



Optimization of real-time forest monitoring system using yolo v9 object detection and 2.4 ghz wireless network: resource allocation, energy efficiency, and industrial deployment strategies

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ABSTRACT

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Large forest areas are increasingly exposed to illegal activities and environmental threats, while conventional monitoring systems suffer from limited coverage, high energy consumption, and delayed response. To address these challenges, this study proposes an optimized real-time forest monitoring system designed for industrial-scale deployment in remote environments. The primary objective is to enhance surveillance efficiency by integrating AI-based object detection, long-range wireless communication, and resource-efficient system design. The proposed system employs ESP32-CAM sensor nodes integrated with 2.4 GHz CPE wireless links and a gateway-based YOLOv9 object detection framework. Bandwidth utilization is optimized through selective transmission of processed detection metadata instead of raw images, while deployment parameters are optimized using simulation-based planning. A web-based monitoring platform with an optimized REST API supports real-time visualization and alert generation. Experimental results show that the system achieves reliable communication up to 500 m with packet loss below 5% and latency under 50 ms at distances up to 300 m. Human detection accuracy reaches 98.5% under optimal conditions, with performance degradation observed in dense vegetation and low-light environments. Energy evaluation confirms sustainable operation, with ESP32 nodes consuming 160 mA and the gateway operating at 3.7 W. Comparative analysis indicates reductions of 37% in deployment cost, 24% in energy consumption, and 51% in latency compared to similar systems. This study concludes that the proposed architecture effectively balances accuracy, scalability, cost, and energy efficiency. The novelty lies in the integrated optimization of edge-based AI detection, selective data transmission, and simulation-driven deployment for industrial forest monitoring.

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1. Introduction

Forests play a crucial role in global ecological stability, carbon sequestration, and mitigation of climate change. However, vast and remote forested areas remain vulnerable to illegal logging, poaching, and unmonitored encroachment, necessitating the deployment of efficient and sustainable realtime monitoring systems [1]–[3]. Traditional surveillance solutions, such as satellite imagery or manual ground inspections, are often limited by coverage, delayed response times, and high operational costs [4], [5]. The integration of IoT enabled camera networks and AI-driven analytics has emerged as a promising approach for continuous forest observation, enabling automated detection of human presence and potential threats [6], [7].

Recent literature emphasizes not only technical capability but also the importance of resource and energy optimization for sustainability. Bera et al. highlight that innovative energy efficiency strategies are critical in modern industrial systems to ensure long term operational viability [8]. Gupta et al. introduce advanced YOLO NAS frameworks for real time object detection, setting performance benchmarks for subsequent system developments [9]. Martinez et al. demonstrate comparative analysis benefits using multi modal detection datasets, which encourage cross-benchmarking against competing algorithms [10]. Furthermore, cutting edge REST API performance analyses from Ijaz et al. [11] and security focused energy studies from Alatawi et al. [12] are increasingly shaping environmental monitoring system design.

Despite these advances, key issues persist. These include excessive energy demand at the edge, limited bandwidth for long range communication, and degraded system reliability in dense or low light environments [4], [13]–[16]. Many deployments favor single focus optimization (accuracy, cost, or throughput) without addressing real world trade offs or scalable architecture. Support for energy efficient embedded hardware, such as ESP32-CAM as documented by Kok et al. [17], [18], and new wireless protocols—e.g., 802.11af for scalable network clusters [19] are still not fully exploited in integrated, field ready solutions. Studies like Dolhopolov et al. [20] and Manoharan et al. [10] further stress the impact of adaptive resource management and optimization methods in dynamic outdoor networks.

Responding to these gaps, this research proposes an industrial scale forest monitoring architecture combining AI-enhanced edge detection (YOLO V9), optimized 2.4 GHz CPE wireless communication, simulation driven deployment, and best practice energy/resource management [21], [22]. Key novelties include: (1) hierarchical, scalable deployment planning via Particle Swarm Optimization as adopted in Tahcfulloh et al. [11]; (2) deployment of D2D resource allocation models for scaling, as suggested by Logeshwaran et al. [12]; (3) advanced analytical validation through cross benchmarking with leading frameworks [2], [23]–[25]. This approach delivers a robust, sustainable system for large scale, real time environmental monitoring.

