INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 16 No. 3 (2024) 36-44
https://publisher.uthm.edu.my/ojs/index.php/ijie

Design of Smart IoT Health and Social Distancing Monitoring System

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DOI: https://doi.org/10.30880/ijie.2024.16.03.004

Article Info

Received: 30 October 2023
Accepted: 17 January 2024
Available online: 29 April 2024

Keywords

Cough detection, health monitoring, IoT, social distancing monitoring

Abstract

Since the outbreak of the COVID-19 pandemic, many companies have started to work from home. As the pandemic recovers, companies slowly start to adapt to the situation by making the workers work from the office. This is an effort to reduce the risks of spreading diseases in the workplace during the endemic of COVID-19. An effective solution is urgently needed to reduce and control the transmission rate of COVID-19. This has motivated us to design an Internet of Things (IoT) Health and Social Distancing Monitoring System (IHDS). This system aims to support that initiative and introduce a system that can control the risks of infection among workers due to a worrying spike in the number of cases in the workplace. The proposed system monitors the health condition of the users and controls social distancing at the workplace by using IoT technology and machine learning. Extensive experiments were conducted to assess the performance of the proposed system. Four critical health metrics were closely monitored: body temperature, pulse rate, blood oxygen saturation, and cough detection, achieving impressive accuracy rates of 99.91%, 94.32%, 99%, and 80.5%, respectively. The proposed system initiates the assignment of red boxes to couples who are separated by less than 1 meter, while it designates green boxes for couples who maintain more than a 1-meter distance from each other.

1. Introduction

COVID-19 was reported in its first case in Wuhan, China. The earliest report was documented on December 1, 2019 [1]. After that, it kept increasing the number of cases and spreading across the globe. In Malaysia, the government had the initiative to track the movement and control the case count by implementing an application called MySejahtera. The application can track the movement of a person by checking in to a premise by scanning a QR code that has been placed at the entrance of the premises. By doing this, it is much easier to do contact tracing, as the record can be traced back to search for possible clusters. This initiative focused more on a larger group of people. This system will be more focused on the workplace due to a worrying increase in cases in workplace clusters lately in Malaysia.

Swab testing is implemented in the workplace not just to check that employers follow the law but also to ensure the safety of all employees. This is an attempt to stop COVID-19 from spreading in the workplace. Due to the high cost of swab tests, the company may find it burdensome to allocate expenditures for swab test kits regularly. It is also uncomfortable to take the test, which must be repeated every two weeks. It is critical for the day-to-day operation to continue and to prevent being shut down. In the workplace, there is no specialized health monitoring system. Body temperature is the sole parameter tested before entering the workplace to ensure that the individual entering does not have a fever, which is a typical indication of COVID-19.

The IoT has become one of the most essential applications today as a result of rapid technological advancements. It elevates our way of life to new heights, and knowledge can be communicated in the blink of an eye. It can assist devices in communicating with one another through the internet. This design will use this application to improve an existing health monitoring system. Body temperature, cough frequency, pulse rate, and, last but not least, oxygen content in the blood are some of the parameters that will be monitored as part of this project. The readings can then be saved in a comma-separated values (CSV) file, which can subsequently be viewed and used as needed. This can assure the health of workers in a workplace, whether or not they are experiencing symptoms. Artificial Intelligence (AI) has grown increasingly popular in recent years as a result of technological advancements. The proposed project will attempt to explore the concepts of computer vision and neural network classification in order to determine social separation and a person's cough frequency.

To ensure that the number of cases rising from workplace clusters is contained, the health monitoring system must be more comprehensive, with additional features to better identify possible spreaders. Because the COVID-19 virus may be spread via the air by minute water particles dispersed in the air, it is critical to maintain a safe distance between people. This is one of the attempts being made to combat the disease's high infection rate throughout the world. The public implementation of this campaign is inept and ineffective. In public, people seldom remember to keep their distance. As a result, a computer vision system has been developed to aid the campaign in becoming more effective while also serving as a reminder to the public to keep their distance from the public in this extremely challenging pandemic. As a result, a health and social distance monitoring system can be established in the workplace to let organizations remotely monitor their employees' well-being while also minimizing outbreaks in workplace clusters.

