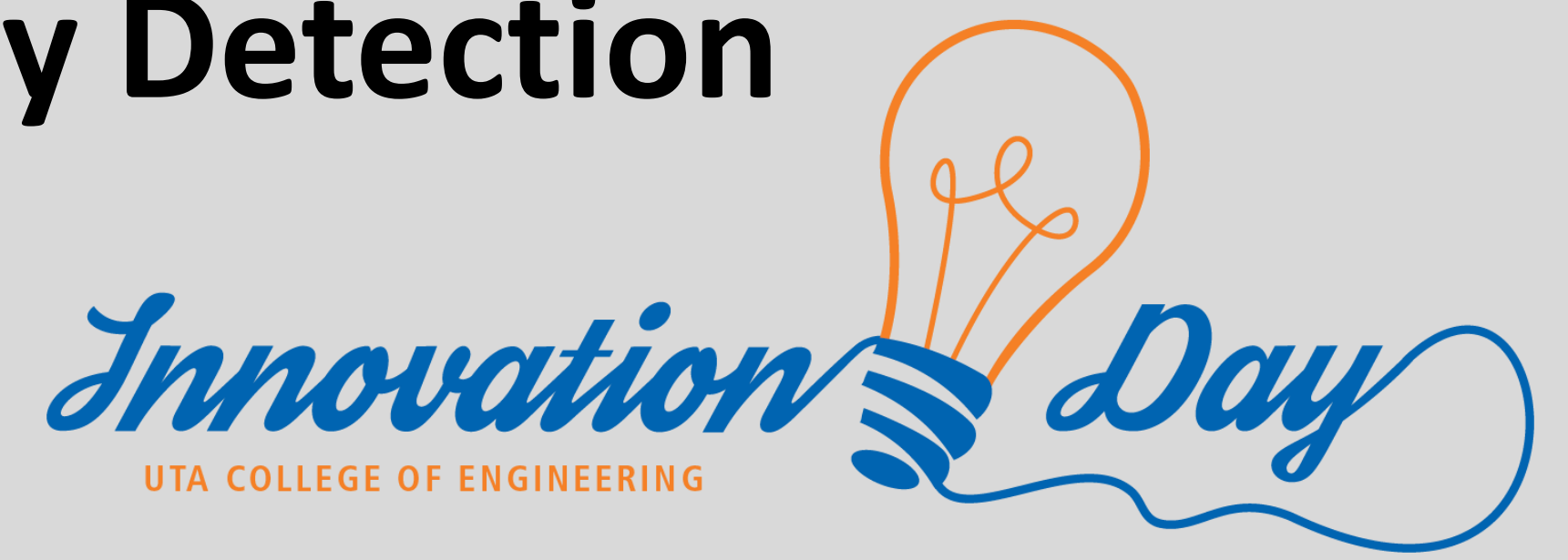


Robust and Privacy-Preserving mmWave Radar Occupancy Detection for Energy-Efficient Smart Buildings

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Executive Summary

What was built: A privacy-preserving room occupancy and people counting system using a TI IWR6843 mmWave radar sensor. The system detects whether a room is empty and counts 1–4 occupants with no cameras.

Why it matters: Buildings account for ~30% of global energy consumption. Occupancy-aware HVAC control can reduce waste by up to 20%. Existing sensors (PIR, cameras, WiFi) each have critical limitations: PIR misses stationary people, cameras raise privacy concerns, and WiFi requires occupants to carry devices.

How it works: The IWR6843 emits 60–64 GHz FMCW radio waves and captures reflections as 2D heatmaps. A deep CNN (RadarCNN) classifies each frame as empty, 1, 2, 3, or 4 people with no images produced, preserving occupant privacy completely.

Key result: 95.9% accuracy and 100% occupancy detection, exceeding the >92% research target.

