An Intelligent System for Automated Monitoring and Control of Patient Conditions

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Abstract. This paper presents a contactless temperature monitoring and patient identification system intended to meet stringent sanitary requirements in modern healthcare. By integrating a Raspberry Pi 4, an MLX90640 thermal sensor accurate to ±1 °C, and a Pi Camera Module 2 with 90–95% face recognition accuracy, it enables rapid, noninvasive detection of abnormal temperatures while minimizing staff-patient contact. The sensor's 24 × 32 infrared array is fused with RGB frames for temperature assessment and identity verification. Controlled trials at ambient temperatures of 16 °C, 24 °C, and 26 °C consistently record ~33 °C on healthy foreheads, closely matching results from standard infrared thermometers. Minor temperature reductions occur with increasing distance, highlighting the need for proper alignment. Automated logging in a local SQLite database streamlines clinical workflows, allowing immediate retrieval of recorded data. Additionally, the approach significantly lowers staff workload by automating identification tasks, promoting safer, more efficient procedures. The findings underscore cost-effectiveness and scalability for continuous screening in diverse clinical environments, while reducing cross-contamination risks through rapid, contactless operation. Future efforts will broaden the dataset for enhanced algorithmic robustness, incorporate multi-parameter assessments of vital signs, and refine sensor calibration across variable conditions.
Overall, this solution offers a promising avenue toward improved operational efficiency and infection control, aligning with contemporary standards for data-driven medical practice.

Keywords: IoT platform, contactless temperature monitoring, patient identification, thermal imaging, Raspberry Pi, facial recognition, machine vision, nosocomial infection prevention, healthcare efficiency, clinical data management

1 Introduction

The outbreak and global transmission of COVID-19 are unprecedented, resulting in extraordinary challenges to health care infrastructures across the globe. It has irreversibly changed global public health paradigms and exposed glaring weaknesses in our healthcare infrastructure and infection containment strategies. As of 2023, the World Health Organization (WHO) reports over 765M confirmed cases and nearly 7M deaths globally — demonstrating the ongoing threat of viral transmission and the need for scalable, adaptive solutions. Gholami et al. [1] reported that during the early months of the pandemic with a meta-analysis of 28 studies involving a total of 119,883 healthcare workers around the world, about 52% of healthcare workers who were tested were confirmed positive for COVID-19. In absolute terms, the global toll is also shocking: an estimated 80,000–180,000 healthcare workers died from COVID-19 between January 2020 and May 2021 according to WHO, with the most likely number around 115,500 deaths [2]. On the other hand, the WHO has urged that concerted action will need to be taken to safeguard health care workers during and in the aftermath of the pandemic. Such measures include ensuring the availability of adequate personal protective equipment (PPE), prioritizing vaccination for medical personnel, and systematically monitoring infection rates and morbidity among medical staff. The post-pandemic surge in telemedicine has given rise to compact remote patient monitoring (RPM) systems capable of providing near-real-time alerts. Ko *et al.* [3] demonstrated the clinical viability of such systems. Systematic reviews by Abdulmalek *et al.* [4] and Rahaman *et al.* [5] converge on the need for secure, low‑latency pipelines and energy‑efficient design, while also highlighting the need of low-cost devices and problems associated with poor analytics on the fringes.

Fever is still one of the key symptoms the medical community relies on for early detection, but conventional means of screening — handheld thermometers, manual checks — have always struggled with reliability, efficiency and safety. Furthermore, even contactless temperature measurement usually needs a dedicated person to record the results and check that the equipment works. Such increases time costs and epidemiological risk. Modern hospitals thus need efficient, automated systems to help reduce the workloads of healthcare staff and the risks of infection. Mobile robots with low-cost but powerful hardware can perform preliminary monitoring tasks —like detecting temperature and identifying patients—while averting direct human contact.

