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FOG COMPUTING-ENABLED SMART SEATING SYSTEMS: OPTIMIZING LATENCY AND NETWORK BANDWIDTH EFFICIENCY IN CLASSROOMS

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ABSTRACT

In modern educational settings, overcrowded classrooms challenge student engagement and learning efficiency. To address these issues, we propose a novel smart seating system powered by Fog Computing that leverages Wireless Sensor Networks (WSN), Internet of Things (IoT), Fog Computing (FC), and Cloud Computing (CC) technologies. Our work introduces the first fog computing-driven smart seating system for classroom settings. It demonstrates significant improvements in latency (3.29 ms in Fog-based vs. 108.69 ms in cloud-based systems) while maintaining comparable network efficiency. Our findings highlight fog computing's potential to transform real-time classroom management. Using iFogSim, we conducted a comparative study between traditional cloud-centric architectures and our fog-based system across various classroom scenarios. Results demonstrate that the fog-based architecture delivers superior real-time responsiveness, making it particularly suitable for dynamic educational environments. This research provides both technical insights into performance improvements and practical implementation guidelines for educational institutions seeking to optimize classroom management systems.

Index words: Cloud Computing (CC), Fog Computing (FC), iFogSim, Latency, Network efficiency, Smart Seating System.

1. INTRODUCTION

University enrolment has been progressively increasing over the years. While this is a positive development, it also brings new challenges, including challenges with event attendance and seating infrastructure [1]. One common issue faced by several institutions is the lack of adequate seating spaces in lecture halls. Traditional seating arrangements often fall short, as they lead to distractions that can affect both students and lecturers [2], overcrowded classrooms, and time wastage as students search for available seats. In some cases, these concerns even discourage attendance completely. They could disrupt the learning process and, as such, highlight the need for smarter, more adaptable classroom solutions that can keep pace with growing student populations and evolving educational demands.

This study introduces a novel fog-based smart classroom seating system and uses iFogSim to simulate our architecture. It is designed to improve the management of lecture hall spaces. By integrating technologies like WSNs, IoT, CC, and, most notably, Fog Computing, the system offers a more responsive and efficient way to organize classroom seating. The idea

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is to move beyond fixed arrangements and towards an intelligent system that can detect available seats, respond to occupancy in real-time, and assist both students and lecturers in making better use of the space while enhancing the speed and network bandwidth usage. Out of the various available simulation tools reviewed by [3], iFogSim has gained enormous attention from many Fog Computing researchers. [4], discuss the various components of the iFogSim to assist researchers in implementing various scenarios of fog computing. [5], For instance, I have modeled and simulated smart surveillance systems in two environments, Cloud Only Network and Fog-Based Cloud Network, using iFogsim.

Our goal is to tackle the limitations found in cloud-based smart systems, chiefly problems with latency, network congestion, and real-time performance. By using fog computing, which brings computation closer to the devices collecting data, we aim to create a faster, more reliable, and energy-efficient solution. This system will improve technical performance and create a smoother classroom experience for stakeholders.

The following research questions serve as a guide to this work:

1. How can a fog computing-based architecture be designed to detect and manage classroom seat occupancy in real-time?

2. What are the measurable performance differences (in terms of latency and bandwidth usage) between fog-based and cloud-based smart seating systems in simulated classroom environments?

3. How does the proposed fog-based system improve responsiveness and scalability compared to traditional cloud-based solutions?

There has been a lot of talk about smart classrooms in recent years. However, there is a lack of studies on how fog computing could be used specifically for seating management in the classroom. This study fills that gap by exploring a practical, tech-driven approach to an everyday problem in higher education. We unite emerging technologies with real-world classroom needs and hope to contribute a solution that improves technical efficiency and also enhances the learning environment in a meaningful way.

1.1. RELATED WORKS

Generally, seating arrangements, whether smart or traditional, have been proven to influence student engagement and behavior. Some researchers have explored this premise.

For example, a study by [6], utilised wearable physiological sensors to examine the impact of individual and group sitting experiences on student engagement and participation. Their findings indicate that, students who were seated in close proximity to each other exhibited greater physiological synchrony, and hence an enhanced cooperative participation. This means that students' interaction and attention levels may be influenced by traditional seating arrangements such as rows or table groups.

Also, in a study on the impact of different seating arrangements (i.e. circles vs rows) on the interaction levels among university students, [7] used wearable Sociometric badges to study speech rate & speaking segment length. They noted that sitting in rows led to more intensive interactions than sitting in circles. They however noted that, the field of study and the facilitator's involvement also had an effect on the result. These findings stress the importance of deliberate seating configurations to improve learning outcomes.

Smart classrooms have introduced dynamic seating techniques designed to enhance situational engagement. A work published by [8] in Sustainability (2023) indicate that, students positioned at the periphery of smart classrooms often exhibit lower engagement levels, as compared to those seated in central locations. The study advocates for deliberate seating configurations to minimize the use of peripheral seats, thereby promoting equitable participation.

