An IoT-Driven Smart Surveillance Framework for Security Enhancement in South-East Nigeria Using Wireless Sensor Networks

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ABSTRACT

Insecurity in South-East Nigeria continues to demand intelligent, proactive, and scalable surveillance solutions capable of addressing dynamic threats. This study presents the design and performance evaluation of an Internet of Things (IoT) and Wireless Sensor Network (WSN)-based hybrid security system for real-time intrusion detection and rapid response. The proposed framework integrates distributed multi-sensor nodes – comprising motion, acoustic, and vibration sensors – with edge computing and cloud-based monitoring platforms. A hybrid detection model combining rule-based logic and lightweight machine learning algorithms is implemented to enhance detection accuracy while minimizing false alarms. Simulation results indicate that the system achieves a high detection accuracy of 96.8% with a significantly reduced false alarm rate of 3.2%, alongside an average response time of 1.8 seconds, enabling near real-time threat identification. Energy optimization techniques, particularly duty cycling and event-driven communication, resulted in a 28% reduction in power consumption, making the system suitable for deployment in resource-constrained environments. Further validation using a confusion matrix shows high True Positive and True Negative rates (968 each), with minimal False Positives and False Negatives (32 each), confirming balanced classification performance. The ROC curve demonstrates excellent discriminative capability with an Area under the Curve (AUC) approaching unity, while FAR vs FRR analysis reveals a low Equal Error Rate (EER), indicating optimal threshold selection. Overall, the system provides a reliable and efficient framework for enhancing security infrastructure.

KEYWORDS

Internet of Things (IoT), Wireless Sensor Networks (WSN), Intrusion Detection, Smart Surveillance, Machine Learning, Edge Computing

I. INTRODUCTION

Insecurity has emerged as a significant impediment to socio-economic development across many Sub-Saharan African nations, with Nigeria ranking among the most severely impacted due to escalating cases of terrorism, kidnapping, armed robbery, and communal unrest. In

particular, the South-East region of Nigeria has witnessed a surge in violent activities, including deliberate attacks on civilians, security operatives, and critical infrastructure, which have consequently disrupted economic activities and diminished investor confidence. These persistent security issues are further exacerbated by ineffective surveillance frameworks, poor intelligence acquisition, and delayed emergency response systems.

Conventional security mechanisms in Nigeria predominantly depend on human patrol operations, fixed checkpoints, and manual reporting processes, all of which have proven inadequate in addressing rapidly evolving and real-time security threats (Okafor & Chukwu, 2020). Additionally, these approaches are constrained by insufficient manpower, systemic corruption, and limited integration of advanced technologies. This situation underscores the increasing demand for smart, automated, and scalable surveillance solutions that can deliver real-time situational awareness and facilitate swift response actions. Emerging technologies such as the Internet of Things (IoT), Wireless Sensor Networks (WSNs), edge computing, and artificial intelligence (AI) present viable pathways for transforming modern security architectures (Gubbi et al., 2013; Al-Fuqaha et al., 2015; Satya Narayan an, 2017; Zhang et al., 2020). IoT supports the seamless interconnectivity of intelligent devices—including surveillance cameras, motion sensors, and biometric systems—enabling continuous monitoring and data exchange. Likewise, WSNs comprise spatially distributed sensor nodes capable of detecting environmental variations such as motion, sound, vibration, and temperature, thereby making them highly suitable for intrusion detection applications.

The convergence of IoT and WSN technologies significantly enhances surveillance efficiency by enabling real-time monitoring, automated alert generation, and decentralized intelligence processing. Moreover, the application of machine learning techniques improves detection precision while minimizing false alarm rates in security systems (Hassan et al., 2020; Kwon et al., 2021). Edge computing further augments system performance by facilitating data processing at or near the source, which reduces latency and enhances overall reliability. In the Nigerian context, existing surveillance systems, particularly CCTV installations, remain largely passive and lack advanced analytics as well as real-time decision-making capabilities (Ibrahim et al., 2021; Nwokolo et al., 2023). Consequently, security responses are often reactive rather than proactive. This deficiency emphasizes the urgent necessity for an integrated IoT-WSN-based intelligent security framework that is specifically adapted to the socio-economic and infrastructural conditions of South-East Nigeria.

