# RANDOM FOREST DETECTS EATING IN NECK-WORN SENSOR

ELI COHEN, RAWAN ALHARBI, KEVIN MORAN, ANGELA F. PFAMMATTER, BONNIE SPRING, NABIL ALSHURAFA

## BACKGROUND

- Objectively detecting and characterizing eating episodes through passive sensing is essential to develop timely eating interventions.
- A major contributing factor to obesity is excess caloric intake resulting in an imbalance between food intake and calories burned.
- It is known that people that exhibit problematic eating may show patterns of long meals and time alone.

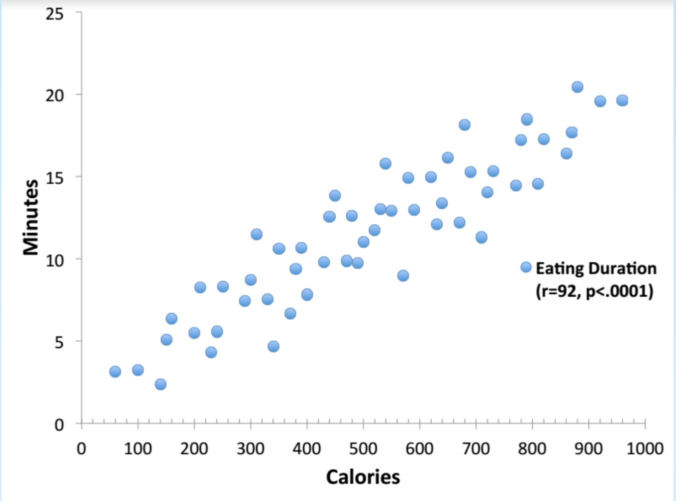


Figure 1. A linear correlation between eating duration and calories consumed.

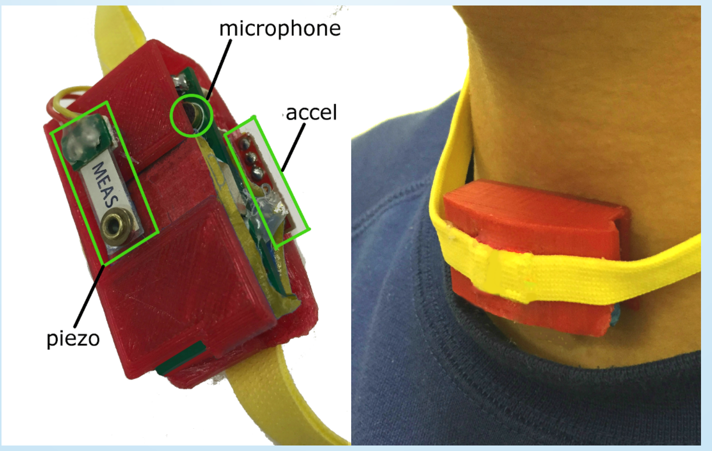


Figure 2. The device is wireless and hands-free, and streams sensor data from the neck to a companion smartphone app.

## OBJECTIVES

A neck-worn device with embedded sensors was designed and used to:

1. Assess viability of eating detection
2. Compare a generalized and personalized machine learning algorithm to detect eating among confounding activities

## METHODS

- The device uses an RFduino BLE-enabled microcontroller, and includes the following sensors:
  a. Piezoelectric sensor
  b. Audio sensor (microphone)
  c. Accelerometer
- Seven participants wore the neck device and consumed breakfast and lunch while performing various confounding activities.

| Activity | Object | Task Method | Calories |
|---|---|---|---|
| Eating | Fruit Cup | Fork | 60 |
| Non-Eating | Glasses | Wear&adjust | - |
| Eating | Pancake | Fork & Knife | 100 |
| Non-Eating | Conversation | Talk naturally | - |
| Drinking | Water | Hands | 0 |
| Non-Eating | Phone | Call | - |
| Eating | Yogurt | Spoon | 140 |
| Drinking | Tea | Hands | 0 |
| Eating | Sandwich | Hands | 340 |
| Non-Eating | Keyboard | Type | - |
| Eating | Soup | Spoon | 230 |
| Non-Eating | Walk | Walk naturally | - |
| Drinking | Sparkling Water | Hands | 0 |
| Eating | Chips | Hands | 150 |

Table 1. Activities and food consumed during breakfast and lunch.

- Signals were divided into 30-second fixed time subdivisions, statistical features were collected, and a Random Forest machine-learning algorithm classified each subdivision as eating or non-eating.
- A generalized model (train on first, test on second) and individual personalized models were tested using Leave One Subject Out Cross Validation.
- Participants were also surveyed about acceptability of wear.

