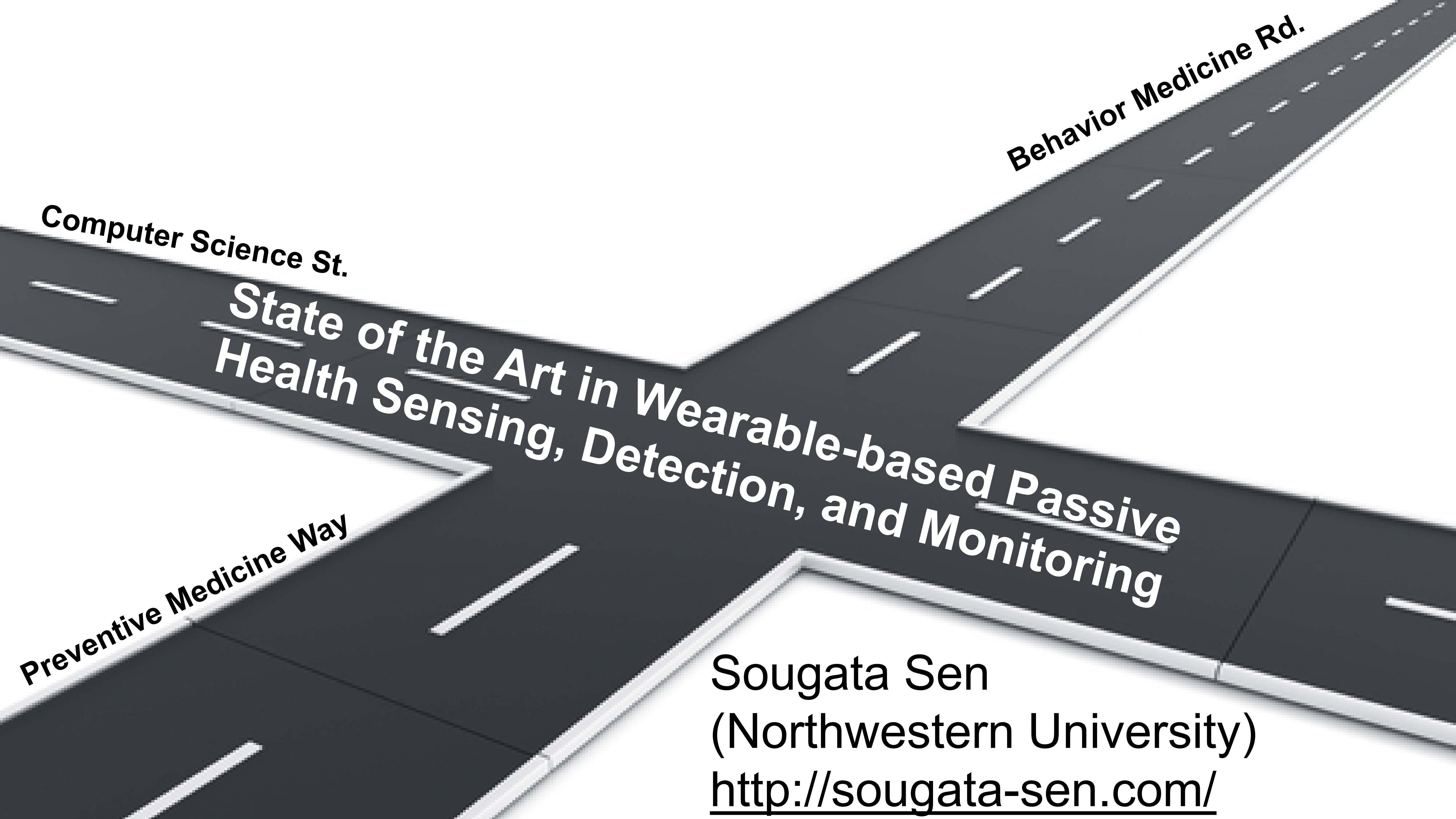
State of the Art in Wearable-based Passive Health Sensing, Detection, and Monitoring



Sougata Sen
(Northwestern University)
http://sougata-sen.com/

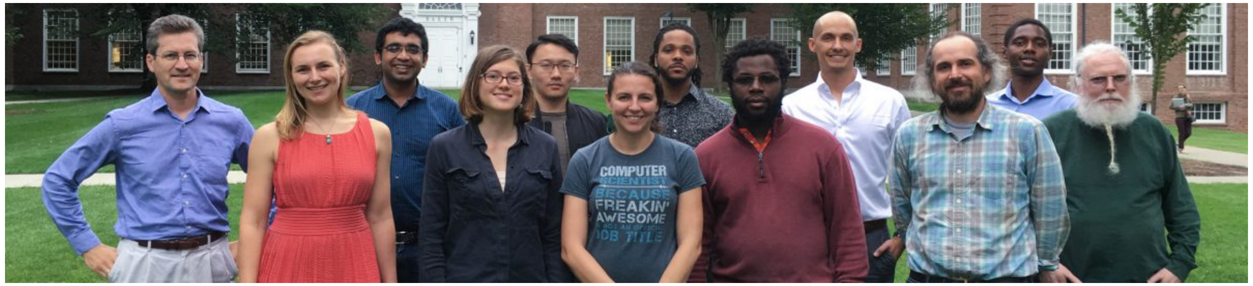
Collaborators

Northwestern University

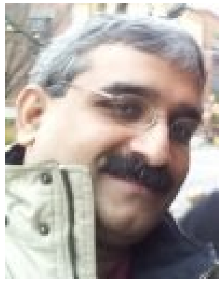
    

DARTMOUTH

CLEMSON UNIVERSITY

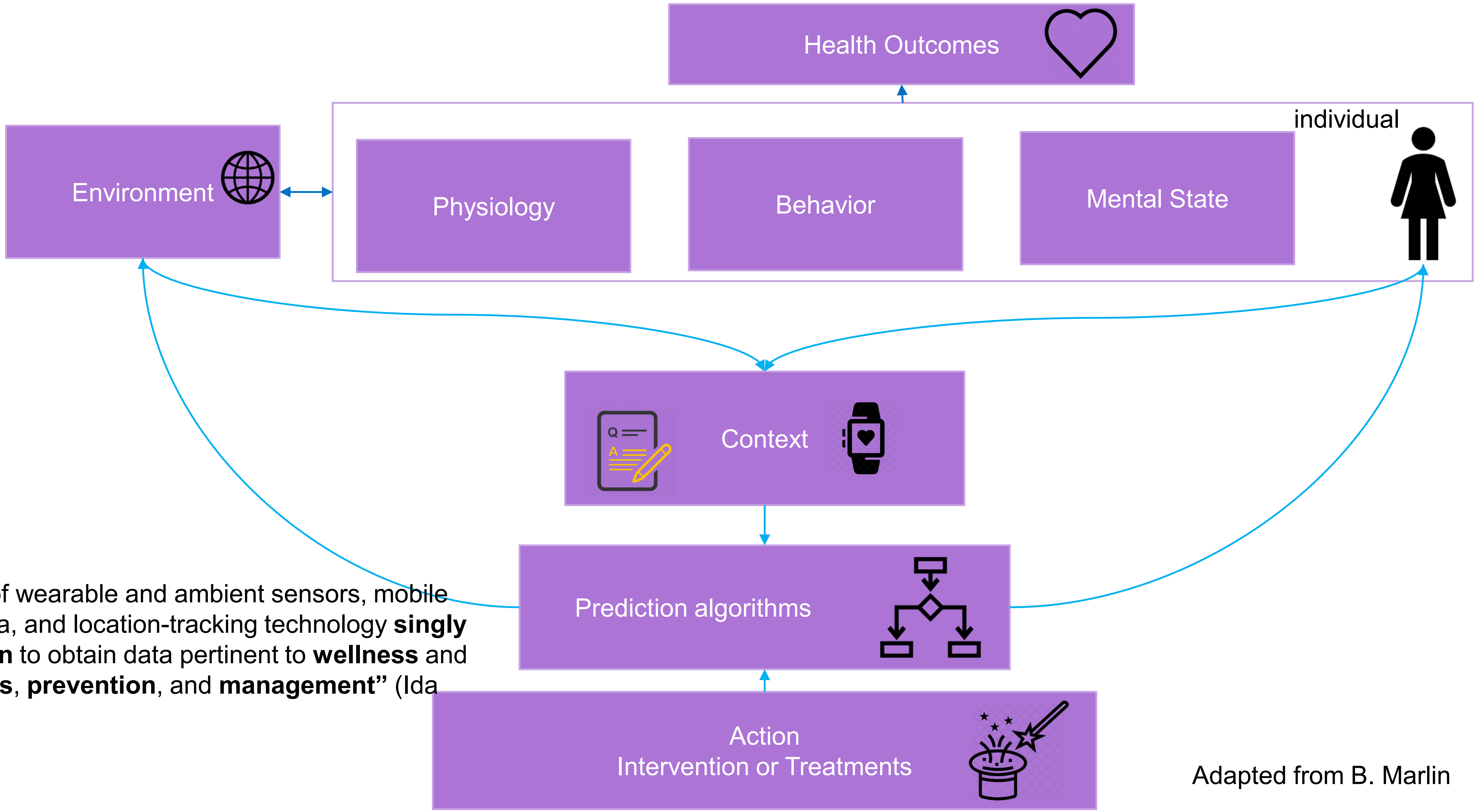


SMU SINGAPORE MANAGEMENT UNIVERSITY

www.habitslab.com http://kamoamoa.eecs.northwestern.edu/ https://auracle-project.org/

Research in mobile health



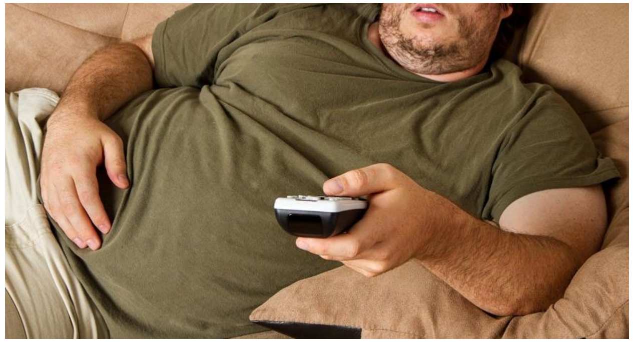
“The application of wearable and ambient sensors, mobile apps, social media, and location-tracking technology **singly or in combination** to obtain data pertinent to **wellness** and disease **diagnosis**, **prevention**, and **management”** (Ida Sim, NEJM)

Adapted from B. Marlin

Effect of habits on health

Overeating

Smoking



Low physical activity

Preventable!!!

Chronic diseases

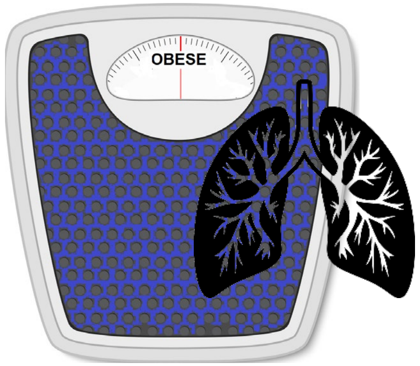
Cardiovascular diseases

High cholesterol

Certain cancers

High blood sugar

Diabetes



Respiratory diseases

Obesity

We should be more proactive

How do we become more proactive?

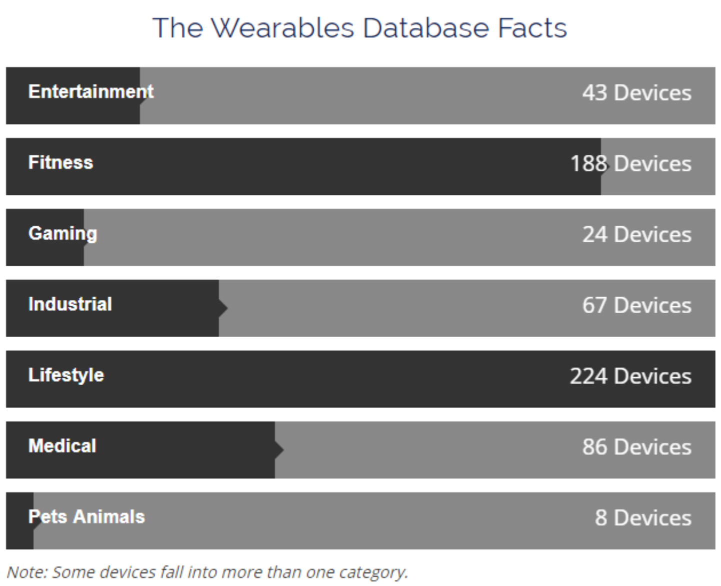
P4 medicine approach: Focus more on wellness than on disease

Measure activities and behaviors!!!

