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Adaptive Multi-Sensor Intrusion Detection System with Baseline Learning Phase for Real-Time Remote Alerting

G Vishnu Datta[1], Mehak Majeed[2]

[1]Embedded System & IoT Intern, SURE ProED, Puttaparthi, Andhra Pradesh, India
[2]Embedded System Engineer, SURE ProED, Puttaparthi, Andhra Pradesh, India

Abstract

Security and surveillance systems play a critical role in protecting residential, agricultural, and industrial environments from unauthorized intrusions. However, conventional motion-based security systems often suffer from high false alarm rates caused by environmental disturbances such as wind, small animals, or background vibrations. This paper presents the design and implementation of an Adaptive Multi-Sensor Intrusion Detection System with Baseline Learning Phase for Real-Time Remote Alerting, developed using a low-cost ESP32 microcontroller platform. The proposed system integrates four directional PIR motion sensors and a vibration sensor to monitor physical activity across a protected perimeter. A key innovation of this system is its Baseline Learning Phase, in which the system autonomously observes and characterizes the surrounding environment for approximately 60 seconds upon startup. During this phase, two vibration parameters pulse frequency and active vibration duration ratio are sampled and averaged to establish a reference profile representing normal environmental conditions specific to the deployment location. Following baseline establishment, the system enters active monitoring mode and continuously computes a Disturbance Index, a weighted metric that quantifies deviation of real-time vibration data from the learned baseline. This index is combined with input from the four PIR sensors to classify the environment into one of three states: normal condition, suspicious activity, or confirmed intrusion. Upon confirmed intrusion detection, the system transmits an instant alert message via the Telegram messaging platform over Wi-Fi, delivering the direction of detected motion and the computed disturbance index value to the user's mobile device in real time

Keywords: Intrusion Detection System, Baseline Learning, False Alarm Reduction, Adaptive Learning, Threat Classification, Multi-Sensor Fusion

1. Introduction

In an increasingly interconnected world, the need for reliable, intelligent, and affordable security systems has grown significantly across residential, agricultural, and industrial domains. Traditional security mechanisms, such as simple motion-triggered alarms or closed-circuit camera systems, often

lack the intelligence to differentiate between genuine threats and routine environmental disturbances.

The core motivation behind this project stems from a practical observation: most low-cost embedded security systems available today rely on static, threshold-based detection logic. These systems treat every motion or vibration event as a potential threat without considering the natural characteristics of the environment in which they are deployed. A farm perimeter, a warehouse floor, and a residential entrance each have vastly different baseline vibration and movement profiles. A system that fails to account for these differences will inevitably generate an unacceptable number of false positives.

To overcome this challenge, the proposed system introduces an Environment Baseline Learning Phase, during which the system autonomously monitors and records the natural vibration characteristics of its deployment location before entering active security mode. By establishing this learned reference, the system is able to compute a Disturbance Index in real time a quantitative measure of how significantly current environmental conditions deviate from normal. This index, combined with directional motion data from four PIR sensors positioned at the front, back, left, and right of the monitored perimeter, enables the system to classify detected events into three distinct threat levels: normal, suspicious, and confirmed intrusion.

Each classification is communicated through an intuitive local interface consisting of tri-color LED indicators and a buzzer alarm. Furthermore, when a confirmed intrusion is detected, the system leverages its onboard Wi-Fi capability to dispatch an instant Telegram alert to the user's mobile device, containing both the direction of the detected intrusion and the real-time disturbance index value. This ensures that the user remains informed regardless of their physical proximity to the monitored location.

2. Literature Survey

The domain of intrusion detection and perimeter security has been an active area of research, particularly with the rapid advancement of embedded systems, wireless communication technologies, and the Internet of Things (IoT). A considerable body of work exists that explores various sensing modalities, microcontroller platforms, and alert mechanisms for security applications. Reviewing these prior works provides important context for understanding both the strengths and limitations of existing approaches, and highlights the specific gaps that the proposed adaptive system aims to address. Early intrusion detection systems relied primarily on single-sensor architectures, most commonly employing Passive Infrared (PIR) sensors to detect human motion based on changes in infrared radiation. These systems operated on a straightforward binary logic: if motion was detected, an alarm was triggered. While effective in controlled indoor environments, such systems demonstrated significant vulnerability to false activations caused by moving shadows, small animals, HVAC airflow, and other non-human motion sources. The lack of contextual intelligence in these designs made them unreliable for outdoor or semi-outdoor deployment scenarios.

Viola and Jones [1] proposed a rapid human detection approach using a Haar Cascade Classifier combined with the AdaBoost algorithm, primarily applied in indoor surveillance environments with fixed camera setups. While the method demonstrated high detection accuracy under controlled lighting

conditions, its performance degraded significantly in the presence of poor or dynamic lighting, leading to increased false positive rates. This limitation makes vision-based approaches less reliable for real-world perimeter security.

Niyogi and Adelson [2] explored optical flow analysis using spatiotemporal filtering techniques to perform motion segmentation in laboratory and indoor corridor environments. The method demonstrated effective detection of motion trajectories; however, it is computationally intensive and highly sensitive to camera vibrations and environmental noise. These limitations significantly restrict its applicability in real-time systems, particularly in resource-constrained embedded platforms and outdoor environments where stability cannot be guaranteed. Such approaches highlight the challenge of achieving accurate motion detection while maintaining low computational complexity and robustness in practical deployments. The proposed system addresses this limitation by employing a lightweight multi-sensor approach that avoids complex image processing, instead relying on motion and vibration-based sensing combined with adaptive learning, making it suitable for low-cost embedded applications.

