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AUGMENTING SMART CITY MANAGEMENT THROUGH THE INTEGRATION OF DIGITAL TWINS WITH FOG COMPUTING

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ABSTRACT

This paper examines the transition from centralized cloud computing to Fog Computing as a foundational enabler for real-time Digital Twin City (DTC) systems in urban environments. By redistributing computational workloads across the fog nodes, the proposed framework significantly reduces data transmission latency by up to 67% and enhances network efficiency by approximately 65–67% compared to the conventional cloud computing architectures. Central to this study is the integration of Digital Twin technology with a three-layer edge-fog-cloud hierarchy, which enables a continuous virtual synchronization with physical urban environments and supports autonomous real-time decision-making through DTC technologies. To validate the proposed model, the research uses the iFogSim simulation environment to systematically compare fog- and cloud-based scenarios in a modeled 25 km² residential city, with surveillance camera counts scaled from 16 to 80 across four operational zones. Ultimately, the outcomes indicate the extent to which fog computing capabilities can improve the quality and efficiency of smart monitoring and management in urban spaces, providing a scalable and sustainable roadmap for highly efficient infrastructure in next-generation cities.

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1. Introduction

Rapid advancements in information and communication technologies (ICTs) have encouraged people to migrate to urban areas, leading to overcrowding in cities. This influx of large numbers of people has placed increased pressure on various urban services and facilities, particularly infrastructure designed to accommodate a limited number of users. Consequently, numerous technical and technological approaches have been developed to address this challenge in current and future urban cities. Where Digital Twin (DT) stands out as a prominent technology and is defined as a dynamic maintained technology that constitutes a cyber-physical simulation framework that synthesizes physical models, IOT sensors, heterogeneous data sources from historical, operational, and spatial data records, and enables virtual objects to autonomously influence and manage physical systems without human involvement. The DT construction is mainly composed of integrated data from multiple disciplines, physical quantities, scales, and probability, with a bench of sensors and cameras within a unified system (Tao et al., 2019). This diverse set of data and devices is subsequently formed the DT systems that functions either as a simulation of physical models in virtual space or as a predictive model for future scenarios And despite these high potentials of DT technology, since its inception at the beginning of the 21st century where it was originally appeared in the aerospace industry and then be evolved in the manufacturing context, it has been largely mis contextualized and misinterpreted as merely a virtual/hypothetical model back then (Inamdar et al., 2024). However, coinciding with this decade's digital revolution, it has reappeared in diverse contexts to keep pace with today's accelerating digital age. It plays a pivotal role in detecting, recognizing, understanding, controlling, and transforming the physical world in the context of different sectors and industries, including automation, shipbuilding, healthcare, energy, and resource distribution, among others, encompassing technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence. This widespread adoption of digital twins across applications and fields in which they can play an active role has led to the emergence of the Digital Twin City (DTC) concept. DTC refers to an extensive and sophisticated system that connects the physical environment with its virtual counterpart, allowing for bidirectional interactions between physical cities in their tangible dimension and digital cities in their informational dimension (Shahat et al., 2021). Constructing the DTC would require a sophisticated data infrastructure that is capable of continuous, high-frequency data acquisition, alongside an advanced technological infrastructure that integrates heterogeneous sensors and surveillance camera networks across urban environments. In parallel, modular digital subsystems are progressively instantiated, calibrated, and optimized to align with the city's evolving operational, spatial, and functional requirements. To ensure a smooth process, the infrastructure was integrated with advanced connectivity mechanisms and technologies, such as 5G, into current city models, enabling data transfer to the cloud and subsequent city management (Li et al., 2017). However, although this step is promising and has the potential to make a real difference in our cities today, it’s faced an inherent challenge, particularly regarding the optimization of data transmission efficiency and speed, which is critical to maintaining real-time, continuous data streams with minimal latency, loss, or system downtime. Smart cities today often integrate cloud computing systems for data storage and processing to leverage distributed computing resources and improve system scalability. Nevertheless, the use of cloud computing for real-time applications remains limited due to significant latency and high bandwidth requirements (Badidi et al., 2020). To address these challenges, the concept of edge computing emerged in the early 2000s, coinciding with the rapid growth of Internet of Things (IoT) devices and their sensitive time- and privacy-sensitive data. While it addressed the challenges of real-time and data security in some contexts. It remained limited in handling the massive amount of data required on a larger scale. Therefore, the concept of fog computing emerged at the beginning of 2010 as an intermediary layer between the cloud and edge devices (Bonomi et al., 2012). It distributes processing and storage across local or regional networks, as well reduce the load on the cloud while maintaining high responsiveness and greater flexibility in data processing. This gives cities today a greater opportunity to adopt digital twin concepts more efficiently and on a wider scale by integrating their technologies with fog computing, especially in smart-city contexts and applications. This paper will demonstrate the actual returns from integrating the fog computing mechanism with the digital twin.