2. Related Works

Since the World Health Organization (WHO) declared a worldwide pandemic in March 2020, the virus has spread rapidly around the world. The first case of COVID-19 was reported in late December 2019 [1]. In recent research on 99 patients, the most prevalent symptoms reported by COVID-19 patients were fever (83 percent) and cough (82 percent). According to the same survey, oxygen therapy is the most prevalent treatment received by patients, accounting for 76 percent of all patients. These figures show that COVID-19 patients had poor blood oxygen saturation, which is linked to the use of ventilators [2].

We cannot expect to physically confine the next influenza pandemic to the location where it arises, nor can we expect to prevent sickness from spreading worldwide for more than a short period, as the COVID-19 pandemic has demonstrated. COVID-19 virus strains are transmitted mostly through intimate interpersonal contact [3]. The purpose of social distancing strategies is to reduce the frequency of interactions and increase the physical distance between people, reducing the risk of transmission from one person to another [4]. Investigations were carried out to identify mask efficacy, social distance, lockdown, and self-isolation, among other things [5]-[6]. The author employed agent-based simulation modelling to provide a multivariate analysis utilizing the Morris Elementary Effects method of simulation, with social distance and wearing a mask as the major variables in controlling the spread [7]. Ahmed et al. evaluate the evidence that social distance in non-healthcare contexts reduces or delays influenza transmission. Workplace social distancing approaches, according to modelling studies, reduced cumulative influenza overall harm by 23% on average [8].

Wearable devices like smartwatches are used to track health metrics, including heart rate, calories burned, and distance travelled, then extract the data and plot it on a graph. In the CSV file, the parameters for the data collected can be defined. With the addition of a social distance monitoring system to provide a safe working space. In addition, a mobile application has been developed to assist users in saving time and energy when accessing data. As a result, the procedure is simplified, and the findings may be more accurate [9]. Furthermore, solutions are proposed to monitor health conditions and develop a real-time face mask detection algorithm for COVID-19 prevention [10].

Home health monitoring is critical for detecting the early stages of diseases. It is impracticable to visit hospitals frequently to check their health conditions. It is also suggested that, by doing so, it would be possible to save a significant amount of money on medical expenses. Data from the past may also be utilized to predict future health patterns. A large amount of data can assist in distinguishing between extraordinary changes in one's health

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state and regular swings. If a significant disease arises, the researcher discovers that a lengthy history of data can help predict when the disease episode begins, which can assist in determining the early signs of a more serious condition [11]. A remote monitoring system is proposed to identify the signs of COVID-19. A device in the form of a wristband is being developed. A survey is being conducted to look at the health equipment that is commonly utilized during pandemics. The pulse oximeter, digital thermometer, and digital blood pressure monitor are used by most of them [12].

Three stages were described in the paper [13]-[14] to develop a social distancing system. The initial phase is object detection, in which they strive to identify and tag everything they find, as well as delete any objects that aren't humans. The next step is to determine the pairwise distance between the centroids of the bounding boxes, which may be done using Euclidean distance. The last phase is a visualization that includes a counter that counts the number of people in the crowd that broke the required social distance. To connect with this work, the designed system employed the OpenCV library to implement a social distance monitoring system that used YOLO v3 as an object identifier. The researcher's work was utilized as a model for the proposed system.

The AI-based solutions had to overcome accuracy, cost, privacy, availability, and power consumption issues [15]-[16]. The foreground detection strategy has the drawback of being unable to recognize foreground objects that have stopped moving because the system's focus is on updating the background model. To anticipate the placement of items in a subsequent scenario, the Kalman filter is used. This is done to get around the disadvantages of using the foreground detection method. The positions in real-world coordinates were determined using the bird's-eye perspective and the location of the objects in pixels. Triangular equations were used to support this approach. The final step is to calculate the distance between objects in Euclidean distance to determine whether two people were in the encounter. The prior research provided valuable insights that guided us in designing the IHDS with Artificial Intelligence and IoT.

