An AI and IoT Framework for Dynamic Optimization and Sustainability in Smart Cities / Review Article

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إطار عمل للذكاء الاصطناعي وإنترنت الأشياء للتحسين الديناميكي والاستدامة في المدن الذكية

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Abstract

Smart cities are emerging as a critical solution for creating more efficient, sustainable, and comfortable urban environments. This transformation is primarily driven by the synergistic integration of the Internet of Things (IoT) and Artificial Intelligence (AI). The IoT provides a pervasive network of connected sensors that collect real-time urban data, while AI serves as the analytical engine that processes this information to optimize city-wide systems. This paper presents a comprehensive framework that leverages this AI-IoT convergence for dynamic optimization to achieve long-term urban sustainability. The framework focuses on enabling intelligent, data-driven decision-making across core urban domains. The discussion and analysis reveal that the integration of AI and IoT is revolutionizing smart cities by fostering decentralized, intelligent systems. This synthesis of real-time data, advanced analytics, and distributed computing generates significant gains in efficiency, sustainability, and security, evidenced by reduced latency, lower energy consumption, and enhanced threat detection. However, the implementation of such frameworks faces persistent challenges, including issues of scalability, cybersecurity, data standardization, and equitable access. The paper concludes that proactively addressing these technical and socio-technical barriers is essential for building resilient, inclusive, and truly sustainable urban ecosystems for the future.

Keywords: Smart City, Internet of Things (IoT), Artificial Intelligence (AI), Optimization, Sustainability.

المستخلص

تُعد المدن الذكية حلاً حيويًا لإنشاء بيئات حضرية أكثر كفاءة واستدامة وراحة. ويعتمد هذا التحول بشكل أساسي على التكامل التكاملي بين إنترنت الأشياء والذكاء الاصطناعي . يوفر إنترنت الأشياء شبكة شاملة من المستشعرات المتصلة التي تجمع البيانات الحضرية في الوقت الفعلي، بينما يعمل الذكاء الاصطناعي كمحرك تحليلي يعالج هذه المعلومات بهدف تحسين الأنظمة على مستوى المدينة بأكملها. يعرض هذا البحث إطار عمل شامل يستفيد من تقارب الذكاء الاصطناعي وإنترنت الأشياء لتحقيق التحسين الديناميكي بهدف الوصول إلى استدامة حضرية طويلة الأمد. يركز الإطار على تمكين اتخاذ القرار الذكي المبني على البيانات عبر المجالات الحضرية الأساسية. تكشف المناقشة والتحليل أن دمج الذكاء الاصطناعي وإنترنت الأشياء يُحدث ثورة في المدن الذكية من خلال تعزيز الأنظمة الذكية اللامركزية. ويؤدي هذا التكامل بين البيانات في الوقت الفعلي، والتحليلات المتقدمة، والحوسبة الموزعة إلى تحقيق مكاسب كبيرة في الكفاءة، والاستدامة، والأمان، وهو ما يتجلى في انخفاض زمن الاستجابة، وتقليل استهلاك الطاقة، وتعزيز القدرة على اكتشاف التهديدات. مع ذلك، تواجه تطبيقات مثل هذه الأطر تحديات مستمرة، بما في ذلك قابلية التوسع، والأمن السيبراني، وتوحيد البيانات، وضمان الوصول العادل. ويخلص البحث إلى أن معالجة هذه الحواجز التقنية والاجتماعية-التقنية بشكل استباقي أمر أساسي لبناء أنظمة حضرية مقاومة، شاملة، ومستدامة حقًا في المستقبل.

الكلمات المفتاحية: المدينة الذكية، إنترنت الأشياء، الذكاء الاصطناعي، التحسين، الاستدامة

1. Introduction

A smart city represents an advanced urban environment that utilizes cutting-edge technologies, intelligent systems, and effective management practices to improve infrastructure, public services, and residents' quality of life [1]. It connects essential sectors such as transportation, healthcare, energy, and communication through integrated technologies like the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Artificial Intelligence (AI). These innovations enable real-time data analysis, automation, efficiency, and cost savings. The main objective of smart cities is to ensure safer, more comfortable, and higher-quality living while minimizing operational costs. Practical applications include smart grids that regulate energy use, intelligent transport networks enhancing mobility and safety, remote healthcare systems, and buildings that adjust to environmental changes [2]. Despite these advancements, cities still encounter challenges such as overpopulation, large coverage areas, high infrastructure expenses, complex data management, and environmental degradation. To overcome these issues, smart urban planning emphasizes predictive technologies, renewable energy adoption, strong data management, and sustainable policy frameworks [3]. As urbanization continues to expand, consuming nearly 70% of global natural resources, technologies like ICT, IoT, AI, and big data have become vital in creating adaptive, efficient, and sustainable cities for the future [4].

