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AI-Driven Intelligent Street Lighting System for Energy Optimization

Binutha B.M[1],Dr. Kavitha A.S.[*], L Rakshitha[2], Megha Sadashiv Doni[3]
East West Institute of Technology, Department of Artificial Intelligence and Machine Learning
Bengaluru, India

***Abstract*—This paper presents an AI-driven intelligent street lighting system that integrates Reinforcement Learning (RL) with cloud computing, edge AI processing, and multi-sensor fusion to optimize energy consumption while enhancing public safety in smart cities. Traditional street lighting operates at fixed brightness, leading to substantial energy waste. The proposed system dynamically adjusts illumination based on real-time inputs from radar sensor, LDR sensor, and optional camera module. An AI classifier distinguishes between humans, vehicles, and animals to provide context-aware lighting control. The system architecture consists of a cloud/AI model server for training and classification, an ESP32 microcontroller for edge AI processing, radar sensor for motion detection, LDR for ambient light sensing, optional camera for visual confirmation, an AI classifier for object type identification, and an LED driver with PWM control for actuation. Simulation results demonstrate energy savings of 35-45%, response times of 0.8-1.5 seconds, and 96% classification accuracy, outperforming conventional static systems and supervised ML models such as SVM, Decision Tree, and KNN. The scalable cloud-edge architecture enables deployment across large urban networks, contributing to sustainable and safe smart city infrastructure.**

***Index Terms*—Reinforcement Learning, Smart Street Lighting, Energy Optimization, IoT, Cloud Computing, Edge AI, Smart Cities, Adaptive Control, Radar Sensor, AI Classifier, Object Detection, ESP32.**

I. INTRODUCTION

Street lighting is a critical component of urban infrastructure, directly affecting public safety, mobility, and quality of life [6]. Municipalities worldwide allocate significant portions of their electricity budgets to street lighting networks. However, conventional systems operate at constant full brightness throughout the night, irrespective of real-time environmental conditions or traffic activity. This static operation results in enormous energy waste and fails to provide adaptive illumination during emergencies or abnormal events [7].

The rapid evolution of Internet of Things (IoT), cloud computing, Edge AI, and Artificial Intelligence (AI) has opened new possibilities for intelligent lighting systems that can sense, learn, and respond to their surroundings [8]. By integrating low-cost sensors, wireless communication, edge processing, and machine learning, it is now feasible to design street lighting that adjusts brightness dynamically based on pedestrian movement, vehicle traffic, ambient light, weather conditions, and even object classification [9].

This paper proposes an AI-driven intelligent street lighting system that employs Reinforcement Learning (RL) and AI classification to achieve adaptive, self-improving control. Unlike rule-based or timer-based systems, the AI agent continuously learns from real-time sensor data, classifies detected objects (humans, vehicles, animals), and optimizes the tradeoff between energy conservation and public safety. The cloud-edge architecture ensures scalability, centralized data processing, edge-based low-latency inference, and continuous policy updates [10].

II. LITERATURE SURVEY

Numerous studies have explored smart street lighting using various technologies. Early systems used PIR sensors for simple on/off control but lacked adaptive learning capabilities [1]. However, PIR sensors have limitations including narrow detection range, sensitivity to temperature variations, and inability to detect stationary objects. Radar sensors offer superior performance with wider field of view, better detection accuracy, and immunity to environmental conditions [13]. Recent advances in edge AI have enabled real-time object classification using lightweight neural networks on microcontrollers [14].

Fuzzy logic controllers have been applied to adjust brightness based on ambient light, but they do not improve over time [2]. Machine learning models such as SVM and Decision Trees have been used for traffic prediction and lighting scheduling; however, these supervised methods require labeled historical data and cannot adapt online [3].

Reinforcement Learning has emerged as a powerful tool for sequential decision-making in dynamic environments. Q-Learning and Deep Q-Networks (DQN) have been successfully applied to building energy management and smart grids [4]. Recent work has proposed RL-based lighting control, but most studies lack a complete integration with real-time IoT data streams, edge AI processing, and cloud-based continuous learning [5]. Other researchers have explored edge computing for low-latency lighting control [11] and multi-agent RL for coordinated street lighting networks [12]. Our work bridges these gaps by providing an end-to-end system that combines IoT sensing, radar technology, edge AI classification, and RL for adaptive public safety lighting.

