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Indoor Campus Surveillance with HTTP Communication via Animaloid Robots

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***Abstract* -** The vision of a smart campus is fundamentally rooted in the deployment of a robust and efficient indoor monitoring system, serving as a cornerstone of its intelligent infrastructure. However, a notable limitation of current indoor surveillance is the lack of mobile monitoring capabilities, which often leaves enclosed hallways/areas insufficiently covered. To address this gap, this study proposes an enhanced surveillance framework specifically optimized for interior campus environments, leveraging HTTP-based communication and mobile telepresence animaloid robots. Designed for real-time, user-friendly operation, the system remains highly accessible within the local indoor network. Each animaloid robot is equipped with a specialized camera module to capture environmental data and stream live video feeds through a dedicated web application. The system underwent modular testing in various indoor conditions to evaluate its performance, targeting key aspects such as navigation control (robot distance from gateway), interactive responsiveness (connectivity and movement), web application performance (frame quality and latency), and operational endurance (speed and uptime). Experimental results demonstrate that the proposed system is both feasible and effective for deployment within a campus building layout. While performance remains highly dependent on local network stability and access point proximity, the findings highlight this solution as a promising platform for scalable extensions and advanced indoor functionalities in future smart campus implementations.

Keywords: animaloid, campus, monitoring, HTTP, real-time, robots

I. INTRODUCTION

The concept of the smart campus has emerged as a rapidly growing trend in recent years, representing a significant phase of digital transformation within higher education institutions. This transformation goes beyond the adoption of new technologies; it encompasses the integration of advanced digital infrastructures, data-driven management systems, and intelligent platforms. Likewise, modern campus transformations increasingly rely on integrating cloud technologies and ICT to create immersive, digital-first environments (Papadakis et al, 2024). This movement toward AI-enhanced ICT supports lifelong learning and smarter infrastructure management by bridging the gap between physical hardware and digital monitoring systems (Papadakis et al, 2024). The primary objectives of such initiatives include facilitating more effective and evidence-based decision-making processes, enhancing the quality, accessibility, and personalization of academic and administrative services, and advancing sustainability efforts through efficient resource utilization and environmentally conscious practices (Polin et al., 2023).

The presence of a smart campus can be identified through several defining indicators. One of the most salient indicators is the existence of an effective and integrative monitoring system. This perspective is substantiated by the study of Anagnostopoulos et al. (2021), who outlined five fundamental dimensions essential for comprehensive monitoring within smart campuses. These dimensions encompass (1) infrastructure, which refers to the physical and digital foundations supporting connectivity, (2) enabling technology such Internet of Things (IoT) devices, sensors, and cloud-based platforms, (3) software, (4) security and management, which safeguard the privacy and governance of digital

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operations, and (5) methodologies, which denote the systematic approaches and frameworks for the campus ecosystem. Overall, these dimensions highlight that monitoring in a campus is a complex process that involves both technology and management, making it a key foundation for building campuses that are fully functional and sustainable.

Several studies have sought to explore and apply these five dimensions in different contexts. For instance, Ramasawmy & Nagowah (2023) investigated the environmental dimension by developing a campus waste monitoring system that employs IoT sensors and machine learning to predict the number of cleaning staff required. Similarly, Sneesl et al. (2023) examined the adoption of IoT-based smart campuses in Iraqi higher education, using a two-stage approach that integrates Structural Equation Modeling (SEM) and Artificial Neural Networks (ANN). A comparable strategy was adopted by Ucar et al. (2024), who applied IoT technologies to predict patterns of student attendance. Moreover, research on communication protocols has also advanced, with Kulkarni et al. (2020) and Eldeeb & Alves (2024) who employ Long-Range (LoRa) as a communication method for IoT-based applications.

Zhang et al. (2022) offered a comprehensive survey of intelligent campus technologies with a particular emphasis on human-centered dimensions, although their contribution remained primarily conceptual in nature. Building on more applied perspectives, Antony et al. (2023) integrated IoT technologies with Deep Belief Neural Networks to develop a system designed to monitor both student attendance and environmental conditions within the campus environment. Similarly, Zhou et al. (2020) advanced the technological scope by proposing an IoT-based wireless video surveillance system that incorporates network congestion control, codec rate coordination, and zero-copy buffer mechanisms, further enhanced with multi-camera tracking functionalities. In a related line of inquiry, Bukhsh et al. (2021) developed an IoT-enabled framework characterized by reliability, energy-awareness, and fault tolerance, which effectively optimized energy consumption across IoT clusters, improved system availability, and reduced message transmission failures, thereby demonstrating superior performance under simulated conditions. Nonetheless, these approaches exhibit limitations, particularly in addressing challenges related to mobility and concealed environmental contexts.

Faritha et al. (2020) introduced a comprehensive IoT-cloud–based framework intended to transform traditional classrooms into smart learning environments. Along similar lines, Razzaq et al. (2021) proposed a hybrid auto-scaling model for cloud services that combines vertical scaling, which augments resources within a single server, with horizontal scaling, which expands capacity by adding multiple servers. By incorporating predictive analytics and classification techniques, this model is designed to manage workload surges more effectively, thereby maintaining Quality of Service (QoS), reducing the risk of service interruptions, and improving cost efficiency. Despite these advancements, both frameworks remain largely conceptual, having been assessed only through simulation studies rather than real-world campus monitoring applications, thereby raising questions regarding their practical reliability and scalability.