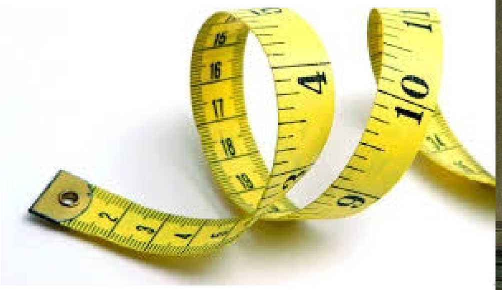
"If you can measure behavior, you can change it."

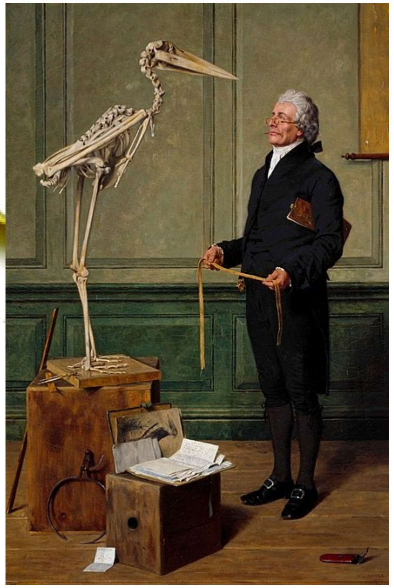
Reference: Hood, Leroy. "Systems biology and p4 medicine: past, present, and future." *Rambam Maimonides medical journal* 4, no. 2 (2013).

Science is **measurement** (Henry Stacy Marks, 1879)



Vandrico, Inc.

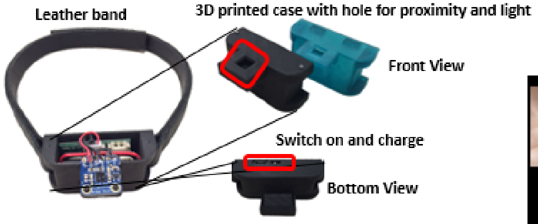


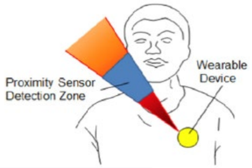


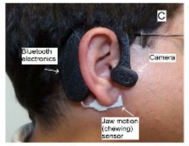
427 Number of Devices

$326 Average Price (USD)

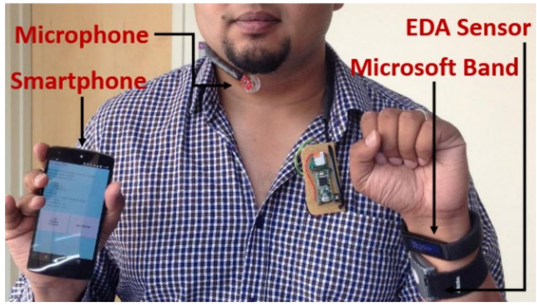
266 Number of Companies







Concept of the next generation of Automatic Ingestion Monitor (2016)



Unobtrusive

Sensing capabilities

Real-time monitoring

Just-in-time interventions

Mobile and wearable sensor devices **can enable** proactive health monitoring.

Personalized

Custom deployment

Cost efficient

Battery life

Size

Computation capabilities

Privacy

Challenges of Mobile and wearable sensor devices that needs addressing

Data Labeling

Data modeling/ validation

Adaptability

Seamless deployability

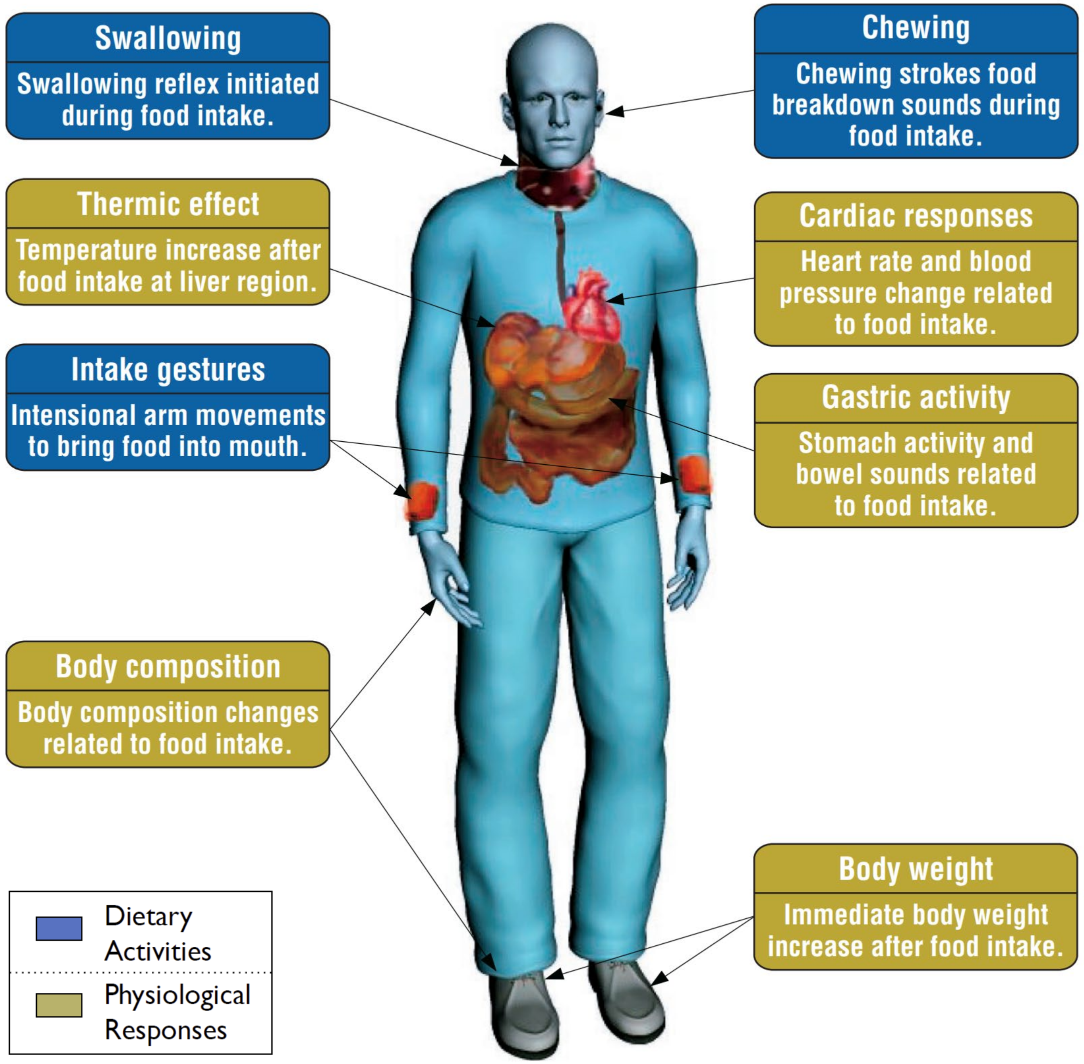
Can passive sensing help us ...

… understand behavior and predict problems?

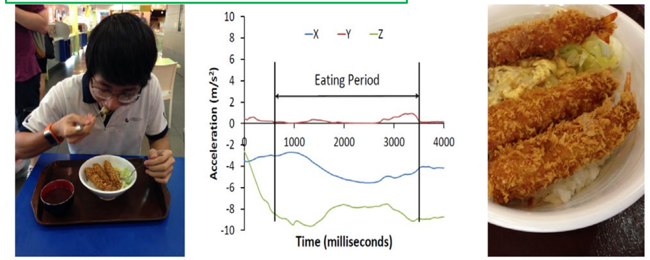
… intervene to prevent?

What
When
Where
How

Eating detection using wearable sensors



Annapurna



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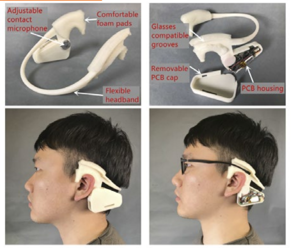
IEEE PerCom Adjunct’15
ACM MobiSys Adjunct’17
IEEE WoWMoM’18
Elsevier PMC’20

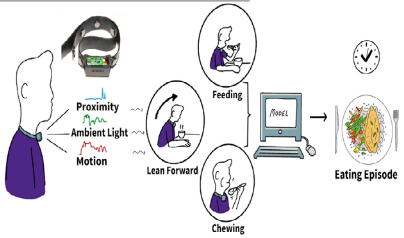
Auracle



DARTMOUTH

ACM MobiSys Adjunct’17
ACM IMWUT’18
IEEE ICHI’20

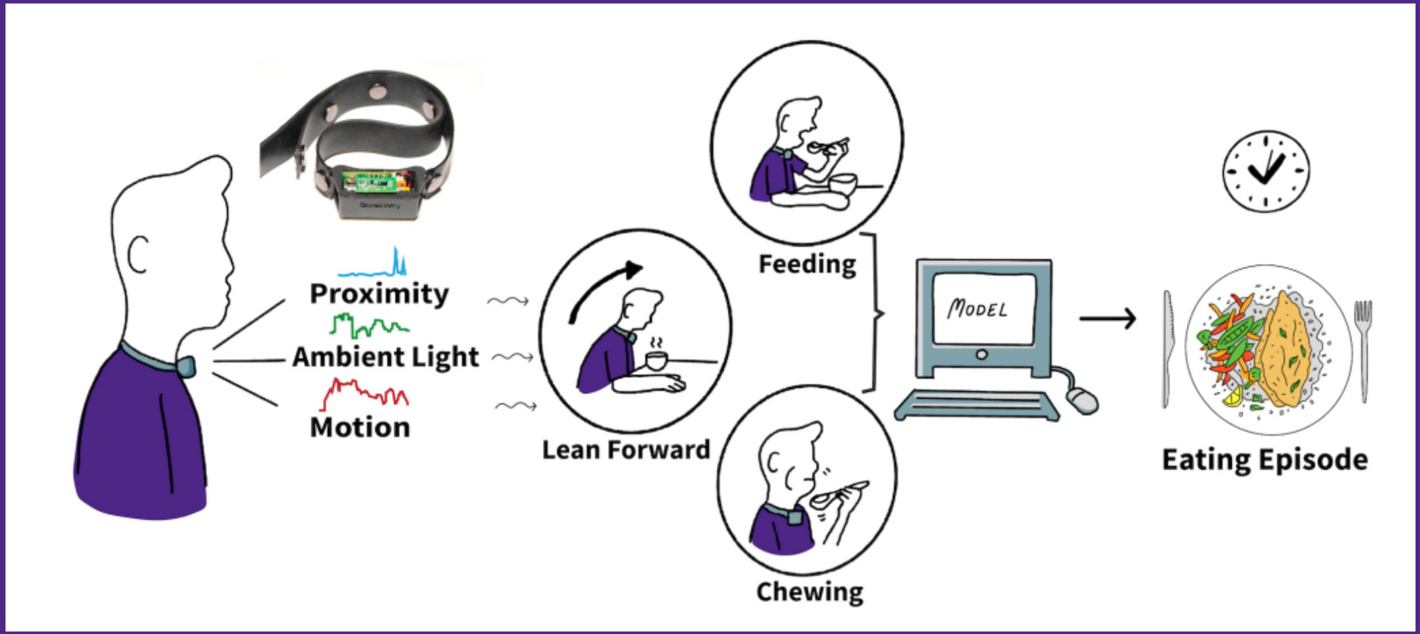
NeckSense



Northwestern University

ACM UbiComp Adjunct’18
ACM IMWUT’20

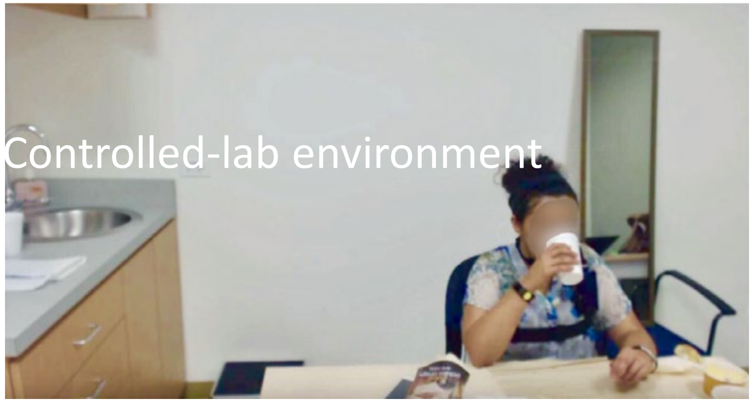
Reference: Amft, Oliver, and Gerhard Troster. "On-body sensing solutions for automatic dietary monitoring." *IEEE pervasive computing* 8.2 (2009): 62-70.

