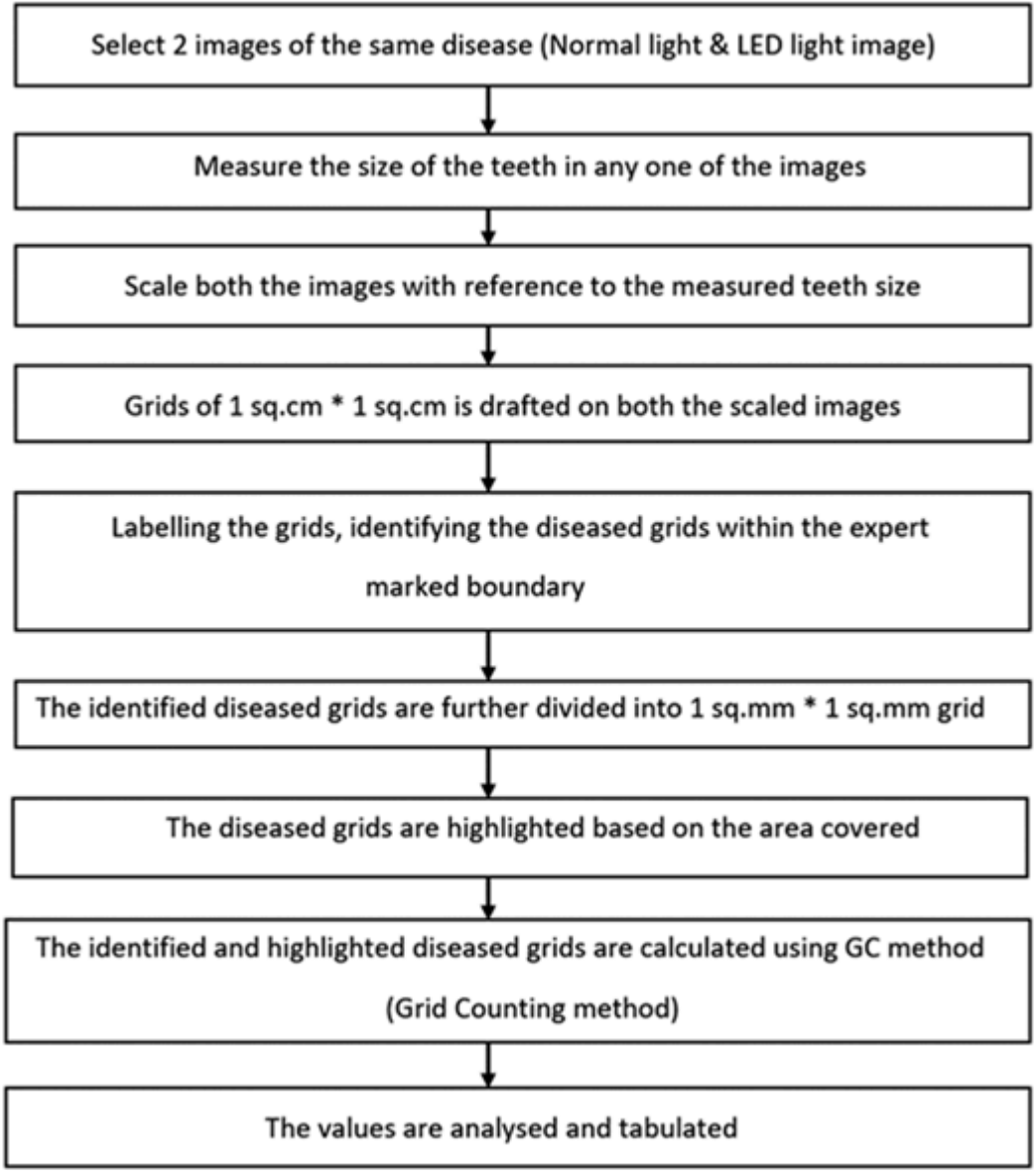
Thresholding is a technique that involves selecting a threshold (*T*) to isolate an object or multiple objects with similar values from the background. In color thresholding, the threshold is determined by minimizing the variance within the class between two pixel groups separated by the threshold [36]. The color thresholding method allows users to load an image and interactively adjust the RGB or hue, saturation, value (HSV) thresholds. With this function, users can define a region of interest, select or deselect pixels, and fine-tune the threshold filter by observing the resulting image and scatter plots of RGB/HSV values [37]. The tool supports segmentation across four color spaces, displaying the image, individual color channels, and a 3D plot of pixel values for each color space. Users can select colors in the mask by adjusting the color channel values or drawing a region of interest on the image or 3D plot. Among the tested color spaces—RGB, hue, saturation, intensity, and HSV—RGB was identified as the most effective for implementing the color thresholding technique. The threshold value is derived from the intensity ranges of the RGB components to extract the relevant segments from the image. This method leverages color information specific to oral diseases to isolate affected areas [38]. The essential features of the image are extracted by analyzing the properties of the RGB pixel. The color thresholding algorithm aims to accurately identify and extract pixels associated with the disease while excluding irrelevant features [36].

