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Assessment of the Stress Level with Help of "Smart Clothing" Sensors, HRV-Based Markers and Machine Learning Algorithms, Presented at the ECSA-10 †

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Abstract: Physiological stress in healthy subjects was assessed using heart rate (HR) monitored with help of Hexoskin smart garments. The HR was collected in daily life activity and in laboratory settings during stress tests. Heart rate variability parameters were computed and referenced with expert level of stress. The data were processed with help of Machine Learning Algorithms (Random Forest, CatBoost, XGB, LGBM, SVR). The Random Forest Regressor provided the best rate of correct entries (86%), and the CatBoost Regressor—the shortest time (2 ms) for assessment of the stress level.

Keywords: textile wearable sensors; machine learning; artificial intelligence; HRV; stress

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1. Introduction

Stress is a multisystem compensatory response of the body to external and internal stimuli (stressors) [1,2], and it evolved to preserve the constancy of its vital parameters, or homeostasis [1,2]. The response to stressors is represented by the intensification of metabolism due to changes in hormonal, autonomic, nervous and motor functions [1]. The reaction to stress is characterized by stages [1,2] and several levels of its intensity [3]. Despite its originally protective nature, stress can lead to functional "over taxation" [1] and dysregulation of stress-sensitive systems—nervous, cardiovascular, gastrointestinal, and immune [1,4]. Stress can significantly reduce such indicators of human well-being as working capacity, quality of life, personal capital, and social adaptation. Thus, instrumental assessment, control, prediction, and prevention of stress is recognized as critical scientific problem [1,5]. To address this problem, informative biosignal-based markers of stress must be identified [5].

2. Theory

Several groups of stress markers have been proposed, e.g., psychophysiological, autonomic, and cognitive, as well as blood and saliva tests for hormones [5–9]. The autonomic markers, e.g., skin sympathetic response, pupil response, and heart rate variability (HRV) attract growing attention [6,9–13]. For example, time- and frequency-domain parameters of HRV are promising for assessing the level of stress [9]. Nonlinear parameters (dimension and entropy) of HRV are increasingly being used to detect disorder of autonomic nervous system [13], what can be used to assess stress. Textile sensors ("smart clothing" technologies) are suitable for monitoring physiological functions in daily life mode. Typically, HRV, temperature, respiratory rate, skin sympathetic response, and motility are measured with textile sensors. The search for stress markers can be carried out with help of Machine Learning (ML) algorithms, which are especially well suited for nonlinear metrics [14]. In this study, we aimed to assess the stress level with HRV markers in healthy individuals in their daily activities using HRV parameters obtained from smart clothing sensors, and treated with ML algorithm technologies. The Hexoskin Smart Shirt was chosen for smart clothing because there are reports that it provides reliable HR signal [15,16].

3. Experimental

3.1. Subjects and Protocol

19 practically healthy subjects, aged 19 to 55 years, volunteered to participate in the study. All subjects signed their informed consent before the study. The study protocol was approved by joint Ethic committee of the Ministry of Health care of the Republic of Karelia and Petrozavodsk State University (No. 30, 16 June 2014). The whole study was conducted within the time period November 2021–January 2022, in the city of Petrozavodsk (Republic of Karelia, Russia). The study was conducted in two settings. In the laboratory (15 subjects), three conventional tests were used to induce stress: (1) reaction time tests (simple and choice reaction time, manual target interception) (detailed in [17]), (2) physical exercise (3 min of pedaling on an ergometer with growing load [7]), (3) cold press test (CPT) [7] (3-min immersion of a hand in ice water at 3–4 °C, detailed in [18]). Rest, "without stress", conditions were used for comparisons. A total of 10 different conditions were applied, in a mixed order, within two or three individual days. The HR data was obtained either with laboratory instruments (VNS-Spectr, Neirosoft, Ivanovo, Russia) or Hexoskin Smart Shirt.

In field conditions, eight subjects practiced their daily life activities (25 individual measurements), which included walking in- and outdoors, mental activities (PC- and Internet-based, sitting, phone calling), taking meals (including coffee), sleeping, visiting a fitness center, driving a car, visiting a dental clinic, etc. All subjects were making records of their activity in a form, with 15-min intervals. In different trials, measurement lasted 2 to 12 h, depending on the will of a subject. The data was collected only with Hexoskin Smart Shirt.

