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# Human recognition for resource-constrained mobile robot applied to Covid-19 Disinfection

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***Abstract*—The global COVID-19 pandemic has stimulated the use of disinfection robots: in September 2021, following a European Commission's action, 200 disinfection robots were delivered to European Hospitals. UV-C light is a common disinfection method, however, direct exposure to UV-C radiation is harmful and disinfection can be operated only in areas strictly forbidden to human personnel. We believe more advanced safety mechanisms are needed to increase the operational flexibility and safety level. We propose a safety mechanism based on vision and artificial intelligence, optimised for execution on mobile robot platforms. It analyses in real-time four video streaming and disables UV-C lamps when needed. Concerning other detection methods, it has a relatively wider and deeper range, and the capability to operate in a dynamic environment. We present the development of the method with a performance comparison of different implementation solutions, and an on-field evaluation through integration on a mobile disinfection robot.**

***Index Terms*—Covid-19, UV-C based disinfection, artificial intelligence, human recognition**

## I. Introduction

The global COVID-19 pandemic has stimulated the production of disinfection robots by institutions and companies. In September 2021 the delivery of 200 disinfection robots produced by the UVD Robots company to European Hospitals was concluded [9]. It was part of the European Commission's action to help hospitals cope with the coronavirus.

Given the results, the Commission ordered further 100 robots, bringing the total donations to 300. This is the following of a trend that began in 2020 in China when the first disinfection robots were applied in the Smart Field Hospital in Wuhan [16].

The concept of automated disinfection without involving human operators looks interesting from the perspective of the hospital management, and not only. It can save lives by avoiding the cleaning personnel working in highly infected environments. At the same time, it can reduce costs by diminishing the required number of human operators. Consequently, these robots are being applied also in the disinfection of public spaces, such as the metro [17] and supermarkets [15].

The most commonly adopted robots, like the one from the UVD company [13] [14], use UV-C light to disinfect surfaces. UV-C radiations alter DNA and RNA so that organisms cannot replicate. Others use also vapour and fogging systems that spray chemical disinfectants, such as ozone [10].

However, these robots are not ready to operate in a fully automated and flexible way. Because of the presence of UV-C lamps, strict safety mechanisms have to be applied, since UV-C radiation must not reach humans. In the end, there's a need for a human supervisor.

Evolving security mechanisms can reduce the risk of exposure to UV-C radiation due to supervisor errors.

The work has already been published in the proceedings of the 6th International Conference on System-Integrated Intelligence (SysInt 2022), held in Genova, Italy on September 7-9, 2022 [18].

## II. Related works

Today, autonomous disinfection robots seem to be the most effective way to reduce the risk of infections in public spaces such as hospitals, grocery stores, stations, etc... The most commonly adopted disinfection method uses UV-C light to disinfect surfaces, which has proven to be effective in reducing surface microbial contamination, cross contamination, and the spread of multidrug resistant bacterial infections in hospitals [4]. Figure 1 shows an example of a UV-C-based disinfection robot.

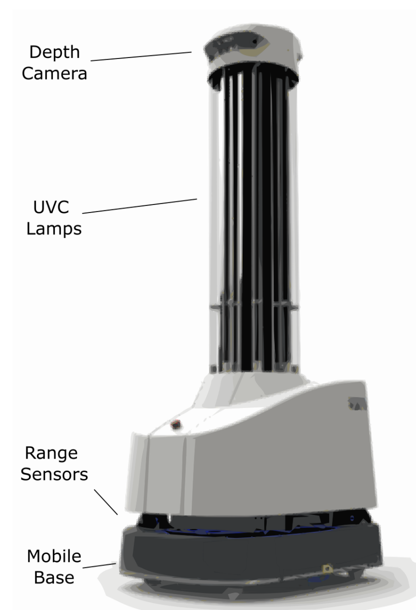



Fig. 1: An example of a UV-C-based disinfection robot.

UV-C radiations alter DNA and RNA so that organisms cannot replicate. Unfortunately, the majority of UV-C lamps emit small amounts of UV-B radiation which proved to be carcinogenic. Both high dose or prolonged low doses of radiation from some UV-C lamps can potentially contribute to skin cancer [11]. Nevertheless, even brief direct exposure of skin and eyes to UV-C radiation from UV-C lamps can cause painful eye injury and burn-like skin reactions [11]. Thus strict safety mechanisms are required to avoid radiation reaching humans.

Given that detecting human presence nearby is not an easy task, the majority of UV-C-based disinfection robots are designed to work in protected environments, where human is not present. Usually, the access to the space under disinfection has to be restricted by obstacles, signals, or sensors at the entrances, which are used as safety measures. When one of them is removed the robot stops working since it assumes that a person entered the protected area. This procedure is the case of disinfection robots by UVD Robots [13] [14].

