# MilliFit: Millimeter-Wave Wireless Sensing Based At-Home Exercise Classification


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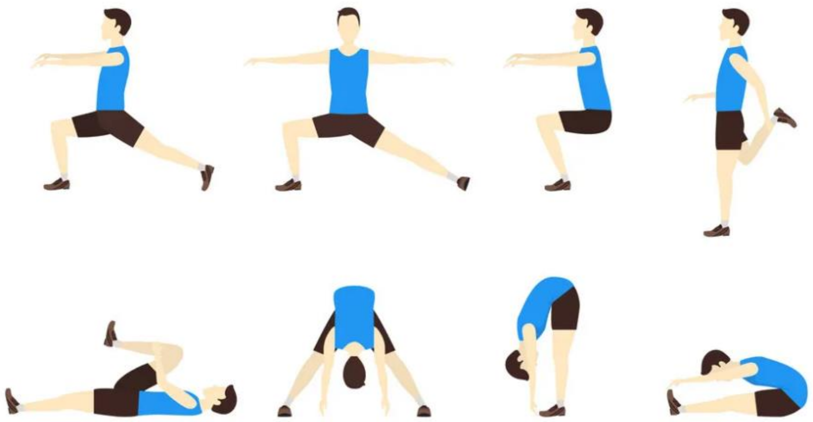
# Human Activity Recognition

- At-home Human Activity Recognition enables many healthcare applications

*Exercise monitoring*



*Elderly patient care*

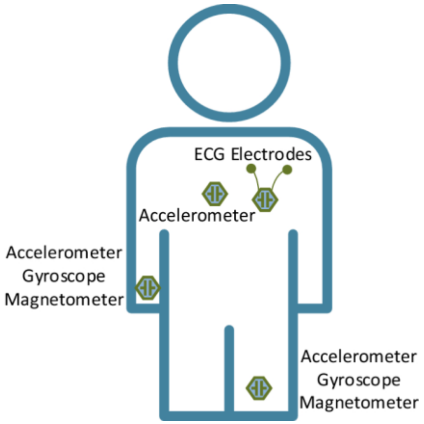
- Classification is a key component to unlock these applications, and it is the focus of this work