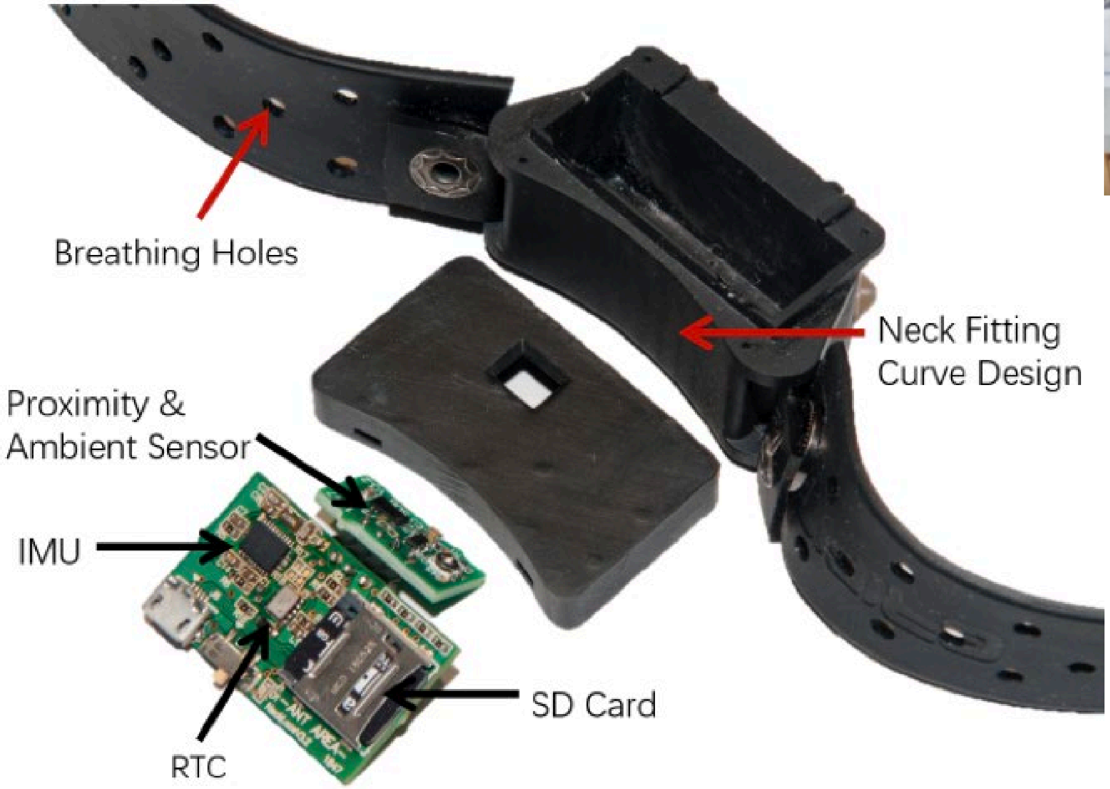


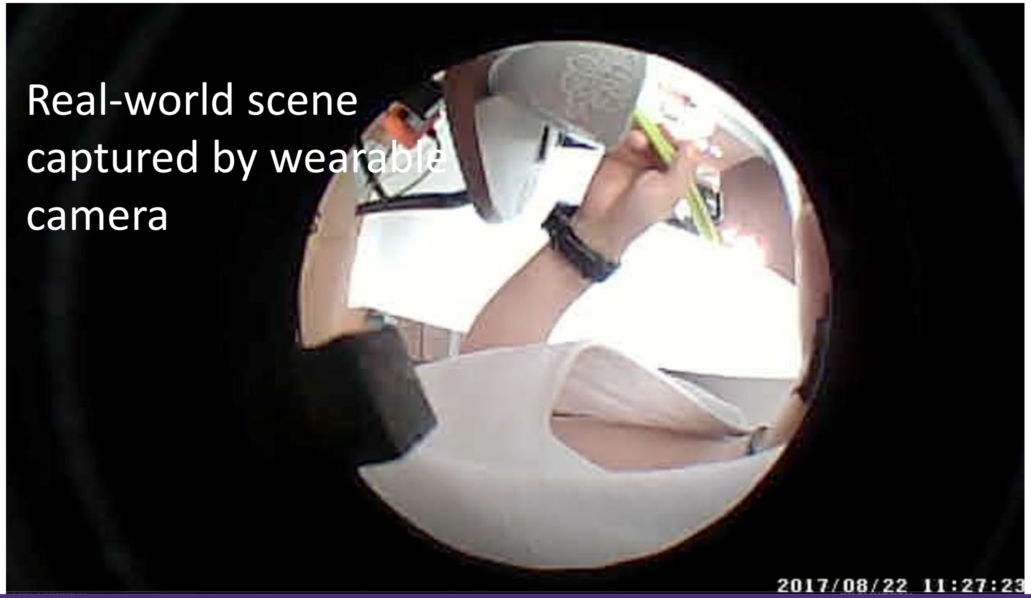
NeckSense

www.necksense.info

novel **neck-worn** device with multiple embedded sensors
…**infer eating behavior** from **contactless** sensors
…**tested** on clinical population
…tested in **real-world settings**





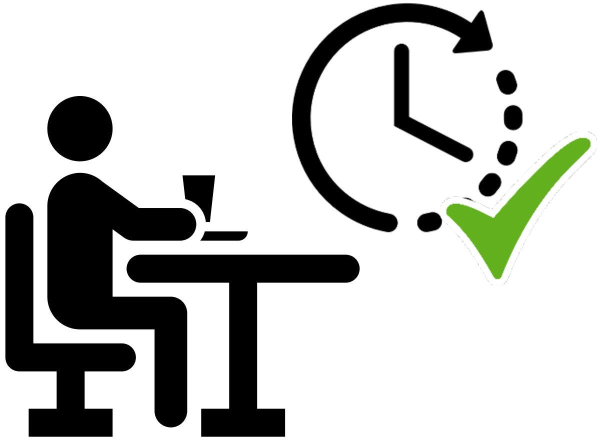


benefits to NeckSense

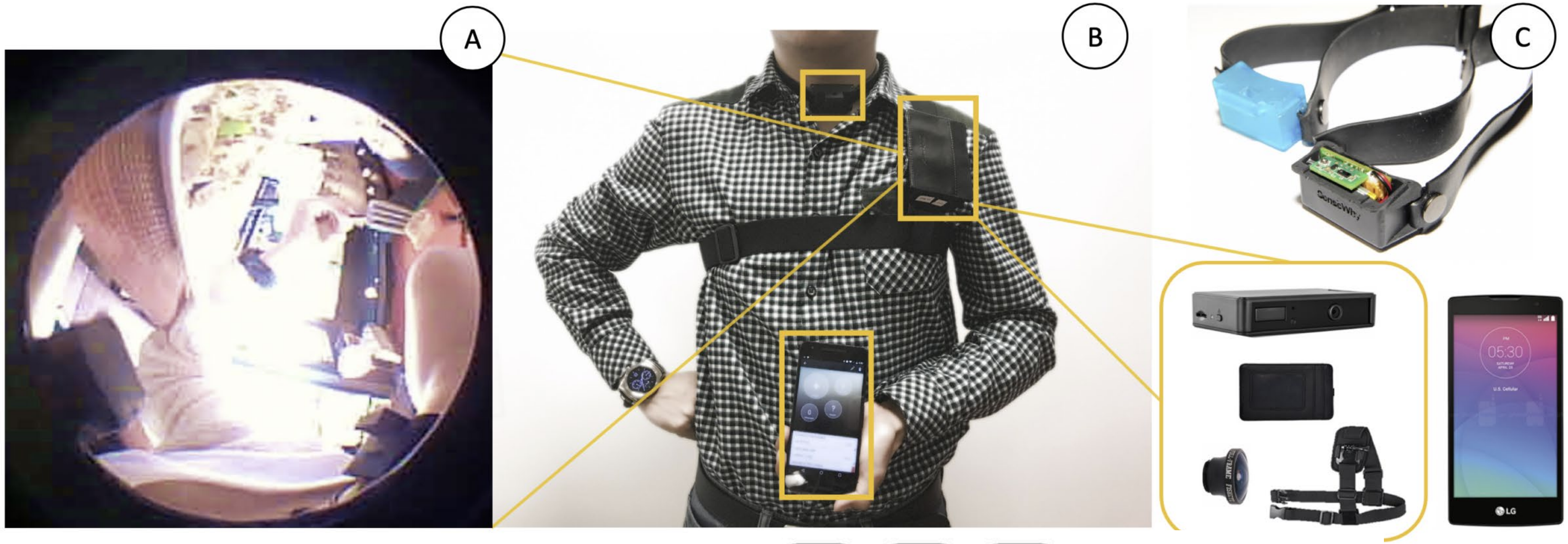
… understand characteristics of an eating episode