Momentarily perceived stress was assessed with visual analogue scale (VAS) [4,7,19]. In VAS, the left end (value "1") corresponded to "no stress at all" condition and the right end (value "10"—to maximal "perceived stress"). The VAS was administered at each of the 10 experimental conditions. In field conditions, subjects marked the level of their momentarily perceived stress with VAS every 15 min.

3.2. Data Acquisition with Smart Clothes

HR was collected by the Hexoskin Smart Shirt (Hexoskin Smart Sensors & AI, Montreal, QC, Canada). It was put on the subject according to instructions, and connected to the logger. After the experiment, data was uploaded into the HxServices (v.4.05) software (Figure 1).

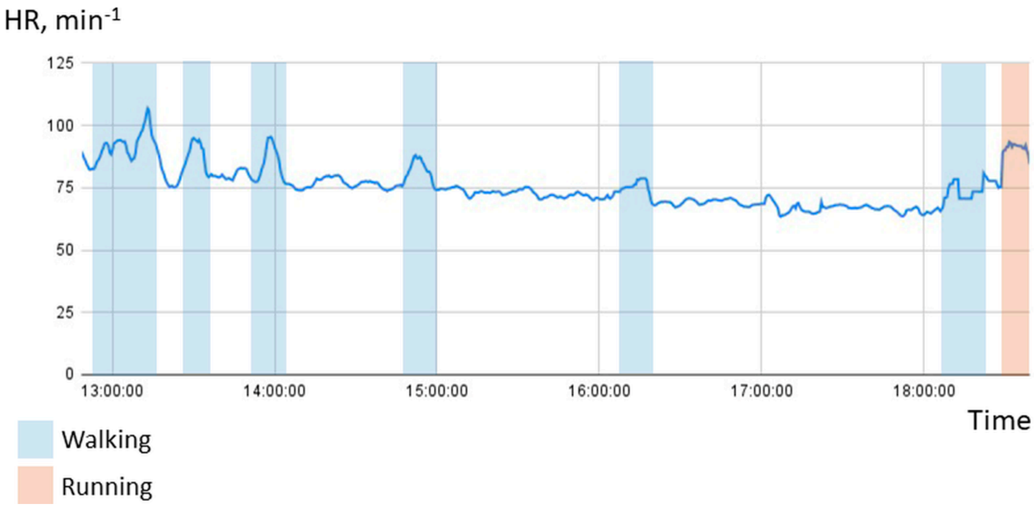

Figure 1. A representative HR signal recorded with Hexoskin Smart Shirt in field conditions.

3.3. HR Data Processing

Hexoskin Smart Shirt provides a wav sound file. This format is convenient for processing in terms of ready-made libraries of the Python language. To extract signal peaks from a wav file, the ecg_peaks function of the neurokit2 library [20] was used. With a known value of the pulse frequency (for HxS it is 256 Hz), the value of the time between the peaks was computed, which allowed calculating the values of the intervals between neighboring R waves (RR interval, RRi). The resulting data set of RRi was filtered with cutoff HR values < 45 and >180 beat per min. After that, each time series of a trial was subdivided into 3-min serial segments. Then, HRV parameters were calculated for each of the segments with help of the pyHRV toolbox [21]. Each segment was labeled with the expert level of perceived stress marked by individual subjects with VAS, in one dimension.

The time-domain HRV parameters included HR (hr_mean), standard deviation (sdnn), root mean squared difference (rmssd), and proportion of successive intervals greater than 50 ms (pnn50) of normal RR intervals (nni). The frequency-domain HRV parameters included the total power spectrum of RRi (fft_total), power spectrum at very low (vlf; <0.04 Hz), low (lf; 0.04–0.15 Hz), and high frequency bands (hf; 0.15–0.40 Hz), and spectrum structure (vlf_pct, lf_pct, hf_pct, lf_nu, hf_nu). Nonlinear parameters included sample (sampen) and approximate entropy (apen), and sd1 and sd2 of the Poincare plot.

Altogether, 11,570 segments were available in the data set for analysis. Table 1 shows the distribution of the number of records corresponding to 10 different levels of stress. Of 11,570 segments over 53% segments had the stress level "2", 17%—the level "3", with further systematic decrement to levels "7–9" (some 1%) and 10 (0%). Of the whole data set, 75% segments were randomly assigned to the "training" set, and remaining 25%—to the "test" set (Table 1).

Table 1. Distribution of segments among the data sets and their reference to the level stress.