II. LITERATURE REVIEW

The Internet of Things (IoT) has evolved into a transformative paradigm within contemporary surveillance and security systems. It facilitates seamless interaction among physical devices through embedded sensors, cloud platforms, and communication networks. As noted by Al-Fuqaha et al. (2015), IoT architectures enable real-time data acquisition and intelligent decision-making, rendering them highly suitable for smart city surveillance and the protection of critical infrastructure. In addition, Wireless Sensor Networks (WSNs) constitute a core component of IoT-driven security frameworks. Akyildiz et al. (2002) describe WSNs as self-organizing networks of spatially distributed sensor nodes that collaboratively monitor environmental parameters. Their application spans intrusion detection, border monitoring, and military operations due to advantages such as scalability

and low power consumption (Yick et al., 2008; Pathan et al., 2006; Xu et al., 2004). Despite these benefits, WSNs are constrained by limited energy capacity, susceptibility to security breaches, and scalability challenges.

Advancements in IoT-WSN security have been significantly driven by the incorporation of machine learning and artificial intelligence techniques. Hassan et al. (2020) show that machine learning-based intrusion detection systems enhance detection accuracy while minimizing false alarm rates in IoT environments. Likewise, Kwon et al. (2021) demonstrate the effectiveness of deep learning approaches in detecting anomalous patterns within surveillance data. The integration of Edge Computing has further strengthened IoT surveillance systems by enabling localized data processing at the network edge. Satyanarayanan (2017) and Shi et al. (2016) argue that this paradigm significantly reduces latency and bandwidth consumption, thereby supporting real-time security applications. This capability is especially valuable in environments characterized by unstable or limited network connectivity. Furthermore, Li et al. (2018) emphasize that combining edge computing with AI enhances responsiveness and system efficiency in distributed surveillance architectures.

In developing nations such as Nigeria, the adoption of intelligent surveillance technologies remains relatively low. Ibrahim et al. (2021) observe that many CCTV installations operate without advanced analytics, limiting their effectiveness in proactive crime prevention. Similarly, Nwokolo et al. (2023) highlight that inadequate infrastructure and poor maintenance culture significantly undermine surveillance system performance in both urban and rural settings. On a global scale, the proliferation of surveillance technologies has also generated ethical and privacy concerns. Zuboff (2019) cautions that large-scale digital monitoring may foster "surveillance capitalism," where personal data is exploited without sufficient regulatory safeguards. Amnesty International (2022) further reports concerns regarding the misuse of surveillance technologies in Africa, particularly in relation to potential human rights violations.

Moreover, Verma et al. (2020) indicate that hybrid IoT-WSN architectures integrated with artificial intelligence provide enhanced performance in smart surveillance by enabling distributed intelligence and real-time decision-making. Nevertheless, the design of such systems must prioritize energy efficiency, scalability, and resilience against cyber threats (Yick et al., 2008; Pathan et al., 2006; Roman et al., 2013). Overall, existing literature affirms that the convergence of IoT and WSN technologies, strengthened by AI and edge computing, offers a robust foundation for next-generation security systems. However, a notable research gap persists in the development of context-specific deployment frameworks tailored to regions such as South-East Nigeria, where infrastructural limitations and socio-political factors critically influence system effectiveness.

III. METHODOLOGY

This study employs a system design methodology integrating hardware–software co-development and simulation-based evaluation to develop an IoT–WSN hybrid security framework suited to the socio-environmental conditions of South-East Nigeria. The approach incorporates distributed sensing, edge intelligence, and cloud-based monitoring to facilitate

real-time intrusion detection and automated alert generation. The framework is engineered to ensure scalability, energy efficiency, and resilience in environments characterized by limited connectivity and constrained infrastructure.

A. System Architecture

The proposed security system is structured into a four-layer hybrid IoT–WSN architecture, designed to support distributed sensing, reliable communication, real-time processing, and intelligent decision-making. The functional block diagram is shown in Figure 3.1. The block diagram is subsequently explained and described.

