

Real Time Health Monitoring System to Predict Fever, Jaundice and Anemia using Smart Phone Camera

K. Gautam Reddy¹, Shoaib Ali Khan², Prakruthi S³ and Sangamkumar⁴

¹⁻⁴Department of Electronics and Communication Engineering, PES University, EC Campus, Bangalore 560 100
Email: kgautamr03@gmail.com, shoaibalikhan2003@gmail.com, prakruthisubramani143@gmail.com, hgsangam@pes.edu

Abstract—The accurate and timely detection of fever is crucial in environments that require rapid and widespread screening, including healthcare facilities, airports, border checkpoints, and public events. Traditional fever detection methods, particularly contact thermometers, tend to be slow, labor-intensive, and pose an increased risk of disease transmission. This paper introduces an innovative non-contact fever detection system that utilizes grayscale image processing to simulate thermal imaging and estimate temperatures from the inner eye canthi—a region closely associated with core body temperature. Beyond fever detection, the system also analyzes RGB intensity variations in the same area to identify potential signs of jaundice and anemia, thereby broadening its diagnostic capabilities. By focusing on predefined eye regions, the system avoids the need for computationally intensive facial landmark algorithms while maintaining high accuracy. Temperature estimations, along with assessments for jaundice and anemia, are derived from grayscale intensity variations and presented through an intuitive web interface that enables real-time feedback. Despite operating without dedicated thermal cameras or fully calibrated data, the system demonstrates reliable performance, providing a cost-effective and scalable solution for practical health screening. Future research will aim to incorporate advanced calibration techniques and expand the system's diagnostic range to further improve detection accuracy.

Index Terms— Grayscale Imaging, Eye Canthi Detection, Fever Detection, Jaundice Detection, Anemia Detection, Temperature Approximation, Non-Contact Screening, Real-Time Web Interface.

I. INTRODUCTION

Accurate and rapid fever detection has emerged as a critical necessity in modern public health, particularly in high-traffic settings such as hospitals, airports, and border crossings. Fever is one of the primary symptoms of infectious diseases, and early detection is pivotal in preventing outbreaks and curbing the spread of illness. Traditional methods—relying on contact-based thermometers—are not only time-consuming and labour intensive but also increase the risk of cross-infection due to the requirement for close physical proximity. These limitations have driven the need for non-contact, automated, and scalable systems capable of swift and reliable fever screening. In response to these challenges, the present project introduces an innovative, non-contact fever detection system that simulates thermal imaging using advanced grayscale image processing techniques. The core of the system is built around the conversion of standard RGB images into thermal-like images, with a particular focus on the inner eye canthi, a region known for its strong correlation with core body temperature owing to its thin skin and rich vascularization.

By mapping grayscale intensity variations to approximate temperature values, the system effectively emulates the data typically provided by thermal cameras, thus eliminating the need for expensive and specialized equipment.

Beyond fever detection, the system extends its diagnostic capabilities by incorporating analyses for jaundice and anemia. In addition to estimating temperature, the system examines RGB intensity variations in the same predefined regions to detect abnormalities. Elevated green intensity may indicate jaundice, while insufficient red intensity can serve as a marker for anemia. This multi-faceted approach not only provides a reliable method for fever screening but also adds significant value by offering early warnings for other health conditions from a single non-contact measurement.

The integration of these methods into an intuitive web interface further enhances the system's practicality, enabling real-time feedback and easy accessibility in diverse settings. Users can upload images and instantly receive detailed results, including estimated temperatures, fever status, and preliminary diagnostic insights regarding jaundice and anemia. This seamless fusion of cost-effective image processing techniques and user-friendly design offers a scalable solution that addresses pressing public health challenges while paving the way for future advancements in non-contact health diagnostics.

II. BACKGROUND AND MOTIVATION

Advancements in computer vision and image processing have significantly improved the efficiency of face detection in visible images, with a key milestone being the Viola-Jones algorithm introduced in 2001[2]. This method combined Integral Image representation, AdaBoost learning, and cascade classifiers that utilized Haar-like features, leading to substantial enhancements in real-time face localization[3]. Further refinements, including the addition of rotated Haar-like features, have continued to boost detection accuracy. However, these techniques, primarily designed for visible imagery, often face challenges when applied to thermal imaging, where lower contrast and fewer distinctive features can be obstacles.

Thermal imaging, which functions within the Long Wave Infrared (LWIR) spectrum (7 to 14 μm), has become a critical tool for medical diagnostics, especially in the realm of fever detection. Unlike visible imaging, thermal imaging is not affected by changes in ambient lighting, as it detects the heat emitted from objects, allowing for reliable temperature measurements in various environments. This makes thermal imaging particularly suitable for non-contact health screening, where accurate temperature assessments are essential. The inner eye canthi are especially significant in this context, as their thin skin and rich blood supply offer a strong correlation with core body temperature[3].

