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Vision-Based Zone-Wise Classroom Energy Management System

Dr. (Mrs.) S. P. Muley, Abhinay Utane, Harshal Titarmare, Likhit Kapgate, Nishant Thakre, and Sahil Khade

Department of Electrical Engineering, Priyadarshini College of Engineering, Nagpur, Maharashtra, India

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ABSTRACT—

Classroom environments in higher education in-stitutions routinely suffer from substantial electrical energy waste because lighting and ventilation units remain operational across the entire room regardless of localized student occupancy. Conventional classroom automation predominantly relies on passive infrared (PIR) detectors or automated timers. However, PIR sensors merely capture broad binary motion, fail when occupants remain seated and stationary during academic tasks, and cannot localize seated occupants within discrete sectors. This paper presents an automated, vision-based zone-wise energy management system designed to eliminate unneeded electrical consumption without requiring dense arrays of physical sensors. The proposed architecture acquires real-time overhead camera feeds, executes image filtering and frame preprocessing via OpenCV, and deploys a YOLO (You Only Look Once) deep learning model for human detection. Centroid coordinates of detected occupants are dynamically mapped to predefined spatial zones. Zone-specific actuation vectors are dispatched across a serial UART link to an ESP32 microcontroller, which selectively switches lighting and ventilation loads through an opto-isolated relay interface. An experimental hardware prototype comprising four independently actuated zones was implemented to vali-date detection reliability, switching accuracy, and operational efficiency. Under partial occupancy scenarios (50% room uti-lization), the proposed system achieves a 50% electrical power reduction compared to conventional continuous-duty operation.

Index Terms—Classroom automation, Computer vision, Em-bedded systems, Energy conservation, ESP32, Object detection, Relay control, Spatial zoning, YOLO.

I. INTRODUCTION

Electrical energy conservation within public and educational facilities has become a critical operational priority. Standard classrooms, laboratories, and lecture theaters account for sig-nificant cumulative energy demand via lighting and ceiling fan networks. In typical academic schedules, classrooms often host smaller batches, tutorial groups, or staggered student cohorts where only a small cluster of desks is physically occupied. Despite this localized distribution, complete electrical circuits are typically left energized across the entire room due to manual oversight, lack of individual sub-circuit access, or occupant negligence.

To address manual shortcomings, various automation tech-niques have been deployed. Passive Infrared (PIR) sensors and basic ultrasonic detectors are common commercial options. However, these systems exhibit notable limitations in academic settings:

- Stationary Blind Spots: PIR sensors detect differential infrared changes caused by motion. When students sit still during lectures, tests, or self-study, sensors register false absences and shut off power prematurely.
- Lack of Granular Localization: A typical ceiling PIR detector provides binary room-level detection, forcing every fixture in the room to power ON if even a single person is detected.
- Deployment Overheads: Segmenting a large room into discrete micro-zones using hardware sensors requires ex-tensive sensor deployment, discrete power wiring, struc-tural modifications, and regular maintenance.

Computer vision offers a non-intrusive alternative capable of granular spatial tracking. Rather than retrofitting an en-vironment with intrusive multi-sensor grids, institutions can leverage existing surveillance and CCTV cameras. Modern convolutional neural networks, specifically single-stage object detection architectures such as YOLO (You Only Look Once), enable real-time human detection with high spatial precision. This study implements and validates a Vision-Based Zone-Wise Classroom Energy Management System. The platform pairs an overhead video feed with a deep-learning coordinate detection pipeline. By segmenting the floor plan into calibrated two-dimensional bounding zones, the software identifies indi-vidual desk occupation and directs an ESP32 microcontroller to switch the matching lighting and ventilation units.

II. RELATED WORK AND MOTIVATION

A. Survey of Prior Art

Classroom energy management typically balances occupant comfort with energy reduction. Pushpendra Mishra investi-gated an AI-based smart CCTV monitoring framework de-signed to detect occupied spaces and confirm whether ceiling fans remained running when spaces emptied [1]. While effective as an alert notification and auditing system, it focused on alerting facilities rather than providing direct, zone-by-zone autonomous load switching.