Manickam *et al.* [6] highlight the role of artificial intelligence in improving detection accuracy and decision-making in IoMT-connected POC devices. Dubey and Tiwari [7] conclude that Artificial Intelligence (AI) algorithms that can successfully categorize patients rather than just enhance device functionality are what the market needs.

This innovation in automated health monitoring, particularly in high-risk conditions, has been catalyzed by recent advances in AI and Internet of Things (IoT) technologies in Elhanashi *et al.* [8] Kamil *et al.* [9]. Using an AMG8833 thermal imager, Abdullah et al. [10] implemented an ultrasonic sensor investigation and a pyrometer improved the temperature data accuracy with multiple linear regression to calibrate the data pipeline. During the COVID-19 pandemic, Astawa *et al.* [11] offered contactless solutions like Roboswab as efficient for early diagnosis that integrate thermal imaging with face recognition. Mabboux and Steinwendner [12] demonstrated embedded devices that can implement thermal screening are scalable and cost-effective and can be deployed widely during health emergencies. Spasov *et al.* [13] study demonstrate that an inexpensive MLX90640 infrared array connected to the Wi-Fi card is capable of generating indoor heat maps and transmitting them via a web interface, offering an economical alternative to classic IR cameras.

In response to these issues, the current study presents an alternative, autonomous robotic solution for contactless temperature measurement combined with facial recognition for patient identification. The system consists of an MLX90640 thermal sensor and a Pi Camera 2, both controlled by a Raspberry Pi 4 microcomputer. The modules are attached to a mobile robotic platform specifically designed for these operations and operate either autonomously or are teleoperated via programmed paths in high-risk / congested zones. The proposed platform utilizes advanced machine vision algorithms and embedded computing to enable accurate detection of body temperature anomalies and specific person identification for reduced cross-infection risk and effective medical intervention.
The flexibility of this platform is inherently suited to integration into advanced telemedicine systems, and the creation of so-called “smart hospital” ecosystems to enhance patient throughput, safety, and outcomes.

2 Material and Method

2.1 System for contactless temperature screening and face recognition

Our proposed system uses a Raspberry Pi 4 as the central processing unit, selected for its computational power, versatility, and cost-effectiveness in edge computing applications. The MLX90640 thermal sensor, a compact and high-resolution infrared array, is used for contactless temperature measurement, which provides accurate temperature readings across a wide field of view. In addition to the thermal sensor, the Pi Camera 2 is integrated for capturing high-resolution visual images, for face recognition and identification functionalities. The integration of thermal imaging with face recognition provides a dual-modality approach. The system takes advantage of the benefits of face recognition, which include user-friendliness and the absence of physical contact, unlike conventional methods such as card recognition or fingerprint scanning [4].
By collecting thermal data in conjunction with synchronized RGB images, we sought to determine the efficacy of this low-cost embedded system for real-time human subject screening and identification.

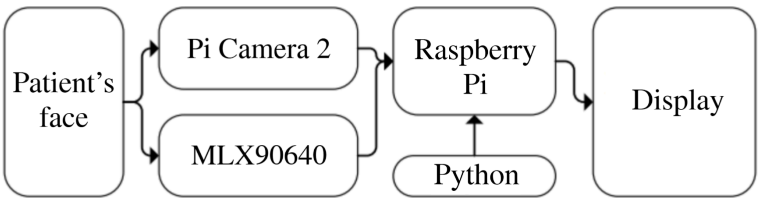

Figure. 1. System architecture for contactless temperature screening and face recognition.

The system workflow appears in Figure 1 as a schematic diagram. The Pi Camera 2 and MLX90640 serve as distinct sensing modalities which receive the patient's face as their principal input on the left side. Real-time signal processing occurs on the Raspberry Pi after both data streams enter the system. The Pi Camera 2 delivers a stream of digital images for face detection and recognition purposes while the MLX90640 provides temperature values from its 24×32 IR array pixels. The Raspberry Pi uses OpenCV computer vision library to combine the complementary data sources and produces a result that shows temperature measurements and patient name identification.

