

Auracle: a wearable device for detecting and monitoring eating behavior

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Introduction

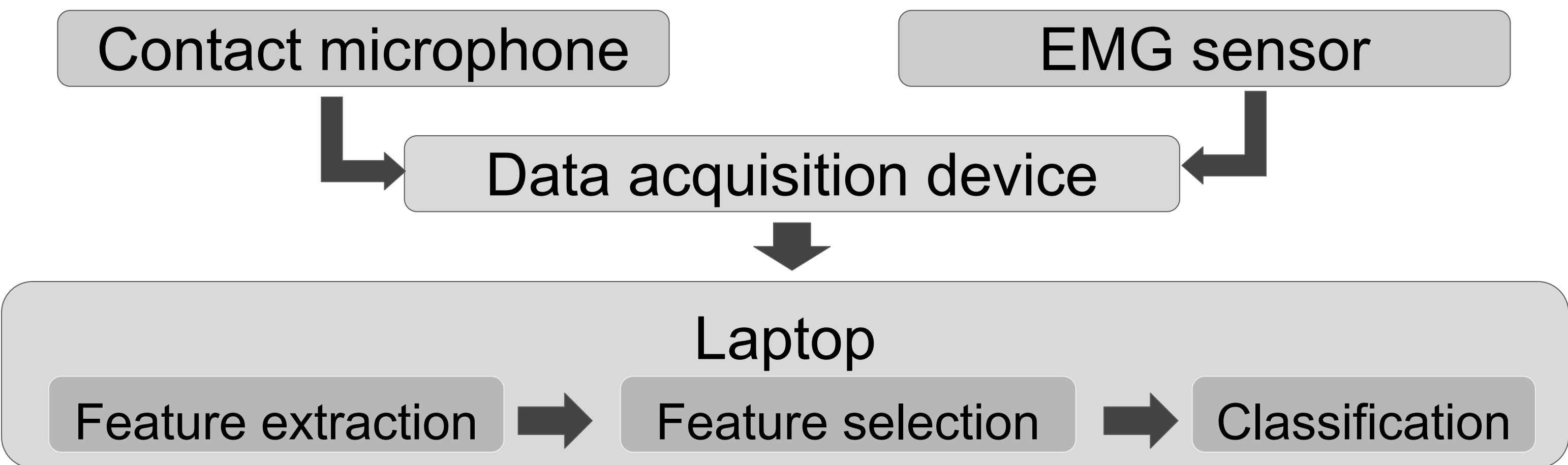
Motivation: Use technology to track and understand eating behavior, in support of eating-behavior research.

Problem: Health science has no effective means for automatically measuring eating behavior in real life.

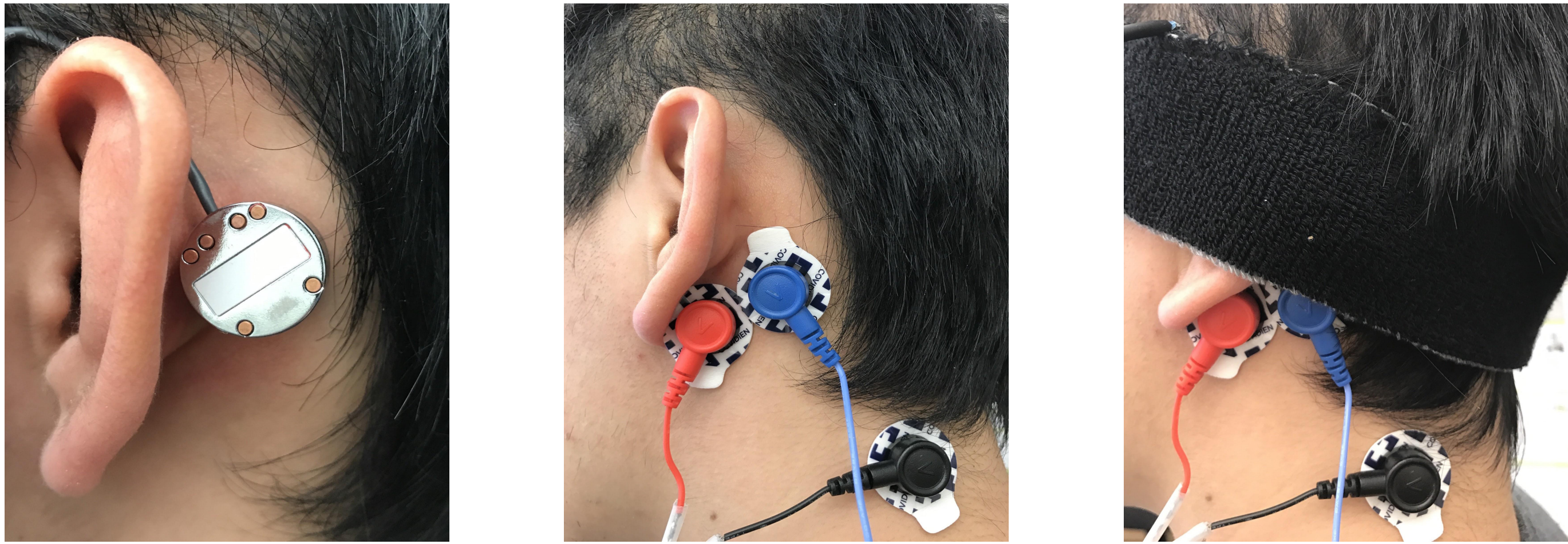
Goal: Develop a wearable earpiece to monitor eating through a waking day, unobtrusively, in free-living conditions.