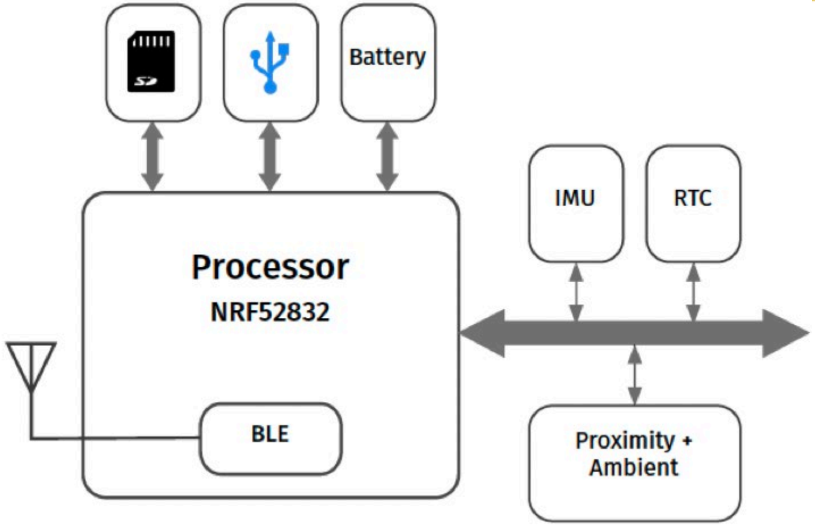
… **detect eating** in real-time

… **trigger timely interventions** for diet recall and behavior change



NeckSense Deployment

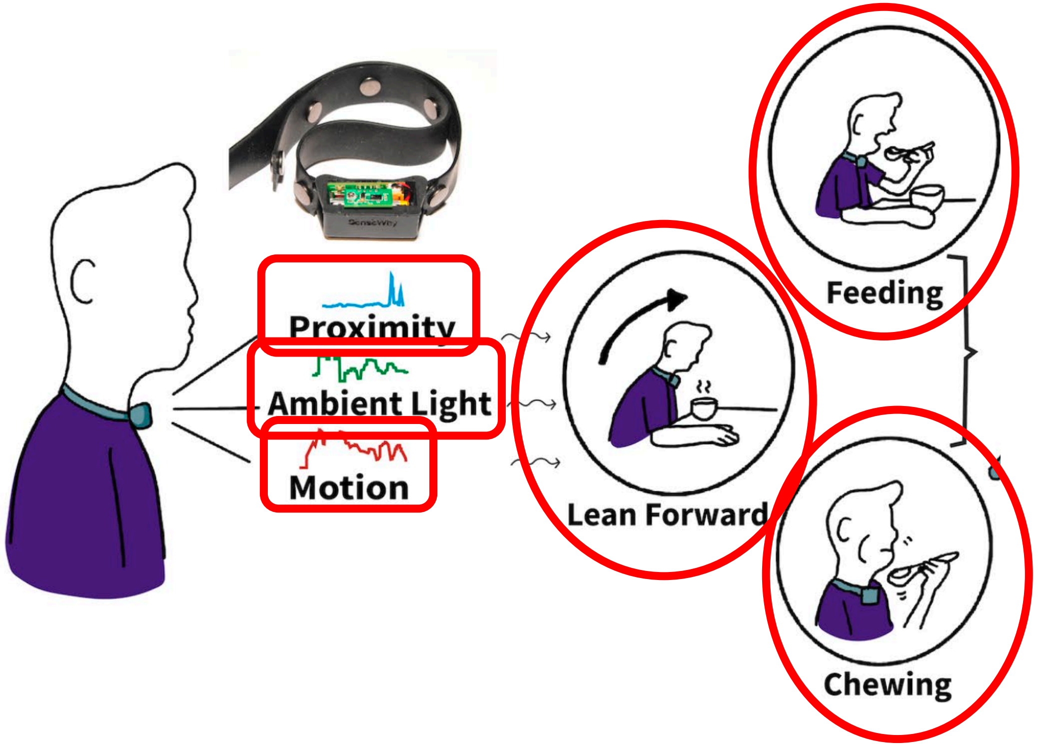




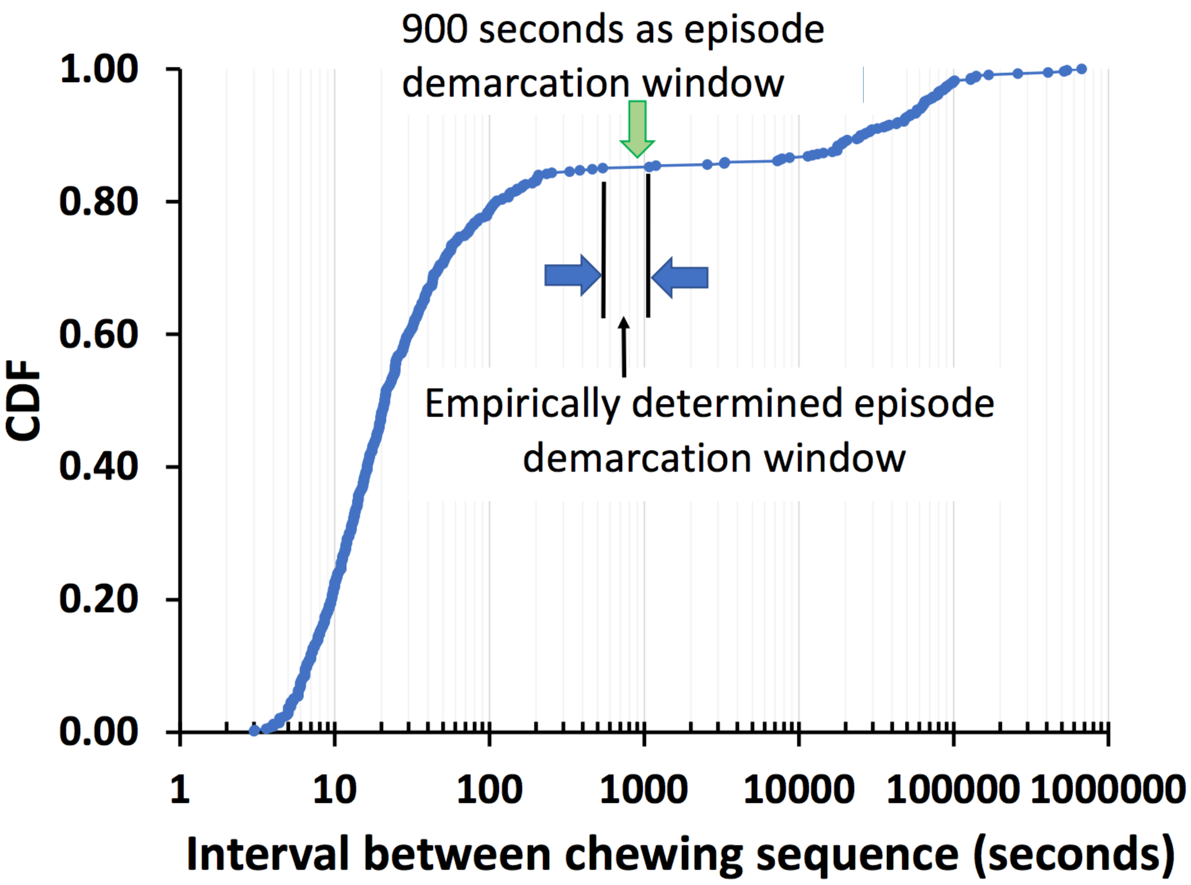
validated using a wearable video camera for **270 hours in-the-wild**
…data and **code** available freely for research purpose

Multiple sensors capture eating

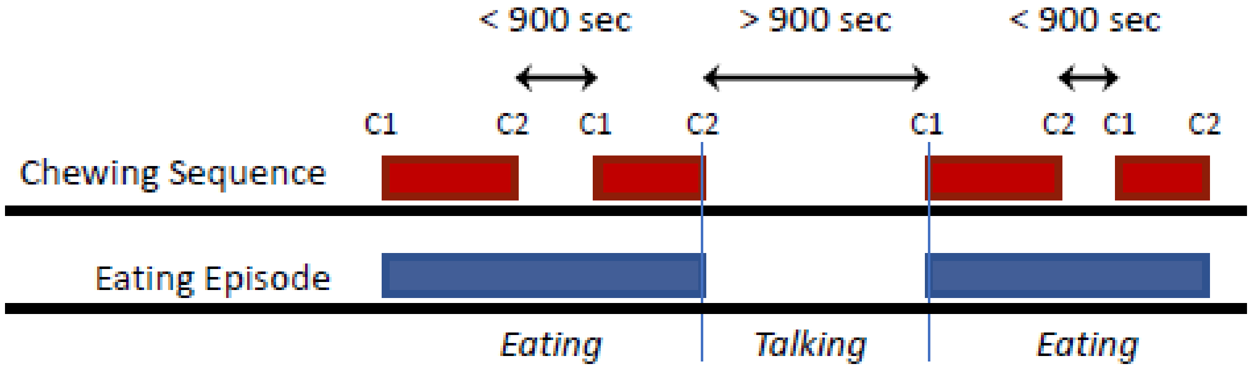
… **proximity signal** captures periodicity of chew
… **ambient light** as a proxy to feeding gestures
… **IMU** calculates leaning forward and backward angle to infer bite



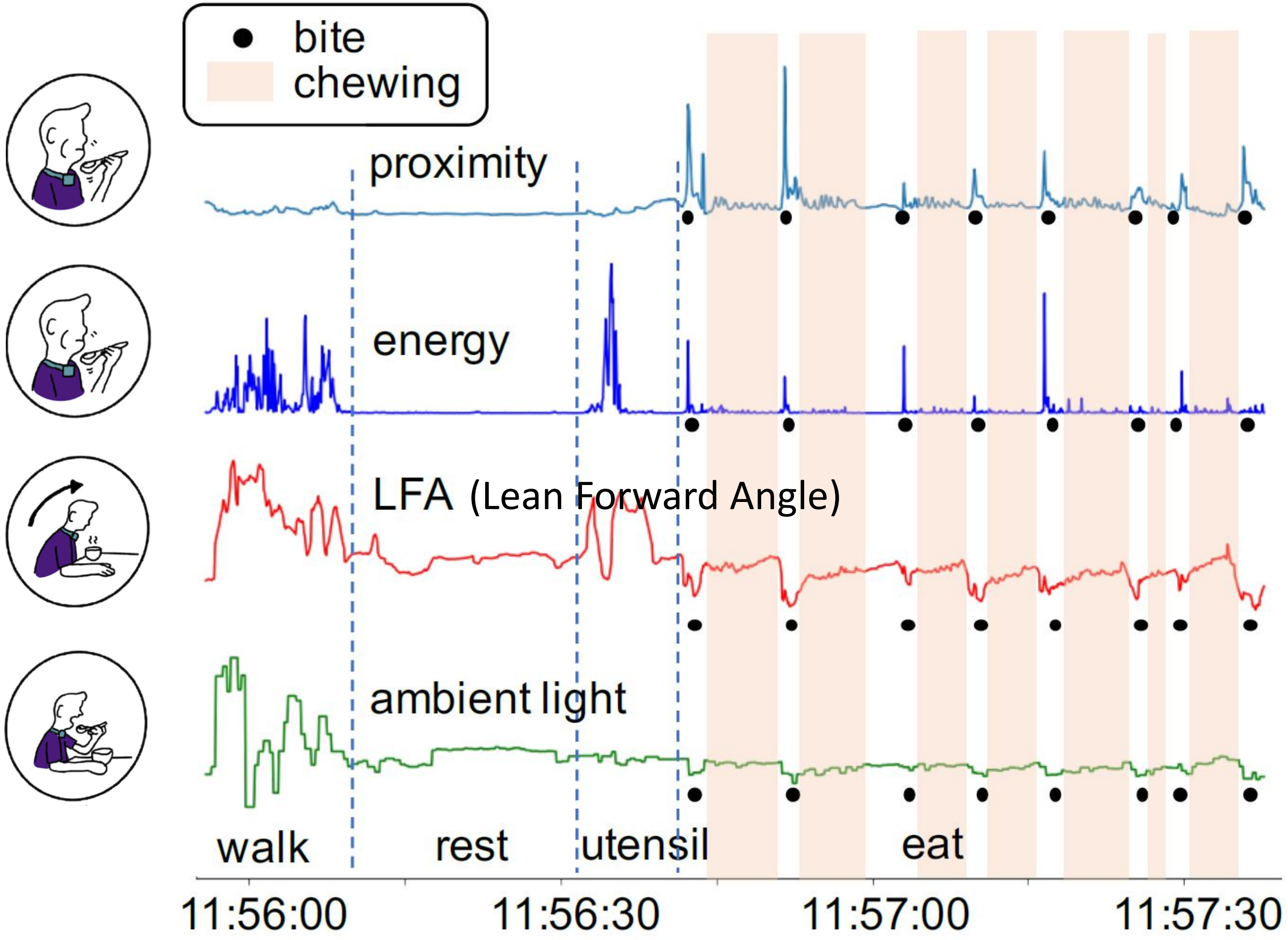
Defining an **eating episode**



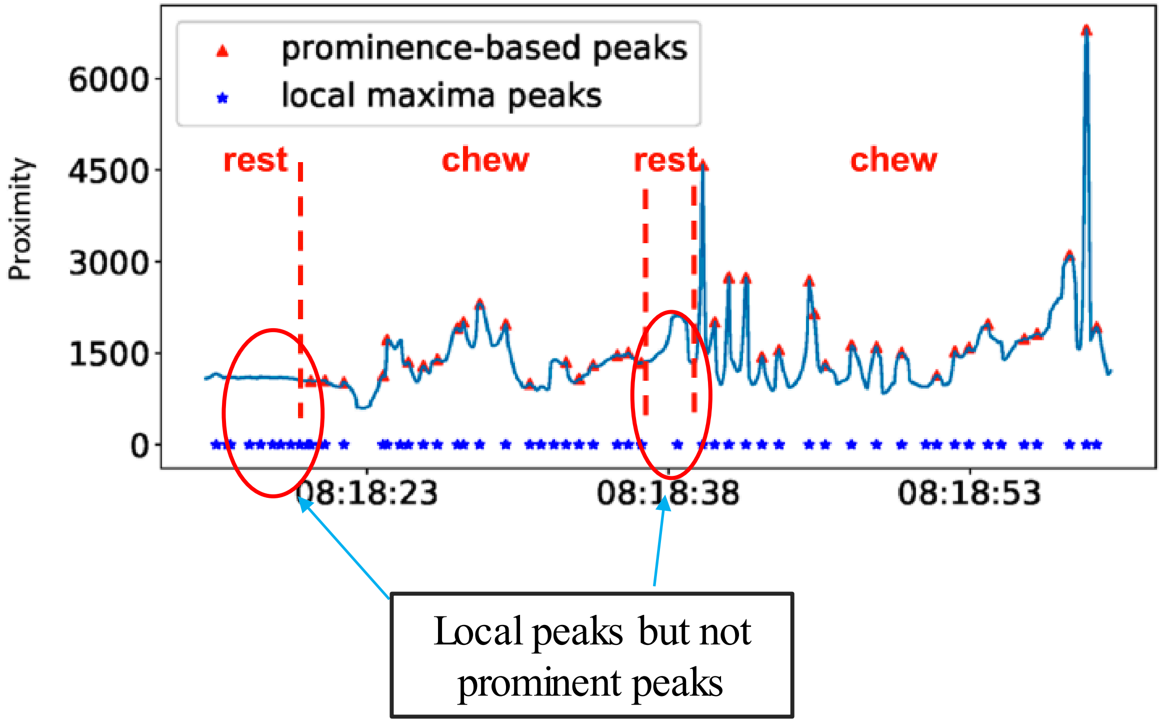
“A group of chewing sequences with inter-chewing sequence breaks no larger than 900 seconds.”



processing **four** signals from NeckSense

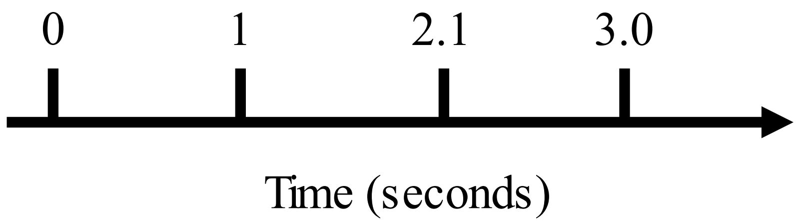


segmentation using proximity sensing signal

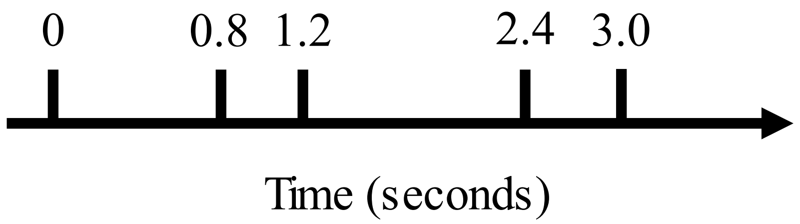


$$\epsilon\text{-periodic: } \frac{p_{max}}{p_{min}} < 1 + \epsilon$$

Pmin (0.9) and Pmax (1.1) close in distance



Pmin (0.4) and Pmax (1.2) far in distance



feature extraction

Category	Features
Statistics	Max, min, mean, median, standard deviation, RMS, correlation, skewness, kurtosis, 1st and 3rd quartile, interquartile range
Frequency	Frequency amplitude of 0.25 Hz, 0.5 Hz, 0.75 Hz, 1 Hz, 1.25 Hz, 1.5 Hz, 1.75 Hz, 2 Hz, 2.25 Hz, 2.5 Hz
Statistics of Frequency	Skewness and kurtosis of spectrum from frequency features
Time-series	Count below/above mean First location of min/max Longest strike below/above mean Number of peaks
Periodic subsequence	p_{min}, p_{max}, ϵ, length
Time	Hour of datetime

Chewing Sequence?

