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Original Article

Development of a Building Energy Management System Integrated with Image Processing and Internet of Things (IoT) Technologies

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Abstract - *This study is aimed at developing a building energy management system integrated with image processing and Internet of Things technologies for human detection, energy measurement, and automatic electrical device control. Unlike existing approaches that address occupancy detection or energy monitoring separately, the proposed system integrates both functions in a single low-cost closed-loop edge device. This system uses Raspberry Pi 4 as the central processing unit linked to webcams for human detection and processing with the YOLOv4 model, the PZEM-004T module for system electrical measurements, and relay modules for controlling opening/closing electrical loads. Human detection conditions were set to be based on a resemblance of over 60%, after which the system would issue commands to turn on the light and the fan, along with giving notice via Telegram. Results were displayed via the Blynk application, and information was logged in Google Sheets. Testing was carried out in 7 x 7-meter laboratory with 49 positions. Results from testing with humans wearing black, white, and green shirts showed the system had total detection accuracy at 71.77%, with black shirt detections having the highest accuracy at 75.51%, followed by white shirt detections at 74.49%, and green shirt detections at 65.31%, respectively. In the area of energy measurement, the system was able to measure and log voltage, current, and electrical load in the system with a mean deviation of 4.56%. This indicates that the developed system can be used as a prototype for energy management in smart buildings to reduce unnecessary energy consumption and support electrical device control in real use.*

Keywords - *Building Energy Management Systems, Internet of Things, Image processing, Human detection.*

1. Introduction

Buildings are an energy-intensive sector directly associated with greenhouse gas emissions, particularly from electricity consumed by air conditioning systems, lights, ventilation systems, and indoor equipment. The International Energy Agency stated that buildings make up 30% of global energy consumption and are associated with 26% of greenhouse gas emissions [1, 2]. Additionally, Bayasgalan et al. reported that Building Energy Management Systems (BEMS) play a role in energy consumption measurement, analysis, and control to reduce unnecessary energy consumption [3]. However, many buildings continue to use timed control or user control, which may be inconsistent with real user numbers and environments.

Therefore, Internet of Things technologies have been applied to link sensors, control devices, communication systems, and display systems in order to track real-time energy consumption [4]. Nikpour et al. reported that IoT integration with smart analysis enhanced measuring, control, and decision-making efficiency [5], while Hong et al. found that building user behaviors to have affected energy consumption and building model accuracy [6-8]. Image processing, therefore, can be used to detect the presence, number, and density of users in support of energy control.

In a study conducted by Cui et al., a proposal was made to use low-resolution thermal images with computer vision to detect area possession and reduce privacy concerns [9], while Ciholas et al. reported cybersecurity and personal data risks in smart buildings [10]. However, existing studies mostly address occupancy detection [9, 29] or energy monitoring and analysis [17, 18] separately. Few studies integrate camera-based human detection, automatic load control, per-load energy measurement, notification, and data logging into one low-cost closed-loop system, and the effects of shirt color, distance, and position in the camera view on detection reliability are rarely quantified.

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Therefore, the objectives of this study are (1) to develop a building energy management system prototype on a Raspberry Pi 4 that combines YOLOv4-based human detection, relay-based load control, and per-load energy measurement with PZEM-004T modules; (2) to provide real-time monitoring, notification, and data logging through Blynk, Telegram, and Google Sheets; and (3) to evaluate detection performance at 49 positions with three shirt colors using FPR, FNR, and accuracy, together with energy measurement accuracy. The novelty of this work lies in the closed-loop integration of vision-based occupancy detection and per-load energy metering on a single edge device, and in the systematic position- and color-based evaluation that reveals the practical limitations of camera placement. The significance of this work is a low-cost and reproducible prototype that reduces the time devices are left on unnecessarily in classrooms and offices.

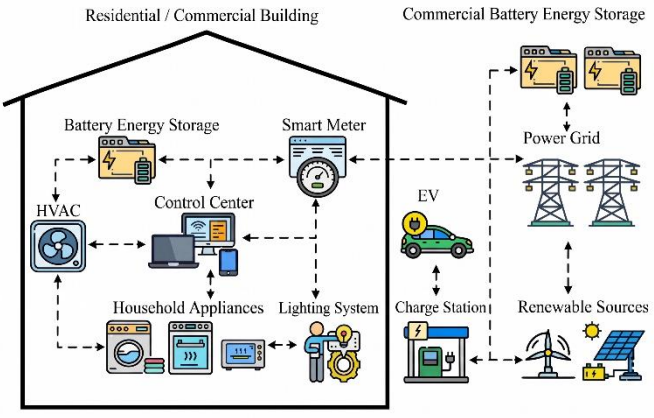


Fig. 1 Building Energy Management System: BEMS [31]

2. Relevant Literature

2.1. Building Energy Consumption

Energy consumption in buildings is important for cost and environmental impact reduction because school buildings, offices, government buildings, commercial buildings, and public buildings use electrical, air conditioning, lighting, and ventilation systems, office supplies and amenities. Air conditioning and lighting systems usually have high energy consumption ratios [11].

Dounis and Caraiscos stated that appropriate control of building systems helps to enhance energy efficiency [12], while Zhao and Magoulès indicated energy management systems need data from real devices for energy consumption pattern analysis and control decision support [13].

Furthermore, Erickson et al. found area possession data use with lighting and air conditioning system controls to have reduced unnecessary energy consumption [14]. Therefore, studies on energy consumption models provide a basis for developing measurement, analysis, and energy control systems that are consistent with real use to enhance efficiency and reduce energy loss in buildings.

2.2. IoT in Smart Buildings

Internet of Things (IoT) technologies network devices, sensors, and control systems to transmit data in real-time, as shown in Figure 2, by integrating electricity sensors, temperature sensors, humidity sensors, light sensors, relays, cameras, microcontrollers, databases, and display systems to work together. IoT technologies were reported by Al-Fuqaha et al. to have helped with linking physical devices to communication and processing systems, making device tracking and control flexible [15]. Similarly, Minoli et al. indicated IoT technologies support energy measurement, control, and management in smart buildings [16], while Pan et al. focused on use of energy data to adjust system functions for consistency with real use [17]. Furthermore, Huang et al. found that energy management systems based on IoT technologies to have been able to analyze energy consumption patterns and reduce unnecessary energy consumption [18]. Therefore, IoT technologies cover data measurement, control, notices, logs, and analyses for energy efficiency enhancement.

