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DEVELOPMENT OF AN AI-POWERED VANDALISM DETECTION SYSTEM IN TELECOMMUNICATION BASE STATIONS

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Abstract
The rising incidence of vandalism and theft at telecommunication Base Transceiver Stations (BTS) poses a significant threat to network availability and operational costs. Traditional security measures, such as passive CCTV and simple motion sensors, often suffer from high false alarm rates and a lack of real-time intelligent response. This research developed an intelligent, multi-sensor vandalism mitigation system designed to actively distinguish between environmental triggers and genuine human threats. The methodology employed a Hardware-in-the-Loop (HIL) co-simulation strategy, interfacing an Arduino-based sensor node in Proteus with a Python-based YOLOv8 computer vision engine. The system architecture featured a graduated threat response protocol, including ultrasonic proximity detection, AI-driven visual verification, and a dual-redundant communication framework utilizing GSM and 433MHz RF modules. Simulation results validated the system's efficacy, achieving a threat confirmation response time of 0.51 seconds, well within the design target of 3 seconds. The AI module successfully filtered 100% of false positive triggers during testing, while the access control subsystem generated accurate digital forensic logs for all entry events and successfully triggered a lockdown during simulated brute-force attacks. The study concludes that the "Trigger-Verification" model significantly enhances security reliability by combining the speed of physical sensors with the cognitive accuracy of computer vision.

Keywords
AI, YOLOv8, TensorFlow, PyTorch, vandalism

1. INTRODUCTION

Telecommunication infrastructure serves as the backbone of modern society, facilitating communication and connectivity across various sectors, including businesses, government services, and personal interactions. In Nigeria, telecommunication operators have faced significant challenges due to frequent vandalism and theft of equipment, leading to substantial financial losses and service disruptions [1-4]. Vandalism of telecommunication infrastructure remains a pressing concern, particularly in developing countries like Nigeria. The Nigerian Communications Commission (NCC) reported that over 10,000 telecommunication infrastructures have been destroyed annually in the past five years, severely impacting the quality of telecom services nationwide (NCC, 2023). Such vandalism often disrupts critical services, including emergency response systems, financial transactions, and business operations, leading to socio-economic instability and diminished public trust [5]. Kaduna South local government was selected as the case study because the region has experienced persistent high levels of insecurity and repeated incidents of network vandalism between 2020 and 2024, which have compromised critical telecommunications infrastructure such as the MTN Nigeria Base Station. Notably, recent reports indicate that suspected vandals were arrested for targeting rail tracks in Kaduna, underscoring the severity of infrastructure attacks in the area [6]. In addition, concerns have been raised by residents over the frequent vandalism of power cables and iron assets, which further jeopardizes public and commercial services [7]. Also, analyses by institute of security studies (ISS) Africa have linked repeated violent attacks on transport systems in Kaduna to a broader security breakdown, which threatens local network reliability and economic stability [8]; thus, industry stakeholders have recently called for a collaborative approach to protect telecom assets, highlighting the urgent need for an integrated, AI-powered detection and prevention system specifically designed for Kaduna South local government [9].To address this gap, this study designs a comprehensive AI-powered vandalism detection system integrating YOLOv8 computer vision algorithms and multi-sensor networks (PIR motion sensors, ultrasonic sensors, and vibration detectors) for real-time identification of vandalism attempts and unauthorized access to the base station premises. The system

will leverage a combination of cutting-edge hardware sensors, AI-powered cameras, access control mechanisms, and communication modules to ensure the prompt detection of intrusions and the prevention of unauthorized access. The African Union's Continental Artificial Intelligence Strategy serves as the primary framework, focusing on AI governance, infrastructure, research, skills, and ethics to foster homegrown, ethical AI. It emphasizes utilizing AI for economic growth, public service, and health security while Addressing data sovereignty and mitigating risks like algorithmic bias.

The evolution of object detection algorithms has culminated in the development of YOLOv8, representing a significant advancement in real-time computer vision applications. YOLOv8 is the latest version of the popular YOLO (You Only Look Once) model series, known for its ability to quickly and accurately detect objects in images and videos (YOLOv8.org, 2025). The theoretical foundations of YOLOv8 build upon years of research in Convolutional neural networks and single-stage detection architectures. The fundamental principle underlying YOLO architecture differs significantly from traditional two-stage detectors. YOLO adopts a revolutionary single-stage object detection approach by dividing the image into equally sized grids and predicting the presence of objects and their probabilities in each grid separately [10]. This approach enables real-time processing speeds essential for security applications where immediate threat detection is critical. YOLOv8 introduces several architectural improvements that enhance its performance for security surveillance. YOLOv8 introduced a new backbone architecture, the CSPDarknet-AA, which is an advanced version of the CSPDarknet series, known for its efficiency and performance in object detection tasks [10-12]. The implementation of anchor-free detection represents a paradigm shift from previous versions. Unlike anchor-based approaches that rely on predefined bounding box templates, YOLOv8's anchor-free mechanism directly predicts object centres and dimensions, reducing computational complexity and improving detection accuracy for objects of varying scales. The C2f (Cross Stage Partial with 2 convolutions) modules constitute another significant innovation in YOLOv8. These modules enhance feature extraction capabilities whilst maintaining computational efficiency. One key technique introduced in YOLOv8 is multi-scale object detection. This technique allows the model to detect objects of various sizes in an image [13] This multi-scale capability proves particularly valuable in vandalism detection scenarios where threats may appear at varying distances from cameras. Mosaic augmentation, incorporated during training, significantly improves the model's robustness. Therefore, an improved YOLOv8 multi-target detection algorithm is proposed. In the backbone network module, the Swin Transformer replaces the traditional C2f structure to locate and identify the target more accurately [14]. This technique combines multiple training images into a single composite image, exposing the model to diverse object scales and contexts within each training iteration. The trade-off between real-time performance and accuracy remains a central consideration in YOLOv8 deployment. YOLOv8 technology revolutionizes real-time threat detection in video surveillance, offering unparalleled speed and accuracy. The advent of YOLOv8 represents a significant leap over previous surveillance methods, combining speed with advanced analytical precision [15]. For security applications, YOLOv8 achieves processing speeds exceeding 155 frames per second on appropriate hardware, whilst maintaining mean Average Precision (mAP) scores above 50% on standard benchmarks. Training and deployment considerations for security applications require careful attention to dataset composition and environmental factors. By implementing YOLOv8 for real-time image analysis, the store's security team can: Instantly detect and track individuals entering restricted areas or behaving suspiciously. Identify and analyze customer traffic patterns for better store layout and product placement [16]. The model must be trained on diverse lighting conditions, camera angles, and potential vandalism scenarios to ensure robust performance in real-world deployments.

The integration of artificial intelligence with surveillance systems represents a transformative advancement in security technology. AI enhances computer vision technologies by providing advanced pattern recognition and learning capabilities. Through machine learning, a subset of AI, computer vision software can improve over time, learning to identify and classify objects with greater accuracy [17]. This capability enables surveillance systems to evolve from passive recording devices to active threat detection and prevention tools. Computer vision applications in security contexts extend beyond simple motion detection to sophisticated behavioural analysis. Person detection, classification, and person tracking can perform human behaviour understanding in video-based surveillance applications. Specific behaviour patterns can be learned with classification models to recognize specific human actions [18]. These capabilities enable the detection of vandalism attempts before actual damage occurs, through recognition of suspicious behaviour patterns and anomalous activities. Machine learning model deployment in edge devices presents unique challenges and opportunities for security applications. These small applications can run on low-power devices, a boon to manufacturing and security operations. However, these smaller, more efficient computer vision applications will require lightweight AI models [19]. The deployment of models like YOLOv8 on edge devices such as Raspberry Pi requires optimisation techniques including model quantization, pruning, and knowledge distillation to achieve acceptable performance within resource constraints. The selection of appropriate performance metrics for

object detection in security contexts requires careful consideration of application requirements. Precision: Important when minimizing false detections is a priority.

