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Investigation of the Impact of Illumination on Deep Learning-based Equipment Load Detection for Energy Demand Estimation

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ABSTRACT

The main aim of this paper is to investigate the impact of lighting conditions on the detection accuracy of the vision-based equipment load detection approach. The work will be using artificial intelligence cameras to detect equipment information in different lighting levels, employing deep learning method to analyze and generate real-time equipment usage profiles for offices which can be inputted to the demand-based building controls to increase the efficiency of heating, ventilation, and air-conditioning systems. The performance of the developed approach in various illumination conditions was compared by using a building energy simulation tool. The results showed that as compared with the conventionally-scheduled heating, ventilation, and air-conditioning systems, the system with the use of equipment usage profiles conducted by the proposed approach can achieve up to 15% reduction in energy consumption depending on the setup of the camera in terms of indoor lighting levels. The finding indicates that adequate illumination level contributes to the decrease of building energy demand by achieving an effective deep learning approach.

Keywords: Artificial Intelligence; Deep Learning; Equipment Detection; Building Energy; Built Environment

NONMENCLATURE

Abbreviations	
AI	Artificial Intelligence
BES	Building Energy Simulation
CNN	Convolutional Neural Network
GPU	Graphics Processing Unit
HVAC	Heating, Ventilation and Air-conditioning
IESVE	Integrated Environment Solutions Virtual Environment
PC	Personal Computer
PIR	Passive Infrared Sensor
RCNN	Region-based Convolutional Neural Network
RFID	Radio Frequency Identification
Symbols	
n	Number of the specific type of appliance in use
Q_a	Heat gain of the specific type of appliance

1. INTRODUCTION

When designing HVAC system control strategies, equipment heat emission is a significant factor as it is one of the main sources of internal heat gains. For office buildings, more electronic devices are installed within the conditioned spaces, and not all devices are in use during the conditioned period. Hence, accurate equipment usage detection is valuable for energy consumption reduction and carbon emission reduction in the built environment. Generally, there are three techniques of detecting and predicting equipment information including presence, mode, location, identity and count – collecting consumption data from power meters [1], clustering from surveys [2], and forecasting based on occupancy information [3].

Using the collected equipment usage information, the actual thermal demands in different conditioned space can be achieved by adjusting the operation of HVAC systems. Previous studies [4] highlighted that the use of conventional control strategies in office buildings such as the use of “static” operation schedules could cause large energy waste in particular during unoccupied hours. There is a potential for increasing energy efficiency by allowing HVAC systems to dynamically react to the indoor-outdoor environment changes instead of using the fixed or “static” control strategies. However, common equipment loads detection methods discussed as above are unable to provide comprehensive and real-time equipment information necessary for demand-driven strategies. It highlights the importance of the development of strategies such as computer vision and deep learning that can be implemented into building HVAC systems.

A number of studies have developed the models to detect different types of objects with high detection accuracy by employing computer vision and deep learning techniques. For example, Mneymneh et al. [5] created a CNN-based framework that can automatically detect a failure to wear a hardhat using computer vision techniques applied on videos capture from construction sites. The technique achieved high precision and recall rates by 90% and 98.5% respectively. Building up from our previous research [6-8], a computer vision and deep learning-based equipment load detection approach which employs artificial intelligence (AI) enabled cameras is proposed in office building. Because of the use of cameras, illumination is an important factor necessary to be considered.

Due to some factors such as the changing sun direction, weather conditions, and partial or complete obstacle of light source, the illumination conditions of the scene and the target might change greatly [9]. For an indoor scene, although the environment is under-controlled, unexpected light source variations and blockages may occur [10]. In addition, the proposed approach could be classified as a color-based detection method as the displayed colors are the basis of determination of monitor’s status when detecting equipment usage. Hence, varying illumination often causes issues since the observed color and the type of any object which is being presented may be perceived to be different [11]. It’s necessary to investigate the impact of illumination levels as improper lighting conditions can probably lead to poor detection performance of the proposed approach and further cause inaccurate building energy demand estimation, which not only influences the building system design in the early stage but also results in under- or over-consumed energy in order to meet the requirement of thermal comfort.

