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A NOVEL DEEP LEARNING APPROACH FOR EQUIPMENT LOAD DETECTION FOR REDUCING BUILDING ENERGY DEMAND

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ABSTRACT

The present work aims to develop a learning-based approach for a demand-driven control system which can automatically adjust the HVAC set points and supply conditions in terms of the actual requirements of the conditioned space. Internal heat gains from typical office equipment, such as computers, printers and kettle will be the focus of this paper. Due to its irregular use during scheduled heating or cooling service periods, an opportunity is offered to reduce unnecessary energy demands of HVAC systems related to the actual use of the equipment and its heat gains, i.e. over- and under-utilization of equipment indicate whether indoor spaces are required to be conditioned or not. The work will be using deep learning enable cameras which can locally run trained algorithms to analyze and take action based on how equipment is utilised in a space real time. This proposed strategy automatically responds to the equipment usage for optimizing energy consumption and indoor conditions. The work will compare the performance of the developed approach with a conventional approach such as the use of static heating or cooling profiles. To highlight its capabilities, building energy simulation was used and initial results showed that while maintaining thermal comfort levels, up to 11% reduction of the energy consumption can be achieved by the proposed strategy in the comparison to conventionally-scheduled HVAC systems, while only focusing on three types of equipment.

Keywords: Artificial intelligence; Built environment; Deep learning; Equipment detection; Energy savings; HVAC

NONMENCLATURE

b_k	Bias for the feature map
f	Activation function
W^k	Value of the kernel connected to the kth feature map
AI	Artificial Intelligence
BES	Building Energy Simulation
CNN	Convolutional Neural Network
GPU	Graphics Processing Unit
HMM	Hidden Markov Model
HVAC	Heating, Ventilation and Air-conditioning
IESVE	Integrated Environment Solutions Virtual Environment
KNN	K-Nearest Neighbour
MEL	Miscellaneous electric load
NN	Neural Network
PC	Personal Computer
PIR	Passive Infrared Sensor
RFID	Radio Frequency Identification
SVM	Support Vector Machines
UK	United Kingdom

1. INTRODUCTION

In recent years, there has been an emphasis on "smart" technology, and everything has been imbued with intelligence. The popularity and applications of using smart technology to create digital and energy efficient buildings have increased and show no signs of slowing down [1]. Artificial Intelligence (AI) technology is used in this study to achieve the goal of smarter built environment and reduce its consumption, up to 36% of global total energy demand. Specifically, the deep learning method which is a form of machine learning based on neural networks. In this study, it is selected to address the limitations of providing real-time equipment usage profiles for Heating, Ventilation and Air-conditioning (HVAC) controls automatically without using costly measurement meters. It performs classification tasks directly from videos, images, text, or sound. It means that the equipment information can be obtained intuitively from the input image or video by using deep learning technique for this study. Instead of traditional machine learning algorithms, deep learning has higher performance in terms of object detection with the increase of the amount of data and extracts features by itself for reducing the complexity of the data [2]. In this study, a streamlined and intuitive technique based on convolutional neural network (CNN) is proposed to automatically process the images or videos captured by cameras and obtain the actual equipment information. The proposed framework of this technique is demonstrated in Fig 1a. It can not only enhance the number of load detection of equipment, but also collect an intuitive and real-time usage profile of office appliances which can be used to assign the operation settings of HVAC.

Therefore, the aim of this work is to develop a real-time equipment usage detection strategy using the deep learning technique to optimize the efficiency of HVAC systems in office buildings. To achieve this aim, this study will cluster datasets from real offices and online sources for the training and testing process. A deep learning model will be developed, trained and tested for detecting various types of equipment such as PC, printer and kettle using the collected data. The deep learning model will be deployed in an actual office environment and carry out an experimental test using typical office cameras. Then, the deep learning model will be validated using the field data and energy modelling will be used to estimate the effect on the energy demand.

2. EQUIPMENT LOAD SCHEDULING AND DETECTION TECHNIQUES FOR HVAC CONTROL

In general, there are three techniques commonly found in commercial buildings to control HVAC by performing equipment prediction – following predefined schedule, or detection – using power meters and analyzing clustered occupant information.