Artificial Intelligence (AI) acts as the brain of the smart city, transforming IoT data gathered through the IoT into intelligent data for efficient decision-making The application of AI is a key determinant in improving the efficiency levels and prediction capacities in all domains [5]. It is fundamental to applications like intelligent traffic management, real-time threat detection in cybersecurity, agriculture, and proactive smart healthcare systems. Techniques such as computer vision, natural language processing, and predictive modeling are used to analyze trends, optimize systems, and personalize services. However, the integration of AI introduces its own set of challenges, such as ethical use of AI [6]. Future research directions stress the necessity of developing secure, scalable, and explainable AI solutions to ensure these technologies are deployed responsibly and effectively to serve citizens.

This study investigation focuses on an integrated AI and IoT framework essential for achieving dynamic optimization and sustainability in smart cities. This paper is structured as follows. First, an introduction establishes the context of smart cities and examines the roles of IoT and integrated AI within them. This is followed by a literature review that identifies a gap, motivating a detailed exploration of key application domains and optimization case studies. These domains include smart mobility and traffic optimization, energy management, security, and specific application areas such as agriculture, medical imaging, and health monitoring. The subsequent section presents a discussion and analysis, detailing how AI-driven insights from IoT data yield measurable improvements in efficiency and conservation across these domains.

2. Literature Review

This section reviews recent research on IoT and AI, focusing on four key areas for smart cities: mobility, traffic optimization, energy, security, and specialized fields like agriculture and healthcare. A common theme is that combining real-time IoT data with advanced AI techniques leads to major improvements in city efficiency, sustainability, and safety.

2.1. Smart Mobility and Traffic Optimization

Current studies show that integrating AI with IoT is becoming a central strategy for addressing the multifaceted problems in smart mobility and traffic optimization. Qaffas [7] introduced a novel, AI-driven framework for dynamic smart city traffic optimization that relies on a distributed IoT network. The framework's core strength is a hybrid AI model, combining a Vision Transformer (ViT) for real-time visual detection and a Temporal Convolutional Network (TCN) for predictive analysis, which is deployed on edge nodes to ensure high-speed, low-latency decision-making. Using the Dublin Traffic Sensor Dataset, the framework significantly improved traffic efficiency, achieving a 40.4% reduction in average vehicle delay time and a 32.7% increase in intersection throughput. The distributed architecture proved highly responsive, yielding a total decision latency of only 64.9 milliseconds, which substantially surpasses the performance of centralized and cloud-based systems. The proposed Eco-Assistive Fog-based Traffic Management System (EAFTMS) introduced a four-tier architectural model integrating IoT, fog, cloud, and application layers to deliver scalable, real-time urban traffic optimization [8]. Central to the framework is an AI-powered Point Exchange System (PES), designed to incentivize sustainable commuter behaviour, reducing vehicle dependency and encouraging eco-conscious choices through a gamified reward mechanism.

Performance metrics confirm EAFTMS's superior efficacy: a 30% reduction in latency, 40% improvement in response time, 25% increase in traffic flow efficiency, and 35% decrease in CO_2 emissions. This positions EAFTMS as a benchmark solution for developing intelligent, green urban ecosystems that are both operationally effective and environmentally responsible.

Almaazmi *et al.*, [9] , introduced an innovative solution to the limitations of traditional, centralized Energy Management Systems (EMSs), which suffer from poor adaptability, high overhead, and privacy issues Click or tap here to enter text.. The research proposed an Explainable Federated Learning (XFL) framework for vehicular energy optimization in smart cities. This decentralized approach uses Federated Learning (FL) to enable collaborative AI model training across edge devices while preserving data privacy. The addition of Explainable AI (XAI) increases the transparency and trustworthiness of the system's decisions. The XFL framework, utilizing a Multi-Layer Perceptron (MLP)-based global model on real-world vehicle data, demonstrated superior performance, achieving high predictive accuracy with R^2 values of 94.73% for energy consumption and 99.83% for traffic density. This paper [10] presented DST-FedRL, a decentralized traffic management framework that combines reinforcement learning, Deep Spatial–Temporal Transformer Networks, and federated edge artificial intelligence. To protect privacy and facilitate cooperative model updates, the system processes local traffic data. Trained on the Road Traffic Video Monitoring Dataset, DST-FedRL achieves 97.8% vehicle detection accuracy, reduces travel time by 30%, and lowers fuel consumption by 27.9%, offering an efficient, scalable, and sustainable solution for smart city mobility.

As illustrated in [11] proposed a novel AIoT vehicle safety framework designed for smarter, safer cities. This system proactively reduces risks by seamlessly integrating ultrasonic, eye blink, and alcohol sensors. It boosts road safety through immediate driver alerts based on eye blink detection and utilizes Li-Fi for rapid, efficient vehicle-to-vehicle communication. Critically, if high alcohol levels are detected, the system autonomously controls vehicle speed and instantly notifies authorities via GPS/GSM. This resilient architecture lays a sustainable and safer foundation for intelligent urban transport. A novel framework that combines IoT, AI, and autonomous vehicles (AVs) to revolutionize urban logistics and reduce traffic was presented by Mohsen [12]. The system significantly improves demand prediction, traffic light synchronization, and delivery route planning by "crunching" real-time IoT data using intelligent AI. The product is a highly integrated approach that drastically lowers carbon emissions, greatly improves traffic flow, and creates a sustainable urban delivery future.

