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An Intelligent System for Light and Air Conditioner Control Using YOLOv8

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ABSTRACT

High energy consumption in classrooms is a significant concern, often resulting from inefficient lighting and air conditioning systems. Specifically, the problem lies in the lack of automated control mechanisms that adjust energy use based on real-time occupancy data. This study aims to develop and evaluate a system that employs a camera integrated with the YOLOv8 algorithm to detect human presence and optimize energy usage by controlling lights and air conditioning. The system's performance was assessed in three different classroom environments: two large and one small. The system's accuracy for occupancy detection varied from 13.64% to 100%, depending on lighting conditions and room size. Light control accuracy was highest in the classrooms with consistent lighting, reaching 99.77%. Air conditioning control achieved perfect accuracy of 100% in the classroom with a SHARP brand AC, with a maximum remote-control range of 7 meters. These findings indicate that the system's performance is influenced by lighting conditions and room size, with smaller rooms showing better results. The system demonstrates promising potential for reducing energy consumption in classroom settings, thereby contributing to more sustainable energy practices.

1. INTRODUCTION

In recent years, the urgency to address climate change and the rising energy costs have spurred the need for more sustainable and efficient energy management practices. Educational institutions, including universities and colleges, are significant energy consumers, particularly in operating classroom facilities. Several recent studies have shown that buildings account for about 40% of the total energy consumption worldwide, with a significant portion attributed to Heating, Ventilating, and Air-Conditioning (HVAC) and lighting systems [1]. In many educational settings, lights, air conditioning, and other electrical equipment are often left on even when unoccupied classrooms, leading to unnecessary energy waste and increased carbon emissions. This inefficiency inflates operational costs and contradicts the growing global commitment to environmental sustainability.

Given this context, there is a pressing need to develop and implement solutions to optimize energy usage in campus environments. One promising approach is deploying an automatic energy-saving system to detect room occupancy and manage electrical devices accordingly. Such a system can ensure that energy is only used when needed, significantly reducing waste. By focusing on classrooms with high energy consumption, this project aims to contribute to broader sustainability goals, including Indonesia's target of

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achieving net-zero emissions by 2060 [2]. This initiative supports the university's operational efficiency and serves as a model for other institutions looking to implement sustainable energy practices.

Numerous products and research initiatives have been developed to control electrical equipment based on human presence, serving as key references for our project. These existing solutions typically employ sensor technology and motion detection systems for various applications. For instance, ENERLITES products integrate Passive Infrared (PIR) and ultrasonic technology to accurately detect motion, enabling the control of lighting and electronic devices based on room occupancy [3]. Similarly, the TOPGREENER In-Wall PIR Motion Sensor Light Switch is a wall-mounted switch that regulates lighting by detecting the presence or absence of individuals [4].

In another approach, a system designed with the ESP32 CAM uses a PIR sensor to detect motion. It integrates a Wi-Fi module and camera to transmit images to a Telegram bot, functioning as an IoT-based security system [5]. Further research has explored the use of computer vision technology for detecting human presence in classrooms by controlling electronic devices based on occupancy detection, thereby contributing to developing efficient smart buildings [6]. Additionally, the implementation of Arduino and ESP32 CAM in smart homes has demonstrated the potential of IoT in controlling home appliances and monitoring security. These innovations have successfully optimized control and monitoring in various contexts, from residential spaces to classrooms and smart buildings [7].

While these technologies effectively control electrical equipment, many rely primarily on motion detection sensors, which can be limited by environmental factors such as lighting conditions or object movement outside of human presence. Furthermore, most existing systems need to integrate advanced computer vision algorithms, limiting the accuracy of occupancy detection in dynamic environments like classrooms. This highlights the need for more robust and intelligent systems that can accurately detect human presence in real-time for energy optimization, especially in educational institutions where occupancy varies frequently.

Our project addresses this gap by integrating computer vision technology with object detection capabilities using cameras designed for energy optimization in classroom settings. This study aims to develop an automatic lighting and air conditioning control system based on occupancy detection using YOLOv8. The distinctive feature of our system is its ability to automatically manage lighting and air conditioning based on real-time occupancy detection, leveraging the YOLOv8 algorithm for enhanced accuracy. This approach not only promises energy savings but also ensures precision in detecting human presence, thereby optimizing the use of resources. Through this project, we aim to contribute to the development of intelligent systems for energy management, particularly in educational institutions.

2. METHOD

2.1. Theoretical Basis

Occupancy refers to the extent a space or facility is utilized, expressed as a percentage of its total capacity [8]. This measure reflects how much of a place is used compared to its maximum capacity. Occupancy detection systems are designed to identify whether people or objects occupy a room or area. These systems can employ various methods, such as Passive Infra-Red (PIR) sensors, which detect temperature differences between objects and their surroundings [9], [10], [11], [12], [13], [14], [15], and ultrasonic sensors, which utilize the "Doppler Effect" to detect movement [16], [17]. Another advanced approach is computer vision, a branch of artificial intelligence that analyzes and interprets visual information from images or videos, enabling object recognition and motion detection [18], [19].

