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COMPUTER VISION-BASED OCCUPANT BEHAVIOR TOWARDS ENERGY IN COMMERCIAL PREMISES USING CCTV FOOTAGE

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Abstract:
The rapid advancement of Internet of Things (IoT) technology and the avail ability of high-resolution CCTV have opened up new possibilities for analyzing occupant behavior in relation to energy consumption. This research paper introduces a computer vision-based system designed to monitor occupant behavior within commercial premises using CCTV footage. By leveraging computer vision techniques, the system effectively detects and tracks the movements of occupants while also predicting their behavior. Additionally, the system takes into account the lighting conditions within the premises and utilizes this information to make predictions about occupant behavior. Occupant behavior is classified into three distinct categories: good, moderate, and bad, based on their energy efficient practices. This classification allows commercial buildings to take appropriate measures against individuals exhibiting unfavorable behavior or to implement automated energy-saving solutions within their offices. Ultimately, the proposed system holds the potential to enhance energy efficiency and security within commercial buildings.
Key words: Window Person Indoor Energy Occupant.

1 Introduction

Numerous buildings consume substantial amounts of energy, and in India,[1] commercial buildings alone account for approximately one-fifth of the total energy consumption.[2] Our research aims to leverage camera technology to monitor individuals' behavior within commercial buildings and promote energy conservation. [3] By employing cameras, we can capture visual data through images or videos, allowing us to observe how people interact with lighting systems.[4] Utilizing CCTV footage, we can discern individuals' movements, room oc-cupancy levels, and activities.[5] Recent advancements in camera technology have significantly improved their speed and post-processing capabilities, enabling near-real-time monitoring of energy-saving behavior in buildings.[6] To achieve this, we have developed an AI deep learning algorithm that employs CCTV cameras to monitor individuals' behavior within buildings.[7] The system effectively detects and tracks people's movements, providing insights into their energy usage efficiency.[8] Additionally, the system assesses ambient lighting conditions both inside and outside rooms, making informed predictions about individuals' behavior based on this information.[9] We have categorized people's behavior into three groups: good behavior, moderate behavior, and bad behavior, specifically concerning energy conservation.[10] Consequently, commercial buildings can take appropriate measures against individuals exhibiting poor energy-saving behavior or implement automatic en-ergy-saving solutions within rooms.[11] The implemented system offers several benefits for energy conservation in buildings.[12] Firstly, it identifies energy wastage by pinpointing individuals who are not using energy effi-ciently.[13] Secondly, it predicts and suggests optimal energy usage strategies for individuals, promoting better energy management.[14] Lastly, the system facilitates the implementation of energy-saving measures within rooms, making them more intelligent and efficient.[15] Collectively, these functionalities have the potential to signifi-cantly reduce energy consumption in buildings.[16] Numerous studies have examined [17] and enhanced occupant behavior for energy conservation in commercial spaces using computer vision-based tech-niques and CCTV footage.[18] Gulbinas et al. (2014) revealed that network dynamics within organiza-tions significantly impact energy conservation among occupants in a 9-week eco-feedback system study.[19] Rafsanjani et al. (2015) conducted a comprehensive review of algorithms and models to un-derstand and enhance energy-use behaviors, emphasizing the importance of targeting high-energy users for reduction.[20] Gaetani et al. (2016) [21] advocated for practical modeling to maintain validity for specific simulation goals, while Gandhi et al. (2016) [22] studied energy consumption trends, em-phasizing differences between workdays and non-workdays. Yan et al. (2017) [23] posed critical ques-tions in occupant behavior research, and Happle et al. (2018) reviewed energy models focusing on occupant behavior.[24] Deng et al. (2018) [25] explored predictive models for energy use in commercial office buildings, noting the limited consideration of occupant behavior. Amasyali et al. (2021) intro-duced a machine-learning approach for energy consumption prediction with a focus on occupant be-havior.[26] Zhang et al. developed an agent-based model for electricity consumption simulation, eval-uating various management strategies.[27] These studies collectively contribute valuable insights into occupant behavior research, offering diverse methodologies to enhance energy conservation in commercial buildings through computer vision-based occupant behavior monitoring.