Approach

Bench-top apparatus:
We used the following setup to select optimal sensors, features, parameters and classifiers for wearable devices.



Placements for contact microphone, Electromyography (EMG) electrodes, and both sensors respectively.



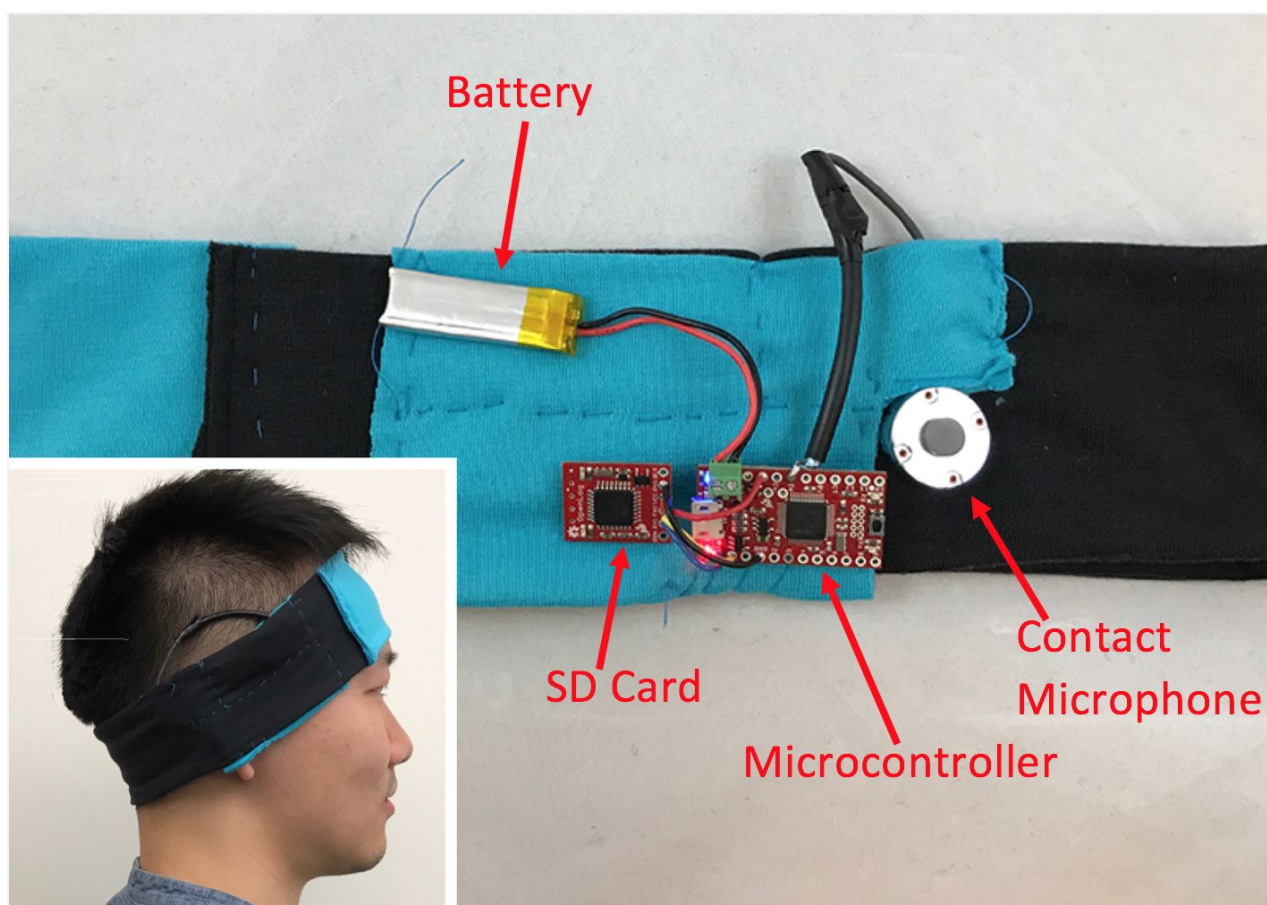
We conducted a study with 20 participants. We collected data using both sensors for the first 10 participants and using contact microphone only for the second 10 participants. Each participant ate 6 types of food and performed 8 types of activities in laboratory conditions.



