Online Human Activity Recognition using Low-Power Wearable Devices

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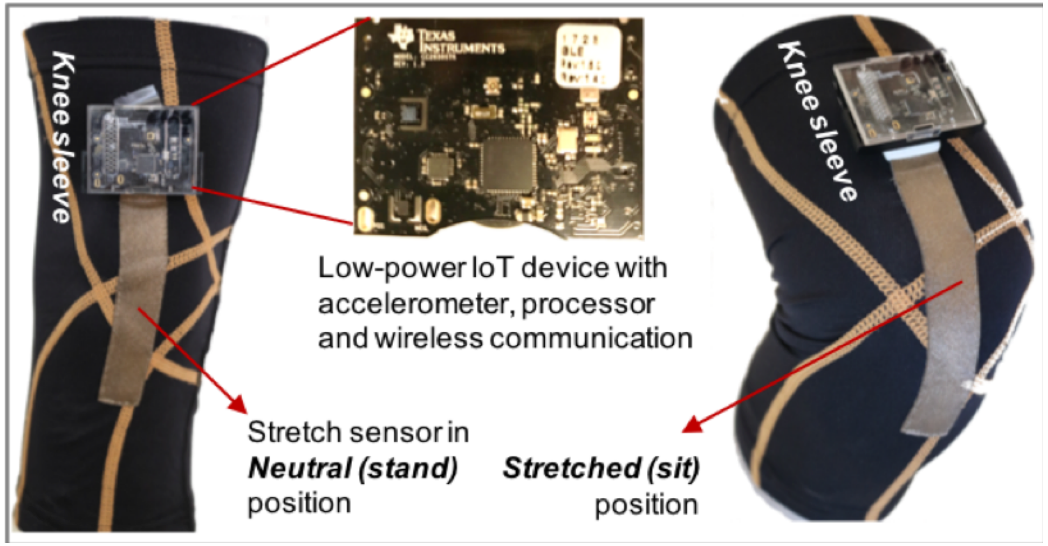
Outline

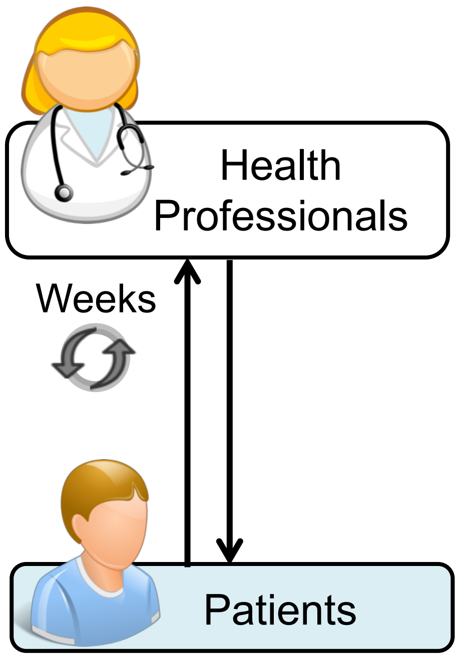
- **Motivation**
- **Human Activity Recognition**
  - Feature Set and Classifier Design
  - Online Reinforcement Learning with Policy Gradients
- **Experimental Results**
- **Conclusions**



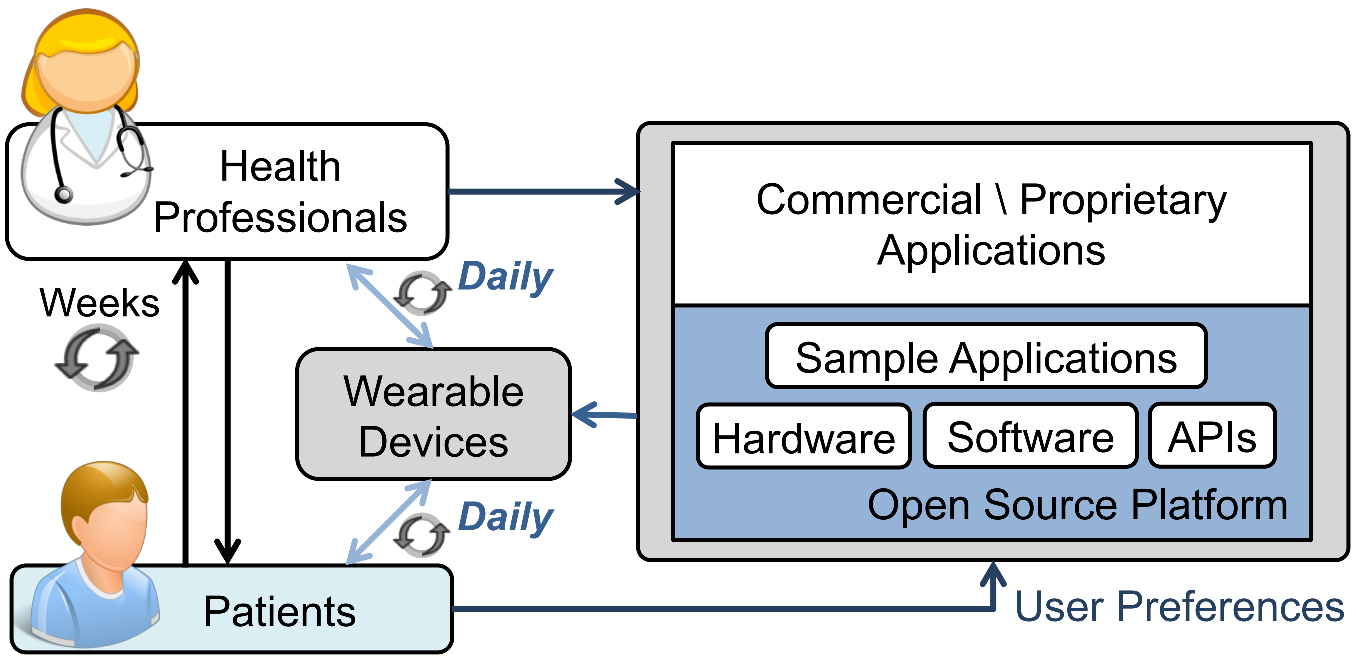
Health Monitoring using Wearable Devices

- **15% of the world's population lives with a disability**
- **110-190 million people face significant difficulties in functioning**
- ***Intl. Parkinson and Movement Disorders Society Task Force on Technology:***
  - Low-cost and small form-factor wearable devices offer great potential
  - Enabled by advances in low power sensors, processors, communications

Current Health Practice



OpenHealth Wearable Vision



Why Human Activity Recognition (HAR)?