Currently, the existing techniques have limitations in terms of performing real-time detection and recognition of equipment usage, which can allow the HVAC system to dynamically respond to the changes within the thermal or indoor environment. Although the computer vision and deep learning method could be a feasible way to achieve real-time and automatic response for the proposed system, there are still many challenging problems to solve, such as varying illumination levels in spaces. Therefore, to fill these gaps, the proposed approach in this work was developed using computer vision and deep learning techniques to perform real-time equipment usage detection and prediction to create the heat gain or load patterns. Moreover, the current study gives an insight into the impact of illumination conditions on the detection performance of vision-based detection and recognition technologies.

Based on our previous work, this study investigates the influences of varying lighting conditions on the detection performance of the vision-based equipment load detection approach and the building energy demand estimation in office buildings. To achieve the aim of this study, the Faster RCNN model will be trained and tested by using the dataset clustered from online sources and capture from actual offices to detect electronic appliance usage within the offices. To assess the impact of illumination, the proposed method will be implemented in the case study building using a camera to carry out field tests, under 12 different detection scenarios with various lighting conditions. The accuracy of the selected model for live equipment detection will be assessed by using the collected field data. Then the energy modelling will be carried out for the case study building to compare the effect of using conventional schedules and the proposed approach on the energy demand with the use of a building energy simulation (BES) software.

2. METHOD

In our previous work, a data-driven framework employing computer vision and deep learning methods to enable the system to gain insight into equipment usage information which could be inputted into the building energy management system to attain efficient building energy consumption within the office buildings was developed and the workflow of this framework is shown as Fig 1. In this study, the influences of varying lighting conditions on the performance of this framework and building energy demand estimation.