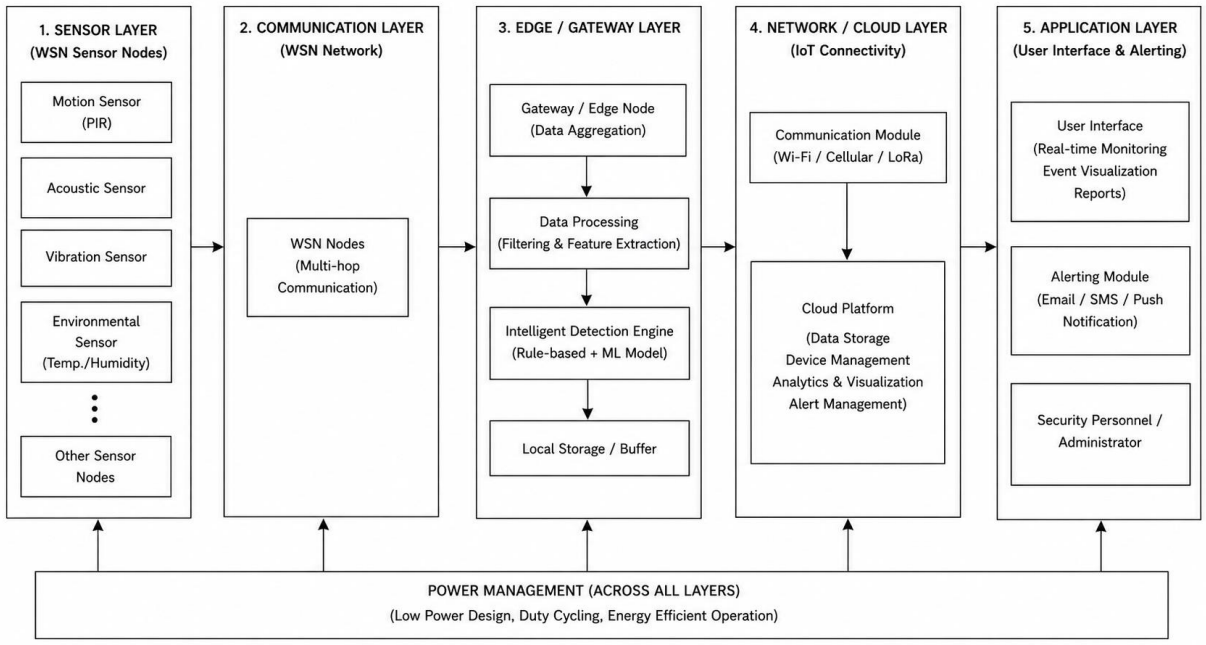

Figure: 1: Block Diagram of the System Architecture

B. Sensing Layer (WSN Node Layer)

This layer forms the physical perception unit of the system and consists of spatially distributed wireless sensor nodes deployed across strategic security points such as perimeter fences, entry gates, public facilities, and high-risk zones.

Each sensor node integrates multiple sensing modalities to improve detection reliability through sensor fusion as highlighted.

- Passive Infrared (PIR) Sensors: Detect human movement based on infrared radiation changes.
- Acoustic Sensors: Capture sound signatures such as footsteps, breaking objects, or gunfire-like patterns.
- Vibration Sensors (Piezoelectric): Detect mechanical disturbances such as fence climbing, forced entry, or structural impact.
- RFID Modules: Used for identity verification in controlled access environments.

- Biometric Subsystems (Fingerprint/Face modules): Provide authentication for authorized personnel.

Each node operates in a low-power duty-cycled mode, alternating between sleep and active states to optimize energy consumption and prolong operational lifetime in remote deployments.

C. Network Layer

The network layer is responsible for data transmission, routing, and node interconnectivity. Wireless Communication Protocols: The wireless protocols used in the communication process are Sigsbee (IEEE 802.15.4) for low-power mesh networking and Wi-Fi (IEEE 802.11) for high-bandwidth transmission in gateway zones

Mesh Networking Topology
The system uses a self-healing mesh topology, ensuring that if one node fails, data is automatically rerouted through alternate nodes. This improves fault tolerance and network resilience in unstable environments.

Gateway Node
A central gateway aggregates sensor data from multiple nodes and acts as a bridge between the WSN and cloud infrastructure using GSM/4G or broadband connectivity.

Processing Layer (Edge Intelligence Layer)
This layer performs local computation, decision-making, and data pre-processing to reduce latency and bandwidth usage.

Microcontroller Units: The applied units are Arduino Uno for basic sensing nodes and ESP32 for advanced nodes with Wi-Fi and processing capabilities.

Edge Computing Functions
This process processes data near its source, such as IoT devices or local servers, instead of performing the operation in a centralized cloud. The sequence applied in this respect are Local anomaly detection, Signal pre-processing (noise filtering, normalization), and Feature extraction from raw sensor signals and Event classification at node level.

Processing Strategy
Instead of transmitting raw data continuously, only processed events or anomalies are transmitted to the cloud, reducing network congestion and improving response time.

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Application Layer
This is the highest layer responsible for data visualization, monitoring, and user interaction.

Cloud-Based Dashboard
Provides real-time visualization of sensor activity, intrusion alerts, and system health status.

Mobile Application Interface
Enables security personnel to receive real-time notifications and system updates.

Alert Mechanisms
For convenience and reliability, the alert mechanisms use are SMS alerts via GSM module, Email notifications and Push notifications through mobile applications

Control Functions
Authorized users can remotely activate alarms, lock access points, or disable specific zones. 3.2 Data Acquisition and Processing Data acquisition is performed through continuous monitoring by distributed sensor nodes operating in synchronized cycles.