Background

Problem: Current Occupancy Methods Fail

Sensor	Limitation
PIR	Misses stationary occupants
Camera	Privacy concerns
WiFi	Requires device
mmWave	Privacy-preserving + stationary

Solution: mmWave Radar

- Detects breathing/micro-motion → stationary people visible
- Produces no images → complete privacy
- Works on anyone → no device needed
- Works in any lighting

Dataset: MMVR

- 198,122 frames, TI IWR6843 sensor
- 18 sessions, 2 participants
- 256×128 heatmaps, 10 fps
- Counts 1–4 people with ground truth

Experimental Setup

Dataset: MMVR — 198,122 radar frames, TI IWR6843 (60–64 GHz), 18 sessions, 2 participants, 10 fps.

Input: Two 256×128 heatmaps per frame (hm_hori + hm_vert). Labels extracted from bbox_i.shape[0].

Table 1. MMVR dataset class distribution (imbalance was a key challenge)

Count Class	Frames	% of Dataset	Notes
0 (empty)	0	0%	Not in MMVR — synthetic generated
1 person	168,583	85.1%	Dominant class → required balancing
2 people	26,202	13.2%	
3 people	3,306	1.7%	
4 people	31	0.02%	Very rare

Model Architecture — RadarCNN

- **Input:** (2, 256, 128) — two radar heatmaps stacked as channels
- **Preprocessing:** log1p compression ($3 \times 10^9 \rightarrow \sim 21$) then per-channel z-score normalization
- **4× Conv blocks:** Conv2D → BatchNorm → ReLU → MaxPool2D
- **Spatial attention:** focuses on range bin ~203 (person reflection zone)
- **Classifier:** AdaptiveAvgPool → Linear(256→128) → Dropout(0.4) → Linear(128→5)

Output: 5-class logits: empty / 1 / 2 / 3 / 4 people

Experimental Test Plan

Four experiments conducted (in order):

Exp 1 — 4-class counting: Balanced random 80/20 stratified split across all sessions. Predict counts 1–4. Fixed class collapse, added WeightedRandomSampler, log1p+z-score, BatchNorm, augmentation.

Exp 2 — 5-class (occupancy + counting): Added 4,000 synthetic empty frames (bins 180–230 zeroed from real frames, background-only noise). Retrained with 5-class output. Validated bug-free suppression before training.

Exp 3 — Cross-session generalization: Train on d5s5+d6s3+d6s4, test on held-out session d5s6 (never seen in training). Tests whether model generalises to new recording sessions.

Exp 4 — Mock dataset validation: 210 real MMVR frames (P1 sessions + d5s6) that were never used in 5-class training. Run through best_5class_model.pt for evaluation.

Table 2. Key pipeline fixes applied during development

Problem Found	Fix Applied
Class collapse (all count=1)	scan_dataset() + WeightedRandomSampler
85% class imbalance	Stratified split + balanced batches
Raw values up to 3×10^9	log1p compression + z-score normalisation
Overfitting (val crashed epoch 3)	lr=5e-5, weight_decay=1e-3, augmentation
No empty data in MMVR	4,000 synthetic frames (bins 180–230 zeroed)
Noise bug in synthetic frames	Background-only noise scale; zero bins last