Object detection is a technique in computer vision that aims to identify specific objects in images or videos. This involves using algorithms and machine learning models to recognize objects and draw bounding boxes around them [18]. An example of an object detection algorithm is You Only Look Once (YOLO), a one-stage object detection method that offers incredibly fast inference speeds, making it highly useful for real-time applications. YOLO and its architectural variants have significantly improved object detection accuracy, making it one of the top choices in various object detection applications [20]. The YOLO algorithm has versions that show its updates. One of the latest versions is YOLOv8, published in 2023. YOLOv8 aims to combine the advantages of many real-time object detectors. This model continues to adopt ideas from CSP in YOLOv5, features fusion methods (PAN-FPN), and the SPPF module. YOLOv8 is also highly extensible and flexible. This framework supports previous versions of YOLO and can switch between different versions, making it easy to compare the performance of various YOLO versions [21].

Other object detection algorithms are Convolutional Neural Networks (CNN), a type of artificial neural network architecture specifically designed to process structured data, especially image and picture data [22]. Another technique in computer vision that can be applied is the Region of Interest (ROI). This technique reduces the problem of high processing time by marking specific areas, allowing for system performance optimization [23], [24]. Several platforms can be used to store data from counting the number of people, including ThingSpeak. ThingSpeak is an Internet of Things (IoT) platform that collects, stores, analyzes, and visualizes data from connected sensors and devices in real-time. In the context of the automatic people-counting system project, ThingSpeak is important in updating and sending notifications regarding the number of people in the target area, enabling real-time decision-making and efficient resource management [25].

2.2. Overview of the System

This system is designed to manage electrical equipment, focusing on controlling air conditioners (AC) and lighting. It converts 220V AC voltage to 5V DC using an adapter and includes a 9V battery to power the infrared (IR) remote control. The system features a 30-second delay for turning off the lights, allowing a brief period before the lights are switched off when the room is unoccupied by people. Lights are turned on in real-time without any delay upon detecting occupancy. For air conditioning, the system can be scheduled to turn on and off based on a predetermined timetable and adjust according to room occupancy, turning off the air conditioner when the room is unoccupied. Additionally, the IR remote has a range of up to 7 meters, enabling users to control the air conditioner from a comfortable distance. These features collectively enhance energy management and user comfort by precisely controlling lighting and temperature.

