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AN IOT BASED SOCIAL DISTANCING MONITORING SYSTEM IN PUBLIC AREA FOR REDUCING THE IMPACT OF COVID-19

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Abstract— The massive pandemic of the 2019 novel influenza virus, identified as COVID-19 by the World Health Organization (WHO), has put hundreds of governments all over the world in jeopardy. Nearly every single country on the planet has been highly worried about the COVID-19 virus outbreak. To avoid the spread of this disease, we must thoroughly protect ourselves with sufficient measures. Fear of the health consequences of Marburg and Ebola has led some countries to make bad decisions, such as changing their basic health care systems and partially or completely discontinuing some medical procedures, though some have made choices. If communicable diseases such as cold sores, chicken pox, and influenza virus are to be avoided, social distance is demanded. We minimize the probability of catching and spreading the disease to everyone else in the community by holding people away from one another. Since its inception, the pandemic has been rapidly exploited by various scientific communities, and IoT is one of the pioneers in this field, using a broad variety of technologies to combat this global threat. The IoT procedure was used in the course of the respective COVID-19 clinical therapies to "reduce" COVID-19 distributed to someone else as the patient supervision following a diagnosis of the disorder in compliance with the "liability" of the relevant "devices" and "applications." At the moment, we'd like the pedestrian counting method to rely on open computational vision and artificial intelligence rather than manual measurement. There are small, concealed cameras installed at the scene, and police can obtain footage from these clips to closely track the nature of the incident. This also applies to drones, which can now use videos as testimony.

Keywords— COVID-19, IoT, OpenCV, Social Distancing, Deep Learning, Computer Vision

I. INTRODUCTION

COVID-19, an abbreviation for "Coronavirus-2019," is a respiratory infection associated with extreme coronavirus-2 (SARS-CoV-2) acute respiratory syndrome, a highly infectious virus in the coronaviridae family with a single-strand, positive-sense RNA. SARS-CoV-2, like the influenza virus, affects the respiratory system and causes symptoms such as cough, fever, exhaustion, and shortness of breath. Despite the fact that the virus's exact origin is uncertain, scientists have mapped the SARS-CoV-2 gene sequence and established that it is a member of the coronavirus family of -CoV genera, which usually derives its gene sources from bats and rodents[1]. COVID-19 was first confirmed to have had an effect on human life in December 2019 in Wuhan City, Hubei Province, China. COVID-19 has since spread like wildfire in the rest of the world, with a presence in 213 countries and autonomous territories. The figures for the world's worst COVID-19 affected nations, as well as the total number of cases and deaths, are shown in Figs. 1, 2, and 3.

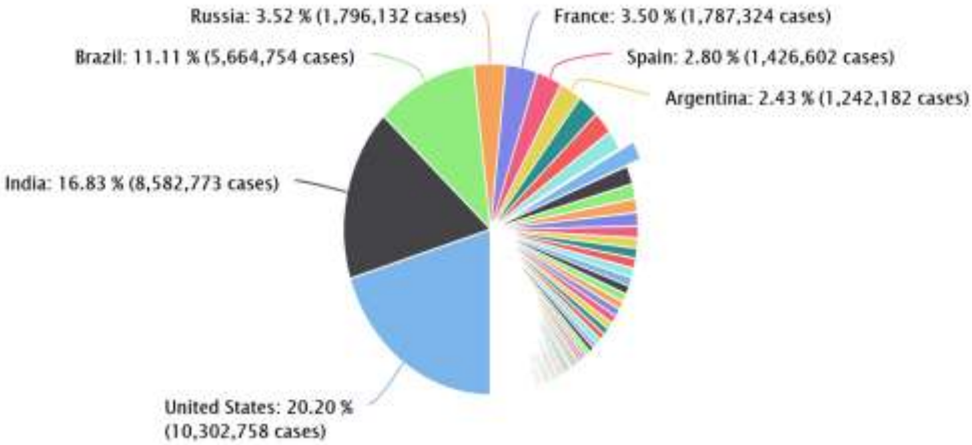


Figure 1. Statistics in regards to the COVID-19 (Data Source: WHO Situation Report - 05 November 2020 [3]).

