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Deep learning and computer vision based occupancy CO_2 level prediction for demand-controlled ventilation (DCV)

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ABSTRACT

The present study investigated the potential of the application of a live occupancy detection approach to assist the operations of demand-controlled ventilation (DCV) systems to ensure that sufficient interior thermal conditions and air quality were attained while reducing unnecessary building energy loads to improve building energy performance. Faster region-based convolutional neural network (RCNN) models were trained to detect the number of people and occupancy activities respectively, and deployed to an artificial intelligence (AI)-powered camera. Experimental tests were carried out within a case study room to assess the performance of this approach. Due to the less complexity of people counting model, it achieved an average intersection over union (IoU) detection accuracy of about 98.9%, which was higher than activity detection model of about 88.5%. During the detection, the count-based occupancy profiles were produced according to the real-time information about the number of people and their activities. To estimate the effect of this approach on indoor air quality and energy demand, scenario-based modelling of the case study building under four ventilation scenarios was carried out via building energy simulation (BES). Results showed that the proposed approach could provide demand-driven ventilation controls data on the dynamic changes of occupancy to improve the indoor air quality (IAQ) and address the problem of under- or over-estimation of the ventilation demand when using the static or fixed profiles.

1. Introduction and literature review

Sustainable and energy-efficient solutions have gained more public interests as a way to counter the growing carbon dioxide emissions and mitigate the effects of global climate change. The European Commission has established a clear goal of reducing greenhouse gas emissions by at least 40% by 2030 and achieving carbon neutrality by 2050 under the Paris Agreement [1,2]. To pay more attention to energy access challenges, organisations such as the International Energy Agency (IEA) evaluated future scenarios. IEA developed the 'Sustainable Development Scenario' and the '450 Scenario', which demonstrated a feasible path that ensures the achievement of sustainable and modern energy services by 2030 to achieve climate goals with the utilisation of the current technologies and considerations of human health implications [3]. However, the COVID-19 pandemic resulted in one of the worst ever for energy efficiency improvement, the rate of improvement requires to be doubled from current levels to accomplish the goal of net-zero carbon emission by 2050 [4]. This higlights the significant need for more energy-efficient and sustainable technologies. The UK

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government has also set a goal of achieving net-zero greenhouse gas emissions by 2050 [5]. This substantial decrease in emissions is not unachievable, however, it will necessitate a societal shift away from energy-intensive activities and toward low energy and the development of zero-energy technologies. In addition, the building sector is one of the greatest energy consumers, which accounts for 36% of the global final energy consumption and 37% of the world energy-related greenhouse gas emissions, and continuously grows at unprecedented rates, creating a huge potential to reduce CO_2 emissions [6]. Therefore, new solutions are essential to address the issue of the design and operation of buildings to reduce the building energy demand.

Indoor air quality (IAQ) is directly and strongly related to the well-being, health, and comfort of occupants in indoor spaces. Poor indoor air quality could significantly increase the health risks and reduce the productivity of occupants. This is a critical issue as people spend about 80–90% of their time in indoor spaces, either at home, in offices, or in other types of buildings. Especially, children, the elderly, and people with pre-existing medical issues are among those who spend practically all of their time inside [7]. Moreover, one of the top five threats to public health is indoor air pollution [8]. According to the report produced by World Health Organization (WHO), it claimed over 3.8 million deaths in 2021 [9].

Additionally, according to the World Green Building Council (WGBC), better IAQ (lower CO_2 and pollutant concentration) due to high ventilation rates can improve productivity by 8–11% [10]. Furthermore, enhancing IAQ could not only improve occupant health, wellbeing, and comfort, but also contribute to significant economic benefits. For instance, in the United States, improving IAQ is estimated to save over 20 billion dollars per year by improving workers' productivity and lowering healthcare expenses [11]. In 2015, for example, Building Research Establishment (BRE) researchers Kukadia and Upton [7] conducted research on the cost of substandard housing to the National Health Service (NHS), finding that optimising the 3.5 million England's 'poor' dwellings would save the NHS £1.4 billion in first-year treatment costs alone. Overall, it highlights the significance of IAQ improvement for buildings and there has been a growth in interest in optimising building ventilation design and operation to create a healthier and more comfortable indoor environment.

Furthermore, the COVID-19 pandemic has recently brought IAQ upfront and will play a crucial role in minimizing the transmission of viruses [12,13]. Guidance is emerging from a variety of sources [14] suggesting increasing the outdoor air ventilation; however, this could also create poor thermal environment in some buildings, affecting the comfort and health of occupants. Furthermore, this could also result in increased ventilation heat loss in cold climates and conditions or ventilation heat gain in hot climates [15] due to the large temperature difference between indoor and outdoor. This causes unnecessary energy consumption and wastage and compromises the heating, ventilation, and air-conditioning (HVAC) efficiency; therefore, minimising ventilation heat loss/gain in cold/hot climate can significantly reduce the heating/cooling demands. This is further exacerbated when the ventilation system is operated using fixed or static schedules and when spaces are partially occupied or unoccupied for significant periods, leading to unnecessary over-ventilation and -conditioning of spaces. During the pandemic, occupancy levels and patterns in buildings, such as in offices, have varied greatly due to social distancing requirements, self-isolation, lockdown, and more employees getting accustomed to working remotely [16]. Although employees had started to return to the office when restrictions were lifted, the pandemic has made businesses rethink their workplace strategies, with many moving towards flexible workspace models after seeing its benefits [17]. This also means that the design and operation of HVAC systems require rethinking to adapt to the change in occupancy.

A potential solution is the use of demand-driven or occupant centric control measures, such as demand-controlled ventilation (DCV), which varies the ventilation of a space according to the pollution level or occupancy [18,19]. There has been a rise in studies on occupant- or human-centred control strategies for HVAC systems [20]. Such strategies actively reflect real-time occupancy information and behaviour in the control of building systems. The study [21] suggested that a reduction of 20–45% in building energy consumption can be achieved by such strategies in medium offices. Central to the effective implementation of such control strategies is accurate information on the occupancy, such as location, number, presence, and activities. This can be achieved by employing occupancy detection methods such as motion sensors, CO2 sensors, Wi-Fi, Bluetooth and cameras [22,23]. Unlike other sensors, cameras can work like human eyes, which can detect changes in occupancy without delay, inherent with CO2-based detection systems [24], and at the same time recognise occupants performing sedentary activities or minimal movements. The use of cameras coupled with vision-based occupancy detection and recognition technology has been garnering a lot of interest. The use of cameras and computer vision is not exactly new and has been studied for a long time for detecting objects, including occupants. However, the computer vision field has been a subject to increased interest due to the increased accessibility to larger computational power and rise of artificial intelligence (AI), specifically the success of convolutional neural network (CNN).

Recently, there is a spike in research employing camera, computer vision and deep learning to detect occupants in buildings. Many of the earlier research focused on occupancy counting and presence [25]. While the others focused on enhancing the performance of the occupancy detection model or algorithm by increasing the accuracy or speed of detection. The recent works of [26–29] highlighted a lack of research investigating the impact of such an approach on the building energy demand. Choi et al. [26] indicated that 10.2% of annual HVAC and lighting energy consumption could be reduced by occupancy-centric control based on occupancy counting using computer vision method in small offices. Meng et al. [27] proposed an air-conditioning control strategy according to the occupancy load changes with the use of real-time occupancy detection and simulation results showed a 6.70% reduction in building energy consumption. The studies [28] employed a computer vision approach to detect and predict the internal heat gains in office buildings, based on the detected activities such as walking, sitting, etc. Recently, the approach was also used to predict internal heat gains from equipment such as computer and PC monitors [30] in office spaces. The predicted information can be used to adjust the control and operation of the HVAC to reduce the energy demand. In addition, it can generate realistic occupancy profiles for building energy models, which can reduce the performance gap. However, there is a lack of investigation of the impact of such an approach on IAQ and ventilation heat loss/gain in indoor spaces, which is also a significant factor affecting indoor comfort. Wang et al. [31] proposed an image-based occupancy positioning detection system to provide real-time occupancy information to demand-oriented ventilation

(DOV) systems. DOV systems could adjust the air supply based on the occupancy positioning and orientation, which can enhance the building energy efficiency by preventing over- or under-estimation of the ventilation demand. Studies [32,33] employed an image-based method for window opening state recognition, which provides better understanding of the utilisation and impact of natural ventilation in buildings. Tien et al. [34] developed a vision-based framework to detect and recognise manual window operation and conduct scenario-based tests. The simulation results indicated that the proposed method could provide high detection accuracy and help efficiently operate HVAC systems or notify people in the buildings to avoid unnecessary heating demand. However, the the use of mechanical ventilation and the impact on ventilation energy demand were not investigated.

The present study will use the same approach to detect occupancy in real-time. An integrated approach or tool that can detect occupancy and predict internal heat gains and CO_2 emission from occupants simultaneously in real-time is desirable and will be further developed in this study. It is envisaged that a significant reduction in energy and cost can be achieved if the building services are correctly controlled during periods when spaces are partially occupied or unoccupied for significant periods, minimizing the unwanted air change rates and heating or cooling loads. The control and coordination of an HVAC system with occupancy can play a significant role in reducing energy consumption and improving comfort and indoor air quality. As discussed, the over ventilation of spaces in cold conditions can cause two main issues: (1) increased fan energy consumption and (2) ventilation heat loss. The present study will aim to resolve these issues using the proposed computer vision-based occupancy detection approach. It can be complementary or an alternative to using CO_2 sensors, which has several disadvantages. Although there are several occupancy detection methods available, there are limited studies on its application and integration with demand-driven controls for managing energy and air quality in buildings. More studies on its implementation in real-world environments are necessary to provide more insight into its capabilities. This is particularly evident in the context of highly populated spaces such as university lecture rooms, classrooms, recreation spaces, etc. To date, only limited studies attempted to demonstrate the usage of the vision-based occupancy detection approach to control the ventilation operation. Finally, the impact on the building energy demand must be investigated.

Therefore, building on previous research method, the present study investigates the potential of the application of a real-time occupancy detection approach to assist with HVAC system operations to ensure that sufficient interior thermal conditions and air quality are attained while reducing unnecessary building energy loads to improve building energy performance (see Fig. 1). Faster region-based convolutional neural network (RCNN) models are trained to detect the number of people and occupancy activities respectively and deployed to an AI-powered camera. Experimental tests are carried out within the case study room to assess and compare the performance of the trained models. During the detection, the count-based occupancy profiles are produced according to real-time information about the number of people and their activities. To estimate the impact of this approach on indoor air quality and ventilation energy demand, scenario-based modelling of the case study building under four ventilation scenarios are carried out via building energy simulation (BES). Detailed comparisons are provided for indoor CO2 concentration and energy consumption using the different detection model development strategies.

