Integrated Simulation and Assessment in Donning and Doffing for Healthcare Professionals (ISADD)

Neville Schembri, Daren Scerri, Gerard Said Pullicino, Dorianne Cachia, Phyllis Farrugia Abanfi, Jonathan Vella and Lorna Bonnici West

January 10, 2022

Integrated Simulation and Assessment in Donning and Doffing for Healthcare Professionals (ISADD)

Neville Schembri, MCAST, Malta, neville.schembri@mcast.edu.mt

Daren Scerri, MCAST, Malta, daren.scerri@mcast.edu.mt

Gerard Said Pullicino, MCAST, Malta, gerard.said@mcast.edu.mt

Dorianne Cachia, MCAST, Malta, dorianne.cachia@mcast.edu.mt

Phyllis Farrugia Abanifi, MCAST, Malta, phyllis.farrugia.abanifi@mcast.edu.mt

Jonathan Vella, MCAST, Malta, jonathan.vella@mcast.edu.mt

Lorna Bonnici West, MCAST, Malta, lorna.bonnici.west@mcast.edu.mt

Abstract

There is an unprecedented increase in the requirement for healthcare staff trained in infection control principles due to the COVID-19 pandemic. This paper presents an example of a technological solution to correctly explaining the sequence of donning and doffing Personal Protective Equipment (PPE) in preparation for dealing with patients who may be infected with a virus. Image processing and machine learning techniques are used to identify articles of PPE as they are worn, and an innovative client server architecture is used to mitigate performance issues given the need for near real time response (NRT). A powerful inference server is used to identify PPE and human activity, while the donning/doffing sequence is monitored by the client application. If the user does not follow the correct steps, the user is notified regarding the missed step in the sequence and has the option to begin the process again. A technical evaluation of the effectiveness of the identification of PPE based on image processing gives a technical insight into how correctly image processing is being carried out, while a qualitative evaluation of the donning and doffing process with qualified infection control staff, as well as nurse trainees is also being carried out to gain an understanding of the possible acceptance of the application.

Keywords: healthcare; machine-learning; image processing; health-tech; ed-tech

1. INTRODUCTION

With the continuous evolution of the COVID-19 outbreak, there is the potential tangible occurrence of larger-scale community outbreaks, both locally and globally. Healthcare professionals (HCPs) must, therefore, act unfailingly with updated protocols, on the appropriate use of a hierarchy of control measures, including the appropriate wearing (donning), removal (doffing) and disposal of personal protective equipment (PPE), designed for the mitigation of transmission risks associated with infectious diseases.

Protocol breaches during donning/doffing PPE, such as touching the face while doffing, can increase transmission of COVID-19; thus, the importance of strict adherence to PPE protocols is paramount. Therefore, the overall aim of this research is to build and test an augmented reality and voice controlled prototype which can support appropriate donning and doffing PPE processes by HCPs and to explore perception and acceptability of the final packaged prototype amongst a purposive sample of experienced and non-experienced HCPs.

Current process and experiences of donning and doffing PPE will be explored amongst a purposive sample of: (i) HCPs (nurses) working at MCAST, and (ii) expert/s from the Infection Control Unit at Mater Dei Hospital. A voice control system and a PPE evaluation system will be developed to allow for effective voice commands to be relayed to a smart device and to highlight if PPE has been correctly donned and whether the correct sequence was followed during doffing, respectively.

Iterative testing and feedback through qualitative interviews will be obtained from the following to develop the finalized packaged prototype: (i) HCPs (nurses) working at MCAST, (ii) experienced HCP users of the donning and doffing process recruited through the Infectious Disease Unit at Mater Dei Hospital, and (iii) nursing students from MCAST who are familiar with the donning and doffing process but are not considered to be experienced. The study is split into two phases, with this paper covering the technical evaluation of the AI and ML components of the application being developed, and further research presenting the qualitative conclusions based on the experiences of professional nursing staff while using the application.

1.1. Research motivation

A recent Times of Malta article reported comments by Prof Michael Borg, Head of Department of Infection Prevention and Control at Mater Dei Hospital, who stated that at Mater Dei Hospital "every healthcare quarantine case could have been avoided had the hospital's personal protective equipment protocol been followed appropriately". The article continued to add that globally, healthcare workers contracted the virus either because they did not wear, or, more importantly, did not remove, the PPE correctly (Carabott, 2020).

Evidence generated from this research, if successful, may demonstrate that the proposed design concept is feasible and acceptable and will, therefore, result in disciplinary advancement by impacting future research in the direction of using AI in healthcare. If successful, this research project can, therefore, provide the basis for a useful tool for infectious disease prevention and control. This would be especially useful for the clinical and educational advancement of the following stakeholders:

(i) HCPs who do not perform the process regularly as part of their daily routine and are called to assist with patients suffering of infectious diseases, especially during times of an epidemic or pandemic. This could be the first step to fully or partially replace the traditional educational process with the use of the augmented reality and voice-controlled solution, as suggested in this project proposal. Exploitation of results can, therefore, have a positive impact on the healthcare system by minimizing the need for experienced HCPs to educate and train in a traditional manner HCPs with less experience of donning and doffing PPE processes and, thus, reducing the burden on the healthcare system.

(ii) HCPs who are well-experienced with donning and doffing PPE processes but may inadvertently succumb to fully adhere to protocols in times of stress and pressure, such as during a pandemic. The final packaged prototype aims to alert the experienced HCPs of the inappropriate step they are performing, thus, minimizing the risk of incorrect use of PPE and possible risk of viral transmission. While this research is limited to development, testing and evaluation with a limited purposive sample of expert HCPs, if the prototype is found to be valuable, the research can be extended further, with eventual evaluation and testing in real-life expected environmental conditions with a random sample of HCPs.

(iii) HCP educators can present the basis for an innovative tool which provides clear signage and visual alerts in a classroom setting. This goes beyond traditional teaching methods and, if found to be effective, it can provide simulation which does not allow trainees to progress further during a donning/doffing educational process if this is done incorrectly. The research brings together a network of interdisciplinary experts (mainly from the health and communication technology disciplines) to exchange and transfer ideas and knowledge. The research results will enhance links between the professional (doctors and nurses from the Department of Infection Prevention and Control and the Infectious Disease Unit) and academic health realms (nursing lecturers and IT lecturers at MCAST).