To also minimise student distractions, innovative proposals such as fuzzy logic-based seating configurations have been presented by some researchers. A 2025 study by [9] introduced "CUB", a Fuzzy Inference-Based Tool for Classroom Seating Arrangement to Minimize Distraction, which actually resulted in a reduction in classroom distractions.

Building upon these insights, this study proposes a novel fog computing-enabled smart seating system that not only considers seat availability but also enables real-time and automated seat allocation based on sensor-driven occupancy detection. Unlike traditional seating systems or standalone AI tools, our system integrates edge-level processing (via fog nodes) with real-time input from classroom IoT devices (e.g., cameras and microcontrollers). This makes room for immediate feedback, equitable seating optimization, and scalability across multiple classrooms and hence bridges the gap between theoretical seating strategies and fully functional, dynamic seat management systems.

Recent research has shown that smart seating systems have the potential to improve classroom management, enhance student engagement, and promote more inclusive learning experiences [1], [10], [11]. Most of these works have delved into how these smart seating systems can be enhanced using cloud computing, mostly for storing, processing, and analyzing classroom data [12]. Some other studies have explored how these systems impact the dynamics of classroom interaction, student participation, and even the effectiveness of instructors [1], [2]. This research demonstrates the strengths and limitations of our proposed fog-based smart seating solutions compared to cloud-based designs in academic settings.

Currently, fog computing has gained traction as a powerful approach for managing resources in distributed systems. Unlike traditional cloud computing, where data is processed in distant data centers, fog computing brings processing closer to the source where the data is generated [13], [14]. This allows for faster data processing, reduced latency, and increased system responses. This makes fog computing particularly useful in situations that demand real-time interaction, such as smart seating in lecture halls.

Because Fog Computing places processing power closer to users, it shortens the distance data needs to travel. This leads to faster responses and smoother system performance [14], [15]. Additionally, fog nodes can handle tasks locally, which implies that less data needs to be sent to the cloud. This not only reduces network load but also cuts down on energy usage [14]. Also, the decentralized nature of fog computing allows institutions to scale up easily by adding more local nodes where necessary [16]. This makes it a great fit for expanding smart seating systems.

Previous research on smart classroom technologies has focused on enhancing student engagement through interactive displays and personalized learning environments [17], [18] but has often overlooked the fundamental logistical challenges of classroom management. Studies by [1] and [19] explored IoT-enabled classrooms but employed cloud-centric architectures that inherently suffer from latency issues unsuitable for real-time applications. Our work extends these efforts by specifically examining the computational advantages of fog computing for addressing the practical challenge of seat allocation in overcrowded lecture halls. Unlike [19] and [20], which primarily discussed the theoretical benefits of fog computing in educational contexts, our work provides empirical evidence through simulation-based performance comparisons between fog and cloud architectures. This empirical focus represents a significant advancement over existing literature, which has largely remained conceptual or limited to small-scale proof-of-concept implementations.

Despite all the recent interest in fog computing, there is still a noticeable gap in research on its application in educational environments. Very few studies have directly compared fog based systems with traditional cloud-based ones exclusively in the context of smart classroom seating [19]. While individual studies point to fog computing's advantages, which include reduced latency, better energy usage, and improved scalability, there is a lack of head-to-head comparisons under similar conditions [19]. These kinds of comparative studies are crucial. They provide solid evidence on whether fog really outperforms cloud systems in educational settings and also help guide the design of the next generation of smart seating solutions [20].

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2. METHODS

We explore the design and performance evaluation of a smart seating system powered by Fog Computing (FC), Wireless Sensor Networks (WSN), Cloud Computing (CC), and Internet of Things (IoT) technologies.

Simulations are conducted using iFogSim to assess the effectiveness of the proposed fog-based smart seating system over traditional cloud based systems. The simulation models a university lecture hall environment, where data is collected in real-time from cameras embedded in the lecture halls and processed by nearby fog nodes.

The simulation environment was configured as follows: Each classroom was modeled with varied numbers of sensors (1-5 cameras). Each sensor generated data at 30 frames per second, with 1080p resolution. Processing requirements were considered with respect to image analysis algorithms requiring approximately 4800 MIPS (for Cloud devices), 2800 MIPS (for Proxy devices), and 500 MIPS (for Classroom-level devices) per frame. Network bandwidth was configured according to typical educational institution specifications (i.e., 100 Mbps uplink, 10 Gbps downlink).

The simulation was run about 10 times for each configuration to ensure consistency and statistical validity, with each run representing a 60-minute classroom session. Statistical analyses included Mean, Median, and independent t-tests and their related p-values for both latency and bandwidth utilization comparisons. This helped to determine the statistical significance of these differences, particularly in latency, which is critical for real-time applications. Sensitivity analysis was also performed to assess the system's robustness under varying workloads and network conditions, ensuring the reliability of the results.