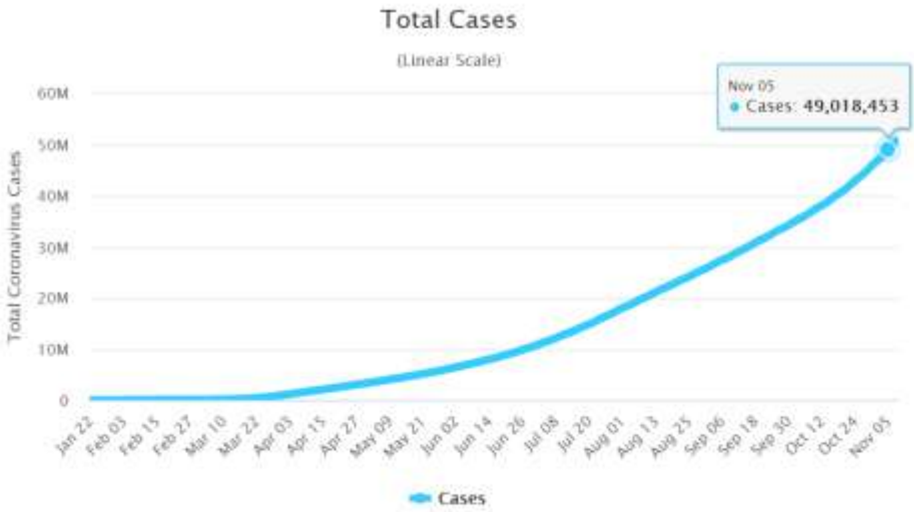


Figure 2. Total Number of Cases Worldwide as of 5th Nov. 2020

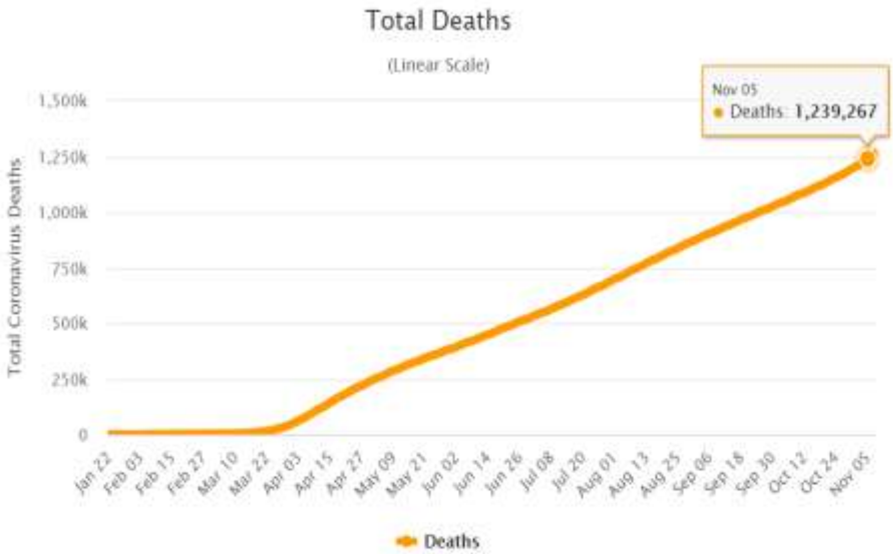


Figure 3. Total Number of Deaths Worldwide as of 5th Nov. 2020

The WHO estimated that there are total 4,90,18,453 cases, out of which there are 12,39,267 cases of coronavirus that are now tallying worldwide resulted into deaths[2]. The rapid increase in COVID-19 incidents around the world has resulted in immediate countermeasures needed to mitigate the catastrophic impact of COVID-19.

This infection has similar symptoms to influenza, like fever, health effects and fatigue, which are essential to diagnosis and treatment. COVID-19 takes 1 to 14 days for incubation. Interestingly, a non-symptomatic patient can potentially be a COVID-19 virus transmitter to others. This is needed if these people are to be quarantined. The recovery time of this disease also varies according to the age, condition, and so on, but can take between 6 and 41 days in general. Although there are many active attempts and many research initiatives to mitigate this virus while this disease has a high potential to be transmitted easily in contrast with similar diseases within the coronavirus family.

The worldwide pandemic situation is worsening and vaccination against the contagious disease is currently in developing stage and social distancing has thus proved to be one of the best means of preventing COVID-19 spread. As the name implies, social distancing means that people should distance each other physically. The cases have escalated very rapidly across the world, and social distance is therefore important.