Anderson [3] investigated PIR sensor arrays configured with static threshold-based zonal detection logic across residential and office indoor environments. The system demonstrated reliable human presence detection under stable conditions; however, it lacked adaptability to dynamic thermal and environmental variations. This reliance on fixed threshold values is a significant limitation, as changes in ambient temperature, environmental noise, or long-term deployment conditions can lead to degraded performance and increased false alarms over time. These limitations highlight a critical gap in conventional PIR-based systems, which fail to adjust to evolving environmental conditions. The proposed system addresses this issue by incorporating an adaptive baseline learning mechanism that continuously updates reference values based on real-time observations. This enables the system to maintain detection accuracy over time while significantly reducing false alarms, making it more suitable for practical real-world deployment

Microchip and Rowe [4] proposed a combined sensing approach integrating ultrasonic ranging with fixed-threshold PIR triggering for warehouse and large indoor perimeter monitoring. While this method improved spatial coverage compared to PIR-only systems, it continued to rely on static threshold-based detection logic. As a result, the system exhibited a high false alarm rate in environments with reflective surfaces and airflow disturbances caused by HVAC systems, which affected sensor readings and system reliability. These observations reaffirm a key limitation in conventional multi-sensor systems, where the absence of adaptability leads to inconsistent performance under varying environmental conditions. The proposed system addresses this gap by incorporating an adaptive baseline learning mechanism along with multi-sensor fusion, enabling dynamic adjustment to environmental changes and significantly improving detection accuracy while reducing false alarms.

Zappi [5] advanced intrusion detection by introducing an edge computing framework utilizing a Support Vector Machine (SVM) classifier trained on multi-PIR sensor data for smart home and assisted living environments. This approach significantly improved activity classification accuracy compared to traditional threshold-based methods. However, the system relies on extensive labeled datasets and offline training processes, which increase system complexity and computational requirements. Such dependencies make it impractical for real-time adaptive deployment on low-cost embedded platforms without dedicated processing resources. These limitations highlight a critical gap between intelligent, learning-based systems and their feasibility in resource-constrained environments. The proposed

system addresses this challenge by implementing a lightweight adaptive learning mechanism that does not require prior training data or complex computation. This enables real-time adaptability while maintaining low hardware and computational requirements, making it suitable for cost-effective embedded security applications.

The survey of existing literature reveals a consistent gap in current intrusion detection approaches, particularly in achieving a balance between adaptability, computational efficiency, and cost-effectiveness. While vision-based and optical flow methods are sensitive to environmental conditions, conventional PIR-based systems rely on static thresholds and lack adaptability over time. Although advanced machine learning-based approaches improve detection accuracy, they introduce significant computational complexity and dependency on labeled data, making them unsuitable for low-cost embedded deployment. The proposed system addresses this gap by introducing a lightweight, self-calibrating mechanism through an on-device baseline learning phase combined with a computationally efficient disturbance index. This approach enables real-time adaptability to environmental variations without relying on complex models or high-end hardware. As a result, the system achieves reliable intrusion detection with reduced false alarms, positioning it as a practical and scalable solution for modern low-cost embedded security applications.

Ref	Authors	Method	Environment	Key Results
[1]	Viola & Jones	Cascade Classifier with AdaBoost for motion-based Human Detection	Indoor Surveillance with fixed Camera Setup	High detection accuracy in controlled lightning; significant false positives under poor lighting.
[2]	Niyogi & Adelson	Optical low Analysis	Laboratory and Indoor Corridor Environments	Effective Motion Trajectory detection; Computationally intensive and sensitive to camera vibration and environmental noise.
[3]	Corey Anderson	PIR sensor array with static threshold-based zonal detection logic	Residential and office indoor spaces ;	No adaptability to changing thermal or environmental conditions.
[4]	Microchip & Rowe	Ultrasonic ranging combined with fixed-threshold PIR triggering	Warehouse and large indoor perimeter areas	High false alarm rate in environments with reflective surfaces and HVAC-induced airflow
[5]	Zappi et al.	Edge computing framework	Support Vector Machine (SVM) on multi-PIR Data	Improved classification of occupant activities; required extensive labelled training data and offline model training.

Table 1: Summary of Existing Model of Intrusion Detection Systems

3. Perimeter Detection Model

The intrusion detection zone is defined as 3m around the intersection.

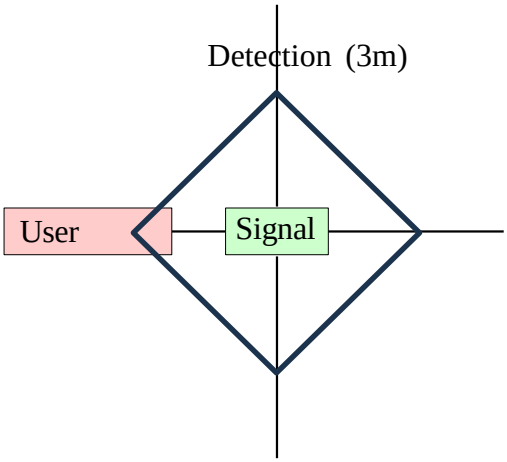

Figure 1: Perimeter Detection model

The Perimeter detection model illustrated in Figure 1 defines the spatial boundary within which the intrusion detection system actively monitors for unauthorized physical activity. The detection zone is established as a 3-meter radius around a central intersection point, forming a diamond-shaped coverage area that extends in four cardinal directions, front, back, left, and right. This geometric arrangement directly corresponds to the placement of the four PIR motion sensors in the physical hardware setup, each responsible for monitoring one directional quadrant of the perimeter.

At the center of the model lies the Signal node, which represents the ESP32 microcontroller unit along with its connected sensors. This central node continuously processes incoming sensor data and evaluates disturbance conditions in real time. The User node, positioned to the left of the signal center, represents the remote end-user who receives instant Telegram notifications whenever a confirmed intrusion event is detected within the defined zone.