3. Details of the Design

IHDS is divided into four sections: data collection from each component, data transmission from a microcontroller to an IoT platform, image processing for social distancing detection using computer vision, and last but not least, sound recognition for cough sound detection using Artificial Intelligence software. The systems are independent of one another and function on their own, yet they work together to support the IHDS proposed. Fig. 1 shows the overall structure of the proposed IHDS system.

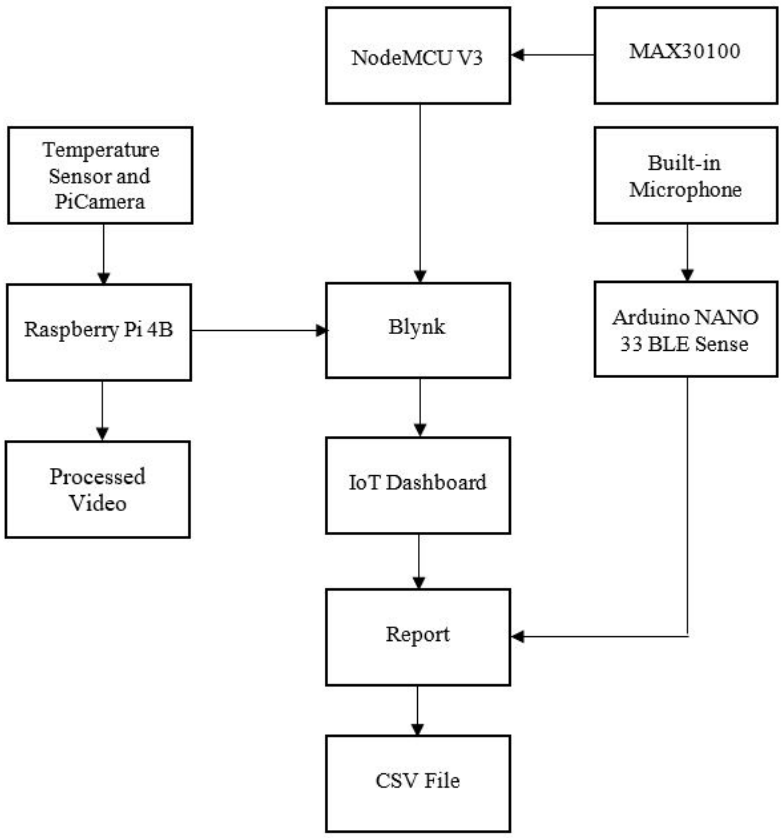

Fig. 1 *System architecture of the IHDS*

The MLX90614 sensor connected to the Raspberry Pi 4B was used to capture temperature data for the body temperature reading. Through WiFi connectivity, body temperature readings will be transmitted to the Blynk platform. The data was sent from the Raspberry Pi 4B to the Blynk IoT platform, where it can be seen on a dashboard using smartphones. The MAX30100 sensor was utilized for the oxygen level concentration in blood and heartbeat readings, and it was attached to the NodeMCU V3 board, which has integrated an ESP8266 module. The sensor will employ an LED to create light, which will be used to measure oxygen levels. Blood that has been oxygenated absorbs more infrared light and emits more red light. Deoxygenated blood, on the other hand, interacts more with red light and less with infrared light. As a result, the sensor takes advantage of the situation and detects the absorption levels for both red and infrared light, storing them in a buffer that is subsequently read through the Inter-Integrated Circuit (I2C). The data from the sensor will be transferred to the microcontroller board to be processed before being sent back to the IoT platform, Blynk, to be seen on the dashboard through WIFI connectivity.

The Arduino Nano 33 BLE Sense with a built-in microphone was used to detect coughs. It accomplished its goal by employing a machine-learning approach. Edge Impulse is the system's supporting software. Edge Impulse can generate multiple functions and systems using a machine-learning method. Sound recognition is utilized in IHDS to distinguish between background noise and cough sounds. It can also make a library for use with the Arduino Integrated Development Environment. It allows the user to choose the algorithms they want to utilize. The information from this board may be saved in a CSV file to demonstrate how often a person coughs over time. IHDS was established to keep track of individual health reports. As a result, a report in the form of a CSV file may be generated from the Blynk server. Throughout the day, users may examine their health status and upload the information to the company for extensive review.

