UNIVERSITÄT
LEIPZIG

Masterthesis interim presentation

PRIVACY PRESERVING TRANSFORMER FOR STRESS DETECTION ON SMARTWATCH DATA

Leipzig, 07.12.2022

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RESEARCH QUESTIONS

Stressdetection

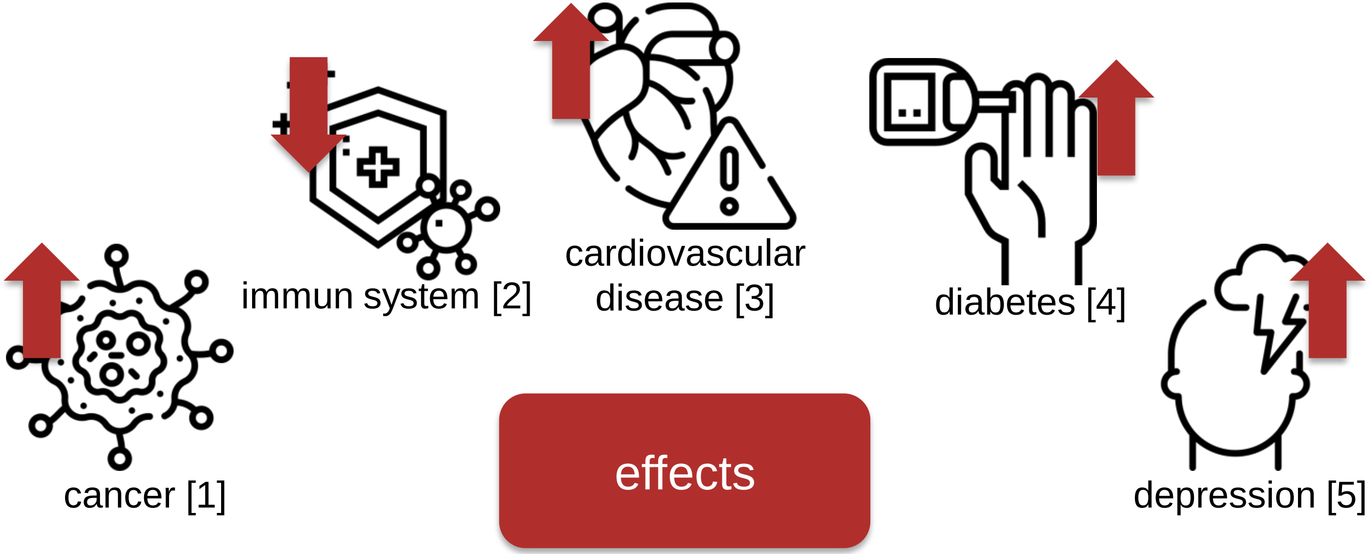
- is a transformer-architecture suitable for the classification of stress?
- How good, also in comparison to the results of Gil-Martin et al. [9], is this approach?
- How big are the losses in the results if the data set is anonymised using differential privacy?

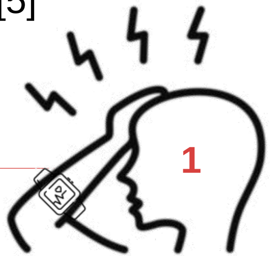
AGENDA

- Motivation
- Related Work
- Background
- Method
- Outlook
- Summary

STRESS

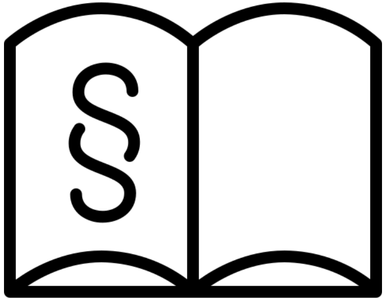
What makes stress dangerous?



