Towards Device Agnostic Detection of Stress and Craving in Patients with Substance Use Disorder

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Abstract

Novel technologies have great potential to improve the treatment of individuals with substance use disorder (SUD) and to reduce the current high rate of relapse (i.e. return to drug use). Wearable sensor-based systems that continuously measure physiology can provide information about behavior and opportunities for real-time interventions. We have previously developed an mHealth system which includes a wearable sensor, a mobile phone app, and a cloud-based server with embedded machine learning algorithms which detect stress and craving. The system functions as a just-in-time intervention tool to help patients de-escalate and as a tool for clinicians to tailor treatment based on stress and craving patterns observed. However, in our pilot work we found that to deploy the system to diverse socioeconomic populations and to increase usability, the system must be able to work efficiently with cost-effective and popular commercial wearable devices. To make the system device agnostic, methods to transform the data from a commercially available wearable for use in algorithms developed from research grade wearable sensor are proposed. The accuracy of these transformations in detecting stress and craving in individuals with SUD is further explored.

Keywords: Machine Learning, Substance Use Disorder, Wearable Computing, Stress, Drug Craving

1. Introduction

1.1. Wearable Sensor Applications in Substance Use Disorder

Substance use disorder (SUD) is defined as the repeated use of alcohol and/or drugs that causes significant impairment and negative health, social, and/or legal consequences (SAMHSA, 2022). The adverse outcomes of SUD pose a major public health problem with nearly 92,000 drug overdose deaths in the year 2020 alone (Volkow & Collins, 2017; Center for Disease Control and Prevention, 2022). Current treatment options for SUD rely on behavioral and pharmacological interventions. Some interventions are targeted toward managing high-risk states, such as episodes of drug **cravings** (strong desires to use a drug, specific for an individual's drug of choice (Sinha, 2001)) and **stress** (perception of a situation as harmful, threatening, or challenging (Tiffany & Wray, 2012)). Both stress and craving (which are related constructs) have been linked to poor outcomes in SUD treatment and increase rates of return to drug use (Sinha, 2009; Sinha, 2001; Tiffany & Wray, 2012).

Retrospective self-reporting provides a subjective estimate of when an individual experiences cravings or stress, however, it is unreliable and tedious. Ecological momentary assessment (EMA) involves collecting experiential data from individuals in near real time and in their natural environment in order to improve reporting efficacy and to diminish recall bias (Shiffman et al., 2008; Marciniak et al., 2020). Ecological momentary assessment can be used to identify risk states for individuals with SUD in the real world and deliver "just-in-time" and "just-in-space" interventions (Carreiro et al., 2020).

Recent advances in wearable sensor technology have

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resulted in a paradigm shift in healthcare monitoring (E. J. Wang et al., 2017; Y. Wang et al., 2022; Wu et al., 2021). Moving a step beyond EMA (which requires *active* participation), wearable technologies that can *passively* and non-invasively detect digital biomarkers of behavioral and physiological events in real-time have enabled clinicians to assess underlying medical conditions remotely. In the SUD treatment space, the ability to identify digital biomarkers of cravings and stress have the potential to revolutionize clinical care.

Remote monitoring of craving and stress experienced by patients with SUD provides crucial information during their recovery (Carreiro et al., 2020). Continuous monitoring of objective markers of craving and stress can help clinicians to provide appropriate just-in-time interventions to prevent these patients from return to drug use. In addition, such remote monitoring can help understand patterns of contextual information surrounding behavioral states (e.g. the time of day, social circumstances).

1.2. Previous Work

In our previous work (Carreiro et al., 2020), we conducted a pilot study to assess the acceptability and feasibility of using wearable sensor-based detection of stress and cravings in patients with SUD. Thirty individuals in treatment for SUD were asked to use a wearable sensor to continuously record physiologic data, and annotate self-reported episodes of stress and craving. The pilot study was conducted using a research grade device- the Empatica E4 (Empatica, Milan, Italy). The E4 provides tri-axial (3-axis) accelerometry, electrodermal activity, skin temperature, heart rate, and heart rate variability. The machine learning classifier models developed on E4 accelerometer data (MLE4) could differentiate stress from no-stress with an accuracy of 74.5% and craving from no-craving with an accuracy of 75.7% on a 10-fold cross validation data set. Adding additional features from electrodermal activity and heart rate provided a modest increase in accuracy of slightly more than 5% for each of the conditions. Thus, 3-axis accelerometer data was found to the most important data stream to detect stress and craving.

