TÜRCK Engineering
Optical Design • Data Science

Deep Learning in Action

Annotating Quasi-Periodic Signals with MATLAB

Who is Dr. Türck Engineering?

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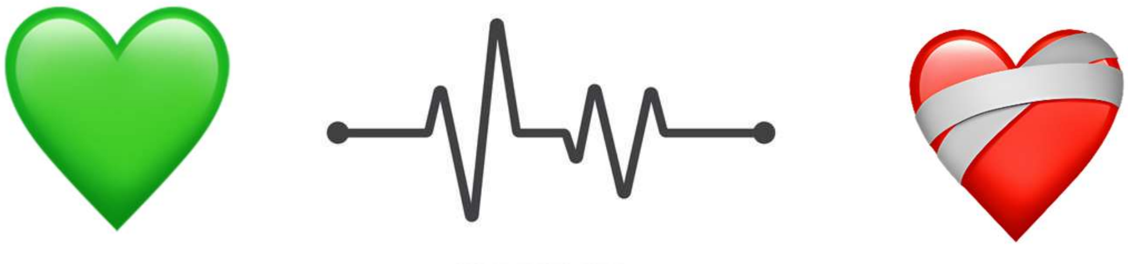
Created by Bastian Klampke

Who is Dr. Türck Engineering?

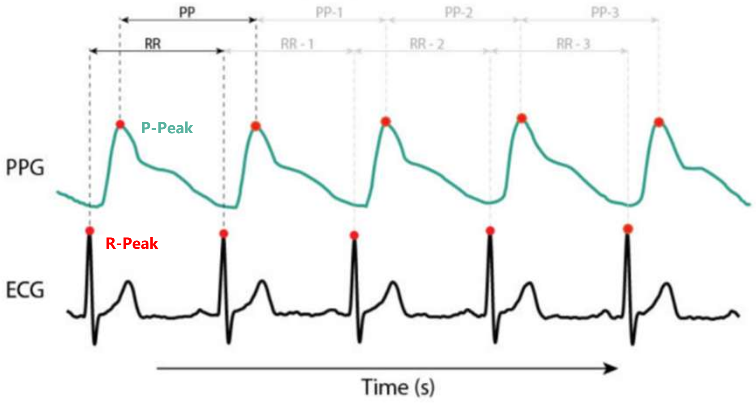
PYTHON AND OPTICSTUDIO® Optical Industry and Photonics	NEW DEVELOPMENT OF A MEASUREMENT ALGORITHM Medical Technology	INSPECTION OF SURFACES FOR MAINTENANCE TASKS Mechanical Engineering & Manufacturing
PHYSICAL MODELLING OF AN ELECTROCHEMICAL CELL FOR CONTROLLER DESIGN Measurement Technology & Sensors	IMAGE ANALYSIS ACCOMPANYING MEASUREMENT Measurement Technology & Sensors	DETECTION OF FAULTY BEHAVIOUR IN A BIOSENSOR Medical Technology
DATA ANALYSIS IN CONNECTION WITH COMPLAINTS ABOUT MEASURING DEVICES Measurement Technology & Sensors	PREDICTIVE MAINTENANCE USING MATLAB Automotive Industry / Mobility	LENSES FOR CINEMA PRODUCTION Optical Industry and Photonics

More on https://tuerck-ing.de/en/projects/

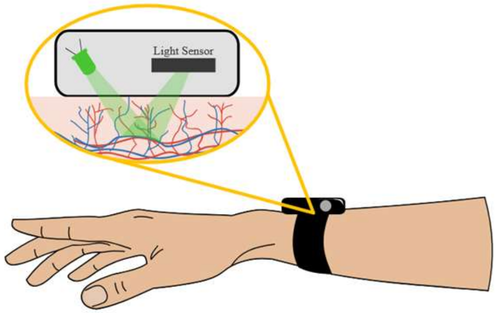
Motivation



Motivation – Heartbeat as Quasi-Periodic Signal



PhotoPlethysmoGraphy:
- Measures **blood volume changes optically** in the skin
- **P Peaks** mark highest peripheral blood volume in the skin resulting from the propagated pulse wave after heart (ventricular) contraction