- **HAR identifies activities, such as walking, sitting, driving, jogging**
- **It is the first step to solutions for movement disorders**

We have to know what the patient is doing to reach a conclusion

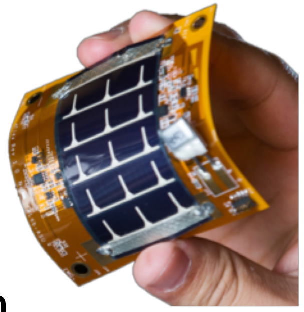
- **HAR can provide valuable insight to health specialists**
- **Applications of HAR**
  - Patient rehabilitation
  - Fall detection
  - Physical activity promotion

Why Online Learning on Wearable Devices

- **Smartphones have been popular:**
- **But, they are not appropriate**
  - *Some patients cannot even carry them*
  - Large power consumption & charging requirements
  - Cannot provide real-time guarantees (e.g., sampling rate)
  - ***They are not designed for this purpose***

- **Existing work on wearables and smartphones**

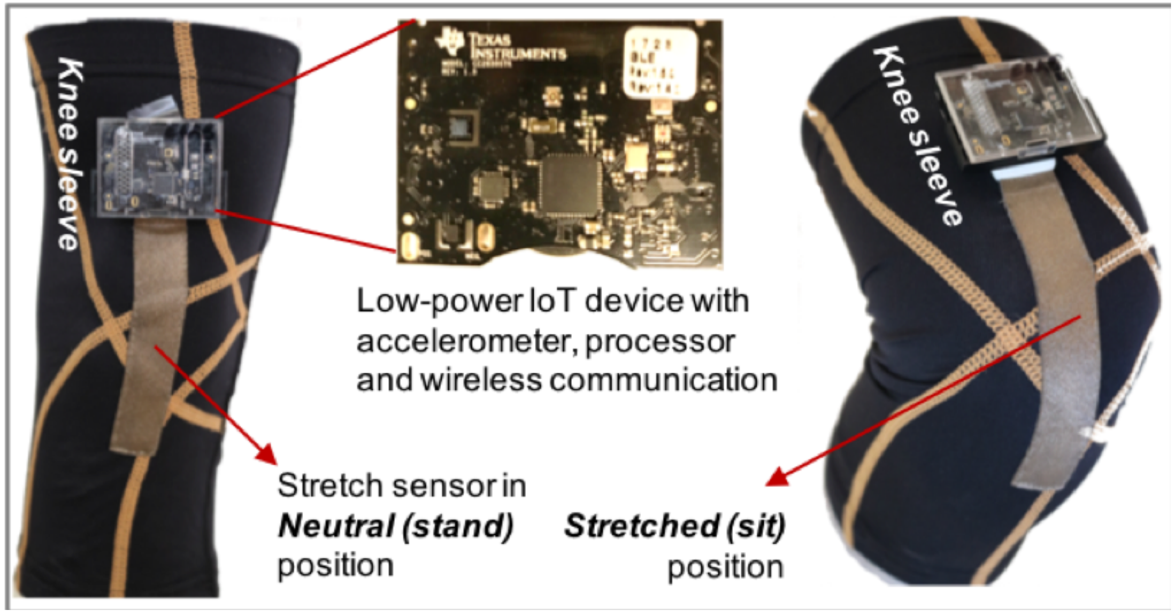
	Offline	Online
Data Collection	✓	✗ → ✓
Learning	✓	✗ → ✓
Inference	✓	✓



- **Our solution**
  - Tailored to the problem
  - Low power & Energy-harvesting
  - Adapt to new users and changing user conditions

Proposed Solution: Online Learning for HAR

- **We use a wearable device to enable online learning for HAR**
  - Uses a combination of motion and stretch sensors
  - **First work to use stretch sensor** for HAR



- ***Our Novel Contributions***
  - **Novel technique to segment the sensor data as a function of user motion**
  - **Online inference and training using reinforcement learning**
  - **Low power implementation on a wearable device**

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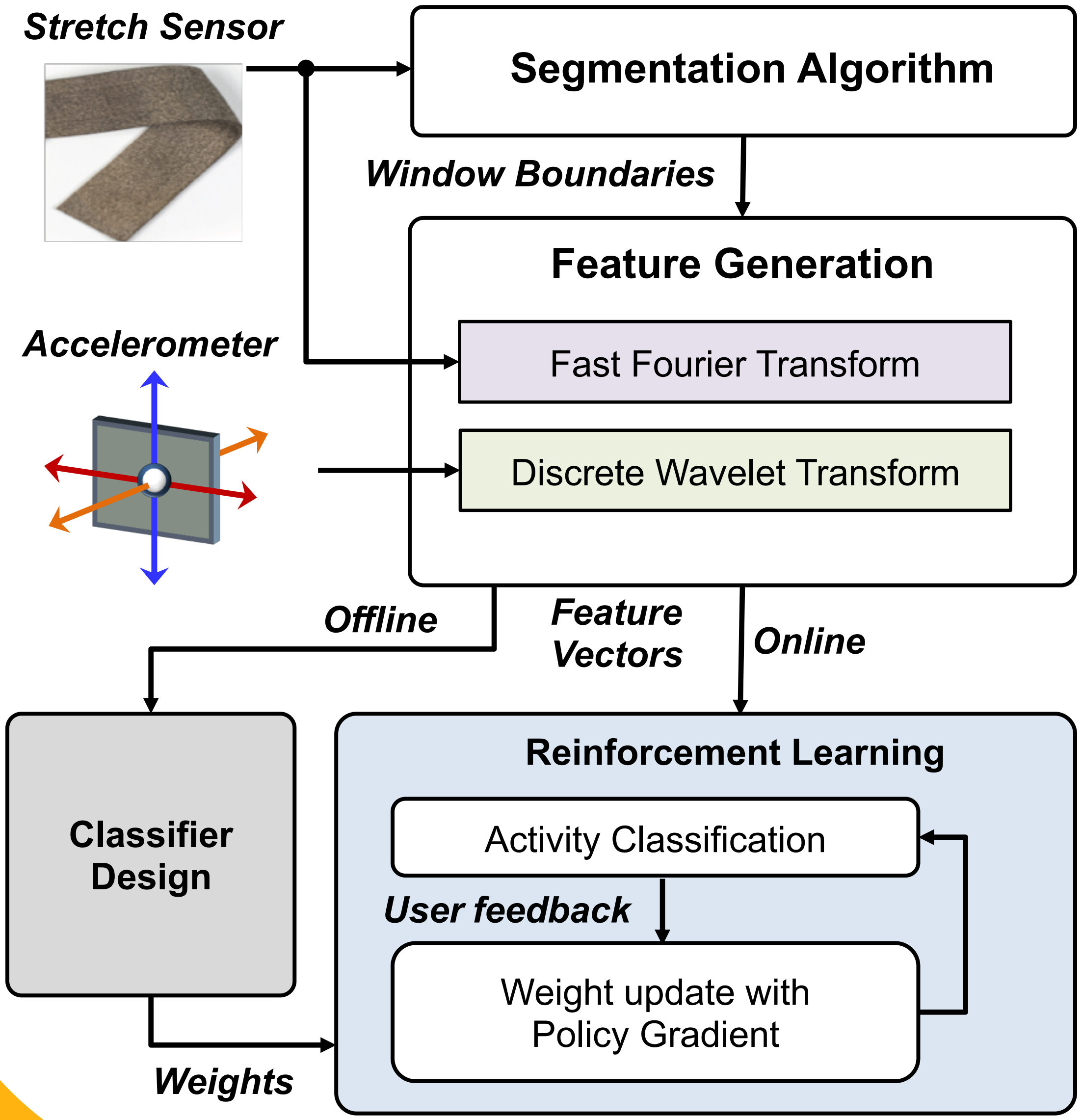
Goals and Problem Statement