Based on data from the pilot study, an mHealth system was developed. The system, Realize Analyze Engage or RAE Health (ContinueYou, LLC) includes a mobile app that streams wearable sensor data via a Bluetooth connection and then transmits data to a secure cloud-based served where the MLE4 for stress and craving are embedded. If either stress or craving is detected, the user receives a mobile phone notification and is given an opportunity to engage in several de-escalation tools including mindfulness-based breathing exercises, journaling exercises, or a call for help for a support person. The RAE system also has a clinical portal to aggregate data, provide monitoring capabilities and provide actionable insight to treatment providers. The RAE systems (app and clinical portal) are HIPAA, HITECH Act, and CFR 42 part 2 compliant (Carreiro et al., 2021).

The E4 provided excellent data quality for the purposes of algorithm development. There were however several practical barriers noted during our pilot study with usage of a research grade device for a long term, real-world application, including:

- Lack of standard smart watch features: Wearing a research device on the wrist would interfere with devices normally worn by study participants, such as traditional watches and smart watches. Participants suggested adding additional features to the sensor, such as a clock and fitness tracking capability, in order to reduce the interruption that the sensor had on their daily activities (Carreiro, et. al, 2020) As an even more desirable alternative, study participants requested the system work with their own smartwatch of choice.
- Price-point: Due to its research grade nature, the E4 has a price value of more than 1500 US dollars, which makes this device inaccessible to the general population. In order to realistically reach the target population of individuals in SUD recovery, optimizing the platform to function with less expensive wearable sensors is necessary.
- Size and Aesthetic: To facilitate long-term wear, study participants indicated that a lower-profile sensor would be necessary. Study participants also had different aesthetic preferences, with some wanting more ”fashionable” and ornate devices while others wanted more neutral appearing devices. Because SUD recovery is a long-term process, it is critical that patients will comfortably wear the device long-term in order to maintain the operability of the stress and craving detection system, and having a variety of sensor options will be critical to achieve this goal.

Because of the reasons listed above, we sought to incorporate other devices with 3-axis accelerometry to increase options available to target end-users. Most wearable devices provide some form of accelerometer data, albeit formatted differently than that of a research grade device. Hence, to determine whether other cost effective, widely available, and light-weight wearable sensors can be used for the detection of stress and craving, experiments were performed with the Garmin Vìvosmart 4 (GV4), which fits these requirements.

1.3. Need for Data or Feature Transformations

Since the accelerometer data from E4 and the GV4 are formatted and recorded differently, the originally developed MLE4 algorithm cannot be directly used on alternate devices. Ideally, a new machine learning model would need to be trained on annotated data obtained from the alternate device. However, it is expensive and time consuming to repeat a previous experiment by recruiting new subjects using the original experiment protocol and using the GV4 instead of the E4, and thereby develop the machine learning models using the features derived from GV4 data. Furthermore, this would be impractical to do for every new compatible candidate device in order to make the platform more device agnostic.

To circumvent this problem, the process of developing an appropriate transformation of 3-axis accelerometer data can be obtained that can either map the raw GV4 accelerometer data to raw E4 accelerometer data, or map the features derived from GV4 data to the features derived from E4 data.

To verify the utility of these transformations, the performance of the following models with transformations were evaluated:

- MLE4 algorithm with raw data transformation applied (MLE4DT)
- MLE4 algorithm with derived feature transformation applied (MLE4FT)

The method to find appropriate transformations of raw data or derived features from a commercial device, such as the GV4, to a research-grade device, such as the E4, could be extended to any other devices where raw accelerometer data is accessible. By developing transformations for multiple devices, this approach will make the detection of stress and craving, using MLE4, device agnostic.

