# Prediction of Emotional and Cognitive States from OpenSignals sensor data using Deep Neural Networks

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# Analyse von Sensordaten zur Klassifizierung von Lernzuständen und Lernsituationen

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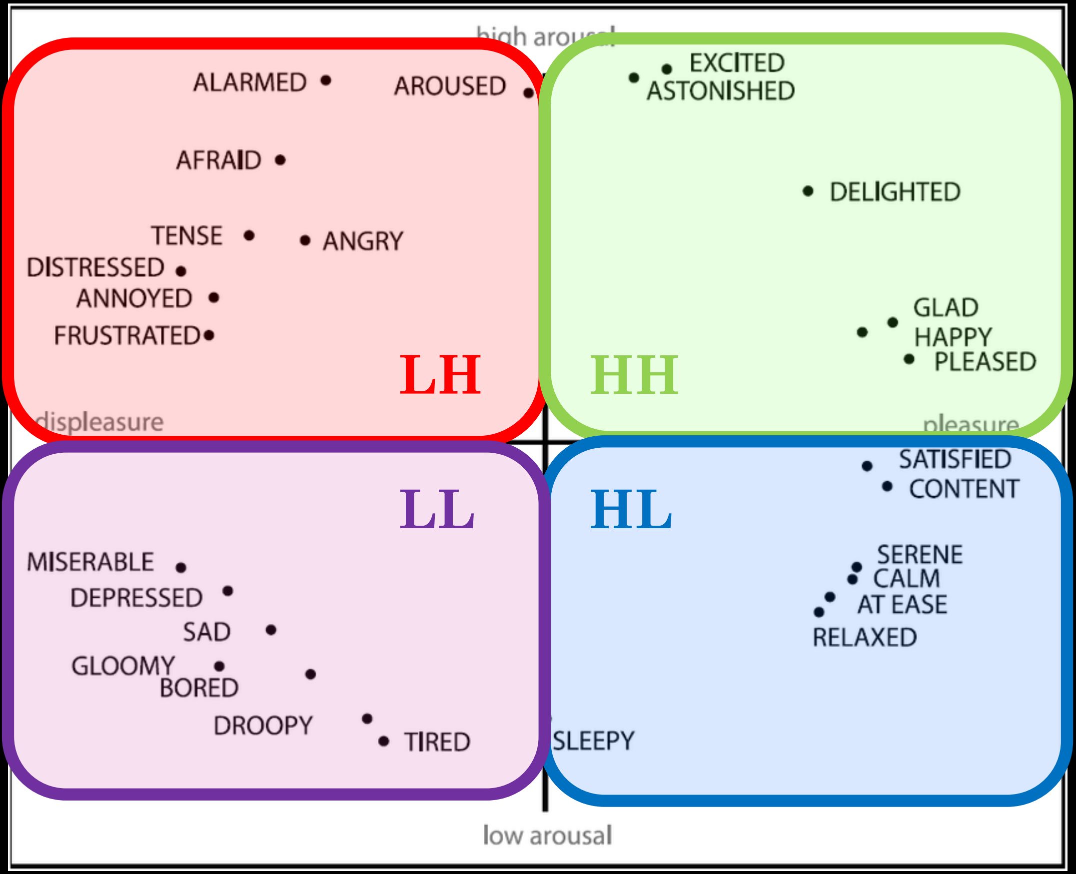
# Introduction

- IAPS-Pictures experiment (visual stimuli)
- Multiple sensors (including ECG & EDA)
- Prediction emotional states (circumplex)

https://www.researchgate.net/profile/Philippe_Zimmermann/publication/285895436/figure/fig1/AS:341962390556673@1458541595472/Two-dimensional-affective-space-defined-by-valence-and-arousal-The-circumplex-model-of.png



# Content

- State of the Art
- Deep Learning on OpenSignals data
- Results
- Outlook/Discussion

# State of the Art

# DEAP Dataset (Koelstra u. a., 2012)

- **D**ataset for **E**motion **A**nalysis using EEG, **P**hysiological and video signals
- 32 Participants (aged between 17 & 32)
- One minute long videos
- Dimensions: arousal, valence, liking, dominance
  - Each classified in a scale of 1- 9
- EEG data in 32 channels for all, facial expressions for 22 subjects

