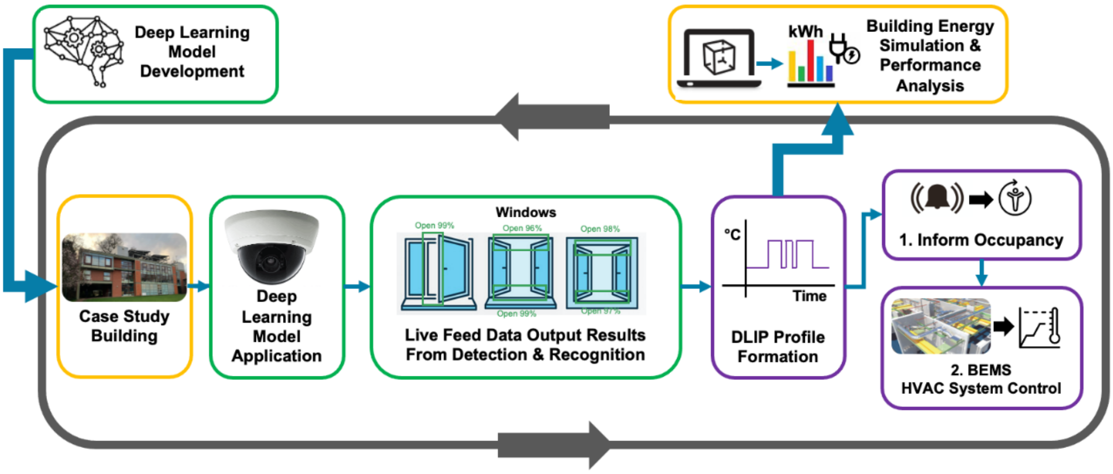
A Deep Learning Approach Towards the Detection and Recognition of Opening of Windows for Effective Management of Building Ventilation Heat Losses and Reducing Space Heating Demand

Paige Wenbin Tien[1*], Shuangyu Wei[1], Tianshu Liu[1], John Kaiser Calautit[1], Jo Darkwa[1] and Christopher Wood[1]

[1]Department of Architecture and Built Environment, University of Nottingham, Nottingham, NG7 2RD, UK

[*]Corresponding author. paige.tien@nottingham.ac.uk, paige.tien@gmail.com

Graphical Abstract



Abstract

Building ventilation accounts for up to 30% of the heat loss in commercial buildings and 25% in industrial buildings. To effectively aid the reduction of energy consumption in the building sector, the development of demand-driven control systems for heating ventilation and air-conditioning (HVAC) is necessary. In countries with temperate climates such as the UK, many buildings depend on natural ventilation strategies such as openable windows, which are useful for reducing overheating prevalence during the summer. The manual opening and adjustment of windows by occupants, particularly during the heating season, can lead to substantial heat loss and consequent energy consumption. This could also result in the unnecessary or over ventilation of the space, or the fresh air is more than what is required to ensure adequate air quality. Furthermore, energy losses build up when windows are left open for extended periods. Hence, it is important to develop control strategies that can detect and recognise the period and amount of window opening in real-time and at the same time adjust the HVAC systems to minimise energy wastage and maintain indoor environment quality and thermal comfort. This paper presents a vision-based deep learning framework for the detection and recognition of manual window operation in buildings. A trained deep learning model is deployed into an artificial intelligence-powered camera. To assess the proposed strategy's capabilities, building energy simulation was used with various operation profiles of the opening of the windows based on various scenarios. Initial experimental tests were conducted within a university lecture room with a south-facing window. Deep learning influenced profile (DLIP) was generated via the framework, which uses real-time window detection and recognition data. The generated DLIP were compared with the actual observations, and the initial detection results showed that the method was capable of identifying windows that were opened and had an average accuracy of 97.29%. The results for the three scenarios showed that the proposed strategy could potentially be used to help adjust the HVAC setpoint or alert the occupants or building managers to prevent unnecessary heating demand. Further developments include enhancing the framework ability to detect multiple window opening types and sizes and the detection accuracy by optimising the model.

Keywords

Deep learning, building energy management, building ventilation, window opening, window detection, HVAC systems

Word count

8603 (excluding the abstract, references, tables and figures)

1. Introduction and Literature Review

Buildings are known as one of the fastest-growing sectors, which is responsible for up to 40% of the total energy demand [1]. Heating, ventilation and air-conditioning (HVAC) systems and its associated operations are currently the largest contributors to the consumption of buildings [2, 3]. Therefore, reducing the energy demand of HVAC is crucial towards the overall energy conservation and the reduction of greenhouse gases. Ventilation systems are critical as ventilation accounts for up to 30% of the heat loss in commercial buildings and 25% in industrial buildings [4]. Energy-efficient techniques and strategies that can minimise ventilation and uncontrolled air infiltration losses are continuously being developed [5]. However, these strategies should also comply with the building requirements, which require the building to be adequately ventilated to provide a healthy and safe indoor environment for occupants.

Natural ventilation can aid the reduction of moisture levels of indoor spaces and reduce building energy consumptions via passive cooling [5,6]. It also provides substantial cost savings as compared to other mechanical ventilation systems [7,8]. According to CIBSE Guide B [9], there is a demand for natural ventilation in mild or temperate climates such as the UK. This is due to high amounts of large city-centre office buildings currently being mechanically ventilated but have the ability to employ a mixed-mode ventilation strategy or even solely natural ventilation-based strategy. In addition, smaller and public buildings, such as schools and hospitals also employ natural ventilation strategies.

More guidelines are being put in place to encourage the use of natural ventilation systems in buildings. The UK Commission for Architecture and the Built Environment (CABE) suggests natural ventilation must be used wherever possible and should be an integral part of any new building or building refurbishment design process. In addition, the carbon reduction strategy of the UK National Health Service (NHS) [10] states that buildings designed with natural ventilation would be more resilient to energy supply failure than mechanically ventilated buildings.

Lomas and Ji [11] suggests the need for building to become resilient to climate change and increasing internal heat gains [12]. However, compared to other ventilation systems, natural ventilation is still considered a system with many requirements for it to be an efficient and effective option for specific types of buildings [13]. The unreliability of natural ventilation system operation and the indoor air quality indicated by Rasheed et al. [14] influences many buildings to consider other options. Many buildings cannot solely rely on the use of natural ventilation due to these limitations. Hence building is increasingly using solutions such as the ‘mixed-mode or ‘hybrid’ approach to ventilating buildings [15].

Natural ventilation by openable windows relies on natural forces of wind and buoyancy forces to ventilate and passively cool the desired building space [16, 17]. However, this strategy's effectiveness depends on the conditions between the indoor and outdoor environment [18] and the window opening patterns [19]. Two important parameters that influence energy consumption in buildings are indoor temperature and air change rate, directly linked to the occupant’s usage of the window [20]. According to Pan et al. [21], many studies explored occupants’ window-opening behaviour and indicated that the indoor and outdoor air temperatures, outdoor seasonal environmental factors, personal preferences are important factors that can influence window-opening behaviour.

Furthermore, Oropeza-Perez [6, 7, 22] highlights the importance of operation or handling of the natural ventilation or passive methods required to increase or decrease the indoor temperature. Hence, improper window use in buildings can have a negative impact on the building energy demand and indoor environment [23]. This indicates the need for the development of solutions such as demand-based controls or strategies that can coordinate the use of building technologies to occupancy patterns reducing energy use and providing adequate comfort conditions [24].

Solutions are being developed to aid various aspects of the built environment to improve safety, security and efficiency [25]. This includes various types of sensors and detectors to reduce the risks of accidents within home dwellings and in commercial buildings, through the triggering of sound or signal indication [26]. The advancement of these techniques will improve window operations and their suitability for current and future building needs. To understand window operations, Du et al. [27] performed a qualitative and quantitative investigation, whereby data from a series of surveys, photographic image observations and onsite measurements were collected and performed on existing windows. The work suggests that most of the window operations were performed for the provision of most of the window operations were performed to provide natural ventilation. The data collected can be integrated into building simulations with realistic profiles for a more accurate prediction of buildings' energy consumption. Since data were highly dependent on the selected case study building and occupancy behaviour, the window operations patterns cannot be used to predict other window conditions.

Furthermore, for example, Ou [28] along with companies such as Geze UK [29], Pressac [30] and Window Master [31] developed technologies for windows that employs artificial intelligence, which was intended to cope with future advancements and technical requirements. GEZE [29] products consist of window sensors connected to a building management system that effectively monitors the opening or closing of windows. However, the solution requires sensors to be installed with every window, which is not cost-effective, and it also requires windows of existing buildings to be replaced with automated windows.

Approaches based on the use of machine learning techniques have been developed for the investigation of window operations. Machine learning regression algorithms are commonly used in the form of a forecasting method to predict window conditions or to identify the cause-and-effect relationship between both indoor and outdoor environmental variables with the window operations. For example, Chen et al. [32] collected data in the form of common environmental indicators such as temperature, the CO_2 concentration of both indoor and outdoor conditions. These indicators were selected and formed as an input variable for a Cox model (proportional hazard model) to identify occupancy behaviour's influence towards window operations. Similarly, Rouleau and Gosselin [33] used indoor and outdoor temperatures environmental and temporal parameters with a logit regression model to identify window opening behaviour differences between different households. Therefore, these solutions suggest the ability to predict window conditions based on environmental conditions.

Furthermore, Shi et al. [34] proposed a novel reinforcement learning (RL) method for the advanced control of the window opening and closing. Correspondingly, Shi et al. [34] also acknowledged that window conditions are highly dependent on occupancy behaviour and environmental conditions. However, using a reinforcement learning technique enabled the identification of the window opening/closing through observing and learning from the environment. Results suggest that the developed strategy can improve indoor thermal and air quality by up to 90%. Hence, the development of solutions highlighted here suggests a desire for novel approaches that implement AI-based techniques that can accurately detect and monitor window opening behaviour.

Besides machine learning, deep learning (DL) is becoming a popular and widely used tool for solving building-related problems and improving building HVAC systems. This includes the use of deep learning-based models for detecting and recognising problems in buildings such as damage [35], faults and diagnosis issues [36]. Other applications include energy prediction methods [37], energy management and control [38] and improving building energy efficiency [39]. This indicates that emerging, deep learning-based methods are becoming fundamental techniques that can provide solutions to several aspects of building problems.

The majority of the HVAC system deep learning methods are for mechanical systems. Such application includes [40], where a data-driven ventilation control system based on a deep reinforcement learning (DeepDL) algorithm was developed and [41] where techniques were designed for mechanical ventilation systems. However, deep learning could also be a viable technique to enhance building natural ventilation strategies, but limited solutions are currently available in the literature. Chen et al. [42] proposed an approach for ventilation systems where deep learning is used to predict the building thermal responses for the building HVAC system.

Deep learning techniques have recently been adopted in the development of window opening models. Markovic et al. [43] used a deep feed-forward neural network to model the opening of windows in offices which showed an evaluation accuracy between 86% and 89%. In addition, Markovic [44] suggests that deep learning can be used for the prediction of the time of window opening actions performed by occupants. This study shows the potential for deep learning techniques for enhancing building system operations.

Since most buildings do not have strict operation times, it leads to uncontrolled operations of windows. This is also strongly influenced by occupancy behaviour and the variation within the indoor-outdoor conditions. The time delay between the prediction results and the ability to inform the occupants of the situation and the system performance's effectiveness must be taken into account. In addition, the approach suggested by Markovic [43, 44] only focuses on the accuracy of the detection and prediction of the window opening.

Future works should quantify the impact of the approach on energy performance and practicality. In addition, there is a need for further developments towards the use of deep learning techniques to enable real-time building window detection specifically for the effective application of natural ventilation systems. Additionally, Fabi et al. [19] indicate that existing studies on window opening behaviour are aimed at investigating the state of the window itself instead of the transition from one state to another (opening and closing). Hence, there is a need to develop a solution that recognises the opening and closing of windows and the time when these actions were performed.

1.1 Novelty and Gaps in Knowledge

The most common methods for window detection are based on the use of window sensors which uses a magnet and reed switch and motion or passive infrared (PIR) sensors located on every window of a building. The majority of these sensors are used for security and alarm purposes, with limitations such as their sensitivity to environmental parameters, including temperature and sound, resulting in up to 25.5% of false-positive results [45]. The study by Surantha and Wicaksono [46] improved a traditional home security system by incorporating AI techniques. Initial detection was performed by the PIR sensor, and further recognition was performed using machine learning techniques to provide detection of intruders with up to 89% accuracy.

While there are many window detection methods available, there is limited research on the use of window detection to aid demand-driven control solutions for energy and comfort management in buildings. This is necessary to allow building control systems for HVAC systems to dynamically adjust to the indoor-outdoor environment changes [43]. Strategies such as computer vision and artificial intelligence (AI) techniques can be implemented into building controls for higher accuracy monitoring and control [48]. This can also provide solutions to effectively employ natural ventilation in buildings while minimising the associated heat loss [49].