- **Recognize *six common activities* and *transitions* between them**
  - Achieve greater than 90% accuracy
  - Power budget in milliwatts
- **These goals make HAR practical for daily use**
  - Low power budget enables day-long operation using flexible batteries

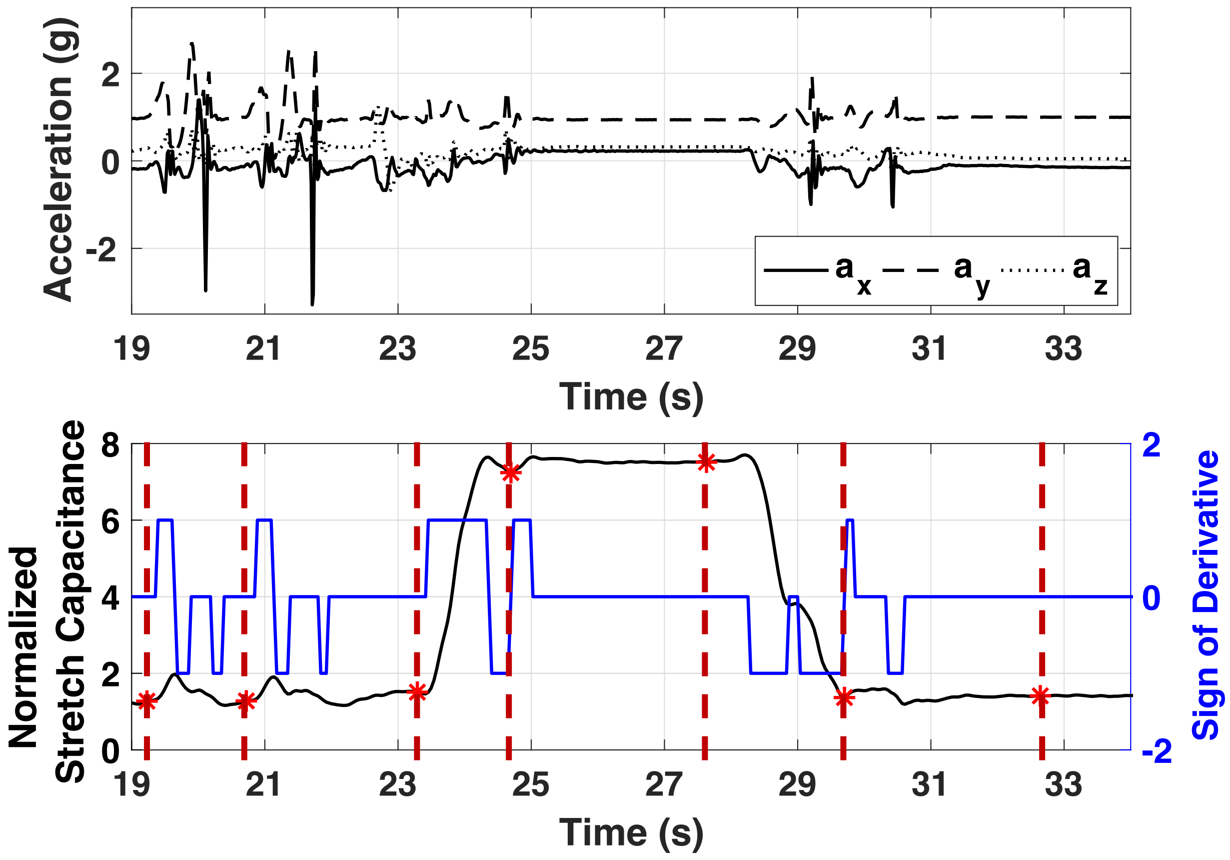
Overview of Proposed HAR Framework



- **Segmentation**
  - Streaming stretch sensor data is processed to generate variable length segments
- **Feature Generation**
  - Accelerometer and stretch sensor data are processed to extract the features
- **Classifier Design**
  - Offline training of neural network using labeled segments
- **Reinforcement Learning**
  - Neural network weight updates using user feedback and policy gradient algorithm

Segmentation Algorithm

- **Need for variable length segmentation**
  - Fixed length segments may contain multiple activities
  - This makes it harder to label and classify
- **We use stretch sensor data to segment the activities**
  - Accelerometer is more noisy
  - In contrast, stretch sensor provides a clean data for segmentation