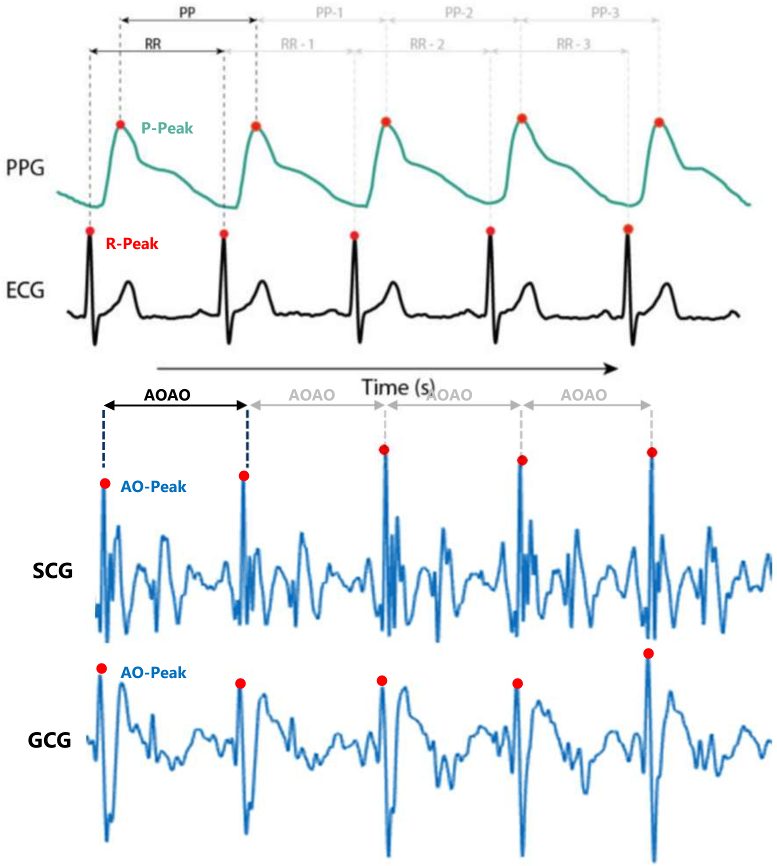



Electrodes are placed on a patient's chest to record the heart's electrical signals.

ElectroCardioGraphy:
- Measures **electric activity** of the heart
- **R Peaks** mark highest electric activity caused by ventricular depolarization, which leads to heart (ventricular) contraction

Image Sources: FibriCheck, SlateSafety, KID-PPG

Motivation – Heart Beat as Quasi-Periodic Signal



Inertial **M**easurement **U**nits
→ Cheap and small
→ Almost everywhere nowadays
→ MechanoCardioGrams can be measured with your Smartphone (using e.g. the App PhyPhox)

MechanoCardioGraphy:
- **S**eismo**C**ardio**G**raphy measures **acceleration**
- **G**yro**C**ardio**G**raphy measures **angular velocity**
- **AO Peak** (**A**ortic Valve **O**pening) marks the highest change in acceleration and angular motion due to heart (ventricular) contraction