The monitoring system for social distancing is run on a Raspberry Pi 4B using a Python script. The operation flow chart of the monitoring system for social distancing is shown in Fig. 2. It made extensive use of computer vision to identify a variety of parameters. The social distancing monitoring system in IHDS identifies people and their distance from one another. To help this system distinguish the objects, an additional algorithm, such as YOLOv3, is required to recognise the object detected as a human. OpenCV is the library that was utilized in this technique (a computer vision open-source library that can be used in Python scripts). This setup used the PiCamera to record video and save it on the Raspberry Pi 4B. The program can then process the captured footage further. In a recorded version, it will demonstrate if the individual conforms to social distance or not. This captured and processed video may subsequently be used for a variety of purposes, including proof and reminders.

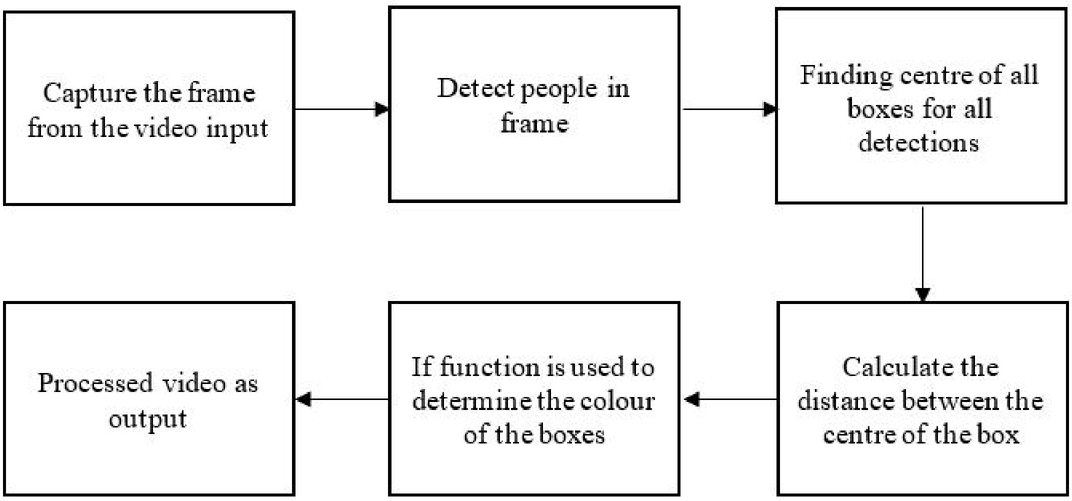

Fig. 2 *The block diagram of the social distancing monitoring system*

4. Results and Discussion

4.1 Body Temperature Monitoring System

Multiple temperature data points were collected daily to assess the temperature sensor's accuracy and precision. With 15 temperature readings recorded during each session, the following data was obtained in the morning, afternoon, evening, and night. The results of the MLX90614 measurement were compared to those of a conventional infrared thermometer. After that, the error will be calculated to evaluate the reading variation compared to the conventional device. The formula used to calculate the error is shown in (1).

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$$Error = \left|\frac{Actual\ Value - Measured\ Value}{Actual\ Value}\right| \times 100\% \quad (1)$$

The average error percentage of body temperature measurements recorded with MLX90614 ranged from 0.07% to 0.09%, which is quite low. This demonstrates that the MLX90614 readings are accurate and acceptable for body temperature monitoring in the proposed system. The distance between the skin and the sensor when the reading was taken varies for each measurement, which might explain why the temperature reading varies.