# SEED Dataset (Zheng u. Lu, 2015)

- **D**ataset for Emotion recognition using **EE**G **S**ignals
- 15 Participants
- 15 videos, 4 minutes each
- Positive, negative, neutral emotions
- EEG data in 32 channels & eye tracking for all

# SVM

- Support Vector Machine
- Textual data (e.g. CSV)
- Classification, Regression, …

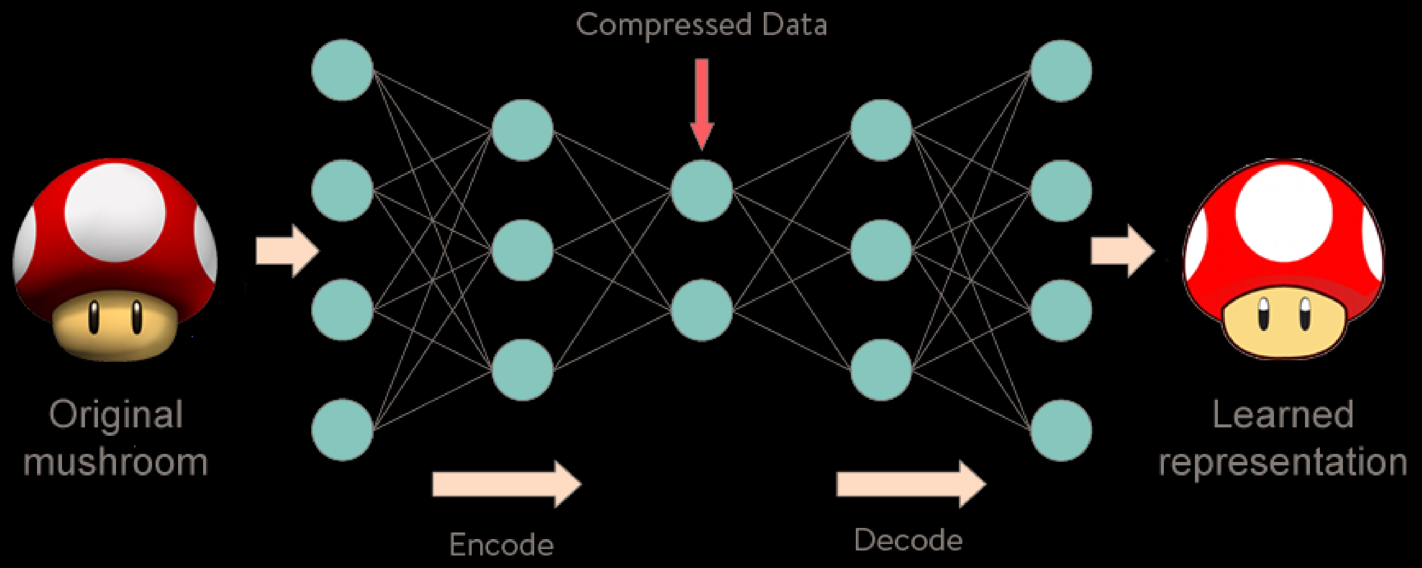
# Neural Networks

- CNN
  - Convolutional Neural Networks
  - Visual features
  - Classification, Regression, Detection, Recognition, …

- RNN / LSTM
  - Recurrent Neural Networks / Long Short Term Memory
  - Temporal features
  - Classification, Regression, ….

