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DSAI
DATA SCIENCE & ARTIFICIAL INTELLIGENCE

Research Summary

Stress-level Management via Smartwatch Monitoring

Course: Machine Learning: Supervised Techniques

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1. Problem Definition

Stress is a really prevalent health concern among many students and professionals in many fields, contributing to a decrease in productivity and reduced well-being which causes long-term mental health issues. Even though stress can be measured with the use of biometrics such as with heart rate variability (HRV), blood volume pulse and temperature, these stress-monitoring solutions have notable and significant limitations.

Smartwatch systems often struggle with: inaccurate detection of stress, lack of user-friendly interfaces and limited real-time intervention features.

Because of these struggles and shortcomings, there exists a need for a robust and accurate stress monitoring system based on smartwatch data and ML techniques. That type of system must bridge the gap between physiological stress responses and perceived subjective stress to support reliable early observations and well-being management.

2. Research Summary

The research explores the application of smart wearable devices, the Internet of Things (IoT), and Machine Learning (ML) for the continuous, automatic detection and monitoring of stress and related mental health conditions such as anxiety and depression. At its foundation, this area utilizes both specialized and commercially available smartwatches to gather various biometric data, which includes physiological signals such as Heart Rate Variability (HRV), skin conductance, body temperature, blood volume pulse, and in some cases, chemical biomarkers like cortisol. This raw sensor data is then subjected to analysis using different Machine Learning models, including Decision Tree, Random Forest, and Support Vector Machine (SVM), which are employed to classify or predict an individual's stress levels. For instance, one system called "Stress-Track" demonstrated a high accuracy rate (99.5%) by integrating measurements of body temperature, sweat, and motion rate. Systematic reviews within this body of work confirm that the field is rapidly advancing, with wearables tracking fluctuations in depression, anxiety, and stress across various settings. Specifically in occupational stress monitoring, often focusing on health professionals, the Empatica E4 device was noted as a common tool, although researchers still frequently rely on standardized, subjective questionnaires to complement the objective sensor data. A significant complexity identified is the challenge posed by the discrepancy between physiological stress, as measured by a device, and the user's self-reported feeling of stress (perceived stress). One small study found no clear association between the daily physiological measurements from a smartwatch and the self-reported perceived stress, indicating that user interpretation and trust in the data remain a major hurdle. Finally, the utility of smartwatches extends beyond detection to include stress reduction interventions, such as providing prompts for breathing exercises, with overall user adoption being sensitive to factors like comfort and ease of use.

3. Conclusion

While developing wrist-worn wearables for real-time stress identification is challenging, it is generally viewed as possible and applicable. Current limitations include a lack of user-friendly devices specifically for stress detection and the continued reliance on subjective questionnaires alongside objective data. Results show significant variability in classification accuracy even when using similar physical signals.

To advance the field, researchers need to focus on robust, automated methods for classifying different stress levels and conducting large-scale studies to ensure the reliability of the data and algorithms.

4. Project Proposal

Title: Time Series Modeling of Stress from Smartwatch Physiological Signals

Overview

This project develops a machine learning system for automatic stress detection using smartwatch and wearable sensor data. It targets continuous, objective monitoring, in contrast to current systems that rely mainly on questionnaires and self-report, which are subjective and do not capture fast, real-time stress dynamics. By modeling physiological signals as time series, the system links patterns in the data to stress states and supports future integration into IoT-based mental health monitoring.

Methodology

The project uses supervised learning with time series modeling to classify stress levels from physiological signals. Input signals include heart rate variability (HRV), blood volume pulse (BVP), electrodermal activity (EDA), skin temperature, and motion, which are well-established markers of autonomic activation during acute stress. In addition to classic feature-based models (Random Forest, SVM), the project explores sequence models such as LSTM-based recurrent networks that learn temporal patterns from sliding windows of physiological data.

Data

Two public datasets will be used:

- **SWELL-HRV / SWELL-Knowledge Work**
  HRV features extracted from office tasks with time pressure and email interruptions, recorded in 25 knowledge workers. Labels: baseline, time-pressure stress, interruption stress.

- **PhysioNet Wearable Device Stress Dataset**
  Empatica E4 wristband recordings (BVP 64Hz, EDA 4Hz, temperature 4Hz, accelerometer 32Hz, interbeat intervals) during baseline, mental stress tasks (Trier test, math, counting), rest periods. Self-reported stress scores (1-10) thresholded to baseline/stress/recovery states.

Model Development

The classification task is to assign each time window or sequence to one of three states: baseline (no stress), stress (e.g., time pressure, cognitive stress tasks), and recovery/post-stress where present in the data. HRV time and frequency-domain metrics, EDA tonic and phasic components, temperature trends, and motion cues are extracted per window and used to train Random Forest and SVM models, as widely done in stress detection work. In parallel, LSTM-based time series models (and, where feasible, simple CNN-LSTM variants) are trained directly on sequences of HRV, EDA, and BVP to learn temporal dynamics that are difficult to capture with static features alone.

Validation

Evaluation follows a cross-subject strategy to test generalization across individuals rather than memorizing personal patterns. Metrics include accuracy, F1-score, precision, recall, and specificity, with particular emphasis on reducing false positives so that users are not overwhelmed by incorrect stress alerts. Where possible, cross-dataset checks between SWELL-HRV and the PhysioNet wearable dataset are used to probe robustness across different protocols and devices.

Expected Outcome and Future Use

The expected outcome is a time series–based model that achieves high accuracy in distinguishing baseline, stress, and recovery states from smartwatch data, with reasonable cross-subject robustness. Literature suggests that Random Forest and SVM perform strongly on HRV-based stress classification, while LSTM-based models can further exploit temporal structure in the signals. This system can act as a backend for IoT stress-monitoring applications that provide breathing prompts, trend tracking, and personalized interventions, while future work can address the known gap between physiological stress indices and perceived stress reported by users.

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