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Enhancing Urban Safety Through Intelligent Street Lighting: A Review of AI-Driven Detection and Monitoring Approaches

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Abstract— With the rapid urbanization and growing demand for public safety, intelligent street lighting systems have become an essential part of smart city infrastructure. In today's street lighting systems, beyond the traditional light provision function, Internet of Things (IoT) and edge computing, artificial intelligence (AI), and computer vision technologies have been integrated to enable real-time monitoring and decision-making. This review paper offers a thorough overview of intelligent street lighting systems and the various detection and monitoring strategies that utilize artificial intelligence (AI) to improve street lighting safety. The study covers the latest developments in IoT-powered sensing, Edge AI, video analytics, deep learning-based object detection, intelligent surveillance, hazard detection, traffic monitoring and emergency response systems. In addition, the review emphasizes that cutting-edge technologies like graph-based networks, federated learning, and explainable AI solutions are crucial for enhancing situational awareness and forecasting urban safety. Important issues such as privacy, cybersecurity, scalability, interoperability, and the limited size of the datasets are examined in detail. The paper also highlights new research opportunities related to lightweight edge intelligence, multimodal sensing, privacy-preserving AI, and integrated smart city platforms. This review, which brings together recent advances from various fields, offers significant insights into the potential of AI-driven intelligent street lighting systems to enhance and transform urban environments into safer, smarter, and more sustainable spaces.

Keywords: Intelligent Street Lighting, Smart Cities, Artificial Intelligence, Internet of Things (IoT), Edge Computing, Computer Vision, Deep Learning,

I. INTRODUCTION

As urbanization accelerates and cities become more complex, there is a growing need for smart infrastructure that can help to improve public safety, energy efficiency, and sustainable urban development. Street lighting systems are among various smart city elements that have been transformed from simple light sources to more interconnected and intelligent objects that can work on the city monitoring platform, environmental sustainability and citizen security issues. This incorporation of Internet of Things (IoT) technologies, wireless communication, sensors, cloud-based management etc., has enabled smart street lighting system that can adjust the operation of lights depending on the weather conditions and the needs of the operation (Khemakhem et al. [1]; Parkash and Rajendra et al. [2]). The initial smart lighting systems were energy-saving, using automation, motion detection and remote monitoring features. (Abhishek and Srikanth et al. [3]). The street lighting infrastructure has evolved beyond its traditional function of providing light to that of a key element of the urban intelligence ecosystems, in a new era of smart cities. In recent years, the significance of energy efficient urban infrastructures and sustainable city management in solving environmental issues and decreasing carbon emissions has been emphasized (Yang et al. [4]; Nozari et al. [5]). At the same time, the development of edge computing, edge intelligence and artificial intelligence (AI) has allowed for real-time processing of vast amounts of urban data, made quick decision-making possible, and has reduced communication latency (Badidi et al. [6]; Chen et al. [7]). Smart city applications are being increasingly integrated with Edge AI and TinyML technologies for distributed analytics, resource optimisation and smart surveillance applications (Trigkas et al. [8], Velaga et al. [9]). Computer vision and video analytics are among the most important advances in smart city research, with their application in urban monitoring systems. The Edge-based video analytics frameworks have shown the ability to detect objects, analyse their behaviours and recognize events in real-time without overly consuming network bandwidth (Hu et al. [10]). Moreover, the AIoT smart city architectures have opened opportunities for embedding surveillance, environment monitoring, traffic control and public safety services on a single smart city platform (Bibri et al. [11]). With the advent of huge data and progress in deep learning, intelligent systems are emerging to identify traffic accidents, monitor road condition, and aid in emergency response operations (Adewopo et al. [12]).

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Research into computer vision-based urban safety systems is successfully used in intelligent traffic management, vehicle monitoring and accident detection. The use of deep learning has substantially enhanced the performance of traffic signal control systems, traffic control systems (TCS), and congestion monitoring (CM) systems (Ubaid et al. [13]; Reza et al. [14]). In recent times, edge-assisted frameworks have shown the capability to detect hazards and monitor road safety in distributed transportation systems in real-time (Sahu et al. [15]). Edge AI-based detection systems for emergency vehicles have also demonstrated the enabling potential of smart city infrastructures for critical public services with low latency (Lanjewar et al. [16]). In other sectors, like healthcare and crisis response, comparable AI-driven surveillance architectures have been implemented using sensor fusion and distributed decision-making systems (Alshuhail et al. [17]).