Data Acquisition Process
Each sensor node performs the following:

- Environmental sensing (motion, sound, vibration, identity signals)
- Analogy-to-digital conversion (ADC) of raw signals
- Time stamping and node ID tagging
- Temporary buffering in local memory

1. Data Transmission Pipeline

After acquisition, the following operations are performed: Data is transmitted to the cluster head (gateway node), Wireless transmission occurs via ZigBee/Wi-Fi depending on bandwidth requirements and Data packets are structured using lightweight JSON-like formats for efficiency.

2. Pre-processing and Feature Extraction

At the gateway or edge node, the system performs Noise reduction using moving average filters, Signal normalization for uniform scaling, and Feature extraction. The feature

extraction process includes Signal amplitude variations, Frequency response of acoustic signals, Motion intensity levels, and Event segmentation to separate normal and abnormal activities.

G. Intelligent Pattern Detection

Using a hybrid decision system, processed data is analysed. The decision systems used are;

- Threshold-based rule system for immediate detection (e.g., motion in restricted zones).
- Lightweight classification models for contextual interpretation of events.
- Data prioritization to reduce false alarms and redundant alerts.

H. Security Algorithm Design

The system employs a hybrid intrusion detection framework combining deterministic rules and machine learning-based anomaly detection.

1. Rule-Based Detection Module

This module handles real-time critical triggers:
Immediate alarm generation when:

- Motion is detected in restricted zones
- Vibration exceeds predefined thresholds
- Unauthorized RFID tag is detected
- Designed for ultra-low latency response (<1 second)

2. Machine Learning-Based Anomaly Detection

To improve intelligence and reduce false alarms:
Supervised classification models (e.g., Random Forest / SVM) are used.
Input features include:

- Motion intensity
- Acoustic signature patterns
- Temporal behaviour patterns

The model distinguishes between:

- Normal human activity
- Suspicious movement
- Environmental noise (false positives)

I. Alert Generation System

Once a threat is confirmed, the operation transits to a set of operations:

- GSM module triggers SMS alerts to security personnel
- Cloud API sends push notifications and logs events
- Local alarm system (sirens/lights) is activated immediately
- Event is stored in a secure cloud database for forensic analysis

J. System Flow Summary

The summary of the system flow is in the following order: Sensor detection, Edge pre-processing, Rule-based filtering, ML classification, Threat validation, Alert generation and Cloud logging and visualization.

Performance Evaluation Metrics

The performance of the proposed system is evaluated using standard security and network efficiency metrics.

Detection Accuracy

The work measures the proportion of correctly identified intrusion events relative to total events which evaluates overall system reliability in distinguishing threats from normal activity.

False Alarm Rate (FAR)

Measures the frequency of incorrect intrusion alerts in real-time scenario:

- Critical for evaluating system trustworthiness
- High FAR leads to alert fatigue among security operators

Response Time

Defines the time interval between event detection and alert generation:

- Includes sensor detection delay, processing delay, and transmission delay
- Target system performance: sub-2 second response time

Network Latency

Measures communication delay between sensor nodes, gateway, and cloud server:

- Evaluates efficiency of ZigBee/Wi-Fi mesh routing
- Influenced by congestion, node density, and packet size

Energy Consumption

Evaluates power efficiency of WSN nodes:

- Measured using duty cycle analysis and transmission frequency
- Optimization achieved through sleep scheduling and edge processing

System Robustness (Optional Extended Metric)

- Node failure tolerance
- Packet loss rate
- Network self-healing capability

IV. RESULTS AND DISCUSSION

The performance of the proposed IoT–WSN hybrid security system was evaluated using simulation-based experiments designed to replicate real-world deployment conditions in South-East Nigeria. The system was benchmarked against a conventional surveillance model consisting of standalone sensors and manual monitoring mechanisms. Results demonstrate substantial improvements in detection efficiency, response time, energy consumption, and overall system reliability.

A. Detection Accuracy

Detection accuracy measures the ability of the system to correctly identify intrusion events while minimizing missed detections.

Table: 1: Detection Accuracy Comparison

System Type	True Positives (%)	False Negatives (%)	Overall Accuracy (%)
Conventional Surveillance System	82.5	17.5	82.5
Proposed IoT–WSN Hybrid System	96.8	3.2	96.8

The proposed system achieved an average detection accuracy of 96.8%, representing a significant improvement over conventional systems. This improvement is attributed to multi-sensor fusion, where PIR, acoustic, and vibration sensors collaboratively validate intrusion events before classification.