The diamond-shaped detection boundary ensures uniform angular coverage across all four directions, minimizing blind spots and providing a balanced sensing field around the protected area. This model forms the conceptual foundation of the system's directional threat detection capability, enabling the system to not only confirm an intrusion but also report the specific direction from which it originates

4. Proposed Algorithm

Algorithm 1 Adaptive Multi-Sensor Intrusion Detection
Require: PIR sensor inputs and vibration sensor data
1: Initialize the system and establish WiFi connection
2: Perform baseline learning for a fixed duration
3: Store baseline values representing normal environmental conditions
4: Continuously read inputs from PIR sensors and vibration sensor
5: Extract vibration features such as frequency and activity level
6: Compare current sensor readings with baseline values
7: Determine the level of disturbance based on deviation
8: if motion is detected and disturbance is high then
9: Trigger intrusion alert (activate buzzer, red LED, and send notification)
10: else if motion is detected then
11: Indicate warning state (yellow LED)
12: else
13: Continue normal monitoring
14: end if
15: Update baseline values over time to adapt to environmental changes
16: Repeat the process continuously

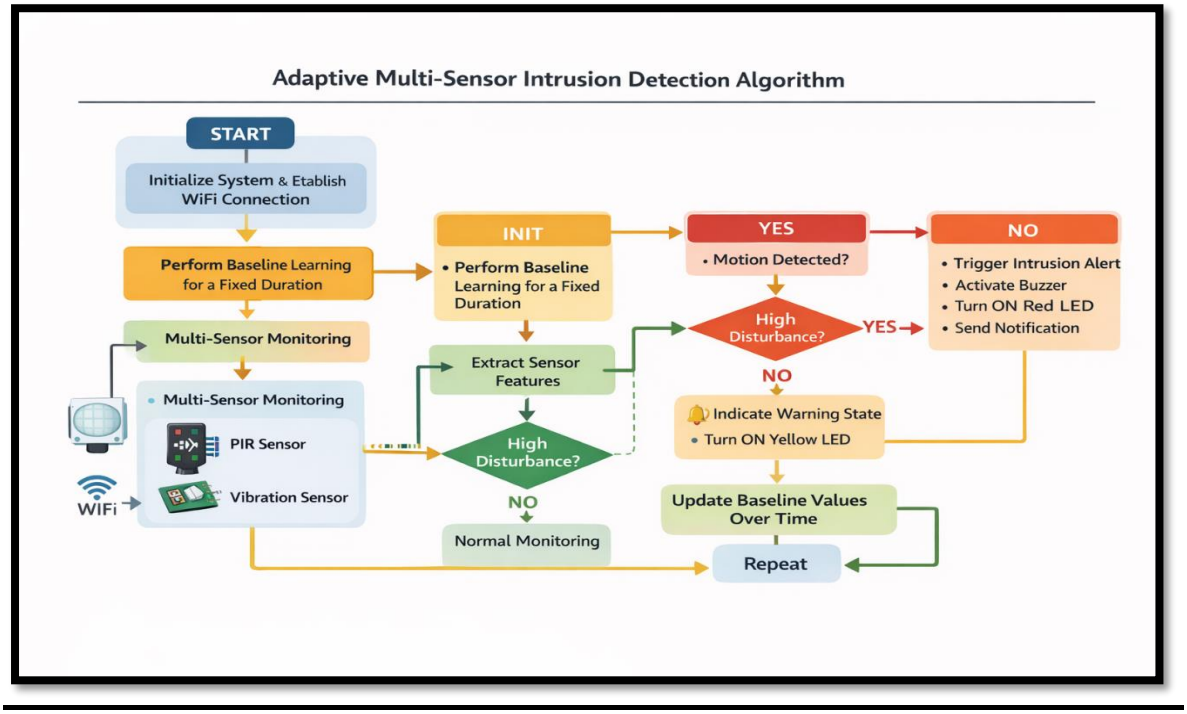

Figure 2: Flowchart of the Proposed Adaptive Multi-Sensor Intrusion Detection Algorithm

5. Mathematical Model

Baseline Calculation(Learning Phase): $F_{base} = (\Sigma F) / N$,

$$R_{base} = (\Sigma R) / N$$

Deviation From Baseline : $\Delta F = |F - F_{base}|$,

$$\Delta R = |R - R_{base}|$$

Disturbance Index: $0.6 \times \Delta F + 0.4 \times \Delta R$

Adaptive Baseline Update $F_{base} = 0.99 \times F_{base} + 0.01 \times F$

$$R_{base} = 0.99 \times R_{base} + 0.01 \times R$$

The disturbance index serves as a quantitative measure of environmental activity by combining both the intensity and duration of vibration signals into a single parameter. Higher values of the disturbance index indicate significant deviations from baseline conditions, suggesting a higher likelihood of intrusion, while lower values correspond to normal environmental variations such as minor vibrations or background noise. The weighting factors used in the disturbance index were selected based on empirical observations during testing. It was observed that vibration frequency responds more sensitively to sudden disturbances such as footsteps or object movement, whereas the activity ratio reflects the duration of such disturbances. Therefore, a higher weight of 0.6 is assigned to frequency and 0.4 to activity ratio, ensuring both responsiveness and stability in detection. The sum of the weighting factors is maintained equal to unity, which ensures that the disturbance index remains normalized and bounded, thereby simplifying interpretation and comparison across different conditions. The computed disturbance index is evaluated against a predefined threshold to classify events as normal or abnormal, enabling efficient real-time decision-making. Additionally, the adaptive baseline update mechanism allows the system to gradually adjust to long-term environmental changes while maintaining sensitivity to sudden disturbances, thereby improving the robustness and reliability of the intrusion detection system.