Paper [13] details a three-layer architecture for AI-driven vehicular networks to enhance urban mobility. Authors demonstrate how integrated AI optimizes routing and traffic control, while rigorously addressing paramount cybersecurity risks through cryptographic authentication and AI-based anomaly detection. Validation via simulation and real-world testing confirms that this secure, adaptive framework significantly improves traffic efficiency and network integrity, establishing a foundation for safe and intelligent transportation systems. Jadhav, *et al.*, proposed an integrated AI, IoT, and VANET framework for advanced smart parking solutions [13]. The system leverages real-time sensor data and AI analytics to predict availability, optimize routes, and reduce driver search time. This significantly cuts fuel consumption and congestion, boosting urban sustainability. The framework prioritizes robust cybersecurity for secure data sharing and system stability.

Furthermore, paper [14] directly tackles the common frustrations of parking scarcity and network congestion in modern smart cities. The research introduces a robust, unified framework that expertly blends AI, IoT, and vehicular communication networks. Machine Learning is utilized to forecast where parking will be available, and Deep Reinforcement Learning is employed to boost the efficiency of the VANET routing protocols. Critically, the framework integrates edge computing and block chain technology to ensure both robust security and data integrity, resulting in a highly scalable and sustainable system for dynamic urban parking management through significantly improved V2I/V2V communication.

An automated road safety system using a Hybrid Vision Transformer (ViT) model for instantaneous traffic accident detection via video streams was proposed by Ahmad, *et al.*, [15]. By fusing transformer and CNN capabilities, the model achieves high accuracy in recognizing spatio-temporal events. The system leverages edge computing (e.g., Raspberry Pi) and GSM alerts for immediate notification of emergency services, significantly reducing response time and enhancing overall road safety infrastructure. In [16], authors proposed a novel deep learning approach to next-generation route planning in VANETs. By integrating real-time traffic, road conditions, and environmental factors, the algorithm accurately forecasts optimal routes. Extensive simulations confirm that this method substantially reduces travel time and emissions while increasing transportation throughput, offering a significant advancement for safer, smarter, and greener urban mobility systems.

Securing high-mobility VANETs in IoT-enabled smart cities against evolving attacks demands enhanced security. Research [17] introduced a unique AI-block-chain hybrid system that combines machine learning (CNN/LSTM) for intrusion detection (96% accuracy) with block-chain for decentralized trust and unbreakable data verification. This approach, which also uses ECC for robust authentication, significantly reduces Sybil attacks and outperforms traditional PKI and centralized frameworks, establishing a strong, privacy-aware basis for resilient smart transportation. Furthermore, the following study [18] compared Machine Learning

(ML) algorithms for Intrusion Detection Systems (IDS) in resource-constrained VANETs. Analysis confirms Decision Tree (DT) as the optimal choice, delivering high accuracy and exceptional efficiency crucial for such environments. Random Forest (RF) is best for models requiring continuous learning adaptability, while K-NN suits small datasets needing fast deployment. These findings guide the selection of appropriate ML algorithms based on specific network performance and resource limitations.

2.2. Smart Energy Management

Addressing high energy consumption and local optima issues in WSN routing, the paper [19] proposed a regional energy balance routing algorithm based on the Intelligent Chaotic Ant Colony (ICAC) approach. The method utilizes an adaptive perturbation strategy and an energy-delay metric to find the global optimum and ensure uniform node energy distribution. Simulation results show significant performance gains, including a 7.3% average energy consumption reduction compared to similar algorithms, effectively extending the network life cycle. Chen *et al.* introduced an energy-efficient IoT framework for smart street lighting, replacing metal halide lamps with mesopic LED lamps [20]. The system utilizes a smart decision module, Pulse Width Modulation (PWM) dimming, and a DALI controller to tune intensity based on traffic and occupancy. Powered by PV solar and an MPPT dynamic charging algorithm, experiments confirm significant energy savings across various urban areas, reducing overall consumption and carbon emissions.

A CNN-IoT framework for enhanced energy management in smart buildings was provided by the study [21]. By integrating deep learning with real-time IoT data, the framework significantly improves prediction accuracy and operational efficiency over traditional methods. Performance metrics confirm its robustness, achieving an 88% accuracy and a 0.88 F1-score. This solution offers proactive anomaly detection and superior energy optimization, positioning it as a key advancement for sustainable building management. An innovative deep learning framework to optimize energy management in IoT-enabled smart cities was proposed by Aljohani [22]. Leveraging real-time data from smart grids and sensors, the system uses neural networks and RNNs for precise, dynamic demand forecasting. Detailed simulations show significant reductions in energy usage, cost savings, and greenhouse gas emissions, establishing a versatile and scalable route toward a more sustainable and economically efficient urban future.