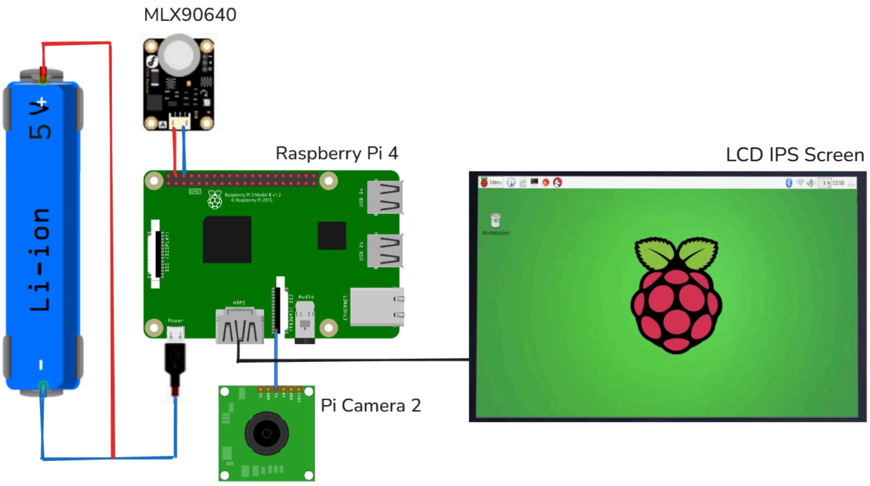

Figure. 2. Physical hardware layout of the system.

The schematic (see Fig.2) shows the core components and wiring of the proposed contactless temperature screening platform. A 5 V Li-ion battery (left) supplies power to the Raspberry Pi 4, enabling a portable or mobile setup that does not rely on stationary power sources. The MLX90640 thermal sensor is mounted above the Pi, interfaced via the I²C bus lines (SCL and SDA), allowing the board to acquire infrared thermal data in real time. Meanwhile, the Pi Camera 2 connects to the Pi through its dedicated CSI (Camera Serial Interface) ribbon cable, capturing high-resolution color images of the subject. An LCD IPS screen on the right displays the Raspberry Pi's desktop environment.

A. Raspberry Pi 4 Model B

The Raspberry Pi 4 Model B represents a paradigm in compact, low-cost computing that is particularly well-suited for embedded systems research and real-time applications. In the context of our study, the Raspberry Pi 4 Model B serves as the central hub for orchestrating sensor data acquisition and processing. It runs a Linux-based operating system (Raspberry Pi OS), which provides a stable and open-source environment conducive to both rapid prototyping and long-term deployment. The board utilizes a USB Type-C power input capable of delivering a steady 5 V at 3 A.

B. MLX90640 Thermal Sensor

The MLX90640 is an advanced microelectromechanical system (MEMS)-based infrared thermal sensor designed for cost-effective, two-dimensional thermal imaging applications. In our system, the MLX90640 functions as the primary means of capturing temperature data, providing a thermal image. The most important details are summarized in table 1.

Table 1. Specifications of MLX90640 Thermal Sensor.

Parameter	Specification
Resolution	24 × 32 (768 IR pixels)
Field of View (FOV)	55° × 35°
Temperature Measurement Range	–40 °C to +300 °C
Interface	I²C
Refresh Rate	0.5 Hz to 64 Hz

The area of the target object and the distance measured by the module are correlated according to the relationships outlined below:

$$S = \frac{D}{2 \cdot tan\alpha} \quad (1)$$

C. Pi Camera Module 2

The Pi Camera Module 2 is an essential imaging component for embedded vision applications, making it well-suited for real-time face detection and recognition tasks.

Table 2. Specifications of Pi Camera Module 2.