Several studies have also explored robot-based monitoring systems as an emerging approach. Ramachandran et al. (2022) proposed a structured resilience framework that enables heterogeneous robots to optimize information-sharing links and coordinate spatial reconfigurations, thereby allowing them to leverage neighboring resources more effectively. This method holds considerable potential for deployment in multi-animaloid monitoring scenarios. Nonetheless, the framework is constrained by its reliance on simulation-based evaluations rather than real-world implementations, which raises concerns regarding its practical applicability. In a related direction, Cittadini et al. (2022) advanced a robot-based system for contactless health monitoring, with their principal contribution being the integration of a robotics layer that extends beyond passive data collection. This system offers a safer and more comfortable alternative to traditional wearable sensors, particularly in contexts where physical contact is either undesirable or impractical, thus enabling non-invasive monitoring. The present work introduces a more interactive robotic embodiment in the form of an animaloid, which not only preserves the functional benefits of contactless monitoring but also enhances user engagement and acceptance through its anthropomorphic design. Beyond security, the deployment of animaloid robots in academic settings aligns with growing trends in social robotics and AI-driven educational infrastructure. As noted by Lampropoulos & Papadakis (2025), the presence of social robots in educational environments can enhance user acceptance and provide significant interactive value.

Another work by Preethichandra et al. (2025) provides a broad review of recent developments in robotic systems for environmental monitoring, structured around the underlying technologies. The paper's contributions can be outlined in three main areas: (1) its wide coverage, encompassing sensor technologies, robotic platforms, and applications, (2) the diversity of environmental use cases, such as terrestrial and aquatic monitoring, and (3) the emphasis on multi-platform integration. The review underscores the essential role of robotic platforms in advancing ecological data collection, thereby supporting more effective and efficient monitoring. Nevertheless, it offers limited experimental contributions. Chen et al. (2025) introduce an advanced monitoring system for natural resource surveys in complex and high-risk environments. By integrating ground vehicles, crewless aerial vehicles, and quadruped robots, the system effectively mitigates challenges related to limited data acquisition, elevated operational hazards, and substantial costs inherent to such contexts.

However, despite its robustness, the system's scale and capabilities render it disproportionate for relatively low-demand applications such as campus monitoring.

Several studies have also engaged with the theme of surveillance and monitoring in campus environments. Suresh & Menon (2023) examined the problem of optimal surveillance camera placement to maximize coverage in both indoor and outdoor settings. Their findings demonstrate that coverage targets can be achieved with fewer cameras when supported by improved orientation planning. Nevertheless, the study is limited by its reliance on map-based simulations and does not extend to evaluations in dynamic or obstructed real-world contexts. Similarly, the works of Wang et al. (2023) addressed related concerns regarding campus security and the development of extensible surveillance systems. However, these contributions remain constrained to static monitoring approaches, thereby limiting their applicability in more complex and evolving scenarios. In this study, we examine ways to address these potential constraints. Following the framework established by Addula et al. (2025), this study adopts a proactive and adaptive risk assessment strategy. This approach is essential for identifying vulnerabilities within HTTP-based web platforms and ensuring the system can evolve against emerging threats.

The study by Zarpellon et al. (2024) successfully demonstrates the design and implementation of a layered, scalable, flexible, and cost-effective IoT architecture for a campus in Brazil. By integrating diverse sensors, open-source technologies, and real-time monitoring capabilities, the system enables efficient management of multiple campus resources such as energy, water, and environmental conditions. However, the present implementation primarily serves the purpose of monitoring and data visualization. In a complementary effort, Shihao et al. (2025) presented a comprehensive survey of Smart Campus Resource Information Management (SCRIM) systems situated within the IoT paradigm, offering a structured overview of how IoT-enabled data collection and advanced analytics can facilitate the efficient management of diverse campus resources, including but not limited to energy consumption, environmental conditions, water distribution, and related domains. While the proposed SCRIM framework provides a useful conceptual foundation and identifies promising directions for future development, the study ultimately remains at a non-practical level, as there is limited demonstration of real prototyping and large-scale pilot testing that could substantiate the framework's practical viability in operational campus settings.

A prospect that aligns closely with the objectives of this work has been conducted by Zahedi et al. (2025), which introduces a sophisticated game-theoretic framework to model the interactions between a human supervisor and a robotic agent. Within this framework, the human supervisor can strategically monitor the robot's behavior in a manner that minimizes the overall cost of observation.

From the earlier review of existing research, it is evident that most surveillance systems remain predominantly static, both in their positioning and services. While such systems demonstrate effectiveness within their defined scopes, they generally lack mobility and do not fully support real-time interactive experiences. To address these limitations, the present study proposes the development of a comprehensive surveillance framework specifically designed for campus environments. The core objective is to design and implement a mobile solution that enables real-time monitoring and control through the integration of robotic platforms managed via a web-based application.