XGBoost Classifier

Eating episode?

Fusion

Yes? No?

we performed the following **exploratory** study…

Total Hours: 134 hours

in-the-wild

- Camera wear
- Data transfer and delete
- 24-hour diet recall

Baseline | 14 partial days (2 weeks) | Assessmen

- Taught to use technology
  - Told to **wear during eating episodes**
- Pre-study questionnaire

- Returned technology
- Post-study questionnaire
- Trained Labelers Annotate using ELAN

we performed the following **free-living** study…

Total Hours: 137 hours

in-the-wild

- Camera wear
- Data transfer and delete
- 24-hour diet recall

Baseline | 2 complete days | Assessmen

- Taught to use technology
    - Told to **wear all day**
- Pre-study questionnaire

- Returned technology
- Post-study questionnaire
- Trained Labelers Annotate using ELAN

in the exploratory study… **81.6% Average F-score**
in the free-living study… **77.1% Average F-score**

When trained on people without obesity,
show **poor** test performance on people with obesity

		Test	
		Obese	Non-obese
Train	Obese	71.21%	75.33%
	Non-obese	66.75%	79.88%

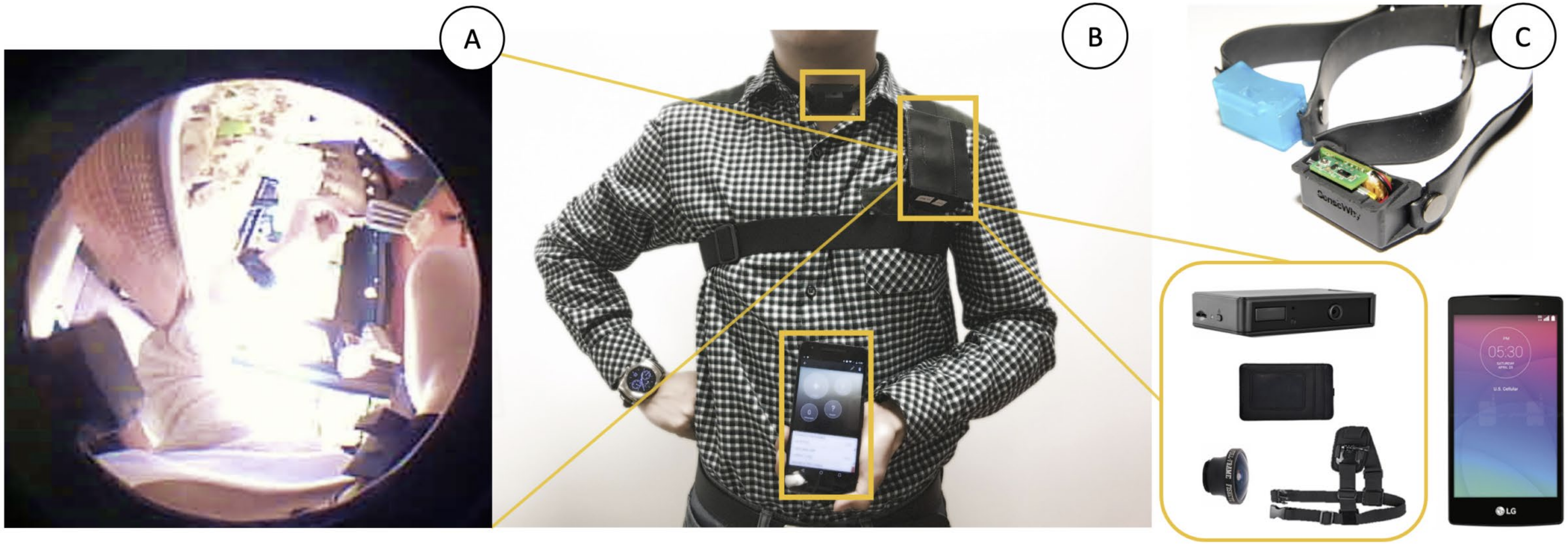
Per-episode LOPO evaluation

NeckSense is …

- designed to detect eating episodes in the real-world for long-term wear
- validated using longest periodic subsequence algorithm
- validated on people with and without obesity and solely in free-living settings

Data set available and device available upon request (www.necksense.info)

NeckSense Deployment



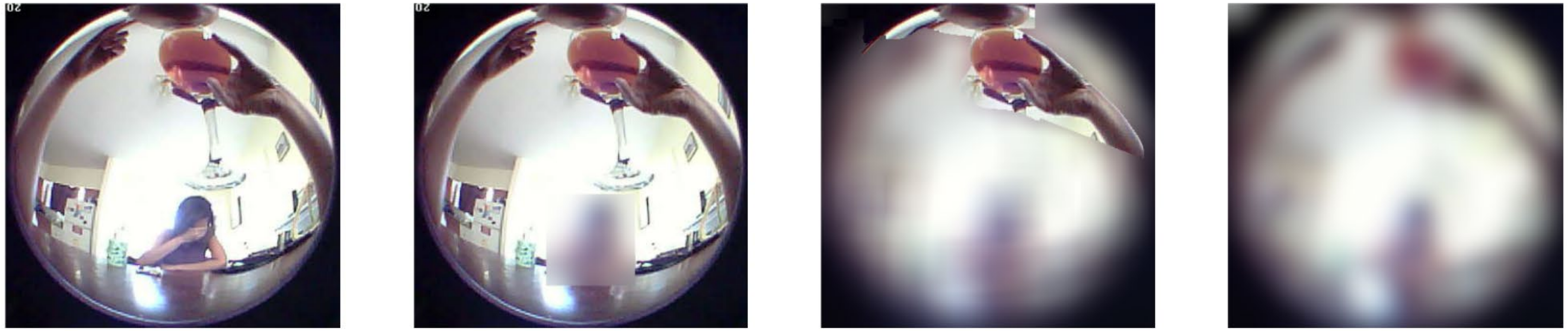
RESEARCH-ARTICLE

I Can't Be Myself: Effects of Wearable Cameras on the Capture of Authentic Behavior in the Wild

Authors: Rawan Alharbi, Tammy Stump, Nilofar Vafaie, Angela Pfammatter, Bonnie Spring, Nabil Alshurafa Authors Info & Affiliations

Publication: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies • September 2018 • Article No.: 90 • https://doi.org/10.1145/3264900

