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Internet of Things (IoT) Model for the Detection of an Infectious Disease (COVID-19)

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Abstract
The COVID-19 pandemic, originating in late 2019 due to the highly transmissible SARS-CoV-2 virus, has precipitated a global health crisis with profound impacts on healthcare systems, economies, and societal structures. Despite advancements in vaccination and treatment development, persistent challenges endure due to viral mutations, necessitating continuous vigilance and robust screening efforts. In response, remote photoplethysmography (rPPG) technology has emerged as a critical tool for contactless heart monitoring during COVID-19 screening protocols. This innovation reduces virus transmission risks by eliminating physical contact during vital sign assessments, capturing crucial data including heart rate, body temperature, and oxygen saturation levels. The presented thesis investigates the utilization of IoT devices, incorporating an RGB camera and an infrared camera, to non-invasively predict the presence of COVID-19. The methodology entails video capture, frame extraction, facial detection techniques, and prediction of vital signs including body temperature, heart rate, and oxygen saturation. Leveraging an artificial neural network trained on a COVID-19 dataset, the implemented system achieves an impressive 95% accuracy in infection prediction. This system offers promising prospects to mitigate infection risks, enhance case detection, and find application across various settings, including entry points, containment zones, and home quarantine.

Keywords: COVID-19, Internet of Things (IoT), Lockdown, Vaccines, photoplethysmography,

1. Introduction

Infectious diseases are pathological conditions resulting from pathogenic organisms or their toxic byproducts, transmitted from infected hosts or contaminated surfaces to susceptible individuals [17, 6]. These diseases encompass various types, with viruses, bacteria, fungi, and parasites being the most prevalent. Pathogens spread through diverse routes, including direct skin contact, bodily fluids, airborne particulates, fecal matter, and contaminated surfaces. Notably, the recent COVID-19 outbreak, originating in Wuhan, China, in late 2019, has rapidly disseminated worldwide, exemplifying the potential of infectious diseases to precipitate global crises.

In recent years, the Internet of Things (IoT) has emerged as a multifaceted domain, garnering substantial attention across academic and industrial sectors, particularly within healthcare and educational institutions. Within the context of the COVID-19 pandemic, IoT-enabled devices and applications serve pivotal roles in mitigating transmission risks through early diagnosis, patient monitoring, and adherence to prescribed protocols post-recovery.

The unprecedented impact of the COVID-19 pandemic on educational systems is evident, with widespread disruptions and lockdown

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measures affecting approximately 1.6 billion learners across more than 190 countries and continents [16]. These disruptions have necessitated the closure of educational institutions, religious centers, commercial establishments, and government offices, with remote work advisories becoming prevalent.

Given the current scenario, a pertinent query arises regarding the timing and conditions for easing lockdown measures to facilitate economic and societal reopening while mitigating the risk of a potential resurgence of COVID-19 cases. Despite limited vaccination coverage, with only 0.7 percent of Nigerians fully vaccinated, there remains a critical need for innovative solutions to augment detection and containment efforts.

In light of these considerations, this study endeavors to leverage IoT technology to develop a walk-through scanner model for the detection of COVID-19. By harnessing IoT capabilities, this model aims to enhance screening efficiency, enabling rapid and contactless identification of the virus, thereby contributing to the overall containment strategy amidst the ongoing pandemic.

2. Review of Literature

The integration of IoT technology into healthcare, as highlighted by Nasajpour, *et. al.* [10], is increasingly recognized as a promising avenue for addressing the formidable challenges posed by pandemics such as COVID-19. Wang *et al.* [19] echo this sentiment, highlighting the strain on healthcare systems and the consequential loss of essential manpower during such crises. Consequently, there is a pressing need for innovative solutions to mitigate the impact of pandemics on both individual health and global economies.

Researchers have extensively studied temperature detection, a cornerstone of COVID-19 screening efforts. Wang *et al.* [18] stress its importance in early case detection, albeit acknowledging limitations such as the variable presentation of fever among infected individuals, as noted by Oran and Topol [11] and Chen *et. al.* [4]. Islam and Rashedul [8] further elucidate the multifactorial nature of temperature readings, highlighting environmental and physiological variables that may affect accuracy. At the same time, pulse oximetry has become an important tool for finding COVID-19. It lets doctors keep an eye on oxygen saturation levels and pulse rates so they can act quickly when a patient's condition gets worse.