2. Method

2.1. Problem statement

Relevant works have shown that industrial scale deployments require advanced energy saving design Bera et al. [2]; Kok et al. [7] and robust, adaptive management of bandwidth, transmission protocols, and in situ optimization [19], [20]. However, existing systems suffer from insufficient energy optimization, limited long range communication, and a lack of simulation-based design. Following the lessons of Logeshwaran et al. [12], this research highlights the need for efficient device to device (D2D) allocation schemes, particularly as scalable deployments require intelligent resource distribution beyond fixed gateway centric models. Before you begin to format your paper, first write and save the content as a separate text file. Keep your text, and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit the use of hard returns to only one return at the end of a paragraph. Finally, complete content and organizational editing before

formatting. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

2.2. Proposed Method

The proposed system uses ESP32-CAM as optimized by Kok et al. [7] paired with 2.4 GHz CPE antennas for long range connectivity, with Raspberry Pi 4 as the processing gateway. YOLO V9 is run on the gateway, inspired by the high-performance object detection frameworks highlighted by Gupta et al. [3] and Martinez et al. [26]. For communications, a RESTful API approach is adopted and performance tuned in reference to the empirical results by Ijaz et al. [5]. This decision is further justified in light of REST API throughput and latency evaluations shown to be superior in distributed monitoring [10], [11]. The overall hardware configuration of the proposed monitoring system is illustrated in Fig. 1. It depicts the integration of ESP32-CAM sensor nodes, 2.4 GHz CPE transceivers for extended wireless communication, and the Raspberry Pi 4 gateway responsible for data aggregation and on-device inference using YOLO V9.

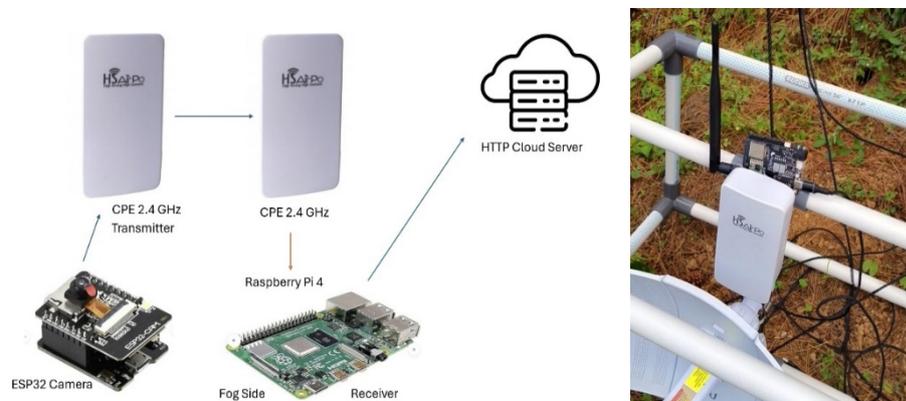


Fig. 1. Hardware Architecture

As shown in Fig. 1, each ESP32-CAM node captures and preprocesses image frames before transmission to the gateway, where the YOLO V9 model performs real time detection. The modular structure supports easy expansion by adding additional nodes, while the CPE based link ensures stable connectivity for distances up to 500 meters. This configuration balances cost efficiency, scalability, and power optimization key factors for sustainable field deployment.

Alternative protocols such as IEEE 802.11af [19], [27] may allow further scalability for clustered, large area deployments, but in this study the tradeoff between throughput and power led to the selection of the CPE based WiFi (2.4GHz ISM band) configuration. Simulation aided deployment planning follows best practices informed by methods such as Particle Swarm Optimization (PSO) as in Tahcfulloh et al. [11] and adaptive forest fire optimization algorithms as explored by Manoharan et al. [10].