Activity	Description	Duration
Eating	Eat a protein bar	2 minutes
Eating	Eat several baby carrots	2 minutes
Eating	Eat several crackers	2 minutes
Eating	Eat canned fruit	2 minutes
Eating	Eat instant food	2 minutes
Eating	Eat yogurt	2 minutes
Talking	Read an article aloud	5 minutes
Silence	Relax and avoid chewing	5 minutes
Coughing	Cough	24 seconds
Laughing	Laugh	24 seconds
Sniffing	Sniffle	24 seconds
Deep Breathing	Deep breath	24 seconds
Drinking	Drink water	24 seconds

Food used and activity performed for data collection.

Wearable apparatus:

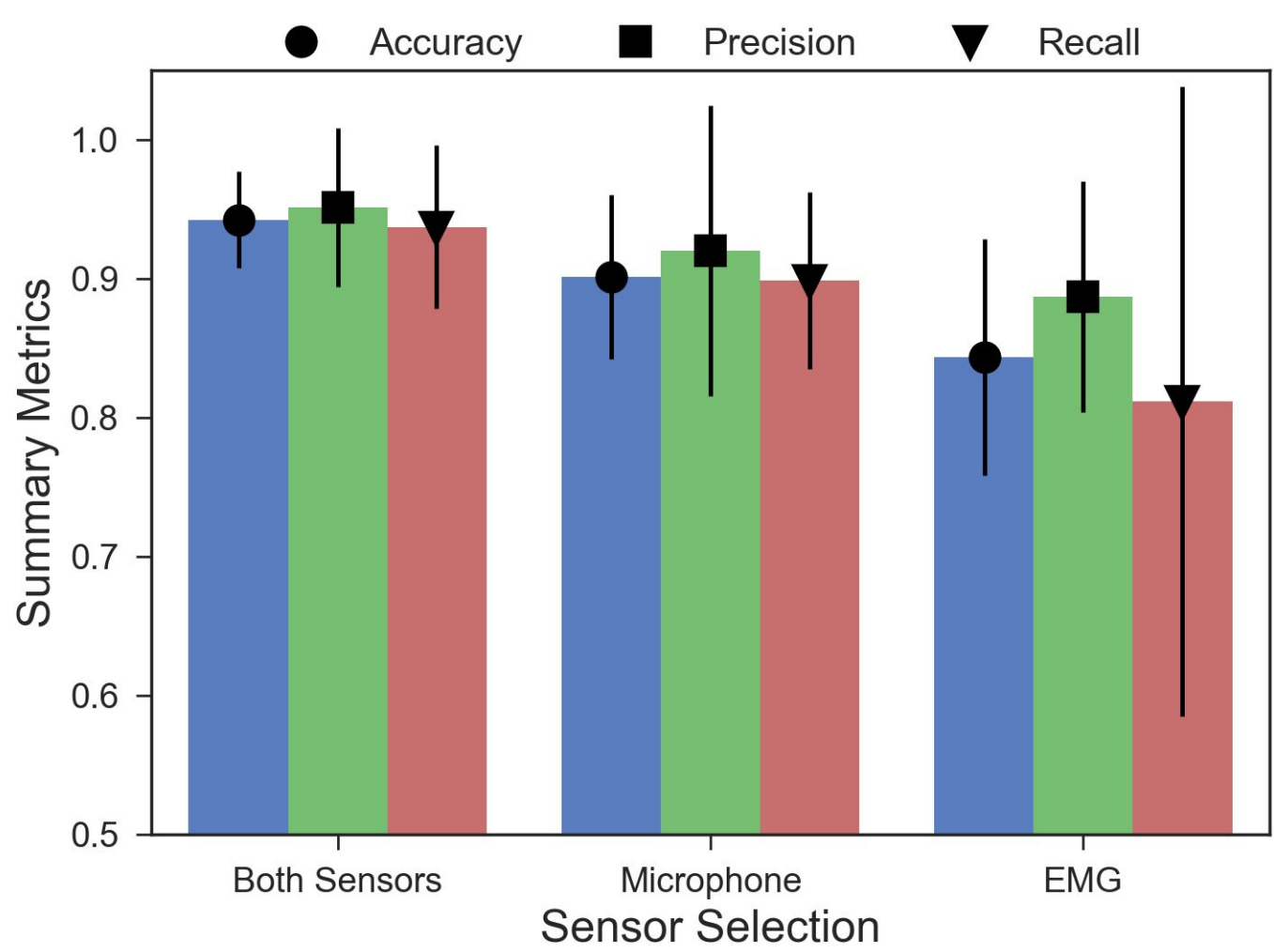


We fused the contact microphone, microcontroller, SD card and battery into a headband; we excluded EMG based on evaluation results and feasibility for free-living scenarios.

