Institute for the Wireless Internet of Things at Northeastern University

MAGIC: Meta-Learning Adaptive Gesture Recognition with mmWave MIMO CSI

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Agenda

- Introduction
- Contribution
- Related Work
- System Workflow
- Preprocessing
- Adaptation Process
- Setup
- Results
- Conclusions

AR/VR Applications

Demanding higher data rates to support AR/VR applications

What are the bottlenecks?

120 Hz @ 8K ⟶ 40 Gbps ⟶ WiFi supports 1.2 Gbps

LARGER AND RELIABLE BANDWIDTH IS NEEDED!!!

mmWave spectrum is the choice.

mmWave Spectrum

- Offers substantial bandwidth
- More precise wireless sensing capabilities

Human Activity Classification [1, 2]

Gesture Recognition [3, 4]

Intrusion Detection [5]

Patient Monitoring [6]

[1] Haque, K.F., Zhang, M. and Restuccia, F., 2023, June. Simwisense: Simultaneous multi-subject activity classification through wi-fi signals. In *2023 IEEE 24th International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM)* (pp. 46-55). IEEE.

[2] Haque, K.F., Zhang, M., Meneghello, F. and Restuccia, F., 2025. Beamsense: Rethinking wireless sensing with mu-mimo wi-fi beamforming feedback. *Computer Networks*, *258*, p.111020.

[3] Yu, J.T., Tseng, Y.H. and Tseng, P.H., 2024. A mmWave MIMO radar-based gesture recognition using fusion of range, velocity, and angular information. *IEEE Sensors Journal*, *24*(6), pp.9124-9134.

[4] Xu, L., Wang, K., Gu, C., Guo, X., He, S. and Chen, J., 2024, July. GesturePrint: Enabling user identification for mmWave-based gesture recognition systems. In *2024 IEEE 44th International Conference on Distributed Computing Systems (ICDCS)* (pp. 1074-1085). IEEE.

[5] Cenkeramaddi, L.R., 2023. Recent Advances in mmWave-Radar-Based Sensing, Its Applications, and Machine Learning Techniques: A Review.

[6] Pan, P., Zhang, F., Zhou, A., Ma, H. and Jia, H., 2024, July. mmCare: A Nursing Care Activity Monitoring System via mmWave Sensing. In *Proceedings of the ACM Turing Award Celebration Conference-China 2024* (pp. 18-22).

Contributions

Proposed *MAGIC*, a novel gesture recognition system

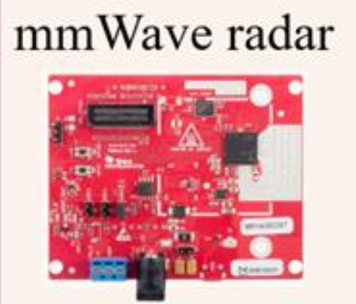
Developed adaptive temporal embedding network for efficient long-range temporal feature extraction

Evaluated through a wide range of subjects and environments

Previous Work

mTransSee [1]