The use of video or vision-based methods to detect occupancy behaviour within a building space is promising [40]. Compared to other shallow learning methods, the use of deep learning techniques can lead to a better detection and recognition performance [51]. Recognition tasks are performed by detecting the shape, characteristic or motion. Zheng et al. [42] proposed a non-intrusive measurement method to identify window positions and their opening proportion. Unlike other research-based solutions where numerical and textual data were used along with deep learning techniques as a forecasting method, Zheng enhanced the method by using an image recognition-based approach. It consisted of a collection of photographs of windows from various angles which were then processed to allow further understanding of the window opening state. In conjunction with this, data on the internal and external environmental conditions were also collected. This enabled the analysis of the direct impact of window openings towards building performances.

The work [52] proposed Convolutional Neural Network (CNN) in future studies to enhance the window recognition method. Hence, the present work aims to address this by using a vision-based convolutional neural network-based deep learning method. Many works have already implemented vision-based deep learning methods to identify human presence [53] and object classification with high performance and detection accuracies [54]. However, the application of detection and recognition-based techniques for the building sector, in particular towards the improvement of building system controls and energy management is limited.

Based on the review of previous works on detection methods and the impact of unprecedented occupancy behaviour towards building energy demands, it was observed that there is a necessity for the development of a demand-driven control and management solution. Whereby novel deep learning-based detection approaches can be used [55 - 57]. Specifically, to prevent windows from being left unintendedly opened over long periods, real- a better understanding of the utilisation of spaces for enhancing the building operation and energy effective detection and recognition of window operations must be achieved. No work has attempted to use computer vision-based window detection and recognition method to provide data that could provide real-time information of the window state or condition for building occupants and building control systems.

1.2 Aims and Objectives

To address the issues and gaps detailed previously, the present study proposes a vision-based deep learning framework that enables the real-time detection and recognition of the conditions of windows being opened or closed by occupants. It is based on a similar detection framework proposed by Tien et al. [53]. For this window detection and recognition approach, it can provide real-time notification to building occupants and data for building control systems, which can allow it to respond in real-time depending on the requirements of a space. This could effectively reduce the unnecessary building energy loads resulting from windows unintendedly left open by the occupants.

A faster region-based convolutional neural network (Faster R-CNN) was developed and trained for the classification and detection of windows using a camera. Validation of the developed deep learning model is conducted using a set of testing data, and the accuracy and suitability for live detection were also evaluated. Experiments are carried out within a case study university lecture room to test the capabilities of the proposed approach. Using building energy simulation, the case study building was simulated with different scenario-based operation profiles, to assess the potential energy savings that can be achieved.

2. Method

The following section presents an outline of the proposed research approach and the framework for the development of a method for detecting and recognising the conditions of windows, specifically focusing on the detection of opened windows.

2.1. The Proposed Approach

The proposed approach is based on a data-driven deep learning framework that enables the detection and recognition of window openings within a building for effective management of windows and building HVAC systems. An architectural engineering lecture room within a case study building was selected to carry out the initial testing of the deep learning framework. The room was also modelled for the evaluation of its potential impact on the energy usage of the building. The approach can be split into two parts; 1. development and implementation of the proposed deep learning framework and 2. framework performance analysis.

Part 1 consists of the formation of a suitable deep learning model for the application of window detection. The developed deep learning framework is based on the convolutional neural network (CNN), trained, and validated for real-time window detection and recognition of opened windows. Part 2 is the utilisation of the deep learning model for real-time detection. The model was deployed to an AI-powered camera, and the detection data are used to form the DLIP of the window operation. This enables the system to alert occupants/building managers that specific windows are left open during unoccupied periods. In addition, the profiles could feed into the control system to make adjustments to minimise unnecessary loads. However, for the initial analysis, different scenarios will be simulated in BES to predict the potential impact on energy demand. Further details are presented in Figure 1 and are discussed in the next sections.

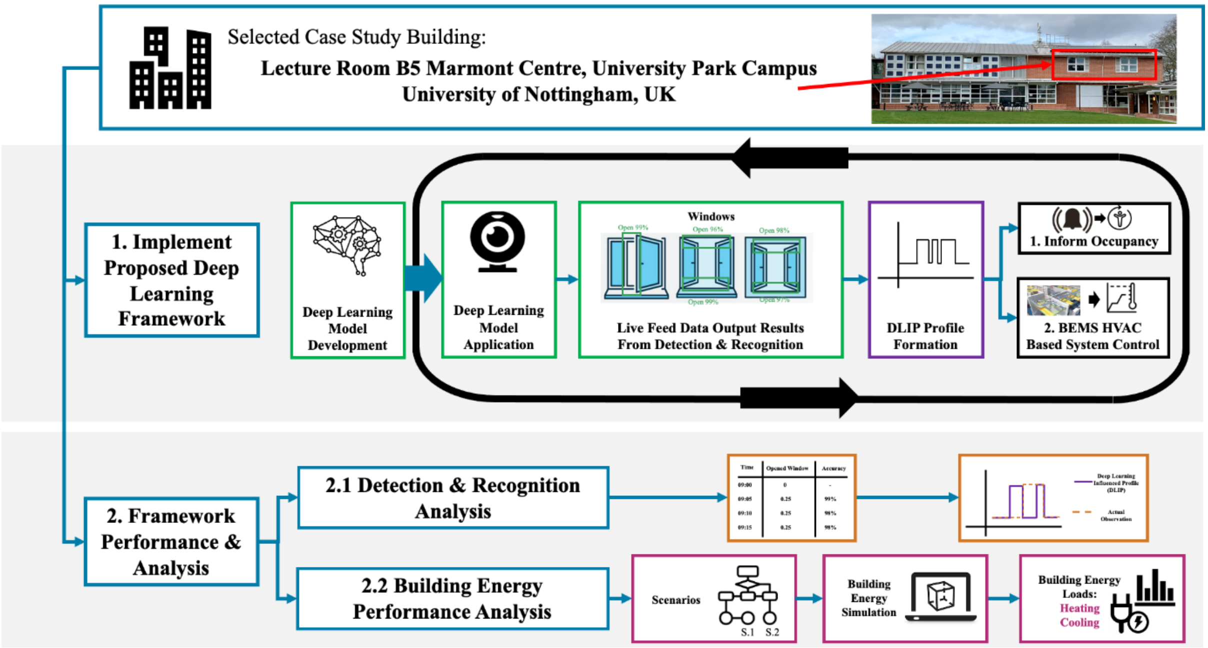


Figure 1. The proposed research method for the detection and recognition of window conditions.

2.2. Deep Learning Method

The classification-based algorithm Convolutional Neural Networks (CNN) is employed to form the deep learning window classification detection model (Figure 2a). It is a form of deep, feed-forward artificial neural network which is most suited to perform modelling for computer vision-related tasks with image datasets [51]. Deep CNNs have been extensively used to form various types of object detection frameworks. It directly learns the automatic designated features to produce a state-of-the-art recognition result, which is ideal for the project's purpose by enabling the actions of detection and recognition. Figure 2b presents the method used to develop and test the window detection deep learning model. Following a general deep learning workflow [58], this consists of data collection and processing, model training and deployment of model.

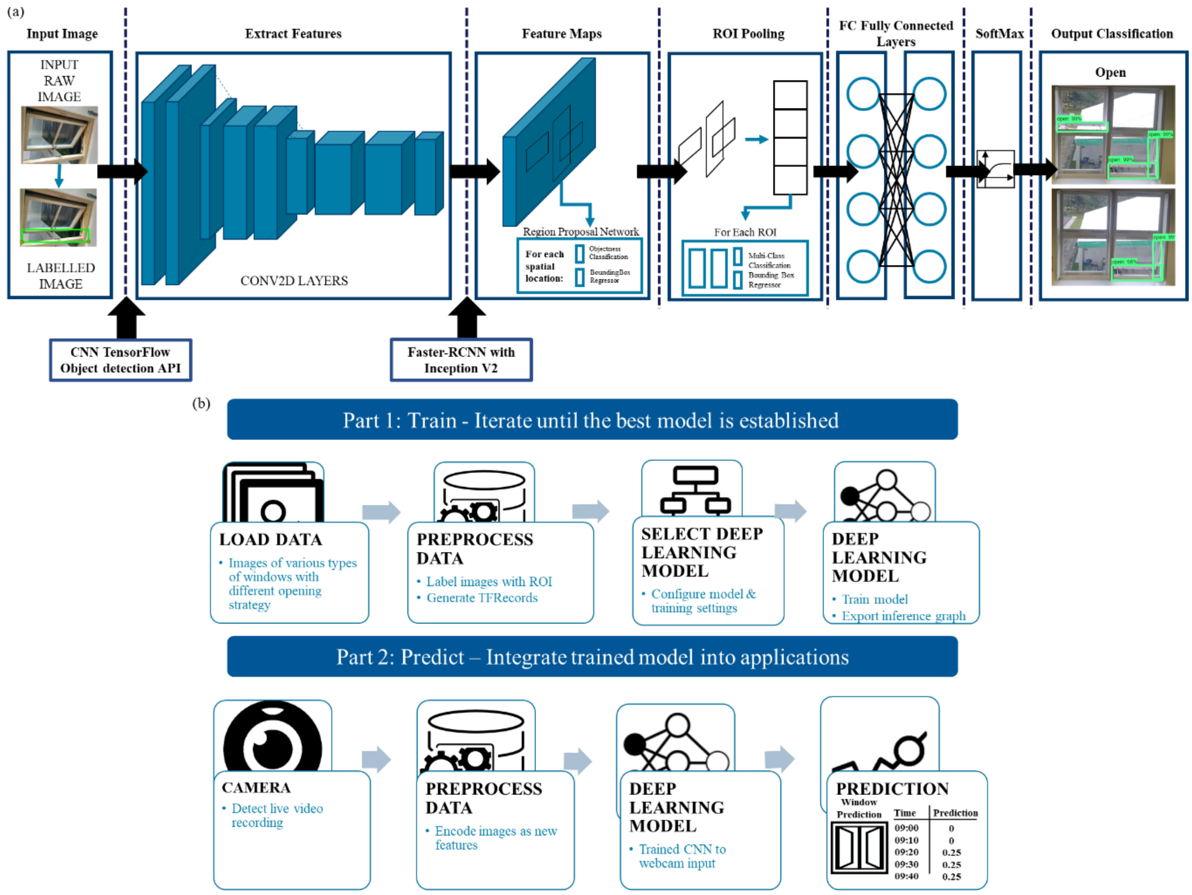


Figure 2. (a). CNN-based model configuration used for the training of the model. (b). Workflow for model development and application.

2.2.1. Datasets and Pre-Processing Stages

To enable the identification of window opening on any buildings, the first step of any deep learning detection and classification models was to form the input datasets and pre-process the input data to the desired format for training. Like other object detection models, images are used as the desired input data to form a large dataset that was used to define the condition of windows. The dataset used for this initial study was limited to the ‘open’ categories of window conditions.

The initial data consisted of more than 650 images in the training dataset, and more than 150 images in the testing dataset. The number of images used approximately followed the rule of thumb and the suggestion given by Ng [59] with 80% of the images was assigned for training and 20% for testing. The images within the datasets must be pre-processed before enabling the data to become ready for model training. All images were labelled manually using the software LabelImg [60].

Figure 3 shows an example of the images of opened windows assigned to the dataset and how bounding boxes were drawn manually around the specific region interest of each image. Bounding boxes were explicitly assigned to the opening gaps of the windows. Using the images in the dataset, 1,398 labels were assigned to the images in the training dataset and 318 labels in the testing dataset. For some cases, multiple numbers of labels were assigned to each image as this was highly dependent on the appearance of the gaps of the windows across the multiple sides of each window in the individual images.

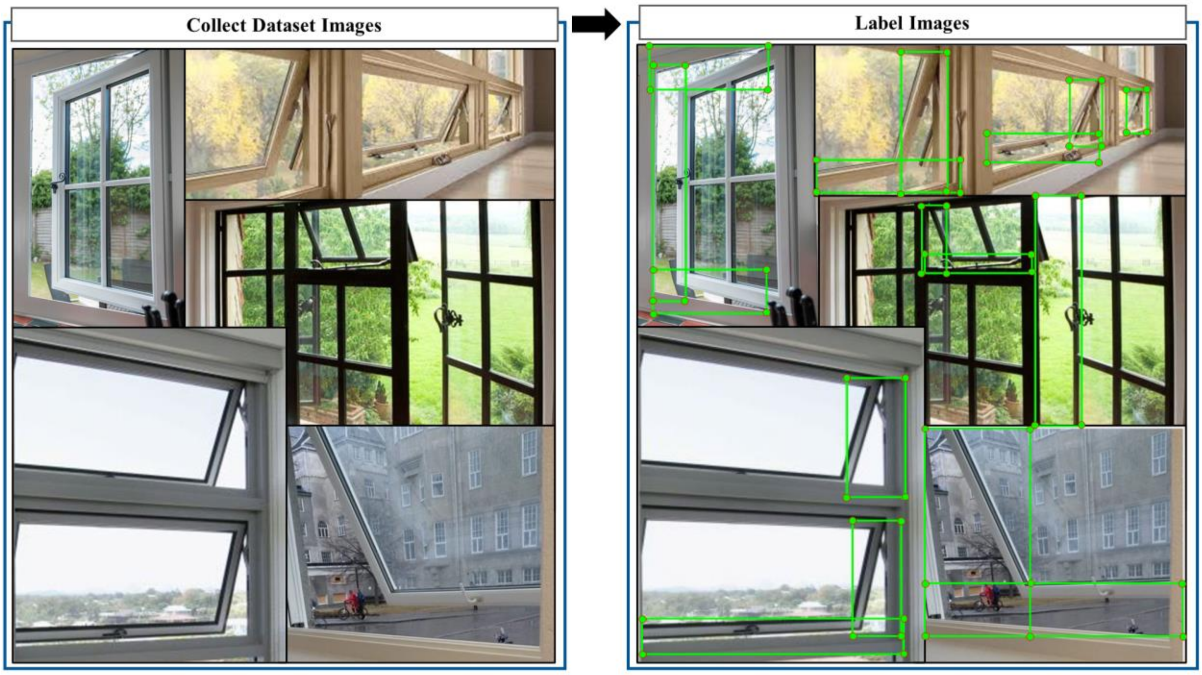


Figure 3. Example images, obtained from Google Images, of various window opening types.