IoT technology is a safe and efficient way to deal with the COVID-19 pandemic in this context. In this context. This document presents a cost efficient IoT system that helps Organisations, in order to reduce the disease spread, to meet COVID-19 safety standards and guidelines. We focus on most common indoor actions – people should maintain at least a distance of 1.5-2 meters between people. We use the Raspberry Pi2 computer with one board equipped with camera for two other scenarios to take advantage of computer vision techniques.

In spite of the abundance of research in the field of the COVID-19 analysis and vaccine development, as far as we know, the outbreak and its potential implications are not fully examined at the moment of this writing. In this work, we present the potential technological solutions for COVID-19 pandemic impact management.

II. PANDEMICS IN THE PAST CENTURY

A host of outbreaks and epidemics have occurred in the last century. While the majority of these outbreaks are accountable for coronaviruses like SARS-Cov & MERS-CoV (refer to Table 2), the four pandemics have been led by various different types of ASV, including H1N1 H2N2 and H3N2 over the last 105 years. Two epidemics were responsible for the H1N1 virus alone-one of the Spanish flu in the years 1918-1919, and one of the two of Swine < bal > in the years 2009-2010. Asian flu in the years 1958-1958 and 1968-1969 respectively were responsible for H2N2 and H3N2 in the pandemic. We present a summary of all these pandemics in this section.

A. Spanish Flu Pandemic (1918-1919)

Many know of the Spanish flu as the deadliest pandemic in mankind's history, with a total of over 50,000 deaths[3]. The illness was caused by the H1N1 virus supposedly derived from birds. Contrary to many diseases, Spanish Flu is particularly lethal to young and healthy populations. This was because of cytokine storms in the immune system of the patient that attacked hosts by the virus, often leading to death [4]. As young people had stronger immune systems than older adults, the virus was more likely to affect them.

B. Asian Flu Pandemic (1957-1958)

The pandemic in Asia started in Singapore in February 1957. After the Spanish influenza pandemic in 1918, it was the second major 20th century pandemic. The estimated deaths in the United States have been 116,000 and worldwide, totaling 1,1 million[5]. The disease was caused by a virus of type A, which is believing to have avian origin as the H1N1 virus . The virus was the same as the H2N2 virus. Eleven years after the outbreak of the H2N2 virus, a strain which could no longer affect human hosts subsequently mutated.

C. Hong Kong Flu Pandemic (1968-1969)

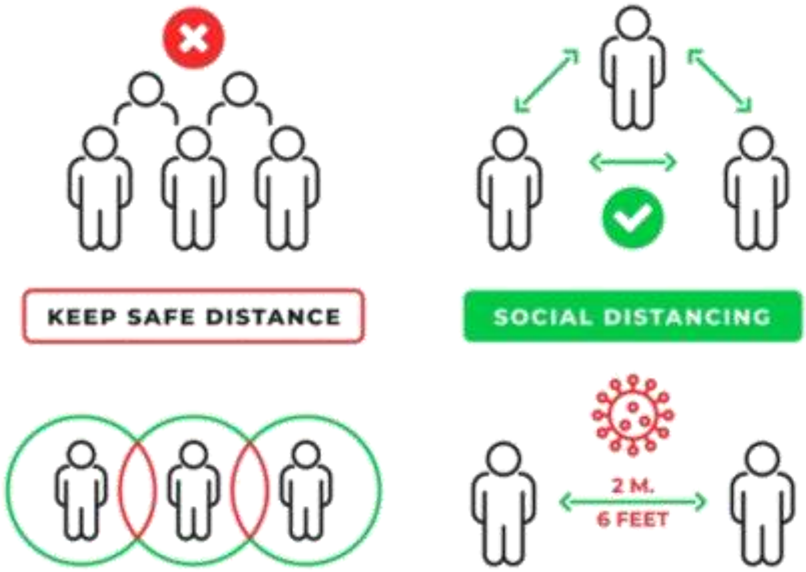
The pandemic of Hong Kong flu was the third major in 20th century Kenya flu pandemic. It was caused by the H3N2 virus, which is thought to have been developed by the Asian pandemic H2N2 virus. A mutated HA antigen present in H2N2, but the same N2 antigen was maintained by the H3N2 virus There have been sporadic descriptions of the impact of the Hong Kong flu pandemic across the world as a result of previous immune to the N2, due to the Asian flu pandemic[4]. The H3N2 virus has been more aggressive to persons aged over 65, unlike the H1N1 virus behind the Spanish flu pandemic.

