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Deep Learning-based Occupancy Behaviour Approach Towards the Improvement of the Indoor Air Quality Within Building Spaces

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ABSTRACT

This study presents a vision-based deep learning approach for detecting and recognising occupant' activities and window opening behaviour to help control the heating, ventilation, and air-conditioning (HVAC) system according to space's actual thermal and ventilation requirements. A convolutional neural network (CNN) model was developed, trained, and deployed to a camera for real-time detection. The results of an experimental test within the case study building indicated an overall detection accuracy of 92.72% for occupancy activities and 87.74% for window operations. Real-time detection and recognition provided the generation of the deep learning influenced profiles (DLIP) used as input for building energy simulation to evaluate the impact of the approach on energy demand and indoor air quality. The present work assesses the importance of the proposed approach for predicting indoor air quality and comfort while optimising building HVAC operations to provide an effective demand-controlled ventilation strategy.

Keywords: Deep learning, building energy management, window and occupancy detection, HVAC systems, building energy performance, indoor air quality

NOMENCLATURE

Abbreviations	
ANN	Artificial Neural Network
BES	Building Energy Simulation
CNN	Convolutional Neural Network
DLIP	Deep Learning Influenced Profiles
HVAC	Heating, Ventilation and Air-Conditioning
IAQ	Indoor Air Quality
ML	Machine earning
UK	United Kingdom

1. INTRODUCTION

One of the highest energy demands comes from the building sector, about 40% globally [1]. HVAC is an important contributor to the total building energy demand [2] and, on average, accounts for over 50% of demand in the West [3]. Regardless, ventilation is an important component providing clean and fresh air inside indoor spaces. Good indoor air quality (IAQ) ensures the health and safety of occupants while providing a conducive environment for carrying out necessary tasks [4,5]. The recent pandemic has highlighted the importance of IAQ, to which the HVAC industry has responded with various innovations and guidelines, including its rational use [6]. This can help prevent the spread of pathogens while also ensuring judicious energy usage.

Apart from pathogens, indoor pollutants include various oxides of Carbon, Sulphur, Nitrogen etc., and chemicals like radon, VOCs, ozone, toluene etc. While sources are quite diverse, ranging from stoves, cigarettes, office equipment, cleaning activities, etc. Even outdoor pollutants contribute to indoor IAQ [7]. An effective ventilation system ensures that their concentration remains below the recommended level. In recent years various sensors have emerged to monitor the pollutant level in indoor space [8]. Monitoring can help determine the source and strength of the pollutant, and the data can be fed into the HVAC system to take necessary action. Some models, including machine learning algorithms, have also been developed to forecast IAQ based on meteorological parameters and indoor measurements [9]. Such preventive models may further create an effective means to provide a comfortable indoor environment.

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With the development of data mining methods, especially the recent growth in deep learning neural networks, advanced control and management of HVAC systems can be achieved. The emergence of data-mining methods contributes to three main control strategies for HVAC systems: (1) building energy load prediction [10,11]; (2) HVAC system operation pattern recognition [12,13]; (3) fault detection and diagnosis [14,15]. Within the scope of building energy load prediction for this study, a great number of previous studies focus on the estimations of cooling/heating load and electricity load to achieve an optimal and timely response of HVAC control for the load variations. Paudel et al. [16] proposed methods for predicting heating load using a support vector machine (SVM) for low energy buildings where the heat transfer between the internal spaces of these buildings and the ambient environment is slow. Besides, Fan, Ding and Liao [17] evaluated and compared five data-mining models for forecasting cooling load for a case study library and found that multiple nonlinear regression models indicated the best forecast accuracy and less training data requirements and computational power with the other four models. In addition, Amber et al. [18] tested and compared five building electricity consumption forecast models and indicated that artificial neural network (ANN) demonstrated the lowest mean absolute percentage error in predicting electricity consumption for a case study office building.

The initial approaches introduced by [19,20] consisted of a framework approach that utilises vision-based deep learning techniques to provide a real-time understanding of occupancy behaviour within a building space allows effective building and HVAC system controls designed to enhance building energy performances. However, the recent pandemic suggests the importance of the achievement of good indoor air conditions.