2. Methods

The study protocol has been previously described in Carreiro et al. (2020) and Carreiro et al. (2021). However, because of the propriety nature of the GV4 device, the data collection procedure is different from E4. The data analysis, feature selection, and machine learning training and testing procedures are kept as close as possible as the original work.

2.1. Study Protocol

The study protocol was approved by the institutional review board (IRB) at the University of Massachusetts Chan Medical School. Informed consent was obtained from all participants.

Prior to the actual experiments, a healthy volunteer was asked to wear both the E4 and GV4 on the non-dominant wrist for one hour while doing extraneous tasks. Tri-axial accelerometer data were collected from both devices and downloaded for deriving appropriate transformations.

For the experimental study, a convenience sample of 60 participants was recruited from outpatient SUD treatment recovery programs. Potential participants were identified by treatment providers, and those that opted to participate were enrolled by study staff during routine treatment visits. The inclusion criteria were: age 18 years or older, enrollment in an outpatient treatment program for SUD, ability to speak English, own a smartphone, and the ability to provide informed consent. Exclusion criteria included: physical inability to wear a wrist-mounted sensor (i.e. upper extremity amputation or fracture), prisoner status (including use of court-mandated tracking device), or pregnancy.

2.2. Wearable Sensor System

The wearable sensor used for the experiment is the commercially available Garmin Vìvosmart 4 (Garmin, Olathe, KS, USA), referred to as GV4. The GV4 can collect and stream data continuously via Bluetooth connection to a mobile app. The GV4 retails around 100 US dollars, which makes it a cost effective option.

The GV4 has a touch screen interface, up to 7 days of battery life, is waterproof, and also functions as a standard fitness tracker. The GV4 is equipped with a barometric altimeter, 3-axis accelerometer, heart rate monitor, and pulse oxygenation sensor. While users can easily download raw sensor data from the E4 using a web portal, such capability is not available for GV4 because of the propriety nature of the device. The data from GV4 is obtained using the RAE Health data acquisition system (developed by ContinueYou, LLC) (Carreiro et al., 2021).

2.3. Data Collection

Each participant was enrolled in the study for 30 consecutive days. During the enrollment visit, a training session to demonstrate the proper techniques for wearing, using, and charging the sensor was provided. Participants were also given a tutorial on how to operate the RAE app. Participants were then instructed to wear the GV4 on their non-dominant wrist at all times for the duration of the study period and to only remove the sensor for charging. Additionally, participants were instructed to keep the app open in the background of their phone to maintain pairing between the app and the sensor. When participants experienced a stress or craving, they were instructed to self-report this through the RAE mobile app.

Data collected by the GV4 was streamed via Bluetooth to the RAE app, which then stores data on the cloud-based server. Data are collected as five-minute segments. The E4 collects data continuously and can be obtained through a web portal developed by Empatica (Emaptica Connect).

Two sets of data were collected: *calibration data* and *annotated time series data*. Calibration data was a pair of time series data collected from both an E4 and a GV4 taken concurrently from a healthy individual with no prior history of SUD. Calibration data was used to find the transformations of raw data and derived features from GV4 to E4. Annotated time series data was the 3-axis accelerometer data, annotated with stress and craving timestamps designated by and collected from patients with SUD.

2.4. Feature Extraction

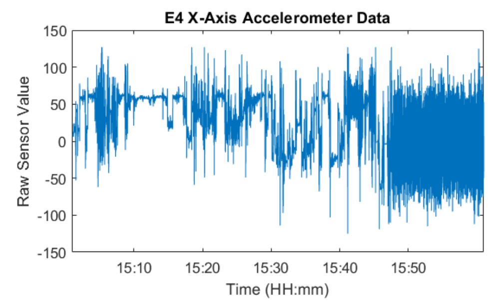
Features required for the original machine learning model (MLE4) were derived from the instantaneous amplitude of the 3-axis accelerometer data. Each five-minute segment of E4 data is subjected to the Hilbert transformation. This is a powerful technique in signal processing to estimate the amplitude instantaneously from rapidly fluctuating (non-stationary) data (Benitez et al., 2001; Hahn, 1996). The estimated amplitude corresponding to each axis was non-Gaussian. Thus, the instantaneous amplitude values were fitted to the gamma distribution characterized by the parameters: shape (S_h) and scale(S_c).