6. System Implementation Architecture

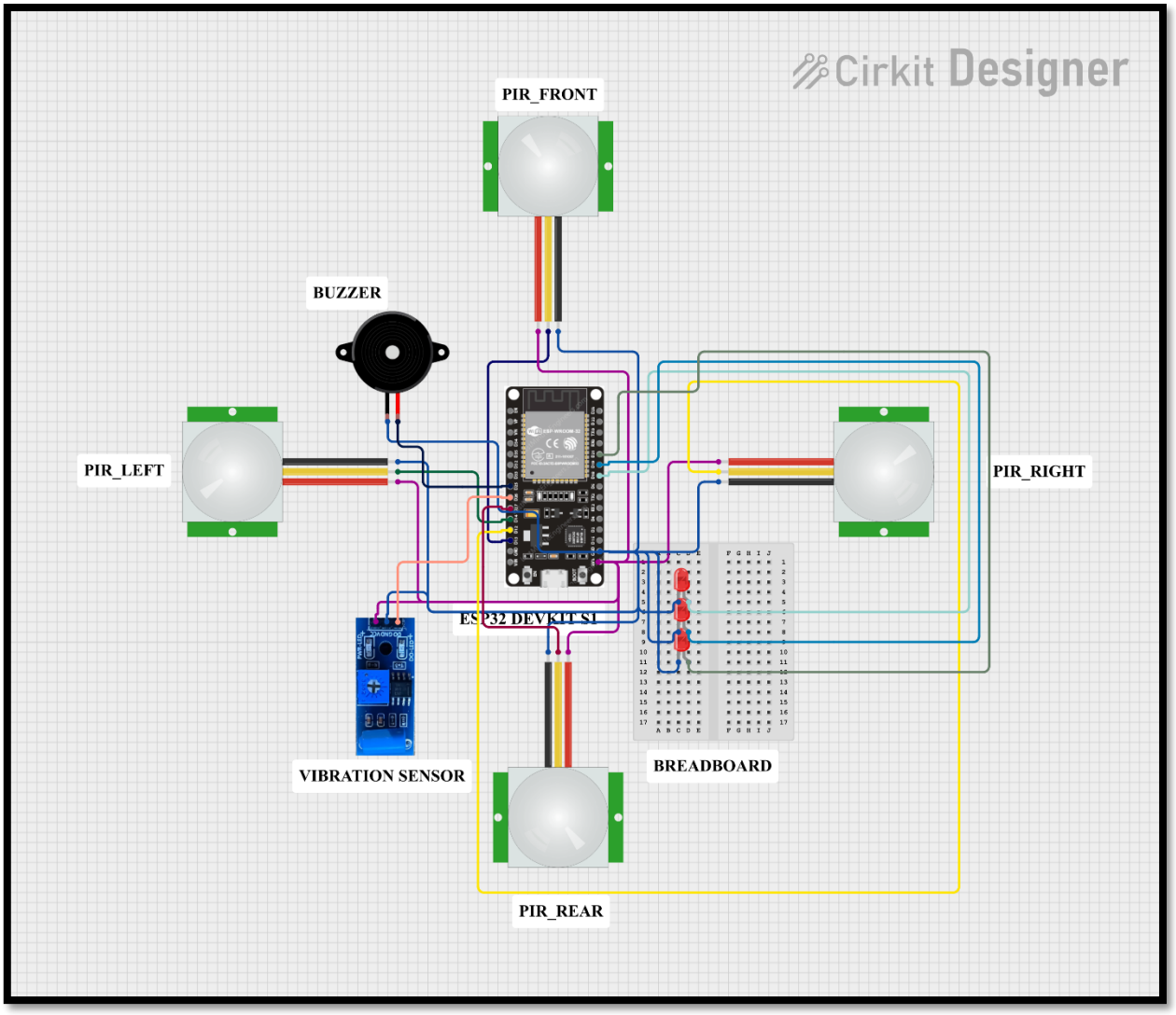

Figure 3: Overall Circuit Diagram of the Project

The implementation architecture of the proposed system integrates multiple sensing and processing components within an IoT-enabled smart security environment. The system is built around an ESP32 microcontroller, which acts as the central processing unit, interfacing with multiple PIR sensors and a vibration sensor to continuously monitor the surroundings. The PIR sensors are strategically placed to detect motion from different directions, while the vibration sensor captures physical disturbances in the protected area. These sensors continuously transmit data to the ESP32, where real-time processing is performed. During the initial phase, the system establishes baseline environmental conditions, which are later used as a reference for detecting anomalies. When motion is detected and the measured disturbance exceeds the predefined threshold, the system classifies it as an intrusion. The controller then activates local alert mechanisms such as LEDs and a buzzer, and simultaneously sends a notification to the user through a wireless communication interface. Communication is enabled using

WiFi, allowing integration with IoT platforms for remote monitoring. The system also supports real-time alert transmission via Telegram, enabling instant user notification and response.

7. Simulation Setup

The simulation setup of the proposed system is designed to validate the performance of the intrusion detection mechanism under controlled conditions. The system considers multiple PIR sensors placed in different directions to simulate motion detection, along with a vibration sensor to capture physical disturbances. Key parameters such as sampling window, learning duration, and disturbance threshold are predefined to model real-time operation. The learning duration of 60 seconds was selected to ensure sufficient sampling of environmental conditions, including minor vibrations and background disturbances, thereby establishing a stable and representative baseline without introducing excessive delay in system activation. The disturbance threshold value of 1.0 was determined empirically through multiple simulation trials, where it was observed that normal environmental variations resulted in disturbance index values below this threshold, while actual intrusion events consistently exceeded it. This selection provides a balanced trade-off between detection sensitivity and reduction of false alarms.

Parameter	Value
No. of PIR Sensors	4
Vibration Sampling Window	1 s
Sampling Interval	10 ms
Learning Duration	60 s
Disturbance Threshold	1.0

