Passive Monitoring of Physiological Precursors of Stress Leveraging Smartwatch Data

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2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) | 978-1-6654-6819-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/BIBM55620.2022.9995354

***Abstract*—Developing the capability to continuously and non-invasively monitor the mental health status of individuals is a critical focus in the mHealth domain. The use of passively-generated data gathered via smart and portable electronic devices to monitor specific indicators of mental health has shown potential to serve as an effective alternative to traditional intrusive survey-based approaches to monitoring mental health remotely. In this study, we propose a remote health monitoring framework for dynamic, flexible, and scalable assessment and detection of physiological precursors of a stress response. Our method comprises a smartwatch-based system for continuous monitoring of primary physiological signals, followed by a deep neural network architecture that performs the fusion and processing of the multi-modal sensor readings. We empirically validate our system on a cohort of university-affiliated members of the military. Our findings demonstrate the effectiveness of our passive-sensing system for tracking perceived stress, the results of which can be used to obtain a better understanding of patient behavior and improve personalized treatments[1].**

***Index Terms*—mental health, machine learning, ehealth, adversarial learning, mobile health, time-series.**

I. Introduction

Effectively managing mental health-related disorders is a growing challenge to the healthcare community. In the United States alone, estimates are that 20% of the population suffers from at least one mental health condition. Spending on therapeutics and treatments has now reached hundreds of billions of dollars each year [1]. In addition to the significant costs and considerable resources required to provide proper help for patients, limited access to care renders seeking treatment further challenging for the individuals in need of it [2]–[5].

Stress and anxiety disorders are among the most common mental health problems within the mental health spectrum. Around 60 million adults are affected by at least one anxiety-related disorder (e.g., generalized anxiety disorder (GAD) and social anxiety), with less than 40% of them seeking treatment [6], [7]. Additionally, the rise of the COVID-19 pandemic, which led to widespread quarantines, loss of loved ones, and long-term health effects, has adversely affected the mental health status across the population [8]. Anxiety disorders negatively impact the quality of life, with effects ranging from increasing the risk of mental health and behavioral disorders (e.g., depression, suicide) to physical health issues [9].

Remote monitoring of stress, anxiety, and other mental health disorders has significant benefits, such as helping with early detection and improving treatments at the level of individuals by providing medical experts with an abundance of information on relevant behavioral patterns exhibited by patients.

Given technological advancements in the past decades, more focus has been put on personal electronics as potential means to scale remote health monitoring systems.

A. Wearable Sensing and Mental Health

Within the spectrum of personal electronics, smartwatches offer unique potential in the realm of remote health monitoring [10]. While smartphones are the platform most typically associated with mobile healthcare applications, smartwatches are worn continuously and directly on the skin, enabling a host of physiological sensing modalities that smartphones cannot emulate. The watch's location, worn at a distal point of a major appendage (the user's wrist), also typically results in a more accurate reading of a user's activities than smartphones, whose location in relation to the user's body may vary throughout the day [11].

Embedded smartwatch sensors now increasingly rival the capabilities and sophistication of dedicated wearable sensors such as chest straps. Additionally, smartwatches have advantages over dedicated sensors in that their interactive features provide a means for engaging the user with additional queries and therapeutic responses [12].

Finally, the generalized nature of smartwatches increases the likelihood that users will utilize their healthcare features in addition to the broader set of desirable functions that users find in smartwatches. This is much like how a user is likely to be more inclined to use a healthcare application on a smartphone

[1]We have released the codes for our framework at https://github.com/shayanfazeli/tabluence

rather than purchase and use a custom device solely for the same intended purpose.

As previously noted, smartwatch devices provide near real-time data measurements, allow users to provide feedback via interactive queries, and enable intervention mechanisms in normal day-to-day situations outside of clinical environments. Furthermore, this platform aggregates and analyzes data from patients that can then be communicated to their healthcare providers and family members to improve their treatment experience.

Due to their utility, this study focuses on the application of smartwatch devices to the mental health domain.

B. The disconnect between emotional and physiological stress

While smart devices, like smartwatches, have demonstrated the technical capacity to monitor physiological stress to varying degrees of accuracy, they demonstrate only a partial picture of a wearer's overall mental health.

This stems from the intrinsic disconnect between emotional perceptions of stress and the underlying physiological stress response. There is growing evidence that there are notable differences in how individuals perceive their stress levels and the actual physiological manifestation of a stress response. For instance, a meta-analysis found that a significant correlation between physiological stress and perceived emotional stress was found in only 25% of social stress studies [13].

