Cleaner Energy Systems 3 (2022) 100038

Contents lists available at ScienceDirect

Cleaner Energy Systems

journal homepage: www.elsevier.com/locate/cles

Enhancing the detection performance of a vision-based window opening detector

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A R T I C L E I N F O

Keywords:
Computer vision
Deep learning
Detection
Ventilation heat loss
Window opening

A B S T R A C T

In favorable climates and building types, employing natural ventilation can lead to significant energy savings and health benefits. However, in cold climates or conditions, the use of natural ventilation could result in significant heat loss and, consequently, excessive heating bills. This is further exacerbated when windows are left unintentionally open by occupants during the heating season, causing unnecessary energy consumption and wastage, which compromises the heating, ventilation and air-conditioning (HVAC) efficiency. Occupant behavior influences and shapes the building's energy use and indoor environment quality. In particular, the occupant's interaction with the building and its elements, such as window openings, has a considerable effect on the air change rate and the thermal load for ventilation. Studies have shown that real-time occupancy information can improve the operation of HVAC, lighting and utilization of building zones or spaces by coupling it with demand-driven control and occupant-centric strategies. The present study introduces a computer vision and deep learning-based detection approach for the real-time monitoring and recognition of the opening and closing of windows. The study aims to use the detection approach to reduce the energy demand by correctly controlling the HVAC or alerting the building users/operators during periods when windows are left open, minimizing the unwanted air change rates and heating or cooling loads. The study will take an in-depth look into the performance of the detection model, in particular, the influence of data curation, labelling and training employed. Four types of window detectors were configured and evaluated based on the detection of a set of windows within a case study building, which will help seek the most accurate detection and recognition of window opening status. The impact of the detection method on building energy demand was investigated through a series of building energy simulation (BES) scenarios. Simulations were conducted using predefined fixed profiles, along with the window detection and 'actual' profiles. The study has shown that the detection and recognition ability of the models ultimately influenced the prediction of the ventilation heat loss and heating energy demand.

1. Introduction and literature review

The built environment sector is responsible for a significant part of global energy consumption and energy-related carbon emissions (Abergel, Dean and Dulac, 2017). One of the largest energy consumers in buildings is the heating, ventilation, and air conditioning (HVAC) system (Amin, Hossain and Fernandez, 2020). Hence minimizing HVAC's energy usage and enhancing its efficiency will be crucial for reducing emissions and achieving the climate change targets set by Governments around the world (Chen et al., 2020). An alternative strategy to mechanical HVACs is using natural ventilation in buildings (Bienvenido-Huertas et al., 2020), which reduces energy consumption by relying on natural wind forces and temperature differences to circulate airflow in buildings. Natural ventilation can be achieved by fully or partly opening windows, air vents, trickle vents, chimneys, etc. (Zhang et al., 2021). In addition, natural ventilation provides fresh air and removes stale air, enhancing the indoor air quality of buildings (Calautit et al., 2020). Recently due to the COVID-19 pandemic, it has been recommended (GOV.UK, 2021) and established that natural ventilation strategies could reduce the chance of spreading the virus indoors (Park et al., 2021).

In favorable climates and building types, employing natural ventilation can lead to significant energy savings and health benefits (Jomehzadeh et al., 2017). However, in cold climates or conditions, the use of natural ventilation could result in significant heat loss and, consequently, excessive heating bills (Liu, Jimenez-Bescos and Calautit, 2022). Building heat loss occurs in buildings through fabric and ventilation heat loss. Introducing fresh and cold air into the space via operable windows could lead to significant ventilation heat loss during the heating season (Najjar et al., 2019). Furthermore, it could cause ther-

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https://doi.org/10.1016/j.cles.2022.100038
Received 24 January 2022; Received in revised form 25 October 2022; Accepted 1 November 2022
Available online 2 November 2022

Nomenclature and Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
BES	Building Energy Simulation
CNN	Convolutional Neural Network
COCO	Common Objects in Context
CO2	Carbon Dioxide
DL	Deep Learning
DLIP	Deep Learning Influenced Profile
HVAC	Heating, Ventilation and Air-conditioning
IoU	Intersection of Union
mAP	mean Average Precision
R-CNN	Region-based Convolutional Neural Network
UK	United Kingdom

mal discomfort and, in some cases, lead to occupants using personal or portable heaters (Shahzad et al. 2018), which further increases the energy demand (Shahzad et al., 2016). This is further exacerbated when windows are left unintentionally open by occupants (Tien et al., 2021a) during the heating season, causing unnecessary energy consumption and wastage, compromising the HVAC efficiency.

Occupant behavior influences and shapes the building's energy use and indoor environment quality (Zhang et al., 2022). In particular, the occupant's interaction with the building and its elements, such as window openings (Fabi et al. 2012), has a considerable effect on the air change rate and the thermal load for ventilation. Building designers and operators run the risk of putting unpredictable loads on the HVAC and unwanted or unreliable air change rates (Ackerly et al., 2011) if operable windows are left up to the control of the occupants. The degree of opening, how often and for how long windows are opened by the occupants will affect the air change rate. Hence, different behavior patterns will result in differences in energy consumption and the indoor environment quality of the buildings. This makes predicting the energy performance of buildings more challenging, which is a critical process during the design stage. The study (Delzendeh et al., 2017) highlighted that the occupants' behavior impact had been overlooked in the analysis of building energy performance, and hence there is an alarming performance gap between actual and predicted building energy consumption.

Furthermore, HVAC systems designed and operated using fixed schedules, predefined by building designers and operators based on assumed occupancy levels or patterns, can lead to spaces being unnecessarily over-or under-conditioned (Tien et al., 2020a). There has been a rise in studies on occupant- or human-centred control strategies for HVAC systems to address such issues (Choi et al., 2021a). Such strategies actively reflect occupancy information and behavior in the control of building systems. The work (Pang et al. 2020) suggested that such strategies can achieve a reduction of 20-45% in building energy consumption. 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 (Park et al., 2019). A comparison of sensors for obtaining occupancy information is reviewed in (Tien et al., 2022b).

Unlike other sensors, cameras can work like human eyes, which can detect changes in occupancy without delay, and at the same time, recognize occupants performing sedentary activities or minimal movements. The study (Tien et al., 2020a) recently highlighted the potential of using a vision-based approach that integrates camera and computer vision approaches to detect occupancy information and activities in real time. The study showed the impact of using the proposed approach on the building energy demand as compared to the use of static or fixed occupancy profiles. The proposed approach can predict the internal heat gains and feed the data into demand-driven control to help minimize unnecessary heating or cooling energy loads and effectively manage indoor conditions.

The study mainly focused on office buildings and evaluated the approach based on activities such as sitting, standing and walking. A similar approach can be used to detect other occupancy behavior or activities, such as the opening and closing of windows (see Fig. 1). It is envisaged that a significant reduction in energy and cost can be achieved if the building services are correctly controlled during periods when windows are left open, minimizing the unwanted air change rates and heating or cooling loads. The control and coordination of an HVAC system with occupancy and natural ventilation can play a significant role in reducing energy consumption and improving comfort and indoor air quality.

1.1. Novelty, research gaps and the aims and objectives

Many studies have shown that real-time and detailed information on occupancy can improve the operation of HVAC, lighting and utilization of building zones or spaces by coupling it with demand-driven control and occupant-centric strategies (Tien et al., 2020b). Occupancy information such as presence, location, number, and activities can be detected using different occupancy measurements or sensor systems, as detailed in the study (Labeodan et al., 2015). The use of cameras coupled with vision-based occupancy detection and recognition technology has garnered 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 (Zhang et al., 2022). However, the computer vision field has been a subject of increased interest due to the increased accessibility to larger computational power and the rise of artificial intelligence (AI), specifically the success of convolutional neural networks (CNN) (Tien et al., 2022b).

Recently, there has been a spike in research employing a camera, computer vision and deep learning to detect occupants in buildings (Tien et al., 2020c). Many earlier research focused on occupancy counting and presence (Choi et al., 2021b). 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 Tien et al. (2022a) and Wei et al. (2020) highlighted a lack of research investigating the impact of such an approach on the building energy demand. The study by Wei et al. (2020) employed a computer vision approach to detect and predict the internal heat gains in office buildings based on the detected activities. Recently, the approach was also used to predict internal heat gains from equipment such as computers and monitors in office spaces (Wei et al., 2022). 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.

The present study will use the same approach to detect the window status or condition in real time. An integrated approach or tool that can detect occupancy, equipment usage and window simultaneously in real-time is desirable and will be further developed in our study. The proposed approach can be an alternative to using window sensors, which must be installed on every building window. Although several window detection methods are available, there are limited studies on their application and integration with demand-driven controls for managing energy and comfort in buildings (Park, 2020). 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, recreational spaces, etc.

To date, only limited studies attempted to demonstrate the usage of the detected window opening information to control the HVAC operation. For example, Tien et al. (2021a) showed the potential of a vision-based framework for detecting and recognizing manual window operations in buildings. The initial results showed that the approach could reduce the over-or under-estimation of ventilation heat loss. The work introduced a system that can help alert building users or operators when windows are left open and prevent unwanted air change rates. However, the study did not take an in-depth look into the performance of the detection model, in particular, the influence of data curation, labelling and training employed. Furthermore, the impact on the detection performance of changing environments, such as the lighting conditions and occupants blocking the target object, was not evaluated.

Therefore, the present study will focus on investigating the performance of window detection model, in particular, the influence of data curation, labelling and training employed. Four types of window detectors will be configured and evaluated based on the detection of a set of windows within a case study building, which will help seek the most accurate detection and recognition of window opening status. Building energy simulation is used to evaluate the impact of the detection method on ventilation heat loss and energy consumption.

2. Method

The present work will develop an accurate window detector for controlling the operation of building energy systems or alerting the building users/operators during periods when windows are left open, as shown in Fig. 1. Several detection model configurations will be evaluated based on real-time detection and recognition experiment tests. Particular focus will be given to the data set used and the labelling of the training data. For each detection model, a series of evaluation metrics were used to assess the performance of the trained models on the detection of the same window in the selected case study building. Profiles, also called here the deep learning influenced profiles (DLIP), are generated from the real-time detection and compared with the ground truth. Building energy simulation (BES) was also performed to predict the potential impact of the detection performance on the ventilation heat loss and building energy demands.

2.1. Development of the deep learning window detector

Convolutional Neural Networks (CNN) is a classification-based algorithm suitable for developing computer vision-based detectors (Yamashita, Nishio and Togashi, 2018). It has been extensively used to provide accurate detection frameworks, including object detection (Galvex et al., 2018), face recognition (Hu et al. 2015), and speech recognition. Previous works focusing on the initial development of individual detectors for occupancy activities (Tien et al., 2021a) and windows (Tien et al., 2022a) both employed CNN models. These studies showed the potential of such an approach and highlighted the requirement for further development to increase detection accuracy and reduce the number of no/missed detections and incorrect detections.

