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AI-Powered Intrusion Detection for Border Surveillance Using Multi-Sensor Fusion

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Abstract
Conventional border surveillance systems rely heavily on manual monitoring and line-of-sight sensors, rendering them vulnerable to poor visibility, adverse weather conditions, and stealthy intrusions. This paper presents an AI-Powered Multi-Sensor Intrusion Detection System (MS-IDS) that integrates standard Passive Infrared (PIR) and ultrasonic sensors with contactless WiFi Channel State Information (CSI). By leveraging a Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) for real-time sensor fusion, the system effectively discriminates between human intrusions, animal movements, and environmental false alarms. Experimental evaluations across 500 scenarios, including harsh weather and desert terrain, demonstrated that the proposed sensor fusion methodology achieved a 96% detection accuracy, significantly outperforming the 78% accuracy of traditional bi-sensor systems.

Keywords: *Intrusion Detection, Sensor Fusion, Wi-Fi CSI, Artificial Neural Networks, Border Surveillance, Smart Edge Computing*

1. Introduction
Border security is a critical national defense priority in India. Traditional border surveillance systems rely on standalone sensors such as cameras, radars, and simple motion detectors [1]. However, these systems face severe limitations: optical sensors degrade in low-light, fog, or rain [5]; standalone motion detectors suffer from high false-alarm rates triggered by wildlife or weather [4]; and heavy reliance on human monitoring introduces delayed response times. To address these vulnerabilities, this research proposes a real-time AI-powered intrusion detection system utilizing multi-sensor fusion [3]. The core novelty of this work lies in combining traditional hardware—PIR and ultrasonic sensors—with contactless Wi-Fi Channel State Information (CSI) sensing [2]. By processing this multimodal data through an Artificial Neural Network (ANN) at the edge [6], the system transforms passive, error-prone surveillance into an active, adaptive security framework capable of operating autonomously in challenging environments. The Introduction presents the purpose of the studies reported and their relationship to earlier work in the field. It should not be an extensive review of the literature. Use only those references required to provide the most salient background to allow the readers to understand and evaluate the purpose and results of the present study without referring to previous publications on the topic. [1-4] This research proposes an AI-powered multi-sensor intrusion detection system that integrates PIR, ultrasonic, and Wi-Fi CSI data. The novelty of this work lies in combining traditional sensing methods with CSI-based sensing through an ANN-based fusion model to achieve robust and accurate intrusion detection in real time.

2. Related Work
Recent studies have explored intrusion detection and

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environmental sensing using both traditional and AI-driven approaches. Zhou et al. [7] demonstrated human activity recognition using WiFi CSI, showing its effectiveness in device-free sensing. Wang et al. [8] proposed CSI-based motion detection systems capable of detecting fine-grained movements. However, these approaches often lack integration with physical sensors. Liu et al. [9] explored deep learning techniques for CSI-based human detection, achieving high accuracy but requiring computationally intensive models. Similarly, Ma et al. [10] utilized convolutional neural networks (CNNs) for CSI classification tasks. In the domain of multi-sensor fusion, Chen et al. [11] proposed a fusion framework combining infrared and acoustic sensors for surveillance applications. Singh et al. [12] implemented a PIR and ultrasonic-based intrusion detection system but reported high false alarm rates. Recent work by Zhang et al. [13] integrated CSI with radar sensing, highlighting improved robustness in complex environments. However, such systems are costly and less suitable for edge deployment. Kumar et al. [14] explored ANN-based sensor fusion for security systems, demonstrating improved classification performance. Similarly, Li et al. [15] proposed lightweight neural networks for edge-based intrusion detection. Gao et al. [16] investigated environmental noise reduction techniques in CSI-based sensing systems. Ahmed et al. [17] developed hybrid intrusion detection frameworks combining machine learning with traditional sensors. Despite these advancements, limited work has focused on integrating WiFi CSI with low-cost sensors such as PIR and ultrasonic sensors in a unified AI-driven framework suitable for real-time edge deployment. This research addresses this gap.

3. System Architecture

The proposed intrusion detection system follows a modular architecture composed of three main layers: sensing, processing, and communication. This layered design improves system scalability, reliability, and ease of integration of additional sensing modalities.