There are a number of factors that are presumed to contribute to this low correlation. Foremost among them is that, somewhat counter-intuitively, a direct linear relationship between these two stress profiles is not present but instead is influenced by many additional factors. A detailed study concluded that self-reports of perceived stress did not provide useful information about physiological stress responses [14]. Differing populations may also exhibit different correspondence patterns that population-level models fail to account for (e.g., individuals with ADHD, those who experience chronic stress, those with family histories of substance abuse, etc.). [13]

It is also theorized that differing response patterns may impact how stress manifests physiologically. For instance, differing degrees of cognitive regulation of negative emotions may result in individuals being able to adapt to stress differently [15]. Previous work demonstrating a higher correspondence between self-reported anxiety and physiological arousal in women when compared to men is hypothesized to be explained by men showing emotion-suppressing coping strategies to a greater extent than women [15]. Finally, it has been observed that positive emotions are more strongly associated with physiological responses than negative emotions. This may be due to their social acceptability and disinclination to control or dampen a physiological response when compared to negatives ones [15].

Perhaps the most challenging effort in effectively mapping these two stress profiles stems from the fact that accurate and consistent measurement of emotional stress experiences is currently considered an intractable challenge for the academic community [14]. While multiple scales have been developed to assess differing quantifiable measures of mental health, there is no clinically validated gold standard for assessing emotional well-being accurately and consistently, both across a population and across individuals over time. This stems from issues with an individual's recall and perception of stress, particularly if data is collected after the fact, their evolving willingness to be forthright and transparent regarding emotional well-being and differences in the subjective assessment of stress across individuals (what constitutes a *moderate* level of stress may differ dramatically across individuals) [14].

In this work, we present a complete wearable stress recognition and monitoring framework that provides the opportunity for continuous, scalable, and low-cost monitoring of relevant mental health indicators over time. Our contributions are as follows:

- Focusing on users' usual anxiety responses during everyday life events, we propose a smartwatch-based system for non-invasive and efficient monitoring of key physiological attributes, including heart rate, heart rate variability, respiration, and pulse oximetry readings.
- In a 10-day anxiety study approved by the Internal Review Board (IRB)[2], we created a corpus of primary physiological data from monitoring 14 college students with an active-duty or ex-military affiliation.
- We designed a survey-based self-assessment method for the subjects to receive feedback regarding *time* and *intensity* of the moments and episodes they perceived as stressful throughout the day. These assessments correspond to the stressful episodes in their everyday lives and their perceived levels of experienced anxiety. Labeling these self-reported episodes was done with the help of domain experts, which rendered our corpus an informative benchmark for empirical performance evaluations.
- We designed deep inference pipelines for the fusion and processing of our smartwatch data [16]. Our framework enables the efficient use of artificial intelligence for stress-focused deep representation learning. This is done by pre-processing preparation and fusion of the multi-modal physiological time-series data recorded via smartwatch sensors as well as leveraging the details of self-reported stressful events.
- We employed an adversarial regularization technique in enhancing subject invariance in the learned latent representation, leading to improve generalization performance.
- Our empirical evaluation shows the advantages of our integrated framework for continuous monitoring of everyday anxiety.

II. Related Works

The primary focus of mHealth research in remote monitoring of individuals has been on smartphones, smartwatches, and custom body-area-networks (BANs). Personal electronics

[2]The Internal Review Board approved our study at the University of California, Los Angeles.

such as mobile phones and smartwatches have been the core component of numerous mHealth studies on remote monitoring of the physical and mental well-being of patients. An example is the location readings captured via the phone's Global Positioning System (GPS). These data have been used in the assessment of the likelihood of suffering from social anxiety among college students [17]–[20]. In addition to the location readings, almost all phones are equipped with various sensors (e.g., motion sensors) that can be leveraged in passive sensing frameworks. It has been shown that there can be significant relationships present between features extracted from these data and indicators of mental well-being [21].

To further bolster the efficacy and scalability of such a monitoring framework, in addition to proposing systems for obtaining patient observations, researchers have worked on automating the assessments of mental health status. Specifically, the methodologies in machine learning and artificial intelligence domains demonstrate the potential of *learning* systems for effective monitoring of psychological indicators [21], [22].