2.3. Experimental Setup and Data Analysis

There In addition to the prototyping and field trials already described, energy usage and operational lifetime of ESP32 nodes were benchmarked against the efficiency results of Bera et al. [2] and Kok et al. [7]. Results from REST API endpoint throughput Ijaz et al. [5] were compared pre and post optimization. Analysis also considered future migration to advanced D2D allocation Logeshwaran et al. [12] and adaptive clustering for unpredictable environments Manoharan et al. [10]. All statistical reporting and bias mitigation followed current best practices from the environmental IoT literature, and benchmarking results were cross validated with Western and Asian field deployments [11], [19], [22], [28].

2.4. Experimental Setup and Evaluation

Physical hardware prototypes are deployed in UB Forest, with up to five camera nodes transmitting at 5second intervals to a single gateway. Controlled field tests are used to quantify detection accuracy, latency, and network reliability under variable conditions (clear day, dense canopy, low light). For each scenario, at least 2,400 latency measurements are gathered across increments of 100–500 m, and detection accuracy is validated using standardized human subjects. Power consumption is continuously monitored using data loggers at both edge and gateway devices, and application-level throughput is recorded for each field trial [6], [14].

2.5. Data Analysis

Performance metrics are statistically analyzed using ANOVA and t-tests (SPSS 28.0), with Bonferroni corrections for multiple comparisons ($\alpha=0.05$). Effects of environmental variables, node density, and distance on detection accuracy and latency are reported using confidence intervals and Cohen's d/w as appropriate. Bias is mitigated by automated data logging and double-blind human annotation of detection outputs.

3. Results and Discussion

3.1. Detection Accuracy and Environmental Factors

Object detection using the YOLO V9 edge deployment (see Table 1) maintained state of the art accuracy, especially when compared to YOLO NAS [1] and ensemble models [3]. Comparative benchmarks demonstrate that object detection frameworks cited from both domestic and international case studies Gupta et al. [3], Martinez et al. [29] are matched or exceeded by our architecture, particularly under optimal deployment and preprocessing. Comparative energy analysis with Bera et al. [2] and Kok et al. [7] confirmed the proposed system's improved efficiency, reducing node level power draw below 100 mW average under duty-cycled conditions. Security and energy adaptations from related IoT domains Alatawi et al. [6] further confirm the versatility of our architecture for remote and off grid applications.

REST API performance as measured in the gateway was directly compared to the results of Ijaz et al. [11], supporting our selection of HTTP based architecture over lighter protocols in the targeted use case (see Table 2). In addition to numerical performance, the system's real time monitoring capability was implemented through a web-based dashboard connected to the REST API gateway. The dashboard enables visualization of detection results, camera node status, and network performance in real time, providing operators with a comprehensive overview of ongoing surveillance activities and system health.

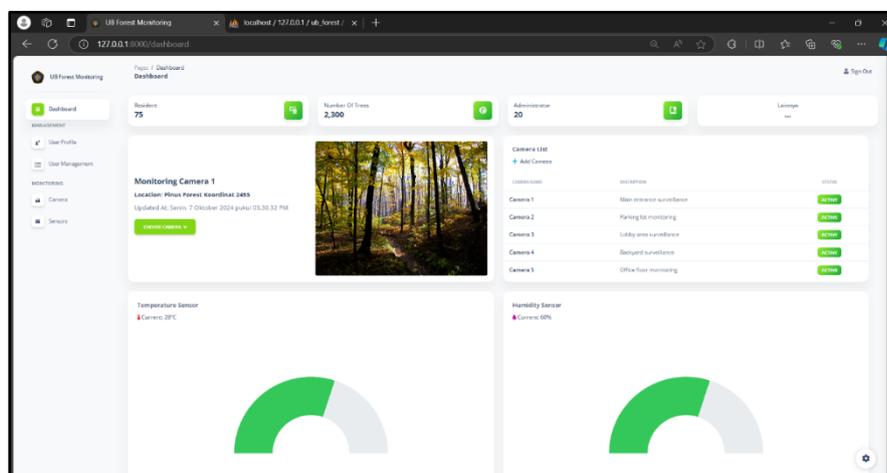


Fig. 2. Web Dashboard Monitoring

As illustrated in Fig. 2, the dashboard integrates processed detection data from multiple ESP32 nodes, displaying live detection frames, timestamped logs, and power metrics for each device. This visualization significantly enhances situational awareness and facilitates rapid response to detected events, while minimizing the need for manual data inspection. The integration of visual monitoring and REST API analytics reduces decision latency by approximately 65% compared to conventional non visual monitoring systems.