# Autoencoder

- DNN architecture with conv and deconv-layers



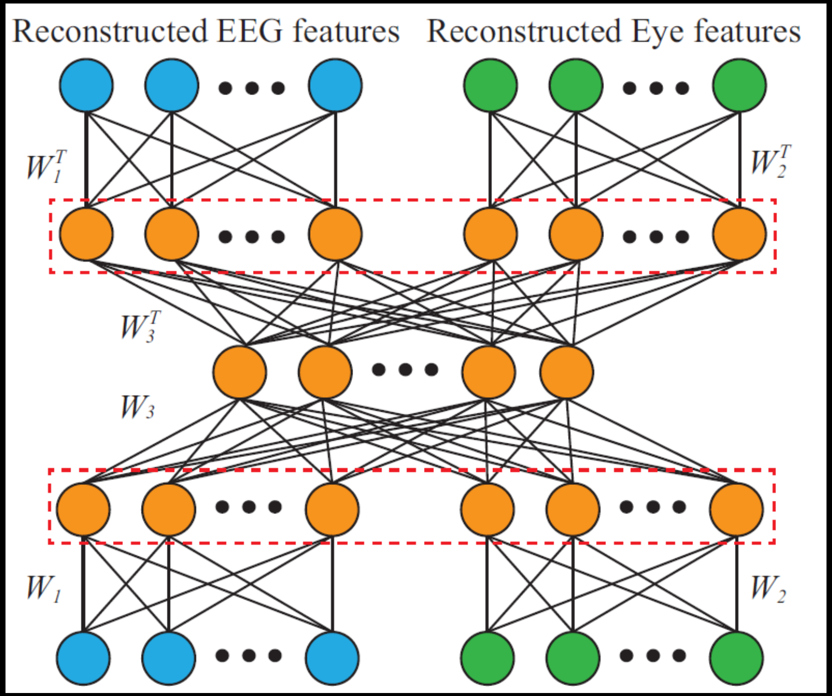

From https://www.curiously.com/media/data-imputation-2/mushroom_encoder.png

- Hidden layer carries compressed information
- Dimension reduction, compression, feature learning

# Emotion Recognition from EEG Data

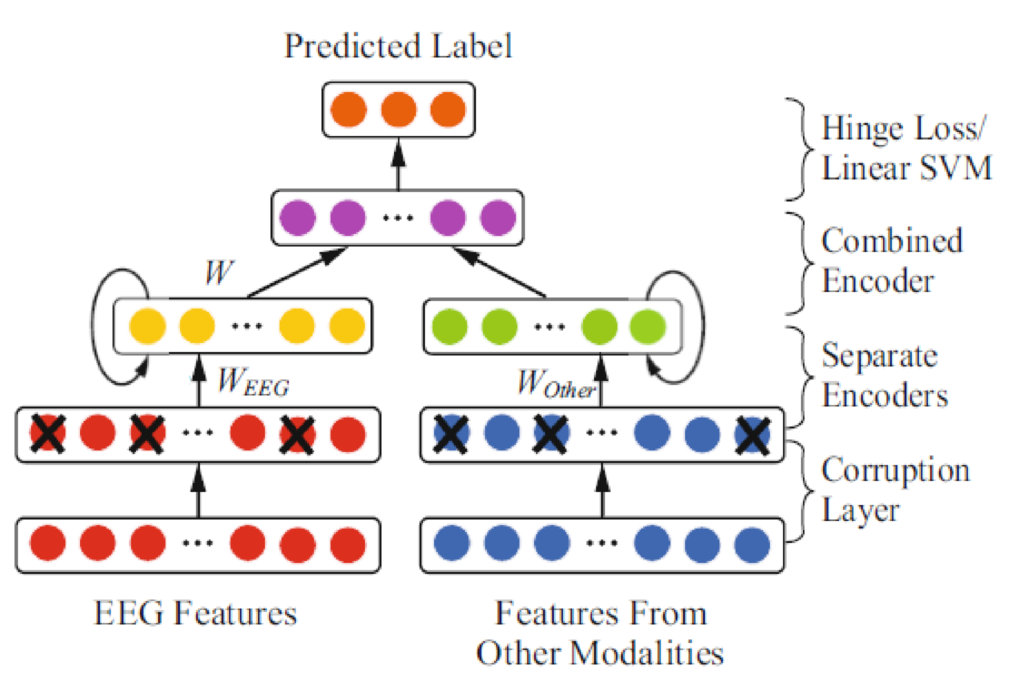
# Bimodal Deep AutoEncoder (BDAE) (Liu u. a., 2016)

- SEED & DEAP dataset
- AutoEncoder with Restricted Boltzmann Machine & SVM
- 91.01 % ± 8.91 - SEED
  85.2 % (Valence), 80.5 % (Arousal), 84.9 % (Dominance), 82.4 % (Liking) [each high/low] - DEAP
- Individual AE for each subject -> Individual BDAE



