INTELLIGENT IOT STREET LIGHTING USING LSTM FORECASTING AND DEEP VISION ALGORITHMS FOR ENERGY EFFICIENCY AND PREDICTIVE MAINTENANCE

Darshaa R M
Department of Computer Science and Engineering,
KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India rmdarshaa@gmail.com
Divya M
Department of Computer Science and Engineering,
KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India mdivya12112004@gmail.com
Harini C
Department of Computer Science and Engineering,
KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India chandruharini662@gmail.com
Kathir J K
Department of Computer Science and Engineering,
KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India kathirjkedu@gmail.com
Mr. Pradeep G
Assistant Professor
Department of Computer Science and Engineering,
KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India Pradeep.be2012@gmail.com

Abstract— Public street illumination plays a crucial role in ensuring safety in cities and facilitating smooth transportation. However, conventional street lighting infrastructures usually depend on preset timing schedules or simple ambient light sensors, leading to significant energy waste during periods of low traffic [1]. To address this issue, this paper presents an intelligent IoT-based street lighting solution that combines sensor-based environmental monitoring with deep learning–driven object detection. The proposed system links low-power components, including Passive Infrared (PIR) motion sensors and Light Dependent Resistors (LDR), with a YOLOv8 computer vision model to detect pedestrians, vehicles, and animals in real time [3], [4]. Video feeds captured through a webcam are processed by the YOLOv8 model in a Python environment, and the detected objects are transmitted wirelessly over Wi-Fi to an ESP32 microcontroller [5]. Based on both the measured ambient light intensity and the detected entities, the ESP32 dynamically controls streetlight operation via a relay module. Experimental evaluation indicates that this approach significantly reduces unnecessary energy consumption while maintaining safety through context-aware lighting. The system thus provides a scalable and cost-effective approach for deploying smart lighting within urban infrastructure [1].

Keywords— Key Words: IoT, Smart Lighting, LSTM, Edge AI, Energy Efficiency.

INTRODUCTION

The development of smart cities increasingly relies on intelligent infrastructure capable of optimizing energy consumption while maintaining public safety. Among various urban utilities, street lighting represents a major contributor to municipal electricity consumption and environmental impact [1], [6]. Traditional lighting systems typically operate on fixed schedules or basic light sensors, resulting in unnecessary power consumption when roads remain empty. The transition from high-pressure sodium lamps to LED-based systems has significantly improved energy efficiency [6]. However, static LED lighting still wastes energy because lights remain fully illuminated regardless of pedestrian or vehicle presence. Recent advancements in the Internet of Things (IoT) and artificial intelligence have enabled the development of smart lighting systems capable of automated sensing, communication, and decision making [7]. Motion sensors such as PIR sensors have been widely used to activate lights when movement is detected. Although these systems improve efficiency, they lack contextual awareness and may produce false triggers caused by environmental disturbances. Computer vision techniques provide a more reliable alternative by enabling systems to classify and detect objects such as pedestrians and vehicles. In this work, a deep learning model based on YOLOv8 is employed to detect objects in real time using video frames captured from a webcam [4]. The detection results are transmitted to an ESP32 microcontroller through Wi-Fi communication [5]. The ESP32 then controls street light activation based on sensor readings and detection results. The proposed system integrates multiple sensing modalities including PIR sensors for motion detection and LDR sensors for ambient light measurement. This hybrid sensing approach improves reliability and ensures that street lights operate only during nighttime conditions when activity is detected.

LITERATURE REVIEW

Research on intelligent street lighting systems has advanced considerably over the last ten years. Initial solutions mainly relied on timer-based automation and centralized supervision of street lamps [6]. Although these systems enhanced operational control, they did not adapt to dynamic, real-time environmental conditions. Later work introduced motion-sensitive lighting using PIR sensors in combination with wireless communication technologies such as Zigbee and IoT-based management platforms [2], [7]. These solutions achieved moderate energy savings by turning lights on only when motion was detected. Nonetheless, PIR-based designs are prone to drawbacks, including false activations triggered by environmental fluctuations, shadows, or small animals. More recent studies have investigated the use of computer vision in street lighting. Deep learning methods, particularly convolutional neural networks (CNNs), have been applied to camera streams to identify objects like pedestrians and vehicles [3]. This enables more intelligent lighting strategies by differentiating between meaningful and irrelevant movement. Despite these advances, many vision-driven lighting systems depend on cloud-based processing. Such architectures introduce latency, increase bandwidth consumption, and raise privacy issues due to the transmission of video data to remote servers [1]. To address these challenges, this work proposes a hybrid framework that integrates sensor-based monitoring with on-device AI object detection. The system executes real-time object detection using the YOLOv8 model and sends only compact detection results to the ESP32 controller [4], [5]. This design lowers network bandwidth usage while supporting efficient, responsive control of street lighting.