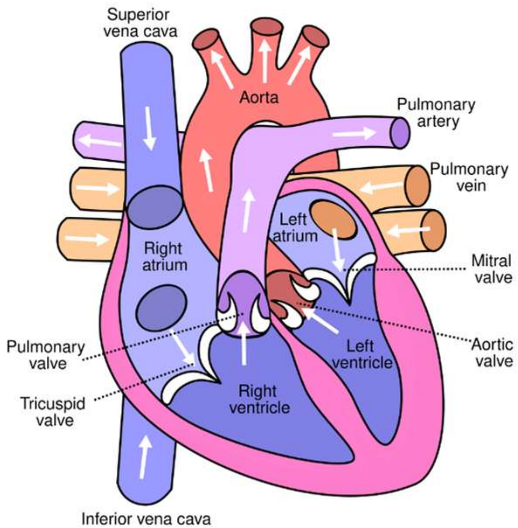
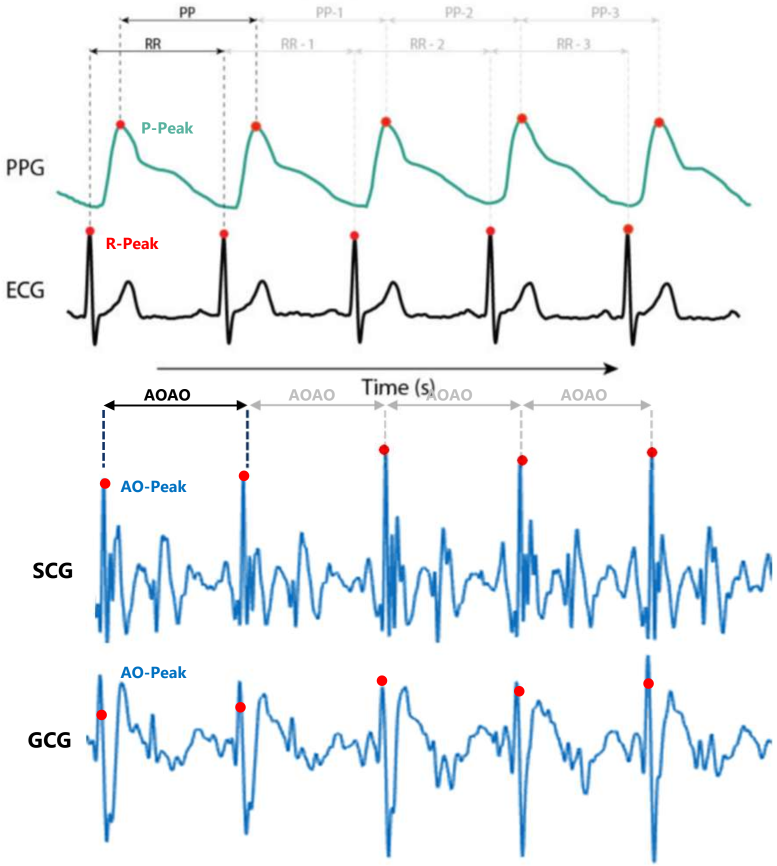


Image Sources: CardioSignal, Wikipedia

Motivation – Heart Beat as Quasi-Periodic Signal



Heart Beat Intervals (**RR**, **PP**, **AOAO**) are used for statistical analysis to quantify heart rate, **heart rate variability** and related features, which is an important indicator of a patients health status.

→ A reliable heart beat annotation algorithm is essential!

Goal:
Customer wants a robust solution for heartbeat annotation in **M**echano**C**ardio**G**rams for **clients with pathological** (unhealthy) **heart conditions**

Approaches

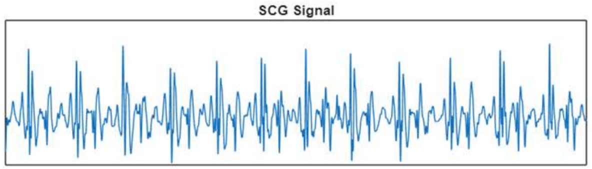
First Approach – Pan Tompkins Algorithm

Pan Tompkins Algorithm is widely applied in slight variations to annotate heart beat signals from **ECG** and **PPG**

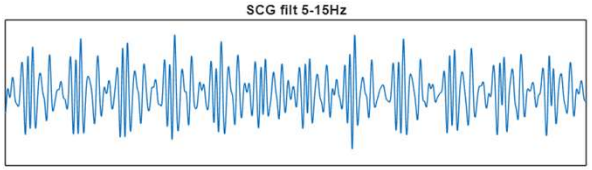
Only five steps!

1. Bandpass Filter
2. Differentiate filtered signal
3. Square differentiated signal
4. Moving mean
5. Find peaks that are larger than a certain threshold

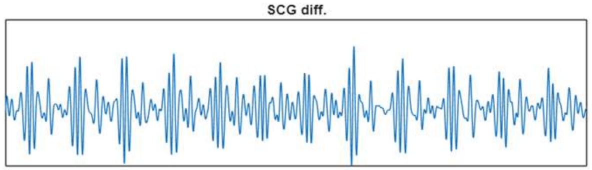
→ Easy to apply
→ Easy to tweak



Healthy person*
Age: 20-30 years



1.