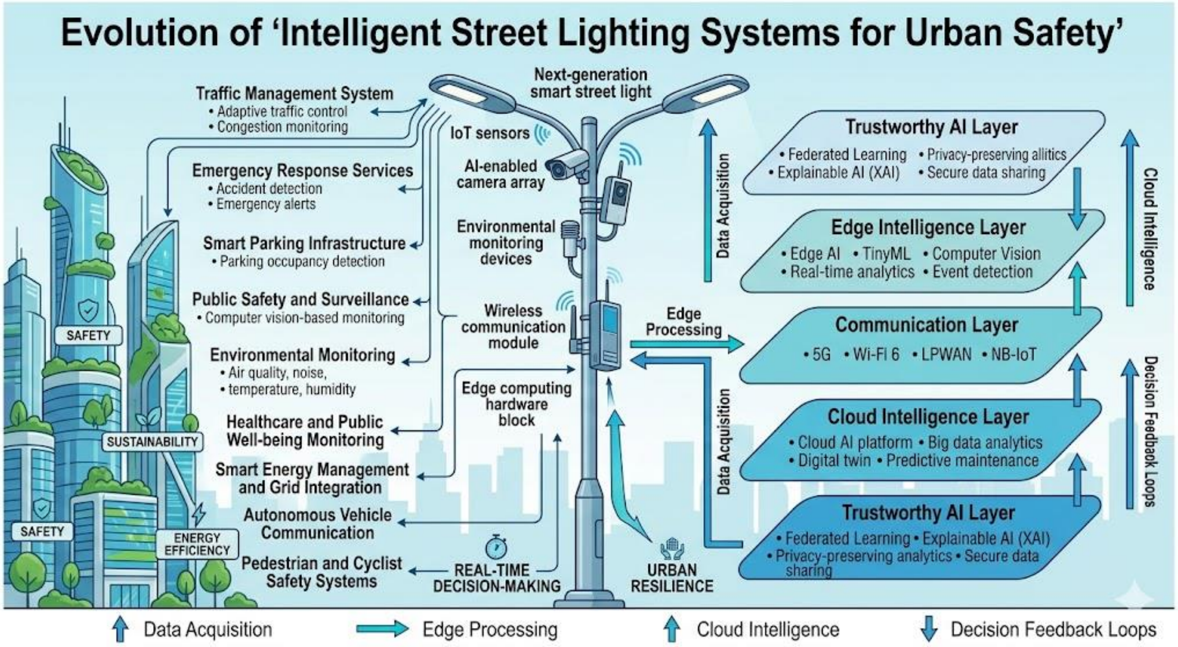

Figure 1: Evolution of Intelligent Street Lighting System for Urban Safety

In addition to transportation, urban security has become a major research topic in the implementation of smart city initiatives. AI is increasingly being applied for predictive policing, monitoring of public space, crime prevention and protection of citizens (Stubbs et al. [18]). The use of this AI-driven surveillance technology, however, has led to significant concerns about privacy, ethical governance, transparency and the responsible use of AI in urban settings (Pesqueira, de Bem Machado et al. [19]). Therefore, the installation of intelligent street lights with AI functions needs to be done with a sense of responsibility and respect for ethics and regulations.

The ability of smart city systems to learn the traffic dynamics, identify anomalies and predict urban events has been further enhanced by recent advancements in spatio-temporal modeling, graph neural networks, and urban analytics (Hosseini et al. [20]; Wang et al. [21]; Bai and Thirumaran et al. [25]). At the same time, the monitoring platforms based on IoT are proliferating in different smart city areas such as real-time monitoring, smart parking, and edge-fog computing infrastructures (Amutha et al. [22]; Deepan Kumar et al. [23]; Jana et al. [24]). These advancements offer solid tech support for the intelligence of streetlights on the street as distributed sensing/monitoring nodes in urban areas.

In addition, the fast development of deep learning models for object detection has contributed to the advancement of the intelligent surveillance system. Some of the modern vision architectures, like the YOLO family, provide high detection accuracy and real-time processing performance, which is appropriate for the edge deployment (Jocher et al. [26]). These models can be used for real-time detection of pedestrians, vehicles, suspicious activity, accidents and environmental hazards in the intelligent street lighting system. Moreover, advances in crime hotspot prediction and explainable AI-based surveillance systems are helping to create more proactive and transparent urban safety solutions (Muhammad et al. [27]; Zhukabayeva et al. [28]).

Although significant advances have been made in smart lighting, edge computing, computer vision and intelligent surveillance, the literature is scattered across various fields of research. The review study that focuses on a single technology, such as smart street lighting, edge AI, video analytics, traffic management or urban surveillance, does not offer a comprehensive examination of how the technology is collectively contributing to intelligent street lighting-based

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systems for urban safety. Furthermore, scarce research has been conducted for the integration of real-time detection, monitoring, event recognition, edge intelligence, explainable AI and ethical governance in a comprehensive urban safety context. Hence, this review paper summarizes the latest research on the detection and monitoring solutions for intelligent street lighting systems in order to improve the safety of the urban environment by using artificial intelligence. The paper comprehensively discusses the enabling technologies such as the Internet of Things, edge computing, computer vision, deep learning, and intelligent surveillance architectures. It also reviews some of the most recent applications in traffic management, hazard detection, emergency response, crime prevention and citizen safety, and addresses the difficulties of implementing them, ethical issues and future research directions. This comprehensive review integrates recent advancements in these interrelated fields, offering a complete perspective of the potential contribution of AI powered "intelligent street lighting" to the creation of safer and smarter cities for researchers, practitioners, and policymakers.

II. LITERATURE REVIEW

Intelligent street lighting systems have developed hand in hand with the development of smart city technologies, Internet of Things (IoT) infrastructures, edge computing and artificial intelligence (AI). The first studies in this area were primarily directed to the energy-efficiency of light control using sensor-based automation and remote control. Parkash and Rajendra et al. [2] suggested an intelligent street lighting system based on IOT concept that automatically controls the lights based on the environment conditions, thus minimizing energy consumption and operation cost. In the same context, Abhishek and Srikanth et. al. [3] designed a smart street lighting system that used sensor-controlled street lighting techniques to enhance the efficiency of energy consumption and maintenance management. Very recently, Khemakhem and Krichen et al. [1] introduced a detailed review on the integration of IoT, cloud computing, wireless communication and intelligent control technologies in smart public lighting systems.

With the development and progress of smart cities, sustainability and energy efficiency have become integral parts of city infrastructures. To this end, Yang and Hu et al. [4] discussed the carbon emission efficiency in urban regions and argued that the smart infrastructure is crucial to achieving sustainable urban development targets. Nozari and Tavakkoli-Moghaddam et al. [5] highlighted how edge computing could help to build an energy-efficient super-smart city by decreasing communication overhead and facilitating local decision-making. The studies suggest that smart street lighting has the potential to play a substantial role in promoting environmental sustainability and optimizing urban resources.

Edge Computing has changed the AI application environment in the smart city. In this regard, Chen et al. [7] presented edge-intelligent networking solutions to optimize the communication and resource utilization of IoT in urban infrastructure. Badidi et al. [6] performed a systematic review of edge-AI supported video analytics and highlighted the potential of using the technology for real-time application in urban surveillance, traffic management, and public safety. Likewise, Hu et al. [10] analyzed edge-based video analytics methods and proved the efficiency in analyzing high volume of visual data with low latency. Trigkas et al. [8] then investigated how TinyML could be used in the context of smart cities, suggesting the potential for the deployment of resource efficient AI models on the edge of networks. Building on this, Velaga et al [9] discussed the basics, challenges and opportunities for using Edge AI in smart city ecosystems.