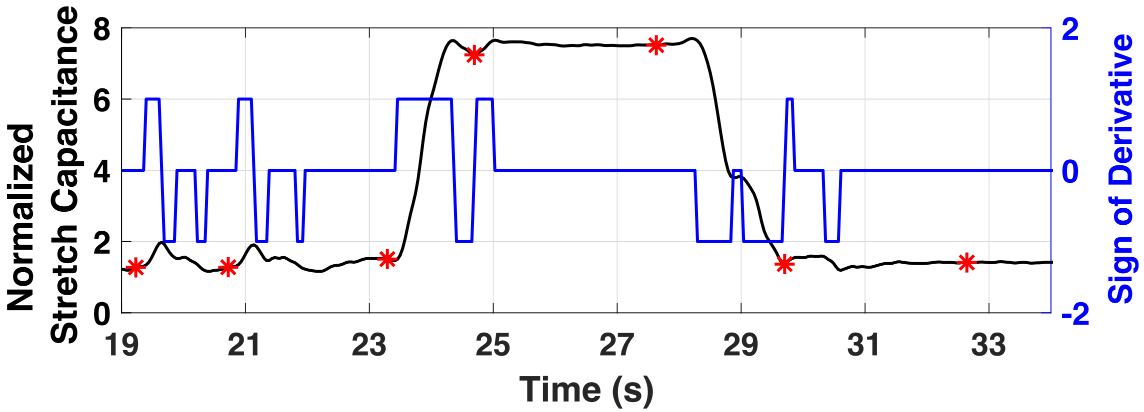
Result: Non-uniform activity segments

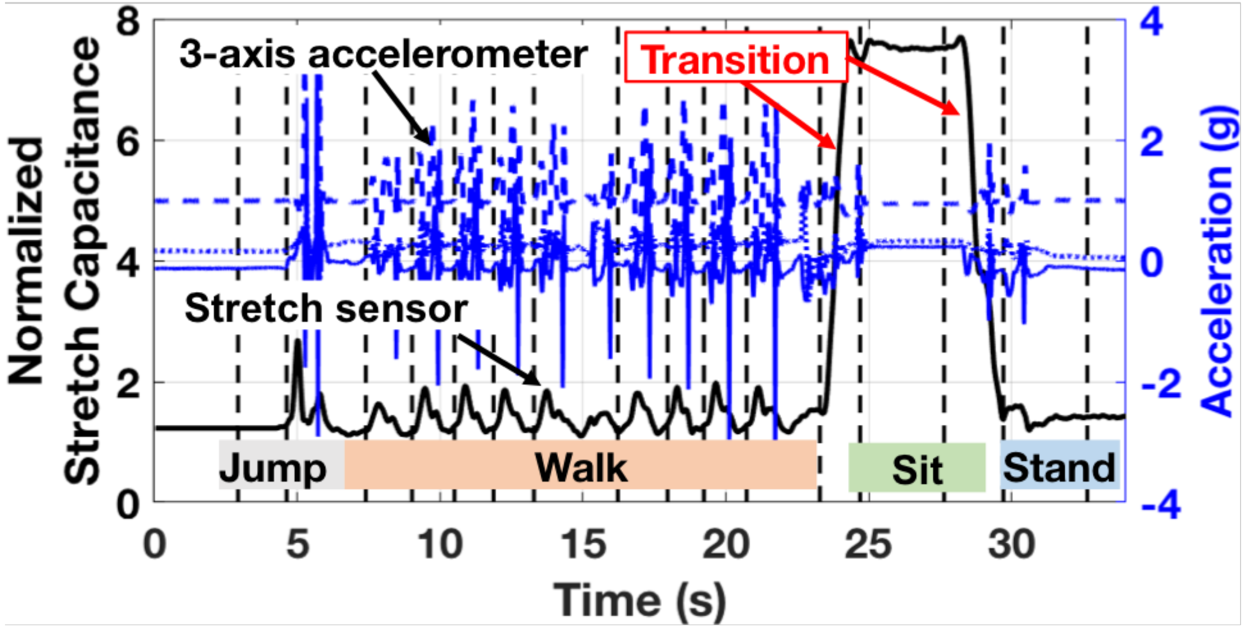
Segmentation Using Stretch Sensor

- **Detect local minimas in stretch sensor to define activity segments**
- **Use five-point derivative to track trend**

$$s'(t) = \frac{s(t-2) - 8s(t-1) + 8s(t+1) - s(t-2)}{12}$$

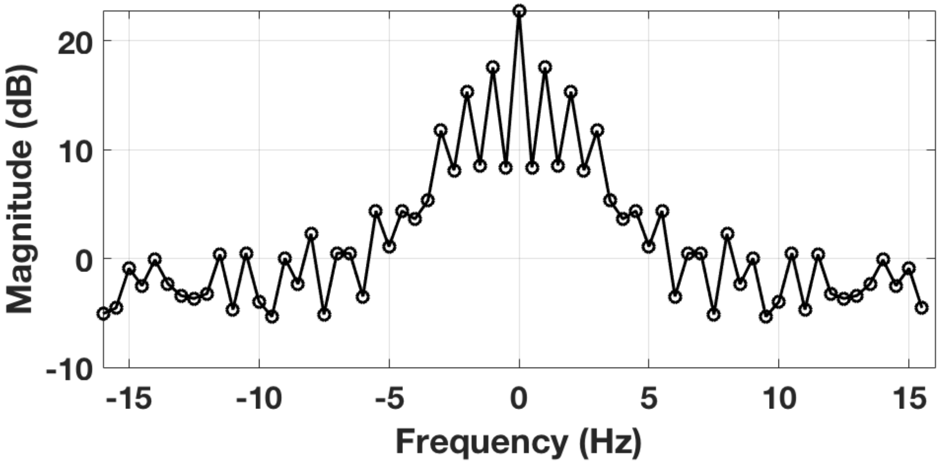
- **Define the "Trend" as**
  - *Increasing if* $s'(t) > 0$
  - *Decreasing if* $s'(t) < 0$
  - *Flat if* $s'(t) = 0$
- **Create a new segment when the trend changes from**
  - *Decreasing* to *Increasing*
  - *Flat* to *Increasing*

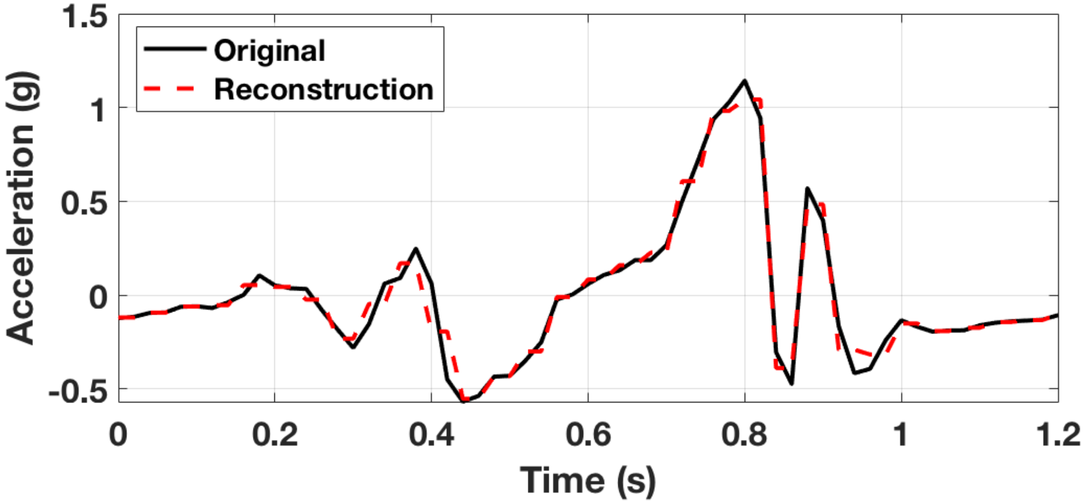




Feature Generation

- **Most of the prior work on HAR uses statistical features for activity classification**
  - *However, statistical features do not provide insight into the actual shape of data*
- **In contrast, we use DWT and FFT to get better insight**
- **Using this insight we generate the following features**
  - Stretch Sensor : **16 FFT coefficients**, minimum and maximum values in the segment
  - Accelerometer : **32 DWT coefficients** for a_x, a_z and body acceleration, mean of a_y
  - General features : Length of the segment and previous activity label