The findings demonstrate that the fog-based system significantly outperforms the cloud-based system in terms of latency while maintaining comparable network usage. This suggests that fog computing offers substantial advantages in the real-time management of smart classroom environments. However, the study also acknowledges limitations related to the simulation environment and the scalability of the proposed system, suggesting areas for future research. Table 1 presents a Summary of the Configuration Setup for this simulation.

Table 1. Summary of Configuration Setup

Component	Description
CPU	Intel Core i7
RAM	16 GB
Operating System	Windows 11
Simulation Tool	iFogSim
Programming Language	Java (for iFogSim simulations)
Network Bandwidth	Uplink: 100 Mbps, Downlink: 10 Gbps
Fog Device Processing Power	4800 MIPS (Cloud); 2800 MIPS (Proxy); 500 MIPS (Classroom-level devices)
Edge Node Components	IoT devices (e.g., environmental sensors, cameras), Raspberry Pi, Mobile Phones
Latency Configurations	Proxy-to-Cloud: 100 ms; Sensor-to-Fog: 1 ms
Sensors	Cameras, PTZ Controls, Environmental Sensors. (Generated data at 30 frames per second with 1080p resolution)
Fog Node Components	Proxy servers, routers, smart cameras
IoT Framework	Sensor data transmitted to Fog and Edge nodes
Deployment Configuration	Cloud deployment (for comparative analysis), Fog deployment (for proposed framework evaluation)

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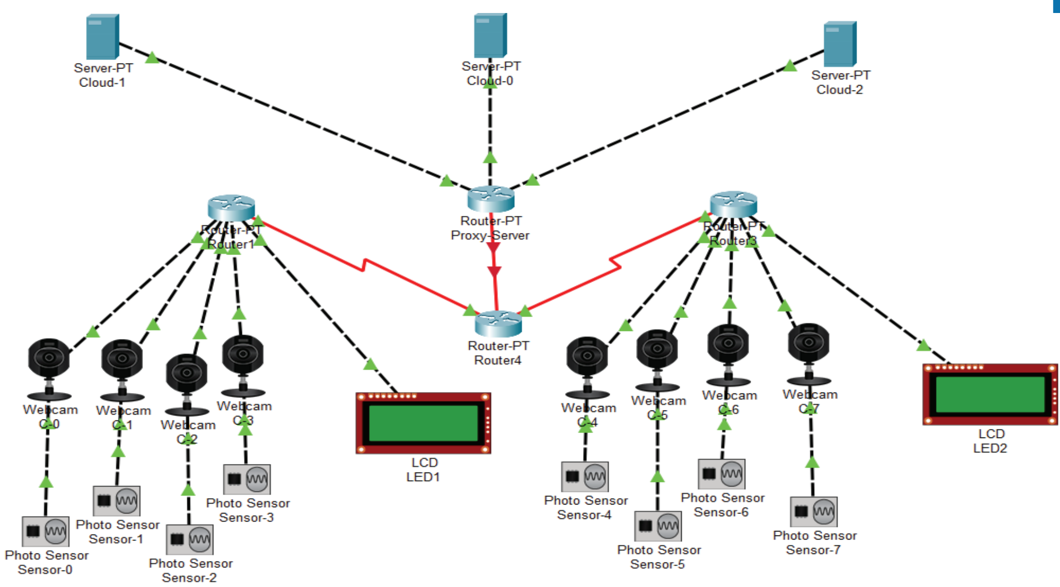

Figure 1. A logical design of a fog-based smart lecture hall

2.1.1. THE FUNCTION AND POSITION OF THE CLOUD IN THE PROPOSED SYSTEM.

In our proposed smart seating architecture, the cloud server is strategically positioned as a centralized platform for storage and analytics. The deployed Fog nodes manage real-time processing tasks, including seat detection and user interface updates in the classroom, whereas the cloud facilitates long-term data archiving, historical analytics, system-wide monitoring, and remote administrative access. Cloud servers analyze seating usage trends over time, produce reports for institutional decision-making, and enable remote updates to system software.

The cloud infrastructure is presumed to be located off-premises, potentially at a university-operated data center or with a commercial, public cloud provider such as AWS or Google Cloud in a nearby regional data zone. This geolocation is critical as it introduces network latency when handling time-sensitive operations like real-time seat detection. Due to this physical separation, it is projected that round-trip delays can exceed 100 milliseconds, as confirmed in our simulations. In contrast, fog nodes positioned locally within campus networks drastically reduce this latency, enabling near-instantaneous feedback and responsiveness. Therefore, fog computing is intentionally prioritized for latency-sensitive tasks, while the cloud is retained for its strength in storage capacity, backup, and system-wide coordination.