As features, the gamma distribution parameters: S_h and S_c were calculated in five-minute windows. Furthermore, the mean (M) and variance (V) of the sensor data for each five-minute window were calculated. In addition, the distance measure, $D_k = \sqrt{S_c^2 + S_h^2}$ was defined. Thus, for each segment, five characterizing parameters M, V, S_h, S_c and D_k were calculated for each axis. This yielded a total of fifteen features. The obtained features were cleaned by removing non-numeric values, empty values, values outside of physiologic range, and opcode values based on the software platform.

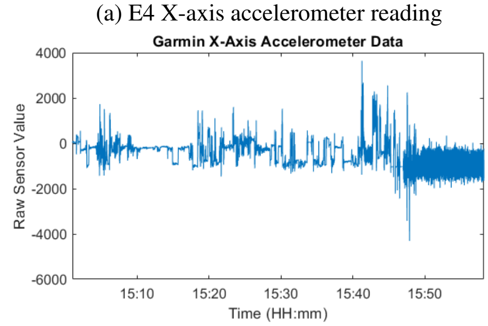
2.5. Calibration

For developing the data transformation, each segment of 3-axis accelerometer data from the GV4 is matched with the same time interval of continuously collected data from the E4. Thus, time matched five-minute segments were obtained from the GV4 as well as the E4.

2.5.1. Data Transformation To develop a transformation from the raw GV4 accelerometer data to the raw E4 accelerometer data format required by the MLE4 algorithm, the GV4 data had to be adjusted to match the same accelerometry unit scaling and axis positioning as the E4 data, due to the signal differences shown in Figures 1, 2, and 3.



(a) E4 X-axis accelerometer reading

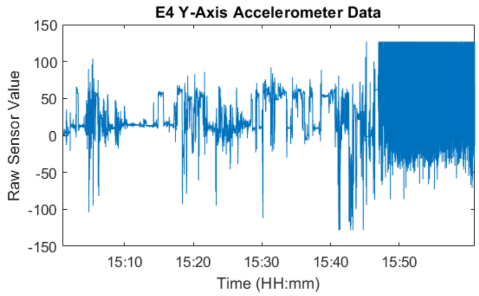


(b) GV4 X-axis accelerometer reading

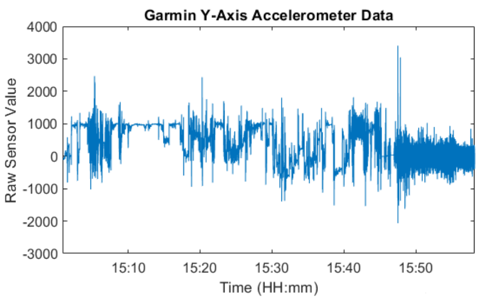
Figure 1: Accelerometer X-axis data comparison

Specifically, the raw E4 data values are signed 8-bit integers ranging from -128 to 127 representing an accelerometry range of -2g to 1.98g, while the GV4, whose raw data is recorded units of milli-gs, exceeds the E4 range. To correctly scale the GV4 data to the E4's scale, the milli-g units were converted to gs (divided by 1000), and any resulting value higher than 1.98gs or less than -2gs from the GV4 was capped to 1.98 or -2 respectively. Then, the values were multiplied by 64 and cast as integers to map to the -128 to 127 range of the E4.