2. Method

The proposed vision-based approach framework for a demand-based ventilation control is presented in Fig. 1. The occupancy detection model is implemented in a conditioned space to collect real-time occupancy information using an AI-enabled camera. Then a real-time occupancy profile will be generated based on the obtained information and inputted into the building energy management system to adjust the HVAC system operations automatically to provide demand-based ventilation. In this study, a classroom in a

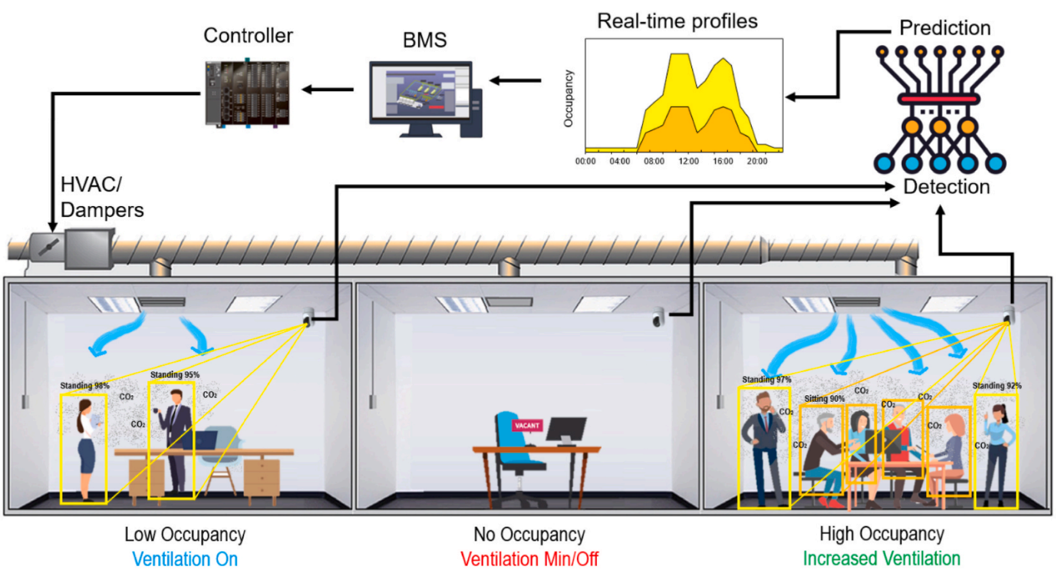


Fig. 1. Vision-based approach framework for demand-based ventilation control.

university building was chosen as the case study room for the evaluation of the developed approach. The following sub-sections provide the details of each of the key steps, including the vision-based detection approach development and implementation and the methods for performance analysis.

2.1. Vision-based detection approach

In the field of artificial intelligence (AI), computer vision enables computers to understand valuable and detailed information extracted from images, videos and other visual data and make further decisions and recommendations. In other words, a computer vision system senses the surroundings and identifies the targeted objects through a camera, which is similar to a human vision system which performs sensing by eyes and identification by the brain [35]. Currently, deep learning techniques have outperformed previous machine learning methods in computer vision problems [36]. Among the existing deep learning methods, convolutional neural network (CNN) has become the most frequently used technique due to its outstanding performance in various vision-based tasks such as object detection [37], facial recognition [38], activity recognition [39], and motion tracking [40].

In recent years, various CNN-based detectors have been developed to enhance the accuracy and speed of object detection and recognition. UC Berkely has developed Region-based CNN (RCNN) by combining region proposals with CNNs [41]. Due to the success of region proposal methods in object detection [42], it can identify multiple objects in the input data by using the selective search to extract the regions of interest, then creating region-based features from the pretrained CNN, and finally classifying the objects through support vector machines (SVMs) [43]. However, RCNN is still computationally expensive and can take a huge amount of time to train the network. To address these problems, with further evolution, the Faster RCNN has been developed by Microsoft using a region proposal network (RPN) to generate the region proposals instead of the selective search algorithm [44]. This has extremely reduced the computational cost and time for network training. Therefore, Faster RCNN was selected for this study. As an open-source platform consisting of various pre-trained detection models, the TensorFlow Object Detection API was employed to train and deploy the occupancy detection model. The COCO-trained model of Faster R–CNN with Inception V2 was selected for the present work. Fig. 2 presents the architecture of the detection model. The training loss function for Faster RCNN is defined in Ref. [44] as:

$$L(\{p_i\},\ \{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i,\ p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i,\ t_i^*) \tag{1}$$

Where, i is the index of an anchor in a mini-batch, p_i is the predicted probability of anchor i being an object, p_i^* is the ground-truth label (if the anchor is positive, $p_i^* = 1$; if the anchor is negative, $p_i^* = 0$), t_i is a vector standing for the four parameterised coordinates of the predicted bounding box, t_i^* is that of the ground-truth box associated with a positive anchor, L_{cls} is classification loss, L_{reg} is regression loss, N_{cls} and N_{reg} are the nominators used to normalise the outputs of the *cls* and *reg* layers, and λ is a balancing weight.

Two models were developed and trained to perform occupancy detection. As the occupancy rate is positively correlated with airborne bacteria and indoor CO_2 concentration, a great variation in the indoor air quality can be caused by the varied number of occupants. Thus, Model 1 was employed to predict the number of occupants only in the test. Additionally, according to CIBSE Guide A [45], occupant activity is one of the factors affecting the amount of ventilation required for air quality. When a person performs

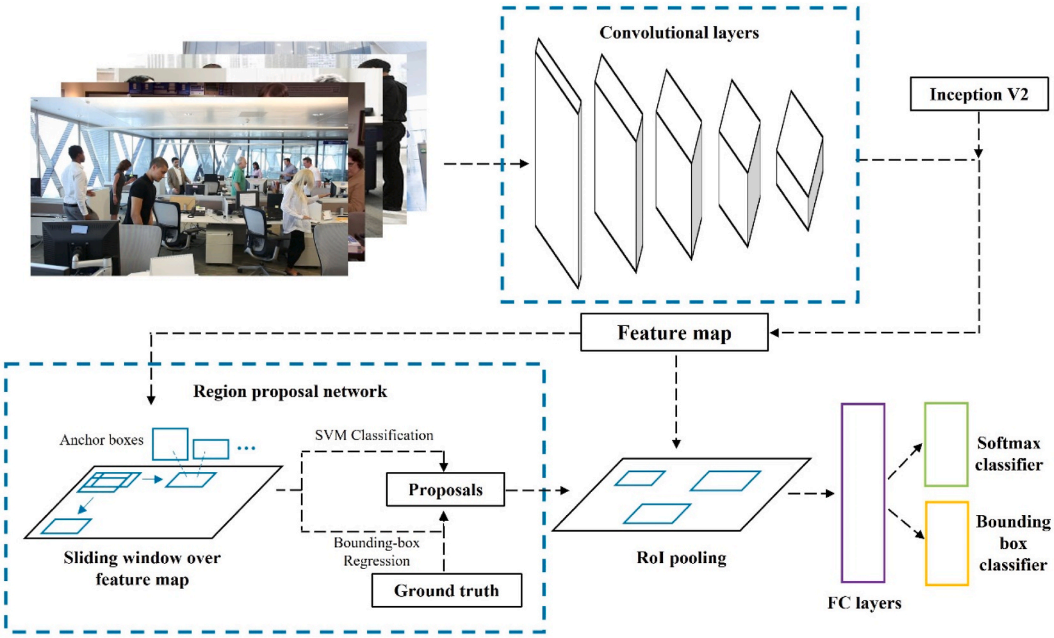


Fig. 2. Architecture of Faster RCNN with Inception V2.

different activities resulting in a variation of the human metabolic rate, the rate of CO_2 generated from the person is changed. Yoon et al. [46] developed an activity detection model based on environmental sensing and energy use data and the outcomes indicated that indoor CO_2 concentration varied with the occupants' activity and different activities resulted in variations of the CO_2 concentration. This could also lead to a significant change in CO_2 level within a space, especially when the space has a high occupancy density. Hence, during the test, Model 2 was used to detect both the number of occupants and different occupants' activities including walking, sitting, and standing and its performance was compared with Model 1. In future work, other types of activities will be considered in the study to attain a more precise estimation of the amount of CO_2 generation.

To enable this, a dataset consisting of images including different numbers of people (for Model 1) and images with people performing various activities (for Model 2) were required to train and test the models. To enable the models to adapt to various detection conditions within different spaces, this study required a variety of images of occupants indoors including different numbers of people and activities in buildings, various distances from the camera, various angles and heights of photo capture, brightness and quality of the indoor space. The public dataset is still limited in terms of the variety of the images of occupants indoors. Therefore, the images obtained from Google were used and then labelled using LabelImg. An example of image collection and labelling is shown in Fig. 3. The images within each dataset and class were randomly divided into training and testing sets with an 80-20 split. The number of images and assigned labels is presented in Fig. 4. The number of labels varied due to the diversity of the content of each image. In most cases, there were multiple labels assigned to each image. During the model development stage, the training and testing processes were iterative with the improvement of the architecture of the models and the size and quality of the datasets in order to continuously enhance the performance of the detectors. After the sufficient and successful training of these models using the processed datasets, the models were then deployed to an AI-enabled camera to perform detection tasks.

2.2. Vision-based approach implementation

After the selection and preparation of the detection model, the proposed approach was implemented in the case study building to evaluate its feasibility and performance. In the present work, the Paton House located in the Department of Architecture and Built Environment at the University of Nottingham, shown in Fig. 5(a) was selected as the case study building to carry out the vision-based occupancy detection tests. This building is naturally ventilated with openable windows and a simple heating system to provide essential heating service. The experimental test was conducted in a classroom with a floor area of 36.62 m^2 and a floor to ceiling height of 3.52 m on the first floor of this building. There are six sliding sash windows which can be opened at the bottom for ventilation. The layout of the first floor and test room and the setup of the test are presented in Fig. 5(b). Due to COVID-19 restrictions, the maximum capacity of the room was 11 people. To enable the capture of the whole test room, a camera, which has a resolution of 1080p and a wide 90-degree file of view, was fixed in a corner of the room close to the ceiling. The view from the camera is shown in Fig. 5(c). It should be noted that the case study building would also be used for building energy modelling to show the impact of using the proposed approach on CO2 level and building energy demand under the designed scenarios.

