Wi-Sense: A Lightweight Deep Learning Framework for Device-Free Intrusion Detection and Occupancy Estimation Using Wi-Fi CSI with ESP32 Edge Deployment

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***Abstract*—The increasing demand for privacy-preserving smart surveillance systems has driven research toward device-free sensing approaches that leverage existing wireless infrastructure. Traditional camera-based intrusion detection systems raise privacy concerns and require controlled lighting conditions, while Passive Infrared (PIR) sensors suffer from limited spatial sensitivity and high false alarm rates. This paper presents Wi-Sense, a lightweight deep learning framework for device-free physical intrusion detection and multi-class occupancy estimation using Wi-Fi Channel State Information (CSI). The proposed system captures fine-grained CSI amplitude variations using an ESP32-based CSI receiver and processes the data through a structured signal preprocessing pipeline including outlier removal, smoothing, normalization, and sliding window segmentation. A compact one-dimensional Convolutional Neural Network (1D-CNN) is designed to extract spatial correlations across subcarriers and classify occupancy levels ranging from 0 to 5 persons. Binary intrusion detection is derived from occupancy classification results. Experimental evaluation in a realistic furnished indoor environment demonstrates 96.8% intrusion detection accuracy and 92.4% occupancy estimation accuracy. Furthermore, the architecture is optimized for TinyML deployment, enabling standalone inference and alert transmission directly from the ESP32 microcontroller without reliance on external computation. The results validate the feasibility of scalable, low-cost, and privacy-aware smart building security using commodity Wi-Fi infrastructure.**

***Index Terms*—Wi-Fi CSI, Device-Free Sensing, Intrusion Detection, Occupancy Estimation, ESP32, TinyML, Edge AI, 1D CNN**

I. Introduction

The proliferation of Internet-of-Things (IoT) technologies has transformed modern buildings into interconnected smart environments. These environments increasingly demand intelligent security mechanisms capable of detecting unauthorized access, monitoring occupancy, and enabling automated responses. Traditional surveillance systems primarily rely on camera-based monitoring, which introduces significant privacy concerns and ethical considerations. Moreover, camera systems depend heavily on proper illumination, unobstructed views, and continuous storage infrastructure. Similarly, Passive Infrared (PIR) sensors detect thermal radiation changes but lack fine spatial resolution and frequently produce false positives due to temperature fluctuations or non-human movement. In recent years, wireless-based device-free sensing has emerged as a promising alternative. Unlike vision-based sys- tems, Wi-Fi signals naturally propagate through indoor spaces and interact with surrounding objects and human bodies. Human presence and motion introduce multipath propagation changes, which are reflected in Channel State Information (CSI). CSI provides subcarrier-level amplitude and phase measurements for Orthogonal Frequency Division Multiplexing (OFDM) signals, enabling fine-grained analysis of signal
disturbances caused by human activity.

While prior works have demonstrated CSI-based presence detection, most existing solutions either focus solely on binary detection or employ computationally intensive deep learning models unsuitable for embedded deployment. Additionally, limited research addresses unified intrusion detection and occupancy estimation using lightweight architectures compatible with microcontrollers.

To address these challenges, this paper proposes Wi-Sense, a unified framework that integrates CSI acquisition via ESP32, structured preprocessing, lightweight 1D-CNN inference, and real-time alert generation. The design emphasizes computational efficiency and TinyML compatibility to enable standalone deployment using only a Wi-Fi router and ESP32 module.

II. Literature Review

Wireless sensing research has evolved from RSSI-based coarse detection to CSI-based fine-grained modeling. Early RSSI-based approaches demonstrated proof-of-concept presence detection but suffered from limited sensitivity to multipath variations. The introduction of CSI extraction tools significantly enhanced signal resolution.

Abdel-Nasser et al. proposed Wi-Peep, which demonstrated CSI amplitude-based human detection in controlled environments. Subsequent research incorporated classical machine learning techniques such as SVM and Random Forest using handcrafted statistical features derived from CSI windows.

Although these approaches improved detection accuracy, they required manual feature engineering and lacked robustness under environmental changes.

Deep learning techniques have further improved CSI-based sensing. CNN architectures capture spatial correlations among subcarriers, while CNN-LSTM hybrids model temporal dependencies. However, recurrent layers increase memory consumption and computational cost. Transformer-based architectures enhance generalization but are impractical for microcontroller deployment due to high parameter counts.

