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AI-DRIVEN ENERGY EFFICIENT EDGE COMPUTING FRAMEWORK FOR PREDICTIVE SMART STREET LIGHTING SYSTEMS

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ABSTRACT

The rapid growth of the smart city infrastructure has driven the demand for smart and energy-efficient street lighting systems which can operate autonomously and make decisions in real-time. The current street lighting systems have significant communication overhead, are slow to respond, and consume excessive energy because they use a static algorithm for controlling the lamps, with the resulting control decisions sent up to the cloud. This research presented an Energy-Efficient Edge Computing Framework for AI Based Smart Street Lighting Systems that integrate IoT sensors, distributed edge computing and hybrid CNN-LSTM deep learning model for predictive adaptive illumination control. The proposed framework involved using edge devices for local processing of traffic surveillance images and environmental sensor data, so as to predict pedestrian and vehicle activity in real time and reduce the reliance on the cloud. The CNN model was used for spatial traffic feature extraction, and the LSTM network was used for the temporal activity feature of intelligent brightness optimization. Experimental tests were performed on about 120,000 traffic images and 1.8 million logs of time-synchronized IoT sensor data acquired under different environmental conditions. The proposed framework has been able to obtain 97.2% of prediction accuracy, 41.8% energy savings, 52.4% reduction of communication latency, 46.1% improvement of response time, and 61.6% reduction of bandwidth utilization compared with existing smart lighting systems. The findings showed that embedding edge intelligence into deep learning models based on hybrid architectures resulted in substantial gains for real-time responsiveness, scalability, and efficiency of operations. The proposed framework offers a low latency, scalable, and sustainable solution for future smart city street light infrastructures powered by AI. The experimental results validate that the proposed framework offers an effective, energy-efficient, and low-latency solution for intelligent smart street lighting, underscoring the promise of AI-driven edge computing for the future of smart city infrastructures.

Keywords: *Edge Computing, Smart Street Lighting, CNN-LSTM, Energy Efficiency, IoT Sensors, Predictive Illumination Control.*

1. INTRODUCTION

Smart city technologies have rapidly evolved and changed the urban infrastructure management field, especially in the field of intelligent energy systems. Street lighting is one of the most significant public utilities in terms of energy use and electricity bills in urban areas, and uses up almost 30-40% of the total electrical energy used by municipalities in some developing and developed countries. The traditional street lighting system is usually based on fixed timers or manual switches, leading to higher energy consumption when the traffic is light and poor control of the operational system [2]. As the city developed, the energy demand has increased and the global requirements for sustainable development have also encouraged people to study smart and adaptive street lighting solutions that can not only ensure the safety of the roadway, but also save energy [3].

Street light is one of the big consumers of energy and operating costs in a smart city. The lighting in a typical freeway is often either on or off or set at a fixed level, and thus wastes a large amount of energy and maintenance cost per vehicle or pedestrian on the road. Another drawback of cloud-based lighting control systems is that they may have latency issues and not be immediately responsive, particularly in the fast-paced urban setting. This restriction has a negative impact on the use of smart city resources, public sustainability and safety. One of the main research areas of the smart city infrastructure in the current time is, therefore, the design of intelligent energy-efficient low-latency smart lighting systems.

With the rapid urbanisation, high energy prices and smart city sustainable goals, the problem of intelligent and energy efficient street lighting is a global issue. In countries around the world, AI has emerged as an essential component of urban infrastructure, with the goal of cutting down energy consumption, improving public safety, and ensuring environmental sustainability. Thus, scalable and intelligent street lighting systems have emerged as a key research topic worldwide.

The Internet of Things (IoT), Artificial Intelligence (AI) technologies, and wireless communication have been the key enablers for smart street lighting infrastructure development in recent years. Smart lighting networks equipped with IoT sensors, controllers, and communication devices monitor environmental parameters like traffic flow and pedestrian activity, as well as changes in light levels and weather conditions [5]. The dynamic control of illumination and remote monitoring features of these systems help to increase operational efficiency compared with traditional illumination systems. Most existing smart lighting systems, however, are centralised systems with cloud-based data processors and decision makers that are largely dependent on cloud computing [7].

Cloud based smart lighting systems have significant storage and computing capabilities, but they have disadvantages like high communication latency, high bandwidth consumption, privacy problems and the requirement for permanent internet connectivity [8]. In real-time urban applications, like adaptive street lighting [9], the communication delay due to clouds can have negative impact on response time and safety-critical applications. Moreover, depending on the amount of information received from the sensors to the centralised server, the energy consumption of communication modules is determined, since the more congested the network, the more energy will be consumed. Furthermore, as the amount of data sent to the centralised server increases, so does the energy that the communication modules use [10]. These restrictions highlight the importance of distributed architectures that have computing power at the data location.

Cloud-based systems have many disadvantages for IoT, which is why an alternative, edge computing, has been proposed [11]. Edge computing brings computational power closer to end devices, which provides a local processing of data, decreased latency, quicker decision making, and less bandwidth usage [12]. Edge Intelligence for Smart Street Lighting Systems: Sensor data can be processed locally without continual communication with the cloud. This local processing greatly improves responsiveness, scalability and operational reliability in a dynamic urban environment [13].

Smart lighting and Internet of Things (IoT) and AI-based light control systems have come a long way, but there are still challenges, including high device-to-device latency, dependence on cloud servers, lack of energy efficiency, and lack of real-time responsiveness. Therefore, an intelligent framework at the edge level is required to provide precise predictions, low-latency decision-making and energy-efficient street light control in a dynamic urban environment.