Raval *et al.*, used an energy management framework addressing both hardware modelling and software control [23]. A Multi-Agent Distributed Intelligent System (MAS) is introduced, with parameters optimized by a Genetic Algorithm (GA) to achieve decentralized intelligence. Simulation results reveal substantial energy savings, including a 40% reduction in total energy consumption, validating the framework's effectiveness. Smart cities require dynamic waste management to tackle inefficiency and high fuel use. This research [24] proposed a Deep Reinforcement Learning (DRL) framework for optimizing Autonomous Waste Collection Vehicle (AWCV) routes using IoT smart bins. Utilizing Deep Q-Networks (DQNs) to analyse real-time traffic and energy data, the system achieves a 30% reduction in distance and a 30% decrease in energy usage over baseline methods, demonstrating a sustainable and highly efficient operational strategy.

Chui *et al.*, introduced a novel Hybrid Genetic Algorithm Support Vector Machine Multiple Kernel Learning (GA-SVM-MKL) approach for Non-Intrusive Load Monitoring (NILM) across 20 appliance types [25]. GA optimizes kernel design to solve the multi-objective problem. The proposed method achieves an Overall Accuracy (OA) of 91.8%, representing a >21% performance improvement over traditional kernels. This integration of AI, IoT, and big data analytics significantly advances energy transparency and utilization in smart cities. Addressing the high latency and energy drain of traditional cloud-based IoT in smart cities, the study [26] validated adaptive edge computing as a key sustainable solution. The framework achieves significant gains in power efficiency and reduced data transmission overhead by adaptively distributing workloads and using AI-driven optimization. Findings confirm that localized edge decision-making drastically improves scalability and real-time responsiveness, promoting energy sustainability and performance in future urban environments.

Intelligent Deep Optimized Energy Management (Int-DEM), a novel cognitive IoT-enabled framework for effective energy management in smart grid systems was developed by Ganesh *et al.*, [27]. Int-DEM addresses grid data limitations using an intermediate cloud analysis concept and employs the hybrid deep learning model Stacked Convoluted Bi-Directional Gated Attention Network (SCon-BGAN), optimized by the novel Hybrid Darts Seagull Optimizer (HDSO) technique, for precise energy load forecasting. Comparative analysis confirms that Int-DEM significantly outperforms existing deep learning models, achieving superior accuracy with lower computational complexity, which establishes a robust and efficient tool for sustainable smart grid management. This study [28]proposed the Ensemble Red Fox Optimization with Energy Powered Artificial Neural Network (ERFO-EPANN), a hybrid deep learning model for precise solar irradiance and wind speed forecasting. Combining bio-inspired optimization with neural learning, ERFO-EPANN integration of RES with Energy Storage Systems (ESS), thereby maximizing grid resilience and sustainable urban infrastructure.

Nazari *et al.* [29] suggested a multi-stage, energy-efficient routing protocol for IoT networks integrating Ladybug/Butterfly Optimization (LBO/BOA) and Q-learning Click or tap here to enter text.. The protocol uses hybrid clustering for load balancing and dynamic Q-learning for multi-hop routing. Simulations confirm superior performance, including a 43% reduction in energy consumption and up to 47% extension of network lifetime compared to state-of-the-art methods, significantly enhancing network stability and coverage. This study introduced a new framework that integrates Quantum Computing, AI, and IoT for power quality management in renewable energy-driven Flexible AC Transmission Systems (FACTS) [30]. To counter RES variability and stability issues, the core method utilizes AI-enhanced quantum algorithms for real-time grid optimization, including efficient fault detection and load balancing. The system employs Unified Power Quality Conditioners (UPQC) and smart meters for continuous monitoring and compensation of power disturbances like voltage sags. Validated by simulation and hardware, this quantum-AI synergy successfully enhances grid resilience and security, demonstrating a practical approach to deploying advanced computational technology in clean energy infrastructures.

Deep Learning-augmented Predictive Energy Modeling (DL-PEM) framework combined with Multi-Objective Particle Swarm Optimization (MOPSO) for occupancy-based energy management in smart buildings was developed by this article [31]. Using indoor environmental data, the system optimizes HVAC and lighting to balance energy consumption and thermal comfort. Achieving 99.8% accuracy and up to 85% optimization efficiency, this framework significantly outperforms traditional models, promoting sustainability and scalable urban solutions. Singh *et al.* designed a Scalable Cloud-Based Continuous Monitoring Platform (SC-CMP) for real-time optimization of microgrids in EV-dense, renewable-integrated environments [32]. Fusing cloud computing, ML, and IoT data, the platform enables continuous monitoring, V2G coordination, and adaptive energy management. SC-CMP achieves 97.34% predictive accuracy and 96.81% grid stability improvement over existing baselines.