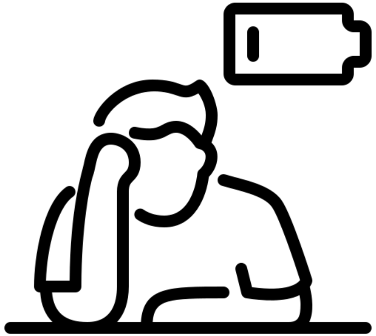


STRESS

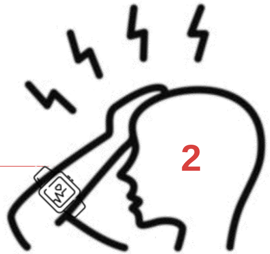
Stress at work



employers have a legal obligation to ensure that employees do not become ill

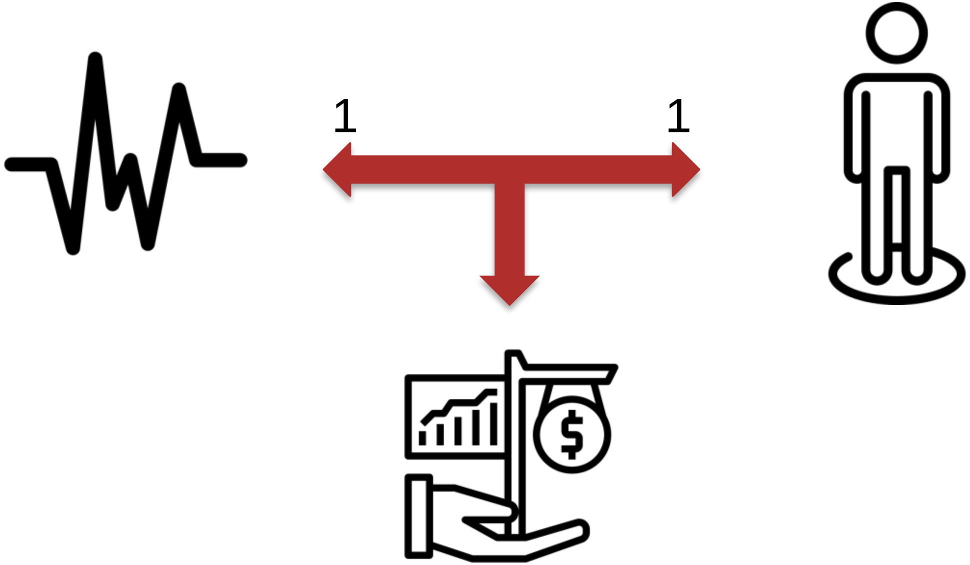


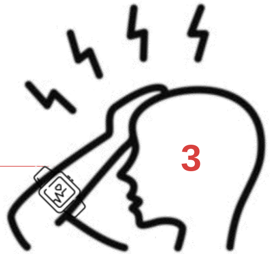
high staff turnover
increase in absenteeism
early retirement
reduced work performance [6]



PRIVACY

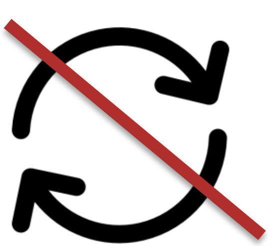
Biosignals are personal data

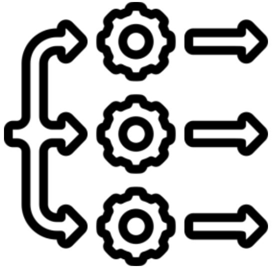




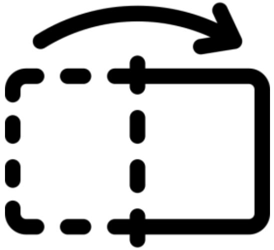
TRANSFORMER

Why not LSTM?





Why not CNN?



elimination of recurrence, thus decreasing complexity

enabling parallelization, thus improving efficiency in computation [7]

capability of capturing long-distance dependencies [12]

WESAD

Introducing WESAD, a Multimodal Dataset for Wearable Stress and Affect Detection

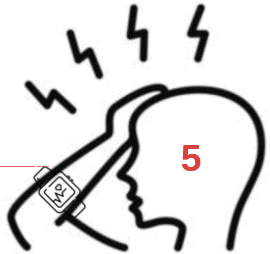
Philip Schmidt, Attila Reiss, Robert Dürichen, Claus Marberger, Kristof Van Laerhoven [8]

- Decision Tree
- Random Forest
- AdaBoost DT
- Linear discriminant analysis
- k-nearest neighbour

Table 4: Evaluation of the given modalities and classifiers on the binary (*stress vs. non-stress*) classification task.