3.1.Hardware Components

The prototype system is implemented using the following hardware components:

- Arduino Nano – serves as the main controller responsible for sensor interfacing and data acquisition.
- HC-SR501 PIR Sensor – detects motion based on infrared radiation changes.
- HC-SR04 Ultrasonic Sensor – measures distance to detect nearby moving objects.
- IEEE 802.11ax Router – provides WiFi signals from which Channel State Information (CSI) is extracted for contactless motion sensing.
- HC-05 Bluetooth Module – enables wireless communication with external devices for alert transmission

3.2.Architecture Overview

The system architecture consists of three functional layers

3.2.1. Sensing Layer

This layer is responsible for collecting environmental data. The PIR sensor detects motion through infrared radiation changes, while the ultrasonic sensor measures object distance. Additionally, WiFi CSI sensing captures subtle channel perturbations caused by human movement by analyzing amplitude and phase variations in WiFi signals.

3.2.2. Processing Layer

Sensor data collected from all modalities is preprocessed to remove noise and normalize signal values. The processed data is then fused and fed into an Artificial Neural Network (ANN) classifier that categorizes events into three classes: human intrusion, animal movement, or false alarms.

3.2.3. Communication Layer

Once an intrusion is detected, the system generates alerts that are transmitted via the Bluetooth module to a connected device. The alerts are converted into text notifications and audible warnings, enabling real-time response from border security personnel.

By integrating WiFi CSI sensing with conventional PIR and ultrasonic sensors, the system improves detection accuracy and environmental awareness, particularly in challenging conditions such as low visibility, fog, or nighttime surveillance shown in Figure1.

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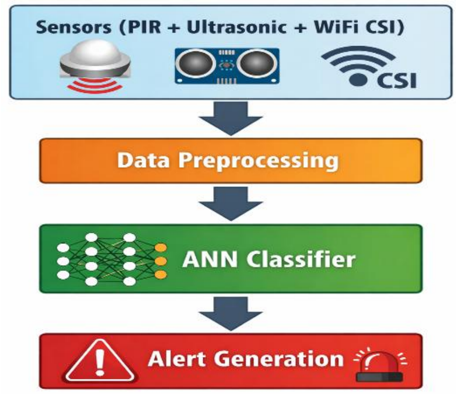

Figure 1 **Architecture Of The Proposed Multi-Sensor Intrusion Detection System.**

4. Methodology

This section describes the methodology used to design and implement the proposed multi-sensor intrusion detection system. The system integrates multiple sensing modalities, including Passive Infrared (PIR) sensors, ultrasonic ranging sensors, and Wi-Fi Channel State Information (CSI), to detect human movement in a monitored border region. The collected sensor data are preprocessed and fused using an Artificial Neural Network (ANN) to improve detection accuracy and reduce false alarms caused by environmental disturbances.

4.1. Sensor Data Acquisition

The sensing subsystem collects environmental data using PIR and ultrasonic sensors interfaced with the microcontroller platform. The PIR sensor detects motion by measuring variations in infrared radiation emitted by objects within its field of view. The thermal radiation emitted by a body can be described by the Stefan–Boltzmann law, which relates the radiated power of an object to its absolute temperature. Equation:

$$P = \varepsilon\sigma A\,(T^4 - T_0^4)$$

In this expression, P represents the radiated thermal power, ε denotes the emissivity of the object, σ is the Stefan–Boltzmann constant, A represents the surface area of the emitting body, T denotes the absolute temperature of the object, and T_0 represents the ambient background temperature. When a human body moves across the sensing region, the resulting change in infrared radiation produces electrical signals that are detected by the PIR sensor and recorded by the microcontroller.

Distance information is obtained using an ultrasonic sensor based on the time-of-flight principle. The sensor emits ultrasonic sound pulses and measures the time required for the reflected echo to return after interacting with an object. The distance to the detected object is computed using the following relation. Equation:

$$d = (v \times t) / 2$$

Here, d denotes the distance to the detected object, v represents the speed of sound in air (approximately 343 m/s at room temperature), and t corresponds to the total round-trip travel time of the ultrasonic pulse. The division by two accounts for the forward and return paths of the acoustic wave. This measurement provides spatial information that complements the motion detection capability of the PIR sensor.