Four different window detection model configurations were established and compared in the present study. Table 1 summarises the specification of each model with varying types (opened and/or closed) and several datasets. Model 1 and 2 (Windows M1.0 and 2.0) consisted of two response categories: ‘Open’ and ‘Closed’ windows, while Model 3 and 4 (Windows M3.0 and 4.0) consisted of only one detection response ‘Open’ windows. Model 1 represents the base model trained with the lowest number of images within the dataset. This will show the capabilities of the model to detect and recognize window openings with a limited amount of data. The number of images in Model 2 is increased while having the same types of categories and images. This will allow the evaluation of the influence of the number of images in the training datasets on detection performance. Models 3 and 4, which only detect ‘open’ windows, will have a lower number of training and testing images.

Pre-processing was conducted, which involved the preparation of the data for the model training. The main tasks include manual labelling each image within the training and testing datasets using the software

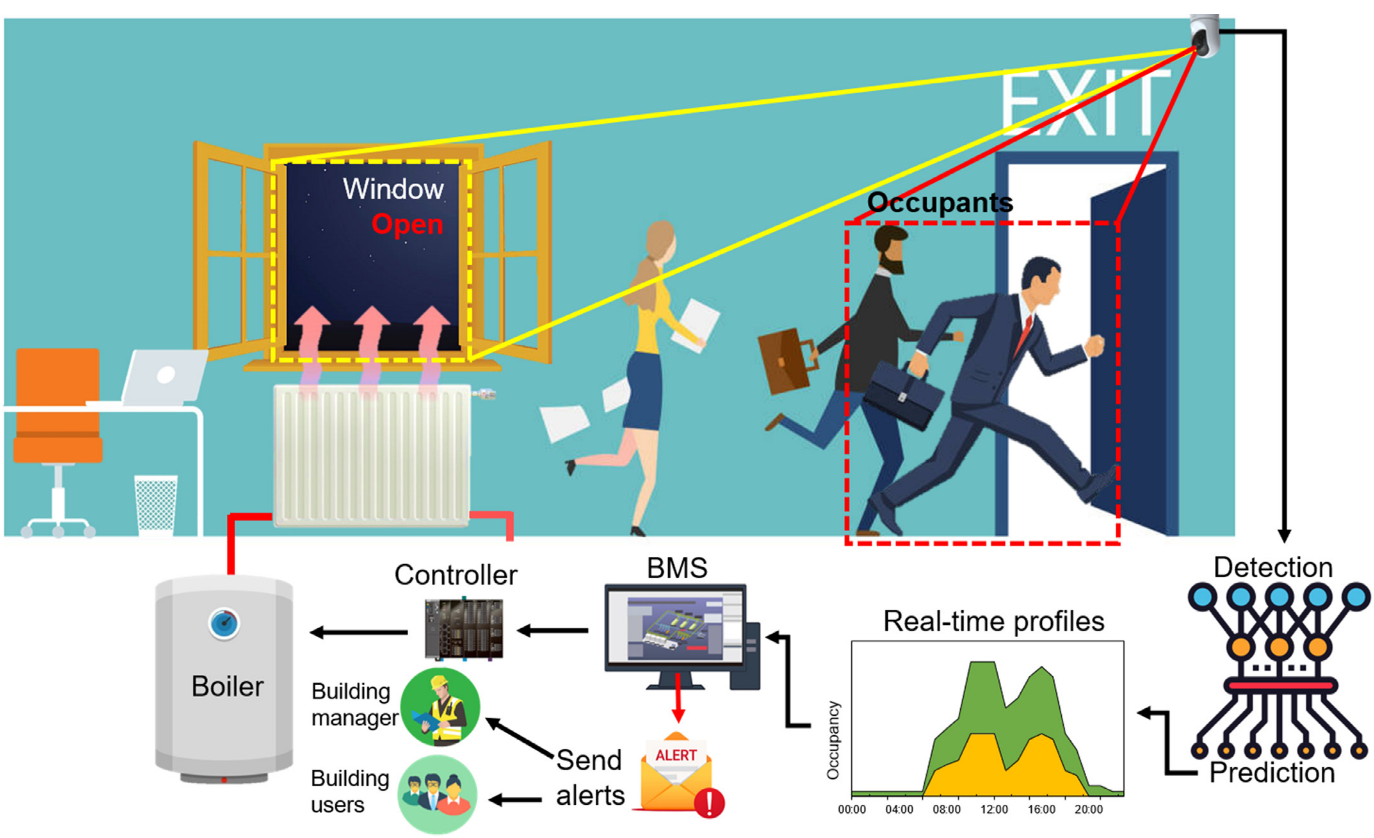


Fig. 1. The proposed approach for the detection of window status and occupants in coordination with the HVAC control system.

Table 1
Description of the training and testing image dataset for the different window detection models.

Model Name	Category	Dataset Size					
		No. of Images			No. of Labels		
		Training	Testing	Total	Training	Testing	Total
Window M1.0	Closed	100	25	125	164	36	200
	Open	100	25	125	108	27	135
	Total	200	50	-	272	63	-
Window M2.0	Closed	1000	250	1250	2185	576	2761
	Open	1000	250	1250	899	157	1056
	Total	2000	500	-	3084	733	-
Window M3.0	Open	500	125	625	865	191	1056
	Total	500	125	-	865	191	-
Window M4.0	Open	666	160	826	1398	318	1716
	Total	666	160	-	1398	318	-

LabelImg (Tzutalin, 2019). Different methods of labelling were used for M1.0, M2.0, M3.0 and M4.0. Fig. 2 presents example images indicating the types of images collected and how they were labelled. Bounding boxes were drawn manually around each image's selected region of interest. As shown in Fig. 2, Models 1 and 2 labelling method consists of selecting the regions around the full area of the windows for both open and closed windows. For Models 3 and 4, only open windows were considered for detection and recognition. Model 3 followed the same labelling method for open windows as Models 1 and 2. While for Model 4, bounding box regions were assigned around the opening gaps of the windows. In most cases, multiple numbers of labels were assigned to each image. The justification for only detecting open windows in Models 3 and 4 and opening gaps in Model 4 will be further discussed when evaluating the results in Section 3.

Fig. 3 presents the CNN-based model used to develop the detection approach, following the process in Tien et al. (2021a). The TensorFlow Object Detection API was used for the model training. This framework platform provides pre-trained models to be used through a transfer learning approach that enables the development of an effective vision-based detector (GitHub, 2020). Existing models provided in the TensorFlow Detection Model were explored to establish the model configuration, as highlighted in Fig. 3. Through the assessment of the different models available, the Faster R-CNN (With Inception V2) was selected. The time required for the training of the models would vary due to the differences in the input data and the desired detection output responses, and each of these trained detectors can be deployed to an AI-powered camera.

Fig. 2. Example images of windows obtained from Google Images that were used to form the different image datasets for the various window detection models.

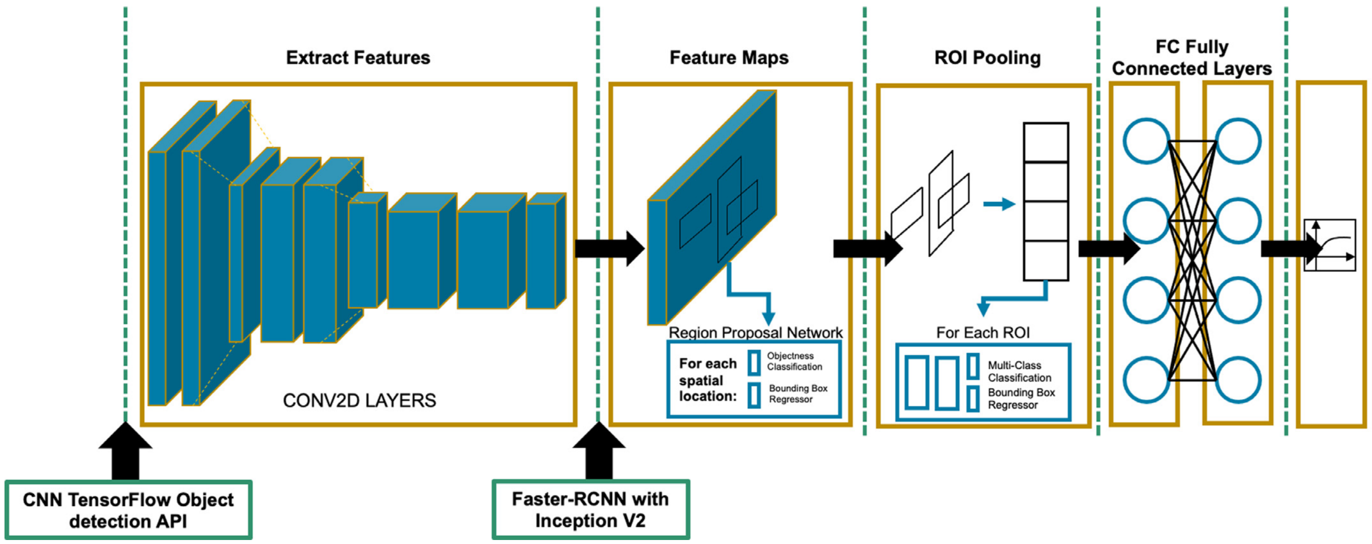


Fig. 3. CNN-based model configuration used to develop the four window detectors.