- Transfer-Learning Approach
- 77-81GHz
- 3 * 4 Communication System

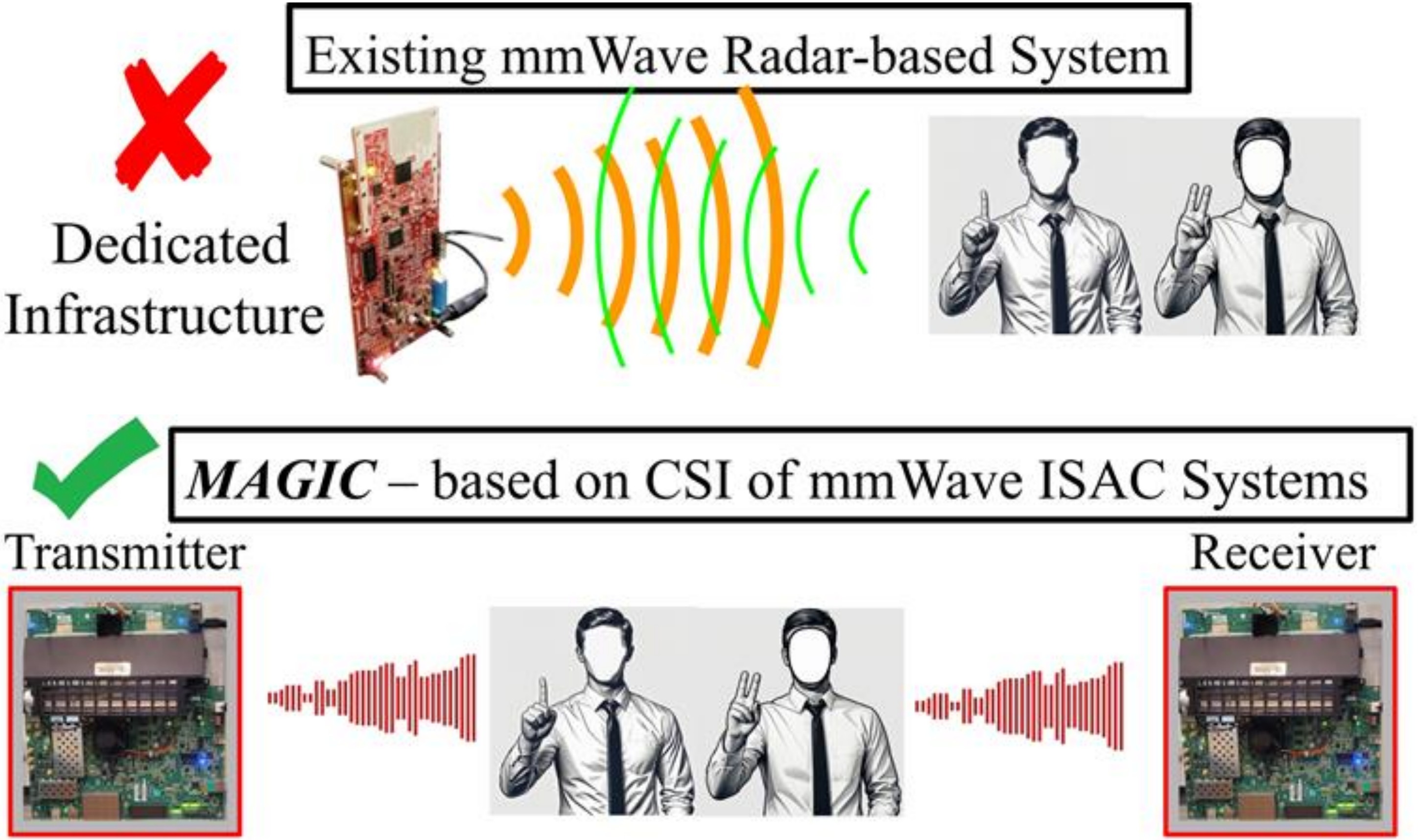


Gesture-mmWAVE [2]

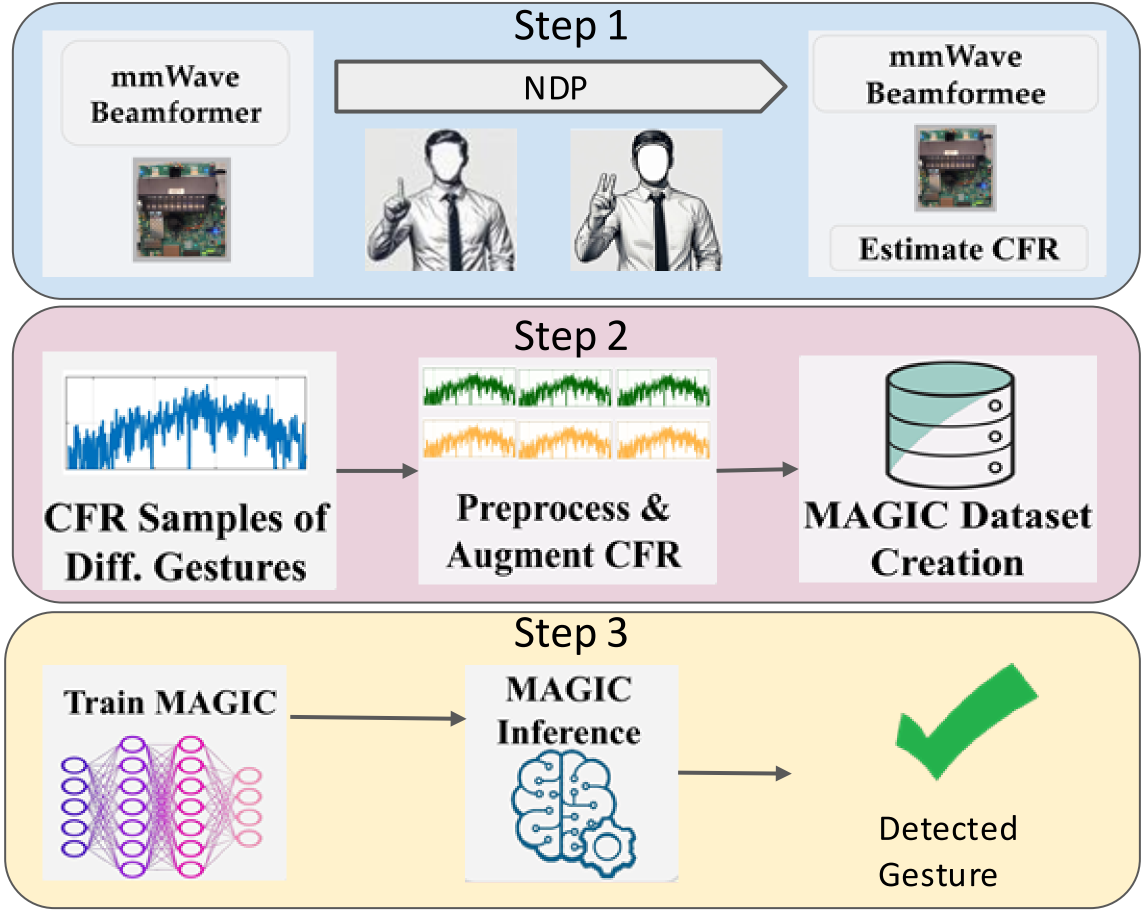
- Transformer Network
- 77 GHz
- 2 * 4 Communication System