	DT		RF		AB		LDA		kNN	
	F_1-score	Accuracy	F_1-score	Accuracy	F_1-score	Accuracy	F_1-score	Accuracy	F_1-score	Accuracy
Motion:										
ACC wrist	55.36 ± 0.47	64.08 ± 0.49	59.02 ± 0.78	69.96 ± 0.55	61.70 ± 0.80	**71.69 ± 0.45**	44.93	60.02	52.72	63.80
ACC chest	61.92 ± 0.83	71.75 ± 0.53	59.91 ± 0.25	72.87 ± 0.08	62.17 ± 0.45	**73.87 ± 0.30**	57.52	72.05	47.79	57.81
Wrist:										
BVP	78.27 ± 0.17	81.39 ± 0.15	81.35 ± 0.15	84.18 ± 0.11	81.23 ± 0.15	84.10 ± 0.13	83.08	**85.83**	78.94	82.06
EDA wrist	70.95 ± 0.37	76.21 ± 0.27	70.88 ± 0.20	76.29 ± 0.14	75.34 ± 0.57	**79.71 ± 0.43**	69.86	78.08	68.30	73.13
TEMP wrist	63.15 ± 0.18	68.22 ± 0.19	62.90 ± 0.10	67.82 ± 0.11	62.27 ± 0.25	67.11 ± 0.34	56.37	**69.24**	60.18	64.46
Wrist physio	82.37 ± 0.21	84.88 ± 0.11	86.10 ± 0.29	**88.33 ± 0.25**	85.86 ± 0.20	88.05 ± 0.18	83.77	86.46	78.93	81.96
Chest:										
ECG	77.01 ± 0.37	80.17 ± 0.29	79.64 ± 0.15	82.78 ± 0.11	80.20 ± 0.25	83.37 ± 0.20	81.31	**85.44**	75.39	79.19
EDA chest	69.88 ± 0.41	73.55 ± 0.44	73.63 ± 0.18	77.51 ± 0.23	71.97 ± 0.26	75.50 ± 0.29	74.51	**81.70**	66.64	69.73
EMG	47.06 ± 0.20	56.25 ± 0.05	49.42 ± 0.35	63.44 ± 0.18	50.84 ± 0.44	62.88 ± 0.31	52.49	**67.10**	51.84	58.74
RESP	79.92 ± 0.19	83.03 ± 0.17	84.33 ± 0.10	86.63 ± 0.08	84.64 ± 0.06	86.87 ± 0.06	85.61	**88.09**	69.17	75.67
TEMP chest	57.40 ± 0.08	64.33 ± 0.07	56.75 ± 0.25	64.75 ± 0.28	55.03 ± 0.27	63.46 ± 0.21	41.00	**69.49**	51.64	58.25
Chest physio	81.29 ± 0.22	84.18 ± 0.20	90.44 ± 0.66	92.01 ± 0.51	87.11 ± 0.57	89.76 ± 0.48	91.47	**93.12**	77.27	81.05
All wrist	78.71 ± 0.53	82.19 ± 0.44	84.11 ± 0.3[illegible]	**87.12 ± 0.24**	80.11 ± 0.93	83.98 ± 0.75	84.05	86.88	52.72	63.80
All chest	78.26 ± 0.46	81.29 ± 0.38	90.04 ± 0.8[illegible]	[illegible]	89.57 ± 0.61	91.58 ± 0.46	91.07	**92.83**	64.20	69.70
All physio	83.03 ± 1.61	85.16 ± 1.50	86.02 ± 0.55	87.91 ± 0.54	87.78 ± 1.38	89.77 ± 1.17	90.93	**92.51**	79.44	83.16
All modalities	80.83 ± 1.13	83.60 ± 1.08	85.71 ± 0.63	87.74 ± 0.60	83.88 ± 0.93	87.00 ± 0.78	90.74	**92.28**	69.14	74.20

Baseline	Random Guessing		Sophisticated guessing	
	F_1-score	Accuracy	F_1-score	Accuracy
	47.96	50.00	41.15	69.94



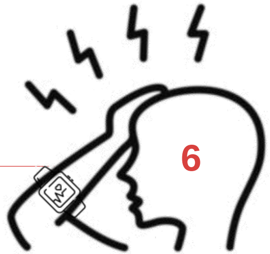
WESAD

Introducing WESAD, a Multimodal Dataset for Wearable Stress and Affect Detection

Philip Schmidt, Attila Reiss, Robert Dürichen, Claus Marberger, Kristof Van Laerhoven [8]

Table 6: Feature importance for the three-class and binary classification task considering all modalities.

Importance	Three-class	Importance	Binary Task
0.23	$\sigma_{E}^{RESP,\,chest}$	0.35	$\sigma_{E}^{RESP,\,chest}$
0.11	$\mu_{HR}^{ECG,\,chest}$	0.20	$\mu_{HR}^{ECG,\,chest}$
0.07	min_{TEMP}^{wrist}	0.09	max_{TEMP}^{wrist}
0.06	$\mu_{ACC,3D}^{chest}$	0.07	$range_{EDA}^{wrist}$
0.05	$range_{EDA}^{wrist}$	0.05	$\#_{SCR}^{chest}$

