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Deep learning occupancy activity detection approach for optimising building energy loads

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ABSTRACT

The main aim of this paper is to develop a vision-based deep learning method for real-time occupancy activity detection and recognition to help the operations of building energy systems. A faster region-based convolutional neural network was developed, trained and deployed to an artificial intelligence (AI)-powered camera for the application of real-time occupancy activity detection. Initial experimental tests were performed within an office space of a selected case study building. The detection provided correct detections for the majority of the time (97.32%). Average detection accuracy of 92.20% was achieved for all activities. Building energy simulation of the case study building was performed to assess the potential energy savings that can be achieved. The impact of using the typical schedules and deep learning influenced profiles (DLIP) were assessed. The work has shown that the generation of the real-time DLIP from the ability to enable prediction and generation of real-time occupancy activity-based internal heat gains data can inform building energy management systems and controls of the heating, ventilation and air-conditioning (HVAC) for a more accurate and optimized operation.

Keywords: Artificial intelligence, energy management, occupancy detection, activity detection, HVAC system, deep learning.

NONMENCLATURE

Abbreviations	
AI	Artificial intelligence
BES	Building energy simulation
CNN	Convolutional neural network
DLIP	Deep learning influenced profile
HVAC	Heating, ventilation and air-conditioning

1. INTRODUCTION AND LITERATURE REVIEW

The built environment sector is responsible for up to 35% of the global energy use and energy-related emissions [1]. Reducing the energy consumption of buildings requires innovative methods. Solutions such as occupancy-based controls can achieve significant energy savings by eliminating unnecessary energy usage.

A significant element affecting the usage of these energy consumers is the behaviour of the occupants [2]. For instance, rooms in offices or lecture theatres are not fully utilised or occupied during the day. While the HVAC systems which operates based on a fixed set point schedules assumes maximum occupancy. The use of fixed set points in combination with varying occupancy patterns could lead to rooms frequently being over- or under-conditioned. Peng et al. [3] have shown that those average daily occupancy rates were rarely over 60%, in particular in single-person offices. While equipment or appliances in offices can be kept in operations during the entire working day, irrespective of the patterns of occupancy [4]. This indicates the need for the development of solutions such as demand-driven controls that adapts to occupancy patterns in real-time and optimise HVAC operations while providing comfortable conditions. Shih [5] have shown that the integration of occupancy information into the HVAC operation can lead to significant energy savings.

Information on real-time occupancy patterns is central to the effective development and implementation of a demand-driven control strategy for HVAC [6]. Several sensors and technologies [7] can be used to measure and monitor real-time occupancy. This includes motion sensors, environmental sensors,

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wearables and Wi-Fi sensors. These have shown the capabilities of strategies in sensing occupancy information through the count and location of occupants in spaces and aid demand-driven control systems. However, there is limited research on sensing the actual activities performed by occupants which can affect the indoor environment conditions. The activities of occupants can affect the internal heat gains (sensible and latent heat) in spaces directly [8] and indirectly [9]. This suggests the need for a solution to enable accurate understanding of occupancy activity levels to provide greater understanding of the heat emitted by occupants for better estimation of the building heating and cooling requirements. A potential solution is to use artificial intelligence (AI) based techniques. This includes a computer vision based approach based on deep learning techniques to detect and recognise the activities of occupants [10].

Several works [11, 12] have been developed using on vision-based deep learning methods to identify human activities. Studies attempted to improve the performance of understanding human presence within a building space rather than achieving data to understand occupancy actions to seek solutions towards the minimisation of unnecessary building energy loads. Additionally, no work has attempted to predict the associated occupancy heat emission of both sensible and latent gains. Limited studies performed tests of the proposed vision-based deep learning methods in an actual office environment and assessed its performance in terms of energy savings and indoor environment quality. Finally, the heat emission profiles generated can also be used as input for building energy simulation (BES) tools which can increase the reliability of results since unpredictability of occupant behaviour is one of the parameters which creates difficulties in BES. Hence, the study aims to develop a vision-based deep learning method for real-time occupancy activity detection and recognition.