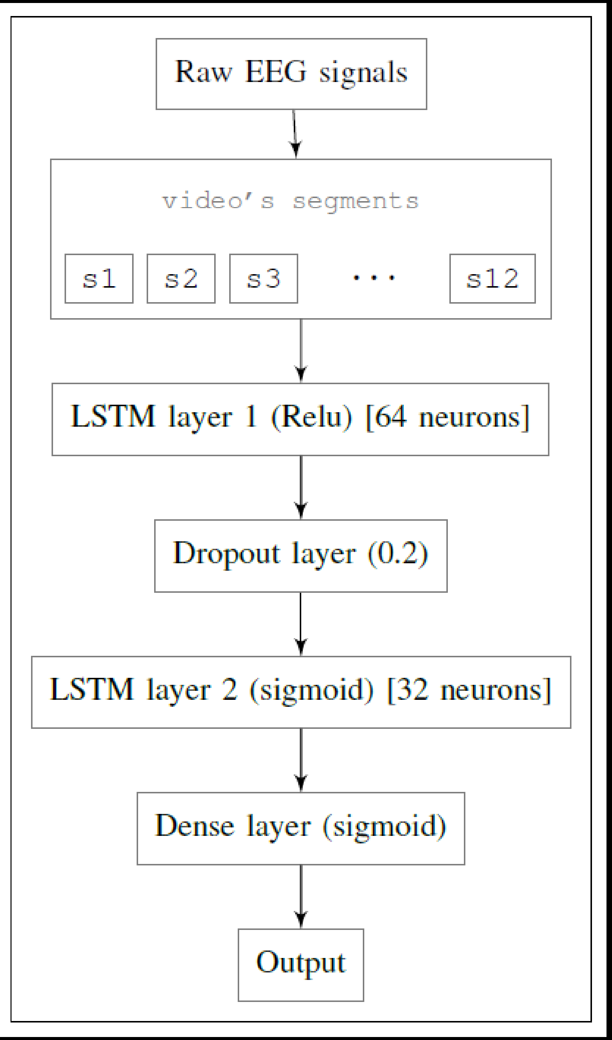
# BDDAE (Tang u. a., 2017)

- SEED & DEAP dataset
- Used AutoEncoder, SVM & LSTM
- 93.97 % (positive/neutral/negative) - SEED
  83.23 % (high/low Arousal), 83.82 % (high/low Valence) - DEAP
- Denoising with AutoEncoder trough corrupt training data
- Independent trainings process of each component



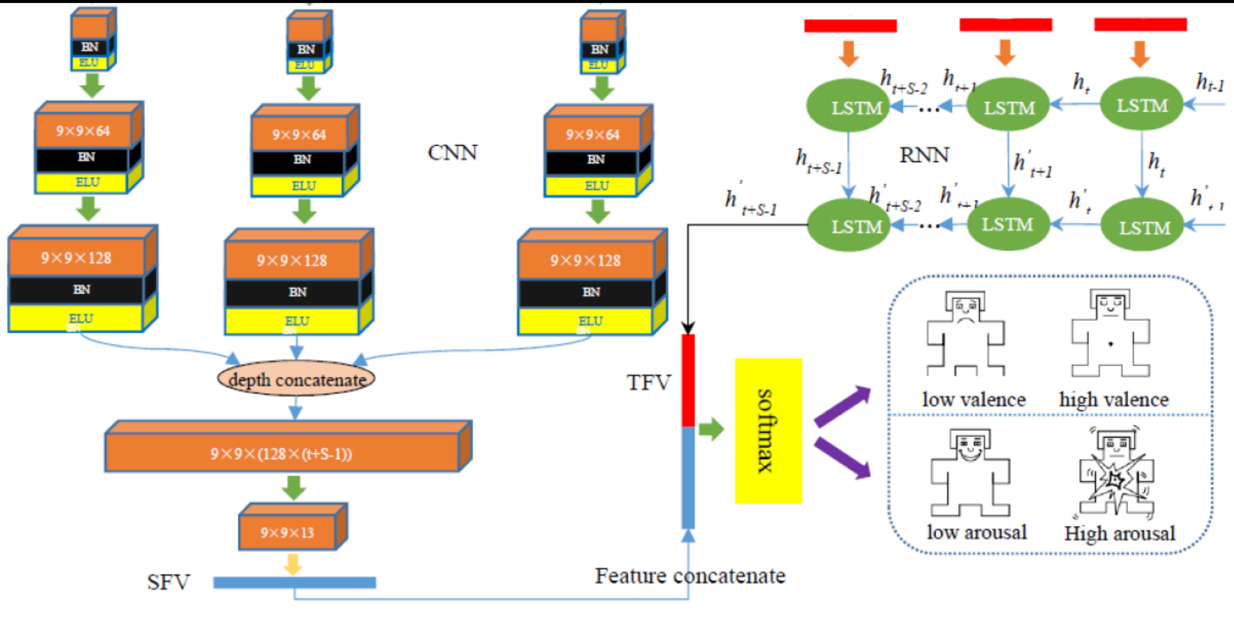
# LSTM (Alhagry u. a., 2017)