Smartwatches have been widely used for health monitoring frameworks [23], [24]. Their motion sensors provide information on human activity types and movement levels. This mobility information captured by them has been used to efficiently track asthma patients' health status [25], [26]. Some smartwatches provide access to less common sensors such as skin temperature and galvanic skin response. These data have been used in [22] to enable accurate classification between healthy groups and patients from three critical disorders: depression, bipolar, and schizoaffective. Cardiovascular and respiration activity is shown to be especially associated with stress levels. Specifically, the model in [27] is designed to leverage particular handcrafted attributes (e.g., 80th R-R intervals) in determining the stress. Using the same model proposed in [27], a system centered around a physiological sensor set was proposed in [28]. In that work, a wearable suite was provided to the participants that they would wear underneath their clothes. The data regarding chest compression via inductive plethysmography as well as a 2-lead electrocardiogram and accelerometer reading were then transmitted to the participant's smartphone. The data was then analyzed to make inferences regarding stressful episodes. Measurement of stress and inference regarding participants' academic performance is done in [29]. In [30], the authors focused on *perceived* stress levels as well as predicting whether a 1-minute reading of ECG and respiration data is a response to a stressor. In general, the utilization of sensor data and processing their time-series in making assessments regarding the inference is a difficult problem and imposes numerous challenges [31].

Our work is different from the above mainly in the following aspects: 1) Our system is focused on stress and general anxiety responses, which is a more common and relatively less-investigated problem in the domain of remote monitoring of mental health indicators. 2) Our system is a single-device framework relying on the smartwatch alone, improving the overall convenience and usability of the proposed solution. 3) Additionally, features that we employed in this system were recorded via the usual physiological sensors on smartwatches, which are commonly available in average commercial smartwatches. This makes it easy to adapt our framework and use it with similar hardware and input signals, and improves the accessibility of the proposed methodology.

III. Data

A. Cohort

Our cohort in this study consists of 14 students within the University of California, Los Angeles community, who were also active-duty or ex-members of the United States military. This cohort is critical for our evaluations given that both military members and college students are amongst the groups more prone to higher levels of work-related stress in their lives [32]. These individuals were asked to use our wearable system for a period of 10 days as they go about their everyday lives, allowing us to record and analyze their main physiological time series data. The details of participant counts per categorization by duty status and by service branch are available in Table I.

TABLE I
NUMBER OF PARTICIPANTS IN OUR COHORT PER CATEGORY BASED ON THEIR DUTY STATUS AND SERVICE BRANCH

	Duty Status
National Guard	2
Active Duty	3
Veteran	9
	Service Branch
Airforce	2
Marine	3
Navy	4
Army	5

B. System

The main component of our system is a smartwatch capable of recording physiological measurements concerning heart rate, heart-rate variability, pulse-oximeter, and respiration readings. In this work, we have used a Garmin vivoactive 4S watch; nevertheless, our system is easily generalizable to other devices as almost all smartwatches are able to perform the required physiological measurements continuously.

We requested the participants to fill out a survey on a daily basis with regards to the details of the events they perceived to be stressful. Given that our focus has been on *perceived* anxiety, the subjects were asked to provide the approximate timespan of such episodes, and the intensity by which they perceived it to be stressful (`None`, `Low`, `Medium`, and `High`). These data serve a crucial role in our framework in connecting the quantitative measurements pertaining to physiological sensory readings and the qualitative user perception of the events.

IV. Methods

A. Pre-processing

Leveraging the smartwatch system, we would gather K types of physiological time series (e.g., heart rate every 15