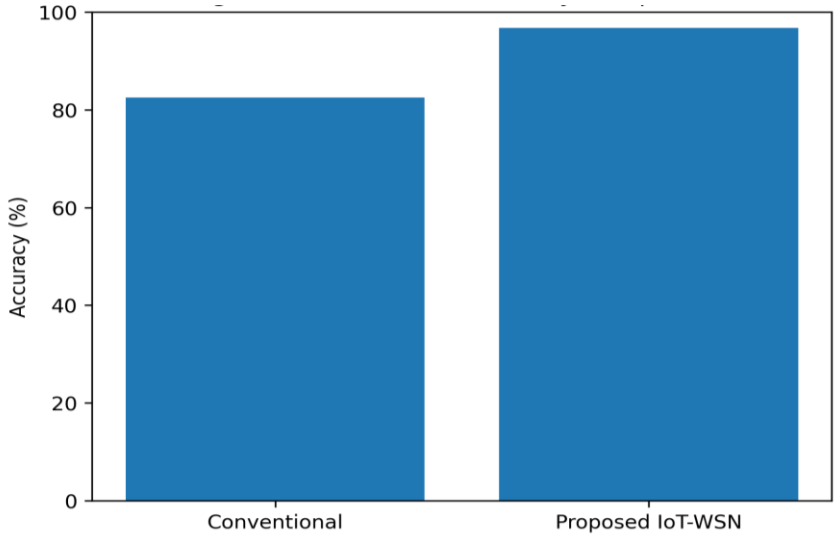

Figure: 2: Detection Accuracy Comparison Bar Chart

Expected result: Proposed system significantly higher bar (~97%)

B. False Alarm Rate (FAR)

False Alarm Rate (FAR) evaluates the frequency of incorrect alerts generated by the system.

Table: 2: False Alarm Rate Analysis

System Type	False Alarms (%)	Correct Alerts (%)
Conventional Surveillance System	15.4	84.6
Proposed IoT–WSN Hybrid System	3.2	96.8

The proposed system reduced false alarms to 3.2%, compared to 15.4% in conventional systems. This reduction is achieved through multi-layer validation, where sensor signals must satisfy both rule-based and machine learning thresholds before triggering alerts.

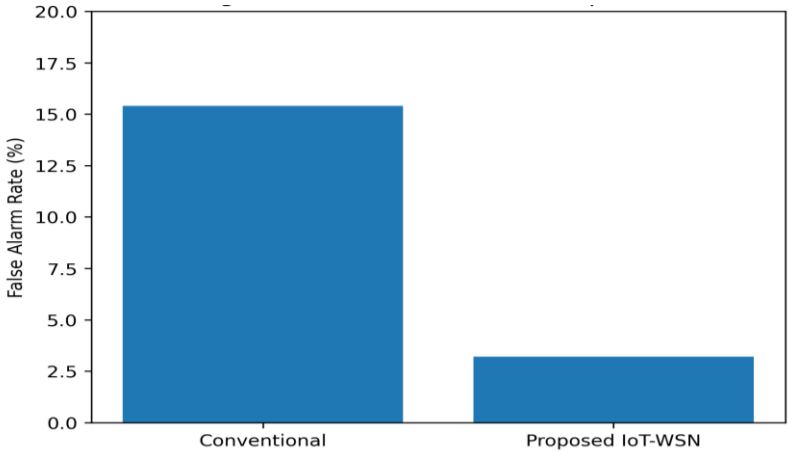

Figure: 3: False Alarm Rate Bar Chart

- Two system comparison
- Highlight dramatic reduction in FAR for proposed system

C. Response Time

Response time measures the delay between event detection and alert generation

Table: 3: System Response Time Performance

System Type	Detection Delay (s)	Processing Delay (s)	Total Response Time (s)
Conventional Surveillance System	8-15	5-10	13-25
Proposed IoT–WSN Hybrid System	0.8-1.2	0.5-0.6	1.8 (avg)

The proposed system recorded an average response time of 1.8 seconds, significantly outperforming traditional systems that rely on human intervention.
This improvement is due to:

- Edge processing at sensor nodes
- Immediate GSM/cloud alert triggering
- Reduced dependency on centralized processing