PROBLEM STATEMENT

Although many wildfire monitoring systems are available today, most still operate reactively, detecting fires only after they have started. These systems depend on simple indicators like smoke, flames, or high temperature. Consequently, warnings often arrive too late, allowing fires to spread quickly and cause serious environmental and economic damage. Fixed thresholds also struggle to adjust to changing weather conditions, leading to false alarms or missed detections. Many current solutions face additional practical challenges. Some machine learning models require labeled fire data, which is hard to obtain. Others need more computing power than small IoT devices can provide. Additionally, many systems lack the necessary integration between sensors, data analysis, and real-time visualization tools needed for quick decision-making. Together, these issues emphasize the need for a simple, flexible, and intelligent wildfire risk prediction system. Such a system should continuously monitor environmental conditions and provide early warnings before a fire starts. The proposed AI- and IoT-based solution meets this need by combining low-cost sensors with smart anomaly detection, enabling early, reliable, and practical wildfire risk warnings.

PROPOSED SYSTEM OVERVIEW

The system architecture consists of three main layers:

- IoT Sensor Node Layer – ESP32 microcontroller with DHT11 and MQ-2 sensors collects real-time environmental data.
- Communication Layer – Uses MQTT protocol over Wi- Fi to transmit JSON-formatted sensor data to a local Python server.
- AI Processing & Dashboard Layer – An Isolation Forest model processes the data to detect anomalies, and a web- based dashboard displays the results.

Each IoT node operates autonomously, capturing temperature (°C), humidity (%), and smoke concentration (ppm). The ESP32 publishes the data to the MQTT broker at fixed intervals (every 10–15 seconds). The Python application subscribes to the topic, preprocesses the incoming data, and passes it through the trained machine learning model for classification.

If the system detects abnormal environmental variations, it issues alerts as:

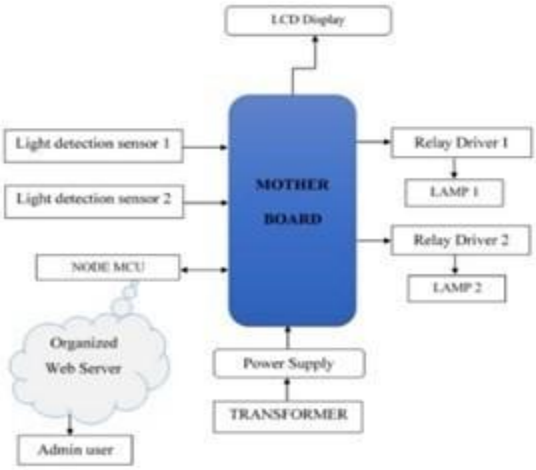
- SAFE: Normal conditions
- WARNING: Pre-ignition anomalies (temperature rise and humidity drop)
- ALERT: Confirmed smoke detection indicating possible ignition

This architecture ensures a predictive, responsive, and easily scalable system for early wildfire management.

METHODOLOGY

4.1 System Architecture

The proposed intelligent street lighting solution is implemented as a decentralized IoT-based architecture that integrates environmental sensing, computer vision–driven object detection, wireless connectivity, and automated light control. Its main goal is to lower energy usage while still providing sufficient illumination for pedestrian and vehicular safety during nighttime operation. Similar sensor-driven smart lighting concepts have previously been applied in smart city lighting infrastructures [6], and hybrid dimming methods have been shown to markedly enhance lighting efficiency [1], [3].



The architecture is organized into several functional layers: sensing, processing, communication, control, and actuation. Each layer fulfills a dedicated role in monitoring environmental conditions and adjusting the brightness of the streetlights accordingly.