Table 2: Simulation Parameters

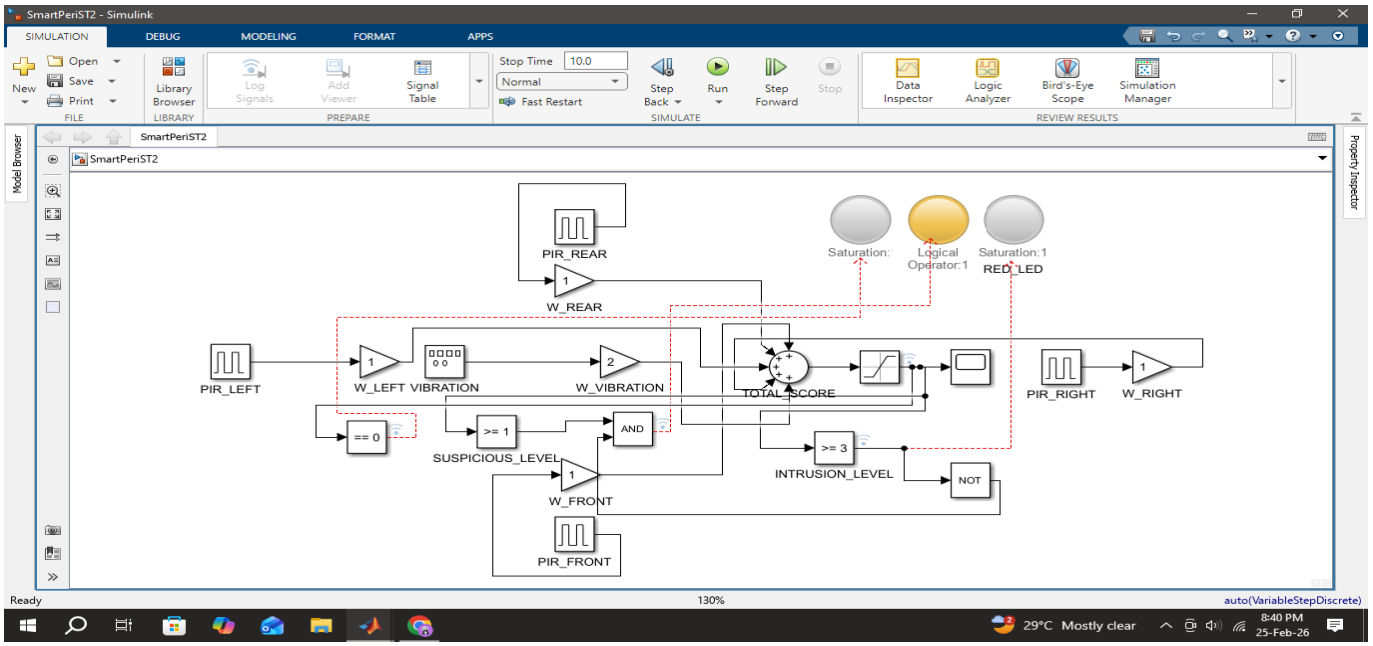

Figure 4: Disturbance Index Computation

Fig. 4 represents the core computation of the disturbance index used in the system. It takes vibration features such as frequency and activity ratio as inputs, along with their baseline values obtained during the learning phase. The model calculates the deviation from normal conditions and applies weighted parameters to generate a disturbance index. This helps in quantifying the level of disturbance in a simplified and effective manner.

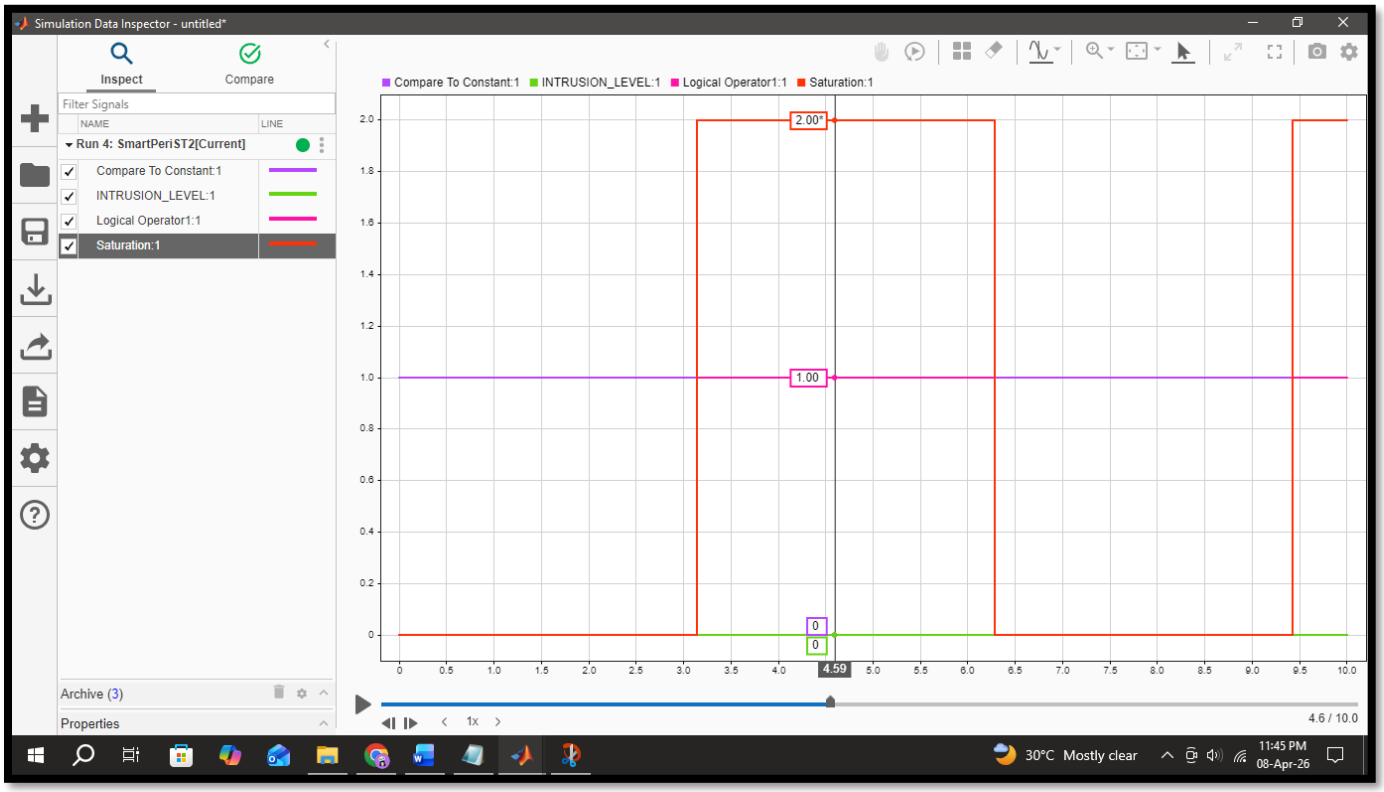

Figure 5: Simulation Output Showing Intrusion Detection Logic and Disturbance Threshold Comparison