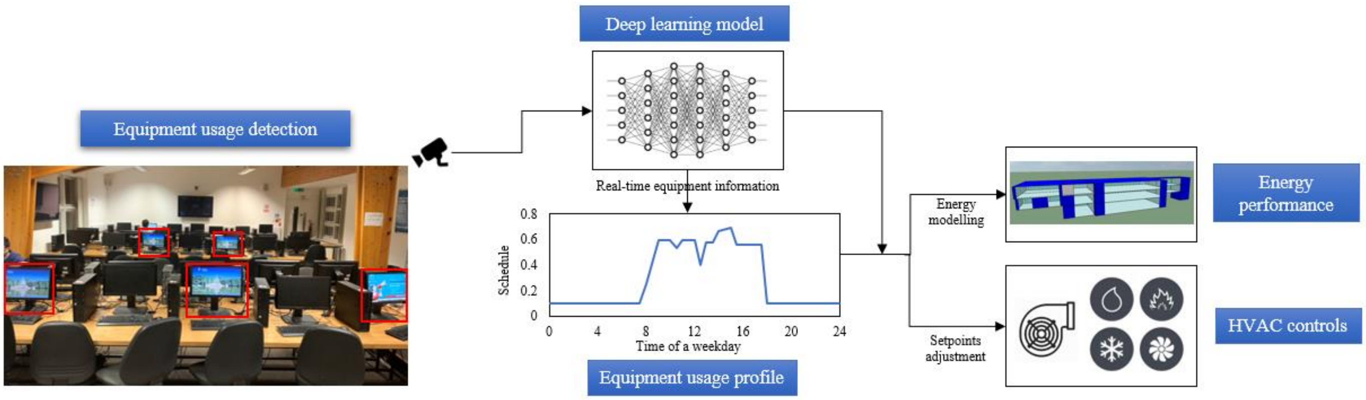

Fig 1 The workflow of the proposed framework

2.1 *Equipment detection and recognition*

Python and TensorFlow object detection API were employed to implement the equipment detection using the CNN algorithm. The workflow of the TensorFlow object detection API can be summarized in six steps. Firstly, a proper pre-existing model is selected to perform the detection task. As Faster RCNN is much faster than other CNN-based algorithms [12] and the Inception module could improve the utilization of the computing resources inside the network [13], Faster RCNN with InceptionV2 is selected as the equipment detection model to achieve the aim of real-time detection and recognition. Secondly, to train a robust detection classifier, at least hundreds of images of the desired objects are required to be collected and then randomly separated into training and testing sets with the percentage of 4:1. With the use of LabelImg, the objects of interest within each image in both sets are labelled. After setting up the label map and configuration file, the model training could be deployed then a newly trained object detection classifier is created. Finally, this new classifier would be implemented via an AI-enable camera in a real office to detect the desired equipment usage information under different illumination levels. To summarize the detection results of the proposed model, precision, recall and F1 score are used to evaluate the accuracy of the object detection algorithm. To carry out the training process, a Graphics Processing Unit (GPU) with 2560 CUDA cores, 1607 MHz graphics clock, 10 Gbps memory clock, and 8 GB GDDR5X memory was used as GPU to run the implementation of this computationally expensive task.

The total heat gains from equipment is the sum of heat emission of different types of office equipment, which can be expressed as Eq. (1). The number of equipment in use is the output of the proposed deep learning-based detection model. As the developed model is not able to detect the practical equipment heat gains so far, the typical values of the heat released which can be obtained from relevant standards will be utilized to calculate the total equipment heat gains in this study.

$$\text{Equipment heat gains} = \sum n \times Q_a \qquad (1)$$

where n is the number of the specific type of appliance in use, and Q_a is the heat gain of the specific type of appliance.

2.2 *Case study building*

The Sustainable Research Building is selected as the case study building, which located in the University of Nottingham. The open-plan office on the first floor was selected as the test space to conduct the experiment in the present study. The experimental setup was carried out and presented in Fig 2. A camera was installed close to the ceiling in the office space and connected to a computer to perform equipment detection using the trained detection model. Within the detectable range, there are eight monitors (heat rate of 50 W) and each monitor is connected with a desktop computer (heat rate of 200 W) [14]. The equipment usage information was gathered every minute for a typical workday via the detection model. According to the clustered information, the actual daily equipment load profile could be created. In order to evaluate the effect of employing the proposed model on the energy performance of the case study building, the created equipment load profile will be inputted into a BES software to simulate the energy demand for this office.

To evaluate the impact of various illumination, twelve scenarios were used with various daylighting and artificial lighting conditions. Within the office, as the most common way to control the amount of natural light entering the space, the curtains were opened and closed to modify the natural lighting levels. Similarly, the artificial lights were on and off to create scenarios with high and low indoor illumination levels. The details of these scenarios are listed in Tab 1. As shown in Fig 2, a lux meter was set on a desk close to both natural and artificial lights to measure the value of lighting levels.

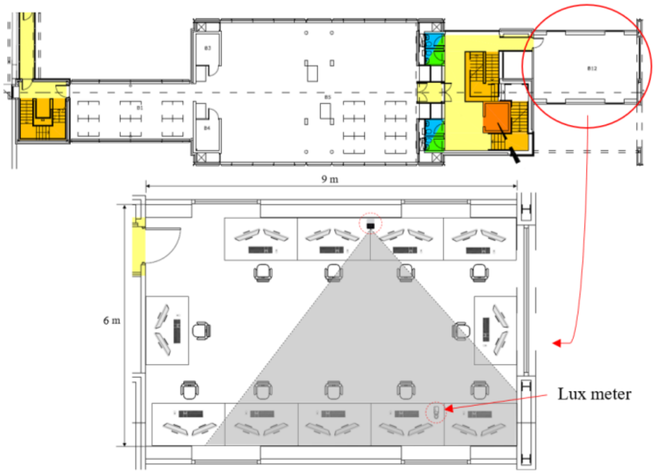

Fig 2 Floor plan and experimental setup of the test room

Table 1 Details of different detection scenarios

Time	Scenario	Artificial lighting	Curtain
Morning	1	X	X
	2	X	O
	3	O	O
	4	O	X
Afternoon	5	X	X
	6	X	O
	7	O	O
	8	O	X
Evening	9	X	X
	10	X	O
	11	O	O
	12	O	X

