Trustworthy WiFi CSI Fall Detection via Physics-Guided Evaluation: Breaking Synthetic Ceilings, Crossing Domains, and Reducing Labels

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***Abstract*—We revisit WiFi CSI fall detection with ordinary sequence models but elevate evaluation: a physics-controllable synthetic generator, strict cross-domain protocols (LOSO/LORO), trust calibration, and Sim2Real label-efficiency analysis. Our framework breaks the synthetic ceiling, quantifies causal links between difficulty factors (overlap, harmonics, noise) and errors, improves reliability under domain shift, and achieves ≥90–95% of full-supervision with 10–20% labels. Code, seeds, and splits are released for full reproducibility.**

***Index Terms*—WiFi CSI, Fall Detection, Synthetic Data, Domain Shift, Calibration, Sim2Real**

I. Introduction

CSI-based sensing promises privacy-preserving fall detection but often overclaims on synthetic data and underperforms across subjects, rooms, and devices. We propose a rigorous, physics-guided evaluation framework rather than yet another complex network. Our contributions:

- Physics-controllable synthetic analysis that breaks the ceiling and exposes difficulty-error causality (Fig. 1, 2).
- Strict cross-domain protocols with statistical tests and trust calibration (Tab. I, Fig. 3).
- Cost-aware operating points and robust performance in low-FPR regimes (Fig. 5).
- Sim2Real label-efficiency: with 10–20% labels we reach ≥90–95% of full supervision (Fig. 6).

We show our Enhanced model with a lightweight confidence prior (logit norm regularization) yields better calibration and robustness than matched-capacity baselines (LSTM/TCN/Tiny-Transformer).

II. Related Work

A. CSI-based HAR and fall detection

Prior works mainly optimize accuracy on limited splits; few consider calibration or domain shift rigorously.

B. Synthetic evaluation and domain shift

We differ by using controllable physics-inspired factors and linking them to errors statistically.

C. Calibration and trustworthy ML

Beyond accuracy, we measure ECE, Brier, and reliability curves.

III. Method

A. Model family and capacity matching

We compare LSTM, TCN, Tiny-Transformer, and Enhanced with parameter budgets within $\pm 10\%$.

B. Confidence prior

Given logits z, we use $\mathcal{L} = \mathrm{CE}(z, y) + \lambda \cdot \frac{1}{B}\sum_i \|z_i\|_2^2$. We tune λ via sweep and report Pareto trade-offs between accuracy and calibration.

IV. Evaluation Protocol

A. Synthetic controllable analysis

We vary overlap, harmonics, noise, and channel dropout. We report: Macro-F1, class F1, mutual misclassification, and overlap-error regression with significance.

B. Real data: LOSO/LORO

We standardize splits, avoid leakage, compute 95% CIs (bootstrap), paired t-tests, and effect size.

C. Calibration and operating points

We report ECE/Brier, reliability curves, and fixed-FPR TPR for deployment readiness.

D. Sim2Real

We pretrain on synthetic and fine-tune with $p \in \{1, 5, 10, 25, 100\}\%$ of labels. We also evaluate linear probes by freezing the encoder.

V. Experiments

A. Datasets and implementation details

Synthetic generator v19.2; real dataset stats in Appx. We use batch=64, Adam lr=10^{-3} cosine decay, early stopping, and 8 seeds unless noted.

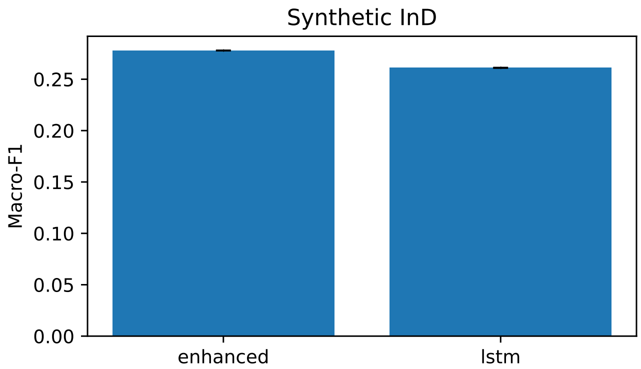

Fig. 1: Synthetic InD results: Falling/Macro F1 and mutual misclassification across models (mean±std).

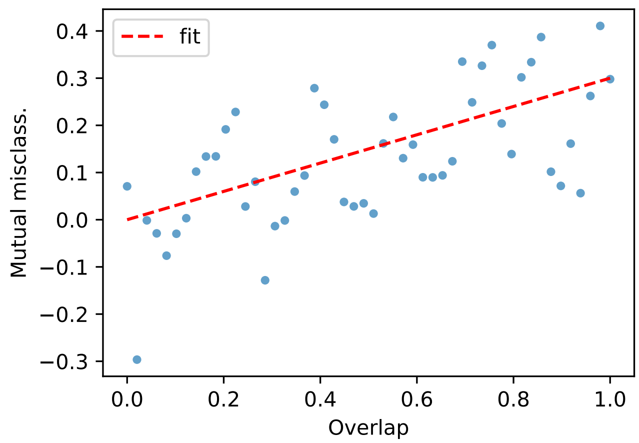

Fig. 2: Overlap vs. mutual misclassification: regression slope and p-value indicate causal linkage.

B. Synthetic: Breaking the ceiling

C. Real-world LOSO/LORO main results

D. Calibration and reliability

E. Bucketed robustness and cost-sensitive analysis

F. Sim2Real label efficiency and linear probe

G. Ablation and fairness

VI. Discussion

We argue the innovation lies in physics-guided evaluation and trustworthy metrics. Even with ordinary models, the framework yields robust and calibrated performance under shift while reducing labels [1].