# Current Approaches

## Vision-based

- Reliant on sufficient lighting and visibility
- Privacy concerns

## Wearable-based

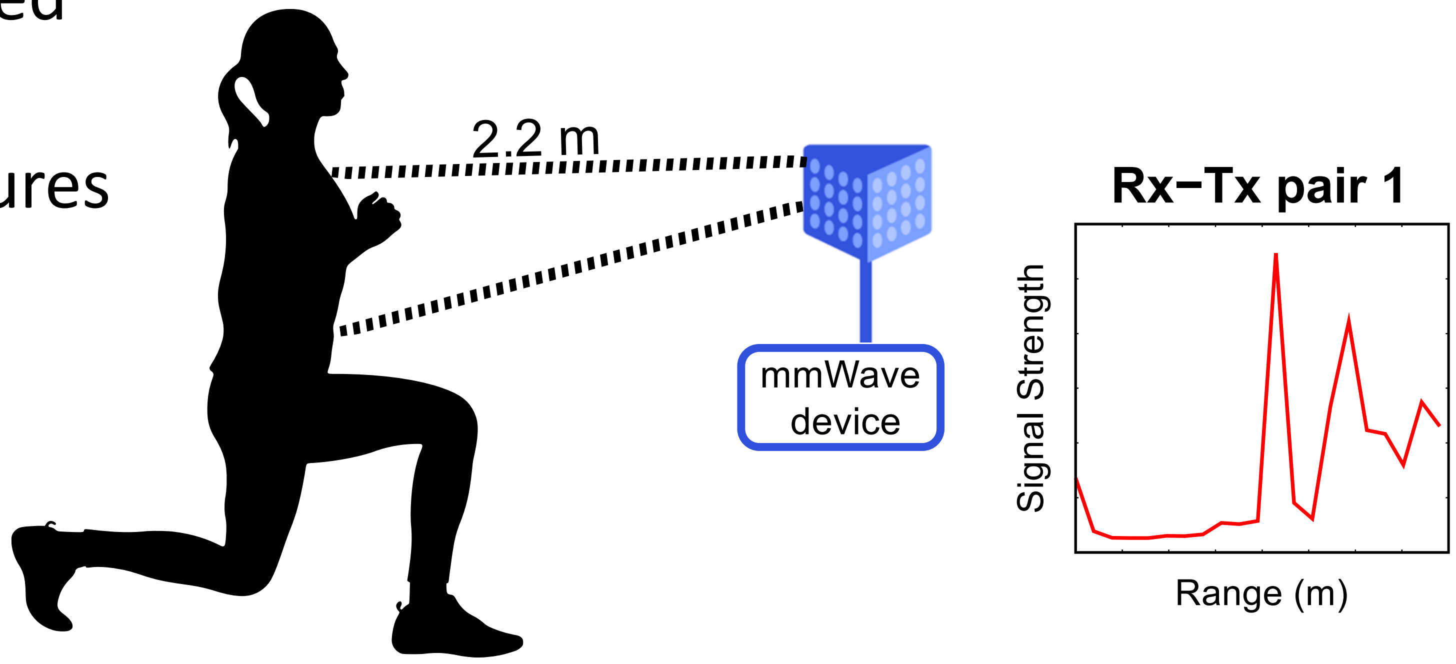

- Inconvenient to users
- Provide limited information

# RF-Based Approaches


- Use Wi-Fi signals or RFID tags to detect human activity
- Mostly focused on reconstructing silhouettes or skeletons
- Low resolution due to limited bandwidth for Wi-Fi

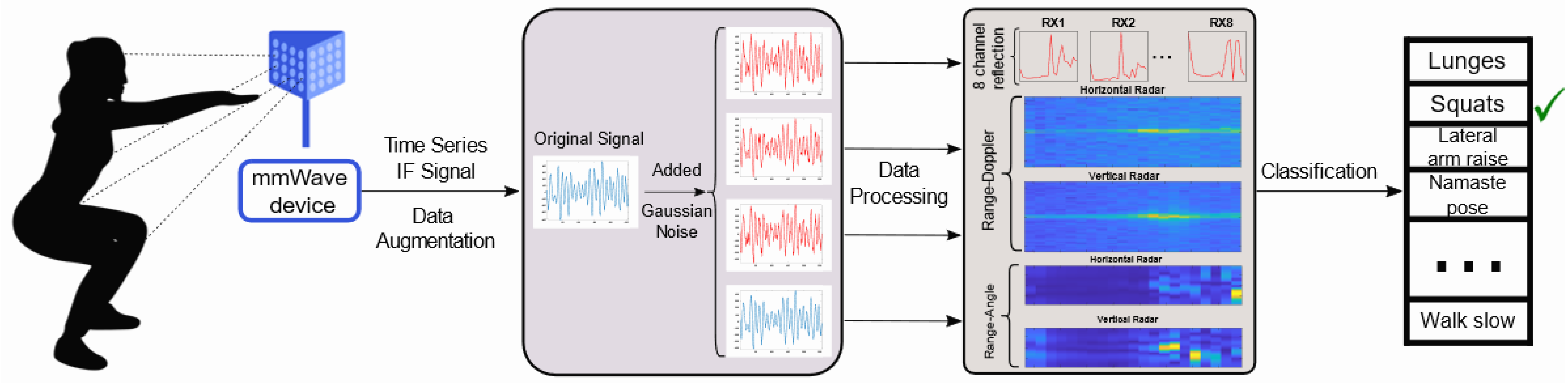
# MilliFit Intuition and Objective

- Reflected mmWave signal embeds distinctive features about the activity being performed
- Can exploit deep-learning techniques to extract features and classify exercise