Advancements in breath analyzer technology, as elucidated by Rashedul and Pfefer [12], offer promising avenues for rapid COVID-19 diagnosis, boasting impressive accuracy rates and expedited testing times. However, to ensure widespread applicability and reliability, further validation and standardization are necessary. Laboratory testing remains pivotal in confirming COVID-19 infections, with various modalities such as nucleic acid detection, antigen testing, and antibody testing. The CDC [3] underscores the need to take precautions to ensure sample integrity and accuracy, even though each method serves a distinct purpose.

Empirical research has explored diverse approaches leveraging IoT technology. Salama and Eassa [15] propose a cloud-based blockchain model for infection spread control, emphasizing early detection and contact tracing. Similarly, Wankhede *et. al.* [20] investigate the efficacy of machine learning algorithms in COVID-19 detection, highlighting the potential of federated learning for decentralized data processing. Reddy *et. al.* [14] present an IoT-based system for intelligent face mask and body temperature detection, offering a low-cost solution to enforce COVID-19 safety protocols. Aldahiri and Hussain [1] leverage IoT and machine learning for health prediction systems, aiming to optimize resource allocation in healthcare settings.

Furthermore, Islam and Rashedul [7] design a comprehensive IoT-based healthcare system for real-time patient monitoring, emphasizing the importance of data analytics in crisis management. Petrović and Kocić [13] contribute to indoor safety monitoring for COVID-19, highlighting the role of IoT technology in implementing protective measures.

In summary, the integration of IoT technology into healthcare holds immense promise for addressing the multifaceted challenges posed by pandemics such as COVID-19. By leveraging innovative technologies and empirical research, stakeholders can collaboratively develop effective strategies to mitigate the impact of infectious diseases on global health and economies.

3. System Analysis and Design

The IoT-based walk-through scanner system comprises multiple layers, from the application layer for visualization and configuration interfaces, through the network layer transmitting data over the Internet, to the perception layer consisting of sensors and devices like RGB Webcam, IR camera, Arduino board, and Router. Here is a description taking these layers as shown in Figure 1into consideration:

Application Layer: At the application layer, there are several interfaces:

- **Visualization Interface**: Users interact with the system through a user-friendly interface that displays real-time data, such as temperature readings, video streams, and system status.
- **Configuration Interface**: Administrators configure system settings and parameters through a dedicated interface, allowing customization and adjustments to the operation of the walk-through scanner.
- **Web Service API:** The system exposes a web service API for seamless integration with other applications or platforms, enabling data exchange and interoperability.

Network Layer: Data transmission occurs over the Internet, facilitated by networking technologies. The system leverages network protocols to securely transfer data between different components and remote servers. This layer ensures reliable communication between the walk-through scanner and cloud-based services.

Perception Layer: The perception layer consists of various sensors and devices.

- **RGB Webcam**: Positioned at the entry section, the RGB webcam captures video footage of individuals passing through the scanner. The cloud receives this visual data for further analysis.
- **IR Camera**: Mounted alongside the RGB webcam, the infrared camera measures the body temperature of individuals using non-contact thermal imaging technology, providing valuable health information.
- **Arduino Board**: A microcontroller similar to the Arduino processes incoming signals and controls the system's response based on predefined algorithms. It interacts with sensors, triggers alarms, and communicates with other components.
- **The router** facilitates network connectivity, ensuring seamless communication between the walk-through scanner system and external servers or databases.

In operation, when an individual enters the scanner's vicinity, the motion detector at the entrance triggers the system. The individual is prompted to face the cameras for a designated period of time. The IR camera captures temperature readings, while the RGB webcam streams video data to cloud servers hosted on platforms like Google Cloud Platform (GCP) and Amazon Web Services (AWS). Video processing algorithms analyze facial regions of interest (RoIs) to extract raw blood volume pulse (BVP) signals, which are further processed to compute vital signs like heart rate (HR) and blood oxygen saturation (SpO2).

The results, along with any detected anomalies indicating a potential COVID-19 infection, are stored in a cloud-based database. The network sends an alert back to the Arduino board if it detects a possible infection. The Arduino triggers an alarm, notifying nearby personnel of the potential risk. A medical facility isolates the individual and directs them to undergo further screening and treatment. Additionally, the walk-through scanner system incorporates a lightning system for night visibility, enhancing its usability and safety under low-light conditions.