[1] Jin, B., Ma, X., Hu, B., Zhang, Z., Lian, Z. and Wang, B., 2024. Gesture-mmWAVE: Compact and accurate millimeter-wave radar-based dynamic gesture recognition for embedded devices. *IEEE Transactions on Human-Machine Systems*.
[2] Liu, H., Cui, K., Hu, K., Wang, Y., Zhou, A., Liu, L. and Ma, H., 2022. mTransSee: Enabling environment-independent mmWave sensing based gesture recognition via transfer learning. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *6*(1), pp.1-28.

MAGIC vs Existing mmWave Radar-based system



System Workflow



Domain-adaptive Preprocessing Pipeline (DAPP) (1)

- Path Loss Compensation

CFR Matrix

$$\mathbf{C}_{\text{comp}}(f) = \mathbf{H}_r^{m,n} \cdot A_{PL}(d)$$

Attenuation Factor

- Frequency Normalization

$$\mathbf{C}_{\text{norm}}(f) = \frac{\mathbf{C}_{\text{comp}}(f)}{||\mathbf{C}_{\text{comp}}||}$$

Frobenius norm

- Entropy-Guided Filtering

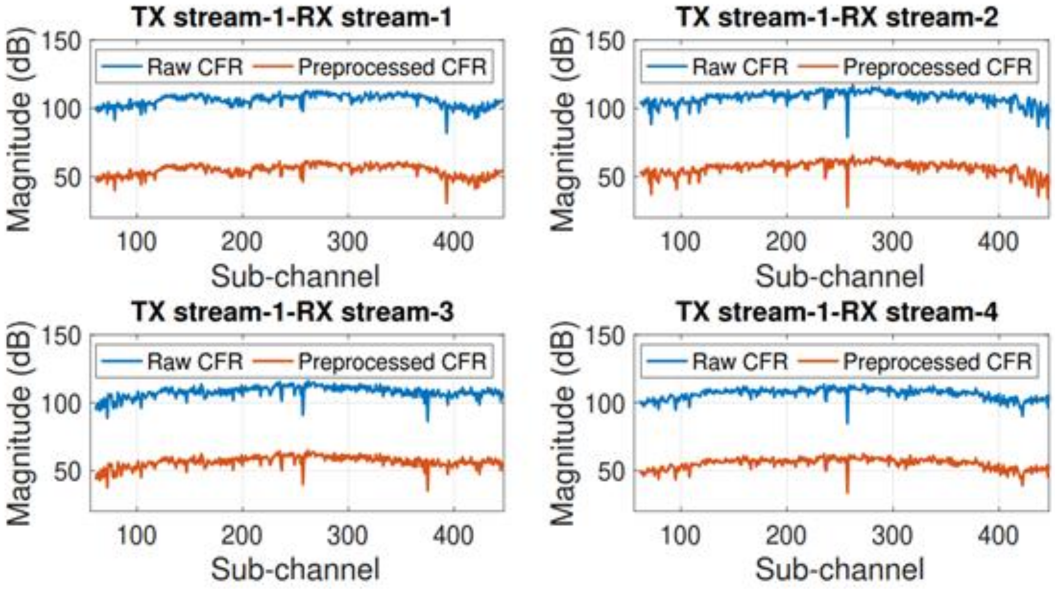
$$E(k) = -\sum_{i=1}^{M \times N} p_i \log p_i$$

$$\frac{|\mathbf{C}_{\text{norm }k,i}|^2}{\sum_{j=1}^{M \times N} |\mathbf{C}_{\text{norm }k,j}|^2}$$