4.3.2 Grid Counting Method.

The analysis involves comparing the values of the diseased areas, as measured by the grid counting method across all images, as illustrated in Figs. 1 and 2. In this method [39], a grid overlay comprising boxes is applied to the dataset (demonstrated in Fig. 1). The number of boxes intersected by the boundary marked by an experienced dentist is counted, shaded based on the filled region, and then calculated to determine the area in square millimeters [39]. Quantitative data were analyzed using area values of the normal images/LED images/MATLAB-processed images. The images show an overestimation/underestimation of the diseased area.

Fig. 2

S



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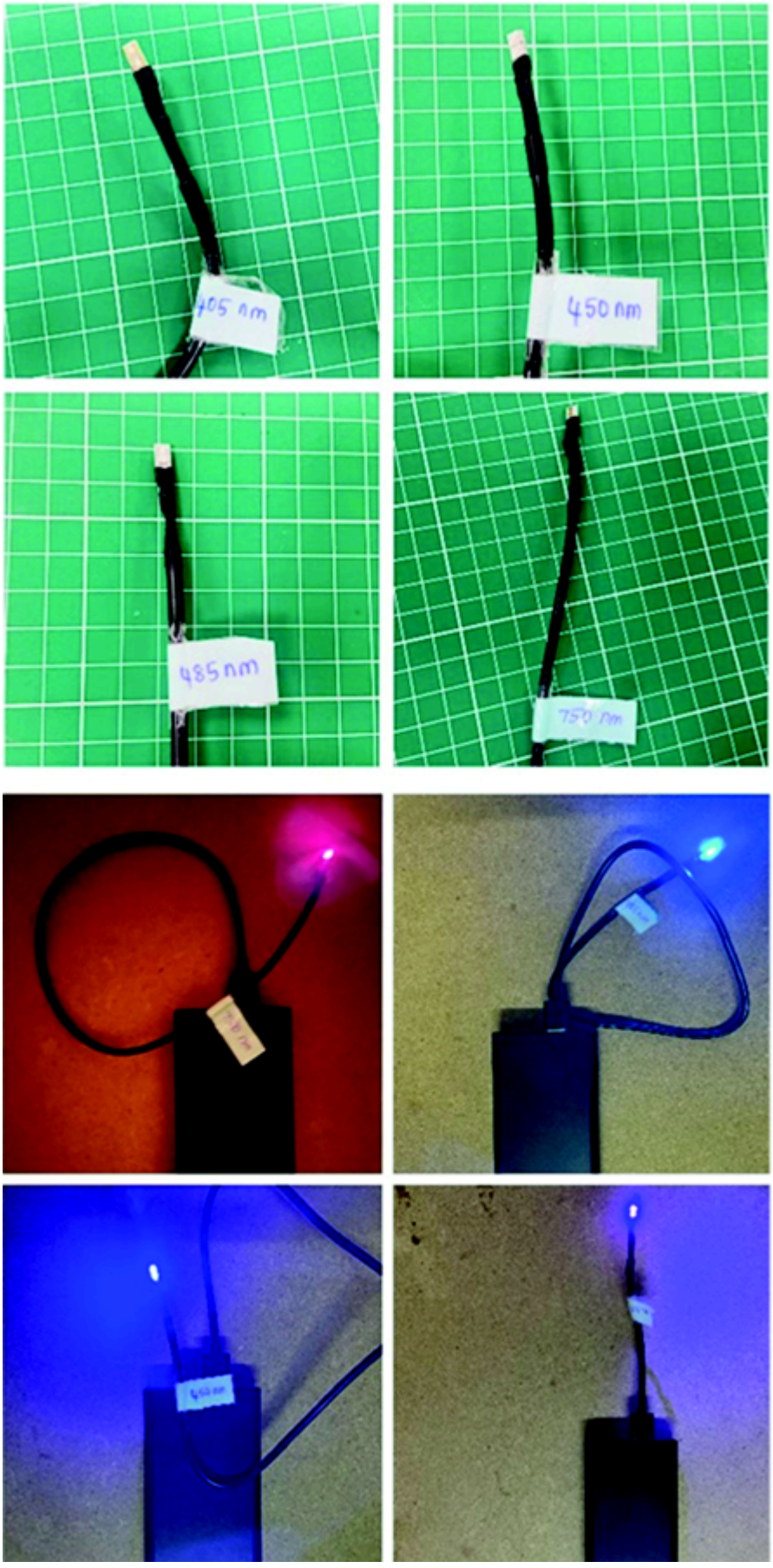
Work flow of study after data collection—GC method