Then, axial comparisons between each axis's data were performed to determine if like axes corresponded

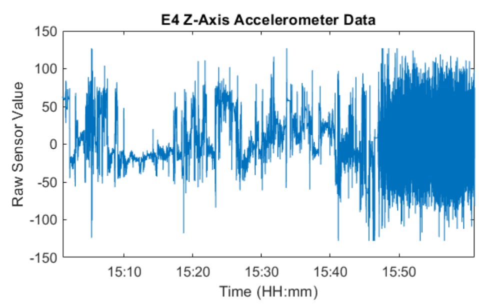


(a) E4 Y-axis accelerometer reading

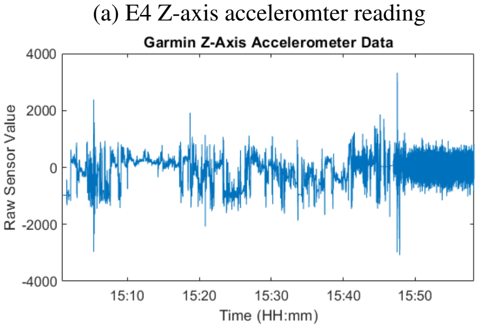


(b) GV4 Y-axis accelerometer reading

Figure 2: Accelerometer Y-axis data comparison



(a) E4 Z-axis accelerometer reading



(b) GV4 Z-axis accelerometer reading

Figure 3: Accelerometer Z-axis data comparison

to each other between the E4 and GV4 (i.e. determine if the X-axis of the E4 is the same axis position as the X-axis as the GV4). After inspection, the X axis of the E4 corresponded to the Y-axis of the GV4, the Y-axis of the E4 corresponded to an inverted X-axis of the GV4, and the Z-axis of the E4 corresponded to the inverted Z-axis of the GV4.

2.5.2. Feature Transformation On each of the fifteen features derived from the GV4 accelerometer data, linear regression was employed to find a linear mapping from GV4 features to E4 features. This mapping can be defined using equation 1.

$$Feature_{E4} = \alpha \times Feature_{GV4} + \beta \tag{1}$$

2.6. Testing of Machine Learning Models

For the model MLE4DT, the transformed raw data from the GV4 is used to derive the features. These features were used as input to the MLE4 model to detect stress and craving. Whereas for the model MLE4FT, the features are derived from raw GV4 data and then those features are transformed and used as an input to the MLE4 model. All data analysis was performed using MATLAB (version 2020b, MathWorks, Natick, MA).

To compare these transformations of the MLE4 model to a native implementation on GV4 devices, a new set of classifier models, MLGV4, was developed to distinguish between the following classes: craving vs. no craving, stress vs. no stress, and craving vs. stress. In all, twenty-five classification models were tested from the following categories: decision trees, discriminant analysis, logistic regression, naïve Bayes classifiers, support vector machines, nearest neighbor classifiers, and ensemble classifiers using the MATLAB classification learner app.

For these analyses, the data set was not split into a training set and testing set because of the limited amount of user-reported stress and craving instances (40 craving, 60 stress instances, and 100 baseline/no stress instances). Instead, to avoid over-fitting the model, the data set was subjected to 10-fold cross validation (separated into 10 folds, trained with nine folds, and tested on the other fold until each fold was used as a test set). Each classification algorithm was evaluated with the following standard metrics: sensitivity, specificity, accuracy, and area under the curve (AUC) of the receiver operating characteristic (ROC) curve.

3. Results

The performance of the original machine learning algorithm, which was developed using E4 sensor data, was studied with transformed data as well as transformed features of GV4. The three sets of machine learning models, MLE4 (original), MLE4DT (with GV4 data transformation), and MLE4FT (with GV4 feature transformation) were evaluated and compared using sensitivity, specificity, and accuracy metrics.

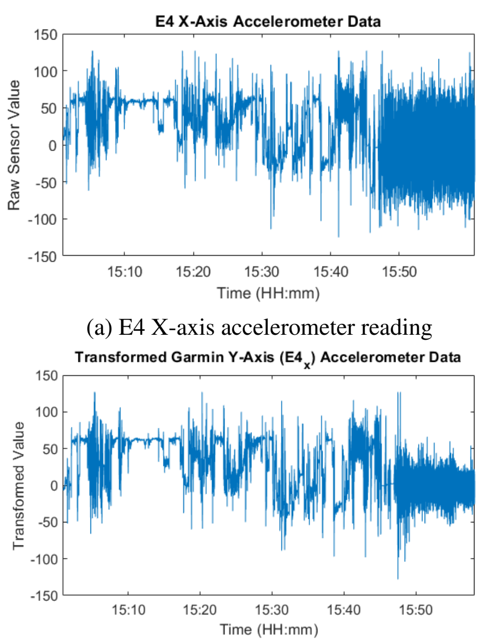
3.1. Data Transformation of GV4

Figures 1, 2, and 3 represent the GV4 3-axis accelerometer data from X, Y, and Z axes collected simultaneously with E4 data from a healthy individual. By applying the accelerometry unit scaling and axial comparisons between the E4 and GV4 data, the following per-axis raw data transformations were determined as outlined in Table 1.