2. LITERATURE REVIEW

2.1. General background

Currently, the world is confronted by a global health emergency, the COVID-19 pandemic, which has brought about extensive challenges, especially related to human health and suffering and serious threats to the global economy (UN, 2020). The COVID-19 outbreak is going through continuous evolvement and the potential tangible occurrence of larger-scale community outbreaks, both locally and globally (Ambigapathy et al. 2020), is now being experienced through a second wave. Inpatient management of patients suffering from COVID-19 has resulted in an increasing pressure and need for more qualified and trained HCPs and, subsequently, hospitals recruited more doctors and nurses. This increased recruitment drive brought about challenges such as the need to re-instate back into practice doctors and nurses who had previously left the setting, as well as preparing newly graduates to practice in a more challenging environment.

On the other hand, HCPs, experienced or non-, must act unfailingly with updated protocols on the appropriate use of a hierarchy of control measures, designed for the mitigation of the risks associated with infectious diseases. PPE (e.g. face masks, gloves, gowns and eye protectors), is an important type of such control measures, which exists along with other types of controls, including administrative, environmental and engineering ones (WHO, 2014). Research has explored current materials used for face masks and respirators and the feasibility of reusing masks (O'Dowd et al., 2020). Swennen et al. (2020) worked on a prototype of a custom made three-dimensionally (3D) printed face mask that can be reused, although these have provoked some dermatological issue concerns.

Apart from being able to choose the right types of PPE, HCPs must always be aware of, and adhere to the latest guidelines, standards and methods available regarding the wearing (i.e. donning), removal (i.e. doffing) and disposal of PPE (Ministry of Health Malaysia, 2020). This generated a significant pressure to provide adequate and timely training to HCPs, whether they are, or are coming back, in the profession, to help during the pandemic to perform tasks, such as diagnostic swabbing of patients. However, performance of such tasks entail a number of skills, including appropriate use of PPE, which are not routinely within their line of normal practice but are imperative for the mitigation of COVID-19 transmission.

To-date, donning and doffing of PPE has relied on traditional methods, i.e. HCPs follow specific written guidelines. Whilst these are considered to be evidence based and imperative to prevent and control infectious disease, a major concern is that written guidelines do not alert the HCP if s/he is conducting the donning and doffing PPE process incorrectly. In line with this concern, Ambigapathy et al. (2020) argued that the long-term use of PPE under prolonged periods of stress or pressure, such as the COVID-19 pandemic, can lead to complacency, carelessness or a false sense of security and, therefore, lead to protocol breaches such as those relating to face-touching and surface-contact, which are drivers of viral disease transmissions (Kwok et al., 2015). Research by Phan et al. (2019) showed that inappropriate doffing of PPE in healthcare workers (HCWs) is common, with the commonest malpractices being inappropriately touching the front of the mask while doffing and touching a potentially contaminated PPE surface with a non-gloved hand. Another research by Lan et al. (2020) showed that the face was the more frequent site of skin damage in Chinese HCWs managing COVID-19, related to pressure from wearing face masks and goggles as part of PPE. In line with Phan et al. (2019), Lan et al. (2020) stated that HCPs may be tempted to touch their face after removal of PPE. Therefore, given the respiratory route of transmission of COVID-19 the importance of strict adherence to PPE protocols is paramount.

The use of artificial intelligence (AI), in particular computer vision, has been widely used in areas of medical imaging (Suzuki, 2017; Roy et al., 2020). Some research has been conducted in using AI for face mask detection, without delving into a complete donning and doffing of PPE process (Loey et al., 2021). There is a paucity of research that explored the application of AI to reduce the complexity of the process of donning and doffing of PPE, whilst still following evidence-based guidelines. Therefore, this research aims to build and test an augmented reality and voice controlled prototype which can support appropriate donning and doffing PPE processes by HCPs and to explore perception and acceptability of the final packaged prototype amongst a purposive sample of experienced and non-experienced HCPs. Since to-date donning and doffing of PPE has relied on specific written guidelines, this project goes beyond existent research by building and testing an innovative technology which could be the first step towards (1) providing a more attainable solution than the traditional methods of training during a time of crisis (e.g. during a pandemic), (2) ensuring that HCPs adhere to donning and doffing PPE guidelines, and (3) providing an innovative tool which can support HCP educators in providing a simulation environment to students which goes beyond traditional teaching methods.

3. METHODOLOGY

Figure 1 explains the 3 main phases of our project; namely, the creation of custom datasets and AI model training, the backend inference engine which takes care of PPE recognition and action validation, and the generation of states and donning/doffing sequencing client-side sub-system. An evaluation of accuracy, recall, precision, mAP, was conducted followed by ground-truth and performance testing.