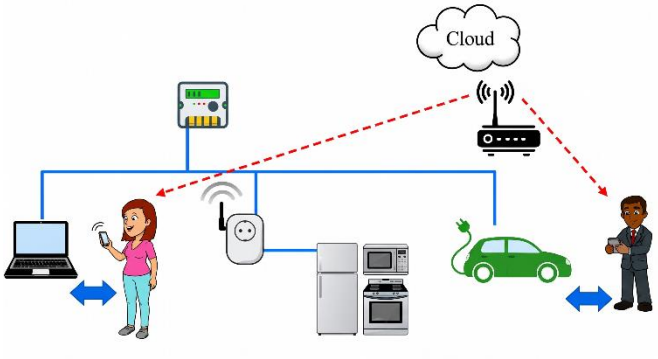


Fig. 2 Internet of Things: IoT [18]

2.3. Human Detection with Image Processing

Human detection with neural networks is the processing of images from cameras for the system to learn, distinguish, and automatically identify the person's position. Conventional methods use image characteristics, such as shapes, image edges, and edge line directions, with Histograms of Oriented Gradients (HOG) [19]. Subsequently, Convolutional Neural Networks (CNNs) capable of learning image properties automatically with greater efficiency than conventional methods were developed [20, 21]. Girshick et al. introduced R-CNN, which generates candidate regions before object classification [22]. Girshick developed Fast R-CNN proposals to improve performance detection [23]. Ren et al. proposed Faster R-CNN, which uses a Region Proposal Network (RPN) to generate regions [24]. These region-based methods support learning major human characteristics, such as the head, torso, arms, legs, posture, and differences between humans and the background. Within the network, the convolution layer would extrapolate characteristics from the basic level, such as color, edges, shape, and surface, including height properties such as human body shapes, posture, and image context [25]. For real-time applications, single-stage models such as YOLO and

SSD are preferred because they predict object locations in a single pass. Redmon et al. introduced YOLO [26, 27], Liu et al. proposed SSD [28], and Ganagavalli and Santhi demonstrated YOLO-based real-time anomaly detection for surveillance applications [29]. However, effectiveness is dependent on image quality, training data, distance, shirt color, posture, light, background, and the specified reliability score.

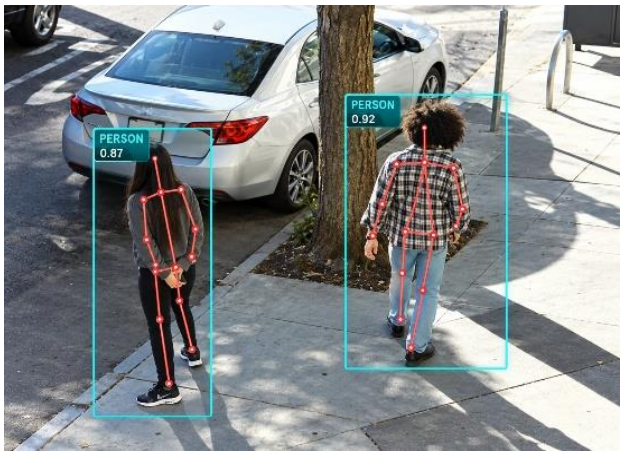


Fig. 3 YOLO human object detection model [29]

2.4. Research Gap

The reviewed studies show that existing methods have developed in separate directions. Occupancy-based control such as OBSERVE [14] improves HVAC efficiency but relies on a dedicated camera sensor network and does not measure the energy of individual loads. IoT frameworks [16-18] focus on data acquisition and energy analysis, whereas vision-based studies [9, 29] focus on detection accuracy without linking the results to load control. In addition, deep learning detectors are usually evaluated on public datasets rather than at systematically defined positions in a real room. Therefore, this study integrates these components into one low-cost closed-loop system and evaluates it under practical indoor conditions, as compared in Table 8.

3. The Proposed System

3.1. Working Principles

The energy management system's structure was designed to enable hardware, Internet networks, and software to work together in concert to systematically measure, analyze, control, and display data on energy consumption in buildings. This consists of sections for data input, processing, display, device control, networking, and monitoring, warning, and record-keeping software in four sections, as shown in Figure 4.

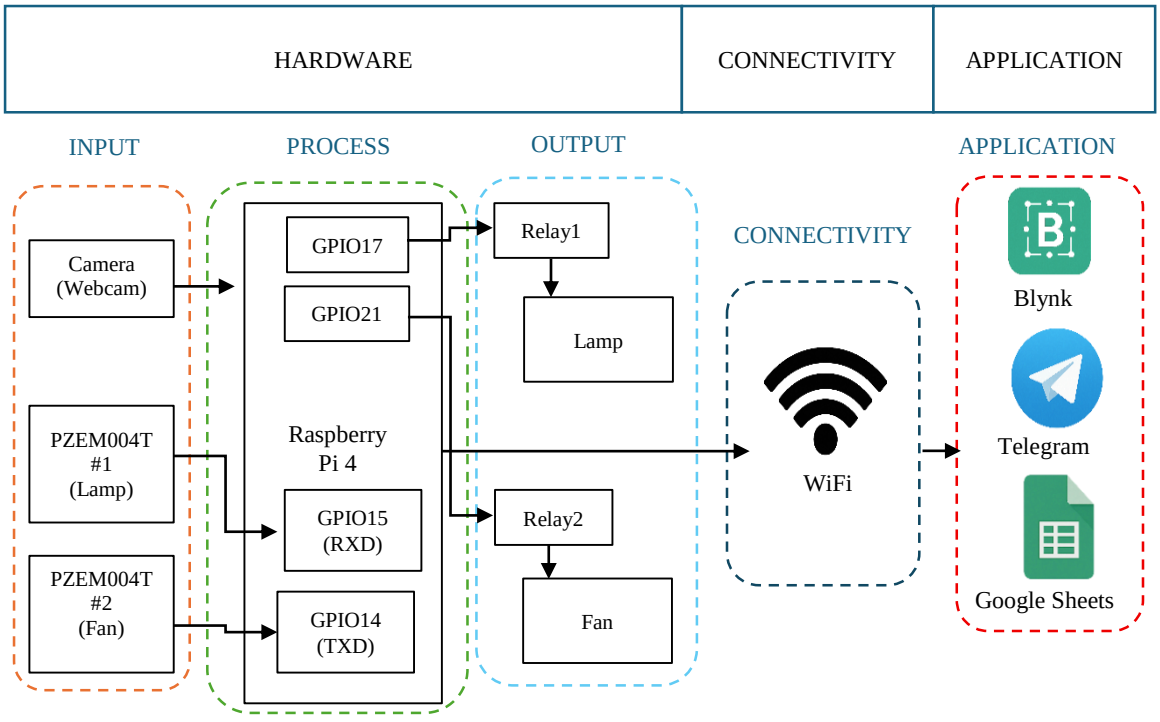


Fig. 4 System operating structure

Section 1 is for data input and consists of webcams for capturing images within buildings in order to detect users, and the PZEM-004T module for measuring electricity voltage, current, power, and stored energy before data is transmitted to the central processing unit.