2.2.2. Convolutional Neural Network Model Selection and Configuration

To configure the main deep learning model, conditions for the formation of the deep learning model for window detection must be established. Suitable deep learning framework platforms that were previously selected for modelling were explored. Many deep learning framework libraries and platforms such as TensorFlow, PyTorch and Keras are highly popular and is recommended according to Google Trends (as of February 2020) [61] and along with the comparison of deep learning frameworks by Fonnegra et al. [62], it suggests that TensorFlow [63] is one of the highest-ranked tools used for deep learning due to its high capabilities, compatibility, speed, and support it provides.

According to previous works, many choose TensorFlow as the desired platform for the development of solutions for building-related applications. This includes [43], which used TensorFlow as a platform to train the desired deep learning model. Vázquez-Canteli et al. [64] fused the TensorFlow technique with building energy simulation (BES) to develop an intelligent energy management system for smart cities and Jo, and Yoon [65] indicated that TensorFlow was used to establish a smart home energy efficiency model. In this present study, the CNN TensorFlow Object detection Application Programming Interface (API) [61] framework was used to configure the desired window model. Applications such as [62-64] suggest the ability of the framework to aid the provision of a highly effective and accurate detection model.

To train the convolutional neural network model to perform classification tasks, the general process requires defining the network architecture layers and training options. Based on the findings of existing research which utilised the CNN TensorFlow Object detection API, a transfer learning approach was incorporated into the model configuration [70]. For the window detection model, the network architecture layers were not defined from scratch. Instead, the TensorFlow detection model zoo [71] provided a collection of detection models pre-trained on various large-scale detection-based datasets specifically designed for a wide range of machine-learning research.

For the initial development of the deep learning model, the COCO-trained model of Faster R-CNN (With Inception V2) was selected and fine-tuned from the list of various types of models. This was selected due to the popularity in the use for in many object detections models, including [72, 73]. Faster-RCNN with Inception V2 uses the Faster R-CNN method and inception V2 architecture directly to find the type of window condition in an image. More details about the selected training model can be found in [71]. Figure 2a summarises the architecture and the pipeline configuration of the model used for window detection.

2.3. Application of the Deep Learning Model

Once the model was trained to a sufficient level where losses did not decrease any further, the associated inference graph was exported. Directly, the model was prepared for real-time detection via the deployment to a camera. During the real-time detection, continuous predictions of the window were classified to the predicted output response of 'open' when opened windows were identified, while also displaying the accuracy of the recognition in terms of percentages.

2.3.1. Case Study Building

An architectural engineering lecture room located on the first floor of Marmont Centre at the University of Nottingham (Figure 4a) was used as a case study to support various stages of the design and testing of the framework. The building is naturally ventilated and integrated with a simple heating system. This building was also modelled using Building Energy Simulation (BES) tool IESVE [74] to further assess the potential of this framework and the impact of the method on building energy loads.

The selected room has a floor area of 96.9m^2 with the dimensions of 12.75m x 7.6m and a floor to ceiling height of 2.5m. The room consists of four sets of windows. Figure 4b presents the experimental setup in the test. The setup consists of a 'detection camera' located near the centre of the room. The camera used was a standard 1080p camera with a wide 90-degree field of view.

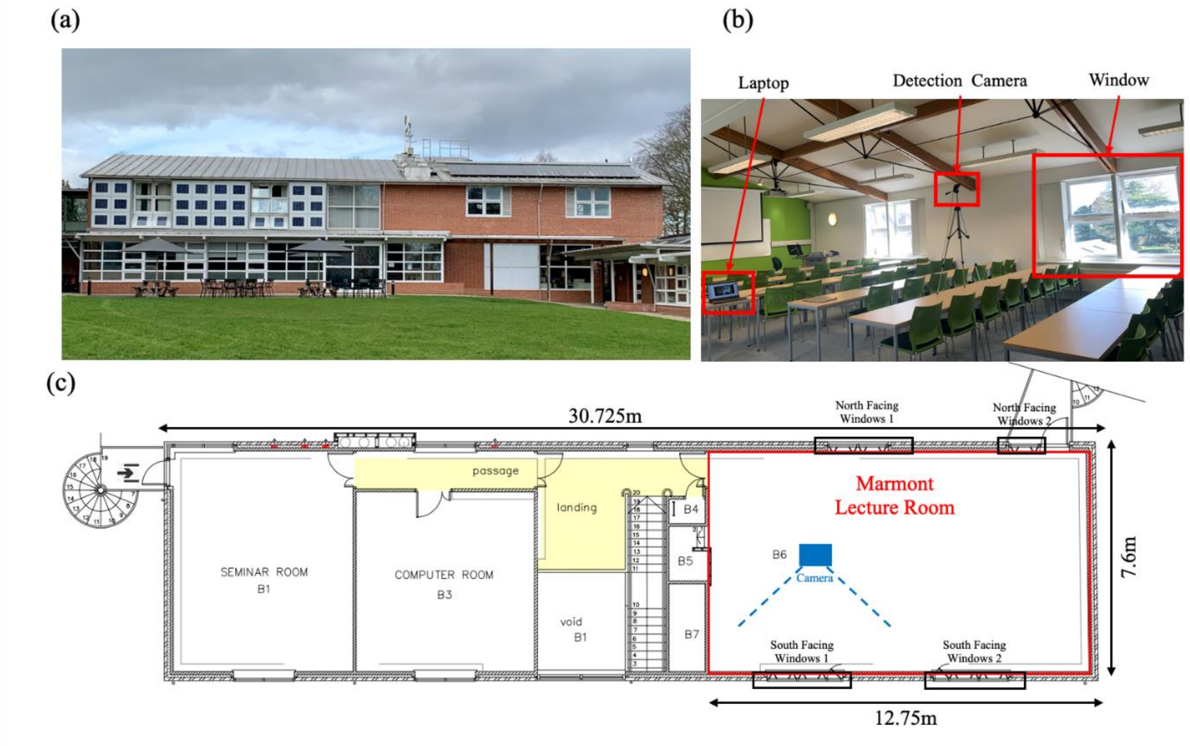


Figure 4. (a) Marmont Centre Building at the University of Nottingham, UK. (b). Experimental set-up for the experimental test. (c). 1st Floor plan.

Figure 5 shows two different window configurations within the lecture room. The north-facing windows are in an arrangement of 2 x 3 with a total of six 0.915m x 0.416m (0.38m^2) glazing panels. The two south-facing windows are in an arrangement of 4 x 4 with a total of 8 0.835m x 0.657m (0.55m^2) glazing panels. The windows have a top hung opening strategy, and they are double glazed with a U-value of 2.20 W/m^{2}K. For the purpose of building energy simulation, an assignment of 50% of the maximum opening area was selected for an opened window, and 0% was assigned for a closed window. From architectural drawings, the building components of the wall, roof, ground and doors consist of U-values of 0.33, 0.22, 0.32 and 3.00 W/m^{2}K.

Figure 5. Marmont building lecture room window types.

Furthermore, Nottingham, UK weather data file was used for the simulation. Heating profiles were set to maintain an indoor temperature of 21°C during occupied hours. Details about the associated profiles for windows and occupancy assigned were given in the BES section. For the air exchanges, the infiltration rate value was set to 0.5ach.

2.3.2. Real-time Detection and Deep Learning Influenced Profile (DLIP) Formation

Based on the setup given in Figure 4, two 15-minute experimental tests were performed within the selected room, focusing on the detection of the south-facing windows 1. This is an initial real-time detection for the assessment of the capabilities of the method. The experimental test would start with all windows being closed. After a while, the person will open some of the windows.

In experimental test 1, the person would open one of the windows, and in experimental test 2, two windows from different heights will be opened. The windows would be opened while the person is present within the detection frame. Later on, the person left the room, and the windows will be kept open under the conditions of lights staying on and when the lights were switched off.

During both experimental tests, the continuous real-time detection provided response output window detection data which were recorded at every two seconds. This was used to form the DLIP. Figure 6 shows an example of the process of DLIP formation. It presents several snapshots of the recorded frame indicating the detected window condition and the percentage of prediction accuracy. Due to the method in the labelling of the gaps of opened windows within the images in the training dataset, it resulted in instances of windows to achieve two bounding boxes assigned to one window.

For example, this was indicated by the detection shown in frames 2 and 3 with one horizontal and one vertical bounding box assigned. This suggested the gaps across the whole window were identified, indicating the response of showing the window is opened. Since more than one bounding box could be assigned to an opened window, a rule was set to ensure that a single-window opening will only be detected once.

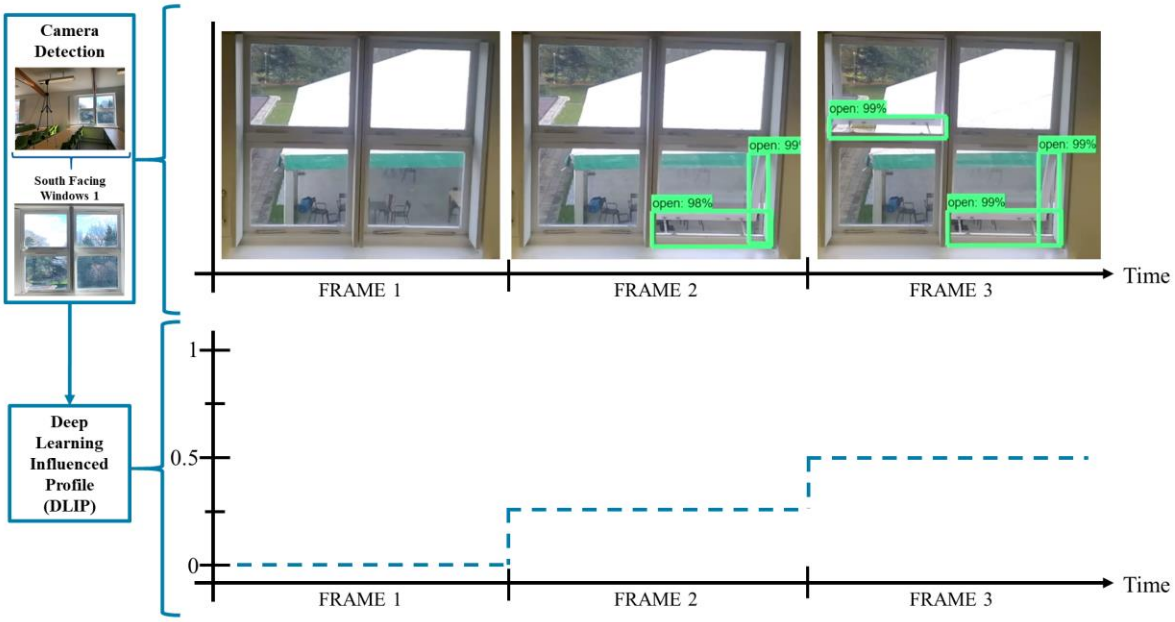


Figure 6. The formation process of the DLIP from window detection data.

The DLIP would be set based on a modulating profile. The maximum value achieved in the profile is dependent on the possible number of windows which can be identified as open from the number of windows present within the camera detection region. Based on the experimental setup given in Figure 4 for the experimental tests with a focus on the south-facing windows, a total of 4 windows can be classified. This is equivalent to the value of 1, as shown in the profile. Effectively, as shown in frame 2 when one opened window is detected, the profile presents a value of 0.25, and when two opened were identified as opened in frame 3 a value of 0.5 will be recorded.

Furthermore, this DLIP profile will be assessed along with the use of three other profiles; constantly open, constant closed and the actual observation, which represents the true window condition during the experiment time and enables the verification of the results obtained for the DLIP.

2.4. Conditions for Framework Performance and Analysis

The performance of the model would be assessed based on real-time window detection. As indicated in Figure 1, further analysis would be conducted using a scenario approach through BES. The following section provides the conditions used to perform such analysis.