- DEAP dataset
- Pure LSTM with Raw EEG signals
- 85.65 & (Arousal), 85.45 % (Valence), 87.99 % (Liking) [each high/low]
- 60s video split into 12 segments (each segment 128Hz x 32 Channel)



# Hybrid Neural Network (CNN + RNN)
(Li u. a., 2016) (Li u. a., 2017) **(Yang u. a., 2018)**

- DEAP-Dataset: high/low Valence & high/low Arousal
- Combination of CNN (spatial features) & RNN (temporal features)
- 90.8 % ± 3.08 (Valence) , 91.03 ± 2.99 % (Arousal) – Training Accuracy
- 60s segments each 128 Hz
- 128 Individual CNNs & LSTMs
- Takes baseline EEG signal (signal without stimulation) into account



# Emotion Recognition from various Data

# Multimodal LSTM (Chao u. a., 2015)

- RECOLA-Dataset (audio, video, ECG, EDA)
- LSTM for arousal & valence regression
- RMSE: 0.122  valence [audio, lgbp-top, geo], 0.102 arousal [audio, lgbp-top, geo, landmarks, ECG]

$$\text{RMSE}_{fo} = \left[ \sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N \right]^{1/2}$$

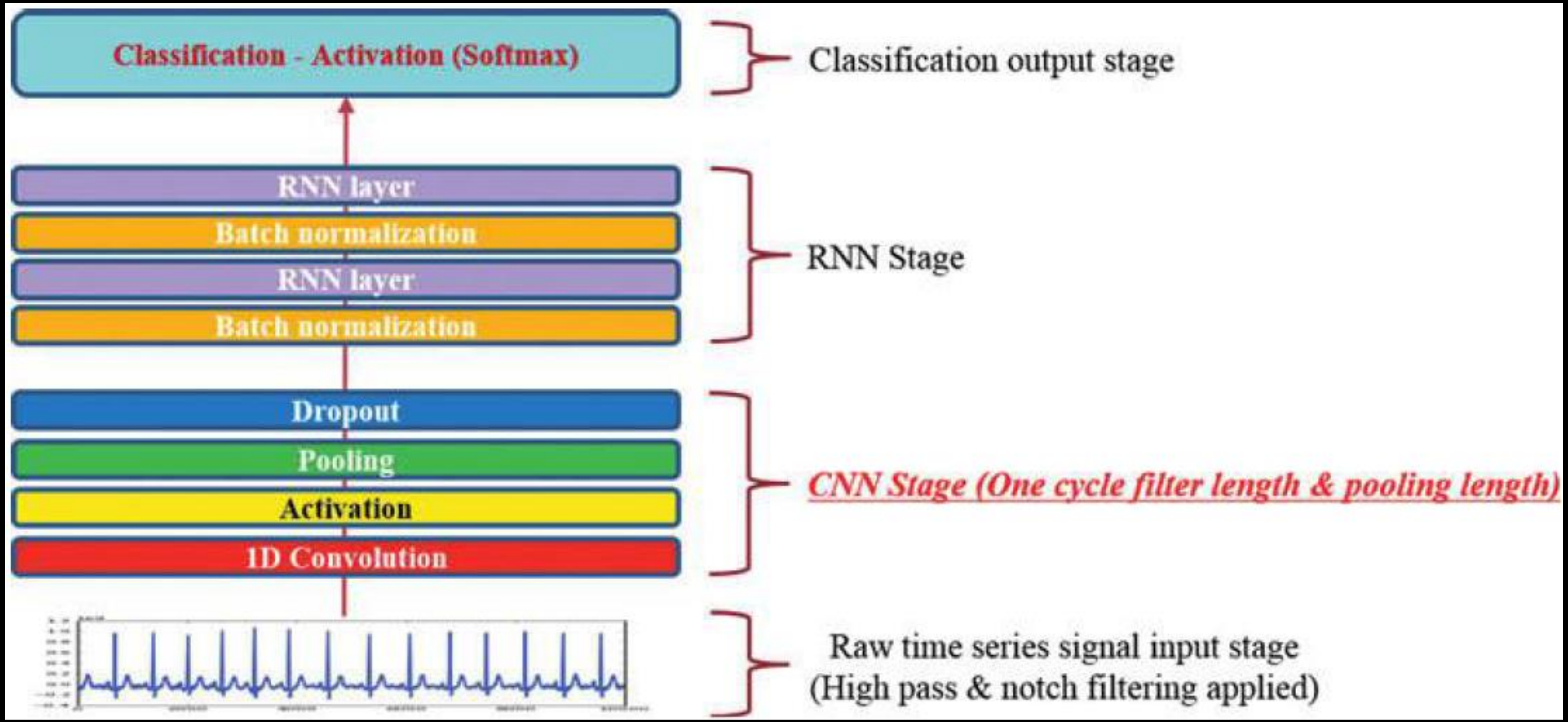
- 62 EDA extracted features
- "Physiological modality shows the worst results in CCC"
- ε-insenstice loss & temporal pooling increased accuracy massively