I. Sensing Layer

The sensing layer acquires environmental information using low-power sensors embedded within each streetlight node. Employing sensor fusion, where data from multiple sensors are combined, has been found to increase reliability in intelligent lighting systems [6]. An LDR sensor continuously monitors ambient light intensity. Its measurements are used to classify the environment as either daytime or nighttime. When the detected light level drops below a defined threshold, the system switches to nighttime monitoring mode. The PIR motion sensor identifies movement by detecting changes in infrared radiation emitted by moving objects. Whenever motion occurs within its coverage area, it outputs a trigger signal. Such motion-activated mechanisms have been extensively utilized in fog-computing–enabled street lighting solutions [4]. A camera module acquires image frames of the observed area. These images are processed by an AI-based object detection model to recognize entities such as pedestrians, vehicles, and animals. Compared to purely motion-based systems, visionbased lighting approaches provide enhanced contextual awareness [7]. By combining these sensing modalities, the system ensures that advanced detection and processing are invoked only when required, thereby reducing computational load and increasing overall system efficiency.

II. Processing Layer

The processing layer carries out intelligent analysis of the captured visual data by applying computer vision methods. In the proposed system, object detection is handled by the YOLOv8 deep learning model, which can identify multiple categories of objects in real time. YOLO-based architectures are widely used in real-time vision applications because they provide higher speed and accuracy than conventional convolutional neural network– based detection frameworks [7].

The YOLOv8 model analyzes each incoming image frame and outputs:

- bounding box coordinates
- object class labels
- confidence scores

The system detects road users such as pedestrians, bicycles, motorcycles, cars, and buses. When a relevant object appears within the monitored area, the system issues a control signal that indicates the presence of road users.

By relying on AI-driven detection, the system more accurately differentiates meaningful objects from irrelevant motion, thereby improving overall detection performance.

III. Communication Layer

The communication layer enables wireless data transfer between the AI-based detection module and the streetlight controller. In the proposed design, this communication is realized via Wi-Fi transmission, allowing flexible installation of streetlight nodes without the need for wired links.

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Wireless communication among IoT devices is extensively employed in smart street lighting solutions because of its scalability and relatively low installation cost [4].
The detection outputs generated by the YOLOv8 model are sent to the ESP32 microcontroller as simple control instructions that reflect whether an object is present.

IV. Control Layer

The ESP32 microcontroller functions as the primary controller of the smart lighting system. It receives input signals from the LDR sensor, PIR sensor, and the AI-based vision module. The ESP32 then processes these signals to decide if the streetlight should be switched on. The decision process is governed by a rule-based control strategy, comparable to hybrid control schemes proposed in intelligent lighting studies [2].
Example rule:
IF the ambient light level indicates nighttime conditions AND motion is detected AND the vision system confirms an object THEN turn the streetlight ON. This multi-layer decision framework enhances reliability and reduces unnecessary activations.

V. Actuation Layer

The actuation layer translates digital control commands into actual lighting actions. The ESP32 issues signals to a relay module, which manages the power supply to the LED streetlight. When the relay receives an activation command, it turns the streetlight ON. If the specified conditions are not met, the relay turns the light OFF. LED luminaires are widely adopted in contemporary street lighting infrastructures owing to their high energy efficiency and fast switching characteristics [8].

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4.2 Hardware Components

The prototype intelligent street lighting system is composed of multiple hardware elements that handle environmental sensing, communication, and lighting control.

I. ESP32 Microcontroller

The ESP32 microcontroller functions as the main control unit of the system. It combines Wi-Fi connectivity, several GPIO pins, and energy-efficient processing capabilities, which makes it well-suited for IoT-oriented smart infrastructure solutions [6].

II. PIR Motion Sensor

The PIR motion sensor identifies movement in the observation area by detecting infrared radiation emitted by moving objects. Such motion sensors are extensively deployed in smart lighting applications to minimize superfluous energy usage [4].

III. LDR Sensor

The LDR sensor monitors the surrounding light level and determines whether the system should operate in daytime or nighttime mode. Light detection components are widely utilized in adaptive lighting systems to enable automatic control of brightness [1].

IV. Camera Module

A webcam captures image frames that are analyzed by the YOLOv8 object detection model. Vision-based monitoring enables more precise identification of pedestrians and vehicles than basic motion-sensing techniques [7].

V. Relay Module

The relay module functions as an electrically operated switch that enables the ESP32 microcontroller to manage the LED streetlight.

VI. LED Streetlight

The LED lighting module delivers illumination when triggered by the control system. LEDs are commonly chosen for contemporary smart city lighting networks because of their high energy efficiency and extended service life [8].