During the experiment, when live occupancy detection using two models was implemented, the real-time information on the number of occupants and performed activities were gathered and used to form the occupancy count and activity profiles. An example of the formation of count-based profiles is presented in Fig. 6. It is important to note that in practice the camera will not take any images or videos during the live detection and recognition. Instead, the model will solely generate the DLIP graphs which enable the estimation of CO_2 concentration within the detected space. The images shown here were only employed as an example to demonstrate the way that the proposed approach performs detection tasks.

2.3. Detection approach performance analysis

The detection approach performance was investigated based on the experimental results of occupancy detection and recognition and building energy simulation results. The methods and conditions used for performance analysis are provided in this section.

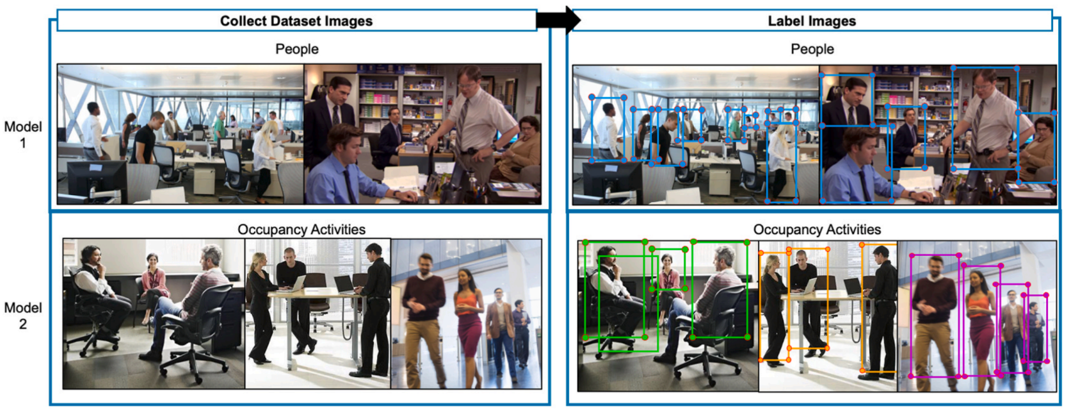


Fig. 3. Examples of the image collection for the datasets of people and occupancy activities and labelling (Source: Google Images).

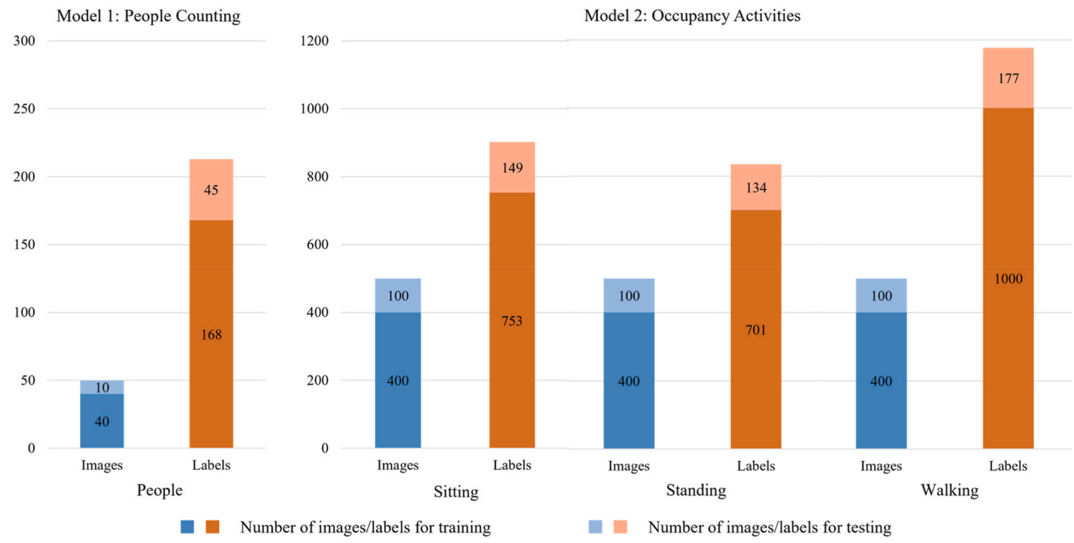


Fig. 4. The number of collected images of people and their activities and assigned labels for each class.

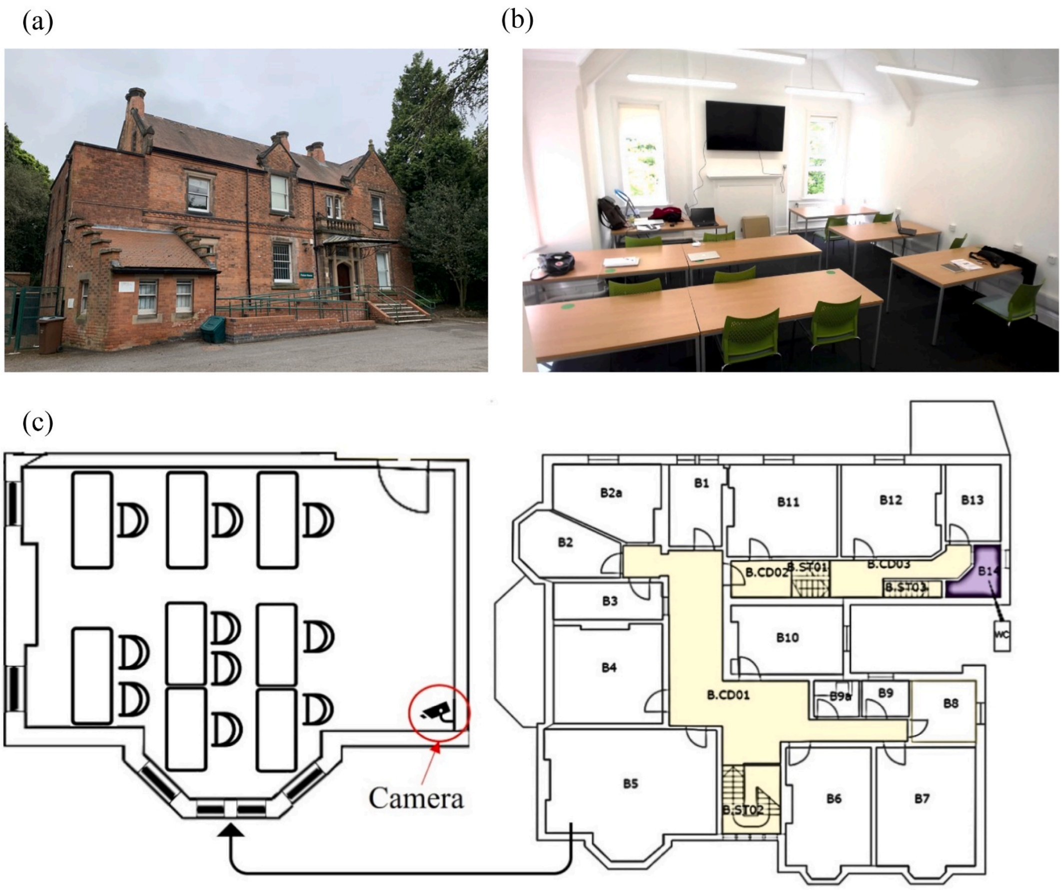


Fig. 5. (a) External view of Paton house; (b) View of test room from the camera; (c) Layout of the first floor and test room (B5).

2.3.1. Detection technique evaluation

After the training process, the models were tested with the use of the collected test dataset detailed in Fig. 3 to evaluate and compare the performance of the trained models. The testing results were presented in confusion matrices which then were used to

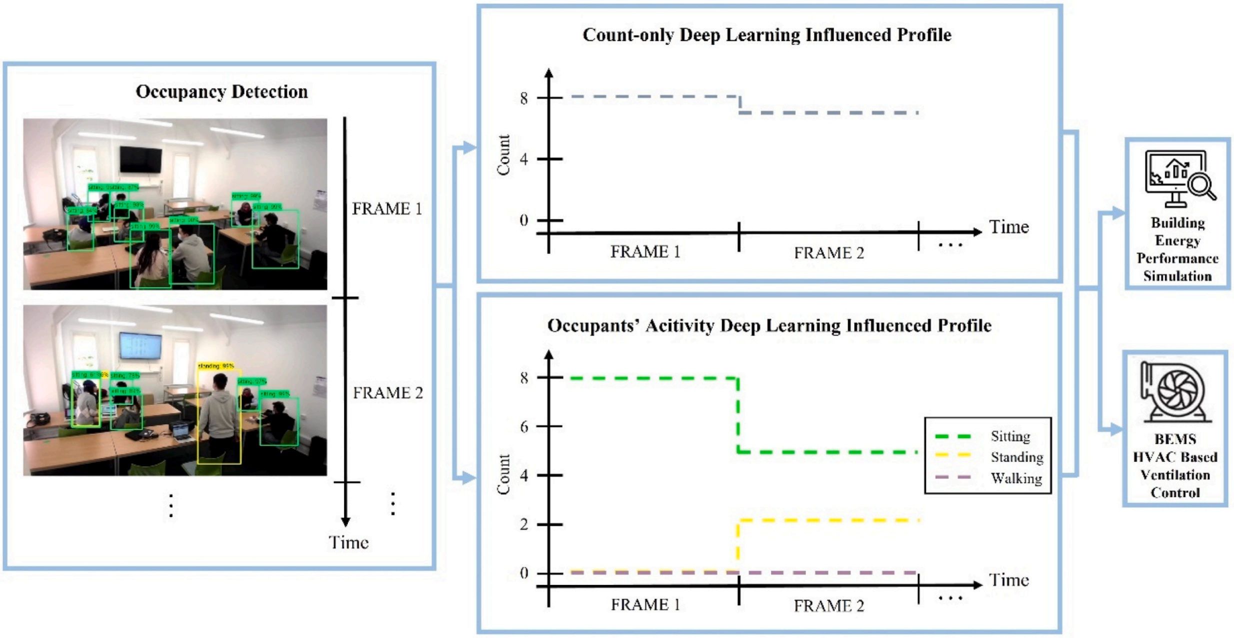


Fig. 6. An example of occupancy detection and recognition and the formation of count-based DLIPs.

compute the classification evaluation metrics including accuracy, precision, recall and F1 score. These evaluation metrics are frequently used to assess the detection and recognition performance of vision-based models. It should be noted that instead of showing the number of instances, the confusion matrices in this study showed the percentage of correct or wrong instances in each class since the number of labels for each class was different. Then, to evaluate the models' performance when conducting live detection and recognition, the Intersection over Union (IoU) detection accuracy which was displayed along the bounding box was obtained. During the experimental tests, the average IoU value was obtained from the detections.