2.1.2. GLOBAL VIEW OF PROPOSED SMART SEATING SYSTEM FOR LECTURE HALLS

Implementing the proposed architecture involves five major layers, as presented in Figure 3 (i.e., the cyber-physical layer, the data management layer, the data processing layer, the domain application layer, and the cloud). These layers can be further summarized into three (3) as presented in Figure 4 (i.e., the Cyber-physical layer, Fog-layer, and the Cloud layer). The cyber-physical layer consists of various sensors like GPS, RFID tags, and surveillance cameras, which enable data collection from multiple sources. IoT technology facilitates direct interactions among these sensors, routers, and gateways. Data management, positioned between the cyber-physical and data processing layers, handles tasks such as data description and fusion to manage collected data efficiently, removing redundancy and integrating data for consistency. Central to fog-based computing, the data processing layer processes data types via fog computing, handling tasks locally and transferring overloaded tasks to cloud data centers when necessary. The domain application layer provides specific intelligent applications and services, such as guiding students to available seats in smart seating systems and enhancing efficiency and convenience. Figure 2 and Figure 3 present

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the "Detailed Hierarchical structure of fog computing-based smart seating system" and the "Condensed high-level Hierarchical structure of fog computing-based smart seating system," respectively.

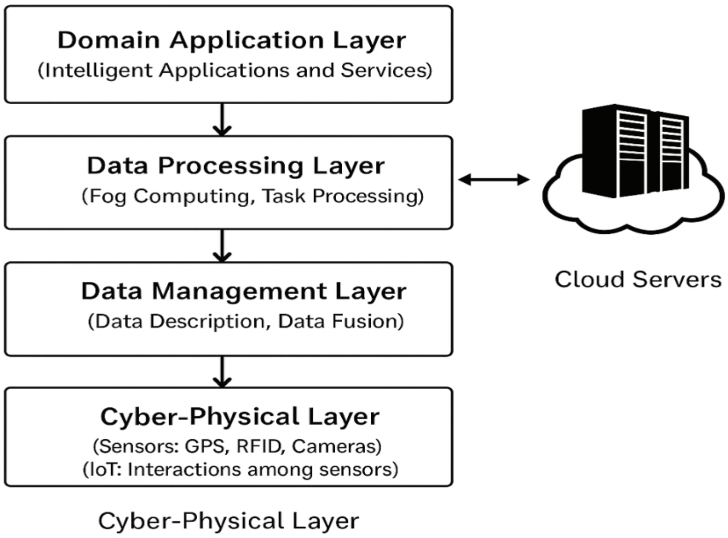

Figure 2. Detailed Hierarchical structure of fog computing-based smart seating system

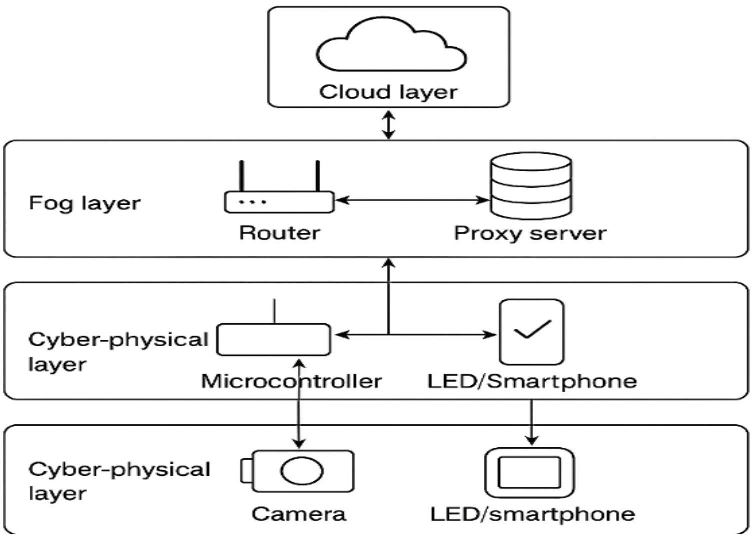

Figure 3. Condensed high-level Hierarchical structure of fog computing-based smart seating system.

2.1.3. IMAGE PROCESSING WORKFLOW FOR SEAT DETECTION

Although the simulation environment in this study (iFogSim) does not support direct integration of image processing modules, the proposed fog-based smart seating system is designed to conceptually support real-time computer vision tasks. The system assumes that each classroom is equipped with IP surveillance cameras capable of capturing video frames at 1080p resolution and 30 frames per second. The captured frames are processed locally at the fog nodes to detect available or occupied seats using a lightweight object detection pipeline.

A typical image processing workflow for seat detection would involve the use of pre-trained object detection models, such as YOLOv5 or YOLOv7, which are capable of detecting chair outlines and distinguishing occupancy based on motion and form, as discussed in detail by

[21]. The first step involves frame acquisition and preprocessing (e.g., resizing, normalization, and background subtraction). Following this, real-time object detection algorithms are applied to identify human presence in proximity to predefined seat locations. Motion detection and frame differencing can also be employed to enhance accuracy, especially in low-light or static conditions.

Thresholding techniques are then applied to determine occupancy. For instance, if a seat region contains a detected object (i.e. a person) for more than a specific number of consecutive frames, the seat is classified as "occupied"; otherwise, it is marked as "available." This processed information is transmitted to the fog node, which handles further decision-making and updates the smart classroom interface in real-time.