Parameter	Specification
Sensor	Sony IMX219, 8-megapixel CMOS sensor
Video Modes	1080p at 30 fps, 720p at 60 fps, 640 × 480 at higher frame rates
Field of View	Approximately 62.2° (diagonal FOV)
Interface	CSI (Camera Serial Interface)
Supported Frame Rates	Up to 30 fps in full HD

The table 2 was constructed based on standard specifications widely available for the Pi Camera Module 2. These key points capture the fundamental characteristics required for integration in a contactless temperature screening and face recognition system, ensuring readers can understand and duplicate the hardware configuration.

Accurate body temperature assessment has emerged as a critical frontier in modern medical diagnostics, particularly in the context of infectious disease surveillance and preventive healthcare. Traditional thermometric approaches, while foundational, often grapple with trade-offs between precision, invasiveness, and scalability. Advances in infrared thermography, however, have unlocked novel paradigms for non-contact, high-resolution temperature mapping.

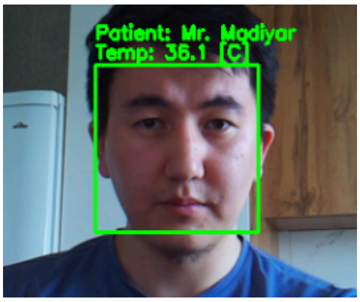

Figure. 3. Face recognition and temperature indicating.

The impressive accuracy rates of 99.49% in temperature detection and over 94% in mask identification showcase the systems reliability and efficiency, making it a valuable tool for mitigating the spread of infectious diseases, particularly in high-risk settings like nursing homes, as emphasized in Abdullah et al. [10]. The system described in the present study attains a 90-95% mean accuracy for the combined tasks of face detection and temperature indication.

Fig. 3 shows the output frame captured by the device. A green rectangular frame bounds the face area, while the superimposed label located at the top displays the name of the object and the corresponding body temperature estimate (in this case 36.1 °C). The results of detection and thermal measurements are displayed in the embedded platform in real time.

D. Database

id	username	temperature	record_time	abnormality_notification
1	Patient A	32.5	2025-04-12 08:30	Below Normal
2	Chingiz	35.4	2025-04-12 10:15	Normal Range
3	Madiyar	36.1	2025-04-12 14:52	Normal Range
4	Patient D	36.5	2025-04-12 14:46	Above Normal / Fever
5	Patient E	38.1	2025-04-12 14:40	Above Normal / Fever

Figure. 4. Measurement data stored in SQLite database

Fig. 4 presents a representative excerpt from the system's contactless temperature screening data in a lightweight SQLite database. Each row corresponds to an individual measurement event, including a unique identifier (id), the recognized username, the measured temperature in degrees Celsius, and a record_time timestamp indicating when the reading was acquired. The final column, abnormality_notification, provides an automated assessment of whether the recorded temperature is within the normal physiological range or indicates potential fever.

By leveraging SQLite's compact footprint and low overhead, the Raspberry Pi 4 can reliably store these data without necessitating external server connectivity. This architecture is especially advantageous in environments that demand real-time or offline operation. Additionally, the system can flag measurements that deviate significantly from baseline norms (e.g., "Below Normal" or "Fever Detected")—thereby streamlining triage and early warning procedures in scenarios where swift and systematic temperature monitoring is essential.

3 Results and discussion

The main research results can be summarized as follows. Laboratory tests demonstrated face recognition accuracy averaging between 90% and 95%, with a system response time of under three seconds. The MLX90640 sensor reliably measured body temperature within ±1 °C.

Fig. 5 depicts sample results from the contactless temperature measurement and face recognition system at three discrete subject-to-camera distances—50 cm (a), 100 cm (b), and 150 cm (c). On the left in each subfigure, the Raspberry Pi Camera 2 captures an RGB image showing the recognized participant ("Madiyar"), with a bounding box marking the detected face region and displaying temperature measurement. On the right, each thermal image (24 × 32 pixel grid) reflects the corresponding MLX90640 output, where the false-color scale ranges from lower temperatures (blue) to higher temperatures (red). Notably, the relatively low temperature recorded on the subject's forehead is attributed to the measurements being conducted in a low-ambient-temperature environment. To ensure accuracy, the readings were independently validated using an electronic pyrometer. The rectangular region in the thermal images highlights the face area used to compute and display the maximum or representative temperature value.