4.4 Custom-Built Light-Emitting Diode Device and Its Features.

Our team developed custom-built multispectral LEDs as shown in Fig. 3, which can be powered by a power bank source and connected to different cameras at Hi Rapid Lab, Public Health Foundation of India, Indian Institute of Public Health—Hyderabad. We further finalized the wavelengths of all four types of LEDs after a literature search. Image-based disease identification using LEDs can be an ideal method to detect oral conditions quickly and easily. As this process is noninvasive, it will enable the documentation and detection of oral conditions at an early stage without causing discomfort for the patient.

Fig. 3

S



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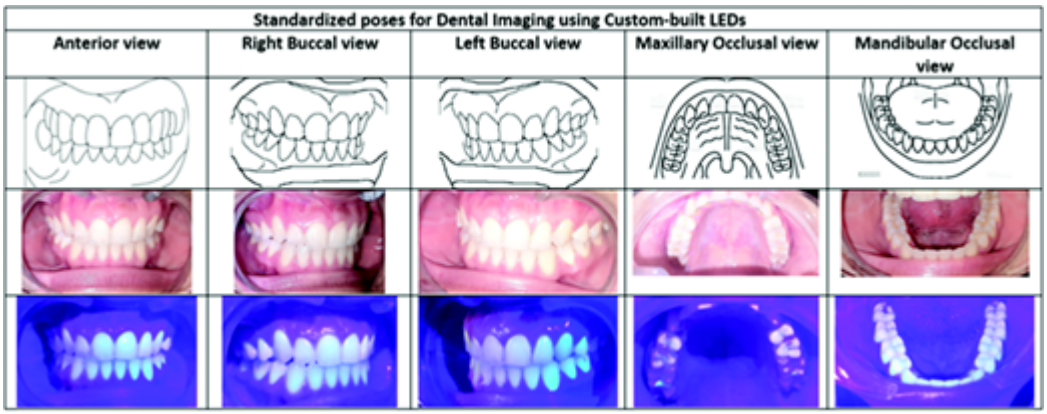
LEDs with the special wavelength tagged and lighten up with the power source

4.5 Technology Used.

This study employed a combination of hardware and software tools for capturing, processing, and analyzing oral images. The custom-built multispectral LED imaging device was utilized to

illuminate the oral cavity at specific wavelengths, enhancing the visualization of dental conditions. A standard mobile camera was used to capture white-light images, providing a baseline for comparison. A total of 50 samples were visually examined by an examiner using the custom-built LED imaging system. The images were captured following standardized imaging poses, as illustrated in Fig. 4. Subsequently, an experienced dentist was engaged to manually annotate the disease boundaries in the selected images, marking the extent of visible diseased areas. Simultaneously, MATLAB was used to automate disease detection by analyzing the image dataset. A comparative analysis was conducted between expert-labeled images and MATLAB-processed images to assess the consistency and accuracy of disease area detection. The workflow of the analysis process is illustrated in Figs. 2 and 5, detailing the step-by-step execution of image processing and comparative evaluation.