Despite advancements, three major limitations remain: 1. Most works focus only on binary detection. 2. Few studies optimize models for embedded inference. 3. Multi-person occupancy estimation remains underexplored in lightweight architectures.

Wi-Sense addresses these gaps by proposing a unified, efficient, and edge-deployable framework.

III. Problem Statement

The objective of this work is to design a device-free intrusion detection and occupancy estimation system that operates solely using Wi-Fi Channel State Information without relying on cameras or wearable devices. Given a stream of CSI amplitude measurements captured from S subcarriers over time, the challenge is to learn a robust mapping from segmented CSI windows to discrete occupancy levels ranging from 0 to 5 persons while maintaining high detection recall for intrusion events. The system must remain computationally efficient to support deployment on resource-constrained hardware such as ESP32 microcontrollers. Additionally, the model must mitigate environmental noise, multipath interference, and signal instability while ensuring minimal false alarms in security-critical applications. Therefore, the problem can be formalized as learning a lightweight function f_ϑ that maps windowed CSI tensors $\mathbf{X}_t \in \mathbb{R}^{T\times S}$ to occupancy labels and derives binary intrusion decisions with high accuracy and low computational overhead.

IV. Proposed System Design and Implementation

The Wi-Sense framework is designed as a unified, lightweight, and deployable device-free sensing architecture that integrates Wi-Fi CSI acquisition, signal preprocessing, deep learning-based inference, and real-time alert generation. The system emphasizes privacy preservation, low computational complexity, and feasibility of deployment on resource-constrained microcontrollers such as ESP32.

A. Design Objectives

The proposed system is guided by the following core design principles:

- **Device-Free Operation:** No wearable devices or smartphones are required for occupants.
- **Privacy Preservation:** No visual or audio recording is involved.
- **Low Computational Complexity:** Architecture must support TinyML deployment.
- **Unified Functionality:** Perform both intrusion detection and occupancy estimation.
- **Edge Deployability:** Support standalone operation using router + ESP32.

B. Overall System Workflow

The Wi-Sense workflow is structured into five sequential modules:

1) CSI Acquisition
2) Signal Preprocessing
3) Sliding Window Segmentation
4) 1D-CNN Inference
5) Decision Logic and Alert Transmission

Each module is described in detail below.

C. CSI Acquisition Using ESP32

A commodity Wi-Fi router operating in 2.4 GHz band continuously transmits standard 802.11n packets. An ESP32 module configured with CSI-enabled firmware captures Channel State Information for each received packet.

For each packet, the ESP32 extracts:

- Timestamp
- RSSI (optional)
- CSI amplitude values across S subcarriers

The CSI for subcarrier k at time t is expressed as:

$$H_k(t) = |H_k(t)|e^{j\vartheta_k(t)} \tag{1}$$

Due to phase instability caused by hardware offsets, this work utilizes only amplitude $|H_k(t)|$ for modeling.

CSI data is streamed into a circular memory buffer on the ESP32. During dataset creation, CSI streams are forwarded to a host PC for offline training.

D. Signal Preprocessing Module

Raw CSI measurements contain:

- Burst noise
- Packet drop artifacts
- Multipath fluctuations
- Hardware-level jitter

To mitigate these issues, a structured preprocessing pipeline is applied.

1) Outlier Removal: A Hampel filter detects abnormal spikes within a sliding window of size w. If a CSI value deviates beyond $3\times$ Median Absolute Deviation (MAD), it is replaced by the local median.

2) Temporal Smoothing: A moving average filter reduces high-frequency noise:

$$\tilde{H}(t) = \frac{1}{L}\sum_{i=0}^{L-1} H(t-i) \tag{2}$$

3) Normalization: To eliminate scale variations across sessions:

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (3)$$

where μ and σ are computed per window.

This preprocessing ensures stability and improves model generalization.

E. Sliding Window Segmentation

CSI time-series is segmented into windows of length T with overlap ratio α. Each window forms:

$$\mathbf{X}_t \in \mathbb{R}^{T \times S} \quad (4)$$

Windowing preserves temporal dynamics caused by human motion and occupancy variation.