ActiSight Camera

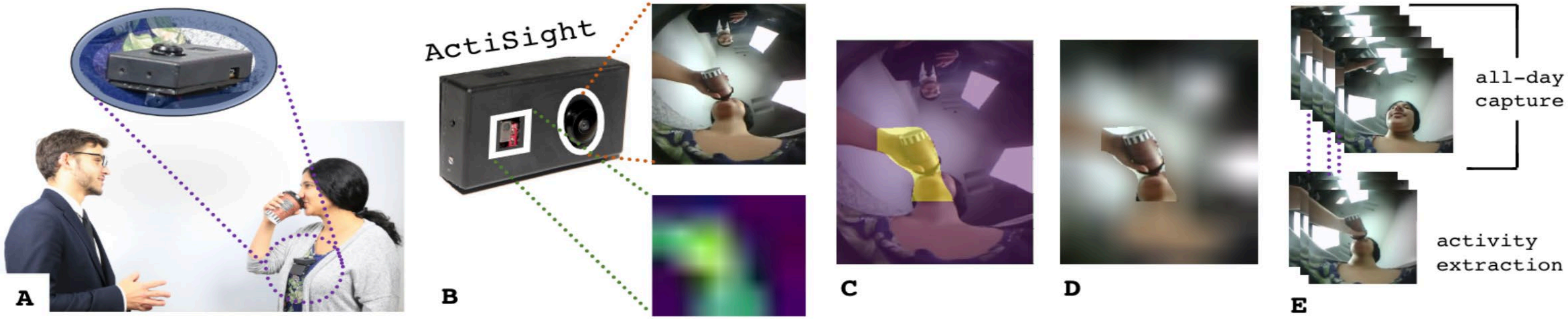


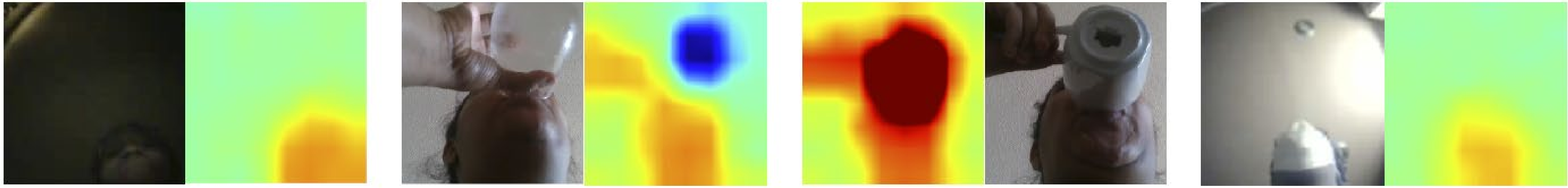
No Obfuscation

Partial Obfuscation by Blocklist

Activity-Oriented Partial Obfuscation

Total Obfuscation





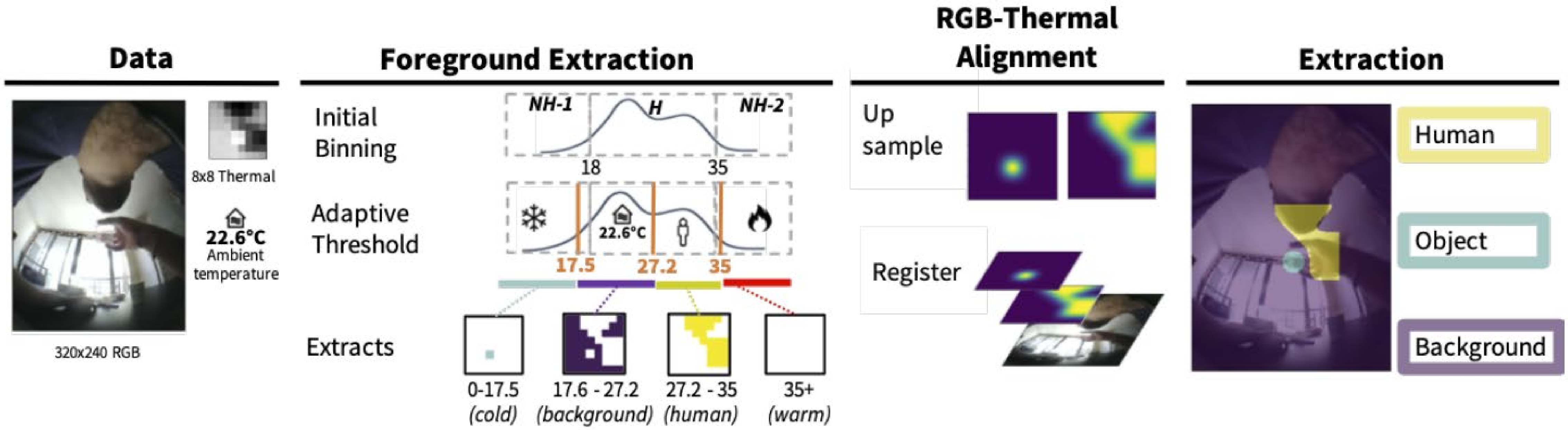
(a) In the Dark

(b) Low Contrast

(c) Extra Information

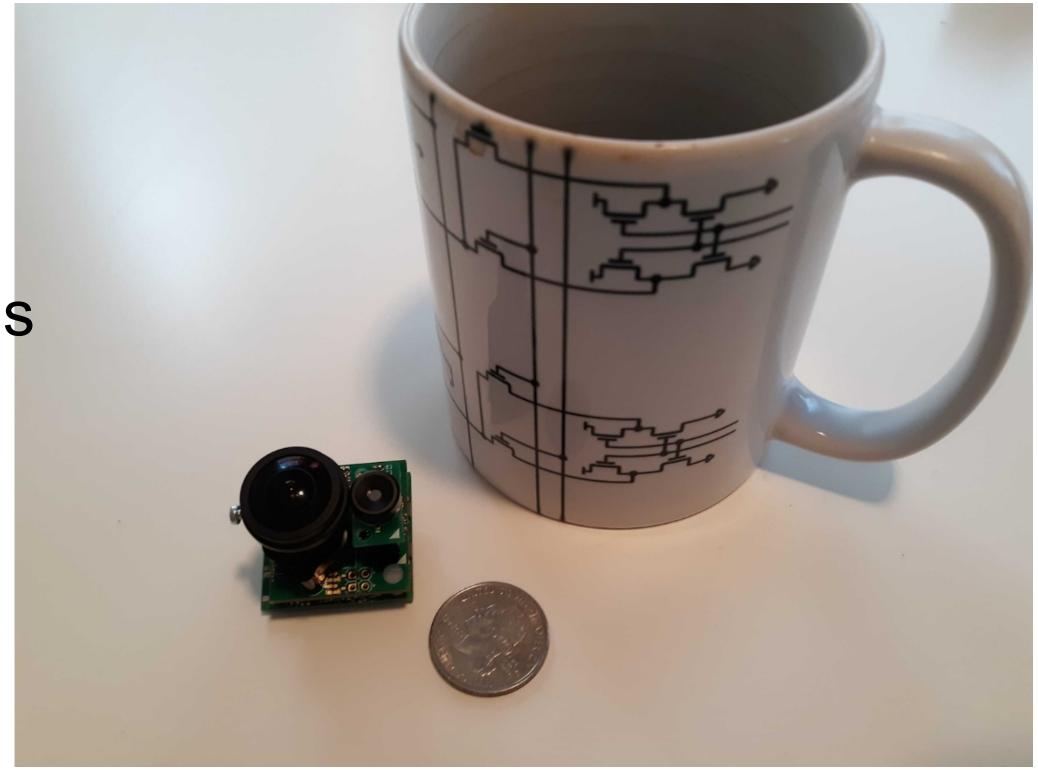
(d) Robust to Occlusion

Processing pipeline



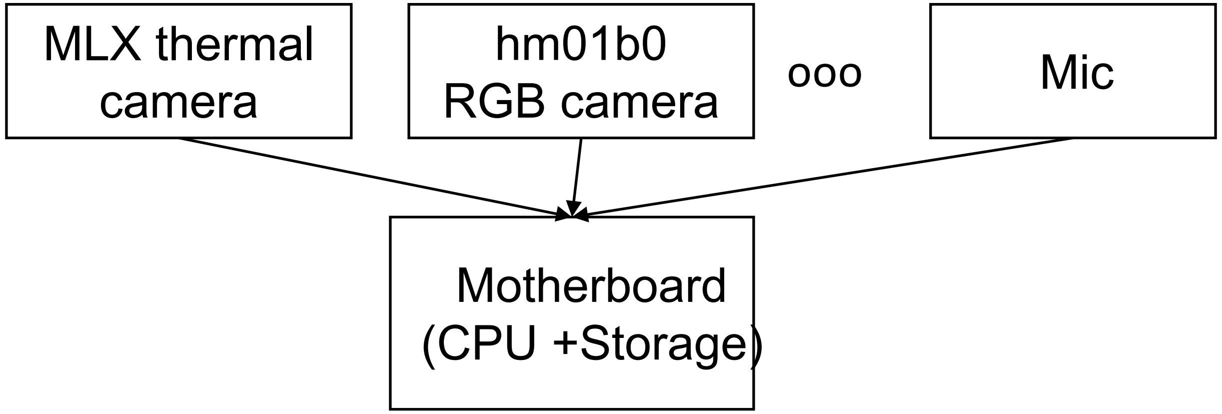
ActiSight v2 implementation

- Onboard DNN compute can enable…
  - Enhanced privacy through obfuscation
  - User interactions in real time
    - Vibrates when problematic behavior is detected
    - Send EMA on detecting problematic behavior
  - Recording selectively



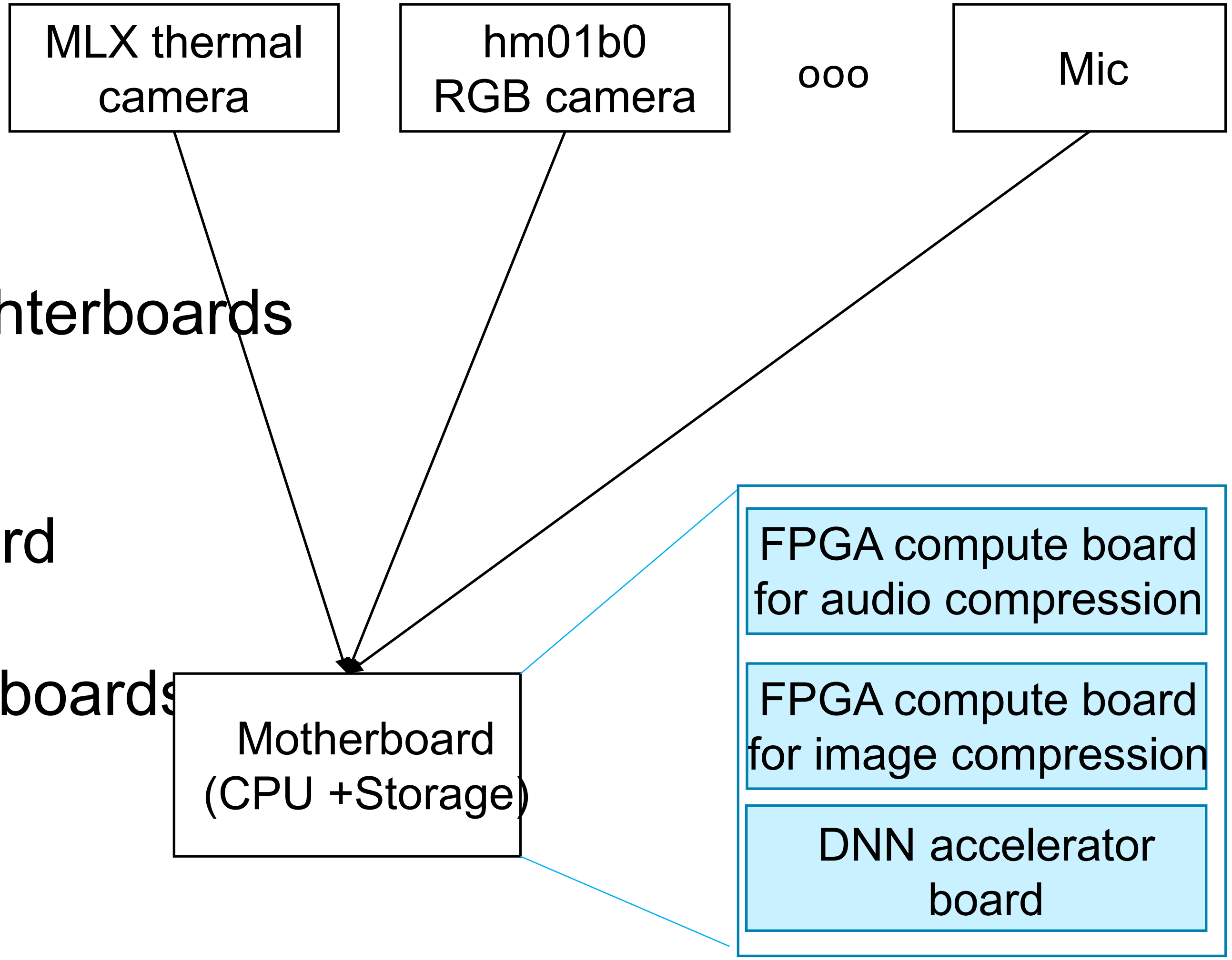
Current Hardware implementation

- Motherboard
  - Cortex M4
  - Storage
- Camera daughterboard
  - < 1mW hm01b0 camera
  - MLX Thermal Camera
  - Onboard iCE40 FPGA
    - JPEG compression in < 5mW
    - Accelerate small DNNs (100k- 500k 8-bit weights) < ~50mW
- Modular Sensor Daughterboards
  - Microphone
  - Temperature
  - Distance
  - And more!
- Full-day battery life



Future plans for ActiSight (v3)

- Motherboard
    - Cortex M4
    - Storage
- Up to 4 swappable compute daughterboards
    - FPGA
    - MAX78000 DNN accelerator
    - Stackable on top of motherboard
- One camera daughterboard
- Many swappable sensor daughterboards



Can passive sensing help us ...

… understand behavior and predict problems

… intervene to prevent?

Future directions in mHealth sensing

Fine-grained activity monitoring

Multi-day battery life

Privacy conscious

Personalized Real-time interventions

Multiple task inference

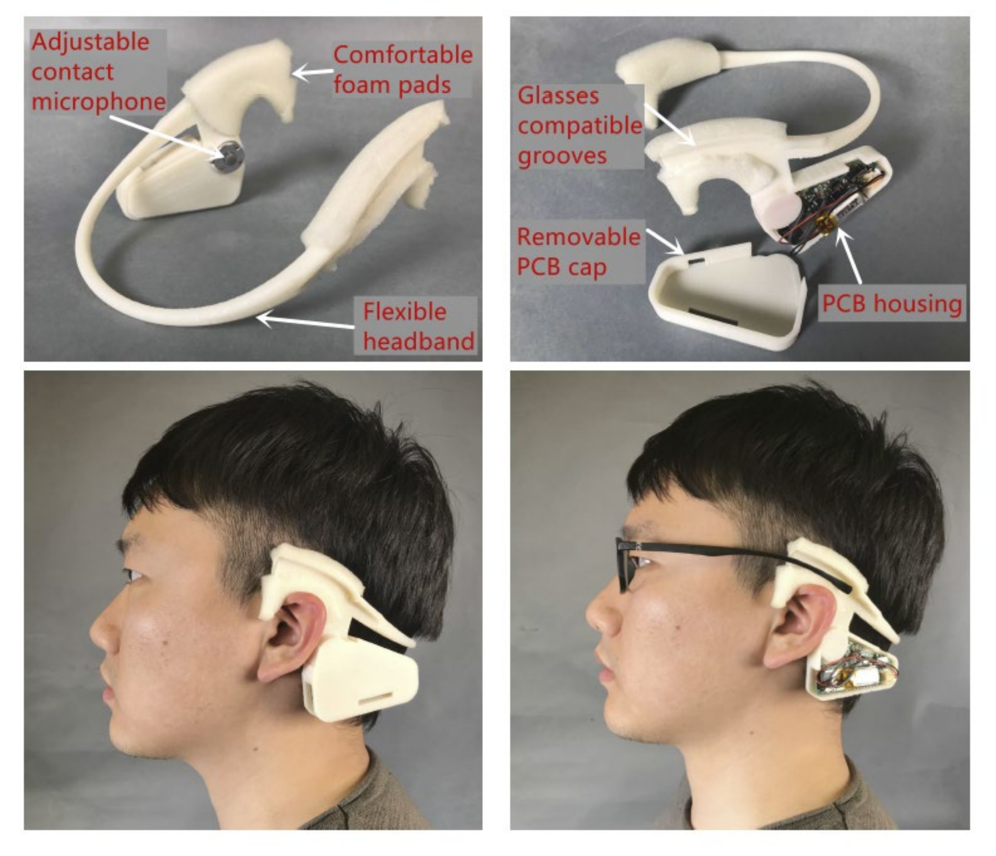
Thank you!!!

Sougata.sen@northwestern.edu

Summary

Auracle

https://auracle-project.org/



Auracle goal

- **Objective:**
  - Detect the eating activity in free-living.
  - Provide day-long battery life.

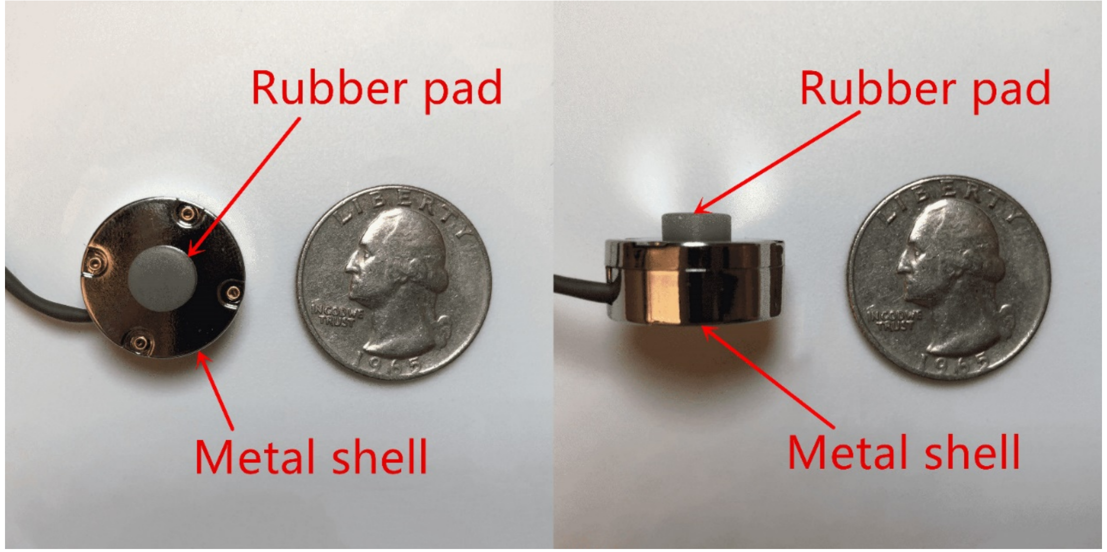
- **Intuition:** the sound of chewing can be an indicator of eating

Definition of Eating: an activity involving chewing of food that is eventually swallowed.

