Improving Operational Processes for COVID-19 Ready Smart Campus

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***Abstract*—The current COVID-19 pandemic has elevated the importance of cleanliness and social distancing. These needs will continue to be important as the world moves to a new normal whilst navigating through a post-covid environment. This paper presents a use case application that focuses on enforcing safe distance measures inside a campus building where there is limited manpower resources. Amidst the social setting within the university, staff or students may at times accidentally congregate, which may lead to spread of diseases inconveniencing all affected parties. Our proposed integrated solution consists of a network of video cameras and sensors which allows one to monitor behavior within the building. The integrated smart devices communicate with (1) an analytics server that processes the data from the various sensors and (2) a platform that integrates the analytic results and optimizes the action items to be reflected to the environment. A pilot prototype has been deployed and evaluated within a living lab setting on campus. Results show that the system is useful in streamlining the operational process resulting in more efficient processes and procedures to help enforce safe management measures needed to maintain proper social distancing among occupants in campus.**

***Index Terms*—video analytics, internet of things, sensors, crowd detection**

I. Introduction

To provide an authentic learning environment, Singapore Institute of Technology (SIT) is transforming its campus into a living lab. The university has piloted the scheme at the SIT@NYP campus where the building is equipped with a network of smart sensors to collect data such as temperature, ambient light, and human presence. The collected data is analyzed and used to enhance operation processes in the building for optimum building environment, enhancing the overall campus experience and workspace efficiency.

As Singapore learns to live with the COVID-19 coronavirus for the long term, the various institution and enterprises in the country must adapt to a new normal and learn to adjust their work processes to ensure that measures are taken to prevent the spread of the virus, thus safeguarding the health of stakeholders. The occupants in various buildings will need to continue to be socially responsible by adhering to Safe Management Measures (SMM).

As part of the operational processes supporting SMMs, Safe Management Officers (SMOs) in the workspaces are appointed to assist in the implementation, coordination, and monitoring of compliance of SMM. At SIT, staff from the Safety and Health division have been appointed as SMOs. The duties of Safe Management Officers (SMO) include:

- Conducting inspections and checks in all SIT workplaces to enforce compliance with SMM
- Take action to remedy non-compliances
- Report any non-compliance to management, and
- Maintain a comprehensive record of inspections, checks conducted, and corrective actions taken

SMOs will patrol the campus to ensure the following:

- No congregation in groups exceeding the allowed maximum number
- Individuals maintain at least one-meter safe distance

Currently, periodic random checks are performed across the different locations in the building. The main challenge in enforcing this 'new-normal' work process is the fact that manpower resources for patrolling (and disinfecting) is limited. Due to the manpower limitation, and the high number of students and occupants in the building, there is a high probability that overcrowding events are missed.

In this paper, we present an applied research collaboration between SIT and Hitachi Asia Ltd. that has resulted in an integrated solution that aims to improve the operational processes in a smart campus. The integrated solution consists of a network of video cameras and sensors which allows one to monitor behavior within the building. The various smart devices communicate with (1) an analytics server that processes the data from the various sensors and (2) a platform that integrates the analytic results and optimizes the action items to be

Manuscript received April 30, 2022; revised June 28, 2022; accepted July 15, 2022.

reflected to the environment. A pilot prototype has been deployed and evaluated as part of the SIT@NYP Living Lab. Testing results show that the system is useful in streamlining the operational process resulting in more efficient processes and procedures to help enforce safe management measures. The solution will ensure a safe campus that adheres to safe distancing measures without incurring high labor cost. With this system in place, fewer officers are needed for foot patrolling, thus improving the efficiency of operations.

The deployment of the pilot prototype is part of the exploration on how such platform can augment ground operations for safe distance management and can potentially be extended for other public health offences such as smoking in prohibited areas, littering, or illegal actions. With the historical captured data, insights into behaviors can be gained more efficiently and effectively using real time sensing and analysis and subsequently used to further improve operational processes.

II. Related Work

A. Social Distancing Detector

There have been several efforts geared towards streamlining the process of enforcing social distancing measures to ensure that places of business can operate without much hindrance. Such efforts usually make use of video analytics technologies and deep learning methods to automate the process of detecting people in image frames from existing CCTVs, and automatically trigger an alarm when people are too close to each other.