Fig. 4



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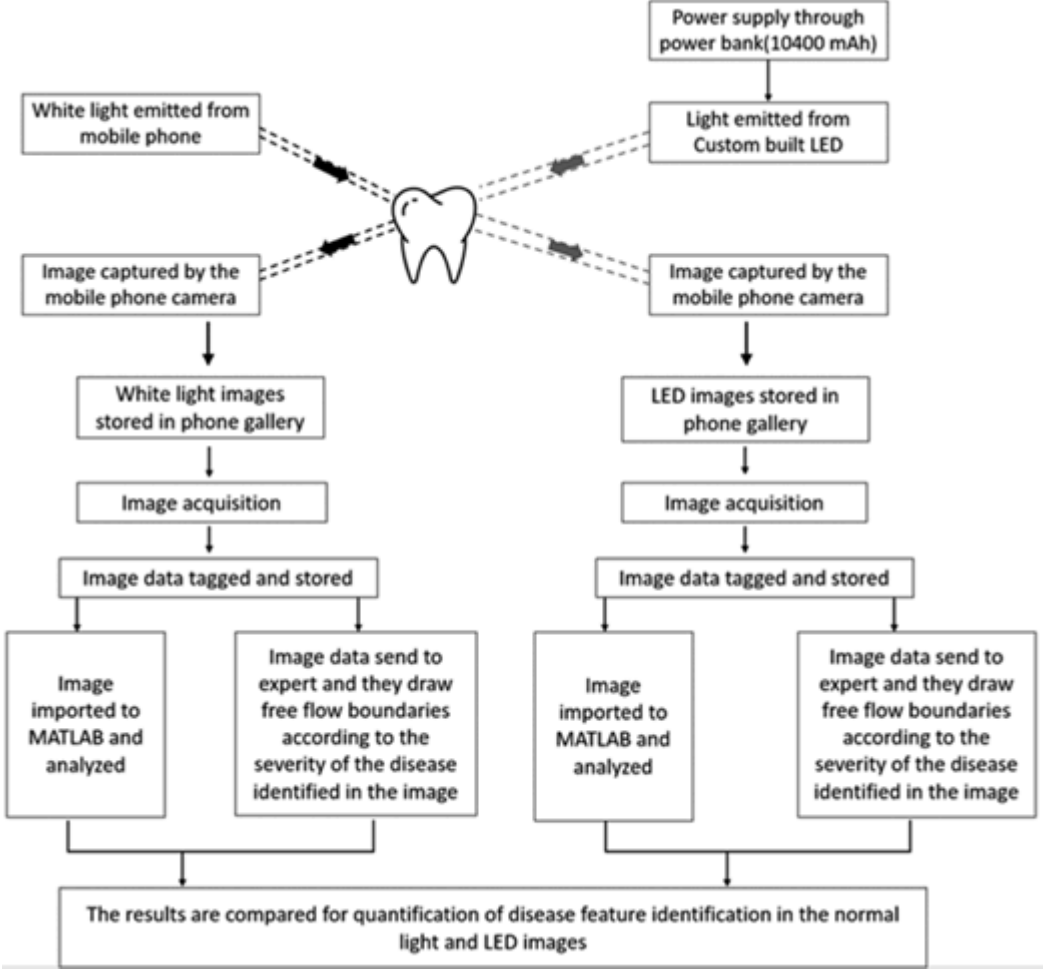
Standardized poses for photography

Fig. 5



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Workflow of study

4.6 Acquisition of Images.

The custom-built LEDs used in this study were portable ones. When the LED light (e.g., 405 nm) from the device fell on the surfaces of the teeth, the scattered light was detected through a camera and created the images. White-light images and LED images can be taken consecutively. A dentist captured both white-light and LED images using a mobile camera of different dental conditions in different patients using the white-flash light of mobile and custom-built LED devices after examining the tooth surfaces with a mouth mirror and dental probe. All images were taken in a darkened room and under the same lighting conditions. The soft tissues and lips were pulled with a cheek retractor to maximize the quality of the images taken [40].

4.6.1 Inclusion Criteria—(To Take Pictures).

Subjects with the following criteria were included in the study.

1. willingness to participate in the study
2. valid informed consent prior to the study procedure
3. male or female subjects of any age category
4. subjects with or without oral conditions