2.3. System Design

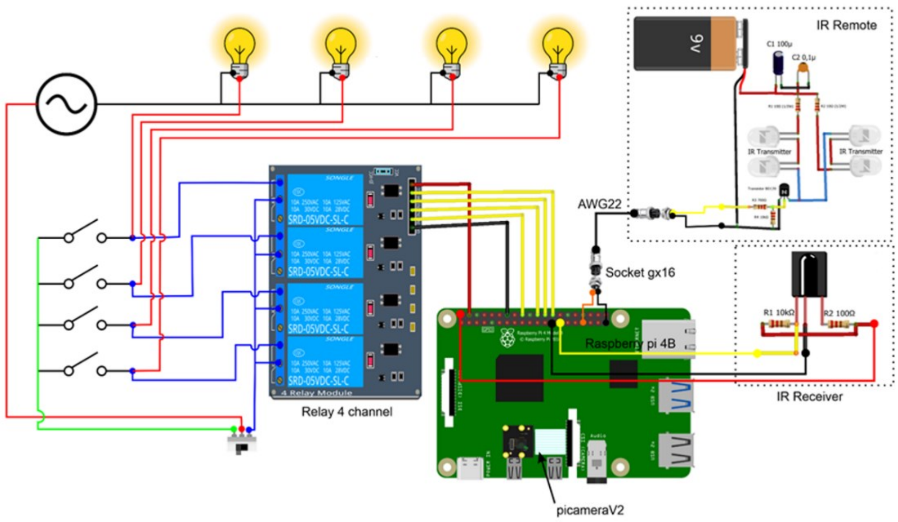


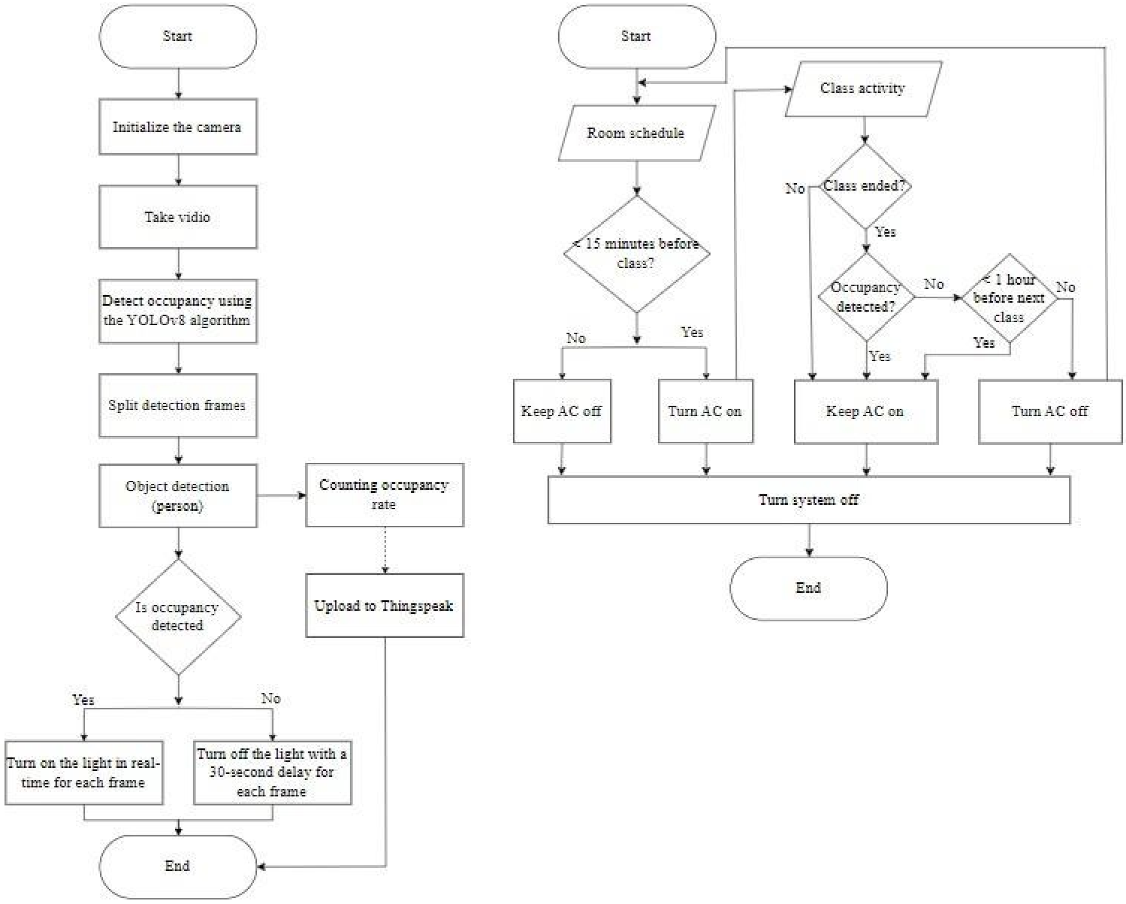
Figure 1. Automated and manual control system

The Raspberry Pi 4B controls classroom lights via a 4-channel relay, using YOLOv8-based occupancy detection from a Camera Module V2. It supports automatic lighting with a manual override and delayed off function. The Raspberry Pi wirelessly manages the air conditioner using stored IR remote codes. The system is powered by a 5V DC adapter and a 9V battery for the IR remote.

Figure 1 illustrates the automatic and manual systems for controlling electrical equipment in the classroom. At the core of this system is the Raspberry Pi 4B, which functions as the central controller for automation. The Raspberry Pi is connected to a 4-channel relay module, which acts as an electronic switch to manage the power flow to the classroom lights. In the diagram, four lights are connected to this relay module, allowing the Raspberry Pi to control whether the lights are turned on or off based on its signals. The Raspberry Pi is also connected to a Camera Module V2, which detects the presence of people in the room using the YOLOv8 algorithm. When the camera detects individuals, the Raspberry Pi sends a signal to the relay module to turn on the lights. Conversely, if no people are detected, the Raspberry Pi will turn off the lights after a preset delay.

The system includes a switch that allows users to toggle between automatic and manual modes, providing flexibility in controlling the lights. In manual mode, a separate switch enables direct control of the lights. Additionally, the system features an IR receiver that captures codes from the air conditioner's remote control. These codes are stored by the Raspberry Pi, which can then transmit them via an IR remote connected through a GX16 socket and AWG 22 cable. This IR remote allows the Raspberry Pi to wirelessly control the classroom air conditioner by sending the stored remote codes. The system is powered by a 5V DC supply connected to the Raspberry Pi, provided through a 220V AC to 5V DC adapter. An additional 9V battery is used to power the IR remote. This setup ensures comprehensive control of classroom lighting and air conditioning.