Section 2 is for processing. Raspberry Pi 4 is used as the main control unit, functioning to receive images transmitted via USB ports and detect humans with the YOLOv4 model [30], along with receiving data transmitted from PZEM-004T via the GPIO14 and GPIO15 ports. The GPIO17 and GPIO21

ports are used to control relays for the 20-watt light and the 40-watt fan. Section 3 is for load control. Two relays are used to control the light and the fan. The system would turn on devices upon detecting a human and turn off upon failure to detect a human in order to reduce unnecessary energy expenditure.

Section 4 is for applications. Blynk is used to display energy values and device status in real-time. Telegram is used to give notice about significant events. Google Sheets is used to log the date and time, electrical values, device status, and human detection results for retrospective analysis.

3.2. Hardware & Software Design

The hardware structure is designed to connect devices in the system, consisting of a Raspberry Pi 4, webcams, the PZEM-004T sensor, Relay Module 4CH, the lamp, the fan, and the monitor as shown in Figure 5 and Table 1.

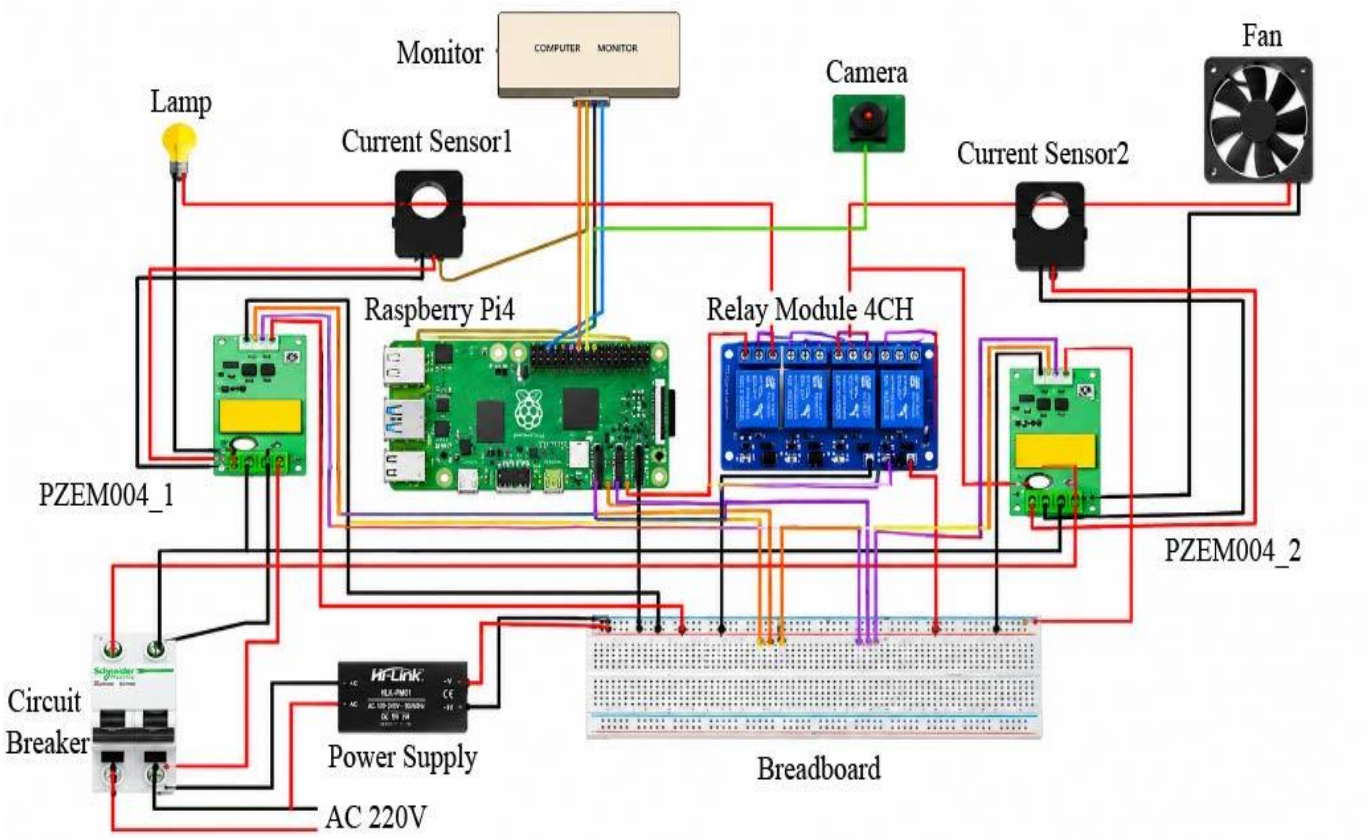


Fig. 5 Circuit connection of the system

Table 1. Circuit connection locations of the system

Pi4	PZEM-004T 1	PZEM-004T 2	Relay 4CH	Lamp	Fan
GPIO14	TX	TX			
GPIO15	RX	RX			
GPIO17			IN1		
GPIO27			IN3		
GND	GND	GND	GND		
5V	5V	5V	5V		
	L OUT1	L OUT2	COM		
			NO	220V	220V
	L IN1	L IN2		GND	GND
	N IN1	N IN2			
	N OUT1	N OUT2			

The software structure is the order of operations of the building energy management system integrated with image processing and Internet of Things technologies, which has steps as shown in Figure 6.