2.2. Real-time application in a case study building

To evaluate the performance of the different window detector configurations, a lecture room within a case study building was selected to perform experimental tests, which allowed real-time-based detection and recognition. This is the Marmont Centre at the University of Nottingham (University Park Campus, UK) (Fig. 4a). Details about the building construction, materials and features are detailed by Tien et al. (2021a). This building is used mainly for teaching architecture and engineering students. It has several teaching spaces, a laboratory and a café. The teaching spaces include a lecture and seminar room, each with 30-40 students. Students also use both rooms as workspaces during non-lecture hours and can have variable occupancy throughout the day. Both rooms have large openable windows and are often used by the students to ventilate the space. Some windows are left open in some cases, which leads to a significant waste of heating energy during cold periods. Like most

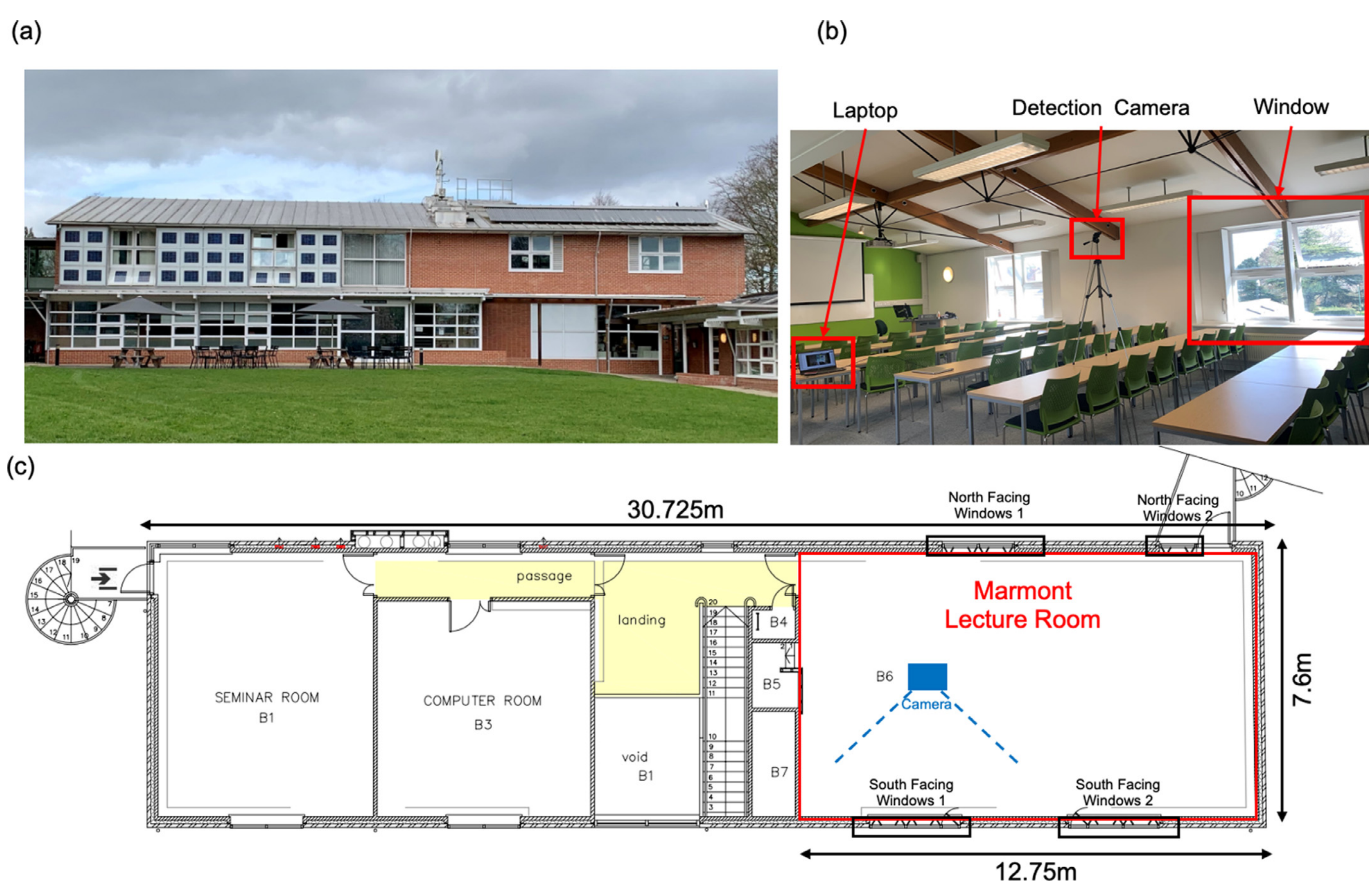


Fig. 4. (a) Marmont centre at the University of Nottingham, UK. (b) Set up for the experimental test, with the floor plan of the first floor of the building in Fig. (c).

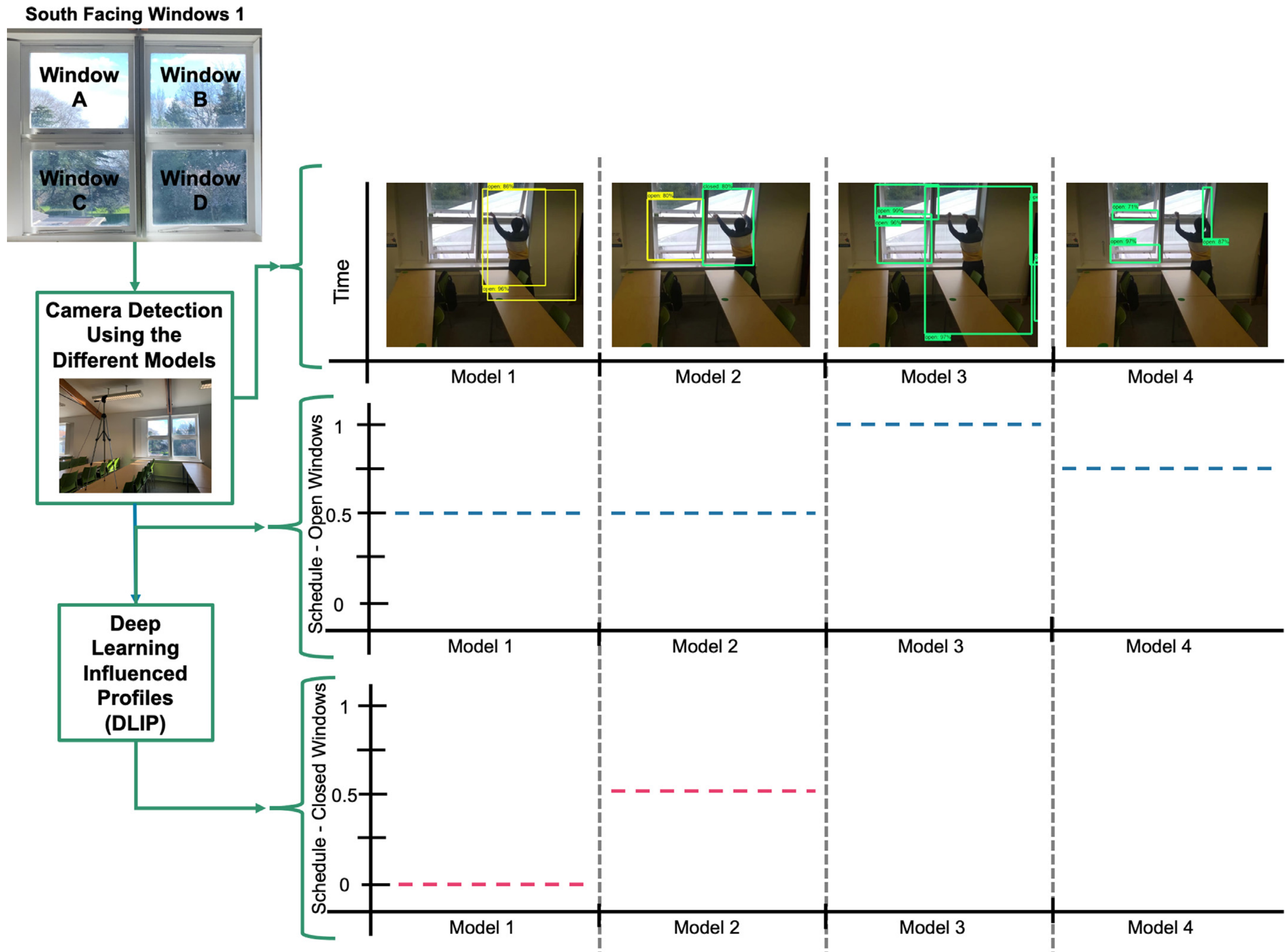


Fig. 5. Example of the process of real-time detection, recognition and formation of the deep learning influenced profiles (DLIP) using different window detectors (Models 1, 2, 3, and 4).

buildings in the University, the windows are manually operated and do not have any sensors to detect and prevent such issues. Such a space could benefit from the installation of a window detector. Fig. 4b presents the setup for the experimental tests. A 90-degree field of view camera was used for the detection, positioned towards the 'South Facing Windows 1' located near the room's ceiling. Fig. 4cc presents the floor plan of the first floor, along with the arrangement of the experimental setup.

To assist in the performance evaluation of all the trained window detectors, a scenario where an occupant would operate the windows within the selected building space was recorded. This ensured that the same scene or segment of occupancy actions towards the opening/ closing of the windows were used to evaluate each detection model configuration. Furthermore, it also ensured that other factors, such as the slight variations in the actions performed by the occupant, indoor lighting conditions and glare, did not influence the results, providing a fair comparison between the model's detection and recognition abilities.

The detection and recognition responses were obtained and recorded every two seconds, generating the DLIP. Fig. 5 presents an example of the process of generating the DLIP using the different detection model configurations for the selected case study building and experimental test. Models 1 and 2 would generate 2 profiles based on two responses, open and closed windows, whereas Models 3 and 4 would only generate a profile for open windows only. The formed DLIPs would be assessed and compared with the true 'actual observation' of the window conditions.

2.3. Detection performance evaluation

A three-step evaluation was performed to assess each generated model's performance and application based on the experimental test. This includes the assessment based on the average intersection over union (IoU), the percentage of the time achieving correct, incorrect and no detections, and the detection performance in the form of classification using a confusion matrix that generates results based on the standard evaluation metrics. Utilising the results presented in the form of the confusion matrix, further evaluation based on the common evaluation metrics of precision, recall and F_1 score was performed. Details about these evaluation metrics are detailed in (Goutte and Gaussier, 2005) and employed in similar studies (Tien et al., 2021b).

2.4. Building energy simulation (BES)

Building energy simulation (BES) was used to predict the potential impact of the detection method on ventilation heat loss and building energy demands. The case study building model was set to operate between 09:00 – 17:00. The base building model employed an HVAC system operating with a conventional control system, which used a fixed operation schedule (Figs. 6d). Additionally, scheduled-based profiles for windows (fully opened and closed), occupancy, and lighting were set, as shown in Figs. 6a-c. The occupancy was assumed to be 40 people and the lighting was 10 W/m^2 during the building operation period.

