Oskooei, A., Chau, S. M., Weiss, J., Sridhar, A., Martínez, M. R., & Michel, B. (2019). DeStress: Deep Learning for Unsupervised Identification of Mental Stress in Firefighters from Heart-rate Variability (HRV) Data. arXiv preprint arXiv:1911.13213.

Here, HRV data of about 100 firefighters had been collected which accounts for 90 % of data and rest 10 % data from a normal human. They trained both LSTM Long Short-Term Memory) and convolutional but LSTM failed to identify useful patterns. While convolutional encoders were able to produce clusters that were verifiably distinct.

The AEs were implemented using TensorFlow 1.12.0 (tf.keras) deep learning library. Adam optimizer with a learning rate of 1e-4 and a batch size of 64 was used to train the AEs (Autoencoders). 5-fold cross-validation scheme was used to train the models and tune the hyperparameters. Both CAE (Convolutional Autoencoders) and LAE were trained for 300 epochs. CAE loss plateaued afternearly150 epochs while LAE (Locality Aware Autoencoders) plateaued much later at about 290 epochs. Both models were trained using a virtual machine with a 12-core CPU and 24GB of RAM.

The CAE clusters show a significant discrepancy in the HRV markers between the two clusters while the LAE clusters exhibit an insignificant difference in the four HRV markers. These results further confirm our hypothesis that the CAE clusters are reproducible and relevant in the context of mental stress detection while the LAE clusters fail to stratify the samples in a meaningful manner.

Skotte, J., Korshøj, M Kristiansen, J., Hanisch, C., & Holtermann, A. (2014).
Detection of physical activity types using triaxial accelerometers. *Journal of physical activity and health*, 11(1), 76-84.

The main focus of this study is to validate a triaxial accelerometer setup for identifying everyday physical activity types (sitting, standing, walking, walking stairs, running, and cycling).

Methodology: Seventeen subjects were equipped with triaxial accelerometers (ActiGraph GT3X+) at the thigh and hip carried out a standardized test procedure including walking, running, cycling, walking stairs, sitting, and standing still. A method was developed to discriminate between these physical activity types based on threshold values of the standard deviation of acceleration and the derived inclination. Moreover, the ability of the accelerometer placed at the thigh to detect sitting posture was separately validated during free-living by comparison with recordings of pressure sensors in the hip pockets.

Sensitivity for discriminating between the physical activity types sitting, standing, walking, running, and cycling in the standardized trials was 99%–100% and 95% for walking stairs. Specificity was higher than 99% for all activities. During free-living (140 hours of measurements), sensitivity and specificity for detection of sitting posture were 98% and 93%, respectively.

Chen, Z., Wu, M., Wu, J., Ding,., J., Zeng, Z., Surmacz, K., & Li, X. (2019, May).
A Deep Learning Approach for Sleep-Wake Detection from HRV and Accelerometer Data. In z (pp. 1-4). IEEE.

In this paper, they have proposed a deep learning framework for sleep-wake detection using acceleration and heart rate variability (HRV). Since data was quite imbalanced, they employed an oversampling technique SMOTE for data imbalance correction. They also tested the impact of SMOTE and HRV on the performance of sleep-wake detection. The results showed that both SMOTE and HRV data are important for classifying sleep and wake states.

• Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics

and norms. Frontiers in public health, 5, 258.

The authors provide an overview of HRV assessment strategies for clinical and optimal performance interventions. Circadian oscillations in circadian variations in core body temperature, metabolism, sleep-wake cycles, and the renin-angiotensin system contribute to 24 h HRV measurements. The complex dynamic relationship between the sympathetic and parasympathetic branches and homeostatic regulation of HR via respiration and the baroreceptor reflex is responsible for short-term and ultra-short-term HRV measurements. They caution that 24 h, short-term, and ultra-short-term normative values are not interchangeable. This encourages professionals to supplement published norms with findings from their own specialized populations.

 Park, H., Dong, S. Y., Lee, M., & Youn, I. (2017). The role of heart-rate variability parameters in activity recognition and energy-expenditure estimation using wearable sensors. Sensors, 17(7), 1698.

In this paper, they have proposed a novel approach to recognize human static and dynamic activities. Also, estimate EE out of a collective dataset of IMU and ECG signal of 13 subjects. The subjects had to perform six activities (sitting, standing, walking, ascending, resting, and running) under laboratory observation. According to this study, the tri-axial accelerometer has few drawbacks including various locations on which the sensor can be placed (chest, wrist, ankle, thigh, elbow, and hip) and classification methods used (SVM, ANN). Shimmer3 was which is high-performance IMU used an accurate that integrates 10-degree-of-freedom inertial sensing via an accelerometer, gyroscope, magnetometer, and altimeter. The sampling rate is set to 128 Hz, which is high enough to capture the details of human daily motions.