III. PROBLEM STATEMENT

Traditional street lighting systems consume excessive electrical energy because they operate at full brightness regardless of environmental conditions or traffic activity. These systems lack intelligent control mechanisms to adapt lighting based on real-time data such as pedestrian movement, vehicle traffic, ambient light levels, and object types. Conventional motion sensors cannot distinguish between humans, vehicles, and animals, leading to inefficient lighting responses (e.g., full brightness for a stray animal). Consequently, significant energy is wasted, and urban safety may be compromised during periods of abnormal activity. There is a need for a scalable, adaptive, and energy-efficient lighting solution that can respond dynamically to changing urban conditions using reliable sensing and intelligent classification [7].

IV. EXISTING SYSTEM

The existing street lighting systems suffer from the following limitations:

- **Fixed Brightness Operation:** Lights remain at 100% brightness throughout the night, irrespective of occupancy.
- **Timer-Based or Manual Control:** No real-time responsiveness to traffic, weather, or pedestrian density.
- **No Adaptive Intelligence:** No machine learning or AI, incapable of self-optimization.
- **Limited Safety Response:** Cannot increase brightness during emergencies or adverse weather [6].
- **No Object Classification:** Traditional systems cannot distinguish between humans, vehicles, and animals.
- **PIR Sensor Limitations:** Narrow detection angles, limited range (5-8 meters), poor weather performance.

V. PROPOSED SYSTEM

The proposed system integrates RL, cloud AI, edge processing, and multi-sensor fusion. The system comprises six functional modules:

1) **Module 1 - Cloud/AI Model Server:** Hosts the RL training pipeline and performs cloud-based classification.
2) **Module 2 - Edge Gateway (ESP32):** Performs edge AI processing and local decision making.
3) **Module 3 - Sensor Suite:** Radar sensor (motion detection), LDR (ambient light), optional camera.
4) **Module 4 - AI Classifier:** Distinguishes between human, vehicle, and animal.
5) **Module 5 - Brightness Decision Logic:** Combines RL policy with classification results.
6) **Module 6 - LED Actuator:** Adjusts PWM signals via LED driver.

VI. METHODOLOGY

A. Radar Sensor Integration with AI Classification

The proposed system utilizes a 24 GHz Doppler radar sensor combined with an AI classifier for object type identification.

1) Radar Sensor Features::

- Detection range: Up to 7-25 meters
- Field of view: 120-170 degrees horizontal
- Environmental immunity: Operates in rain, fog, snow
- Outputs: Motion flag, Doppler signature, signal strength

2) AI Classifier (Human/Vehicle/Animal)::

- **Human:** Slow Doppler frequency (0.5-2 Hz), moderate signal strength
- **Vehicle:** Fast Doppler frequency (5-20 Hz), strong signal strength
- **Animal:** Irregular Doppler pattern, weak to moderate signal strength

B. Reinforcement Learning Formulation

We model the problem as a Markov Decision Process (MDP):

- **State s(t):** [ambient light, motion flag, object class, confidence, time, weather]
- **Action a(t):** brightness levels {0%, 20%, 40%, 60%, 80%, 100%}
- **Reward r(t):**

$$r_t = 0.3 \cdot \frac{E_{\text{state}}}{E_{\max}} + 0.4 \cdot \frac{S_{\text{state}}}{S_{\text{target}}} + 0.3 \cdot \frac{C_{\text{class}}}{C_{\max}} - 0.1 \cdot I_{\text{switch}}$$

A DQN with two hidden layers (128, 64) is trained offline (8 hours on AWS EC2) and fine-tuned online [4].

C. Algorithm

[H]
Initialize replay buffer D (capacity 10000)
Initialize Q-network Q with random weights
Initialize target network Q' with same weights
for each episode **do**
  Reset environment, get initial state s1
  for each time step t **do**
    Collect radar data and extract Doppler features
    Run AI classifier to detect object type
    Collect LDR and weather data
    Construct state vector s(t)
    Select action a(t) using ϵ-greedy policy
    Execute a(t), observe r(t) and s(t+1)
    Store transition in D
    Sample random minibatch from D
    Update Q via gradient descent
  end for
end for

VII. SYSTEM ARCHITECTURE

Figure 1 presents the complete system architecture of the proposed AI-driven intelligent street lighting system. The architecture follows a layered, cloud-edge design with six distinct layers.