Stress Level	Number of Segments	Number of Segments in the Training Set	Number of Segments in the Test Set
1	577	433	144
2	6225	4669	1556
3	2051	1538	513
4	1140	855	285
5	584	438	146
6	530	397	133
7	155	116	39

8	184	138	46
9	124	93	31
10	0	0	0
Total number of records	11570	8677	2893

The calculated parameters were checked for correlation. In the matrix in Figure 2, there is a strong correlation dependence for some pairs of features, which necessitates the selection of significant features. For the regression model for predicting the level of stress, the final set of features was formed from 11 features: pnn50, nni_mean, hr_mean, sd1, sd2, sampen, lf_pct, hf, lf, vlf, hf_pct. The CatBoost Regressor with the random_state = 42 parameter was used as the regression algorithm. The rest of the algorithm parameters had default values.

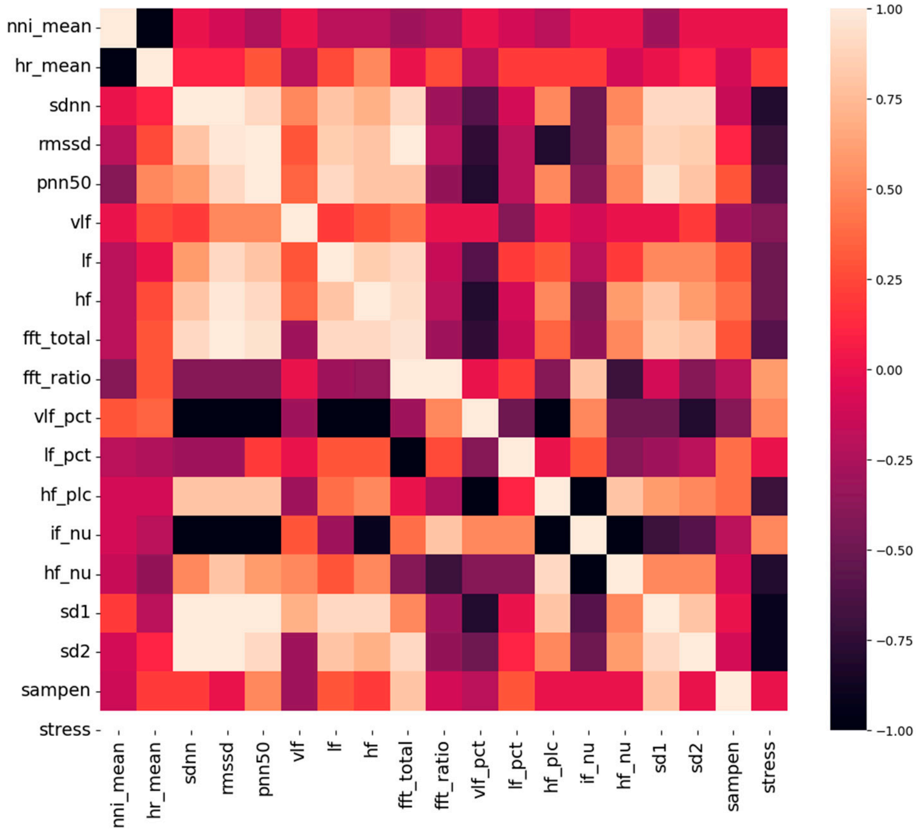

Figure 2. Correlation of features in the data set with the original set of features.

To reduce the dimension of the input data and the error metrics, the following algorithm for selecting significant features was developed:

- The CatBoost Regressor model was trained on data containing all available features.
- Using the get_feature_importance method from the CatBoost library [22] for the Python language, we obtain an array of feature significance scores for the model, the score values are sorted in descending order.
- An empty current feature set, an empty final feature set, and a minimum mean absolute error (MAE) are initialized, which is initially set to infinity.
- The model is iteratively trained and tested on fixed training and test sets.
- The next feature is added to the current set of features in descending order of significance for the model.
- The model is trained on the current set of features; MAE is calculated on the test set of records with the current set of features.

If the obtained MAE value is less than the current minimum MAE value, then the considered feature is stored in the final feature set, and the minimum MAE value becomes equal to the current one, otherwise the considered feature is not stored in the final feature set.

For the regression model for predicting the level of stress, the final set of features was formed from 11 features: pnn50, nni_mean, hr_mean, sd1, sd2, sampen, lf_pct, hf, lf, vlf, hf_pct. The test was carried out for five types of modes: Random Forestv Regressor, CatBoost Regressor, XGBoost Regressor, LightGBM Regressor, and Support Vector Regressor.