Table 1: GV4 to E4 Per-Axis Data Transforms

E4 Axis	Data Transforms
$E4_x$	$0.064 * GV4_y$
$E4_y$	$-0.064 * GV4_x$
$E4_z$	$-0.064 * GV4_z$

Using these data transformations, the raw accelerometer data collected from GV4 devices was then able to be transformed to the E4 formatting for use in the MLE4 algorithm, as shown by the sample in Figure 4.



(a) E4 X-axis accelerometer reading

(b) Transformed GV4 Y-axis accelerometer reading

Figure 4: Transformed E4 X-axis data comparison

3.2. Feature Transformation of GV4

The original MLE4 algorithm requires fifteen features which were obtained from five characterizing parameters for each of the axis. These features from GV4 were transformed to E4 using a linear transformation defined by equation 1. The (α, β) values of each feature are shown in Table 2.

Table 2: Coefficients after Linear Transformation

Features	α	β
M_x	1.907703	8.044723
M_y	1.979138	-1.050642
M_z	2.000000	-4.000000
V_x	3.802909	14.763977
V_y	4.300000	-2.968212
V_z	3.250000	4.642617
S_h_x	0.900000	0.000000
S_h_y	0.900000	0.000000
S_h_z	0.840000	0.000000
S_c_x	2.150000	0.000000
S_c_y	2.150000	0.000000
S_c_z	2.000000	0.000000

Using these feature transformations, the features extracted from the raw accelerometer data collected from GV4 devices was then able to be fed to the original MLE4 algorithm.

3.3. GV4 Based Machine Learning

To provide a GV4 based comparison for the MLE4 transformations, a set of classifiers were trained to develop a new GV4 based algorithm (MLGV4) utilizing the same fifteen accelerometer data features as MLE4. The confusion matrices and ROC curves of the best classifiers developed for differentiating between stress, craving, and no stress are detailed below.

Using a Gaussian SVM for the craving vs. no craving analysis (CvNC), with craving set as the positive class, the sensitivity was 69.8% and the specificity was 72.1%. The AUC of the model's ROC was 0.74, and the model's accuracy was 71.0% (Figure 5).

Using an ensemble bagged tree classifier for the stress vs. no stress analysis (SvNS), with stress set as the positive class, the sensitivity was 76.0% and the specificity was 67.2%. The AUC of the model's ROC was 0.78, and the model's accuracy was 71.6% (Figure 6).

Using an ensemble bagged tree for the craving vs. stress analysis (CvS), with craving set as the positive

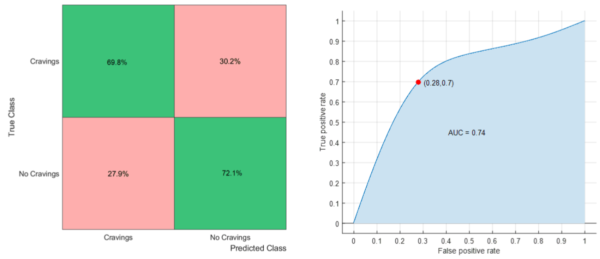


Figure 5: CvNC confusion matrix and ROC

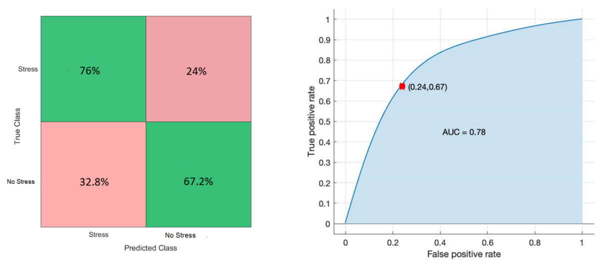


Figure 6: SvNS confusion matrix and ROC

class, the model had a sensitivity of 85.0% and a specificity of 55.0%. The model's AUC was 0.75, and its accuracy was 70.0% (Figure 7).