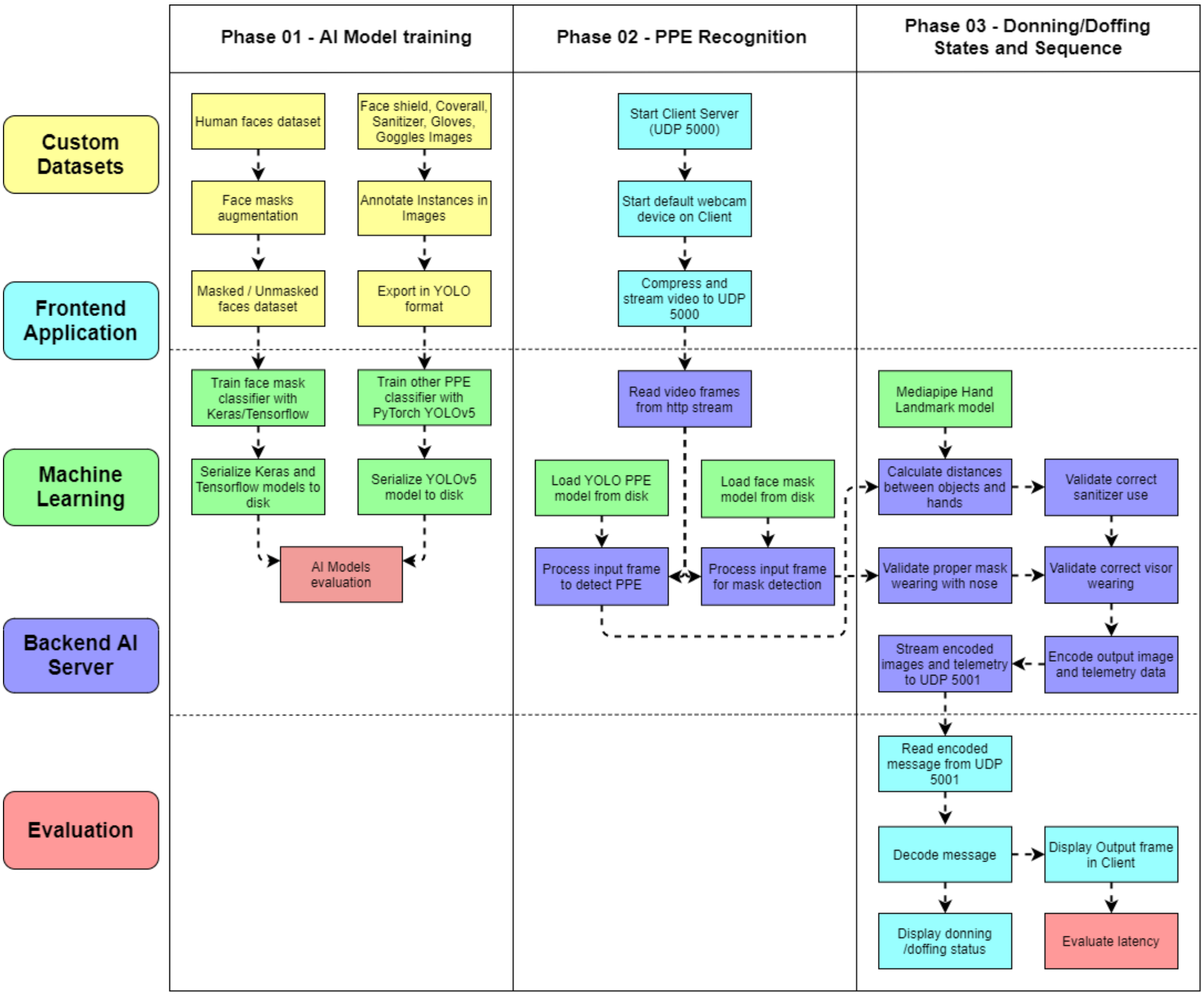

Figure 2.1 - PPE Donning/Doffing Assistant Pipeline

3.1. Phase 01 - Dataset and AI Model Training

For AI model training a two-stage system was proposed. Due to the variety of faces, mask types and position on face, correct mask wearing classification was kept separate from the other PPE objects, to allow the inference engine to distinguish between only two opposing classes i.e. mask-on (positive images) or mask-off (negative images). This approach also mitigated the effect of face intersections with other objects, like for example the face shield, which would negatively alter the accuracy of the algorithm at different phases of the donning/doffing process.

Given its critical importance for this study's success, two datasets were also considered and evaluated; a Kaggle dataset of masked and unmasked faces made of 853 images, and a dataset made of 1376 images with half of them automatically generated through augmenting face-masks as an overlay on the unmasked faces as suggested by Prusty et al. (2021). Both datasets obtained highly similar results. However, the augmented approach was preferred due to its versatility should the dataset be improved to include IDU staff, allowing different masked faces to be augmented from staff photos. The dataset was then formatted for Keras/Tensorflow model training and no annotations were required. Face mask classification and inference algorithm was done with Tensorflow and kept separate from the other PPE detection system (YOLOv5), to allow further processing in a separate GPU space, which was required to assess correct mask wearing, especially nose cover.

Kuznetsova et al. (2020) proposed a system for apple detection using both YOLOv3 and YOLOv5 to aid in apple harvesting. In the end, pre-processed YOLOv3 obtained a Recall of 90.8%, whereas YOLOv5 with no pre-processing obtained a higher Recall of 97.2%, making it the obvious better choice. Table 2.2 presents the results obtained from using different base models with over 5000 COCO val2017 images, using a V100 GPU and a batch size of 32, together with image pre- Table 2.1 presents the mAP comparison between YOLOv3 and other object detection algorithms for a Ground penetrating radar (GPR) pattern-recognition application presented by Li et al. (2020), where YOLO outperforms all other technologies in mAP score. A visualisation of these results can be shown plotted on the graph presented in Figure 2.5, where the FPS is shown plotted against the batch size of each algorithm.

Algorithm	**Backbone**	**mAP_{50}**	**mAP_{75}**	**mAP_{sc}**	**mAP_{mc}**	**mAP_{mb}**
SSD	ResNet-34	75.66	79.80	79.37	71.44	66.31
Faster-RCNN	ResNet-18	81.45	66.22	74.21	77.09	68.51
YOLOv2	Darknet-19	80.34	72.05	80.08	66.15	68.92
YOLOv3	Darknet-53	83.16	77.15	85.82	76.30	79.90
VIoU-YOLOv3	Darknet-53	82.71	75.90	84.56	83.17	76.10

Table 3.1: mAP comparison for five detection algorithms, where mAP_{sc}, mAP_{mc} and mAP_{mb} represent the single GPR images classification, multi-class classification and single layer steel bars scenes, respectively (Li et al., 2020).

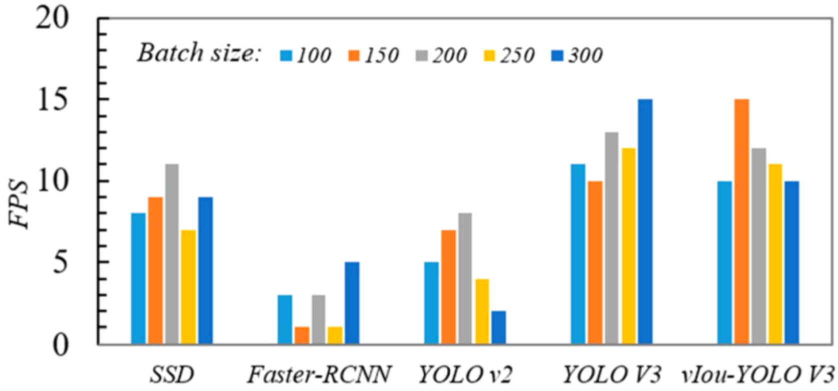

Figure 3.1 - FPS versus batch size for five popular detection algorithms (Li et al., 2020).

Benefits of using YOLO include the fast speed of detection and recognition of the algorithm, due to not needing a complex pipeline. YOLO was the fastest one by a wide margin, making it an optimal choice. Moreover, when trained on natural images, this algorithm performs better than top detection algorithms, such as R-CNN and DPM. This is because, since YOLO is generalizable, it is not as likely to break down when used in new domains or given unexpected inputs. On the other hand, YOLO does not predict as accurately as other state-of-the-art detection algorithms when it comes to detecting small objects, due to its speed (Redmon et al., 2016). For this study, a custom dataset was created by combining new images relevant to this research and other public datasets which may include some type of PPE. Figure 3.2 shows the instances for the different PPE types in the current dataset.

