Machine Learning algorithms applied to detect feeding gestures

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BACKGROUND

- Obesity caused primarily by overeating, is a preventable chronic disease yielding staggering healthcare costs.
- Being able to passively detect eating episodes in real time will enable researchers to understand the antecedents and causes of overeating.
- Confounding eating gestures with other activities (wearing and adjusting glasses, having a conversation, typing on the keyboard, getting up for a walk) can confound detection of eating.
- Feeding gestures have been shown to strongly correlate with calorie consumption in eating episodes. We proved there was a positive correlation between kiloCalorie consumption and feeding gestures in an eating episode (r=0.85, p<.0001).

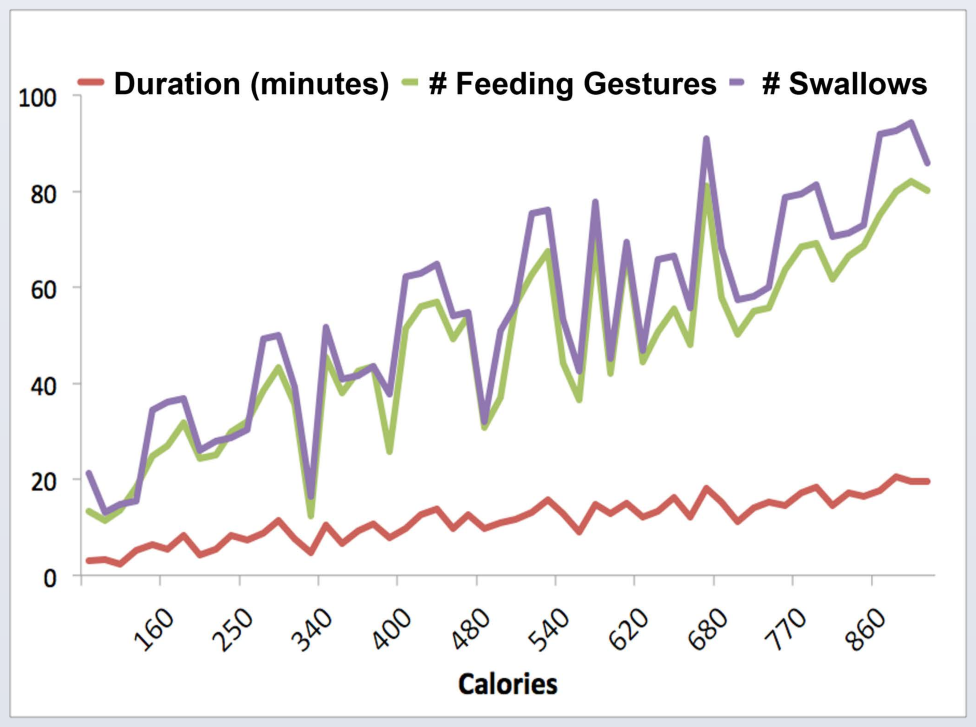

Figure 1. Relationship between kilocalories and feeding gestures for 54 combination of food items consumed by 15 participants.

OBJECTIVE

- Use wearable sensors to objectively identify eating episodes by counting feeding gestures.
- Compare the effects of personalized versus generalized machine learning models in predicting feeding gestures.
- Show user comfort which directly impacts the success of such a system in detecting eating in real life.

METHODS

- Performed an in-lab experiment where participants were requested to wear two wrist-worn sensors (Microsoft band 2), one on each hand, while following an eating and activity protocol. We recruited 15 participants, 7 male and 8 female. Two participants were left-handed.
- 15 participants consumed two meals while performing confounding activities.

		Breakfast	
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

Table 1. Activities and food consumed during breakfast

		Lunch	
Activity	*Object*	*Task Method*	*Calories*
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 2. Activities and food consumed during lunch

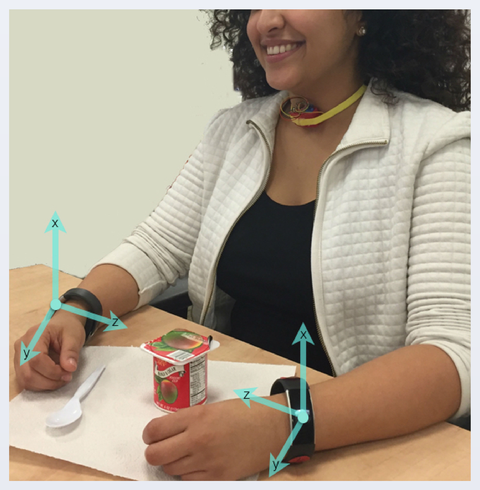

Figure 2. A participant wearing two Microsoft band 2's (one on each wrist) prepared to begin eating.

- Removed poor data and applied a rolling mean smoothing method and normalization.
- Used Chronoviz for labeling, including eating, drinking, non-eating, food-to-mouth (F-M), bite, back-to-rest (B-R), chewing duration, and swallows, as in Figure 3.

