Towards a Minimalistic Stress Classification Method based on HRV

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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 Fields: Development of mobile Applications for Healthcare (Fields: Addiction, Fetal Alcohol Syndrome Disorder, Melanoma detection)
- 2017-2022: BA and MA 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

Photo of Demonstrator

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],

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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:

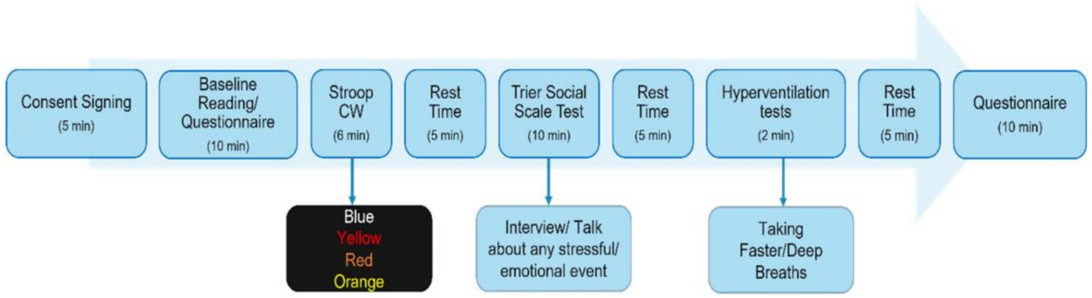
HR – Heart Rate
EDA – Electrodermal Activity
IBI – Inter Beat Interval
ST – Skin Temperature
ECG – Electrocardiogram
HRV – Heart Rate Variability
TEMP – Temperature
RESP – Respiration Rate
EMG – Electromyography
EDA – Electrodermal Activity

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]

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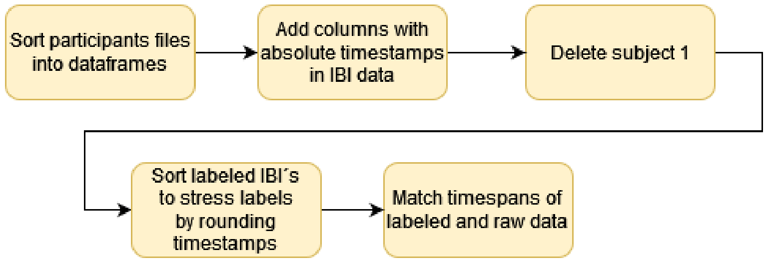
Preparation of the dataset and preprocessing

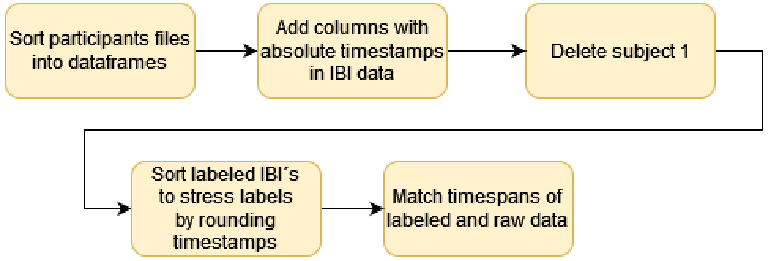
- Dataset was not mainly composed to detect stress from HRV-Features, but from HR and RESP
- Original Data: processed data folder and raw data folder
- First folder contains list, with merged patient label, Heart Rate, Respiration Rate a stress-label and a **timestamp for every second**, given in milliseconds 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



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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

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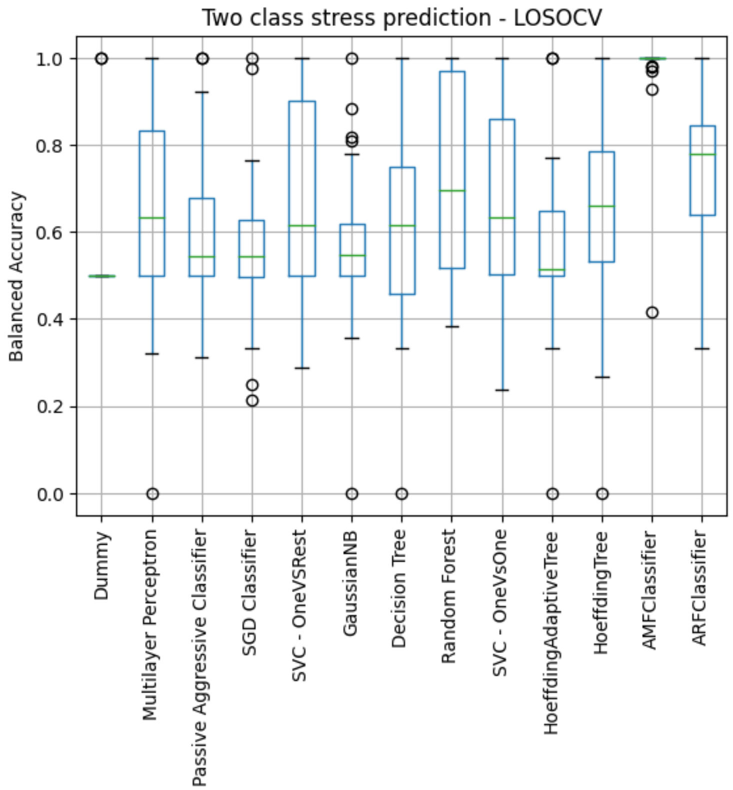
ML-Methods and Learning

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



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Conclusion and Future Work

- AMF was able to classify ”No Stress” and ”Stress” nearly perfect
- 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

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Thank you for your Attention!

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