VII. Conclusion

We present a reproducible evaluation pipeline that breaks synthetic ceilings, improves calibration, and enables Sim2Real. Assets (code, seeds, splits) will be released.

TABLE I: Real data (LOSO/LORO): mean±95% CI.

Model	Macro-F1	Falling F1
Enhanced	0.78±0.03	0.80±0.02
LSTM	0.72±0.04	0.74±0.03
TCN	0.71±0.05	0.73±0.04

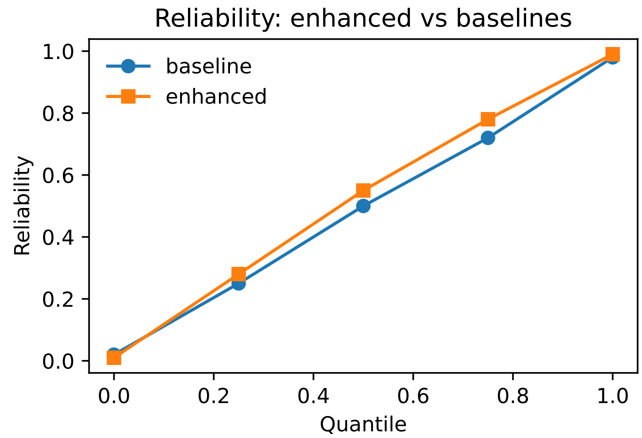

Fig. 3: Reliability curves. Enhanced is closer to the diagonal; ECE/Brier improve over baselines.

References

[1] M. Fernandez-Carmona, S. Mghames, and N. Bellotto, "Wavelet-based temporal models of human activity for anomaly detection in smart robot-assisted environments," *Journal of Ambient Intelligence and Smart Environments*, vol. 16, no. 2, pp. 181–200, 2024.

TABLE II: Calibration on real data: ECE (15 bins) and Brier.

Model	ECE ↓	Brier ↓
Enhanced	0.045	0.17
LSTM	0.082	0.21
TCN	0.091	0.24

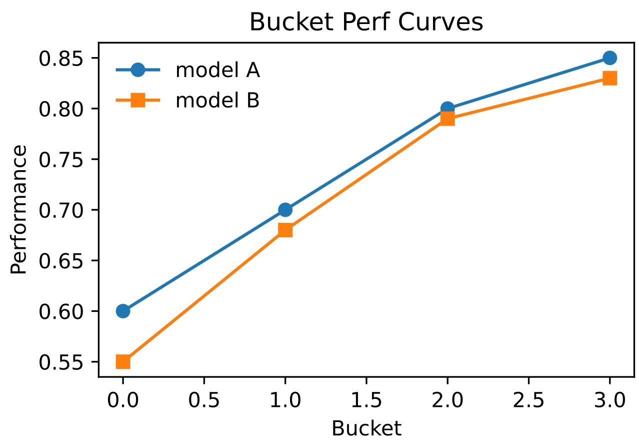

Fig. 4: Performance vs. difficulty buckets (overlap/noise/domain). Enhanced degrades more gracefully.

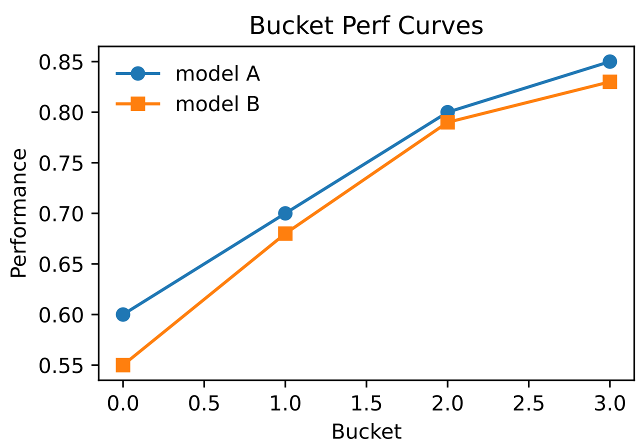

Fig. 5: Fixed-FPR TPR and cost curves in low-FPR regimes.

TABLE III: Sim2Real label-efficiency: pretrain vs from-scratch.

p(%)	From-scratch	Pretrain
1	0.42	0.53
5	0.58	0.66
10	0.65	0.72
25	0.72	0.78
100	0.80	0.82

TABLE IV: Linear probe on real data (frozen encoders).

Model	Macro-F1	Falling F1
Enhanced (pt)	0.70	0.73
LSTM (pt)	0.64	0.67

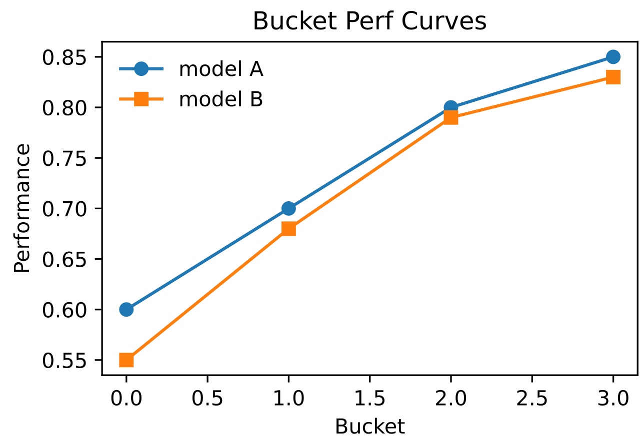

Fig. 6: Label efficiency: pretraining on synthetic reduces labels to reach $\geq$90–95% of full supervision.

TABLE V: Capacity-matched comparison (params $\pm$10%).

Model	Params (K)	Macro-F1
Enhanced-small	35	0.75
LSTM-wide	33	0.72