AIoT technologies have ushered the era of smart monitoring systems that can provide service support for various urban services. Bibri et al. [11] analysed the environmental sustainability and smart city management solutions based on AIoT with special attention to intelligent sensing and automated decision making. Amutha et al. [22] presented the applications of IoT for real-time monitoring and tracking, showing how distributed sensing systems can enhance awareness in the operation of urban systems. In another similar approach, Kumar et al. [23] presented an IoT-based cloud-integrated smart parking system which employed AI-driven optimization techniques to optimize space utilization and mobility management. Jana et al. [24] also pointed out the necessity of agile edge and fog computing architectures in the management of real-time smart city services. The introduction of computer vision and deep-learning techniques has turned them into indispensable elements of smart city monitoring systems. These technologies of computer vision and deep learning have become indispensable in the context of intelligent monitoring systems in urban context. Adewopo et al. [12] proposed a comprehensive dataset suitable for detection of traffic accidents using artificial intelligence and computer vision in smart cities. To alleviate traffic congestion and enhance traffic flow, Ubaid et al. [13] proposed an intelligent traffic signal automation system based on deep learning and computer vision methods. Reza et al. [14] presented a system for traffic management based on image processing and deep learning that can contribute to urban safety by monitoring and controlling the traffic in real time. The results of these studies have proven the applicability of vision-based systems to improve situational awareness and operational efficiency in urban environments.

Recently, there has been a growing emphasis on the development of real-time safety applications that utilize the concept of edges.In recent years, research has increasingly turned to the concept of edges for real-time safety applications. Sahu

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et al. [15] suggested the edge-based distributed architecture for detection of hazard and monitoring of the road safety, which showed very remarkable improvement in terms of response time and reliability. Lanjewar et al. [16] introduced a Smart Traffic Signal System with Edge Artificial Intelligence for emergency vehicle detection, to enhance emergency response and priority-based traffic management. Alshuhail et al. [17] introduced an edge-aware IoT system with sensor fusion and AI-based emergency response solutions, further demonstrating the potential of edge intelligence in public safety. With the development of smart city, safety and intelligent surveillance have become important research directions in urban safety. Stubbs et al [18] analysed the expanding importance of AI in contemporary policing and city security structures. Pesqueira and de Bem Machado et al. [19] discussed ethical governance issues with AI based urban security, highlighting privacy and transparency, the accountability, and public trust. These matters are especially important when it comes to smart street lighting systems that include surveillance and monitoring capabilities. The smart city monitoring systems are also strengthened with advanced urban analytics and spatio-temporal intelligence. Hosseini et al. [20] introduced a hybrid graph convolution and graph Fourier neural operator model for traffic prediction, which was able to better model complex urban traffic patterns. The decentralized AI approach is shown to be effective in cross-city traffic prediction by Wang et al. [21] who presented a personalized federated spatio-temporal learning framework. Bai and Thirumaran et al. [25] developed an anomaly-aware spatio-temporal graph attention network capable of simultaneously performing traffic forecasting and event detection, thereby improving urban situational awareness.

Due to the fast-paced development of Deep Learning Object Detection algorithms, the intelligent surveillance has been greatly improved. Jocher et al. [26] proposed a YOLO26, a single real-time vision system which not only detects objects with high accuracy but also reduces the computing time. All this has led to the rapid deployment of intelligent monitoring systems that can detect and report on vehicles, pedestrians, accidents, and suspicious activity in real time. Muhammad et al. [27] further explored machine learning and deep learning crime hotspot prediction methods, highlighting their increasing significance in helping city planners create safer urban environments. The authors of this paper, Zhukabayeva et al. [28] introduced an explainable multi-backbone deep feature fusion framework for intelligent surveillance and citizen safety, which is a pressing demand for transparency and interpretability in AI-driven urban monitoring systems.

Overall, the literature highlights a significant advancement in the developments of smart lighting systems, monitoring with the support of IoT, edge intelligence, computer vision, and AI-based urban safety systems. Current research, however, tends to concentrate on a single aspect, like smart lighting or traffic monitoring, edge computing, surveillance, or predictive analytics. There is a lack of a comprehensive synthesis on the role of the intelligent street lighting infrastructure as a single platform for the detection, monitoring, hazard recognition, crime prevention and enhancement of urban safety, using AI technologies. The gap drives the current review to summarize recent developments and set future research agenda for intelligent street lighting systems in next generation of smart cities.

TABLE 1. COMPARATIVE REVIEW OF RECENT STUDIES RELATED TO INTELLIGENT STREET LIGHTING AND URBAN SAFETY

Ref.	Author(s)	Year	Main Focus	Technology Used	Key Contribution	Limitation
[1]	Khemakhem & Krichen	2024	Smart Street Lighting Survey	IoT, Sensors, Cloud	Comprehensive review of smart lighting systems	Limited AI surveillance discussion
[2]	Parkash & Rajendra	2016	Intelligent Street Lighting	IoT	Automated lighting control	No AI integration
[3]	Abhishek & Srikanth	2015	Smart Lighting Design	Sensors, Automation	Energy-efficient lighting architecture	Basic functionality only
[4]	Yang & Hu	2026	Carbon Emission Efficiency	Data Analytics	Sustainable urban infrastructure insights	Not safety-focused
[5]	Nozari & Tavakkoli-Moghaddam	2026	Energy-Efficient Smart Cities	Edge Computing	Edge-enabled sustainability framework	Limited surveillance application
[6]	Badidi et al.	2023	Edge-AI Video Analytics	Edge AI, Computer Vision	Systematic review of urban video analytics	General smart city scope