2. METHOD

The development of the proposed framework has three main sections. Section 1 is the development and application of a deep learning model for occupancy activity detection and recognition. The model is based on a trained and validated convolutional neural network (CNN) which is deployed to an AI-powered camera. Section 2 is the formation of the deep learning influenced profiles (DLIP) using the live occupancy detection. The DLIP can be fed into building energy management system and controls of the building HVAC system to make adjustments based on the actual building conditions while minimising unnecessary loads. However, for initial analysis, the DLIP profiles were inputted into building energy simulation to identify potential reductions in building energy consumption and changes within the indoor environment.

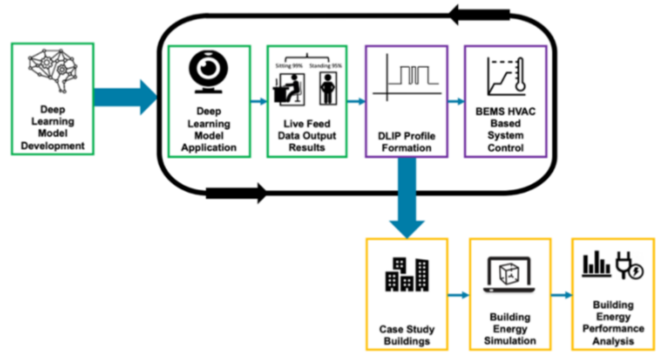

Fig 1 An overview of the proposed framework approach and method

2.1 Deep Learning Method

To enable the application of occupancy activity detection, the general process to establish a convolutional neural network (CNN) based deep learning detection model was followed. Images of various types of occupancy activities were gathered and processed to form the input datasets. Images related to the activities of napping, sitting, standing, walking and none (for no occupant present) were selected. The training dataset consisted of a total of 500 images and 662 labels. For each of the images, manual image labelling was performed by assigning bounding boxes around the specific region of interests.

CNN was selected as the main type of network architecture. CNN is designed to establish applications for computer vision-related tasks with image datasets [30]. It has been extensively used for deep learning object detection projects. The provision of pre-existing open-source deep learning-based models by TensorFlow, such as the CNN TensorFlow object detection API (application interface) [13] was utilised as the base configuration for detection-based applications. This object detection model is part of the TensorFlow pre-defined model's repository; it consists of the incorporation of high levels API's and includes the ability to localise and identify multiple objects in a single image. Therefore, the TensorFlow platform with the CNN TensorFlow object detection API was employed for the development of a suitable model for occupancy detection.

To train the CNN model, the network architecture layers, and training options were defined by applying a transfer learning approach. The COCO-trained model of Faster R-CNN (With Inception V2) was selected and configured to train the desired occupancy activity detection model. The architecture and the pipeline of the model used is given in Figure 2.

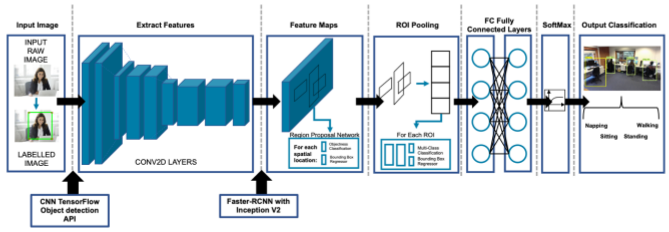

Fig 2 Convolutional Neural Network (CNN) based deep learning model configured for the training of the model for occupancy activity detection and recognition

2.2 *Application of the Deep Learning Method*

An office space located on the first floor of the Sustainable Research Building at the University Park Campus, University of Nottingham, UK was used to perform the initial application of the occupancy activity detection.