Figure 5 illustrates the simulation output of the proposed intrusion detection system under varying input conditions. The red signal (Saturation block) represents the computed disturbance level, while the pink signal (Logical Operator output) indicates the predefined threshold level of 1.0. The green signal (Intrusion Level) represents the final detection output of the system. It can be observed that during specific time intervals, the disturbance level rises to approximately 2.0, exceeding the threshold value of 1.0. During these instances, the system correctly identifies the condition as an intrusion. Conversely, when the disturbance level remains below the threshold, the system maintains a normal or non-intrusive state.

The clear separation between the disturbance signal and the threshold level demonstrates effective decision-making capability. The system successfully classifies intrusion events based on threshold comparison, thereby validating the correctness of the detection logic. Additionally, the sharp transitions in the output indicate a prompt and reliable system response to changing input conditions.

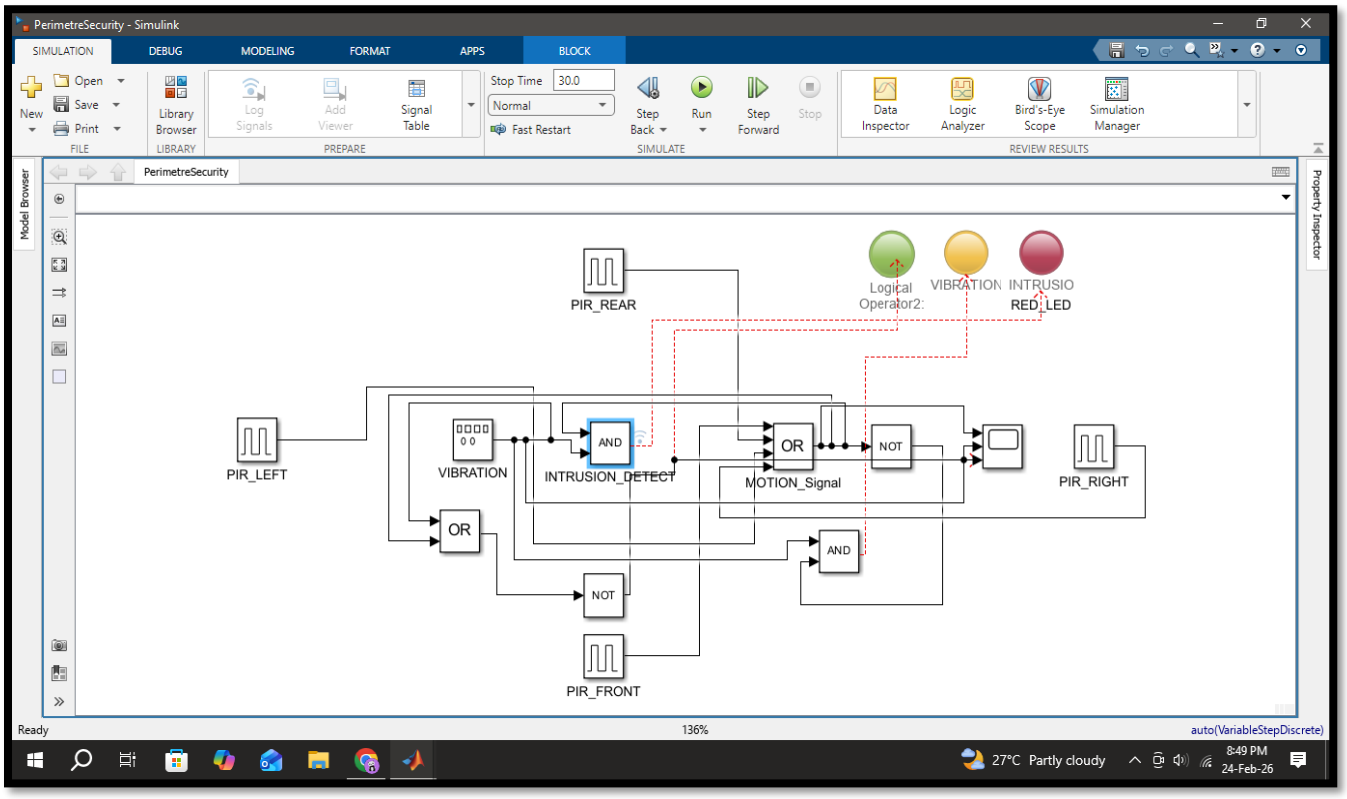

Figure 6: Intrusion Detection Logic

The intrusion detection model illustrates the decision-making logic of the system by combining motion detection and disturbance analysis. Inputs from multiple PIR sensors and the computed disturbance index are processed to classify the system state as normal, warning, or intrusion. The model is designed to simulate real-time operating conditions and ensures that alerts are triggered only when both motion and significant disturbance are detected, thereby minimizing false alarms

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Figure 6 presents the simulation output of the intrusion detection logic. It can be observed that when the disturbance level exceeds the predefined threshold, the system successfully identifies the condition as an intrusion. The output signals clearly demonstrate correct logical transitions between normal, warning, and intrusion states based on input conditions. These results confirm that the system is capable of making accurate and real-time decisions.