D. Swine Flu Pandemic (2009-2010)

A new strain type A H1N1, leading to the swine flu pandemic, emerged in the spring of 2009. Like Spanish Flu, the Swine — Teenu Pandemic was more fatal for people under 65 years of age because of a different strain of the same virus. One reason is believed to be pre-acquired immunity in elderly people due to previous H1N1 exposure. The US CDC estimates that over 43.3 million people, 195,086 admissions and 8,868 deaths alone from the virus were reported in the United States, while the worldwide death toll rates exceed 151,700 [6]. The US CDC estimates this figure to be more than 35 million.

III. PREVENTION FOR COVID- SOCIAL DISTANCING

With the pandemic in the world , social distance is one of the most important precautions.



As they come together in crowds, they are likely to get in touch with someone who has COVID-19 and therefore has a strict law on maintaining 1 meter of distance (3 feet) in each pair from the World Health Organization. This idea of a social distance sensor has therefore emerged to track the social distance between the public.

This paper provides a pinpointing solution for monitoring social distancing in public areas. We can track human activities in public sites during this pandemic using CCTV and drones and from that point on calculate and summaries distances between persons as well as monitor violations of social distance across the city. In addition, this proposed survey will prevent people from gathering and prevent social gatherings. Individuals collecting in large sums in religious areas can worsen conditions. Recently, every country on earth has been and is mainly during the locks and that has made it impossible for the citizen to be in the house. However, with the passage of time, people tend to visit more and more public places or religious places and tourist destinations.

With computer vision and depth learning and CCTV installed, we can track human beings and measure their distance in pixels using algorithms on computer distance, set the standard distance to track and obtain overviews of lawbreakers and the authorities concerned can take appropriate action[7].

IV. RELATED WORK

Dr. S Syed Ameer Abbas and his co-authors suggested using raspberry-pi and Open-CV for human-person tracking and crowd control in 2017. Using OpenCV's hair features, a cascade classifier for head detection was trained from the scene. Their whole idea was to film an entire scene using an ARMv8 central processing unit that processes the frame by frame using a camera and Raspberry Pi3. When the value is compared to the threshold, the count of heads is estimated, the crowd is monitored, and mitigation can be done accordingly if it reaches the threshold [8].

In 2018, Joel Joseph Joy and his colleagues proposed a traffic density recognition method based on image processing. The camera captured images of the queue length and traffic density. The video input was used, and the definition of partial reality was treated gently. The product of the partial truth conception may be somewhere between fully true and completely false [9].

Adrian Rosebrock published an article [6] in 2020 about an OpenCV, Computer Vision, and Deep Learning concept focused on the social distancing detector. The article emphasizes social distancing throughout the pandemic and focuses on social distance control using street-wide CCTV cameras. The camera calculates the distance between people in pixels and compares it to the normal measurement, serving as a social distancing sensor. This application for social distance sensors is contained in the file.py script, and it ensures that people maintain a healthy distance from one another through the frame of a video stream. Video and webcam streams are also supported.

Neel Bhave and her co-authors presented a complete working model in 2019 that included an algorithm for reinforcement and object detection. They used real-time object detection YOLO (You Look Just Once) with less bugs, faster performance, and the potential to be taught for more than 200 lessons. Strengthened learning is a machine learning domain that adapts the green step schedule to current traffic conditions and learns from previous activities [10].

WHO officials said at a press conference in March 2020 that "People who are sick before they know they are sick should avoid contact with others, even if they have no symptoms, since they can spread the virus. Because social distancing is necessary to prevent the spread of Covid-19, social distancing has been observed in a public setting, giving rise to the notion that social distancing is being violated." In this study, we use object detection to track the safe distance between individuals [10].

CCTVs and drones can be used to detect humans. Closed Circuit TV (CCTV) has long been used as a surveillance method, but it is not fully effective due to its limitations. As a result, the drone has stronger contact with the rest of the swarm in a specific region to pursue the human being, while also separating the areas between the drones to keep the human being on track. OpenCV, computer vision, and extensive expertise are used to track social distance throughout the field. Initially, object tracking in a video stream is used to identify pedestrians. The next step is to measure the pair distances for all detected people and then compare the standard distance (6 feet or 2 meters) with the red frame if it is violated, and the green frame is another way. If 5-6 people assemble in a specific location, the state or local police stations are immediately informed.