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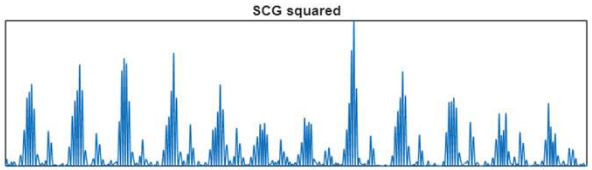
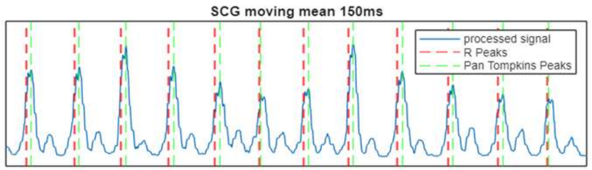


3.



4. + 5.

*public dataset (healthy and unhealthy people, contains also R-Peaks)

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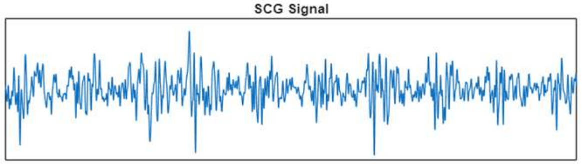
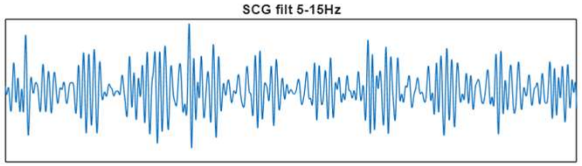


Healthy person*
Age: 78 years



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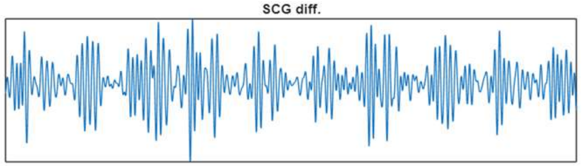

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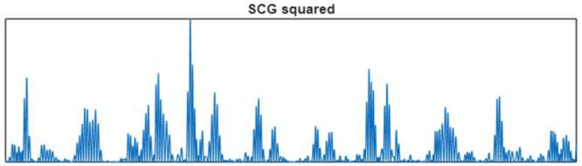

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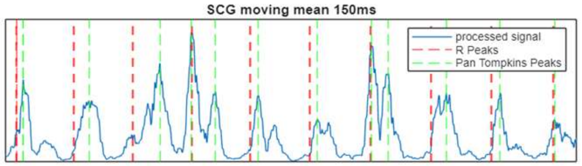

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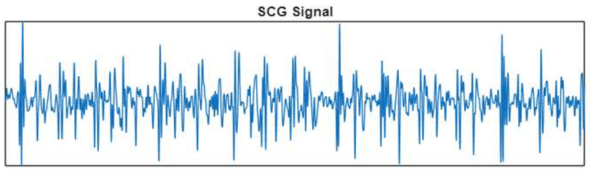
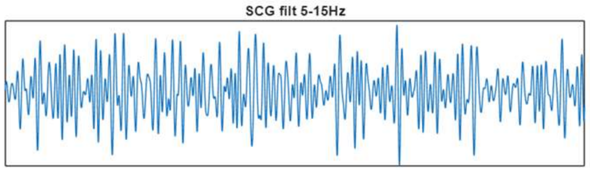
→ Easy to apply
→ Easy to tweak

→ Pan Tompkins fails for more complex heartbeat signatures as it is the case for older or unhealthy people



Unhealthy person*
Age: 46 years



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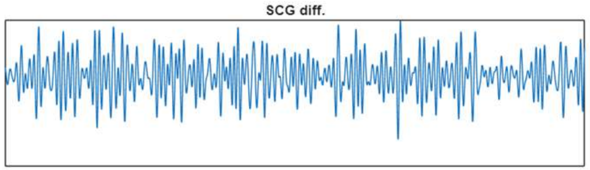

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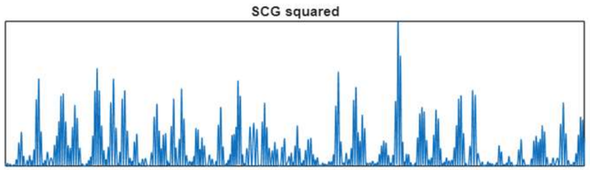