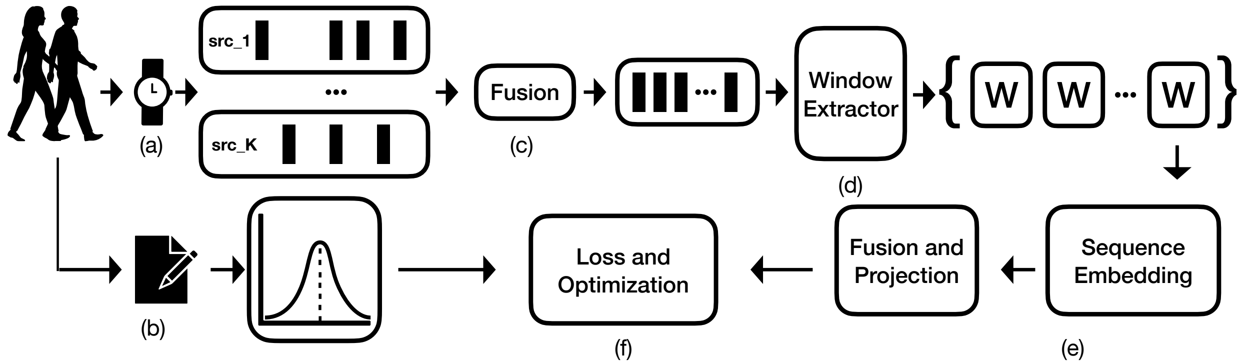

Fig. 1. Pipeline overview: (a) Our smartwatch system and app capture the physiological data monitored through time as users go about their everyday lives and store them in our cloud database. (b) Subjects' responses to our survey are utilized to create *teacher* functions which provide the supervision signals for guiding the training process. (c) The data will go through preprocessing, transformation, and fusion across different sequential data from various sources (e.g., respiration). (d) Through a sliding window approach, the preprocessed sequential data will be used to create a training corpus of windows, each serving as an observation in the D_{train}. (e) The inference model composed of source-specific recurrent neural networks in Long-Short Term Memory configuration will process these windows. The gradient resulting from matching its prediction against the supervision signals from teacher function determines the training direction. (f) The resulting predictions are used in computing the training loss.

minutes), which are stored as a list of tuples of timestamps and value readings. Specifically, we have:

$$D_{k,i} = \{(t_j, x_j)\}_{j=1}^{T_{i,k}}$$

Where k is a physiological signal type (e.g., *heart-rate*), each (t_j, x_j) is a single sampled datapoint consisting of timestamp t_j in unit of seconds and reading value x_j. To account for discrepancies in sampling rate and filling the missing values, we consider the highest sampling frequency and use interpolation to fill in the missing values during the fusion phase as needed.

B. Supervision Signals

We gathered the responses input by the study participants in our daily surveys and leveraged them to create the supervision signals for training our models. An example of such a data point and the data it contains is shown in Figure 2.

The following questions come to mind with regards to using these data points to guide the training:

- How can we connect such single data points to continuous observation windows?
- How can we account for the reported *intensity* levels associated by the subject with the perceived episode?

To address these challenges, we propose a method to formulate continuous *teacher functions* using these data for each individual. This allows us to query information on stress level at any timestamp defined in subject's trajectory, so as to use them as supervision signals.

It is noteworthy that there is not just one way to deal with the challenges that this data structure and problem definition impose. Nevertheless, our approach has the benefit of being intuitive, simple to implement, and practical, as validated through empirical observations.

The process for creating this teacher function for each subject is as follows:

- We start with the *teacher function* for each subject being a constant 0 function, which means that our assumptions with regards to timestamps that we do not have data for is *non-stressed* as it is the majority class.
- Every entry d obtained from user inputs has a `probe_datetime`, the value for which is either a single timestamp or a time-range. For instance, the subject could indicate *I was stressed because of X at 4:30 pm*, or *I was stressed because of X from 2pm to 5pm*. For each datapoint, we would update $f(\cdot)$ as follows:

$$f(\cdot) \leftarrow f(\cdot) + \lambda(d) \cdot \exp(-\frac{t - \mu(d)}{2\sigma(d)^2})$$

  The mean μ, coefficient λ, and standard-deviation for this gaussian function will be computed based on the details of each label, and the *gradual* nature of the function would help account for the build-up and cool-down times as well as the intensity-related magnitude, with decreasing magnitude as we go further away from the peak. Figures 3. and 4 show case an example data window and its corresponding teacher function.

C. Inference

Considering the multi-modal nature of our data, the question of how and when to fuse these different branches throughout the inference pipeline is particularly important. The core model used in this study can have a separate branch for each sequence after fusion, followed by the latent representation fusion via fully connected projections as shown in Figure 1. Therefore, the current architecture allows both techniques of *early* and *late* fusion.

Subject Invariant Features: In order to enhance the generalizability of our latent representations, we propose to *unlearn* the redundant subject-specific features by following an adversarial setup. Consider a discriminator model $D(\cdot; \psi_1)$ that takes the latent representation $z \in \mathbb{R}^{d_{\text{emb}}}$ and predicts the subject identifier. There also is a generator model $G(\cdot; \psi_2)$,

```
{
    "subject_id": "12345",
    "stress_type": "general",
    "perceived_rate": "low",
    "stress_rate": "low",
    "stress_description": """
    I was stressed because of a deadline
    """,
    "probe_datetime": (
        datetime(
            2021, 5, 10, 9, 0, 0,
            tzinfo=timezone.utc),
        datetime(
            2021, 5, 10, 18, 0, 0,
            tzinfo=timezone.utc))
}
```