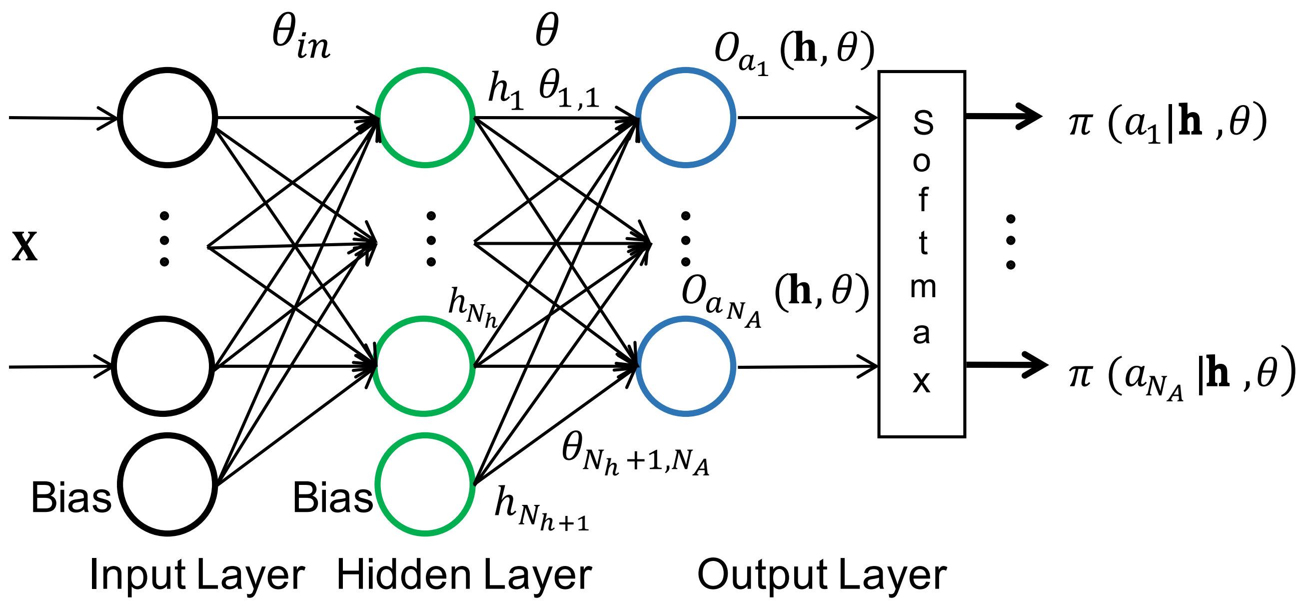
Supervised Learning for Activity Classification

- **We use a parameterized neural network to classify activities**
  - Neural networks can be easily used for online learning

- **Neural network configuration**
  - One fully connected hidden layer
    - ReLU activation
  - Fully connected output layer
    - Softmax activation

- **Probability of each activity is**

$$\pi(a_i|\mathbf{h},\theta) = \frac{e^{O_{a_i}(\mathrm{h},\theta)}}{\sum_{j=1}^{N_A} e^{O_{a_j}(\mathrm{h},\theta)}}$$



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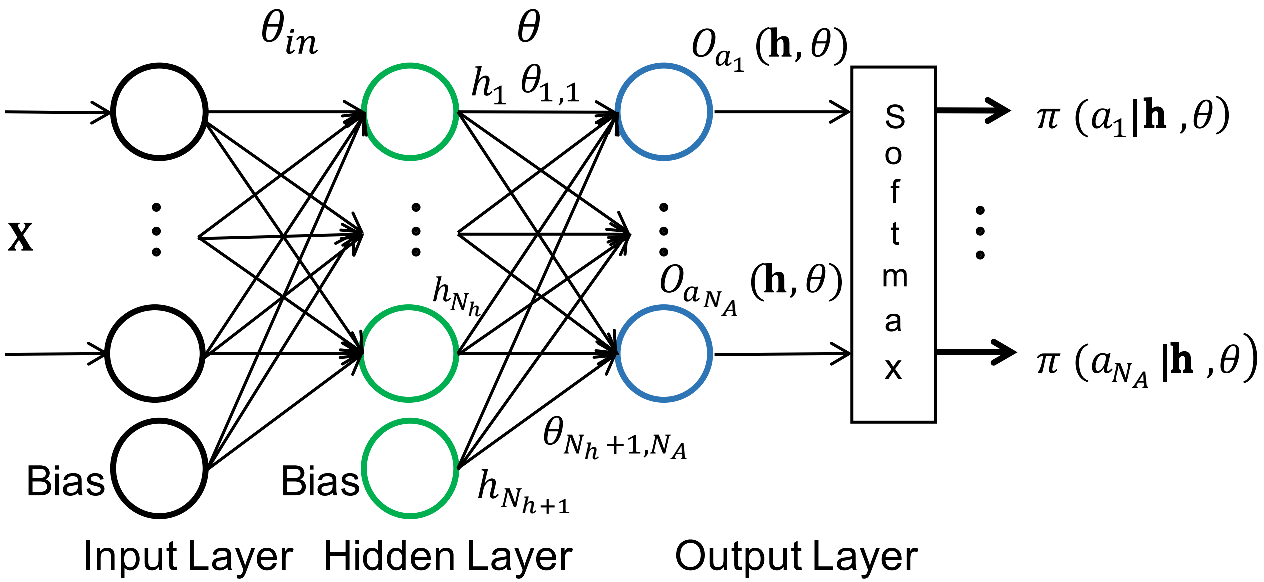
Why Online Learning?

