# *Towards a Minimalistic Stress Classification Method based on HRV*

Roswitha Duwenbeck
Systeme der Medizintechnik
Universität Duisburg-Essen
Duisburg, Germany
E-Mail: roswitha.kressner@uni-due.de

Elsa Andrea Kirchner
Systeme der Medizintechnik & Robotics Innovation Center
Universität Duisburg-Essen & German Research Center for Artificial Intelligence
Duisburg, Germany & Bremen, Germany
E-Mail: elsa.kirchner@uni-due.de & elsa.kirchner@dfki.de



Open-Minded

Résumé of the presenter

# Roswitha Duwenbeck

- Since 2022: Scientific Assistant at University Duisburg-Essen
  - Chair: Medical technology systems
  - Research Project: „AudEeKA“ → Emotion recognition in humans with biophysiological signals
  - Other Pojects: Development of mobile Applications for Healthcare (Fields: Addiction, Fetal Alcohol Syndrome Disorder, Melanoma detection)
- 2017-2022: B.Sc. and M.Sc. in Medical Technology
  - Focus on programming and artificial intelligence

# AudEeKA

- Goal: Lightweight Emotion recognition in humans
- Combine Emotion detection from multiple sources with stress detection
  - Auditory
  - Biophysiological Signals (Heart Rate Variability, Breathing Rate, Skin Temperature…)
- Use cases: (Long time) space travel, Healthcare (remote, direct)
- Preferably needing little resources (processing power, energy), use cases set restrictions and requirements
  - Additional difficulties:
    - Computation must be fast and exact
    - Possible groups of end users are a very heterogenous group of people
    - Wide range of noise probable
- To tackle issue of heterogenous users: apply continuous learning

AudEeKA: First Demonstrator
Source: Own image

# What is Stress in humans?

- Well-known definition by Hans Seyle: ”Stress is the non-specific response of the body to any demand” [1]
- Different Types of Stress, subdivision possible by nature of cause, for example physical and psychological [2], [3]:

| | **Physical Stress** | **Psychological Stress** |
|---|---|---|
| Cause | Physical strain, Pain | High cognitive requirements in a task, Social situations, Life events |
| Similar Effects | Changes in Blood Pressure [4]/Heightened (Nor-) Epinephrine secretion [5], Sweating [6], Changed Breathing Rate [7], Dry Mouth/mucosal Disease/Halitosis [8] | |
| Different Effects | harm of the nervous, musculoskeletal, respiratory, cardiovascular, gastro-intestinal, reproductive, or other systems [9] | luminal permeability [10], differences in corticosterone serum-levels [11] |

# State of the Art

- Stress detection: not a new in the area of machine learning (ML)
- Many existing approaches with already good accuracy and more than just a binary classification problem

| Paper | Signals | ML-Methods | Best Results |
|---|---|---|---|
| [12] | HR, EDA, IBI, ST, Acceleration | LDA, SVM, kNN, LR, **RF**, MLP | Accuracy of 97.92% |
| [13] | ECG (HRV) | Minimum Distance Classifier | Accuracy of 89.92% |
| [14] | ECG, TEMP, RESP, EMG,EDA | kNN, LDA, **RF**, AB, SVM | Accuracy of 84.17% |
| [15] | ECG (HRV) | kNN, SVM, MLP, RF, **GB** | F1 of 79% |
| [16] | ECG (HRV) | SVM, MLP, IBK, **DT**, LDA | Accuracy of 94% |

*Abbreviations:*

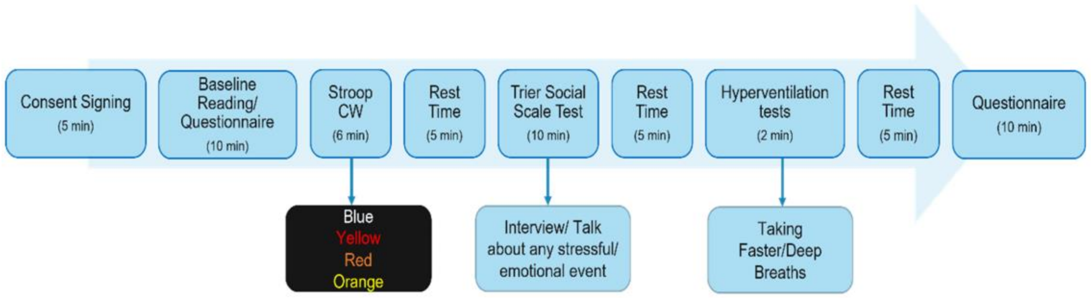
HR – Heart Rate
EDA – Electrodermal Activity
IBI – Inter Beat Interval
ST – Skin Temperature
ECG – Electrocardiogram
HRV – Heart Rate Variability
TEMP – Temperature
RESP – Respiration Rate
EMG – Electromyography
EDA – Electrodermal Activity