(O = on/opened, X = off/closed)

To estimate the energy demand of the selected office, IESVE has been employed in this study. The case study building was modelled with several features of the buildings simplified and surrounding buildings and vegetation not taken into account. Several areas of the building were and set as different thermal zones with different operation profiles in the BES tool. To assess the impact of using the proposed approach on the energy demand, the generated equipment usage profiles called "deep learning-based profiles" were inputted into IESVE software to simulate the internal heat gains from equipment in the office space. To evaluate the potential of energy savings by using the proposed approach, a "typical or static heat gain profile", which is commonly used in the field when modelling equipment heat loads or setting the operation of HVAC, was employed for comparison. It is plotted as Figure 12. During the occupied period, the office was set to maintain at 22 °C. The Nottingham weather data file was employed to conduct the simulations.

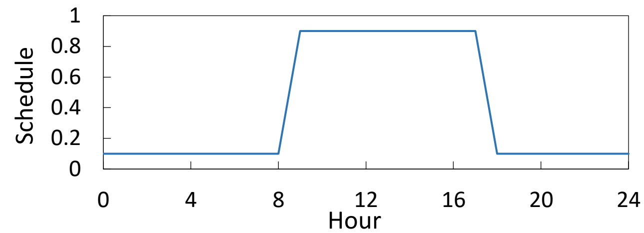

Fig 3 Typical or static daily equipment usage profile

3. RESULTS AND DISCUSSIONS

3.1 Impact of illumination on the detection performance

Due to the use of cameras for the proposed detection approach, illumination is a key factor affecting the performance of a detection task, which was indicated in the above detection results and needed to be considered. In order to investigate the impact of illumination levels, twelve scenarios were designed in terms of the different time of the day and various daylighting and artificial lighting conditions. Tab 2 listed the detection performance under different scenarios. It includes the individual values and average values of Precision, Recall and F_1 score for all detection scenarios. Based on their definitions, Precision and Recall values can indicate the error rate of the wrong prediction and missed detection, respectively. As the results showed (Table 3), the trained detection model has the ability to identify the desired object under different lighting conditions within the detection region with relatively high accuracy (average F_1 score of 0.746). However, some obvious mistakes, such as missed detection and wrong prediction, often occurred. The lack of the amount and variety of collected training data could be the main factor. If a scene newly captured in the detection region have a new feature which is not contained in the training dataset, the model may not be able to accurately detect the desired objects from the scene. Reducing these errors is the next step for model improvement. Moreover, the results indicate that different illumination conditions significantly affect the performance of the detection task. At daytime, higher illumination levels around the object of interest could achieve a better detection performance; while at night-time, the selected model performed better under dimming lighting. In other words, various lighting conditions can probably result in either great or poor detection performance of the proposed detection model, which may further affect the building energy demand estimation. To enhance the detection model to adapt to different lighting condition, sufficient training data must be collected.