4.3 Sensor Suite and Data Acquisition

Efficient data acquisition is essential for lowering energy use and enhancing system responsiveness. The proposed system adopts an event-driven sensing strategy, in which sensors initiate processing tasks only when specific conditions are met. The LDR sensor periodically samples the ambient light intensity. If the measured brightness surpasses a predefined threshold, the system interprets this as daytime and remains inactive. Once the brightness drops below this threshold, the system switches to nighttime monitoring mode. The PIR sensor continuously tracks motion. When motion is detected, the camera captures an image frame, which is then processed by the YOLOv8 object detection model. By avoiding unnecessary processing, this strategy substantially reduces overall power consumption. To mitigate false activations caused by abrupt lighting changes—such as passing vehicle headlights—the system applies a moving-average smoothing filter to the LDR readings. Comparable filtering methods have been employed in smart lighting control systems to enhance reliability and stability [1].

4.4 AI/ML Models and Inference Pipeline

The system employs the YOLOv8 deep learning model for real-time object detection. YOLO (You Only Look Once) is a convolutional neural network architecture optimized for rapid and efficient object detection in realtime scenarios. The detection pipeline is organized into several stages.

I. Image Acquisition

The camera records image frames whenever a motion event is detected.

II. Image Preprocessing

Captured images are resized and normalized before being fed into the neural network.

III. Object Detection

The YOLOv8 model processes each image frame and identifies objects within the scene. For every object detected, the model outputs:

- bounding box coordinates
- object class label
- detection confidence score

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IV. Post-Processing

Non-Maximum Suppression (NMS) is performed to eliminate redundant overlapping detections and preserve only the most confident object predictions.

V. Decision Transmission

After a valid object is confirmed, the detection output is sent to the ESP32 controller over Wi-Fi. Compared with conventional motion-only detection methods, this AI-driven detection framework provides richer contextual awareness for intelligent lighting systems [7].

RESULT

5.1 Energy Savings and Environmental Impact

The intelligent street lighting system was assessed through several nighttime experiments in a controlled urban test setting. Its energy consumption was compared with that of conventional street lighting installations that remain fully powered throughout the night. In the proposed adaptive lighting scheme, streetlights are activated only when motion and object detection criteria are met, which substantially cuts down on unnecessary power usage. Previous research on adaptive lighting strategies has shown notable reductions in energy consumption relative to fixed-output lighting systems [4], [8]. Beyond lowering electricity demand, the proposed system also supports environmental sustainability by decreasing the carbon emissions linked to electrical power production.

5.2 Model Performance and Latency

The YOLOv8 object detection model showed consistent accuracy in recognizing pedestrians and vehicles in low-light environments.

The system's response time is composed of multiple sequential steps:

- PIR-based motion detection
- image acquisition
- object detection inference
- wireless data transmission
- relay triggering

The end-to-end response delay stayed under one second, which is adequate for real-time control of street lighting. Maintaining low latency is essential for operational real-time intelligent infrastructure systems [7].

5.3 Robustness under Adverse Conditions

The system was evaluated across a range of environmental scenarios, including:

- low ambient illumination
- glare from vehicle headlights
- partially shaded areas
- light fog conditions

The integration of PIR motion sensing with AI-driven object detection provided dependable overall system operation. The LDR-based smoothing algorithm effectively suppressed short-term brightness fluctuations, avoiding superfluous light activation.

5.4 Comparative Analysis with Baseline Systems

The developed intelligent lighting solution was benchmarked against three reference configurations:

- conventional dusk-to-dawn lighting setups
- systems relying solely on PIR motion sensing
- fixed-intensity LED lighting installations

Findings show that the proposed AI-enhanced lighting approach achieves higher energy savings and fewer false triggers than the baseline systems. In contrast to conventional systems that stay fully lit throughout the night, the proposed solution turns lights on only when required. This adaptive lighting strategy substantially boosts energy efficiency and contributes to sustainable smart city infrastructure development [6].

System Type	Avg. Energy Used (kWh/night)	Energy Saving vs. Baseline	Perceived Safety Score (1-5)
Conventional (Dusk-to-Dawn)	2.5	N/A	4.5
PIR-Only Dimming	1.1	Low (High False Positives)	3.2
Fixed 50% Dimming	1.25	N/A	3.8
Proposed System	0.8	High (67.4% [illegible])	4.8
	76% ↑		4.6