SVM – Support Vector Machine
kNN – k Nearest Neighbours
LR – Linear Regression
MLP – Multilayer Perceptron
RF – Random Forest
AB – AdaBoost
GB – Gradient Boosting
DT – Decision Tree
IBK – Neighbour Search
LDA – Linear Discriminant Analysis

# The Stress-Predict Dataset

- Relatively new (2022), to the authors knowledge not used before to detect stress solely from Heart Rate Variability Features
- Physiological changes were measured by an E4 watch from Empatica (PPG)
- PPG Signal was used to derive Blood Volume Pulse, Heart Rate, Inter Beat Interval and Respiration Rate

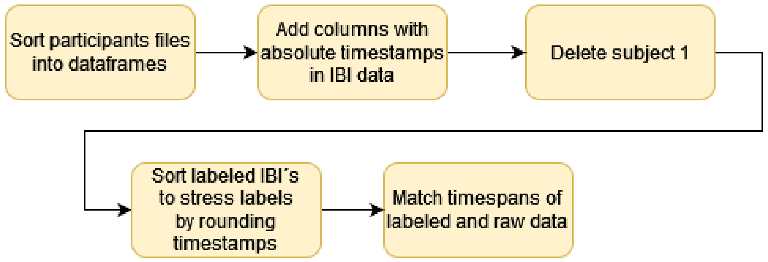
[17]




Source: [17]

# Preparation of the dataset and preprocessing

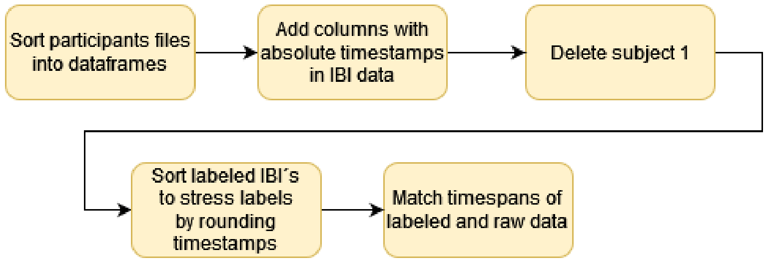
- Dataset was not mainly composed to detect stress from HRV-Features, but from HR and RESP
- Original Data: processed data folder and raw data folder
- First folder contains list, with merged patient label, Heart Rate, Respiration Rate a stress-label and a **timestamp for every second**, given in milliseconds with one decimal place
- Raw data contains separate lists of the physiological signals with the **passed time since the start**, given in milliseconds with 6 decimal places, and the starting time of the experiment in milliseconds as header, for every subject
- Goal: Assign Labels to the Inter Beat Intervals




Source: Own Image

# Preparation of the dataset and preprocessing

1. Sorted Subjects Data in Data frames
2. Sorting labels to IBI´s: Added new column for the absolute passed time since start, as given in the processed file, filled with iterative addition of the start- and passed time
3. Processed data which could not be associated to any IBI data was deleted
4. Labeled data was sorted to each IBI by rounding the IBI-times: Each raw timestamp, given in milliseconds, was rounded to match a processed timestamp
5. Matched timespans of labeled and raw data: processed data is timewise longer than the raw IBI data. Processed data which could not be associated to any IBI data was deleted




Source: Own Image

# The Features

- Features were extracted from 60 second windows, which had more than 30 IBI´s
- Library used: pyhrv [18]
- Time Domain Features
  - NN-Parameters (Counter, Mean, Minimum, Maximum, Differences, Standard Deviation, Average, Root Mean Square, Number of Pairs that differ by more than 50 (NN50) or 20 (NN20) milliseconds, Proportion of NN50 and NN20 divided by total number of NN (pNN50, pNN20)
- Frequency Domain Features
  - Used Welch´s Power Density Spectrum
  - Absolute powers of the very low (0.00Hz - 0.04Hz), low (0.04Hz - 0.15Hz) and high frequency (0.15Hz - 0.40Hz) band was used.
  - Total power of all frequency bands and the ratio of the power of the low and high frequency bands
- Non-linear Features
  - SD1 and SD2, which are the Standard Deviation of the data series along the minor axis and the major axis of the Poincaré-Plot