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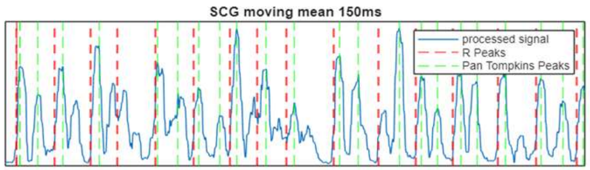

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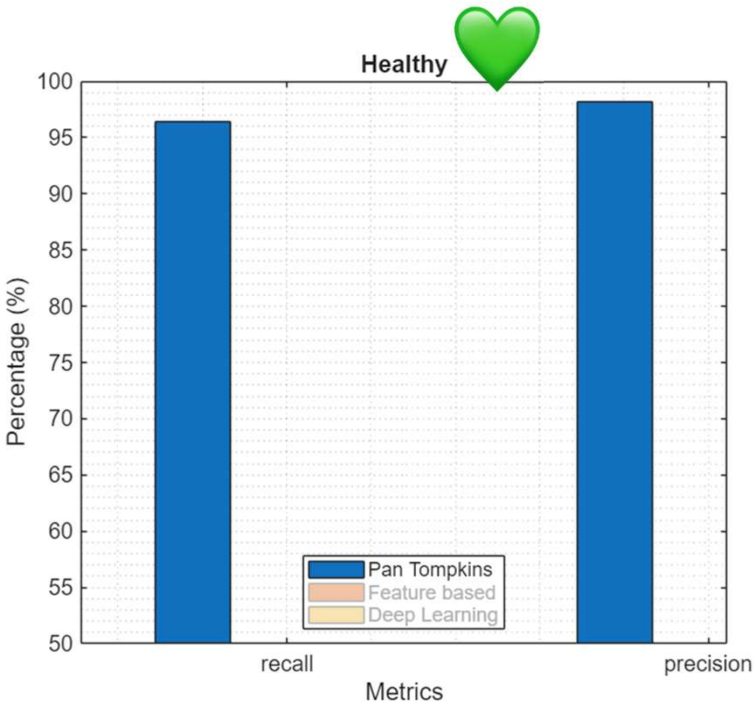

