How wonderful would it be if our body-worn accessories, such as wearable medical sensors (WMSs), were able to track our health in a round-the-clock fashion? Breakthroughs in the field of machine learning and rapid advancements in sensor technologies hold great promise to actualize this dream through automation of decision-making processes.


As shown in Figure 1, Akmandor and Jha’s proposed system—called SoDA—collects physiological signals through five WMSs: electrocardiogram, galvanic skin response, respiration rate, blood pressure, and blood oximeter. SoDA processes the data by eliminating unwanted noise, outliers, and interpersonal variations. Then, SoDA extracts features for each section of the processed data and inputs them into previously trained machine-learning models. These models determine whether the user is stressed, and activate the stress alleviation protocol if needed.

The stress alleviation protocol starts with the most effective stress therapy (determined during the training stage) and tracks the physiological signals. If the physiological signals indicate that the user is benefiting from the therapy, SoDA proceeds with it for a predefined time period; otherwise, it switches to the next therapy and repeats the steps. SoDA continuously collects, processes, and analyzes the data. Because it is awake 24/7 or as long as the
user wears the sensors, SoDA has the potential to take action at the onset of a stressful situation and help the user circumvent its negative effects.

Depending on the user’s expectations, current condition, and available resources, SoDA offers two modes: individualized and generalized. The individualized mode utilizes only the corresponding user’s data to build the machine-learning model. Because the model requires the user’s data, the user needs to be available for data collection for approximately two hours. In the generalized mode, the machine-learning model is trained with previously collected data from a large group of individuals. Because the individualized mode is personalized to the user, it exhibits a higher classification accuracy. The generalized mode eliminates the need for personalized data collection, at the expense of reduced classification performance. Akmandor and Jha carried out analyses on 32 individuals under both modes. They obtained a stress detection accuracy of 95.8 and 89.3 percent, respectively, for the individualized and generalized modes. Moreover, the authors also tested the effects of various stress alleviation therapies (for example, micromeditation, good news, and warm stone) and verified their efficacy by comparing them with a control case that did not include stress alleviation therapy.

SoDA provides end-to-end stress coaching by not only detecting stress but also suggesting therapies, tracking physiological signals, and modifying the therapy accordingly when needed. Although SoDA exhibits high performance and real-time response and offers a user-friendly setup and multiple stress therapies, the authors state the need for longer experimental duration, integration with more WMSs, a larger experimental population, and an increased set of stress therapy options. SoDA’s current implementation and the stated future steps open up the opportunity to tackle other serious health conditions.

Figure 1. The SoDA stress detection and alleviation system. WMS is wearable medical sensor.