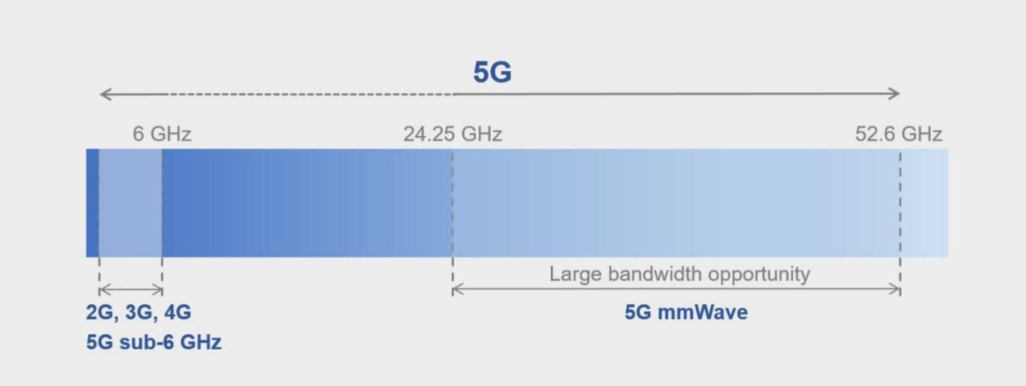


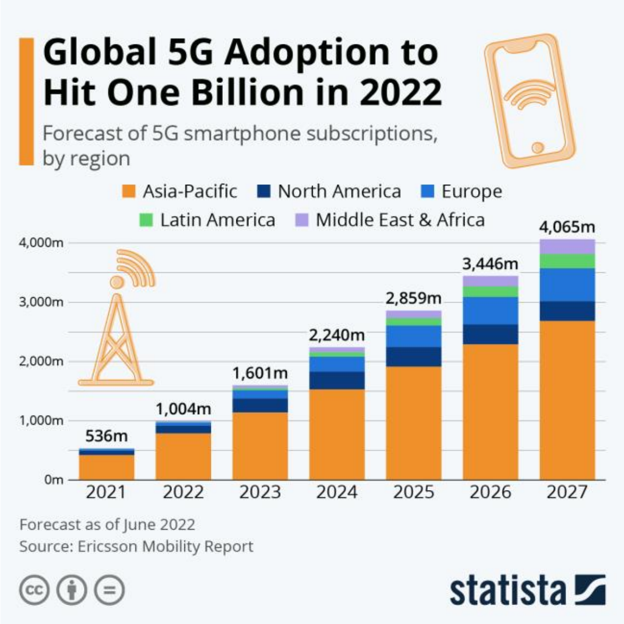
# MilliFit Overview

- Use only the reflected signal to predict exercise type
  - ❑ 18 classes with combination of static and dynamic exercises
- Data-driven deep learning approach to extract features and classify exercise
- Three signal representations: 1-D FFT reflection, Range-Doppler, Range-Angle



# Millimeter-Wave

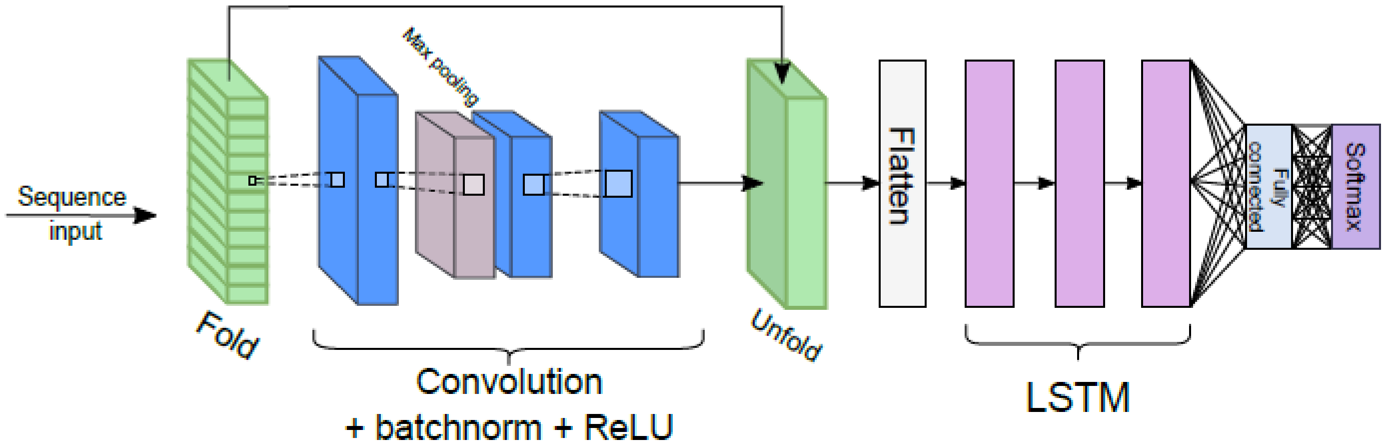



- Millimeter-Wave (mmWave) has small wavelength and high bandwidth
- Very sensitive to small movements, making it well-suited for activity recognition
- mmWave is the core technology of 5G
- mmWave poised to become ubiquitous in at-home networking devices