Griffith university researchers have developed a video surveillance system that relies on AI to detect social distancing breaches in airport without compromising privacy [1], [2]. Several researchers have also presented different variations of their deep learning models with the hope of perfecting the detection [3]-[11]. Amazon has already released a commercial solution for social distance detector available through its AWS Marketplace [12].

Separately, there are existing commercial solutions that are leveraging machine learning platforms to dynamically adjust the response in the environment. Examples of such solutions include Zensors [13]. Zensors is a pioneering active deep learning platform that dynamically adapts to optimize environment. The technology encompasses several products such as smart campus and smart retail that leverages on IP camera and intelligent video analytics for activity detection. The company has recently begun to develop solutions that cater to COVID-19 situation including using AI for retail compliance monitoring.

B. COVID-Ready Smart Campus

The advancement of technologies such as Internet of Things (IoT) has fueled the advancement of smart cities, smart facilities, and smart campuses. Agarwal *et al.* [14] presented a five layered framework to implement sustainability leveraging basic ecosystem and to quickly respond to requirements. The idea is that the framework will enable quick implementation and deployment of operational requirements that caters to the stringent requirement of a COVID-19 ready smart campus.

There are several commercial solutions targeted for smart campus. Siemens [15] has been developing an integrated solution that combines renewable and intelligent energy supply and energy efficiency, smart buildings, and e-mobility charging solutions across the entire university campus, however the current smart campus solution does not cater to compliance monitoring. Honeywell Forge [16] has piloted its machine learning and autonomous control technologies to a university that includes a closed-loop solution that evaluates the building's heating, ventilation and air-conditioning at set time intervals to determine if the building is running at peak capacity. Analytics is performed on the data captured to automatically calculate adjustments at every 24-hour period to reduce energy consumption.

While there are a few initiatives [17]-[19] that aim to automate the enforcement of Safe Management Measures such as social distancing, most are standalone analytics solution that are not integrated with an operational process. We propose an integrated solution that encompasses both the analytics and event management system that automatically provides the appropriate response action in the environment such as dispatching of staff for compliance monitoring and enforcement.

III. Implementation

The SIT@NYP building has been augmented to embody the vision of a smart campus. Powered by IoT, the building-wide sensor network provides data analytics and uses artificial intelligence for timely decision making. Leveraging on the smart campus facilities, our proposed system is designed to be a seamlessly integrated application that uses video analytics and Internet of Things (IoT) sensors to detect crowd that do not adhere to the current safe management measures and automatically dispatch the nearest officer to the event location to disperse crowd and enforce crowd management measures.

A. Overall System Framework

As shown in Fig. 1, the general flowchart of the general system framework consists of several phases:

1) A managing officer sets up the rule engine dashboard for each target location by indicating the threshold that determines the number of people allowed in a group based on the latest official guidelines
2) Continuous real-time video analytics automatically detects people. When the set group threshold is exceeded in classrooms and corridors on campus, the rule-engine registers a violation, which triggers an event in the event management system
3) Patrolling staff receives notification and is dispatched to the event location. The notification includes snapshots of the violation and the violation specific location. System optimizes such

that staff that is closest to the violation location is dispatched
4) Staff arrives on location and disperses crowd
5) Staff completes the dispatch order and submits report

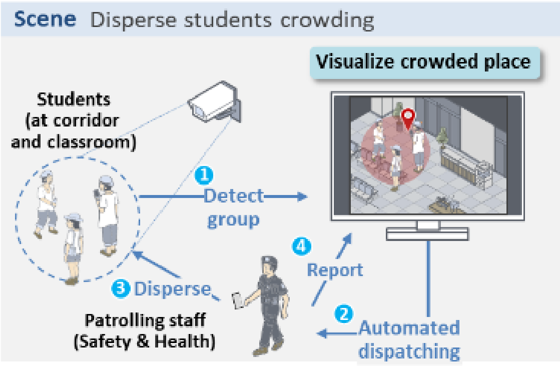

Figure 1. General flowchart of the overall approach.

B. System Architecture and Methods

Fig. 2 shows the overall system architecture of the application. The system consists of several components: (1) Event management system, (2) Video analytics server, (3) AWS dashboard for visualization, (4) Various smart sensors, and (5) Mobile application for staff.