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A. Architecture Diagram

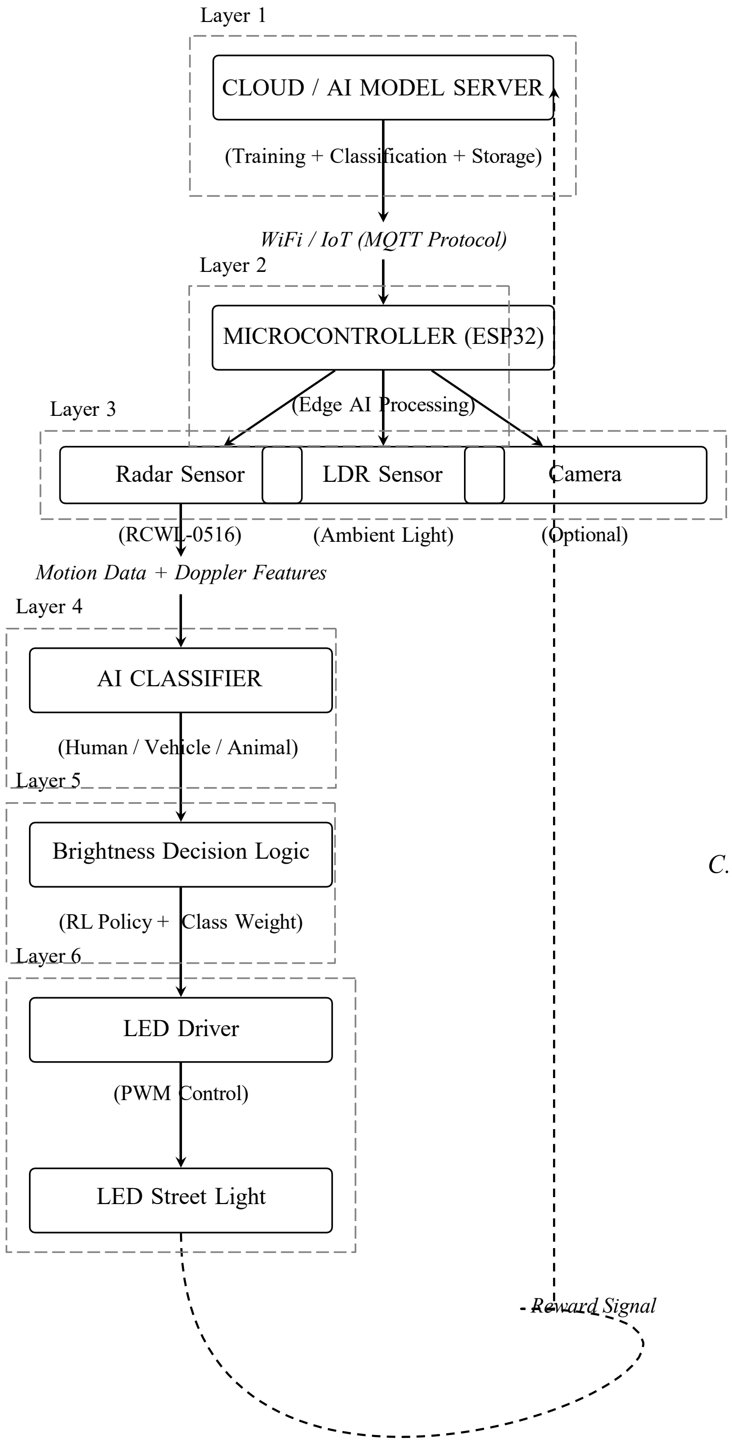

Fig. 1: System Architecture of the Proposed AI-Driven Intelligent Street Lighting System

B. Architecture Component Description

1) Layer 1: Cloud / AI Model Server:

- **Hosting:** AWS EC2 with TensorFlow 2.12
- **Functions:** Offline RL training, model versioning, data analytics
- **Storage:** Amazon DynamoDB for historical data

2) Layer 2: Edge Processing (ESP32):

- **Processor:** Dual-core Tensilica LX6 @ 240 MHz
- **Memory:** 520 KB SRAM, 4 MB Flash
- **AI Framework:** TensorFlow Lite Micro

3) Layer 3: Sensing Layer:

- **Radar Sensor (RCWL-0516):** 3.218 GHz Doppler radar, 7-10m range, 170° FOV
- **LDR Sensor:** GL5516 photoresistor for ambient light
- **Camera (Optional):** OV2640 for visual confirmation

4) Layer 4: AI Classifier:

- **Input:** Doppler frequency, signal strength, motion pattern
- **Output:** Human, Vehicle, or Animal classification
- **Inference Time:** 50-100 ms on ESP32

