Human Activity Recognition using Physiological Data from Wearables

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Introduction

Human Activity Recognition (HAR) is a process that uses wearable sensor data to classify which activity a person is doing at a given time. Typically, only mechanical sensor data, such as accelerometry, is used in HAR models. We examined if including physiological sensor data, such as heart rate, improves HAR model accuracy and generalizability.

Objectives

1. Assess if adding physiological data sources into a HAR model improves classification performance.
2. Develop an open-source HAR code module for the Digital Biomarker Discovery Pipeline (DBDP).

Methods

Our data (STEP) comes from a study on sources of inaccuracy in sensor data (Bent et al., 2020).

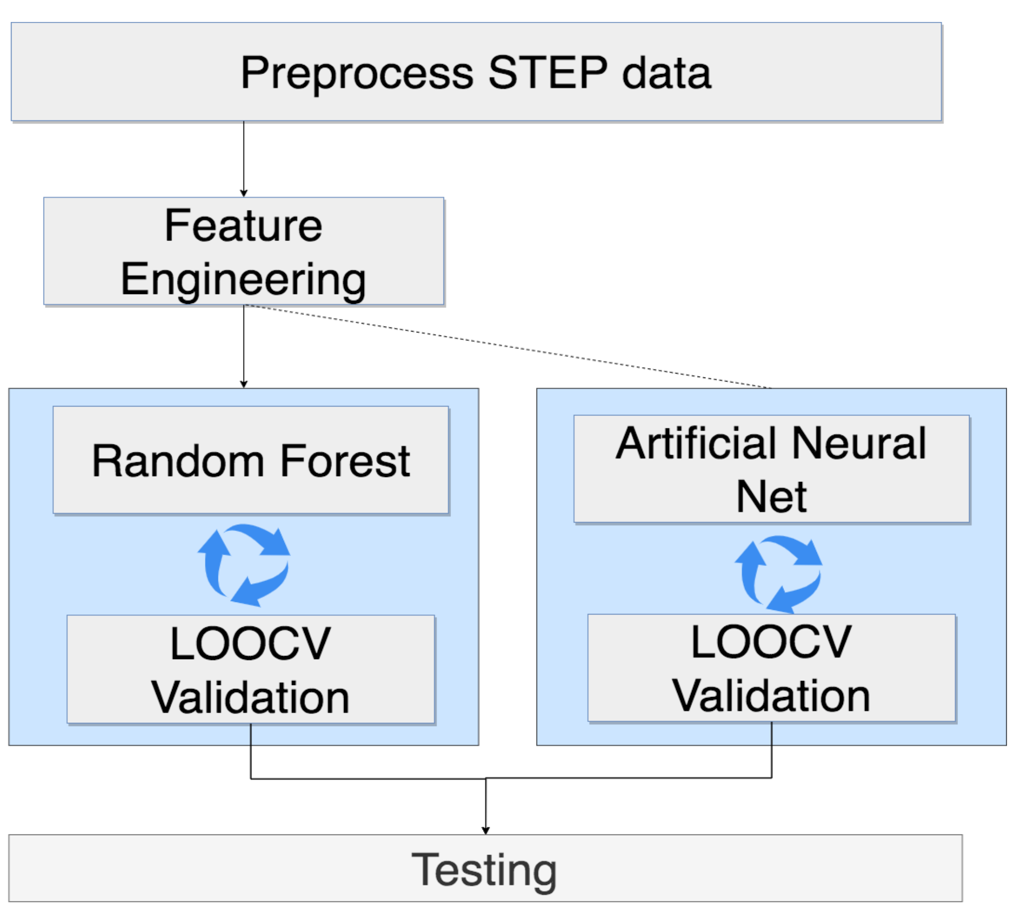

Figure 1. Methods Flowchart

For a baseline comparison model, we made a Random Forest model and an Artificial Neural Network that classified individual timepoints. Next, we generated summary statistics from windowed data (20 seconds with 10 seconds overlap) and used that data in the deep learning and Random Forest models to classify the windows. To check the generalizability of our models, we also trained and tested them on an open source dataset called PAMAP2 that is like the STEP dataset (Reiss, 2012).