2.4. System Algorithm



(a) (b)

Figure 2. (a) Flowchart illustrating the occupancy detection and lighting control system using YOLOv8. (b) Flowchart depicting the air conditioner.

As shown in Fig. 2, the flowchart is divided into two interconnected sections, with the first flowchart representing the workflow for the camera and light control. In contrast, the second flowchart focuses on the control of the AC system. Fig. 2(a) shows an occupancy detection and light control system that begins by initializing the camera and then recording classroom video footage. This video is analyzed in real-time using the YOLOv8 algorithm to detect the presence of people. The video is split into individual frames, and the algorithm checks each frame for human occupancy. If occupancy is detected, the lights are turned on to ensure adequate lighting. If no people are detected, the system activates a 30-second delay before turning off the lights, preventing unnecessary flickering from brief absences. Simultaneously, the system counts the occupancy rate based on detection frequency, and this data is uploaded to the cloud

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platform ThingSpeak for remote monitoring and analysis. The process continues in a loop, ensuring optimal energy usage by turning lights on or off based on real-time occupancy.

Figure 2(b) illustrates the air conditioner (AC) control process based on the classroom schedule and occupancy. The process starts by checking the room schedule. If a class is set to begin within the next 15 minutes, the system turns on the AC. If there are more than 15 minutes before the next class, the AC remains off to conserve energy. Once the class starts, the system monitors whether the class has ended. If the class is still ongoing, the AC stays on. After the class ends, the system checks if people are still in the room. If the room is occupied, the AC remains on to ensure comfort. If the room is empty, the system checks the time until the next class. If the next class is over an hour away, the AC is turned off to save energy. However, if the next class is less than an hour away, the AC stays on to avoid the extra energy consumption from frequently turning it off and back on. Finally, when no more classes are scheduled, the system turns off entirely, ensuring efficient energy management throughout the day.

2.5. Performance Metrics

Performance measurement of the system used to assess system performance consists of two main parameters:

1. *Occupancy Detection Accuracy*: Occupancy detection accuracy measures how accurately the system detects the number of people in the room. Data is averaged from the readings uploaded to the ThingSpeak platform. This accuracy is calculated for each trial with varying numbers of people and then compared with the system's readings to determine the accuracy percentage. The accuracy of occupancy detection is calculated based on the absolute error value using Equation (1).

$$ODA = \frac{AO - |AO - DO|}{AO} \times 100\% \quad (1)$$

where:
ODA is occupancy detection accuracy,
AO is actual occupancy, and
DO is detected occupancy.

1) *Confusion Matrix*: We used a confusion matrix to evaluate the system's performance in controlling electrical equipment in the classroom, such as lights and air conditioning. The lighting control system relies on occupancy readings to determine whether the lights should be turned on or off. For this, the confusion matrix compares the system's predictions with the actual presence of people in the classroom. In this context:
   - True Positive (TP): The system correctly predicts that people are present and turns the lights on.
   - True Negative (TN): The system correctly predicts that no one is present and turns the lights off.
   - False Positive (FP): The system incorrectly predicts that people are present and turns the lights on when the classroom is empty.
   - False Negative (FN): The system incorrectly predicts that no one is present and turns the lights off when people are in the classroom.

   On the other hand, the confusion matrix is more complex for air conditioner control because it must consider both the occupancy and a predetermined schedule. The air conditioner should be turned on only when the schedule dictates and turned off if it is outside the scheduled time and no one is present. In this context:
   - True Positive (TP): The system correctly predicts that the air conditioner should be off when it's off-schedule and no one is present.
   - True Negative (TN): The system correctly predicts that the air conditioner should be on during the scheduled time or when people are present.
   - False Positive (FP): The system incorrectly predicts that the air conditioner should be outside the scheduled time or when the classroom is empty.
   - False Negative (FN): The system incorrectly predicts that the air conditioner should be off on schedule or when people are present.

These values—TP, TN, FP, and FN—are then used to calculate the accuracy, which measures the system's success rate in controlling the lights and air conditioner. The accuracy of electrical equipment control can be calculated using Equation (2).

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$$Control\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (2)$$

2.6. Experimental Setup

Experiments were conducted in three different classrooms: two large and one small. Large classrooms are 12 m × 9 m, while small classrooms are 9 m × 6 m. Fig. 3 visualizes the classroom setup with equipment placement and its region of interest (ROI). A camera was positioned at the upper front of each classroom to capture a full view of all seats. The camera setup included an embedded microcontroller (Raspberry Pi) and a relay system for controlling the lights. The relay was directly connected to the classroom lighting, enabling automated on/off control. Each classroom was divided into three regions of interest (ROIs) to assess the lighting system's performance: the front (ROI 1), middle (ROI 2), and rear (ROI 3). This division allowed for a detailed analysis of how the lighting control system functioned in different room areas.