Following the spread of this epidemic, policing officials have recently been forced to patrol the city over time. With this definition of social distance detection, the police will track and reach the exact location as well as monitor the situation immediately. COVID-19 spread can thus be regulated socially and prevented indirectly [11].

Cloud-based data clients may be used to move data from their systems to cloud-based servers [12]. As a result, the customer saves money on repairs while still providing high-quality data storage services. Many security issues are posed by cloud storage. Cloud service providers and data servers aren't perfect. The defragmentation technique is used to decide whether a file that a user wants to store in cloud storage already resides on the cloud server. This device is strong and resistant to malicious server-launched replace attacks.

V. IMPLEMENTATION

Ontology is often used for interoperability in IoT systems in order to integrate data from heterogeneous devices and their sensors to unify the control. In this article, we adopt a similar approach in the context of COVID-19 safety monitoring for semantic representation, but extend it with spatial reasoning elements.

Inspired by a systems surveillance system using Raspberry Pi Single Board Computers and Edge Servers[12], the system architecture presented in this article. Our main aim is to offer a comprehensive safety monitoring solution for COVID-19 that relies as much on IoT devices as possible to make it affordable at the same time.

In the figure 1, a general overview of the IoT-based solution proposed to ensure proper implementation of the COVID-19 safety guidelines indoors.

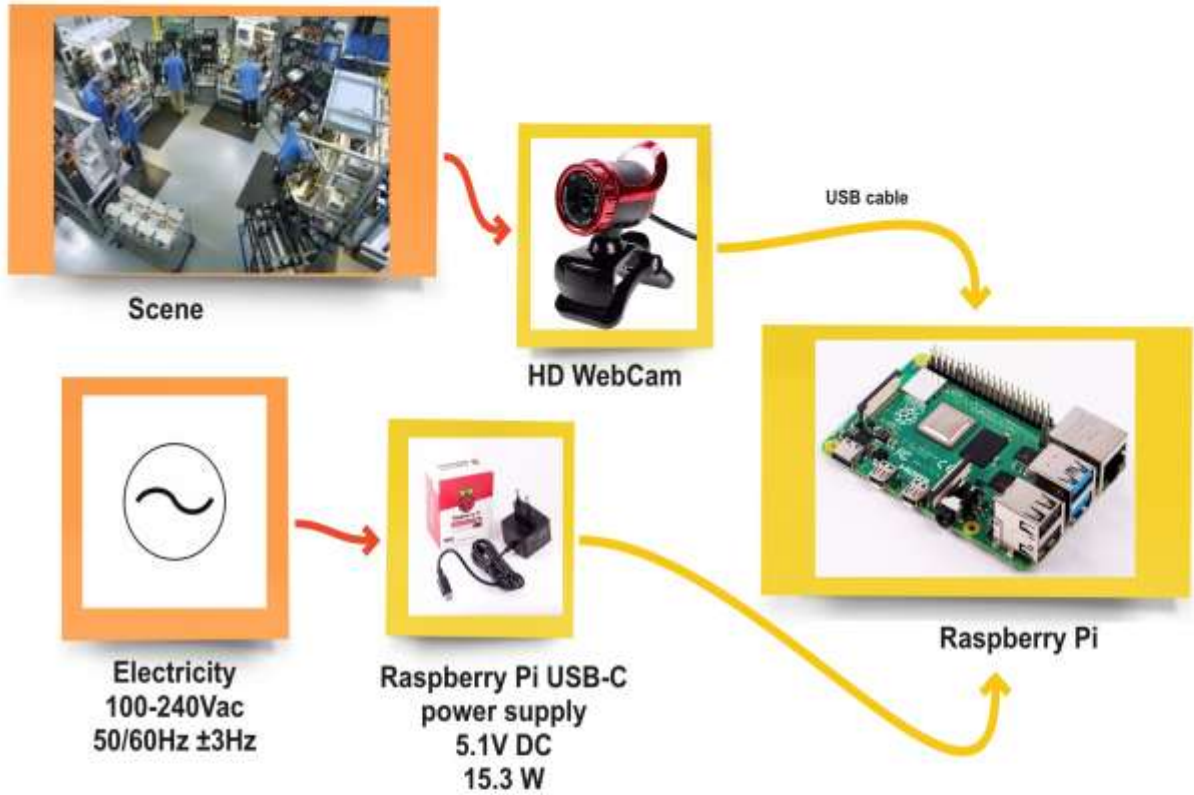


Figure 1. Architecture for Proposed System

Social Distancing Check Algorithm

As per as the social distancing check algorithm is concern, it leverages OpenCV's haarcascade_fullbody classifier for human body detection within the captured image. In following pseudo-code, the algorithm for social distancing check based on computer vision is given.