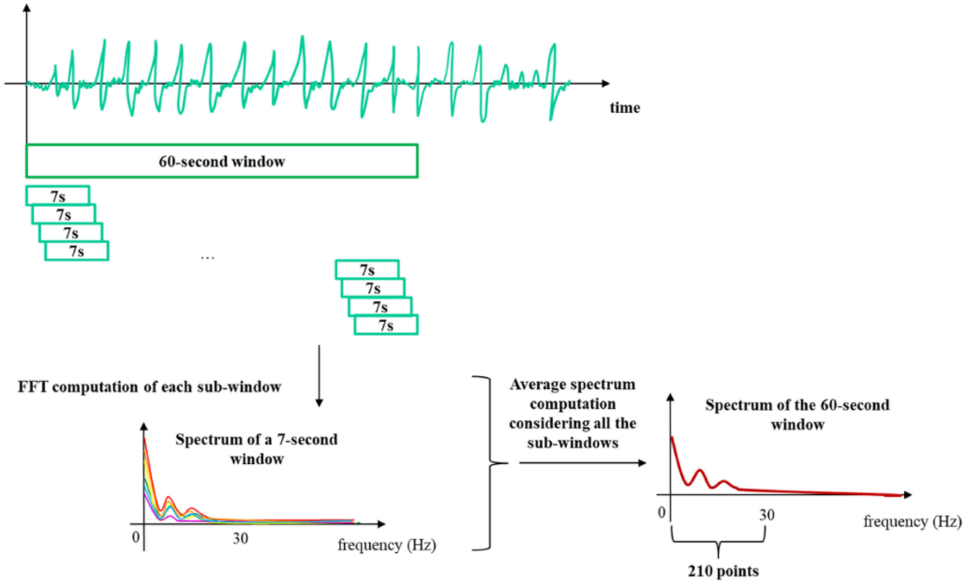


STRESS DETECTION VIA CNN

Human Stress Detection With Wearable Sensors Using Convolutional Neural Networks

Manuel Gil-Martin, Ruben San-Segundo, Ana Mateos, Javier Ferreiros-Lopez [9]

Signal preprocessing



STRESS DETECTION VIA CNN

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Signal preprocessing

Table 1.

Processing Details Per Signal

Device	Signal	Sampling frequency	Frequency range	Sub-window length	Number of inputs to CNN
RespiBAN (Chest)	Accelerations (*X*, *Y*, and *Z*)	700 Hz	0–30 Hz	7 seconds	210
	ECG	700 Hz	0–7 Hz	30 seconds	210
	EDA	700 Hz	0–7 Hz	30 seconds	210
	EMG	700 Hz	0–250 Hz	0.84 seconds	210
	RESP	700 Hz	0–6 Hz	35 seconds	210
	TEMP	700 Hz	0–6 Hz	35 seconds	210
Empatica E4 (Wrist)	Accelerations (X, Y and Z)	64 Hz	0–30 Hz	7 seconds	210
	BVP	64 Hz	0–7 Hz	30 seconds	210
	EDA	64 Hz	0–7 Hz	30 seconds	210
	TEMP	64 Hz	0–6 Hz	35 seconds	210

STRESS DETECTION VIA CNN

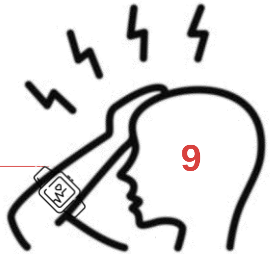
Human Stress Detection With Wearable Sensors Using Convolutional Neural Networks

Manuel Gil-Martin, Ruben San-Segundo, Ana Mateos, Javier Ferreiros-Lopez [9]

Table 4.

Accuracy (%) and F1-Score (%) Comparison with Schmidt et al. [12] Classifying Between Stress and Non-Stress Situations

Stress versus Nonstress				
	Schmidt *et al.* [12]		This article	
	Accuracy	F1-score	Accuracy	F1-score
Wrist physiological signals	88.33	86.10	87.30 ± 0.21	87.00 ± 0.21
All inertial signals (acc)	–	–	91.50 ± 0.17	91.30 ± 0.17
All physiological signals	92.51	90.93	95.01 ± 0.13	94.78 ± 0.13
All chest signals	92.83	91.07	93.10 ± 0.16	93.01 ± 0.16
All wrist signals	87.12	84.11	92.70 ± 0.16	92.55 ± 0.16
All signals	92.28	90.74	**96.62 ± 0.11**	**96.63 ± 0.11**



HUSFORMER

Husformer: A Multi-Modal Transformer for Multi-Modal Human State Recognition

Ruiqi Wangy, Wonse Joy, Dezhong Zhao, Weizheng Wang, Baijian Yang, Guohua Chen and Byung-Cheol Min [10]