Real-time computer vision owes significant performance improvements to single-stage detectors. Redmon et al. intro-duced YOLO, framing object detection as a unified spatial bounding regression problem that executes at high frame rates [2]. Bradski and Kaehler established robust foundational methodologies for frame acquisition, matrix transformations, color space filtering, and morphological processing through OpenCV [3].

B. Identified Research Gaps

Existing literature presents three primary gaps:

1) Most commercial systems operate at binary room-scale thresholds rather than dynamic zone-scale thresholds.

2) Passive sensor networks create single-point operational failures, require added retrofitting costs, and suffer from dead zones.

Software-only computer vision models often operate purely in analytical offline software without interfacing with physical electrical switchgear

The objective of this research is to bridge these gaps by designing, assembling, and experimentally validating an end-to-end prototype that coordinates vision pipelines with relay actuation hardware.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The system architecture is split into a Vision and Decision Engine (hosted on an edge-capable computing unit) and a Physical Control and Switching Unit (implemented on an ESP32 embedded controller).

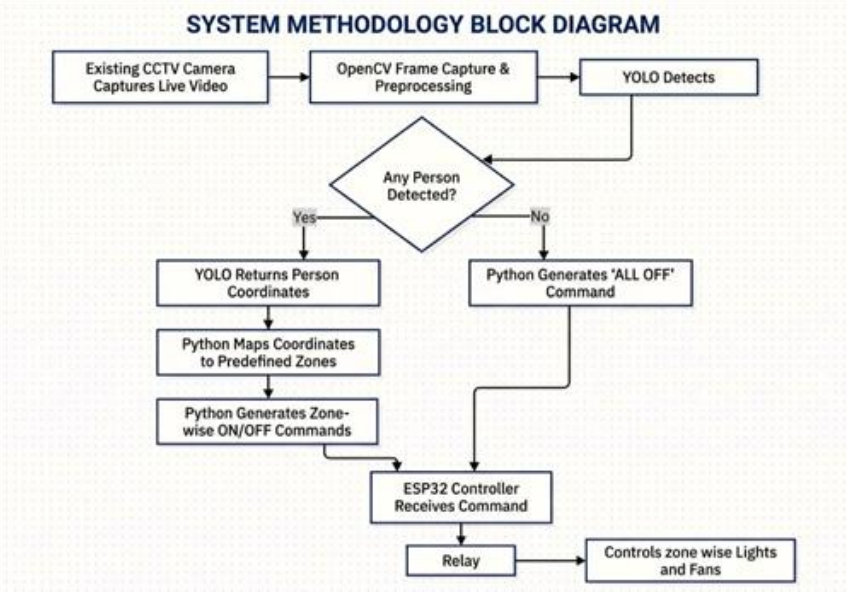


Fig. 1. System functional block diagram and decision pipeline.

A. Vision Unit and Spatial Preprocessing

Video frames are acquired at 1080p resolution and 30 frames per second (FPS) via an overhead wide-angle optical sensor. Frame processing is handled using OpenCV:

1) Geometric Normalization: The input stream is down-sampled to match network input dimensions (640 × 640 pixels) while preserving aspect ratio.

2) Color Space Standardization: Frames are structured into regularized BGR matrices, and contrast normalization is applied to reduce false negatives from sunlight gradients entering via exterior windows.

