Recognizing Eating Activities in Free-living Environment using Consumer Wearable Devices

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Abstract

The study of eating behavior has become increasingly important due to the alarming high prevalence of lifestyle related chronic diseases. In this study, we investigated the feasibility of automatic detection of eating events using affordable consumer wearable devices, including Fitbit wristbands, Mi Bands, and FreeStyle Libre continuous glucose monitor (CGM). Random forest and XGBoost were applied to develop binary classifiers for distinguishing eating and non-eating events. Our results showed that the proposed method can recognize eating events with an average sensitivity of up to 71%. The classifier using random forest with SMOTE resampling exhibited the best overall performance.

Introduction

The monitoring of eating behavior can help detect eating patterns and disorders. Many systems have been developed to achieve accurate detection of eating episodes using ubiquitous computing technologies.

The most used sensing modalities include accelerometer, photoplethysmogram (PPG), electromyography (EMG), and sound recorder. These sensors are used to measure jaw movement, wrist movement, chewing sound, and blood flow variation, which are fed into the detection models as input signals. The dilemma in eating activity detection is that the most effective method, which is detecting jaw movement, requires special devices that are not widely available, while using popular consumer wearable sensors cannot achieve satisfactory detection accuracy.

Our challenge is to improve the detection of eating activities by using wearable devices. We investigated whether glucose level might improve detection results. This sensing modality is easy to obtain because devices measuring glucose level are widely used by diabetic patients, so they're easily available and usable.

Methods and Materials

- **Dataset preparation:** Data were collected from 10 participants (19-51 years old) using 3 sensors (**Fig. 2-4**). Ground truth was recorded via the aTimeLogger app (**Fig. 1**). The data collection experiment last up to two weeks.
- **Feature construction and selection:** 2 datasets
  - Dataset I - steps and heart rate data of both wristbands for all participants
  - Dataset II - steps, heart rate and glucose data of all participants.

  The datasets were labelled based on the ground truth and were preprocessed to handle conflicting, erroneous and missing data. Features were constructed by using the tsfresh Python library and selected by applying a random forest algorithm. Table I shows the number of features extracted from each sensory modality after feature selection,
- **Model training and performance evaluation:**

  - **Resampling:** random down sampling, SMOTE, random up sampling
  - **ML algorithms:** random forest (RF) and extreme gradient boosting tree (XGB)
  - **Model tuning and testing:** grid search with nested 10-fold cross validation, performing binary classification between eating and non-eating events
  - **Performance measures:** accuracy, F1-score, Matthew's correlation coefficient (MCC), precision, sensitivity, specificity