Authors developed a system which utilizes a hybrid deep learning (DL) framework to significantly boost energy efficiency within IoT wireless networks [33]. This intelligent system integrates Convolutional and Recurrent Neural Networks (CRNN) with the Krill Herd Optimization (KHO) algorithm, allowing it to efficiently forecast energy consumption trends and dynamically optimize resource allocation. Validation through simulations demonstrated that this framework yields substantial performance improvements, achieving up to a 52% decrease in energy consumption and maintaining high predictive accuracy 93.34%, thus presenting a highly scalable solution for dynamic energy management in complex IoT environments. Khan *et al.* addressed critical energy constraints in IoT networks by enhancing the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol using Digital Twin simulation and AI analytics [34]. This novel framework optimizes cluster head selection and assesses performance through virtual network models. Findings confirm significant network longevity improvements, including an 83% reduction in non-functioning nodes and a 1.66-fold increase in node energy levels, showcasing a viable direction for resilient, energy-efficient IoT networking.

2.3. Smart Cities Security

Agajo *et al.*, developed a system for monitoring and securing smart city infrastructure by integrating Block-chain, AI, and IoT [35]. Their work addresses security and data privacy concerns in cloud-based IoT platforms by proposing a distributed communication and storage mechanism via a block-chain-based infrastructure. The study is relevant as it provides an implementable model for secure data management in smart city networks. A hybrid model integrating LSTM networks and advanced feature engineering (IDS-SIoDL), was proposed by Hazman *et al.*, [36]. Evaluated on IoT datasets (Bot-IoT, Edge-IIoT), it achieves high accuracy and low latency, demonstrating effectiveness for real-time threat detection in smart cities.

The article [37]addressed smart city IoT security by proposing a two-tier cooperative framework. It integrates CNNs with AdaBoost, LightGBM, and XGBoost, optimized via Evolutionary Adaptive Firefly Algorithm (EAFA) for simultaneous feature selection and hyper parameter tuning. This approach, featuring simultaneous feature selection and hyper parameter tuning via EAFA, achieved 0.995565 accuracy, with performance further validated through XAI interpretability. Indra, *et al.*, [38] introduced an Ensemble Gradient Random Forest-based Leopard Seal Search (EGR-LSS) algorithm to improve intrusion detection in IoT-based smart cities. It addresses key research gaps in existing systems, such as insufficient data samples, high execution time, and computational complexity, by integrating ensemble voting and an optimization algorithm for hyper parameter tuning. The model achieving an accuracy of 98.75%, a recall of 97.4%, a precision of 98.7%, and an F1-score of 96.9%. These results surpass the performance of current leading techniques, including CNN, AI-BC, and NB.

To address the shortcomings of existing smart parking systems, such as vulnerabilities in privacy, security, and centralization, this paper [39] introduced Hybrid Deep learning and Redactable consortium block-chain based Secure Framework (HDLRCBSF). The framework utilizing a specialized Bi-LSTM model to intelligently predict parking availability and the Threshold Chameleon Hash algorithm (TCH) to ensure secure and verifiable data communication. It achieved a 21.32% improvement in optimal parking space allocation compared to baseline methods, while also providing drivers with enhanced privacy and security. The study [40] introduced a privacy-preserving AI framework for IoT-based smart cities. By combining federated learning with local differential privacy and FPGA edge acceleration, it enables secure, efficient model training. The system maintained near-centralized accuracy with just a 1.2–1.5% drop, while reducing the success of privacy attacks by over 50%. This demonstrates an effective balance between high performance and robust data protection.

To tackle the shortcomings of current IoT intrusion detection systems (poor adaptability and scalability), the study [41] presented the FOFSDL-SCD model. By combining a Fox Optimizer for feature selection, a Temporal Convolutional Network for classification, and Dung Beetle Optimization for parameter tuning, the framework significantly improves detection performance and efficiency. It achieved an impressive 99.38% accuracy, along with precision, recall, and F1-score all above 96%, outperforming existing methods. Chakrabarty, *et al.*, suggested a new security model [42]. It combines Black Networks for full communication encryption with Artificial Intelligence to enable intelligent, self-governing, and decentralized oversight. This strategy offers a direct defense against the complex array of cyber threats that modern urban infrastructures now encounter.

2.4. Smart City Application Areas

Keote *et al.*, designed a new IoT and AI framework that significantly advances structural health monitoring [43]. The system integrates physics-based simulations with intelligent sensor optimization to provide real-time, adaptive, and accurate strength prediction, transforming structures like dome trusses into self-learning systems. Empirical results demonstrate substantial performance gains over conventional methods, including a 35% reduction in sensor count, a 34% decrease in strength prediction Root Mean Square Error (RMSE), and a 60%reduction in bandwidth consumption. Author introduced PANDFOG, a novel fog computing framework designed for the real-time, multi-site analysis of heterogeneous medical imaging data, addressing the critical challenge of pandemic screening in smart cities [44]. By overcoming the latency and data inconsistency issues of centralized cloud-based AIoT systems, PANDFOG utilizes a specialized multi-decoder deep learning network to enable rapid, on-site diagnosis and achieve high segmentation accuracy, thereby enhancing clinical decision-making. The paper [45] introduced the INRwLF routing algorithm to address the limitations of existing protocols in large-scale I-IoT healthcare networks. By combining AI-driven Software-Defined Networking with hybrid metaheuristic optimization, it enables adaptive, load-balanced clusters and fault-tolerant routing. This design effectively reduces energy consumption and latency, substantially enhancing network lifespan and reliability in dynamic, resource-constrained settings.