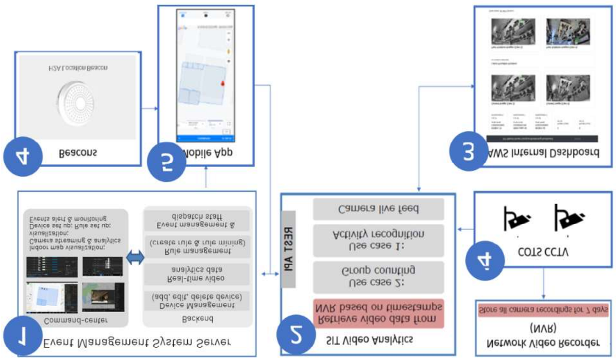

Figure 2. Overall system architecture.

1) Event management system

The event management system is a platform that performs real-time data analytics based on video and IoT sensor data. The system is installed on a GPU server. The platform serves as the command center to detect, dispatch and visualize events. The platform system allows for customization of workflow or policy for specific events. Events that are triggered by the rule engine are registered in an event page where an automated workflow is executed. The workflow includes automatic and smart task allocation to appropriate staff(s) using dispatch optimization and automatic dispatching of assigned staff(s). The system communicates with the video analytics server through REST API, where information such as bounding box of detected people is retrieved.

Dispatch Optimization (DO) is a service inside event management system that computes optimal task allocations for active events from the given pool of staffs. The DO service is required to handle complex scenarios comprising both scheduled events (whose information is known aprior) and dynamic events (which can occur unpredictably at any time, e.g. medical emergency). To get optimal solutions, DO is implemented using Mixed Integer Linear Programming (MILP) based approach, which computes the task allocations by formulating it as combinatorial optimization problem by defining objective function and sets of mathematical constraints To compute the optimal task allocations in near real-time (within few seconds) so that staff(s) can be dispatched as soon as possible, especially for dynamic events, DO utilizes temporal batch decomposition method [20]. This method handles dynamically occurring events immediately without having to recompute the schedule for the entire time horizon but instead do batchwise assignment.

2) Video analytics server

The analytics server takes in the RSTP streams from the video cameras and analyses the streams frame by frame. YOLOv5 algorithm [21]-[26] is used to carry out human object detection for each camera stream. Vanilla Yolov5 model was selected as a tradeoff between speed and accuracy. The detected objects are converted into a bird's eye view format. As the cameras are static, this can be achieved by the pre-calibration of the corners of the room, and a simple transformation is applied to convert the location of the people to that of a bird's eye view (Fig. 3).

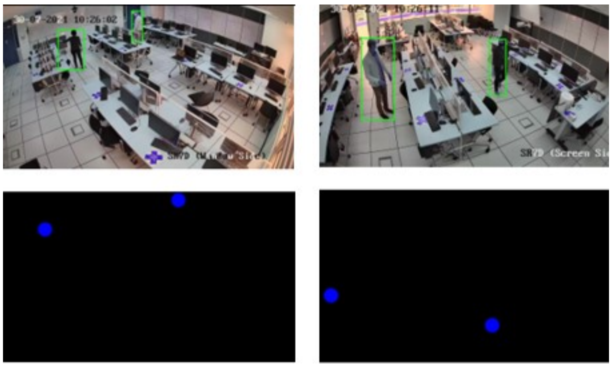

Figure 3. Detected people in camera frame (top row) and projected location in bird's eye view (bottom row).

From the bird's eye view, the inter person distance between the human points in the bird's eye view is calculated. Given the distances, a minimal spanning tree (MST) is constructed using Prim's algorithm. If the resulting MST exceeds a certain number of points (set threshold), it is deemed to have violated social distancing conditions. This will trigger a rule violation in the event management system where snapshots of the violation are sent to be displayed in the mobile application of the dispatched staff.

3) AWS internal dashboard

A dash board was developed for internal visualization and evaluation of the working components. Fig. 4 shows the various information displayed on the dashboard including (1) real-time location of the patrolling staff (Ambassador 0/1/2), (2) real-time video streams of the various cameras, and (3) snapshot of the last detected violation.