2. Methodology

This study employs a TaS (Test and Simulation) methodology to systematically evaluate and compare the performance of both fog computing and a traditional cloud-based computing. The primary purpose is to quantify the performance differences between them to understand and identify the benefits of each. All simulations were performed using iFogSim, which is an opensource (Gupta et al., 2017). iFogSim is based on the CloudSim framework, which was chosen for its native support of hierarchical IoT environments encompassing edge devices, middle fog computing nodes, and central cloud computing servers, directly mirroring the architecture layers adopted in this paper. Two experimental scenarios were independently defined and simulated under identical baseline conditions to ensure structural symmetry in comparison, with the presence or absence of a fog layer as the sole independent variable driving performance differences between them. In a fog scenario, the urban environment is modeled as four operational zones, each served by a dedicated fog node responsible for local image processing, alert generation, and data caching, with an intermediary server managing the connection to the cloud layer. In cloud scenarios, the only exception is to stop the fog nodes to observe how system performance changes. Hardware parameter details for this configuration are shown in Tables 1 and 2 later in Section 3. In both scenarios, the number of cameras used starts at 16, 4 cameras at each zone, and gradually increases during simulations, while all other parameters remain constant. And to ensure the effectiveness of the outcomes of the paper, in addition to the concept of iterative simulation in the iFogsim environment, the paper adopts a mathematical model that calculates both the latency and network utilization. 1st model is Latency that defined as the duration gap between the data acquisition until it's processed, and it's calculated through summing three essential elements: Processing Execution Time (α), Data Transfer Delay (μ) and Operator Response Time (ϕ), and expressed as Eq. 1:

$$\text{Latency} = \alpha + \mu + \phi \qquad (1)$$

The second metric is the Network Usage, which is calculated by multiplying response time by network data volume, reflecting the total connectivity burden imposed by the system architecture and expressed mathematically as Eq. 2:

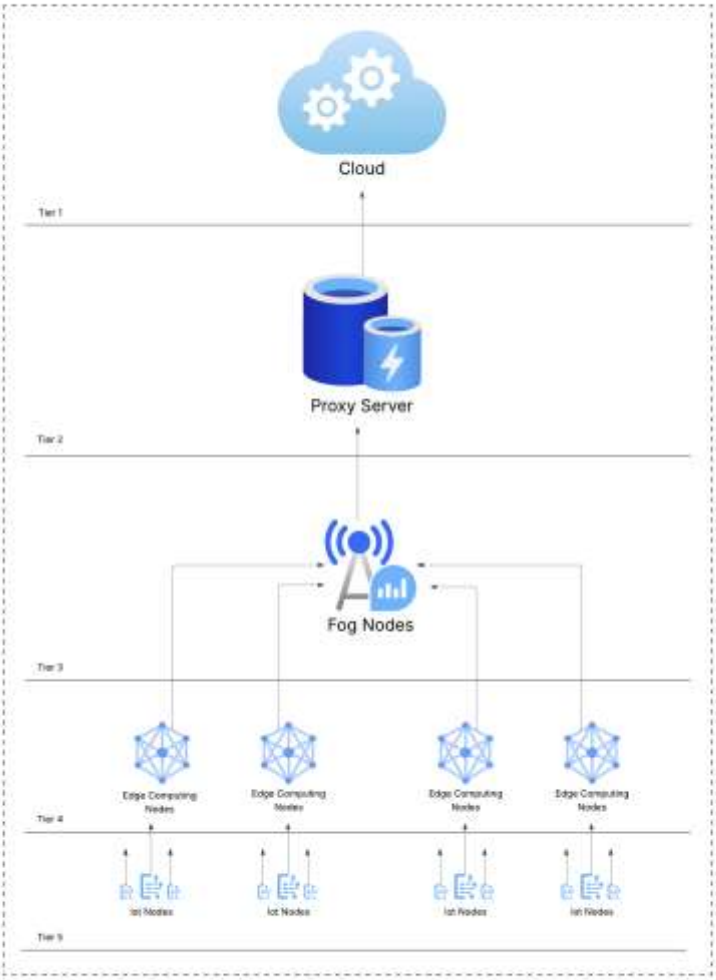
$$\text{Network Usage} = \text{Latency} \times \text{tupleNWSize (500 bytes)} \times \text{numCameras} \qquad (2)$$

The test environment and the digital twin-based simulation framework, along with the proposed system architecture, are described in Section 3.

3. The Adopted Architecture

This section provides a detailed account of how the experimental procedures were implemented. It includes the layout and configuration of the test setup, the measurement tools used to capture response data, and the step-by-step loading procedures followed during testing. The proposed model consists of a 3-layer architectural system that integrates a digital twin mechanism with fog computing. The model combines cloud, fog, and edge computing into a unified, interdependent system, as illustrated in Figure 1. This model operates across 5 hierarchical levels: At the lowest level (Tier 4 and 5), where edge computing nodes which represented as the cameras on this paper and they with a microcontroller that responsible of continuously capture visual data from the physical urban area and transmit it wirelessly to their assigned fog node which locate at(Tier3) receive and processing the received data in a real time, detecting anomalies, and coordinating between nodes without referring to the cloud. Where (Tier 2) contain the proxy server, which organizes and manages the upstream flow of processed data from the fog layer to the cloud at (Tier 1) where the cloud receives the data and being responsible of its long term storage and the management of the historical data, and offline analytics, while all the processing tasks remain intentionally restricted on the fog layer to minimize both latency and network usage.

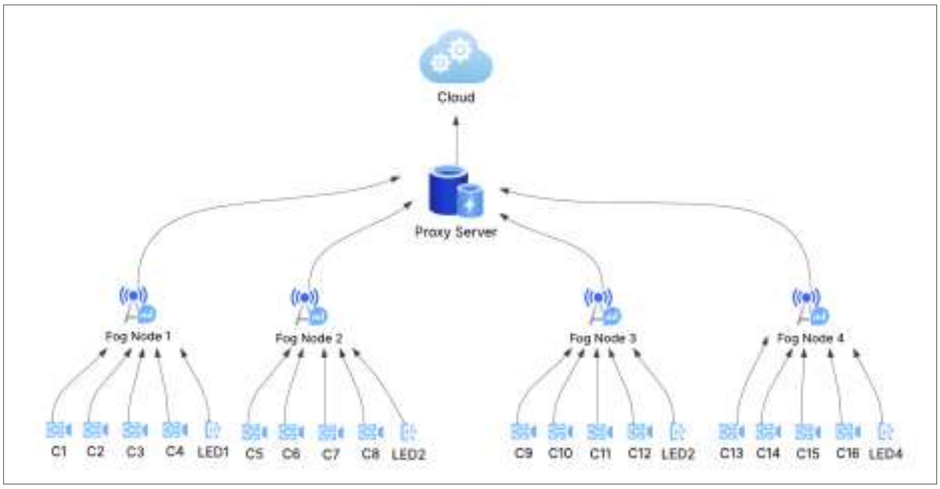
Figure 1. The tiers of the adopted architecture.



