Stress DeTech-tion: Revolutionizing Wellbeing in Future Networks

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ABSTRACT

As healthcare is becoming increasingly digitally connected, the use of wearable technologies for self-monitoring of overall health and mental well-being has become ubiquitous, bringing new challenges related to the data transmission and processing. This research project explores the cross-impact of information and communications technologies in improving stress-related emotion recognition systems in future networks. Two distinct tracks are delved into: the application of learning architectures and the Internet of Things (IoT) sensors for stress detection, and the investigation of challenges related to telecommunication technologies in the transmission process of emotion recognition data. We aim to pave the way for the widespread adoption of emotion-aware technologies by simultaneously investigating cutting-edge algorithm models for real-time stress detection and tackling issues in telecommunication technologies. The ultimate goal of this project is to improve Human-Technology Interaction (HTI) and advance wellbeing in users' day-to-day life through a multidisciplinary approach.

CCS CONCEPTS

• **Social and professional topics** → *User characteristics*; • **Human-centered computing** → **Human computer interaction (HCI)**.

KEYWORDS

Stress, emotions, detection, recognition, wearables, technology, IoT, sensors, AI, ML, HTI

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1 INTRODUCTION

Stress is a state of being overwhelmed and pressured, which various environmental stressors can provoke [4]. It can manifest a range of physiological, psychological, and behavioral responses to uncontrollable or unpredictable circumstances and trigger nerve and immune systems to react, as well as the production of hormones (such as adrenaline and cortisol) that are meant to help an individual cope with the situation. Majority of people experience stress in the course of their lives. Depending on the individual, the course and intensity of the stress response are shaped by the objective and subjective perceptions of stress, which can be influenced by personal, work-related, and environment-related factors [7, 9, 12].

Interestingly, stress can have both positive and negative effects on life consequences. On the one hand, stress is essential in helping humans to cope with challenging life situations. On the other hand, stress has become a major contributor to morbidity including various chronic physical and mental conditions. Examples of common conditions related to stress include inflammatory (e.g., ulcer), metabolic diseases (e.g., diabetes), cardiovascular diseases (e.g., hypertension), neurodegenerative disorders (e.g., Alzheimer's), and psychological conditions (e.g., anxiety, depression, post-traumatic stress disorders (PTSD)) [3, 8]. The complexity of stress response mechanisms including physiological responses and psychological reactions highlights the profound interaction between the mind and body when faced with stressors. With the multidimensional interplay between stress and general health, recent research endeavors have spurred efforts to develop stress detection systems in order to identify the symptoms early and further prevent long-term consequences and stress-related chronic diseases.

In recent years, the application of Machine Learning (ML) techniques in the Artificial Intelligence (AI) domain has gained importance in the biomedical realm. The deployment of ML approaches to measure physiological parameters opens the opportunity to uncover distinctive patterns in large amounts of data that are relevant to individuals' responses to stress. Driven by the advancement of technology, the use of smart wearable devices is on the rise and becoming ubiquitous in monitoring general health and mental wellbeing in a non-invasive manner. The prevalence of wearable technology stems from its affordability, usability, and embedded sensors' capacity to continuously monitor physiological signals (e.g., Electrodermal activity (EDA), skin temperature, heart rate variability, or respiratory rate). Wearable technologies collect a combination of multimodal data that provide contextual, behavioral,

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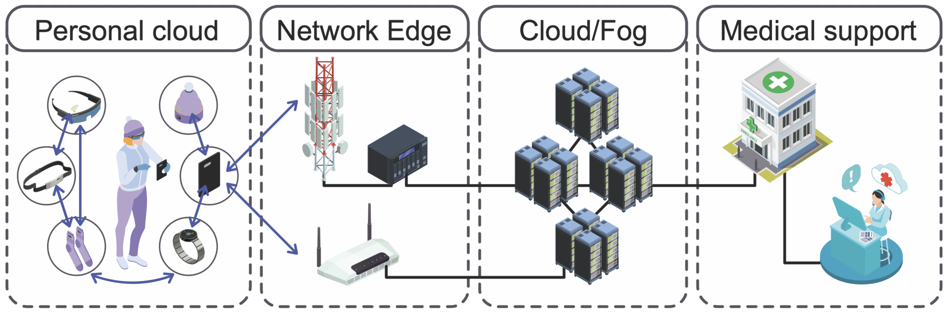

Figure 1: Stress-related emotions detecting system through telecommunication technologies

and demographic information about an individual, which yield more evidence regarding nature, specific indicators, and sources of the stress response. That demonstrates the significant potential of integrating AI-powered applications to facilitate the healthcare ecosystem [2, 14].