2. METHOD

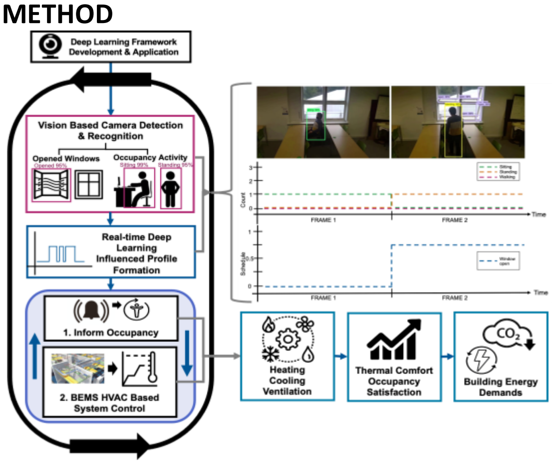

Fig 1 Overview of the framework approach.

This present study builds upon the framework design by developing the approach to improve indoor air quality within indoor building spaces (Figure 1). Similarly, the method consists of 2 parts. Part 1 focuses on developing and implementing the proposed deep learning framework, while Part 2 uses a series of different building energy simulation (BES) cases to analyse the whole framework approach under common scenario-based situations.

2.1 Deep Learning Method

To form the vision-based detector, an image-based training and testing dataset were established. It consisted of images of common occupancy behaviour within an indoor office and lecture spaces, including sitting, standing, and walking. With window opening as the most common natural ventilation strategy used in places with temperate climates such as the United Kingdom, to enable the detector to assist towards the conditions of indoor air quality, images of opened windows were also gathered. All images were pre-processed by using the software, LabelImg to highlight each image's specific region of interest. For most cases (such as the images shown in Figure 2), multiple labels were assigned by highlighting a bounding box around each occupant, and on each of the gaps of the windows across all sides.

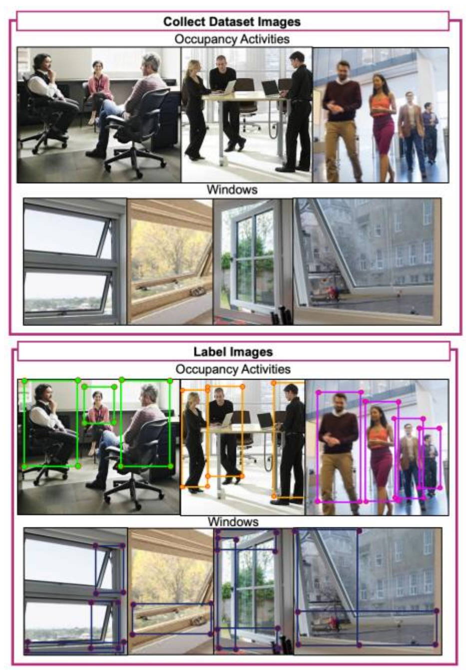

Fig 2 Example images gathered from Google Images to form the image datasets, along with the examples of how images were manually labelled to highlight the specific region of interest.

A model from the TensorFlow detection zoo was selected and applied to allow real-time detection and recognition. This assisted the pipeline configuration of the model used to train the desired detector. The TensorFlow Detection Model Zoo consisted of a collection of detection models pre-trained on various common image-based datasets. The COCO-trained model of Faster R-CNN (With Inception V2) was selected. Two models were configured and trained separately, with one model for occupancy activity detection and the second for window detection. Once both models were successfully trained, they were combined and deployed in a single AI-powered camera, and a validation of the trained models was performed using a set of still images located from the testing dataset.