This study proposes the implementation of an animaloid robotic platform that integrates wireless HTTP communication to support real-time surveillance and control within a campus environment. In contrast to earlier approaches, the proposed system offers a more flexible and dynamic solution, enabling autonomous navigation across diverse areas of the campus while simultaneously conducting monitoring tasks. To enrich its surveillance capabilities, the robot is equipped with environmental sensing modules capable of recording parameters such as temperature and humidity, thereby extending its functionality beyond visual monitoring.

Furthermore, the research undertakes a systematic evaluation of the system's performance, examining critical operational aspects including response time, energy consumption and battery longevity, as well as communication stability and effective operational range. Collectively, these features underscore the potential of the animaloid robotic system to serve as a more adaptive, multifunctional, and sustainable alternative to conventional static surveillance solutions.

II. METHODS

The study is structured around four fundamental requirements, each serving an important role in the overall system design. The first requirement focuses on the animaloid robot, which acts as the primary mobile platform for movement. The second component integrates the camera, which is mounted on the robot and designed to capture and transmit real-time data for monitoring and analysis. The third is the web application, which functions as the user interface for controlling the system. Lastly, the communication system connects all these components, ensuring smooth data exchange and reliable coordination among the different subsystems.

To justify the design of the proposed system, several quadruped robotic platforms were examined: Bittle/Nybble, the PuppyPi Quadruped Robot, and the CM4 XGO Robotic Dog. Although each of these robots possesses distinct strengths and limitations, Bittle/Nybble was ultimately selected as the most cost-effective option due to its ability in providing mobility capabilities comparable to the other two platforms. A detailed technical comparison is presented in Table 1. Within the proposed framework, the selected robot functions as a mobile surveillance station, capable of navigating the campus and accessing areas that are beyond the coverage of static surveillance cameras.

Table 1. Quadruped Robot Comparison

Spec	Bittle/Nybble	PuppyPi	CM4 XGO
Board	NyBoard	RasPi 4	RasPi 4
Servo	Coreless	Coreless	Serial bus
Battery	Li-on	Lipo	Lithium
Comm.	Wi-Fi, Bluetooth	Wi-Fi, Bluetooth	Wi-Fi, Bluetooth
Price	228 - 269 USD	559 USD	599 USD
Weigh	265-290g	1500g	620g
Chasis	Plastic	Alumunium	Alumunium

The camera (see Figure 1) is mounted on the animaloid robot to capture live video streams, which is a critical component for real-time surveillance and security assessment. To ensure effective operation, the camera must support continuous live streaming capabilities, enabling video data to be transmitted seamlessly over the network to the web-based control station, where it can be accessed for monitoring and decision-making purposes.

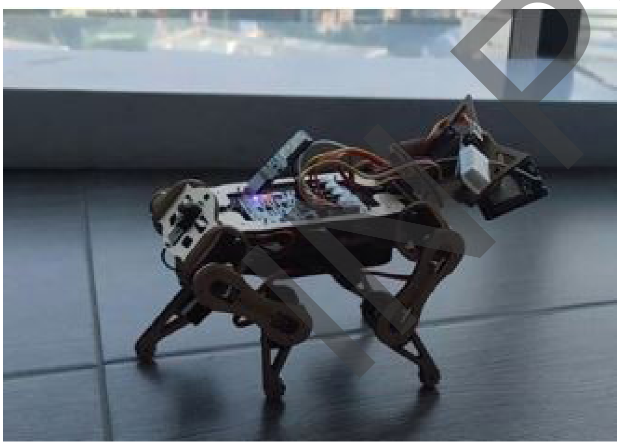

Figure 1. Nybble with mounted camera

The web-based application serves as the primary interface for remote tele-presence, providing both robot control and live video monitoring. As illustrated in Figure 2, the application is structured into two main components: the user control interface and the video feed module. Rather than operating autonomously, the interface features a dashboard that allows users to dispatch navigation commands to the Nybble robot manually. Complementing this, the video feed module displays real-time streams from the robot-mounted camera, granting users the situational awareness necessary to monitor various indoor campus areas.

Figure 2. Web Application Design

The communication system constitutes a critical component for ensuring seamless data exchange between the Nybble robot, its mounted camera, and the web application. In this work, wireless transmission relies on standard Wi-Fi protocols operating over HTTP for command exchange and real-time video streaming. Ensuring reliability and stability is of paramount importance, as even minor disruptions or delays in transmission may compromise the integrity of monitoring tasks and hinder precise navigation control. A robust and fault-tolerant communication framework is therefore essential to maintain uninterrupted system performance, especially in surveillance scenarios where real-time responsiveness and continuous monitoring are required.

The system architecture is depicted in Figure 3, which integrates the key components: the animaloid robots, the underlying communication infrastructure, and the web-based application interface. The block diagram highlights the design and functional responsibilities of each module, emphasizing their interactions in the overall surveillance system. To complement this high-level architectural overview, an operational workflow diagram is presented in Figure 4. This diagram illustrates the sequential workflow and the bidirectional exchange of data and control signals. It traces the flow of operations from the robot initial detection phase to the final user interface. This clarifies the contribution of each subsystem in remote monitoring, as well as the synchronization required between hardware and software components to ensure reliable system performance.