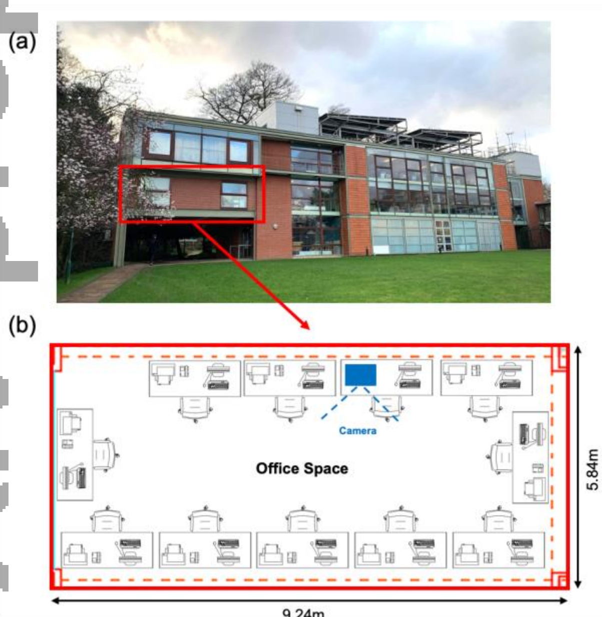

Fig 3 a). Case study building: Sustainable Research Building at University Park Campus, University of Nottingham b). Experimental set up

Indicated in Figure 3a, this office space was also modelled using Building Energy Simulation (BES) tool to further assess the potential of this framework and the impact towards building energy loads. Figure 3b presents experimental setup with the 'detection camera' located on one side of the room to enable the detection of occupancy situated on the opposite side. A 1080p camera with a wide 90-degree field of view was operated using the trained deep learning modelThe building is equipped with natural ventilation along with simple air-conditioning system to provide an internal set point temperature maintained at 21°C. The Nottingham, UK weather data was inputted into building energy simulation model. Standard occupancy profiles with a sensible and latent heat gain of 70W and 45W per person was assigned [14].

A range of activities was performed by the occupants during the rea-time detection experiment. The output data for each of the detected occupants were used to form the occupancy heat emission profiles (DLIP). Figure 4 presents an example process of DLIP formation. Detected occupancy activity condition and the percentage of prediction accuracy were recorded in the DLIP with values corresponding to each of the detected activity heat emission data.

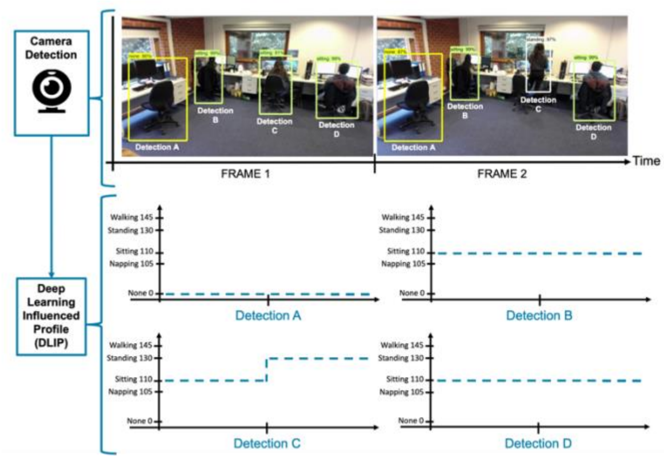

Fig 4 Process of forming the deep learning influenced profile from the application of the deep learning approach for occupancy activity detection and recognition

A building energy simulation tool was used to model the office space with the conditions given above. Building energy simulation consisted of a dynamic thermal simulation of the heat transfer processes between the modelled case study building and the outdoor conditions of the building location. General heat transfer processes of conduction, convection and radiation between the building fabric was modelled. Within and around the selected thermal space of the building, the heat transfer process were also considered within the modelling of air exchange and heat gains. The DLIP building occupancy profile was compared with three other profiles; the actual observation profile and two conventional fixed schedule profiles, Typical Office Profiles 1 and 2. A comparison between the results obtained from these different occupancy profiles enables the analysis of the potential impact of the DLIP profile on the building energy demand. Typical office 1 and 2 represents current building operational systems based on using static or fixed control setpoints. Typical office 1 assumes that the occupants are sitting most of the time during the selected period (sedentary activity), and Typical office 2 assumes that the occupants are walking most of the time during the selected period.