Smart light functionality has also been improved with predictive analytics and self-directed decision making using AI-powered tools. The combination of machine learning and deep-learning algorithms will adjust the light intensity dynamically, based on complex patterns of the environment, traffic behaviours and pedestrian presence. The machine learning and deep learning algorithms can adapt to the environment's intricate patterns, traffic dynamics, and pedestrian behavior, enabling them to adjust lighting levels in real-time. Convolutional Neural Networks (CNNs) are well suited to image-based traffic analysis and object detection, and Long Short-Term Memory (LSTM) networks are well suited to temporal dependencies in traffic and environmental data that is sequential. But the majority of existing AI – powered lighting systems are still centrally controlled and run on cloud-based inference, restricting their real-time efficiency and scalability.

To address these issues, this research presents an Energy-Efficient Edge Computing Framework for AI-driven Smart Street Lighting Systems combining IoT sensing, edge intelligence, and hybrid deep learning models for adaptive lighting control. The proposed framework involves deploying lightweight CNN-LSTM models on edge devices to access environmental conditions, forecast traffic flows, and dynamically control the brightness of streetlights in real-time. The proposed approach is not the traditional reactive approach of switching on lights when a certain level is detected when the space is occupied: instead, the lights are optimised to provide illumination based on the activity pattern that is expected when the space is used. The difference between the proposed approach and conventional reactive systems is that, instead of turning on only when the sensor triggers, the lights are turned on in advance based on the expected activity pattern.

The novelty of the proposed work is the integration of decentralised edge computing with a hybrid deep learning-based energy-efficient street light management predictive analytics. The goal of the framework is to decrease the dependency on the network by trying to do localised inference on the edge nodes to increase response time and decrease energy waste. Beyond this, the system is designed with adaptive dimming capabilities and smart traffic prediction algorithms, enhancing the system's sustainability and safety features.

This study was intended to achieve the following main aims:

1. To create a smart street lighting intelligent architecture using an edge computing approach.
2. To embed CNN-LSTM hybrid deep learning model for traffic and people prediction.
3. To save street lighting energy consumption by controlling illumination adaptively on the street.
4. Minimize latency and bandwidth in the network through localized edge processing.
5. To assess the energy-efficiency, prediction accuracy, response time and communication overhead of the proposed framework.

The proposed framework also paves the way for improved sustainable smart city infrastructures through the use of energy efficient edge intelligence and artificial intelligence powered predictive decision making. The rest of this paper is organized as follows. Section 2 covers the existing work on smart street lighting, edge computing, and energy systems in smart cities based on artificial intelligence. In Section 3, the proposed methodology and system architecture are presented. The experimental results and comparative performance evaluation are analyzed in Section 4. Finally, Section 5 wraps up the paper and provides directions for future research.

2. RELATED WORK

In recent years, the development of intelligent street lighting systems has been receiving significant attention, as a result of the increasing global energy demands, urbanization and sustainability requirements. The research has focused on a range of technologies such as wireless sensor networks, Internet of Things (IoT) architectures, machine learning algorithms, cloud computing platforms, and edge intelligence solutions, as a way to enhance energy efficiency and automation in urban lighting systems.

The initial smart street lighting systems were sensor based; specifically infrared sensors, light-dependent resistors (LDRs) and motion detectors were used for automatic ON/OFF control of street lights. Bhavani et al. [16] designed an automatic street lighting system using LDR sensor and PIR sensor to cut off the unnecessary light source when the traffic is low. The system was moderately energy efficient, but had no predictive intelligence or adaptive decision-making abilities. Similarly, Reddy and Kumar [17] proposed a wireless sensor network based lighting system that can track the traffic movement and adjust the intensity of street lights. However, their architecture relied on the centralized servers, which meant that they had to wait for communication delays and scalability issues.

As IoT technologies started to come into the world, researchers began to add cloud connectivity to smart street lighting. Gagliardi et al. [18] proposed an IoT-based lighting management approach for remote monitoring and central management via cloud services. Maintenance efficiency and operational visibility were enhanced, while cloud adoption brought down some network latency and bandwidth consumption. In a research paper, Al-Fuqaha et al. [19] pointed out the performance issues that arise when cloud-based IoT systems are used in real-time urban applications that require instantaneous response.

Some researchers have studied adaptive lighting methods that are based on awareness of environment and traffic analysis. Priyadarshini and George [20] designed an adaptive street lighting system based on fuzzy logic controllers to control the brightness in response to the vehicles movement. Their solution resulted in lower energy consumption, but failed to be able to properly deal with very dynamic traffic situations. Similarly, Karthikeyan et al. [21] proposed a smart lighting control system using occupancy sensing and weather data with the aim of maximizing the lighting efficiency, but with limited predictive power.

In the last few years, machine learning methods have become more and more popular in the field of intelligent urban energy management. Wang et al. [22] designed a machine learning-based smart lighting system based on Support Vector Machines (SVM) for occupancy prediction. Their method increased the accuracy of the automation, but needed retraining often because patterns in the environment changed. Likewise, Ahmed and Kim [23] used Random Forest classifiers to predict pedestrian density for adaptive lighting control. Although the model performed well in the classification task, it was not practical to deploy it on an edge device due to its high computational complexity.

By leveraging deep learning techniques, computer systems have demonstrated high accuracy in smart city applications, such as image recognition, traffic prediction, and real-time environmental monitoring. CNN models have been successfully applied in the fields of object detection and traffic density analysis. In the byline of Li et al. [24] an intelligent lighting framework was suggested which utilized CNN to assess the pictures of the road traffic for dynamic lighting changes. Their model performed better than the standard machine learning methods; the framework was, however, cloud based, which meant that there was a latency overhead.