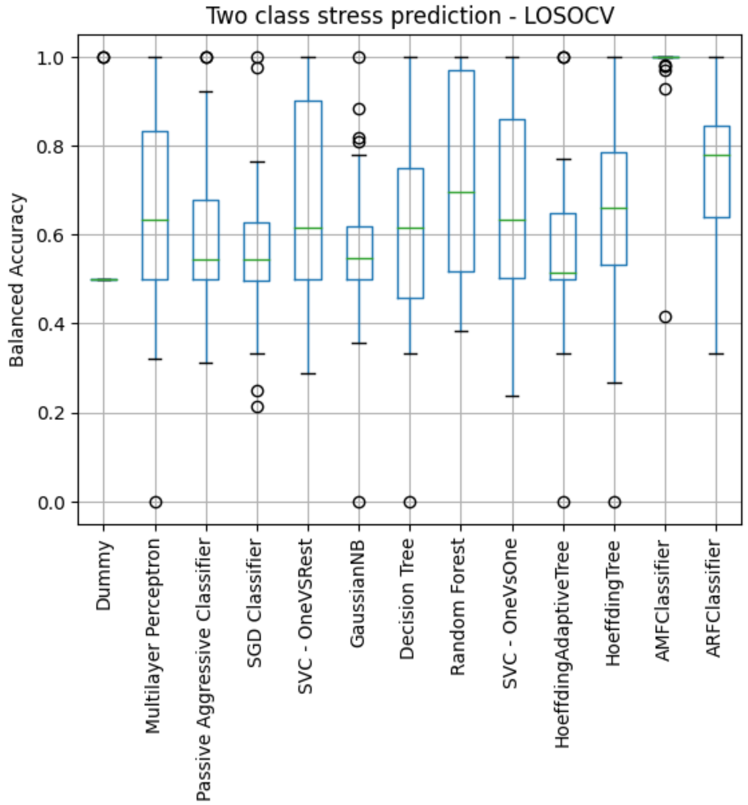
# ML-Methods and Learning

- Data was balanced with Synthetic Minority Oversampling and scaled with a Standard-Scaler
- First nine are taken from Scikit-Learn [19]
- Last four are from River [20]
- Leave One Subject Out Crossvalidation

| Classifier | Parameters |
|---|---|
| Dummy Classifier | strategy = most frequent |
| Multi Layer Perceptron | max_iter=45, hidden_layers=45, 20, batch_size=15 |
| Passive Aggressive Classifier | C=0.0, fit_intercept=False, early_stop=True, max_iter=50 |
| SGD Classifier | penalty='l2', alpha=0.01, max_iter=100, eta0=0.1, epsilon=0.01, early_stop=True |
| Support Vector Machine One Vs. Rest | C=100.0, degree=10 |
| Gaussian Naive Bayes | All standard |
| Decision Tree | criterion=entropy |
| Random Forest | All standard |
| Support Vector Machine One Vs. One | C=100.0, degree=10 |
| Hoeffding Adaptive Tree | grace_period=100, delta=1e-5, seed=0 leaf_prediction='nb', nb_threshold=10 |
| Hoeffding Tree | grace_period=100, delta=1e-5, binary_split=True |
| Aggregated Mondrian Forest | n_estimators=5, seed=45 |
| Adaptive Random Forest | n_models=7, seed=45 |

Source: Own image

# Experimental Results




Source: Own Image

UNIVERSITÄT DUISBURG ESSEN
Open-Minded

# Conclusion and Future Work

- AMF was able to classify ”No Stress” and ”Stress” very good
- Performance still has to be investigated
- Incorrect infusion of the output label in the testing data has been ruled out
- Future Tasks:
  - Test the same classifiers on a different dataset (Maybe MIT Drive DB [21])
  - Investigate more than one time window, because different window lengths seem to result in varying accuracies
  - Individual baseline
  - Hyperparameter Tuning
  - Distinguish between the causes for stress, psychological or physical

# References

[1] H. Seyle, Stress in health and disease, Butterworth-Heinemann, p. 15, 2013

[2] Y. Li, J. Qin, J. Yan, N. Zhang, Y. Xu, Y. Zhu, L. Sheng, X. Zhu and S. Ju, “Differences of physical vs. psychological stress: evidences from glucocorticoid receptor expression, hippocampal subfields injury, and behavioral abnormalities,” Brain Imaging And Behavior, vol. 13, pp. 1780-1788, 2019.

[3] S. Rao, R. Hatfield, J. Suls and M. Chamberlain, “Psychological and physical stress induce differential effects on human colonic motility,” The American Journal Of Gastroenterology, vol. 93, pp. 985-990, 1998.

[4] M. Trapp et al., “Impact of mental and physical stress on blood pressure and pulse pressure under normobaric versus hypoxic conditions,“ PLoS One, 9.5, p. e89005, 2014.