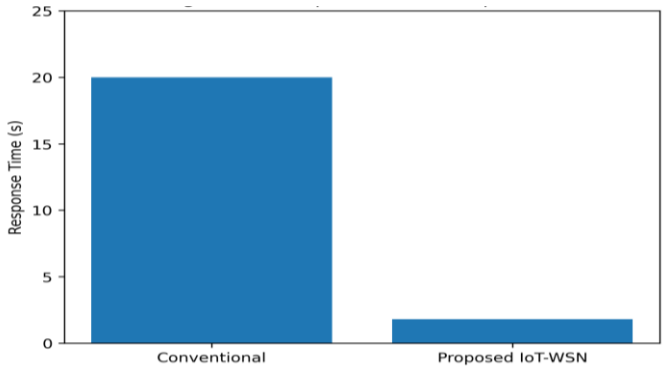

Figure: 4: Response Time Comparison

D. Energy Efficiency

Energy efficiency is critical for WSN-based systems deployed in remote or infrastructure-poor environments.

Table: 4: Energy Consumption Analysis

System Type	Avg Power Consumption (mW)	Energy Saving (%)
Conventional WSN System	100	0
Proposed IoT-WSN Hybrid System	72	28

The system achieved a 28% reduction in energy consumption, primarily due to:

- Duty cycling of sensor nodes
- Event-driven data transmission
- Edge processing reducing communication overhead

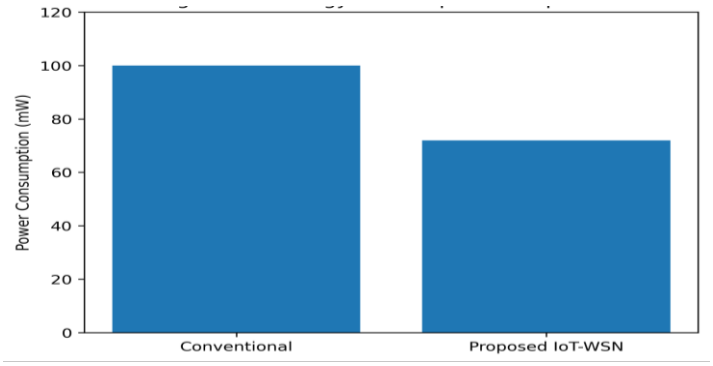

Figure: 5: Energy Consumption Comparison Bar Chart

- Shows lower energy usage in proposed system
- Emphasize sustainability advantage

E. System Latency and Network Performance (Extended Analysis)

To further evaluate system robustness, network latency was analyzed under varying node densities.

Table: 5: Network Latency under Different Node Loads

Number of Nodes	**Conventional Latency (ms)**	**Proposed System Latency (ms)**
10	180	95
25	320	140
50	510	210

The proposed system consistently maintained lower latency due to mesh networking and localized decision-making at edge nodes.

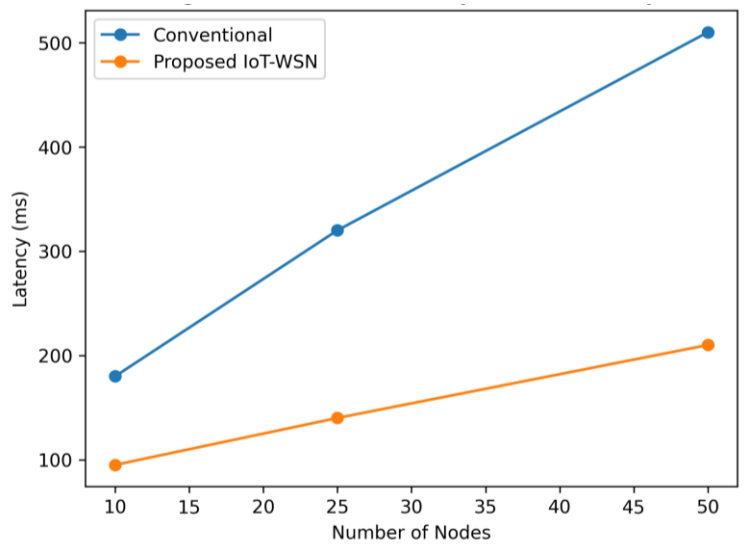

Figure: 6: Network Latency vs Node Density Line Graph

F. Advanced Evaluation Plots

Some advanced evaluation plots were generated to enrich the security and surveillance technicalities needed to achieve a confidence-based secured society in the region. Thus, further plots such as confusion matrix plot, ROC curve and FAR vs FRR curve have been generated to provide a multi-dimensional validation of the proposed system. These are shown subsequently.