# HRV & EDA (Ménard u. a., 2015)

- 12 video based stimuli per participant (30s to 2 minutes), 35 participants, 6 exclusive dimensions (disgust, joy, anger, surprise, disgust, fear, sadness)
- Fourier transormation (preprocessing) & SVM
- 89.58 %

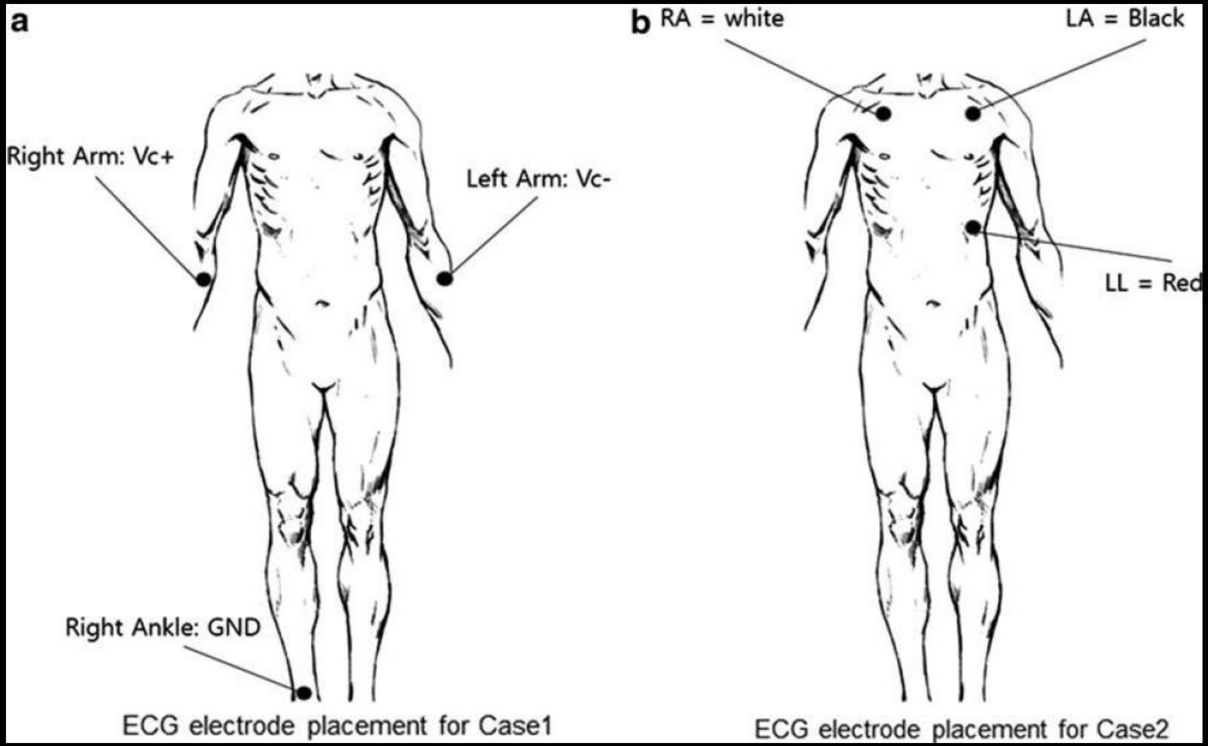
# DeepECGNet (Hwang u. a. 2018)