Source: Own elaboration, 2026.

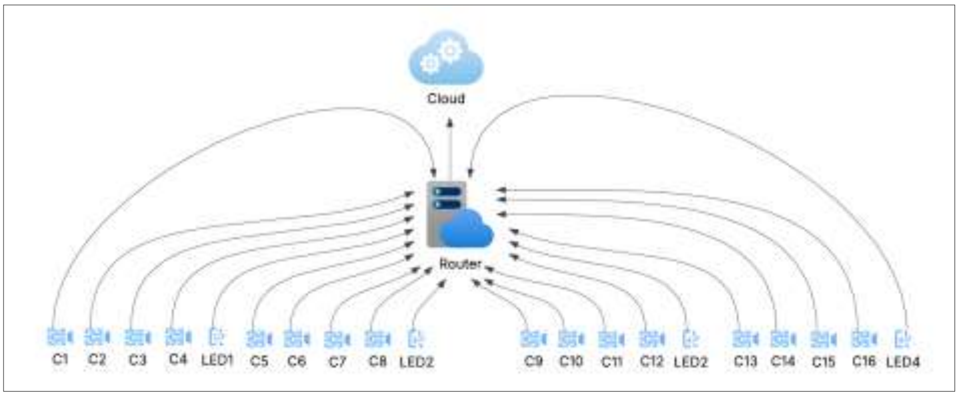
The cameras are strategically deployed at the edge layer across the target geographic area, where each camera is integrated with a dedicated microcontroller that serves as a local intermediary. The cameras capture data and transmit it to the fog layer afterward. At regular intervals, the microcontroller wirelessly transmits the captured frames to the fog node over Wi-Fi, ensuring that the virtual representation of the city remains synchronized with its physical counterpart. Any changes in the physical environment, whether it's a structural defect, a traffic accident, or a resource leak, would be instantly captured, encoded, and transmitted upward through the system without human intervention. Data captured at the edge layer is then transmitted to the fog layer, which serves as the computational core of the proposed architecture and is the tier at which the digital twin transitions from passive data representation to active environmental management. The fog layer consists of geographically distributed fog nodes, each assigned to a specific operational zone within the modeled urban environment, enabling localized decision-making independent of communication with a central server, thereby minimizing response time and reducing the communication overhead that characterizes cloud-only systems. Upon receiving image data from the edge layer, each fog node applies pre-programmed image processing models to analyze the captured frames and determine the current spatial condition of its assigned zone, identifying whether intervention is required based on the detected state, such as a water leak, a road obstruction, or an unauthorized access event, and triggers the appropriate alert within the system automatically and in real time. Beyond alert generation, each fog node temporarily caches the processed data to maintain a short-term operational record of its zone and exchanges state information with neighboring fog nodes through a peer communication mechanism (Dastjerdi, Ghosh, and Poya, 2017). At this layer the predictive and prescriptive capabilities of DT are operationalized where the fog node does not merely report what is happening in the physical environment but through integrating DT with the existed nodes the system would be able to determines next step and initiates the corrective response automatically, which distinguishing the proposed architecture from simpler sensor alert systems that lack the semantic understanding of urban conditions that a digital twin framework provides. To operationalize this architecture in the iFogSim simulation environment, the urban environment is modeled as four distinct operational zones, each served by a single fog node. The initial deployment consists of sixteen cameras, four per zone, and each group is directly connected to its corresponding fog node. In the fog scenario, a proxy server is introduced between the fog and cloud layers to manage upward communication, as shown in Figure 2. In the cloud scenario, all cameras connect directly to a centralized cloud server via a router, with processing and memory specifications equivalent to those of the proxies, as illustrated in Figure 3. To ensure that the research outcomes are consistent with global standards for comparing and evaluating the Fog Computing model, the hardware parameters used in the scenarios were derived from the iFogSim benchmark toolkit published by Gupta et al. (2017), as shown in Tables 1 and 2, for the cloud-based scenario parameters.