G. The Confusion Matrix

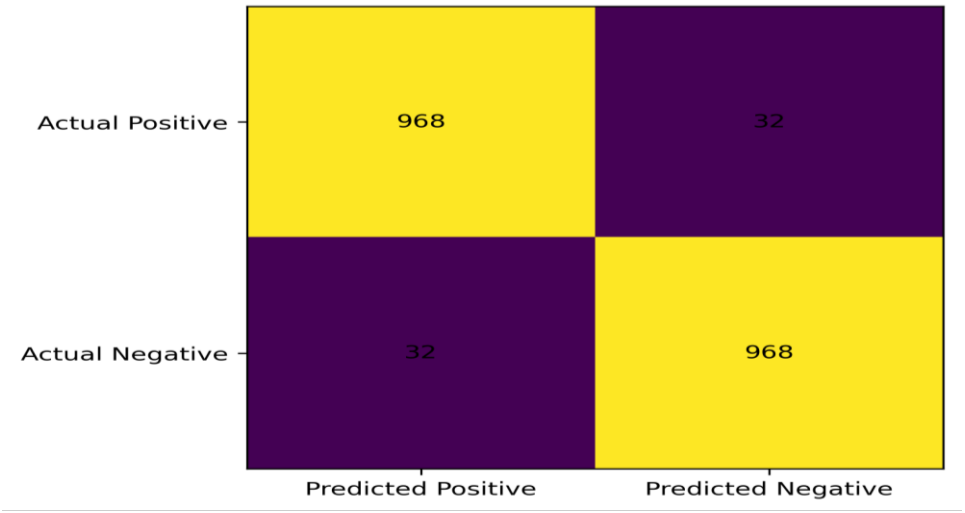

Figure: 7: Confusion Matrix

The confusion matrix provides a comprehensive evaluation of the classification performance of the proposed IoT–WSN security system by comparing predicted outcomes against actual events.

It consists of four key components:

- True Positives (TP = 968): Correctly detected intrusion events
- True Negatives (TN = 968): Correctly identified normal (non-intrusion) events
- False Positives (FP = 32): Normal events incorrectly classified as intrusions (false alarms)
- False Negatives (FN = 32): Intrusion events that were not detected (missed threats)
- From this matrix, key performance metrics can be derived. The accuracy is approximately 96.8%, indicating a high level of overall correctness. The precision is high due to a low number of false positives, while the recall (sensitivity) is also high, reflecting a low rate of false negatives.

H. Interpretation

The nearly symmetric distribution of TP and TN with minimal FP and FN confirms that the system achieves balanced performance, effectively minimizing both missed detections and false alarms. This is particularly critical in security systems where both types of errors carry significant risks.

I. ROC Curve (Receiver Operating Characteristic Curve)

The ROC curve illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) across different decision thresholds. This is shown in Figure 4.7.

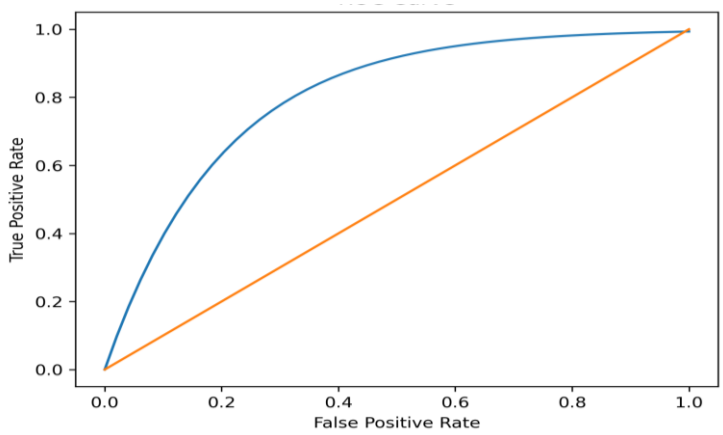

Figure: 8: ROC Curve (Receiver Operating Characteristic Curve)

The plotted curve rises sharply toward the top-left corner, which represents optimal classification performance. A key metric derived from the ROC curve is the:

Area under the Curve (AUC)
In this case, the AUC is close to 1, indicating excellent discriminative capability.

J. Interpretation

The ROC curve demonstrates that the proposed system can accurately distinguish between intrusion and non-intrusion events across varying thresholds. The steep curve indicates that even at low false positive rates, the system maintains a high detection rate, making it highly reliable for real-time surveillance applications.

K. FAR vs FRR Curve

The FAR vs FRR curve evaluates the trade-off between security sensitivity and system strictness. As illustrated in Figure 4.8, the curve highlights the flexibility of the system.