3. RESULTS AND DISCUSSION

3.1 Deep Learning Model Training and Results

The model was trained using the graphics processing unit (GPU) NVIDIA GeForce GTX 1080 with the total losses indicated in Figure 5. Using the Faster-RCNN with InceptionV2 as the training model, results provided training for 102,194 steps and a minimum loss of 0.01007 was achieved. The convergence of the loss function implies that the model has been adequately trained.

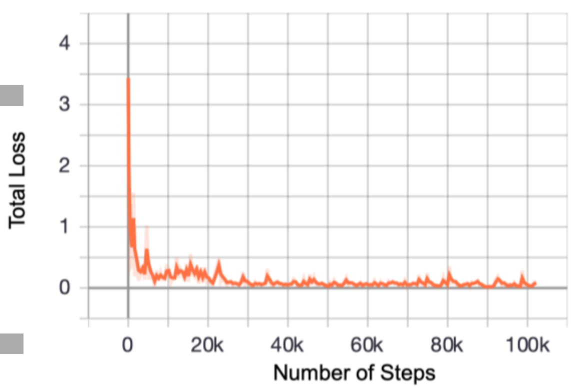

Fig 5 Deep learning model training results of the total loss against the number of training steps

3.2 Experimental Detection and Recognition Results

The trained deep learning model was applied during the experimental test. Figure 6a shows the capability of the method to detect and recognise activities performed by each occupant, along with the detection accuracies. It provided correct detections 97.32% of the time. 1.98% of the time were incorrect detections and 0.70% of the time were no detections. Figure 6b presents the performance of detection based on the selected activities. Accuracies for each activity includes walking with 95.83%, standing 87.02%, sitting 97.22% and 88.13% for none. This shows the capabilities of the deep learning model to recognise the differences between the corresponding human poses. This indicates that the selected model provides accurate detections and highlights the importance of achieving high accuracy for all activity detections to enable the provision of an effective detection approach for building HVAC system controls.

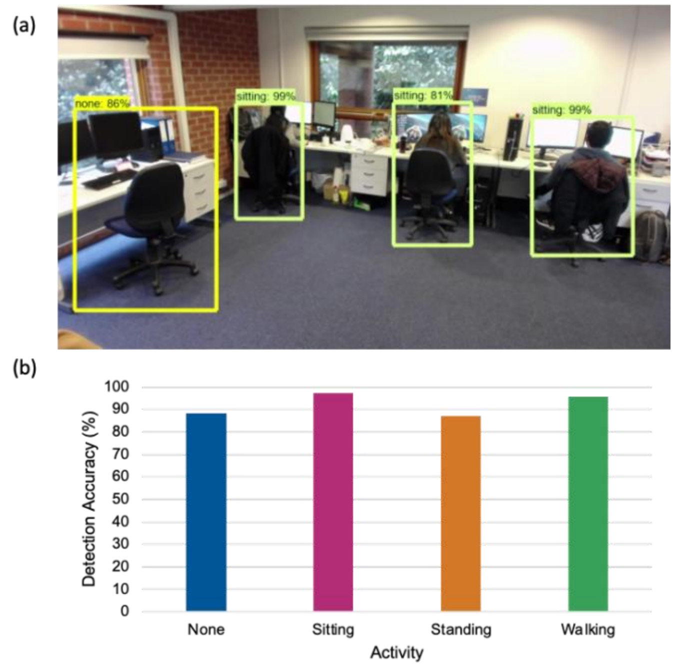

Fig 6 (a). Example detection and recognition result. (b) Detection performance based on each activity

Time-stamped data of the detected activities and accuracy achieved were recorded. The data will be used to provide a better understanding of the occupancy patterns. The results presented in Figure 7, shows the number of occupants performing each activity. This was formerly used to establish the deep learning influenced profile (DLIP) in Figure 8. The initial results showed that the DLIP could enable the detection of various activities, while also the provision of times when there are variations in occupancy heat gains. The DLIP were plotted against the Actual Observation Profile, as the 'actual' occupancy activities performed. A minimal difference was observed between the DLIP and the Actual Observation Profile. The prediction errors were mostly due to the DLIPs alternating between the different activities.