Figure 3. (a) Visualization of the main system and manual switch, (b) Main system and remote setup, (c) ROI division in detection frames in the large classroom, (d) ROI division in detection frames in the small classroom.

Twenty-two students from the Department of Electrical Engineering at Universitas Islam Indonesia voluntarily participated in the experiments. The study included two distinct scenarios. In the first scenario, students were directed to occupy specific regions of interest (ROIs) within the classrooms, allowing for controlled testing of the lighting control system's performance. In the second scenario, students could choose their seats, simulating a typical classroom setting to assess the system's effectiveness under more natural conditions. Based on the specified performance metrics, the following is the process for data collection during experimentation:

1) *Occupancy Detection Accuracy*: The accuracy of occupancy detection is obtained using Equation (1). Actual occupancy represents the actual number of people in the classroom, while the detected occupancy is the number of people recorded on ThingSpeak. The detected occupancy value is obtained by calculating the average historical readings stored on ThingSpeak under the same condition (number of people).

2) *Confusion Matrix*: Similar to the detected occupancy data, the parameters in the confusion matrix, i.e., true positive (TP), false positive (FP), true negative (TN), and false negative (FN), are also derived from the historical data of people readings stored on ThingSpeak, which is then matched to the actual condition of the electrical equipment (on/off). Each piece of data stored on ThingSpeak will be individually recorded and matched with the condition of the electrical equipment (off/on) to determine the values of TP, FP, TN, and FN.

3. RESULTS AND DISCUSSION

3.1. Accuracy of Occupancy Detection

In the large classroom A, external lighting from the back of the room potentially causes detection errors and frequent detection failures (a preliminary hypothesis), such as chairs being detected as people and people not being detected at all. The accuracy test results for occupancy detection in large classroom A show varying results depending on the number of people in the room. Out of ten experimental conditions, the highest accuracy was achieved when the number of people ranged from 6 to 10, with a peak accuracy of 90% in the fourth trial with 10 people. It was observed that the system is accurate when the number of people is relatively small. However, accuracy tends to decline as the number of people increases. Accuracy begins to drop significantly after the number of people exceeds 10. In trials with 16 to 23 people, accuracy dropped to less than 50%, with the lowest point being 13.64% in the tenth trial with 22 people. This significant decrease in accuracy indicates a weakness in the detection system when faced with higher occupancy, possibly due to limitations in the camera sensors or the algorithms used. This can be seen in Fig. 4, where the graph shows a decline in accuracy from 90.00% with 10 people to 13.64% with 22 people. The graph clearly illustrates this trend, showing a peak in accuracy early in the trials, which declines sharply as the number of people increases.

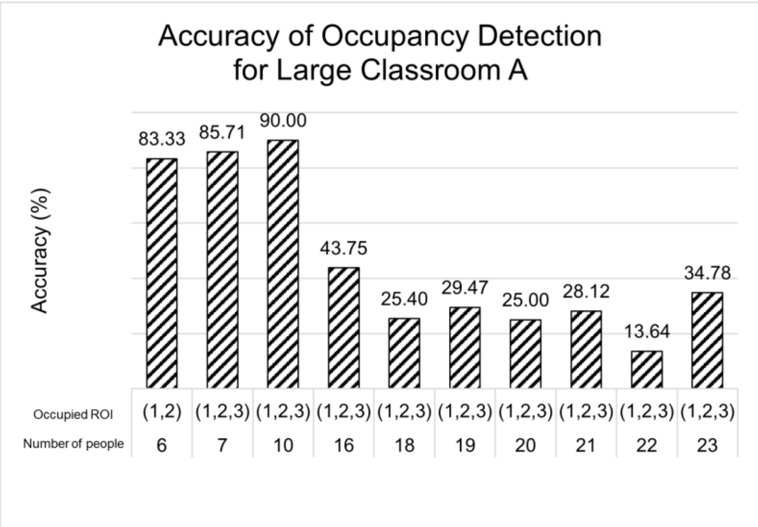

Figure 4. Accuracy of classroom occupancy detection for large classroom A

Unlike the conditions in large classroom A, in large classroom B, no external lighting from the back could interfere with the camera and result in detection errors and failures (a preliminary hypothesis). The accuracy test results for occupancy detection in large classroom B show varying results depending on the number of people in the room. Out of fourteen trials, accuracy ranged from 39.29% to 57.52%. This is depicted in Fig. 5, where the occupancy detection accuracy graph shows fluctuating accuracy levels without a clear trend. Nevertheless, the results from large classroom B show more stable accuracy values than those from large classroom A. In trials in large classroom A, when the number of people exceeds 16, accuracy drops below 35.00%. Meanwhile, in large classroom B trials under the same conditions, accuracy remained above 35.00% and up to 54.00%. When the number of people is less than 16, the trials in large classroom A showed higher accuracy than those in large classroom B. This can be observed from the data, wherein large classroom A, ROI 1 and 2 were filled, whereas in large classroom B, ROI 2 and 3 were filled first. Based on this condition, it can be inferred that accuracy in reading occupancy in ROI 1 and 2 is better than in ROI 3 (a preliminary hypothesis).