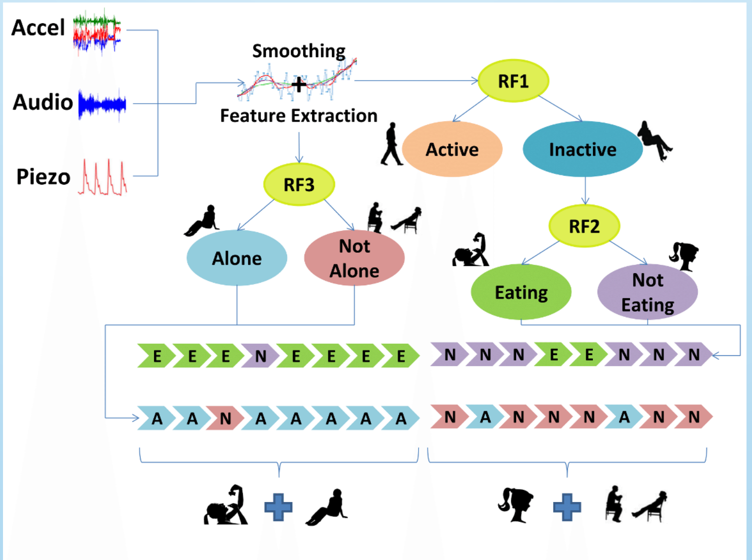


Figure 3. The hierarchical classification technique to predict eating events.

## RESULTS

- The generalized model resulted in a 79.1% average precision and an 81.8% average recall, yielding an average F-measure of 78.3% to detect a feeding gesture.
- Personalized models, yielded an average precision of 79.0%, average recall of 86.5%, and average F-measure of 80.8%.
- 78% reported sensor was comfortable and 64.3% were willing to wear it for one month if compensated.

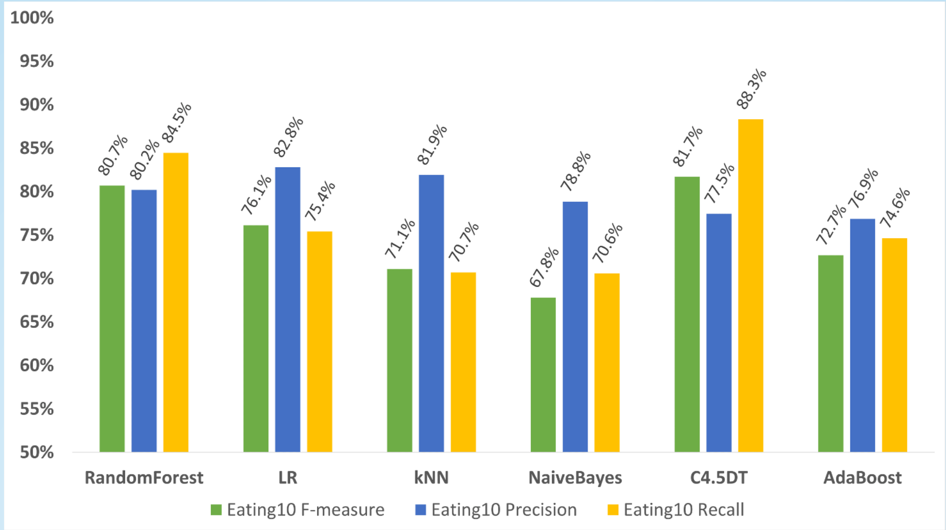


Figure 4. The precision, recall, and F-measure of various classifiers.

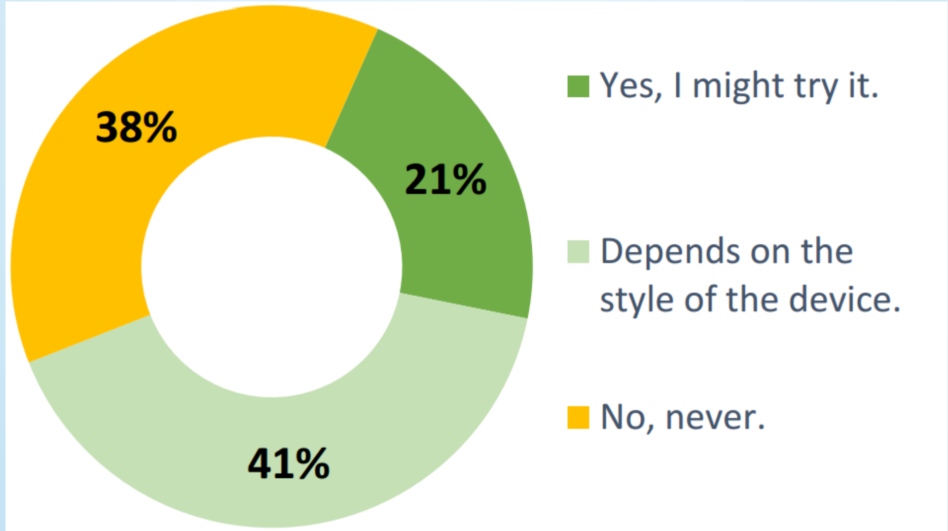


Figure 5. A survey of study participants revealing the desirability of the device as a neck accessory.

## CONCLUSION

- The device was capable of eating detection despite confounding factors.
- Personalized models performed marginally better at detecting eating episodes than a single generalized model.
- Future studies will test the device's performance in the wild and utility as part of an eating intervention.