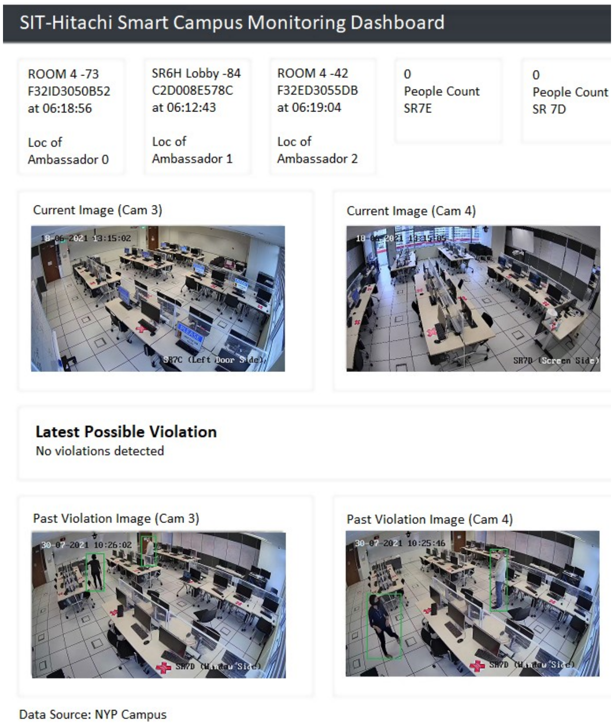

Figure 4. AWS internal dashboard.

4) Various smart sensors

The sensors used in the pilot prototype includes: (1) off-the-shelf dome video cameras installed in classrooms and corridors, and (2) indoor beacons deployed across multiple floors in the building [27]. A Network Video Recorder (NVR) is paired with the cameras to manage the streaming and recording from the video cameras.

Real time localization and tracking of patrolling staff is done using Bluetooth beacons. A staff's device detects the signals from the various deployed beacons nearby. The beacons transmit approximately at the rate of five times a second. The MAC addresses and beacon corresponding RSSI's are transmitted to the server to pinpoint the location of the nearest beacon. The nearest beacon to a staff is defined as the beacon with the lowest average RSSI value over a one second time period.

The nearest beacon location is used as reference for the current staff location. The Event Management System calculates the distance along the indoor route between current staff location and a triggered event. The calculated distance is used to determine the nearest staff assigned to handle an event. Beacons were also dispatched in lifts to enable tracking of the staff more accurately and more accurate calculation of distance.

5) Mobile/Web application for patrolling staff

A mobile app is used to register the patrolling staff and provide visualization of relevant information. Fig. 5 shows a screenshot of the web application. The application displays an alert when a violation is detected together with relevant information such as event time, location, and snapshot of the event. Staff can select to accept or reject the assignment through the web application. The application visualizes the digitized floor plan of the building and real-time location of the patrolling staff. It also provides indoor navigation information from the current staff location to the location of the event (Fig. 5 (right)). All information is obtained real-time from the event management system.

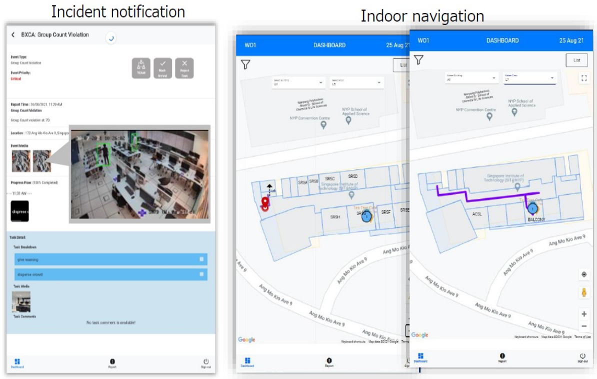

Figure 5. Mobile application for patrolling staff. The mobile app provides snapshots of the relevant incident information (left), and navigation information from the current staff location to the location of the event (right).

To complement the overall system framework, additional key measures such as privacy preservation were incorporated in the implementation. Three (3) safeguards were implemented to provide for privacy considerations: (1) technical, (2) administrative, and (3) data safeguards accordingly. To ensure technical safeguarding, the server and data is kept in the intranet which is inaccessible by the public. All forms of remote access such as SSH, FTP and Teamviewers are disabled on the server. Hence, all development had to be done on site. This indeed added to the complexity of the development during the pandemic as physical access was curtailed at time. To provide administrative safeguards, the project had to undergo internal Institutional Review Board (IRB). The process confirmed that due to the technical safeguards planned, it was sufficient that the privacy of the students were preserved. In addition, in the unlikely event that information as leaked, IRB had determined that the consequence of the leak were minimal. The last safeguarding measures were related to the data itself. At any point of time, only two days' worth of data were kept in the video storage and past data were deleted synchronously. As such, in the unlikely event of a leak, only two days' worth of data would be leaked.