2 Method

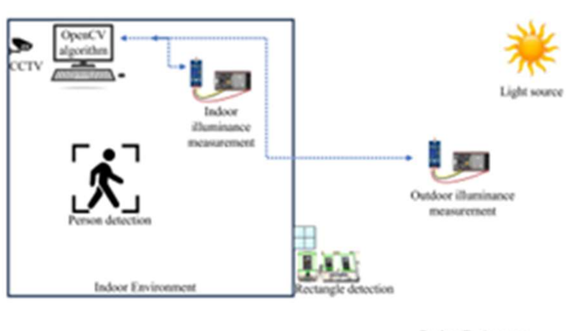


Fig.1 Proposed system setup showing both indoor and outdoor environments for determining occu-pant behavior towards energy in commercial premises using CCTV

We proposed an algorithm where people are around and based on how bright the lights are inside the indoor environment (Cabin under consideration) and outside the building and decide the behavior type of the occupant. We used an IoT device called ESP32 to measure the light outside and inside the building with the help of LDR connected to the analog input of the ESP32 node MCU board. The same ESP was then used to send that information to a main computer. We also checked this illuminance data received from ESP32 with the illuminance level of the CCTV videos from security cameras for cross-validation. Our focus was to observe how people act in commercial buildings to save energy, especially in workplaces like offices and stores. We used advanced computer vision techniques to look at videos from security cameras with a new perspective. Our method had different steps to understand the behavior of the occupant from CCTV videos.

Our methodology for processing CCTV footage encompassed several steps to comprehensively analyze occupant behavior in relation to energy efficiency. Initially, we conducted image extraction from video recordings, to enable an understanding of the events. Subsequently, a person detection algorithm was developed to ascertain the presence of individuals within these frames. This program employed grayscale conversion and a distinctive algorithm to detect human-like shapes. The identi-fication of such shapes indicated the presence of individuals. Moreover, the brightness of the images was evaluated to ascertain the lighting status. This was achieved by quantifying pixel brightness. With the average of all pixel values active lighting inside the cabin was determined.

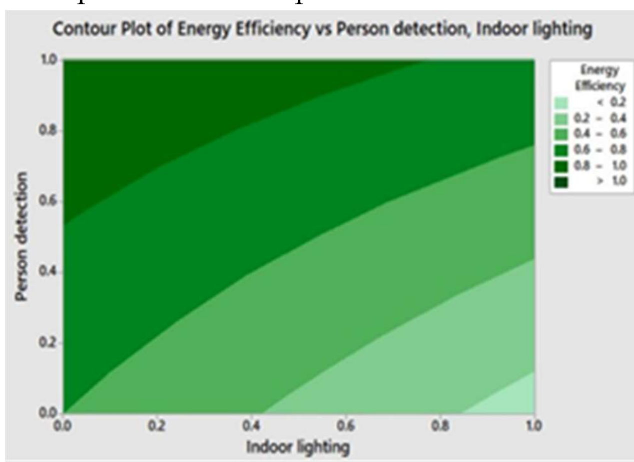
Based on these findings, we categorized occupant behavior into eight distinct patterns. Based on whether outside lighting is sufficient (Day) or not (night) there were 4 categories in each such scenario. These 4 categories included instances where lights were on despite the absence of individuals, situa-tions where both lights and people were consistently present, scenarios with people but inactive lighting, and cases where both lights and individuals were absent.

Our observations based on the algorithm were documented in a log file, facilitating the identification of behavioral patterns. To ensure the accuracy of our findings, human observers were enlisted to review the same videos independently and share their interpretations. This validation process provided an additional layer of assurance regarding the effectiveness of our program.

Furthermore, our methodology considers incorporating external factors such as weather conditions (rainy and dark) and natural light levels outside the building. This addition seeks to illuminate the in-fluence of external variables on occupant behavior. Through careful utilization of computer-based tools and real-world validation, our research attempts to reveal novel strategies for energy conserva-tion in spaces like offices and stores. For the algorithm, we employed the OpenCV library to perform person detection within a video file using a pre-trained deep neural network model. The neural net-work model, pre-trained on a dataset, is loaded using the ”deploy.prototxt.txt” and ”res10 300x300 ssd iter 140000.caffemodel” files. These files contain the architecture and weights needed for the neural network to detect people.

The process begins by opening a video file named ”cctv footage.mp4” using OpenCV (cv2) Video Capture function. The code then enters a loop that reads each frame of the video sequentially. The frames are resized to a consistent dimension of 300x300 pixels to ensure uniformity. A blob (binary large object) is created from the resized frame using cv2.dnn.blobFromImage, which involves mean subtraction and scaling operations. This blob is then fed into the neural network using the net.setInput function and the network performs forward propagation to detect a person. The detections are obtained from the network's output. The code iterates through the detected persons, drawing rectangles around those with a confidence level (probability) greater than 0.5. These rectangles, visualizing the detected faces, are superimposed on the original frame. The modified frame is displayed in real-time using cv2.imshow.