Experimental Results

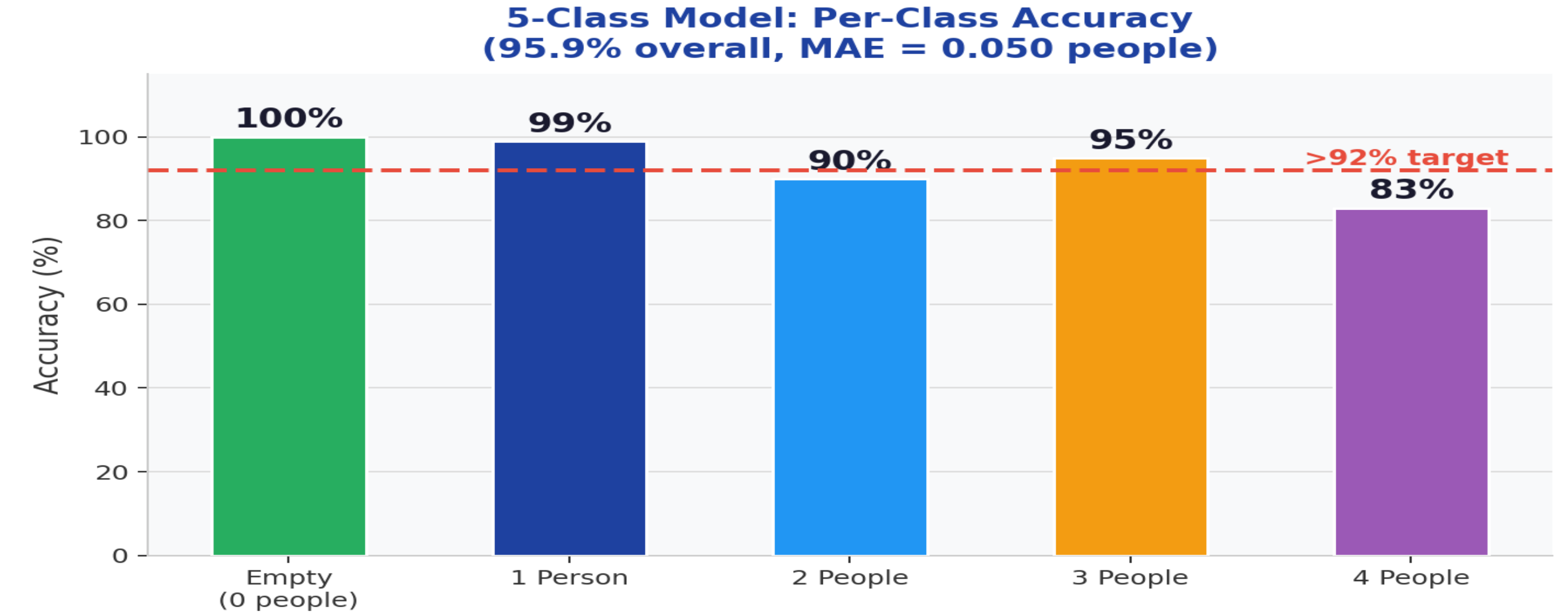


Figure 1. Per-class accuracy of the 5-class RadarCNN model evaluated on a held-out validation set (n=1,206 frames)