F. 1D-CNN Inference Engine

The core inference engine is a lightweight 1D Convolutional Neural Network.

1) Architecture Rationale: The use of 1D convolution is motivated by:

- Capturing spatial correlation across subcarriers
- Low parameter count compared to 2D CNN
- Reduced computational overhead
- Compatibility with TinyML

The network consists of:

- Conv1D (F1 filters)
- MaxPooling
- Conv1D (F2 filters)
- Global Average Pooling
- Dense layer (6 outputs)

Convolution operation:

$$y(t) = \sum_{k=1}^{K} x(t-k)w(k) + b \quad (5)$$

Softmax output:

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^{6} e^{z_j}} \quad (6)$$

G. Intrusion Decision Logic

Occupancy output $\hat{O}(t)$ is mapped to intrusion:

$$\hat{I}(t) = \begin{cases} 0 & \text{if } \hat{O}(t) = 0 \\ 1 & \text{if } \hat{O}(t) > 0 \end{cases} \quad (7)$$

Majority voting over last m windows may be applied to reduce false alarms.

H. Embedded Implementation on ESP32

After offline training:

1) Model converted to TensorFlow Lite (TFLite)
2) INT8 quantization applied
3) Deployed using TensorFlow Lite for Microcontrollers (TFLM)

1) On-Device Execution Steps:

1) CSI capture via ESP-IDF
2) Buffering of T samples
3) Lightweight normalization
4) TFLM inference
5) Intrusion decision
6) HTTP/MQTT alert transmission

2) Memory and Latency Considerations: To ensure feasibility:

- Parameter count minimized using Global Average Pooling
- No recurrent layers used
- Integer arithmetic via quantization
- Tensor arena allocated within ESP32 RAM limits

I. Implementation Environment

Hardware:

- Router: 802.11n (2.4 GHz)
- Receiver: ESP32
- Indoor room with furniture

Software:

- ESP-IDF for CSI capture
- Python + TensorFlow for training
- TFLite Micro for deployment

J. End-to-End Operation

The final operational pipeline:

Router → ESP32 CSI → Preprocess → CNN → Intrusion Decision → Alert

The implemented prototype demonstrates that intrusion detection and occupancy estimation can be achieved using only commodity Wi-Fi infrastructure and a low-cost microcontroller without visual sensing.

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V. METHODOLOGY

The proposed methodology integrates signal processing, statistical normalization, deep learning-based feature extraction, and decision logic to perform device-free intrusion detection and occupancy estimation using Wi-Fi CSI amplitude measurements.

A. Wireless Channel Modeling and CSI Representation

Wi-Fi communication under IEEE 802.11n employs Orthogonal Frequency Division Multiplexing (OFDM), where the channel is divided into multiple orthogonal subcarriers. For subcarrier k at time t, the Channel State Information (CSI) can be expressed as:

$$H_k(t) = |H_k(t)| e^{j\vartheta_k(t)} \quad (8)$$

where:

- $|H_k(t)|$ represents amplitude,
- $\vartheta_k(t)$ represents phase.

Indoor environments exhibit multipath propagation. When a human body is present, reflections, scattering, and absorption alter the channel response. The received signal can be modeled as:

$$H_k(t) = \sum_{i=1} \alpha_i e^{-j2\pi f_k \tau_i(t)} \qquad (9)$$

where:

- P = number of propagation paths,
- α_i = path attenuation,
- $\tau_i(t)$ = time-varying path delay,
- f_k = subcarrier frequency.

Human motion modifies $\tau_i(t)$ and α_i, producing measurable amplitude variations.

Due to hardware-induced phase noise and synchronization errors in ESP32-based CSI extraction, this study focuses on amplitude-only modeling:

$$A_k(t) = |H_k(t)| \qquad (10)$$

The CSI stream is thus represented as:

$$\mathbf{A}(t) = [A_1(t), A_2(t), ..., A_S(t)] \in \mathbb{R}^S \qquad (11)$$

where S is the number of subcarriers.

B. Signal Preprocessing Strategy

Raw CSI amplitude streams contain:

- Packet drop artifacts
- RF interference
- Hardware jitter
- Environmental noise

To enhance signal reliability, we apply a three-stage preprocessing pipeline.