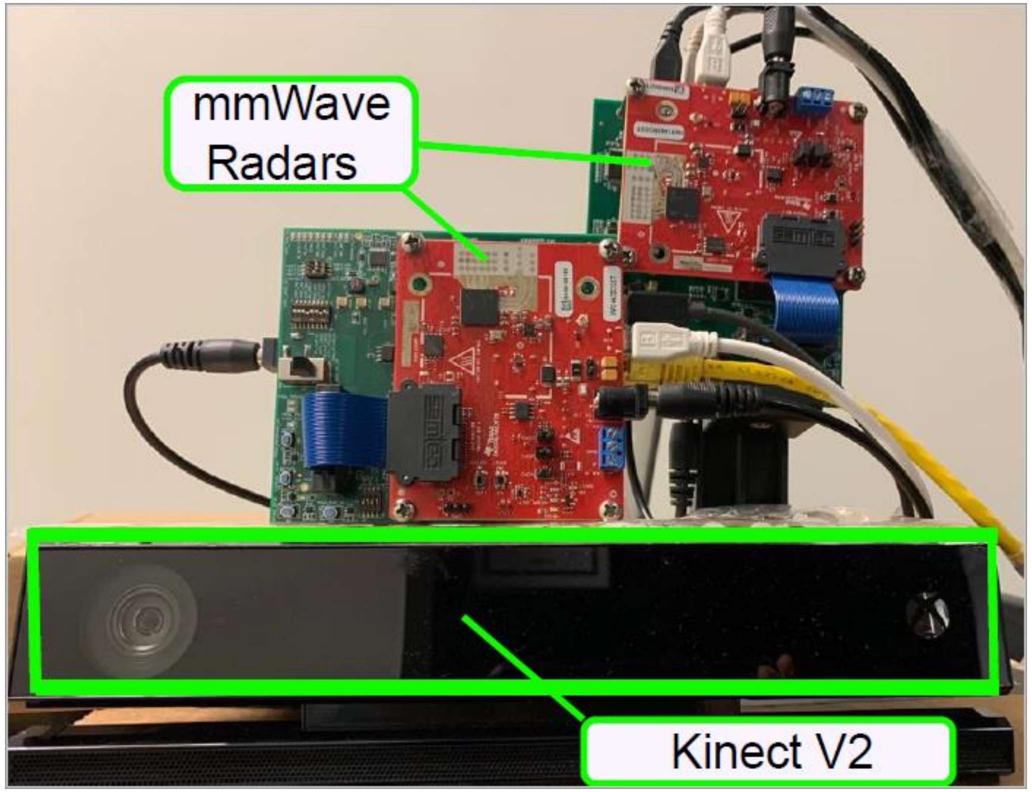
# Classification Network Design

- Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM) recurrent component
  - ❑ Extract spatial features for each frame with CNN
  - ❑ Learn temporal variations with LSTM
- Predicts probability that input belongs to each of the 18 classes
- Cross-entropy loss function



# Data Collection and Implementation

- Two TI-IWR1443 plus two TI-DCA1000EVM capture mmWave reflections along azimuth and elevation
  - ❑ FMCW starting at 77 GHz, increasing linearly over bandwidth of ≈1.8 GHz
- Co-located Kinect collects depth data to isolate the target range