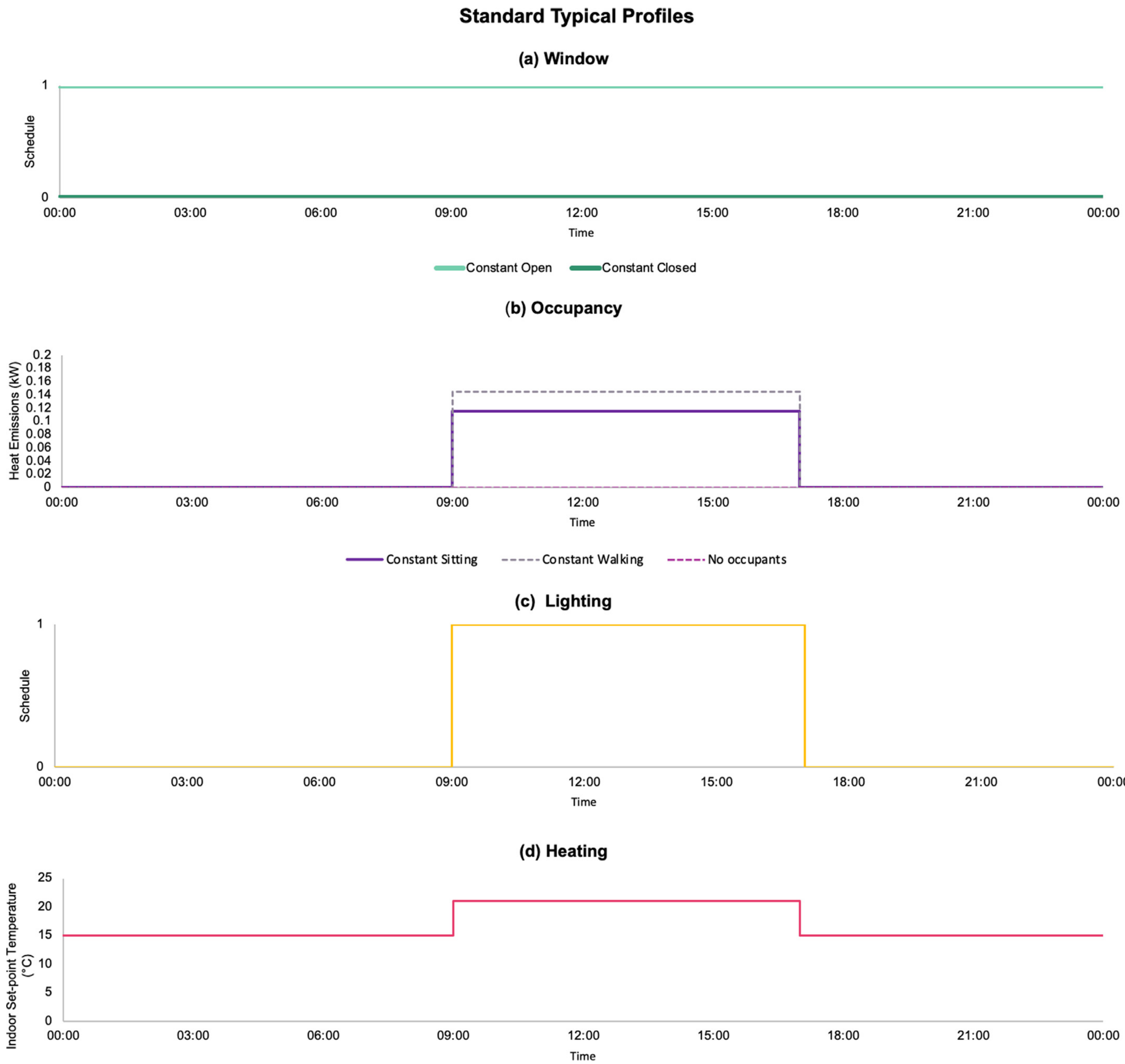


Fig. 6. Predefined profiles for (a) windows, (b) occupancy, (c) lighting, and (d) heating.

Scenario-based simulations were carried out to evaluate the impact of the vision-based detector on the ventilation heat loss and heating energy demand. While it is ideal that the profiles generated using the detection method are directly inputted into the BES model, the minimum simulation time step in IES VE is 10 min. Hence, smaller time steps would be necessary for the direct input of these profiles. This is because the detection and recognition responses were obtained and recorded every two seconds. Future works should consider employing other methods which can capture the detail of the detection operation in simulations. However, for the purpose of comparison, the generated profiles were extended to an entire class period. This means every detection is now equivalent to 1 min in the simulation. While this does not directly correspond to the real-time detections, it would still allow us to evaluate the impact of detections (correct, incorrect and missed detections) on the predicted ventilation heat loss. While occupancy can also be detected using a similar approach as the window detector (Tien et al. 2021a), this was not evaluated in this study. Table 2 summarises all the different combinations of assigned profiles used for all the simulation cases.

3. Results and discussion

All models were trained until converged, as detailed in Table 3, and the duration varied across the different detection model configurations. This is due to the differences in the pre-processing approach and size of the model's training datasets of the different window detectors.

Table 4 presents the models' performances based on the detection and recognition ability on still images from the testing dataset (Table 1). The results were presented in the form of a confusion matrix and assessed in terms of the common classification metrics. The different labelling techniques and data set size clearly influence the detection performance, as observed from the results in Table 4. Models 1 and 2, which predicted if the windows were 'Open' or 'Closed', had an overall

Table 2
Summary of the profiles assigned to the different simulation cases.

Simulation Cases		Assigned Profiles			
		Window (Fig. 6a)	Occupancy (Fig. 6b)	Lighting (Fig. 6c)	Heating (Fig. 6d)
Fixed Profiles	**1**	Constant open	Constant sitting during operational hours	Standard typical	
	2	Constant closed			
Deep Learning Influenced Profiles	**1, 2, 3, 4**	DLIP profiles (extended to full class period)	Actual (extended to full class period)	Actual (extended to full class period)	
Actual		Actual (extended to full class period)		Actual (extended to full class period)	

Table 3
Results of the training of different window detection models.

Training Conditions and Results	**Model**			
	(a) 1	**(b) 2**	**(c) 3**	**(d) 4**
Pre-trained Model Used	Faster RCNN with InceptionV2			
Total Steps	91,842	104,396	86,523	199,630
Training Duration	6 hours, 1 minute, 49 seconds	7 hours, 19 minutes, 2 seconds	5 hours, 29 minutes, 49 seconds	11 hours, 29 minutes, 46 seconds
Maximum Loss	2.876961	2.037059	1.821876	1.236806
Minimum Loss	0.005654	0.000113	0.010038	0.01519

Total loss versus the number of training steps

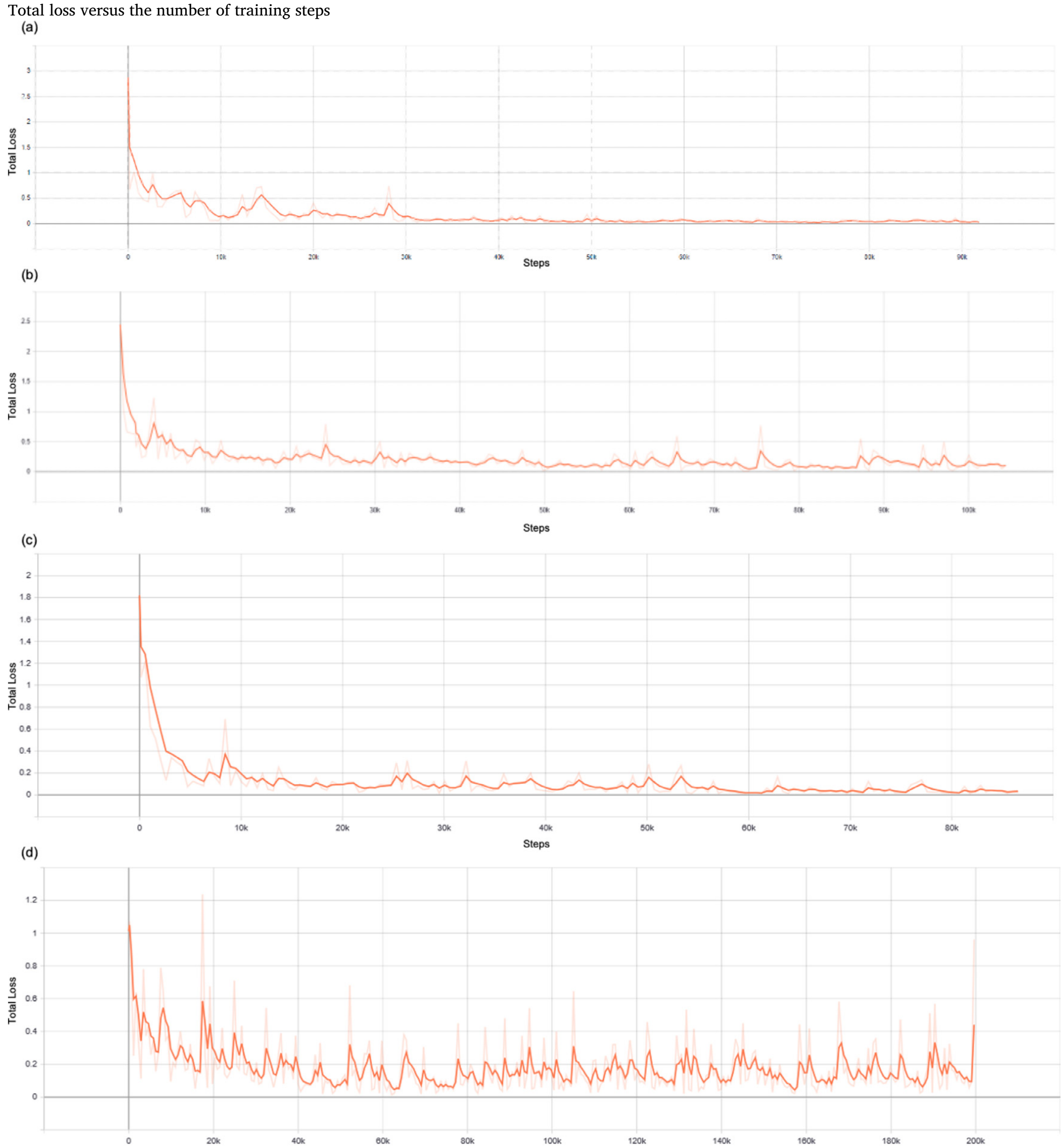
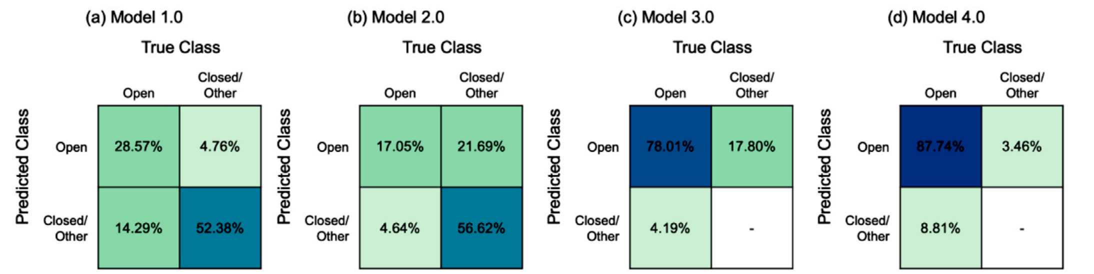


Table 4
Detection performance results based on the still images from the test dataset, assessed in terms of common evaluation metrics.