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[7]	Chen et al.	2021	Edge Intelligent Networking	Edge Computing, IoT	Network optimization for smart cities	Does not address surveillance directly
[8]	Trigkas et al.	2025	TinyML in Smart Cities	TinyML, Edge AI	Lightweight AI deployment	Limited urban safety applications
[9]	Velaga et al.	2025	Edge AI Review	AI, Edge Computing	Foundations and opportunities of Edge AI	Conceptual review
[10]	Hu et al.	2023	Video Analytics Survey	Edge Computing, Vision AI	Real-time video processing techniques	Broad coverage
[11]	Bibri et al.	2024	AIoT Smart Cities	AIoT	Sustainable smart city solutions	Limited safety discussion
[12]	Adewopo et al.	2024	Traffic Accident Dataset	Deep Learning, Vision	Dataset for accident detection	Dataset-oriented
[13]	Ubaid et al.	2022	Traffic Signal Automation	Computer Vision, DL	Intelligent traffic management	Focused on signals only
[14]	Reza et al.	2021	Urban Traffic Safety	Deep Learning	Traffic monitoring and control	Limited edge deployment
[15]	Sahu et al.	2026	Hazard Detection	Edge AI	Real-time road hazard monitoring	Transportation-centric
[16]	Lanjewar et al.	2026	Emergency Vehicle Detection	Edge AI, Vision	Priority traffic management	Specific use case
[17]	Alshuhail et al.	2025	Emergency Response	Sensor Fusion, AI	Real-time health monitoring and alerts	Healthcare-oriented
[18]	Stubbs	2026	AI in Policing	AI Analytics	Future urban policing framework	Conceptual discussion
[19]	Pesqueira & Machado	2026	Ethical Urban Security	AI Governance	Privacy and ethical AI framework	Limited technical implementation
[20]	Hosseini et al.	2026	Traffic Prediction	Graph Neural Networks	Spatio-temporal traffic forecasting	Traffic-specific
[21]	Wang et al.	2026	Cross-City Traffic Prediction	Federated Learning, GNN	Personalized traffic modeling	Limited safety applications
[22]	Amutha et al.	2026	Real-Time Monitoring	IoT	Monitoring and tracking applications	General IoT focus
[23]	Deepan Kumar et al.	2026	Smart Parking	IoT, AI	AI-based parking optimization	Mobility-focused
[24]	Jana et al.	2026	Edge-Fog Smart Cities	Edge/Fog Computing	Agile smart city software framework	No surveillance focus
[25]	Bai & Thirumaran	2026	Event Detection	Graph Attention Networks	Integrated forecasting and anomaly detection	Traffic-centric
[26]	Jocher et al.	2026	YOLO26	Deep Learning, Computer Vision	Real-time object detection framework	Generic vision model
[27]	Muhammad et al.	2026	Crime Prediction	ML, DL	Crime hotspot prediction review	Predictive focus only
[28]	Zhukabayeva et al.	2026	Intelligent Surveillance	Explainable AI, Deep Learning	Explainable surveillance framework	Computational complexity

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III. INTELLIGENT STREET LIGHTING SYSTEMS FOR URBAN SAFETY

With the quick expansion of the city population, the growth of urban traffic, and the public safety issues, the transformation of traditional street light systems into smart urban systems has been accelerated. Street lights were traditionally created for use at night to illuminate the streets and public areas. Now, with developments in sensing, wireless communications, artificial intelligence (AI), Internet of Things (IoT) and edge computing, they are no longer confined to the light-based role but can also be used for environmental monitoring, traffic control, security, disaster response and public safety measures. Smart Streetlight systems are a distributed sensing platform that is constantly gathering, processing and sharing urban information for real-time decision making and situational awareness. They are now considered as important parts of smart city system, leading to sustainable urban development and citizen security (Khemakhem and Krichen et al. [1]; Bibri et al. [11]).

The adoption of AI-powered monitoring tools in urban street lighting systems has opened up fresh possibilities for urban safety applications. Smart lights with cameras, motion and environmental sensors, and communication modules can sense abnormal events, track traffic, pinpoint hazards, and assist emergency response efforts on the street. Moreover, since the introduction of Edge AI, the ability to perform these functions can be achieved at street level devices to minimize latency and increase operational efficiency (Badidi et al. [6]; Velaga et al. [9]). Consequently, smart street lighting is becoming a smart city platform for future safe and surveillance applications

A. Evolution of Smart Street Lighting

Smart street lighting has come a long way, starting with energy-efficient lighting systems and then moving towards urban intelligence platforms powered by AI. Previous street lighting systems were operated manually and used fixed schedules, leaving a lot of energy wasted and adaptability limited to environmental changes. In order to overcome these challenges, the researchers came up with the idea of implementing sensor-based automation techniques that would allow for a dynamic lighting system that would light up according to the ambient light levels, the movement of vehicles and the presence of pedestrians (Abhishek and Srikanth et al. [3]).

The wide spread of IoT technologies changed the street lighting systems again so that it became possible to monitor, control and communicate between the lighting nodes remotely and in real-time. Parkash and Rajendra et al. [2] introduced an IoT-based intelligent street lighting system using interconnected sensors and wireless communication to achieve optimal energy efficiency without compromising lighting levels. This has improved the operational efficiency and lowered the maintenance costs significantly. Research that followed further developed street lights in smart city infrastructures. According to Khemakhem and Krichen et al. [1] in the last few years, smart lighting systems are increasingly using different types of environments sensors, communication gateways, and cloud-based management platforms, enabling them to act as key nodes in the urban IoT network. This change fits into the general smart city goals in the areas of sustainability, energy conservation and smart infrastructure management.

The introduction of AI, machine learning, and computer vision has also contributed to the rapid progress of smart street lighting. Smart street lighting has continued to evolve with the introduction of AI, machine learning, and computer vision technologies. By combining surveillance cameras with AI-powered analytics, streetlights can identify traffic violations, track pedestrian activity, alert for suspicious behavior, and assist in crime prevention efforts. The research by Ubaid et al. [13] and Reza et al. [14] illustrates the potential of intelligent traffic monitoring systems, leveraging computer vision for real-time detection and automated decision making, to boost urban safety. Likewise, today's object detection methods like YOLO26 are capable of fast and precise identification of cars, pedestrians and danger scenarios, which is particularly applicable to implementation in an intelligent street lighting network (Jocher et al. [26]).

The next generation of smart street lighting systems features predictive analytics and urban intelligence, taking its role in monitoring and control to the next level. Using historical data and real-time information, AI systems can forecast traffic jams, accident hot spots, and help our communities be proactive in managing safety. Intelligent urban infrastructures have shown great potential in predicting and preventing safety issues before an incident by employing graph neural networks and federated learning methods in traffic forecasting applications (Hosseini et al. [20]; Wang et al. [21]). Smart street lighting has therefore emerged from the passive street lighting application as an active platform of urban safety that can enable comprehensive city-wide monitoring and decision-making.