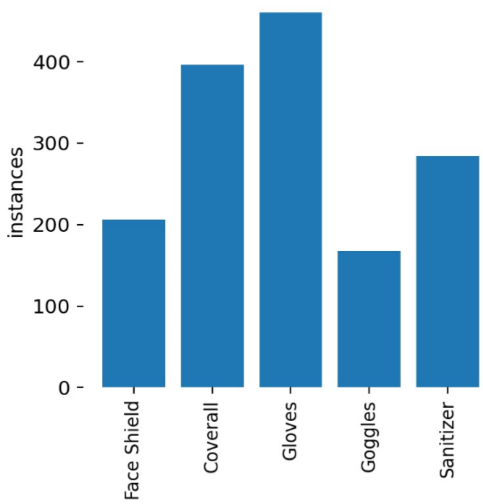

Figure 3.2 - PPE dataset (YOLOv5)

3.2. Phase 02 - PPE component recognition with real-time activity validation

The second phase in the pipeline attempts to identify if the different PPE objects together with face, nose, eyes and hand landmarks. The human face and hands detection was required to assess the activity of the user in relation to the PPE objects. For example, checking for correct mask wearing, if the face shield is being worn correctly or whether the sanitizer was used. Firstly, to identify a facial element, two methods were proposed. The first method which was tested involved the use of Haar cascade classifiers to detect a human face. The system compares the frame from the live feed with the cascade classifier and if there are enough similarities, it determines if it is a face or not. The idea was to check if the face visor was within the bounding box of the individual's face using the facial classifiers. The second method which was also tested, works by using eye cascades to detect the individual's eyes, which will then be used to see if they are within range of the visor bounding box. The second step of this phase was to determine the distance between the bounding box of the face shield and the bounding boxes of the eyes. Euclidean Distance is mostly used to tackle such an issue (Witten et al., 2002). The Euclidean Distance is calculated as the square root of the sum of the squared differences between the two vectors (ibid.), which is given in (1).

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \qquad (1)$$

A number of scenarios were created, with different distances from the camera, to determine the optimal distance between the eyes and the face shield. In each frame, upon detection of both the

Figure 3.3 - Correct face shield wearing validation.

face shield and the eyes, the x and y coordinates for both bounding boxes were stored in separate variables and passed to the Euclidean Distance function for calculation accordingly. The value generated by the Euclidean function was then compared with the optimal distance. To account for varying camera distances, a dynamic threshold was generated by dividing the width of the face shield by an appropriate ratio value. To determine this value, a number of testing experiments were performed to check which configurations are optimal in relation to the ground-truth. The dynamic threshold was then used to see if the distance calculated between the two objects is within range or not.

Secondly, instead of just passing the face shield starting x point and the ending y point of detection for calculation, the centroid of the face shield head band was considered. If the face shield is detected and the eyes are not present in the frame, a statement indicating that the face shield is not being worn properly is shown.

A similar on-the-fly approach considering distances and intersections between object/s and human was employed to validate sanitizer use. The YOLOv5 model and Mediapipe SDK were used to detect sanitizer and hand landmarks respectively. The intersections of thumbs and/or index fingers with the top nozzle of the sanitizer bottle were used. To account for the temporal dimension frames were pushed and popped using a double-ended queue consisting of the last 20 frames. On each iteration the queue was checked to check if it predominantly contained sanitizer use states or not, and change status for user accordingly as shown in Figure 3.4.

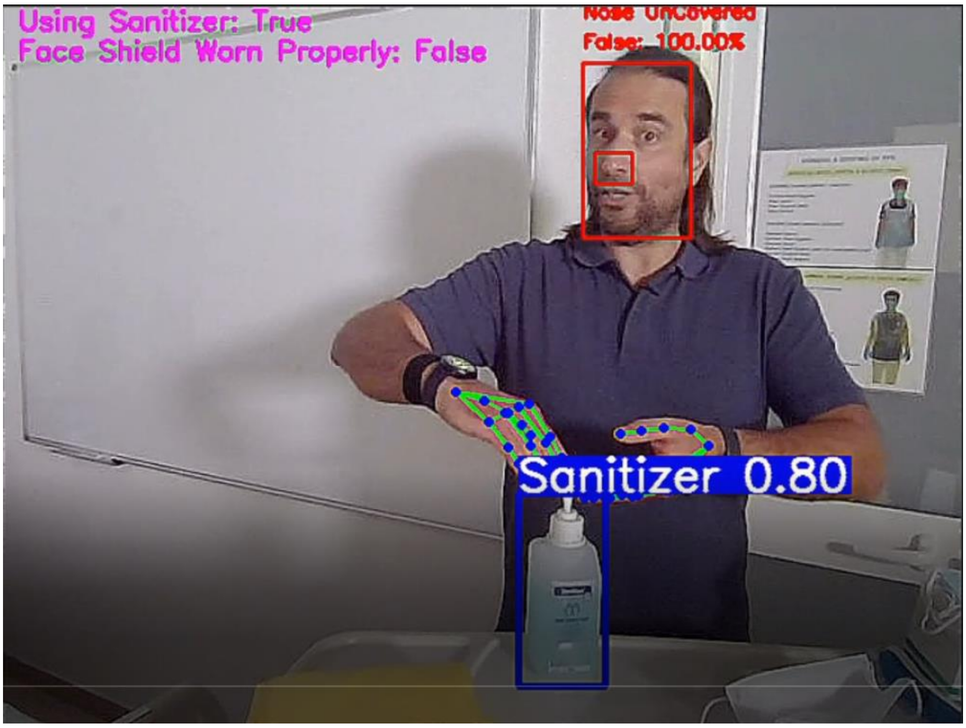

Figure 3.4 - Sanitizer use tracking.

3.3. Phase 03 – Donning/doffing statuses and sequencing.

The ISADD application is based on a client-server architecture. Following an evaluation of different techniques to perform client server data transfer, a networked architecture was selected to feed data into the inference engine which annotates the images on a GPU installed on an offsite machine. The client application was developed using the Unity game engine, which allows us to program the frontend using C#, and to simply interact with the python inference engine.