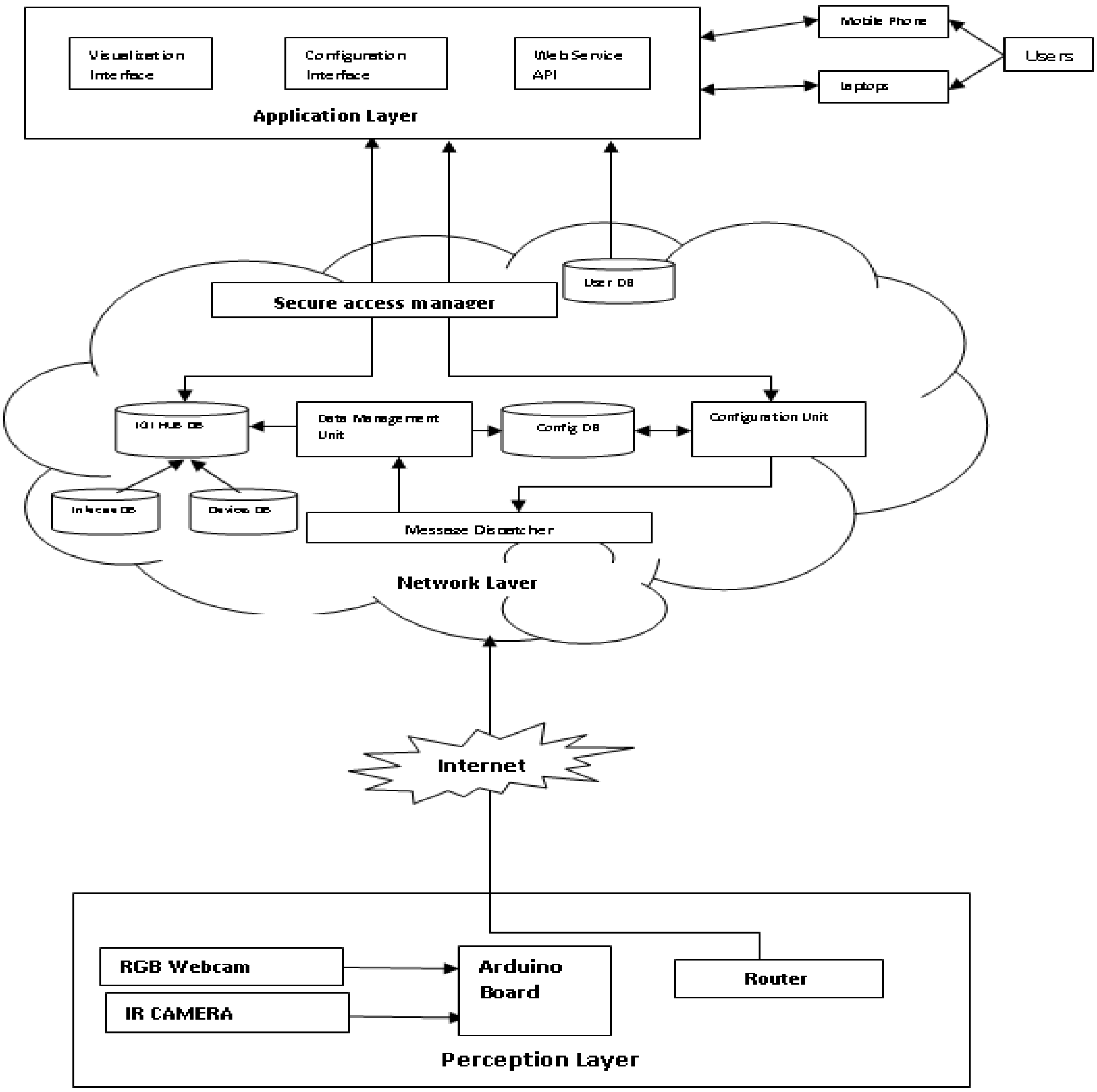

Figure 1: Architectural design of the developed system

Mathematical Model

The mathematical model for the IoT – based walk-through scanner, as described, involved multiple steps for processing physiological characteristics such as heart rate, oxygen saturation and temperature. Additionally, there is a neural network model for detecting possible COVID – 19 infection-based on these characteristics. Below is a summary of the mathematical models involved:

1. **Physiological Characteristics Processing:**

- Motion detection: upon entry, motion detection triggers the person to look into the camera for 30 seconds.
- Image processing:
  - Infrared and RGB cameras capture video frames.
  - Check for appropriate luminance and brightness
  - Face detection through segmentation into regions of interest (ROIs).
  - Extract raw blood volume pulse (BVP) signals from multiple ROIs
  - Median blur image filtering for noise reduction
  - Fast fourier transform (FFT) for color segmentation and frequency domain isolation.
  - Derive heart rate: *Heart Rate* (BPM) = *Peak frequency* x 60
  - Derive oxygen saturation:
  - $SpO2 = \frac{HbO2}{HbO2 + Hb} \times 100$
  - Derive temperature using Stefan – Boltzmann formula

2. **Neural Network Model for COVID – 19 Detection**

- Define input features x_1, x_2, x_3 as oxygen saturation, temperature and heart rate.
- Define weighs w_{ij} and biases b_i for each neuron in the network
- Define the activation function: Y_i= Activation_function($\Sigma^n_{j=1}x_j.w_{ij} + b_i$)
- Shorter notation: $Yi = \partial(W.x + b)$
- Values less than 0.5 indicate no infection, while values higher than 0.5 indicate positive infection.

3. **Cost function and training:**

- Cost function: $W_i = \frac{W_i - \alpha.\partial_{cost}}{\partial W_i}$
- Activation function: Sigmoid: $\partial(x) = \frac{1}{1+e^{-x}}$
- Use back propagation to update weights and biases during training.

4. System Implementation

Appropriate implementation that adheres to design principles is necessary for a well-designed system. In order to comply with the system design, some considerations must be taken in this research. Coding, setting up hardware and software, and running tests and experiments to evaluate the system's functionality and performance in a virtual setting are all included in this.

Software: Python, Scikit-learn Library, Tensor flow and Keras Libraries, Open CV, MySQL Database, Matplotlib and Seaborn Libraries, Fast Fourier Transform Library

Minimum Hardware: An RGB camera, IR camera pixel of 320 by 240 pixel emissivity of 0.98