Domain-adaptive Preprocessing Pipeline (DAPP) (2)

$$\mathbf{C}_{\text{filtered}} = \mathbf{C}_{\text{norm}} \cdot \text{diag}(w(k))$$

$$w(k) = \exp(-E(k))$$



Data Augmentation

- Noise Addition

$$C_{\text{aug1}} = C_{\text{filtered}} + N$$

- Scaling

Scaling Factor

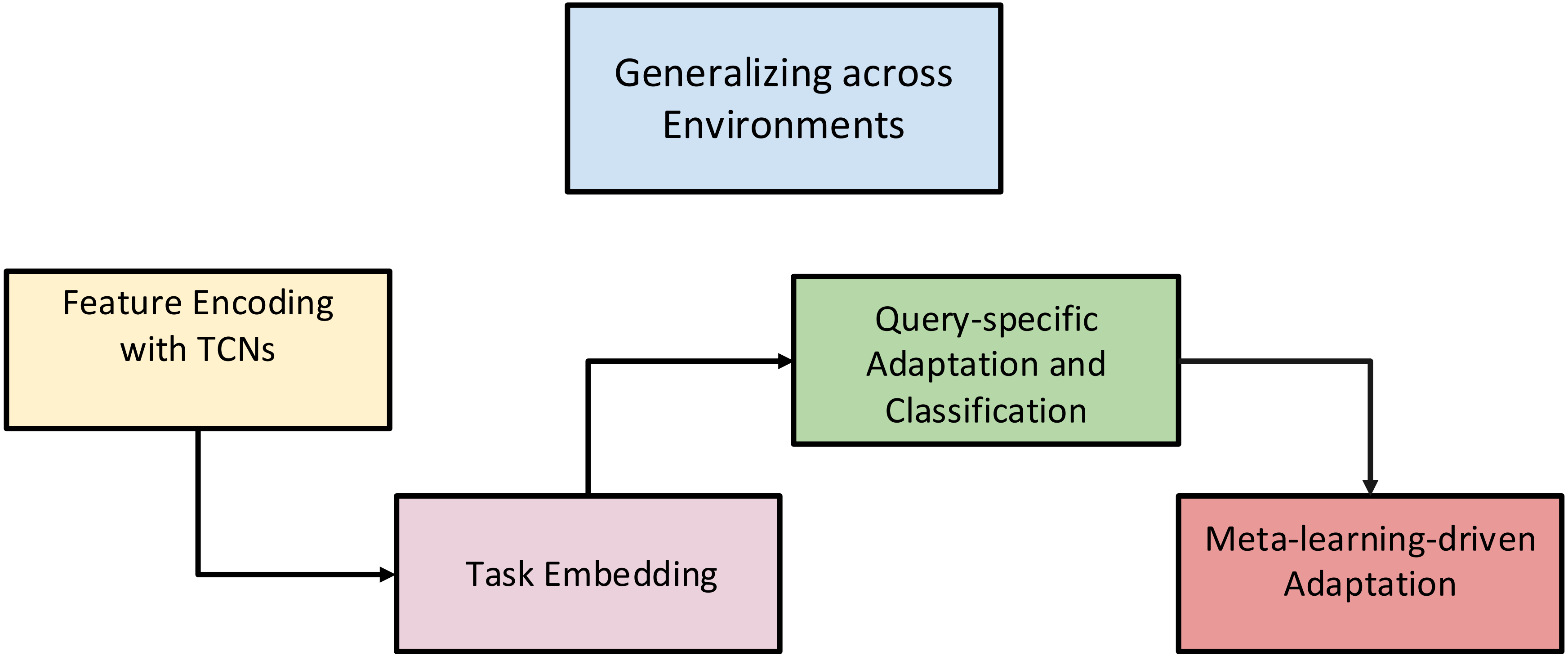
$$C_{\text{aug2}} = \alpha \cdot C_{\text{filtered}}$$

- Phase Perturbation

Random Phase Shift

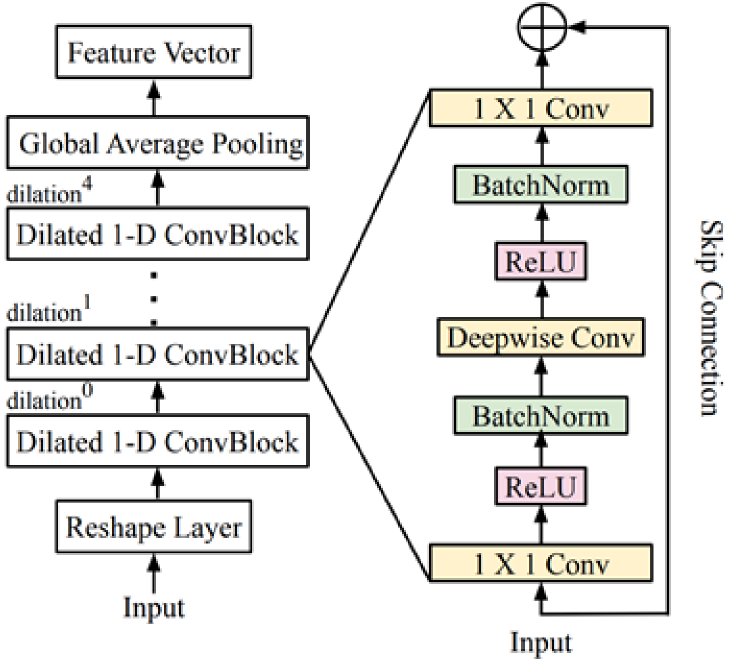
$$C_{\text{aug3}}(f) = C_{\text{filtered}}(f) \cdot e^{j\phi}$$