IV. Evaluation and Discussion

To evaluate the performance of the various components and the overall integration of the system, a pilot prototype was deployed on campus. Multiple rounds of experiments and testing were conducted to ensure the feasibility of the overall system framework. This involved performance testing of individual web components and integrative testing of the complete system.

Individual components were tested independently to ensure that each component satisfied their functional requirements including:

- Beacon localization was tested by having staff walk through the building across different levels to ensure that the application can continuously track the staff
- The people detection video analytics was rigorously tested and evaluated for both obstructed and unobstructed people detection by testing different positions and angles

Testing of the individual components was performed using tools such as jMeter and Android components (memory, GPU, CPU tests). The average response time between the staff Android phones and the Server is less than 15ms.

Several scenarios were tested to ensure that all components are working correctly in an integrated manner. A testing procedure was designed to test different violation events and dispatching scenarios. The tested events included the following:

- Scenario 1 – multiple staffs are on the same floor as the event location
- Scenario 2a and 2b – multiple staffs are on different floors from the event location
- Scenario 3 – staff is already occupied with another event and the dispatch needs to be re-routed

Visualization results of the various scenarios are depicted in Fig. 6-Fig. 9. All crowded triggered event were located on Level 7. Fig. 6 shows the results for Scenario 1. In this scenario, two patrolling staff were on the same floor as the event location. The staff nearest to the crowding event location was dispatched. The arrival time of the staff was 55 sec. Fig. 7 shows the results for Scenario 2a. In this scenario, both staff were on the same floor (Level 6) which differs from the event location (Level 7). Staff 2 that was nearest to the event location was dispatched. The arrival time of the dispatch staff was 88 sec. Fig. 8 depicts results for Scenario 2b where multiple staffs were on different from event location (Level 7). Staff 1 was located at Level 5, while Staff 2 was located at Level 4. Staff 1, who was closer, was dispatched to handle the event. The response time was 108 sec, this includes riding the lift. Fig. 9 shows results for Scenario 3. In this scenario, both staff and event were on Level 7, however Staff 2 was already occupied with another event and dispatch was rerouted to the next nearest staff. Staff response time was 20 sec for first event, and 64 seconds for the second event. A similar trial was conducted where Staff 1 was on Level 6, while Staff 2 was on Level 5 with similar results.

Experiments on all scenarios were passed successfully. Multiple trials were conducted for each scenario for a total of 10 trials. The average arrival time across all trials for the dispatched staff to the event location was less than 3 minutes. Fig. 10 shows the arrival time for all the different trials. The application was able to optimally dispatch staff when a violation was triggered. The dispatched staff were able to respond quickly by following the protocols listed in their mobile app and document the event accordingly.

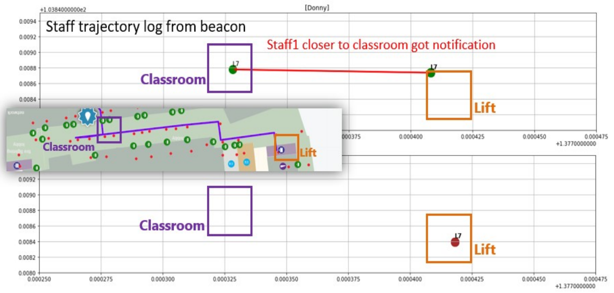

Figure 6. Scenario 1 - multiple staffs are on the same floor as the event location.

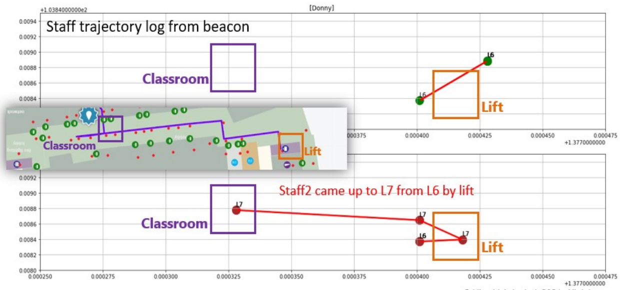

Figure 7. Scenario 2a - multiple staffs are different floor from the event location (Level 7). Both staff are at level 6.