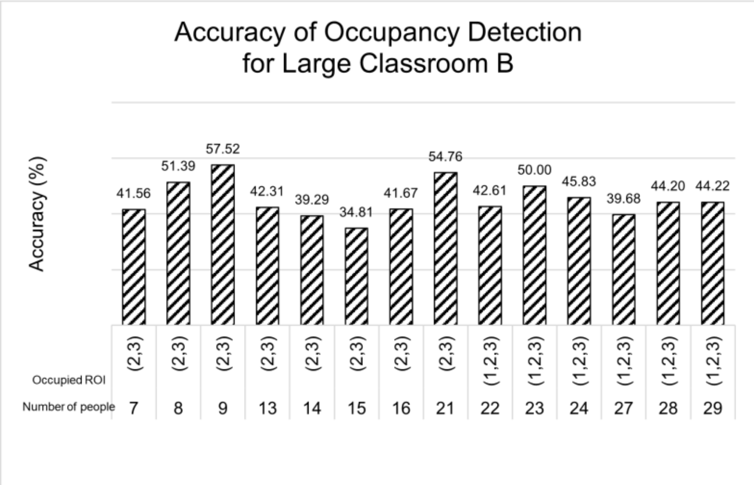

Figure 5. Accuracy of classroom occupancy detection for large classroom B

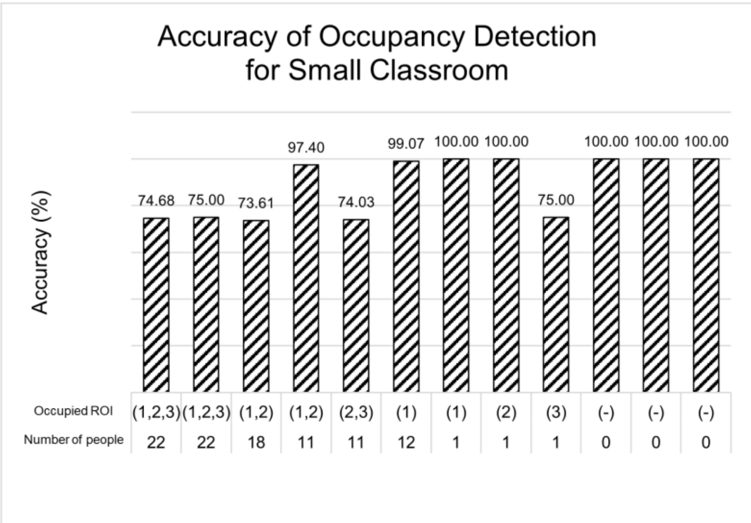

Figure 6. Accuracy of classroom occupancy detection for small classroom

The condition in the small classroom is like that in large classroom B, where there is no interference from backlighting. This results in no disturbance to the camera, reducing detection errors and failures. Occupancy detection accuracy in the small classroom was stable and generally higher than in the other two large classrooms. Therefore, lighting conditions and room size affect the stability of occupancy detection accuracy. Based on the graph in Fig. 6, it can generally be seen that occupancy detection accuracy is higher when the number of people is smaller. This can be seen when the classroom has 18 and 22 people, which shows a lower accuracy level than when the classroom has fewer people, such as 1, 11, and 12.

Another factor that can be observed is the filled ROI, where the detection area in the ROI closest to the camera has a higher accuracy. This is evident in the trial with 11 people, where when ROIs 1 and 2 were filled, accuracy was higher than when ROIs 2 and 3 were filled. This factor is supported by the test with 1 person, where when ROIs 1 and 2 were filled, accuracy was 100%, better than when ROI 3 was filled, where accuracy dropped to 75%. The influence of ROI sequence is further supported by the comparison of occupancy detection accuracy for each ROI in Fig. 7. Additionally, for tests when the classroom is empty, the average accuracy is 91.66%, indicating that the system is quite good at detecting the absence of people or preventing false object detection.

Based on the results and analysis of the tests conducted in the small classroom above, it can address the hypothesis in the previous analysis of the large classroom experiments. The occupancy detection in ROI 1 and 2 has higher accuracy than in ROI 3. This trend is observed in all three tested classrooms, as seen in the comparison graph of occupancy reading accuracy for each ROI in Fig. 7. However, even when ROIs 1, 2, and 3 were all occupied in the small classroom test, the accuracy readings were still higher than those in the large classroom tests where ROIs 1, 2, and 3 were also occupied. Therefore, besides the influence of ROIs on the readings, the detection area also affects the accuracy level. When the system is implemented in a large room, there are limitations in the reading range and camera resolution when detecting occupancy. This contrasts with when the system is implemented in a small room with a smaller/narrower detection range.