Adaptive Temporal Embedding Network (ATEN)



Feature Encoding with TCNs

- Encode **temporal patterns** from mmWave **CFR sequences**
- Capture both **short- and long-term dependencies** in gesture dynamics
- Generate **compact and informative feature vectors** for classification
- Temporal Convolutional Network (TCN)



Task Embedding

Summarize the **essence of a task** using its support examples

Enables the model for **adaptation** to new and unseen tasks

Core idea

A **feature extractor** processes each input to a latent vector

Vectors are **aggregated** into a single task embedding

Refinement

Query-Specific Adaptation and Classification

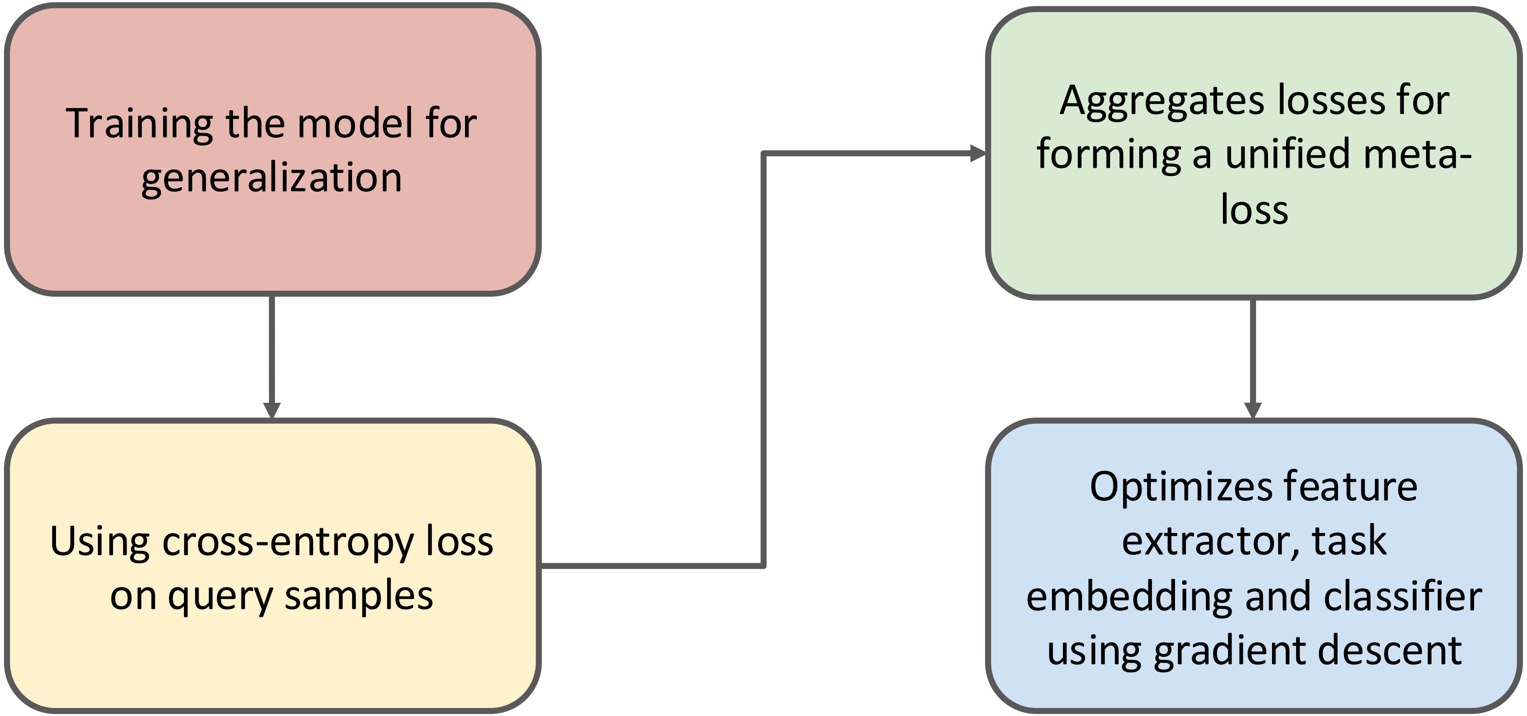
Adapts query features using task embedding to align with task-specific context

Combines query representation and task summary through a learnable transformation