4.2 Pulse Rate Monitoring System

A set of data was acquired to evaluate the MAX30100 sensor's performance. This sensor was used to assess pulse rate and blood oxygen levels. The data collected by the MAX30100 was compared to that recorded by a conventional pulse oximeter, such as the Oxitech Pulse Oximeter, to evaluate the accuracy of the data collected by the MAX30100. The Medical Device Authority Register (MDAR) lists the Oxitech Pulse Oximeter as a registered device. This is to ensure that the sensor's reference value is as accurate as possible in order to verify the sensor's reading. The data was captured in six separate events: 1) before eating breakfast, 2) after eating breakfast, 3) before taking a test, 4) in a relaxed state, 5) before the workout, and 6) after the workout. The data was recorded for 1 minute and 10 seconds, with 5 seconds intervals for each occurrence. The data was interpreted by calculating the mean pulse rate in 30 seconds and 1 minute, as pulse rate is the measurement of the average value of the heartbeat over time, as shown in Table 1.

Before breakfast, during resting, and before working out are examples of low-pulse-rate activity occasions. Because the heartbeat is low throughout these activities, one should have a low pulse rate. After breakfast, before taking an exam, and after working out are the events specified in the high pulse rate activity class. These activities prompted the heart to beat quicker, resulting in a faster pulse rate. Low pulse rate activity should, in theory, have a lower average BPM measurement than high pulse rate activity. It can be seen from Table 1 that it supports the idea. As a result, the sensor data becomes more reliable.

Table 1 *The average data reading for all events*

Mean BPM	MAX30100	Oxitech	MAX30100	Oxitech
	Before Breakfast		After Breakfast	
30 secs	73	73	88	83
1 min	73	71	88	84
	When Relaxing		Before a Test	
30 secs	82	80	83	86
1 min	80	82	81	87
	Before Workout		After Workout	
30 secs	74	75	78	76
1 min	75	73	76	74

4.3 Oxygen Saturation in Blood, SpO2 Monitoring System

The data was gathered using the MAX30100, which can detect both pulse rate and blood oxygen saturation, or SpO2. The data for oxygen saturation was collected at the same time as the data for pulse rate, and the events were comparable. The data was also compared to the Oxitech Pulse Oximeter, which is an identical device. The MAX30100 reading before and after calibration is shown in Fig. 3.

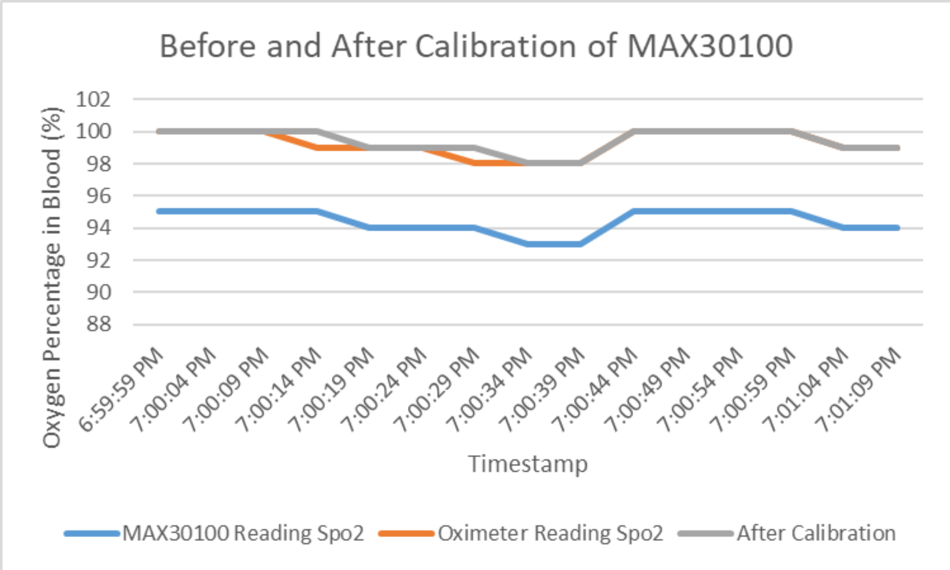


Fig. 3 *The SpO2 readings before and after calibration*

The y-axis displays the percentage of oxygen saturation in the blood, while the x-axis represents the time when the reading was taken. The blue line depicts the reading from MAX30100 before calibration, whereas the grey line depicts the value from MAX30100 after calibration. The reading from the Oxitech pulse oximeter is represented by the orange line. With two outliers found, the result received after calibration is virtually identical to the data acquired from the pulse oximeter device. The reading from the sensor and the result from the device are nearly identical. The sensor's correction factor is 5, based on the outcomes of the study. This correction factor can be used to tweak the sensor's code so that it produces more precise results. However, it must not exceed 100; otherwise, the calibration will become faulty, rendering the sensor unusable.