2.3.2. *Ventilation scenarios and building energy simulation*

To evaluate the impact of using the proposed approach on indoor CO2 concentration and building energy performance, the case study building was modelled using different ventilation scenarios by a BES tool. The details of the simulation and set conditions are given in this section. Four ventilation scenarios were employed to estimate the effectiveness of using the proposed approach. For each scenario, four weekdays of a typical week (Monday – Thursday) in the heating and cooling season was chosen and simulated. Scenario A represents no ventilation within the conditioned space, meaning all windows were always closed, and the mechanical ventilation was always off. It was assumed as the worst case for IAQ. For Scenario B, as presented in Fig. 7(a), the windows in the space were fully opened for natural ventilation during the working hours (8:00–18:00). Since the windows installed in the room are sash windows, each window contains only one movable panel, 50% of the window area is the maximum open area for natural ventilation supply. Both Scenario C and Scenario D used mechanical ventilation to control indoor CO_2 concentration. According to CIBSE Guide A [45], the fresh air ventilation rate required for each person was 10 L/s in this study to fit between medium and moderate IAQ standards. For Scenario C, as the room maximum capacity is 11 people, the max ventilation rate of 110 L/s was constantly supplied to the room, as shown in Fig. 7(b), to provide the best air quality during the working hours. While, for Scenario D, the ventilation rate was applied based on the scenario-based occupancy profile which adjusted based on the actual occupancy variation in the case study room given in Fig. 8. In other words, the ventilation rate was varied with the number of people present in the room for the whole day which could be predicted by the deep learning detection model. Fig. 7(c) demonstrates the detection-based mechanical ventilation profile (Scenario D).

It should be noted that Scenario B can be applied or occur during the heating season in practice, although this would lead to a significant ventilation heat loss. For example, some buildings in the University will have openable windows which will be opened by the building users during the occupancy period. This is a result of the COVID-19 pandemic which has recently brought indoor air quality upfront and the increased awareness of the importance of ventilation to reduce the spread of COVID-19. At the same time, there are instances when building users have left windows open after leaving the space, during the winter which can then cause significant ventilation heat loss in the buildings. This scenario was taken into account as although it satisfied the fresh air requirements, it resulted in increased energy demands to heat the space up to the desired comfort level. The ach was estimated by the building energy simulation tools, which takes a value of 5 ach to model ventilation by window opening. In practice, this will vary throughout the day depending on several factors and this could be evaluated later when the proposed approach is combined with a window detection model, for instance.

Integrated Environment Solutions Virtual Environment (IESVE) was employed as the BES tool and its validation is demonstrated in

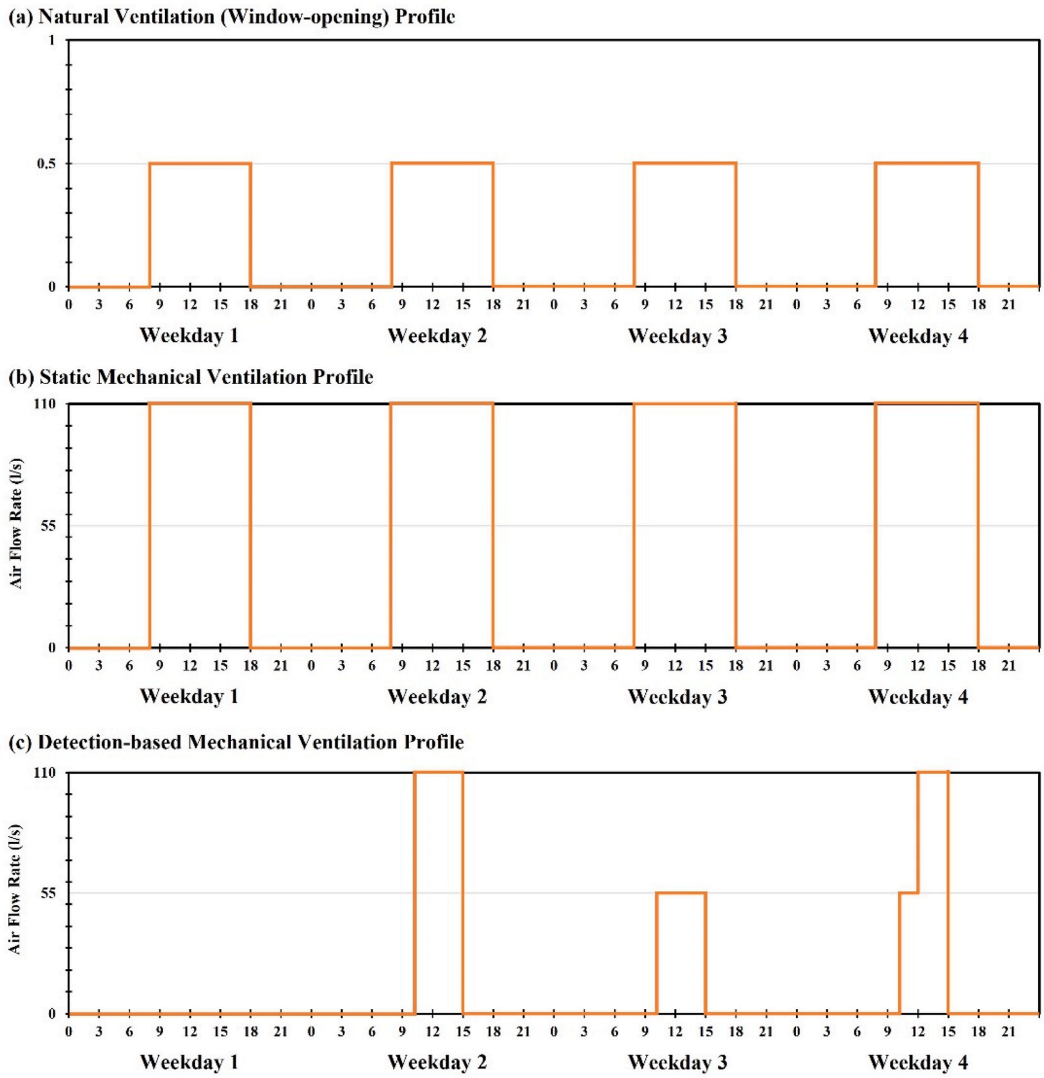


Fig. 7. (a) Scenario B (natural ventilation), (b) Scenario C (static mechanical ventilation), and (c) Scenario D (detection-based mechanical ventilation) profiles.

detail in our previous studies [47,48]. The BES was based on the dynamic thermal simulation of the heat transfer processes between a modelled building and its microclimate. Heat transfer processes of conduction, convection and radiation between each building fabric were modelled and included within the modelling of air exchange and heat gains, within and around the selected thermal space of the building. The heat gain/loss generated during the process of air exchange within or around the thermal space, which influences the amount of heating/cooling demand, is computed by the BES tool. The equations are fully detailed in our previous work [47,48].

During geometry modelling, some simplifications were applied to the model. For example, some features were excluded such as vegetation, surrounding buildings, and interior furniture. Effectively, the people in the space were assumed to be constantly sitting during the occupied period. The heating and cooling temperatures during the building operational period were set to be 21 °C and 25 °C according to ASHRAE standards [49,50]. The details of each scenario and building simulation setups are provided in Table 1.

3. Results and discussion

In this section, the results and discussions of the proposed CNN-based occupancy detection approach are presented. This includes the analysis of the models' detection performance during the implementation and its potential to improve the energy performance and indoor environment of buildings.

3.1. Evaluation of model training

Two proposed occupancy detection models, which detect the number of people and the occupants' activities respectively, were trained with the use of the Faster RCNN with the InceptionV2 and the labelled images in the training dataset detailed in Fig. 3. The

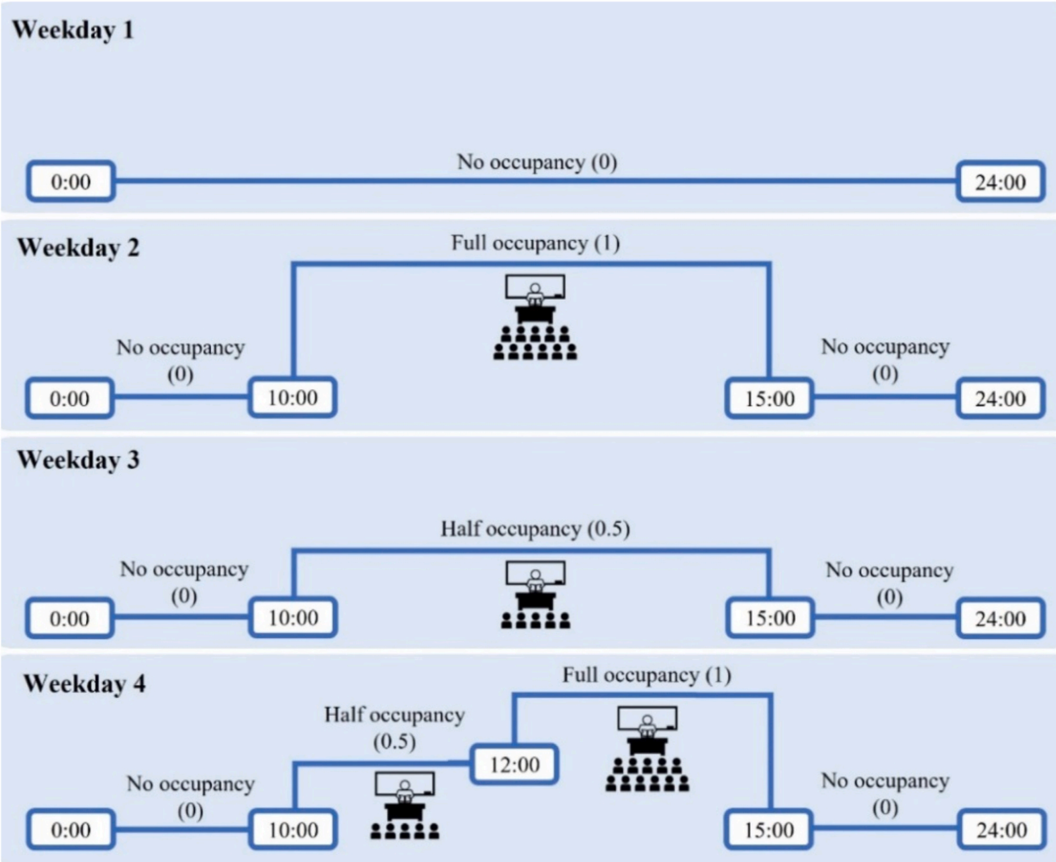


Fig. 8. Scenario-based occupancy profile for four weekdays.

corresponding training results for both models are detailed in Table 2. Fig. 9 presents the total loss graphs for both models. The convergence of their loss functions indicated that the models were trained adequately. Since the complexity of the detection tasks is different, in comparison to the occupancy counting model, a longer training duration was required for the occupants' activity model to be trained to achieve the convergence.