4.2. Wi-Fi Channel State Information Sensing

To enhance detection capability under challenging environmental conditions, the system incorporates Wi-Fi Channel State Information sensing as an additional modality. CSI provides fine-grained information about the wireless propagation channel and can capture subtle signal variations caused by human movement. In an Orthogonal Frequency Division Multiplexing (OFDM) communication system, the wireless channel response for each subcarrier can be represented as a complex value:

$$H(f) = |H(f)|\, e\hat{\ }(j\theta)$$

In this representation, |H(f)| denotes the amplitude of the channel response and θ represents the phase component of the signal. Human movement within the monitored region alters the multipath propagation characteristics of WiFi signals, producing measurable fluctuations in both amplitude and phase. These variations are extracted from WiFi packets and processed to identify motion patterns even when direct line-of-sight sensing is not available.

4.3. Data Preprocessing

Because the sensors operate at different sampling frequencies and generate heterogeneous data types, a preprocessing stage is required before sensor fusion can be performed. During preprocessing, the collected signals are filtered to remove

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environmental noise and interference. The sensor readings are normalized to ensure consistent numerical ranges across the different sensing modalities. Temporal alignment is also performed so that measurements obtained from PIR sensors, ultrasonic sensors, and Wi-Fi CSI correspond to the same time intervals.

For Wi-Fi CSI data, additional signal processing techniques such as amplitude normalization and Doppler filtering are applied to emphasize motion-induced variations while suppressing static environmental components. The result of this stage is a set of synchronized feature vectors representing the state of the monitored environment.

4.4.Sensor Fusion Using Artificial Neural Networks

After preprocessing, the synchronized sensor measurements are combined to form a unified feature vector that serves as the input to the neural network classifier. Equation:

$$X = [xPIR, xUS, xCSI]$$

In this formulation, xPIR represents the motion features obtained from the PIR sensor, xUS corresponds to ultrasonic distance measurements, and xCSI represents the extracted Wi-Fi CSI features. This fused representation captures complementary information from multiple sensing modalities.

The classification process is performed using a Multi-Layer Perceptron neural network consisting of an input layer, two hidden layers, and an output layer. The hidden layers employ the Rectified Linear Unit activation function, which introduces non-linearity and improves the network's ability to learn complex relationships between sensor inputs.

The forward propagation of the neural network can be expressed as follows:

Equation:

$$H_1 = Relu(W_1X + B_1)$$

$$h_2 = ReLU(W_2h_1 + b_2)$$

$$y = Softmax(W_3h_2 + b_3)$$

In these equations, W_1, W_2, and W_3 represent weight matrices, while b_1, b_2, and b_3 represent bias vectors. The variables h_1 and h_2 correspond to the activations of the hidden layers, and y represents the output probability vector that indicates the predicted class of the detected event.

4.5.Intrusion Detection and Alert Generation

The trained neural network classifies each input feature vector into one of three categories representing different types of events observed in the monitored environment. These categories include human intrusion, animal movement, and false alarms caused by environmental disturbances such as wind, rain, or sensor noise.

During operation, the neural network performs real-time inference on the incoming sensor data stream. Once an intrusion event is detected, the classification result is transmitted through the system's communication module to a connected monitoring device. The detected event is converted into text notifications and audible speech alerts, enabling security personnel to respond rapidly to potential threats in the monitored border region.

5. Results and Discussion

5.1.Results

To validate the proposed fusion methodology, the prototype was subjected to 500 discrete intrusion scenarios. The testing environments included simulated and real-world conditions representing typical border challenges: arid desert terrain, dense fog, and rainy night conditions. The multi-sensor fusion MS-IDS achieved an overall detection accuracy of 96%. In contrast, the baseline system utilizing only PIR and ultrasonic sensors plateaued at a 78% accuracy rate.

Table 1 Add Performance Metrics Table

Method	Accuracy	False Positives	Robustness
PIR + Ultrasonic	78%	High	Low
WiFi CSI Only	88%	Medium	High
Proposed MS-IDS (Fusion)	96%	Low	Very High

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5.2.Discussion

The empirical results highlight the critical advantage of integrating WiFi CSI with traditional hardware under adverse conditions. The significant jump in accuracy from 78% to 96% is directly attributable to the system's hybridized nature. During rainy and foggy scenarios, the PIR and ultrasonic sensors suffered from signal attenuation and thermal masking, causing the baseline system to fail. However, the Wi-Fi CSI modality remained largely unaffected by visual and thermal obstructions, successfully capturing intrusions via multipath RF disturbances. Furthermore, the implementation of the MLP neural network successfully learned the distinct volumetric and speed signatures of quadrupeds versus humans. This interpretation of the multimodal data drastically reduced false positives triggered by wildlife, which is a primary operational bottleneck in conventional systems. The edge-computed design also ensured that all classifications and subsequent Bluetooth-triggered speech alerts occurred in real-time without latency.