Table 2 Detection performance under different scenarios

Scenario	Precision	Recall	F_1 score
1	0.629	0.925	0.706
2	0.578	0.969	0.696
3	0.825	0.975	0.874
4	0.747	0.808	0.764
5	0.543	1.000	0.699
6	0.527	0.986	0.669
7	0.721	1.000	0.823
8	0.758	0.779	0.761
9	0.758	1.000	0.853
10	0.596	0.994	0.732
11	0.608	0.894	0.705
12	0.671	0.694	0.672
Average	0.663	0.917	0.746

3.2 Energy modelling results

Based on the live equipment detection and recognition and typical heat gain values (0.25 kW per computer), the deep learning-based equipment heat gains profile were generated. While the typical or static profile was formed by computing the product of peak equipment heat gains and the schedule presented in Fig 3. The typical and deep learning-based profiles are plotted and compared in Fig 4. As observed, the daily total heat gain predicted by using the deep learning detection method was lower than the heat gains obtained from the typical or static schedule. This was expected for an office room which has varying occupancy rate and PC usage during a workday from day to day, and also over the longer term. In comparison to the typical or static heat gain profile, the deep learning-based profile showed variations in equipment usage corresponding to the specific time of the day which resulted in the increase or reduction of heat gains. It implies that incorporating the proposed method to an HVAC control system can help it assess the real-time cooling or heating requirements of a space. Hence this can help avoid the resulting over cooling or ventilation of spaces, wasting significant cooling or fan power, resulting in energy waste, and even causing discomfort for occupants in some spaces from overcooling. However, as mentioned before, through the comparison between real-world observation and deep learning detection results, there is still a number of obvious errors existing which resulted in the over- or under-estimation of heat emission from equipment. Thus, before applying it to the controller, further optimizations must be carried out.

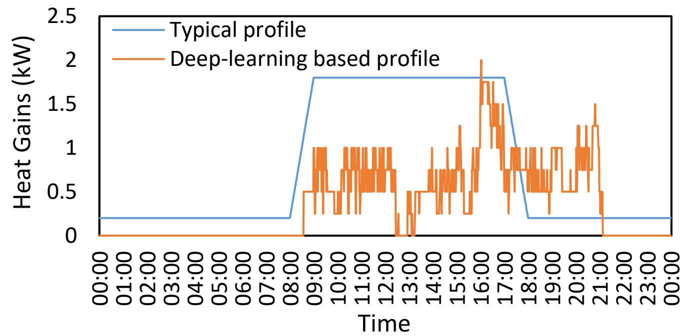

Fig 4 Daily equipment heat load profile

The simulation was conducted using two equipment heat gains profiles – typical and deep learning-based profiles for evaluating the impact of applying the deep learning detection model on the energy consumption. As the case study building is located in the UK, which has a temperate maritime climate, only the period which may need the cooling service (May-Aug) is simulated and evaluated in the initial tests. Fig 5 presented the simulation results of sensible cooling loads based on the typical and deep learning-based profiles. It indicated up to 14.92% potential cooling energy saving to be achieved by using the proposed approach. The initial result highlighted that the deep learning technique for equipment detection could affect energy consumption by making the HVAC system adapt to the actual energy demands in real-time. However, the energy modelling results will vary due to the different buildings and locations and the proposed detection model may perform more effectively in the regions especially with tropical and hot weather where a large amount of cooling is required all over the year. Furthermore, it could also be more effective in spaces where there are many and several types of equipment in use, such as in computer rooms and large open-plan offices. These will be investigated in our future works.