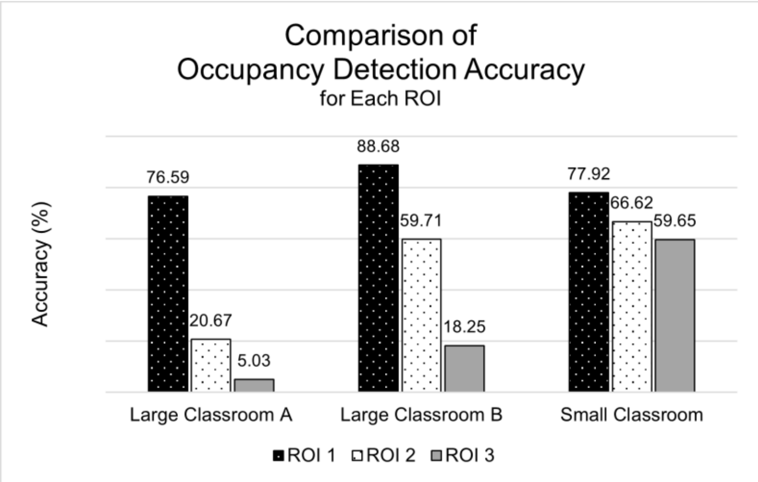

Figure 7. Comparison of occupancy detection accuracy for each ROI

3.2. Confusion Matrix

Occupancy reading accuracy in Classroom A demonstrates significant variability, which negatively impacts the performance of the lighting control system. According to the confusion matrix presented in Table 1, Classroom A's system achieved an accuracy of 70.50%. The confusion matrix also reveals that the system correctly identified the presence of people only 2.56% of the time (2 true positives out of 78 total cases where people were present), resulting in a high false positive rate, where the lights were unnecessarily turned off 76 times despite people being present.

In contrast, implementation in Classroom B shows a much more stable and reliable performance, with a lighting control accuracy of 99.77%. As shown in Table 2, the confusion matrix for Classroom B indicates a high level of precision and recall, with the system correctly predicting the absence of people 100% of the time (57 true positives out of 57 cases with no person present) and misclassifying only 1 instance where a person was present, resulting in just one false negative. This indicates that the system implemented in Classroom B is highly effective in making correct predictions about occupancy, thereby optimizing lighting control to reduce energy waste and improve user comfort.

Testing in the small classroom demonstrates strong performance in lighting control accuracy. The similarity in lighting conditions between this small classroom and Classroom B, particularly the absence of lighting at the back of the room, minimizes the chances of object recognition errors and detection failures. This reduction in errors significantly enhances occupancy reading accuracy. Furthermore, the smaller room size allows for more precise detection, contributing to better performance than the two larger classrooms. The confusion matrix for the small classroom (see Table 3) shows a lighting control accuracy of 98.39%. The system correctly identified 100 instances where no one was present, with no false positives, and only 3 false negatives, where the lights were turned off despite people being present. This high accuracy indicates that the system is highly effective in predicting the occupancy of small-size classrooms, ensuring that lights are turned on or off following the actual presence or absence of people.

Table 1. Confusion matrix for experimenting with lights in a large classroom A

		Actual Value	
		No person	Person present
Predicted Value	Light off	TP = 2	FP = 76
	Light on	FN = 1	TN = 182

Table 2. Confusion matrix for experimenting with lights in a large classroom B

		Actual Value	
		No person	Person present
Predicte Value	Light off	TP = 57	FP = 0
	Light on	FN = 1	TN = 377

Table 3. Confusion matrix for experimenting with lights in a small classroom

		Actual Value	
		No person	Person present
Predicted Value	Light off	TP = 100	FP = 0
	Light on	FN = 3	TN = 83