- **Classifiers shipped with the device can be trained using *known user data sets***
- **User patterns can change with**
  - Physical condition, age, gender, and, demographics
- **Even, condition of a given user may change over time**
- **Classifiers learned offline must adapt to**
  - New users
  - Varying conditions of its user
- ***Challenges***
  - Online training can be computationally intensive
  - Wearable devices do not have large storage area

Online Learning Preliminaries

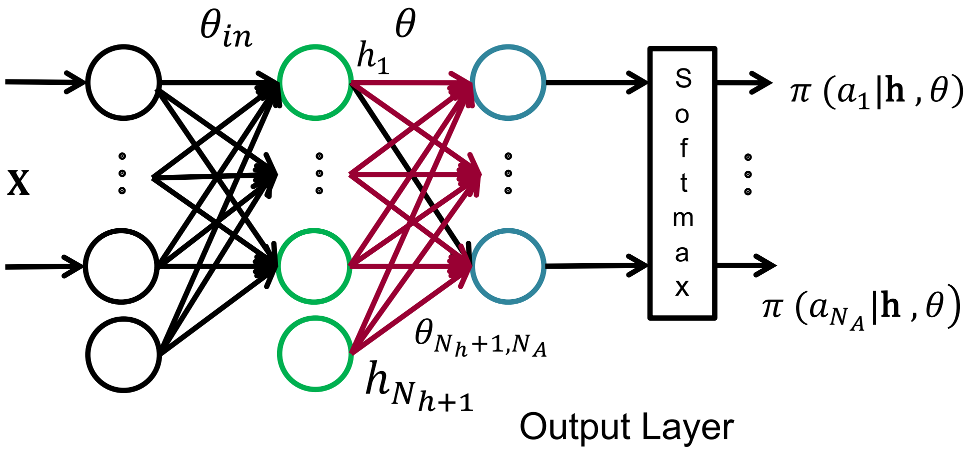
- **State ($\mathbf{X}$):** Accelerometer and stretch sensor readings within a segment define the continuous state space
- **Policy model (π):** The activity probabilities
- **Action:** Activity performed in each segment
- **Reward:** User provides the reward as a function of the classified action:
  - *If correct*: **+1**
  - *else*: **-1**



Objective: Maximize the total reward with respect to the classifier weights

Policy Gradient Weight Update

- **In general, all weights in the policy network are updated**
  - *Useful when starting from an untrained network*



- **We start with a trained policy network**
  - First few layers provide broadly applicable features
  - Hence, we update only the output layer weighs
- **Derived the policy gradient:** $\boldsymbol{\nabla_\theta \pi(a_t|\mathrm{h}, \theta_t)}$
- **Found the weight update equation as**

$$\boldsymbol{\theta_{t+1} \equiv \theta_t + \alpha r_t \frac{\nabla_\theta \pi(a_t|\mathrm{h}, \theta_t)}{\pi(a_t|\mathrm{h}, \theta_t)}}$$

where α: *Learning rate*, r_t: *Reward*

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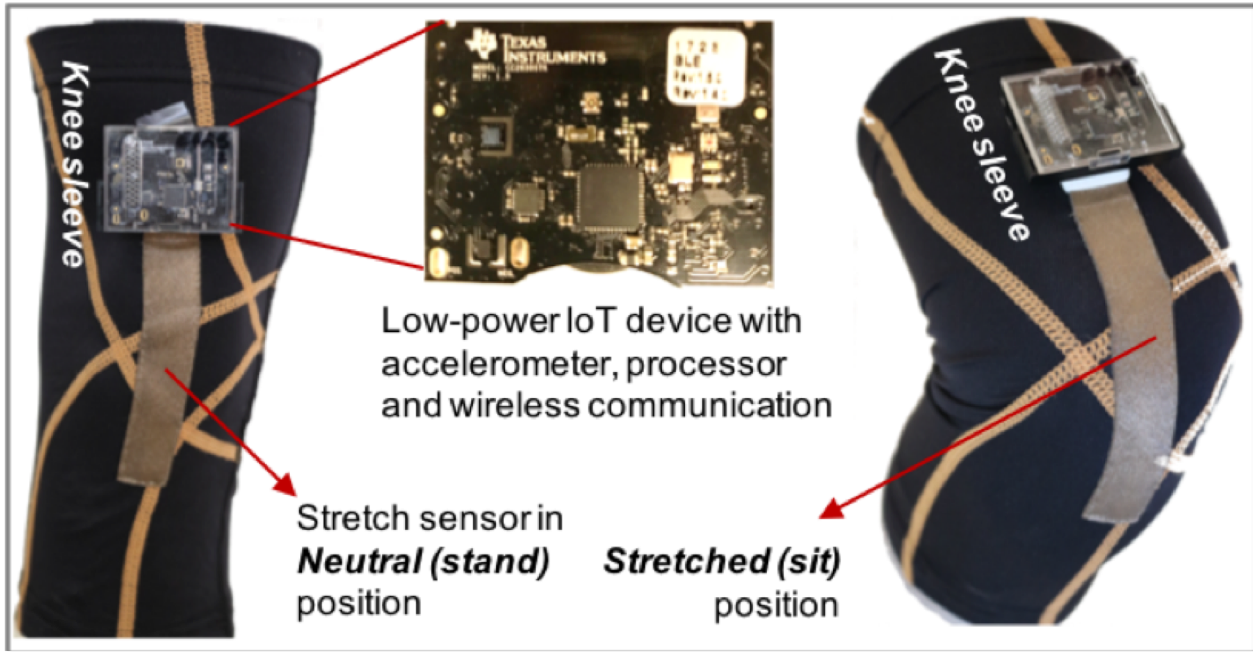
Experimental Setup

- **Wearable Device**
  - TI CC2650 MCU, InvenSense MPU
  - Stretchsense Stretch Sensor
  - MPU is sampled at 250 Hz
  - Stretch sensor at 100 Hz

- **Device Placement**
  - MPU is placed at the ankle
  - Stretch sensor is placed at the knee