- Raw ECG data
- CNN & RNN based model
- Binary classification (stressful/not stressful)



# DeepECGNet - data

- Two individual experiments
- Case 1: Kwangwoon university multiple stress stimuluts experiments
- Case 2: KU Leuven university mental arithmetic task experiments



# Deep ECGNet - Case 1

- Five sessions with five different stressful stimuli
  - Mental arithmetic test
  - Stroop Color-Word test
  - Interview
  - Visual Stimuli test
  - Cold pressor test
- Each experiment lasted 5 minutes
  - Except Cold pressor test of 1 minute
- Rest session of 4 minutes

# Deep ECGNet - Case 2

- Modified version of Montrèal Imaging Stress Test
  - Subjects perform arithmetic calculations
  - Difficulty was modified by an algorithm
    - Average 60-70% correctly answered
  - Competitive test
    - Own accuracy and of opponent were displayed
    - But manipulated so opponent always seemed better
  - In Control blocks neither time nor bars were shown

# Deep ECGNet

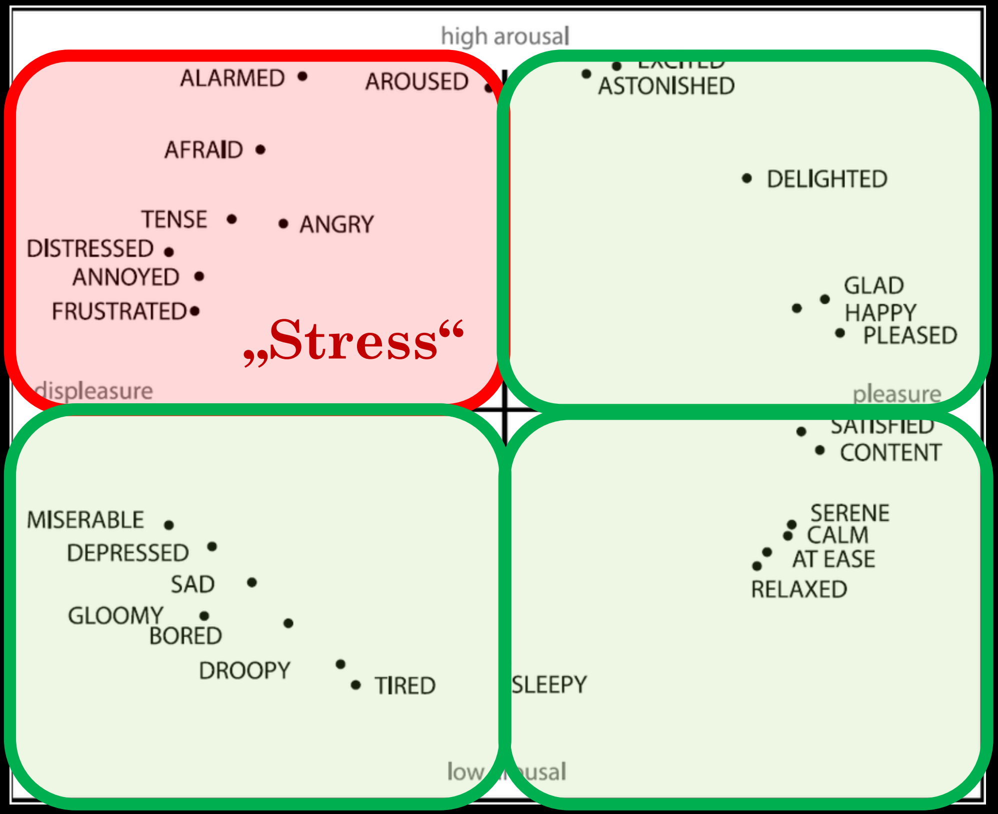
- 85.77% accuracy in Case 1
- 73.12% accuracy in Case 2