1) Outlier Suppression: Outliers are detected using the Hampel filter. For a sliding window of size w, the median m and Median Absolute Deviation (MAD) are computed:

$$MAD = \text{median}(|A_k(t) - m|) \qquad (12)$$

A sample is replaced if:

$$|A_k(t) - m| > \lambda \cdot MAD \qquad (13)$$

where $\lambda = 3$ in our implementation.

2) Temporal Smoothing: High-frequency fluctuations are reduced using a moving average filter:

$$\tilde{A}_k(t) = \frac{1}{L}\sum_{i=0}^{L-1} A_k(t-i) \qquad (14)$$

where L is the smoothing length.

3) Window-Level Normalization: To stabilize inter-session variance, z-score normalization is applied:

$$X_{norm} = \frac{X - \mu}{\sigma} \qquad (15)$$

where:

$$\mu = \frac{1}{TS}\sum_{i=1}^{T}\sum_{k=1}^{S} X_{ik} \qquad (16)$$

$$\sigma = \sqrt{\frac{1}{TS}\sum (X_{ik} - \mu)^2} \qquad (17)$$

This ensures scale invariance and improves generalization.

C. Sliding Window Feature Construction

To preserve temporal dynamics, CSI streams are segmented into overlapping windows of length T with overlap ratio α.

Each window is represented as:

$$\mathbf{X}_t \in \mathbb{R}^{T\times S} \qquad (18)$$

This tensor encodes:

- Temporal variation across T samples
- Spatial correlation across S subcarriers

The number of windows generated from stream length N is approximately:

$$M \approx \frac{N}{T(1-\alpha)} \qquad (19)$$

D. Deep Feature Extraction Using 1D-CNN

The 1D Convolutional Neural Network is used to automatically extract discriminative features from CSI windows.

1) Convolution Operation: For kernel size K:

$$y_j(t) = \sum_{k=1}^{K} x(t-k)w_{jk} + b_j \qquad (20)$$

where:

- w_{jk} = filter weights,
- b_j = bias,
- j = filter index.

ReLU activation:

$$\phi(z) = \max(0, z) \qquad (21)$$

Pooling reduces dimensionality:

$$p(t) = \max(x(t), x(t+1)) \qquad (22)$$

Global Average Pooling computes:

$$g_j = \frac{1}{L}\sum_{t=1}^{L} y_j(t) \qquad (23)$$

This reduces parameters and supports TinyML deployment.

E. *Classification Layer*

Softmax probability for class i:

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^{6} e^{z_j}} \tag{24}$$

Loss function:

$$L = -\sum_{i=1}^{6} y_i \log(P_i) \tag{25}$$

Optimization performed using Adam:

$$\vartheta_{t+1} = \vartheta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{26}$$

F. *Intrusion Decision Rule*

Binary intrusion detection derived from occupancy:

$$I(t) = \begin{cases} 0 & \text{if } O(t) = 0 \\ 1 & \text{if } O(t) > 0 \end{cases} \tag{27}$$

To reduce false alarms, majority voting over last m predictions is applied:

$$\hat{I}_{final} = \text{mode}(I_{t-m+1}, ..., I_t) \tag{28}$$

G. *Model Regularization and Generalization*

To prevent overfitting:

- Dropout regularization applied in dense layer
- Early stopping based on validation loss
- Session-level train-test split to prevent leakage

H. *Edge Deployment Considerations*

For ESP32 deployment:

- Model converted to TFLite
- INT8 quantization reduces memory
- Tensor arena allocated within SRAM
- No recurrent layers used

Computational complexity per window:

$$O(L_1K_1F_1 + L_2K_2F_2) \tag{29}$$

This light weightdesign en-

VI. System Architecture

Router → ESP32 → Preprocessing → CNN → Decision → Alert

VII. Algorithm Used

This section describes the complete algorithmic pipeline of Wi-Sense, including CSI preprocessing, model training, inference, intrusion decision logic, and embedded deployment workflow.