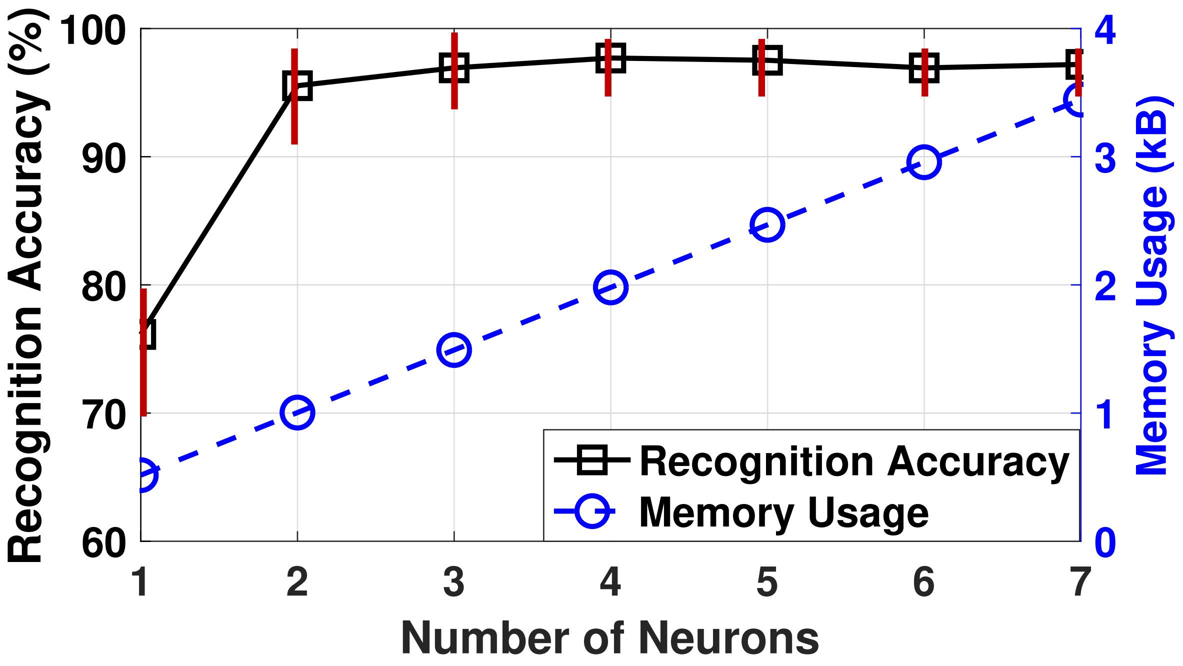
- **User studies**
  - Total of 2614 segments from nine users
  - Five users used for offline training
  - Four users in online training



Our user data is available to public at OpenHealth page

Training by Supervised Learning

- **We use a neural network for supervised learning**
  – Needs to implemented on a device with 20kB of RAM
- **First, we fix the number of hidden layers to one**
  – Then, vary the number of neurons in the hidden layer
- **We swept the number of neurons**
  – Memory requirement increases linearly
  – Accuracy saturates after four neurons
- **We choose four neurons in our NN**
  – Overall accuracy of 97.7 %
  – Memory requirement of 2 kB



Confusion Matrix for All Activities

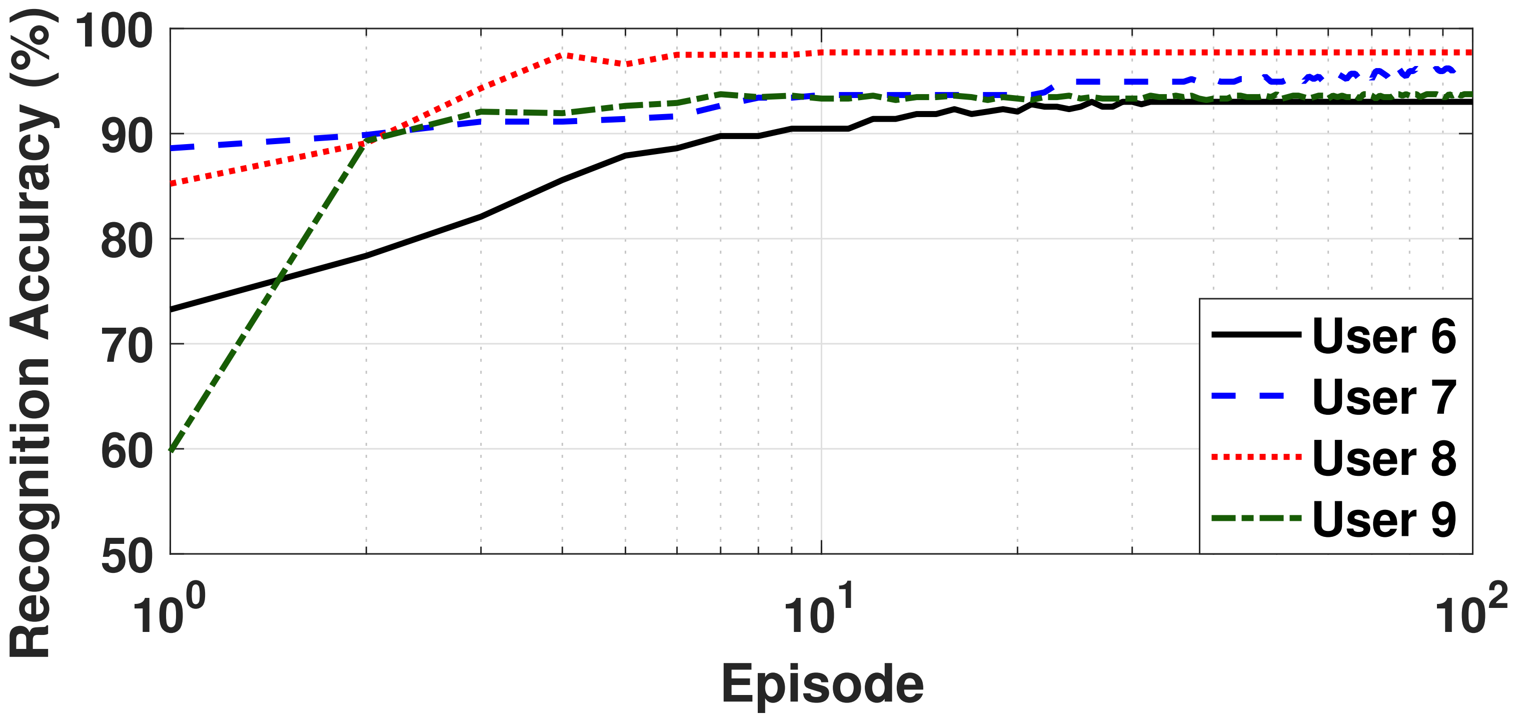
- **We analyze the confusion matrix for five users**
- **All activities except Jump show an accuracy greater than 95%**
  - Jump shows higher variation among the users
- **Transitions have a lower accuracy**
  - This is acceptable as we can infer transitions from segments before and after