4. Results

The final outcome is presented in Table 2. As can be seen from the Table 2, Random Forest Regressor algorithm provided the highest % of correct entries (86.3%). From the other hand, the shortest execution time was produced by the CatBoost Regressor algorithm, which was the second best in terms of correct entries.

Table 2. Stress level regression quality metrics provided by different algorithms.

Method	MAE	R^2	Target Variable Prediction Time for One Record, ms	Number of Correct Entries, %
RandomForestRegressor (random_state = 42)	0.0018	0.9992	8.48	86.3
CatBoostRegressor (random_state = 42	0.0822	0.975	2.02	85.3
XGBRegressor (random_state = 42)	0.0837	0.9719	4.63	80.1
LGBMRegressor (random_state = 42)	0.1628	0.9044	1.97	82.9
SVR(kernel = «rbf»)	0.3913	0.4503	29.93	64.1

5. Conclusions

In conclusion, given the quality of the outcome and prediction time value, the CatBoost Regressor algorithm can be regarded as the reliable algorithm for the assessment of the stress level with HRV parameters obtained with a “smart clothing” device. We also conclude that 85–86% rates of correct entries (correct linking of HRV parameters to the level of stress) looks promising. Still, one sound limitation can be identified to the study. Namely, the diversity of the level of stress was not high enough in this study, as more than 70% segments were referenced to the stress level 2–3, which means “low stress”. In future studies, longer periods of HR monitoring with textile sensors would be reliable.