After the training process, validations were carried out by feeding the images within the test datasets into both models respectively to estimate the initial detection performance. The results were presented in the form of confusion matrices as shown in Fig. 10 and Table 3, which include the percentage of the correct, incorrect, and missed detection for each class. Model 1 was trained to recognise occupants and provided a correct recognition by up to 82.76%. Model 2 was trained to classify not only occupants but also their activities. The results showed that the correct classifications of sitting, standing, and walking by 87.92%, 82.84%, and 92.66% were achieved. It indicates that although the classification task of Model 2 was more complicated than Model 1, Model 2 provided a better performance on occupants and activities detection. One of the reasons could be that the number of images within the dataset for Model 1 is not sufficient, which could lead to lower detection accuracy.

3.2. Detection performance and profiles

The analysis provided in this section was according to the detection performance of the proposed approach during experimental tests. Fig. 11 presents the example snapshots of the test room with no detection, people detection, and occupancy activity detection at two specific times during the tests. It indicated that both models were capable of providing occupancy detection in terms of the number of occupants or their activities. However, it can be seen that mislabelling occurred during the detection task especially when people were walking or standing. It suggests that the current trained models still require a lot of improvements such as using different models and detection methods, and this could be carried out in future works. It should be noted that the present study mainly introduces how this concept can be used to better control ventilation systems and potentially minimise ventilation heat loss/gains.

When implementing occupancy detection, the IoU accuracy was shown along with the bounding boxes of the recognised objects for each instance. The average IoU detection accuracy that were displayed along the bounding boxes for both models are summarised in Fig. 12. The pictures shown here were used as an example to demonstrate the implementation of the detector. In practice, no image or video is recorded, instead, only the number of people and their activities are extracted from the scene by the detector. Individual detection accuracy for each person using Model 1 is shown in Fig. 12(a) and accuracy for each activity performed by each person using

Table 1
Overview of the ventilation scenarios for the BES model.

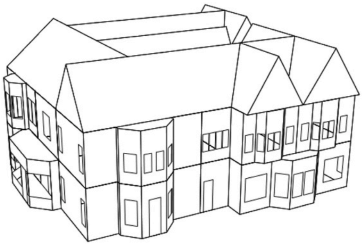
	Scenario A: No Ventilation	Scenario B: Natural Ventilation (Window-opening)	Scenario C: Static Mechanical Ventilation	Scenario D: Detection-based Mechanical Ventilation
Profile	Windows were always closed, and mechanical ventilation was off.	The windows were half-open during working hours (Figure (a)).	Maximum ventilation rate of 110 L/s was applied during working hours (Figure (b)).	Ventilation rate was applied based on the number of occupants present (Figure (c)).
Building Model				
Overall U-value	External wall (brick + gypsum plaster): 1.42 W/m^{2}K External floor (cast concrete + air cavity + timber + carpet): 0.95 W/m^{2}K External roof (clay tiles + timber frame + gypsum plaster): 1.46 W/m^{2}K Door (timber): 2.33 W/m^{2}K Window (single glazing): 5.20 W/m^{2}K			
Infiltration	0.5 ACH			
Weather File	Nottingham			
Occupancy Gains	Max sensible gain: 75 W/person Max latent gain: 70 W/person			
Lighting	10 W/m^2			
Heating Profile	21 °C during building operational hours (8:00–18:00)			
Cooling Profile	25 °C during building operational hours (8:00–18:00)			

Table 2
Model training summary.

	Model 1: Occupancy Counting	Model 2: Occupants' Activity
Model	Faster RCNN with InceptionV2	
Total Steps	41,901	102,194
Training Duration	2 h, 54 min	10 h, 29 min, 52 s
Average Loss	0.0761	0.1344
Min Loss	0.00357	0.00565

Model 2 is presented in Fig. 12(b). The results showed that Model 1 achieved an average accuracy of about 98.9% on people detection and Model 2 achieved an overall IoU accuracy of up to 88.4% on all activities' detection with the individual activity detection accuracy of about 92.6%, 85.1%, and 71.4% for sitting, standing, and walking respectively. It indicated that both models enabled the occupancy detection with high accuracy while Model 1 performed better than Model 2 due to the less complexity of Model 1. As can be seen, some activities were not performed by the occupants which led to no results for them. Specifically, the walking activity was only performed by two people achieving accuracies of 80.3% and 62.5%, giving a lower overall detection accuracy of walking activity. Hence, a longer duration of the experimental test will be required to attain a more precise analysis of the activity detection performance of Model 2. In addition, the variations in the detection accuracy implied that the results could be affected by several factors such as the distance between the detected occupant and the detector (camera), the angle of the camera, and the lighting distribution in the detection range.

When implementing the real-time detection, count-based occupancy DLIPs were generated during the experiment corresponding to the process demonstrated in Fig. 6. Fig. 13 shows the generated DLIPs for (a) Model 1: the total number of people present and (b) Model 2: the number of people performing each activity. Comparing the DLIPs with the actual situation within the detected space during the test, some errors occurred especially for Model 2. In addition, the frequent variations of the deep learning profile for Model 2 indicated the instability of this model. Therefore, further improvements are required to enhance the detection performance. Although Model 1 had higher accuracy in the counting detection, the outcomes of Model 2 would be more helpful for a better understanding of the variation of actual heat emissions within the space as performing different activities can lead to different metabolic rates of human bodies. This could assist the HVAC system to adjust its operation to make a timely response to dynamic variations of the occupancy activity to achieve demand-driven controls.

It should be highlighted that the profile presented here is not the only profile which can be generated by the developed CV technology. For example, if it is used in spaces with the varied number of occupants and activity levels, a highly variable or fluctuating profile can be obtained in real-time. In the future, it is envisaged that the detection technology can enable the detection of occupancy,

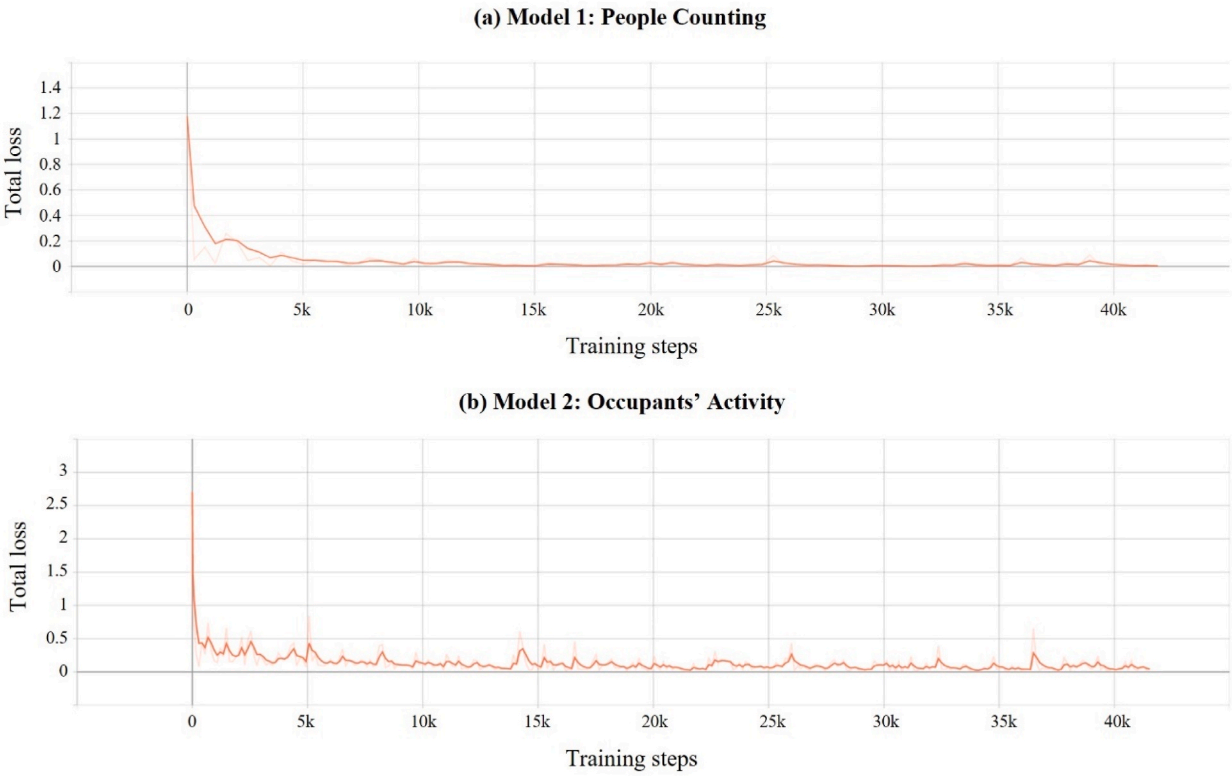


Fig. 9. Total training loss versus training steps.

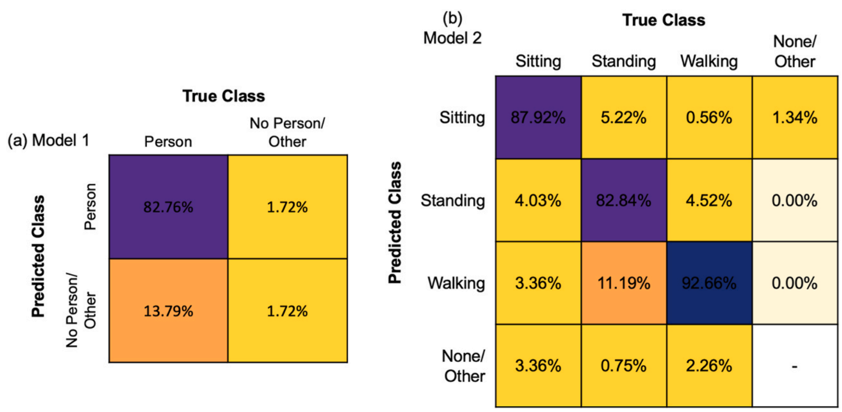


Fig. 10. Initial performance on still images from testing dataset – confusion matrices.

Table 3
Initial results using common evaluation metrics (on still images from testing dataset).