2.4.1. Detection Model Performance Evaluation Metrics

To perform an initial evaluation of the performance of the model, images assigned in the test dataset will be used to evaluate the detection performance to provide results in the form of a confusion matrix. Values for the terms of true positive (TP: representing the achievement of a correct detection), true negative (TN: representing correct detection when windows are closed or as other), false positive (FP: representing the number of instances that the prediction was not true, or another instance being wrongly identified as this response, and false negative (FN: representing the number of instances as predicted to be something else, but it wasn’t).

Based on the created confusion matrix, precision and recall are frequently used to evaluate the accuracy of the algorithm for object detection, which is defined by Eq. (2) and (3) respectively. Precision is the measure of exactness or quality, while recall is a measure of completeness or quantity. However, it is not sufficient to evaluate the detection performance when precision and recall were separately used. With the consideration of a balance between precision and recall, a measure called F_1 Score is formed by combining these two measures and expressed as Eq. (4).

$$Accuracy = \frac{(TP + TN)}{(P + N)} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F_1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

2.4.2. Test Scenarios and Building Energy Simulation

During the winter seasons in cold or temperate climate locations such as the UK, high amounts of energy would be wasted due to windows being left open while building heating systems would still be in operation. An example is the lecture room within the Marmont Centre, where it relies on conventional control systems for the HVAC. Typical "static" or fixed operation schedules were used. However, this cannot adjust according to the actual requirements of the space [55, 56].

The following presents the set-up of test scenarios used to investigate the impact on building energy demand when the deep learning approach is applied. The scenario consists of the schedules indicated in Figure 7. The four-day period, Friday to Monday timeline provides a sample structure of how the room is occupied during a typical weekend during the winter months, between Friday 10th and Monday 13th January. Specifically, the heating season was selected for analysis as parameters such as outdoor airflow and temperature must be considered when designing the control strategy i.e., night cooling and passive cooling.

The room was timetabled to have a lecture session on Friday (day 1) at 14:00–16:00 and another session at 10:00–12:00 on Monday (day 4). At these times, it was assumed that the building had maximum occupancy with 40 students present. Furthermore, the room was assumed to be unoccupied for the rest of the time. These occupancy-based conditions were presented as the scenario-based occupancy profile in Figure 8c.

For all scenarios (S1 – S3), it was assumed that only the highlighted south-facing windows in Figure 7 were opened by occupants during the lecture session at 15:00 on Friday (Day 1). For Scenario 1, the window was left open until 10:00 am on Monday, where a person who attended the session decided to close these windows.

In scenario 2, the window detection strategy is employed which is assumed to have the ability to inform the occupants or building manager. This was highlighted in Figure 1 as the first response when windows are detected as opened when they are not intended to be in this state. For this scenario, the opened windows were detected, and it informed the occupants/building manager to close the windows at 17:00. Scenario 3 adopts an approach in which the opened windows were continuously detected after alerting the occupant/ building manager and hence adjustments were made to the setpoint temperature.

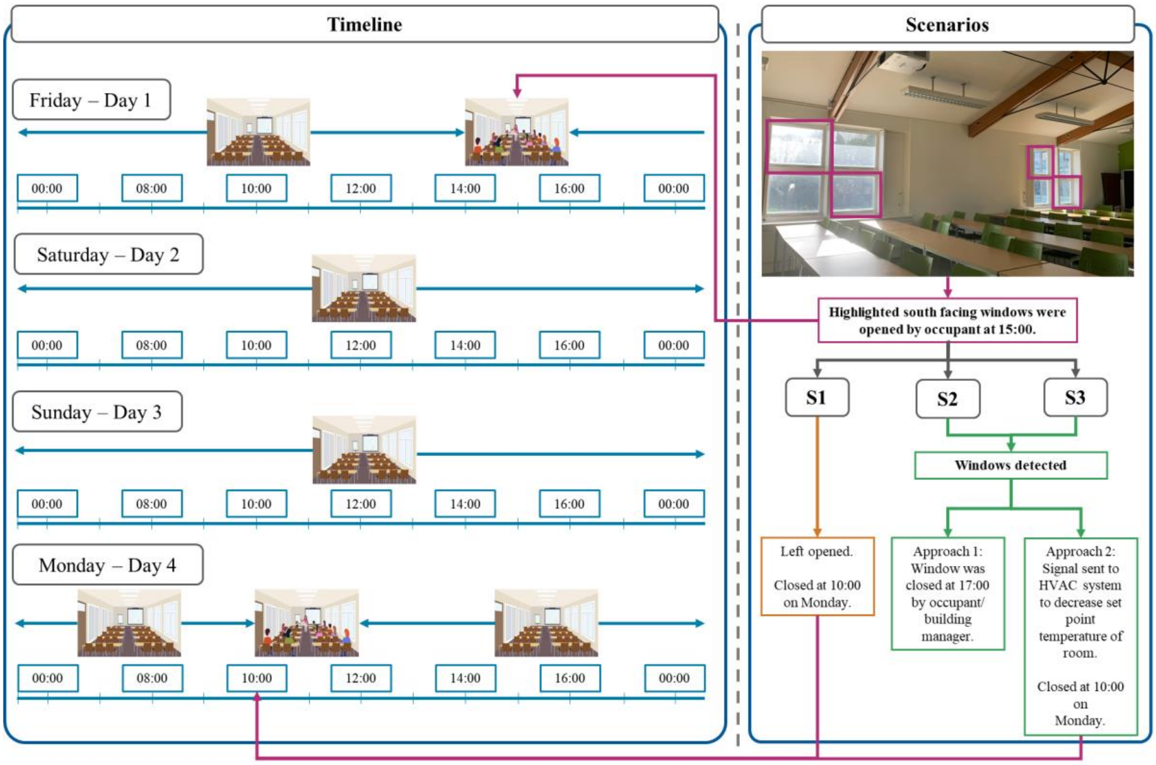


Figure 7. Description of the scenario schedules.

Figure 8 presents the window operation and heating setpoint profiles used within BES. The static profiles are presented in Figure 8a and are incorporated within the scenario-based building energy modelling. The comparison of the static profiles (Figure 8a) with the DLIP would provide an understanding of the difference between actual window conditions and the use of static profiles.

Based on the scenarios described above, Figure 8b presents the corresponding window profiles. The set indoor room temperature was based on ASHRAE 90.1 [75] and ASHRAE 55 [76]. For occupied hours, it advised a temperature of 22 – 27°C for cooling and 17 – 22°C for heating, while during unoccupied hours it suggested 27 – 30°C for cooling and 14 – 17°C for heating.

Effectively, given in Figure 8d, a generalised room setpoint temperature of 21°C was set during the typical occupied hours of 09:00 – 17:00 and 15°C during the unoccupied hours. It should be noted that occasionally students may occupy this room during both Saturdays and Sundays. Hence, the standard heating profile shows the same profiles for all four days. However, due to the approach given for Scenario 3, it, therefore, follows the heating profile indicated in Figure 8e.

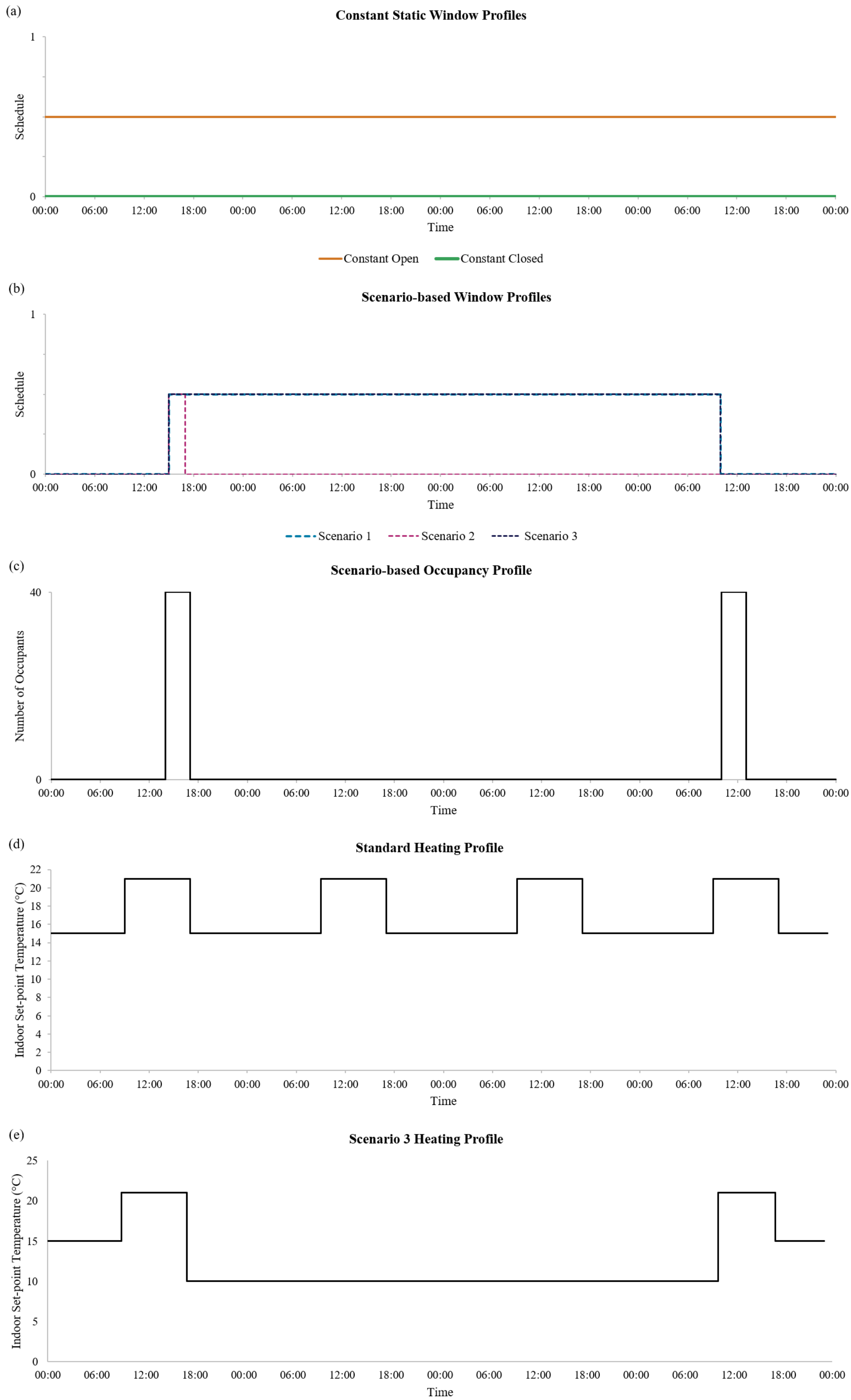

(a)
Constant Static Window Profiles
Schedule
Time
Constant Open
Constant Closed
(b)
Scenario-based Window Profiles
Schedule
Time
Scenario 1
Scenario 2
Scenario 3
(c)
Scenario-based Occupancy Profile
Number of Occupants
Time
(d)
Standard Heating Profile
Indoor Set-point Temperature (°C)
Time
(e)
Scenario 3 Heating Profile
Indoor Set-point Temperature (°C)
Time

Figure 8. Window and building energy modelling profiles.

The modelling of the windows consisted of an exposed wall type exposure, with a top hung window opening. Following Figure 5, the windows were assigned with an openable area of 50% and a maximum openable angle of 45°. The degree of the opening was assigned with a modulating profile corresponding to the window profiles created (Figure 8a and b). Table 1 summarises the simulation cases and the associated window and heating profiles used.

Table 1. Summary of the building energy performance simulation scenario cases.

<table>
<tr><th rowspan="2">Simulation Case</th><th colspan="3">Assigned Profiles</th></tr>
<tr><th>Window</th><th>Heating</th><th>Occupancy</th></tr>
<tr><td>Constant Open</td><td>Constant open (Figure 8a)</td><td rowspan="4">Standard (Figure 8d)</td><td rowspan="5">Scenario-based (Figure 8c)</td></tr>
<tr><td>Constant Closed</td><td>Constant closed (Figure 8a)</td></tr>
<tr><td>Scenario 1</td><td rowspan="3">Scenario-based (Figure 8b)</td></tr>
<tr><td>Scenario 2</td></tr>
<tr><td>Scenario 3</td><td>Scenario 3 (Figure 8e)</td></tr>
</table>

3. Results and Discussion

The following presents the results and discussion of the developed deep learning-based window detection model. The trained model was used to conduct the described experimental tests and the following section shows the initial performance and analysis along with the further evaluation based on scenario-based building energy performances.

3.1. Deep Learning Model Training Performance and Evaluation

The initial deep learning model was trained using the graphics processing unit NVIDIA GTX1080. The training was conducted for 199,630 steps, and it took eleven hours, 29 minutes for the total losses to reach the level indicated in Figure 9. Using the pre-trained model Faster-RCNN with InceptionV2 to aid the training of the model for the detection of windows, the results provided a maximum loss of 1.237 and a minimum loss of 0.0152.