2.1 Follow the predefined schedule

Following the load schedules predefined by relevant standards, such as ASHRAE Standard 90.1 which is shown in Figure 1b [3], is a traditional and widely used method for the prediction of internal heat gains to perform the predictive control for the HVAC systems [4, 5]. In Menezes's study [6], the usage profiles for different equipment in four states (transient, strict hours, extended hours and always on) were established based on the standards set in CIBSE Guide F and TM54. However, for a specific building, it may not be appropriate to apply the typical schedules to the control system because different types of buildings have different functions and features. Moreover, the stochastic and diversified information of the equipment patterns could not be reflected by the typical profiles in reality [7].

2.2 Collecting data from smart meters

As the awareness of energy saving increases, a number of portable devices for measuring and visualizing the energy consumption of equipment are increasingly being utilized. More devices are being developed and employed in buildings for demand-driven controls recently. Power meters, which are installed on the equipment such as personal computers and printers, are frequently used for energy use measurement as investigated by studies [8-10]. However, considering deployment in energy intensive building such as commercial offices, it could be costly and impractical to install smart meters on every appliance.

2.3 Analyze occupant information for equipment usage prediction

In previous occupancy detection studies, many techniques were developed to collect occupancy and thermal state information, which is further processed to predict the equipment usage within a space and then fed into the HVAC control system. Frequently used techniques for occupancy information collection are wireless ambient sensors [11], passive infrared sensor (PIR) [12], WIFI [13], radio frequency identification (RFID) [14], and cameras [15]. In recent studies, machine learning algorithms were commonly selected to implement data analysis, such as support vector machines (SVM), hidden Markov model (HMM), k-nearest neighbor (KNN), and neural network (NN). Ortega et al. [11] proposed an approach to monitor occupancy behavior with the utilisation of the SVM method dealing with the complex datasets of different features gathered from wireless ambient sensors. Although the equipment load is strongly related to occupancy, this method is still limited due to the necessity of the combination with multiple sensors to improve its performance.

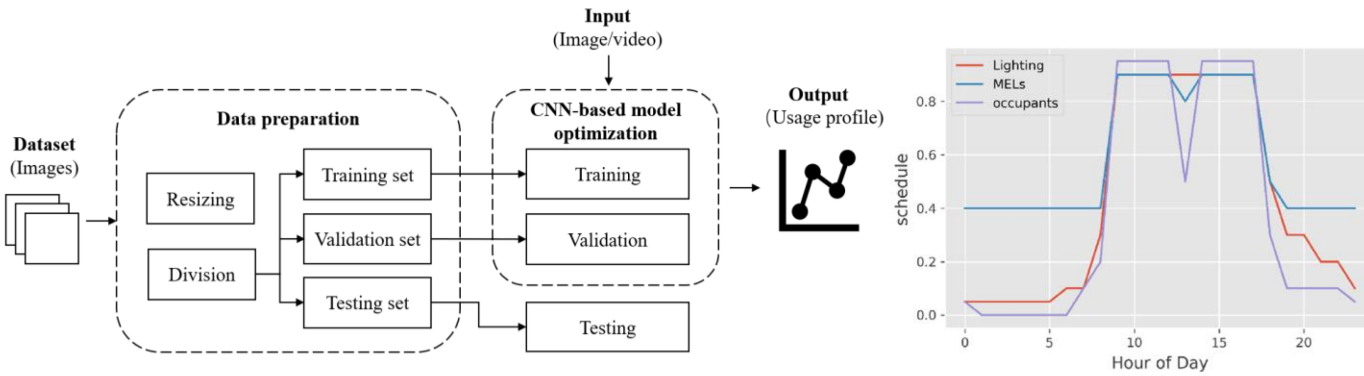

Fig 1 (a) Proposed framework of CNN-based equipment detection (b) ASHRAE Standard 90.1 Internal heat gains schedule [3]