4.4 Cough Detection System

The Edge Impulse can provide users with cough detection results. A red LED is added to the Arduino Nano 33 BLE Sense to indicate whether the board caught a cough or a noisy sound. As shown in Table 2, 90.4% of the training dataset marked cough was properly labelled as cough by the algorithm, whereas the rest, which is also cough data, was wrongly classified. This suggests that cough was incorrectly identified as noise in 9.6% of the training dataset. The same can be said for the noise training datasets, which accurately identified 97.9% of the noise data. As a result, the model misidentified 2.1% of the noise data, which the model mistook for a cough.

After the model has been trained, it is time to put it to the test. The test dataset's data was left unlabeled, as it should be. This is done to see if the model can correctly predict the unlabeled data in the test dataset. This test dataset serves as the penultimate step before deploying the model. The results are shown in Table 3. In the test dataset, the model accurately recognized cough sounds at 80.5%. It did, however, categorize the dataset inaccurately in 9.4% of the cases. The data under the uncertain category simply implies that the model failed to recognize the data was either cough or noise, which accounted for a solid 10% of the dataset. This signifies that the model was unable to determine the type of 10% of the dataset. The model, on the other hand, accurately recognized 97.2% of the noise in the test dataset. This shows that the model can simply recognize a noise sound. The data that the algorithm mistook for a cough but turned out to be a noise sound accounts for around 0.7% of the test dataset. Uncertainty was assigned to 2.1% of the test dataset.

Table 2 *Confusion matrix for the training dataset*

	COUGH	NOISE
COUGH	90.4%	9.6%
NOISE	2.1%	97.9%

Table 3 *Confusion matrix for the test dataset*

	COUGH	NOISE	UNCERTAIN
COUGH	80.5%	9.4%	10.2%
NOISE	0.7%	97.2%	2.1%

4.5 Social Distancing Monitoring System

On the deployment of the social distancing monitoring system, a set of factors in terms of the distance of the person from the camera and the distance between individuals were examined. This is done to see where the algorithm's boundaries are in terms of accurately detecting distance. The camera's footage is then sent into the algorithm, which generates a video file with the detection output encoded in it. The algorithm's result will be a human enclosed in a colored box. If the individual kept a safe distance, they received a green box, and if they did not, they received a red box. The centroid computation is used to compute distance.

Fig. 4 shows the output of the Social Distancing Monitoring System. If the individual was within 5 meters of the camera, the result is invalid. Because the distance between the centroids is large enough to be identified as the allowable distance, the algorithm cannot determine the right distance within a close range. As a result, even if the people are near each other, they will be bound by a green box. When the person's distance from the camera is between 6 and 9 meters, the algorithm's result becomes legitimate. The algorithm begins to assign red boxes to couples who are 0.5 meters apart and green boxes to couples who are 1 meter or more apart at 6 meters. The outcome became more consistent after 7 meters from the camera, since the algorithm only provided green boxes to those who were 1.5 meters apart and red boxes to those who were less than 1.5 meters apart. This output occurs only until the person and the camera are separated by 9 meters. After 10 meters, the system begins to only show green boxes to couples who are 2 meters apart. This was caused by the camera's perspective view and the fixed distance between the centroids that was established in the source code that controls whether green or red boxes are displayed.