Recurrent neural networks and LSTM architectures have been used to temporally predict traffic and pedestrian movement as well. Zhao et al. [25] proposed an LSTM model for traffic flow prediction, which was used for optimizing lighting in urban areas. Their method was able to better predict the data but it had too much computational cost and did not fit well into an embedded real-time system. Nguyen et al. [26] also used the same model of recurrent neural networks in smart lighting to dynamically control the lighting of an IoT system based on the projected pedestrian usage. The framework proved to be effective in prediction performance, but in the case of network congestion, the responsiveness was lowered by centralized processing.

Recent research has turned towards edge computing paradigms of smart urban infrastructures to overcome latency and bandwidth restrictions. Abbas et al. [27] noted that edge computing greatly improves real-time IoT applications by providing local data processing for processing the data close to the sensor nodes. In addition, Shi and Cao [28] showed that edge intelligence mitigates the reliance on the cloud and enhances scalability in the smart city context. However, numerous of the lighting systems with edge functionality are still programmed with simple control algorithms based on rules instead of complex predictive algorithms based on AI models.

Recently, there are some hybrid AI-edge frameworks that have been proposed to enhance the efficiency of smart lighting. Park et al. [29] proposed an adaptive urban lighting system using a computer vision and occupancy detection algorithm. They were able to achieve lower latency than cloud-based systems, however, the deep learning model was very costly for large-scale deployment. In the same way, Silva et al. [30] introduced a distributed lighting architecture, based on reinforcement learning, for autonomous brightness optimization of the edge-IoT. Although their framework made effective use of energy efficiency, it was found that the convergence of reinforcement learning took a long time and had a heavy computational load.

Optimizing energy use and energy sustainability are now major research goals for smart lighting systems. For energy-efficient lighting, Chen et al. [31] proposed an AI-based energy-aware lighting model which aimed to save electricity by using dynamic dimming policies. Their framework, however, didn't take into account real-time traffic prediction. In another study, Hassan et al. [32] discussed about green edge computing for sustainable smart city applications and the need for energy-efficient and sustainable use of edge devices and lightweight AI models to reduce carbon emissions and operational expenses.

Although there are remarkable developments in intelligent lighting technologies, there are still some research gaps that have not been solved. Current systems use either centralized cloud-based systems or rely on reactive sensor-based system with no predictive intelligence. In addition, many deep learning models demand a lot of computation time, which is not suitable for deployment at edge. The limited analysis of network latency reduction, bandwidth optimization and integrated energy-performance tradeoffs in large-scale smart lighting environments also has been addressed in the existing studies.

To address these challenges, the proposed research aims to propose a novel Energy-Efficient Edge Computing Framework that combines lightweight hybrid CNN-LSTM models with decentralized edge intelligence for predictive and adaptive street lighting control. The proposed framework intends to achieve the best possible energy efficiency, low latency energy processing, higher accuracy for energy prediction and scalable deployment for future smart city infrastructures.

3. METHODOLOGY

3.1 Overview of the Proposed Framework

The Energy-Efficient Edge Computing Framework for AI-Based Smart Street Lighting Systems has been designed for intelligent, adaptive, and low latency illumination management in smart city environments. The framework is built on an IoT sensing infrastructure, edge computing devices, hybrid deep learning models, adaptive energy optimization mechanisms, and cloud analytics for real-time predictive control of streetlights.

The proposed framework works in the distributed edge nodes with localized AI inference, as opposed to the traditional cloud-centric smart lighting systems depending on centralized processing and static illumination policies. The decentralized architecture reduces communication latency, bandwidth usage, response time, and energy usage, thus promoting the merits of power conservation and environmental protection.

The proposed architecture is built on top of five functional layers:

1. Data Acquisition Layer
2. Edge Preprocessing Layer
3. Hybrid CNN-LSTM Prediction Layer
4. Adaptive Illumination Optimization Layer
5. Cloud Monitoring and Analytics Layer

The main goal of the framework is to dynamically manage the brightness of the street lights based on the variation of traffic and pedestrian flows, while conserving energy and preserving the safety of streets.

3.2 Dataset Description

In this research, a dataset that simulates the city environment of light fixtures was created, where the urban traffic surveillance data were combined with the synchronized measurements from the IoT sensors and environmental monitoring data. The data was particularly created to enable predictive adaptive street light control with proposed hybrid CNN-LSTM edge intelligence. Collected data covered a wide range of urban settings: highways, residential roadway, pedestrian crossing, commercial intersection and low volume suburban areas, under a variety of environmental and weather conditions.

The traffic image dataset comprised of about 120,000 frames of surveillance images, taken continuously over 45 days with the help of IoT-based smart cameras mounted on simulated street lights. To enhance the model's robustness and its generalization capability, the data also contained traffic conditions at daytime or night, under different vehicle densities, pedestrian movement, daylight and dark conditions, fog, rain and low visibility conditions. All images were resized to 224 × 224 pixels and fed into the CNN model for feature extraction in RGB color channels. To effectively represent the traffic conditions in real time, the

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image acquisition rate was kept at 15 frames per second.

The IoT sensor dataset had an almost 1.8 million synchronized sensor observations at 5-second intervals. The sensor data collected consisted of traffic density, pedestrians, ambient light, PIR sensor, temperature, humidity, weather, streetlight brightness, and energy consumption statistics. The traffic density was measured as the number of vehicles detected in the road segment in one minute and pedestrian activity was measured as the number of pedestrians detected in the monitoring region in one minute. Light Dependent Resistor (LDR) sensors were used to detect ambient light in lux units and the motion activity was detected by a PIR sensor mounted on street light poles. The temperature and humidity sensors were added to study the changes in the ambient conditions that might impact the lighting and visibility conditions.