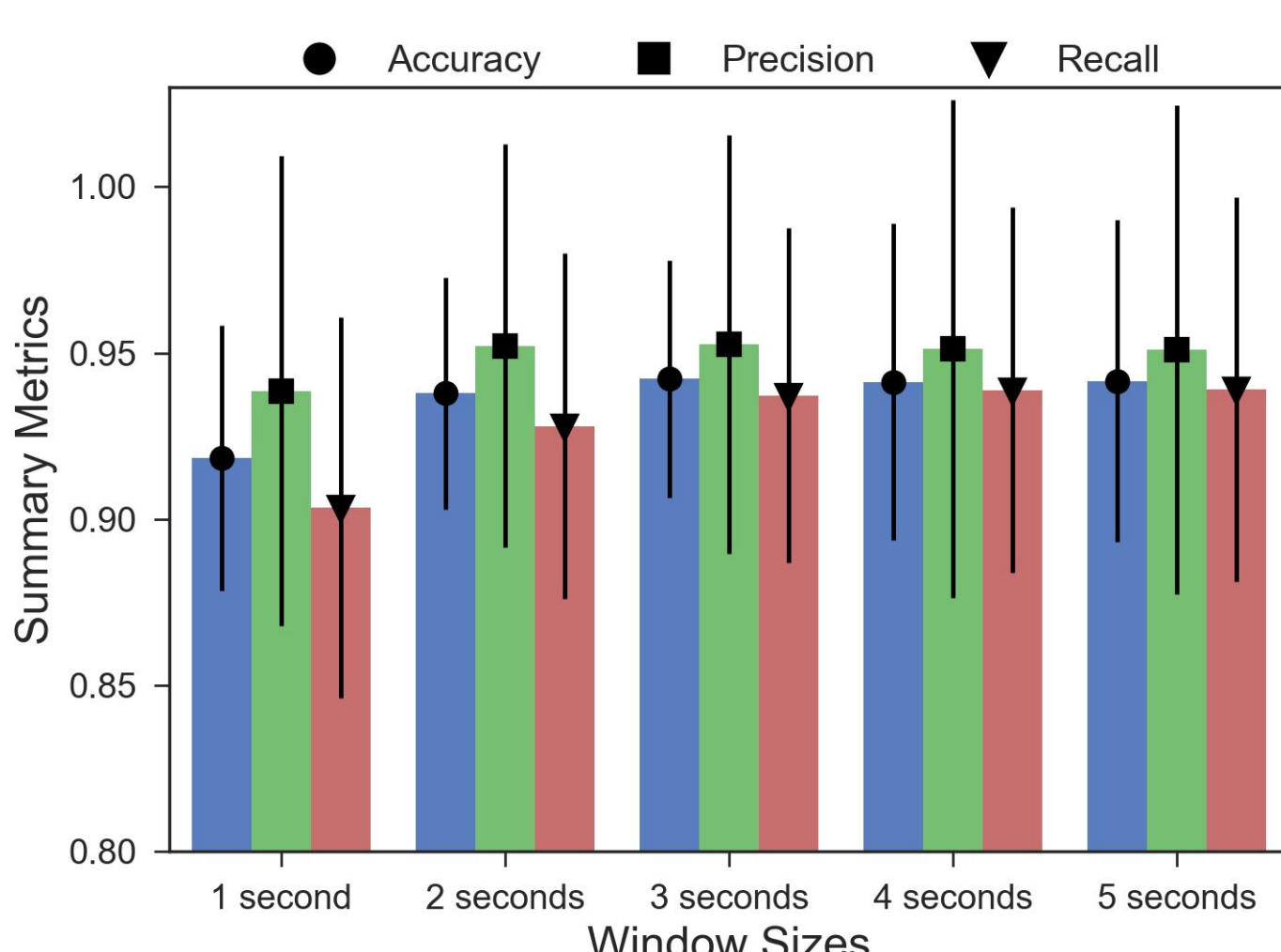
Results

After testing a range of sampling rate from 250 Hz to 4000 Hz, we found 500 Hz is high enough. All the raw data was first downsampled to 500 Hz, filtered by a 20 Hz high-pass filter to remove low-frequency noise, and segmented into time windows with uniform length and 50% overlap.