# Deep Learning on OpenSignals data

State of the Art | **DL on OpenSignals** | Results | Discussion

# Our approach

- Applied DeepECGNet
  - Binary Classification
- Our Data
  - 4 classes
- Modified Network to train with 4 classes
  - Accuracy 25-26% each class
  - Model not learning
- Creating binary data
  - Stressful state (low valence, high arousal)
  - LL, HL, HH -> not LH
  - Accuracy of 75%



# Deep Learning on OpenSignals data

Source: http://www.bergfuehrer-soelden.com/start/wp-content/uploads/2014/07/SimilaunST041_gipfel.jpg

# Deep Learning on OpenSignals data

- Add weights to give LH more relevance than Not LH
- Duplicate LH for data evenness
- Reduce Not LH for data evenness

# Deep Learning on OpenSignals data

- Both methods lead to the same results
- High consideration of LH and low consideration of Not LH
  - 50-51% accuracy (Depending on weight initialisation)
- Maximizing consideration of not LH step by step
  - True Positives for Not LH maximized
  - True Positives for LH still guessing

# Deep Learning on OpenSignals data

| Weights: None | Not Stressful (actual) | Stressful (actual) |
|---|---|---|
| Not Stressful (predicted) | 701 | 226 |
| Stressful (predicted) | 11 | 3 |

# Deep Learning on OpenSignals data

| Weights:<br>0.9 – Not Stressful<br>0.3 – Stressful | Not Stressful (actual) | Stressful (actual) |
|---|---|---|
| Not Stressful (predicted) | 544 | 183 |
| Stressful (predicted) | 168 | 46 |

# Deep Learning on OpenSignals data

- CNN used for feature generation
- Timeline file already consists of generated features
- Using only RNN to classify from given features
- Evaluate with calculated features (HR, SDNN, RMSSD, pNN50) and basic machine learning algorithms

# Deep Learning on OpenSignals data

- RNN from Deep ECGNet without CNN
  - ~50% accuracy, loss not minimised
- Modifying the RNN didn’t lead to better results

# Results

State of the Art | DL on OpenSignals | **Results** | Discussion

# Results

- Deep ECGNet implementation
  - Did not train with our data
- Own approaches had the same issues
- Every paper using Neural Networks already had good results with SVMs and machine learning algorithms

# Discussion

# Improve Accuracy

- Normalize Data
  - Scale to value range (y-direction)
- Cope with intersubject variability
  - AutoEncoder (Tang u. a., 2017)
  - Normlize with baseline data (Yang u. a., 2018)
- Implementation Ideas
  - Temporal Pooling layers (Chao u. a., 2015)
  - Fourier Transformation (Ménard u. a., 2015)
- Use self-rating as label

# Thanks for your attention!

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| | CASE1 | | CASE2 | |
|---|---|---|---|---|
| ALGORITHMS | HRV-1 | HRV-4 | HRV-1 | HRV-4 |
| Nearest neighbors | 0.6807 | 0.7108 | 0.5646 | 0.6389 |
| Linear SVM | 0.6801 | 0.6937 | 0.5660 | 0.6505 |
| RBF SVM | <u>0.6949</u> | 0.7239 | 0.5583 | 0.6225 |
| Gaussian process | 0.6920 | 0.7261 | 0.5597 | 0.6447 |
| Decision tree | 0.6591 | 0.6875 | 0.5590 | 0.6082 |
| Random forest | 0.6710 | <u>0.7290</u> | 0.5708 | 0.6220 |
| MLP | 0.6813 | 0.7188 | 0.5757 | <u>0.6664</u> |
| AdaBoost | 0.6528 | 0.6994 | 0.5715 | 0.5730 |
| Naive Bayes | 0.6926 | 0.7023 | 0.5743 | 0.6288 |
| QDA | 0.6915 | 0.7131 | <u>0.5757</u> | 0.6521 |
| Average accuracy | 0.6796 | 0.7105 | 0.5676 | 0.6307 |
| STD | 0.0146 | 0.0143 | 0.0069 | 0.0266 |

Underscored values represent the best performance algorithm for each case.

# Results

(Deep ECGNet: An Optimal Deep Learning Framework
for Monitoring Mental Stress Using Ultra Short-Term ECG Signals, p. 8)
HRV-1: Heart Rate
HRV-4: HR, SDNN, RMSSD, pNN50