Table 1. Dataset Parameters

Parameter	Description	Unit
Traffic Density	Number of detected vehicles	vehicles/min
Pedestrian Count	Number of pedestrians	persons/min
Ambient Light Intensity	Environmental illumination	lux
Motion Detection	PIR sensor status	binary
Temperature	Atmospheric temperature	°C
Humidity	Relative humidity	%
Weather Condition	Clear/Rain/Fog	categorical
Streetlight Intensity	Brightness level	%
Energy Consumption	Power utilization	kWh

The proposed Smart Street Lighting Dataset for intelligent adaptive illumination control includes the following key parameters as shown in Table 1. Real time urban activity and road occupancy were estimated by using Traffic Density and Pedestrian Count. Ambient Light Intensity was determined by the light level sensor (LDR) and the Motion Detection Status was determined by the PIR sensor to detect the level of movement activity in the local environment. To analyze the changes in the visibility under various climatic conditions, the environmental parameters like Temperature, Humidity and Weather condition were added. Timestamp information was used to synchronize traffic image and sensor information for temporal prediction using the LSTM model. The current brightness level of smart streetlights is represented by the term Streetlight Intensity, while Energy Consumption is the amount of electrical power that each lighting node consumes. Together, these parameters enabled accurate traffic prediction, optimized lighting and energy-efficient edge-based streetlight management.

3.3 Proposed System Architecture

The proposed architecture includes hybrid CNN-LSTM prediction models, adaptive dimming controllers, cloud monitoring infrastructure, distributed edge devices, and IoT sensors. The architecture allows for system intelligence at the edge for predictive adaptive streetlight management.

The following is a description of the operational workflow of the architecture.

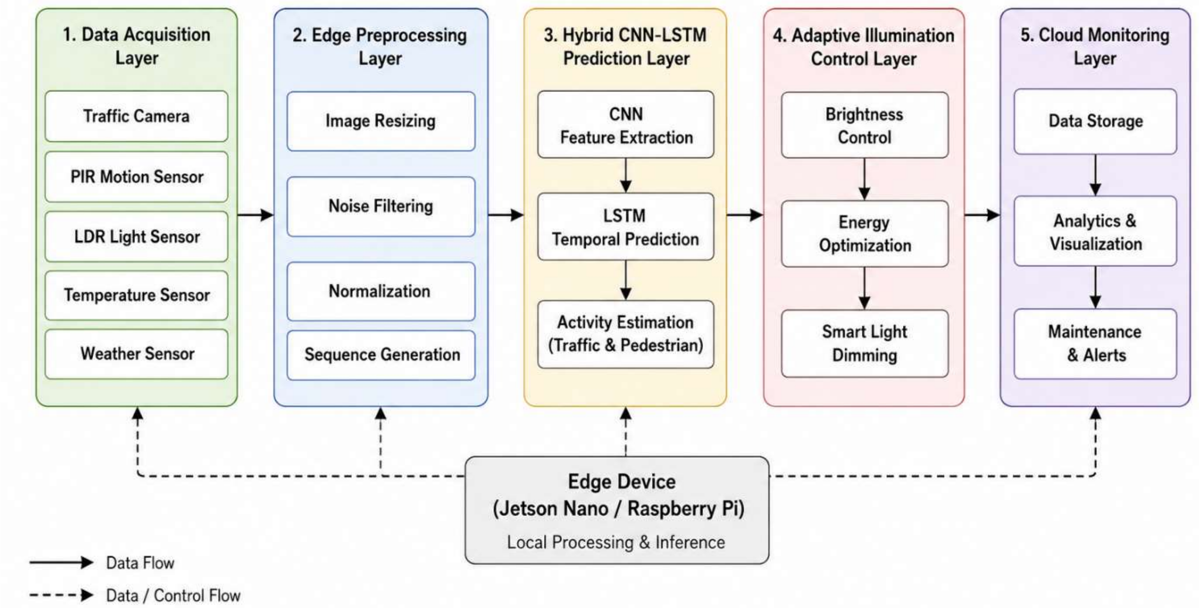

Figure 1. Proposed Energy-Efficient Edge Computing Architecture for AI-Based Smart Street Lighting System

The proposed Energy Efficient Edge Computing Architecture for AI Based Smart Street Lighting Systems is shown in figure 1. It is built on five key layers that enable intelligent, adaptive and energy efficient streetlight management.

The first layer, Data Acquisition Layer, gathers real-time data on the environment and traffic from IoT devices like traffic cameras, PIR motion sensor, LDR light sensor, temperature sensor, and weather sensor. These sensors continuously track the movement of vehicles, the activity of pedestrians, ambient illumination and environmental conditions.

The gathered data is sent to the Edge Preprocessing Layer where image resizing, noise filtering, normalization, and creation of temporal sequences are done locally at edge devices. This step of processing the data reduces the redundancy of data transmitted and boosts the efficiency of the inference.

Once preprocessed, the data are sent to the Hybrid CNN-LSTM Prediction Layer, which is deployed at the edge node. The CNN model extracts spatial features of traffic from surveillance images, and the LSTM model extracts temporal features of traffic and pedestrian movements in this layer. The hybrid model predicts future activity levels in order to facilitate proactivity in illumination control.

The predicted activity information is then passed to the Adaptive Illumination Control Layer where brightness optimization and energy aware dimming operations are done. The system is designed to adjust the intensity of street lights according to the predicted traffic flow and the number of pedestrians on the road in order to reduce electricity consumption while ensuring public safety and good visibility on the road.