4.6.2 Exclusion Criteria—(For Taking Images).

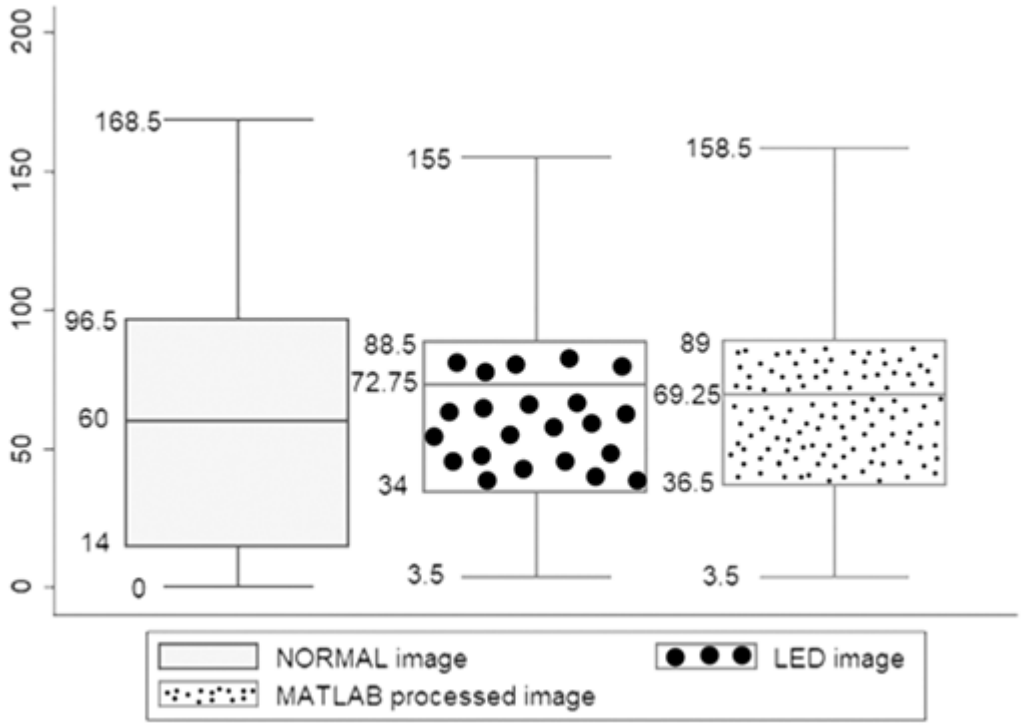
Subjects with the following criteria were excluded from the study.

1. Subjects with late-stage diseases (or) requiring hospitalization (or) with diseases requiring immediate treatment are excluded.

5 Results

The study's findings demonstrate the effectiveness of multispectral LED imaging in enhancing disease detection accuracy compared to traditional white-light imaging and MATLAB-processed images. A quantitative analysis was performed using the grid counting method to measure the diseased area in square millimeters across different imaging techniques. The results revealed that white-light images had the lowest detection capability, with a median diseased area of 60 mm^2, whereas LED-based imaging provided superior contrast, detecting a median diseased area of 72.75 mm^2. MATLAB-processed images closely aligned with LED imaging, identifying diseased regions with a median value of 69.25 mm^2, as shown in Fig. 6. These findings indicate that multispectral LED imaging significantly enhances disease visualization, making it a more effective diagnostic tool than conventional imaging methods.

Fig. 6



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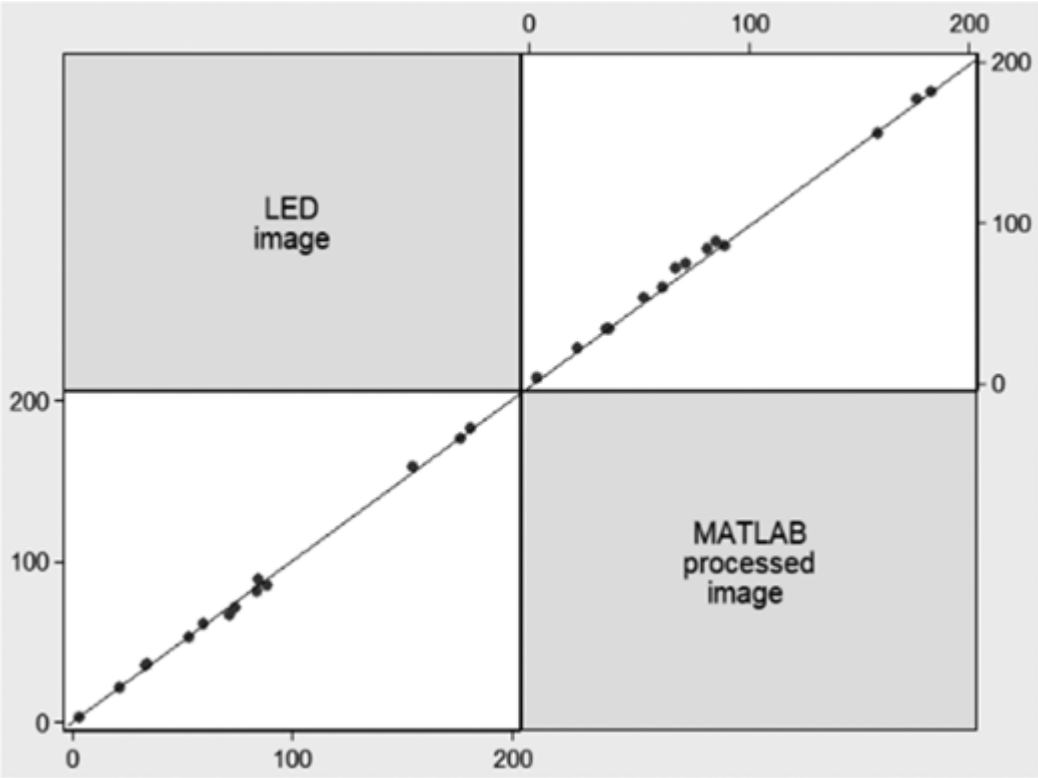
Boxplot shows the distribution of the diseased area in normal image, LED image, and MATLAB-processed image