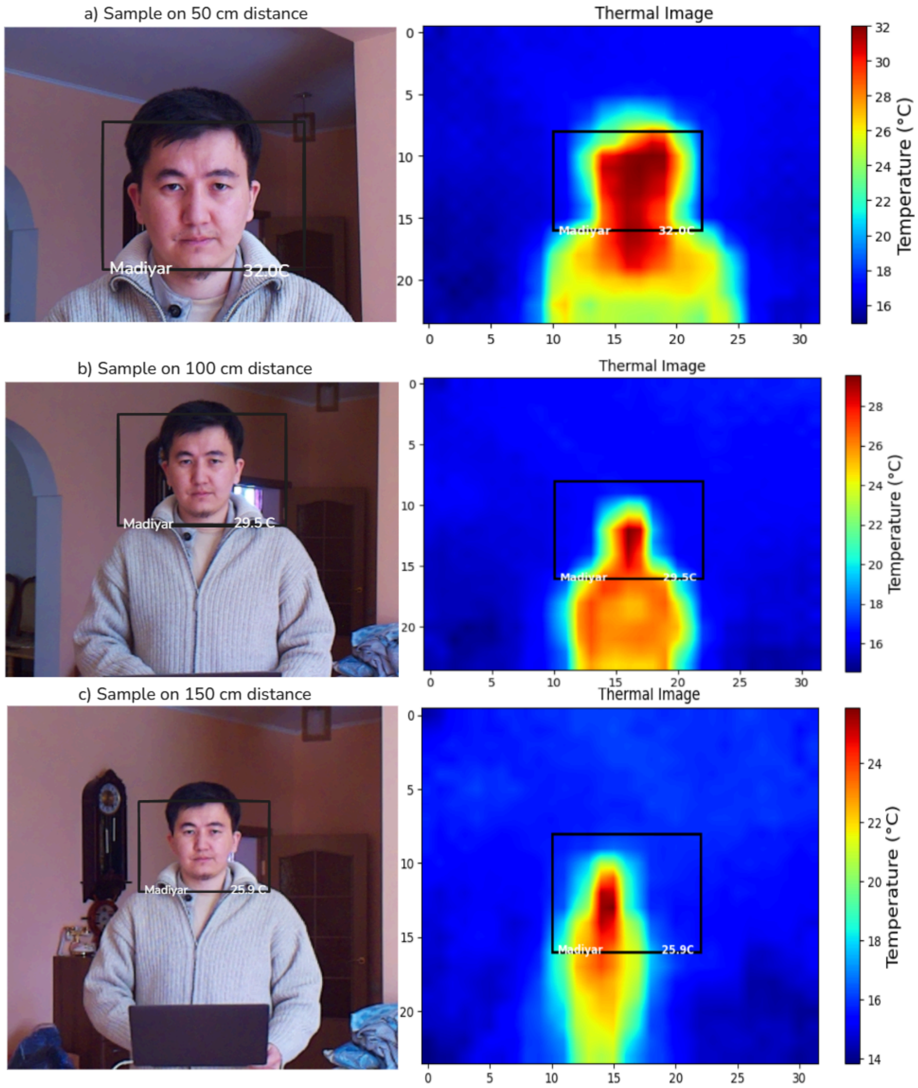

Figure. 5. RGB and thermal outputs at varying distances (50 cm, 100 cm, 150 cm)

A decline in the measured temperature (e.g., 32.0 °C at 50 cm, 29.5 °C at 100 cm, and 25.9 °C at 150 cm) occurs as the subject moves further from the thermal sensor. This trend arises primarily because the MLX90640, operating at relatively low spatial resolution, integrates a larger portion of the cooler background at greater distances, effectively reducing the apparent temperature reading of the face. Additionally, infrared irradiance diminishes with increasing distance, thereby lowering the temperature signal recorded per pixel. Nevertheless, the face detection and temperature annotation remain stable across all three distances, indicating that the combined system can successfully map and overlay thermal data on the subject's face in real time, albeit with diminished temperature precision as distance increases.