Figure 2. The architecture of the proposed Fog-based scenarios.



Source: Own elaboration, 2026.

Figure 3. The architecture of the proposed Cloud-based scenarios.



Source: Own elaboration, 2026.

Table 1. Simulation parameters for the Fog-integrated urban monitoring scenario (Gupta, Dastjerdi, Ghosh, & Buyya, 2017).

Parameter	Cloud	Router (CPU)	Parameter
CPU length (MIPS)	44,800	2,800	CPU length (MIPS)
RAM (MB)	40,000	4,000	RAM (MB)
Uplink bandwidth (Mbps)	100	10,000	Uplink bandwidth (Mbps)
Downlink bandwidth (Mbps)	10,000	10,000	Downlink bandwidth (Mbps)
Hierarchy level	0	1	Hierarchy level
Rate per MIPS (MIPS)	0.01	0.00	Rate per MIPS (MIPS)
Busy power (W)	1,648.00	107.34	Busy power (W)
Idle power (W)	1,332.00	83.43	Idle power (W)

Source: Own elaboration, 2026.

Table 2. Cloud-based scenario simulation parameters (Gupta, Dastjerdi, Ghosh, & Buyya, 2017).

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RAM (MB)	40,000	4,000	4,000
Uplink bandwidth (Mbps)	100	10,000	10,000
Downlink bandwidth (Mbps)	10,000	10,000	10,000
Hierarchy level	0	1	2
Rate per MIPS (MIPS)	0.01	0.00	0.00
Busy power (W)	1,648.00	107.34	107.339
Idle power (W)	1,332.00	83.43	83.34

Source: Own elaboration, 2026.

4. Results and discussion

The simulation in this paper models a 25 km^2 smart residential city divided into four heterogeneous zones integrated with a fog computing architecture to support a real-time Digital Twin (DT) system. The zones were distributed as: Zone 1 covers 35% of the total area (8.75 km^2) with a standard 2,800 MIPS fog node and a 4 ms uplink latency; Zone 2 covers 20% (5.00 km^2) with a 2,800 MIPS node and an uplink latency of 3 ms; Zone 3 covers 30% (7.50 km^2) with a 2,400 MIPS and fog node coupled with a 5 ms uplink, reflecting both its larger geographic footprint and degraded hardware infrastructure; and Zone 4 covers the rest 15% (3.75 km^2) with a 2,800 MIPS node and a lowest uplink latency of 2 ms. Each zone is equipped with an initial four surveillance cameras that operate at a 5-second transmission interval, resulting in a total of 16 cameras for the city at the initial base. However, to evaluate system scalability under increasing data loads and assess the system's operations under harsh conditions, the number of cameras per zone was deliberately increased during execution in iFogsim. This increase was adjusted and tested and simulated to monitor and measure the impact of adding more cameras to the system. The number of cameras was gradually increased across five divisions: 4, 8, 12, 16, and 20 cameras per zone, for a maximum of 80 cameras city-wide, while the number of fog nodes remained fixed at four across all scenarios. Each camera generates 500-byte data tuples that are transmitted to the processing layer for image analysis and DT state computation. Evaluating is based on both Latency and Network Usages that mentioned previously on Section 2, where α represents CPU execution time computed as the product of tuple length and number of cameras per zone divided by the node MIPS capacity, and μ captures the full network traversal path comprising sensor to camera data acquisition (40 ms), camera to fog uplink (2 ms), zone-specific fog to proxy uplink, and network transmission overhead (0.05 ms), and φ denotes the operator response latency (1 ms) in this model. However, these constants are not fixed absolutes and vary with the specific hardware features and capabilities, network conditions, and deployment environments in each urban scenario. However, since the simulation in this study is conducted under standardized benchmark conditions mirroring these values, they were adopted as representative defaults to ensure consistency and reproducibility. The results were obtained by iterating over different numbers of cameras and extracting the outcomes for each zone over time. Additionally, the results for Fog scenarios were presented in Table 3, and those for Cloud-based scenarios in Table 4. Correspondingly, to measure the variance and differences between these scenarios, Table 5 presents the numerical performance differences. The differences are also illustrated graphically in Figure 4, which shows the Fog system's superiority in achieving lower latency and reducing network congestion by 67% to 65.1%, demonstrating its overall efficiency in minimizing bandwidth consumption. Furthermore, the stability of the Network Reduction metric, which remained above 65% even at peak capacity (80 cameras), underscores the robustness of the proposed fog architecture in managing large-scale, intensive data. This performance consistency highlights the decentralized nature of the fog layer; it demonstrates how the system compensates for localized hardware limitations, such as the lower MIPS capacity and higher latency in Zone 3, by preventing a total system bottleneck. Consequently, these findings collectively validate that integrating a fog-based layer is not merely an optimization but a fundamental requirement for Digital Twin systems. Such systems inherently consume significant energy, undermining their effectiveness in cloud computing environments already characterized by excessive power demands. Therefore, combining them may result in an unsustainable cumulative energy footprint, rendering the solution economically infeasible. Since urban areas are defined by a highly complex and stochastic nature, alongside high density and data demands, there is an urgent necessity for sustainable, scalable, and automated solutions, which is precisely what the integration of Fog computing and DT systems in this paper aims to provide.