- Excludes drinking actions (usually does not involve chewing).
- Excludes chewing gum (usually does not involve swallowing).

Contact microphone

Off-shelf microphone

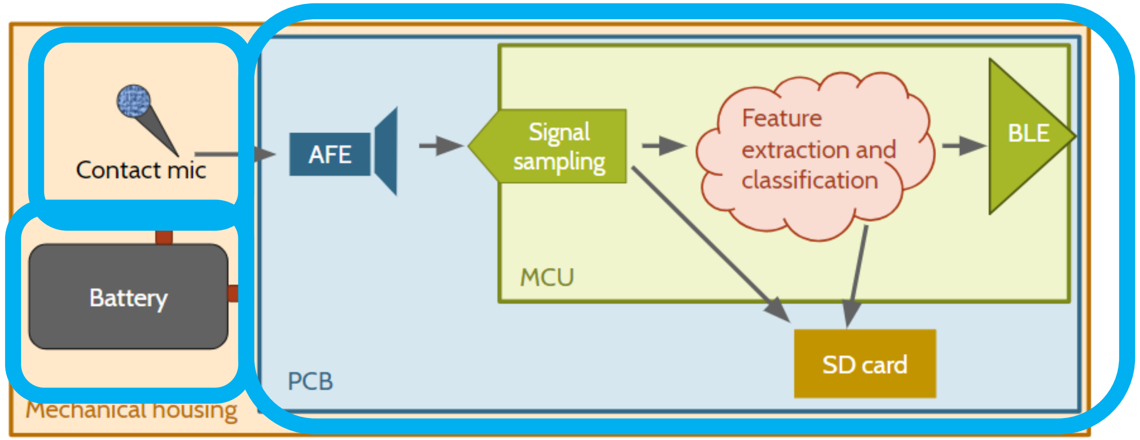


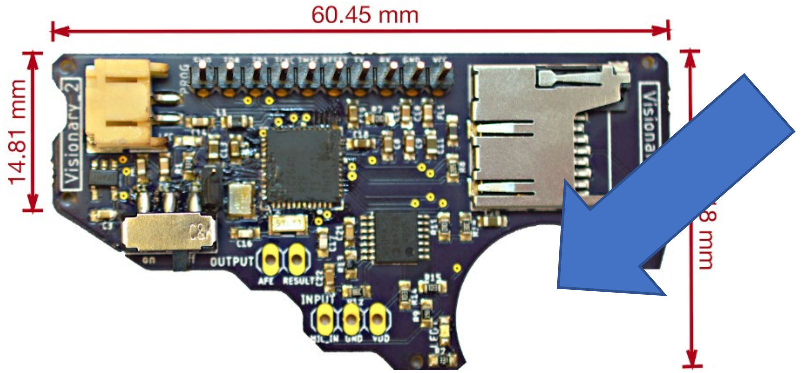
Placed behind the ear

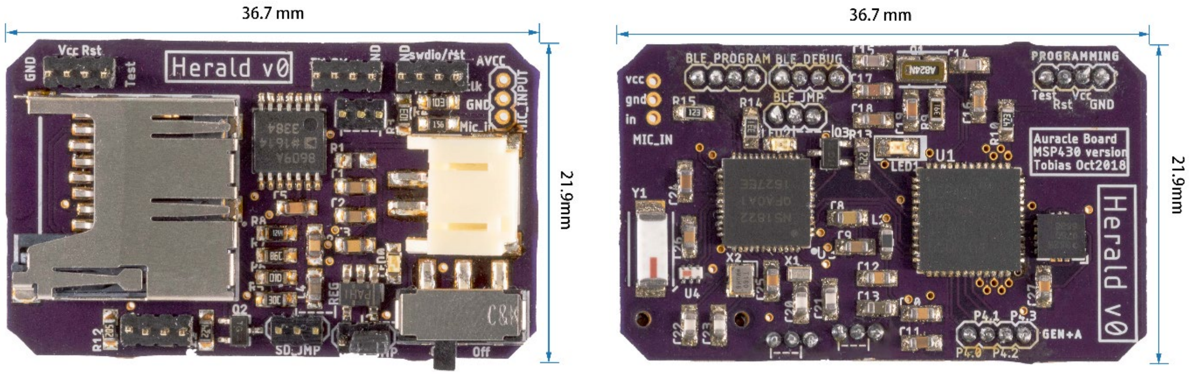
- Strong chewing signal
- Does not impede hearing
- Could be miniaturized to become unseen

System design

Auracle includes:
- Contact microphone
- Printed circuit board
  - Analog front end
  - MSP430 microcontroller
  - SD card
  - Bluetooth
- Battery
- 3D printed mechanical housing





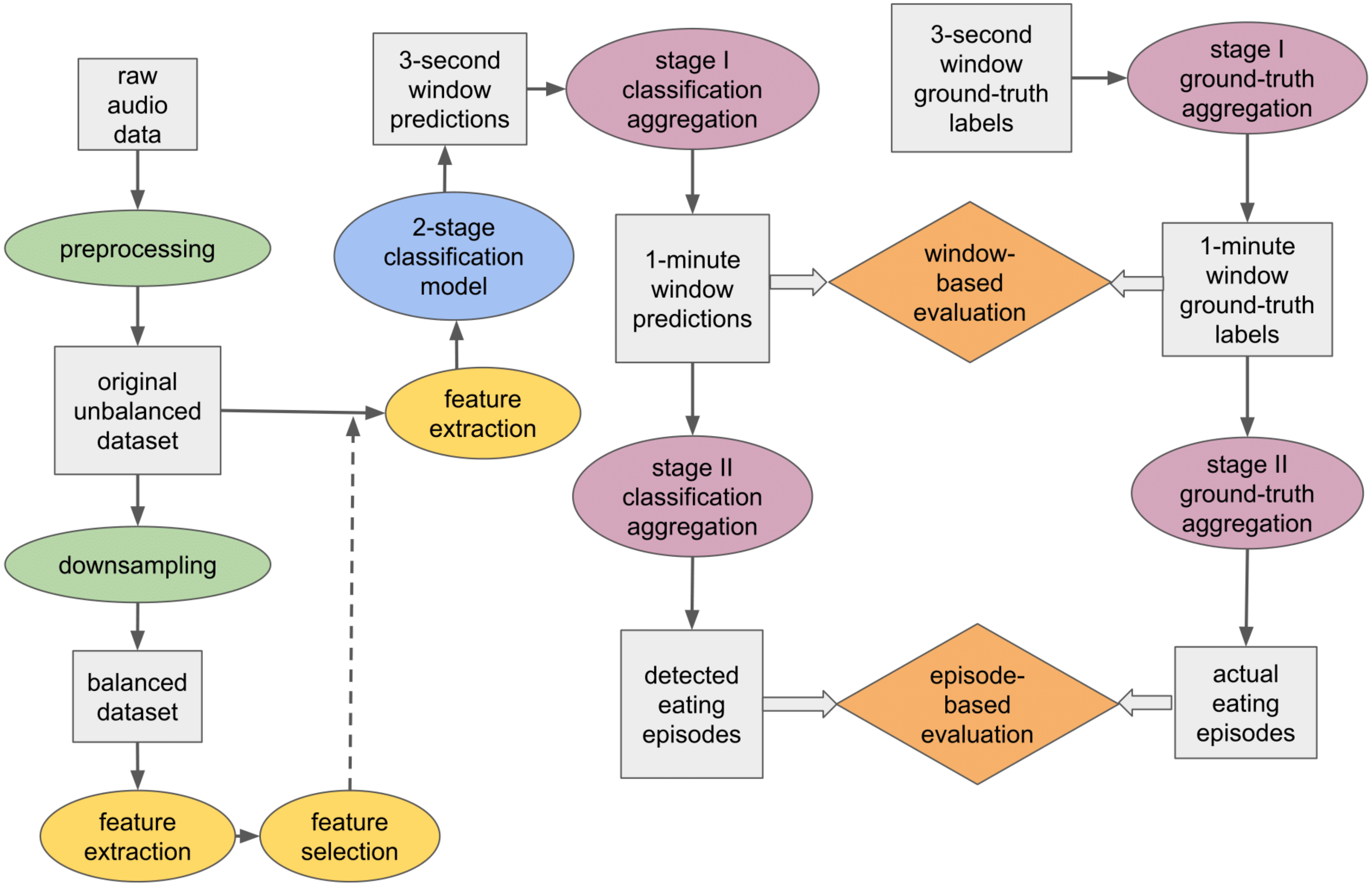


Feasibility of Auracle

- Recruited 14 participants
  - 2-hour session per participant
  - 26 eating episodes

- Evaluation metric:
  - Leave-one-person-out cross validation at 1-minute resolution
  - Leave-one-person-out cross validation at episode level

Auracle: Data Analysis Pipeline



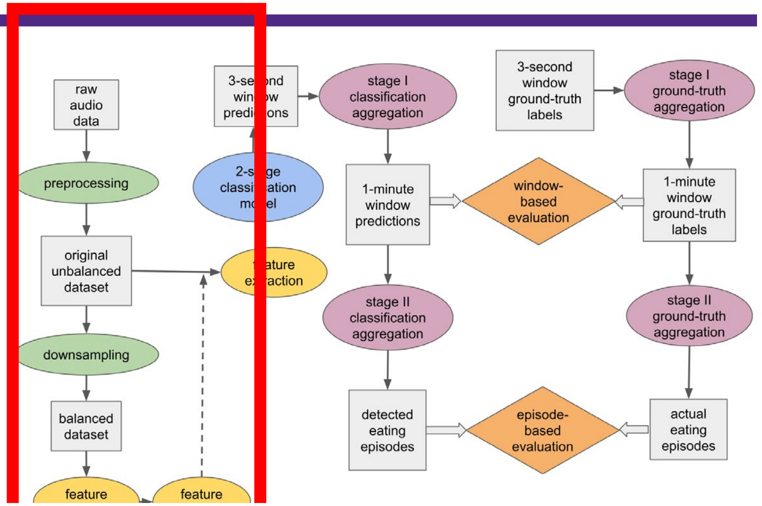
Preprocessing and feature selection

Raw Data: 20 to 250 Hz range

Preprocessing:
- Framing
- Normalization

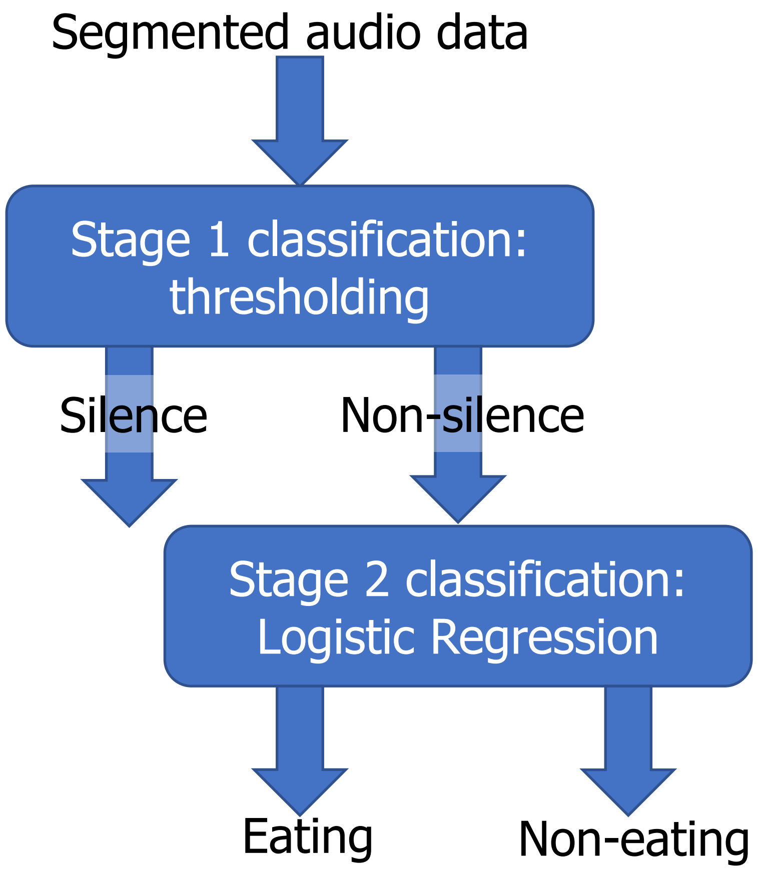
Feature extraction:
700 features extracted