B. IoT and Edge-Enabled Lighting Infrastructure

At the heart of smart street lighting solutions is the adoption of Internet of Things (IoT) technologies and edge computing architectures. The Internet of Things (IoT) is an emerging technology that enables seamless communication and connectivity among various sensors, communication modules, embedded controllers, cameras, and cloud services, all of

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which help to monitor and exchange data in the urban environment. These components form a distributed sensing network that can collect the data about traffic, pedestrian, environmental data and public safety events (Khemakhem and Krichen et al. [1] and Amutha et al. [22]). Streetlights can be connected to each other as smart nodes in larger urban infrastructures with the help of IoT connectivity. Lighting systems can use wireless communication technologies like Wi-Fi, ZigBee, LoRaWAN, NB-IoT and 5G networks to share data with central management platforms and other smart city services. Parkash and Rajendra et al. [2] show how an IoT-based lighting system can effectively boost energy management, operational efficiency and automation features through remote monitoring and control. Similarly, the integration of cloud computing into IoT architectures enables scalable deployment and cities to be managed via data (Deepan Kumar et al. [23]). Although cloud-centric architectures offer many advantages, the quantity of visual and sensor data created by smart streetlights poses bandwidth, latency, privacy and computational issues. In response to this challenge, a new paradigm for computing has emerged, called edge computing, which places computing resources near data sources. In the context of smart cities, Chen et al. [7] pointed out that the edge intelligence plays an important role in optimizing communication and resources allocation in IoT. By decentralizing data processing, edge computing helps alleviate network strain and facilitates real-time data analysis and quick responses to critical safety incidents. Edge-AI frameworks are key to urban surveillance and monitoring applications. Badidi et al. [6] pointed out that, processing the surveillance data locally by using edge enabled video analytics will reduce the transmission delays and improve the privacy protection. Hu et al. [10] also showed that edge-based video analytics systems can be efficiently deployed at the edge to detect objects, recognize events, and detect anomalies in smart city scenarios. Edge and AI can be used together to make street lights smarter and more intelligent, allowing them to detect pedestrians, vehicles, accidents, items left behind or suspicious activity without having to use the centralized cloud only. The pursuit of a tinyML system and lightweight deep learning models has also come to the fore, further bolstering the viability of embedding AI at the street level. Trigkas et al. [8] have reported that TinyML technologies enable to execute real-time inferences for resource constrained embedded systems with low energy consumption. Likewise, Velaga et al. [9] noted that Edge AI will be crucial in the adoption of smart city solutions because it facilitates distributed intelligence and localized decision-making. The impact that edge-enabled lighting infrastructure has successfully brought to a number of urban safety applications has been proven in numerous instances. Sahu et al. [15] proposed an edge-based hazard detection approach that can detect hazards in real-time, while Lanjewar et al. [16] applied edge AI for detecting emergency vehicles and enabling intelligent traffic signal control. Moreover, edge-aware sensor fusion architectures have been found to be suitable for enabling quick emergency response and decentralized monitoring systems (Alshuhail et al. [17]). The progress in these advancements show that IoT and edge computing technology are the technological infrastructure of the next generation of smart streetlights. In summary, the integration of IoT connectivity, edge intelligence, AI-powered analytics, and distributed sensing infrastructure has revolutionized street lighting systems into smart urban safety solutions. The use of IoT and edge-enabled lighting infrastructures allows for real-time monitoring, localized processing, predictive analytics, and automated decision-making, creating a comprehensive platform for advancing public safety, boosting emergency response capabilities, and building resilient smart cities.

IV. AI-DRIVEN ACCIDENT AND CRIME DETECTION TECHNIQUES

As intelligent street lighting infrastructure becomes more widespread, urban lighting systems have evolved into distributed sensing platforms to provide public safety, surveillance, and emergency response systems. The Internet of Things (IoT), Edge AI, computer vision, and deep learning are key technologies for modern smart cities, where the goal is to continuously monitor and detect safety-critical events in real time. Instead of the traditional street lighting system used to light streets and manage energy consumption, AI-based lighting networks consist of cameras, environmental sensors, communication modules and edge computing devices for automating accident detection, crime monitoring and anomaly recognition (Khemakhem and Krichen et al. [1]; Badidi et al. [6]). AI and intelligent lighting systems work together to create a proactive capability for responding to urban incidents, provide situational awareness, and make citizens safer.

A. Computer Vision Approaches

With the ability to automatically analyze visual information captured from cameras mounted on the street lighting poles and urban infrastructure, computer vision has become one of the most useful technologies in urban surveillance and accident detection. Initial computer vision research was about object detection and motion detection, but in recent years there have been significant advances in sophisticated scene understanding, behaviour analysis and even event detection capabilities (Hu et al. [10]). One of the most widely studied computer vision applications in smart cities is traffic monitoring. Adewopo et al. [12] created a large dataset for supporting AI traffic accident detection systems, which is useful for building strong computer vision models for detecting collisions, vehicle anomalies and dangerous road conditions. In the same way, Ubaid et al. [13] used computer vision methods for intelligent traffic signal control that will allow automatic identification of vehicles and optimizing traffic flow. Reza et al. [14] also showed that image-processing

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and vision-based systems are effective for urban traffic management and enhancement of safety. The recent surveillance systems rely on algorithms of object detection, object tracking and recognition of activities to identify suspicious activities, unauthorised access, abandonment of objects, and crimes in public spaces. By using edge-based video analytics, surveillance streams can be processed in real-time, and the communication latency and bandwidth can be reduced (Badidi et al. [6]; Hu et al. [10]). Additionally, explainable computer vision systems are becoming part of intelligent surveillance systems, enhancing transparency and trustworthiness in high-stakes decision-making processes (Zhukabayeva et al. [28]). The combination of computer vision functions with the smart street light system offers an ongoing awareness of the environment and the ability to detect urban events in a timely way. Smart lighting poles equipped with cameras can provide data on pedestrian behavior, traffic conditions, and public spaces to form a distributed surveillance system that helps make cities safer to live in (Bibri et al. [11]).