B. YOLO Deep Learning Detection Pipeline

Human subjects are detected using a pre-trained YOLO model optimized for person-class extraction. Each frame pro-duces detection bounding boxes:

Bi = [xmin, ymin, xmax, ymax, ci]

where ci represents class confidence. A detection threshold of ci ≥ 0.50 is enforced. For every confirmed occupant, the centroid ($\bar{x}_i$, $\bar{y}_i$) is calculated:

$$\bar{x}_i = \frac{x_{min} + x_{max,}}{2} \qquad \bar{y}_i = \frac{y_{min} + y_{max}}{2} \qquad (2)$$

C. Spatial Coordinate Mapping and Decision Logic

The room layout is partitioned into distinct spatial zones. Boundaries for each zone k (Z_k) are defined using pixel limits across the camera field of view:

$$Z_k = \{(x, y) \mid X_{min,k} \leq x < X_{max,k} \wedge Y_{min,k} \leq y \leq Y_{max,k}\} \qquad (3)$$

TABLE I

Spatial Zone Definitions and Assigned Channels

Zone	X**-Range (px)**	Y **-Range (px)**	**Assigned Output Channel**
A	$0 \leq x < 256$	$0 \leq y \leq 720$	Relay 1 (Light 1), Relay 2 (Fan 1)
B	$257 \leq x < 512$	$0 \leq y \leq 720$	Relay 3 (Light 2), Relay 4 (Fan 2)
C	$513 \leq x < 768$	$0 \leq y \leq 720$	Relay 5 (Light 3), Relay 6 (Fan 3)
D	$769 \leq x \leq 1024$	$0 \leq y \leq 720$	Relay 7 (Light 4), Relay 8 (Fan 4)

The decision engine applies the following logic across all zones:

- Let N_k be the count of detected centroids falling inside Z_k.
- If $N_k > 0$, Zone k status is set to OCCUPIED; the corresponding lighting and fan relays are driven to HIGH.
- If $N_k = 0$, Zone k status is set to VACANT; the corresponding relays are driven to LOW.
- If $N_k = 0$, an ALL_OFF broadcast command is triggered, powering down every load.

A 5-second persistence buffer is incorporated to prevent rapid relay cycling caused by brief occlusions.

D. Microcontroller Interfacing and Actuation

Control vectors are converted into a compact serial payload and transmitted over UART at 115,200 bps to an ESP32 microcontroller. The ESP32 decodes incoming zone states and writes output logic levels across dedicated GPIO pins (GPIO 25, 26, 27, 14, 12, 13, 32, and 33). These pins drive an 8-channel, 5V opto-isolated relay board. Status data is displayed across an I^2C bus using a PCF8574 expander to a 16×2 LCD.

IV. Hardware Implementation and Experimental

Testbed

To validate the architecture, an experimental miniature classroom testbed was constructed.

The physical classroom structure incorporates scaled desk clusters divided into four zones. An elevated overhead mount holds the vision sensor to maintain an unobstructed line-of-sight across desks.