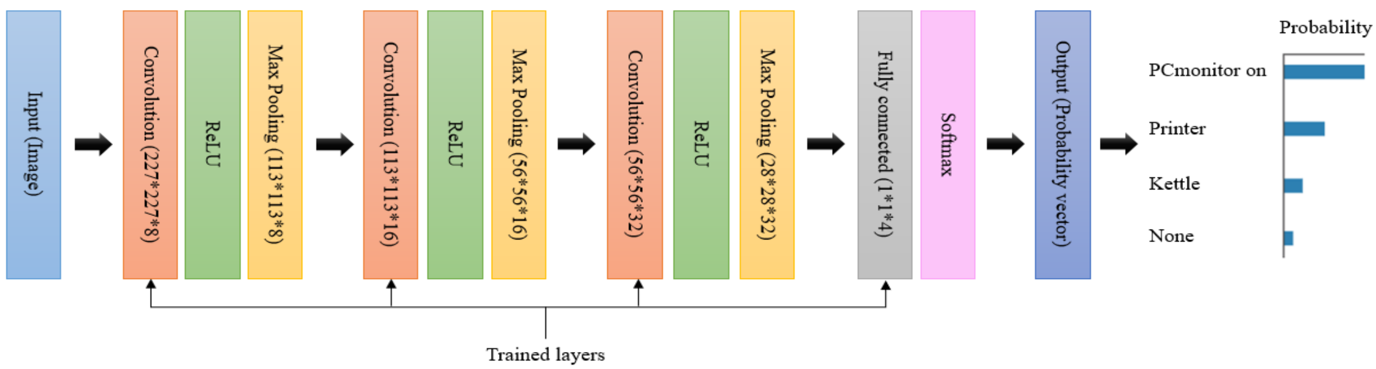

Fig 2 Architecture of CNN equipment detection model with a software layer

2.4 Literature gaps and novelty

As reviewed above, only a few researches explored the detection and prediction of the magnitude and profile of equipment usage in offices. Thus, there are only a few studies which established models which are able to provide comprehensive equipment information for the optimal design, performance simulation and control of building systems instead of using typical profiles. Deep learning method has been popularly used in real-time detecting and predicting applications. Given this circumstance, the present approach in this study was proposed to fill these gaps by using a deep learning algorithm to detect real-time equipment information and generate the load patterns.

3. METHODOLOGY

The simplified implementation framework of the proposed CNN-based deep learning approach in this study is presented in Figure 1a. Firstly, a large number of images is collected, resized if the original size differs from what required, and randomly divided into training, validation and testing sets in a certain proportion. After that, the model is optimized via a number of rounds of training and intermittent validations. Then the model is tested to evaluate the detection accuracy. Finally, the optimized model is utilized to detect the equipment status within a space and generate the usage profile.

3.1 CNN-based deep learning strategy

Before testing the algorithm, a dataset of images of different appliances within offices is required for the purpose of training and validation. Because there is no relevant dataset in previous and current researches, the dataset used in the present study is generated to address it. Through using web search, large amounts of images in different views, scale and illumination are collected from several offices. They are classified into four categories: PC in use, a printer in use, kettle in use and nothing in use.

Fig 2 shows the architecture of the network which is the initial configuration for equipment detection. It is composed of three convolutional layers, a fully connected layer and a softmax layer. A generalization with the reduction of spatial size is carried out on the input data when the input data goes through the architecture. Finally, the type of office equipment presented in each input image is predicted in the softmax layer after the fully connected layer.

The convolutional layers in this structure all have 3*3 image kernels that stride over the whole image, pixel by pixel, to generate 3D volumes of feature maps. The widths of convolutional layers are 8, 16, and 32 respectively. After each convolution operation, a function called ReLU, which is a non-saturated activation function used on the matrixes follows. For each trained layer, a convolutional operation and ReLU in the forward propagation phase is utilized. It is expressed as:

$$X_{ij}^{k} = f(W^{k} * x)_{ij} + b_{k} \quad (1)$$

where f is activation function, b_k is the bias for this feature map, W^k is the value of the kernel connected to the kth feature map. For this study, max pooling is employed for all pooling layers. The softmax function is employed as the predictive layer. Its output demonstrates the probabilities of individual categories of each input. The metric used to evaluate the predictions is the multi-class loss function.