In iFogSim, this behavior is abstracted by modeling data generation at the sensor level and processing tasks at fog nodes using AppModules. The modules simulate the computational demand of image processing (configured at 500 MIPS per frame for classroom-level devices) while omitting the image content itself. The abstraction ensures scalability testing and performance benchmarking without actual video processing yet aligns conceptually with how the system would operate when deployed with real image analytics capabilities. Figure 4 presents a pictorial description of the Image Acquisition workflow for seat detection in this study.

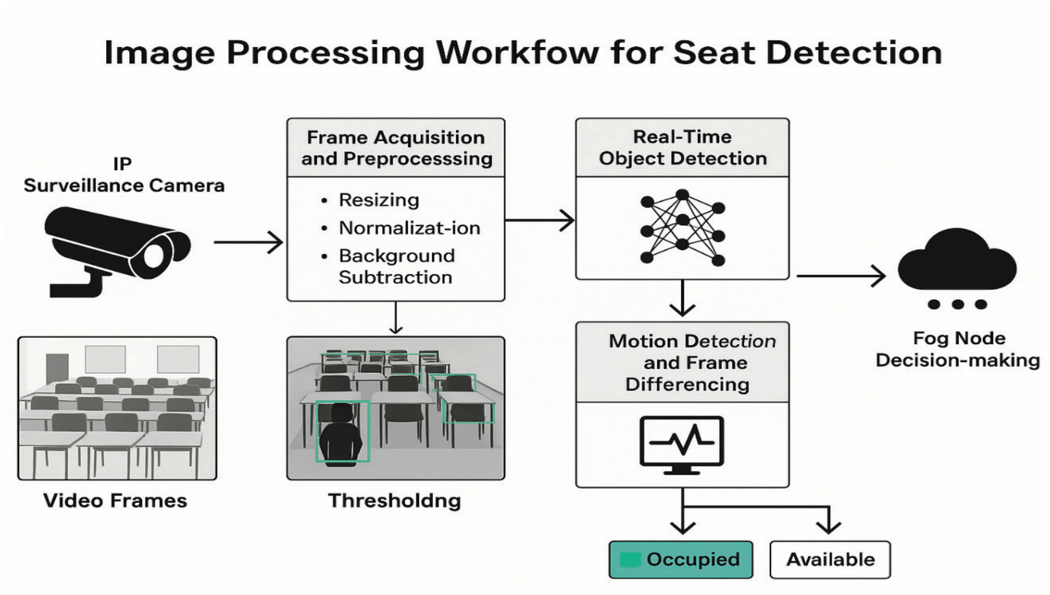

Figure 4. Image Acquisition workflow for seat detection

3. SIMULATION SET UP FOR SMART SEATING SYSTEM IN IFOGSIM

Ifogsim comprises three primary components, i.e., physical, logical, and management components. These components are discussed below. The codes used in creating the various components can be found on the authors' GitHub repository at:

https://github.com/NobleITSoultions/SmartCampusContract2024/blob/main/SmartSeatingSystemSimulation.

A. PHYSICAL COMPONENT

The physical components include all fog devices (fog nodes). The fog devices are made in a hierarchical order. The lower fog devices are directly connected to the sensors and actuators. Fog devices act as data centers in the cloud computing paradigm by offering memory, network, and computational resources. Each fog device must have specific

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parameters such as processing power, memory capacity (MIPS), computational power, uplink and downlink bandwidth.

Physical components must be created with specific parameters, including RAM, processing capability in a million instructions per second (MIPS), cost per million instructions processed, uplink and downlink bandwidth, and busy and idle power, along with the hierarchical order. While creating the lower-level fog devices, the associated IoT devices, sensors, and actuators need to be created. The particular value in the transmit Distribution object that is set in creating an IoT sensor refers to its sensing interval. In addition, the creation of sensors and actuators requires the reference of application ID and broker ID.

B. LOGICAL COMPONENT

Application modules (AppModules) and Application edges (AppEdges) are the logical components of iFogSim. AppModules represent the application components or modules of the fog computing application. These modules can include different tasks or functionalities that must be executed within the fog computing application. AppEdges represent the communication link or edges between different application modules within fog computing applications. They define the data flow and communication patterns between various modules, capturing how data is exchanged among application parts.

Logical components such as AppModule, AppEdge, and AppLoop are required to be created. While creating the AppModules, their configurations are provided, and the AppEdge objects include information regarding the tuple's type, its direction, CPU, and networking length, along with the reference of the source and destination module. In the background, distinct types of tuples are created based on the specifications given for AppEdge objects.

C. MANAGEMENT COMPONENTS

The management component of iFogSim consists of the Controller and Module Mapping objects. This is responsible for managing and coordinating various aspects of the simulated fog computing environment, overseeing the execution of applications, and handling the dynamic nature of resources in fog computing. These functionalities include resource management, task scheduling, communication management, monitoring and logging, and fault tolerance.