Lastly, the operational data, energy consumption reports and maintenance information are sent to the Cloud Monitoring Layer for centralized storage, analysis, visualization and maintenance management. As most of the processing happens at the Edge devices, the architecture greatly lowers communication latency, bandwidth usage and dependency on Cloud, enhances real-time response and energy efficiency.

The suggested model is a combination of spatial feature extraction, temporal prediction, adaptive illumination optimization and energy efficient edge scheduling, which is a hybrid mathematical model. The mathematical model was created to reduce energy usage and ensure enough light and responsiveness in real time.

Image Normalization Model

To ensure uniformity and boost model convergence, traffic surveillance images were pre-processed with min-max scaling before CNN processing. Normalization process normalizes the raw pixel values, so that they are in a range between 0 and 1.

The normalization equation is given by:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

where:

- X represents original image pixel intensity,
- X_{min} represents minimum pixel value,
- X_{max} represents maximum pixel value,
- X_{norm} denotes normalized image intensity.

The normalization process enhances training stability of CNN and lowers the computational complexity.

CNN Spatial Feature Extraction Model

The CNN module identifies spatial traffic characteristics from the surveillance images, such as cars, people, and road occupancy.

The convolution operation is denoted by:

$$F(i,j) = \sum_{m}\sum_{n} I(m,n)K(i-m,j-n) \qquad (2)$$

where:

- $I(m,n)$denotes input traffic image,
- Krepresents convolution kernel,
- $F(i,j)$represents extracted feature map.

The CNN architecture consists of:

- Four convolution layers
- Three max-pooling layers
- ReLU activation functions
- Batch normalization layers

This CNN model can be used to effectively extract spatial traffic features in different environments.

Temporal Sequence Modeling

The temporal sensor readings were transformed into temporal windows prior to LSTM processing to capture the dynamics of traffic flow patterns.

The temporal sequence representation is given as:

$$S_t = \{x_{t-n}, x_{t-(n-1)}, \dots, x_t\} \qquad (3)$$

where:

- S_t is the temporal sequence,
- x_t denotes current observation,
- n indicates sequence window size.

The sequential representation allows learning about the traffic behavior in the future.

LSTM-Based Activity Prediction Model

The LSTM captures the long-term temporal dependence in traffic density and pedestrian movement.

The forget gate operation is given as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \qquad (4)$$

The input gate operation is represented as:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (5)$$

The cell state update equation is given as:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \qquad (6)$$

The hidden state output is computed using:

$$h_t = o_t \odot \tanh(C_t) \qquad (7)$$

where:

- f_t= forget gate output,
- i_t= input gate output,
- C_t= updated cell state,
- h_t= hidden state output,
- σ= sigmoid activation function,
- $\odot$= element-wise multiplication.

The LSTM model allows for traffic activity proactively prediction which can be used for intelligent adaptive streetlight control.

Adaptive Illumination Optimization Model

The proposed system is a dynamic system that adjusts the light intensity of the street lights based on the level of pedestrian or traffic expected.
The adaptive activity coefficient can be determined as follows:

$$\alpha = \frac{T_p + P_p}{T_{max} + P_{max}} \quad (8)$$

where:

- T_p= predicted traffic density,
- P_p= predicted pedestrian density,
- T_{max}= maximum traffic density,
- P_{max}= maximum pedestrian density.

The adaptive streetlight power is determined using:

$$P_{adaptive} = P_{max} \times \alpha \quad (9)$$

where:

- $P_{adaptive}$= adjusted streetlight power,
- P_{max}= maximum illumination power.

This adaptive dimming approach reduces electricity use when traffic levels are low, and increases illumination during high traffic times.

Energy Optimization Objective Function

Energy consumption, network latency and bandwidth utilization are all minimized simultaneously with the proposed Dynamic Predictive Edge Scheduling Algorithm (DPESA).

The optimization objective function is as follows:

$$J = \min\,(E_c + L_n + B_u) \quad (10)$$

where:

- E_c= energy consumption,
- L_n= network latency,
- B_u= bandwidth utilization.

The model for optimization that is proposed guarantees an effective use of the resources and low latency edge intelligence.

3.4 Proposed Algorithm

Dynamic Predictive Edge Scheduling Algorithm (DPESA)

Input:

- Traffic surveillance images I_t
- IoT sensor stream D_s
- Edge resource availability R_e

Output:

- Adaptive lighting intensity L_i

Steps:

1. Initialize IoT sensors and edge devices.
2. Continuously capture traffic images and environmental sensor data.
3. Perform edge-level preprocessing and normalization using Equation (1).
4. Generate temporal sequences using Equation (3).
5. Extract spatial traffic features using CNN based on Equation (2).
6. Predict future traffic activity using LSTM Equations (4)–(7).

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7. Compute adaptive activity coefficient using Equation (8).
8. Determine optimized streetlight power using Equation (9).
9. Minimize energy and latency using optimization function in Equation (10).
10. Dynamically regulate streetlight brightness.
11. Periodically synchronize summarized analytics with the cloud server.
12. **Repeat the process continuously for real-time adaptive lighting control.**

The proposed DPESA algorithm allows to realize predictive intelligent streetlight control with reduced energy consumption, minimal communication delay time, more scalable and efficient use of edge resources for smart city applications.