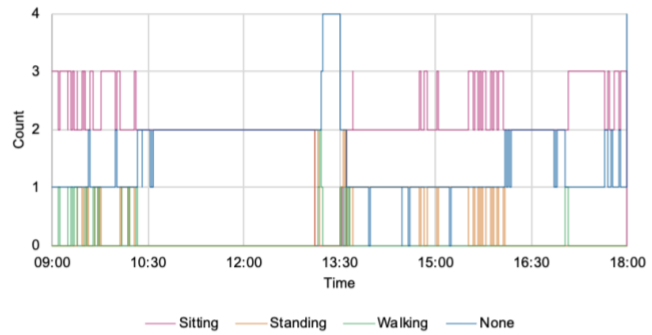

Fig 7 Number of detected occupants performing each activity

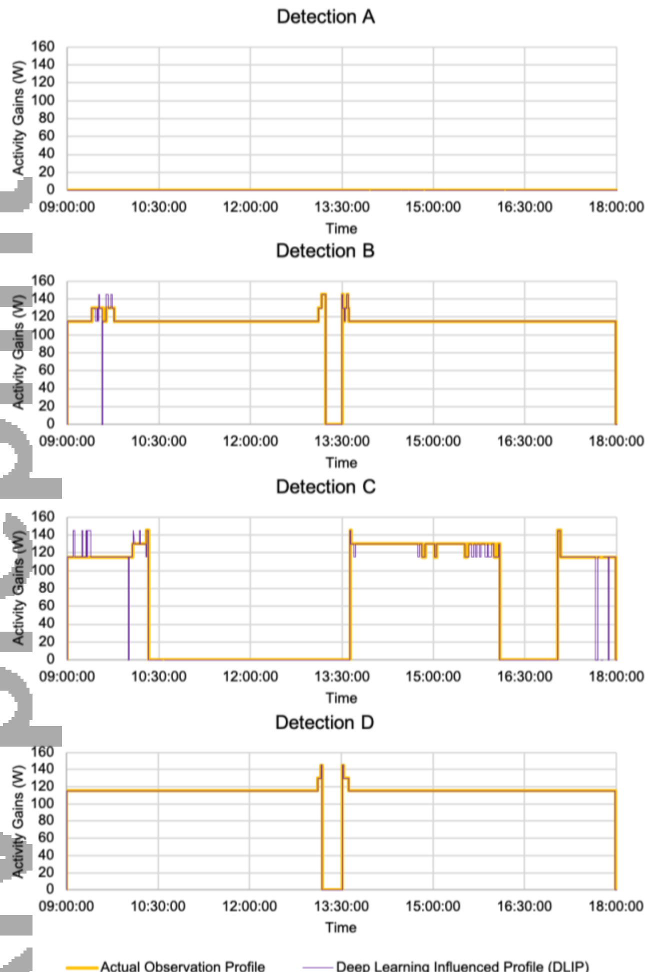

Fig 8 Generated deep Learning Influenced Profile (DLIP) based on the occupancy activity detection results with the corresponding actual observation for the selected one-day detection.

3.3 *Building Energy Performance Results*

Figure 9 presents the total occupancy heat gains. Based on the occupant's actions for this given day, occupancy gains achieved by Typical Office 1 and 2 suggests an overestimation by 22.86% and 54.92% with Actual Observation. This is equivalent to 83.21kWh and 199.846kWh. In comparison, the deep learning approach had a 1.13% (4.09kWh) difference when compared with the Actual Observation.