The implementation of the proposed system is conducted through a series of methodical steps, each designed to ensure the seamless integration and performance of the individual components. This approach not only guarantees functional consistency across the system but also enhances its adaptability to diverse operational contexts. The detailed schematic representation, presented in Figure 5, offers a comprehensive overview of the system’s architecture. Consequently, highlights the interconnections between hardware modules, communication interfaces, and software components, demonstrating a real-time monitoring and control framework.

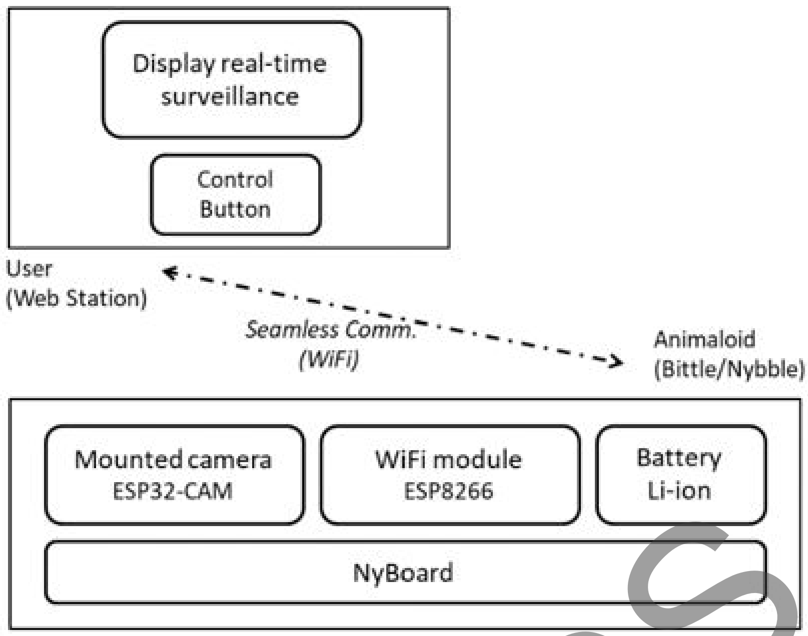

Figure 3. System Architecture Design

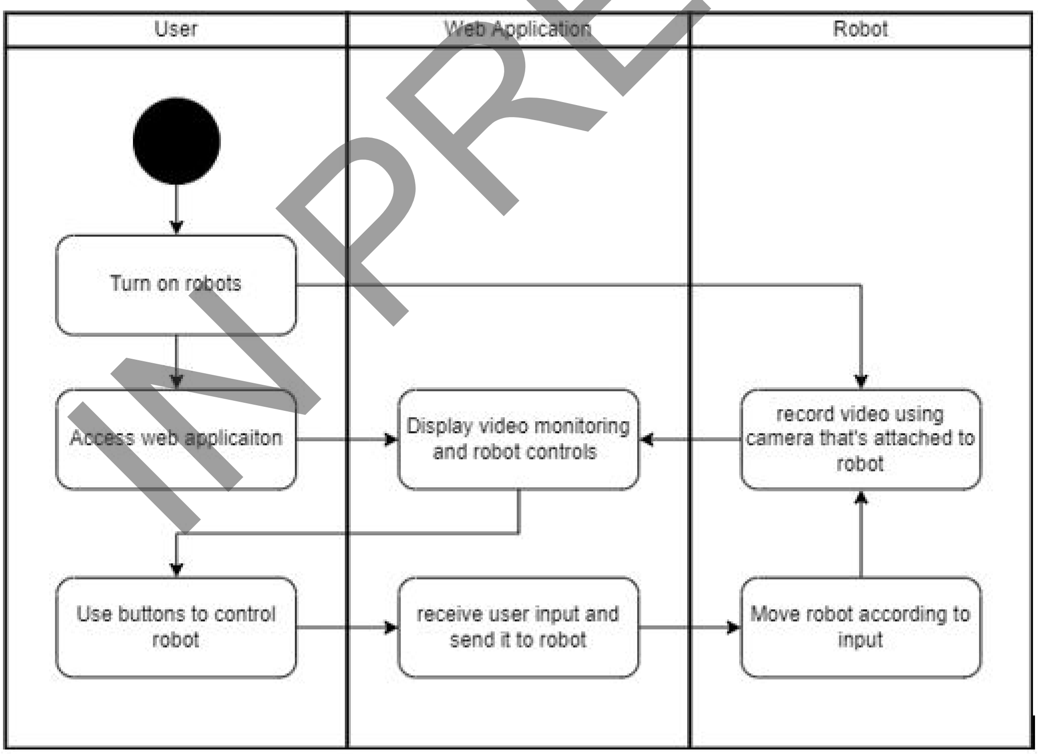

Figure 4. Operational Workflow Diagram

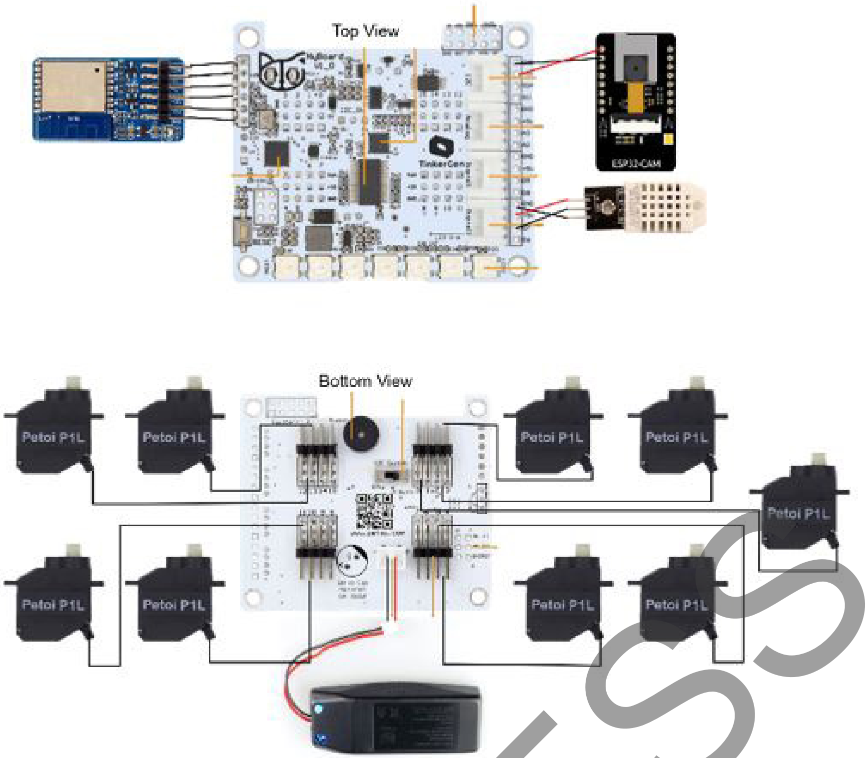

Figure 5. Hardware Schematic of the System

Figure 6. Mounted Surveillance Camera

Each robot is equipped with a NyBoard, which functions as the central unit responsible for coordinating and executing locomotion commands. To facilitate mobility and movements, the robots are also fitted with nine to eleven servomotors, enabling actuation of the legs, tail, and head. Each servo motor supports a rotational range of approximately 250 degrees, thereby allowing a wide spectrum of movement and enhanced flexibility. Power is supplied by a rechargeable 7.4 V, 1000 mAh lithium-ion battery, which provides a continuous operational runtime of 50 to 60 minutes under standard monitoring conditions.

The animaloid robots are equipped with an external ESP32-CAM module, which is Wi-Fi compatible, to facilitate the acquisition of real-time video footage (see Figure 6). This lightweight yet powerful module has integrated both camera and wireless communication capabilities, allowing the robots to capture visual data continuously without the need for bulky hardware. Once the video is captured, the ESP32-CAM processes the data and transmits it over the Wi-Fi network, thereby enabling seamless video streaming to the designated web application. Through this mechanism, operators or end-users can remotely monitor the robot's environment in real time, improving situational awareness and