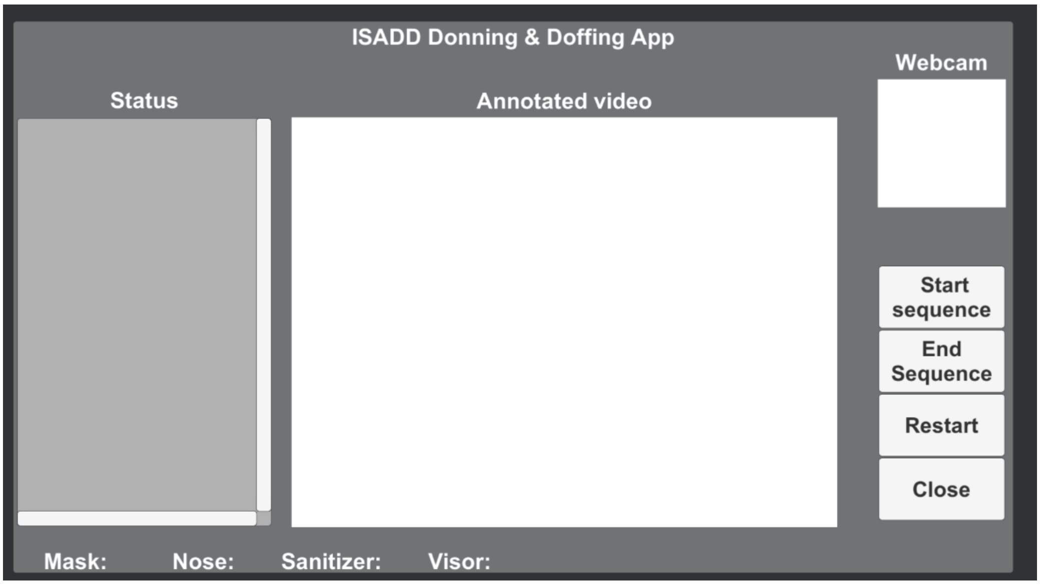

Figure 3.5 - Unity App UI

The Unity app contains two main components and runs two threads which communicate over the network with the inference engine.

Client and server are connected via a VPN setup. Both machines are set to a static IP address on the VPN. One the VPN connection is established, the inference server is started. The feed periodically checks for data on the static IP of the client on port 5000. If data is found, inference begins, but if no data is being served, the inference engine waits for the feed to begin.

When the app is started, an http server starts up. This server captures the webcam on the client device at 25 frames per second, then serves them via an http server as an mjpeg image. In this way, the client sends data to the inference server, which can then process them according to the algorithms as described above.

The client also establishes a connection via zmq (a specific network sockets implementation) over port 5001. This connection is used to receive both the annotated video from the server as well as telemetry (in the form of a correctly formatted json file), showing the current objects being detected and the additional data being detected by the inference engine. This code runs in a separate thread, which also contains a specific callback function which happens every time new data is being received.

The callback function receives data from the server as an array containing 6 elements, with the last element containing a base64 encoded string containing the annotated video result of the inference engine. The other fields are set to true or false depending on the presence or absence of a particular object, with the sequence being set as follows:

Order	Field name	Value
0	Mask On	True/False
1	Nose Covered	True/False
2	Sanitizer Used	True/False
3	Visor On	True/False
4	Video size	Json file
5	Video	Base64 encoded string

Table 3.2 - Order of network data fields

The Unity application runs asynchronously to the server sending the webcam data, but the statuses in the JSON file are parsed and listed in the application. It is possible to run the Unity application as a mobile app or on a desktop computer, given a network connection.

The implemented architecture is an important aspect of the methodology as the flexibility of the application allows the client to be run on a very wide variety of hardware, with the complex setup only happening on the inference server, which can be located offsite.

The sequencing buttons are used to reset or begin the sequence for the user, as required for training purposes. Each step in the process is document in the front end of the application and is listed in the scroll-view on the right hand side of the application. Every change in state is illustrated by an update on the right-hand side of the screen.

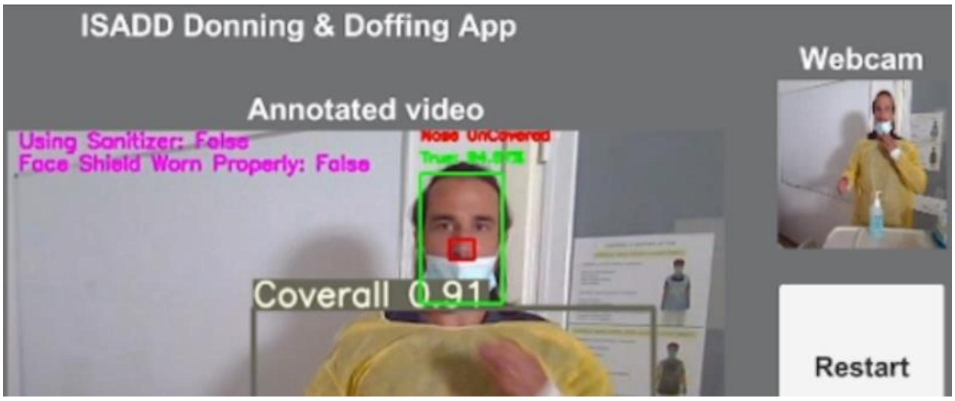

Figure 3.6 - Nose uncovered detection

The user interface of the system is designed to be responsive to different screen sizes however is meant to be used in the landscape orientation. The system setup has been tested using an external DSLR camera connected via USB to a laptop, as well as while using an internal webcam. The camera feed is selectable through the unity application, however on a mobile device, it defaults to the front facing camera of the device itself.

As part of the test, the counts of the ‘true’ values are shown in the labels across the bottom of the screen. These values highlight the threshold values of the different statuses. Thresholds increase and the telemetry is polled using an asynchronous task which runs every 50 milliseconds. As the frames are read via zmq, the async task updates the counts of each of the elements and checks whether the correct sequence has been carried out, based on the relative counts of each of the five elements.

The correct sequence (based on CDC literature) is therefore worked out in the following way:

1. Wear mask (ensure it is worn correctly and covers nose)
2. Use sanitizer (ensure that the sanitizer lever is fully depressed)
3. Wear visor (ensure that it is worn correctly)
4. Use sanitizer
5. Wear gloves (ensure they are worn correctly)
6. Don coverall

Threshold values are determined for each step, with a fixed number of true values required for each of the steps. The initial ‘wear mask’ state, for example, requires 10 true values of the state to be registered.

If at any point, the nose uncovered status is higher than 10 true values, the program switches to ‘invalid status’, and the sequence is reset. This means that if the process is not correctly followed, and an element is done out of turn, the sequence will default to invalid status and restart with the test for the mask.