Class	Accuracy	Precision	Recall	F1 Score
Model 1: Occupancy Counting				
People	0.845	0.980	0.857	0.914
Model 2: Occupants' Activities				
Sitting	0.940	0.925	0.891	0.908
Standing	0.914	0.906	0.828	0.866
Walking	0.927	0.864	0.927	0.905
Average	0.927	0.899	0.882	0.893

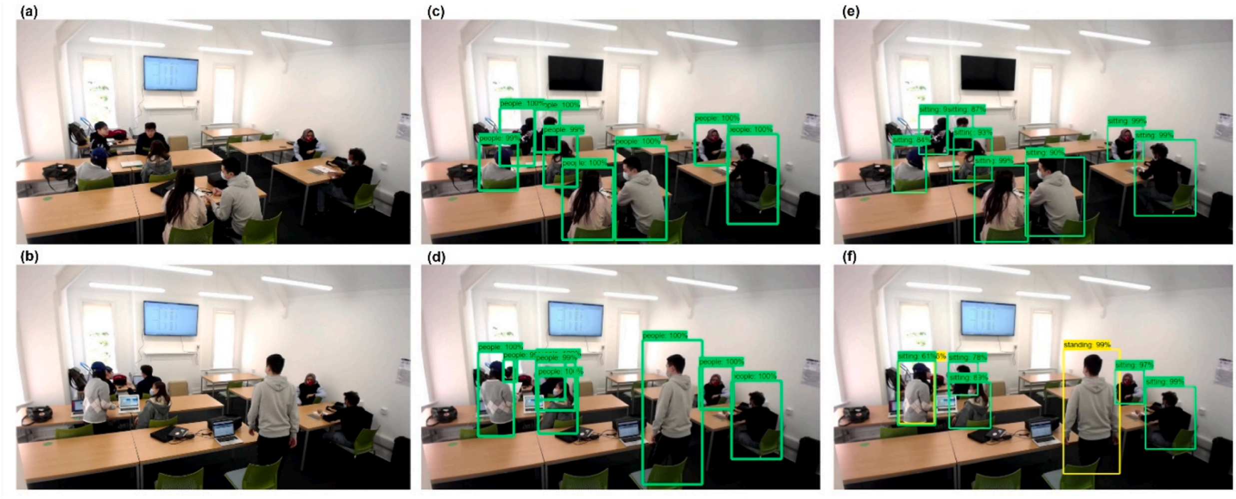


Fig. 11. Example snapshots of the test room with (a-b) no detection, (c-d) people detection, and (e-f) occupancy activity detection at two specific time during the experimental tests.

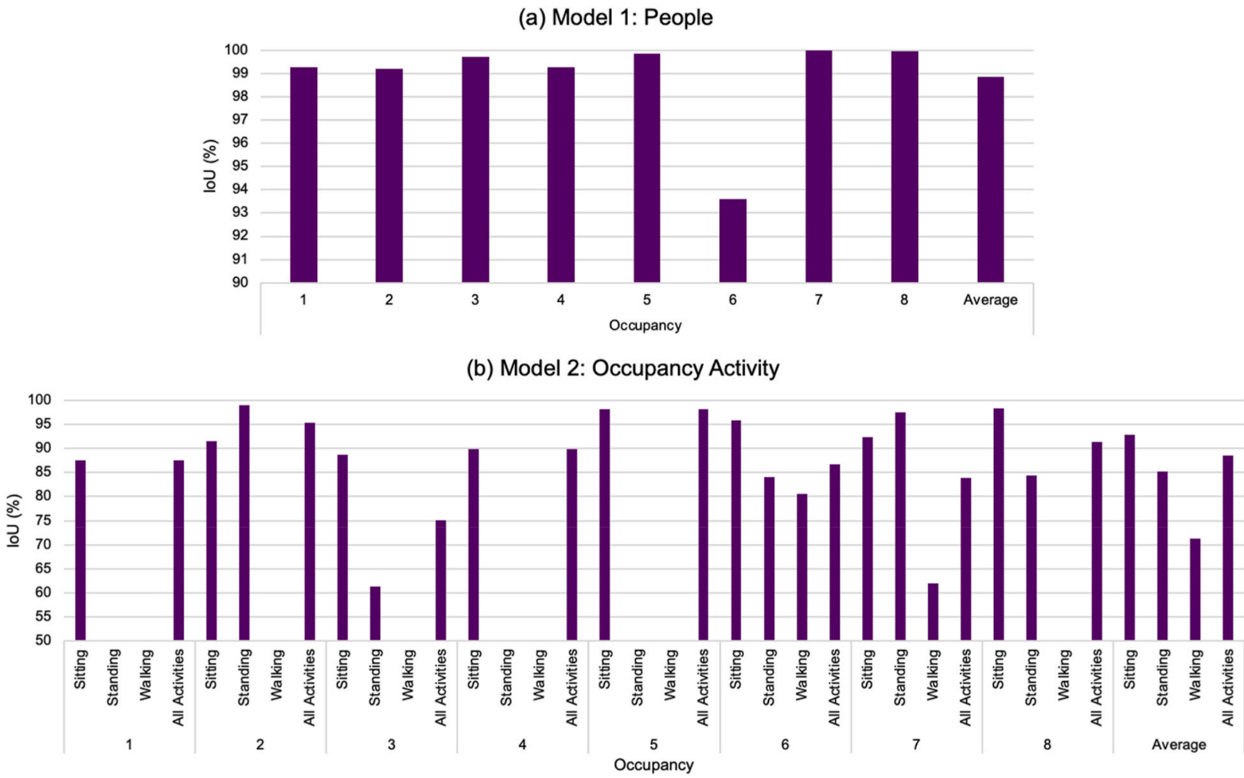


Fig. 12. The average intersection over Union (IoU) detection accuracy that were displayed across in form of the bounding boxes.

appliance/equipment use, fire and smoke, and so on in buildings to help improve building energy efficiency, health and safety. As the focus of this paper is on how this technology can optimize ventilation in buildings, only occupancy profiles were presented.

3.3. Indoor air quality and energy performance analysis

The room IAQ can be assessed by the CO_2 concentration. According to ASHRAE standard [51], a room with a CO_2 level of lower than 1000 ppm can be considered as a space with fairly good air exchange. When the CO_2 level is higher than 1000 ppm, it indicates that the room is polluted, which can lead to poor wellbeing, health, and productivity. While using different ventilation methods to

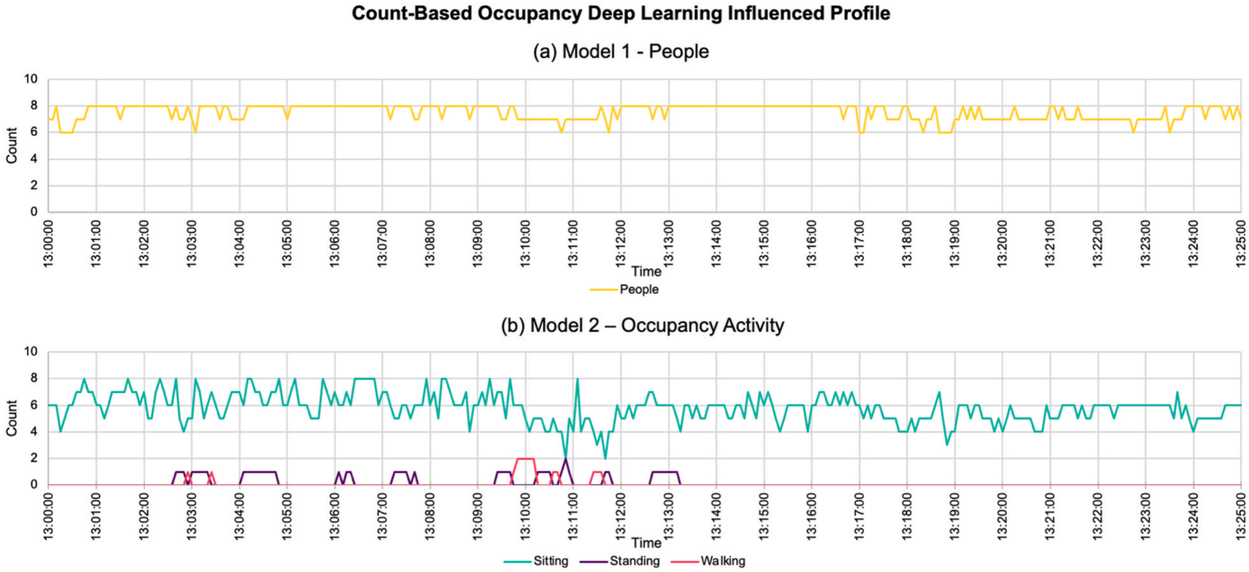


Fig. 13. Count-based occupancy DLIPs for Model 1 and 2.

maintain an adequate supply of fresh air could result in a significant difference in ventilation heat gain or loss depending on the indoor-outdoor conditions. This correspondingly affects the building energy consumption required to keep a good thermal comfort level for occupants. Thus, a balance between CO2 level and building energy demand should be achieved. This section shows the analysis of the impact of the proposed approach on the CO2 level and building energy performance within the conditioned spaces based on the comparison with other commonly used ventilation scenarios. Building energy simulation was carried out to assess the CO_2 concentration and ventilation heat gains within the selected case study room.

Figs. 14 and 15 present the simulation results of CO_2 concentration, ventilation gain variation, and total ventilation gain using different ventilation scenarios for four weekdays during the heating season (Dec 15–18) and the cooling season (May 12–15) in the selected case study room. Scenarios A-D stand for no ventilation, natural ventilation, static mechanical ventilation, and detection-based mechanical ventilation, respectively. As shown in the figures, the CO_2 concentration varied with the occupancy profile given in Fig. 8. The ventilation heat losses changed in response to the ventilation profiles (Fig. 7) and the variation of external temperature. The losses were smaller on the less cold days in winter.

As illustrated in Fig. 14, during the heating period, although Scenario A achieved the minimum ventilation heat loss, it caused the maximum CO_2 level which could reach over 3000 ppm within the test room, which suggests the necessity of ventilation to improve the IAQ. For Scenario B which provided natural ventilation by opening the windows, the lowest CO_2 level was achieved during the occupied period. However, a remarkable ventilation heat loss was produced due to the large indoor-outdoor temperature difference in winter. The lower the outdoor temperature is, the higher ventilation heat loss is within the space. This caused extreme discomfort and therefore an enormous increase in heating demand to maintain a comfortable indoor temperature. It indicates that during the cold period, in terms of thermal comfort and building energy efficiency, natural ventilation by opening windows is not a suitable ventilation strategy. For mechanical ventilation (Scenario C and D), both scenarios could provide low CO_2 levels with less ventilation heat losses. However, in comparison to Scenario C which supplied a static airflow rate during the building operation period, Scenario D provided the dynamic airflow rate based on the variation of occupancy rate and led to a ventilation loss reduction of up to 54.56% (32.89 kW). In comparison with Scenario B, up to 90.96% (266.98 kW) reduction of ventilation heat loss was achieved by Scenario D. It highlighted that using Scenario D could reduce the unnecessary energy demand for heating and system operation. It suggested that providing the real-time occupancy information collected from the proposed detection approach to the building ventilation system to achieve demand-driven controls could offer an opportunity to significantly improve the building energy efficiency while maintaining a good IAQ for occupants.