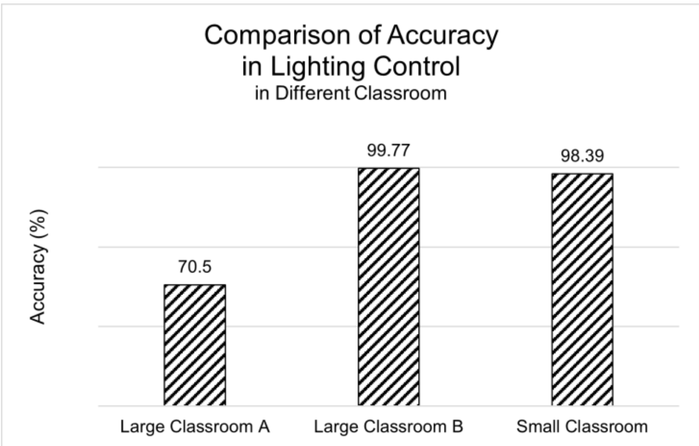

Figure 8. Comparison of accuracy in lighting control in different classrooms

Figure 8 compares the lighting control accuracy across three classrooms: Large Classroom A, Large Classroom B, and the small classroom. The data reveals that the small classroom and Classroom B achieved high accuracy rates of 98.39% and 99.77%, respectively. This similarity can be attributed to the consistent lighting conditions in both classrooms, particularly the absence of lighting interference from the back of the room, which minimizes errors in occupancy detection. In contrast, Classroom A, with an accuracy of 70.50%, experiences significantly lower performance. This decline is primarily due to backlighting, which interferes with the camera's ability to detect occupants accurately. These findings suggest that lighting from the back of the classroom can substantially impact the effectiveness of the lighting control system, leading to reduced accuracy in occupancy readings.

Based on the confusion matrix test results shown in Table 4, the air conditioner control system achieved a perfect accuracy of 100% using Equation (1). This indicates that the system can manage the air conditioner according to actual conditions, including the scheduled times and the presence or absence of

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people in the classroom. The matrix reveals that the system correctly identified all scenarios where the air conditioner should be turned on or off. Specifically, it avoided any false positives or negatives during scheduled times and when the classroom was occupied or unoccupied. Additionally, it accurately handled cases when the air conditioner needed to be turned off during off-schedule periods with no occupants, demonstrating its reliability in optimizing energy usage without compromising comfort.

Table 4. Confusion matrix for experimenting with Air Conditioner

		Actual Value			
		On Schedule		Off Schedule	
		No person	Person present	No person	Person Present
Predicted Value	Air Conditioner on	TN = 5	TN = 5	FN = 0	TN = 5
	Air Conditioner off	FP = 0	FP = 0	TP = 10	FP = 0

3.3. Discussion

The accuracy rates observed in the system's occupancy detection across different classrooms provide valuable insights into its real-world applicability. In the smaller classroom, where the lighting was stable, detection accuracy reached 100%, indicating the system's effectiveness in controlled environments. However, in larger classrooms with varying lighting conditions, the detection accuracy dropped to as low as 13.64%. These variations reflect how environmental factors, such as lighting and room size, can significantly affect the system's performance. In real-world class settings, particularly in larger or less controlled environments, the system may require further calibration or integration with other sensors (e.g., infrared) to maintain high accuracy.

The error values in the confusion matrix emphasize potential challenges distinguishing between occupied and unoccupied states under difficult conditions. Misclassifications, particularly false negatives, where the system fails to detect occupants, could result in lights or air conditioning remaining off, leading to discomfort for students. Conversely, false positives could cause unnecessary energy consumption, especially in cases where the system detects people but the classroom is empty. Thus, minimizing errors is critical for ensuring the system provides a reliable balance between energy efficiency and user comfort.

Another important consideration is the system's limitation in handling various lighting conditions, as seen in the performance discrepancy between stable and unstable lighting environments. The system's reliance on a single type of sensor (camera) and YOLOv8 algorithm may limit its robustness, especially in larger spaces with more complex environmental factors. Furthermore, while the 30-second delay for turning off the lights was designed to reduce unnecessary power cycling, there is potential for further optimization. For instance, future system iterations could include adaptive delays based on room usage patterns or integrate machine learning models that predict room occupancy based on historical data. Lastly, while integrating real-time data with ThingSpeak allows for remote monitoring, this functionality could be enhanced with more comprehensive analytics for users to gain insights into energy consumption patterns. Such advancements would make the system more responsive and allow for better decision-making in energy management across different building types.

4. CONCLUSION

This study successfully developed an automated system for controlling classroom lighting and air conditioning using computer vision and the YOLOv8 algorithm. The system demonstrated high accuracy in smaller rooms and under stable lighting conditions. In large classrooms with inconsistent lighting, occupancy detection accuracy ranged from 13.64% to 90.00%, while in smaller classrooms, accuracy reached 100%. Light control accuracy varied similarly, from 70.50% in the large classrooms to 99.77% in more stable conditions. Air conditioning control achieved 100% accuracy, demonstrating the system’s reliability in optimizing energy usage. These results highlight the system’s effectiveness in reducing energy consumption by accurately detecting occupancy and adjusting electrical systems accordingly. However, performance can be influenced by room size and lighting conditions, suggesting the need for environmental adjustments to ensure optimal system functionality. This study contributes to developing intelligent energy management systems in educational settings, offering a practical solution for reducing unnecessary energy usage.

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