Another common safety mechanism relies on the assumption that the protected environment is static. No motion is allowed. If something moving is detected, the robot has to stop working, waiting for the next activation by the supervisor. In this way, if a person accidentally enters the area under disinfection, its motion is detected and the lamps are shut down. This is the case of the disinfection robot proposed by Guettari et al. [1].

Motion detectors are not reliable solutions to detect human presence. A patient sleeping inside a hospital room doesn't produce enough movement to be detected. A careless check by the supervisor would expose the patient to the entire disinfection process.

Moreover, this mechanism strongly limits robots' cooperation capability. No other robot can work in the same area, since if something moves the disinfection is stopped.

Other disinfection robots proposed in scientific literature do not implement any human-detection safety mechanism [3].

The last type of safety mechanism encountered uses cameras and artificial vision to detect humans. This is the case of Ultrabot [2] by Perminov et al. and the PHS-M8 by Rayrobotics [12].

Ultrabot uses four cameras, placed in the front and the rear of the robot, to detect humans. However, no details about the algorithm operation and performance are provided, and the sensor placement does not seem to fully cover the operating area. No camera looks in the irradiation direction, so a human standing in front of the lamps would not be detected.

Instead, the PHS-M8 uses artificial intelligence to detect people by one video stream. The camera used cannot check the whole area surrounding the robot with its field of view. No details about the worst-case observed latency, the frame rate, and the accuracy are given.

## III. Proposed safety mechanism

The proposed safety mechanism makes use of multiple camera sensors and Artificial Intelligence to detect the presence of humans. In particular, it implements convolutional neural networks (CNNs), to analyze in real-time the streaming video coming from four cameras mounted on board the disinfection robot. Figure 2 shows a schematic view of the hardware. This solution overcomes the limitations of the single-camera system while avoiding the issues related to motion detectors. Artificial vision algorithms can require in general relevant computational power to work in real-time: the main contribution of the presented work aims at developing a multiple-camera, real-time human detection system, capable of running on embedded processing units suitable for mobile robots applications.

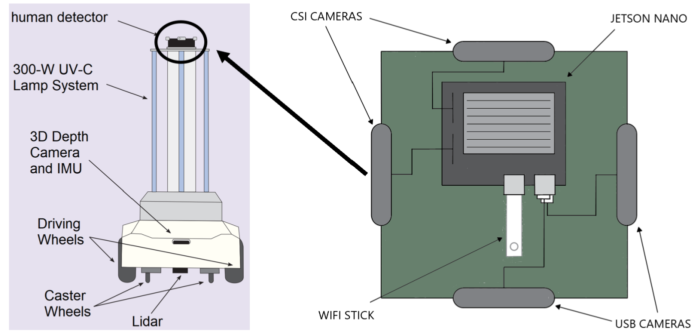


Fig. 2: A schematic view of the robotic mobile platform, on the left, alongside the human detector, on the right.

The NVIDIA Jetson Nano has been chosen as the target computing platform. It is an embedded system equipped with an NVIDIA Maxwell graphic processing unit (GPU) with 128 NVIDIA CUDA® cores and 4 GiB of shared memory, able to run quite large CNNs, like VGG16, at 10 frames per second (FPS).

Two of the cameras used are Raspberry Pi Camera Module V2 connected through the two CSI connectors on the board, able to acquire at 1080p30, with an angle of view of 62.2 x 48.8 degrees. The others two are Logitech C270 cameras able to acquire at 720p30, with a diagonal field of view of 55 degrees, connected through two USB-2 connections.

The inference results are advertised through the robotic operating system (ROS) so that lamps are shut down whenever human presence is detected in at least one frame. Connectivity to other robot modules is provided by a WiFi USB stick.

The whole system is enclosed in an electronic box and placed on top of the robot, as shown in figure 2, to have a good point of view. The mobile disinfection robot used for the experimental evaluation was developed at the IIM Institute of the Scuola Superiore Sant'Anna of Pisa [3].

## IV. Design and test of the artificial intelligence application

The artificial intelligence application has been designed and trained thanks to the Keras API using Google's Colab free online service which offers limited GPU usage for research purposes. Then it has been exported in the ONNX data format and parsed by TensorRT to obtain an executable for NVIDIA GPUs. During the conversion, a cast to half-precision floating-point is performed. The obtained file has been executed directly on the onboard GPU thanks to the CUDA programming model obtaining the best performance.