Table 3. Fog-based scenario latency results per zone across all camera configurations (ms).

Cameras /Zone	Total Cameras	Latency Zone 1 (ms)	Latency Zone 2 (ms)	Latency Zone 3 (ms)	Latency Zone 4 (ms)	Fog Average (ms)
4	16	47.764	46.764	48.883	45.764	47.294
8	32	48.479	47.479	49.717	46.479	48.038
12	48	49.193	48.193	50.550	47.193	48.782
16	64	49.907	48.907	51.383	47.907	49.526
20	80	50.621	49.621	52.217	48.621	50.270

Source: Own elaboration, 2026.

Table 4. Cloud-based scenario latency and network utilization results.

Total Cameras	Cloud Latency Zone 1 (ms)	Cloud Latency Zone 2 (ms)	Cloud Latency Zone 3 (ms)	Cloud Latency Zone 4 (ms)	Cloud Latency Average (ms)	Cloud Network Usage (byte·ms)
16	143.229	143.229	143.229	143.229	143.229	1,145,832

32	143.407	143.407	143.407	143.407	143.407	2,294,512
48	143.586	143.586	143.586	143.586	143.586	3,446,064
64	143.764	143.764	143.764	143.764	143.764	4,600,448
80	143.943	143.943	143.943	143.943	143.943	5,755,720