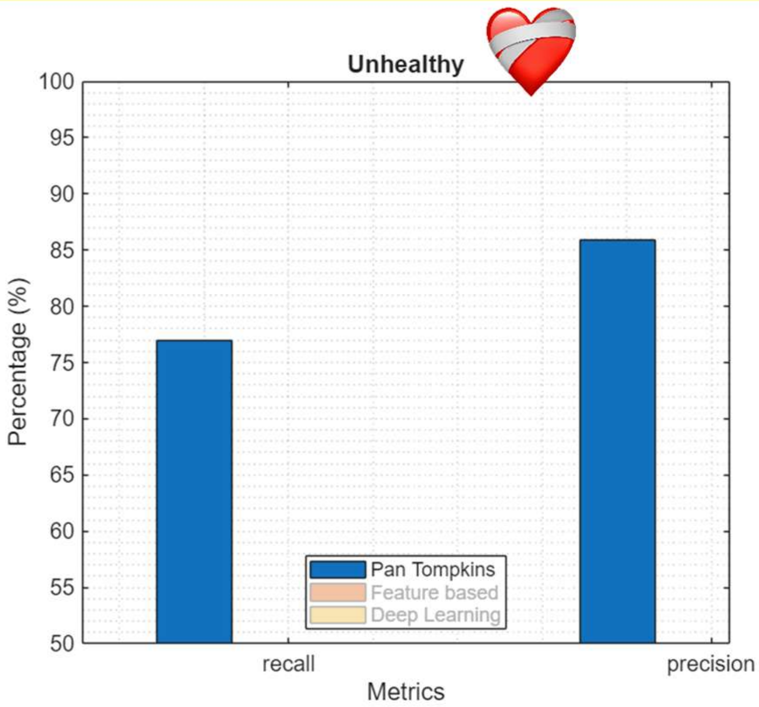

→ Fails with unhealthy MechanoCardioGraphs

Recall = TP / (TP + FN)
Precision = TP / (TP + FP)
True Positive (TP) Heartbeat Peak = appears AFTER R peak within 200ms
False Positive (FP) Heartbeat Peak = every other annotated peak that is NOT a heart beat
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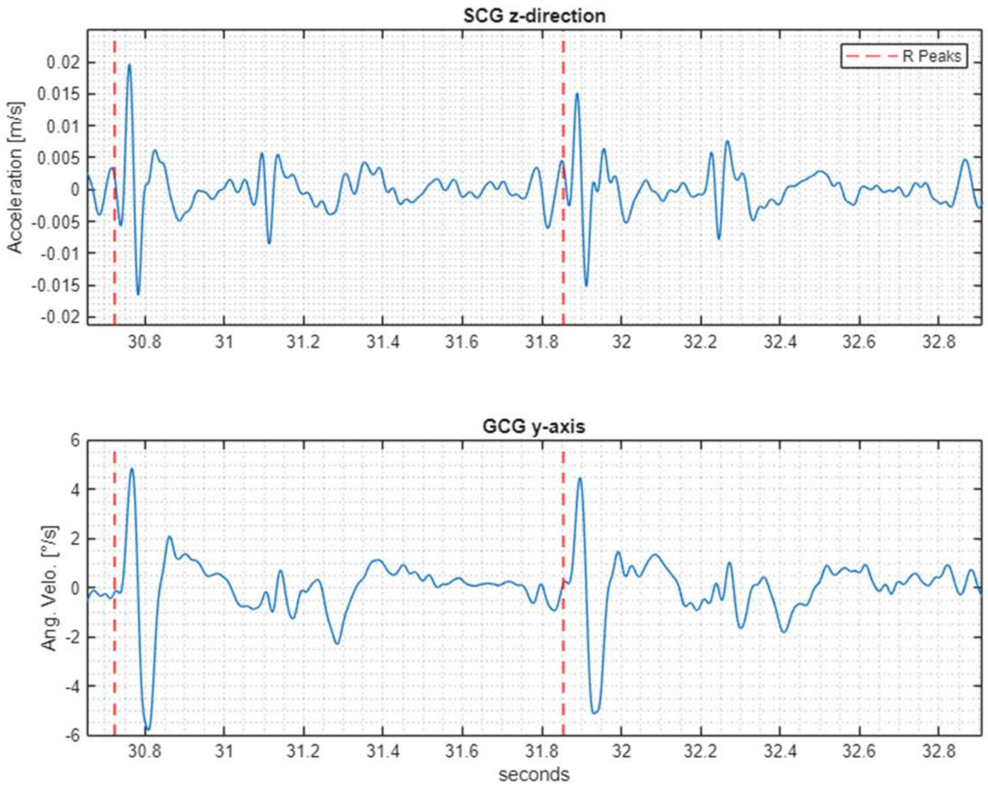
Recall
- "have **all heartbeat peaks** been found?"
- **100%** means we found **every heartbeat!**

Precision
- "how **few false heartbeat peaks** have been found?"
- **100%** means **no false positives!**