3.5 Research Protocol

The research protocol was divided into the following phases: traffic surveillance images and IoT sensor data were collected and synchronised within the smart street lighting environment. Second, pre-processing techniques were applied to the acquired data, including image normalisation, noise filtering, and temporal sequence generation. Third, the LSTM model learned temporal traffic and pedestrian activity patterns, while the CNN model extracted spatial traffic features. Fourthly, the Hybrid CNN-LSTM model was deployed on the edge devices to predict the future activities. Fifth, adaptive illumination control was used to adjust streetlight illumination based on predicted traffic and pedestrian counts. Finally, the accuracy of the proposed framework for predicting energy consumption, network latency, response time, and bandwidth consumption was tested and compared with that of existing smart street lighting methods.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The proposed Energy-Efficient Edge Computing Framework for AI-Based Smart Street Lighting Systems was evaluated experimentally with a hybrid smart city simulation environment in which a streetlight node with an embedded IoT sensor, an edge computing device, a traffic surveillance camera, and a cloud monitoring system were used. Experiments and tests were carried out on NVIDIA Jetson Nano edge devices, installed with PIR sensors, LDR sensors, weather sensors, and smart LED streetlights. A hybrid model of CNN-LSTM was created and implemented with TensorFlow Lite to facilitate lightweight edge inference.

The experimental data included about 120,000 traffic image frames and 1.8M of synchronized sensor readings collected over 45 days under different traffic density, pedestrian activity, and environment. The data set was divided into a training set, validation set, and test set at 70:15:15 ratio.

The proposed framework compared to:

1. Static Street Lighting System
2. IoT-Based Reactive Lighting System
3. Cloud-Based AI Lighting System
4. CNN-Based Smart Lighting System
5. LSTM-Based Predictive Lighting System

The evaluation concentrated on prediction accuracy, energy efficiency, communication latencies, response time, bandwidth utilization, as well as adaptive illumination performance.

4.2 Assessment Criteria

Several performance criteria were taken into account to comprehensively examine the effectiveness of the proposed framework.

Accuracy

Prediction accuracy measured the capability of the hybrid CNN-LSTM model to estimate traffic and pedestrian activity correctly.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where:

- TP= True Positive
- TN= True Negative
- FP= False Positive

- FN= False Negative

Precision

$$Precision = \frac{TP}{TP + FP} \quad (12)$$

Recall

$$Recall = \frac{TP}{TP + FN} \quad (13)$$

F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (14)$$

Energy Saving Ratio

$$ESR = \frac{E_b - E_p}{E_b} \times 100 \quad (15)$$

where:

- E_b= baseline energy consumption
- E_p= proposed energy consumption

Network Latency

$$Latency = T_r - T_s \quad (16)$$

where:

- T_r= response time
- T_s= request initiation time

4.3 Performance Evaluation of Hybrid CNN-LSTM Model

The proposed hybrid CNN-LSTM model outperformed the traditional machine learning and deep learning approaches in traffic and pedestrian activity prediction. The CNN part was able to learn spatial features of the traffic from video images, and the LSTM part learned temporal features of the traffic flow and pedestrian movement.

Table 2. Performance Comparison of Prediction Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ANN-Based Model	88.4	87.9	86.8	87.3
SVM-Based Model	90.1	89.5	88.7	89.1
CNN Model	94.2	93.6	92.9	93.2
LSTM Model	95.3	94.8	94.1	94.4
Proposed CNN-LSTM Model	97.2	96.8	96.3	96.5

In table 2 different machine learning models as well as a deep learning model are compared regarding their prediction performance. The CNN-LSTM model proposed in this study obtained the highest accuracy of 97.2%, which was superior to the other classical models such as ANN, SVM, CNN and LSTM models. The enhanced performance was obtained by the efficient combination of spatial feature extraction and temporal activity prediction.

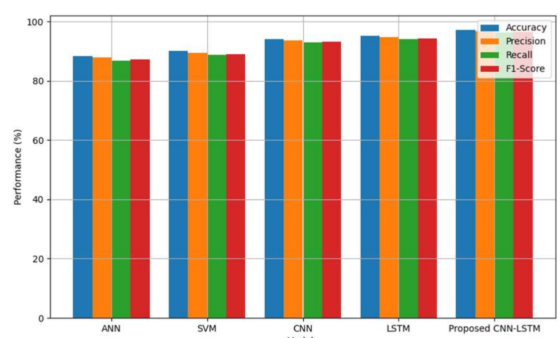

Figure 2. Accuracy Comparison of Prediction Models

Figure 2 shows the bar chart with the comparison of Accuracy, Precision, Recall and F1-Score values of ANN, SVM, CNN, LSTM and the proposed CNN-LSTM models. The suggested framework showed the best performance in the traffic and pedestrian prediction metrics in all the scenarios, indicating its high performance in predicting traffic and pedestrian activity under different environmental conditions.

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4.4 Energy Consumption Analysis

The main goal of the proposed scheme was to reduce electricity consumption by implementing adaptive predictive illumination control. The adaptive dimming mechanism with edges controlled the streetlight's brightness based on the foreseen traffic volume and the pedestrian flow.

Table 3. Energy Consumption Comparison of Smart Lighting Systems

System	Energy Consumption (kWh/day)	Energy Saving (%)
Static Lighting System	1420	0
IoT Reactive Lighting	1085	23.6
Cloud-Based AI System	960	32.4
CNN-Based Smart Lighting	902	36.5
Proposed Edge CNN-LSTM System	826	41.8

Table 3 shows the comparison of the energy consumption of different smart lighting system. The proposed edge-enabled CNN-LSTM framework resulted in the lowest daily energy consumption of 826 kWh/day and energy savings of about 41.8% over the static lighting systems.