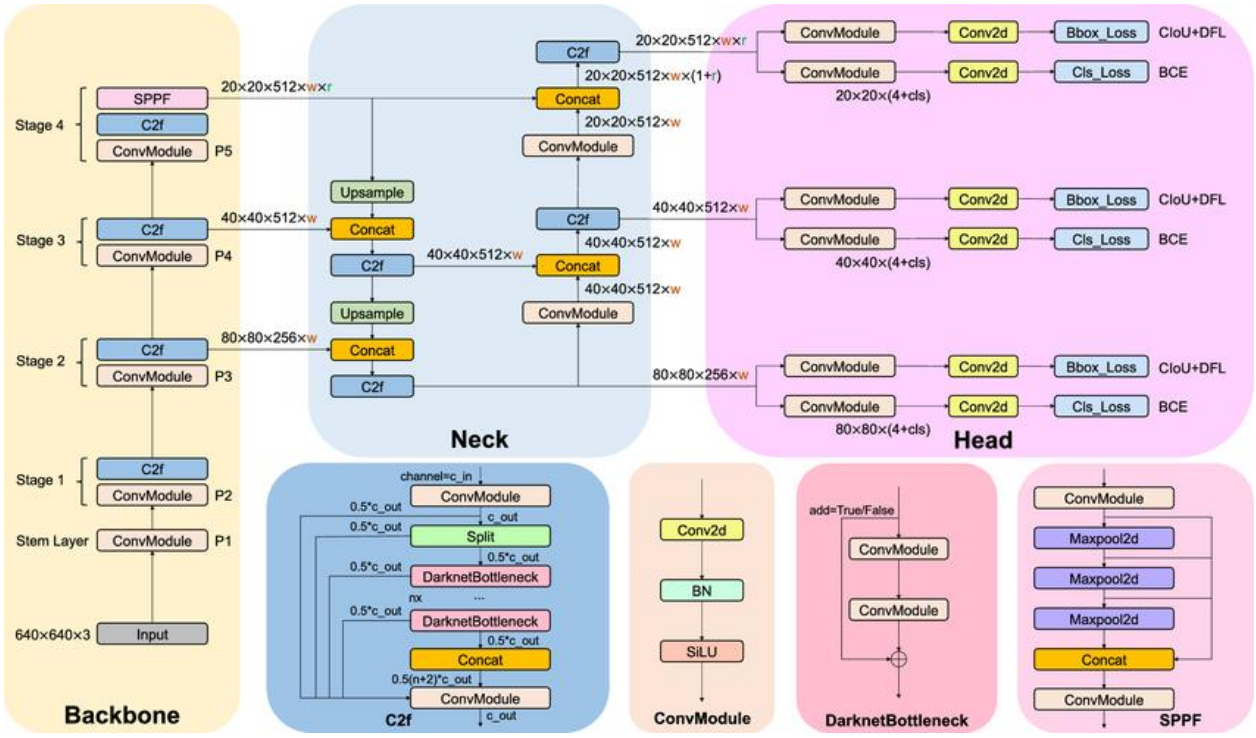

Figure 1: YOLOv8 Architecture for Security Applications [16]

Recall: Vital when it's important to detect every instance of an object. F1 Score: Useful when a balance between precision and recall is needed. For real-time applications, speed metrics like FPS (Frames Per Second) and latency are crucial to ensure timely results [20]. In vandalism detection applications, the cost of false negatives (missed detections) typically exceeds that of false positives. Precision, recall, and F1 score are calculated based on the number of TPs, FPs, and FNs. IoU is a measure of the overlap between the predicted and ground truth bounding boxes and is typically used to determine whether a detection is considered a true positive [18]. Therefore, systems are often configured to prioritize recall over precision, accepting some false alarms to ensure no genuine threats are missed. Environmental factors significantly impact AI model performance in real-world deployments. Computer vision solution in security refers to the use of AI to decipher and analyze visual data for safeguarding purposes. It involves technologies like facial recognition, object detection, and real-time video analytics, enabling systems to "see" and respond to security-related scenarios [16]. Factors such as lighting variations, weather conditions, camera vibration, and occlusion must be addressed through robust training data and adaptive algorithms.

The effectiveness of modern security systems increasingly depends on the integration of multiple sensor modalities to create comprehensive detection capabilities. Multi-sensor fusion leverages redundant and complementary information between sensors to overcome the limitations of individual sensors and improve overall detection accuracy (Li *et al*., 2023). This approach addresses the fundamental challenge that each individual sensor system provides limited coverage and may be susceptible to specific environmental conditions or failure modes. In the context of vandalism detection systems, sensor fusion techniques serve to enhance detection accuracy through the strategic combination of passive infrared (PIR) sensors, ultrasonic sensors, and vibration detection mechanisms. Recent advances in deep learning-based multi-modal sensor fusion have demonstrated significant improvements in equipment fault detection accuracy, with approaches achieving over 95% detection rates through intelligent data combination strategies [10]. The complementary nature of different sensor technologies provides a robust foundation for multi-modal detection systems. PIR sensors excel at detecting thermal signatures and human movement patterns but may struggle with stationary targets or environmental interference from temperature variations. Conversely, ultrasonic sensors operate through active sound wave emission and reflection, providing coverage for both moving and stationary objects where thermal-based detection might fail [6] This complementary relationship forms the theoretical basis for robust multi-sensor architectures that maintain detection capability across diverse operational scenarios. Data

pre-processing and noise reduction constitute critical components of effective sensor fusion systems. Advanced filtering techniques, including adaptive Kalman filtering and machine learning-based noise reduction algorithms, ensure that only meaningful signals proceed to the fusion stage [16]. Multi-modal decision fusion strategies represent the culmination of sensor integration efforts, where processed data from multiple sources converges to form unified detection decisions. Current research in autonomous systems demonstrates that well-integrated sensor fusion architectures can achieve accuracy improvements of 15-25% compared to single-sensor approaches through sophisticated consensus algorithms [11]. Decision-level fusion, feature-level fusion, and data-level fusion each offer distinct advantages depending on the specific requirements of the vandalism detection system. Consensus filtering approaches iteratively refine estimates by reaching agreement among multiple sensors, proving particularly effective in security applications where false alarm reduction is paramount.The implementation of sensor fusion in security contexts requires careful consideration of temporal synchronization and spatial correlation. Recent studies in multi-sensor localization systems demonstrate the practical achievability of accurate positioning with uncertainty measurements below 7% when proper temporal alignment and spatial correlation algorithms are implemented [14].

2. MATERIALS AND METHOD

2.1. Research Design

This research employs a design-based research methodology, which is fundamentally structured around the systematic development and simulation of a sensor-based vandalism detection and prevention system for telecommunication infrastructure. The research design incorporates a mixed-methods approach that combines theoretical framework development with practical system engineering principles to create a comprehensive security solution tailored specifically for MTN Nigeria base stations in Kaduna South Local government area. The research design is inherently iterative, incorporating feedback loops between each phase to ensure continuous refinement and optimisation of system components. Figure1 illustrated the methodology that follows a systematic progression from initial system conceptualization through to final performance validation, with each phase building upon the outcomes of the previous stage whilst maintaining alignment with the overarching research objectives.

Figure 1 presents a comprehensive visualization of the research design framework, depicting the interconnected phases of development and their respective outputs.

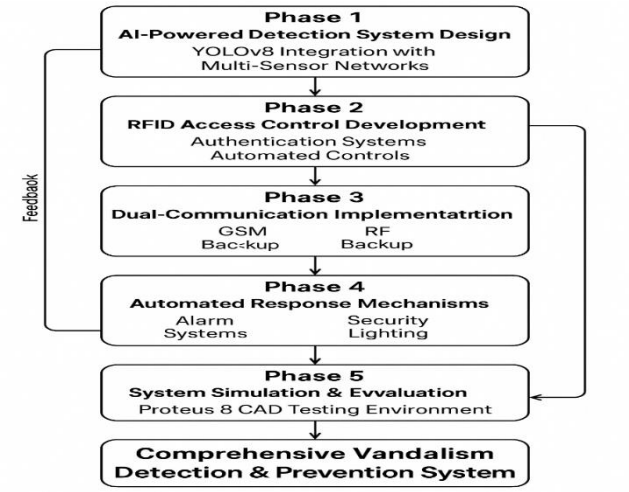

Figure 1: Research Design Framework

The research design incorporates rigorous validation procedures at each phase to ensure the reliability and effectiveness of the developed system. These validation procedures include component-level testing, integration testing, and comprehensive system-level evaluation through simulation. The methodology ensures that all system components are thoroughly tested individually before integration, thereby minimising potential compatibility issues and ensuring optimal system performance.