To further refine disease segmentation, a color threshold analysis was conducted in MATLAB. This technique allowed for precise identification and extraction of diseased areas by utilizing the RGB color space, which was found to be the most effective for thresholding. The analysis confirmed that LED-based imaging produces clearer and more defined disease regions as shown in Fig. 1, supporting its potential use in automated image classification and diagnostic applications.

To validate the effectiveness and consistency of LED imaging, a correlation analysis was conducted across the three imaging techniques. The Pearson correlation coefficient (*r*-value) as shown in Fig. 7 was calculated to measure the agreement between different imaging modalities:

Fig. 7



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Graph shows the *r*-value of LED image versus MATLAB-processed image

- LED versus MATLAB: $r = 0.99 \rightarrow$ Strongest correlation, indicating that MATLAB segmentation closely aligns with LED-detected features.
- White-light versus MATLAB: $r = 0.82 \rightarrow$ Moderate correlation, suggesting that white-light imaging does not fully capture disease features.
- LED versus white-light: $r = 0.75 \rightarrow$ Weakest correlation, confirming that white-light imaging underestimates the diseased area compared to LED imaging.

The study demonstrated that LED-based imaging achieved over 90% precision in detecting nine common dental diseases, significantly improving primary diagnosis accuracy. The high

correlation ($r = 0.99$) between LED and MATLAB-processed images suggests that this approach can be seamlessly integrated into AI-driven automated diagnostic platforms, enabling efficient and scalable disease detection.

A paired *t*-test was conducted to assess the statistical significance of differences between the imaging techniques. The results confirmed that LED-based imaging significantly outperformed white-light imaging ($p < 0.05$), reinforcing its superior disease detection capability. However, no significant difference was found between LED and MATLAB-processed images ($p > 0.05$), indicating that MATLAB-based segmentation provides a computationally reliable alternative to expert-annotated LED images.

5.1 Strengths of the Research.

This study has several notable strengths in methodology and clinical relevance. First, the diagnostic approach is entirely noninvasive, eliminating patient discomfort and potential procedural complications. The system's portable nature and user-friendly interface enable deployment across diverse clinical settings, from established dental facilities to remote healthcare locations. An original device prototype was developed to enhance the diagnostic process. Although similar devices exist on the market, they generally focus on specific diseases; in contrast, our prototype is designed to detect a broad range of dental conditions and is also adaptable for the visual diagnosis of dermal diseases. Approximately 1000 to 1100 images were captured, covering about ten different dental diseases. This differs from the study by Zheng and Hu [41], which collected 3000 images focused solely on dental caries. Standardized photography poses were followed to ensure consistency, and participant identities were de-identified throughout the study to maintain confidentiality. A key technical advantage is the ability to generate real-time imaging data, allowing immediate clinical decision making and patient communication. From a resource optimization perspective, the method demonstrates significant cost-effectiveness compared to conventional diagnostic tools. Notably, the absence of consumable reagents for disease visualization substantially reduces ongoing operational costs while maintaining diagnostic efficacy. This economic advantage makes the technology particularly suitable for large-scale screening programs and resource-limited settings. The system's compatibility with teledentistry platforms represents another crucial strength, enabling remote consultation and expanding access to specialist expertise in underserved areas, as discussed in Refs. [22,31], and [32]. Its demonstrated efficacy as a primary screening tool for the early detection of oral diseases improves preventive care capabilities within the oral healthcare ecosystem. Furthermore, minimal training requirements for operators expand the potential user base beyond dental specialists to include allied health professionals and community health workers, facilitating greater implementation in public health initiatives.