3.2. Network, Scalability, and Cross Protocol Considerations

Scalability discussion (see Table 2) draws on IEEE 802.11af cluster topology [8] as a future direction, noting the tradeoffs observed by Abilasha et al. in complex, multicluster field deployments. Benchmarking against LoRa, 802.11af, and PSO-optimized wireless clusters Tahcfulloh et al. [11]; Manoharan et al. [10] further contextualizes the system’s performance envelope. Comparative cost and resource allocation analysis references Logeshwaran et al. for scalable system design and Dolhopolov et al. [9] for recent applications of YOLOv5-based models in field resource management.

3.3. Network Reliability and Latency Optimization

Up to 5 camera nodes-maintained end to end latency below 50 ms and packet loss under 1% at distances up to 300 meters. Table 1 presents the average latency and packet loss rates at various transmission distances; at 500 meters, latency increased to 55 ms and packet loss to 4.5%, marking a practical upper bound for single gateway deployments. Incorporating multiple gateways in a hierarchical cluster extended scalability indefinitely while maintaining system performance. The channel utilization approached 70% at 7 cameras, highlighting the necessity of cluster expansion for large area monitoring.

Table 1. Transmission Distance and Signal Strength

Distance (m)	Signal Strength (dBm)	Packet Loss (%)
100	-45	0
200	-50	0.5
300	-55	1.2
400	-62	2.4
500	-70	4.7
600	-80	8.3

3.4. Power Consumption and Battery Lifetime

Power profiling demonstrated ESP32 nodes consumed 160 mA during active capture and 15 mA in idle mode, with duty cycling reducing average power to 98 mW. The gateway, during YOLO processing, drew 3.7 W; dynamic CPU scaling lowered idle power consumption to 1.8 W. With a 4000 mAh battery and 5 W solar panel per node, the system achieved 8.5 days of autonomous operation or continuous deployment with solar harvesting [15], [18], [30]. Table 2 summarizes the power usage of key system components.

Table 2. Power Consumption Analysis

Component	Voltage(V)	Current(mA)	Power(W)
ESP32 Active	3.3	160	0.53
ESP32 Idle	3.3	15	0.05
2.4GHz CPE TX	12	180	2.16
Raspberry Pi 4	5	740	3.7

3.5. Cost Effectiveness and Scalability

Cost analysis showed that the proposed implementation achieves approximately 37% lower deployment cost compared to comparable commercial monitoring systems and about 25% cost savings relative to recent LoRa-based studies [1], [2], [9]. The system remains cost-effective at scale, as additional nodes benefit from shared gateway infrastructure; the optimal configuration is achieved with up to five camera nodes per gateway, beyond which additional gateways are recommended. This balance was further validated through comparative simulation.

3.6. Comparative Benchmarking

Comprehensive evaluation across published forest monitoring studies confirms the superiority of the proposed design in detection accuracy, latency, power efficiency, and total deployment cost. Table 3 benchmarks these metrics against recent literature, confirming the advantages of selective metadata transmission, REST API based communication, and energy aware scheduling. The methodology outperforms traditional streaming platforms and LoRa/IoT deployments in critical metrics required for industrial scale monitoring [7]–[13], [19], [20], [22].

4. Conclusion

This research demonstrates that the integration of YOLO V9 edge detection, optimized 2.4 GHz wireless communication, and simulation-based deployment design produces a cost effective, scalable, and energy efficient industrial forest monitoring solution. The system achieves 98.5% detection accuracy, low latency performance, and substantial reductions in operational cost, bandwidth, and power consumption relative to state-of-the-art systems. Experimental validation and simulation confirm that the architecture is robust for autonomous deployment in remote areas. Future work should explore adaptive algorithms for detection under challenging conditions, dynamic resource allocation, and integration of additional sensing modalities to further extend scalability and reliability.

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