The convergence of the loss function implies that the model has been effectively trained. Observations made for this proposed approach can be used to compare with different modifications applied. Table 2 presents the results in form of a confusion matrix and evaluation metrics, which were devised from the total number of predicted labels assigned to the application of the images from the dataset.

A total of 160 images from the test dataset were used. The results suggested that 279 labels out of 318 prediction labels were correctly assigned to the presented opened windows, an average detection accuracy of 87.74%. Furthermore, 11 of the labels were assigned to the opened windows when they actually closed or other, and 28 labels were not assigned to windows when they were presented as opened. Overall, an F_1 score of 0.9347 was achieved. This indicated that the majority of the images of windows were correctly classified and validated the model being suitable for window detection and recognition.

Figure 9. Training results. (a). Classification loss, and (b). A total loss against the number of training steps.

The images assigned in the test data were used to test and assess the initial model performance. Prediction labels were assigned to the images as a response to the application of the detection model. To provide effective evaluations, the dataset consisted of images of various windows with an opened condition. It included images of windows with top-hung and side-hung designs.

Table 2 presents the results in form of a confusion matrix and the common machine learning classification model evaluation metrics, which were devised from the total number of predicted labels assigned to the application of the images from the dataset.

Table 2. Model performance based on the number of predicted labels assigned to the application of the images from the testing dataset.

<table>
<tr><th>Confusion Matrix</th><th>Window Classification</th><th>Accuracy</th><th>Precision</th><th>Recall</th><th>F1 Score</th></tr>
<tr><td><table>
<tr><td></td><td></td><td colspan="2">True Class</td></tr>
<tr><td></td><td></td><td>Open</td><td>Closed/Other</td></tr>
<tr><td rowspan="2">Predicted Class</td><td>Open</td><td>279</td><td>11</td></tr>
<tr><td>Closed/ Other</td><td>28</td><td>0</td></tr>
</table></td><td>Open</td><td>87.74%</td><td>0.9621</td><td>0.9088</td><td>0.9347</td></tr>
</table>

3.2. Framework Performance: Detection and Recognition

The section presents the initial performance of the trained window detection model. The trained model was deployed to form an AI-based camera, enabling real-time detections within the selected case study building. Section 3.2.1. introduces the model's ability in providing effective applications within a series of different types of windows, while Section 3.2.2. presents the application of the model during the selected experimental tests.

3.2.1. Real-time Detection and Recognition of Windows

Figure 10 shows the live detection and recognition results for the different windows located in the room. Predicted bounding boxes were assigned to windows when they were recognised as open. Above the bounding boxes, the accuracy percentage of prediction was displayed. Through the detection of the north-facing window, along with the south-facing window 1 from two different camera angles and lighting conditions, it was observed that windows that were opened were identified. Further training would be made to improve the detection accuracy and to reduce the possibility of achieving false detections.

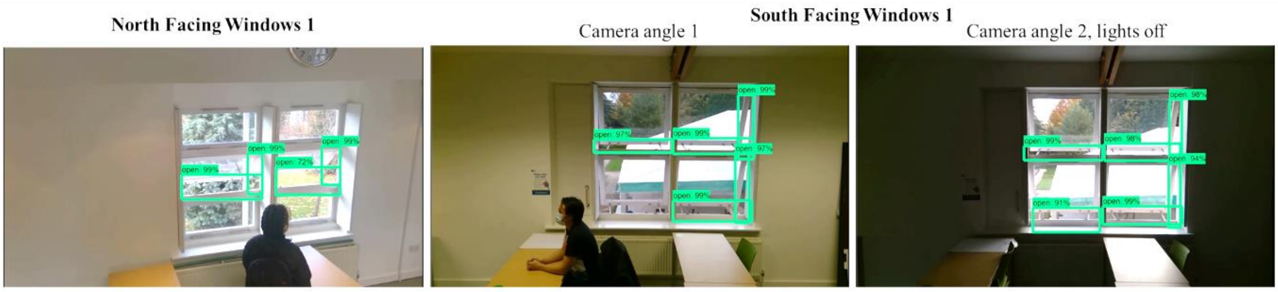


Figure 10. Detection and recognition results on different windows in the selected Marmont Lecture Room.

3.2.2. Experimental Detection and Recognition Results

To show the capability of the proposed approach, two real-time experimental detection tests, Experimental Test 1 and 2 was performed within the Marmont Lecture room. The test was based on the set-up given in Figure 4, and each test was performed for 15 minutes. Figure 11, along with Video 1 and 2 presents a preview of the real-time window detection and recognition model during the two experimental tests, focusing on the south-facing windows 1. Both experimental tests had the camera positioned at the height and angle replicating typical occupancy sensors, by locating the camera near to the ceiling of the room.

It should be noted that in practice, the device won't be storing or outputting images. It will only output real-time information on the number and location of open windows. The images and videos of the detection performance are for visualisation purposes and are to give a preview of how the detection and recognition works. It is envisioned that the detection technology and AI camera will be integrated into a single device and will only output data required by the demand-driven control system.

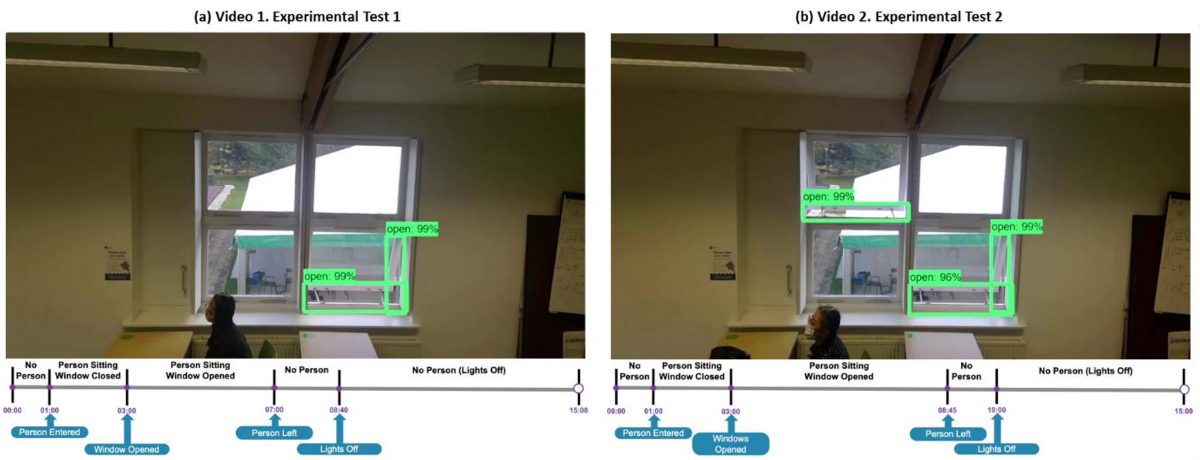


Figure 11. Preview of the real-time window detection and recognition model during (a). Video 1 – Experimental Test 1 and (b). Video 2 – Experimental Test 2. ***See links for the videos on the last page.***

Figure 12 and Figure 13 presents examples of window detection and recognition during Experimental Test 1 and 2, based on the key stages as highlighted by the timelines given in Figure 11 and Videos 1 and 2. The results showed its capabilities in detecting if the windows are open such as when there is no person near the window and when a person is opening the window and sitting near the window. It also showed its capabilities when artificial lighting is switched off.

As given by the snapshots in Figure 12 and Figure 13, the size and shape of these bounding boxes varied between each detection interval. It was dependent on the size of the detected space, the distance of the camera with the detected window, and it was also dependent on the influence of the presence of a person which can be considered as an obstructing object.

Furthermore, due to the method in the labelling of the gaps of opened windows within the images in the training dataset, it resulted in instances of windows to achieve two bounding boxes assigned to one window. For example, this was presented in all the detections highlighted in Figure 12, with one horizontal and one vertical bounding box assigned. Otherwise, in instances such as the top left window shown in Figure 13, only one bounding box was present as the vertical gap within the window was not clearly shown.

Hence, the proposed method of detecting window opening gaps potentially reduces the occurrence of issues such as obstruction as typically, the size of the windows will be larger in comparison to objects such as occupancy body size and size of general objects within a room. This suggests the full window would be unlikely be blocked at all times. In addition, a window should not be blocked at all times as this could lead to other issues such as daylighting and visual comfort within buildings.

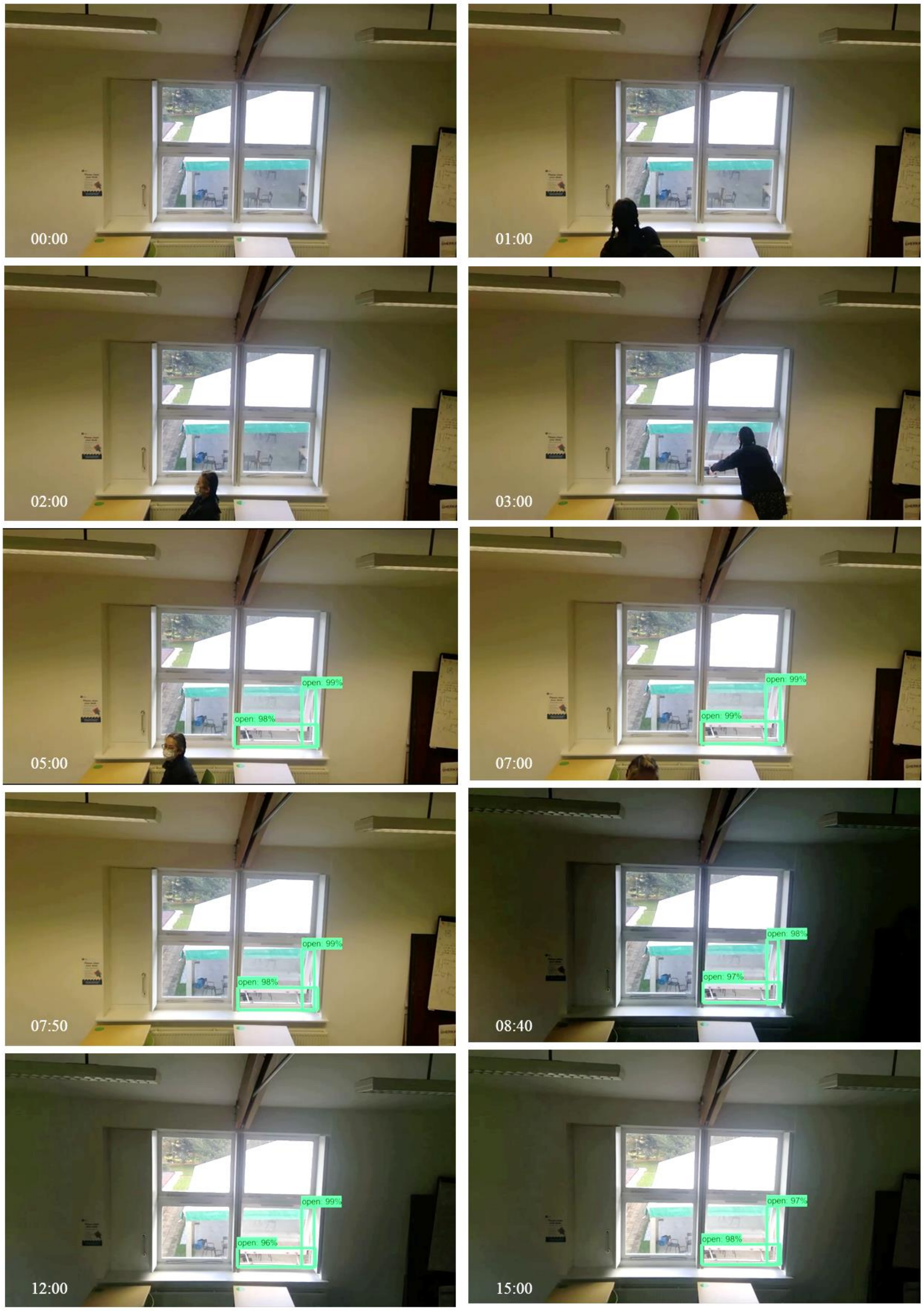


Figure 12. Example snapshots of various key point stages during the application of the window detection approach during Experimental Test 1.

Figure 13. Example snapshots of various key point stages during the application of the window detection approach during Experimental Test 2.

3.3. Framework Performance: Detection Performance Analysis

Based on the detections made in Section 3.2.2., the following shows the analysis of the model detection and recognition performance that was based on the experimental tests conducted within the case study building.

3.3.1. Analysis of the Real-time Detection Performance

Figure 14 presents the average bounding box detection accuracy for both experiments. No results were obtained for parts 1 and 2 of both experiments, as all windows were identified as not being opened. For the other parts, it indicated an average detection accuracy of 98.19% was achieved for experimental test 1, and 96.67% for experimental test 2. A threshold limit with a minimum detection accuracy of 60% was set to only enable the display of detections when the accuracy is above this value. This mitigates any form of uncertain predictions. Stable performance was achieved, as minimal variations were presented within the accuracies between parts 3, 4 and 5 in both experimental tests.