# Data Collection and Implementation

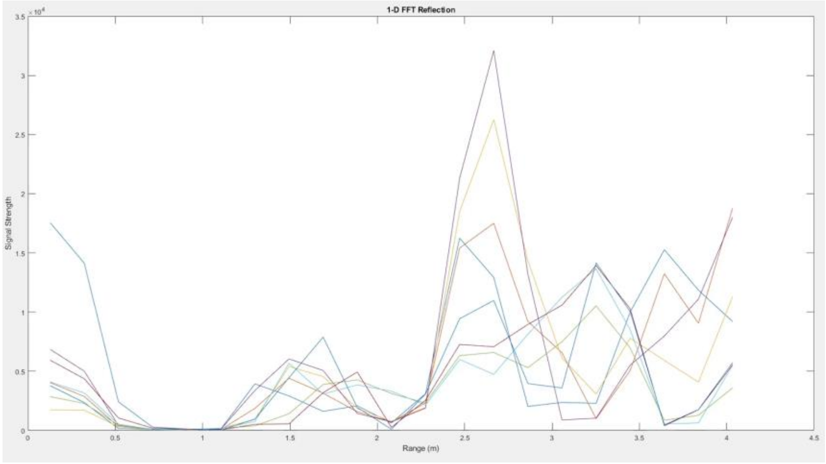
- Data samples contain one individual performing one exercise per trial for a duration of 210 frames (8.4 seconds)
- After collection, data is sent to a host PC, where it is processed
- Data processing and classification model implemented in MATLAB

| Label | Exercise | Label | Exercise |
|---|---|---|---|
| ⋆1 | Lunge | 10 | Leg extension |
| ⋆2 | Zoom in/out | 11 | Namaste pose |
| 3 | Arm stretch | ⋆12 | Pushup |
| 4 | Arm extension | ⋆13 | Squat |
| ⋆5 | Alternating toe touch | 14 | Standing |
| ⋆6 | Alternating one arm up | 15 | Touch toes pose |
| 7 | Arms up pose | ⋆16 | Walk fast |
| ⋆8 | Arms up and down | ⋆17 | Walk normal |
| 9 | Hands on waist pose | ⋆18 | Walk slow |

# Data Processing

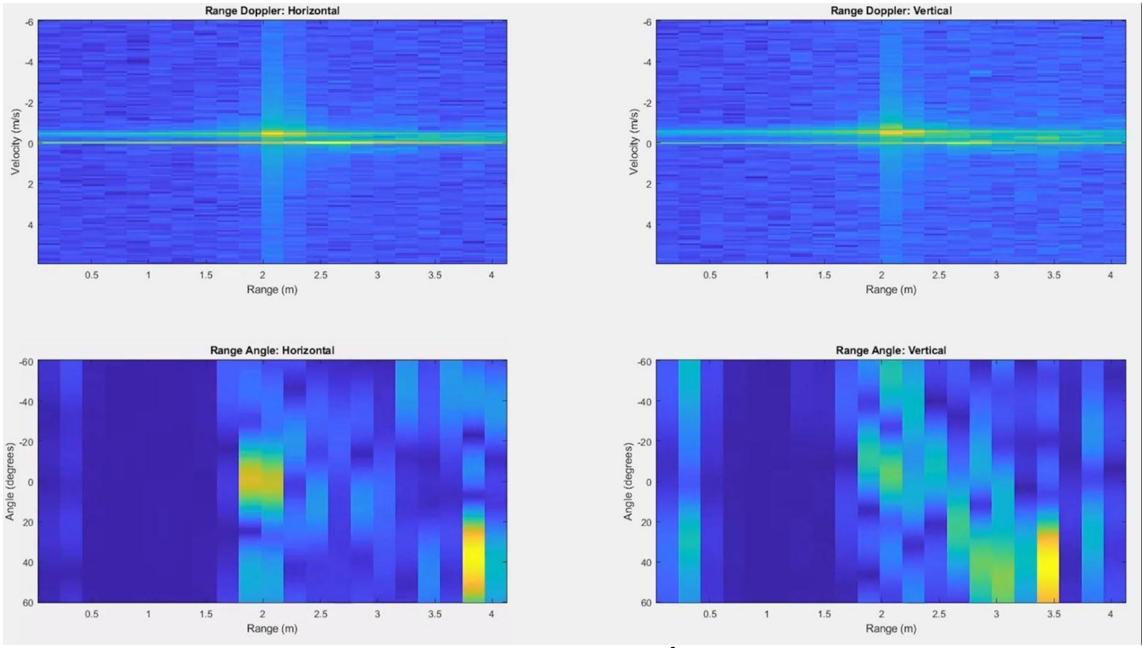
- We process the data to acquire three signal representations: 1-D FFT reflection, Range-Doppler, Range-Angle
- Use Kinect depth data to find max range and remove the reflections from beyond that range