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Data Availability Statement: The datasets generated for this study are available on request to the corresponding author.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. Anisman, H.; Merali, Z. Understanding Stress: Characteristics and Caveats. *Alcohol Res. Health* **1999**, *23*, 241–249.
2. Cohen, S.; Gianaros, P.J.; Manuck, S.B. A Stage Model of Stress and Disease. *Perspect. Psychol. Sci.* **2016**, *11*, 456–463. https://doi.org/10.1177/1745691616646305.
3. Allen, A.P.; Kennedy, P.J.; Cryan, J.F.; Dinan, T.G.; Clarke, G. Biological and psychological markers of stress in humans: Focus on the Trier Social Stress Test. *Neurosci. Biobehav. Rev.* **2014**, *38*, 94–124. https://doi.org/10.1016/j.neubiorev.2013.11.005.
4. LeMoult, J.; Battaglini, A.M.; Grocott, B.; Jopling, E.; Rnic, K.; Yang, L. Advances in stress and depression research. *Curr. Opin. Psychiatry* **2023**, *36*, 8–13. https://doi.org/10.1097/yco.0000000000000831.
5. Han, H.J.; Labbaf, S.; Borelli, J.L.; Dutt, N.; Rahmani, A.M. Objective stress monitoring based on wearable sensors in everyday settings. *J. Med. Eng. Technol.* **2020**, *44*, 177–189. https://doi.org/10.1080/03091902.2020.1759707.
6. Zontone, P.; Affanni, A.; Piras, A.; Rinaldo, R. Exploring Physiological Signal Responses to Traffic-Related Stress in Simulated Driving. *Sensors* **2022**, *22*, 939. https://doi.org/10.3390/s22030939.
7. Skoluda, N.; Strahler, J.; Schlotz, W.; Niederberger, L.; Marques, S.; Fischer, S.; Thoma, M.V.; Spoerri, C.; Ehlert, U.; Nater, U.M. Intra-individual psychological and physiological responses to acute laboratory stressors of different intensity. *Psychoneuroendocrinology* **2015**, *51*, 227–236. https://doi.org/10.1016/j.psyneuen.2014.10.002.
8. Smets, E.; De Raedt, W.; Van Hoof, C. Into the Wild: The Challenges of Physiological Stress Detection in Laboratory and Ambulatory Settings. *IEEE J. Biomed. Health Inform.* **2019**, *23*, 463–473. https://doi.org/10.1109/jbhi.2018.2883751.
9. Chen, S.; Xu, K.; Zheng, X.; Li, J.; Fan, B.; Yao, X.; Li, Z. Linear and nonlinear analyses of normal and fatigue heart rate variability signals for miners in high-altitude and cold areas. *Comput. Methods Programs Biomed.* **2020**, *196*, 105667. https://doi.org/10.1016/j.cmpb.2020.105667.
10. Manser, P.; Thalmann, M.; Adcock, M.; Knols, R.H.; de Bruin, E.D. Can Reactivity of Heart Rate Variability Be a Potential Biomarker and Monitoring Tool to Promote Healthy Aging? A Systematic Review with Meta-Analyses. *Front. Physiol.* **2021**, *12*, 686129. https://doi.org/10.3389/fphys.2021.686129.
11. Pham, T.; Lau, Z.J.; Chen, S.H.A.; Makowski, D. Heart Rate Variability in Psychology: A Review of HRV Indices and an Analysis Tutorial. *Sensors* **2021**, *21*, 3998. https://doi.org/10.3390/s21123998.
12. von Rosenberg, W.; Chanwimalueang, T.; Adjei, T.; Jaffer, U.; Goverdovsky, V.; Mandic, D.P. Resolving Ambiguities in the LF/HF Ratio: LF-HF Scatter Plots for the Categorization of Mental and Physical Stress from HRV. *Front. Physiol.* **2017**, *8*, 360. https://doi.org/10.3389/fphys.2017.00360.
13. Gerasimova-Meigal, L.; Meigal, A.; Sireneva, N.; Saenko, I. Autonomic Function in Parkinson's Disease Subjects Across Repeated Short-Term Dry Immersion: Evidence From Linear and Non-linear HRV Parameters. *Front. Physiol.* **2021**, *12*, 712365. https://doi.org/10.3389/fphys.2021.712365.
14. Hill, J.R.; Caldwell, B.S. Assessment of Physiological Responses During Field Science Task Performance: Feasibility and Future Needs. *Front. Physiol.* **2022**, *13*, 779873. https://doi.org/10.3389/fphys.2022.779873.
15. Haddad, M.; Hermassi, S.; Aganovic, Z.; Dalansi, F.; Kharbach, M.; Mohamed, A.O.; Bibi, K.W. Ecological Validation and Reliability of Hexoskin Wearable Body Metrics Tool in Measuring Pre-exercise and Peak Heart Rate During Shuttle Run Test in Professional Handball Players. *Front. Physiol.* **2020**, *11*, 957. https://doi.org/10.3389/fphys.2020.00957.
16. Keogh, A.; Dorn, J.F.; Walsh, L.; Calvo, F.; Caulfield, B. Comparing the Usability and Acceptability of Wearable Sensors Among Older Irish Adults in a Real-World Context: Observational Study. *JMIR mHealth uHealth* **2020**, *8*, e15704. https://doi.org/10.2196/15704.
17. Meigal, A.Y.; Tretjakova, O.G.; Gerasimova-Meigal, L.I.; Sayenko, I.V. Program of Seven 45-min Dry Immersion Sessions Improves Choice Reaction Time in Parkinson's Disease. *Front. Physiol.* **2021**, *11*, 621198. https://doi.org/10.3389/fphys.2020.621198.
18. Gerasimova-Meigal, L.I.; Sirenev, I.M. Cold-induced reactivity in multiple sclerosis patients. *Patol. Fiziol. Eksperimental'naya Ter. (Pathol. Physiol. Exp. Ther.)* **2017**, *61*, 56–62. https://doi.org/10.25557/0031-2991.2017.03.56-62.
19. Lesage, F.X.; Berjot, S. Validity of occupational stress assessment using a visual analogue scale. *Occup. Med.* **2011**, *61*, 434–436. https://doi.org/10.1093/occmed/kqr037.
20. Makowski, D.; Pham, T.; Lau, Z.J.; Brammer, J.C.; Lespinasse, F.; Pham, H.; Schölzel, C.; Chen, S.H.A. NeuroKit2: A Python toolbox for neurophysiological signal processing. *Behav. Res. Methods* **2021**, *53*, 1689–1696. https://doi.org/10.3758/s13428-020-01516-y.
21. Gomes, P., Margaritoff, P. and da Silva, H.P. pyHRV: Development and evaluation of an open-source python toolbox for heart rate variability (HRV). In Proceedings of the International Conference on Electrical, Electronic and Computing Engineering (IcETRAN), Veliko Gradište, Serbia, 3–6 June 2019; pp. 822–828.

22. Hancock, J.T.; Khoshgoftaar, T.M. CatBoost for big data: An interdisciplinary review. *J. Big Data* **2020**, *7*, 94. https://doi.org/10.1186/s40537-020-00369-8.