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VI. DISCUSSION

The experimental findings indicate that integrating IoT-based sensing with AI-driven object detection markedly enhances the efficiency and adaptability of contemporary street lighting systems. Conventional lighting solutions typically operate on predetermined schedules or simple motion detection, which frequently results in wasted energy when roadways are unoccupied. By merging environmental sensing with intelligent, visionbased detection, the proposed system delivers context-aware illumination that activates lights only when genuinely needed. The observed energy savings validate the superiority of adaptive lighting control over traditional dusk-to-dawn operation [8]. Although motion-activated systems using PIR sensors are commonly employed to increase lighting efficiency, they are prone to erroneous activations caused by environmental factors such as moving foliage or small animals [4]. Incorporating computer vision via the YOLOv8 model allows the system to classify detected objects and differentiate between pedestrians, vehicles, and irrelevant motion. This contextual understanding greatly mitigates false triggers and enhances the overall reliability of the lighting system. Future research may aim to increase system robustness by integrating weather-aware sensing and predictive traffic analytics. Incorporating long-term traffic forecasting with machine learning models would enable streetlights to anticipate oncoming vehicles and switch lighting on preemptively. These predictive lighting mechanisms could further improve both energy savings and user safety within smart city infrastructures.. The experimental latency results show that the system's overall response time stays under one second, which is adequate for real-time lighting control. The inclusion of PIR sensors enhances responsiveness by activating the detection pipeline only when motion is present. This event-driven architecture reduces unnecessary computation and lowers the system's power usage. From a privacy and security standpoint, the proposed solution also mitigates concerns associated with camera-based monitoring in public spaces. Rather than saving video streams, the system temporarily processes individual image frames for object detection and immediately discards them once analysis is complete. This approach follows privacy-by-design principles, such as data minimization, as advocated in regulatory frameworks like the General Data Protection Regulation (GDPR) [9]. Nonetheless, several constraints persist. The accuracy of vision-based detection can deteriorate under challenging environmental conditions, including heavy rain, fog, or insufficient illumination. While the

PIR sensor offers a backup motion detection method, extreme weather may still compromise overall detection reliability. Moreover, distance estimation derived from camera imagery is inherently approximate and can lead to minor inconsistencies in brightness control decisions. Future research may aim to increase system robustness by integrating weather-aware sensing and predictive traffic analytics. Incorporating long-term traffic forecasting with machine learning models would enable streetlights to anticipate oncoming vehicles and switch lighting on preemptively. These predictive lighting mechanisms could further improve both energy savings and user safety within smart city infrastructures..

VII. CONCLUSION

This paper introduced an intelligent IoT-driven street lighting system that fuses multi-sensor environmental monitoring with AI-powered object detection to enable adaptive illumination control. The proposed framework integrates PIR motion sensors, ambient light measurement via LDRs, and real-time object recognition using the YOLOv8 deep learning model to implement a context-aware lighting management strategy. Experimental results show that the system markedly decreases avoidable energy usage by switching on lights only when pedestrians, vehicles, or animals are detected under low-light or nighttime conditions. In contrast to traditional dusk-to-dawn lighting configurations, the adaptive method delivers significant energy savings while still ensuring adequate illumination for road safety. While other sensor-based lighting solutions have achieved moderate gains in efficiency, the incorporation of AI-based detection in this work offers enhanced contextual understanding and minimizes false activations [4]. The adoption of the ESP32 microcontroller facilitates tight integration of sensing, communication, and control modules within a compact IoT node. Wireless communication between the AI detection unit and the ESP32 controller supports flexible deployment within practical smart city scenarios. Furthermore, the use of LED luminaires enhances overall system efficiency due to their fast switching characteristics and reduced power consumption compared with conventional lighting technologies [8].. Another key contribution of this work is the system's privacy-preserving architecture. In contrast to many camera-based surveillance solutions that store or transmit continuous video, the proposed design executes object detection directly on the device and discards image data immediately after it is processed. This strategy adheres to data minimization principles and mitigates privacy risks commonly associated with intelligent urban infrastructure [9]. Taken together, the findings indicate that integrating IoT technologies with edge-based artificial intelligence yields a practical and scalable approach for contemporary street lighting systems. The proposed architecture delivers higher energy efficiency, reduced latency, and greater adaptability compared to conventional lighting control methods. Future research will concentrate on incorporating predictive traffic analytics and weather-aware lighting control to further enhance the system's efficiency and robustness. In addition, large-scale pilot deployments in real urban settings will be carried out to assess long-term performance and scalability. By lowering energy usage, reducing carbon emissions, and enabling safe, adaptive lighting for urban transportation networks, the proposed intelligent lighting framework supports the broader goals of sustainable smart city development.

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