# Contributions and Implications of this Research

This research presents a novel, privacy-preserving solution to the long-standing challenge of reliable human presence detection, particularly where traditional PIR sensors struggles to detect stationary occupants.

### Novelty and Innovation:

A low-resolution thermal sensor (Omron D6T-32L-01A) was deliberately chosen to preserve user privacy, as it captures no identifiable features, making the system suitable for sensitive indoor environments such as restrooms, bedrooms, or offices.

The system introduced an Exponential Moving Average (EMA)-based adaptive background subtraction mechanism, enabling it to dynamically distinguish between human presence and static ambient heat sources such as radiators, electronics, or plumbing fixtures. Unlike static background modeling, this technique learns the thermal baseline empirically, adapting in real-time to both radiator-present and radiator-absent environments.

Empirical testing showed that the EMA-based background model required approximately 12 seconds (60 frames at 5 FPS) of human-free observation to converge to a stable thermal profile. This made the system highly responsive and self-correcting, capable of quickly adapting to new environments or thermal shifts without manual calibration. Crucially, the algorithm automatically halts background adaptation when a human is detected, preventing occupancy from being absorbed into the baseline model, a common failure mode in conventional systems.

This fast, adaptive learning approach allowed the model to maintain high accuracy in thermally cluttered indoor conditions, delivering robust presence detection even in spaces previously considered challenging for thermal-based systems.

### Practical Impact:

By leveraging a Temporal CNN architecture, the model was able to capture both spatial and temporal thermal features, enabling it to detect both motion and static presence — a known limitation in traditional PIR sensors that rely primarily on motion for detection.

The full solution was successfully deployed on both Raspberry Pi (high-end edge platform) and ESP32-S3 (low-power embedded microcontroller). Even after quantization and background suppression removal on the ESP32, the model retained 94% real-time accuracy, proving its robustness and scalability for commercial use.

### Broader Implications:

The system addresses **key challenges in privacy, reliability, and energy-efficient automation**, making it highly applicable to smart homes, workplaces, and elderly care settings.

It bridges the gap between **academic research and industrial deployment** by demonstrating that deep learning models can be effectively compressed, optimized, and deployed in **real-world IoT environments** without sacrificing reliability.

### Impact on Industrial and Academic Communities:

The work directly contributes to **Wygwam’s innovation pipeline**, influencing their R&D direction toward AI-driven, privacy-conscious sensing technologies. Academically, it serves as a **blueprint for translating theoretical machine learning models into practical, deployable systems** through rigorous design, optimization, and validation, showcasing how academic research can drive real-world innovation.

# Limitations

While the system demonstrated high performance and broad applicability, several limitations remain:

1. **Simplified Model for Embedded Deployment**

The ESP32-S3 version required model simplification and INT8 quantization. As a result, the background subtraction module was excluded, slightly reducing accuracy in thermally cluttered conditions.

1. **Limited Environmental Diversity in Testing**

Testing was limited to indoor conditions (e.g., offices, bedrooms, washrooms). The model’s generalizability to **outdoor environments, overlapping occupants,** or **extreme temperature gradients** remains unverified.

1. **Thermal Sensor Constraints**

The Omron D6T sensor has a **limited detection range (~3 meters)** and a low resolution (32×32). While this preserves privacy, it also restricts the larger room coverage. To enable full-room coverage, a **multi-sensor network architecture** or **sensor fusion** may be required.

1. **No Evaluations on Pets or Dense Crowds**

The current system assumes a limited number of human occupants. Scenarios involving **pets, children, or densely populated environments** were not tested and may introduce ambiguity or reduced performance.

# References

**Section 2.3.1.**

**Gradient-Based Features**

1. Trofimova, A.A., et al. (2017). *Indoor Human Detection Based on Thermal Array Sensor Data and Adaptive Background Estimation*. Journal of Computer and Communications. <https://doi.org/10.4236/jcc.2017.54002>  
   Uses gradient-based features and background modeling for thermal-based human detection.
2. Pontes, B., et al. (2017). *Thermal Sensor Data Classification of Postures*. In: Distributed, Ambient and Pervasive Interactions. <https://doi.org/10.1007/978-3-319-58697-7_33>  
   Uses location-based thermal gradients and edge information to improve posture classification.

**Hot Region Variance:**

1. **Zhao, C., et al. (2019).**  
   *Occupancy Detection Using a Low-Resolution Thermal Sensor in a Smart Building.*  
   **Energy and Buildings, 186**, 197–208.  
   https://doi.org/10.1016/j.enbuild.2019.01.035

Talks about clustering hot pixels and using **spatial spread of thermal intensity** — again, similar to what your "hot region variance" captures.

**Edge-based Features:**

1. Park, J., et al. (2020). CNN-Based Person Detection Using Infrared Images for Night-Time Intrusion Warning Systems. Sensors. <https://doi.org/10.3390/s20010034>  
   Demonstrates that edge detection in infrared/thermal images enhances person detection reliability.

**Section 2.4.1.**

1D CNN Model

1. **Sahu, H., & Shaik, R. (2020)**

**Title**: An Improved One-Dimensional Convolutional Neural Network for Human Activity Recognition  
**Journal**: Procedia Computer Science, 171, 148–155.  
**DOI**: 10.1016/j.procs.2020.04.017  
✅ Demonstrates the use of 1D CNNs for classifying sequential sensor data (IMU), showing their strength in time-series learning.

**Section 2.4.2.**

2D CNN Model with Feature Engineering

1. **Park, J., et al. (2020)**

**Title**: CNN-Based Person Detection Using Infrared Images for Night-Time Intrusion Warning Systems  
**Journal**: Sensors, 20(1), 34.  
**DOI**: [10.3390/s20010034](https://doi.org/10.3390/s20010034)  
Applies 2D CNNs to thermal images (infrared) to detect human presence at night — directly aligns with your use case.

1. **Chen, T., et al. (2019)**

**Title**: Thermal Image-Based Human Detection Using Convolutional Neural Network  
**Conference**: IEEE International Conference on Artificial Intelligence and Big Data (ICAIBD).  
**DOI**: 10.1109/ICAIBD.2019.8837022  
Shows how 2D CNNs extract spatial features from thermal frames for real-time detection.

**Section 2.4.3.**

**Hybrid Model (CNN and LSTM) with Feature Engineering**

1. Donahue, J., et al. (2015). Long-Term Recurrent Convolutional Networks for Visual Recognition and Description. CVPR. https://doi.org/10.1109/CVPR.2015.7298965  
   🟢 Shows how CNNs can be paired with LSTMs to capture both spatial and temporal dynamics.
2. Ahmad Mahmud, N.F., & Ramli, N.A. (2020). Hybrid Classification Method to Detect the Presence of Human in a Smart Building Environment. [IEEE ICDABI]