Chapter 10

From Self Reports to Sensors in Machine Learning and Multimodal Advances in Chronic Stress Detection

Mamta Nag
IIIT Naya Raipur, India

J. Vijaya
https://orcid.org/0000-0002-9948-8573
IIIT Naya Raipur, India

K. Mallikharjuna Rao
https://orcid.org/0000-0002-6096-3963
IIIT Naya Raipur, India

ABSTRACT

Traditional stress assessment methods rely on self-reports, which are subjective and lack real-time responsiveness. Recent advances in multimodal stress detection address these limits by integrating physiological, behavioral, and environmental data, improving accuracy and robustness. This review synthesizes findings from 50+ recent peer-reviewed studies, highlighting the role of wearable sensors and AI models in high-stress environments. Physiological markers such as Electrodermal Activity (EDA), Heart Rate Variability (HRV), and respiration emerge as reliable indicators, with EDA distinguishing stress from cognitive load in mobile contexts. Machine learning and deep learning methods—including Random Forests, CNNs, LSTMs, and federated learning—report accuracies above 90%. Key challenges remain in data collection, feature extraction, fusion, and interpretability, alongside ethical concerns over privacy and fairness. Finally, a roadmap is proposed toward explainable, privacy-preserving stress monitoring systems tailored for chronic stress management.

DOI: 10.4018/979-8-3373-3531-5.ch010

INTRODUCTION

Because of the speed of modern life, a significant portion of the global population now experiences chronic stress, which is an undesirable but inevitable part of their lives. It is a silent epidemic, a constant unease of both physiological and psychological pressure: an insidious layer of stress at an experiential level that is far more than just feeling overwhelmed. The clinical evidence is clear: chronic and uncontrolled stress is one of the main causes of serious physical and mental health problems, and is potentially the largest comorbid factor in nearly every serious health condition. Stress is also an established precursor to the development and maintenance of main depressive and anxiety disorders, which often trap the individual in a detrimental cycle that is virtually impossible to break (Aqajari et al., 2024). Stress does not impact just the mind. The physiological wear and tear on the body (physiological damage) caused by recurrent activation of the "fight-or-flight" situations produces a cost to health, contributing to accelerated cellular aging, higher risk of cardiovascular disease, immune dysregulation, and metabolic syndrome. The social and economic cost is staggering: decreased productivity and increased rate of employee 'burnout' for employers and stakeholders globally, and the increased costs in health and social services makes it urgent for governments and public policy to make better progress on strategies to manage stress globally.

At the core of any effective strategy is the capacity to see the problem clearly, to accurately and continuously measure it. The reality is however, we have been poorly equipped to assess stress for decades. Until recently, psychological assessment of stress has primarily relied on retrospective clinical interviews of varying quantifiable importance at formal assessment as well as self-report questionnaires that are wildly inaccurate (Archana & Devaraju, 2020). Our reliance on outdated measures either legitimately or under social pressure (social acceptance bias) understate stressors when presenting data. Regardless, none of the stress measures when reviewing the data dynamically address the timeline or time resolution and suffer from inherent inaccuracies in regards to time. While clinical interviews, administration of self-report questionnaires or some combination of both provides a snapshot of a single period of time, (i.e., weeks, or months) at best that is somewhat wrong since the problem is actually dynamic not static and is therefore best represented as a fluid experience. As such, it does not take into consideration how individuals, clinicians and employers navigate experiences if they do not have a current and accurate map especially if the map is outdated and wholly inaccurate. A deep technological revolution is filling the long-lasting diagnostic gap, revolution stemming from the combination of two technological innovations: the proliferation of biosensors worn on the body and the intelligence of applied machine learning. The first pillar is hardware. Wearable devices have effectively placed a research-quality physiological laboratory on the wrist of millions (AristiZabal et al., 2021). The sophisticated sensors that previously only existed within constrained or controlled research parameters are now applied in consumer-grade smartwatches, fitness trackers, and smart rings. These devices now turn the body's small, analog language (the elegant dance of heart rate variability (HRV), skin conductance (eds), ethnic patterns (like counts of breaths or sleep stages)), into a continuous fidelity digital story. All of the objective real-world data from these continuous streams will be the basis for a new digital data-driven science for mental health monitoring.

This influx of raw physiological data, however is noise without T whisker was or guides someone capacious learning) is signal could mean work is due, a heated argument, walk up a flight of stairs, or pure joy. This dimension to the revolution: a second pillar - the interpretation engine that is as necessary to find the signal in the noise. This added complexity: the amount of data can (require computational brain) many machine learning (ML) algorithms can learn the nuance, multidimensional patterns that consistently distinguish the physiology signature form negative psychological distress from these con-