3.2 Case study building and energy modelling

The Mark Group house at the University of Nottingham was selected as the case study building. The initial experiment was conducted in the open plan office with a floor area of 24.5m^2 and a height of 3m on the ground floor shown in Fig 3. Two cameras were set in the office to record the ground truth of equipment usage schedule on a typical weekday. The videos were captured from various locations and orientations in different sizes by a 5-minute time-lapse interval. With the implementation of CNN-based model, the equipment information was gathered from videos.

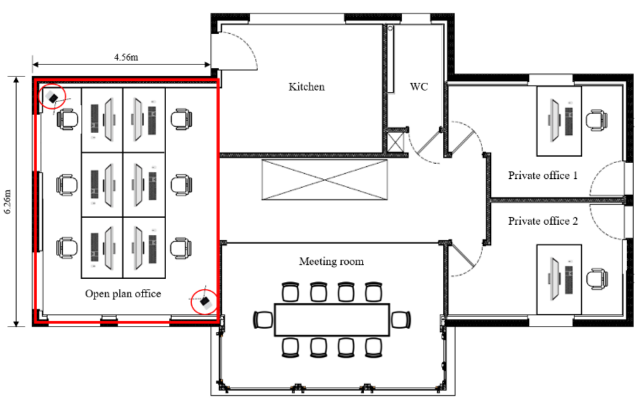

Fig 3 Ground floor layout of the case study building

To test the approach and estimate the energy use from office equipment, a Building Energy Simulation (BES) tool - IESVE was employed with the use of typical profiles and generated deep learning profiles. The U-value of the wall, roof, ground and glazing were 0.25, 0.15, 0.15 and 1.78 W/m^{2}K, obtained from architectural drawings. The window solar heat gain coefficient was 0.46 while the visible transmittance was 0.76. For the air exchanges, infiltration rate value was set to 0.1 ach.

The Nottingham weather data file was used for the simulation. For the "typical office" profile, the building was assumed to be in use from 8:00 to 18:00. To simulate the internal gains from equipment, according to CIBSE Guide A [16], the equipment was set to six computers only because of less use of the printer and kettle. For the "deep learning" profile, the operation period could be directly obtained after implementing the CNN architecture and detecting the usage of each equipment. Due to the ability of detecting different appliances, the equipment was set to six computers, a printer and a kettle with sensible heat gains listed in Tab 1. The office thermal zone was maintained at 22°C during these periods.

Tab 1 Heat gains of office equipment in use [16]