Management Components (Module Mapping) are initiated to define different scheduling and AppModule placement policies. Users can consider total energy consumption, service latency, network bandwidth usage, operational cost, and device heterogeneity while assigning AppModules to Fog devices. They can extend the abstraction of the Module Mapping class accordingly. Based on the information of AppEdges, the requirements of an AppModule need to be aligned with the specification of the corresponding tuple type and satisfied by the available Fog resources. Once AppModules and Fog devices are mapped, the information on physical and logical components is forwarded to the Controller object. The Controller object later submits the whole system to the CloudSim engine for simulation.

The simulation results are compared in terms of latency and network usage. The **"private static boolean CLOUD = false;"** section of the code helps us achieve this result by assigning the values true or false, as it is directly linked to the cloud or fog. Depending on what execution is taking place, the data collected is sent directly to the cloud or fog nodes for processing.

Our simulation framework was specifically designed to replicate real-world classroom conditions. The selection of parameters such as camera frame rates (30 fps) and the resolution (1080p) was based on typical specifications of commercial surveillance systems used in educational settings. The processing requirements (i.e., 4800 MIPS for Cloud devices, 2800 MIPS for Proxy devices, and 500 MIPS for Classroom-level devices) were calibrated to accurately reflect the computational demands of real-time image processing algorithms

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needed for seat detection. These parameters were validated through preliminary testing to ensure they represented a realistic operational environment. This approach allows our findings to be directly applicable to practical implementations in university lecture halls.

4. RESULTS

The simulation was performed for both Fog-based and cloud-based smart seating systems to compare their performance in lecture hall environments. The experiments focused on evaluating key performance metrics, including latency and network bandwidth usage efficiency. Table 2 summarizes the simulation results.

Table 2. Simulation results

	Latency (Milliseconds, ms)		Network Bandwidth Usage (Kilobytes, kb)	
Number of cameras	Average Fog Latency for all 10 simulations	Average Cloud Latency for all 10 Simulations	Average Fog Bandwidth Usage for all 10 Simulations	Average Cloud Bandwidth Usage for all 10 Simulations
1	3.2	108.64	41553.8	41559.0
2	3.3	108.67	83107.6	83118.0
3	3.3	108.69	124656.4	124677
4	3.309	108.72	166205.2	166236.0
5	3.319	108.75	207754.0	207795.0

5. GRAPHICAL INTERPRETATION OF RESULTS

Based on the results presented in Table 2, Figure 5 and Figure 6 are graphical representations of the simulation results for latency and network usage, respectively.

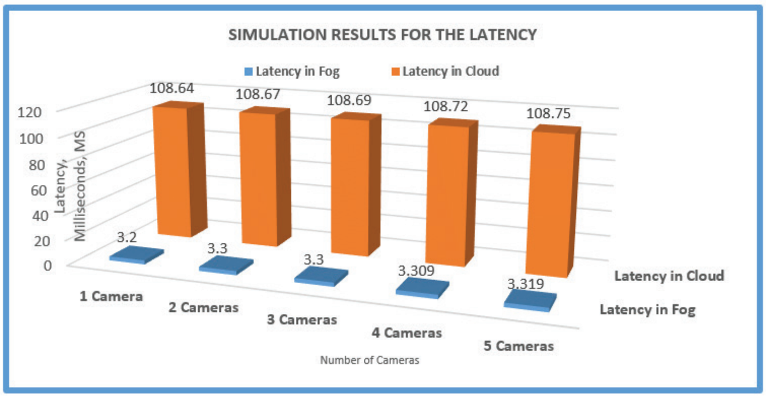

Figure 5. Graphical Representation of the simulation results on the latency

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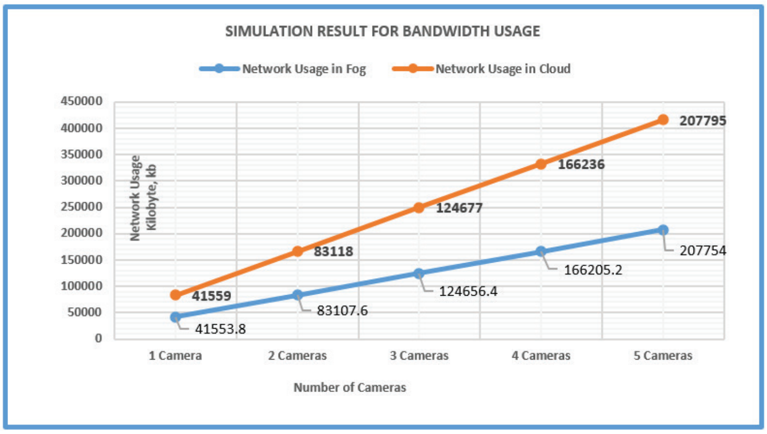

Figure 6. Graphical Representation of the Simulation Results on Network Bandwidth Usage

6. STATISTICAL ANALYSIS

A. **Latency**

a) Mean Calculation: The mean is calculated as:

Mean = $$Mean = \frac{\sum X}{n} \quad (1)$$

- **Fog-Based System Latency: X = [3.2, 3.3, 3.3, 3.309, 3.319] milliseconds and n = 5.**

Fog Latency Mean = 3.2856ms, which means that, on average, the fog-based system had a latency/delay of 3.29 milliseconds.