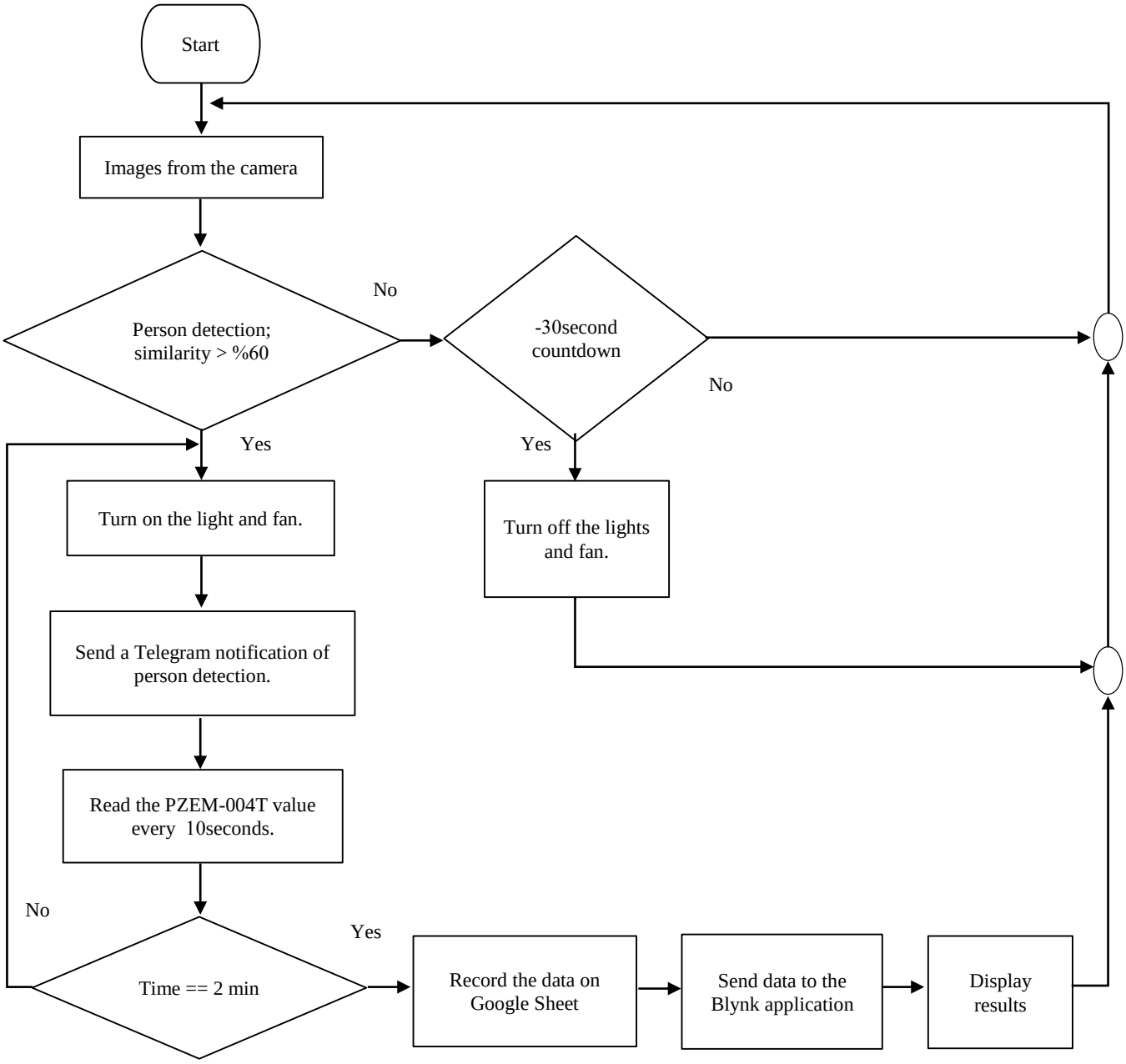


Fig. 6 Software structure

According to Figure 6, the system automatically controls the light and the fan, beginning with receiving images via the camera and detecting humans with a resemblance of over 60% as the detection criterion. If a human is detected, the system will issue commands to turn on the light and the fan, along with sending a notice via Telegram. The PZEM-004T module would then measure electrical values every ten seconds to calculate electrical energy in kilowatt-hours. After the system has functioned for two minutes, data will be logged on Google Sheets and sent to the Blynk application to display energy values and real-time work status before returning to receive images and detecting humans. In the event that a human is not detected, the system would begin a 30-second countdown. If no human is detected within this time, the system would issue commands to turn off the light and the fan in order to reduce unnecessary energy consumption before returning to a continuous detection cycle.

4. Results & Discussion

Tests to detect humans wearing shirts of various colors assessed human detection effectiveness at various positions in the building. Tests were performed with humans wearing shirts of three colors (black, white, and green) within a 7m x 7m laboratory.

1) Human detection tests with humans in black shirts were performed at 49 positions with coverage of distances of 1-7 meters from the camera along the Y axis and 1-3 meters to the left-right of the camera. Detection results from each position are as recorded in Figure 7 and Table 2.

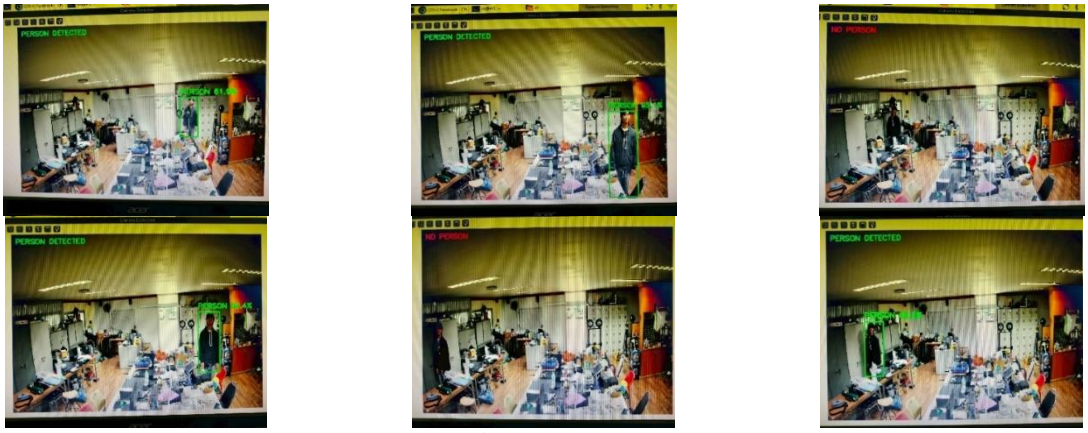


Fig. 7 Detection of a person wearing a black shirt

Table 2. Similarity values detected by the camera for individuals wearing black shirt

Distance from the Camera along the Y-Axis (m)	Person Detection Confidence Score (%)						
	Distance to the Left of the Camera (m)			Center Point	Distance to the Right of the Camera (m)		
	3	2	1	0	1	2	3
1	0	0	80 – 94	80 – 98	60 – 80	0	0
2	0	0	80 – 98	85 – 92	80 – 96	0	0
3	0	0	82 – 98	80 – 95	80 – 98	0	0
4	0	80 – 86	85 – 87	75 – 85	60 – 90	60 – 87	60 – 75
5	0	70 – 76	80 – 87	65 – 85	87 – 95	60 – 75	0
6	0	80 – 90	75 – 82	60 – 83	75 – 80	90 – 98	0
7	0	0	60 - 74	60 – 75	60 – 74	0	0

According to Table 2, results from testing human detection with humans in black shirts at 49 positions in the building (10 times per position) showed the system's detection to be best at distances of 1-3 meters, with a resemblance of 80-98%, while resemblance was at 60-98% at the distances of 4-6 meters and 60-75% at 7 meters. The characteristics of the area used for detecting humans in black shirts are as shown in Figure 8.