The user also has the option to reset the status and begin the process from scratch themselves. In this way, each element in the donning and doffing process is treated separately, with the program polling the presence of each element independently, with a variable denoting the current status of the user. The list of possible statuses is reproduced below:

Status
Mask On
Sanitizer Used
Visor On
Gloves On
Invalid
Default

Table 3.3 - Possible statuses in the donning / doffing app

As the user steps through the possible statuses, the list of statuses that have been passed through is added to the sidebar, unless the status becomes invalid due to an incorrect sequence.

4. RESULTS

The technical evaluation of the neural network's efficacy resulted in a number of metrics being generated. The confusion matrix below shows the relationship between correctly identified elements vs their tags at the end of training for the neural network. Note how there is a clear relationship between dataset size for the respective classes and the confidence in the correct result in the context of predicted true positive and true negative values vs the actual true positive and negative values. The nature of the face shield and its similarity to a coverall from some angles meant that other methods were required to verify the face shield completely.

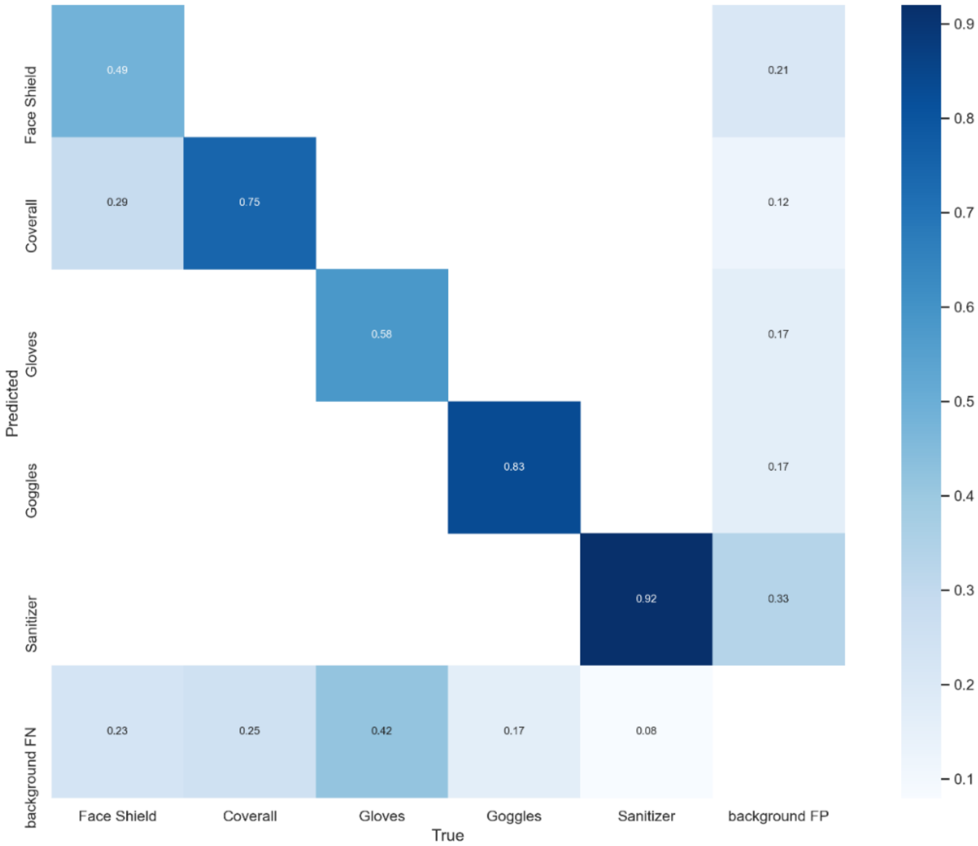

Figure 4.1 - Confusion matrix across PPE object classes

The performance of neural network during training is demonstrated in Figure 4.2. Note that since this is an object localization task, a mAP of 0.704 was reached based on an Intersection of Union threshold of >= 0.5, as may be seen in the graph on the bottom right. All of these graphs show the progress of the model algorithm as it is trained, with the number of epochs being shown on the x-axis.

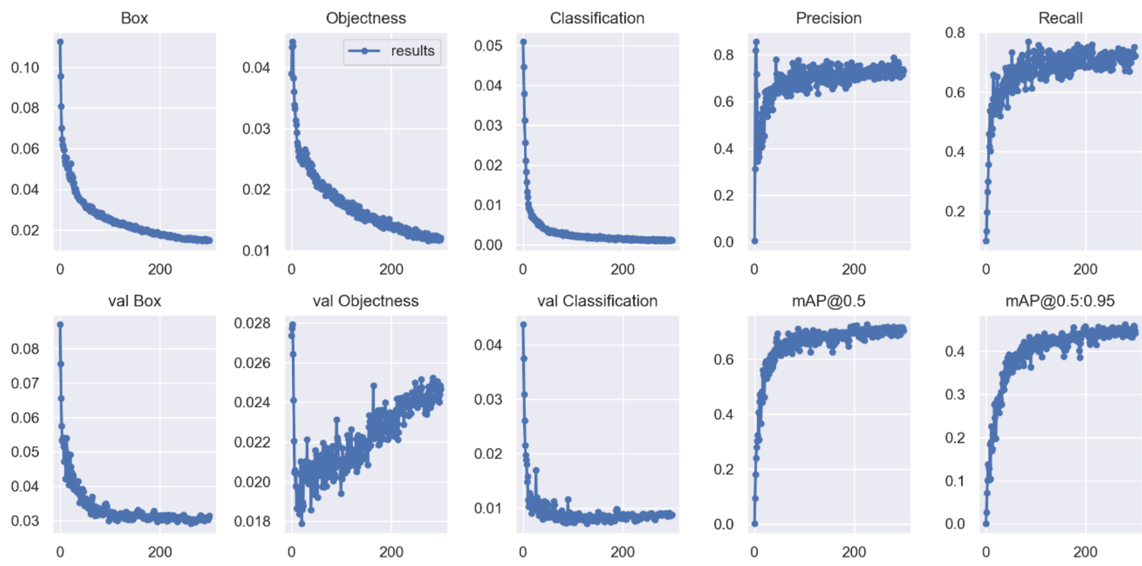

Figure 4.2 - Training metrics with 300 Epochs

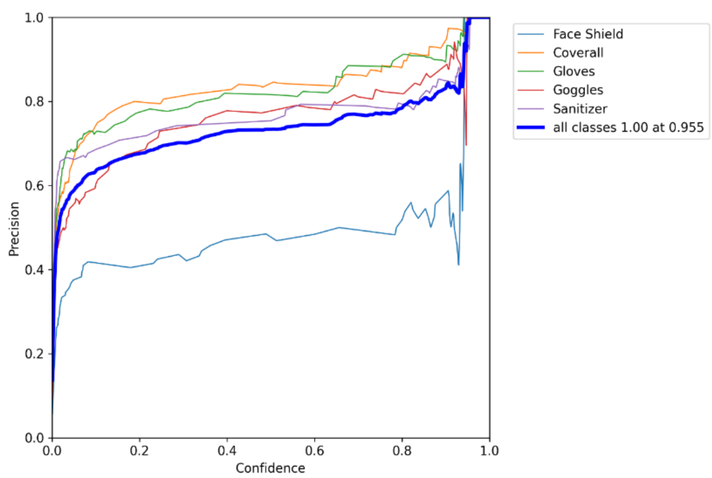

Figure 4.3 - Precision vs Confidence

Figure 4.3 shows how many times elements in the image were classified correctly in the correct class and the confidence level for those elements, so how many of the labelled elements were assessed and correctly listed as being elements of the highlighted class. The aggregation of all classes is displayed in the thicker line.