Confusion Matrix



Classification	Accuracy	Precision	Recall	F1 Score
		(a) Model 1		
Open	80.95%	0.8572	0.9167	0.7500
Closed	80.95%	0.7857	0.7857	0.8461
Average for both types	80.95%	0.8215	0.8512	0.7981
		(a) Model 2		
Open	73.67%	0.4401	0.7861	0.5643
Closed	73.67%	0.9243	0.723	0.8113
Average for both types	73.67%	0.6822	0.7546	0.6878
		(a) Model 3		
Open	78.01%	0.8142	0.9490	0.8765
		(a) Model 4		
Open	87.73%	0.9621	0.9088	0.9346

F1 score of 0.7981 and 0.6878, indicating the occurrence of false positives and false negatives was high when detecting the window condition. This suggests that requiring the detector to recognize both conditions can increase the probability of incorrect detections. It can also be observed that the addition of more images to the training dataset did not lead to an improved detection performance which was unanticipated. This will be further evaluated when testing the detector in the actual case study building.

Due to the detection performance achieved by Models 1 and 2, we decided to consider and test a different approach that could help simplify the detection method. While we initially planned to develop a detector which can recognize both window conditions 'Open' and 'Closed', detecting only one condition may be adequate for the required task or application in this project. This modification led to a higher F1 score of 0.8765 for Model 3, which was configured and trained to only recognize 'Open' windows. We attempted to further improve the detector's performance based on these results. Model 4 was configured and trained to recognize only the opening gaps of windows instead of the entire window. This adjustment led to a higher overall F1 score of 0.9346. To further evaluate the performance of each configuration, all models will be applied to detect and recognize window conditions in a selected case study building, with an occupant moving around the space and manually opening/closing the windows.

Video 1 shows the real-time detection and recognition of the window conditions in the case study lecture room, comparing the different model configurations.

Video 1 Comparison of the detection of open windows using the different models.

Fig. 7 shows examples of the detection and recognition made by each model configuration on the recorded video. Clear variations can be seen among them when looking at the bounding boxes generated around the detected windows, which corresponds to the labelling method employed by each model configuration. The sizes and shapes of these bounding boxes varied between each detection interval. For most of the detection period, Model 1 recognized all four windows as one individual window, and in many instances, the entire window was detected as open and closed simultaneously. Furthermore, it also detected random objects such as walls, desks, drawing board and the occupant as windows. Clearly, this model was highly inaccurate and not well suited for the required application. Whereas Model 2, which was trained with a larger number of images, could recognize windows separately and had fewer false/incorrect detections; however, the model was still not accurate and reliable in identifying all four windows and their actual conditions. Like Model 1, it also detected other objects as a window but less frequently. Contrary to the initial evaluation of the models using still testing images (Table 4), the larger training data set improved the model's overall detection performance when applied in the actual building.

As mentioned, a different approach was taken when configuring Models 3 and 4 window detectors. Both approaches only detected and recognized open windows, and hence only open windows are required to be labelled. This simplified the data set preparation procedure. Although the detection of close/closing of windows could potentially be useful in some applications, detecting the open windows only could be adequate for notifying/alerting users or automatically adjusting the HVAC due to unintentionally open windows. For most instances, Model 3 provided detection responses similar to Model 2 with correct identification of the four separate windows. However, the person and objects outside the window region were frequently detected as open windows. To address this issue, we configured Model 4 to only detect the opening gaps of windows instead of the entire window

As observed, Model 4 was able to detect open windows more accurately and reliably by focusing only on the openings or gaps of the windows. In some cases, two bounding boxes were assigned to a detected open window, increasing the chances of each window being detected and recognized. As observed, bounding boxes could be assigned to the vertical or the horizontal opening gaps. Since the size of the windows could be larger compared to objects, such as occupancy body size and size of objects/furniture within a room, this approach could reduce the occurrence of obstruction, impacting detection performance and leading to incorrect and no detection. This also raises the possibility of estimating the window opening size, which can be developed in future works. While Model 4 was the most accurate, objects outside the window region were occasionally detected as open windows; hence, further model improvement is required. Perhaps different techniques for enhancing the current data set must be considered.

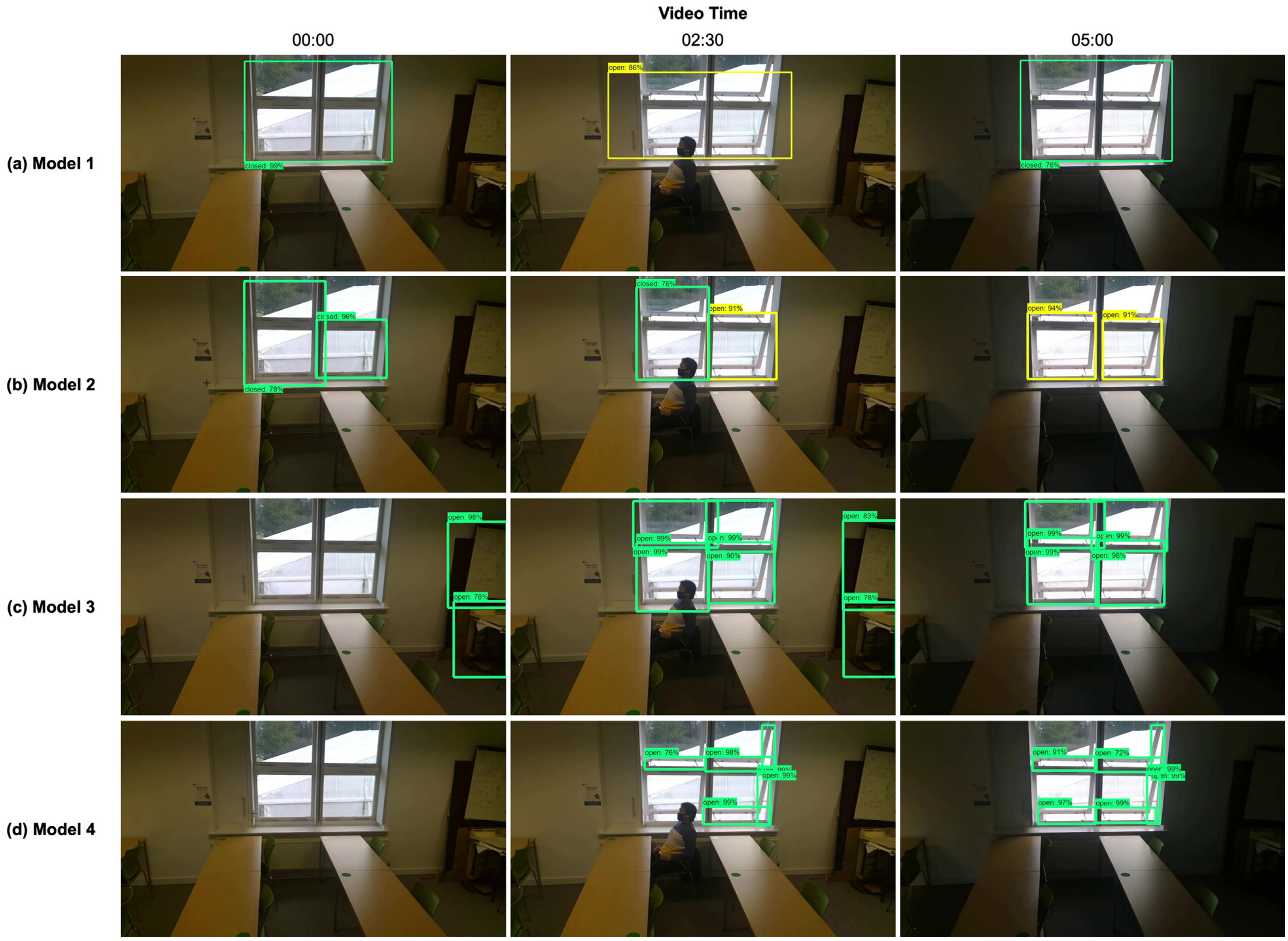


Fig. 7. Snapshots of window detection and recognition during various key stages of the experimental test using the different window detectors.

Table 5
Comparison of Models 1 and 2 performances in terms of the percentage of time achieving correct, incorrect, and no detections.

Percentage of Time Achieving (%)	Open and Closed Windows										
	Window A		Window B		Window C		Window D		All Windows		
	Open	Closed	Open	Closed	Open	Closed	Open	Closed	Open	Closed	Combination of Both
Model 1											
Correct Detections	29.14%	28.48%	27.15%	29.14%	29.80%	28.48%	28.48%	29.14%	28.64%	28.81%	57.45%
Incorrect Detections	16.56%	0.00%	15.23%	3.97%	17.88%	0.00%	14.57%	3.97%	16.06%	1.99%	18.05%
No/Missed Detections	20.53%	5.30%	15.89%	8.61%	20.53%	3.31%	17.22%	6.62%	18.54%	5.96%	24.50%
Model 2											
Correct Detections	3.31%	1.99%	2.65%	2.65%	22.52%	15.89%	43.05%	39.07%	17.88%	14.90%	32.78%
Incorrect Detections	0.00%	0.00%	0.00%	0.00%	11.26%	0.00%	1.32%	0.66%	3.15%	0.17%	3.31%
No/Missed Detections	62.91%	31.79%	55.63%	39.07%	34.44%	15.89%	15.89%	0.00%	42.22%	21.69%	63.91%

The following section further examines the detection and recognition performance of the different model configurations. Tables 5 and 6 compares the different models in terms of the percentage of time achieving correct, incorrect, and no detections. The window was split into 4 sections: top left window is Window A, top right is Window B, bottom left is Window C, and the bottom right is Window D. As observed, Models 1 and 2 did not perform well in terms of the correct detection of both open and closed windows. As observed in Video 1, while Model 2 correctly detected 1 or 2 of the bottom windows during the detection period, it also frequently missed or did not detect the other windows (Windows A and B). Hence, it can be seen that Model 2 had a high number of no/missed detections, up to 63.91% of the time. This shows that both model configurations will not be suitable for the required detection of the windows in the lecture room, as it will lead to many incorrect notifications/alerts and incorrectly adjust the heating of the room. Although the model could potentially be improved by using a larger dataset for training, the detection method in Models 3 and 4 led to higher detection performance, while using a small dataset for training. A significantly higher average correct detections were achieved (Table 6), 80.63% for Model 3 and 85.93% for Model 4.