The highest prediction accuracy was achieved in part 3. This was when the windows were opened, and minimal movement was performed by the person. Similar results were achieved in part 4, and only a slight decrease in accuracy values was achieved when the lights were switched off in part 5. Overall, the results suggest that the developed model is capable of detecting multiple numbers of windows under various room conditions. However, this is only based on the initial detection at the selected period of time. Hence, further model training and testing would be performed to achieve higher detection accuracies for various types of windows.

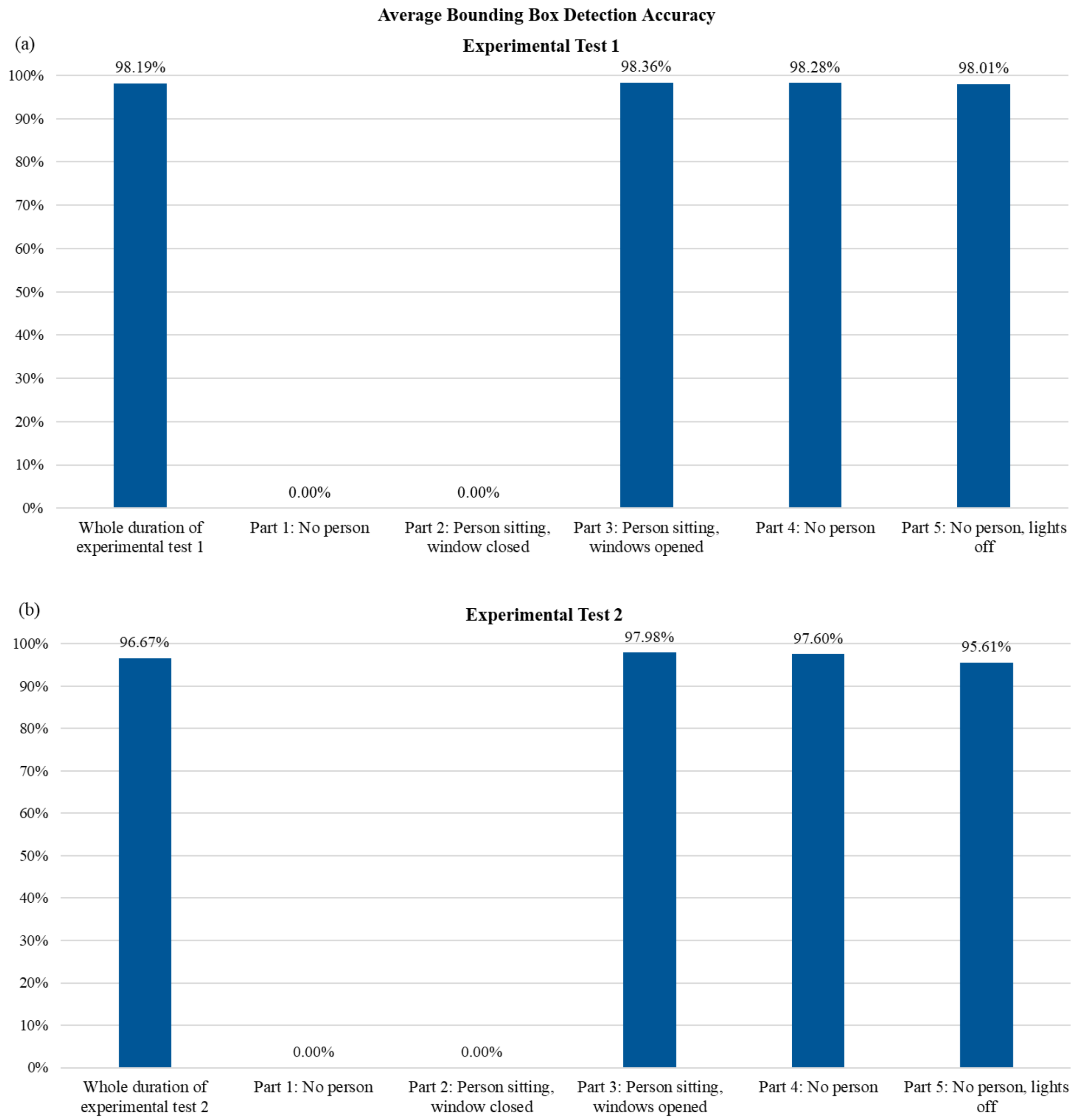


Figure 14. Average detection accuracy based on the displayed bounding box during real-time predictions in a). Experimental Test 1 and b). Experimental Test 2.

Figure 15 presents the overall detection performance of the proposed approach during the two experimental tests. For experimental test 1, Figure 15a showed that the approach provided correct detections for an average of 99.61% of the time, 0.28% of the time to achieve incorrect detections and subsequently, 0.11% of the time with no detections. Similarly, for experimental test 2, Figure 15b suggests it achieved correct detection for 97.56% of the time, 1.94% of the time to achieve incorrect detections and no detections occurred for 0.50% of the time.

Obtaining a correct detection represents the instance when the opened windows were correctly identified as open, and also for the times when detection was correctly not made when windows were closed. Generally, the performance of the model was better in experimental test 1 than experimental test 2.

Based on the breakdown of the detection performance for each of the 5 parts of each of the experimental tests, in experimental test 1, part 2 achieved the most amount of incorrect detection, 1.25% of the time. This could be because the person was within the detection frame and displaying false results in suggesting windows being identified as opened when they were not.

Similarly, this may also cause the result of incorrect detection in part 3 of detection performance during the experimental test 2, with incorrect detections was recorded for 3.13% of the time and no detection for 1.88% of the time.

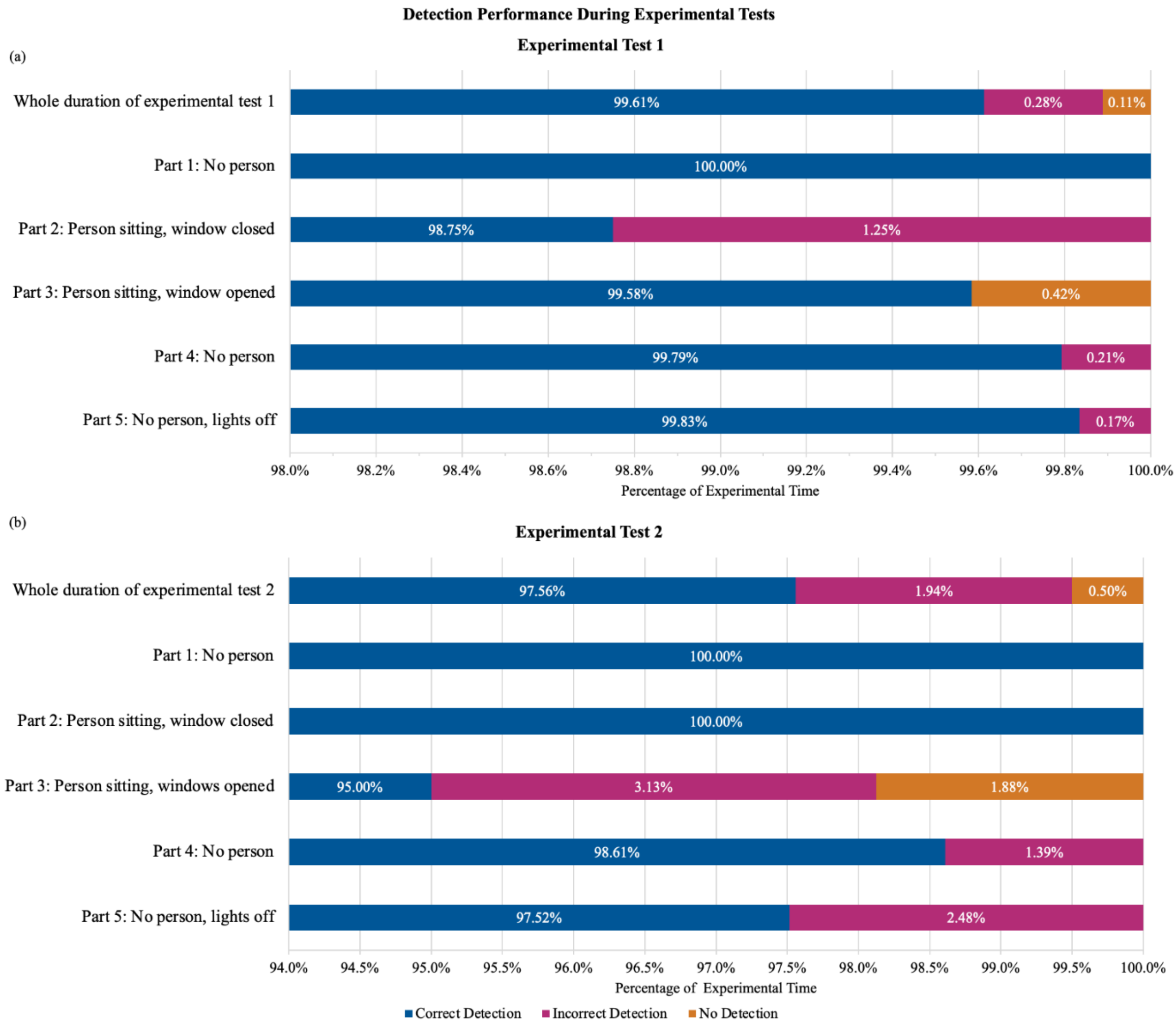


Figure 15. Detection performance during a). Experimental Test 1 and b). Experimental Test 2. Identification of the percentage of time achieving correct, incorrect, and no detections during the whole duration of each test and for each of the sections.

3.3.2. Further Evaluation of the Detection Accuracy Based on Classification Evaluation Metrics

Figure 16 presents the results for the different parts of the experimental tests in the form of a confusion matrix based on the prediction response label of ‘open’ displayed on the detected windows. Since no windows were opened in parts 1 and 2 of both tests, no results were given for the majority of the confusion matrix displayed.

However, for part 2 in experimental test 1, three labels were present in identifying windows as opened, when they were not. This resulted in the only value displayed in this matrix. Similar to the results shown in Figure 15 of the overall detection performance, the results shown in the confusion matrix for parts 3, 4, and 5 for both experimental tests, suggests that most labels were correctly assigned to the opened windows. Only the occasional instances when the opened windows were not identified, so no labels were assigned. Also, times when labels were assigned to windows that were closed.

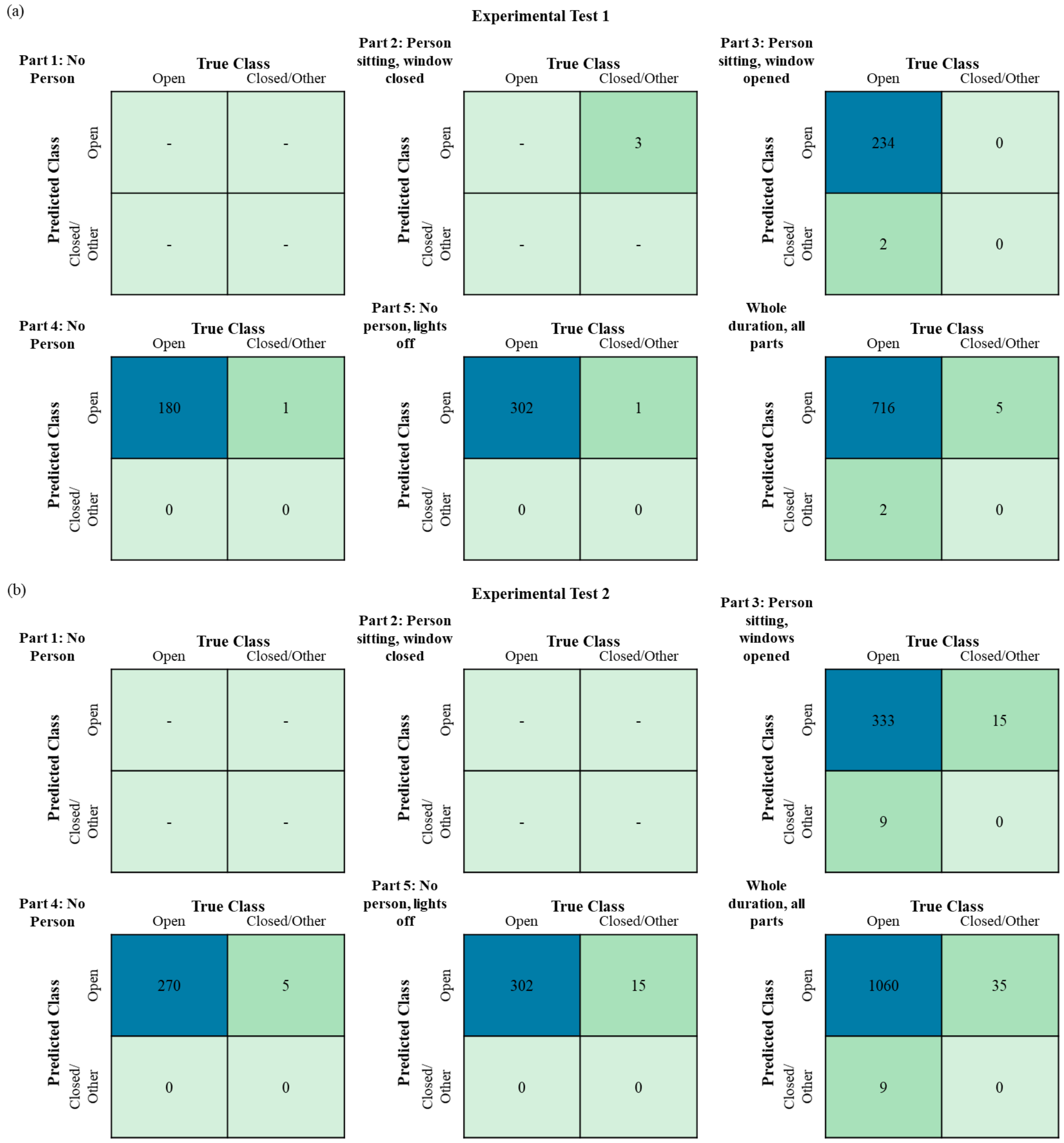


Figure 16. a). Experimental. Test 1 and b). Experimental Test 2 detection performances evaluated in the form of the confusion matrix based on the labels identified. From clockwise; no person, a person sitting with windows closed, a person sitting with windows opened, no person, no person with lights off, entire duration.