Pseudo-Code of Social Distancing Check Algorithm

Input: image, $threshold_d$
Output: label
Steps:
1. gray_image=ConvertToGray(image);
2. bodies=DetectFaces(gray_image);
3. if(bodies.length≤1)
4. text="Not enough people for check!"
5. else
6. for each b1 in bodies
7. for each b2 in bodies
8. $d=sqrt((b1.x-b2.x)^2 +(b1.y-b2.y)^2)$;
9. d_m=ConvertPixelsToMeters(d);
10. if(b1 ≠ b2 and $d_m < threshold_d$)
11. label="Social distancing not applied!";
12. sendMQTT("social distancing alert", "location name");
13. end if;
14. end if;
15. return label;
16. end.

First, the camera frame is converted to a grey image, as required by the OpenCV hair waterfall classification, which is used for face detection. In addition, a new copy is also created with the additional black and white camera frame version. Body detection is also applied.

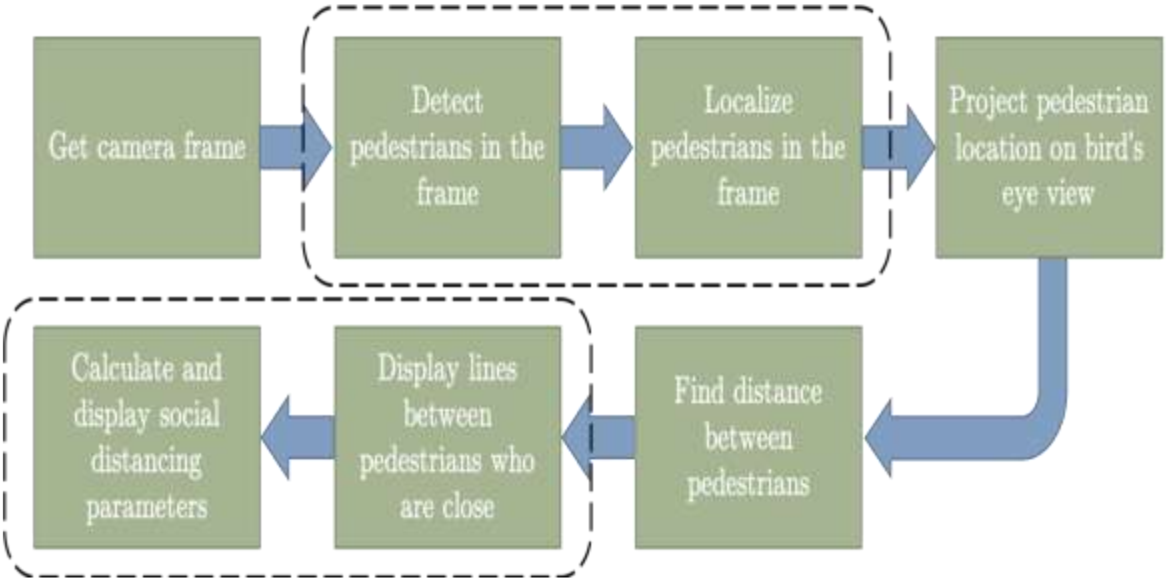


Figure 2. Steps involved in Social Distancing Detection

In addition. The distance between each two persons, when more than one human body is detected, is calculated and compared with a threshold of metres. All distances should, however, be normalised before comparison according to camera properties and object position. The mapping of pixels to real world distances in meters is performed with respect to formula:

$$\frac{\textit{image dimension}}{\textit{focal length}} = \frac{\textit{object dimension}}{\textit{distance to object}}$$

In a certain scenario, social distance shall be applied correctly if the distance between the two bodies is bigger or equal to a threshold. If otherwise, the message will be sent to the security operator and the server if it is not contained in this conditions for at least one pair of bodies. Fig. 3 displays a social remote control application screenshot.