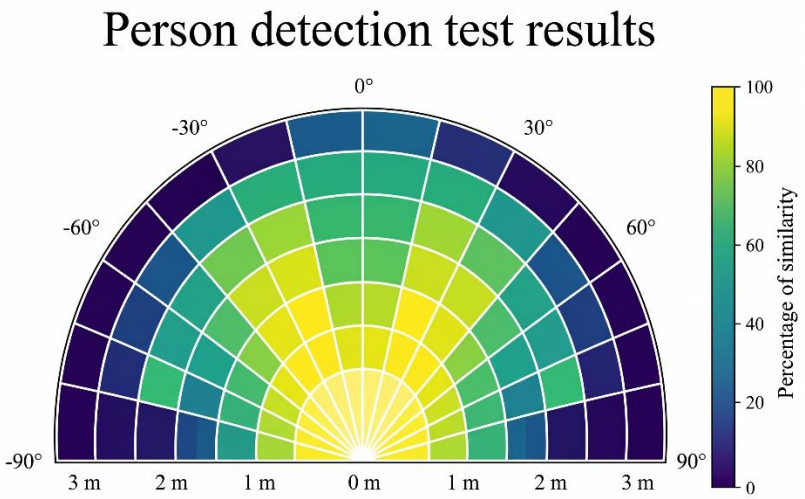


Fig. 8 Characteristics of the area for detecting individuals wearing black shirts

2) Human detection tests with humans in white shirts were performed at 49 positions with coverage of distances of 1-7 meters from the camera along the Y axis and 1-3 meters to the left-right of the camera. Detection results from each position are as recorded in Figure 9 and Table 3.



Fig. 9 Detecting a person wearing a white shirt

Table 3. Similarity values detected by the camera for individuals wearing white shirt

Distance from the Camera along the Y-Axis (m)	Person Detection Confidence Score (%)						
	Distance to the Left of the Camera (m)			Center Point	Distance to the Right of the Camera (m)		
	3	2	1	0	1	2	3
1	0	0	75 – 94	85 – 98	60 – 80	0	0
2	0	0	75 – 98	85 – 92	80 – 96	0	0
3	0	0	82 – 95	82 – 92	80 – 98	0	0
4	0	75 – 84	80 – 85	70 – 85	60 – 95	60 – 85	0
5	0	70 – 80	80 – 87	65 – 85	87 – 92	60 – 80	0
6	0	70 – 75	75 – 82	60 – 83	70 – 85	60 – 75	0
7	0	0	60 - 72	60 – 72	65 – 70	0	0

According to Table 3, results from testing human detection with humans in white shirts at 49 positions in the building (10 times per position) showed the system's detection to be best at distances of 1-3 meters, with a resemblance of 60-98%, while resemblance was at 60-95% at the distances of 4-6 meters and 60-72% at 7 meters. The images used for detecting humans in white shirts are as shown in Figure 10.

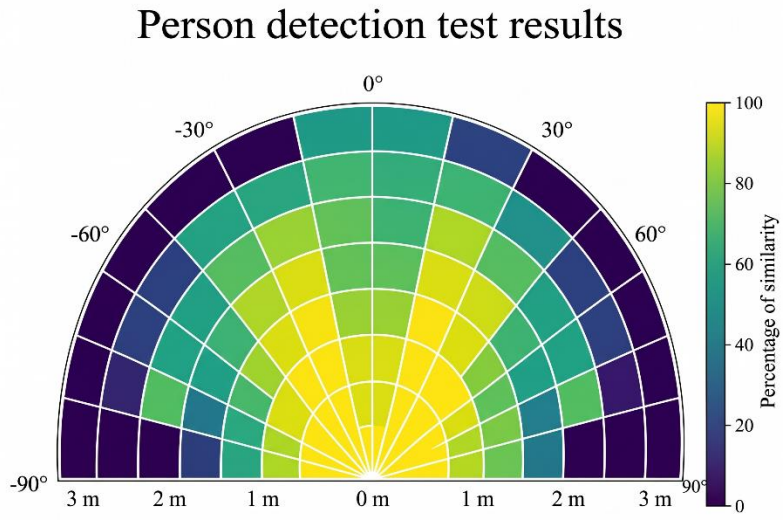


Fig. 10 Characteristics of the area for detecting individuals wearing white shirts

3) Human detection tests with humans in green shirts were performed at 49 positions with coverage of distances of 1-7 meters from the camera along the Y axis and 1-3 meters to the left-right of the camera. Detection results from each position are as recorded in Figure 11 and Table 4.



Fig. 11 Detection of a person wearing a green shirt

Table 4. Similarity values detected by the camera for individuals wearing green shirt

Distance from the Camera along the Y-Axis (m)	Person Detection Confidence Score (%)						
	Distance to the Left of the Camera (m)			Center Point	Distance to the Right of the Camera (m)		
	3	2	1	0	1	2	3
1	0	0	70 – 85	85 – 93	70 – 89	0	0
2	0	80 – 91	80 – 95	83 – 90	80 – 92	0	0
3	0	80 – 94	80 – 94	76 – 90	80 – 94	0	0
4	0	70 – 82	80 – 90	75 – 85	70 – 80	0	0
5	0	0	75 – 85	75 – 85	60 – 80	0	0
6	0	0	0	80 – 90	0	60 – 75	0
7	0	0	0	0	0	0	0

According to Table 4, results from testing human detection with humans in green shirts at 49 positions in the building (10 times per position) showed the system's detection to be best at distances of 1-3 meters, with a resemblance of 70-95%, while resemblance was at 70-90% at the distances of 4-6 meters. The system was unable to detect all at 7 meters, with a resemblance score of 0%. The characteristics of the area used for detecting humans in green shirts are as shown in Figure 12.

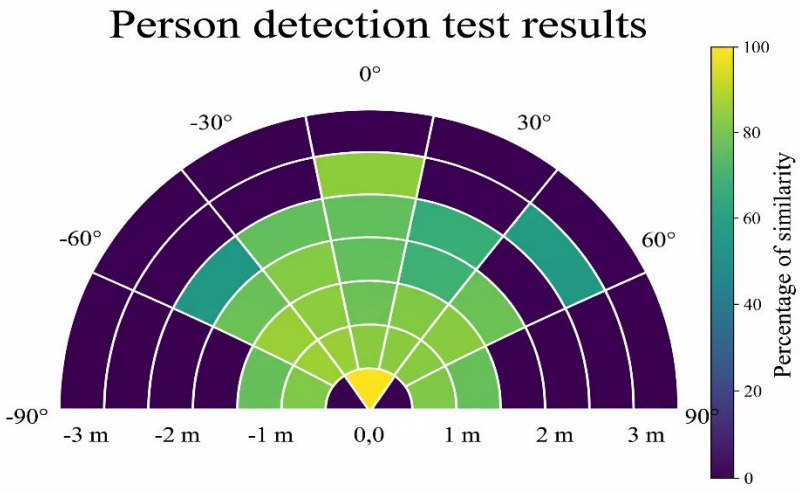


Fig. 12 Characteristics of the area for detecting individuals wearing green shirts

The tests to detect humans wearing shirts of different colors assessed the system's human detection effectiveness at various positions within the building. Testing was performed with shirts of three colors (black, white, and green). Detection results were then calculated for system effectiveness as follows:

1. False alert rate.

$$FPR = \frac{FP}{FP+TN} \times 100 \quad (1)$$

2. The rate at which individuals are not detected.

$$FNR = \frac{FN}{TP+FN} \times 100 \quad (2)$$

3. System accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (3)$$

A "True Positive (TP)" result means the system was able to detect a human when there is a human while a "False Negative (FN)" result means the system failed to detect a human despite the existence of one, a "False Positive (FP)" result means the system reported detecting a human despite the absence of a human, and a "True Negative (TN)" result means the system accurately failed to detect a human when there is no human. "FPR" is False Positive Rate, "FNR" is False Negative Rate, and accuracy is the system's overall accuracy. Based on Equations (1)-(3), calculation results are as shown in Table 5.