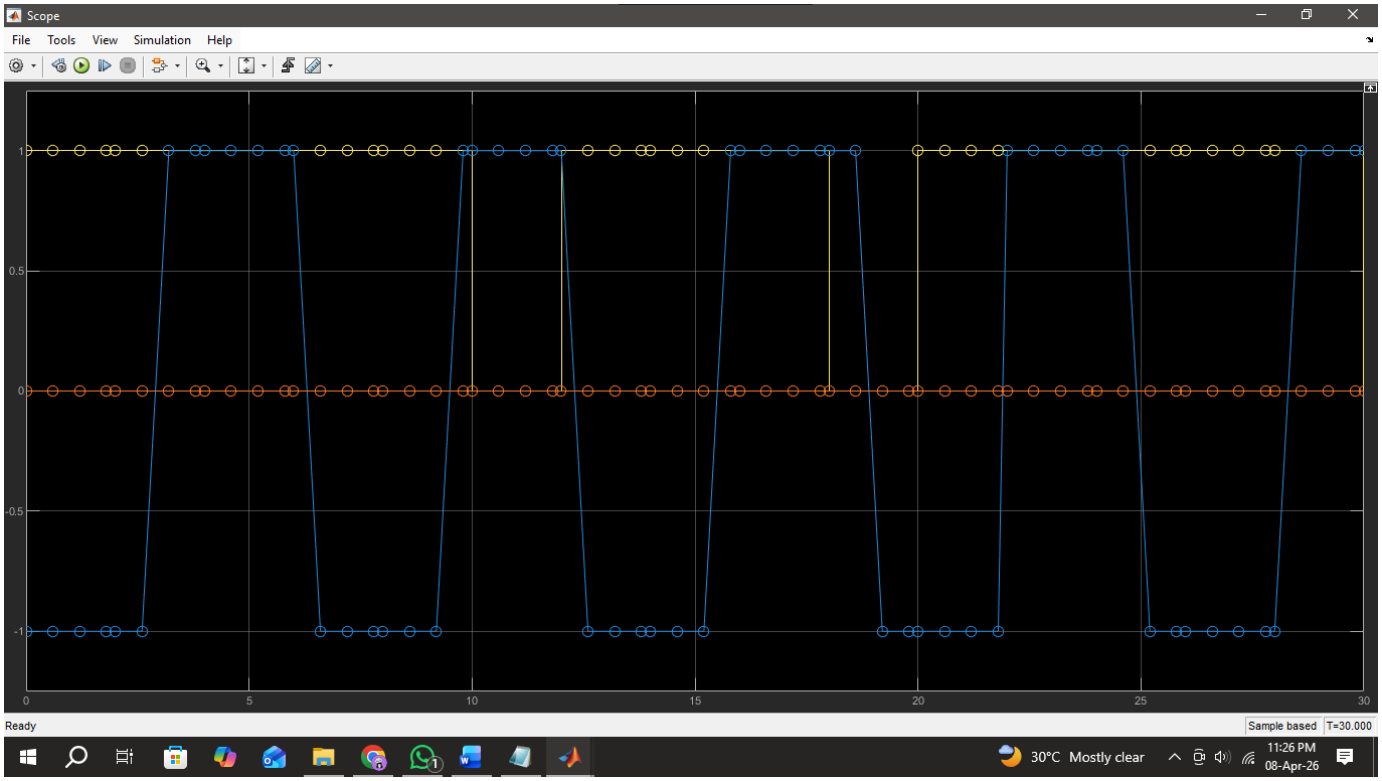

Figure 7: Scope Output of Intrusion Detection Logic Showing System Response Over Time

The simulation output of the intrusion detection logic model is shown in Fig. 7. The graph represents the system response under varying input conditions, where signals are interpreted in a normalized range between 0 and 1. In this representation, a value of 1 indicates an active state (motion detected), while a value of 0 represents an inactive state (no motion). The yellow signal maintains a value close to 1, indicating the presence of motion detected by the PIR sensors, whereas the orange signal remains near 0, representing no-motion conditions. The blue waveform shows transitions between these states, corresponding to the system's response to changing input conditions over time.

These transitions validate that the detection logic correctly identifies motion events and updates the system state accordingly. When motion is detected, the system transitions to an active state (1), and in the absence of motion, it returns to an inactive state (0). This confirms the correct implementation of the logical decision-making mechanism and its ability to process sensor inputs reliably

The simulation results validate the effectiveness of the proposed intrusion detection system under controlled conditions. The disturbance index model accurately reflects variations in vibration patterns, while the detection logic successfully differentiates between normal activity, warning states, and confirmed intrusions. The integration of multi-sensor inputs ensures improved reliability by reducing false alarms caused by environmental disturbances.

8. Experimental Results

The experimental setup of the proposed system is shown below. The system was evaluated under multiple real-world conditions, including indoor and semi-outdoor environments, with disturbances such as human movement, small object vibrations, and background environmental noise. A total of 15–20 test cases were conducted to analyze system performance under different scenarios, including normal conditions, minor disturbances, and actual intrusion events. The objective of these tests was to validate the accuracy, responsiveness, and false alarm reduction capability of the proposed system.