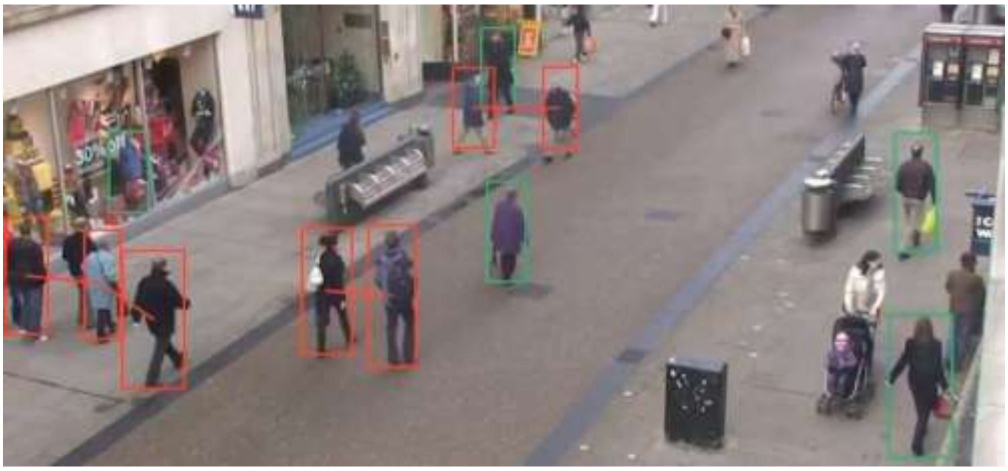


Figure 3. Social Distancing Applications

VI. EXPERIMENTAL ANALYSIS

The following devices were used for evaluation: the laptop with Intel i7 7700-HQ quad-core CPU with DDR4 RAM 16 GB and the 1 TB HDD as edge server at 2.80 GHz; Raspberry Pi 2B (RPi 2B), Raspberry Pi 3 (RPi 3). For the evaluation the following devices were used.
The results of the performance assessment are provided for different scenarios, devices and settings. The first column shows the name of the remote control scenario. The second column shows the set-up of the

hardware used. In addition, the third column is the size of the frame expressed as horizontal multiplied by vertical pixels. Moreover, for a particular configuration, the following column shows the performance results achieved as numbers of frames (fps) processed, or measurements per second (mps). Finally, the last column shows that the scenario was accurate. The percentage of cases found successfully for socially distant violation is expressed on average.

VII. EXPERIMENTAL RESULTS

TABLE I

Distancing check	RPi 2B	640x480	0.72	65-73%
		320x240	2.65	
	RPi 3	640x480	1.12	
		320x240	4.29	
	Laptop	640x480	16.77	
		320x240	61.17	

Taking into account the results shown in Table I, it is possible to conclude that RPi 3 is performer than RPi 2B. The fact that RPi 3 uses newer ARM cortex-A53 quads with a capacity of 1200 M Hz compared to RPi 2Bs can be explained.

Cortex-A7 ARM 900 MHz. However, both have only 1 GB of RAM and the performance behind the laptop is still significant. In addition, all devices show better performance, as expected, for lower resolutions. Compared to the performance of social distance checks, we can see that the other is faster because only one classification (full body) is used. In all experiments in the social distance check processing, CCTV images have been assessed for busy street numbers while the number of people in the camera is expected to decrease. Distance checking performance changes with the distance of the camera objects, as the ratio between pixels and meters is initially calculated. Eventually, with resolution, the effectiveness of both computer scenarios increases, but the cost is paid for with reduced performance.

VIII. CONCLUSION

According to the achievements, the proposed solution may be used for its intended purposes under certain performance constraints (e.g., number of frames or measurements per second). It also refers to open hardware and free software, since these systems have a simple and attractive benefit.

In the future, it will be possible to experiment with various systems for detecting objects on the Raspberry Pi in order to achieve a higher frame rate with deep learning and computer vision. Furthermore, we would like to expand this solution with environmental control mechanisms for adaptive building air conditioning and ventilation airborne protection to reduce the spread of coronavirus indoors, especially during the summer.

Finally, the primary aim is to integrate our resource efficiency planning process in a pandemic crisis with the structure outlined in this paper to allow for efficient protection planning and mask distribution, as well as risk analysis based on compliance with safety guidance and air quality.

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