Table 5. Performance evaluation of the person detection system

Shirt Color	Number of Test Positions with Person	Number of Test Positions without Person	TP	FN	FP	TN	FPR (%)	FNR (%)	Accuracy (%)
Black	49	49	28	21	3	46	6.12	42.86	75.51
White	49	49	28	21	4	45	8.16	42.86	74.49
Green	49	49	20	29	5	44	10.20	59.18	65.31
Total	**147**	**147**	**76**	**71**	**12**	**135**	**8.16**	**48.30**	**71.77**

According to Table 5, the system detected humans with a total accuracy of 71.77%, with accurate human detections in 76 out of 147 positions and failures to detect in 71 positions. When no human was present, the system detected a human erroneously in 12 positions and accurately failed to detect in 135 positions, at an FPR of 8.16% and an FNR of 48.30%. When results were categorized by shirt color, black shirts were found to have the highest accuracy at 75.51%, followed by white shirts at 74.49%, and green shirts at 65.31% with the highest FNR at 59.18%. This indicates the effects of shirt color, positions, distance, and lighting conditions on effectiveness. Therefore, camera angles and models should be adjusted to reduce negative detection results.

The test to measure energy of devices connected to the system was conducted by a 20-watt light and a 40-watt fan. The system began working from human detection by camera. If a human is detected in the area, the system would issue commands for the light and the fan to work, after which energy sensors would read electrical voltage, current, deviation, and percentage of deviation, with test results as shown in Table 6 and Table 7.

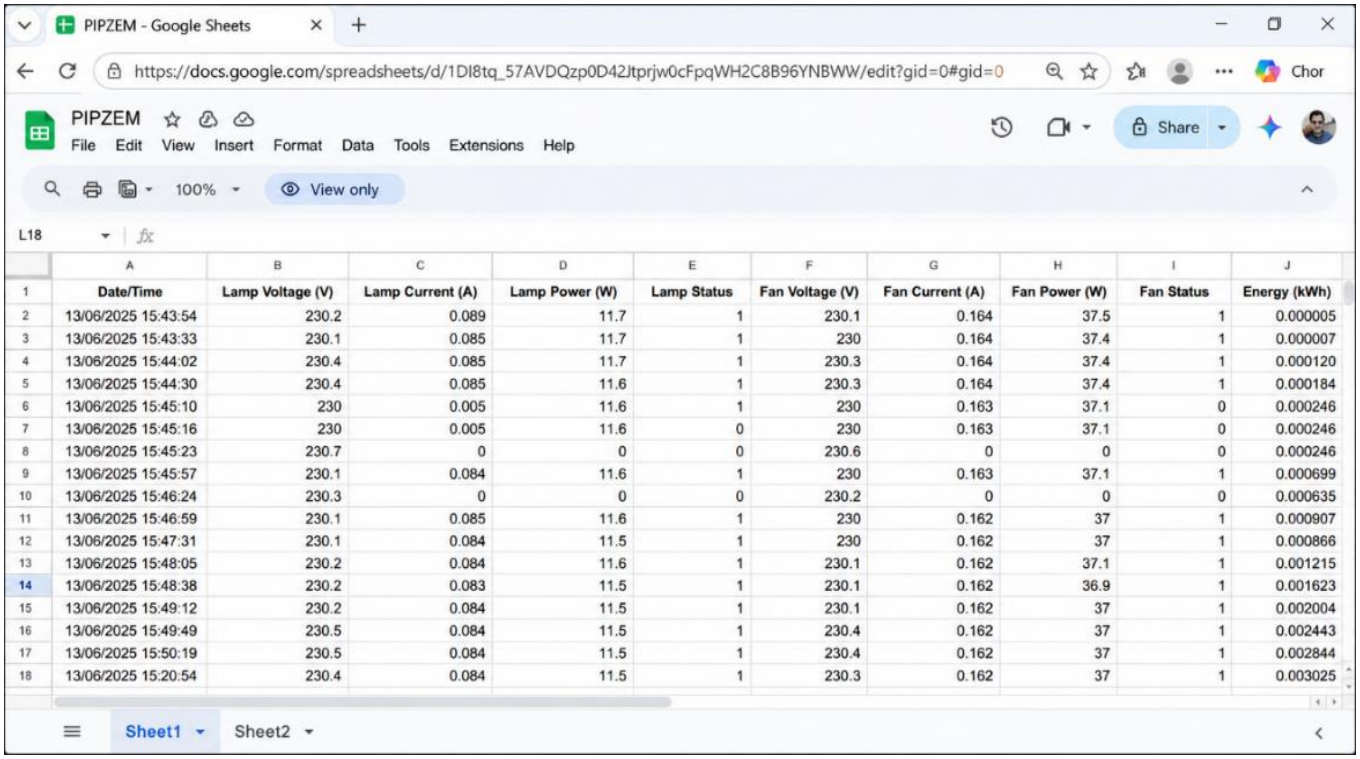
Table 6. Measurement results and electrical errors of the light bulbs

No.	Actual Voltage (V)	Measured Voltage (V)	Voltage Error (V)	Voltage Error (%)	Actual Current (A)	Measured Current (A)	Current Error (A)	Current Error (%)	Actual Power (W)	Measured Power (W)	Power Error (%)
1	230	230.2	0.2	0.087	0.091	0.086	0.0049	5.390	20.907	19.797	5.308
2	230	230.1	0.1	0.043	0.091	0.085	0.0059	6.491	20.907	19.559	6.450
3	230	230.4	0.4	0.174	0.091	0.085	0.0059	6.491	20.907	19.584	6.328
4	230	230.4	0.4	0.174	0.091	0.085	0.0059	6.491	20.907	19.584	6.328
5	230	230.0	0.0	0.000	0.091	0.085	0.0059	6.491	20.907	19.550	6.491
6	230	230.0	0.0	0.000	0.091	0.085	0.0059	6.491	20.907	19.550	6.491
7	230	230.7	0.7	0.304	0.091	0.084	0.0069	7.591	20.907	19.379	7.310
8	230	230.1	0.1	0.043	0.091	0.084	0.0069	7.591	20.907	19.328	7.551
9	230	230.2	0.2	0.087	0.091	0.084	0.0069	7.591	20.907	19.337	7.510
10	230	230.1	0.1	0.043	0.091	0.085	0.0059	6.491	20.907	19.559	6.450
Ave.	230	230.22	0.22	0.096	0.091	0.085	0.0061	6.711	20.907	19.523	6.622

According to Table 6, the measured voltage was at a mean of 230.22 volts. Compared to the true voltage of 230, this measurement had a mean deviation of 0.22 volts or 0.096% with a mean accuracy of 99.904%. Electricity current was measured at a mean of 0.085 amperes. When compared to the true current of 0.0909 amperes, this measurement was found to be lower than the true value, with a mean of 0.0061 amperes or a mean deviation of 6.711%, which is a mean accuracy of 93.289%. When electrical power was calculated based on the formula (P = V x I), true electrical power was found to be at a mean of 20.907 watts while the measured electrical power was at a mean of 19.523 watts, meaning the measurement had a mean deviation of 6.622%.