Produces a **context-aware embedding** tailored to the current task

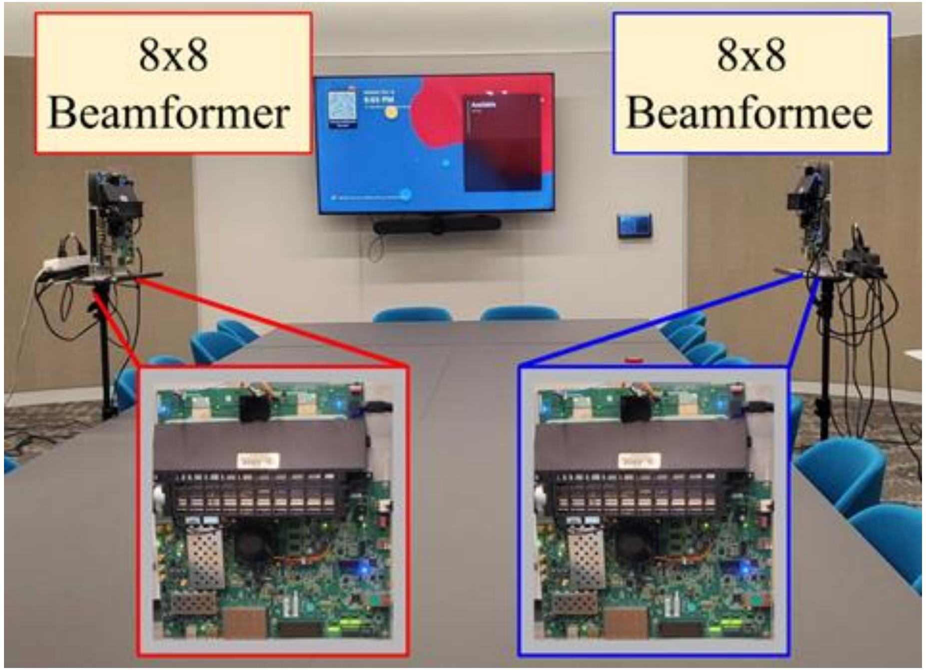
Adapted features are passed to a **classifier**

Meta-learning-driven adaptation



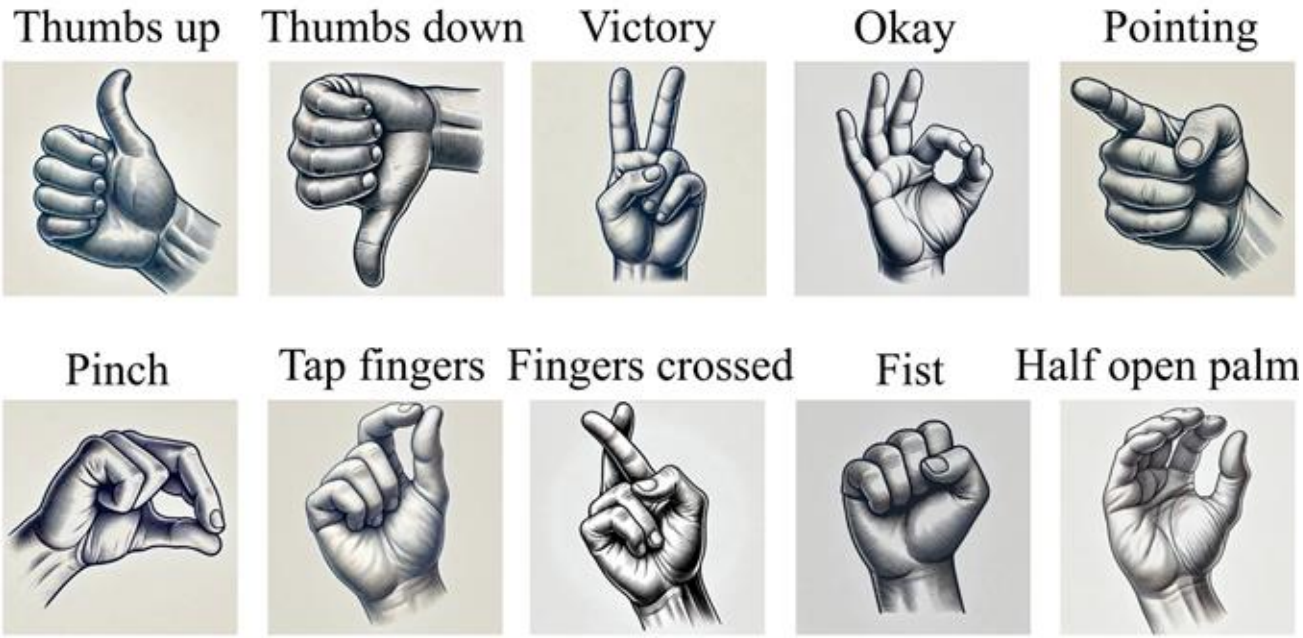
Experimental Setup [1]

- Multiplexing and Diversity Gain
- Digital Beamforming
- P2P, SU-MIMO, MU-MIMO
- Operating in 57-64 GHz
- OFDM
- 1 GHz of bandwidth



[1] Haque, K.F., Meneghello, F., Rumman, K.M. and Restuccia, F., 2024, December. m3MIMO: An 8× 8 mmWave Multi-User MIMO Testbed for Wireless Research. In *Proceedings of the 30th Annual International Conference on Mobile Computing and Networking* (pp. 1922-1929).