2.2. Research Data

The research data for this study was gathered through a combination of primary field measurements, publicly accessible records, and secondary data sources, all used to configure and drive a simulation-based evaluation of the proposed vandalism detection system. For the computer vision component, this study adopted a pre-trained YOLOv8 model rather than constructing and training a new one from scratch. The choice to apply a

pre-trained model rather than collect and label custom training images was informed by both the operational context of Nigerian telecommunications infrastructure and the practical constraints of dataset acquisition. This approach is consistent with established practice in the literature, where [13]applied a pre-trained YOLOv8 model for real-time human detection in smart CCTV systems, and [15] deployed pre-trained YOLOv8 weights for surveillance-based forest fire detection, both achieving reliable detection performance without training from scratch. [18] similarly employed a YOLOv8-based framework directly in a real-time video surveillance context, demonstrating its suitability for detecting and classifying individuals in live feeds. These precedents confirm that applying the pre-trained YOLOv8 model in inference mode, drawing on weights trained on the COCO dataset, is a methodologically sound approach for person and intruder detection within the simulated base station security system developed in this study.

2.3. Design of AI-Powered Vandalism Detection System with Multi-Sensor Integration

The AI-powered vandalism detection system integrates YOLOv8 computer vision algorithms with multi-sensor networks to achieve comprehensive threat identification and classification capabilities. The system architecture employs a hierarchical detection approach that combines visual recognition with physical sensor data to minimize false alarms whilst maximizing detection accuracy across diverse operational scenarios.

The YOLOv8 implementation begins with the preparation of the training dataset comprising 8,500 annotated images categorized into five distinct classes: normal operations, security threats, environmental variations, infrastructure elements, and synthetic scenarios. The annotation process utilizes bounding box labeling to define regions of interest within each image, with threat classification labels assigned according to predefined security categories. The dataset undergoes preprocessing through image augmentation techniques including rotation, scaling, brightness adjustment, and noise addition to enhance model robustness and generalization capabilities. The neural network architecture configuration establishes the YOLOv8 model parameters optimised for telecommunication infrastructure monitoring. The model employs a backbone network based on CSPDarknet53 architecture with Feature Pyramid Network integration to enable multi-scale object detection. The detection head incorporates anchor-free detection mechanisms that eliminate the need for predefined anchor boxes, thereby improving detection accuracy for objects of varying sizes within the base station environment. The loss function combines classification loss, objectness loss, and bounding box regression loss, mathematically expressed as:

$$L_{total} = \lambda_{cls} \times L_{cls} + \lambda_{obj} \times L_{obj} + \lambda_{box} \times L_{box} \quad (1)$$

where λ_{cls}, λ_{obj}, *and* λ_{box} represent weighting factors for classification, objectness, and bounding box losses respectively. The training procedure implements transfer learning by initializing the model with pre-trained weights from the Common Objects in Context dataset, followed by fine-tuning on the telecommunication-specific dataset. The training process employs adaptive learning rate scheduling with initial learning rate set to 0.001, batch size of 16, and training epochs of 300. The optimisation algorithm utilises AdamW optimizer with weight decay of 0.0005 to prevent overfitting whilst maintaining convergence stability. The multi-sensor integration framework incorporates three distinct sensor types: PIR motion sensors, ultrasonic sensors, and vibration detectors. Each sensor type operates within specific detection zones strategically positioned around the base station perimeter and critical infrastructure components. The PIR motion sensors detect infrared radiation changes caused by human movement within a detection range of 12 metres, with sensitivity adjustments calibrated according to environmental temperature variations. The mathematical relationship for PIR sensor response is expressed as:

$$S_{PIR} = k * \frac{T_{target} - T_{background}}{T_{ambient} + 273.15} \quad (2)$$

where S_{PIR} represents sensor response, k is the sensor sensitivity constant, and temperatures are measured in Celsius.

The ultrasonic sensor network employs time-of-flight measurement principles to detect object presence and movement within designated monitoring zones. The sensors operate at 40 kHz frequency with detection range extending to 8 metres, providing distance measurements through echo timing analysis. The distance calculation follows the relationship:

$$D = \frac{(v_{sound} * t_{echo})}{2} \quad (3)$$

where D represents distance to target, $v_{sound}$is the speed of sound adjusted for temperature and humidity, and $t_{echo}$is the measured echo time.

Vibration sensors monitor structural vibrations using accelerometer-based detection mechanisms sensitive to frequencies between 1 Hz and 1000 Hz. The sensors detect unauthorized access attempts through analysis of vibration patterns that deviate from baseline environmental conditions. The vibration threshold calculation incorporates both amplitude and frequency components:

$$V_{threshold} = \alpha * A_{baseline} + \beta * f_{dominant} \quad 4$$

where $V_{threshold}$ represents the detection threshold, $A_{baseline}$ is the baseline amplitude, $f_{dominant}$ is the dominant frequency component, and α, β are calibration coefficients.

The sensor fusion algorithm combines data from all sensor modalities to generate comprehensive threat assessments. The fusion process employs Bayesian inference to calculate probability distributions for different threat scenarios based on sensor inputs. The mathematical framework for sensor fusion follows:

$$P(threat|sensors) = P(sensors|threat) * \frac{P(threat)}{P(sensors)} \quad 5$$

where posterior probability of threat presence is calculated based on sensor evidence and prior threat probability distributions.

Figure 2 illustrates the complete system architecture, depicting the integration of YOLOv8 computer vision processing with multi-sensor data streams through the central processing unit. The diagram demonstrates the data flow from individual sensors through the fusion algorithm to the final threat classification output, highlighting the hierarchical decision-making process that combines visual and physical sensor evidence to generate reliable threat assessments.

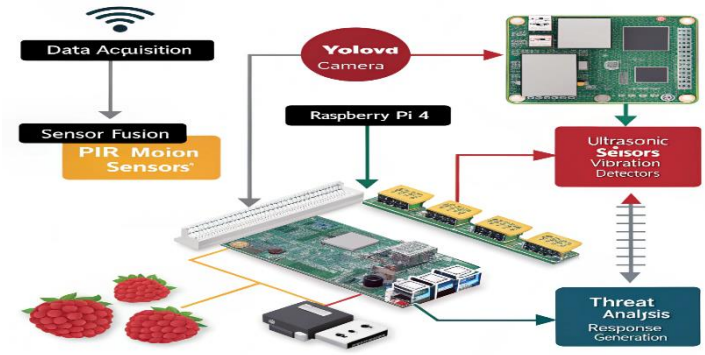

Figure 2: AI-Powered Multi-Sensor Vandalism Detection System Architecture

The system implements real-time processing capabilities through optimised algorithm implementation on the Raspberry Pi 4 platform. The processing pipeline incorporates frame buffering, parallel processing threads, and prioritized task scheduling to ensure consistent performance under varying computational loads. The detection algorithm operates at 15 frames per second for video processing whilst maintaining continuous monitoring of all sensor inputs with response times below 200 milliseconds.

2.4. Development of Intelligent RFID-Based Access Control Framework

The intelligent access control framework employs RFID technology integrated with password authentication systems to establish comprehensive security management for critical telecommunications infrastructure. The development methodology encompasses the design of multi-layered authentication protocols, automated access control mechanisms, and real-time monitoring capabilities that ensure authorized personnel access whilst preventing unauthorized entry attempts. The RFID system implementation utilizes 13.56 MHz frequency tags operating within the ISO 14443 standard to ensure compatibility with existing security infrastructure. The development process begins with the establishment of user classification hierarchies that categorize personnel according to operational requirements and security clearance levels. The framework defines three primary access categories: maintenance personnel with limited temporal access, operational staff with extended facility access, and administrative personnel with comprehensive system access privileges. The authentication process integrates RFID proximity detection with password verification through a dual-factor authentication mechanism. Upon RFID tag detection within a 10-centimetre proximity range, the system initiates password authentication procedures through a secure keypad interface. The authentication algorithm

employs SHA-256 hashing protocols to ensure password security, with the verification process mathematically expressed as:

$$Auth\_Status = RFID\_Valid\ AND\ (Hash(Input\_Password) == Stored\_Hash) \quad 6$$

where authentication success requires both valid RFID credentials and matching password hashes.