[5] I.J. Kopin, G. Eisenhofer and D. Goldstein, “Sympathoadrenal Medullary System and Stress,” Advances in Experimental Medicine and Biology: Mechanisms of Physical and Emotional Stress, vol.245, Springer Science & Business Media, p. 18, 1988.

[6]T. Kamei, T. Tsuda, S. Kitagawa, K. Naitoh, K. Nakashima, T. Ohhashi, “Physical stimuli and emotional stress-induced sweat secretions in the human palm and forehead,” Analytica Chimica Acta, Vol. 365, Issues 1-3, pp. 319-326, 1998.

[7] T. Iqbal, A. Elahi, Sn. Ganly, W. Wijns, A. Shahazad, “Photoplethysmography-Based Respiratory Rate Estimation Algorithm for Health Monitoring Applications,” Journal of Medical and Biological Engineering, Vol. 42, pp.242-252, 2022.

[8] M.H. Hong, “Impact of physical stress symptoms and psycho-emotional stress symptoms on oral health in adults,” Journal of the Korean Academie-Industrial cooperation Society, Vol. 15, Issue 3, pp. 1663-1670, 2014.

[9] K. Hong, “Classification of emotional stress and physical stress using a multispectral based deep feature extraction model,” Scientific Reports, vol. 13, p. 2693, 2023, doi: 10.1038/s41598-023-29903-3.

[10] J. Soederholm and M. Perdue, “II. Stress and intestinal barrier function,” American Journal Of Physiology-Gastrointestinal And Liver Physiology, vol. 280, G7-G13, 2001, doi: 10.1152/ajpgi.2001.280.1.G7.

[11] A. Kavushansk, D. Ben-Shachar, G. Richter-Levin and E. Klein, “Physical stress differs from psychosocial stress in the pattern and timecourse of behavioral responses, serum corticosterone and expression of plasticity-related genes in the rat,” Stress, vol. 12, pp. 412-425, 2009.

[12] Y. Can, N. Chalabianloo, D. Ekiz and C. Ersoy, “Continuous Stress Detection Using Wearable Sensors in Real Life: Algorithmic Programming Contest Case Study,” Sensors, vol. 19, p. 1849, Aug. 2019.

[13] R. Costin, C. Rotariu and A. Pasarica, “Mental stress detection using heart rate variability and morphologic variability of EeG signals,” 2012 International Conference And Exposition On Electrical And Power Engineering, pp. 591-596, 2012.

[14] R. Garg, J. Santhosh, A. Dengel and S. Ishimaru, “Stress detection by machine learning and wearable sensors,” The 26th International Conference On Intelligent User Interfaces-Companion, pp. 43-45, April 2021, doi: 10.1145/3397482.3450732

[15] K. Dalmeida and G. Masala, “HRV features as viable physiological markers for stress detection using wearable devices,” in Sensors, vol. 21, p. 2873, 2021, doi: 10.3390/s21082873.

[16] R. Castaldo, L. Montesinos, P. Melillo, C. James and L. Pecchia, “Ultrashort term HRV features as surrogates of short term HRV: A case study on mental stress detection in real life,” BMC Medical Informatics And Decision Making, vol. 19, pp. 1-13, 2019.

[17] T. Iqbal, A. Simpkin, D. Roshan, N. Glynn, J. Killilea, J. Walsh, G. Molloy, S. Ganly, H. Ryman, E. Coen, A. Elahi, W. Wijns and A. Shahzad, “Stress Monitoring Using Wearable Sensors: A Pilot Study and Stress-Predict Dataset,” Sensors, vol. 22, p. 8135, 2022.

[18] P. Gomes, P. Margaritoff and H. Silva, “pyHRV: Development and evaluation of an open-source python toolbox for heart rate variability (HRV),” Proc. Int’l Conf. On Electrical, Electronic And Computing Engineering (IcETRAN),” pp. 822-828, 2019.

[19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot and E. Duchesnay, “Scikit-learn: Machine Learning in Python,” Journal Of Machine Learning Research, vol. 12, pp. 2825-2830, 2011.

[20] J. Montiel, M. Halford, S. Mastelini, G. Bolmier, R. Sourty, R. Vaysse, A. Zouitine, H. Gomes, J. Read, T. Abdessalem, A. Bifet, “River: machine learning for streaming data in Python,” The Journal of Machine Learning Research, vol. 22.1, pp. 4945-4952, 2021.

[21] J. Healey and R. Picard, “Detecting stress during real-world driving tasks using physiological sensors,” IEEE Transactions On Intelligent Transportation Systems, vol. 6, pp. 156-166, 2005

# *Thank you for your Attention!*

Roswitha Duwenbeck | Systeme der Medizintechnik |Universität Duisburg-Essen | Duisburg, Germany
E-Mail: roswitha.kressner@uni-due.de