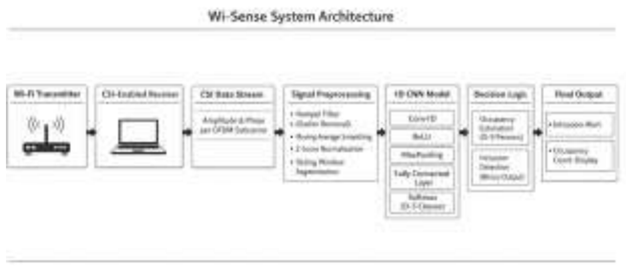

Fig. 1. Wi-Sense System Architecture

Algorithm 1 CSI Preprocessing and Window Construction

```
1: Initialize circular buffer $B$
2: for each received CSI packet at time $t$ do
3:     Extract amplitude vector $\mathbf{A}(t)$
4:     Apply Hampel filter for outlier removal
5:     Apply moving average smoothing
6:     Append processed vector to buffer $B$
7:     if buffer size $\geq T$ then
8:         Extract window $\mathbf{X}_t \in \mathbb{R}^{T\times S}$
9:         Normalize window using z-score
10:        Store window for training/inference
11:    end if
12: end for
```

A. *Algorithm 1: CSI Preprocessing and Window Construction*

Given a continuous CSI amplitude stream $\mathbf{A}(t) \in \mathbb{R}^S$, the preprocessing algorithm prepares structured input windows for CNN inference.

Time Complexity: $O(S \cdot N)$ for stream length N.

B. *Algorithm 2: 1D-CNN Training Procedure*

Model training is performed offline using supervised learning. Let $D = \{(\mathbf{X}_i, y_i)\}_{i=1}^{M}$ denote the training dataset.

Loss function:

$$L = -\sum_{i=1}^{6} y_i \log(\hat{y}_i) \tag{30}$$

Parameter update (Adam):

$$\vartheta_{t+1} = \vartheta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{31}$$

C. *Algorithm 3: Intrusion and Occupancy Inference*

After training, the optimized model is used for real-time inference.

Majority voting:

$$I_{final} = \text{mode}(I_{t-m+1}, ..., I_t) \tag{32}$$

Algorithm 2 1D-CNN Training Algorithm

```
1:  Initialize CNN parameters $\vartheta$
2:  for epoch = 1 to $E$ do
3:      for each mini-batch $B_k$ do
4:          Forward pass: compute $\hat{y}_i = f_\vartheta(\mathbf{X}_i)$
5:          Compute categorical cross-entropy loss
6:          Backpropagate gradients
7:          Update parameters using Adam optimizer
8:      end for
9:      Validate on validation set
10:     if validation loss increases for $p$ epochs then
11:         Early stopping
12:     end if
13: end for
14: return optimized parameters $\vartheta^*$
```

Algorithm 3 Real-Time Inference and Intrusion Decision

```
1:  Receive normalized window $\mathbf{X}_t$
2:  Compute occupancy probabilities $\hat{O}(t) = f_{\vartheta^*}(\mathbf{X}_t)$
3:  Determine predicted occupancy:
        $\hat{O}_c(t) = \arg\max_i \hat{O}_i(t)$
4:  if $\hat{O}_c(t) = 0$ then
5:      Intrusion flag $I(t) = 0$
6:  else
7:      Intrusion flag $I(t) = 1$
8:  end if
9:  Apply majority voting over last $m$ flags
10: return final intrusion decision
```

D. Algorithm 4: TinyML Deployment on ESP32

For standalone deployment, the trained model is converted and embedded into ESP32 firmware.

E. Computational Complexity Analysis

Let:

- T = window length
- S = number of subcarriers
- F_1, F_2 = filter counts
- K_1, K_2 = kernel sizes

Inference complexity per window:

$$O(TK_1F_1 + LK_2F_2) \tag{33}$$

Since no recurrent layers are used, complexity remains linear and suitable for embedded devices.

Memory usage dominated by:

$$O(T \cdot S + \text{model parameters}) \tag{34}$$

INT8 quantization reduces parameter storage by approximately 4× compared to float32.