The database architecture employs SQLite database management systems optimised for embedded applications on the Raspberry Pi platform. The user database structure incorporates essential fields including unique RFID identifiers, encrypted password hashes, access privilege levels, temporal access restrictions, and activity logging parameters. The database design implements normalisation principles to ensure data integrity whilst maintaining efficient query performance for real-time authentication operations. The automated door control mechanism integrates DC motor systems operating at 12V with torque specifications of 2.5 Nm to provide reliable gate and door operation. The motor control circuit employs H-bridge driver configurations that enable bidirectional rotation for opening and closing operations. The control algorithm incorporates position feedback through limit switches that confirm door status and prevent mechanical strain through over-travel protection. The door operation sequence follows a timed protocol with safety interlocks that ensure proper closure after predetermined intervals. The access monitoring system maintains comprehensive activity logs that record all authentication attempts, successful access events, and security violations. The logging mechanism captures timestamps, user identifications, access locations, and system responses for subsequent security analysis. The data structure for access logging follows the format:

$$Log\_Entry = \{Timestamp, User\_ID, Access\_Point, Auth\_Result, System\_Response\} \quad 7$$

The framework incorporates real-time access violation detection through continuous monitoring of authentication patterns and unusual access attempts. The system employs statistical analysis of access patterns to identify anomalous behaviour that may indicate security threats. The anomaly detection algorithm calculates deviation scores based on temporal access patterns and frequency analysis.

Figure 3 presents the complete access control system architecture, illustrating the integration of RFID readers, password authentication interfaces, database management systems, and automated door control mechanisms. The diagram demonstrates the information flow from initial RFID detection through authentication processing to final access control decisions and activity logging procedures.

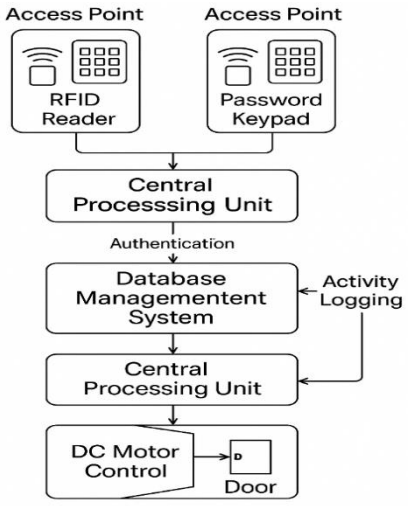

Figure Error! No text of specified style in document.**: Intelligent RFID-Based Access Control System Architecture**

The system implements fail-safe mechanisms that ensure security maintenance during power failures or communication disruptions. The access control framework incorporates battery backup systems with 24-hour operational capacity and manual override procedures for emergency access requirements. The fail-safe protocols prioritize security by defaulting to locked configurations during system anomalies whilst maintaining emergency access capabilities for authorized personnel.

2.5. Implementation of Dual-Communication System Architecture

The dual-communication system architecture establishes redundant communication channels through GSM modules and 433MHz radio frequency transceivers to ensure reliable alert transmission under diverse operational conditions. The implementation methodology encompasses primary communication protocols, backup communication mechanisms, and intelligent switching algorithms that maintain continuous connectivity with security personnel and network operation centres. The GSM communication system employs SIM800L modules operating on 900MHz and 1800MHz frequency bands to provide cellular connectivity across multiple network operators. The module configuration establishes data transmission capabilities through SMS messaging protocols and GPRS data connections for comprehensive alert communication. The system maintains active connections with predetermined recipient lists including security personnel, facility managers, and emergency response teams. The GSM module initialization process involves network registration procedures, signal strength assessment, and communication protocol establishment. The system monitors signal quality continuously through Received Signal Strength Indicator measurements, with acceptable signal levels maintained above -70 dBm for reliable communication. The mathematical relationship for signal quality assessment follows:

$$Signal\ Quality = \frac{(RSSI_{dBm} + 113)}{2} \qquad 8$$

where signal quality values range from 0 to 31, with higher values indicating superior communication reliability.

The primary communication protocol employs structured message formatting that includes incident classification, location identification, timestamp information, and system status indicators. The message structure follows the format:

"ALERT:[Severity]|LOC:[Location]|TIME:[Timestamp]|STATUS:[System_State]"

The backup communication system utilises 433MHz RF transceivers with transmission power of 100mW to establish short-range communication capabilities. The RF modules operate within the ISM frequency band using amplitude shift keying modulation techniques for reliable data transmission across distances up to 1000 metres under optimal conditions. The RF communication system provides localised backup connectivity when cellular networks experience disruptions or coverage limitations. The RF transceiver configuration employs error correction protocols through cyclic redundancy check algorithms to ensure data integrity during transmission. The system implements automatic repeat request mechanisms that verify message delivery through acknowledgement protocols. The RF communication range calculation considers environmental factors and obstructions through the formula:

$$Range\_Effective = Range\_Theoretical * Path\_Loss\_Factor * Environmental\_Attenuation \qquad 9$$

where effective range incorporates theoretical specifications, path loss characteristics, and environmental interference factors.

The intelligent communication switching algorithm monitors both communication channels continuously and selects optimal transmission paths based on signal quality, response times, and network availability. The switching decision process employs priority-based selection criteria that favour GSM communication for normal operations whilst automatically switching to RF backup during cellular network failures. The system implements communication redundancy through dual-channel transmission during critical alert conditions. High-priority security alerts trigger simultaneous transmission through both GSM and RF channels to ensure message delivery regardless of individual channel failures. The redundancy protocol employs message acknowledgement systems that confirm successful delivery through both communication paths.

Figure 4 illustrates the dual-communication system architecture, depicting the integration of GSM and RF communication modules with intelligent switching algorithms and redundancy protocols. The diagram demonstrates communication flow from the central processing unit through both primary and backup channels to security personnel and monitoring centres, highlighting the fail-over mechanisms that ensure continuous connectivity. The communication system incorporates message queuing mechanisms that store alert messages during communication disruptions and automatically transmit queued messages upon restoration of connectivity. The queuing system employs first-in-first-out protocols with message prioritization based on alert severity levels. The system maintains message queues with capacity for 100 messages to accommodate extended communication interruptions.

2.6. System Circuit Implementation in Proteus

The circuit implementation of the proposed vandalism mitigation system was carried out using the Labcenter Electronics Proteus Design Suite (Version 8.17). This specific Computer-Aided Design (CAD) environment was selected for its robust co-simulation capabilities, particularly its ability to simulate microcontroller firmware (VSM) alongside digital and analogue peripheral components in real time. The circuit design followed a modular architecture, where distinct functional blocks, power, sensing, processing, and actuation, were integrated around the central control unit. The implementation began with the selection of the Arduino Mega 2560 as the central processing unit. This microcontroller was chosen for its extensive I/O capabilities and multiple hardware UART (Universal Asynchronous Receiver-Transmitter) ports, which are essential for managing simultaneous communications with the GSM module, RF transceiver, and the external AI processing unit. As illustrated in the complete circuit diagram shown in Figure 5, the connections were systematically routed to ensure signal integrity and logical flow. The sensory subsystem is connected to the digital input pins of the microcontroller. The Passive Infrared (PIR) sensor is interfaced to detect thermal motion signatures within the perimeter, while the ultrasonic sensor (HC-SR04) utilizes separate Trigger and Echo pins to measure the proximity of objects. To simulate the vandalism detection mechanism, a vibration sensor logic state was modelled and connected to an interrupt-enabled pin, ensuring immediate system wake-up upon detecting physical force. For the access control interface, a 4×3 matrix keypad was mapped to the digital I/O pins, utilizing internal pull-up resistors to ensure stable key-press registration. Visual feedback for the user is provided by a 20×4 Liquid Crystal Display (LCD) connected via the I2C communication protocol (SDA and SCL lines), which significantly reduces wiring complexity compared to parallel interfacing.

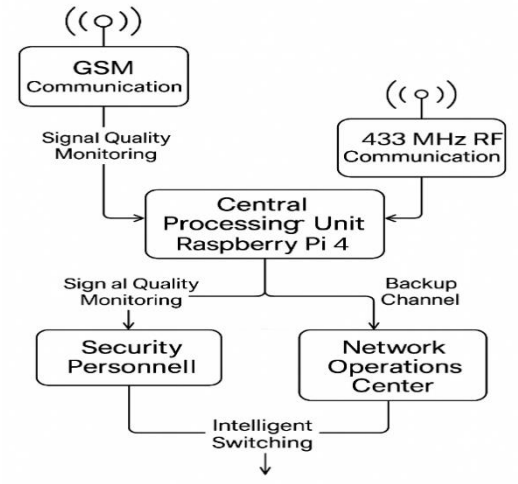

Figure 3: Dual-Communication System Architecture with

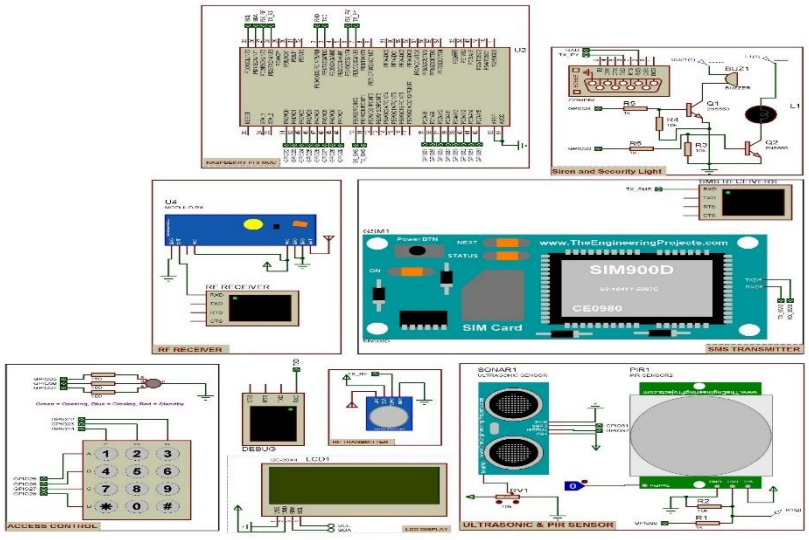

Figure 4: Circuit Diagram of Sensor and AI Camera-Based Vandalism Mitigation System