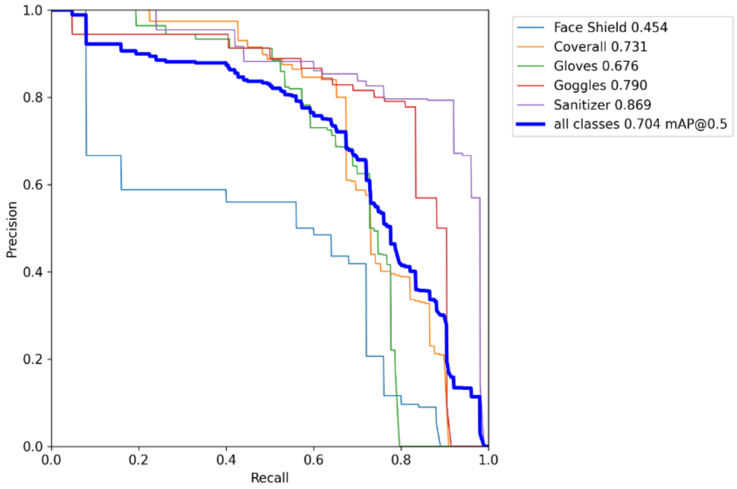

Figure 4.4 - Precision vs Recall

Precision vs recall (Figure 4.4) is measuring the sensitivity of the algorithm to correctly detecting the presence and location of any of the elements and the classes in the image. Note how the precision and recall of the face shield is the lowest as the element itself is hard to detect.

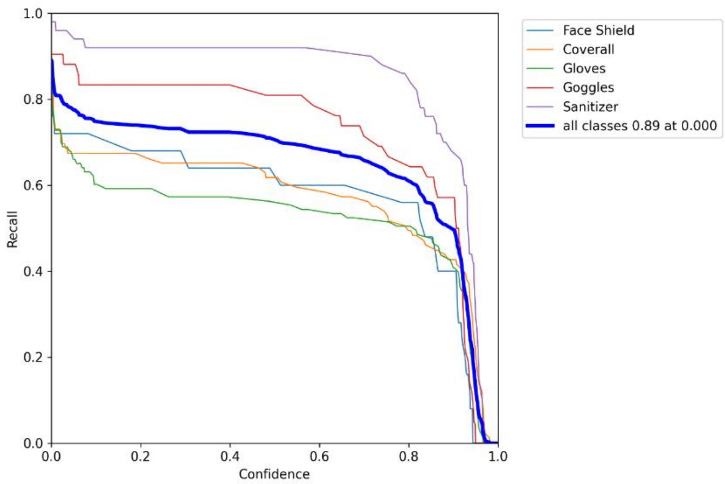

Figure 4.5 - Recall vs Confidence

Recall vs confidence (Figure 4.5) shows the sensitivity of the algorithm to the elements of each class vs the confidence value assigned to the tagged elements that are detected as training progresses. An average recall of 0.89 was achieved when considering all classes.

The inference engine runs on an AMD Ryzen 5 CPU with NVIDIA GeForce GTX 1660 Ti, 6144.0MB. The average frame rate for detection based on a 25 frames per second video feed is 5 frames per second (fps). This allows for near real-time performance as the PPE is being donned or doffed.

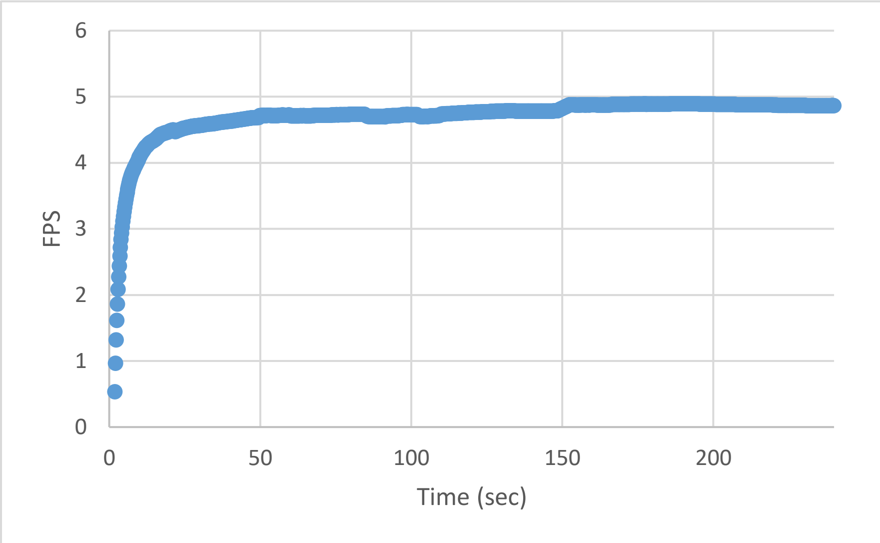

Figure 4.6 - Frame processing rate

5. Discussion

The healthcare informatics field has seen a big expansion in the body of research being dedicated to it, as the central role of technology is being recognized in the context of medical interventions, especially in the context of the global pandemic, where academics and professionals across the globe are united in working for a common goal.

The initial attempts at using image processing and machine learning to detect face masks was the inspiration for this initiative, which is a detailed solution that attempts to classify all the elements, detect them, and combine their detection programmatically.

Many other process-oriented approaches attempt to classify video feeds by taking multiple frames into account and training over the temporal dimension, however, in the case of this machine learning solution, the detections are carried out on a frame-by-frame basis, and the interactions between frames are handled after the inferencing is carried out.