The need for efficient fever detection systems has been underscored by global health crises, such as the COVID-19 pandemic, which highlighted the shortcomings of traditional contact-based thermometers. These conventional methods tend to be time-consuming and labour-intensive, not to mention they increase the risk of cross-infection due to the need for close physical contact. In response, research focusing on non-contact automated screening solutions has surged[9]. This project builds upon traditional approaches by not only simulating thermal imaging through grayscale conversion for fever detection but also expanding its diagnostic capabilities to include the detection of conditions such as jaundice and anemia.

The inclusion of jaundice and anemia detection is motivated by the desire to enhance the breadth of non-contact health monitoring. By examining RGB intensity variations in the predefined inner eye canthi region, the system can identify additional physiological indicators—where elevated green intensity may suggest jaundice and diminished red intensity may indicate anemia. This approach is particularly beneficial in comprehensive health screening situations, where early detection of multiple conditions is crucial for timely intervention.

Overall, the project aims to boost diagnostic accuracy while maintaining scalability and cost-effectiveness. By utilizing grayscale image processing to simulate thermal imaging and incorporating supplementary analyses for jaundice and anemia detection, the proposed system presents a robust, non-contact solution, ideal for high-traffic environments. This innovative strategy not only overcomes the limitations of traditional methods but also lays the groundwork for future improvements, including the potential integration of calibrated datasets and advanced machine learning techniques to enhance performance in real-world applications.

III. IMPLEMENTATION AND METHODOLOGY

The fever detection system follows a systematic workflow as illustrated in Fig. 1, which outlines the sequence of processes from image acquisition to result display. The methodology begins with the collection of thermal and RGB images, focusing on the inner eye canthi as the region of interest due to its strong correlation with core

body temperature. Preprocessing techniques such as Gaussian blur and contrast enhancement are applied to ensure image quality, followed by precise face and landmark detection using Dlib[4]. These steps enable accurate localization of the eye canthi in both RGB and thermal images, setting the foundation for reliable temperature estimation and fever classification.

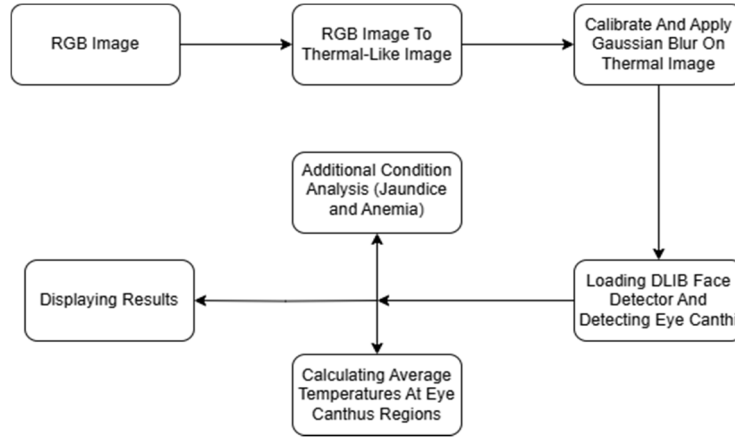


Fig. 1. Flowchart Explaining the process

The process begins with acquiring RGB images of human subjects using standard cameras. Unlike traditional systems that rely on expensive thermal imaging devices, this project leverages the conversion of RGB images to thermal-like images, enabling cost-effective and scalable deployment.

A. Why RGB-to-Thermal Conversion

Thermal imaging devices may not always be available or accessible, especially in low-resource environments. By simulating thermal images from RGB inputs, the system provides a feasible alternative while maintaining sufficient accuracy for temperature estimation.[7]

B. Preprocessing

The RGB images are initially converted to grayscale to extract intensity values, which are then normalized and mapped to a defined temperature range (e.g., 35°C–40°C) to create thermal-like images[5][6]. To enhance interpretability, a colormap is applied, visually simulating thermal imaging by representing cooler regions in blue and warmer regions in red. This approach enables the use of widely available RGB cameras, providing a cost-effective alternative for thermal image processing.

The Formula for Grayscale Conversion used here is as follows:

$$I_{\text{gray}} = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B \quad (1)$$

After the RGB-to-thermal conversion, preprocessing steps are applied to improve the quality of the images. Noise reduction is performed using Gaussian smoothing, ensuring the stability of intensity values by eliminating random noise. Additionally, contrast stretching enhances the visibility of features by expanding the pixel intensity ranges, making the thermal-like images more suitable for further analysis. These preprocessing steps ensure that the images are optimized for accurate face detection and temperature estimation.