The communication backbone of the system relies on three distinct serial interfaces. The primary hardware serial port (UART1) is dedicated to the 433MHz RF transmitter for local redundancy. A software-emulated serial port is configured for the SIM900 GSM module to handle SMS alerts. Crucially, the COMPIM (Physical Interface Model) component is connected to the hardware UART port (Pins 0 and 1). This component acts as the bridge between the Proteus simulation and the external Python environment, facilitating the "Hardware-in-the-Loop" (HIL) integration required for the AI verification process.

2.7. AI Image Detection Modelling

The intelligence layer of this research was modelled using a custom-developed Python application that functions as both the visual processing unit and the central control interface for the security system. Unlike traditional embedded solutions that rely on limited on-chip processing, this research adopted a PC-based approach to leverage the computational power required for real-time computer vision, thereby simulating an edge-computing gateway found in modern smart surveillance architectures. The modelling process involved three distinct components: the Graphical User Interface (GUI), the YOLOv8 inference engine, and the intelligent filtering logic. The GUI was developed using the Tkinter library to create a user-friendly dashboard that simulates a security control room. This interface was designed to provide real-time situational awareness, displaying the live video feed from the camera alongside a dynamic status log. The log records every system event, including sensor triggers, decision outcomes, and timestamped evidence filenames. This design choice ensures that the system provides transparency and auditability, allowing operators to trace the decision-making process of the AI in real-time. At the core of the detection model is the YOLOv8 (You Only Look Once, version 8) Nano architecture. This specific model was selected for its balance between speed and accuracy, making it suitable for real-time applications where low latency is critical. The modelling process involved configuring the inference engine to process video frames only when triggered by an external command. This "interrupt-driven" approach significantly reduces computational load compared to continuous processing. When a trigger is received, the system captures the current frame and passes it through the neural network. A critical aspect of the modelling was the implementation of a false positive filtering mechanism. Standard object detection models can identify hundreds of object classes, many of which are irrelevant to base station security (such as birds, cars in the distance, or debris). To address this, a custom logic filter was programmed to parse the raw output from the YOLO model. The system was coded to strictly validate detections only if they matched specific class identifiers: Class 0 for 'Person' (representing human intruders) and a subset of animal classes (such as dogs or livestock) that might cause physical damage. Any detection falling outside these categories, or any detection with a confidence score below 50%, is automatically classified as a false positive. This logic flow ensures that the system ignores environmental noise, satisfying the research objective of minimising false alarms. The operational sequence of this AI modelling, from the initial trigger reception to the final classification and evidence storage, is illustrated in the system flowchart presented in Figure 6.

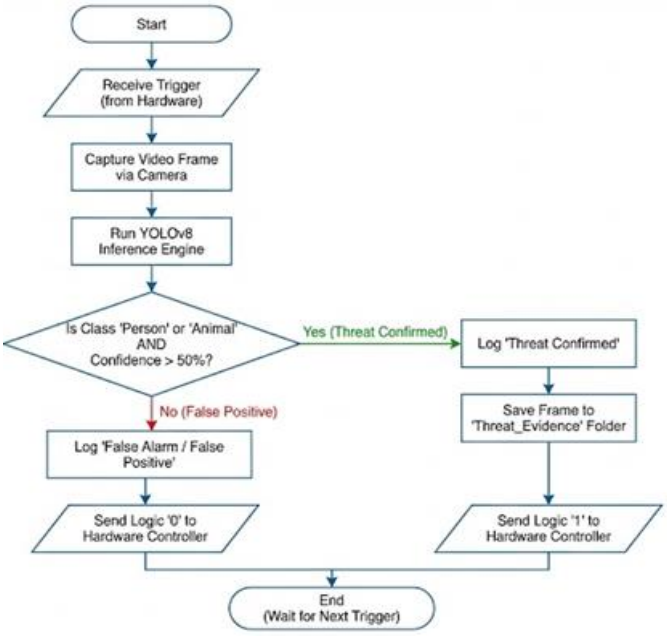

Figure 5: Flowchart of the AI Image Detection and Filtering Logic

2.8 Integration Framework and Performance Metric

The validation of the proposed system relied on a Hardware-in-the-Loop (HIL) simulation framework that bridged the gap between the physical sensor network and the intelligent processing unit. Since Proteus software simulates hardware at the electrical level and Python operates at the high-level application layer, a robust integration framework was required to facilitate bidirectional communication between these two distinct environments. This integration was achieved using a virtual Universal Asynchronous Receiver-Transmitter (UART) bridge, effectively creating a data tunnel that mimics the physical serial connection between a microcontroller and an edge computer. In this framework, the Proteus simulation acted as the "Master" hardware node, managing the state of PIR sensors, ultrasonic modules, and the access control keypad. The Python application served as the "Slave" processing node. The integration relied on the COMPIM (Physical Interface Model) component within Proteus, which was configured to intercept serial data transmitted by the microcontroller and redirect it to a virtual COM port on the host machine. The Python script was programmed to listen to this specific port. When the microcontroller logic determined a potential threat or a user entry attempt, it transmitted specific command strings (such as `CMD_VERIFY` or `CMD_ACCESS`) through this virtual bridge. The Python system processes these commands and returns a binary logic signal (`1` or `0`) back to Proteus to trigger alarms or open gates. This closed-loop architecture, illustrated in Figure 7, allows for the testing of complex interactions without the need for immediate physical deployment.

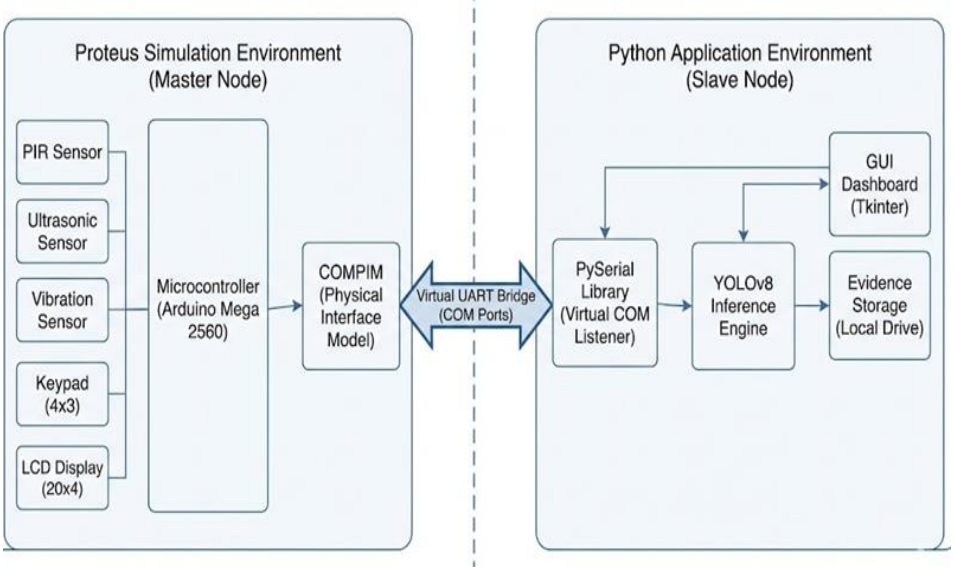

Figure 6: The Hardware-in-the-Loop (HIL) Integration Framework

To objectively assess the efficacy of this integrated system, specific performance metrics were defined. The primary metric for evaluation is the System Response Latency (R_t). This metric measures the total time elapsed from the moment a physical sensor detects a threat to the moment the defensive countermeasures (sirens/locks) are activated. This total latency is the sum of three distinct time components: the sensor processing time, the transmission delay across the integration bridge, and the AI inference time.