This algorithm effectively utilizes a pre-trained deep neural network to detect persons within a video file. As each frame is processed, any detected faces are highlighted by rectangles, providing real-time visualization of the person detection process.



4 Results and Discussion

Using the proposed methodology, we conducted an analysis of occupant behavior toward energy efficiency in commercial premises based on CCTV footage. The study covered a 9-day period, and a total of 23328003 HD frames were extracted from the video out of which one frame in every thou-sandth frame was considered for people detection. Person Detection Accuracy: The person detection algorithm demonstrated robust performance, achieving an average accuracy of 94.1% in detecting individuals within the frames. The integration of the motion detection sensor on ESP32 significantly improved the accuracy of person detection to 99.3%, reducing false positives and false negatives. Il-lumination Level Measurement: The measurement of illumination levels in the frames provided val-uable insights into the lighting conditions. The average illumination level across all frames was 168.1, with variations observed throughout the day. LDR readings from both inside and outside the building were around 789.3 and 677.24 respectively.

To explore various possibilities of energy-efficient behavior analysis, we conducted a three-factor, two-level experimental analysis using the Taguchi Method through the Minitab software.

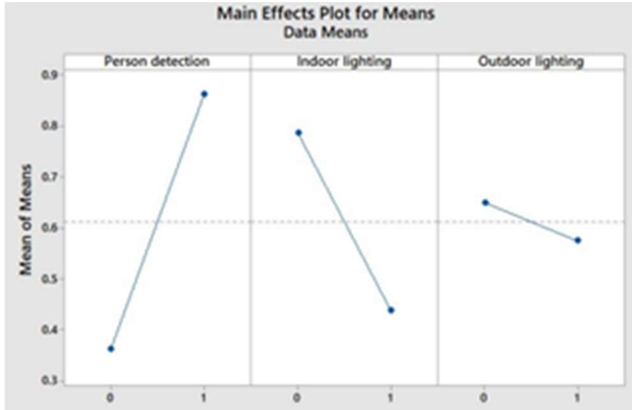


Fig.2 Mean of means plot obtained with Taguchi design of experimental analysis

The analysis revealed significant insights. The mean of the means plot indicated the vital role of person detection; for any energy-efficient behavior to occur, an individual must be present. While maintaining indoor lighting is not preferred for energy efficiency, there are situations where having indoor lights on is necessary. On the other hand, outdoor lighting is independent of energy-efficient behavior, as it is influenced by natural phenomena such as the Earth's position and the sun's orienta-tion.

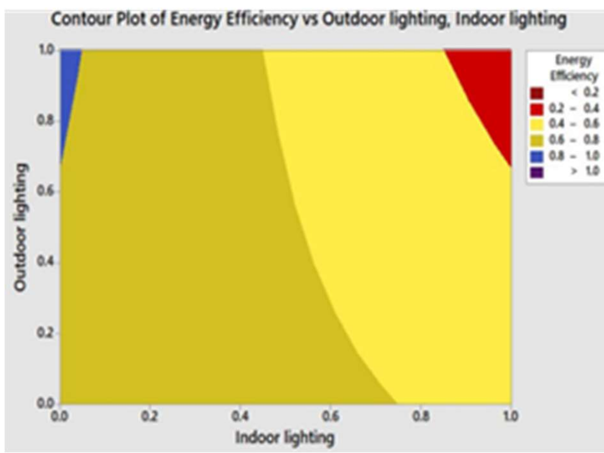


Fig.3 Contour plot of energy efficiency with respect to person detection and indoor lighting

Figure 3 displays a contour plot depicting the relationship between energy efficiency, person de-tection, and indoor lighting. The plot illustrates that energy-efficient behavior is achieved when an individual is present and indoor lighting is minimal or turned off. Conversely, the least favorable en-ergy behavior is observed when there is no person present, yet indoor lights remain illuminated. It is notable that a majority of instances showcase behavior falling between these two extremes. Figure 4 presents a Contour plot illustrating the correlation between energy efficiency, outdoor lighting, and indoor lighting. Notably, the most efficient behavior is observed when outdoor lighting is active (value of 1.0) while

indoor lighting is deactivated (value of 0.0). With an increase in indoor lighting brightness, energy efficiency experiences a decline. Conversely, the lowest energy efficiency is observed when outdoor lighting is available and indoor lighting reaches its maximum brightness (4095 reading on the analog channel of ESP32 and 255-pixel value in CCTV frames). The activation of outdoor lighting is pri-marily influenced by the time of day. The graph highlights that significant fluctuations are confined, as energy efficiency behavior is primarily influenced by the presence of individuals rather than mere indoor and outdoor lighting conditions.