The initial technical results seem to indicate that effectively detecting the objects on a frame by frame basis is successful in detecting individual components, and that this approach, which encodes the heuristics of the step by step tasks as a specific part of the code, and leaves the AI component to detections on a frame by frame basis, is believed to be a more effective and efficient use of machine learning.

As part of the technical evaluation, a comparative analysis of the heuristics carried out within the application vs the heuristics carried out by the AI could yield interesting results with respect to how Machine Learning can be used in the context of classifying sequences of events. It is believed that the use of this design, as well as the networking architecture being used to send the images to the inferencing engine, is an innovative and processing power efficient method of achieving the desired results.

The evaluation of the results of the tests based on both the health sector trainees as well as infection control staff has not yet been carried out, but insights on the usability of the system as well as how it could be implemented in an operational context are going to be collected at the design phase of the system, to allow for enough time for modifications in the final implementation of the system to be carried out. It is understood that the actual implementation of a smart changing room or a smart mirror needs to be put in the context of how the general infection control procedures in a hospital are being carried out, and it is therefore important to gather the feedback of staff from an operational context in a qualitative way, as the insights from experienced nurses are vital to provide the technology in the context in which it will be used.

This design process is meant to ensure that once the artefact has been completed, it will be completely tested both on a technical implementation level, with quantitative metrics proving the fact that it can be used operationally, and on a qualitative level, with qualified nurses' feedback attesting to the fact that it can be implemented in an operational context.

The metrics that will be carried out also include an evaluation of the tool in the pedagogical context. It is understood that the application of this tool in a classroom context could help in the process of training staff in the correct sequence of events. By using this as a feedback tool, a larger cohort of students may be trained and certified in donning and doffing to ensure safety in the context of infectious disease. Qualitative feedback will also be collected from nurse trainers to understand how the tool may be optimized as a learning aid, both in an operational context as well as in a training context. Since several members of the project team are also involved in nurse training, such data can easily be collected during training sessions being carried out with nursing students during lessons.

6. Conclusion

The initial conclusions to be derived from the tests carried out so far are that Machine Learning and AI can be effectively used, with augmented datasets, to identify articles of PPE at a framerate which is acceptable to provide an augmented view of each element in the donning and doffing process. It can also be demonstrated that given the correct dataset, the model can effectively identify elements of PPE in different environments and lighting conditions. Qualitative insights into the process have yet to be collected, but once these have been added, the research will give a good insight into the use of image processing and machine learning in a health automation context.

7. ACKNOWLEDGEMENTS

The research work presented in this paper has been supported by MCST under the Research Excellence Programme ISADD – Donning and doffing process (https://isadd.mcast.edu.mt). The authors would like to thank all the project partners for their contributions to the research for their large contribution in preparing this paper. This paper was a collaboration between Institute of Information and Communications Technology lecturers on the technical side and Institute of Applied Sciences lecturers on the nursing side, both from the Malta College of Arts Science and Technology.

REFERENCES

Ambigapathy S, Rajahram GS, Shamsudin UK, Khoo EM, Cheah WK, Peariasamy KM, Goh PP, Khor SK. How should front-line general practitioners use personal protective equipment (PPE)? Malays Fam Physician. 2020;15(1):2–5.

Carabott (2020) Mater Dei health carers less likely to get virus than in the community. Times of Malta. Available from: https://timesofmalta.com/articles/view/mater-dei-health-carers-less-likely-to-get-virus-than-in-the-community.813594

Kim, J. M., Chung, Y. S., Jo, H. J., Lee, N. J., Kim, M. S., Woo, S. H., ... & Han, M. G. (2020). Identification of coronavirus isolated from a patient in Korea with COVID-19. Osong public health and research perspectives, 11(1), 3.

Kuznetsova, A., Maleva, T., & Soloviev, V. (2020, December). Detecting apples in orchards using YOLOv3 and YOLOv5 in general and close-up images. In International Symposium on Neural Networks (pp. 233-243). Springer, Cham.

Kwok YLA, Gralton J, McLaws M-L. Face touching: a frequent habit that has implications for hand hygiene. Am J Infect Control. 2015;43(2):112-114.

Lan J, Song Z, Miao X, et al. Skin damage among health care workers managing coronavirus disease-2019. J Am Acad Dermatol. 2020;82(5):1215-1216.

Li, Y., Zhao, Z., Luo, Y., & Qiu, Z. (2020). Real-time pattern-recognition of GPR images with YOLO v3 Implemented by TEnsorflow. Sensors, 20(22), 6476.

Loey M, Manogaran G, Taha MHN, Khalifa NEM. A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic. Measurement (Lond). 2021;167:108288.

Ministry of Health Malaysia. COVID-19 Management Guidelines [internet]. Malaysia: MOH; 2020. http://www.moh.gov.my/index.php/pages/view/2019-ncov-wuhanguidelines.

O'Dowd K, Nair KM, Forouzandeh P, et al. Face Masks and Respirators in the Fight Against the COVID-19 Pandemic: A Review of Current Materials, Advances and Future Perspectives. Materials. 2020;13:3363.

Phan LT, Maita D, Mortiz DC, et al. Personal protective equipment doffing practices of healthcare workers. J Occup Environ Hyg. 2019;16(8):575-581.

Prusty, M. R., Tripathi, V., & Dubey, A. (2021). A novel data augmentation approach for mask detection using deep transfer learning. Intelligence-Based Medicine, 100037.

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).

Roy S, Menapace W, Oei S, et al. Deep Learning for Classification and Localization of COVID-19 Markers in Point-of-Care Lung Ultrasound. IEEE Trans Med Imaging. 2020;39(8):2676-2687.

Suzuki, K. Overview of deep learning in medical imaging. Radiol Phys Technol. 2017;10:257–273.

Swennen GR, Pottel L, Haers PE. Custom-made 3D-printed face masks in case of pandemic crisis situations with a lack of commercially available FFP2/3 masks. Int J Oral Maxillofac Surg. 2020; 49(5): 673–677.

United Nations (2020) Sustainable Development Goals. Goal 3: Ensure healthy lives and promote well-being for all at all ages. https://www.un.org/sustainabledevelopment/health/

Witten, I. H., & Frank, E. (2002). Data mining: practical machine learning tools and techniques with Java implementations. Acm Sigmod Record, 31(1), 76-77.

World Health Organization (WHO). Infection prevention and control of epidemic- and pandemic-prone acute respiratory infections in health care. Geneva: WHO; 2014. https://www.who.int/publications/i/item/infection-prevention-and-control-of-epidemic-and-pandemic-prone-acute-respiratory-infections-in-health-care.