interaction with the surrounding context. Furthermore, the adoption of Wi-Fi-based transmission ensures flexibility and scalability, as multiple animaloid robots can be deployed simultaneously while maintaining connectivity to the same monitoring platform. This design choice not only enhances the overall functionality of the system but also underpins its suitability for diverse application scenarios, particularly those that require mobility, adaptability, and minimal physical intrusion.

The web application framework is developed using Python Streamlit, a high-level library that enables rapid prototyping and deployment of interactive applications. One of the primary advantages of adopting Streamlit is its ability to function independently without requiring additional front-end resources such as HTML, CSS, or JavaScript files, thereby significantly reducing development complexity and ensuring ease of maintenance. Within this framework, a user-friendly dashboard is implemented to serve as the primary control interface. The dashboard allows operators to remotely manage the movement of the animaloid through a set of navigation commands that are transmitted over the network with minimal latency.

In addition to control functionalities, the interface incorporates a live video feed that streams real-time footage from the ESP32-CAM modules mounted on the robots. This feature enables continuous monitoring of various areas across the campus as the robots traverse different locations. By integrating both control and monitoring functions within a single application, the framework ensures seamless interaction between users and the robotic system, thereby enhancing usability, accessibility, and situational awareness.

III. RESULTS AND DISCUSSIONS

The testing phase was conducted across several scenarios in a chronological sequence. The initial stage focused on verifying system connectivity. The application was first executed, and upon successful initialization with the local indoor network, the serial monitor displayed the confirmation message *"Wi-Fi connected – Camera ready"* (see Figure 7). Following this, the system automatically configured the optimal camera settings to ensure video quality and stability