The Common Object in COntext (COCO) data-set, 2017 version, is used to train and validate the application. It contains 118,287 training images, 64115 with humans and 54172 without, and 5,000 validation images, 2693 with humans and 2307 without. Because of Google Colab access limits, only 12,000 images are used for training, 6,000 with humans and

| | VGG16 | MobileNetV2 | ResNet50V2 |
|---|---|---|---|
| accuracy | 0.8315 | 0.84330 | 0.84308 |
| WCOET [s] | 0.67 | 0.11 | 0.21 |
| footprint [MiB] | 80.156 | 6.097 | 58.491 |

TABLE I: Accuracy, WCOET, and memory occupancy of each network executed on NVIDIA Jetson Nano.

6,000 without. Also, the validation set has been balanced. 2,307 images are taken for both classes.

The validation set is not used for training to better evaluate the generalization capability of the obtained application. Images with humans are labelled with 0 while the others with 1.

Transfer Learning is used to design the artificial intelligence application. Three different well-known pre-trained CNNs, offered by the Keras API, are tested: ResNet50V2, VGG16 and MobileNetV2.

Only the feature extractor, with frozen weights, is taken. It is fed by a pre-processing pipeline. Then the extracted features are fed to a 2D Global Average Pooling layer to improve the model's generalization capability [7] and finally classified by a perceptron.

In the pre-processing pipeline, the input image is first resized to 224x224 resolution to save computations then min-max standardization is applied to improve the gradient descent convergence rate [8].

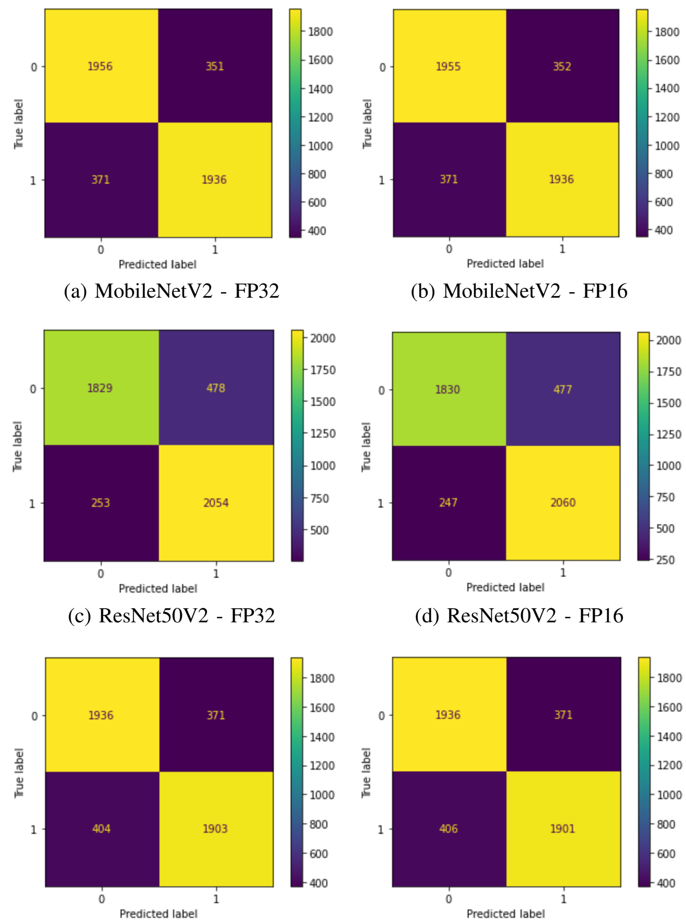
The perceptron is trained for 10 epochs with a learning rate of 0.01 using binary cross-entropy as a loss function. If the output is less than or equal to 0.5 the image is classified as with human presence otherwise no. No data augmentation is applied.

Figure 3 shows the confusion matrices and the accuracy score computed onto the validation set for each application. In the first line, the results obtained in Keras are shown. While in the second line the results computed on the Jetson Nano, using a half-precision floating-point are presented.

As shown from the presented graphs, the results are consistent. There are only a few changes in the confusion matrices due to the cast, which led MobileNetV2 and VGG16 to perform slightly worst. On the contrary, ResNet50V2 slightly improved its score.

Anyway, all the confusion matrices are well balanced except for the ResNet50V2 which shows a trend in detecting the human presence. This is might not be a problem, considering the aim is to build a safety mechanism. On the other hand, it might worsen the usability of the robot due to the higher rate of false positives.

Looking at the table I reporting the worst case observed latency (WCOET), the memory footprint and the accuracy score of each solution, the MobileNetV2 has been chosen as the best approach. It has the higher accuracy score and the lowest WCOET.