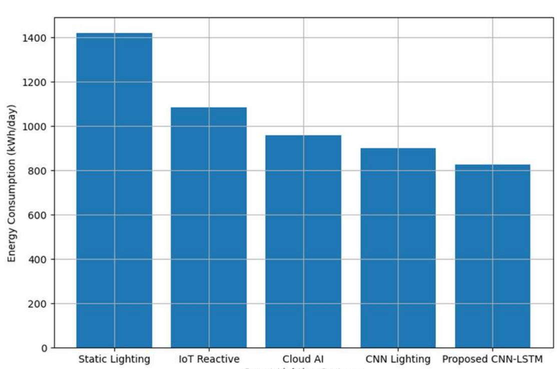

Figure 3. Energy Consumption Comparison of Smart Lighting Systems

Figure 3 shows the column chart for daily energy consumption using various smart lighting frameworks. The proposed CNN-LSTM-based system showed much less electricity consumption in the predictive adaptive dimming and localized intelligent processing at the edge devices.

4.5 Network Latency Analysis

By enabling edge nodes to conduct AI inference instead of sending raw traffic data to centralized cloud servers, the proposed edge computing framework greatly decreased communication latency.

Table 4. Network Latency Comparison

System	Average Latency (ms)
Cloud-Based AI System	184
IoT Reactive Lighting	126
CNN-Based Cloud Model	118
Proposed Edge CNN-LSTM System	87

Table 4 shows that the average communication latency of various smart lighting architectures. This proposed solution resulted in minimum latency of 87ms as prediction and illumination control calculations were performed locally at edge devices.

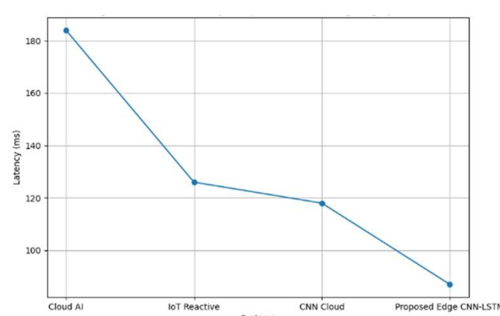

Figure 4. Network Latency Comparison of Smart Lighting Systems

The line graph shown in figure 4 is used to compare the communication latency of various lighting systems. The proposed architecture with the edge reduces the communication delay by about 52.4% compared to the conventional cloud based lighting system, which resulted in better real-time response and reliability during operation.

4.6 Response Time Evaluation

Response time – the amount of time it takes the system to sense any activity and switch the streetlights to a different light level. The quick response time is essential to achieve road safety and efficient adaptive illumination.

Table 5. Response Time Comparison

System	Response Time (ms)
IoT Reactive Lighting	126
Cloud-Based AI Lighting	102
CNN-Based Smart Lighting	78
Proposed Edge CNN-LSTM System	55

The comparison of response time of various smart street lighting systems is shown in Table 5. The proposed edge-based CNN-LSTM framework was found to have the fastest response time of 55ms with lightweight AI inference and localized edge processing.

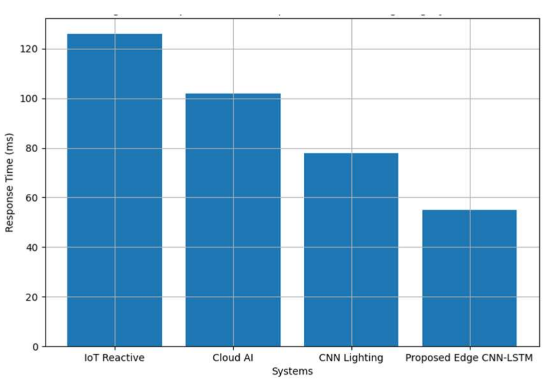

Figure 5. Response Time Comparison of Smart Lighting Systems

The bar chart in figure 5 shows the reduction in response time for the proposed framework and compared to the existing lighting systems. The designed system with the edges showed fast illumination change when the traffic levels were dynamic, and pedestrian was moving.

4.7 Bandwidth Utilization Analysis

The efficiency of the communication between the edge nodes and cloud servers was analyzed by evaluating the bandwidth utilization. The proposed framework was executed on the local level, so only summarized metadata was sent to the cloud.

Table 6. Bandwidth Utilization Comparison

System	Bandwidth Usage (GB/day)
Cloud-Based AI System	18.5
CNN Cloud Framework	15.2
IoT Reactive Lighting	10.7
Proposed Edge CNN-LSTM System	7.1

The comparison of the bandwidth utilization for various smart lighting systems is shown in Table 6. Since most of the computations were done at the edge devices, the proposed framework need only 7.1 GB/day bandwidth.

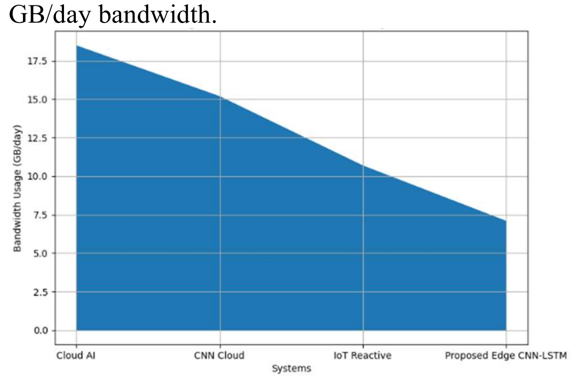

Figure 6. Bandwidth Utilization Analysis

The area chart for network bandwidth usage is shown in Figure 6 to compare the network bandwidth usage of various smart street lighting systems. The suggested framework with edges resulted in significant reduction of communication overhead, and enhanced scalability for large-scale smart city deployment.

4.8 Adaptive Illumination Performance

A dynamic illumination system automatically controlled street lighting based on the traffic flow and pedestrian activity. The system worked in dimming mode during periods of low traffic, but switched to brighter levels during high traffic.