Sekar *et al.*, proposed the SRGA-CGG algorithm to address limitations in existing AI models for smart agriculture, such as high computational costs and poor adaptability to environmental variability [46]. By integrating stacked RNNs, GANs, and an optimized greylag goose algorithm, it enhances predictive accuracy and efficiency in resource management, achieving 98.5% accuracy in crop disease detection. Authors addressed the research gap of integrating actionable AI with low-cost consumer devices by proposing a lightweight Random Forest model for on-device crop yield prediction [47]. Deploying via ESP32 sensors and smartphones, it optimizes irrigation with 90.1% accuracy, enabling real-time, localized water management while reducing cloud dependency in resource-constrained settings.

A research addressed the need for scalable and accurate AI systems in agriculture by assessing hybrid deep learning architectures integrated with IoT-based precision frameworks [48]. Among the evaluated models, the Hybrid ResNet demonstrates superior performance, attaining 97.2% accuracy and 95% security, thereby providing a resilient and adaptable solution for the complexities of heterogeneous farming environments. This review [49] synthesizes 88 studies to examine the integration of deep learning and IoT in smart farming. While these technologies significantly enhance crop recommendation, disease detection, and yield prediction, the analysis identifies critical gaps in IoT security, rural connectivity, and dataset standardization. The paper addresses these limitations by proposing a secure 5G-based framework to advance precision agriculture.

3. Discussion and Analysis

According to the studies in subsection 2.1, intelligent transportation systems have clearly moved from centralized architectures to decentralized solutions based on AI. Essentially, this transition in transport systems is driven by a combination of the IoT, edge computation, and AI. Table 1 provides a comparative summary of the literature, detailing the scope, methodologies, challenges, and key outcomes for each study in the domain of AI and IoT for smart mobility and traffic optimization. One of the main findings highlights the importance of edge and fog computing in overcoming latency, which is common in cloud-centric systems. Empirical studies conducted by Qaffas [1] and the EAFTMS methodology [2] have shown that processing information using AI systems deployed in edges, such as Hybrid Vision Transformers, can achieve latency in terms of milliseconds, which consequently leads to optimized traffic flow performance and enhanced intersection capacity. Furthermore, the field evolves with the implementation of specialized AI approaches. These include federated learning to maintain privacy, deep reinforcement learning with adaptive control, and hybrid AI-block-chain solutions for added security. Individually and cumulatively, these methods address related issues in forecasting, security, and environmentally sound logistics. The achieved results include both functionalities, indicated by alleviated traffic congestion and travel time, and sustainability, indicated by lower fuel consumption and reduced CO_2 emissions. Despite this, a continuation of challenges remains in matters such as the scalability of these distributed systems, resistance to advanced cyber-attacks, and various ethics and regulatory issues related to self-driving city infrastructure.

Table 1: AI and IoT in Smart Mobility and Traffic Optimization

Ref	Scope	Methodologies	Challenges	Results
[7]	Dynamic Traffic Optimization	Hybrid AI (ViT + TCN) model.	High latency and low responsiveness of centralized systems.	40.4% reduction in vehicle delay time; total decision latency of 64.9 ms.
[8]	Sustainable Traffic & Commuter Behavior	EAFTMS &(PES)	CO_2 emissions, traffic congestion, and need for eco-conscious commuting.	30% latency reduction; 25% increase in traffic flow efficiency.
[9]	Vehicular Energy Optimization	Explainable Federated Learning (XFL)	Traditional EMS limitations: poor adaptability, high overhead, and data privacy risks.	High predictive accuracy (R^2 > 94%) for energy consumption and traffic density.
[10]	Decentralized Traffic Management	DST-FedRL	Centralized system inefficiencies and data privacy concerns.	97.8% vehicle detection accuracy; 30% reduction in travel time.
[11]	AIoT Vehicle Safety	Li-Fi for V2V	Immediate road risks, impaired driving, and efficient inter-vehicle communication.	Proactive risk mitigation and autonomous speed adjustment for safety violations.
[12]	Urban Logistics Optimization	AI, AVs, and IoT framework	City congestion, high carbon footprint, and inefficient delivery routes.	Drastically lowers carbon emissions and greatly improves traffic flow for deliveries.
[15]	Next-Generation Route Planning	Deep Learning approach.	High travel time and emissions in dynamic VANET environments.	Substantially reduces travel time and emissions while increasing transportation throughput.
[16]	VANET Security	AI-Blockchain Hybrid	Sybil, GPS spoofing, DDoS, and limitations of centralized security (PKI).	96% accuracy in intrusion detection; significant reduction in Sybil attacks.
[17]	IDS Algorithm Selection in VANETs	K-NN & SVM	Resource constraints and selecting the optimal algorithm for specific network needs.	Decision Tree (DT) is the optimal choice for resource-constrained VANETs due to high accuracy and efficiency.