2.2 Application of the Deep Learning Method

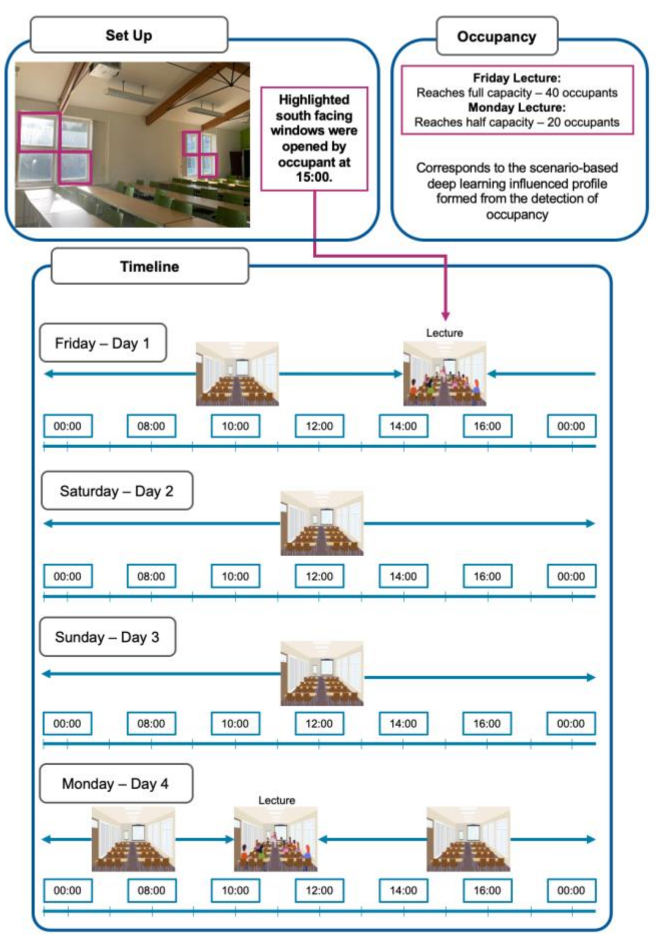

Fig 3 Setup and timeline of the 4-day test scenario within the selected lecture room during a typical week.

To assess the effectiveness of the framework approach that could potentially be applied to buildings, scenario-based building energy simulation cases with different operational profiles for heating, cooling, ventilation, occupancy, and windows were simulated to provide results in terms of internal heat gains, ventilation losses, energy demands and thermal comfort. A 4-day test scenario representing days during a typical weekday and weekend within a lecture room located on the first floor of the Marmont Centre at the University of Nottingham (University Park Campus, Nottingham, UK) was used to support the testing of the proposed deep learning vision-based approach (Figure 3). The building was assumed to be naturally ventilated and is integrated with a central heating system. The selected room has a floor area of 96.9m^2 with dimensions of 12.75m x 7.6m and a floor to ceiling height of 2.5m. Furthermore, Nottingham, UK weather data file was used for the simulation. The infiltration rate value was assumed constant for the air exchanges with 0.5 air changes per hour. The windows were assumed to have a top hung window opening with an openable area of 50% and a maximum openable angle of 45°.

Three scenario-based cases were created (Figure 4). The first case represented the conditions where the building and HVAC systems operated based on predefined or fixed schedules. It includes set heating and cooling profiles to maintain an indoor temperature of 21°C during occupied hours, the assumption of static occupancy profiles where occupants were assumed to be constantly sitting (performing average sedentary activities, represented as Typical Occupancy 1) or to be constantly walking (performing high emission activities, represented as Typical Occupancy 2) during building operational hours, along with window profiles of either constantly opened or closed.

The second and third cases represented when both occupant's activities and window conditions were detected and recognised using the integrated vision-based approach. The detection of occupancy activities aided the adjustments of the operations of the building HVAC. The heating setpoint temperature of 21°C was only set when occupants were detected in the lecture room. While the windows were detected as opened at around 15:00 on Day 1, the system response allowed the building users to be informed about the window condition. The second case represented the situation where the 'inform occupancy' response was operated and the building manager was informed, so the windows were closed at 17:00 (1 hour after the end of the lecture). However, the third case represented the situation where the building users or manager did not respond to the notification made, and the building HVAC controls made a direct response by switching off the heating system when no people and opened windows were detected. Furthermore, since this is a real-time based approach, continuous operation of the framework would further suggest the adjustment of the HVAC operation and informing building users about window conditions to define the number of windows that should be opened would be dependent upon the number of occupants within the room, and the indoor room temperature.

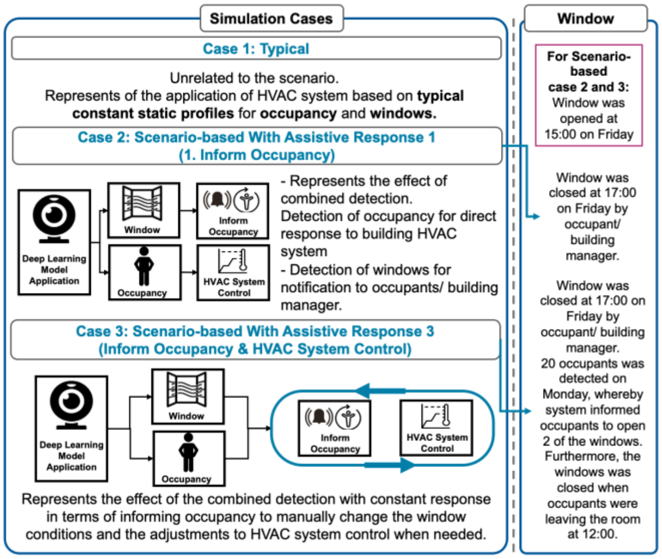

Fig 4 Description of the different simulation cases based on the different system responses.