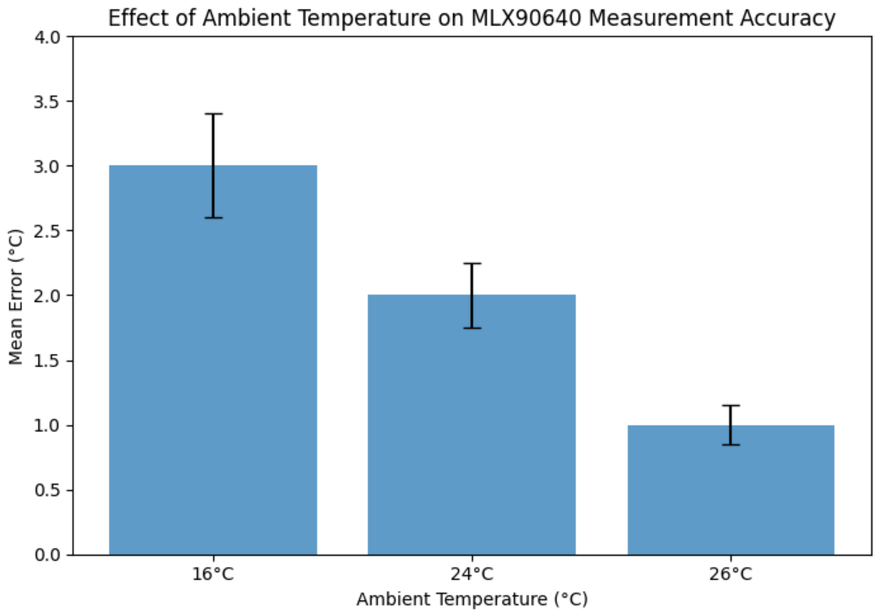

Figure 6. The forehead temperature values obtained using the MLX90640 sensor under three ambient conditions (16 °C, 24 °C and 26 °C).

Each strip represents the average value on the skin surface of the forehead of a healthy subject, and the vertical lines indicate the standard deviation. Mean forehead-temperature measurement error of the MLX90640 sensor decreases from ~3.0 °C to ~1.0 °C as ambient temperature rises from 16 °C to 26 °C (see Fig. 6). According Mah *et al.* [14] research, thermal imaging cameras can exhibit a measurement deviation of up to ±3 °C when used for assessing facial temperature. These results are consistent with findings in the literature indicating that ambient temperature has a substantial effect on forehead temperature readings. Chen *et al.* [15] found that, specifically, at lower ambient temperatures, significant discrepancies are observed between forehead and core (axillary or oral) temperatures, whereas at higher ambient temperatures, forehead temperature tends to converge toward core body temperature values.

4 Conclusion

The results of our research demonstrate that combining an MLX90640 sensor (accurate to within ~1 °C) with a Raspberry Pi 4 and a 90–95% accurate face recognition module produces a robust, contactless system for patient screening. In controlled trials at ambient temperatures of 16 °C, 24 °C, and 26 °C, the device reliably measured forehead surface temperatures.

Furthermore, automating both temperature logging and patient identification lowered staff workload and reduced infection risks by minimizing direct contact. These findings confirm that the proposed system successfully addresses both continuous temperature monitoring and biometric data collection in a single integrated setup. Future improvements will address face recognition under poor lighting, broaden the dataset to boost algorithmic accuracy, and integrate additional vital-sign sensors (e.g., heart rate), paving the way for a fully scalable, data-driven healthcare solution.

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