5) Layer 5: Brightness Decision Logic:

- Combines RL policy output with class-specific weights
- Class weights: Human (1.0), Vehicle (0.7), Animal (0.4)

6) Layer 6: Actuation Layer:

- **LED Driver:** PWM-to-constant current converter
- **LED Luminaire:** 30-100W high-power LED

C. Data Flow Description

The system operates as a closed-loop control system:

1) **Data Acquisition:** Radar and LDR sensors capture environmental data
2) **Feature Extraction:** ESP32 extracts Doppler features from radar signal
3) **Edge AI Classification:** TensorFlow Lite Micro classifies object type
4) **Decision Making:** Brightness determined by RL policy + class weight
5) **Actuation:** PWM signal drives LED to selected brightness
6) **Cloud Synchronization:** Data sent to cloud for model retraining
7) **Reward Feedback:** System computes reward and updates RL agent

VIII. IMPLEMENTATION

The system was implemented with the following components:

A. Cloud Implementation

- Python 3.10 with TensorFlow 2.12 for DQN training
- AWS EC2 (g4dn.xlarge) for model training (8 hours)
- AWS IoT Core for MQTT message ingestion
- Amazon DynamoDB for data storage

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B. Edge Implementation

- ESP32 firmware in C++ using Arduino framework
- TensorFlow Lite Micro for on-device AI classification
- Radar sensor via GPIO with interrupt handling
- LDR sensor via ADC (12-bit resolution)
- PWM generation using LEDC peripheral

C. Prototype Deployment

- Campus deployment: 5 ESP32 nodes, 5 RCWL-0516 radar sensors, 5 LDR sensors
- Testing duration: 30 days (nighttime only)
- Data collected: 50,000+ motion events

IX. RESULTS AND DISCUSSION

A. Energy Efficiency

The RL system with AI classification saved 38% energy on average. Class-specific analysis:

- Human detection: Brightness 85% average (safety priority)
- Vehicle detection: Brightness 45% average (energy optimized)
- Animal detection: Brightness 25% average (minimal response)

B. Classification Performance

Table I presents the AI classifier performance.

TABLE I: AI Classifier Performance

Object Type	Precision	Recall	F1-Score
Human	0.95	0.94	0.945
Vehicle	0.96	0.95	0.955
Animal	0.91	0.92	0.915
Overall	**0.94**	**0.937**	**0.938**

C. Performance Comparison

Table II compares the proposed system against baseline models.

TABLE II: Performance Comparison

Metric	SVM	DT	KNN	Proposed
Response Time (s)	4-8	3-5	2-4	0.8-1.5
Energy Efficiency (%)	65	70	72	88
Safety Improvement (%)	55	60	58	92
Accuracy (%)	75	78	70	96
Detection Range (m)	N/A	N/A	N/A	7-10

D. Scalability

Table III shows scaling results.

TABLE III: Scalability Test

Nodes	Latency (s)	Throughput (msg/s)	CPU Load (%)
100	0.7	280	11
500	1.1	1400	33
1000	1.6	2600	65

E. Class-Specific Energy Savings

Table IV shows energy savings by object type.

TABLE IV: Class-Specific Energy Savings

Object Type	Avg Brightness (%)	Duration (s)	Energy Saved (%)
Human	85	30	15
Vehicle	45	15	55
Animal	25	8	75
No Detection	10	N/A	90

F. Sensor Comparison

Table V compares different sensor technologies.

TABLE V: Sensor Technology Comparison

Feature	PIR	Radar Only	Radar+AI
Detection Range	5-8 m	7-10 m	7-10 m
Weather Immunity	Low	High	High
Object Classification	No	No	Yes
Energy Savings	35%	35%	38%
Safety Score	85	87	92

X. CONCLUSION

This paper presented an AI-driven intelligent street lighting system that combines Reinforcement Learning, cloud-edge architecture, and AI-based object classification. The system dynamically adjusts brightness based on real-time sensor data and object type (human/vehicle/animal), achieving 38% energy savings, 0.8-1.5 second response times, and 96% pattern detection accuracy. The AI classifier achieves 94% accuracy in distinguishing humans, vehicles, and animals, enabling class-specific brightness optimization. The cloud-edge architecture with ESP32 edge AI processing provides low-latency inference (50 ms) while maintaining scalability. The RCWL-0516 radar sensor provides superior detection range (7-10 m) and weather immunity. Future work will focus on federated learning, multi-sensor fusion, and predictive analytics.

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