3. RESULTS AND DISCUSSION

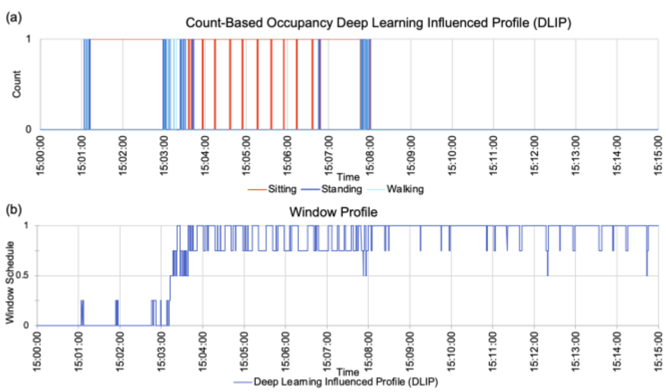

Fig 5 An example generated Deep Learning Influenced Profiles (DLIP) for a). occupancy and b). windows during an experimental test conducted within the selected case study building.

The trained models were validated using a set of still images located from the testing dataset. An average accuracy of 94.04% for sitting, 91.43% for standing, 92.70% for walking and 87.74% for opened windows was achieved. This suggests that the models have been effectively trained and can be used for real-time detection. It should be noted that during the real-time detections, images of the detection are not stored. Instead, deep learning influenced profiles (DLIP) which consists of the data about the number of occupants performing each of the selected activities and the number of opened windows, were recorded for the assistance of response based on informing occupancy and the operations of the HVAC system controls. Figure 5 presents an example of a formed DLIP for occupancy activity (Figure 5a) and windows (Figure 5b). The results show that error still occurs with times of incorrect or missed detection, leading to inaccurate predictions made. However, this will be improved in future works.

Since this is a vision-based approach that requires a camera to perform the following detections, limitations in terms of obstruction can ultimately affect the performance of such an approach. Furthermore, other factors including the room, indoor lighting levels (very low or very high lighting intensities) and at times when lots of glare through windows would have a significant effect upon the performance of such approach. It can result in inaccurate detection of occupants and their actions towards the window conditions to not be identified. Hence, optimisation of the deep learning model to adapt with the ability to perform extensive detection under more infrequent conditions was proposed to further enhance the desired approach.

Figure 6a presents the distribution of heat gains across the simulated period in terms of the use of Typical Occupancy Profiles 1 and 2. It provided benchmark values to represent static occupancy profiles employed within conventional systems in buildings. As shown, this was compared with an example DLIP generated through the application of the vision-based deep learning approach. The lecture room was unoccupied for most of the time, and only a small number of occupants were present for a few hours, which resulted in a predicted occupancy gain of 16.6kWh. This suggests that if the HVAC was operated based on the assumption corresponding to these typical profiles, it could significantly overestimate the indoor heat gains. Therefore, this indicates the importance of such an approach to recognise whether a room is occupied or unoccupied, along with the knowledge of the type of activities performed by occupants at a given time.

Based on the scenario cases, the amount of ventilation heat losses achieved was influenced by the indoor-outdoor conditions and the number of opened windows. The results shown in Figure 6b were directly influenced by the window profiles generated from the detections made due to occupancy behaviour. Hence, this indicates the importance of knowing whether windows are either opened or closed, as it can significantly affect the ventilation conditions and the air quality within an indoor environment.