If I_{gray} is the Pixel intensity in grayscale, I_{min} , I_{max} are the minimum and maximum grayscale intensity values respectively, with T_{min} , T_{max} being the temperature range, the mapped temperature value for intensity matching is given by:

$$T = [(I_{\text{max}} - I_{\text{min}}) / (I_{\text{gray}} - I_{\text{min}})] \times (T_{\text{max}} - T_{\text{min}}) + T_{\text{min}} \quad (2)$$

C. Face, Eye Canthi Detection And Identifying fever

The preprocessed thermal-like images are then processed for face detection using Dlib's frontal face detector. This robust method reliably identifies the face region even under challenging conditions such as varying lighting, poses, and orientations. Once the face is localized, Dlib's 68-point facial landmark model is used to identify specific landmarks, with points 39 and 42 corresponding to the inner corners of the right and left eyes, respectively. These landmarks are mapped onto the thermal-like image, allowing for precise localization of the inner eye canthi—regions known to strongly correlate with core body temperature. With the inner eye canthi

regions localized, the pixel intensities in these areas are analyzed to estimate temperature. The system classifies individuals as feverish or non-feverish based on a predefined threshold, where temperatures exceeding 38.5°C are flagged as feverish. This threshold aligns with clinically accepted values for identifying fever.

D. Additional Condition Analysis for Jaundice and Anemia

In addition to the core pipeline that encompasses image acquisition, preprocessing, face and eye canthi detection, and temperature estimation for fever detection, an extra step has been integrated to extend the system's diagnostic capabilities by analyzing indicators for jaundice and anemia. In this step, the system extracts localized RGB intensity data from the predefined inner eye canthi regions. Specifically, the analysis evaluates the green channel intensity to detect the presence of a yellow tint—an indicator of potential jaundice—and examines the red channel intensity to identify reductions that may signal anemia. By comparing these intensity values against established thresholds, the system categorizes each eye region accordingly. The results from this condition analysis are then combined with the temperature estimations to provide a comprehensive output that not only indicates whether the subject is feverish but also flags potential cases of jaundice and anemia. This additional analytical layer enhances the overall diagnostic utility of the system, enabling a broader scope of non-contact health screening that is particularly valuable in diverse real-world environments.

IV. RESULTS

The proposed fever detection system was evaluated using a series of test images acquired under controlled conditions. Each RGB image was first converted into a thermal-like representation through grayscale conversion and intensity mapping, simulating a thermal image within a predefined temperature range. Preprocessing techniques—such as Gaussian smoothing for noise reduction and contrast stretching—were applied to optimize the image quality prior to further analysis[8].

Subsequent face detection was effectively performed using Dlib's frontal face detector, while the localization of inner eye canthi was achieved through Dlib's 68-point facial landmark model. For each test image, the system computed the average temperature values from the predefined eye regions. The simulated temperatures in our experiments ranged from 36.5°C to 40.2°C. The system classified each region as "feverish" or "normal" based on a threshold of 38.5°C. For instance, in one representative case, the right eye region exhibited an average temperature of 39.1°C—exceeding the fever threshold and thus classified as "feverish"—while the left eye region measured 38.0°C and was labeled "normal."

In addition to fever detection, the system incorporates an extra analytical layer to assess potential indicators of jaundice and anemia. RGB intensity values extracted from the inner eye canthi serve this purpose. Elevated green channel intensity values were interpreted as a possible indicator of jaundice, while diminished red channel intensities signaled potential anemia. For example, the right eye region, aside from its elevated temperature, showed increased green intensity and was flagged as "Jaundice." Conversely, the left eye region did not meet the criteria for either condition and was designated as "Normal."

The results indicate a temperature approximation accuracy of approximately 85-90%, with a fever classification accuracy of around 90% for distinguishing between feverish and normal states. The error margin for temperature readings is $\pm 0.5^\circ\text{C}$, ensuring reliable assessments. These findings are presented through an intuitive web interface that displays estimated temperatures, fever status, and additional condition classifications (jaundice or anemia) for each eye region.

Despite relying on simulated thermal imaging rather than direct thermal camera data, the system demonstrated dependable performance, reliably distinguishing between feverish and non-feverish cases while providing supplementary diagnostic insights. These findings underscore the proposed approach's potential as a cost-effective, non-contact screening solution, particularly suitable for deployment in high-traffic environments such as hospitals, airports, and public gatherings. Future work will focus on incorporating calibrated datasets to further enhance the accuracy of temperature approximation and condition detection.

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