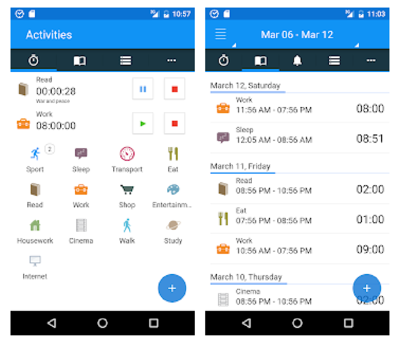
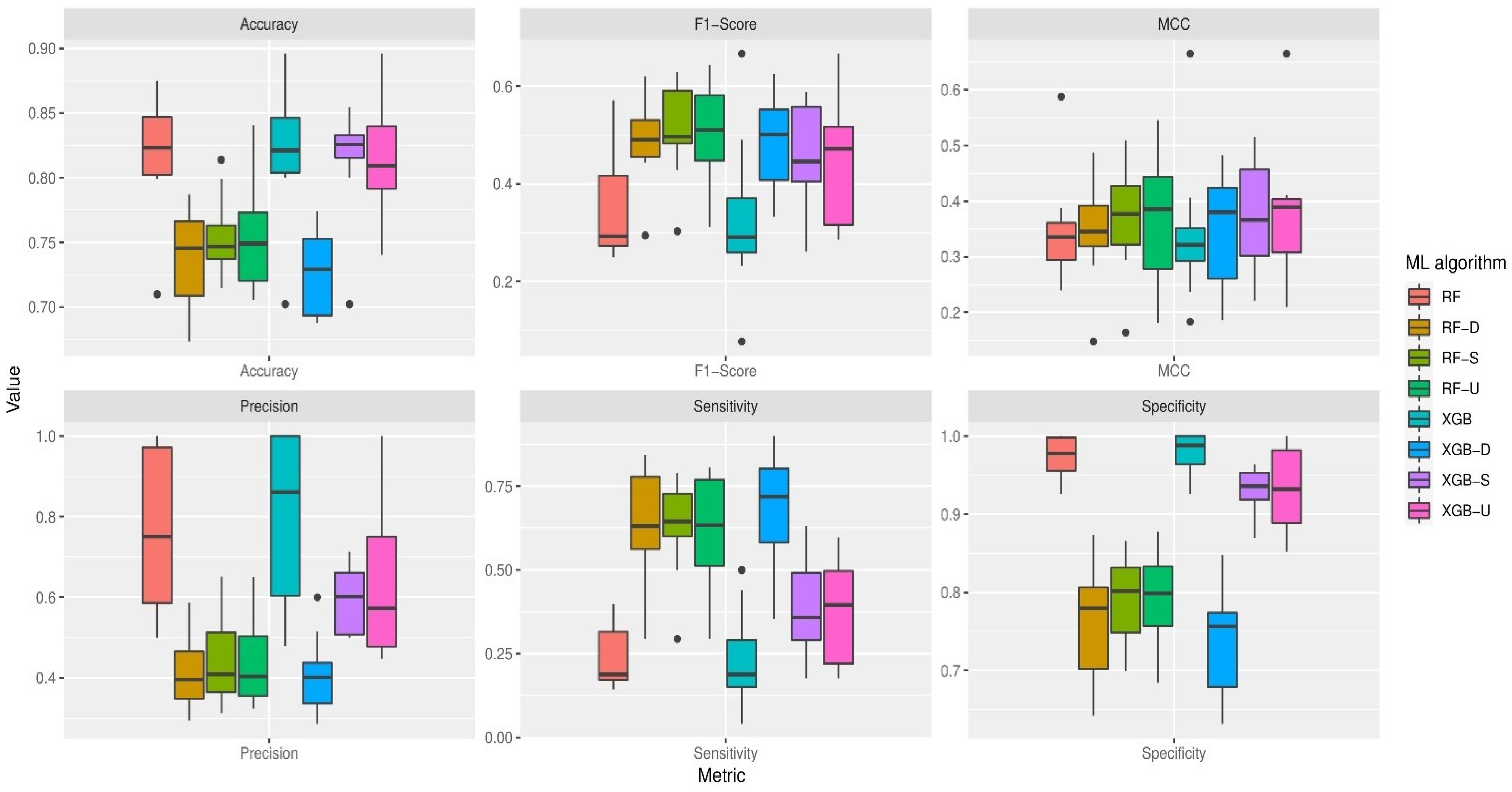


Figure 1. aTimeLogger app.

Figure 2. Freestyle libre 2 sensor.

Figure 3. Fitbit Charge 3 and its app.

Figure 4. Mi band 4 and its app.



Results

- Resampling techniques significantly improved sensitivity (i.e., the accuracy in detecting eating events) and F1-score, but at the sacrifice of precision and specificity (i.e., the accuracy in detecting non-eating events).
- On average, XGBoost with down sampling (i.e., XGB-D) achieved the highest sensitivity of 0.67, which is 180% increase compared to the baseline models (i.e., RF and XGB). Nevertheless, the specificity of XGB-D was reduced by 23% compared to the baseline models. Overall, XGB-D improved F1-score by 42% but did not significantly improve MCC.

Conclusion & Future Work

The performance of the 8 models with different combinations of machine learning algorithms and resampling techniques shows that random forest with SMOTE resampling has the best overall performance in all models.
The performance of our method is comparable to previous studies in terms of accuracy and precision, but with slightly reduced sensitivity.
In the future work we will apply the sliding window approach as well as investigating the model performance with reduced modality of input data.

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