We designed a two-stage classification model based on Logistic Regression. For each time window, we extracted features and compared the output of the classifier (*Eating* or *Non-eating*) against the ground-truth label. We used Leave-One-Person-Out (LOPO) cross-validation to evaluate our classifier's performance.



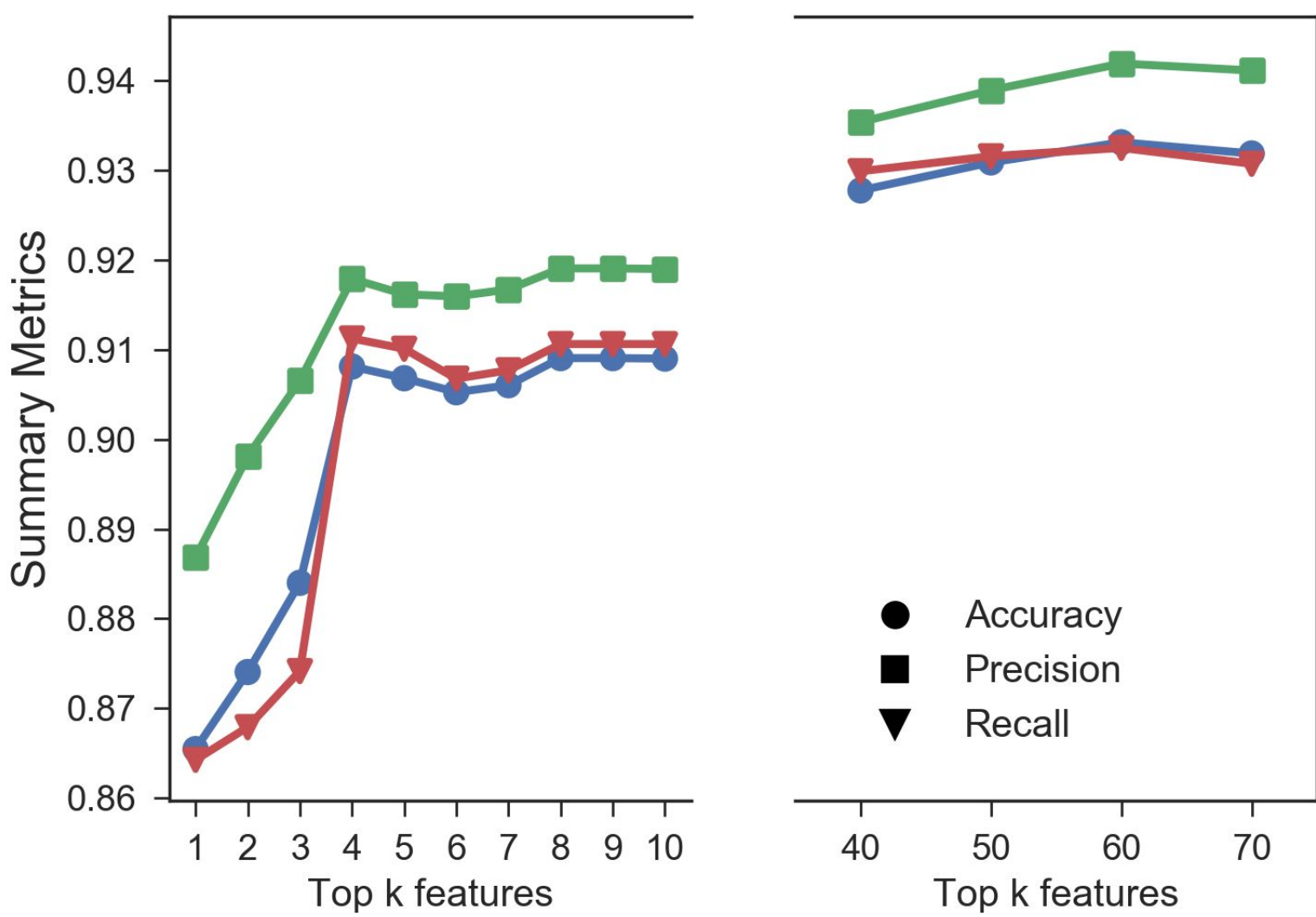
Results when using contact microphone and EMG, independently and combined.