Table 7. Measurement results and electrical errors of the fan

No.	Actual Voltage (V)	Measured Voltage (V)	Voltage Error (V)	Voltage Error (%)	Actual Current (A)	Measured Current (A)	Current Error (A)	Current Error (%)	Actual Power (W)	Measured Power (W)	Power Error (%)
1	230	230.1	0.1	0.043	0.1740	0.162	-0.0120	6.897	40.020	37.276	6.856
2	230	230.0	0.0	0.000	0.1740	0.162	-0.0120	6.897	40.020	37.260	6.897
3	230	230.3	0.3	0.130	0.1740	0.162	-0.0120	6.897	40.020	37.309	6.775
4	230	230.3	0.3	0.130	0.1740	0.162	-0.0120	6.897	40.020	37.309	6.775
5	230	230.0	0.0	0.000	0.1740	0.162	-0.0120	6.897	40.020	37.260	6.897
6	230	230.0	0.0	0.000	0.1740	0.162	-0.0120	6.897	40.020	37.260	6.897
7	230	230.6	0.6	0.261	0.1740	0.162	-0.0120	6.897	40.020	37.357	6.654
8	230	230.0	0.0	0.000	0.1740	0.162	-0.0120	6.897	40.020	37.260	6.897
9	230	230.2	0.2	0.087	0.1740	0.161	-0.0130	7.471	40.020	37.062	7.391
10	230	230.0	0.0	0.000	0.1740	0.162	-0.0120	6.897	40.020	37.260	6.897
Ave.	230	230.15	0.15	0.065	0.174	0.1619	-0.0121	6.954	40.02	37.261	6.893



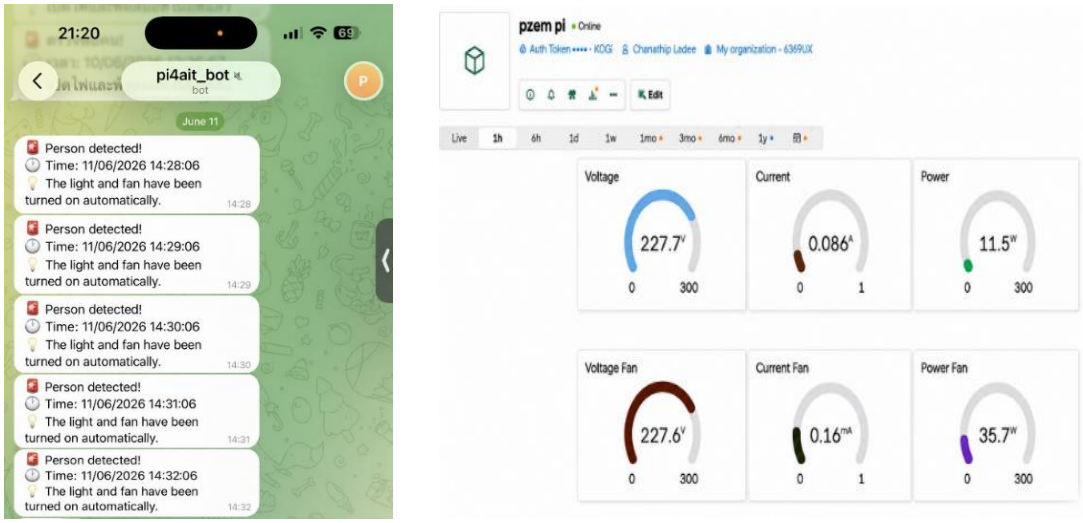
	A	B	C	D	E	F	G	H	I	J
1	Date/Time	Lamp Voltage (V)	Lamp Current (A)	Lamp Power (W)	Lamp Status	Fan Voltage (V)	Fan Current (A)	Fan Power (W)	Fan Status	Energy (kWh)
2	13/06/2025 15:43:54	230.2	0.089	11.7	1	230.1	0.164	37.5	1	0.000005
3	13/06/2025 15:43:33	230.1	0.085	11.7	1	230	0.164	37.4	1	0.000007
4	13/06/2025 15:44:02	230.4	0.085	11.7	1	230.3	0.164	37.4	1	0.000120
5	13/06/2025 15:44:30	230.4	0.085	11.6	1	230.3	0.164	37.4	1	0.000184
6	13/06/2025 15:45:10	230	0.005	11.6	1	230	0.163	37.1	0	0.000246
7	13/06/2025 15:45:16	230	0.005	11.6	0	230	0.163	37.1	0	0.000246
8	13/06/2025 15:45:23	230.7	0	0	0	230.6	0	0	0	0.000246
9	13/06/2025 15:45:57	230.1	0.084	11.6	1	230	0.163	37.1	1	0.000699
10	13/06/2025 15:46:24	230.3	0	0	0	230.2	0	0	0	0.000635
11	13/06/2025 15:46:59	230.1	0.085	11.6	1	230	0.162	37	1	0.000907
12	13/06/2025 15:47:31	230.1	0.084	11.5	1	230	0.162	37	1	0.000866
13	13/06/2025 15:48:05	230.2	0.084	11.6	1	230.1	0.162	37.1	1	0.001215
14	13/06/2025 15:48:38	230.2	0.083	11.5	1	230.1	0.162	36.9	1	0.001623
15	13/06/2025 15:49:12	230.2	0.084	11.5	1	230.1	0.162	37	1	0.002004
16	13/06/2025 15:49:49	230.5	0.084	11.5	1	230.4	0.162	37	1	0.002443
17	13/06/2025 15:50:19	230.5	0.084	11.5	1	230.4	0.162	37	1	0.002844
18	13/06/2025 15:20:54	230.4	0.084	11.5	1	230.3	0.162	37	1	0.003025

Fig. 13 Storing energy usage data on Google Sheets

According to Table 7, the measured voltage was at a mean of 230.150 volts. Compared to the true voltage of 230, this measurement had a mean deviation of 0.150 volts or 0.065%, with a mean accuracy of 99.935%. Electricity current was measured at a mean of 0.1619 amperes. When compared to the true current of 0.1740 amperes, this measurement was found to be lower than the true value, with a mean of 0.0121 amperes or a mean deviation of 6.954%. When electrical power was calculated based on the formula (P = V x I), true electrical power was found to be at a mean of 40.020 watts while the

measured electrical power was at a mean of 37.261 watts, meaning the measurement had a mean deviation of 6.893%. The test to send data to be recorded on Google Sheets tested logging of energy readings from devices connected to the system (one 20-watt light and one 40-watt fan). Data sent to Google Sheets consisted of Date/Time, Lamp Voltage (V), Lamp Current (A), Lamp Power (W), Lamp Status (0,1), Fan Voltage (V), Fan Current (A), Fan Power (W), Fan Status (0,1) and Energy (kWh), as shown in Figure 13. Figure 13 shows log data on date/time, electrical values, and device work status on Google Sheets. The light had a voltage of 230 volts, a current of 0.083-0.086 amperes, and a power of 11.5-11.7 watts, while the fan had a voltage of 230 volts, a current of 0.162-0.164 amperes, and a power of 36.9-37.5 watts.