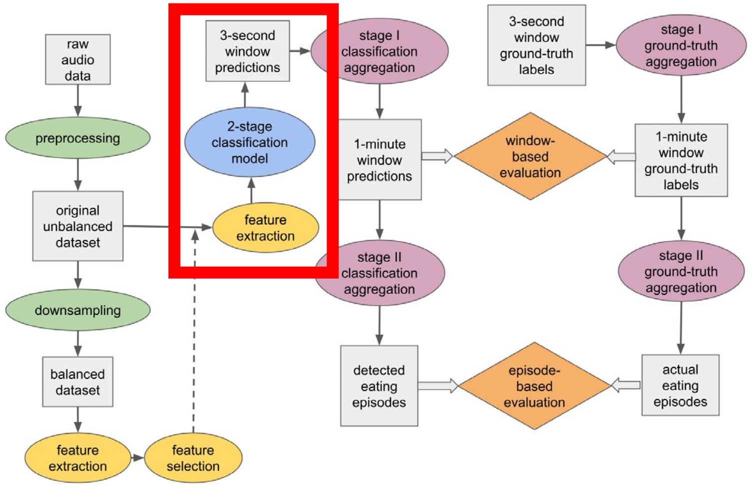
Feature selection:
- Remove irrelevant features



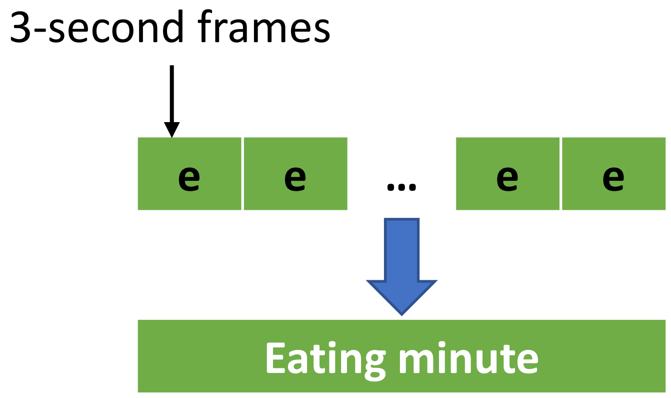
Feature category	Description	Number of features
FFT coefficients	Fourier coefficients of one-dimensional Discrete Fourier Transform	29
Range count	Count of values within a specific range	1
Value count	Count of occurrences of a specific value	1
Number of crossings	Count of crossings of a specific value	3
Sum of reoccuring values	Sum of all values that present more than once	1
Sum of reoccuring data points	Sum of all data points that present more than once	1
Count above mean	Number of values that are higher than mean	1
Longest strike above mean	Length of the longest consecutive subsequence that is bigger than mean	1
Number of peaks	Number of peaks at different width scales	2

2-stage classification

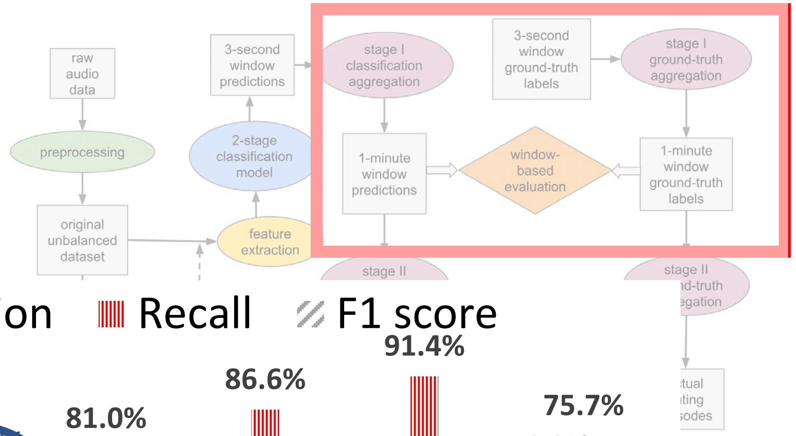


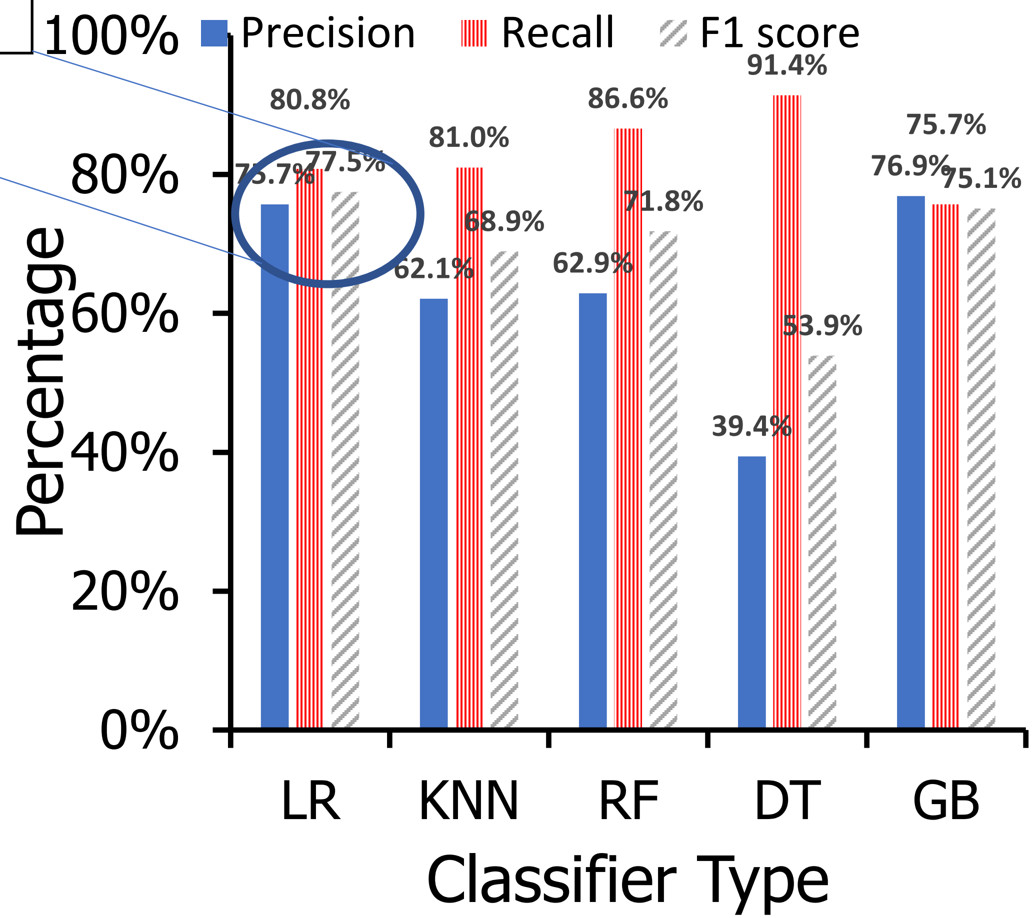


Per-minute evaluation

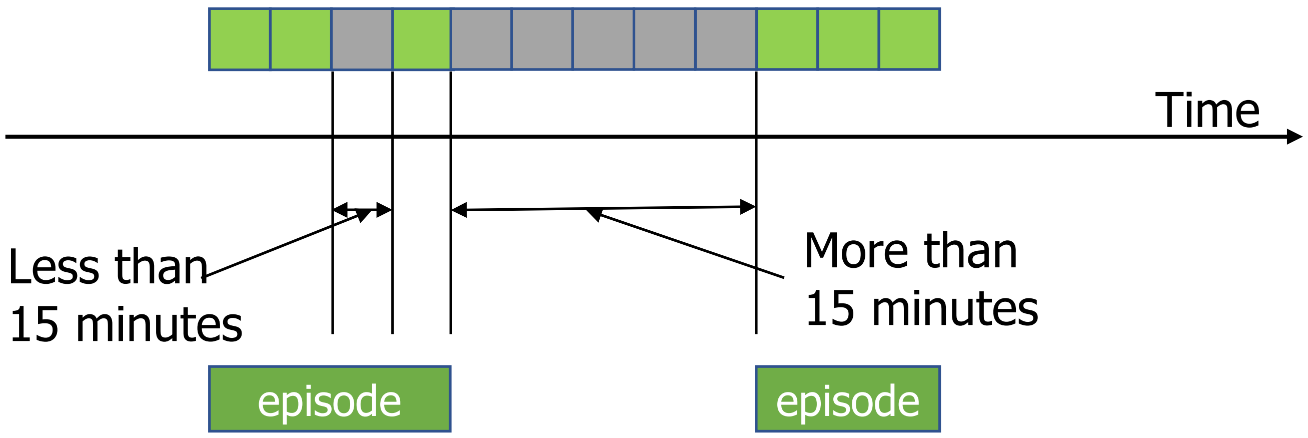


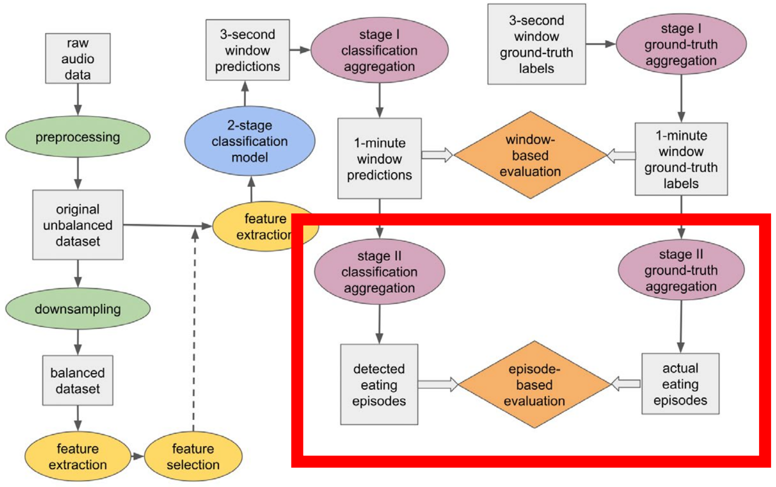
F1 score = 77.5%





Per-episode evaluation





Episode-based evaluation

Jaccard similarity coefficient $\left(\frac{|A \cap B|}{|A \cup B|}\right) > 50\%$

Ground truth	26 episodes
Correctly detected	20 episodes
Episodes missed	6 episodes
Falsely detected	12 episodes

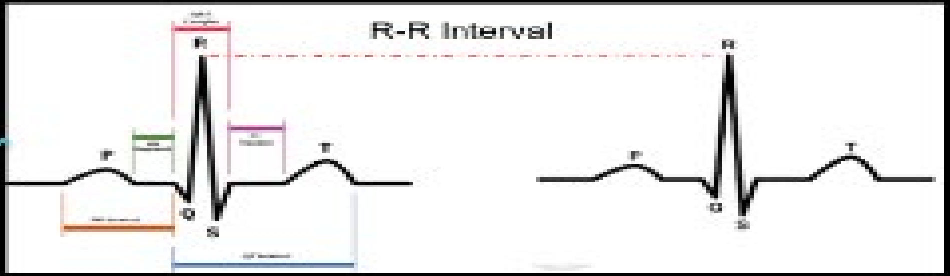
Power evaluation

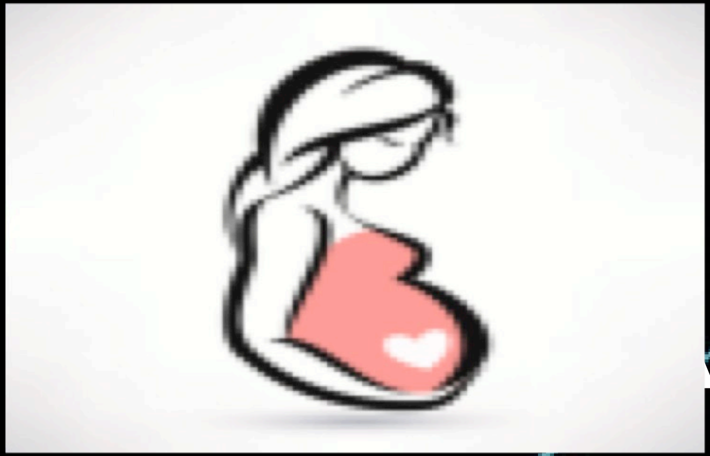
	Avg. power draw (mW)
Sleep state	0.89
Data processing	+18.29
Summary data logging	+2.29
Raw data and summary data logging	+7.28
BLE	+3.37

Battery life with 110 mAh battery → 28.1 hours

ACM Ubicomp 2020

Ann & Robert H. Lurie Children's Hospital of Chicago





microStress-EMA

A Passive Sensing Framework for Detecting
Stress in Pregnant Mot

Zachary King, Judith Moskowitz, Begum Egilmez, Shibo Zhang, Lida Zhang,
Michael Bass, John Rogers, Roozbeh Ghaffari, Laurie Wakshlag, **Nabil Alshurafa**

Northwestern University