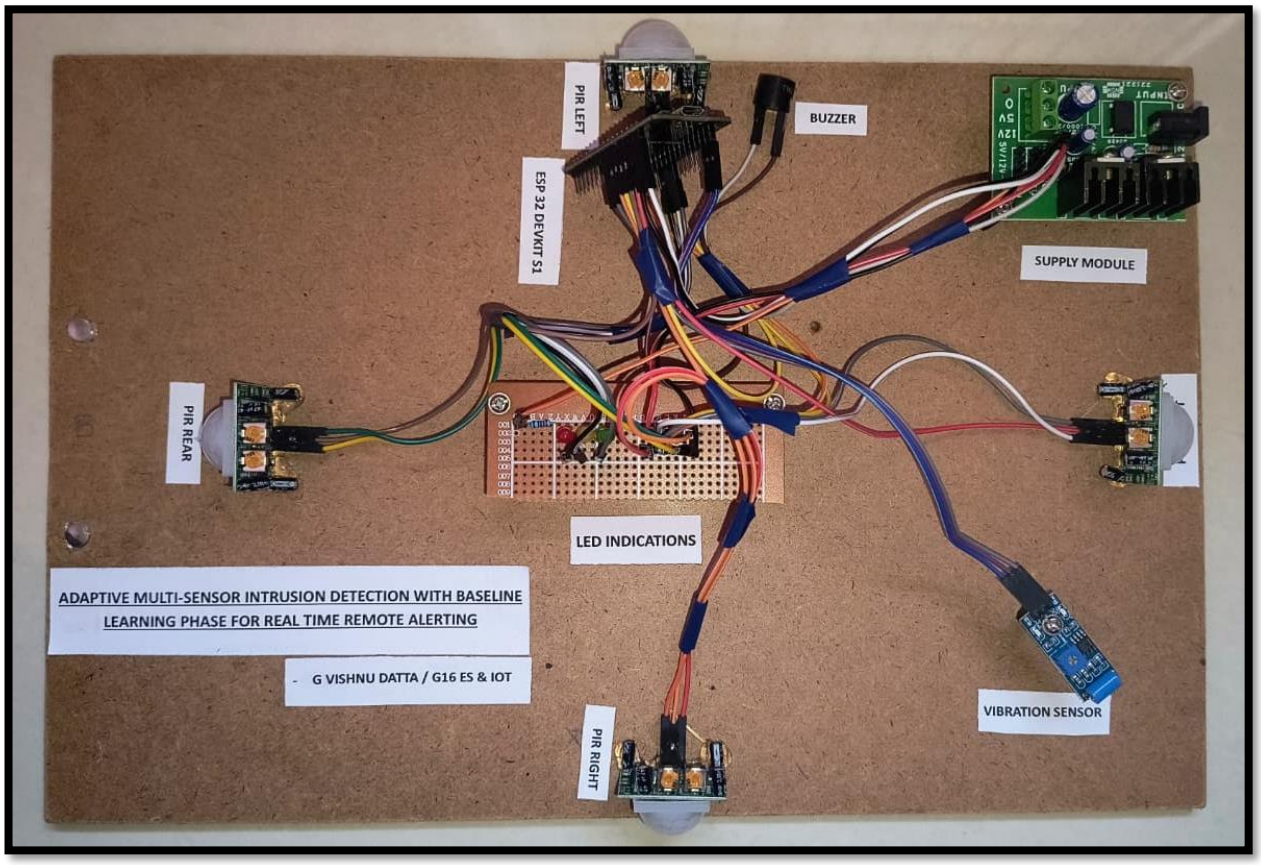

Figure 8: Project Outcome

The hardware setup consists of an ESP32 microcontroller interfaced with multiple PIR sensors and a vibration sensor, all powered through a stable supply. The PIR sensors are positioned to monitor motion from different directions, while the vibration sensor detects physical disturbances in the protected area. During operation, the system initially undergoes a baseline learning phase to capture normal environmental conditions. Once deployed, it continuously processes real-time sensor data and computes the disturbance level based on deviations from the learned baseline, enabling adaptive and context-aware detection.

When motion is detected along with a significant disturbance, the system classifies the event as an intrusion and activates the buzzer and red LED, while also sending an alert message via Telegram over

WiFi. In cases of minor activity, the system indicates a warning state using a yellow LED, whereas under normal conditions, a green LED remains active. The experimental results demonstrate that the system consistently differentiates between normal, warning, and intrusion scenarios. It was observed that minor environmental disturbances did not trigger false alarms, while actual intrusion events resulted in a clear increase in disturbance index, leading to accurate detection and timely alert generation.

To further evaluate the effectiveness of the proposed approach, a comparative analysis was performed with conventional detection methods. The system performance was compared against a PIR-only system and a combined PIR and vibration-based system without adaptive learning.

System Type	Sensors Used	False Alarms	Detection Accuracy	Remarks
PIR Only	PIR	High	Moderate	Sensitive to Environmental Noise
PIR+ Vibration	PIR+ Vibration	Medium	Good	Reduced False Alarms
Proposed System	PIR+ Vibration+ Adaptive Learning	Low	High	Most Reliable & Adaptive

Table 3: Performance Comparisons of Detection Approaches

The comparative results clearly demonstrate the advantage of the proposed system over conventional approaches. The PIR-only system shows a high false alarm rate due to its sensitivity to environmental disturbances. The addition of a vibration sensor improves detection performance; however, it still lacks adaptability to changing environmental conditions. In contrast, the proposed system, which incorporates adaptive baseline learning along with multi-sensor fusion, achieves significantly lower false alarms and higher detection accuracy. This confirms that integrating adaptive learning mechanisms enhances system reliability and makes it more suitable for real-world deployment in low-cost embedded security applications.

9. Conclusion

his work presents an adaptive multi-sensor intrusion detection system that significantly improves the reliability of conventional security solutions. By integrating multiple PIR sensors with vibration sensing, the system is capable of capturing both motion-based and physical disturbances, thereby providing a more comprehensive understanding of environmental activity. The use of multi-sensor fusion ensures that isolated or irrelevant triggers do not lead to false alarms, enhancing the overall accuracy of detection. A key contribution of this project is the introduction of a baseline learning phase combined with a disturbance index-based decision mechanism. Instead of relying on fixed thresholds, the system dynamically learns the normal behavior of its deployment environment and continuously adapts to gradual changes over time. This allows for intelligent classification of events into normal, warning, and intrusion states, making the system more robust and context-aware.

Such adaptive and data-driven approaches are typically found in high-end and computationally intensive security systems. However, this work demonstrates that similar levels of intelligence can be achieved using a low-cost embedded platform based on ESP32, without the need for complex hardware or high processing resources. This makes the proposed solution both economically viable and practically deployable in real-world scenarios. Furthermore, the integration of real-time IoT communication through WiFi and Telegram enables instant remote monitoring and alerting, adding an additional layer of functionality to the system. The successful validation through both simulation and hardware implementation confirms the effectiveness of the proposed approach.

Overall, this project bridges the gap between traditional low-cost security systems and advanced intelligent surveillance technologies by introducing adaptive learning and smart decision-making into a resource-constrained environment. The system offers a scalable, reliable, and cost-effective solution, paving the way for future enhancements and broader applications in modern security systems.

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