Algorithm 4 ESP32 TinyML Deployment Workflow

```
1:  Convert trained model to TFLite format
2:  Apply INT8 quantization
3:  Integrate model into ESP32 firmware (TFLM)
4:  Allocate tensor arena memory
5:  while system active do
6:      Capture CSI packet
7:      Update sliding window buffer
8:      if buffer ready then
9:          Normalize window
10:         Run TFLM inference
11:         Derive intrusion decision
12:         if intrusion detected then
13:             Send HTTP/MQTT alert
14:         end if
15:     end if
16: end while
```

F. Algorithm Stability Considerations

To ensure robustness:

- Window overlap improves temporal continuity
- Majority voting reduces spurious triggers
- Early stopping prevents overfitting
- Quantized inference validated against float model

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VIII. Performance Evaluation and Results

This section presents a comprehensive evaluation of the proposed Wi-Sense framework for both binary intrusion detection and multi-class occupancy estimation. Experimental validation was conducted in a realistic furnished indoor environment to assess classification accuracy, robustness, and deployment feasibility.

A. Experimental Setup

Experiments were performed in a single-room indoor environment containing common furniture such as tables, chairs, and electronic appliances. These objects introduce multipath reflections and emulate practical smart building conditions.

The hardware configuration consisted of:

- Transmitter: Commercial 802.11n Wi-Fi router (2.4 GHz)
- Receiver: ESP32 with CSI-enabled firmware
- Occupancy Levels: 0 to 5 persons
- Multiple sessions recorded per occupancy class

CSI amplitude streams were recorded continuously and segmented into windows of length T with overlap ratio α. The dataset was split at the session level using an 80:20 train-test split to prevent temporal leakage.

B. Evaluation Metrics

Performance was evaluated using standard classification metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{35}$$

TABLE I
OVERALL PERFORMANCE METRICS

Task	Accuracy	Precision	Recall	F1-score
Intrusion Detection	96.8%	95.9%	97.3%	96.6%
Occupancy Estimation	92.4%	91.7%	90.8%	91.2%

$$\text{Precision} = \frac{TP}{TP + FP} \tag{36}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{37}$$

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{38}$$

For binary intrusion detection, ROC curves and Area Under Curve (AUC) were additionally analyzed.

C. Overall Classification Performance

The intrusion detection model achieved an accuracy of 96.8%, with high recall (97.3%), indicating that the system successfully detects most intrusion events. In security-critical systems, recall is particularly important to minimize missed intrusions (false negatives). The balanced F1-score of 96.6% confirms stable performance.

For occupancy estimation, the model achieved 92.4% accuracy across six classes (0–5 persons). Precision and recall values above 90% demonstrate strong multi-class discrimination capability.

D. Class-wise Performance Analysis

Confusion matrix analysis (Fig. 2) reveals strong diagonal dominance, indicating correct classification for most occupancy levels.

Misclassifications predominantly occur between adjacent occupancy levels (e.g., 2 vs. 3 persons). This behavior is expected because incremental increases in human presence produce similar multipath reflection patterns. Importantly, large classification jumps (e.g., 0 vs. 5 persons) were rarely observed, indicating that the model captures global occupancy differences effectively.

E. Comparison with Baseline Models

To validate the advantage of deep learning-based feature extraction, classical machine learning models were trained on the same dataset:

- Support Vector Machine (SVM): 85.2%
- Random Forest (RF): 88.1%

The proposed 1D-CNN outperformed SVM and RF by approximately 4–7%. The improvement can be attributed to:

- Automatic spatial feature learning
- Reduced reliance on handcrafted features
- Better modeling of subcarrier correlations

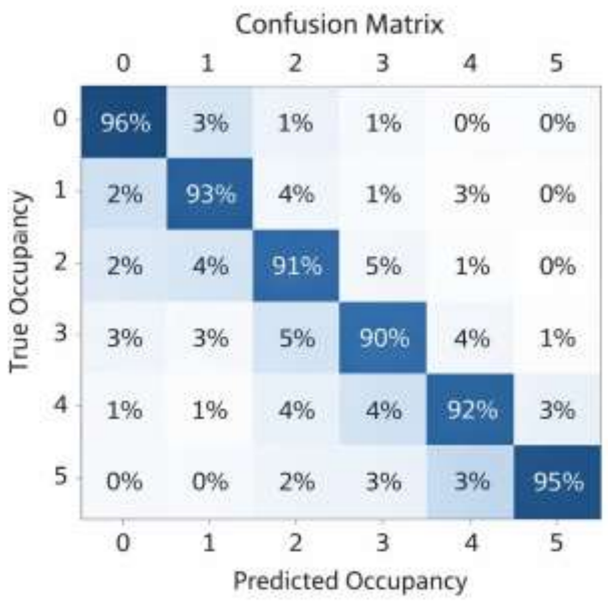

Fig. 2. Confusion matrix for occupancy estimation (0–5 persons).