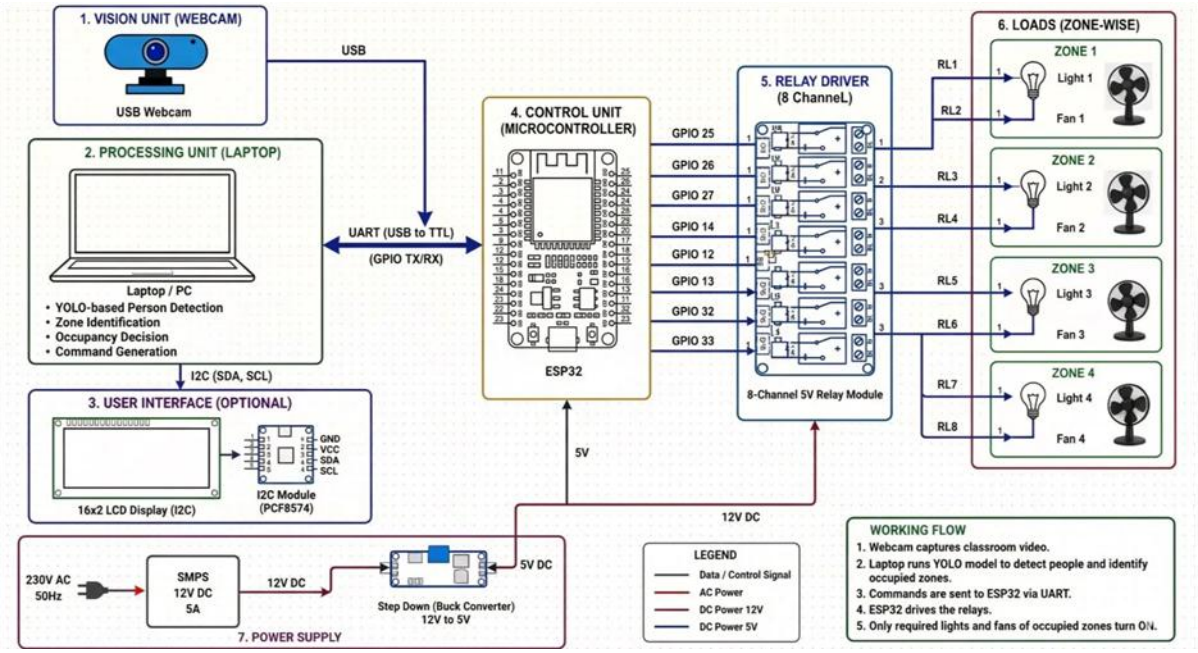


Fig. 2. Complete electrical interconnect schematic highlighting SMPS power conversion, ESP32 GPIO logic assignments, opto-isolated relay driver circuitry, and zone-wise electrical loads.

TABLE II

Component Specifications of Experimental Setup

Module	**Specifications**	**Prototype Role**
Camera	1080p, 30 FPS USB Webcam	Real-time capture
ESP32	Dual Core 240 MHz, 3.3V Logic	Relay drive controller
Relay Driver	8-Ch Opto-isolated, 5V Coil	Load switching
Display Unit	16×2 LCD (I^2C PCF8574)	Status monitoring
SMPS	230V AC to 12V DC, 5A (60W)	Main power supply
Regulator	LM2596 Buck (12V to 5V DC)	Regulated logic bus
Luminaires	5V DC Solid-State LEDs (1W)	Classroom lighting
Ventilation	5V DC Mini Fans (2W,3000 RPM)	Classroom fans

V. Empirical Results and Performance Analysis

A. Detection and Mapping Evaluation

The system was evaluated across multiple student seating arrangements. The vision pipeline processed frames within 32 ms to 48 ms on a standard host machine, sustaining real-time processing at 22–30 FPS.

The model achieved person detection confidence scores between 0.90 and 0.93 across varying lighting conditions.

B. Energy Consumption and Conservation Calculations

Energy usage was measured across traditional unmanaged operations versus the proposed vision-based zone control:



Fig. 3. Photograph of the assembled 4-zone classroom prototype setup showing the elevated camera mount, control housing, and appliance matrix.

TABLE III

EXPERIMENTAL VERIFICATION ACROSS TEST CONFIGURATIONS

Test Case	Occupied Zones	Relays Triggered ON	Fidelity
Full Room	Zones A, B, C, D	Relays 1 through 8	100%
Left Half	Zones A, B	Relays 1, 2, 3, 4	100%
Staggered	Zones A, C	Relays 1, 2, 5, 6	100%
Vacant	None	All Relays OFF (ALL_OFF)	100%

- *Per-Zone Power:*

$P_{zone} = P_{light} + P_{fan} = 1\text{ W} + 2\text{ W} = 3\text{ W}$ (4)

- *Full Prototype Power (4 Zones):*

$P_{total} = 4 \times P_{zone} = 4 \times 3\text{ W} = 12\text{ W}$ (5)

Case 1: Baseline Continuous Operation

Classroom loads operate continuously across a 6-hour aca-demic schedule:

$E_{traditional} = P_{total} \times t = 12\text{ W} \times 6\text{ h} = 72\text{ Wh/day}$ (6)

Case 2: Vision-Based Zone Control

For an occupancy scenario where two of the four zones are occupied for the same 6-hour period:

$P_{occupied} = 2 \times P_{zone} = 2 \times 3\text{ W} = 6\text{ W}$ (7)

$E_{AI} = P_{occupied} \times t = 6\text{ W} \times 6\text{ h} = 36\text{ Wh/day}$ (8)

$\Delta E = E_{traditional} - E_{AI} = 72\text{ Wh} - 36\text{ Wh} = 36\text{ Wh/day}$ (9)

$$\% \text{ Savings} = \frac{(72 - 36)}{72} \times 100 = 50\% \quad (10)$$

C. Scalability to Institutional Facilities

Extrapolating these metrics to a typical academic lecture hall illustrates the real-world utility of the system:

- Consider a hall with 8 ceiling fans (75W each) and 12 LED fixtures (20W each):

$P_{full} = (8 \times 75\text{ W}) + (12 \times 20\text{ W}) = 840\text{ W} = 0.84\text{ kW}$

- Operating continuously for 8 hours daily:

$E_{full\ trad}$ = 0.840 kW × 8 h = 6.72 kWh/day

- Under 50% localized occupancy over the same schedule:

$E_{full\ AI}$ = 0.420 kW × 8 h = 3.36 kWh/day

This yields savings of **3.36 kWh per classroom per day**, or roughly **80 to 90 kWh per month per room**. Across a university campus with dozens of lecture halls, this zone-wise control yields notable financial and carbon emission reductions without requiring new sensor installations.

VI. Conclusion and Future Scope

This project implemented a vision-based, zone-wise class-room energy management system using YOLO-based hu-man detection, OpenCV processing, and an ESP32 embedded controller. The prototype reliably localized human occupants to designated zones and switched independent lighting and ventilation circuits accordingly. Hardware tests show a 50% reduction in power consumption under half-capacity seating conditions while avoiding the false-vacancy problems typical of motion sensors.

Future extensions will evaluate running lightweight quan-tized object detection models directly on low-power edge microprocessors (such as the ESP32-S3 or Raspberry Pi 5) to remove the dedicated PC requirement. Additionally, inte-grating lux sensors can support continuous ambient daylight harvesting, and thermal comfort modeling can adapt fan speeds proportionally rather than using binary switching.

References

[1] P. Mishra, "An AI-Based Smart CCTV System for Classroom Energy Monitoring and Management," *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, vol. 14, no. 2, 2026.

[2] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016, pp. 779–788, doi: 10.1109/CVPR.2016.91.

[3] G. Bradski and A. Kaehler, *Learning OpenCV: Computer Vision with the OpenCV Library*, 1st ed., Sebastopol, CA, USA: O'Reilly Media, 2008.

[4] V. Agarwal, A. Sharma, and K. V. Arya, "Energy efficient smart classroom system using computer vision techniques," in *Proc. 2nd Int. Conf. Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, 2015, pp. 1205–1210.

[5] S. C. M. de Aguiar and P. R. M. Silva, "Automated lighting and climate control based on computer vision occupancy estimation," *IEEE Latin America Transactions*, vol. 18, no. 7, pp. 1198–1206, Jul. 2020.

[6] A. Carcangiu, F. Delussu, and E. Grosso, "Computer vision-based occupancy monitoring for smart energy management in educational buildings," *IEEE Access*, vol. 9, pp. 142104–142116, Oct. 2021.

[7] S. K. Sood and K. D. Singh, "Optical edge analytics for real-time sus-tainable institutional power regulation," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, pp. 3412–3420, May 2021.

[8] M. S. Pan, "An energy-saving and comfort-aware smart lighting control system using camera sensors," *IEEE Sensors Journal*, vol. 17, no. 8, pp. 2496–2507, Apr. 2017.