- **Cloud-Based System Latency: X = [108.64, 108.67, 108.69, 108.72, 108.75] milliseconds and n = 5.**

Cloud Latency Mean: = 108.694ms; this implies the cloud-based system had a much higher latency/delay of 108.69 milliseconds.

b) Standard Deviation Calculation: The standard deviation is calculated as:

$$\frac{\sqrt{\sum(X-Mean)^2}}{n-1} \quad (2)$$

Therefore, using Equation 2 and the simulation results in Table 2, the calculated standard deviations for network usage are:

- **Fog-Based System: 0.0485ms**
- **Cloud-Based System: 0.0428ms.**

Interpretation: Standard Deviation for latency in the Fog environment = **0.0485ms.** This indicates slightly more variation, even though it is still very stable, with only minor fluctuations. Cloud Latency Standard Deviation: = **0.0428ms.** This indicates that the latency in the cloud-based system is slightly more consistent (lower standard deviation) but at a much higher mean value.

B. **Network Usage**

a) Mean Calculations:

- **Fog-Based System Network Usage:** X = [41553.8, 83107.6, 124656.4, 166205.2, 207754.0] KB and n = 5

- **Fog Network Bandwidth Mean = 124655.4KB**; this is the average amount of data transmitted in the fog-based system.

- **Cloud-Based System Network Usage:** X = [41559.0, 83118.0, 124677.0, 166236.0, 207795.0] KB and n = 5

Cloud Network Bandwidth Mean = 124677.0 KB; this is the average amount of data transmitted in the cloud-based system.

b) Standard Deviation Calculation:

Therefore, using Equation 2 and the simulation results in Table 2, the calculated standard deviations for network usage are:

- Fog-Based System: 65,696.00 KB
- Cloud-Based System: 65,710.55 KB

Interpretation: Neither system maintains a stable network usage. The demand increases with time or workload. However, the difference in variation between fog and cloud is minimal, which suggests that both scale similarly in network load.

C. Independent Samples T-Test

The T-test is used to compare the means of two independent groups to see if there is a statistically significant difference between them.

The formula for the t-statistic in an independent samples t-test is:

$$t = \frac{Mean_1 - Mean_2}{\sqrt{\frac{SD^2}{n_1} + \frac{SD_2^2}{n_2}}} \qquad (3)$$

Where:

- $Mean_1$ and $Mean_2$ are the means of the two groups.
- SD_1 and SD_2 are the standard deviations of the two groups.
- n_1 and n_2 are the sample sizes of the two groups.

$$\textbf{Latency T-Test=} \frac{3.2856 - 108.694}{\sqrt{\frac{0.0485^2}{5} + \frac{0.0428^2}{5}}}$$

T-Statistic: t=−3645.06t. This value indicates how far the difference between the two means is from zero, measured in standard error units. As observed here, a very large (absolute) t-value typically indicates a significant difference between the groups.

$$\textbf{Network Bandwidth Usage T-Test} = \frac{124655.4 - 124677.0}{\sqrt{\frac{65696.0^2}{5} + \frac{65710.5^2}{5}}}$$

T-Statistic: t = −0.00052t. This small t-value suggests that the difference between the means of the two groups (fog-based and cloud-based systems) is minimal. This is, however, subject to increase as the number of IoT devices increases.

7. DISCUSSION

The results indicate that the fog-based system consistently maintains latency below 3.5ms across all tested camera configurations. The cloud-based system, however, exhibits latencies that exceed 108ms. Statistical analysis confirms this difference is highly significant (t=3645.06, p<0.0001). Notably, as the number of cameras increased from 1 to 5, the latency difference between cloud and fog architectures remained consistently noteworthy. This points out fog architecture's scalability advantage. Both architectures showed similar network bandwidth usage in absolute terms. However, fog architecture demonstrated superior efficiency in terms of advantages in processing distribution. This is because the computational load was distributed across edge devices rather than concentrated in centralized cloud resources.

Our findings align with theoretical expectations regarding latency reduction in fog computing architectures, as recorded by [13]. Our approach demonstrates particular advantages in bandwidth utilization compared to cloud-based approaches presented by [3], which reported higher bandwidth consumption. However, speed slightly reduces as the camera count increases. This is a result of the increasing amount of real-time videos that are processed in smart environments.

Following the results the following differences between fog-based and cloud-based deployments presented in table 3 can be highlighted around these metrics to support future research works.