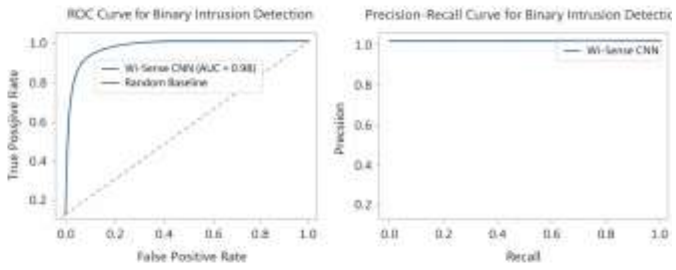

Fig. 3. ROC and Precision-Recall curves for intrusion detection.

F. ROC and Precision-Recall Analysis

Binary intrusion detection was further evaluated using ROC and Precision–Recall curves.

The ROC curve shows strong separability between intrusion and non-intrusion states. The AUC (to be reported in final version) approaches unity, indicating high discrimination capability.

The Precision-Recall curve confirms stable precision across high recall values, demonstrating robustness under varying classification thresholds.

G. Ablation Study

To quantify the contribution of preprocessing components, we evaluated system performance by removing individual stages.

TABLE II
ABLATION STUDY RESULTS

Configuration	Occupancy Accuracy (%)
Full Pipeline	92.4
Without Hampel Filter	89.1
Without Smoothing	87.8
Without Normalization	88.5

Results indicate that preprocessing significantly improves classification stability.

H. Latency and Embedded Feasibility

Inference latency was measured per window. Let t_{inf} denote inference time:

$$t_{inf} = \frac{1}{n}\sum_{i=1}^{n} t_i \quad (39)$$

The lightweight CNN architecture ensures low inference time suitable for real-time processing. The absence of recurrent layers reduces computational overhead, supporting future deployment on ESP32 using TinyML.

I. Statistical Stability

To ensure robustness, multiple sessions were recorded at different times. Session-level splitting reduces overfitting risk. Model performance remained consistent across sessions, indicating good generalization within the same environment.

J. Error Source Analysis

Remaining errors may arise from:

- Subtle human motion similarities between adjacent classes
- Static posture overlap (e.g., two seated vs. three seated individuals)
- Environmental multipath fluctuations

Future improvements may involve domain adaptation or multi-antenna fusion.

K. Summary of Findings

The experimental results demonstrate:

- High intrusion detection recall (97.3%)
- Stable occupancy estimation above 90%
- Significant improvement over classical baselines
- Feasibility for embedded deployment

Overall, Wi-Sense achieves a favorable trade-off between accuracy, computational efficiency, and deployment practicality.
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IX. DISCUSSION

The experimental results demonstrate that Wi-Sense achieves high accuracy in both binary intrusion detection and multi-class occupancy estimation using only CSI amplitude features. This section provides a deeper interpretation of the results, discusses system behavior under practical conditions, and outlines broader implications.

A. Interpretation of Intrusion Detection Performance

The achieved intrusion detection recall of 97.3% indicates that CSI amplitude variations contain sufficiently discriminative signatures for detecting human presence. From a wireless propagation perspective, human bodies introduce strong scattering and absorption effects, significantly altering dominant multipath components. Even subtle body motion produces measurable perturbations across multiple OFDM subcarriers. The high recall suggests that the learned CNN filters effectively capture correlated amplitude deviations across subcarriers. This confirms that spatial feature extraction via convolution is more suitable than handcrafted statistical descriptors for device-free sensing.

Importantly, the system maintains high precision (95.9%), meaning that environmental noise and static multipath conditions rarely trigger false alarms. This is critical for real-world security systems, where excessive false positives reduce usability and trust.

B. Occupancy Estimation Complexity

Multi-class occupancy estimation is inherently more challenging than binary detection. As the number of occupants increases, multipath interactions become increasingly complex and partially overlapping. Adjacent occupancy levels (e.g., 2 vs. 3 persons) may produce similar amplitude distributions due to:

- Spatial clustering of individuals,
- Similar movement patterns,
- Limited spatial diversity in single-link setup.