Total number of windows with the corresponding activity

	Drive	Jump	Lie Down	Sit	Stand	Walk	Tran-sition
D (155)	**99.4%**	0.00	0.00	0.00	0.00	0.00	0.6%
J (181)	0.00	**93.4%**	0.00	0.00	1.1%	3.9%	1.6%
L (204)	0.00	0.00	**100%**	0.00	0.00	0.00	0.00
S (394)	0.25%	0.25%	0.00	**97.7%**	0.76%	0.00	1.0%
Sd (350)	0.00	0.29%	0.00	0.00	**98.6%**	1.1%	0.00
W (806)	0.00	0.50%	0.00	0.00	0.62%	**98.5%**	0.37%
T (127)	0.00	3.1%	0.79%	2.4%	0.79%	2.4%	**90.5%**

Reinforcement Learning for New Users

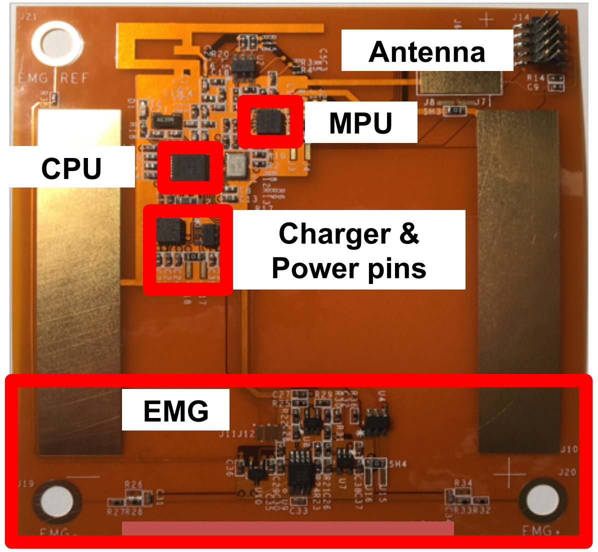
- **Apply reinforcement learning for four new users**
  - Never seen by the offline neural network
- **Run the policy gradient update for a total of 100 epochs**
  - Reward is given after every activity segment
- **Accuracy improvement with online learning:**
  - ***User 6: 74% → 91%***
  - ***User 7: 89% → 94%***
  - ***User 8: 86% → 96%***
  - ***User 9: 60% → 91%***



HAR algorithm adapts to new users

Energy Consumption Analysis

- **Prior studies do not report power & energy breakdown [1]**
- **Added test ports to our custom prototype**
- **Performed detailed power/performance/energy analysis**



	Block	Exe. Time (ms)	Average Power (mW)	Energy (µJ)
Sense	Read / Segment	1,500.00	1.13	1,695.00
Compute	DWT	7.90	9.50	75.05
	FFT	17.20	11.80	202.96
	NN	2.50	12.90	32.25
	Overall	27.60	11.24	310.26
Communication	BLE	8.60	5.00	43.00

Enables close to 60-hour operation with a 200 mAh battery

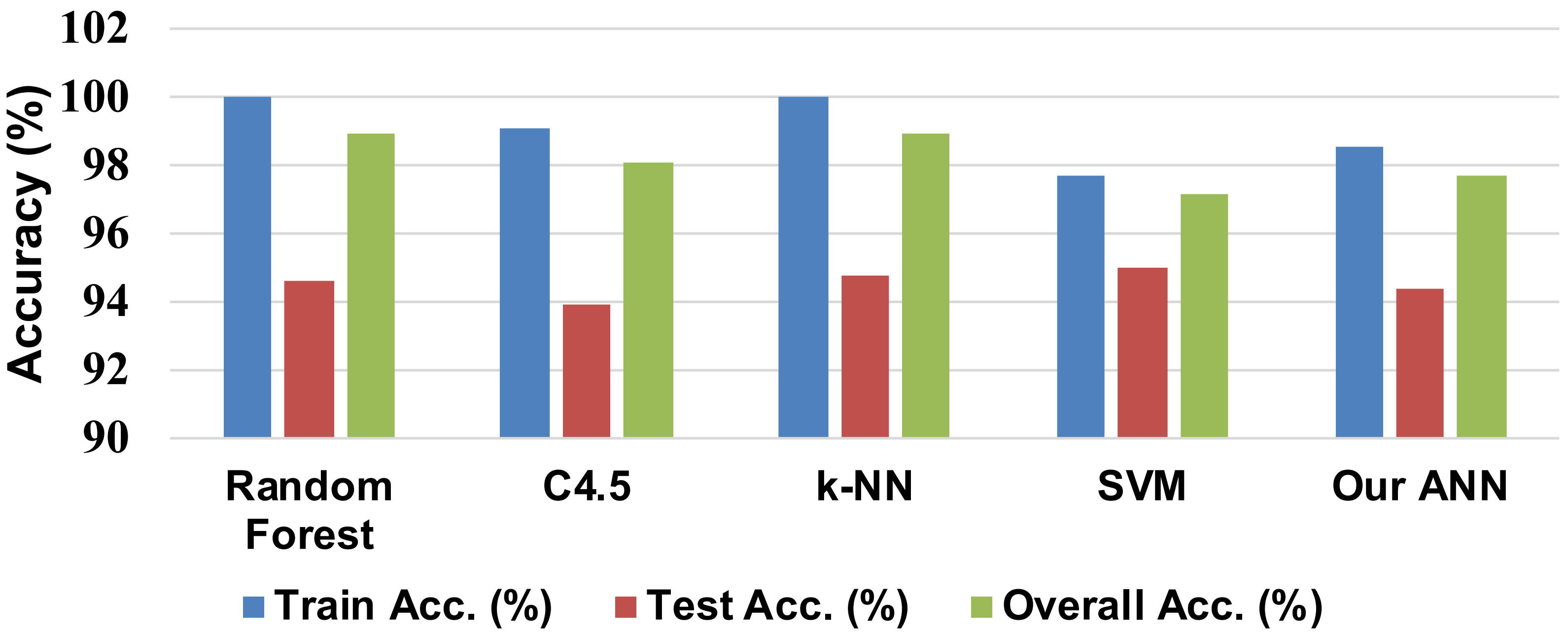
[1] Shoaib, Muhammad, et al. "A survey of online activity recognition using mobile phones." *Sensors* 15.1 (2015): 2059-2085.

Conclusions

- **Wearable IoT devices offer great potential to enable interesting applications**
  - Health monitoring, activity tracking, gesture-based control
- **Presented a Human Activity Recognition framework**
  - Novel algorithm to segment data as a function of the activity
  - Online inference and training using reinforcement learning
  - Low power implementation on a wearable device
- **Data sets and source code will be made public**

Comparison with Other Classifiers

- **Comparison of our classifier to classifiers used by prior work**



Our neural network classifier achieves compatible accuracy *while enabling efficient online learning*