The confusion matrix results displayed in Figure 16 for each part enabled the evaluation of the results in the form of the different classification evaluation metrics, as shown in **Error! Not a valid bookmark**

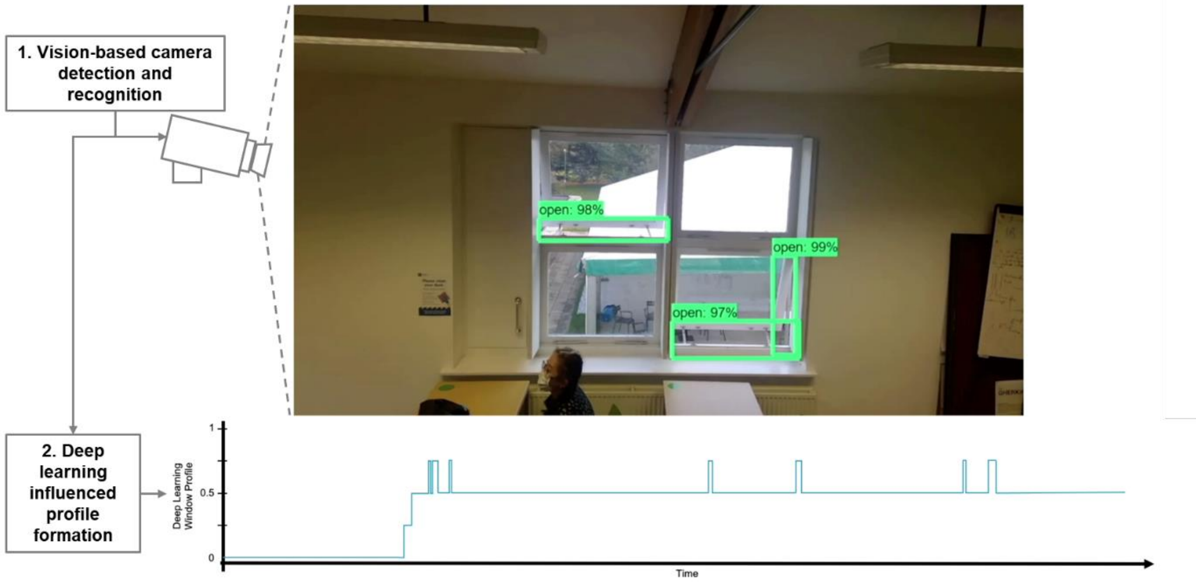
self-reference.. An accuracy of over 99% accuracy with an F_1 score of 0.9951was achieved for the performance during the experimental test 1 and an accuracy of 96% with an F_1 score of 0.9797 for experimental test 2.

Table 3. Evaluation of the model performance during Experimental Test 1and 2, based on common evaluation metrics.

Section	Accuracy	Precision	Recall	F_1 Score
Experimental Test 1				
Part 1: No person	-	-	-	-
Part 2: Person sitting, window closed	-	-	-	-
Part 3: Person sitting, windows opened	99.15%	1.0000	0.9915	0.9957
Part 4: No person	99.45%	0.9945	1.0000	0.9972
Part 5: No person, lights off	99.67%	0.9967	1.0000	0.9983
Whole duration of experimental test 1	99.03%	0.9931	0.9972	0.9951
Experimental Test 2				
Part 1: No person	-	-	-	-
Part 2: Person sitting, window closed	-	-	-	-
Part 3: Person sitting, windows opened	93.28%	0.9569	0.9737	0.9652
Part 4: No person	98.18%	0.9818	1.0000	0.9908
Part 5: No person, lights off	95.27%	0.9527	1.0000	0.9758
Whole duration of experimental test 2	96.01%	0.9680	0.9916	0.9797

3.4. Framework Performance: DLIP of Window Operation

The real-time detections enabled the formation of the DLIP. Video 3 shows an example of the window detection and recognition along with the generation of the DLIP profile. The DLIP was based on a modulating number of detected opened windows, with the value of 1 representing the times when all four windows within the detection frame were identified as open.



Video 3. A video presenting the application of the developed window detection and recognition model in Experimental Test 2 along with the generation of the DLIP. ***See the link for the video on the last page.***

Figure presents the generated DLIP of the opening patterns for the selected windows in the Marmont Room during a). Experimental test 1 and b). Experimental test 2. The formation of the profile corresponds to the process indicated in Figure 6 The Actual Observation Profile defines the ‘actual’ window condition. This profile was used to assess the accuracy of the DLIP, as shown in Figure . Based on the initial experimental results, at times the DLIP still alternates between the values of the window profile schedule, indicating prediction error. Therefore, further improvements are required to enhance the accuracy, reliability and stability of the detection model.

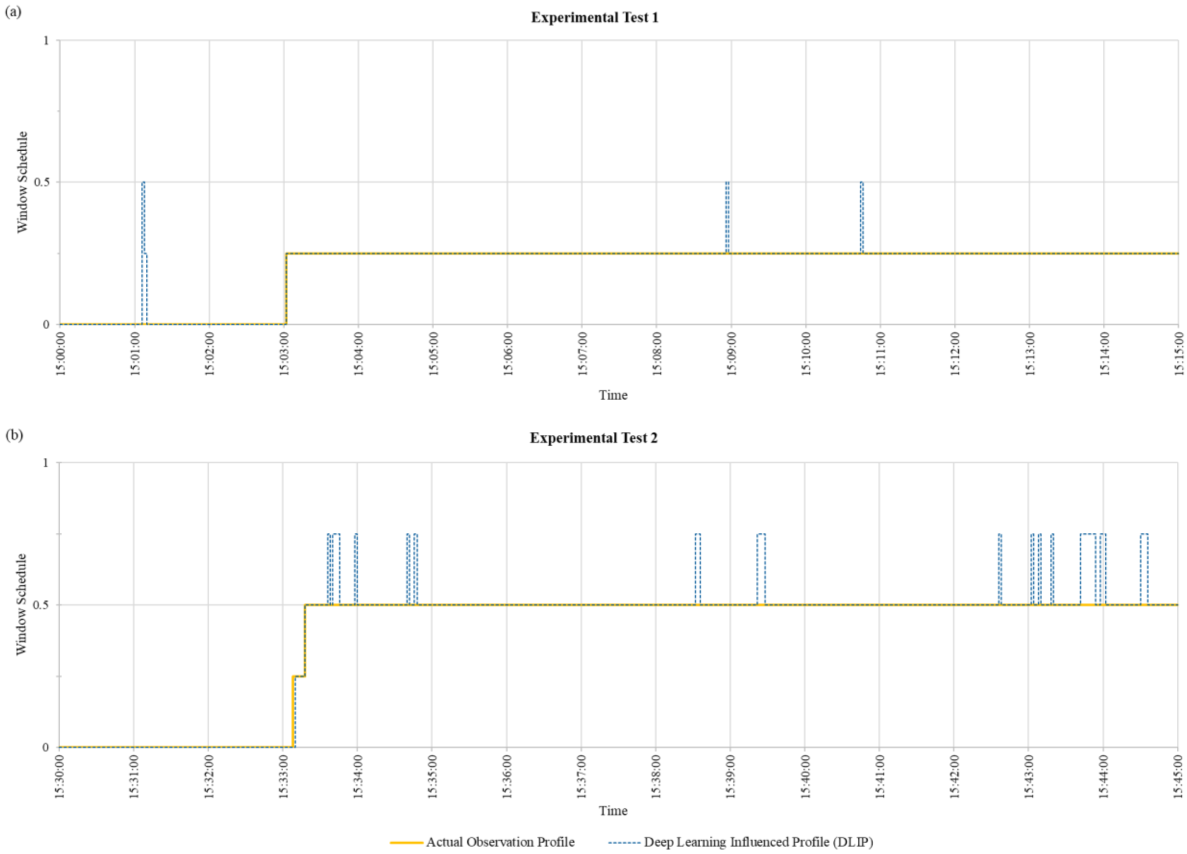


Figure 17. Generated DLIP based on the window detection results performed in Experimental Test 1 and 2, along with the corresponding actual window conditions.

3.5. Scenarios and Building Energy Performance Analysis

Based on the proposed research method shown in Figure 1, this section presents the analysis of the framework performance based on different scenarios-based situations. Building energy simulation was conducted to provide the following discussion in terms of heating demand and ventilation heat losses.

3.5.1. Heating Demand

Figure presents the heating results for the four days under the different simulation cases. Based on the use of “static” profiles for the window operation in the BES, the maximum (constant open) and minimum (constant closed) heating load that can be achieved depending on the window opening is presented in Figure 18a. When the windows were constantly closed, the high number of occupants present within the room led to high internal occupancy heat gains which led to the lower heating requirement for these periods of time.

Figure b shows the results for the heating load for the three scenarios. For scenario 1 the results suggest the heating load would be similar to constant open as the windows were kept open from 15:00 on Friday (day 1) to 10:00 on Monday (day 4). The only differences occurred at the times before the window was opened on Friday (day 1) and after it was closed on Monday (day 2). The opened windows resulted in a high increase in heating loads due to the continuous heating of the room to reach the desired setpoint temperatures (Figure 8d).

For scenario 2, the deep learning method was used to assist the detection of the opened windows and notification was given to either the occupants or the building manager. Prior to the closure of the window at one hour after the lecture was finished (at 17:00), the same amount of heating load as scenario 1 was required. However, once the windows were closed, it resulted in a significant decrease in heating load. For this case, heating was not required for the rest of the day. Instead, heating was only required for the periods where the room had a set point temperature of 21°C.

Scenario 3 was simulated using the same window profiles as for scenario 1 (Figure 8b) since the windows were kept open from Friday night to Monday morning. Instead of a standard heating profile based on the typical room occupied hours, a different heating profile given in (Figure 8e) was used to model the situation where the deep learning detection method assisted the building controls through sensing the opened windows which therefore informed the operations of the building HVAC systems.

Due to it being the end of the office day and no occupants present after 17:00, the second approach given in the deep learning framework shown in Figure 1 was followed. The sensors from the detection model informed the building energy management system controls and influenced the building HVAC system to reduce the heating setpoints until Monday.

Figure 18 presents the corresponding heating load results for Scenario 3. By comparing the results across all three scenarios, similar heating loads were achieved on day 1 and since the room setpoint temperature was changed to 10°C for the times when the window was detected as opened, it resulted in the requirement of no heating.

Furthermore, a high peak in an increase of heating demand was presented a 10:00 on Monday (day 4) as the room setpoint was then changed to 21°C. However, the requirement of a high heating load only occurred for a short period of time as occupants were present within the room.

Figure 18. Heating load results for a weekend (Friday 10th – Monday 13th January) achieved using building energy simulation cases of a). constant scheduled window profiles and b). the three different scenario-based cases.

Figure 19 presents the total heating demand between the scenario simulation days. It suggested the room with windows assumed to be constantly opened required a heating load of 606.6kWh. This is based on a worst-case scenario which indicates the maximum amount of heating that is essential to maintain the room at 21°C during occupied hours. In comparison, for constantly closed windows, heating of

91.4kWh was needed. This was due to no ventilation heat losses through windows. It should be noted that the occupancy profile was assigned in the model and hence the occupancy heat gains led to the requirement of less heating.

Furthermore, Scenario 1, 2 and 3 achieved a total heating load of 238.5kWh, 99.3kWh and 68.0kWh. Given by scenario 2, heating after 17:00 was decreased by approximately 7kW (during the next hour) as the occupancy/building manager was informed about the opened windows, which prevented the windows from being left open.

Additionally, Scenario 3 consisted of the DLIP data to inform the HVAC system to provide lower indoor temperature during unoccupied times. This was shown by the achievement of decreased heating loads to the minimum. With the setpoint temperature of the room being dependent on the window conditions, building demands can be effectively reduced.