5.2 Research Limitations.

This study acknowledges some limitations that warrant consideration. A primary technical constraint was the utilization of a conventional camera system, which required a partially darkened environment to effectively isolate the desired light wavelengths. While this approach proved functional, it introduced certain operational challenges and potential variability in image acquisition conditions. Future iterations of the system would benefit from the integration of specialized spectral cameras capable of selective wavelength capture, thereby eliminating the need for controlled lighting conditions and potentially enhancing image quality and diagnostic precision. The study utilized a sample size of 50 subjects, with a limited number of images per disease due to its exploratory nature. Additionally, as the device is still in its initial prototype stage, further development and refinement are required to design and construct it in a more conventional and user-friendly manner for effective use in clinical settings. Additionally, the requirement for a cheek retractor during image acquisition, while necessary for comprehensive visualization of the oral cavity, presents certain practical limitations. This requirement may impact patient comfort and necessitates additional procedural steps, potentially affecting the workflow efficiency. Although the retractor ensures standardized imaging and full mouth coverage, this aspect of the protocol could benefit from future design modifications to improve both patient experience and clinical practicality. These limitations, while not substantially impacting the overall validity of our findings, provide valuable insights for future technological refinements and protocol optimizations.

6 Discussion

In this article, we implemented and validated a prototype system (custom-built LED) to image the oral cavity and quantify images to detect oral diseases, which is being developed to perform primary oral health screening. Recently, in a similar way, an LED camera equipped with a light-induced fluorescence evaluator (such as VistaCam, Soprolife, and Soprocare) has been developed and clinically validated to improve diagnostic capabilities, serving as a supplement rather than a replacement for clinicians [6,8,20]. These IOCs feature a unique “Cario” mode, which displays different colors to distinguish between healthy, infected, active, and arrested dentin. They provide a magnified view of teeth, along with autofluorescent images of carious enamel and dentin, which aids in diagnosis, treatment monitoring, excavation, and restoration. In addition, they allow for early detection of at-risk pits and fissures for timely sealing. Peycheva and Boteva [42] reported in an in vitro study that LIF with Soprolife IOC accurately diagnosed occlusal fissure caries, though it did not outperform the ICDAS method [43]. The system offers several advantages, including the ability to compare pre- and post-treatment images, capture high-resolution magnified images, and provide reliable scores to avoid unnecessary interventions. Jablonski-Momeni et al. [44] compared a near-infrared imaging system (VistaCam iX Proxi) with conventional radiographs to detect proximal enamel lesions, finding moderate agreement between the methods but no significant differences. A systematic review of LIF with Soprolife concluded that more studies

are needed to confirm its effectiveness in diagnosing occlusal caries. Signori et al. [45] validated intra-oral digital photography using IOC to assess restorations, showing fair to moderate agreement between IOC-based assessments and clinical evaluations. IOC provided benefits such as permanent archiving, repeatable assessments, blinded evaluations, and enabling a single examiner to assess restorations across multiple centers. However, the monitoring of pit and fissure sealants remains underexplored. Al Kheraif et al. [26] used IOC and transillumination to diagnose incomplete cusp fractures, typically identified through patient symptoms. Their approach involved capturing photographs of fractures for archiving and sharing with patients. IOC also has potential applications in diagnosing conditions like pulpal exposure, pulp polyps, and tooth wear, though further research is needed to evaluate its efficiency. Reports on the use of IOC to diagnose plaque, calculus, and gingival inflammation are limited. In these cases, a plaque disclosure solution may be required as minimal plaque is difficult to detect with LED-based IOC due to color clipping effects, which could also mask early signs of gingivitis. In a comparison of single-lens reflex cameras and IOCs for plaque detection, the single-lens reflex system with image analysis and custom frame was found to be more reliable. Staudt et al. [46] introduced a standardized image analysis system using IOC, offering easier access to lingual surfaces, greater objectivity, and sensitivity to small changes in plaque, making it useful for clinical trials. The Soprocare IOC features a "Perio" mode, which addresses some limitations of conventional IOC by highlighting soft and hard deposits with distinct color schemes and magnification. A study evaluating the Perio mode showed higher plaque scores and slightly lower gingival scores than conventional methods, indicating that it is a reliable tool. This mode allows patient education and tracking of treatment progress through repeated image comparisons at follow-up visits. Rechmann et al. [47] analyzed the Soprocare system in Perio mode, correlating its scores with the Turesky modified Quigley Hein microbial plaque index, demonstrating its ability to detect and score microbial plaque effectively. Shakibaie and Walsh used the VistaCam system to compare fluorescence readings for calculus and caries, finding significantly higher readings for calculus [48]. These readings were not affected by saliva or blood but showed some overlap between subgingival calculus and root caries. Further studies explored the feasibility of mobile phone cameras and the WhatsApp platform for remotely screening oral premalignant lesions. The results indicated substantial agreement between remote app-based and clinical diagnoses when classifying lesions as normal or abnormal, suggesting mobile-based screening as a viable alternative. IOCs also show promise in diagnosing and referring conditions that affect oral mucosal regions and could be essential tools to image areas that are difficult to reach in the oral cavity. Future research should explore these potential applications further [49].