The research discussed in section 2.2 demonstrates that by integrating AI, IoT, and optimization algorithms, is driving a major change: smart city energy management is becoming intelligence driven. Ongoing studies are utilizing advanced techniques, utilizing methods such as deep learning (CNN, RNN), hybrid learning models (SCon-BGAN, CRNN), and bio-inspiration for optimization (GA, HDSO, LBO) to accomplish accurate forecasting, dynamic control, and optimized routing. Some major achievements include a dramatic reduction in energy consumption with increases from 7.3% to 52%, prolonging network lifespan by a maximum of 47%, and increasing operational accuracy up to a level of 99.8%. The emerging paradigms of this technology have successfully tackled major technical problems such as localized optimum in wireless sensor networks, intermittency in renewable sources, and real-time demand response with utilization of real-time Internet of Things information and decentralized systems such as edge and cloud computing. A comparative summary of the surveyed Smart Energy Management research is presented in Table 2.

Table 2: Summary of AI and IoT in Smart Energy Management

Ref	Scope	Methodologies	Challenges	Results / Future
[21]	Smart Building Energy Management	CNN-IoT integration deep learning	Low prediction accuracy, inefficient traditional methods	88% accuracy, 0.88 F1-score, proactive anomaly detection
[22]	Smart City Energy Optimization	Neural networks, RNNs	Inaccurate demand forecasting, high energy use	Reduced energy usage, cost, and greenhouse gas emissions
[23]	Decentralized Energy Management	MAS &GA optimization	Centralized inefficiency, lack of adaptive control	40% reduction in total energy consumption
[24]	Waste Collection Vehicle Routing	Deep Reinforcement Learning (DQN)	Inefficient routes, high fuel consumption	30% reduction in distance & energy usage

Ref	Scope	Methodologies	Challenges	Results / Future
[25]	Non-Intrusive Load Monitoring (NILM)	Hybrid GA-SVM-Multiple Kernel Learning	Low disaggregation accuracy for multiple appliances	91.8% Overall Accuracy (>21% improvement)
[26]	Edge Computing for IoT Sustainability	AI-driven workload distribution	High latency, energy drain of cloud-based IoT	Improved power efficiency, scalability, real-time response
[27]	Smart Grid Load Forecasting	SCon-BGAN & HDSO	Grid data limitations, forecasting complexity	Superior accuracy with lower computational complexity
[28]	Renewable Energy Forecasting	ERFO-EPANN	Unpredictable solar/ wind resources	High accuracy (RMSE 1.650, MAE 1.100), enhanced grid resilience
[30]	Power Quality in Renewable Grids	Quantum computing	RES variability, grid stability, power disturbances	Enhanced grid resilience, security, real-time compensation
[31]	Occupancy-Based Building Management	Deep Learning Predictive Modeling	Balancing energy savings with occupant comfort	99.8% accuracy, 85% optimization efficiency
[32]	Microgrid Optimization with EVs	Scalable Cloud-Based Platform	EV integration, renewable intermittency, grid stability	97.34% predictive accuracy, 96.81% stability improvement
[33]	IoT Wireless Network Efficiency	Hybrid CRNN + Krill Herd Optimization (KHO)	High energy consumption in wireless IoT networks	52% energy decrease, 93.34% predictive accuracy

Section 2.3 shows how blockchain technology and artificial intelligence are driving an evolution in smart city security, shown in Table 3. Data privacy, centralized attack surfaces, and real-time threat detection are the three main vulnerabilities of IoT ecosystems that research methodically addresses by moving to intelligent frameworks. The widespread use of hybrid AI models, such as those that combine CNN, LSTM, and ensemble techniques (e.g., IDS-SIoDL, FOFSDL-SCD), optimized with bio-inspired algorithms (EAFA, LSS), achieves remarkable intrusion detection accuracy (up to 99.38%) and low latency. Concurrently, blockchain and cryptographic

methods (TCH) provide immutable data integrity and user privacy for applications like smart parking. Crucially, the paradigm shifts from centralized to federated learning and edge-AI architectures, as demonstrated by frameworks maintaining high accuracy with minimal privacy loss, effectively balance performance with robust data protection. This convergence of explainable AI, adaptive optimization, and decentralized trust mechanisms establishes a resilient, scalable, and proactive security foundation essential for sustainable smart urban infrastructure.