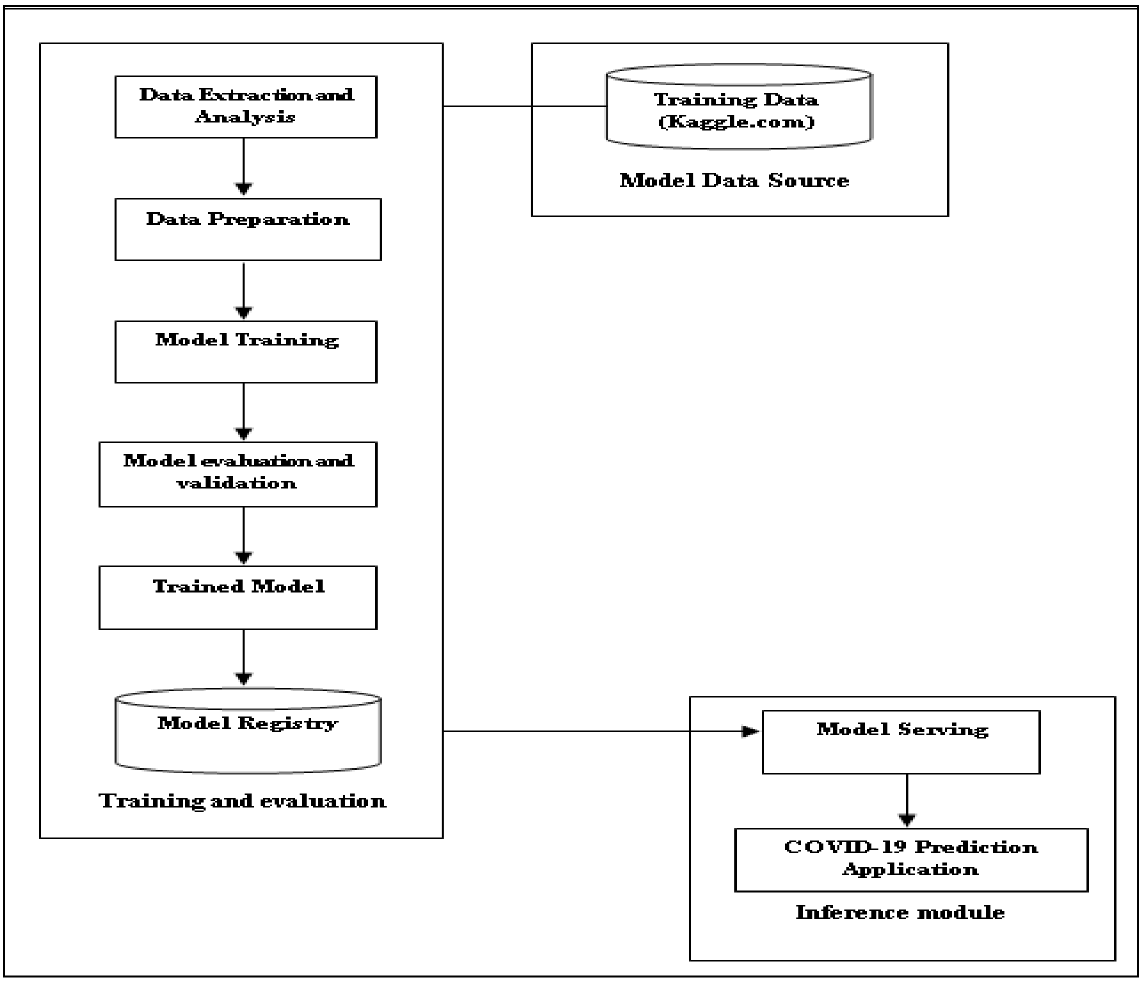

Figure 2: Model Implementation Architectural Design

Data extraction and analysis:
Extracting and analyzing data serves as a foundational step in the machine learning pipeline. Here, raw data undergoes processing and transformation into a format suitable for training machine learning models. Insights gleaned from the data inform crucial decisions such as model selection and feature engineering.

Data preparation:

- **Data Cleaning**: Raw data often contains errors, missing values, outliers, and inconsistencies. Data cleaning involves identifying and rectifying these issues to ensure data accuracy and reliability.
- **Data Transformation**: Data may require transformation for analysis readiness, such as encoding categorical variables and scaling numerical features. For instance, in this dataset, the COVID-19 status feature was transformed into a binary representation (1 for positive, 0 for negative) to align with machine-readable formats. We also applied standard scaling to the data.

Model Training and Evaluation
We used a dataset of 10,000 individuals, sourced from the Kaggle website, for model training. The dataset consisted of 5,010 COVID-19 negatives and 4,990 positives.

- **Preprocessing**: The dataset was cleaned up before it was used for training. For example, null values were removed, and the distributions of the variables were checked using statistics like skewness and kurtosis.

- **Data Splitting**: To ensure an appropriate balance for model evaluation, we partitioned the dataset into 80% for training and 20% for testing.

- **Model Training**: We trained the model over 1000 epochs with the goal of optimizing performance and achieving accurate predictions.

- **Evaluation**: After training, we evaluated the model's performance and found a final loss value of 0.07305776405105588, indicating the model's efficacy in capturing patterns and making predictions.

The confusion matrix was used to determine the accuracy of the model (see figures 3 and 4).

Dataset Preview

	ID	Oxygen	PulseRate	Temperature	Result
0	0	98	65	95	Negative
1	1	96	92	95	Negative
2	2	95	92	99	Negative
3	3	97	56	96	Negative
4	4	88	94	98	Positive
5	5	94	100	103	Positive
6	6	88	81	104	Positive
7	7	91	79	95	Negative
8	8	93	59	101	Positive
9	9	86	117	99	Positive
10	10	94	75	95	Negative
11	11	98	46	96	Negative

Ask me anything.