Figs. 8 and 9 present the case study test results in the form of a confusion matrix. As discussed previously, Model 1 was not able to adequately identify each of the individual windows, and as expected, it led to relatively low percentages for true positives compared to false positives and

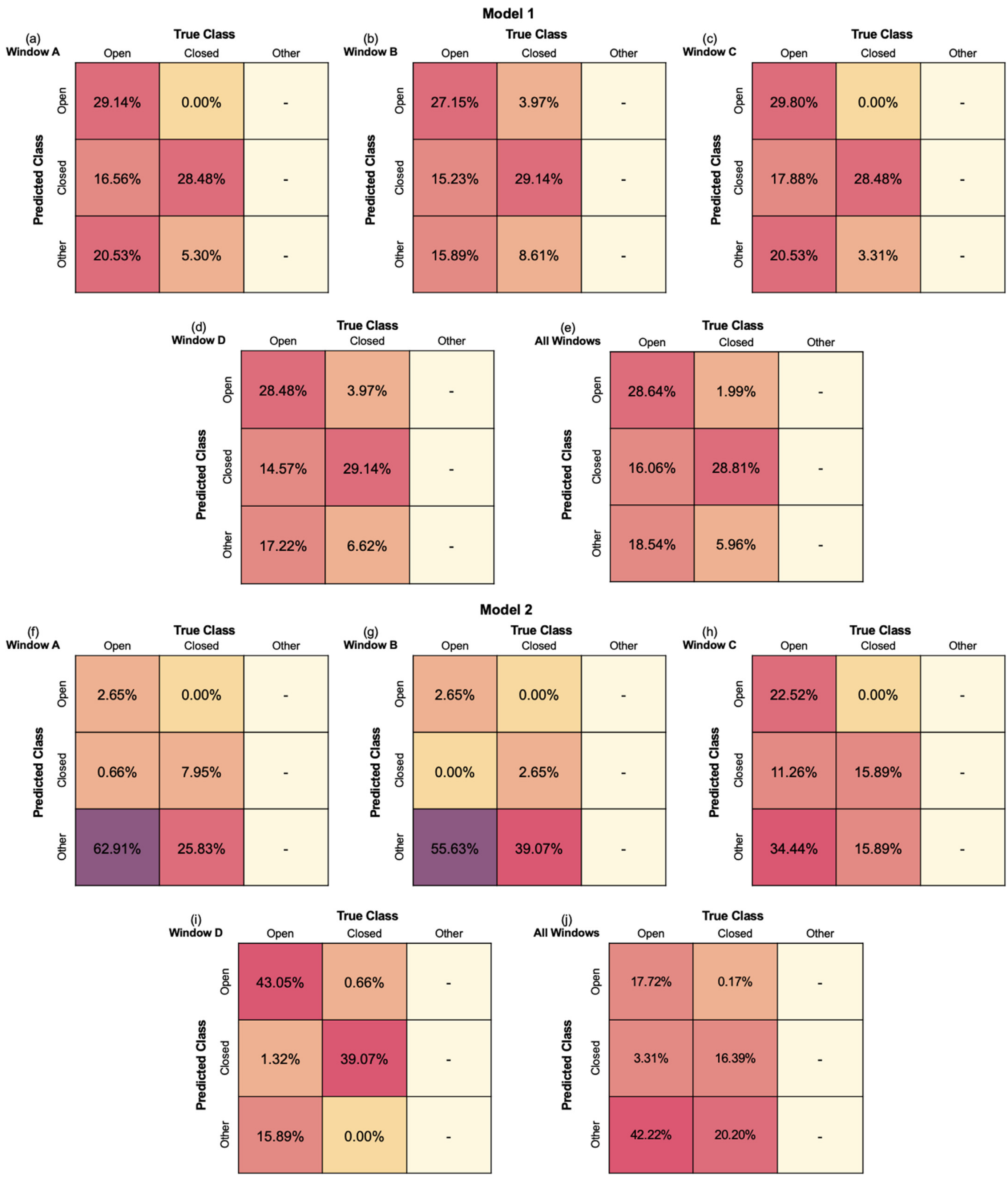


Fig. 8. Detection performance results for Models 1 and 2 in the form of confusion matrix, based on the case study building test.

Table 6
Comparison of Models 3 and 4 performances in terms of the percentage of time achieving correct, incorrect, and no detections.

Percentage of Time Achieving (%)	Open Windows				
	Window A	Window B	Window C	Window D	All windows
Model 3					
Correct Detections	98.68%	62.25%	93.38%	68.21%	80.63%
Incorrect Detections	1.32%	37.75%	6.62%	31.79%	19.37%
No/Missed Detections	0.00%	0.00%	0.00%	0.00%	0.00%
Model 4					
Correct Detections	82.12%	100.00%	63.58%	98.01%	85.93%
Incorrect Detections	2.65%	0.00%	4.64%	0.00%	1.82%
No/Missed Detections	15.23%	0.00%	31.79%	1.99%	12.25%

Table 7
Model 1 detection performance evaluated based on common classification evaluation metrics.

Window	Class	Window	Accuracy	Precision	Recall	F1 Score
A	1	Open	62.91%	1.0000	0.4400	0.6111
	2	Closed	78.14%	0.6323	0.8431	0.7227
		Average for both types	70.53%	0.8162	0.6416	0.6669
B	1	Open	64.91%	0.8724	0.4659	0.6075
	2	Closed	72.19%	0.6568	0.6985	0.6770
		Average for both types	68.55%	0.7646	0.5822	0.6423
C	1	Open	61.59%	1.0000	0.4369	0.6081
	2	Closed	78.81%	0.6143	0.8959	0.7289
		Average for both types	70.20%	0.8072	0.6664	0.6685
D	1	Open	64.24%	0.8777	0.4725	0.6143
	2	Closed	74.84%	0.6667	0.7335	0.6985
		Average for both types	69.54%	0.7722	0.6030	0.6564

false negative results (shown in Figs. 8a-e). For Model 2, similar results were achieved specifically for Windows A and B.

Model 3 indicated good performance, in particular, the detection of Windows A and C with relatively high true positive results of up to 92.08%. However, it indicated lower performance for Windows B and D with false positive values of 41.3% and 34.53%, giving an overall percentage of 76.17% for true positives on all four windows. Model 4 presented the best performance with the highest number of true positives (up to 100%), and only a lower value was achieved for Window C (50%), which may have been affected by the occupant obstructing the window openings. An overall value of 78.43% was achieved for true positives for Model 4.

The following tables (Tables 7—10) present the results in terms of the common evaluation metrics, including the accuracy, precision, recall, and the associated F1 score that was based on the occurence of labelled instances for each of the windows (as shown in Video 1). Overall, Model 4 provided the best performance with the highest overall accuracy of 78.43% and an F1 score of 0.8791. Model 1 (Table 7had the poorest performance based on quantitative and qualitative results. It could not detect the four windows separately, whereby the windows were assumed as one in most instances. Unanticipated results were obtained with Model 2 as given by the results in Table 8, the addition of more images to the training dataset did not lead to improved detection performance. Yet overall, it had a better performance compared to Model 1 in detecting and recognizing the individual windows, but it did not perform well in terms of detecting all windows. As for Model 3 (Table 9), having only one selected response outcome enabled better identification of the separate windows. However, this model was limited and, in some cases, identified other objects as opened windows, such as the drawing board. Model 4 (Table 10) was able to detect open windows more accurately by focusing only on the openings or gaps of the windows.

Table 9 Model 3 detection performance evaluated based on common classification evaluation metrics.

Table 10 Model 4 detection performance evaluated based on common classification evaluation metrics.

Fig. 10 presents the generated DLIP of the opening patterns for the selected windows in the lecture room during the experimental tests using the different models. The Actual Observation Profile defined the 'actual' window condition and was used to assess the performance of each model. For all models, the generated DLIP still alternates between the values of the window profile schedule, indicating prediction error. Therefore, further improvements are required to enhance the detection model's accuracy, reliability, and stability. Comparing the results based on these four models applied to the experiment test indicates that Model 4 provides the least amount of variation in terms of errors in predictions, providing the most accurate results compared to the actual observation profile.

Fig. 10 Deep learning-influenced profiles (DLIP) generated from the application of the different models during the experimental test compared against the Actual Observation Profile.

The following section analyses the impact of the application of the window detection model on the building energy performance, specifically evaluating the heating load and the ventilation heat losses through the window openings. While Model 1 and, to some extent, Model 2 were highly inaccurate and not well suited for the required application, both models are still evaluated here to show their impact on energy performance. As mentioned previously, the generated profiles were extended to an entire class period in the simulation. This was due to the limitation of the BES tool. While this does not directly correspond to the real-time detections, it would still allow us to evaluate the impact of detections (correct, incorrect and missed detections) on the predicted ventilation heat loss.

Fig. 11 presents the predicted hourly ventilation heat loss for all the simulated scenario cases during a typical winter/heating day in the selected case study building. The results were related to the simulated window opening profiles and the airflow conditions across the four windows during the selected time and day. The maximum and minimum ventilation heat losses were obtained in the simulations, which assumed the window to be either constantly open or closed. These were used for comparison purposes. Compared with the "actual" profile results, using fixed or static profiles to simulate the window conditions is insufficient and