Table 3. Edge-based systems vs. Traditional cloud-based systems

Metric	Fog/Edge-Based Systems	Traditional Cloud-Based Systems
Latency	Reduced	Potentially Higher
Mobility	Explicit Mobility	Limited Mobility
Architecture	Decentralized	Centralized
Local Awareness	Yes	Limited
Geographic Distribution	Yes	Limited
Scalability	High	Scalable
Availability	High	High
Service Access	Edge/Handheld Devices	Limited to Internet Access
Remote Work	Enables Remote Work	Limited Remote Work
Real-time Processing	Better Support for Real-time Processing	May Require High Bandwidth
Analytics	Better Support for Real-time Analytics	Analytics May be Centralized
Classroom Management	Enhances Efficiency	May Require Additional Resources
Access to Resources	Easier and More Convenient	Dependent on Internet Connection

7.1. PRIVACY AND ETHICAL CONSIDERATIONS IN CAMERA-BASED SMART SEATING SYSTEMS.

The implementation of our proposed camera-based smart seating system in educational environments raises important privacy and ethical considerations that must be addressed proactively. Our proposed system relies on camera feeds to detect seat occupancy, which introduces several privacy challenges:

First, there is the question of student consent and awareness. Educational institutions implementing such systems should develop clear policies requiring informed consent from students, with transparent disclosure about what data is being collected, how it is processed, and where it is stored. It should also clarify that the system is designed for seat detection rather than individual identification.

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Second, the technical implementation must incorporate privacy-by-design principles. In our system, this could be achieved through:

- Edge-based processing that extracts only occupancy data and discards raw video footage
- Intentional reduction of image resolution to prevent facial recognition
- Implementation of data minimization techniques that store only aggregated occupancy statistics rather than individual seating patterns
- Encryption of any data transmitted between fog nodes and cloud storage

Third, the system should comply with relevant data protection regulations, such as GDPR in Europe or FERPA in the United States, which may require data protection impact assessments before deployment.

Finally, educational institutions should establish ethical governance frameworks that prevent function creep, where a system designed for one purpose (seat management) evolves to serve other functions (such as student attendance monitoring or behavior tracking). Such frameworks should include regular audits, stakeholder consultations, and clear limitations on data usage.

These considerations should be integrated into the early design phases of smart classroom implementations. It should not be treated as an afterthought in order to ensure that technological innovations enhance student privacy and autonomy instead of compromising it.

8. CONCLUSION

Our findings suggest that fog-based smart seating systems could be introduced in university classrooms to significantly reduce classroom management overhead in terms of data processing speed and bandwidth utilization. This potentially translates into several additional instructional minutes per class session. Also, beyond the performance metrics of latency and bandwidth, the proposed system enhances classroom seating by enabling real-time seat detection and allocation. This reduces delays, ensures equitable student distribution, minimizes distractions, and promotes a more focused and engaging learning environment.

The work identified several scalability limitations. As the number of cameras increased from 1 to 5 per classroom, we observed a minor but consistent increase in latency (from 3.2ms to 3.319ms). This suggests potential processing bottlenecks at higher sensor densities. When scaling this system to cover an entire campus with hundreds of classrooms, the hierarchical fog architecture would require careful optimization in order to prevent overloading intermediate fog nodes. While fog computing improves real-time responsiveness, effective fog node deployment is essential to sustain performance.

Additionally, while our simulations demonstrated comparable network bandwidth usage between fog and cloud architectures comprising five (5) cameras, the difference may become more pronounced in larger deployments. The fog-based approach would likely maintain its latency advantage. It might, however, require additional edge nodes to distribute computational load effectively. These limitations underscore the importance of adaptive resource allocation frameworks, which can respond dynamically to varying classroom conditions and student populations.

For practical implementation in educational institutions, we recommend the following hardware specifications: (1) Entry-level IP cameras with 1080p resolution and basic motion detection capabilities would provide sufficient input data while minimizing costs; (2) Fog nodes can be effectively implemented using mid-range edge computing devices such as

Intel NUC mini PCs or equivalent ARM-based systems with at least 8GB RAM and quad-core processors; (3) Network infrastructure should support at least 100 Mbps within buildings, with redundant connections to ensure system reliability. This hardware configuration would support deployment costs of approximately $1,500-2,000 per classroom, with potential ROI realized through improved space utilization and reduced administrative overhead. These specifications represent a balance between performance requirements identified in our simulations and practical budget constraints faced by educational institutions.

Future research should focus on three key areas: (1) optimizing fog node placement algorithms to balance computational load across distributed educational environments, (2) developing adaptive resource allocation frameworks that respond to dynamic classroom conditions, and (3) establishing standardized benchmarks for smart classroom performance evaluation, (4) integrating artificial intelligence (AI) and machine learning (ML) algorithms for predictive analytics and personalized adaptive learning experiences to support students' individual needs. Educational institutions implementing these systems should begin with small-scale pilots in high-density classrooms, establish clear metrics for success (e.g., 95% seat allocation efficiency, 5ms response times), and develop comprehensive privacy policies before deployment.

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