The simulation results of using different ventilation scenarios for four days during the warm period (May 12–15) in the case study room is shown in Fig. 15. Similarly, Scenario A achieved the minimum ventilation heat gain while causing the highest CO_2 concentration, which indicated that the indoor air was highly polluted. Scenario B resulted in the lowest CO_2 level during most of the occupied period and the maximum ventilation heat gain of 13.93 kW due to the higher outdoor temperature in summer. For mechanical ventilation, both scenarios could provide low and similar CO_2 levels. Scenario C generated ventilation heat gain of 4.49 kW while Scenario D generated ventilation heat loss of 1.32 kW during the four weekdays. Up to 5.81 kW difference of ventilation heat gain was created between Scenario C and D. It indicated that using Scenario D could provide real-time demand-driven controls for a good IAQ and also reduce the cooling energy demand in summer. However, because the UK has a temperate climate, the summer is generally warm and wet. The variations of the external air temperature and room air temperature using four scenarios for the four weekdays are presented in Fig. 16. The peak outdoor air temperature was about 27 °C and during most of the days in summer was lower than 25 °C.

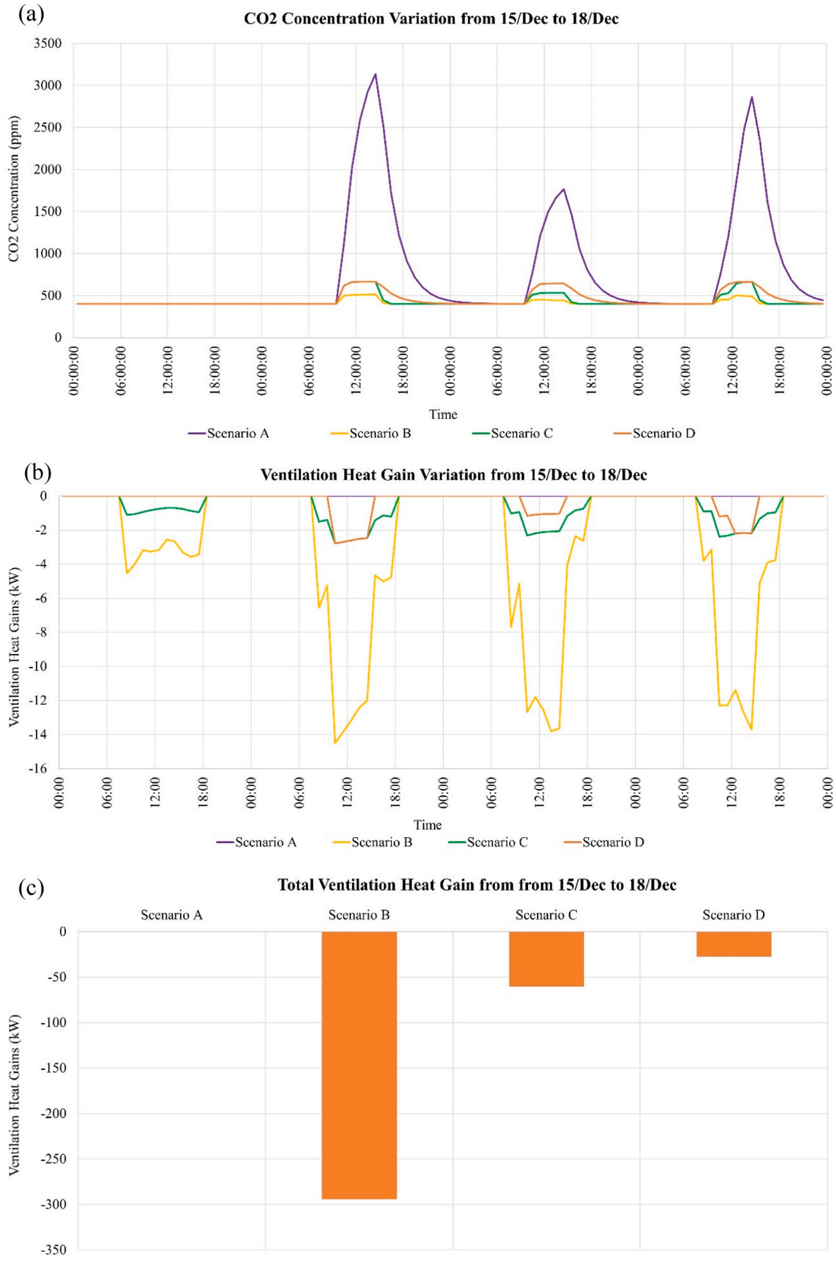


Fig. 14. CO2 level, ventilation heat gain variation, and total ventilation heat gain during heating season. Note that negative result denotes ventilation heat loss.

According to CIBSE Guide A (CIBSE 2015), the general comfort temperature range is 20–26 °C. It demonstrated that the cooling demand for the case study room was small. In addition, room air temperatures using four scenarios during the occupied period were within the comfort temperature range. However, due to the use of natural ventilation, using Scenario B could reduce the energy use while still maintaining a comfortable indoor environment. This highlighted the benefits of employing natural ventilation in buildings' energy cost, greenhouse gas emissions, and air quality.

Based on the simulation results in the selected case study room, Scenario B-D could maintain the CO2 level below 1000 ppm. In the cold period, up to 90.96% and 54.56% reduction of ventilation heat loss could be potentially achieved by the demand-driven mechanical ventilation using the real-time occupancy detection (Scenario D) in comparison with natural ventilation (Scenario B) and mechanical ventilation with a static airflow rate (Scenario C). In the cooling season, using Scenario D could reduce the ventilation heat gain to minimise the building energy demand for cooling and system operation. It indicated that the proposed approach could provide demand-driven ventilation controls based on the real-time changes of occupancy to improve the IAQ and address the problem of under- or over-estimation of the building energy consumption when using the static or fixed profiles. This highlighted the benefits of employing deep learning and computer vision techniques to monitor occupancy behaviour in real-time for effective operation of the

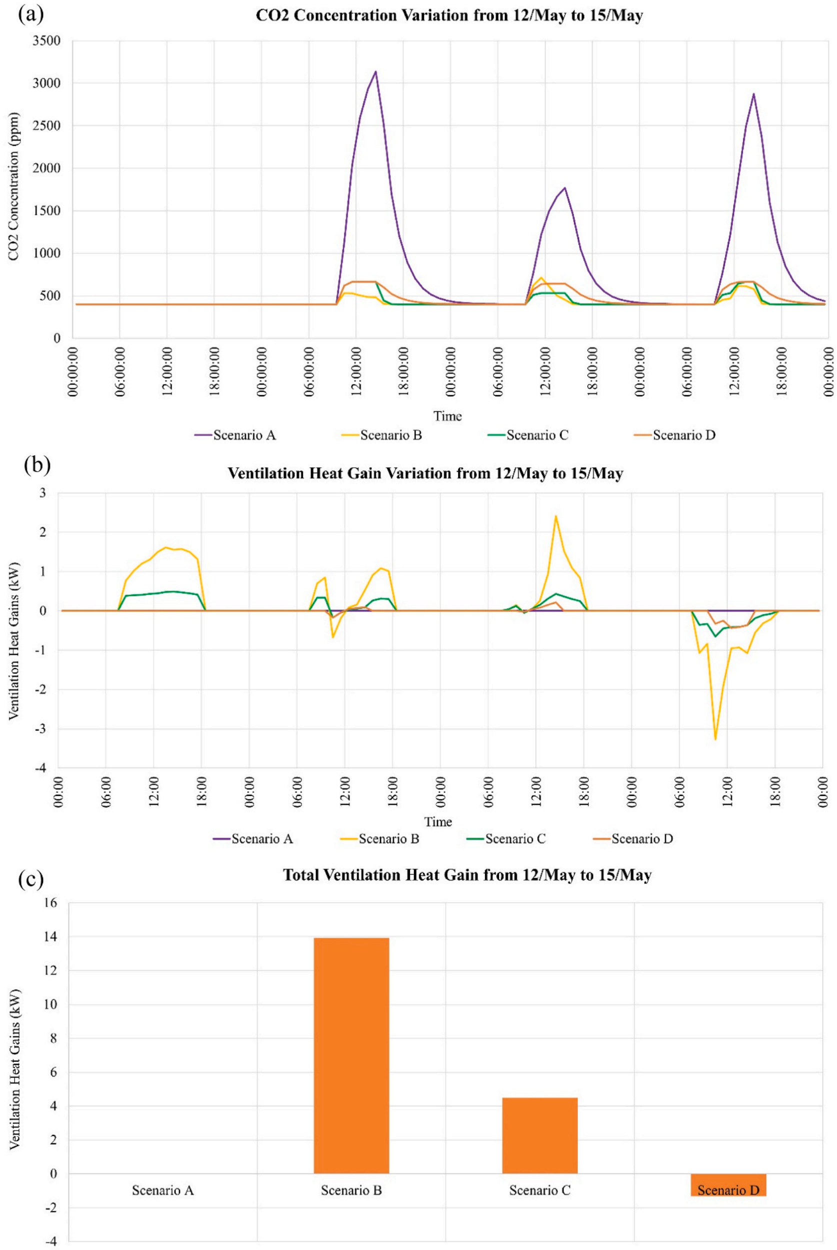


Fig. 15. CO2 level, ventilation heat gain variation, and total ventilation heat gain during the warm period. Note that negative result denotes ventilation heat loss.

HVAC according to occupants' actual needs. However, as the cooling demand was small in the UK due to its mild weather, using natural ventilation is another beneficial option to further reduce the energy cost in buildings with windows or vents. Thus, an alert system which can inform people to open or close the windows will be integrated with the proposed approach to optimise building energy efficiency and keep the space well-ventilated.

3.4. Discussion and limitations

According to the detection results, it indicated that both models were capable of providing occupancy detection in terms of the number of occupants or their activities. However, it can be seen that mislabelling occurred during the detection task especially when people were walking or standing. It suggests that the current trained models still require a lot of improvements. There are lots of opportunities to enhance the detection by using such as different models, training (using videos), and detection method (distinguish standing from walking), and this could be carried out in future works. Additionally, there are some overlapping issues when performing detection and recognition. In the next step, multiple cameras or a 360 camera will be employed to overcome overlapping problems.