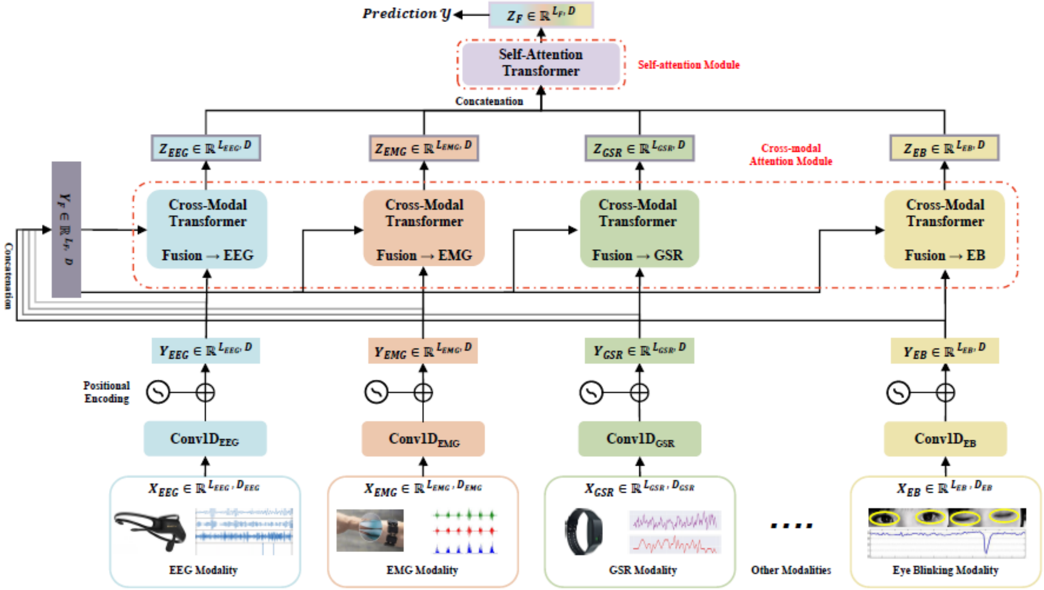


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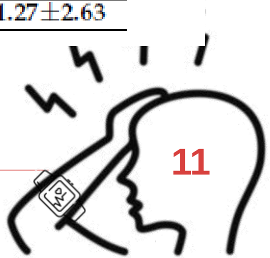
TABLE 7: Performance of different models on WESAD, raw MOCAS, preprocessed MOCAS and CogLoad datasets in terms of average multi-class average accuracy (Acc) and multi-class average F1-score ($F1$) with stand deviations. Results of other models that are within 5% of the *Husformer*'s on Acc or $F1$ are highlighted. ^{h}: higher is better.

Dataset	WESAD		Raw MOCAS		Preprocessed MOCAS		CogLoad	
Metric	$Acc(\%)^h$	$F1(\%)^h$	$Acc(\%)^h$	$F1(\%)^h$	$Acc(\%)^h$	$F1(\%)^h$	$Acc(\%)^h$	$F1(\%)^h$
EF-SVM	46.67±4.21	48.60±3.95	55.69±4.26	55.84±4.87	66.94±4.78	66.08±4.06	45.88±3.67	51.73±3.01
LF-SVM	49.19±2.35	51.72±2.87	52.95±3.27	53.06±3.29	64.01±5.03	64.89±4.94	43.19±2.58	50.08±1.99
EmotionMeter	69.24±1.20	69.44±1.13	77.38±3.27	77.21±3.18	85.03±2.33	86.17±2.40	65.80±1.21	69.22±1.09
MMResLSTM	72.49±0.86	73.05±0.98	82.06±2.15	82.17±1.95	89.54±1.08	89.98±1.14	68.17±1.41	70.12±1.45
HusFuse	74.58±1.37	74.29±1.12	76.46±2.17	77.03±2.20	83.81±1.91	84.62±1.67	64.30±0.49	63.46±0.64
HusPair	80.69±1.57	79.89±1.98	88.24±1.68	88.58±1.48	94.95±3.82	94.87±3.84	71.23±2.92	72.67±3.10
HusLSTM	76.40±0.99	76.76±1.06	84.74±2.50	85.04±2.39	88.16±1.58	88.30±1.56	72.85±0.84	72.36±0.79
HusFormer	85.02±1.91	85.85±2.14	93.71±2.26	93.82±2.41	96.42±2.11	96.51±2.03	80.40±2.34	81.27±2.63



TRANSFORMER

Attention is All you Need

Ashish Vaswani et al. [7]

- parallel computation
- efficiency in computation
- decreased complexity

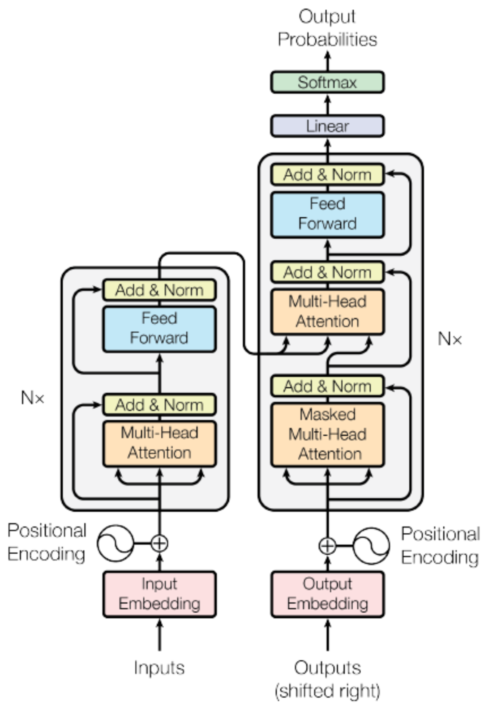


Figure 1: The Transformer - model architecture.