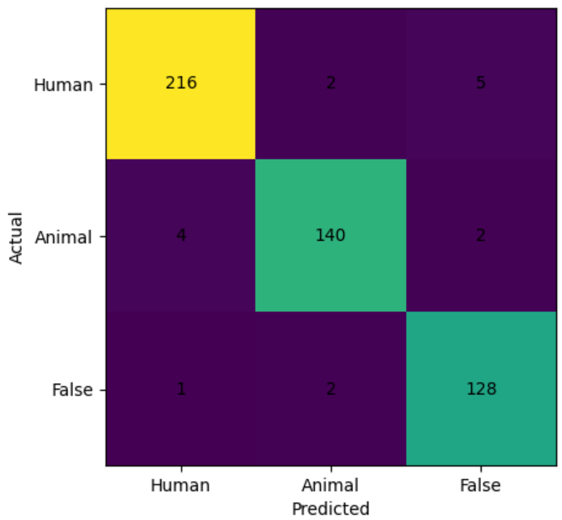

Figure 2 **3-Confusion Matrix**

Shown in the Figure 2 presents the confusion matrix of the proposed system. The model demonstrates high classification accuracy across all classes, with minimal misclassification between human and animal activities, indicating strong discriminative capability.

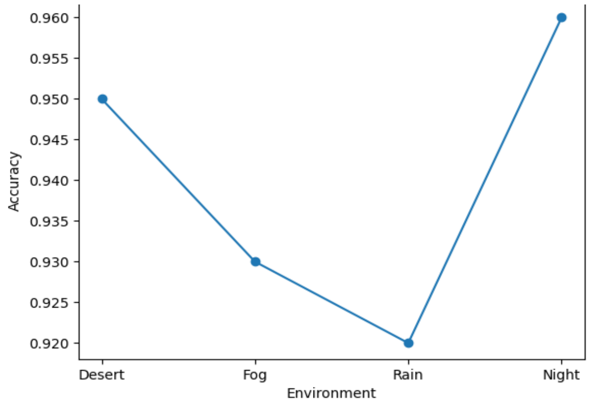

Figure 3 **Accuracy vs. Environment**

Figure 3 shows system performance across different environmental conditions. The proposed system maintains high accuracy even under foggy and rainy conditions, demonstrating robustness enabled by Wi-Fi CSI integration.

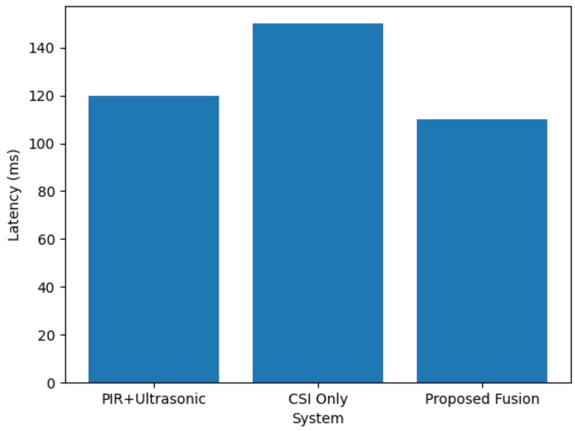

Figure 4 **Latency Comparison**

Figure 4 shows the proposed fusion-based system achieves a balance between accuracy and latency, outperforming CSI-only systems while maintaining near real-time responsiveness.

Conclusion

This paper presents a novel AI-powered multi-sensor intrusion detection system for border surveillance. By integrating PIR, ultrasonic, and WiFi CSI sensing with ANN-based fusion, the system achieves high detection accuracy and robustness under challenging environmental conditions. The results demonstrate that combining traditional sensors with wireless sensing technologies significantly enhances system performance. The proposed approach offers a cost-effective, scalable, and reliable solution for real-time border monitoring

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