B. Deep Learning Models
The effectiveness of AI accident and crime detection systems is often cited as a result of improvements in the capabilities of deep learning algorithms that are able to detect complex patterns in visual and sensor data. The performance of detection and prediction in urban safety applications has significantly improved through the use of Convolutional Neural Networks (CNNs), recurrent architectures, transformer-based models, and graph neural networks. Modern intelligent surveillance systems are based on deep learning-based object detection frameworks. Recent advances include YOLO26 that enables high-speed and high-accuracy object recognition for edge devices and resource-limited smart city infrastructures (Jocher et al. [26]). They can identify vehicles, pedestrians, bicycles, suspicious objects, abnormal activities in real time, which can support urban safety management in an proactive manner.In the context of accident detection, deep learning models look at vehicle trajectories, traffic patterns, and visual information related to collisions to automatically detect any accidents. Adewopo et al. [12] emphasized that to enhance the accuracy of accident recognition, large-scale datasets and deep neural networks are crucial. Likewise, Reza et al. [14] showed that deep learning architectures have proven to be effective in traffic management and incident monitoring. Machine learning and deep learning technologies have also helped in crime detection and prevention. Muhammad et al. [27] surveyed the different methods used for predicting crime hotspots, and how historical crime data, demographic data and spatial data can be used to predict high crime risk areas. More sophisticated surveillance systems also use deep feature fusion and explainable AI methods to enhance the robustness and transparency of crime detection systems (Zhukabayeva et al. [28]). Along with central cloud-based analytics, deep learning models are spreading to the edge of the network to bring low-latency inference and real-time responses to the edge. Edge AI architectures enable local processing, reduce communication overhead and enhance the scalability of system deployments for large urban scale monitoring applications (Velaga et al. [9]; Trigkas et al. [8]).

C. Real-Time Detection Frameworks
Real-time detection is a key element in smart city safety systems, as the time lag between the event and the response can make a significant difference in the aftermath of an accident, crime, or emergency. Today, smart city systems tend to integrate IoT sensors, edge computing and AI-powered analysis to enable real-time analytics of events and response. By processing data close to where it's generated, edge computing is a key enabling technology for real-time urban monitoring. Edge-intelligent networking was shown to be effective in optimizing IoT communication and reduce latency by Chen et al. [7]. Likewise, Nozari and Tavakkoli-Moghaddam et al. [5] pointed out the importance of edge computing to enable energy-efficient and responsive smart city infrastructures. There are a few studies which have suggested distributed architectures tailored for real-time safety applications. Sahu et al. [15] designed an edge-based hazard detection system to detect road safety hazards and transportation risks as quickly as possible. Lanjewar et al. [16] suggested an intelligent traffic signal control system using Edge AI with faster emergency responses and an emergency vehicle detection system. Alshuhail et al. [17] proposed a machine edge-aware IoT framework in which the sensor fusion and AI-based emergency response mechanisms were integrated in a decentralized monitoring environment. Edge analytics and smart lighting systems form a highly distributed safety system that can detect incidents, alert emergency services and create alerts in real-time. In large urban area, theses type of systems is useful in decreasing the need for central cloud processing and increasing the operational resilience (Badidi et al. [6]; Hu et al. [10]).

V. ADAPTIVE RISK SCORING AND SPATIO-TEMPORAL ANALYTICS

The approach to urban safety management is becoming more proactive and predictive, moving from a reactive incident response model. Recent developments in AI analytics, graph-based learning, and spatio-temporal modeling have allowed smart cities to uncover patterns of risk, predict hazardous events, and optimize the use of resources before they happen. Smart street lighting with sensing and monitoring functions is a valuable source of real-time environmental and behavioural data, which can be used to facilitate adaptive risk assessment and predictive safety monitoring.

A. Risk Assessment Models

The goal of risk assessment models is to estimate the probability and potential impact of safety risks, using past incidents and current data, as well as other context-specific factors. These models can be used to assist decision makers in determining high-risk areas, prioritizing actions and enhancing emergency preparedness. Machine learning algorithms are used in urban safety systems to predict accident probabilities, traffic risks, and crime occurrences, with the goal of improving safety and reducing urban crime. Muhammad et al. [27] showed how machine learning/deep learning algorithms can be used to detect crime hotspots based on spatial and temporal crime patterns. Likewise, Stubbs et al. [18] discussed the increasing utilization of Artificial Intelligence in police and urban security and mentioned the usage of predictive analytics in crime prevention strategies. In today's risk assessment approaches, there are several data sources such as surveillance cameras, sensor networks, traffic data and environmental data that can be used. AIoT enables the heterogeneous data streams to be collected and integrated together on the infrastructure and lead to a more precise evaluation of risk and situational awareness (Bibri et al. [11]; Alshuhail et al. [17]). The need for explainable AI is also becoming more significant in the context of public safety applications which call for transparent and accountable decision-making processes (Zhukabayeva et al. [28]; Pesqueira and de Bem Machado et al. [19]).

B. Spatio-Temporal Data Analysis

Spatial and temporal dimensions are natural attributes of urban safety events. Spatio-temporal analytics is therefore an important research area where the dynamics of traffic, the distribution of accidents and the distribution of crime are understood. In recent years, the capability of modelling complex urban systems has greatly advanced with the development of graph neural networks and deep learning. Hosseini et al. [20] introduced an integrated spatio-temporal model that integrates graph convolutions and graph Fourier neural operators for traffic forecasting, yielding improved forecasting accuracy. Wang et al. [21] proposed a federated spatio-temporal learning approach that enables cross-city traffic prediction while maintaining data privacy. Anomaly detection and event monitoring are also important applications of spatio-temporal analysis. To detect unusual events and make accurate traffic forecasts, Bai and Thirumaran et al. [25] designed an anomaly-aware graph attention network. These methods can help in building smart streetlights that can detect abnormal urban activities and provide early warnings of possible safety risks. The ubiquity of IoT devices contributes to spatio-temporal intelligence by generating a flow of data that includes location information. The advantage of these data sources is that they can be used to develop real-time monitoring systems to identify the emerging risk patterns and enhance urban safety management (Amutha et al. [22] and Deepan Kumar et al. [23]).