Fig. 2. A sample stress probe datapoint, showing the record structure

which will be responsible for making it difficult for the discriminator to recognize to which subject the given window belongs. In our case, we consider the generator $G(\cdot;\psi_2)$ to be the main inference pipeline itself, and the discriminator to be a multi-layer perceptron (MLP)-based head on top of the latent representation:

$$D(\cdot;\psi_1) = f_{\text{adv}}(\cdot;\psi)$$

To facilitate this setup, we introduce an additional adversarial regularization term $\mathcal{L}_D - \mathcal{L}_G$ to the final loss, defined as follows:

$$\mathcal{L}_G = \mathbb{E}[l_{\text{ce}}(\text{fr}(f_{\text{adv}})(z(x)), y_{\text{sub}})]$$

$$\mathcal{L}_D = \mathbb{E}[l_{\text{ce}}(f_{\text{adv}}(\text{sg}(z(x))), y_{\text{sub}})]$$

Where $\text{fr}(\cdot)$ is the *freeze* operator (which freezes the parameter set ψ for this adversarial head) and $\text{sg}(\cdot)$ is the stop-gradient operator, not allowing the gradients of this loss to backpropagate through the network. Therefore, the network will be inclined to remove the features that hurt subject invariance.

V. Experiments

A. Signals and Targets

In our experiments, we followed the strategy below in parameterizing the teacher function for every subject:

$$\mu(d) = \begin{cases} d[\text{`}\texttt{probe\_datetime}\text{'}] & \text{if single timestamp} \\ \text{avg}(d[\text{`}\texttt{probe\_datetime}\text{'}]) & \text{if time range} \end{cases}$$

$$\sigma(d) = \begin{cases} 30 \times 60 \text{ sec} & \text{if single timestamp} \\ \dfrac{\text{len}(d[\text{`}\texttt{probe\_datetime}\text{'}])}{(30 \times 60 \text{ sec})} & \text{if time range} \end{cases}$$

In this work and as a proof of concept, we focused on predicting whether a window ends in a high-stress note. We considered the coefficient $\lambda(d)$ which adjusts the magnitude of each probe to be proportionate to the reported stress levels, and respectively defined the high-stress window as one that the corresponding teacher function returning a value larger than 0.5 for its endpoint, which led to a high consistency between the resulting teacher functions and the reported episodes. The sensory data used in our work was based on heart-rate (every 15 seconds), a measure of heart-rate variability (every 3 minutes), pulse-oximeter (every 1 minute), and respiration rate (every 2 minutes). On the input side and to help stabilize the training further, we fit min-max normalizers on the features across the time slices in the train set.

TABLE II
Performance overview for the task of recognizing high-stress windows

	Acc
Supervised Setup	62.0
Supervised Setup + Adversarial Subject Invariance	64.5

B. Modeling and Optimization

The recurrent neural network module we considered is a 4-layer bi-directional RNN in Long Short Term Memory (LSTM) configuration, leading to a $z \in \mathbb{R}^{256}$ latent representation. To prepare the inputs for processing, we perform early fusion of the sensory readings and create a sequence of vectors representing physiological status at each timestamp, as it is a more intuitive approach for modeling the inputs in this case.

Our optimization protocol employed the Adam algorithm with a learning rate of 1e-3 and a weight decay of 1e-4 to help with overfitting. We also made use of cosine annealing scheduling, reducing the learning rate across our 100 epoch experiments.

With regards to adversarial regularization for enhancing subject invariance, our $f_{\text{adv}}(\cdot;\psi)$ is a two-layer MLP mapping the latent representation to the subject identifier label. The results shown in Table II indicate an increase in the generalization performance.

VI. Discussion

A. Limitations

Given the importance and sensitivity of the problem our work tries to address, it is of paramount importance to provide an in-depth discussion of its limitations.

1) Label Noise: The self-labeling mechanism in our framework inquired subjects once per day to indicate the time and level of their perceived stress for stressful events. This implies that the presence of noise is possible. Such label noise takes place due to the subject not remembering an event accurately or at all or misremembering the time and duration of it.