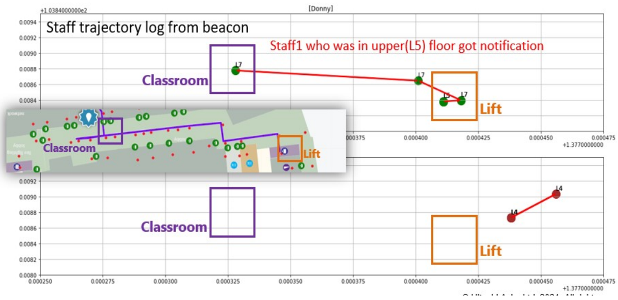

Figure 8. Scenario 2b - multiple staffs are on different floor from event location. Staff 1 is at Level 5, while Staff 2 is at Level 4.

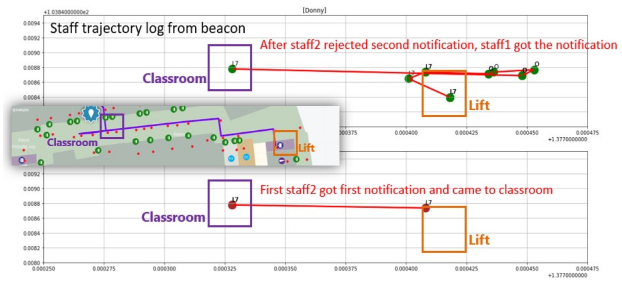

Figure 9. Scenario 3 - Staff 1 is already occupied with another event and dispatch is rerouted to next nearest staff.

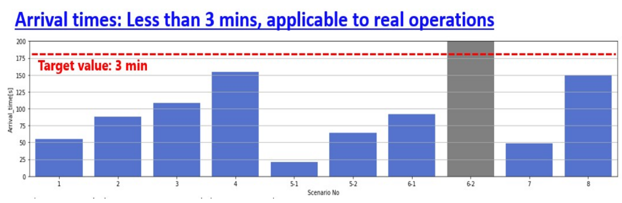

Figure 10. Arrival time for all scenario tested.

V. Conclusion

This paper presents an integrated solution to create a COVID 19 - ready smart campus that can automatically detect and enforce safe management measures such as social distancing. The solution consists of a network of video cameras and sensors that communicate with (1) an analytics server that processes the data from the various sensors and (2) a platform that integrates the analytic results and optimizes the action items to be reflected to the environment. Evaluation of the pilot prototype deployed within the campus building shows that the solution can detect and respond to violation of social distancing measures. This solution is applicable not only for smart campus but has a wide potential of use cases and stakeholders such as real estate developers and management of commercial buildings. The flexibility of the system framework and the modular design of the system allows it to be easily extended for other use cases.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Dr. Soh, Dr. Atmosukarto, Mr. Loo, and Mr. Thirunneepan were responsible for the development and evaluation of the video analytics server, AWS dashboard and deployment of the various smart sensors. Dr. Ishii, Dr. Ranjan, Dr. Shuyang, and Mr. Hirayama were responsible for the development and evaluation of the event management system and mobile application. All authors worked together to implement and evaluate the integrated system, and approved the final version of the paper.

Acknowledgment

The authors wish to thank Hitachi Asia for their generous support. This work was supported in part by a grant from SIT.