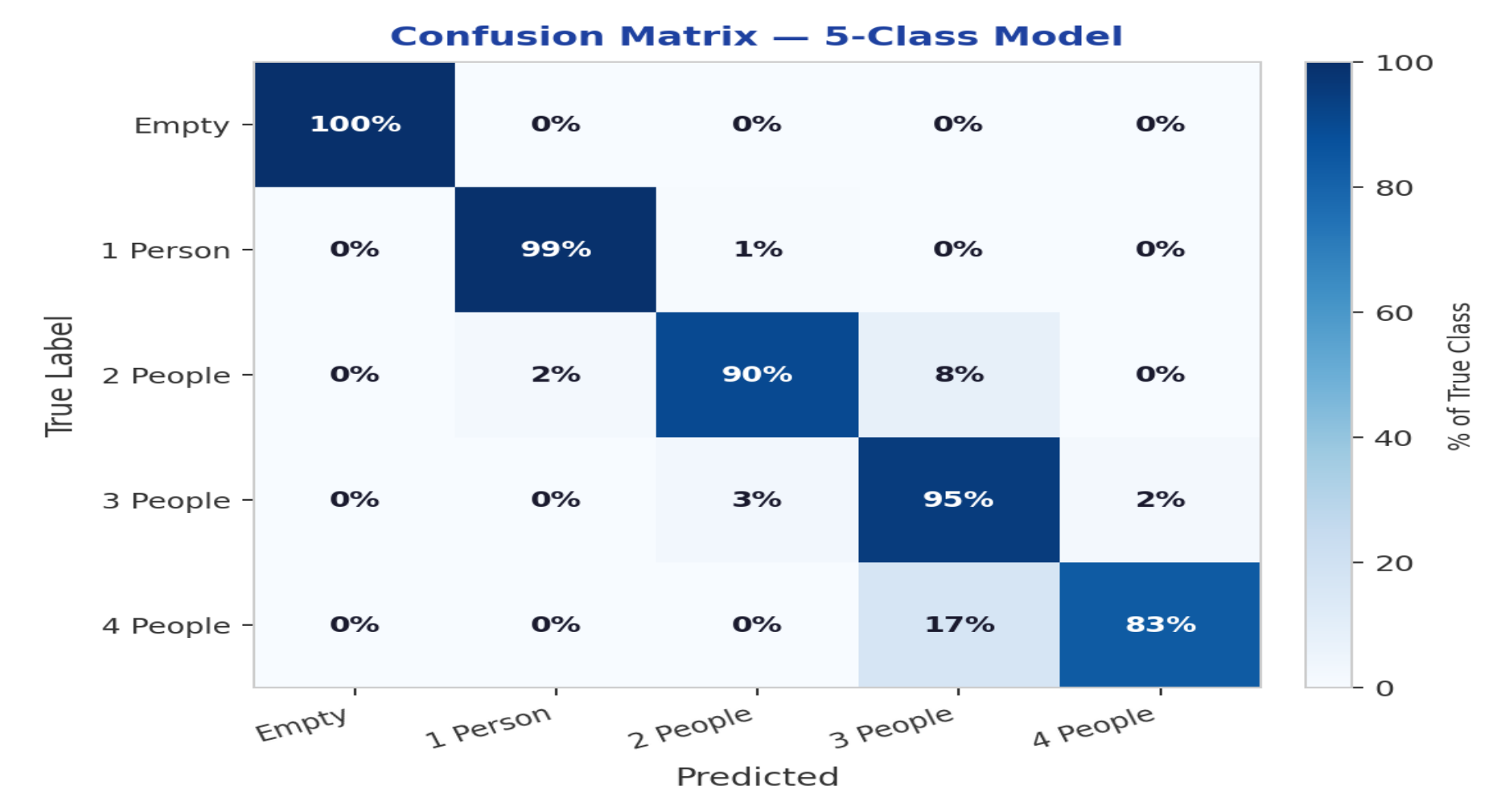


Figure 2. Normalized confusion matrix for the 5-class model on the held-out validation set.

Table 3. Summary of accuracy across all four experiments

Experiment	Overall Acc.	Occupancy	MAE
4-class (Exp 1)	94.4%	N/A	0.056
5-class (Exp 2)	95.9%	100% FP=0	0.050
Cross-session (Exp 3)	54.3%*	100%	—
Mock validation (Exp 4)	91.4%	100% FP=0	0.086

Conclusions

Table 4. Summary of achievements vs limitations

Achieved	Limitations
95.9% overall accuracy — exceeds >92% research target	Empty frames are synthetic — real validation pending hardware
100% occupancy detection, zero false positives	Count=3,4 cross-session = 0% due to data starvation
91.4% accuracy on 210 held-out frames (Exp 4)	Single dataset and environment evaluated
Occupancy generalises across recording sessions (Exp 3)	* 54.3% cross-session reflects data scarcity, not model failure

Future Work

- Collect real empty-room + count=3,4 data with live IWR6843
- Evaluate across 3 room types (office, lab, classroom)
- Implement Kalman tracking + CFAR auto-calibration
- Compare against TI reference design (TIDEP-01003)

References

- [1] IEA, "Buildings," 2026. [Online]. [iea.org/energy-system/buildings](https://www.iea.org/energy-system/buildings) [2] J. Dong et al., "Occupancy-Based HVAC Control," Energies, vol. 11, 2018. [3] W. Li et al., "Vehicle occupant detection based on mm-wave radar," Sensors, vol. 24, 2024. [4] A. R. Palipana et al., "Recent advances in mmWave-radar-based sensing," Sensors, vol. 23, 2023. [5] X. Huang et al., "Application of mmWave radar sensor for people identification," Sensors, vol. 23, 2023. [6] TI, "TIDEP-01003," 2022. [7] DigiKey, "IWR6843ISK EVM," 2026. [8] Y. Zhuo et al., "MMVR: Millimeter-wave Multi-View Radar Dataset," 2024.