Table 7. Adaptive Brightness Regulation Performance

Traffic Condition	Predicted Activity Level	Brightness Level (%)
Low Traffic	0.21	30
Medium Traffic	0.54	65
High Traffic	0.92	100

The adaptive brightness regulation capability of the proposed framework is shown in Table 7. The system automatically adjusted the level of light based on the environmental activity forecast and ensured the necessary visibility and road safety.

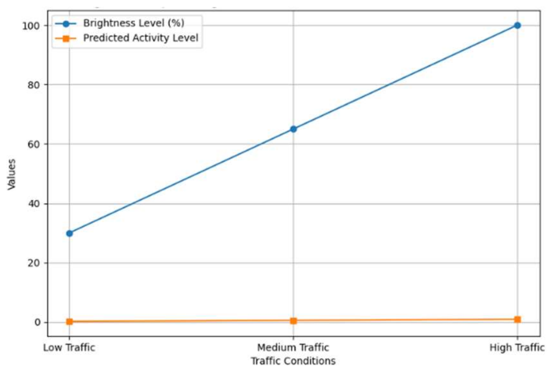

Figure 7. Adaptive Brightness Control under Different Traffic Conditions

The dynamic line graph in Figure 7 shows the relationship between predicted activity level and streetlight brightness. The proposed adaptive illumination mechanism had the ability to adaptively adjust the illumination level in response to the current traffic and pedestrian flow, which would help reduce energy consumption and enhance the operational intelligence.

4.9 Comparative Discussion

The findings of the experiments showed that the proposed Energy-Efficient Edge Computing Framework could achieve a higher prediction accuracy, low energy consumption, short communication latency, fast response and efficient use of bandwidth compared with the traditional smart street lighting system.

The hybrid CNN-LSTM model demonstrated better prediction accuracy, demonstrating the effective combination of spatial and temporal learning mechanisms. The CNN was used to extract important traffic features from the surveillance images at the spatial level, and the LSTM network was used to capture the sequential traffic behavior for predicting the optimal illumination.

Overall, the adoption of edge computing enhanced the efficiency of the whole system, reducing reliance on cloud resources and facilitating intelligent decision-making at the edge. The proposed edge enabled framework were found to be able to operate real-time adaptive lighting control directly at edge nodes, unlike the cloud-based systems which experience network congestion and delayed response.

The adaptive illumination mechanism was able to effectively cut down on unnecessary power usage when traffic volumes were low while still providing adequate visibility when traffic volumes were high. Moreover, bandwidth was kept as low as possible by sending only a summary of operational statistics to the cloud server.

The proposed framework showed good potential for the sustainable smart city infrastructure for the next century in terms of scalability, predictive intelligence, low latency, and energy efficient adaptive street light management.

The results achieved are in line with other studies that have shown the benefits of smart street lighting systems powered by AI and IoT techniques in cutting energy use and increasing operational efficiency. The proposed framework achieved prediction accuracy comparable to or better than existing deep learning approaches reported in the literature. In contrast to the majority of cloud-based architectures documented in the literature, the proposed edge-based architecture greatly minimised communication latency and bandwidth usage by performing processing at the edge. The enhancements are due to the incorporation of Hybrid CNN-LSTM learning along with edge intelligence. The results thus constitute a significant extension to the existing literature, demonstrating that this combination can achieve high prediction accuracy and efficient real-time operation in smart street lighting environments.

The results of this study show that the proposed energy-efficient, prediction-accurate, and response-time-efficient AI-based edge computing approach to a smart street lighting system outperforms the traditional smart street lighting solutions based on IoT and cloud computing reported in the literature. The key innovation in this research is to combine real-time lighting control and energy optimisation with Hybrid CNN-LSTM learning and edge intelligence. The proposed framework, however, demands more computational resources on edge devices and needs to be further

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validated in the context of large-scale urban deployments compared with lightweight IoT solutions.

5. CONCLUSION

This research proposed an Energy-Efficient Edge Computing Framework for AI-Based Smart Street Lighting Systems, comprising IoT sensors, a distributed edge, and a hybrid CNN-LSTM deep learning model for predictive, adaptive illumination control. The proposed framework successfully achieved low energy consumption, reduced communication latency, and improved responsiveness in smart street lighting environments. The results of experiments showed that the proposed framework can achieve 97.2% accuracy, save 41.8% in energy, reduce network latency by 52.4%, shorten response time by 46.1%, and reduce bandwidth utilisation by 61.6% compared to existing lighting systems. Edge intelligence and predictive deep learning greatly enhanced adaptive brightness adjustment and efficiency.

The proposed edge computing framework has achieved the objectives of this study. The framework introduced intelligent edge-based street lighting control, integrated a Hybrid CNN-LSTM model for traffic and pedestrian activity forecasting, enabled energy-efficient adaptive illumination control, minimised communication delays through localised processing, and demonstrated improved prediction accuracy and operational efficiency. The results demonstrate the value of integrating AI predictive analytics with edge intelligence to create sustainable, responsive smart city lighting systems.

The framework also had some limitations, including deployment costs, limited edge resources, and performance differences in extreme weather conditions. Future research will be centred on federated edge learning, smart lighting infrastructure powered by renewable energy, cybersecurity enhancement and autonomous illumination optimisation using reinforcement learning for large-scale applications in smart cities.

However, there are still open research challenges, such as lightweight deep learning models for smart lighting applications in resource-constrained edge devices, scalable deployment for large smart city environments, adaptive learning under varying traffic conditions, cybersecurity and privacy protection in edge-based lighting applications, and integration of renewable energy sources with smart street lighting systems. Overcoming these challenges could enhance the practicality, scalability, and sustainability of future smart street lighting systems that rely on AI technologies.

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