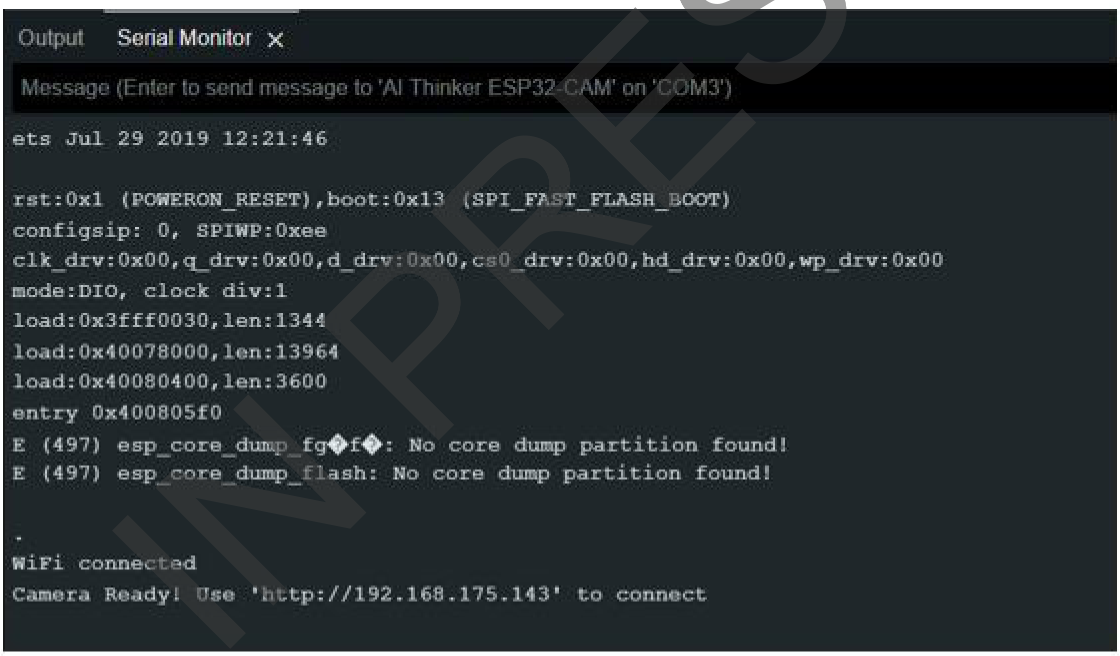

Figure 7. Surveillance System Connection Ready

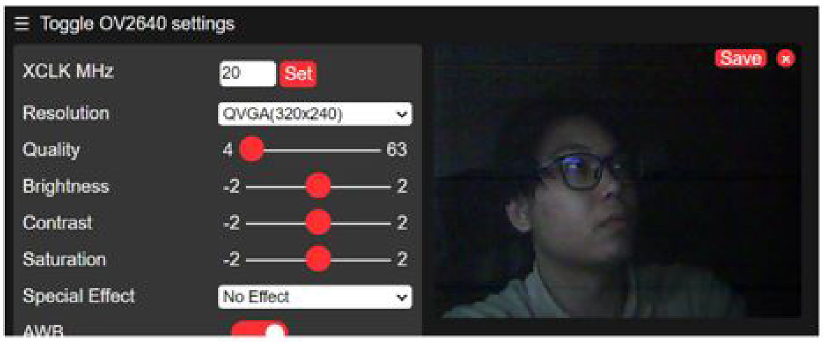

Figure 8. Surveillance System Camera Frame

(see Figure 8). Once these configurations were completed, the web-based application became fully operational and ready for user customization (see Figure 9).

In the second stage of the system, the user can access a web-based interface that serves as the primary platform for controlling the robots. This interface provides an organized layout, allowing the user to view the robot's operational parameters in real time. Through this platform, the user can issue navigation commands such as forward, backward, left, and right movements, enabling precise maneuvering of the robot within the indoor campus environment. As illustrated in Figures 10 and 11, the interface also displays live feedback from the mounted camera, giving the user a visual reference of the robot's surroundings. This feature helps ensure that the robot's movements can be adjusted according to environmental conditions and task requirements. By combining control and monitoring in a single interface, the system allows the user to manage the robot in real time.

It is found that performance is closely tied to gateway proximity; thus, establishing network accessibility is a critical factor. Our evaluation identifies a 10-meter radius as the ideal operational threshold for maintaining indoor surveillance. As detailed in Table 1, exceeding this range leads to diminished responsiveness.