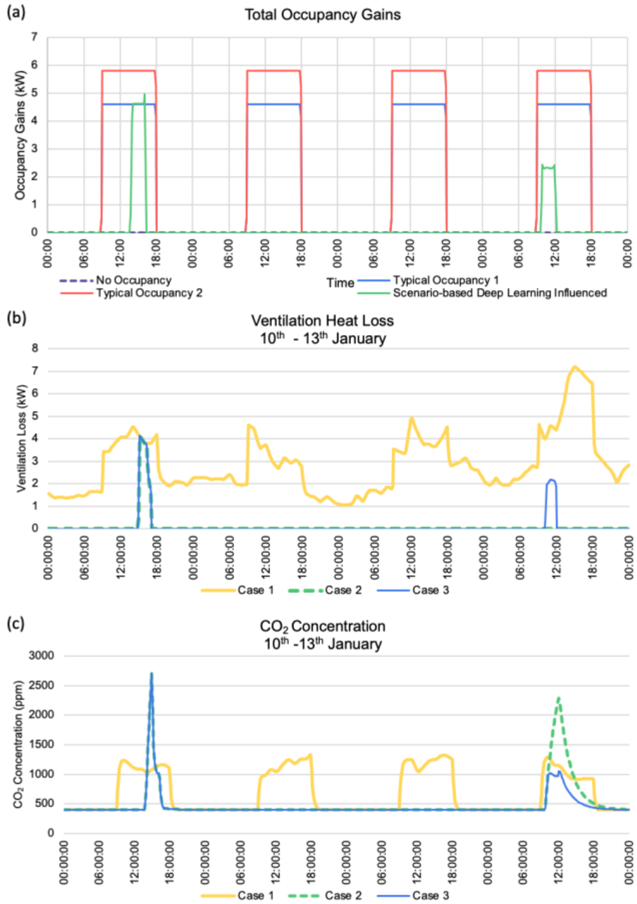

Fig 6 Comparison of the building energy performance results in terms of (a) occupancy heat gains (b) ventilation heat loss and (c) room CO_2 concentration across time during the different scenario cases.

The indoor air quality can be assessed in terms of the room CO_2 concentration levels. Generally, CO_2 levels in rooms that are below 1,000ppm were assumed to be fairly adequate, and anything above this level would indicate the room is highly polluted. This can affect occupancy productivity and increased result of the danger to human health. Figure 6c presents a comparison of the distribution of the CO_2 concentration for the three selected cases. Although a lower ventilation heat loss was achieved for Case 2 during the lecture period in Day 4, it also led to very high CO_2 concentrations levels peaking at 2,288ppm when the occupants did not open the windows. In Case 3, both the number of occupants and windows open were considered in the decision-making process of the control system. It assumed that 2 windows were opened during the lecture period as per the recommendation by the system. This resulted in the CO_2 concentration reducing from 2,288ppm to approximately 1,000ppm. Although the air quality is still not optimal, it can be further improved by enabling the system to suggest occupants for the room to be more naturally ventilated by having more windows opened or to increase the fresh air rates further, if mechanically ventilated.

4. CONCLUSION AND FUTURE WORKS

This present study proposes a data-driven deep learning framework for detecting and recognising occupancy activity and windows. The data generated can be used to make real-time adjustments to the HVAC system operations and provide notifications to building users and managers to minimise unnecessary energy usage and effectively manage the indoor air quality. A Faster R-CNN model was developed and trained using an image-based dataset to enable the detection and recognition of occupancy behaviour. The models were integrated and deployed to an AI-based camera. During the detection, real-time data about the number of occupants performing each of the selected activities and windows open were generated and used to form the deep learning influenced profile (DLIP).

Building energy simulation was performed with various scenario-based cases to assess the deep learning approach and provide insights into how the proposed detection method can enable HVAC systems to adapt and respond to occupancy's dynamic changes. The case study building was modelled, and 3 different scenario-based cases were considered. The cases focused on the application of different response-based solutions. Results indicate that the deep learning approach can reduce the under or overestimation of occupancy and proposes a demand-controlled ventilation strategy that enables the adjustment of the fresh-air intake based on the understanding of occupancy within a building space.

Incorporating the proposed framework with existing building sensors would enable better prediction of the heat gains, ventilation demands and indoor air quality. Future work includes using other numerical-based techniques to verify the proposed approach and provide further assessments of the CO_2 level distribution within the building spaces. The location of the occupants, supply air diffusers and windows can influence not only the energy and ventilation performance but also the CO_2 concentration, which may vary within an occupied space. Hence, it is necessary to develop an approach that can predict the real-time spatial distribution of CO_2 in a room while the occupancy patterns; natural and mechanical ventilation strategies continuously vary throughout the occupancy period. The information will help the control strategy decide and adjust the ventilation level in each zone or alert the occupants to adjust specific openings manually. The performance of the proposed approach will be compared with existing solutions such as CO_2 sensors.

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