Figure 3a: Result of Training

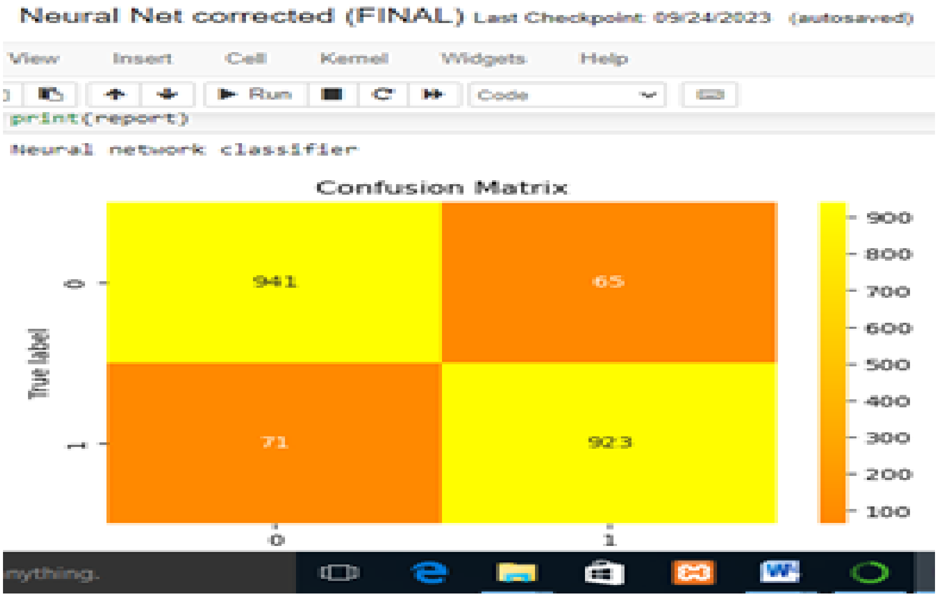

Figure 3b: Confusion Matrix Result of Training

Predicted label

	precision	recall	f1-score	support
Negative	0.93	0.94	0.93	1006
Positive	0.93	0.93	0.93	994
accuracy			0.93	2000
macro avg	0.93	0.93	0.93	2000
weighted avg	0.93	0.93	0.93	2000

Figure 4: Result of the model training

4.1 Performance analysis: The current ground truth method for COVID-19 detection is reverse transcription polymerase chain reaction (RT-PCR) testing of respiratory samples, most commonly taken from the nose or throat. The CDC recommends a COVID-19 test using a nasopharyngeal swab. The technician will insert a special 6-inch cotton swab into both nostrils one by one and move it around for about 15 seconds. It will not hurt, but it might be uncomfortable. This sample is sent to the laboratory for further testing.

This laboratory-based test detects the presence of viral RNA, the genetic material of SARS-CoV-2, the virus that causes COVID-19. It's considered the gold standard for diagnosis due to its high specificity and sensitivity. While RT-PCR testing is considered the gold standard for COVID-19 diagnosis, it has several drawbacks in mass screening settings:

i. **Delays**: It can take hours or even days to process results, slowing decision-making and potentially hindering outbreak control [14].
ii. **Resources**: It requires specialized labs, trained personnel, and costly equipment, limiting accessibility in resource-constrained areas [2].
iii. **Cost**: It's more expensive than rapid antigen tests, making large-scale screening financially challenging [2].
iv. **Potential for False Negatives**: Accuracy depends on sample quality and timing, potentially missing early or late infections (5).

The COVID-19 pandemic, originating in late 2019, is caused by the highly contagious SARS-CoV-2 virus, spreading through respiratory droplets and has widespread symptoms like fever, cough, fatigue, and breathlessness, leading to global healthcare, economic, and societal disruptions with lockdowns and travel restrictions. Despite vaccine and treatment development, ongoing vigilance and screening are crucial due to virus mutations. Remote photoplethysmography (rPPG) facilitates safe COVID-19 screening, allowing contactless vital sign monitoring heart rate, body temperature, and oxygen saturation. This minimizes virus transmission risk during screening, proving invaluable in pandemic management. These systems have the potential to decrease infection risk, enhance case detection, and find applications in various settings, such as entry points, containment zones, and home quarantine.

5. Conclusion

The COVID-19 pandemic, stemming from the highly contagious SARS-CoV-2 virus, emerged in late 2019 and has since wreaked havoc on a global scale, impacting healthcare systems, economies, and societies profoundly with widespread lockdowns, travel restrictions, and significant loss of life. Despite the development of vaccines and treatments, the virus's persistent mutations underscore the ongoing need for vigilance and screening efforts. Remote photoplethysmography (rPPG) emerges as a crucial tool in safer COVID-19 screening by enabling contactless heart monitoring, thereby reducing the risk of virus transmission during vital sign measurements. By capturing critical data such as heart rate, body temperature, and oxygen saturation, rPPG holds promise not only in assessing heart health but also in aiding in COVID-19 detection, enhancing infection risk reduction, and facilitating improved case detection across diverse settings. The study advocates for the proactive implementation of non-contact physiological screening in high-traffic areas to detect COVID-19, suggesting its broader application in diagnosing a range of infectious diseases beyond the current pandemic context.

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