(a) MobileNetV2 - FP32 (b) MobileNetV2 - FP16

(c) ResNet50V2 - FP32 (d) ResNet50V2 - FP16

(e) VGG16 - FP32 (f) VGG16 - FP16

Fig. 3: Confusion matrices - Keras (FP32) vs TensorRT (FP16).

All the data have been measured on the Jetson Nano. The WCOET has been measured running one model at a time with 4 video streams active for 30 minutes each. It includes the time needed to gather the latest frame from each camera, the inference time, and the time to publish the result. The memory footprint has been taken by the file properties of the executable and the accuracy score is the one computed previously on the COCO 2017 validation set.

## V. On-field Experiments

The proposed safety system based on the MobileNetV2 has been implemented and experimented on board the UV-C disinfection robot developed at the IIM Institute of the Scuola Superiore Sant'Anna. The robot was operated inside the laboratory's rooms during normal working activities to gather the frames processed by the system with the inference results overlaid on top. Green overlay numbers indicate a frame classified as human presence. Red numbers indicate the opposite.

During tests, activation of the UV-C lamps was inhibited by a safety switch, and the robot was teleoperated.

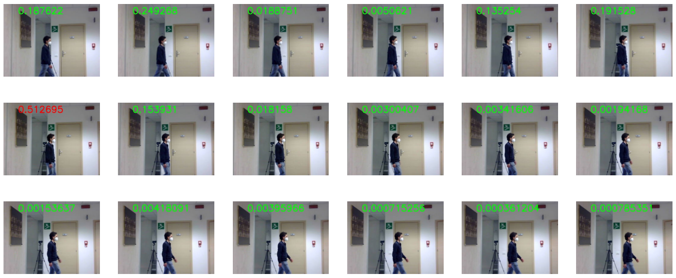


Fig. 4: Example of glitch with human in classification.

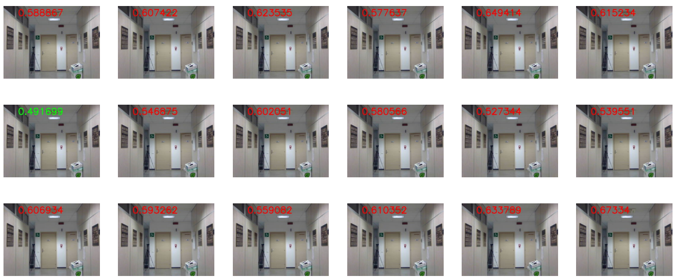


Fig. 5: Example of glitch without human in classification.

The gathered time-lapses evidenced two main behaviours: isolated glitches and gradual classification. Figures 4 and 5 show two examples of glitches in classification. As it can be seen in the images, occurred glitches appeared isolated. Given the relatively high frequency of the frame rate, these glitches can be avoided by implementation of a moving-window filter. In the real operating modality (with UV-C radiation activated) the filter would prevent fast power-off and power-on transients of the UV-C lamps. Anyway, using the whole dataset to train the networks would be a first better solution.

## VI. Conclusion and future works

This paper presented a safety mechanism based on artificial vision that prevents UV-C radiations emitted by autonomous disinfection robots, from reaching humans. It enhances industrial and academic solutions by using artificial intelligence to analyze multiple video streams in real-time. The investigation was performed in order to develop and compare CNN-based algorithms suitable for execution on embedded processing units, typically available in mobile robot applications. The developed artificial intelligence application was validated on the 2017 version of the COCO validation set, not used in training, and obtained an accuracy score of 84.3% with a balanced confusion matrix. The whole system has been implemented and experimented on a mobile disinfection robot to better understand its behaviour in a real case scenario. The evaluation was performed in an office unstructured environment: it confirmed results obtained during test, suggesting the method as a viable solution to increase safety levels on UV-C disinfection robots.

The safety mechanism can be further improved by using the whole COCO training set, applying data augmentation techniques, unfreezing and fine-tuning the last layers of the convolutional base, and connecting more cameras. Since Jetson Nano does not support 8-bit inference, no Quantization Aware Training can be applied to further reduce inference timings.

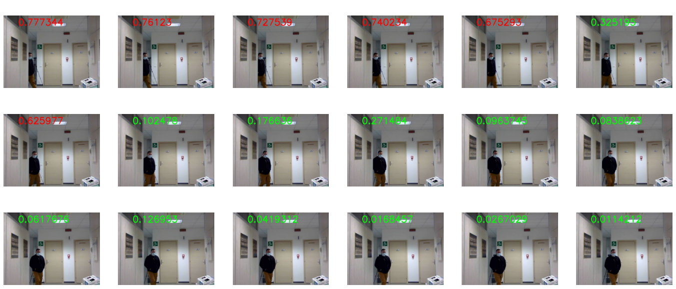


Fig. 6: Example of gradual classification of human.

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