TRANSFORMER INPUT EMBEDDING

Attention is All you Need

Ashish Vaswani et al. [7]

$$\begin{bmatrix}0.32\\0.19\\0.91\\0.01\end{bmatrix}$$

word embeddings are generated one timestep at a time

RNN (Encoder)

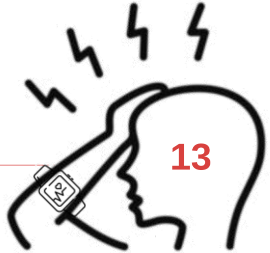
dog

$$\begin{bmatrix}0.76\\0.23\\0.11\\0.21\end{bmatrix} \quad \begin{bmatrix}0.32\\0.88\\0.41\\0.14\end{bmatrix} \quad \begin{bmatrix}0.32\\0.19\\0.91\\0.01\end{bmatrix}$$

Transformer (Encoder)

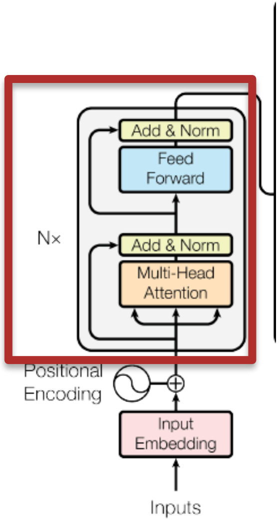
The red dog

word embeddings are generated simultaneously



TRANSFORMER ENCODER

Attention is All you Need
Ashish Vaswani et al. [7]



Attention: what part of the input should be focused?

Attention vectors

The → The big red dog $[0.71 \quad 0.04 \quad 0.07 \quad 0.18]^T$

big → The big red dog $[0.01 \quad 0.84 \quad 0.02 \quad 0.13]^T$

red → The big red dog $[0.09 \quad 0.05 \quad 0.62 \quad 0.24]^T$

dog → The big red dog $[0.03 \quad 0.03 \quad 0.03 \quad 0.91]^T$

$$\rightarrow \begin{bmatrix} 0.48 \\ 0.29 \\ 1.61 \\ 1.28 \end{bmatrix}$$

TRANSFORMER DECODER

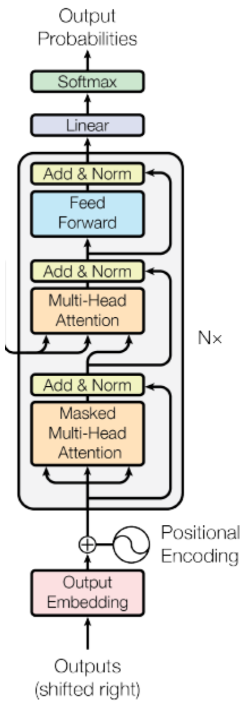
Attention is All you Need

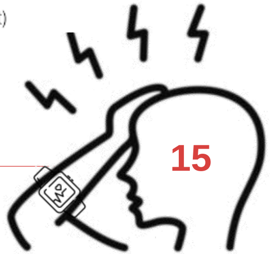
Ashish Vaswani et al. [7]

Le	gros	chien	rouge
$\begin{bmatrix}1\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0.1\\0.9\\0\\0\end{bmatrix}$	$\begin{bmatrix}0.05\\0.40\\0.55\\0\end{bmatrix}$	$\begin{bmatrix}0.16\\0.09\\0.15\\0.66\end{bmatrix}$

The	big	red	dog
$\begin{bmatrix}0.71\\0.04\\0.07\\0.18\end{bmatrix}$	$\begin{bmatrix}0.01\\0.84\\0.02\\0.13\end{bmatrix}$	$\begin{bmatrix}0.09\\0.05\\0.62\\0.24\end{bmatrix}$	$\begin{bmatrix}0.03\\0.03\\0.03\\0.91\end{bmatrix}$