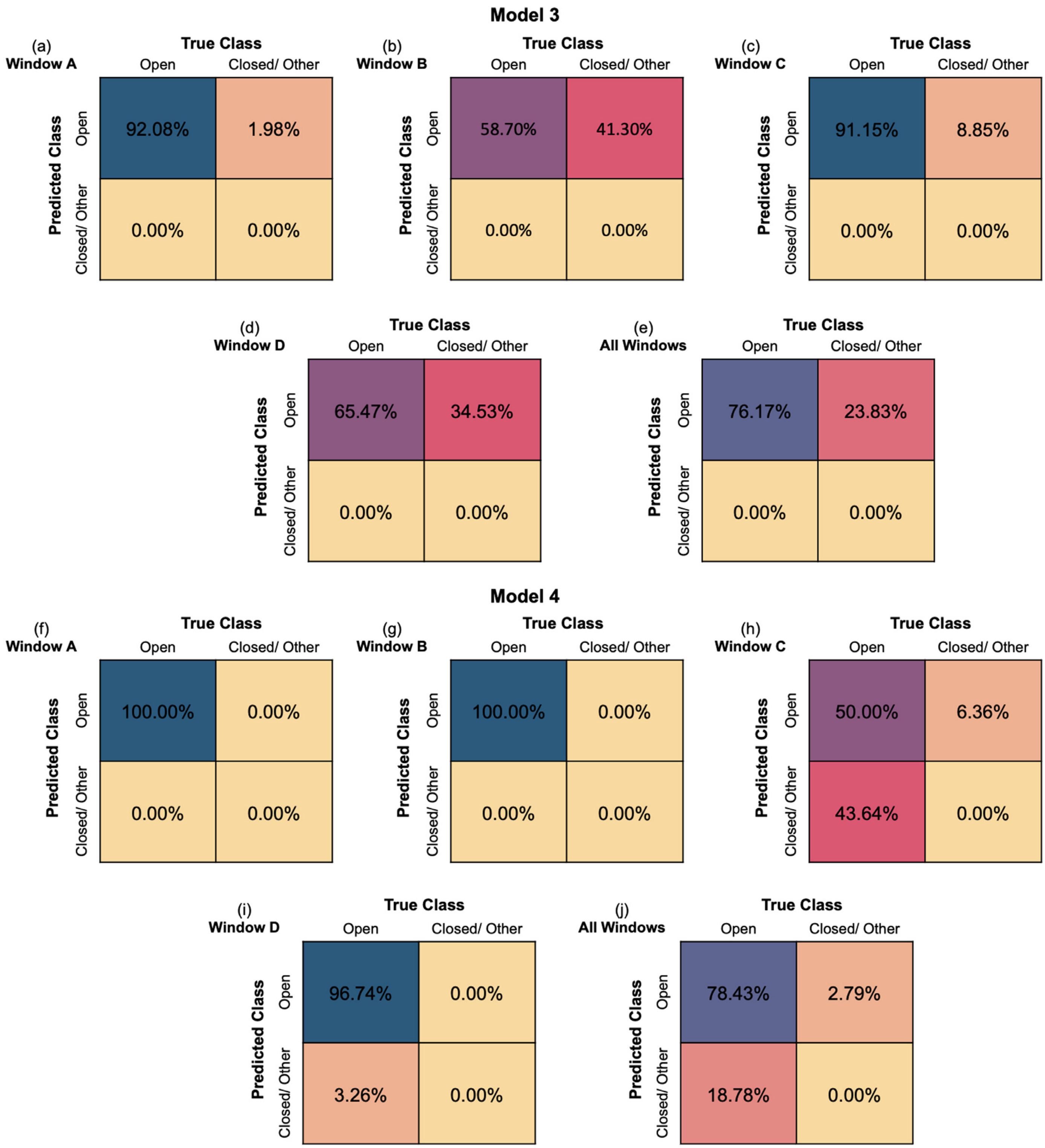


Fig. 9. Detection performance results for Models 3 and 4 in the form of a confusion matrix, based on the case study building test.

can lead to inaccurate prediction of ventilation heat loss. As observed in Fig. 11, higher detection accuracy led to better prediction of the ventilation heat losses. The percentage differences between the results of Models 1, 2, 3 and 4 and the actual profile were 22.83%, 105.38%, 22.07% and 19.60%. While Model 1's performance as a detector was poor, it could still provide a reasonable prediction of heat loss, particularly during the occupancy period. While Model 2, which had difficulties detecting all the open windows, did not perform as well as the others.

Fig. 11 Ventilation heat loss predictions based on the simulation of the predefined fixed profiles, along with the window detection and 'actual' profiles.

Fig. 12 shows the results of the heating energy load in the simulated space. To maintain the room within the setpoint temperature of

Table 8
Model 2 detection performance evaluated based on common classification evaluation metrics.

Window	Class	Window	Accuracy	Precision	Recall	F1 Score
A	1	Open	36.43%	1.0000	0.0400	0.0770
	2	Closed	72.98%	0.9244	0.2353	0.3752
	Average for both types		54.71%	54.71%	0.9622	0.13765
B	1	Open	44.37%	1.0000	0.0455	0.0870
	2	Closed	60.93%	1.0000	0.0635	0.1195
	Average for both types		68.55%	52.65%	1.0000	0.0545
C	1	Open	54.30%	1.0000	0.3301	0.4964
	2	Closed	72.85%	0.5853	0.5	0.5393
	Average for both types		63.58%	0.7927	0.4151	0.5179
D	1	Open	82.81%	0.9849	0.7144	0.8281
	2	Closed	98.02%	0.9673	0.9834	0.9753
	Average for both types		90.42%	0.9761	0.8489	0.9017

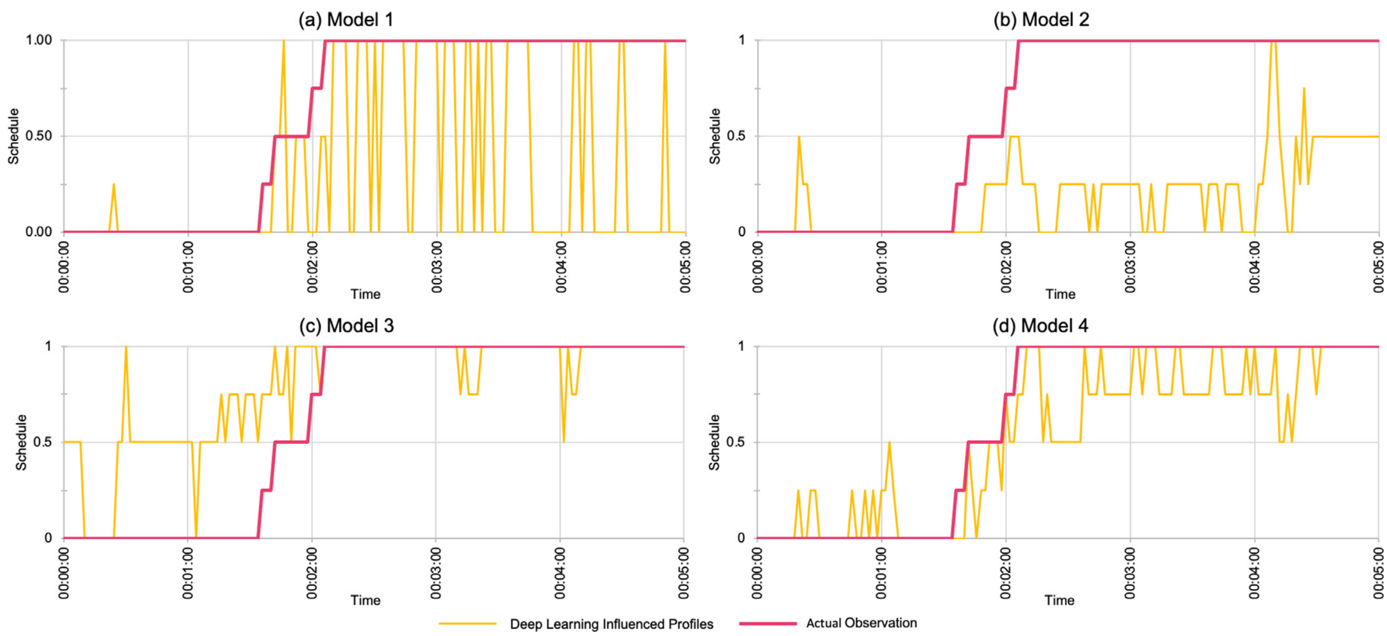


Fig. 10. Deep learning-influenced profiles (DLIP) generated from the application of the different models during the experimental test compared against the Actual Observation Profile.

Table 9
Model 3 detection performance evaluated based on common classification evaluation metrics.

Window	Class	Window	Accuracy	Precision	Recall	F1 Score
A	1	Open	98.02%	0.9802	1.0000	0.9900
B			58.70%	0.5870	1.0000	0.7398
C			91.15%	0.9115	1.0000	0.9537
D			65.47%	0.6547	1.0000	0.6547

Table 10
Model 4 detection performance evaluated based on common classification evaluation metrics.

Window	Class	Window	Accuracy	Precision	Recall	F1 Score
A	1	Open	100.00%	1.0000	1.0000	1.0000
B			100.00%	1.0000	1.0000	1.0000
C			50.00%	0.8872	0.5340	0.5000
D			96.74%	1.0000	0.9674	0.9834

21 °C during occupancy period, a high amount of heating energy would be required at the start of the class during the heating period at 10:00. This immediately decreased once the occupants start to go into the room and generate the internal heat gains. In line with the results shown in Figure 11, Model 4 achieved the closest prediction of heating energy load (as compared to the actual profile), while Model 2 had the worst performance. As observed, Model 2 underpredicted the heating energy demand as it mostly recognizes only one of the four windows open during the occupancy period.

Fig. 12 Building heating load prediction based on the simulation of predefined fixed profiles, along with the window detection and 'actual' profiles.

Based on these results, the detection and recognition ability of the models ultimately influenced the prediction of the ventilation heat loss and heating demand. While the model configuration clearly had a significant impact on the detection performance, other factors, such as the lighting conditions and obstructions, also affected the performance. This led to variations in the detection performance and predictions thought the detection period. The results highlighted the importance of the data set size and labelling method on the performance of the window detector. Model 4 provided the best detection performance, resulting in the most accurate prediction of ventilation heat loss. However, further evaluation and validation of the detection method should be conducted. The model's performance under different room settings and environmental conditions should be explored. Practical aspects, including people blocking the detector view and/or windows within the selected room, lead-

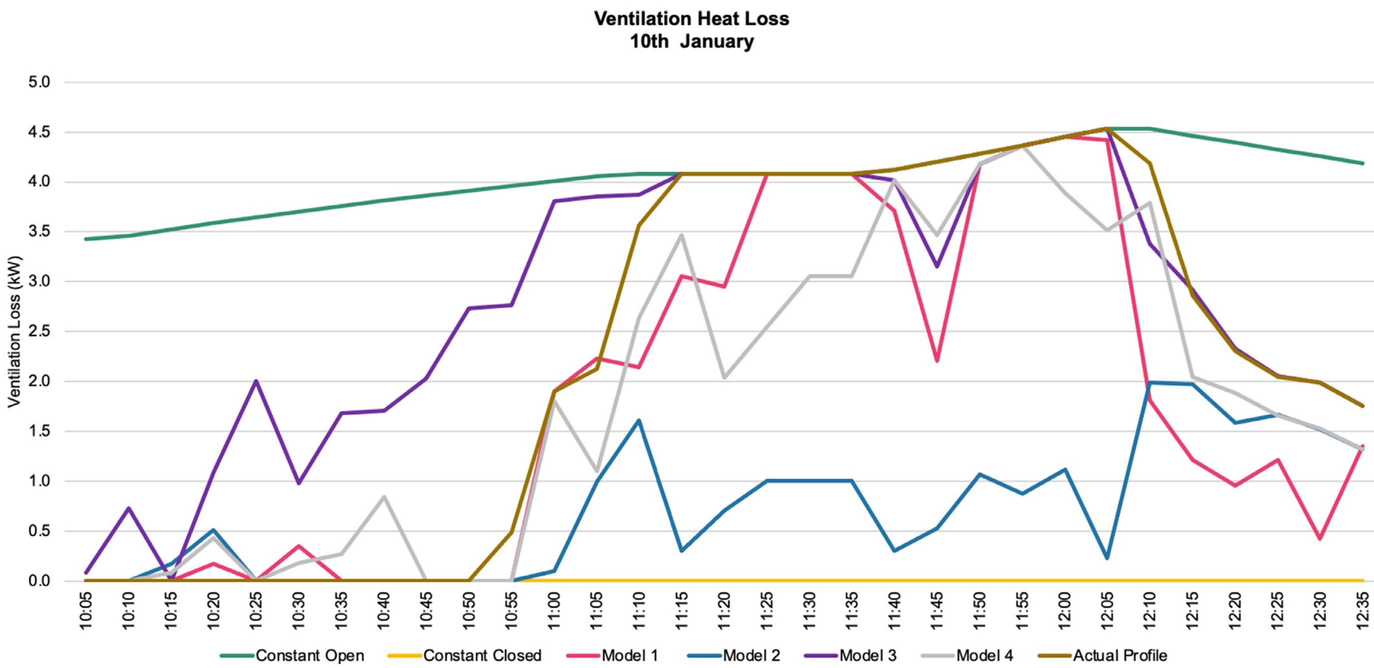


Fig. 11. Ventilation heat loss predictions based on the simulation of the predefined fixed profiles, along with the window detection and 'actual' profiles