The custom-built LED device prototype offers numerous future applications, including supporting treatment, facilitating communication with experts for diagnosis and treatment decisions, and establishing protocols. It can also improve patient compliance and motivation throughout the treatment process and increase awareness of common oral conditions. In

addition, it enables seamless communication between patients, dentists, and healthcare providers remotely. This device provides users with a convenient platform for self-examination, allowing early detection and prevention of dental diseases through captured images, while also promoting better awareness and protection of oral health. Many people have limited understanding of oral health concepts, which makes it difficult for healthcare providers to explain treatment options. Using IOCs with custom LED technology can help familiarize patients with the treatment process before, during, and after care. Advances in information technology have transformed communication between healthcare professionals and patients, enabling remote real-time diagnoses and expert consultations through telemedicine platforms. In the future, a teledental platform will be developed, which integrates the dental device for consultations and follow-ups. The device's image data will soon be connected to AI-powered analysis using deep learning algorithms to detect dental diseases quickly and accurately, providing diagnostic support to dentists and reducing treatment time. In addition, plans are underway to offer remote screening services through an interactive dental health platform that facilitates appointments with nearby dentists, promoting affordable and time-efficient care. This system will optimize underutilized dental resources by connecting patients with idle clinics or primary health centers for lower-cost treatment. Currently, both the device and a mobile camera are needed to capture dental images. To streamline the process, the next prototype will integrate a prime lens and a LED, delivering high-definition images with optimal lens angles to ensure full coverage of the oral cavity, including both hard and soft tissues. As image quality significantly impacts AI analysis, future development will focus on improving hardware design and improving image acquisition efficiency. Further efforts will also focus on refining AI algorithms, increasing recognition accuracy, and building a more extensive dataset for the detection of dental disease.

7 Conclusion

These findings highlight the potential of multispectral LED imaging technology to improve early disease detection rates and optimize oral healthcare resources, particularly at the primary care level. This study shows that the developed hardware system helped visualize and diagnose oral conditions better in LED images than on regular images. This study also proved that automated diagnosis of oral disease using LED images by MATLAB was possible, to aid remote and early diagnosis of oral disease, as well as to provide home-based dental health care service more efficiently. This study proposes a hardware system for imaging and quantifying fluorescence imaging in the oral cavity to detect oral diseases to regulate and optimize the accessibility of dental treatment and provide home dental health care service more efficiently. We have clinically validated the prototype to detect diseases, and AI application software can be developed on the mobile terminal for use at the primary level more efficiently. The software platform will include pre-examination of dental disease, consultation, appointment, evaluation, oral health awareness videos, and make the service

docking between the people and the dentist/healthcare worker a reality. Similar devices are available in the market currently, but by focusing on specific diseases, our prototype is designed in a way to cover a wide range of dental diseases, and further it can be used for visual diagnosis of dermal diseases. This device will help monitor oral health at the primary level and promote awareness of oral health among the population. The innovation of this study lies in our proposed method, which relies solely on dental images to inform healthcare providers about the dental condition of a patient. It can also detect any decline in oral health over time, enabling timely alerts. This information allows healthcare providers to recommend the most appropriate treatment or hygiene practices to improve patient oral health. The high reliability of the LED imaging device suggests that it can serve as a valuable tool for early diagnosis and preventive oral healthcare, supporting greater adoption in home screening, teledentistry applications, and large-scale public health programs.

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- HI Rapid Lab, Hyderabad, India.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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