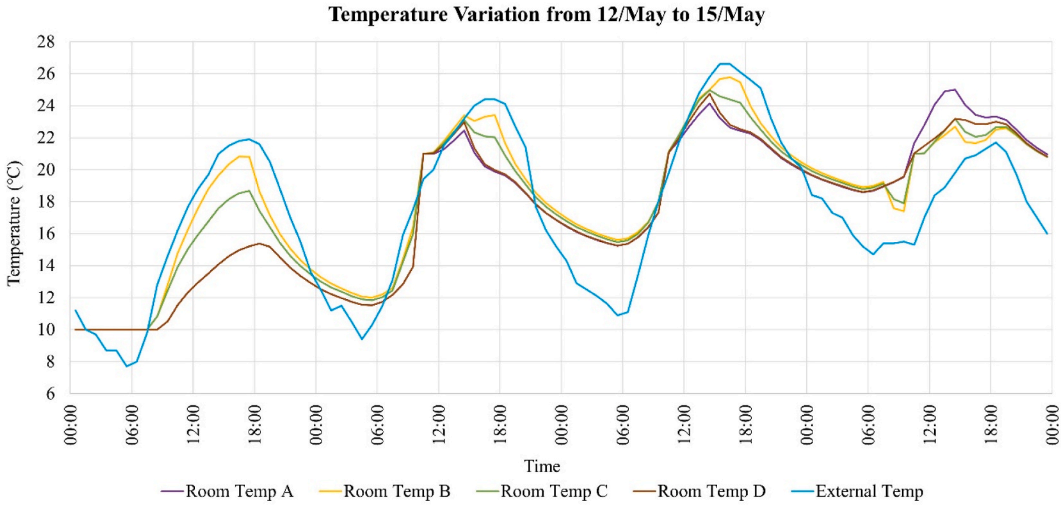


Fig. 16. Variation of external air temperature and room air temperature when using Scenario A-D for the four weekdays during the warm period.

It should be noted that this is a scenario-based study. Scenario-based conditions were designed to evaluate the energy demand of the space when employing different ventilation strategies. This can help investigate the effectiveness of applying the proposed detection approach in lowering the ventilation heat loss/gain within the space in different seasons as compared to the other strategies. However, on-site measurements and implementations are definitely required to provide the data necessary to show the capabilities and benefits of the proposed detection approach integrated with the control system, and this will be carried out in future work.

This study only estimated CO_2 emissions from occupants performing various activities during their presence in a space. The amount of CO_2 emission from per person was based on the typical values from guidelines such as the CIBSE Guide A. While, in practice, the CO_2 concentration in the room is affected by several factors such as the number of people present, the duration that the room has been occupied, infiltration, and natural ventilation. Therefore, it will be the next step of development as a part of our future work. For example, using the same vision-based detection approach, the opening of windows can also be detected as demonstrated in the work of [34]. Combining these strategies can then detect and recognise the period and amount of occupancy generated CO_2 and window opening in real-time and at the same time adjust the HVAC systems to minimise energy wastage (ventilation heat loss) and maintain indoor environment quality and thermal comfort. Moreover, CO_2 from the occupants is not the only indicator of a room's indoor air quality condition. Through the method proposed in this study, the CO_2 generated by occupants performing various activities during

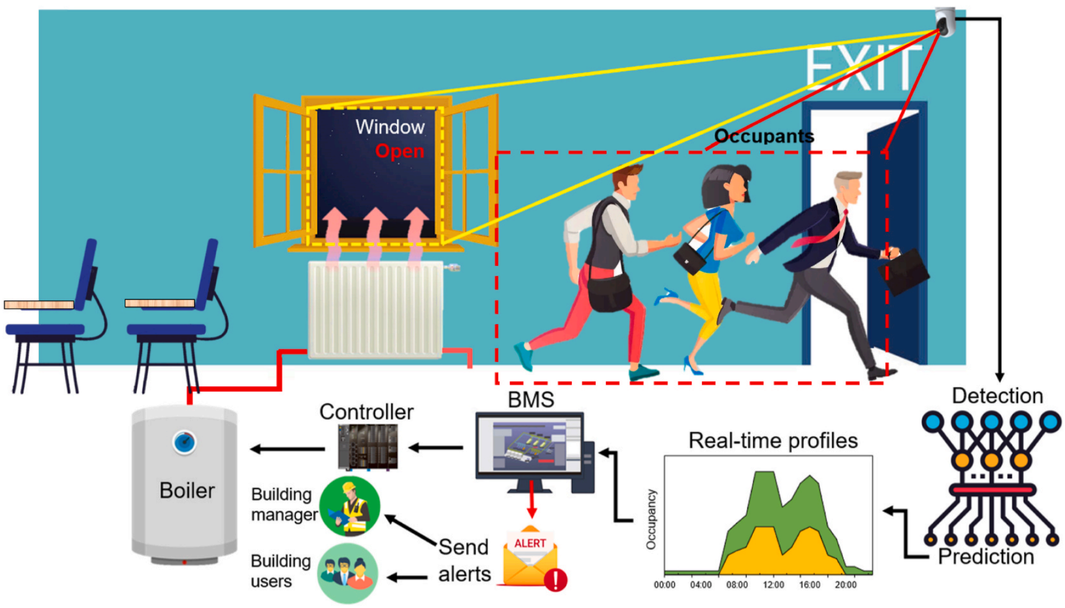


Fig. 17. Potential integration between the occupancy detection method and window opening detection to enhance natural ventilation while minimising energy consumption.

their presence in a space can be predicted in real-time. However, more work is necessary to further evaluate the indoor air quality condition. Other parameters such as the ventilation of the space must be taken into account.

It should be noted that this study is not suggesting eliminating the use of CO_2 sensors but rather it can complement existing systems to enhance the performance of demand-driven controls systems. The detection approach can provide occupancy information quickly and CO_2 sensors can provide precise measurement. The integration of them could ideally achieve fast and accurate controls of ventilation systems. However, this should be evaluated in the future. Additionally, this study is not only focusing on CO_2, but also demonstrating that this could be a possible solution to detect other actions such as people coughing and sneezing, cooking, spraying, and cleaning materials. This could help boost ventilation in such spaces. Moreover, this could be used in large spaces with sub-zonal ventilation systems wherein ventilation can be increased in sub-zones with many people and less in sub-zones with no or less people. Therefore, future studies will carry out a detailed comparison between CO_2 sensors and vision-based approach. This will compare the speed of vision-based approach in predicting the indoor CO_2 level with CO_2 sensors. The integration of both strategies will also be investigated. Furthermore, it is envisaged that such technology can detect multiple objects, activities/actions and equipment use in real time and provide HVAC and users data for optimum control and decision making, i.e., one camera (sensor) can have multiple functions. This could assist the operation of building energy management system based on the actual demands to improve the energy efficiency and comfort level.

Consequently, a system integrating the proposed approach and an alert system should be developed and employed in buildings. This system will combine the live occupancy detector and interior and exterior environmental sensors and connect to the BMS to enable the real-time demand-driven controls performed by the HVAC system. Based on the collected occupancy information from the detector and the environmental conditions, the BMS system will operate the alert and ventilation control systems to adjust the windows (or advice the opening/closing) and settings of the HVAC through a decision-making process to provide adequate IAQ while minimising ventilation energy use (Fig. 17). When the building is predicted as occupied by the occupancy detector and outdoor environmental conditions are suitable to naturally ventilate the building, the system will inform the building manager or users to open the windows instead of using mechanical ventilation. On the contrary, if the outdoor air is not suitable for natural ventilation, the system will send alerts to people to close the windows, and the mechanical ventilation will be implemented by the HVAC to provide fresh air in the building based on the real-time occupancy information from the live occupancy detector. The detailed criteria for the control flow process will be determined and additional applications such as real-time window detection will be further developed and integrated in future works to increase the feasibility and performance of the system.

4. Conclusions

The present study investigated the potential of the application of a live occupancy detection approach to assist the adjustment of the building HVAC systems' operations to make certain that sufficient interior thermal conditions and air quality were obtained while reducing excessive building energy loads to enhance the overall building energy performance. To enable the live occupancy detection, Faster RCNN models were trained to detect the number of people (Model 1) and occupancy activities (Model 2) respectively and deployed to an AI-powered camera. Experimental results showed that Model 1 achieved an average IoU detection accuracy of about 98.9%, which was higher than Model 2 of approximately 88.5%, due to the less complexity of Model 1. Scenario-based modelling of the case study building under four ventilation scenarios during heating and cooling seasons was carried out using BES. Results demonstrated that the proposed approach could provide DCV to improve the IAQ and address the problem of under- or over-estimation of the ventilation demand when using the static or fixed profiles. It gave insights into the way that the proposed approach can enable the adjustment of HVACs based on occupants' dynamic changes and also indicated the potential of this approach in the enhancement of indoor air quality and energy efficiency. This highlighted the benefits of employing deep learning and computer vision techniques to monitor occupancy behaviour in real-time for effective operation of the HVAC according to occupants' actual requirements.

CRediT authorship contribution statement

Shuangyu Wei: Conceptualisation, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualisation. **Paige Wenbin Tien:** Conceptualisation, Software, Data curation. **Tin Wai Chow:** Software. **Yupeng Wu:** Writing – review & editing, Supervision. **John Kaiser Calautit:** Conceptualisation, Resources, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abbreviations and Symbols

AI	Artificial Intelligence
BES	Building Energy Simulation
BMS	Building Management System
BRE	Building Research Establishment
CNN	Convolutional Neural Network
DCV	Demand Control Ventilation
DOV	Demand-Oriented Ventilation
DLIP	Deep learning influenced profile
HVAC	Heating, Ventilation and Air-Conditioning
IAQ	Indoor Air Quality
IEA	International Energy Agency
IESVE	Integrated Environment Solutions Virtual Environment
IoU	Intersection over Union
NHS	National Health Service
R–CNN	Region-based Convolutional Neural Network
RPN	Region Proposal Network
SVM	Support Vector Machine
WBCSD	World Business Council for Sustainable Development
WGBC	World Green Building Council
WHO	World Health Organization
i	Index of an anchor
L_{cls}	Classification loss
L_{reg}	Regression loss
N_{cls}	Nominator to normalise the outputs of the *cls* layers
N_{reg}	Nominator to normalise the outputs of the *reg* layers
p_i	Predicted probability of anchor i being an object
t_i	Vector representing 4 parameterised coordinates of the predicted bounding box
λ	Balancing weight

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