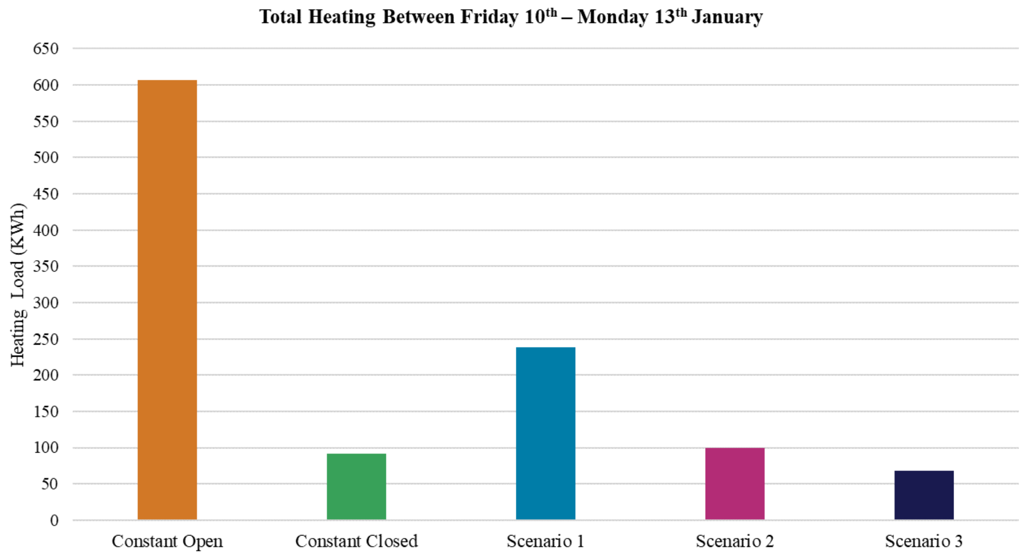


Figure 19. A comparison between the total heating load (Friday 10th – Monday 13th January) predicted based on BES cases of constant scheduled window profiles and the three different scenario-based cases.

3.5.2. Ventilation Heat Loss

Figure a shows the ventilation heat losses within the room throughout the four days. The losses are influenced by the outdoor air conditions on the selected day and also directly with the window profiles given in Figure 8. From the constant open and constant closed results, generally shows the maximum and minimum possible losses.

The results for scenarios 1, 2, and 3 were directly influenced by the window profiles given in Figure 8b which indicates the importance of knowing whether windows are either opened or closed, as it can significantly affect the ventilation conditions within an indoor environment, which therefore justifies the importance of the deep learning detection method. Figure 20b shows the total ventilation heat losses for each scenario.

The ventilation heat loss achieved was solely based on the consideration of the window opening behaviour. However, other contributing factors such as the wind direction, velocity, airflow performance would also have a large impact on the indoor air quality, airflow performance and also the amount of ventilation losses via the opened windows. These contributing factors would be considered within the future development of the approach towards the design of the response system that would be integrated with building controls to enable the achievement of effective operations of building HVAC system.

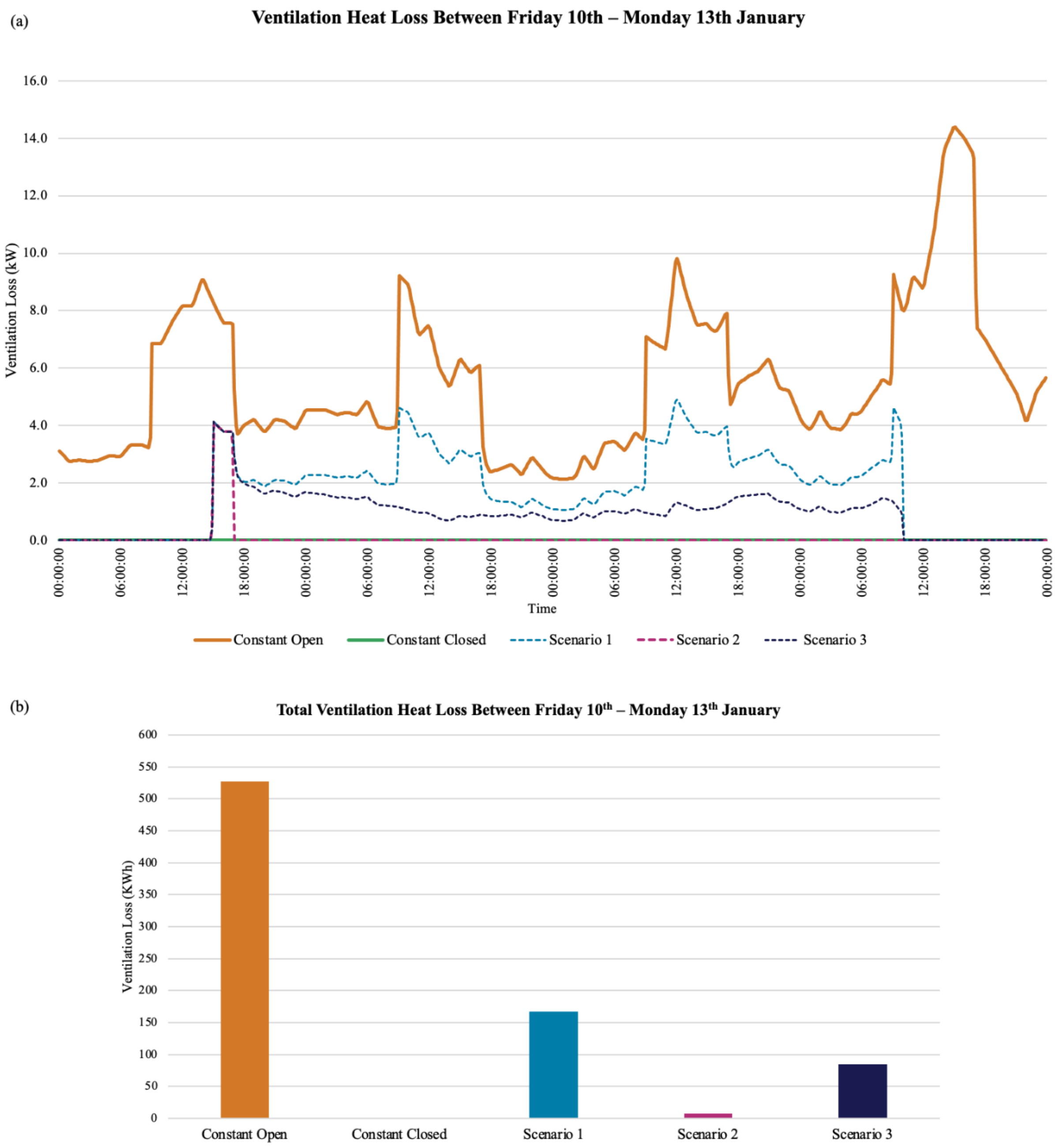


Figure 20. Building ventilation heat loss (Friday 10th – Monday 13th January) predicted based on BES cases of assigning constant scheduled window profiles and the three different scenario-based cases. b). A comparison between the building ventilation losses.

4. Conclusion and Future Work

The present study introduces a data-driven deep learning framework for the detection and recognition of window openings within a typical university building to minimise unnecessary energy usage. A Faster R-CNN model was employed and trained for the classification and detection of windows. The deep learning framework was evaluated using the detection within the selected lecture room in the case study building. The detection and recognition of windows formed the DLIP, which was compared with 'Actual Observation' profiles.

The deep learning framework was evaluated using the detection within the selected lecture room in the case study building. The detection and recognition of windows formed the DLIP which was compared with 'Actual Observation' profiles. To analyse the model detection performance, two experimental tests were performed. Correct detections were achieved for over 95% of the time, with an average detection accuracy of 97.29%. This initial result showed the capabilities of this framework for detecting and recognising the conditions of the windows.

Using BES, the selected room was modelled and simulated to assess the potential impact of the proposed approach on the building energy demand. Results show the assumption of windows being constantly opened can provide an over-prediction of the heating load by up to 208% or the assumption of windows being constantly closed can result in an under-prediction by up to 57%. To further analyse the impact of the DLIP and window detection approach, a typical four-day (Friday – Monday) period was simulated based on three scenarios.

For Scenario 1, leaving the windows open during the entire period led to a total heating load of 239kWh. In Scenario 2, the deep learning method was used to assist the detection of the opened windows and notification was given to either the occupants or the building manager who closed the windows one hour after the lecture was finished. This resulted in the total heating load to decrease by 139kWh. In Scenario 3, adjusting the setpoints based on the detection data led to a much higher reduction in heating loads.

Further developments will be carried in the proposed future works. The deep learning framework can be optimised by adding more training data to improve the detection accuracy with modifications to the deep learning model architecture. Moreover, a streamlined transfer of the data obtained from the deep learning model to the building profile generator would be necessary. It would provide a direct and automated adjustment of setpoints for the HVAC system based upon the detection results. Whereby, the framework would be enhanced to enable direct detection of windows that feeds data to an actual building control system. Future works would also consider the exploration of how the information of the window condition can also be provided to the user or control the openings (for the case of automatically controlled windows) to optimise the indoor air quality and comfort during occupied periods.

As shown in Figure A1, a combination of occupancy [50, 52] and window detection can be evaluated and to improve the model performance, a series of test will be conducted to allow the approach to effectively be able to work under various types of building spaces along with different environmental conditions and settings.

Acknowledgements

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Nomenclature and Abbreviations

AI	Artificial intelligence
AWS	Amazon Web Service
BEMS	Building energy management systems

BES	Building energy simulation
BMS	Building management systems
CABE	Commission for Architecture and the Built Environment
CIBSE	Chartered Institution of Building Services Engineers
CNN	Convolutional Neural Network
CO2	Carbon Dioxide
DL	Deep learning
DLIP	Deep learning influenced profile
FN	False negative
FP	False positive
HVAC	Heating, ventilation and air-conditioning
IESVE	Integrated Environmental Solutions Virtual Environment
IoT	Internet of Things
NHS	National Health Service
MV	Mechanical ventilation
N	Negative
NV	Natural ventilation
P	Positive
R-CNN	Region-based Convolutional Neural Network
U	U-value (W/m2K)
UK	United Kingdom
T	Temperature (°C)
TN	True negative
TP	True positive

Appendix

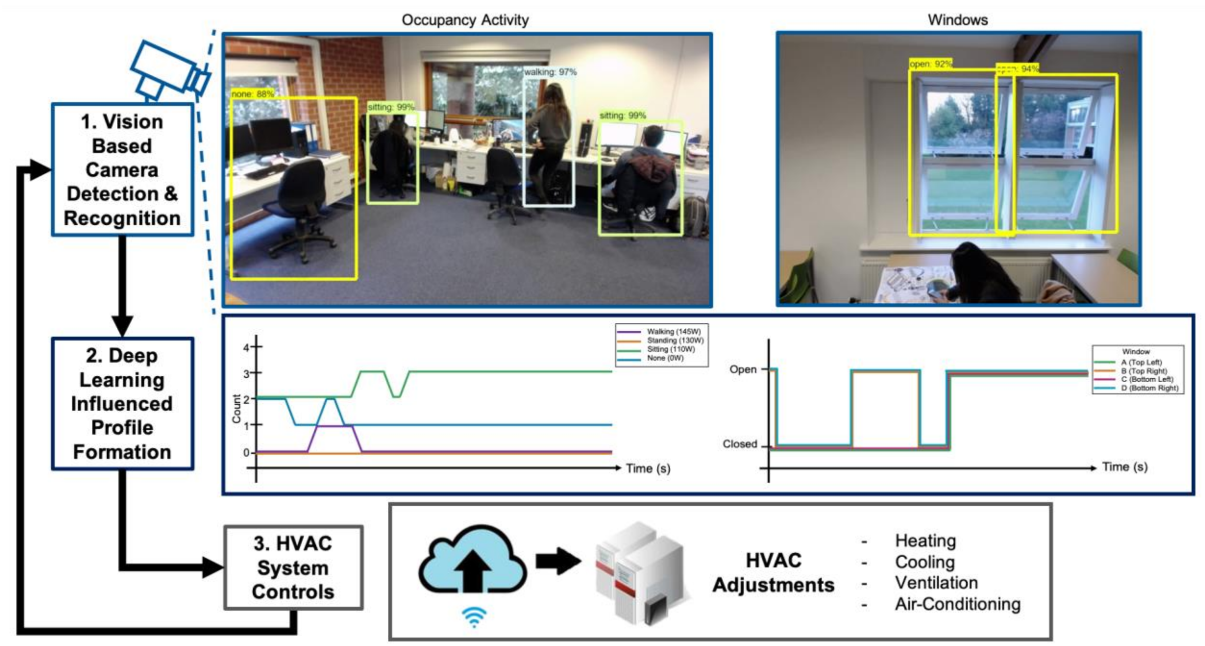

Figure A1. Application of the window detection model with other occupancy-based detection models to provide real-time data in form of various deep learning influenced profiles to inform the controls of building HVAC systems.