Encoder-Decoder-Attention



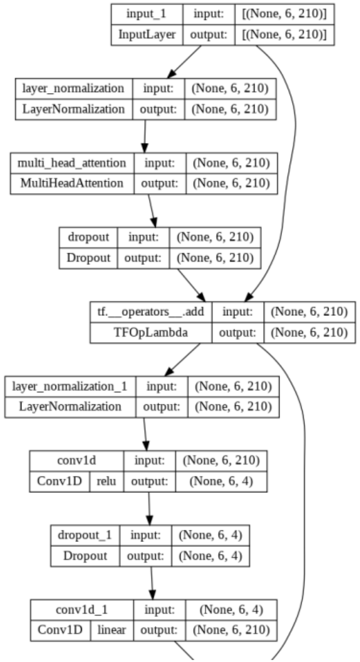


TOOLS

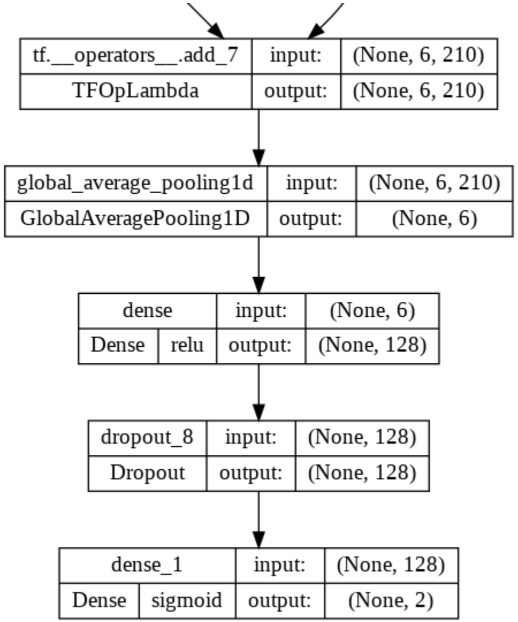
IDE	Transformer	Hyperparameter Tuning
Google colab + Jupyter Notebook	Tensorflow + Keras	Neptune.ai

TRANSFORMER ARCHITEKTUR

x times



+ 1 time

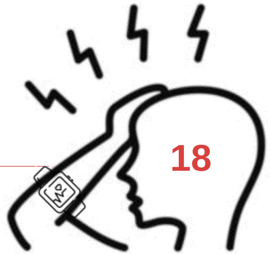


https://keras.io/examples/timeseries/timeseries_transformer_classification/#build-the-model

INTERIM RESULTS

Smartwatch OS: E4
Evaluation of Transformer model trained on 200 epochs

Subject	Accuracy	Precision	Recall	F1-Score
S2	0.91429	0.91429	0.91429	0.91429
S3	0.68571	0.68571	0.68571	0.68571
S4	0.97222	0.97222	0.97222	0.97222
S5	1.00000	0.97297	1.00000	0.98630
S6	0.94444	0.92105	0.97222	0.94595
S7	0.91667	0.91667	0.91667	0.91667
S8	0.94444	0.94444	0.94444	0.94444
S9	0.94444	0.94444	0.94444	0.94444
S10	1.00000	1.00000	0.97297	0.98630
S11	0.78378	0.77778	0.75676	0.76712
S13	0.91892	0.89474	0.91892	0.90667
S14	0.72973	0.71053	0.72973	0.72000
S15	1.00000	1.00000	1.00000	1.00000
S16	0.97297	0.94737	0.97297	0.96000
S17	0.70270	0.70270	0.70270	0.70270
Average	0.89536	0.88699	0.89360	0.89019