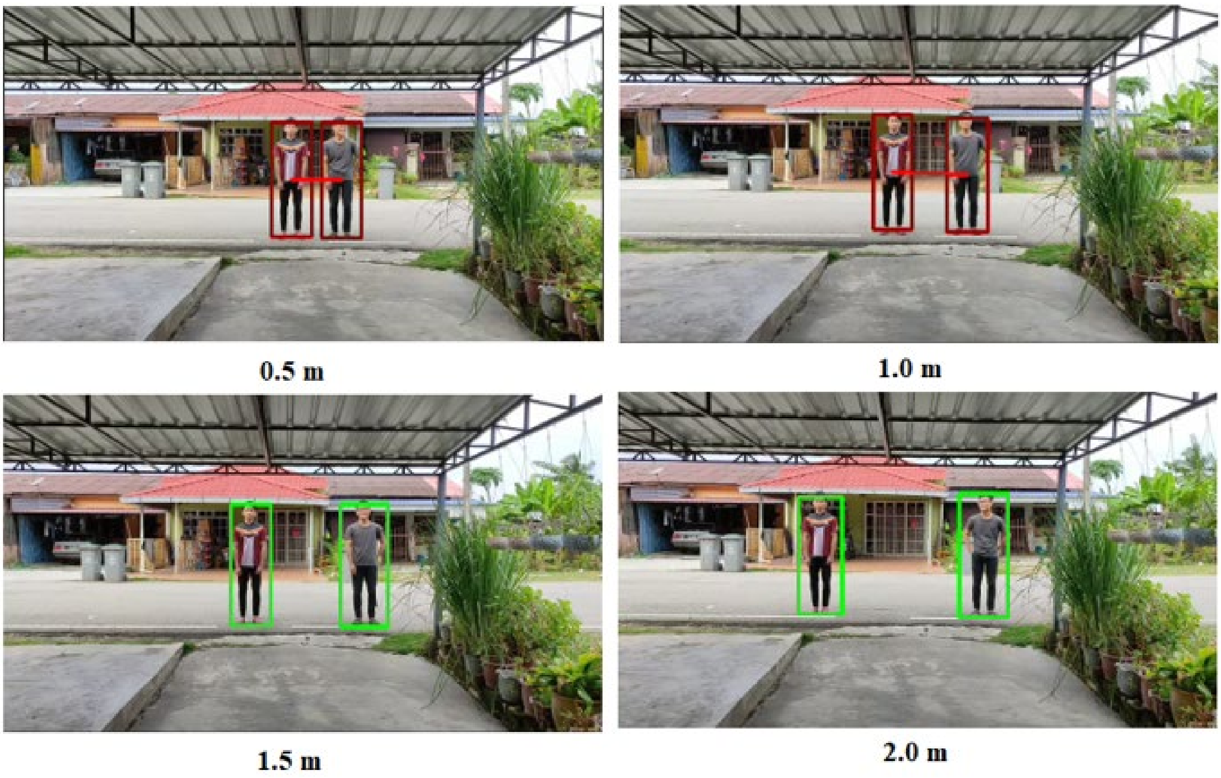
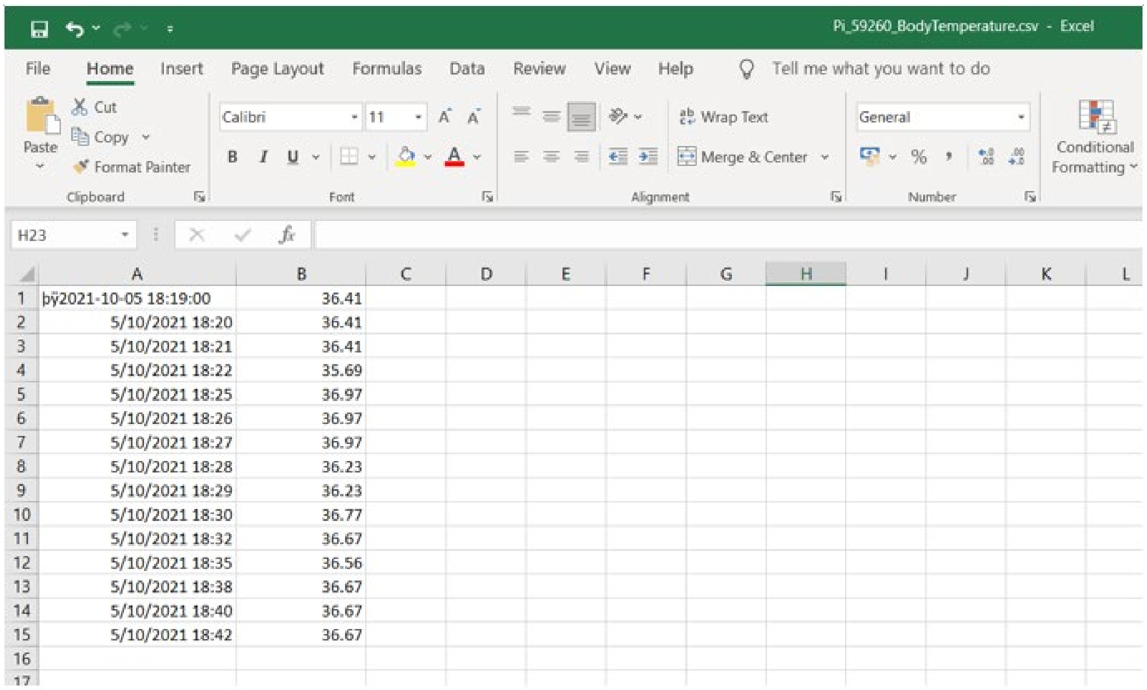