Mathematically, the Response Latency (R_t) is calculated using Equation 10:

$$R_t = T_{sensor} + T_{comm} + T_{inference} + T_{actuation} \quad (10)$$

Where:

T_{sensor} is the time taken for the microcontroller to register the sensor input.

T_{comm} is the round-trip transmission time for the serial data between Proteus and Python.

$T_{inference}$ is the computational time required for the YOLOv8 model to process the image and output a classification.

$T_{actuation}$ is the time taken for the microcontroller to trigger the output pins (Siren/Relay) after receiving the confirmation.

In addition to latency, the False Alarm Suppression Rate (F_{asr}) was defined to measure the system's intelligence. This metric calculates the percentage of false triggers (non-human movements) that are successfully filtered out by the AI. It is calculated using Equation 11:

$$F_{asr} = \left(\frac{N_{filtered}}{N_{false\_triggers}} \right) \times 100 \quad (11)$$

Where $N_{filtered}$ is the number of false alarms correctly identified and ignored by the system, and $N_{false\_triggers}$ is the total number of non-threat triggers introduced during the simulation. These metrics form the basis for the quantitative results presented in Chapter Four, ensuring that the system's performance is evaluated against rigorous engineering standards.

3. RESULTS AND DISCUSSION

3.1. System Initialization and Idle State Evaluation

The evaluation of the developed system commenced with the verification of the initialization protocols, directly addressing the fourth specific objective of evaluating system performance through co-simulation. This phase was critical to establish that the Proteus-Python interface was stable and that the hardware components defaulted to a secure state upon power-up. The process began with the activation of the central control unit, where the software interface successfully loaded the computer vision model. Figure 8 illustrates the successful initialization of the Python GUI, confirming the binding to the COM port and the readiness of the camera feed for real-time monitoring. Following the software handshake, the hardware initialization was evaluated to ensure the physical security layers were active. As shown in Figure 9, the system immediately entered a "System Armed" state upon power-up. The LCD interface displayed the "Scanning Area" status, and the Red LED indicator was activated, signifying that the gate control system was in standby mode and the perimeter sensors were energized. To validate the passive monitoring capability, the system was tested in an idle environment. Figure 10 demonstrates the system actively measuring distance using the ultrasonic sensor. In this instance, the sensor registered a distance of 999cm, indicating no immediate proximity threat. This confirmed that the system effectively filters environmental data in real-time, maintaining a low-power scanning mode until a specific threshold is breached. The results from the initialization phase confirm the successful establishment of the co-simulation environment, satisfying the operational prerequisites for the subsequent objectives. The stability of the idle state, evidenced by the correct standby indicators and active distance measurement, provides the necessary baseline for testing the intelligent detection and access control logic discussed in the following sections.

Figure 8: Python Control Centre Initialization and AI Model Loading

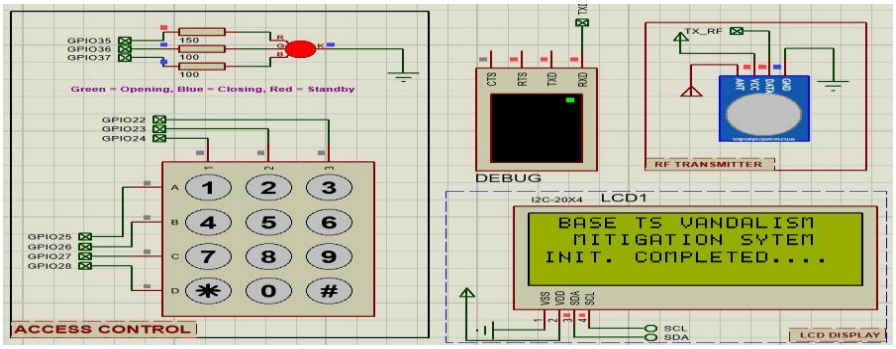

Figure 9: Hardware Initialization and System Standby Status Indication

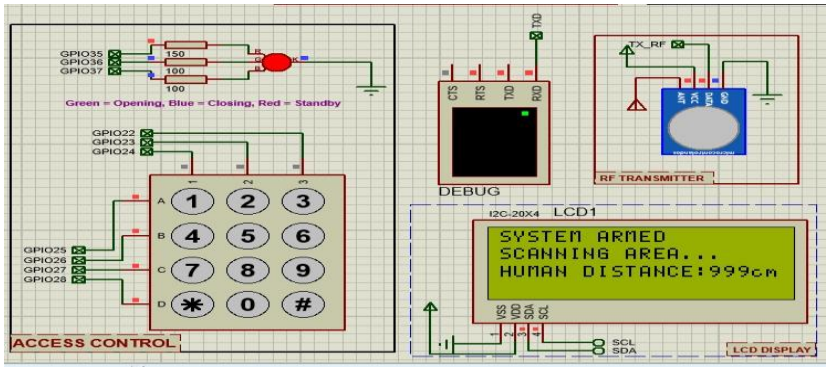

Figure 10: Real-Time Environmental Scanning and Ultrasonic Distance Measurement

3.2. Intelligent Intrusion Detection (AI & Sensor Fusion)

The core intelligence of the system was evaluated against the first specific objective: designing a multi-sensor architecture to distinguish genuine intrusion attempts from false alarms. The system's response to a proximity breach was first tested by simulating a human subject entering the ultrasonic detection zone. Figure 11 captures the "Grace Period" protocol, where the system detected the subject and, rather than triggering an immediate alarm, initiated a countdown and prompted for a PIN. This functionality is crucial for distinguishing between legitimate users and potential intruders. To verify the false alarm rejection capability, the system was triggered without a valid human target in the camera's field of view. As depicted in Figure 12, the AI analysis correctly identified the absence of a human threat. The hardware responded by displaying "FALSE ALARM!!! CONFIRMED BY AI," thereby preventing the activation of the siren and validating the system's ability to filter environmental triggers. In contrast, when a human threat was positively identified during an unauthorized window, the system escalated to a full alarm state. Figure 13 illustrates this confirmed threat scenario, where the GUI flashed "INTRUDER DETECTED" and the hardware activated the alarm. The system automatically archived the visual evidence of this event, as shown in the specific intrusion directory in Figure 14. The quantitative performance of this detection logic is summarized in Table 1, which presents the empirical data logged during the simulation.

