

# Scalable Machine Learning and Deep Learning Project Proposal: Detecting Mental Stress from Real Time Smartwatch Sensor Data

Ashraf Ahmed  
Emil Hardarson

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## 1 Problem description

Long term mental stress is known to have a negative impact on health and wellbeing. A convenient, unobtrusive and inexpensive method of accurately monitoring a person's stress will likely prove to be an important addition to available health services and resources aimed at managing and reducing stress [1]. Therefore we propose a project with the goal to detect mental stress from smartwatch sensor data in real time. Given 60 seconds of biometric smartwatch sensor data, our goal is to correctly classify the user's mental state as *stress* or *non-stress*.

We will be expanding on recent work where machine learning and deep learning methods are used to classify stress in multimodal sensor data from wearable devices [2][3][4]. Specifically, we will be attempting to classify mental stress in data representing a subject wearing an off-the-shelf smartwatch.

Producers of smartwatches and other wearables are already working on stress detection. The Fitbit Sense watch and some wearable Garmin devices have stress detection functionality, for example.<sup>1</sup> Apple are also rumored to be working on implementing a stress monitoring system for the Apple Watch, to be published in the coming years.<sup>2</sup>

## 2 Data

We will be using the WESAD dataset (Wearable Stress and Affect Detection)[2] to train our classification algorithms. This multimodal dataset contains physiological and motion sensor data from 15 subjects during a lab study, where they are exposed to different stimuli (stress, amusement, meditation and baseline). The data includes the subjects' blood volume pulse, electro-cardiogram,

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<sup>1</sup>See [wired.com](http://wired.com), [garmin.com](http://garmin.com) and [firstbeatanalytics.com](http://firstbeatanalytics.com)

<sup>2</sup>See for example [micky.com.au](http://micky.com.au), [t3.com](http://t3.com), [ucla.edu](http://ucla.edu) and [macrumors.com](http://macrumors.com).

electrodermal activity, electromyogram, body temperature, and three-axis acceleration. Although the dataset contains measurements from both a wrist- and a chest-worn device, we will only be using the data from the wrist-worn device, since we are emulating measurements from a smartwatch.

We will make an attempt to augment the data to replicate the frequency and signal-to-noise ratio of commercial smartwatches.

### 3 Tools

We will be using Tensorflow. Since the dataset is quite large (approximately 18 GB), we will be performing some of the pre-processing using Spark.

### 4 Methodology and algorithm

Our approach for classifying parts of the data into *stress* and *non-stress* will be twofold. Firstly we will perform segmentation of the sensor signals using a sliding window, followed by feature extraction and classification algorithms such as Random Forest. Secondly, we will attempt to classify *stress* and *non-stress* segments in data from each of the sensor modalities using RNN with LSTM. We will be using a leave-one-subject-out cross validation to evaluate our models.

### References

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- [2] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, “Introducing wesad, a multimodal dataset for wearable stress and affect detection,” in *Proceedings of the 20th ACM International Conference on Multimodal Interaction*, pp. 400–408, 2018.
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