	PC	Printer	Kettle
Sensible heat gains (W)	113	88	12
Latent heat gains (W)	0	0	8

4. RESULTS AND DISCUSSIONS

4.1 Model implementation results

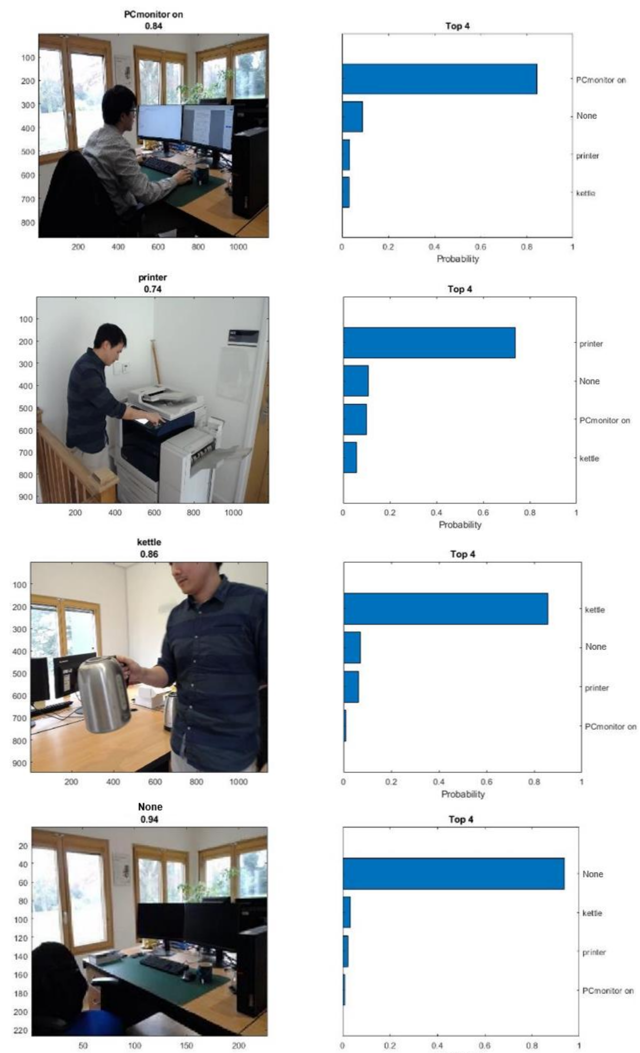

Fig 4 Equipment detection outputs

The proposed model was developed using MATLABR2019. To speed up the training, the CNN architecture, which is a computationally expensive and parallel task, was run on a Graphics Processing Unit (GPU) with 2560 CUDA cores, 1607MHz graphics clock, 10 Gbps memory clock, and 8GB GDDR5X memory. The train accuracy is exceptionally up to 99.6%. However, the test accuracy is 74.6% which is lower than train accuracy. This gap implied that there is an over-fitting occurring in this model. The model has memorized the exact input and output pairs in the training set. And in order to do so, it has constructed an over-complex decision surface that guarantees the correct classification of each training example. That decision surface will include all the coincidences present in the input data, and this will make generalizing to new inputs (test data) work worse.

4.2 Experimental results

After inputting the collected video data to the deep learning model, the probability for each category is computed. The category with the highest probability is selected as the outcome. Example of the representative recognition results for four categories is presented in Fig 4. The outcome in each case is PC, printer, kettle and nothing in use with the highest prediction score of 0.84, 0.74, 0.86, and 0.94 out of 1 respectively. It implies that the proposed model deals well with the identification task. However, the specific angles of view and positions currently affect the accuracy of the prediction that it significantly limits the implementation of detection tasks. One of the main reasons is that the amount and quality of collected data are not great enough. It causes the model not to be able to accurately detect from a fresh input data which may have a new characteristic.