Results

Model Name	Data Input Type	Data Source	Accuracy	F1 Score
ANN	Feature Engineered Windows	STEP	0.85	0.85
Random Forest	Feature Engineered Windows	STEP	0.84	0.81
ANN	Individual Timepoints	STEP	0.64	0.61
ANN	Individual Timepoints	PAMAP2	0.96	0.96

Figure 2. Results table

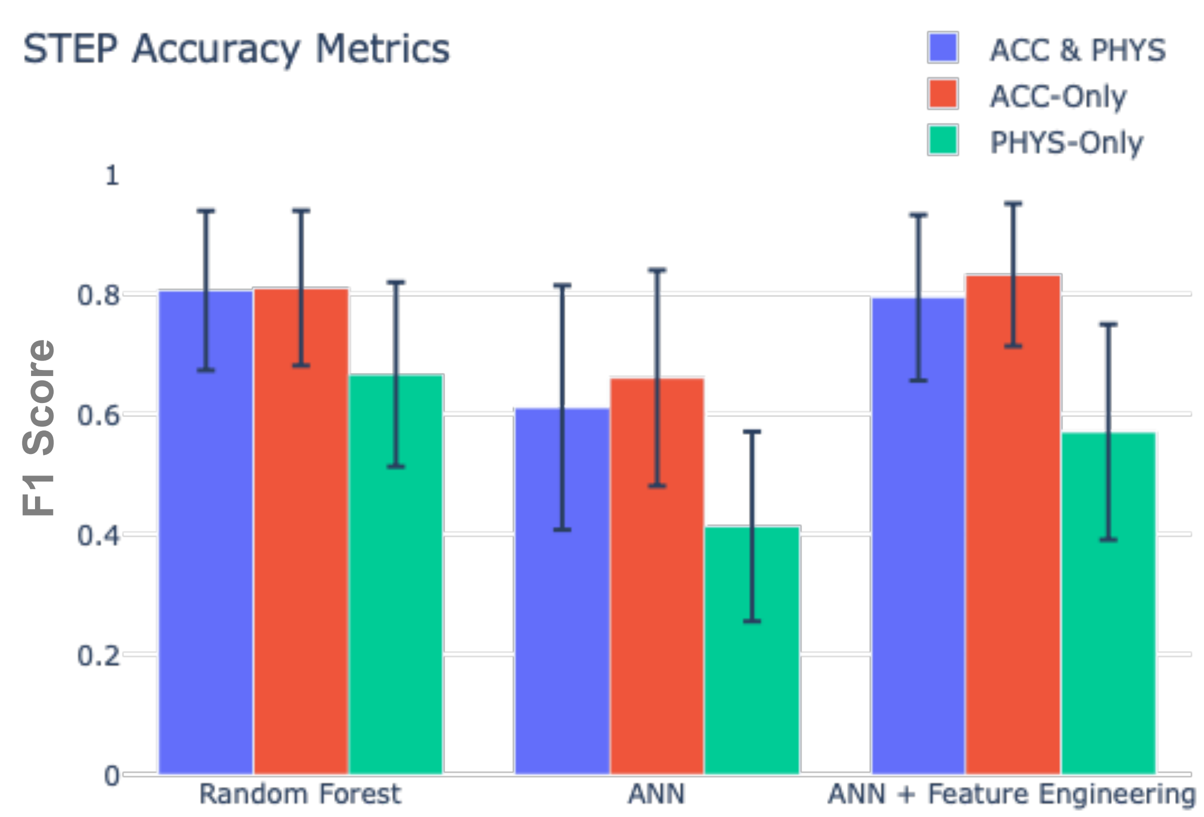

Figure 3. Accuracy across models

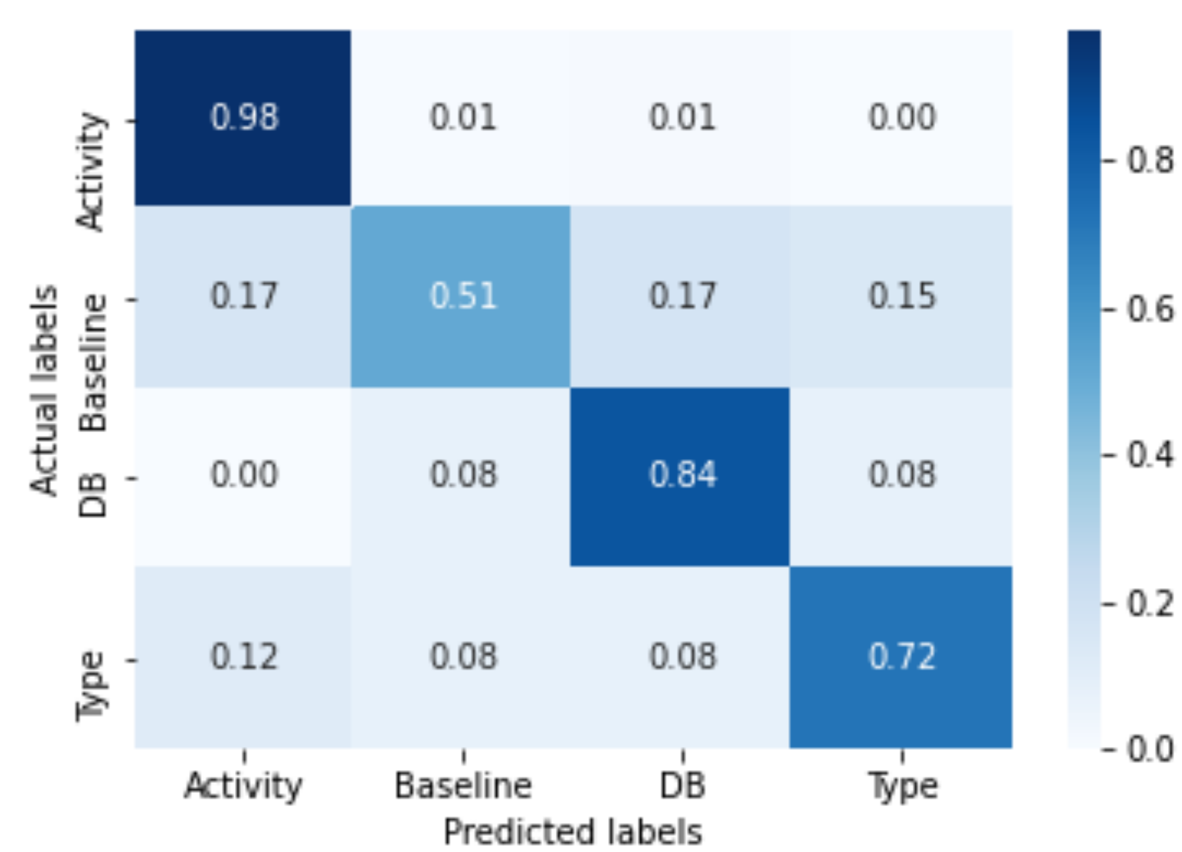

Figure 4. Confusion matrix for ANN with feature engineering

Conclusions

We show minimal differences between models including accelerometry and physiological metrics and models using accelerometry only.

More comprehensive feature engineering is required to make conclusions about the efficacy of including physiological features.

Feature engineering improves classification performance for both the traditional ML model and the deep learning model.

Developed a documented pipeline to make HAR accessible as an open source software.

Future Plans

1. Extract more advanced features from the physiological data.
2. Create an ensemble model which would also include votes from the random forest model.
3. Obtain more data from subject trials with Empatica E4 sensors.

References

1. Bent, B., Goldstein, B.A., Kibbe, W.A. *et al.* Investigating sources of inaccuracy in wearable optical heart rate sensors. *npj Digit. Med.* **3,** 18 (2020). https://doi.org/10.1038/s41746-020-0226-6
2. Reiss, A., and Stricker, D. Introducing a New Benchmarked Dataset for Activity Monitoring. The 16th IEEE International Symposium on Wearable Computers (ISWC), 2012.

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