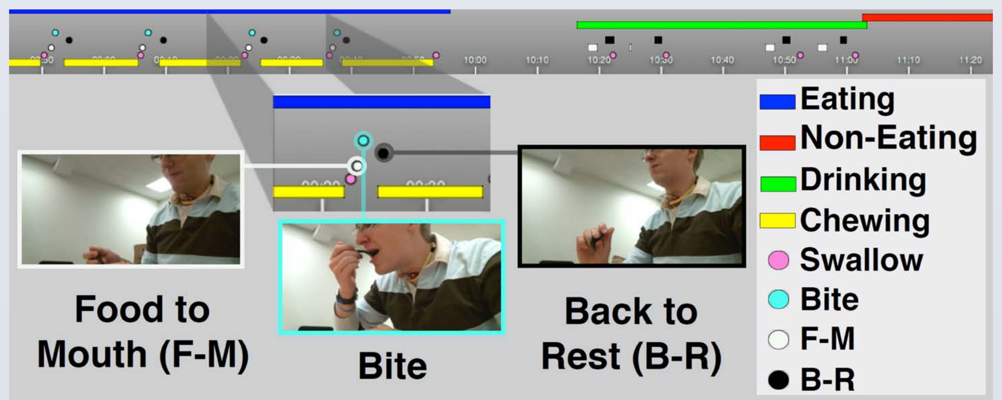

Figure 3. Labeling data using Chronoviz to enable the detection of feeding

- Applied a Random Forest classification algorithm (a commonly accepted strategy to build models) on the time-series data.
- Used DBSCAN clustering on counting feeding gestures, tested a more personalized cluster model setting for each individual. The results are in Figure 5.