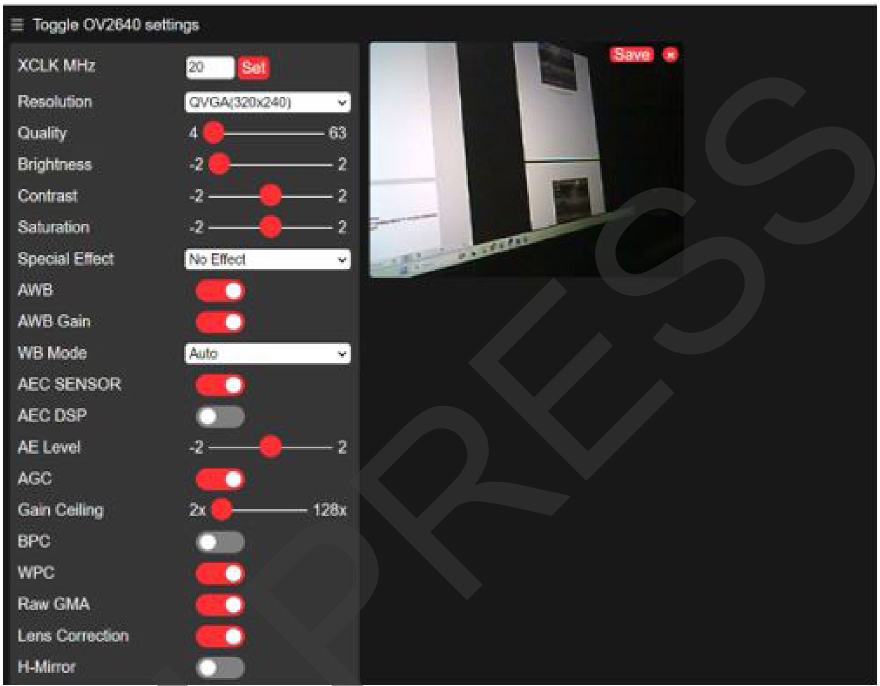

Figure 9. Surveillance System Camera Ready

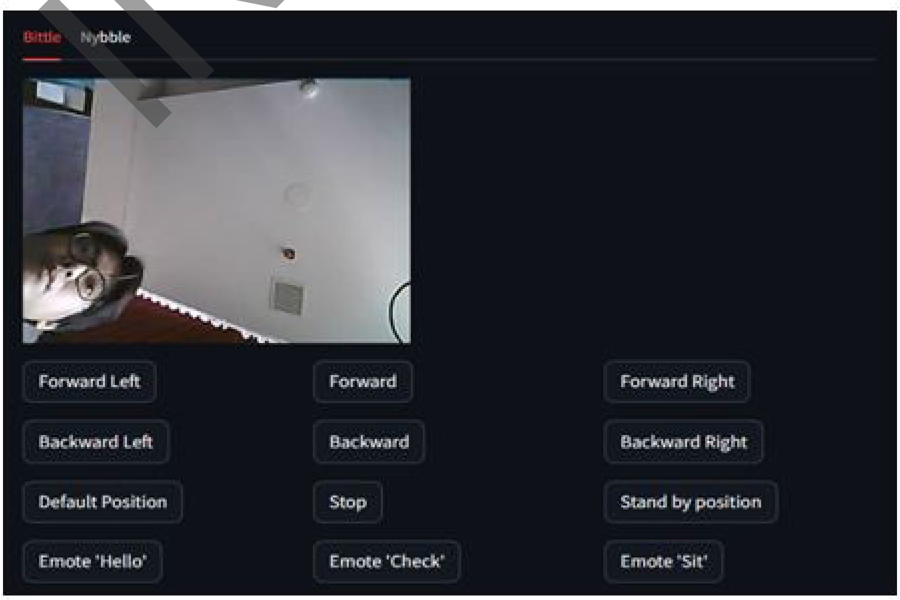

Figure 10. Surveillance System User Ready (1)

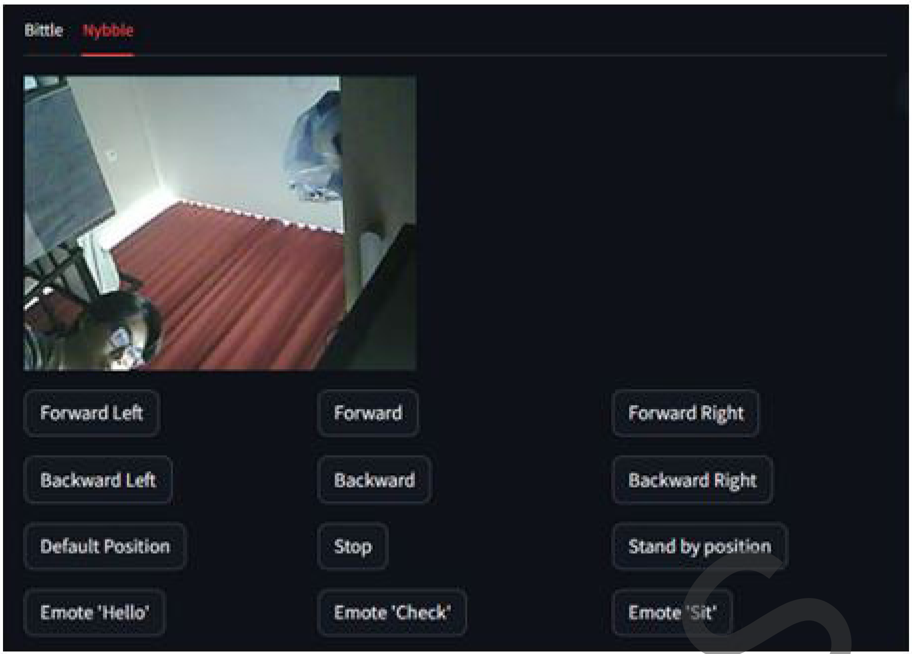

Figure 11. Surveillance System User Ready (2)

Furthermore, additional testing was performed by operating the robots from different locations, including separate floors within the indoor building. We found that the robots remained successfully connected to the same network as the web application, demonstrating that the system can sustain functionality across multiple gateways as long as they are connected to the same network.