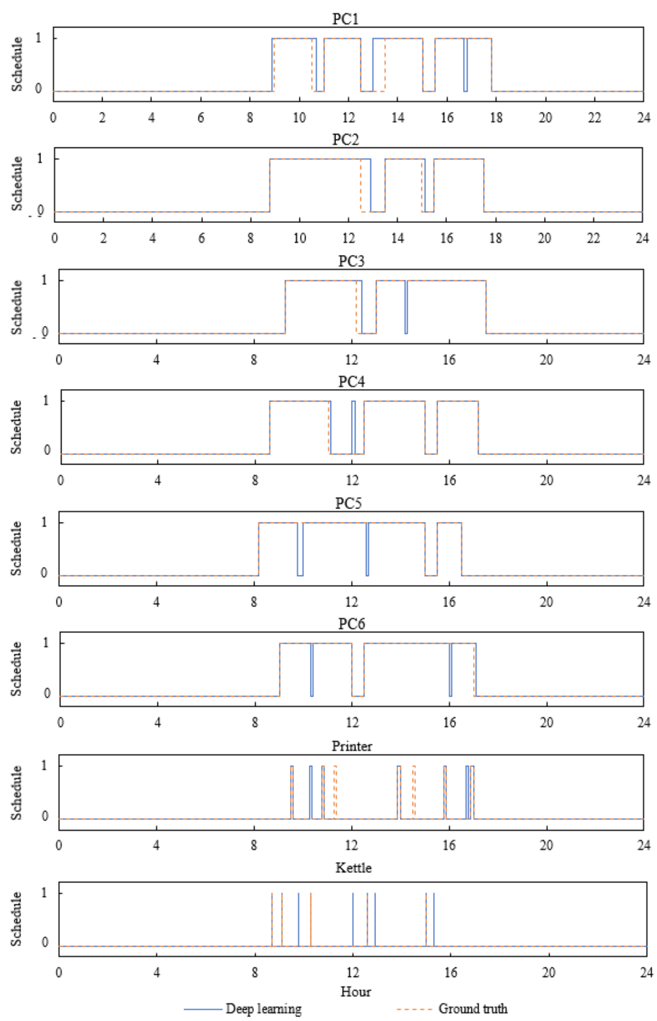

Fig 5 Daily profile of each equipment on a typical weekday

Based on the detection results, the usage patterns for each appliance are created and plotted in Fig 5. The schedules made by ground truth data and deep learning detection results are roughly similar. It illustrates that the detection results of the model do match the real profile of equipment usage. While some apparent errors existed during the period that people were frequently active such as lunchtime. Thus, the stability of the model is required to be improved to tailor the various changes of occupant and equipment status. The process will be automated in the future, i.e. the camera and deep learning model will detect in real time and at the same time process the data automatically to develop a schedule which feeds into the controller of HVAC.

4.3 Modelling results

For assessing the effect on energy consumption of the deployed deep learning model profile, the sensible loads with typical and ground truth profiles were employed for comparison. Fig 6 presented the results of sensible loads based on typical, ground truth and deep learning profiles. These initial results highlighted that the deep learning approach for equipment detection could affect the energy use by making HVAC adapt to actual energy demands in real time. The cooling energy by using deep learning generated equipment load profile was predicted to be 11% lower in maximum as compared with using the typical profile. It should be noted that the

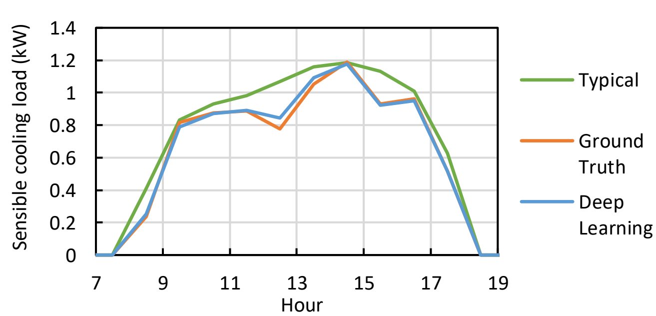

Fig 6 Sensible cooling loads from office equipment

case study building is sited in the region with a temperate maritime climate where the demands for heating are much more than cooling. The proposed model may work more effectively in regions with a warm and hot climate.

5. CONCLUSION AND FUTURE WORKS

In this study, a vision-based approach, which utilizes a pre-trained deep CNNs algorithm, is proposed for detection of the equipment usage in office spaces. The ability of this approach is initially examined based on the collected dataset. It achieved a high accuracy of 99.6% on the training dataset, and an accuracy of 74.6% on the test dataset. Moreover, the approach is applied to detect the equipment profile in a real open plan office and the output is used for energy simulation by IESVE to test its capabilities. The initial results showed that the utilization of the deep learning model for equipment detection could affect the energy use by making HVAC adapt to actual energy demands in real time. The cooling energy by using deep learning generated equipment load profile was 11% lower in maximum compared with using the typical scheduled profile. In practice, this method will use the profile to adjust the setpoint of the HVAC which will result in an increase or decrease of energy loads.

The proposed approach shows significant potential for reducing energy demand in buildings. However, there are some limitations that should be solved in future works. The model is evaluated only using limited dataset. To improve accuracy, using more dataset collected from different types of office and equipment is intended due to the various characteristics in different dataset. Second, an optimal ratio for data division is proposed to reduce the overfitting to narrow the gap between train and test accuracy. Third, a more advanced equipment load detection model based on the present approach, which will be embedded in a camera, is expected which can automatically create real-time usage patterns and send them to a control system. Moreover, examining the performance of the designed model in the regions with a hot climate may be more effective and possible to achieve a larger potential of energy savings.

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