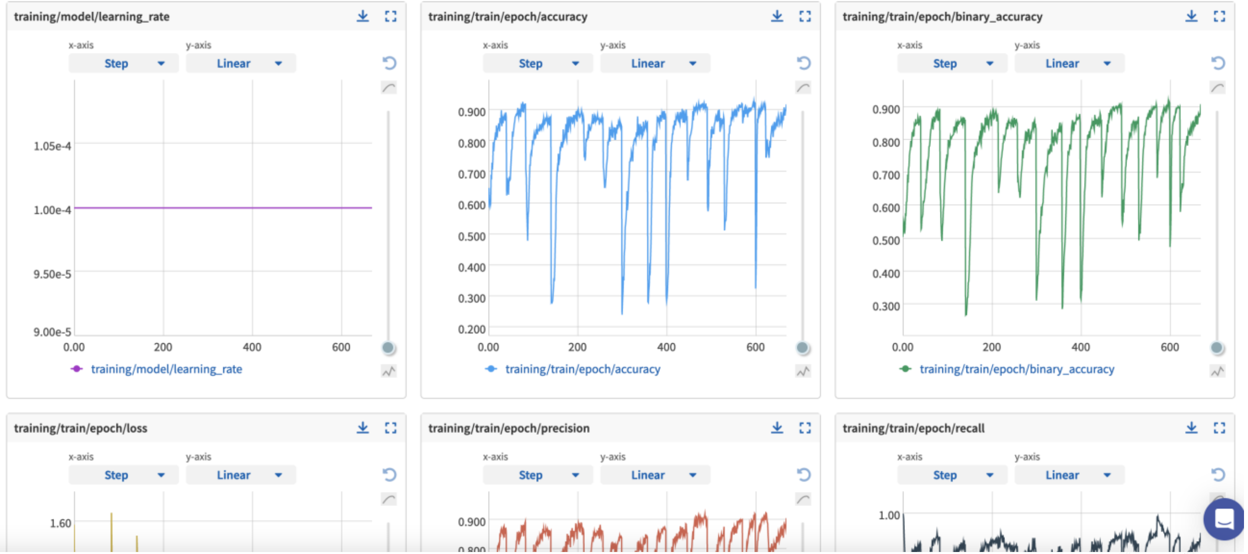
HYPERPARAMETER TUNING

DEMO

neptune.ai

HYPERPARAMETER TUNING

batch_size	50
dropout	0.25
epochs	200
lr	0.0001
min_delta_loss	0.01
mlp_dropout	0.2
momentum	0.4
num_transformer_blocks	7



HYPERPARAMETER TUNING

PINNED COLUMNS

Id	Creation Time	Owner	Monitoring Time	Acc	Loss	F1	LR	#EncBlocks	BatchSize	Tags
STRESS1-23	2022/11/29 12:29:27	boris	1h 14m	0.72973	1.12489	0.702703	0.0001	6	50	all noean
STRESS1-22	2022/11/29 11:23:09	boris	47m	0.72973	1.00632	0.72	0.0001	5	50	all
STRESS1-21	2022/11/29 09:50:01	boris	47m 7s	0.783784	0.573396	0.746667	0.0001	6	50	all
STRESS1-20	2022/11/28 21:12:57	boris	56m 24s	0.72973	0.710102	0.72973	0.0001	7	50	all
STRESS1-19	2022/11/28 18:52:31	boris	1h	0.675676	0.763053	0.666667	0.0001	7	50	all
STRESS1-18	2022/11/28 18:04:24	boris	35m 10s	0.648649	0.900816	0.638889	0.0001	7	50	all val_lo
STRESS1-17	2022/11/28 17:51:13	boris	10m 2s	0.702703	0.64422	0.702703	0.0001	7	50	onlyE4 va
STRESS1-16	2022/11/28 17:18:52	boris	10m 23s	0.837838	0.310676	0.849315	0.0001	7	50	onlyE4
STRESS1-15	2022/11/28 16:06:09	boris	13m 40s	0.837838	0.342507	0.853333	0.0001	7	50	onlyE4
STRESS1-14	2022/11/28 15:52:48	boris	9m 31s	0.702703	0.636979	0.704225	0.001	7	50	onlyE4
STRESS1-13	2022/11/28 14:09:12	boris	18m 52s	0.756757	0.549588	0.756757	0.0001	8	50	onlyE4

OUTLOOK

1. further Hyperparameter-Tuning / architecture changes
   - evaluation of the transformer architecture
2. Insert two LSTM-Layers for better positional encoding [11]
3. differential privacy
   - evaluation of the privacy preserving architecture

OUTLOOK

Differential Privacy with Opacus [13]

```
# define your components as usual
model = Net()
optimizer = SGD(model.parameters(), lr=0.05)
data_loader = torch.utils.data.DataLoader(dataset, batch_size=1024)

# enter PrivacyEngine
privacy_engine = PrivacyEngine()
model, optimizer, data_loader = privacy_engine.make_private(
    module=model,
    optimizer=optimizer,
    data_loader=data_loader,
    noise_multiplier=1.1,
    max_grad_norm=1.0,
)
# Now it's business as usual
```

SUMMARY

1. stressdetection is relevant
2. biosignals are personal data
3. a Transformer is suitable for time-series-problems

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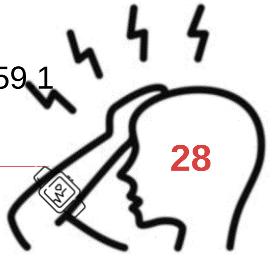

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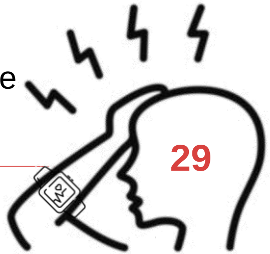

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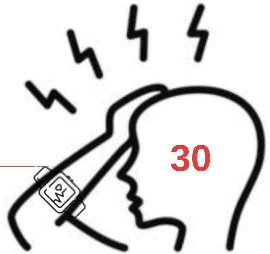

THANK YOU!