Table 2 Distance vs. Responsiveness

No.	Distance (m)	Video response
1.	3	Smooth
2.	5	Smooth
3.	10	Smooth
4.	12	Lag
5.	15	Lag

In its current iteration, the robot operates under a command-dependent manual control scheme, meaning that if the network connection is severed, the robot automatically halts. This behavior serves as an inherent, fail-safe safety measure by preventing uncommanded movement during signal loss. More sophisticated, AI-driven safety features—such as AI-based or computer vision-based obstacle avoidance are earmarked for the next phase of development to support full autonomy.

Another critical parameter influencing system performance is the responsiveness of the web application. Specifically, two aspects require careful measurement: the time required for the application to initialize and the interval between user input and system response. Both factors directly contribute to the real-time capability of the live indoor monitoring framework and, consequently, to the overall reliability of the application. As summarized in Table 2, five testbeds were conducted across different campus locations. On average, the results indicate that the web application requires between 15 and 60 seconds to establish a stable connection with the animaloid robots. Furthermore, the start button interval consistently remained below 1 second, except in cases where the initialization time exceeded 40 seconds, in which minor delays were observed. It should be noted that these testbeds are closely related to the stability of the campus network infrastructure. In this regard, prolonged startup times can be interpreted as an indicator of network instability rather than system instability.

Beyond connectivity and responsiveness, we also evaluated the speed and uptime of the robots, as these parameters determine the extent of coverage achievable within indoor environments. Note that these parameters are constrained by battery capacity and locomotion speed. According to the manufacturer's specifications, each robot is powered by a 1,000 mAh lithium-ion battery with an operating voltage of 7.4 V, capable of drawing between 2 A and 5 A (maximum). The average charging time is approximately 2 hours, providing a nominal runtime of around 1 hour. Following testing, it is revealed that the actual operational uptime of the robots ranged between 45 and 50 minutes. This discrepancy is considered acceptable, as a portion of the battery capacity is consumed by onboard computation and wireless data transmission during operation.

To further assess mobility performance, a series of tests were conducted to measure the time required by the robots to traverse a 1-meter distance. The results, summarized in Table 3, indicate that the Bittle robot recorded times ranging from 11.3 to 13.65 seconds, while the Nybble robot recorded slightly longer times ranging from 12.2 to 13.65 seconds. From these measurements, the estimated velocity of the robots was calculated to fall within the range of 0.072 m/s to 0.088 m/s. These results provide a practical indication of the robots' efficiency and the scale of indoor surveillance areas that can be realistically covered.

Table 3 Web Application Startup Time

No	Startup time (s)	Button interval (s)
1.	28	less than 1
2.	10	less than 1
3.	15	less than 1
4.	45	4-5
5.	53	8-10

Table 4 Robots' Speed for 1 Meter Distance

No	Bittle (s)	Nybble (s)
1.	11.3	12.2
2.	12.5	13.19
3.	13.65	13.65

IV. CONCLUSIONS

This study concludes that indoor campus surveillance can be effectively enhanced through the deployment of mobile telepresence animaloid robots integrated with external sensing devices. These robotic platforms demonstrate the capability to conduct continuous, real-time monitoring via live video streaming, allowing users (operators) to observe diverse interior areas with minimal latency. By moving beyond stationary surveillance, this system extends monitoring capabilities that are unusually difficult for humans to access, such as narrow passages or remote sections inside the campus.

Experimental assessments and field trials indicate that the system maintains seamless connectivity and reliability, provided that the underlying campus Wi-Fi infrastructure remains stable. This highlights the potential and adaptability of animaloid robotic platforms as a flexible and scalable approach to existing campus frameworks. While the current framework prioritizes real-time responsiveness and seamless connectivity, the reliance on standard HTTP for command exchange and video streaming introduces specific security considerations. HTTP operates as an unencrypted protocol. Within a local indoor network, this lack of encryption presents a potential vulnerability where unauthorized parties could theoretically intercept or interfere with the packet. However, the decision to utilize unencrypted HTTP (instead of HTTPS, for example) was a preliminary strategy to minimize initialization latency and maximize the computational efficiency of the ESP32-CAM modules. For future deployment, we propose transitioning toward a hybrid streaming architecture. This would leverage WebRTC to serve instantaneous feedback for rapid response, while utilizing Low-Latency HLS (LL-HLS) to deliver stable, high-quality feeds. This dual-track approach ensures the system remains robust and scalable without compromising on speed where it matters most.

Future development of this system is highly feasible and opens opportunities for the integration of more advanced capabilities. For instance, the incorporation of automated navigation technologies, such as Light Detection and Ranging (LiDAR), would allow the animaloid to move autonomously across the campus with greater precision. In addition, intrusion detection mechanisms powered by Computer Vision could identify suspicious behaviors, unauthorized entries, or unusual patterns in real time. Furthermore, equipping the system with predictive analytics supported by Machine Learning algorithms would allow the infrastructure to learn and adapt to the evolving modern campus, both indoor and outdoor environments.

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AUTHOR CONTRIBUTIONS

Conceived and designed the analysis, E. A. and M. A.; Collected the data, E. A. and M. A.; Contributed data or analysis tools, E. A. and M. A.; Performed the analysis, E. A. and M. A; Wrote the paper, E. A. and M. A.

DATA AVAILABILITY

Data sharing is not applicable – no new data generated. Data sharing is not applicable to this article as no new data was created or analyzed in this study..

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