C. Predictive Safety Monitoring

Predictive safety monitoring is the next step in the development of smart urban infrastructure. Predictive systems are not designed to discover incidents after they happen, but to predict them before they become a reality, or before they could be an accident, crime, or hazardous situation. Some of the technologies that enable predictive monitoring systems are machine learning, deep learning, and Edge AI. In the study reviewed by Muhammad et al. [27] they showed how crime hotspot prediction models can be used to predict future crimes based on historical crime trends. Likewise, the traffic forecasting models proposed by Hosseini et al. [20] and Wang et al. [21] can predict congestion and accident-prone situations in front of the transport authorities. Enhanced predictive capabilities are also achieved by the use of edge-enabled monitoring infrastructures that enable the continuous collection of data and enable localized analytics (Velaga et al. [9]; Trigkas et al. [8]). The real-time hazard detection system suggested by Sahu et al. [15] and the emergency response system designed by Lanjewar et al. [16] show the potential for integrating predictive insights into operational safety management. Predictive safety monitoring, combined with other intelligent street lighting systems, can be used to build a distributed intelligence platform that can predict risks, pinpoint vulnerable locations, and provide proactive intervention strategies for the whole city. These capabilities can play a major role in decreasing accident rates, the effectiveness of emergency response, as well as the urban resilience in the future smart city.

VI. CHALLENGES AND RESEARCH GAPS

The rapid development of smart street lighting systems has already proven to be a powerful enabler for smart cities, offering substantial potential to improve urban safety through real-time monitoring, automated decision making and AI-based surveillance. But there are several technical, operational and ethical issues still to be addressed for the large-scale deployment and wide-spread adoption. Current studies identify significant privacy concerns and limitations in the scalability of street lighting infrastructure, data availability, robustness of models, and interoperability of systems that need to be addressed to unlock the potential of AI-powered street lights.

A. Privacy and Security Issues

The collection and processing of large amounts of visual, environmental and behavioral information from open spaces is one of the most important issues that need to be overcome in the implementation of intelligent street lighting systems.

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The use of cameras, sensors, and AI-powered surveillance systems in street lighting systems poses privacy, data ownership, and ethical governance concerns. AI-based surveillance has the potential to enhance public safety by identifying accidents, criminal activity, and potential hazards but it also raises the issue of over-surveillance and unauthorized surveillance of people (Stubbs et al. [18]). There are also issues of transparency, fairness and accountability in making decisions with AI. Pesqueira and de Bem Machado et al. [19] highlighted the importance of ethical governance mechanisms that consider both the security goals of the cities and the basic rights to privacy. Likewise, Zhukabayeva et al. [28] noted the need for explainable artificial intelligence (XAI) in surveillance solutions to enhance trustworthiness and enable human oversight. Another key concern in street lighting infrastructures with IoT technology is cybersecurity. Smart lighting systems are based on interconnected devices, wireless communication protocols, cloud platforms and edge nodes which can be a potential attack vector. Khemakhem and Krichen et al. [1] showed that street lighting systems that are part of the IoT are vulnerable to various forms of attack such as unauthorized access, manipulation of data, and networks intrusion. Furthermore, secure communication and intelligent networking technology play key roles in ensuring system reliability and safeguarding important city information, as pointed out by Chen et al. [7]. Therefore, it is essential that future smart street lighting systems include advanced encryption techniques, secure authentication methods and privacy-aware artificial intelligence technologies for secure and reliable operation.

B. Scalability and Deployment Challenges

While many smart lighting prototypes and pilot installations have shown to be successful, there is still a challenge in moving from small scale to city wide deployments. In the big cities, the amount of data generated by cameras, environment sensors, traffic monitoring equipment, and connected IoT nodes is huge and heterogeneous. The efficient architectures to process this data in real-time must be able to process data with minimal communication overhead and must be able to handle latency-sensitive applications. One possible approach that can alleviate these problems is through the use of edge computing technology, which allows for the processing of data locally and minimises reliance on centralized cloud systems (Nozari and Tavakkoli-Moghaddam et al. [5]; Badidi et al. [6]). Yet, rolling out at scale of edge powered intelligent street light systems raises new challenges related to hardware resource constraints, distributed model management and infrastructure maintenance. Trigkas et al. [8] reported that complexity of AI models deployed within urban environment can be limited due to resource constraints in an edge device. The issue of interoperability is also a major hurdle. Smart city platforms in use often use various communication protocols, sensor architectures, and vendor-specific technologies, which can make it difficult to integrate. To facilitate effective communication between different types of IoT devices, Chen et al. [7] pointed out that there is an urgent need to have standardized networking frameworks. Likewise, Jana et al. [24] pointed out the significance of agile software management frameworks that can support the dynamics of edge-fog computing environments. The other challenge for deployment is the trade-off between computational costs and detection accuracy. Much of the time, deep learning models, which deliver high performance detection, consume significant amount of computing power. YOLO26 is an improved real time inference model (Jocher et al. [26]), but deployment of these models at thousands of distributed street lighting nodes is a complex engineering challenge. Scalable architectures, lightweight AI models, and adaptive resource allocation strategies are still important research challenges.

C. Dataset and Performance Limitations

Training datasets are critical for the performance of AI-based detection and monitoring systems, with high-quality, diverse, and extensive training sets being essential. While recent developments in computer vision and deep-learning have increased the vast number of datasets being created for specific applications, including traffic monitoring, accident detection, or object recognition, not all these datasets are representative of the wide variety of situations that occur in real environments. Adewopo et al. [12] emphasized the need for complete data to build a robust traffic accident detection system using AI. But, the changes of weather, lighting environment, camera perspectives, seasons and urban layout still have an impact on model performance. When deploying models trained in one city to another, there is a decrease in accuracy because of the differences in infrastructure and environmental characteristics. The difficulty is increased in intelligent street lighting systems such as cameras where they are used in low light and bad weather, fog, rain and varying light intensities. Reza et al. [14] and Ubaid et al. [13] have shown that the accuracy of detection and reliability of the system can be significantly affected by the environmental variability. Likewise, Sahu et al. [15] reported that hazard detection system should have strong adaptation capabilities to achieve the consistency of performance in the changing road environment. One more research gap is the lack of benchmark databases that are specially created for the use of intelligent street lighting. Existing data is generally limited to individual aspects of the problems like traffic prediction, surveillance or crime analysis, but not on combined urban safety monitoring. Moreover, the lack of explainability, fairness and bias evaluation of existing datasets and model evaluation frameworks (Zhukabayeva et al. [28]). To overcome these, multimodal, large scale and publicly accessible datasets, suitable for comprehensive urban safety applications, will need to be developed.