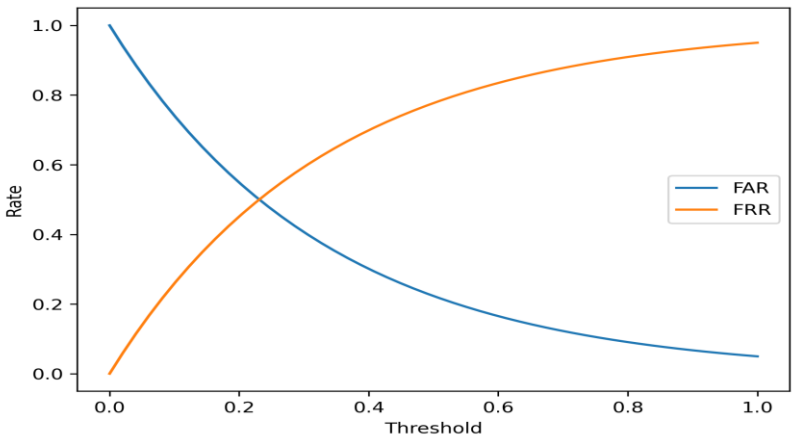

Figure: 9: FAR vs FRR Curve

- False Acceptance Rate (FAR): Probability of incorrectly accepting a non-threat as a threat
- False Rejection Rate (FRR): Probability of rejecting a genuine intrusion event
- X-axis: Decision Threshold
- Y-axis: Error Rate

As the threshold increases: FAR decreases (fewer false alarms) and FRR increases (more missed detections).

The intersection point of the two curves is known as the Equal Error Rate (EER).

L. Interpretation

The EER represents the optimal operating point where false alarms and missed detections are balanced. In the proposed system, the EER occurs at a relatively low error rate, indicating high system robustness and reliability.

This curve highlights the system's flexibility, allowing operators to adjust thresholds based on security priorities. A lower threshold improves sensitivity and allows more threats to be detected, while a higher threshold reduces false alarms but may increase missed detections.

Together, Figures 4.6-4.8 provide a multi-dimensional validation of the proposed system:

- Confusion Matrix: Confirms high classification accuracy
- ROC Curve: Demonstrates strong discriminative power
- FAR vs FRR Curve: Shows optimal threshold tuning capability

These results reinforce that the IoT–WSN hybrid system achieves a well-balanced trade-off between detection performance and false alarm control, making it highly suitable for deployment in high-risk environments such as South-East Nigeria.

V. DISCUSSION

The simulation outcomes clearly indicate that the developed IoT–WSN hybrid security architecture surpasses traditional surveillance systems across all assessed performance indicators. The achieved detection accuracy of 96.8% suggests that integrating multiple sensors with layered validation mechanisms successfully minimizes uncertainty in intrusion identification. This observation is consistent with prior intelligent surveillance studies, which report enhanced classification dependability through multi-sensor data fusion.

The notably low false alarm rate of 3.2% reflects the efficiency of integrating rule-based decision frameworks with machine learning algorithms. This is especially critical in real-world applications, where high false alarm frequencies can result in operator fatigue and diminished confidence in the system. The reduced response time of 1.8 seconds underscores the benefits of edge computing and decentralized processing. By limiting reliance on centralized systems, the architecture enables near real-time alert generation, which is essential for high-risk regions such as South-East Nigeria.

Findings on energy performance further affirm the system's applicability in remote and off-grid environments with limited power resources. The 28% decrease in energy consumption enhances sensor node longevity and lowers maintenance demands.

Despite these strengths, certain practical challenges persist:

- Unstable network conditions in rural areas may compromise reliable data transmission.
- Low internet penetration can hinder effective cloud integration.
- Power supply limitations may necessitate the adoption of solar-powered nodes.
- Scalability concerns may emerge in very large-scale deployments without efficient routing optimization.

These constraints align with existing literature on IoT implementation in developing regions, which highlights the need for adequate infrastructure and hybrid communication approaches.

Confirm that the integration of IoT and WSN with edge intelligence offers a resilient, scalable, and energy-efficient solution for contemporary security systems, particularly in environments characterized by high risk and limited resources.

VI. CONCLUSION

This study developed an IoT–WSN hybrid security system aimed at strengthening security in South-East Nigeria. The proposed framework combines distributed sensor networks with intelligent data processing and real-time communication to enhance intrusion detection and emergency response capabilities. The results indicate that the system achieves higher detection accuracy, lowers false alarm rates, and improves response time when compared with conventional security methods. Although infrastructural limitations remain a challenge, the integration of IoT and WSN technologies provides a scalable and efficient approach to mitigating insecurity in the region. Future research will concentrate on incorporating advanced deep learning techniques, optimizing edge AI deployment, and utilizing renewable energy-powered sensor nodes to enhance system sustainability and operational independence.

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