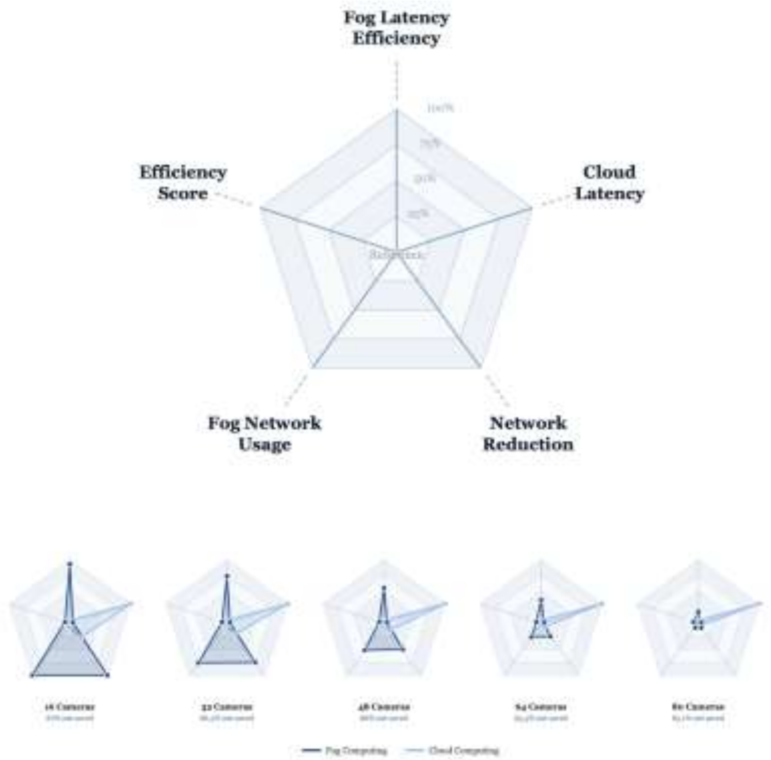
Source: Own elaboration, 2026.

Table 5. Comparative latency and network utilization between fog and cloud scenarios.

Total Cameras	**Fog Average (ms)**	**Cloud Latency (ms)**	**Fog Network Usage (byte·ms)**	**Cloud Network Usage (byte·ms)**	**Network Reduction %**
16	47.294	143.229	378,352	1,145,832	67.0%
32	48.038	143.407	768,608	2,294,512	66.5%
48	48.782	143.586	1,170,768	3,446,064	66.0%
64	49.526	143.764	1,584,832	4,600,448	65.5%
80	50.270	143.943	2,010,800	5,757,720	65.1%

Source: Own elaboration, 2026.

Figure 4. Performance comparison of Fog vs. Cloud across scaling scenarios.



Source: Own elaboration, 2026.

5. Conclusions

This research underscores the transformative potential of integrating Fog Computing with Digital Twin (DT) technology to circumvent the inherent latency and bandwidth constraints of centralization in cloud-based architectures in urban environments. These potentials were demonstrated through the iFogSim simulations, which extracted a quantifiable performance leap. The fog nodes' architecture achieved up to a 67% reduction in network usage and maintained a stable sub-51 ms response threshold, even under high-density scalability stress with 80 cameras. Beyond the immediate technical gains in redaction and the latency and network usage discussed above, the need to implement this integrated solution is driven by socioeconomic and environmental externalities. By minimizing data transmission redundancy, the suggested framework facilitates a substantial reduction in carbon emissions while also mitigating electrical grid strain, aligning perfectly with global sustainability standards. In addition, reducing these aspects collectively would directly increase operational efficiency in the city, thereby enabling a strategic reallocation of financial capital toward other developmental sectors that enhance the overall economic viability of smart city initiatives. Consequently, prioritizing this integrated framework is a priority, especially for nations that are striving for global leadership in sustainable smart cities such as The Line in Saudi Arabia, Khalifa City and Masdar City in the UAE, as well as international benchmarks like Songdo (South Korea), Nusantara (Indonesia), and Tatu City (Kenya). Thus, the accelerating momentum of urban evolution and large-scale infrastructure deployment presents an unprecedented opportunity to redefine digital capabilities by integrating Fog Computing and Digital Twins. This integration represents a transcendent shift in traditional urban design by introducing a systemic paradigm for perceiving city dynamics and data ecosystems. This provides policymakers and stakeholders with a high-fidelity, actionable platform to foster a new era of resilient, automated, and intelligently managed urban environments. Ultimately, the future of research now rests in the hands of those empowered to translate empirical evidence into a tangible framework. Hence, the transition from simulation to practical application requires concerted efforts to measure practical outcomes in real-world urban testing environments, ensuring that technical standards align with socioeconomic objectives. By bridging the gap between theoretical data, governance, and stakeholders, which can eventually translate these findings into tangible results and set a new global standard for designing cities.

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