Data Collection



Lab

50 repetitions of each gesture per subject, with each lasting **3 seconds**

Performance Evaluation

Baselines

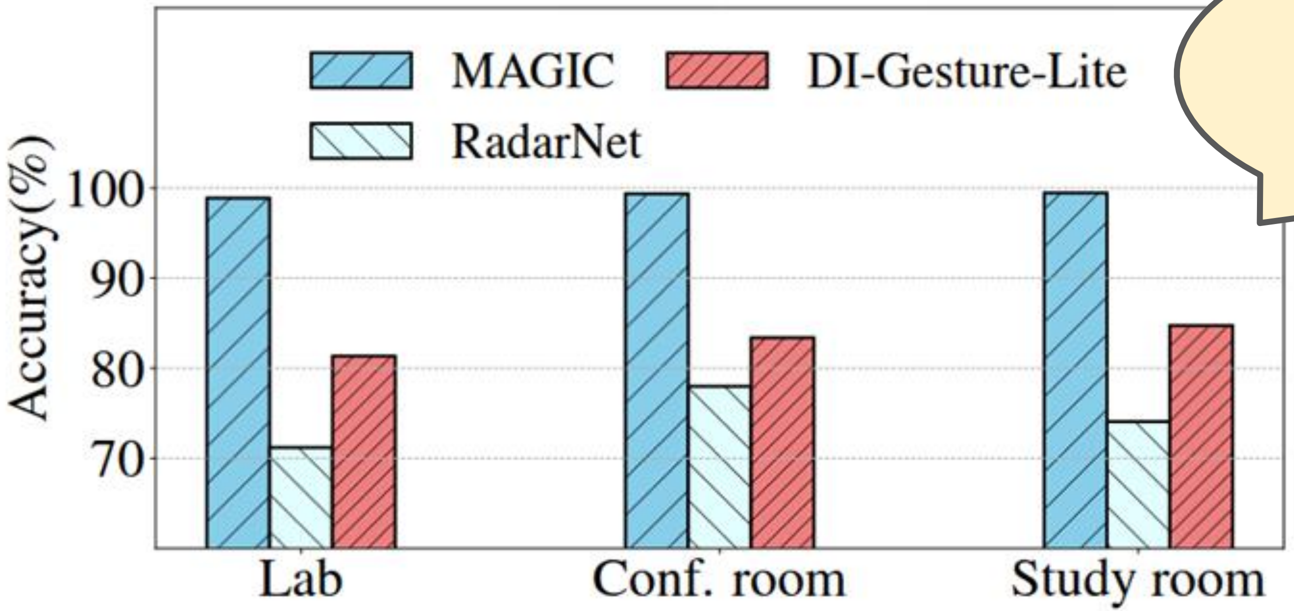
DI-Gesture [1]
Incorporates Dynamic Range Angle Images (DRAI) and basic data augmentation

RadarNet [2]
Processes range-Doppler maps for spatial-temporal motion

[1] Li, Y., Zhang, D., Chen, J., Wan, J., Zhang, D., Hu, Y., Sun, Q. and Chen, Y., 2022, December. DI-gesture: Domain-independent and real-time gesture recognition with millimeter-wave signals. In *GLOBECOM 2022-2022 IEEE Global Communications Conference* (pp. 5007-5012). IEEE.
[2] Hayashi, E., Lien, J., Gillian, N., Giusti, L., Weber, D., Yamanaka, J., Bedal, L. and Poupyrev, I., 2021, May. RadarNet: Efficient gesture recognition technique utilizing a miniature radar sensor. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1-14).

Results

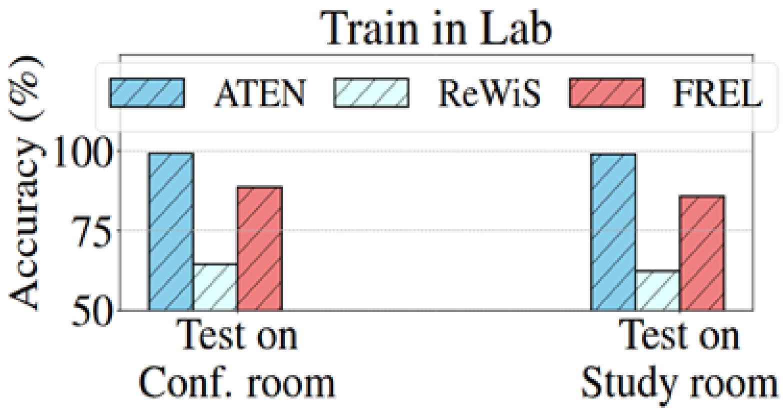
Accuray of gesture recognition methods in different environments