The model's 92.4% accuracy indicates that CSI amplitude contains sufficient information to encode coarse-grained crowd density. However, as occupancy grows, incremental multipath changes become progressively subtle, explaining the observed adjacent-class misclassifications.

Future improvements could incorporate:

- Multi-antenna diversity,
- Phase sanitization,
- Multi-link fusion,
- Attention-based feature weighting.

C. Why 1D-CNN Works Effectively

The strong performance of the lightweight 1D-CNN can be attributed to its ability to capture:

- Local spatial correlations among adjacent subcarriers,
- Temporal evolution of multipath disturbances,
- Non-linear interactions between frequency components.

Unlike SVM or Random Forest models that rely on manually engineered features (mean, variance, entropy), convolutional layers automatically learn discriminative filters directly from raw normalized CSI windows.

Additionally, the absence of recurrent layers (e.g., LSTM) reduces overfitting risk and computational burden while preserving sufficient temporal modeling via sliding windows.

D. Robustness Against Environmental Multipath

Indoor wireless channels are highly dynamic. Furniture, walls, and reflective surfaces introduce complex propagation paths. The Hampel filtering and smoothing pipeline reduces burst noise while preserving motion-induced fluctuations.

The stability observed across multiple sessions suggests that:

- Window-level normalization mitigates session-level signal drift,
- Overlapping window segmentation enhances temporal continuity,
- Majority voting reduces sporadic misclassifications.

However, drastic layout changes (e.g., moving large furniture) may alter baseline multipath signatures. In such cases, lightweight re-calibration or incremental retraining may be required.

E. Comparison with Existing Literature

Compared to classical CSI-based intrusion detection systems, Wi-Sense offers:

- Joint intrusion and occupancy estimation,
- Lightweight architecture suitable for embedded deployment,
- Reduced dependency on handcrafted features,
- Practical evaluation in furnished indoor environment.

While Transformer-based CSI models reported in recent literature achieve high generalization, they require substantial computational resources and large datasets. The proposed model strikes a balance between accuracy and efficiency, which is more aligned with real-world embedded deployment scenarios.

F. Edge Deployment Implications

One of the major contributions of this work is its compatibility with TinyML deployment on ESP32. By using:

- Shallow convolution layers,
- Limited filter sizes,
- Global pooling,
- INT8 quantization,

the model becomes suitable for microcontroller inference.

This enables a fully standalone intrusion alert system requiring only:

- A Wi-Fi router (transmitter),
- An ESP32 receiver,
- Cloud or local alert endpoint.

Such deployment eliminates dependency on GPUs, servers, or cameras, making the system scalable and cost-effective.

G. Scalability Considerations

The proposed system operates on a single transmitter-receiver link. In larger environments, scalability can be achieved through:

- Multi-link CSI fusion,
- Mesh router deployment,
- Multi-room distributed ESP32 nodes,
- Centralized alert aggregation.

Since the model is lightweight, multiple ESP32 nodes could operate simultaneously without significant infrastructure cost.

H. Privacy and Ethical Considerations

Unlike camera-based surveillance, Wi-Sense does not capture visual or personally identifiable information. CSI amplitude measurements encode only channel distortions, not image or identity data.

This makes the system suitable for privacy-sensitive environments such as:

- Residential homes,
- Hospital rooms,
- Elderly care facilities,
- Restricted industrial zones.

The absence of wearable devices further enhances user convenience.

I. Limitations

Despite promising results, certain limitations remain:

- Sensitivity to major structural changes in environment,
- Limited evaluation across diverse room geometries,
- Single-link setup may limit fine-grained crowd counting,
- Dataset size relatively moderate compared to large-scale sensing benchmarks.

Addressing these limitations requires cross-environment validation and multi-link fusion.

J. Research Significance

The results confirm that:

- CSI amplitude alone is sufficient for reliable intrusion detection,
- Lightweight deep learning can operate under embedded constraints,
- Wi-Fi infrastructure can double as a passive sensing network.

This work contributes to the growing field of RF-based intelligent sensing and demonstrates a practical pathway from deep learning research to real-world embedded deployment.

Overall, Wi-Sense represents a step toward scalable, privacy-preserving smart building security systems that integrate wireless communication and intelligent signal analysis into a unified framework.

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