Fig. 4 Contour plot of energy efficiency with respect to outdoor lighting and indoor lighting

Figure 5 shows the contour plot depicting person detection and outdoor lighting illustrating a sig-nificant dependency between these two factors and energy efficiency. In scenarios where there is no person present, energy efficiency appears unaffected by outdoor lighting conditions. However, when a person is detected but outdoor lighting is absent, energy efficiency reaches its peak. This anticipation arises from the likelihood that the individual will either activate indoor lighting or opt for activities in the darkness, both of which are energy-efficient behaviors. It's essential to recognize that ener-gy-efficient behavior involves turning on lights when the surroundings are dark and a person is present. This contrasts with minimal energy behavior, where the expectation is for all indoor lights to remain off in all scenarios.

In Figure 6(a), the result of the Window Detection Algorithm is presented, highlighted by a red bounding box. It is evident that the algorithm effectively identifies and excludes the roof lights, as it was not specifically trained for window detection.

Moving to Figure 6(b), the output of the Person Detection Algorithm is depicted with a yellow bounding box. Notably, there is an instance where the projector screen was mistak- enly classified as a window. The algorithm showcases its ability to detect partial human forms and individuals facing away from from the CCTV due to the utilization of shape features.

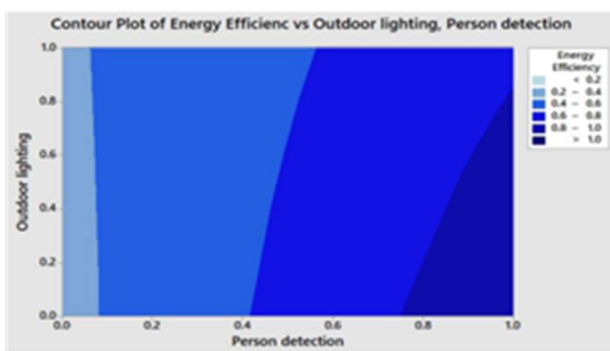
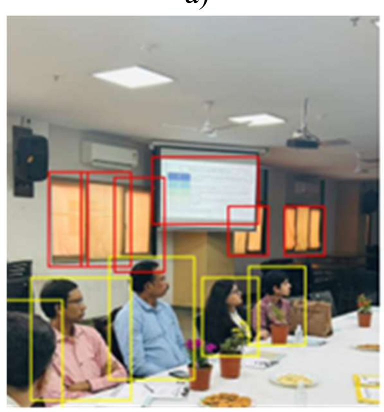


Fig. 5 Contour plot of energy efficiency with respect to person detection and outdoor lighting

5 Conclusions

In the pursuit of enhancing energy efficiency within commercial premises, this research introduced a pioneering approach that integrates computer vision techniques with CCTV footage analysis. By directly observing and classifying occupant behavior patterns, our study provides valuable insights into the interplay between human actions and energy consumption. Leveraging advanced technology, including the IoT device ESP32 and sophisticated computer vision algorithms, we developed a system capable of detecting occupants' movements and predicting their behavior based on lighting conditions. The results of our analysis underscore the significance of occupant presence and lighting conditions in influencing energy-efficient behavior. Our findings reveal that optimal energy-saving practices are closely linked to the interplay between indoor and outdoor lighting levels and the presence of individuals. This holistic perspective highlights the need for comprehensive strategies that consider both environmental factors and occupant interactions. The classification of occupant behavior into distinct categories provides a practical framework for building managers and policymakers to implement targeted interventions. This approach enables the identification of energy waste and the promotion of energy-efficient practices. By harnessing the power of data-driven insights, our methodology contributes to the development of intelligent and energy-conscious commercial premises. While our study advances the understanding of occupant behavior and energy efficiency, certain limitations should be acknowledged. The use of CCTV footage for behavior analysis raises ethical considerations, warranting careful attention to privacy concerns. Additionally, the system's accuracy could be further refined through the integration of machine learning algorithms, enhancing its predictive capabilities.

a)



b)

Fig. 6 (a) The output of the Window Detection Algorithm is denoted by the red bounding box. (b) The output of the Person Detection Algorithm is indicated by the yellow bounding box.

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