When conducting research on emotion detection in the relatively new field of convergent social science and computing sciences, there are arising key challenges in telecommunication technologies that need to be addressed [6]. From a technical perspective, energy consumption is one of the major issues with transmitting data from consumer wearable devices through the technologies changing from 2-5GHz towards 5G New Radio (NR) and THz-level frequencies. The underutilization of the distinctive characteristics of emotion recognition data by the existing telecommunication infrastructure could result in increased energy consumption, transmission inefficiencies, and transmission impairments. Additionally, it is not known how emotion recognition data influences the transmission process and its data optimization for public networks and deserving in-depth research. These obstacles may hinder the development and implementation of real-time emotion detection systems in users' natural environments.

In essence, this research project aims to improve HTI in users' natural environment by focusing on capturing multimodal information from consumer wearable sensors, i.e., smartwatches, smart rings, heart rate monitors, etc., and further exploring potential correlations between heterogeneous physiological, contextual, and behavioral features. In addition, we aim to tackle technical challenges for applications involving emotion detection. It is essential to recognize the research gap and the problems associated with telecommunication technologies that are currently in use and will come into the big play soon. For a long-lasting emotion detection system to be more efficient, accurate, and reliable in the routine of HTI, the sub-objectives of this research project have four pillars. In particular, we aim to:

A1: Investigate the impact of emotion recognition data on telecommunication technologies and to converge and optimize Human-Technology Interaction in inferring emotions.
A2: Identify methods for enhancing the efficiency of data transmission and understand how emotion recognition data can be optimized for public networks and how it affects the transmission of telecommunication technologies.
A3: Examine the effects of wireless networks on emotion recognition data collected from consumer wearable devices.
A4: Improve the system's overall energy efficiency for applications involving emotion recognition data by evaluating energy efficiency computational offloading techniques.

The results of this study will aid in the continued development of communication protocols that more efficiently identify stress-related emotions as well as support the smooth transfer of data, and as in Figure 1.

2 RESEARCH PROJECT

The convergence of social sciences and computer sciences presents a unique opportunity to advance our knowledge and understanding of emotion detection technologies. By leveraging a multidisciplinary approach, this project designs two complementary tracks, both of which contribute to improving stress-detection systems, see Figure 1.

Track 1: Real-time stress detection in the wild by using IoT sensors and machine learning

In the first track, our objective is to explore different ML techniques and further develop a learning-based architecture that can precisely identify stress-related emotions data in the day-to-day environments by leveraging analytics to investigate potential correlations between multimodal information gathered from environmental sensors and wearable devices. This track highlights the benefits and possibilities of how cutting-edge technologies can enhance the effectiveness and precision of stress-related emotions recognition.

Track 2: Exploring the cross-impact of data and communications for improving wellbeing in future networks

In the second track, we focus on the significant obstacles that telecommunications technologies present when transmitting emotion recognition-related data. As 5G-NR and THz-level frequencies become more common, transmission efficiency and energy consumption have become key issues [1]. This track aims to clarify the optimization strategies necessary for smooth data transmission in public networks by examining the effects of emotion recognition data on telecommunication processes. Our goal is to make it easier for users to integrate real-time emotion detection systems into their natural environments by tackling the aforementioned obstacles.

2.1 Objectives of the Project and Research Questions

The main objectives of this research project are two-fold. First, we aim to present a concept of a learning-based architecture for monitoring real-time stress-related emotions and multimodal physiological and psychological features in users' natural environments that are pertinent to their social interactional behaviors. Second, we intend to acknowledge and address the critical issues that current telecommunication technologies possess today, with an emphasis on energy consumption when transmitting emotion recognition data. In this research project, we aim to answer the following Research Questions (RQs), which are formed for each track accordingly:

Track 1 set: **RQ 1.1:** What kinds of physiological and behavioral features can be extracted from consumer wearable sensors in a manner relevant to users' stress-related emotions? Furthermore, how do these multimodal data correlate with each other?

RQ 1.2: How to classify users when experiencing stress-related emotions in their natural environments by using IoT sensors and ML algorithms?

RQ 1.3: To what extent can the user's stress-related emotions be predicted by training ML algorithms on multimodal data?

Track 2 set: **RQ 2.1:** How can emotion recognition-related data affect the wireless medium on both signal and packet levels, especially, for crowded and emergency scenarios?

RQ 2.2: How may emotion recognition data from consumer wearable devices affect wireless networks? And how can these data be redesigned and used in public networks?

RQ 2.3: Which computational offloading technique may improve the system energy efficiency for emotion recognition applications?

2.2 Methodology

Context and Participants: On one hand, we plan to recruit 10 to 20 healthy subjects in Europe, with no history of mental illnesses, and no history of drug or alcohol abuse. Pregnant women and individuals undergoing hormone therapy will not be recruited. All subjects will receive instructions on utilizing the wearable device, documenting their daily activities, and completing periodic self-report surveys on their emotional fluctuations in stress levels via a custom application on their mobiles. On the other hand, the application will transmit related mobile logs and physiological data to the cloud/Edge through available wireless network (the data flow would be analyzed on the appropriate OSI level). The processing is expected to be done according to the General Data Protection Regulation (GDPR). For a minimum of two weeks, participants will carry out their routines while staying connected throughout the investigation.