2) Statistical Sufficience: The relationship between certain short-term attributes of physiological signals and stress is well understood in relatively severe stressful episodes (e.g., increased heart rate is expected when a person is agitated). Nevertheless, such a relationship is less investigated when it comes to low levels of perceived intensity and over longer

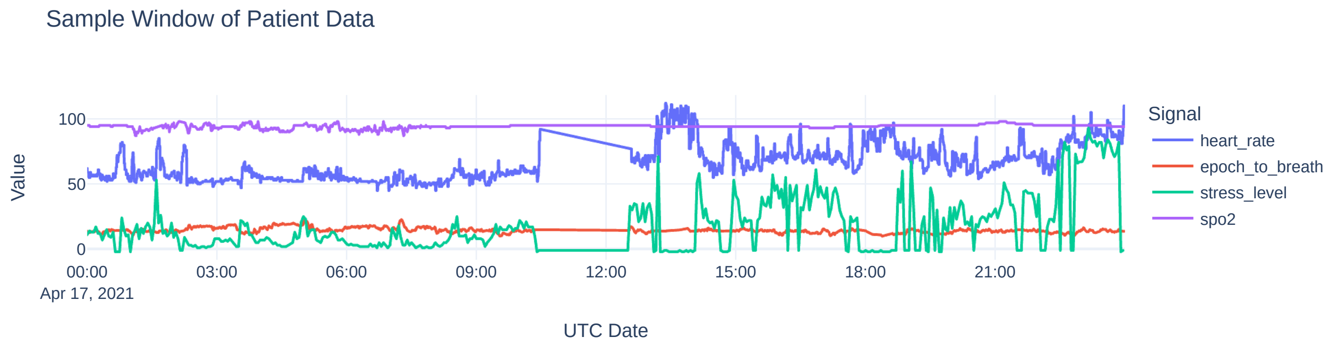

Fig. 3. Example: A slice of patient physiological signals recorded via smartwatch system

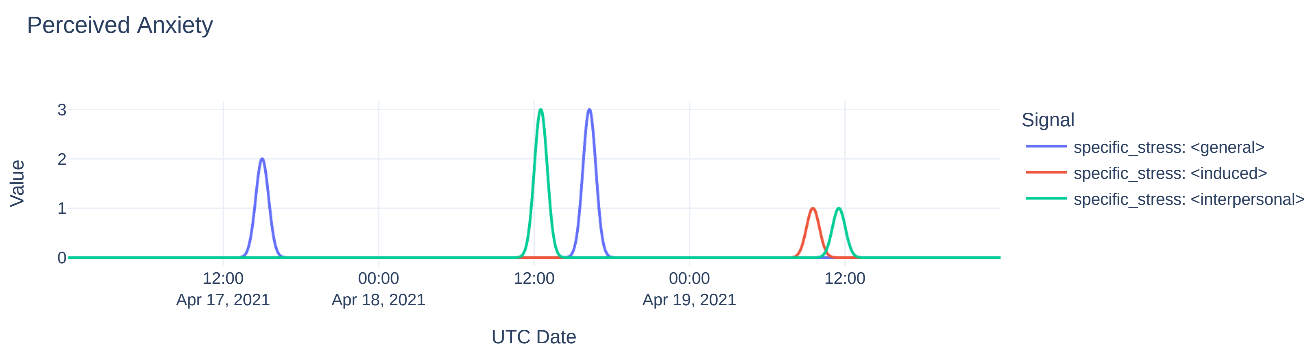

Fig. 4. Example: Anxiety levels - Subject trajectories through time

periods of time. Our results in this work demonstrate that such physiological features are very helpful in efficiently performing stress prediction. That being said, augmenting such a dataset with accurate personal information such as more thorough clinical assessments can lead to further improvements in performance.

3) Stress Types: Due to the small cardinality of our dataset, we focused on the task of predicting stressful versus non-stressful episodes (based on the definition given before). However, it is possible to categorize the reported stressful episodes into different types and look at each category separately (example groups are interpersonal, induced, and general stress). A larger dataset and additional features can pave the way for obtaining better insight into this domain, and to shed light on to what extent the features used in this work are statistically sufficient for distinguishing between such subtypes.

4) Dataset Size: Our dataset focused on a relatively small cohort of college students. Therefore, certain data biases such as skewness towards certain age groups can be expected. We posit that employing a larger dataset with more subjects across different groups and communities can circumvent such issues while using the same inference methodology. The codes for our framework are released for this purpose to help facilitate research in this domain.

VII. Conclusion

In this article, we proposed an end-to-end stress monitoring framework which covers steps from data acquisition to the inference-making pipeline. We conducted a proof-of-concept study on college students with military affiliations and empirically demonstrated the effectiveness of our remote monitoring technology for an accurate and scalable inference mechanism for recognition of perceived anxiety leveraging continuous monitoring data.

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