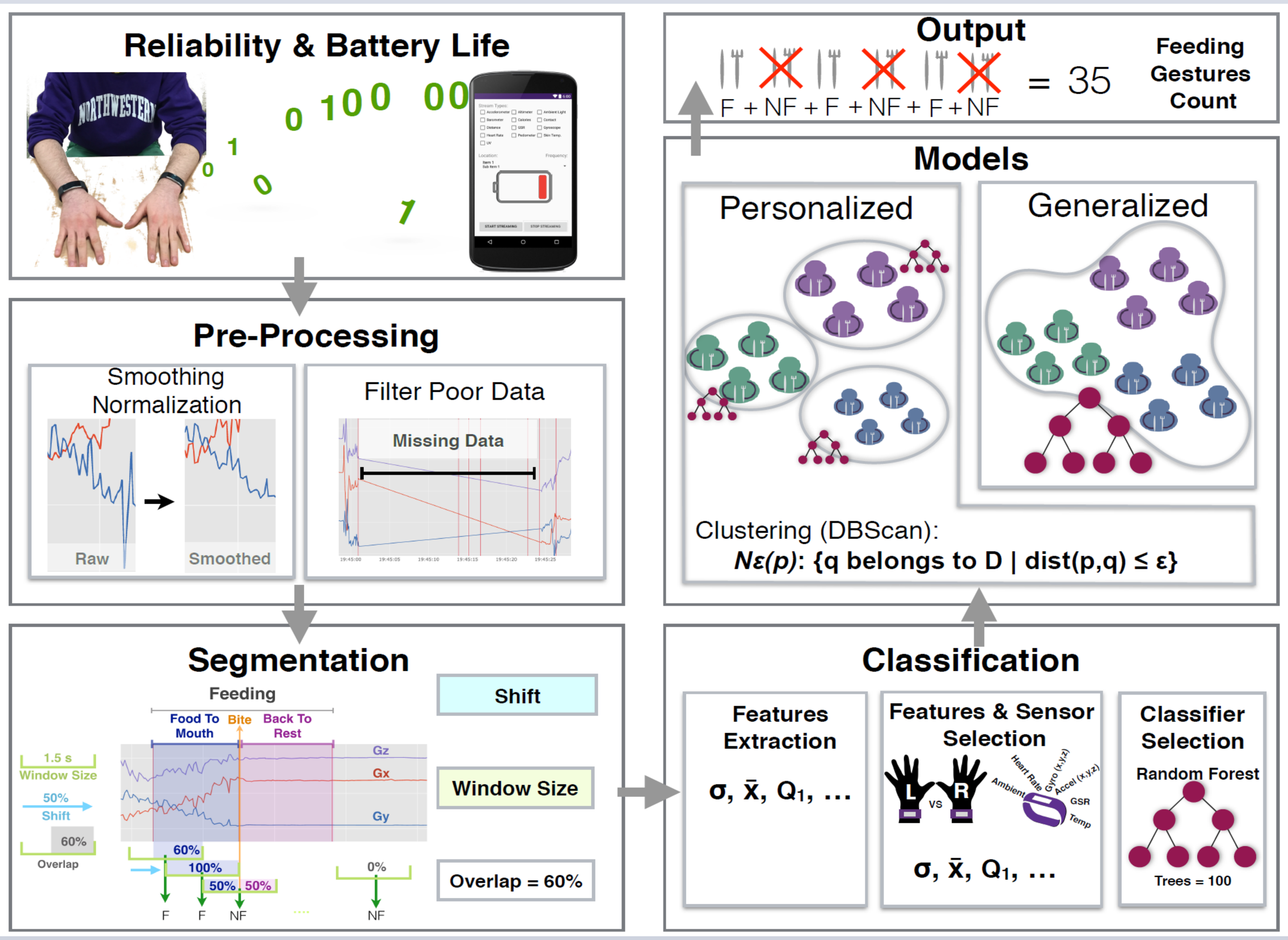

Figure 4. A framework that represents our approach

RESULTS

- The generalized model resulted in an average precision, recall, and F-measure of 76.7%, 76.5%, and 75.2%, respectively; while the personalized model resulted in an average precision, recall, and F-measure of 85.9%, 85.8%, and 85.7%, respectively.
- The results for counting feeding gestures show a feeding gesture RMSE of 8.43, presented in Figure 4.

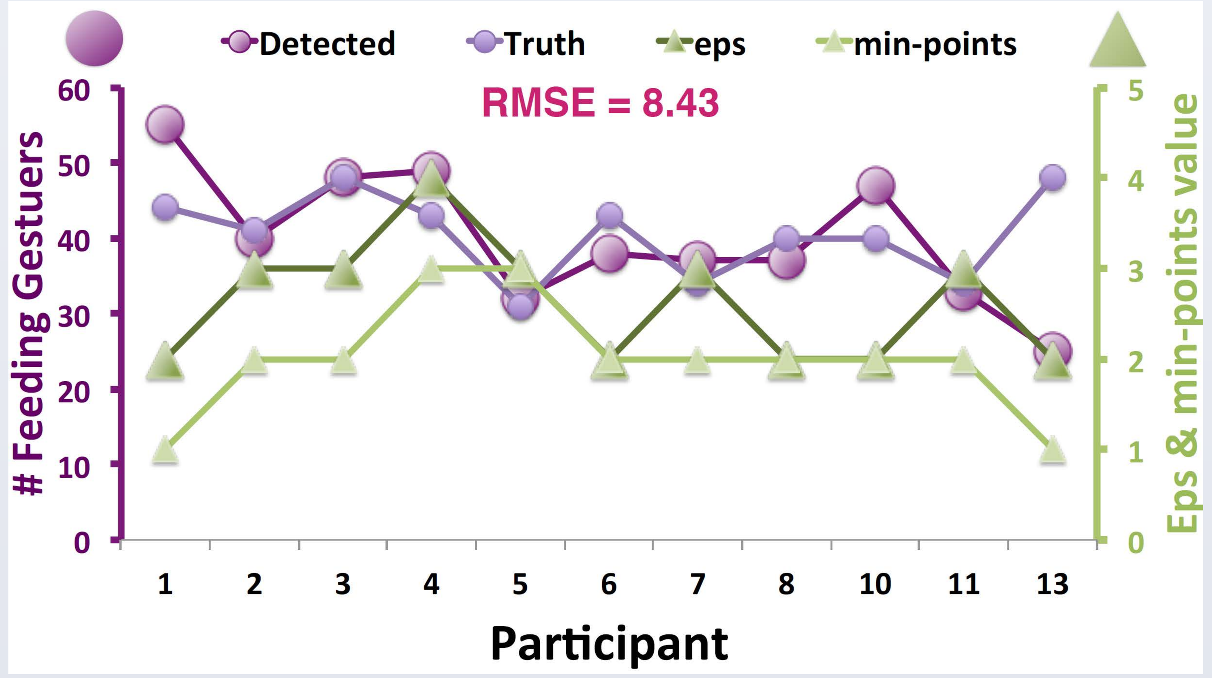

Figure 5. DBscan personalized clustering results

USER COMFORT

- Moreover, 64% reported wearing a single Microsoft Band 2 was comfortable, and 50% were willing to wear for one month if compensated. Only 21% were willing to wear both wrist-worn sensors.

CONCLUSION

- Results demonstrate superiority of a personalized model when detecting eating from wrist-worn sensors, paving the way for personalized timely eating interventions.

RELATED WORK

- “Machine Learning algorithms applied to detect feeding gestures” Shibo Zhang, Rawan Alharbi, William Stogin, Kevin Moran, Angela F. Pfammatter, Bonnie Spring, Nabil Alshurafa
- “Non-invasive monitoring of eating behavior using spectrogram analysis in a wearable necklace” N. Alshurafa, H. Kalantarian and M. Pourhomayoun
- “RisQ: Recognizing Smoking Gestures with Inertial Sensors on a Wristband”. Abhinav Parate, Meng-Chieh Chiu, Chaniel Chadowitz, Deepak Ganesan, Evangelos Kalogerakis
- “A Practical Approach for Recognizing Eating Moments with Wrist-Mounted Inertial Sensing”. Edison Thomaz, Irfan Essa, Gregory D. Abowd