The Lamp Status and Fan Status columns used the values of "1" and "0" to indicate device "On-Off" status, while the Energy (kWh) column displayed accumulated electrical energy values, which increase with device work time, indicating the system's ability to continuously record data on energy consumption. The test to send notices via Telegram Bot API and display results on the Blynk application tested the display of device working status, electrical energy values, and notices via both applications, as shown in Figure 14.



(a) **(b)**

Fig. 14 Shows the display via the Telegram bot API and the Blynk application window.

According to Figure 14(a), when the system detected a human, the system sent notices via the Telegram Bot named "pi4ait_bot", displaying the message "Person detected!" with the date and time of detection. The system then reported "The light and fan have been turned on automatically," indicating that the light and fan were turned on automatically. Figure 14(b) displays real-time energy consumption values via the Blynk application in the dashboard format of the pzem pi system. These values were for electrical voltage, current, and power of each load set. For example, the light had a voltage of 227.7V, a current of 0.086A, and a power of 11.5W, while the fan had a voltage of 227.6V and a power of 35.7W. These data can help users track electrical device status and energy consumption continuously.

5. Discussion of the Findings

According to results from the experiment with the building energy management system integrated with image processing and Internet of Things technologies, the system was found to be functional according to principles in the design by using cameras to detect the existence of a human as a condition for controlling the light and the fan. When the resemblance score exceeded 60%, the system turned on devices and sent a notice via Telegram, along with reading energy values from the PZEM-004T module every ten seconds, logging data on Google Sheets, and displaying results via Blynk in real time. Therefore, the system was able to systematically link human detection, device controls, notices, and data collection.

Human detection results show that shirt color, distance from camera, and position in the image affected the system's effectiveness. The system had a total accuracy of 71.77%, an FPR of 8.16%, and an FNR of 48.30%, reflecting detection error at low levels while limitations from failure to detect a human persist, particularly at image edges and at long distances. Black shirts had the highest accuracy at 75.51%, followed by white shirts at 74.49%, while green shirts had the lowest accuracy at 65.31% and the highest FNR at 59.18%, possibly because of the shirt color blending with the background or inadequate image quality.

In the area of energy measurement, the system was able to log the date, time, electrical voltage, current, power, device status, and stored energy of the light and the fan separately, with voltage measured at 230 volts, the light's electrical power

measured at 11.5-11.7 watts, and the fan's electrical power measured at 36.9-37.5 watts. However, the measured current and power were lower than the actual values. For the fan, the actual power was at a mean of 40.020 watts while the measured power was at a mean of 37.261 watts, a mean deviation of 6.893%; for the light, the mean deviation was 6.622%.

Table 8 compares the proposed system with existing works. Unlike studies that address only occupancy detection [9, 29] or only energy monitoring and analysis [17, 18], the proposed system closes the loop from detection to load control, per-load energy measurement, notification, and data logging on a single Raspberry Pi 4. This result was achieved for three reasons. First, the single-stage YOLOv4 detector processes each frame in one pass, which enables detection on an edge device without a server [26, 30]. Second, the 30-second hold time prevents loads from being switched off when the detector misses a person briefly, which reduces the practical effect of false negatives on control. Third, a separate PZEM-004T module for each load allows the energy consumption of the light and the fan to be tracked individually rather than as a building total. However, the total accuracy of 71.77% is lower than that typically reported for deep learning detectors evaluated on public datasets with high-performance hardware [26, 30], because this study used a single webcam and included positions at the image edges and at long distances under real lighting. Therefore, improved camera placement, multiple cameras, or a model fine-tuned for indoor scenes is needed to reduce the FNR, and the PZEM-004T modules should be calibrated to reduce the systematic power deviation of 6.6-6.9%.

Table 8. Comparison of the proposed system with existing works

Study	Main focus	Occupancy detection	Automatic load control	Energy metering / logging
Erickson et al. [14]	Occupancy-based HVAC control	Camera sensor network	Yes (HVAC)	Not per load
Cui et al. [9]	Occupancy detection	Low-resolution thermal images	Not the main focus	Not the main focus
Huang et al. [18]	IoT energy data analysis	Not the main focus	Not the main focus	Yes (analysis)
Ganagavalli and Santhi [29]	Surveillance activity detection	YOLO-based	Not the main focus	Not the main focus
Proposed system	Closed-loop BEMS on Raspberry Pi 4	YOLOv4 with webcam	Yes (light and fan, 30-s hold time)	Yes (per load; Blynk, Telegram, Google Sheets)

6. Conclusion

This study developed a building energy management system integrated with image processing and Internet of Things technologies. The system consists of cameras for human detection, a PZEM-004T module for measuring light and fan electrical values, and a Raspberry Pi 4 board for processing and relay control, including the Blynk, Telegram, and Google Sheets applications for displaying results, giving notice, and recording data. According to development results, devices in every section were found to be able to function together according to objectives by using human detection results as a condition for continuous electrical device control and energy consumption monitoring. Testing in a 7 x 7 meter laboratory using black, white, and green shirts found the system to have a total accuracy of 71.77%, with black shirts yielding the best result. This was followed by white shirts, while green shirts had the lowest accuracy, indicating that shirt color, distance from cameras, the person's position, and blend with the background affected effectiveness, particularly at image edges and in positions far from the camera. In conclusion, the system was able to turn on the light and the fan when a human is detected and turn devices off when a human is not detected within the specified time, along with giving notice via Telegram, displaying results via Blynk, and logging data on Google Sheets. Furthermore, the system was able to measure the electrical voltage, current, power, and stored energy of each type of load separately.

Therefore, the system can be used as a prototype for smart buildings to reduce time when devices are left on unnecessarily. When considering further development, detection and user-counting accuracy should be increased and tested with air conditioners, ventilation systems, and multi-zone lighting systems, including artificial intelligence implementation to predict energy consumption. In addition, the energy measurement module should be calibrated and tested in real environments with greater data security measures to ensure the system's accuracy, stability, and suitability for real use.

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