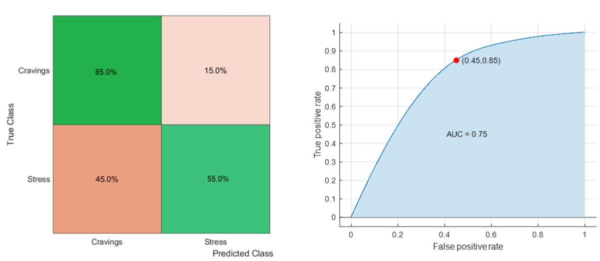


Figure 7: CvS confusion matrix and ROC

3.4. Model Performance Comparison

After obtaining the trained and tested machine learning model for GV4 data, the aggregated performance metrics of these models were compared with the metrics of the models that employed GV4 transformations. Table 3 provides the sensitivity, specificity, and accuracy of the MLE4DT and MLE4FT, along with the original MLE4 and the newly developed MLGV4 by considering the average of all three models (stress vs no stress, carving vs no craving, and stress vs craving) to account for the performance as a whole.

Table 3: Machine Learning Performance Metrics

Algorithm	Sensitivity	Specificity	Accuracy
MLE4	75.3%	76.0%	75.7%
MLE4DT	72.6%	71.8%	73.5%
MLE4FT	71.5%	72.6%	70.0%
MLGV4	76.9%	64.8%	70.9%

4. Discussion

In this work, we demonstrate that the data collected from the commercially available GV4 device can be employed for the detection of stress and craving in individuals with SUD. Our approaches, with data as well as feature transformations, provided an accuracy comparable to the original machine learning model developed with the FDA approved E4. The performance differences were minor for the small data samples tested, and these may be attributed to other inherent differences between the E4 and GV4, such as a difference in accelerometry sampling rates (32Hz for the E4 and 25Hz for the GV4) and data ranges, differences in susceptibility to signal noise, or sensitivity to specific types of motion by the different devices' accelerometers.

While the transformations derived in this research for the MLE4 model to use GV4 data are specific to GV4 devices, similar techniques can be employed to adapt the original algorithms to other commercial wearables. This allows for greater accessibility to the stress and craving detection capabilities of the MLE4 algorithm with little loss to its detection accuracy. Additionally, the utilization of commercial devices over a research grade device would increase accessibility (due to lower cost and ease of access).

The benefits of using a commercial sensor over a research grade sensor can also be viewed in terms of participant acceptability. Participants consistently report that they preferred consumer grade wearbles due familiarity and decreased concern for stigma. An important consideration for the RAE system is that it maintain user privacy by not be readily identifiable as related to SUD. Many research participants also report that they enjoy the interactive features of their own smart watches such as the step tracking and watch face functionalities. Moreover, the majority of participants stated that they would be willing to use the RAE app for a longer period of time if compatible with a commercial grade sensor.

By determining the data accuracy, cost feasibility, and participant acceptability of the GV4, data collection can be expanded to additional populations and tested more widely. Future work will include validating algorithms in a variety of popular off-the-shelf wearable sensors, evaluating end-user experiences with the RAE system coupled with commercially available devices, and clinical trials to evaluate the impact of the RAE system on key outcomes (clinical progress, quality of live, and economic impact).

5. Conclusion

The ability to apply transformations to data collected from a commercial wearable device for use in algorithms and tools developed for separate research-grade devices allow for higher user engagement, as well as time and cost savings for researchers. In this regard, access can be extended to intervention aiding tools, such as the MLE4 stress and craving detection algorithms, thereby benefiting a wider range of patients in SUD recovery while reducing device per-user cost of the intervention. Future research is needed to ensure the transformations can maintain algorithm performance in a larger population and to develop further transformations for other commercially available wearable devices.

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