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VII. CONCLUSION AND FUTURE SCOPE

Street lighting infrastructure is in a dramatic shift from being a simple lighting system to a platform of smart city intelligence that can be utilized for public safety, sustainability and smart city operations. The use of Internet of Things (IoT), Edge Computing, Artificial Intelligence (AI), Computer Vision (CV) and Real Time Analytics (RT Analytics) demonstrated in fig1 has given street lighting networks a new dimension of capabilities and applications beyond energy management, such as traffic monitoring, hazard detection, emergency response support, crime prevention, and intelligent surveillance. Recent development of Edge AI, video analytics and the distributed sensing architectures has shown the potential of street lighting infrastructure to be used as a city-wide monitoring and decision-support system (Badidi et al. [6]; Hu et al. [10]; Sahu et al. [15]).

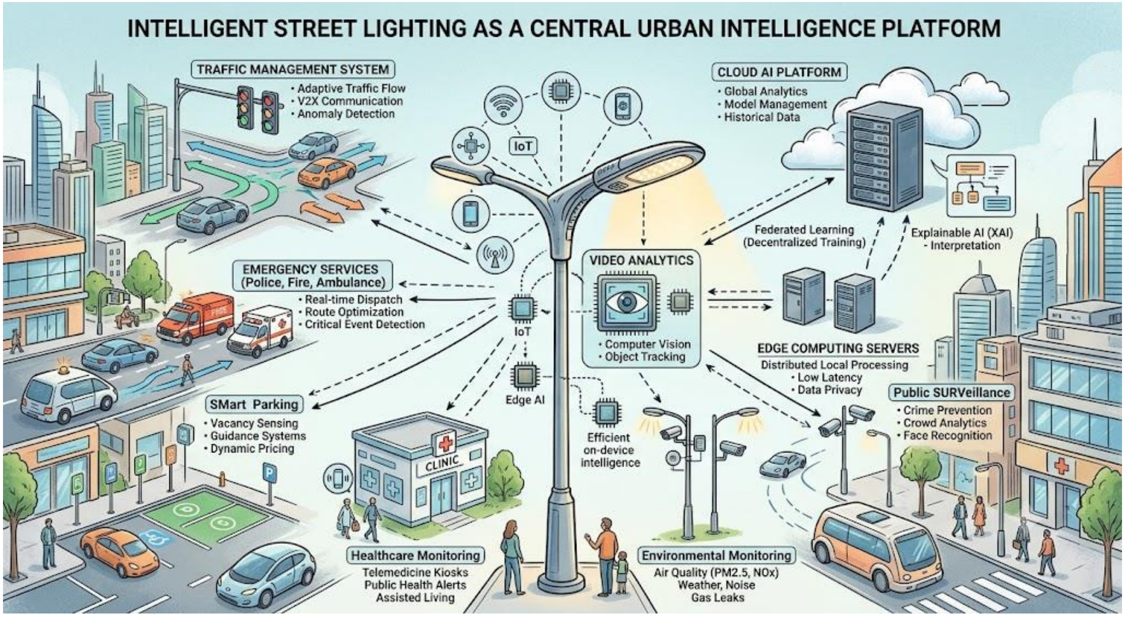

Fig.1. Future integrated smart city ecosystem enabled by intelligent street lighting networks.

From the literature consulted in this study, it could be noted that the use of IoT sensing platforms, edge-intelligent networking, deep learning-based computer vision models and spatio-temporal analytics have remarkably enhanced the capability of urban systems to sense and react to a dynamic event in real-time. For instance, the intelligent traffic management, accident detection, emergency vehicle recognition, hazard monitoring and citizen safety surveillance applications are just a few of the ways AI-powered monitoring systems are vital in today's smart cities (Ubaid et al. [13]; Reza et al. [14]; Lanjewar et al. [16]). Moreover, the development of new object detection models like YOLO26 and explainable surveilling models has improved the precision, performance, and clarity of intelligent urban monitoring systems (Jocher et al. [26]; Zhukabayeva et al. [28]). However, there are still some obstacles that prevent the widespread use of these technologies. The challenges include privacy concerns, cybersecurity risks, interoperability concerns, cost of infrastructure, and lack of consistency of the data sets. The issues of privacy and ethical questions regarding always-on monitoring and decision making made by AI systems highlight the importance of ethical and responsible governance models and privacy-enhancing technologies (Stubbs et al. [18]; Pesqueira and de Bem Machado et al. [19]). Besides, existing AI models still have some limitations and are vulnerable to changes in their environment and low-light conditions, as well as different urban infrastructures and heterogeneous data (Adewopo et al. [12]; Reza et al. [14]). In the future, new solutions for lightweight Edge AI and TinyML systems are needed that can be deployed to perform real-time analytics directly on the street lighting nodes with reduced latency and communication overhead (Trigkas et al. [8]; Velaga et al. [9]). Combining multimodal sensing systems like visual, thermal, acoustic and environmental sensor is one more way of enhancing the detection accuracy and situational awareness. Proactive traffic control, crime hotspot prediction and emergency preparedness are among the areas that are promising opportunities for emerging technologies like federated learning, graph neural networks and predictive urban analytics, which does not impact data privacy (Hosseini et al. [20]; Wang et al. [21]; Muhammad et al. [27]). Furthermore, the future intelligent street lighting systems will be part of the larger, more complex smart city networks, enabling other smart city solutions like smart transportation, healthcare monitoring, intelligent parking, environmental management, and public safety services (Alshuhail et al. [17]; Deepan Kumar et al. [23]). To guarantee public trust and regulatory compliance in these deployments, explainable AI, secure communication protocols, and ethical governance frameworks will be key factors (Zhukabayeva et al. [28];

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Pesqueira and de Bem Machado et al. [19]). Overall, intelligent street lighting powered by AI is a new and promising paradigm that has the potential to significantly improve the safety and efficiency of public spaces. These systems, with the integration of IoT connectivity, edge intelligence, computer vision, and advanced analytics, can deliver real-time detection, monitoring, and decision-making in various urban scenarios. In order to ensure success going forward, current challenges in privacy, scalability, interoperability and dataset size will be key. As AI and smart city technologies continue to evolve, intelligent street lighting systems are set to become an integral part of the safer, smarter, and more sustainable cities of the future.

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