*Kinect depth image*



*1-D FFT Reflection*

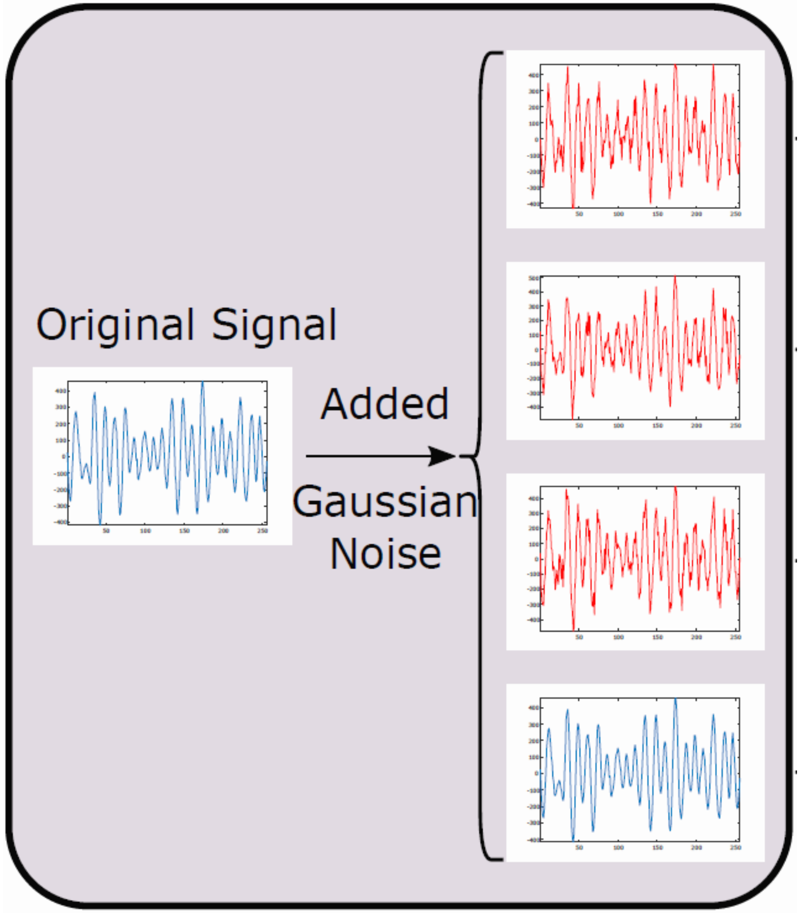
*Range-Doppler*




*Range-Angle*

# Data Augmentation

- Data augmentation can help make deep-learning models more generalizable
- Device noise for wireless sensing is unavoidable in real-world
- We augment our dataset by adding random Gaussian noise to time-series data before processing
- 331 training samples before augmentation
- 1324 training samples after augmentation



# Evaluation

- Evaluation of classification performance for each signal representation on augmented and unaugmented datasets
- Classification metrics include F1-score, MCC, precision, recall

| | | | Matthews Correlation Coefficient | | Accuracy(%) |
|---|---|---|---|---|---|
| | | | Micro Avg. | Macro Avg. | Avg. |
| **Augmented** | **Range-FFT** | **All** | 0.9359 | 0.9331 | 90.69 |
| | | **Static** | 0.9324 | 0.9336 | 90.11 |
| | | **Dynamic** | 0.9386 | 0.9416 | 91.14 |
| | **Range-Doppler** | **All** | 0.9731 | 0.9735 | 94.84 |
| | | **Static** | 0.9401 | 0.9417 | 89.29 |
| | | **Dynamic** | 0.9989 | 0.9989 | 99.16 |
| | **Range-Angle** | **All** | 0.9607 | 0.9609 | 96.13 |
| | | **Static** | 0.9361 | 0.9371 | 93.66 |
| | | **Dynamic** | 0.9801 | 0.9799 | 98.05 |

- Model had much better performance on dynamic exercises than static ones
- Data augmentation improved performance significantly

# Conclusion

- Wireless human activity recognition can enable at-home healthcare applications
  - Ubiquitous mmWave signals can be exploited for fine-grained monitoring
- We experimentally show the feasibility of using millimeter-wave wireless signal reflections for exercise classification, without requiring any high-resolution image representations

Please refer to our paper and
contact me with questions:
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