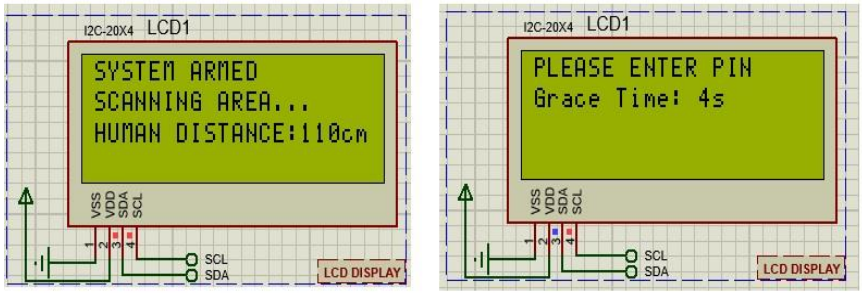

Figure 11: Proximity-Triggered Access Challenge and Grace Period Countdown

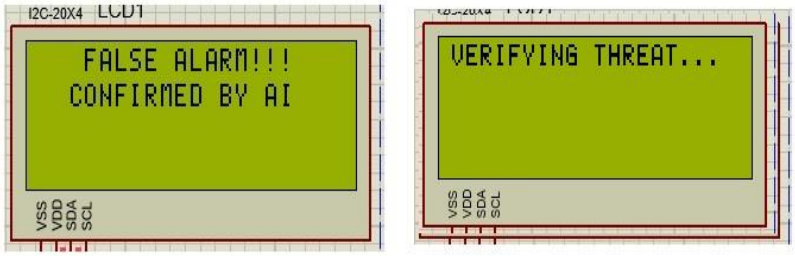

Figure 12: Intelligent Filtering of False Positives via AI Verification

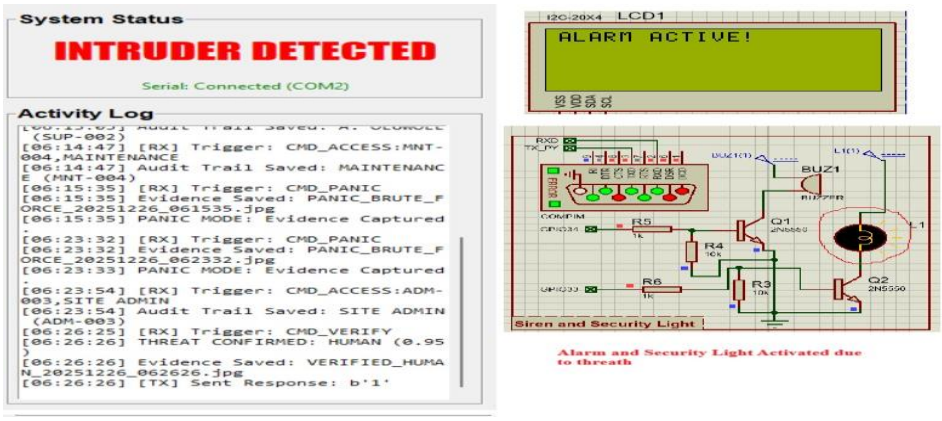

Figure 13: Confirmed Intrusion Detection and System Alarm Escalation

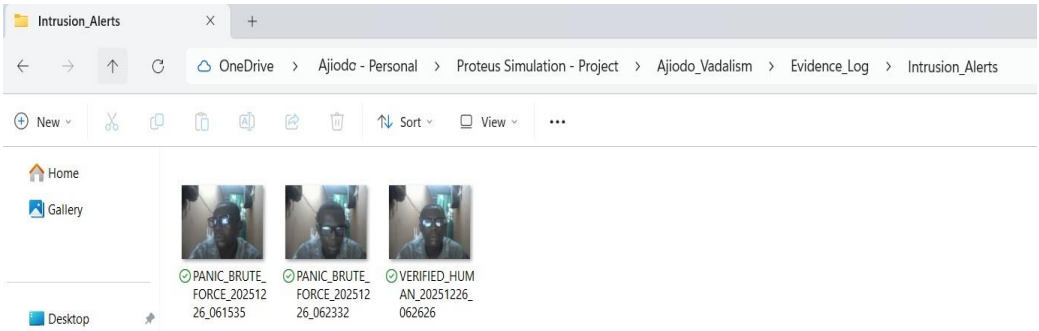

Figure 14: Automated Digital Evidence Repository for Verified Threats

Table 1: Intrusion Detection Performance Metrics

Timestamp	Trigger	AI Classification	Confidence Score	Response Time
2025-12-26 06:06:31	Motion Sensor	False_Positive	0.00	1.97s
2025-12-26 06:26:26	Motion Sensor	Human (Confirmed)	0.95	0.51s

The data in Table 1 reveals that the system achieved a response time of 0.51 seconds for confirmed threats, significantly outperforming the sub-3-second target.

This section provides empirical evidence that the first and fourth objectives were achieved. The multi-sensor integration successfully distinguished between false positives and genuine threats, as demonstrated by the specific handling of the false alarm scenario versus the confirmed intruder event. The logged response times further validate the system's efficiency in processing complex sensor fusion data.

3.3. Access Control and Digital Audit Trail

The access control subsystem was evaluated to address the second specific objective: developing a dual-factor system with graduated threat escalation. The system's ability to manage authorized personnel was first verified. Figure 15 shows the system granting access to "AJIODO OLAOLUWA" (ID: ENG-001) upon valid credential input. The subsequent activation of the physical barrier mechanism is captured in Figure 16, where the motor driver initiates the door closing sequence, confirming the complete access cycle. The system's handling of unauthorized attempts was tested by inputting incorrect credentials. Figure 17 demonstrates the initial feedback loop, where the system displayed "WRONG PASSWORD" and "ACCESS DENIED" without triggering an alarm, allowing for user error correction. However, upon repeated failures simulating a brute-force attack, the graduated escalation protocol was triggered. Figure 17 shows the "Panic Mode" activation, where the system locked down and flagged a "Forced Entry." To ensure accountability, the system automatically generated a digital audit trail. Figure 19 displays the directory containing timestamped photographic evidence of every access event.

The chronological log of these interactions is detailed in Table 2.