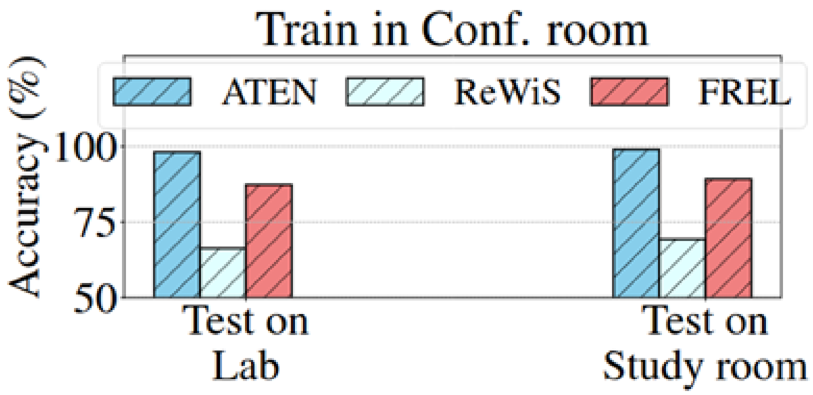


MAGIC outperforms the SOTA Models with the average of **24.13%** across all the environments

Results

Environment Generalization Performance



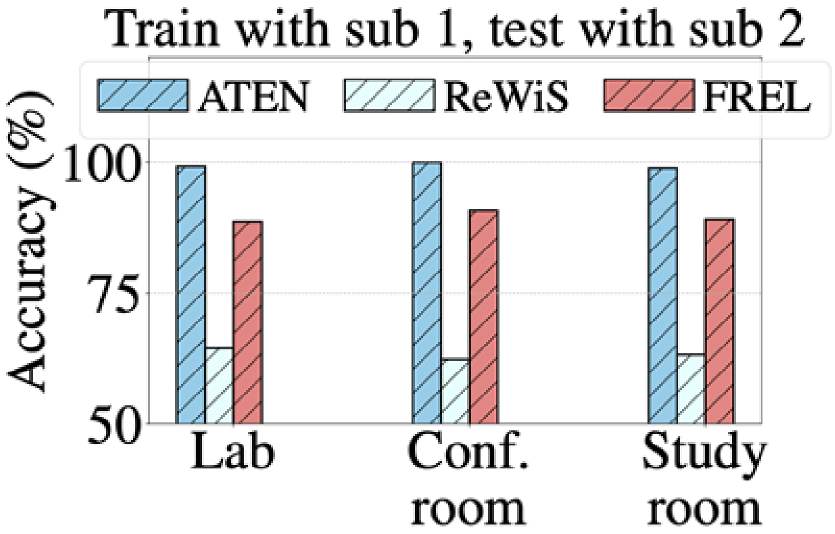


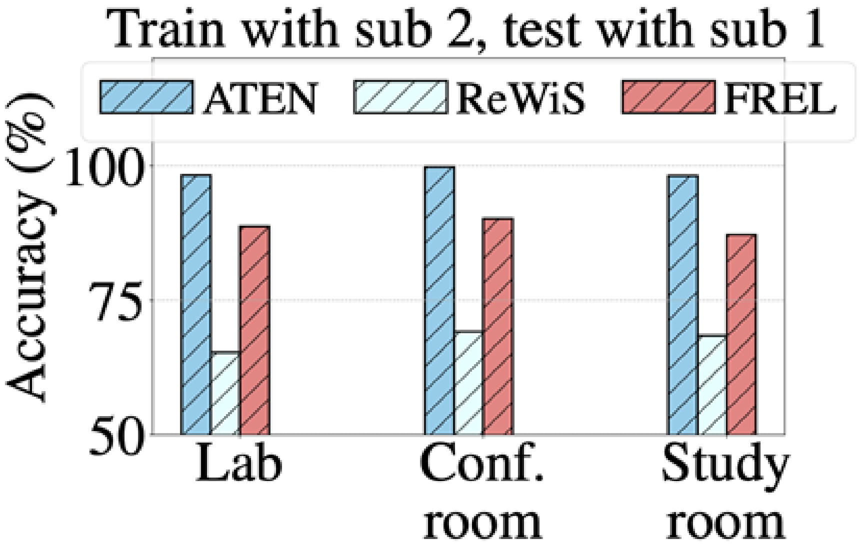
MAGIC outperforms ReWis and FREL by **54%** and **12%** respectively

MAGIC outperforms ReWis and FREL by **66%** and **15%** respectively

Results

Subject Generalization Performance





Outperforming ReWiS and FREL by **55%** and **10%** respectively

Conclusions

- We introduced MAGIC, a novel gesture recognition framework using mmWave CSI, which eliminates the need for radar-specific hardware
- Achieves high accuracy and strong generalization across different subjects and environments
- A scalable, efficient and robust solution for real-world gesture recognition applications

Thanks for your attention!