Methods and Instruments: To answer the RQs, we employ a multimodal approach to overcome the shortcomings of traditional approaches that were carried out in a single mode. We use a combination of sensor-based quantitative and self-report qualitative research methods aiming at addressing a two-fold objective, as well as research through design/prototyping methodology.

Track 1: The primary research method is to carry out a Systematic Literature Review (SLR), which is the current phase where we are working to identify the research gap and select consumer-available wearable devices with embedded sensors that can capture multimodal stress-related emotions data. Then, we will further develop a learning-based architecture to explore various ML techniques corresponding to the combination of psychological, physiological, and behavioral features.

Track 2: After the completion of Track 1, we will evaluate the transmission speed, and latency for the chosen wearable device by utilizing different wireless technologies to gather performance metrics and further assess the impact of emotion recognition data. Several optimization strategies can be explored. Examples are the following:

By looking into data compression and encoding methods to minimize the amount of data needed for emotion recognition; Through evaluating the feasibility of transmitting data based on the state of the network, i.e., by introducing an additional hypervisor/coordinator or utilizing the existing one; By examining various computational offloading techniques, i.e., Mobile Edge Computing (MEC) or Fog computing for emotion detection; Through comparing the energy efficiency of the system with or without computational offloading/compression; By conducting a comparative analysis on capturing multimodal data related to related emotions within a lab setting and, in the user's real-life environment.

The main types of instruments for the social side of research will be employed: self-report, E-diary, and interview; and IoT sensor-based data analysis from the engineering side.

The questionnaire is expected to contain two parts. The first part is used to retrieve demographic information from a participant. The second part including a psychological survey, namely Ecological Momentary Assessment (EMA), is to measure different psychological aspects related to stress in real life [5, 10, 11, 13]. Perceived stress survey, sent periodically daily, is assessed through a 5-point Likert scale on questions relating to individuals' stressed feeling intensity at a current moment. E-diary requires participants' commitments to report their emotional states or experiences on special events throughout the day in a custom built-in application, which participants can download on their mobiles. E-diary can be written, or audio recorded in an individual's preferred language. It is used to capture participants' subjective emotional regulation in their natural contexts corresponding to location data. The interview is a direct observation from the researcher's side to the participants. An ethnography and semi-structured interview, which include open-ended questions, are designed to observe directly from the researcher's side to the participants to gather in-depth information about an individual's unique experiences that are pertinent to the research topic.

In order to comprehend the multifaceted nature of stress-related emotions, we explore IoT sensor-based data from a holistic approach via three dimensions:

D1: The wrist-worn wearable is used to obtain heterogeneous physiological features: heart rate variability measured by a photoplethysmography (PPG) sensor, changes in Galvanic Skin Responses (GSR) captured by an electrocardiography (ECG) sensor, and physical motion patterns identified by an accelerometer;

D2: Behavioral reactions are gathered from smartphone usage and physical activities. Through the custom application, we collect screen log activities (i.e., information about presence of calls, messages, and social media application use). Location-based features and physical navigation (i.e., frequent visits to locations, time spent at work, shops, or home, and step counts) are gathered with the assistance of a Global Navigation Satellite System (GNSS) and accelerometer on both the mobile and the wrist-wearable.

D3: Lighting, humidity, and temperature sensors embedded in mobile phones are used to identify changes in weather or environmental conditions corresponding to individuals' location sensor-based data.

3 EXPECTED RESEARCH RESULTS

We aim at proving the postulate that the analyses and fusion of smart wearable sensor-based data (physiological responses and mobility features), psychological reactions, and behavioral data can yield significance in classifying stress. Expected outcomes: qualitative and quantitative analyses. Due to the collection of participants' daily mobility features coming from their natural environment, the results can better reflect the complexity of human emotions in a real-world setting. Expected outcome: improved methodology. The exploration of different ML algorithms both independently and in combination can generate more accurate results and glean deeper insight into emotion recognition. Expected outcome: adapted ML strategy (or, e.g., with tuned hyperparameters). The combination of the above-mentioned strategies may lay a basis for multimodal future developments. Expected outcome: guidelines and framework.

In summary, ongoing and regular mental health monitoring using AI and ML techniques can provide benefits to a variety of stakeholders. Benefits include helping individuals to manage their stress levels on a personalized basis, equipping medical professionals with actionable insights for tailored treatment planning, and improving the general effectiveness and accessibility of mental health services. This paper outlines two distinct approaches to emotion recognition from emerging engineering and social perspectives.

ETHICAL ISSUES

Due to this research project involving human participants, we will apply for ethical review and approval from the Finnish Ethical Board prior to project implementation. We will take extra care in obtaining consent from participants and make sure all participation is voluntary. Additionally, we will not use cloud-based services to analyze collected data or save the data on personal computers. This research will follow the Finnish National Board on Research Integrity guidelines strictly.

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