Fig. 4 *The output of the social distancing monitoring system*



	A	B
1	þÿ2021-10-05 18:19:00	36.41
2	5/10/2021 18:20	36.41
3	5/10/2021 18:21	36.41
4	5/10/2021 18:22	35.69
5	5/10/2021 18:25	36.97
6	5/10/2021 18:26	36.97
7	5/10/2021 18:27	36.97
8	5/10/2021 18:28	36.23
9	5/10/2021 18:29	36.23
10	5/10/2021 18:30	36.77
11	5/10/2021 18:32	36.67
12	5/10/2021 18:35	36.56
13	5/10/2021 18:38	36.67
14	5/10/2021 18:40	36.67
15	5/10/2021 18:42	36.67

Fig. 5 *The output of the data retrieved from Blynk*

4.6 Retrieve Data from Blynk

When Blynk sends an email, the workers can download the ZIP file containing the sensor's records from the email attachment. The CSV file contains all the data that was transmitted to the Blynk server. The worker can return the health report to the company as a daily health report for extensive analysis using the information in the file. The output of the data retrieved from Blynk is illustrated in Fig. 5.

5. Conclusions

A low-cost IHDS that can aid in the prevention of viral spread in the workplace was proposed. Workers or users may obtain their health information throughout the day by using the IHDS system. The valuable data collected can be used as a dataset for additional health studies in the future. The prototype is designed on a low-cost small computer, i.e., the Raspberry Pi 4B, which significantly reduced the cost of deploying the IHDS. IHDS delivers impressive accuracy, with 99.91% precision in body temperature monitoring, 94.32% accuracy in pulse rate measurement, 99% in blood oxygen saturation, and 80.5% in cough detection. Additionally, IHDS proactively alerts users when they breach social distancing guidelines, particularly when the distance between individuals is less than 1 meter. In a nutshell, the IHDS system is designed to be as low-cost as feasible while achieving all of the goals of the IoT health and social distancing monitoring system. The IoT platform is being used in the IHDS system to create a health data record. This approach aids the organization in minimizing the spread of COVID-19 in the workplace in an indirect manner.

Acknowledgement

This research was funded by the Research Grant, MMUE/220061, from Multimedia University, Malaysia.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Pang Wai Leong, Chan Kah Yoong;* ***data collection:*** *Muhammad Akmal;* ***analysis and interpretation of results:*** *Chung Gwo Chin, Sim Yee Wai, Murman Dwi Prasetio;* ***draft manuscript preparation:*** *Pang Wai Leong, Chung Gwo Chin. All authors reviewed the results and approved the final version of the manuscript.*

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