References

[1] Griffith news. [Online]. Available: https://news.griffith.edu.au/2021/07/28/researchers-design-ai-system-for-social-distance-breach-detection/
[2] This week in FM. [Online]. Available: https://www.twinfm.com/article/university-researches-ai-surveillance-for-social-distancing-monitoring
[3] OpenCV social distancing detector. [Online]. Available: https://www.pyimagesearch.com/2020/06/01/opencv-social-distancing-detector/
[4] M. S. D. Ansari, "Monitoring social distancing through human detection for preventing/reducing COVID spread," *International Journal of Information Technology*, vol. 13, p. 1255-1264, 2021.
[5] Y. Indulkar. Analytics Vidhya. [Online]. Available: https://www.analyticsvidhya.com/blog/2021/05/alleviation-of-covid-by-means-of-social-distancing-face-mask-detection-using-yolo-v4/
[6] A. Rahim, A. Maqbool, and T. Rana, "Monitoring social distancing under various low light conditions with deep learning and a single motionless time of flight camera," *PLoS One*, vol. 16, no. 2, 2021.
[7] S. Gupta, R. Kapil, G. Kanahasabai, *et al.*, "SD-Measure: A social distancing detector," in *Proc. International Conference on Computational Intelligence and Communication Networks*, 2020.
[8] E. Lo, "Target detection algorithms in hyperspectral imaging based on discriminant analysis," *Journal of Image and Graphics*, vol. 7, no. 4, pp. 140-144, December 2019.
[9] F. Utaminingrum, R. P. Prasetya, and Rizdania, "Combining multiple feature for robust traffic sign detection," *Journal of Image and Graphics*, vol. 8, no. 2, pp. 53-58, June 2020.
[10] R. Khan, T. F. Raisa, and R. Debnath, "An efficient contour based fine-grained algorithm for multi category object detection," *Journal of Image and Graphics*, vol. 6, no. 2, pp. 127-136, December 2018.
[11] R. Hasegawa, Y. Iwamoto, and Y. W. Chen, "Robust Japanese road sign detection and recognition in complex scenes using convolutional neural networks," *Journal of Image and Graphics*, vol. 8, no. 3, pp. 59-66, September 2020.
[12] AWS marketplace social distance detector. [Online]. Available: https://aws.amazon.com/marketplace/pp/prodview-g2kceqqshfju2
[13] Zensors. [Online]. Available: https://www.zensors.com/
[14] P. Agarwal, R. K. GVV, and P. Agarwal, "IoT based framework for smart campus: COVID-19 readiness," in *Proc. World Conference on Smart Trends in Systems, Security and Sustainability*, 2020.
[15] Siemens. [Online]. Available: https://new.siemens.com/sg/en/products/buildingtechnologies/smart-buildings/smart-university-campus.html
[16] Honeywell forge. [Online]. Available: https://www.honeywell.com/us/en/honeywell-forge/smart-university-gets-smarter-with-energy-optimization
[17] D. Yang, E. Yurtsever, V. Renganathan, *et al.*, "A vision-based social distancing and critical density detection system for COVID-19," *Sensors*, vol. 21, no. 13, p. 4608, 2021.
[18] Social distancing detector. [Online]. Available: https://aws.amazon.com/marketplace/pp/prodview-g2kceqqshfju2
[19] G. V. Shalini, M. K. Margret, M. S. Niraimathi, *et al.*, "Social distancing analyzer using computer vision and deep learning," *Journal of Physics: Conference Series*, vol. 1916, 2021.
[20] H. T. Reddy, R. Ranjan, and K. Toshihiro, "Dynamic workforce scheduling and routing in a smart city using temporal batch decomposition," in *Proc. International Conference on Transport and Smart Cities*, Frankfurt, 2021.
[21] Ultralytics - YOLOv5. Github. [Online]. Available: https://github.com/ultralytics/yolov5
[22] K. Dinesh and S. Gupta, "Video stabilization, camera motion pattern recognition and motion tracking using spatiotemporal regularity flow," *Journal of Image and Graphics*, vol. 2, no. 1, pp. 33-40, June 2014.
[23] Y. Liu, L. Geng, W. Zhang, *et al.*, "Survey of video based small target detection," *Journal of Image and Graphics*, vol. 9, no. 4, pp. 122-134, December 2021.
[24] S. A. Yaseen and S. Sasi, "Robust algorithm for object detection and tracking in a dynamic scene," *Journal of Image and Graphics*, vol. 2, no. 1, pp. 41-45, June 2014.
[25] C. S. Shieh, Y. S. Jhan, Y. L. Liu, *et al.*, "Video object tracking with heuristic optimization methods," *Journal of Image and Graphics*, vol. 6, no. 2, pp. 95-99, December 2018.
[26] F. Spiess, L. Reinhart, N. Strobel, *et al.*, "People detection with depth silhouettes and convolutional neural networks on a mobile robot," *Journal of Image and Graphics*, vol. 9, no. 4, pp. 135-139, December 2021.
[27] Moko smart H2A indoor beacon location tracking. [Online]. Available: https://www.mokosmart.com/location-beacon-h2a/

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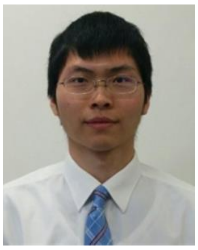

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