Results with window size ranging from 1 second to 5 seconds

Resolution	Accuracy	Precision	Recall
24-bit	0.942 ± 0.036	0.953 ± 0.063	0.937 ± 0.050
10-bit	0.935 ± 0.043	0.943 ± 0.075	0.934 ± 0.052

Results with bit resolution of 24-bit and 10-bit



Results with number of features ranging from 1 to 70

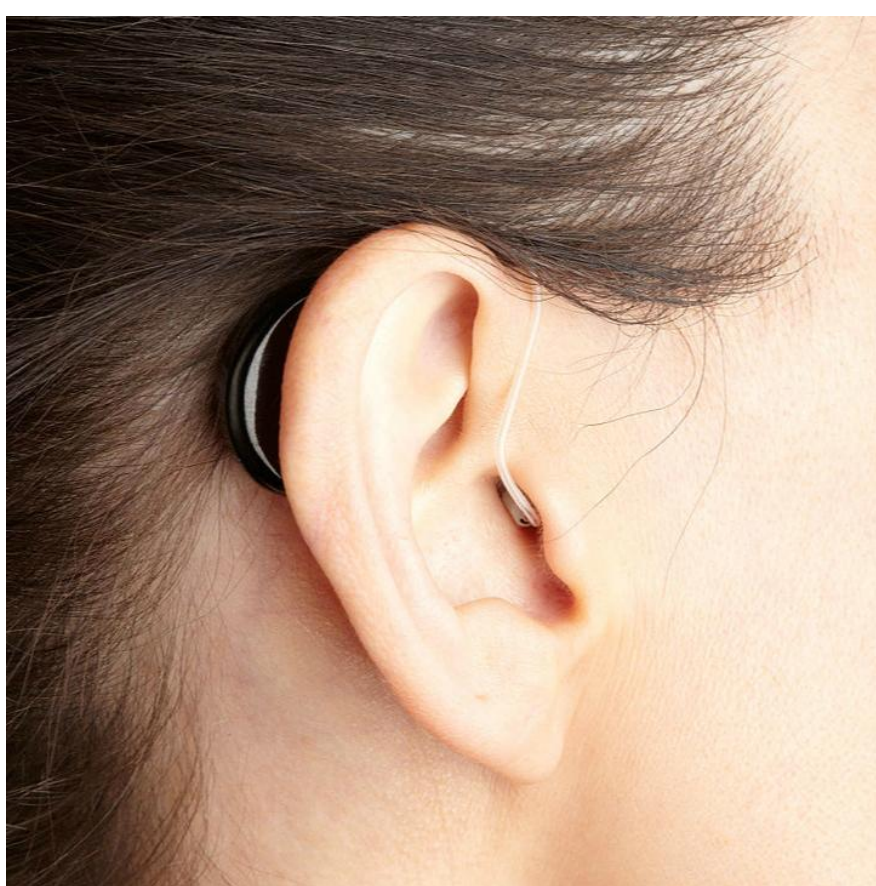
Feature type	Description	Number
Kurtosis	Kurtosis	1
Mean	Number of values higher than mean	1
Sum	Sum over the absolute values of changes	1
Peak	Number of peaks at different width scales	4
Friedrich coefficients	Coefficients of polynomial h(x) fitted to the deterministic dynamic of Langevin model	1

Top 8 features

Conclusion

In LOPO experiments, we achieved accuracy over 90.9% with 500 Hz sampling rate, 10-bit resolution, 3-second window size and 8 features for eating detection of 6 types of food with different crunchiness level (3 crunchy and 3 soft).

Future work



Minimize the entire system into a earpiece.



Evaluate the earpiece in free-living scenarios.