Table 3: Summary of AI in Smart City Security

Ref	Scope	Methodologies	Challenges	Results / Future
[35]	Securing Smart City Infrastructure	Blockchain, AI, and IoT	Security & data privacy in cloud-based IoT platforms	Provides an implementable model for secure, decentralized data management.
[36]	Real-time IoT Threat Detection	IDS-SIoDL	Need for accurate, low-latency intrusion detection	High accuracy & low latency on IoT datasets (Bot-IoT, Edge-IIoT), suitable for real-time use.
[37]	IoT Security & Intrusion Detection	Evolutionary Adaptive Firefly Algorithm (EAFA)	Feature selection, hyperparameter tuning, model interpretability	Achieved 0.995565 accuracy; validated via XAI for interpretability.
[38]	Intrusion Detection for IoT	EGR-LSS algorithm	Insufficient data, high execution time, computational complexity	Superior performance (98.75% accuracy) vs. CNN, AI-BC, NB; high recall & precision.
[40]	Privacy-Preserving AI for IoT	Federated Learning & FPGA	Balancing data privacy with model accuracy in distributed learning	Near-centralized accuracy (only 1.2–1.5% drop); reduced privacy attack success by >50%.
[41]	Adaptive IoT Intrusion Detection	Fox Optimizer + Temporal CNN	Poor adaptability & scalability of current IDS	99.38% accuracy; precision, recall, F1-score >96%; outperforms existing methods.

Table 4 demonstrates how integrating IoT and AI addresses critical challenges in smart city applications, primarily enhancing efficiency and enabling real-time responsiveness. For instance, new approaches to monitoring infrastructure health create intelligent systems that learn as they operate, cutting bandwidth needs by 60%. In healthcare, decentralized tools enable faster pandemic screening at local sites, while smarter network designs keep critical medical IoT devices running longer. Agriculture is seeing a revolution, with AI models now diagnosing crop disease with remarkable accuracy and small, on-device systems allowing for precise water management right in the field. Yet, the analysis also reveals ongoing hurdles, including security risks, inconsistent data, and spotty rural internet access.

Table 4: IoT & AI in Smart City Application Areas

Ref	Scope	Methodologies	Challenges	Results / Future
[43]	Structural Health Monitoring	IoT & AI framework	High sensor cost, bandwidth consumption, and prediction error in conventional monitoring	35% sensor reduction, 34% lower RMSE in strength prediction, 60% less bandwidth use.
[44]	Pandemic Screening via Medical Imaging	PANDFOG fog computing framework	High latency & data inconsistency in centralized cloud AIoT for multi-site medical analysis	Enables real-time, on-site diagnosis with high segmentation accuracy for clinical decision-making.
[45]	Healthcare I-IoT Networking	INRwLF routing algorithm	High energy, latency, and poor reliability in large-scale Industrial IoT healthcare networks	Reduces energy consumption & latency, enhances network lifespan & reliability in dynamic settings.
[46]	Smart Agriculture (Crop Disease)	SRGA-CGG: Stacked RNNs + GANs	High computational cost, poor adaptability to environmental variability in AI models	98.5% accuracy in crop disease detection, enhancing predictive accuracy & resource management.

Ref	Scope	Methodologies	Challenges	Results / Future
[47]	On-Device Crop Yield Prediction	Lightweight Random Forest model	Integration of actionable AI with low-cost devices; cloud dependency in constrained settings	90.1% accuracy; enables real-time, localized irrigation optimization, reducing cloud reliance.
[48]	Precision Agriculture with IoT Security	Hybrid deep learning architectures	Need for scalable, accurate, and secure AI systems in heterogeneous farming environments	Hybrid ResNet achieved 97.2% accuracy & 95% security, providing a resilient solution.

In conclusion, the integration of AI and IoT is transforming smart cities by enabling decentralized, intelligent systems across mobility, energy, security, and specialized applications. This synthesis leverages real-time data, advanced analytics, and distributed computing to drive significant gains in efficiency, sustainability, and security, evidenced by reduced latency, lower energy consumption, and enhanced threat detection. However, challenges in scalability, cybersecurity, data standardization, and equitable access persist. Addressing these barriers is essential for realizing resilient, inclusive, and sustainable urban ecosystem.

4. Conclusion

This paper has investigated the transformative impact of integrating Artificial Intelligence (AI) and the Internet of Things (IoT) on urban development. By processing vast streams of sensor data with intelligent algorithms, this synergy facilitates data-driven optimization across core urban domains, including mobility, energy, security, and public services. A pivotal shift from centralized to decentralized, edge-centric architectures has been instrumental in achieving measurable outcomes, such as decreased traffic congestion, enhanced energy efficiency, and improved cyber threat mitigation. However, realizing the complete potential of smart cities is contingent upon addressing persistent implementation challenges.

Critical barriers include achieving scalable system deployment, fortifying defences against evolving cyber threats, and ensuring interoperability through standardized protocols. Equally important is promoting equitable access to technological benefits to prevent societal disparities and foster inclusive urban growth.

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