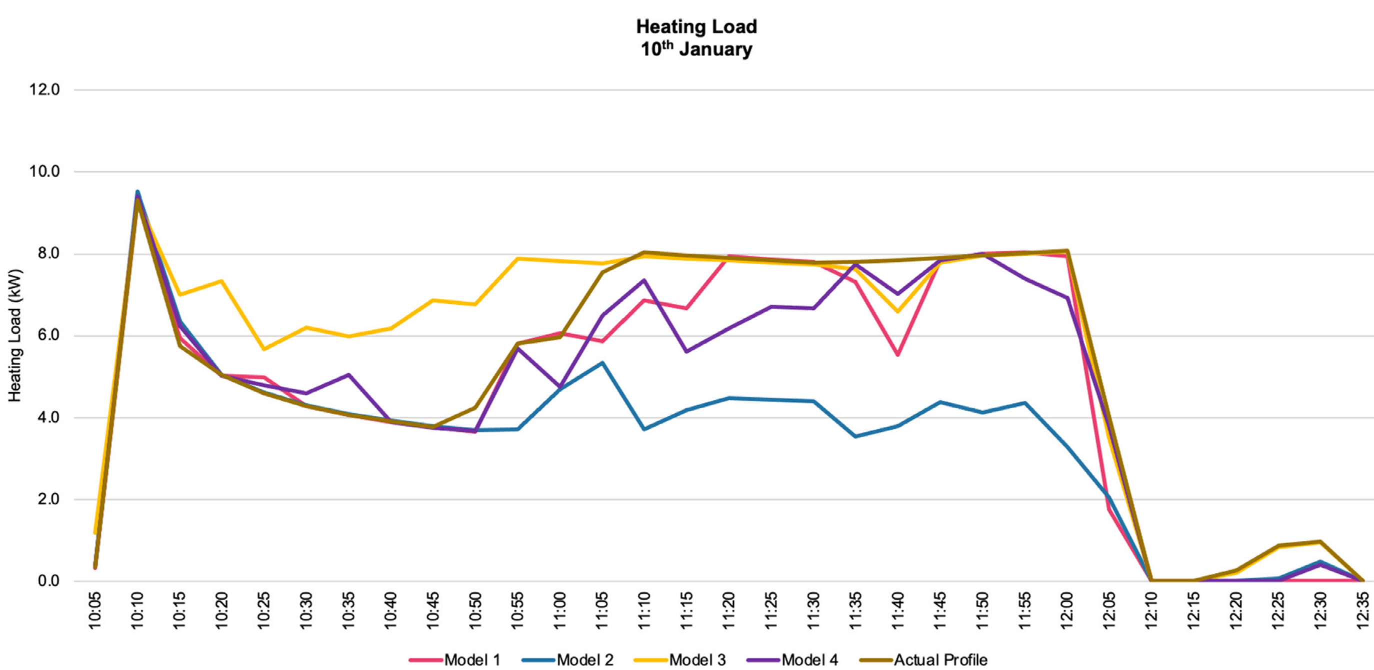


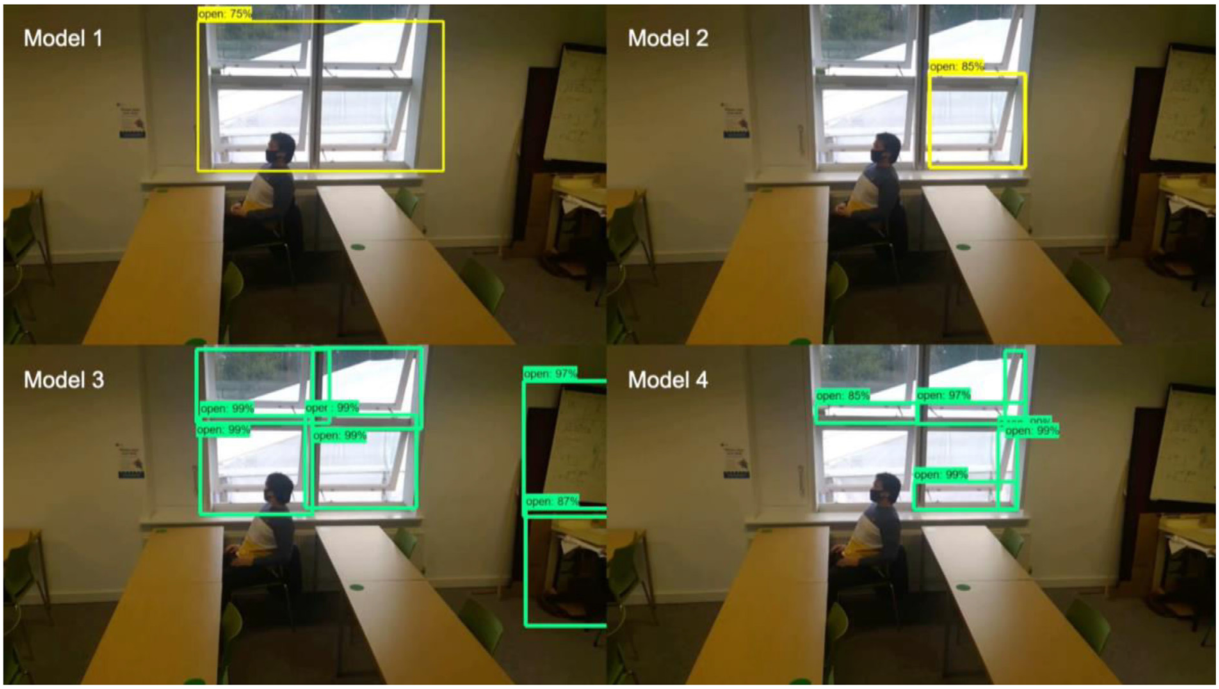
Fig. 12. Building heating load prediction based on the simulation of predefined fixed profiles, along with the window detection and 'actual' profiles.

ing to inaccurate detection and recognition, should be addressed. For example, the device can provide alerts or sound notifications when the detector view is obstructed.

4. Conclusions and future works

The present work employed a computer vision and deep learning-based detection approach for the real-time monitoring of the opening and closing of windows to reduce the energy demand by correctly controlling the HVAC or alerting the building users/operators during periods, there is a demand for a detector that could provide accurate detection and recognition. This present study focuses on developing the deep learning framework via the investigation into the performance of different window detection models. Various modifications to the window detection models based on data curation, labelling, and training were explored. This includes exploring the impact of the types of detection responses selected, the types of images used, the dataset size and how the images were proposed prior to the training of the window detection models.

Four models were developed and tested through the application via a video feed test of a selected case study building. Models 1 and 2 consisted of selecting two response categories of both 'open' and 'closed' windows, with Model 1 as the initial dataset and Model 2 as an enhanced version. Models 3 and 4 focused on one detection response of 'Open' with Model 3 compromising of the same labelling techniques as Models 1 and 2. While Model 4 employed a different labelling process,



Video 1. Video Still Comparison of the detection of open windows using the different models.

with the bounding boxes explicitly assigned to the opening gaps of the windows. All models were trained using the same CNN-based model configuration and evaluated based on the application of an experimental test performed within a selected case study building space.

The detection performance evaluation suggests that Model 1 provided the lowest detection ability. For most instances, it could not detect each of the windows separately. Model 2 was able to detect the windows individually at times. Having only one selected-response outcome for Model 3 enabled better identification of the separate windows. This model had the limitation of identifying other objects as opened windows. Using a different labelling technique for Model 4 aided the improvement of the detection and recognition ability, giving the best performance for Model 4.

The impact of the detection method on building energy demand was investigated through a series of building energy simulation scenario cases. Ventilation heat loss and heating energy demand were simulated using the predefined fixed profiles, along with the window detection and 'actual' profiles. It should be noted that the generated profiles were extended to an entire class period in the simulation due to the limitation of the BES tool requiring a minimum simulation time step of 10 minutes within the inputted window profile. Hence, the recordings of window detection at 2 second intervals achieved during the experimental tests were converted. While this does not directly correspond to the real-time detections, it allowed us to evaluate the impact of detections (correct, incorrect and missed detections) on the predicted ventilation heat loss and heating energy demand. Future works should consider employing other methods to capture the detail of the detection operation in simulations along with longer duration of experimental tests.

The predicted ventilation heat losses were related to the simulated window opening profiles and the airflow conditions across the windows during the selected time and day. Compared with the "actual" profile results, using fixed or static profiles to simulate the window conditions is insufficient and can lead to inaccurate prediction of ventilation heat loss. The results have shown that the detection and recognition ability of the models ultimately influenced the prediction of the ventilation heat loss and heating energy demand. Model 4 provided the best detection performance, resulting in the most accurate prediction of ventilation heat loss. However, further validation of such models is required to ensure that such methods can provide accurate detections in different conditions. Further developments include a series of tests and evaluations of the application of the window detector on various types of window designs in different indoor spaces. The impact on other parameters, such as thermal comfort and air quality, should be considered in future works.

Declaration of Interest Statement

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.

CRediT authorship contribution statement

Paige Wenbin Tien: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Shuangyu Wei:** Software. **John Kaiser Calautit:** Conceptualization, Resources, Methodology, Writing – review & editing, Supervision. **Jo Darkwa:** Writing – original draft, Supervision. **Christopher Wood:** Writing – original draft, Supervision.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the Department of Architecture and Built Environment, University of Nottingham and the PhD studentship from EPSRC, Project References: 2100822 (EP/R513283/1). The present publication was first presented at the 16th Sustainable Development of Energy, Water and Environment Systems SDEWES Conference (Virtual), Dubrovnik, Croatia, 10-15 October 2021.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cles.2022.100038.

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