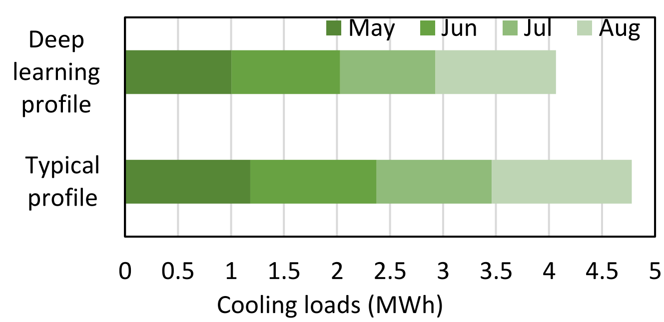

Fig 5 Estimated cooling demand

CONCLUSIONS AND FUTURE WORK

This study investigates the influences of varying lighting conditions on the detection performance of the vision-based equipment load detection approach and the building energy demand estimation. The proposed approach was employed to detect equipment status and predict internal heat emission from equipment using the Faster RCNN model with InceptionV2 in office buildings. The output data is utilized to generate equipment usage profile which can potentially be inputted into the building energy management system to control the HVAC operation based on the actual demand of the conditioned space. Based on the detection results of the tests under 12 lighting conditions, the trained detection model has shown the ability to identify the desired object under different lighting conditions within the detection region with a relatively high accuracy (average F_1 score of 0.746). The results also show that a cooling energy reduction of up to 15% could be achieved by employing the proposed deep learning approach as opposed to using fixed schedule equipment heat gains profile. It indicated that the proper lighting levels contributes to a desirable detection performance and a large potential to reduce energy use in buildings by adjusting the HVAC operation in terms of the actual energy demand. However, further improvements of the current detection method are required to be carried out in future works. To train a robust detection classifier, more images are required which have both desired and random objects within the image and various backgrounds and illumination levels. The desired object in some images should be partially obscured, overlapped with other items, or only halfway shown in the image. Moreover, exploring other object detection models and comparing with the current model would provide more insights on selecting and developing the proposed detection approach.

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REFERENCE

[1] Gandhi, P. and G.S. Brager, *Commercial office plug load energy consumption trends and the role of occupant behavior.* Energy and Buildings, 2016. **125**: p. 1-8.

[2] Wang, Z. and Y. Ding, *An occupant-based energy consumption prediction model for office equipment.* Energy and Buildings, 2015. **109**: p. 12-22.

[3] Gunay, H.B., et al., *Modeling plug-in equipment load patterns in private office spaces.* Energy and Buildings, 2016. **121**: p. 234-249.

[4] Causone, F., et al., *A data-driven procedure to model occupancy and occupant-related electric load profiles in residential buildings for energy simulation.* Energy and Buildings, 2019. **202**: p. 109342.

[5] Eddine Mneymneh, B., M. Abbas, and H. Khoury, *Vision-Based Framework for Intelligent Monitoring of Hardhat Wearing on Construction Sites*. Vol. 33. 2019.

[6] Wei, S., et al. *A Novel Deep Learning Approach for Equipment Load Detection for Reducing Building Energy Demand*. in *11th International Conference on Applied Energy*. 2019. Sweden.

[7] Tien, P.W., et al., *A vision-based deep learning approach for the detection and prediction of occupancy heat emissions for demand-driven control solutions.* Energy and Buildings, 2020. **226**: p. 110386.

[8] Tien, P.W., et al. *A deep learning framework for energy management and optimisation of HVAC systems*. in *International Conference on Sustainable Energy and Green Technology*. 2019. Bangkok, Thailand: IOP Publishing Ltd.

[9] Arad, B., et al., *Controlled Lighting and Illumination-Independent Target Detection for Real-Time Cost-Efficient Applications. The Case Study of Sweet Pepper Robotic Harvesting.* Sensors, 2019. **19**: p. 1390.

[10] Leal-Taixé, L., et al., *Tracking the Trackers: An Analysis of the State of the Art in Multiple Object Tracking.* 2017.

[11] Linderoth, M., A. Robertsson, and R. Johansson. *Color-based detection robust to varying illumination spectrum*. in *2013 IEEE Workshop on Robot Vision (WORV)*. 2013.

[12] John, P., *Review Paper on Object Detection using Deep Learning- Understanding different Algorithms and Models to Design Effective Object Detection Network.* International Journal for Research in Applied Science and Engineering Technology, 2019. **7**: p. 1684-1689.

[13] Galvez, R.L., et al. *Object Detection Using Convolutional Neural Networks*. in *TENCON 2018 - 2018 IEEE Region 10 Conference*. 2018.

[14] Duška, M., et al. *Trend in Heat Gains from Office Equipment*. in *6th International Conference on Indoor Climate of Building*. 2007. Strbske Pleso, Bratislava.