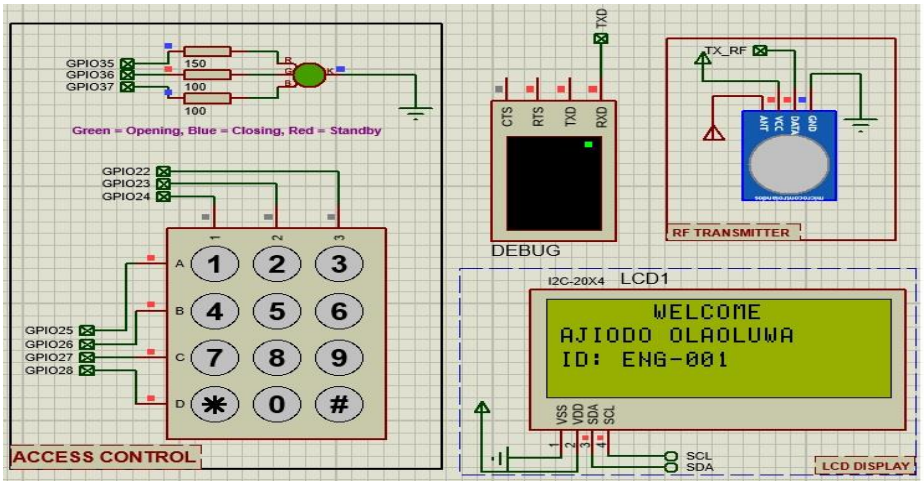

Figure 15: Authorized Personnel Authentication and Access Grant Display

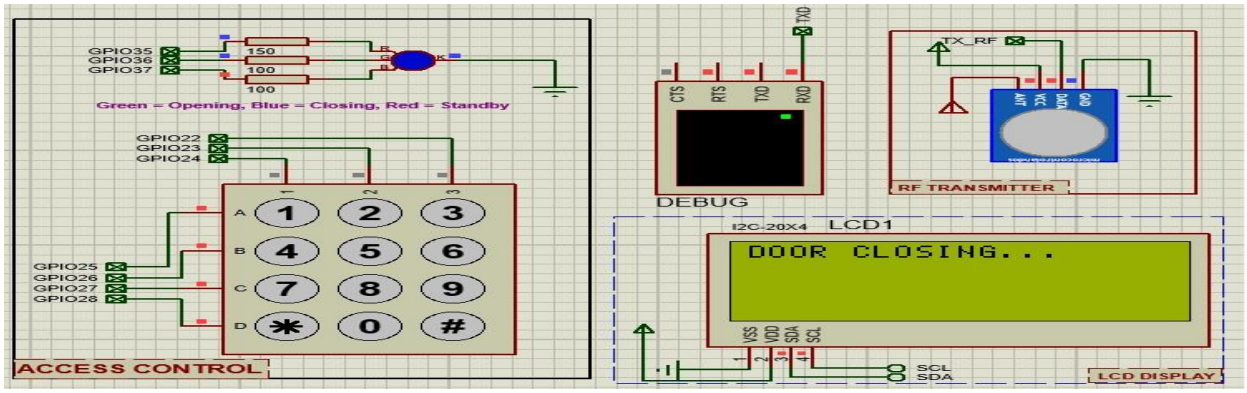

Figure 16: Automated Physical Barrier Closure Sequence Following Entry

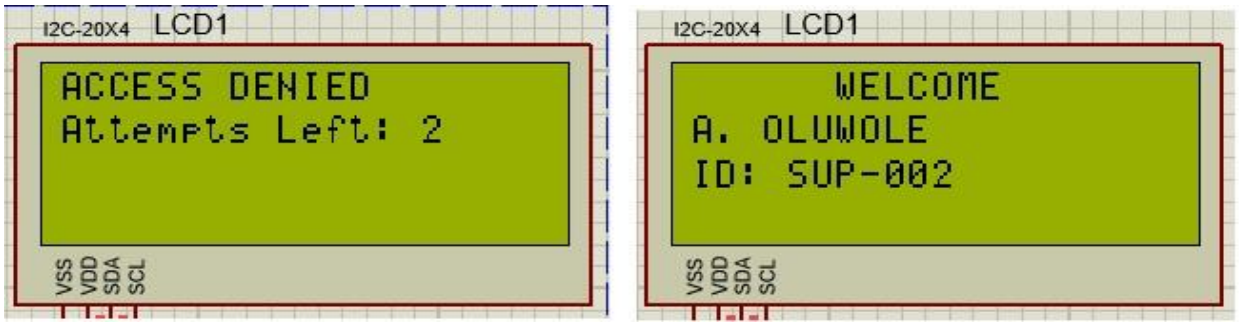

Figure 17: System Response Mechanisms for Invalid Credential Input

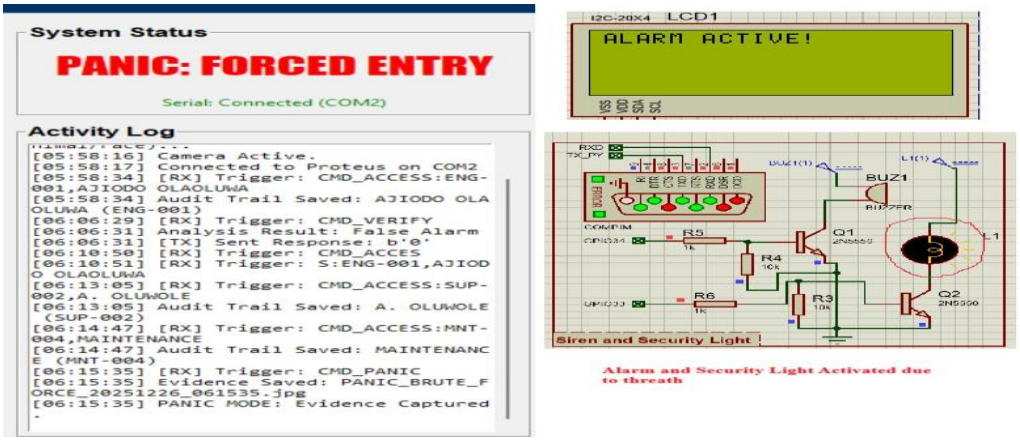

Figure 18: Panic Mode Activation and Lockdown During Brute-Force Attack

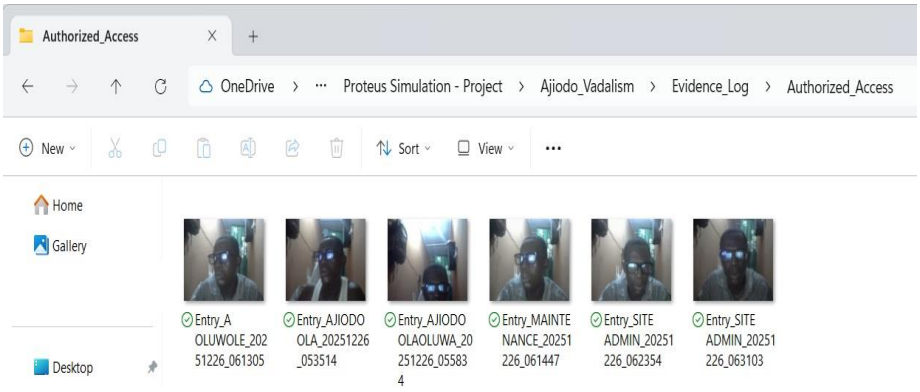

Figure 19: Forensic Audit Trail Repository for Authorized Access Events

Table 2: System Access and Security Audit Log

Timestamp	Event Type	Staff ID / Identity	Proof of Evidence
05:35:14	Authorized Entry	ENG-001 (AJIODO OLA)	Entry_AJIODO...jpg
05:58:34	Authorized Entry	ENG-001 (AJIODO OLAOLUWA)	Entry_AJIODO...jpg
06:13:05	Authorized Entry	SUP-002 (A. OLUWOLE)	Entry_A OLUWOLE...jpg
06:14:47	Authorized Entry	MNT-004 (MAINTENANCE)	Entry_MAINTENANCE ...jpg
06:23:54	Authorized Entry	ADM-003 (SITE ADMIN)	Entry_SITE ADMIN...jpg

The results in this section confirm the achievement of the second objective. The system successfully demonstrated a graduated response capability, escalating from simple feedback for user errors to a full panic state during brute-force attacks. The comprehensive audit logs and organized evidence folders provide the forensic capability required for robust infrastructure protection.

3.4. Automated Response and Communication Redundancy

The final evaluation phase focused on the third specific objective: implementing a redundant communication framework. Upon confirming the threats identified in the previous sections, the system initiated its dual-channel alert protocol. Figure 20 captures the simultaneous transmission of alerts via the GSM and RF modules. The virtual terminals confirm that an SMS command was sent with the payload "ALERT: CONFIRMED_INTRUSION," while the RF transceiver broadcasted a corresponding "RF_ALERT," ensuring message delivery even if one network failed. The internal logic governing these responses is evidenced in Figure 21, which displays the system's debug stream. The log details the sequential decision-making process: from human detection and password prompting to AI verification and final alert transmission.

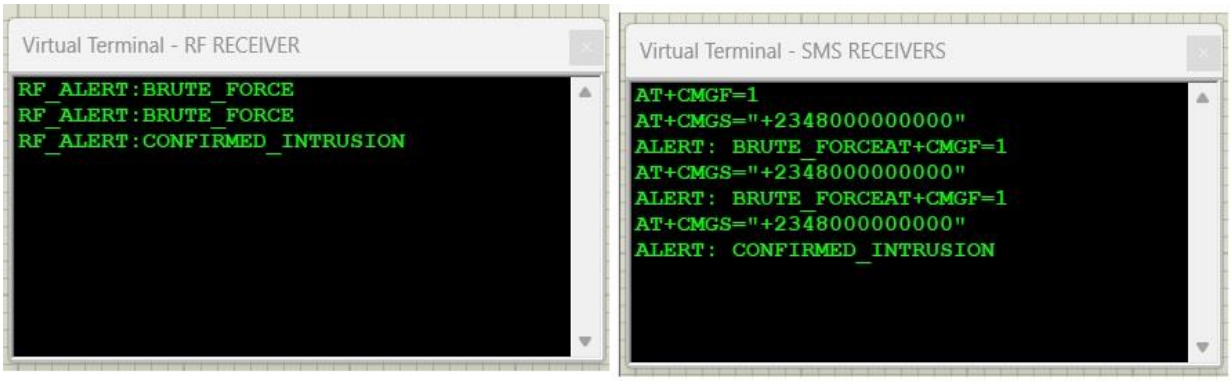

Figure 20: Redundant Alert Transmission via GSM and RF Communication Protocols

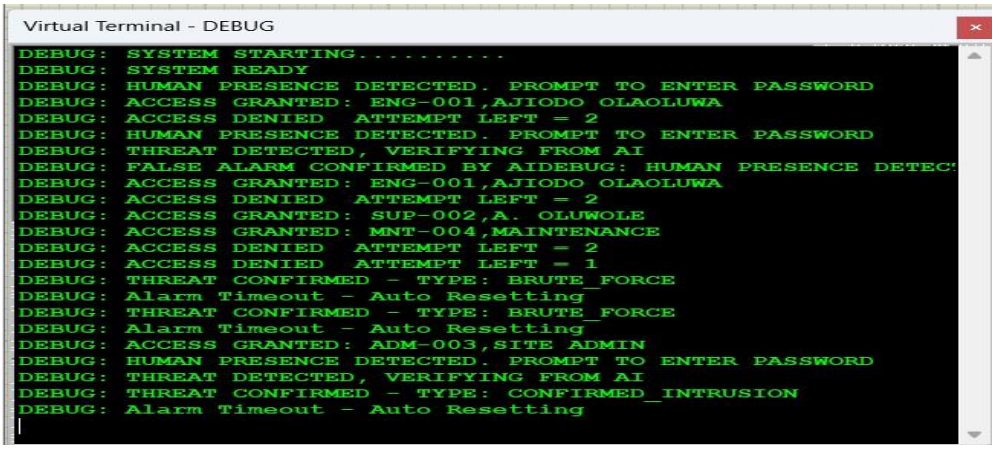

Figure 21: Real-Time System Logic and Decision Processing Log

4. CONCLUSION

In conclusion, this research successfully achieved its primary aim of developing a responsive and intelligent vandalism mitigation system for telecommunication infrastructure. The first objective of minimizing false alarms was met through the implementation of the AI verification logic, which filtered out non-human triggers with a high degree of confidence. The second objective regarding access control was realized through the development of a graduated threat escalation protocol, which proved effective in distinguishing between user error and determined intrusion attempts during testing.

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