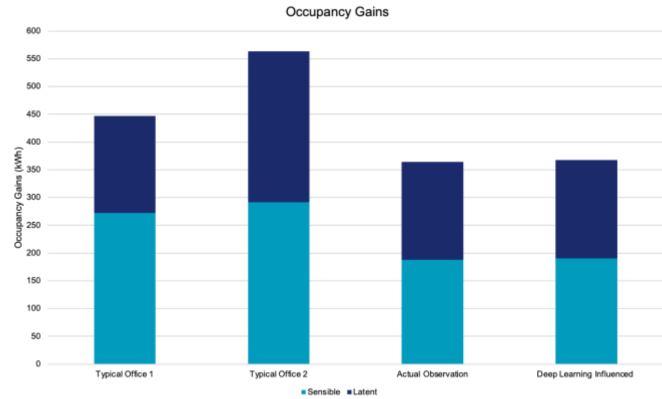

Fig 9 Comparison of the total occupancy gains achieved using the deep learning approach in comparison with the different typical occupancy schedules

Based on the different occupancy profiles, Figure 10 shows the heating demand for a typical winter's day within the office space. The building model simulated with the Actual Observation and the proposed Deep Learning Influenced profiles had a total heating load of 375.54kW and 375.46kW, while the Typical Office 1 and 2 profiles had a total heating load of 372.05kW and 371.81kW. The occupancy heat gains were lower for the Actual Observation and the Deep Learning Influenced as compared to theTypical Office 1 and 2, which reflects upon the predicted heating loads. To enable the provision of adequate indoor conditions to enable occupant satisfaction, it was recognised that for such occupancy patterns within the office space on the selected detection day, greater amounts of heating was required as compared to that of the Typical Office profiles.

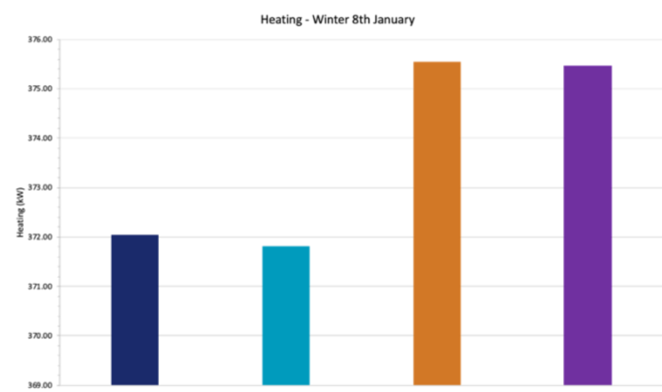

Fig 10 Total heating load for a selected winter's day based on the assignment of the different forms of occupancy profiles

The initial results shows that this approach provides better understanding of real-time occupancy behaviour through the detection of various occupancy activities and can aid BEMS through better estimation of the HVAC requirements.

4. CONCLUSIONS

The study developed a deep learning vision-based multiple occupancy activity approach to enable the generation of real-time data to inform building HVAC system to make adjustments based on the actual building conditions. Based on a faster region-based convolutional neural network, an AI-powered camera was formed for the detection and recognition of common occupancy activities within an experimental test. An average detection accuracy of 92.20% was achieved. The application of the deep learning detection approach provided real-time data to establish the Deep Learning Influenced Profile (DLIP) that provided accurate information to HVAC system controls with the true conditions of occupancy behaviour. Results suggest the use of static occupancy profiles currently used in most building HVAC systems operations and in building energy simulation (BES) presents an overestimation or underestimation of the occupancy heat gains. In the case study presented here, an overestimation of up to 54.92% was observed when compared with the Actual Observation. Based on the initial BES results and set conditions, this is equivalent to 199.846kWh for a single day. In comparison, the deep learning approach had a 1.13% (4.09kWh) difference when compared with the Actual Observation heat gains. Future works consists of further training, testing and analysis of the model and applications within different building types, along with the evaluation of the impact of environmental-based conditions towards the system performance.

ACKNOWLEDGEMENT

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