Second Approach – Feature Based Classification



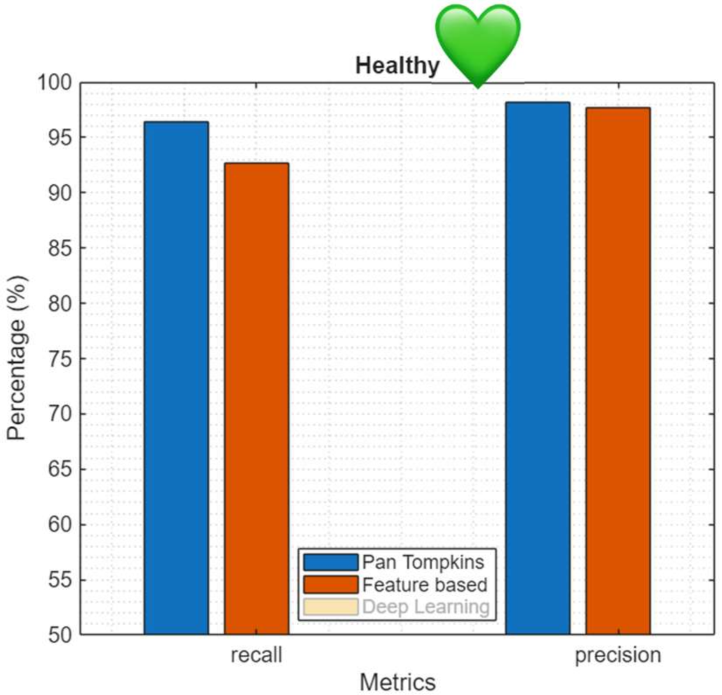
Train Machine Learning Model*

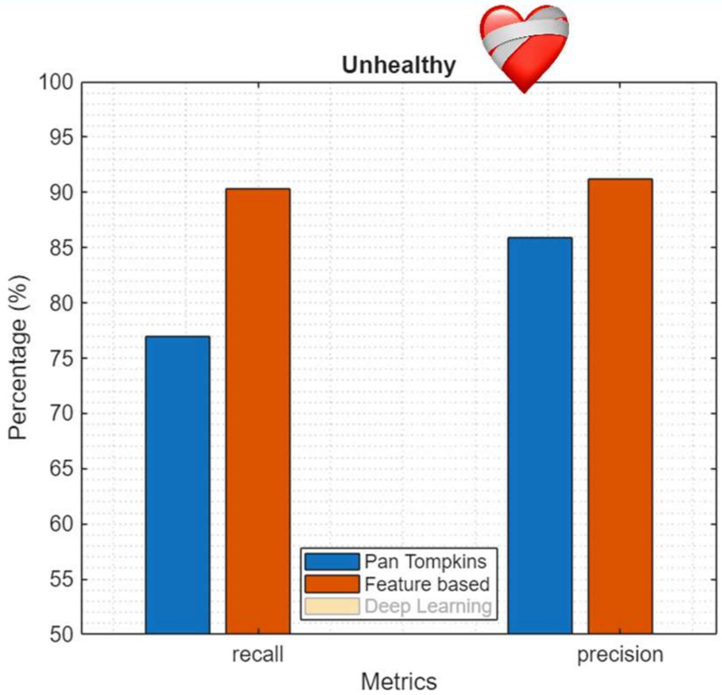
1. Peaks are characterized by
   - Abs. Amplitude
   - Rise-Time
   - falling-Time

   … many more features (20 – 30)
2. Classify peaks with random forest

*Trained on public data (healthy and unhealthy people)

Second Approach – Feature Based Classification





→ Less good for healthy MechanoCardioGraphs

→ But improves for unhealthy MCGs

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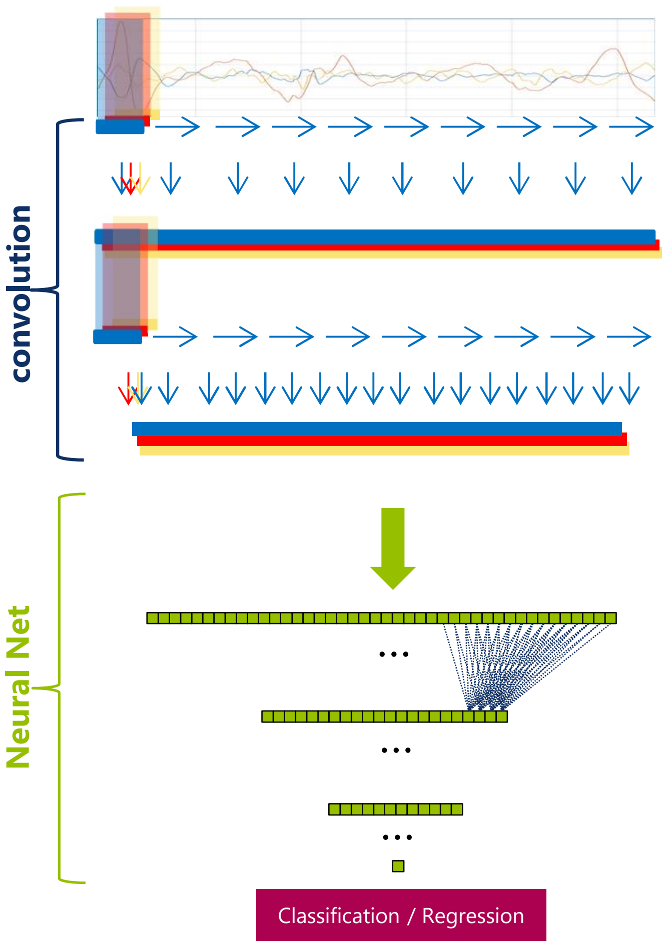
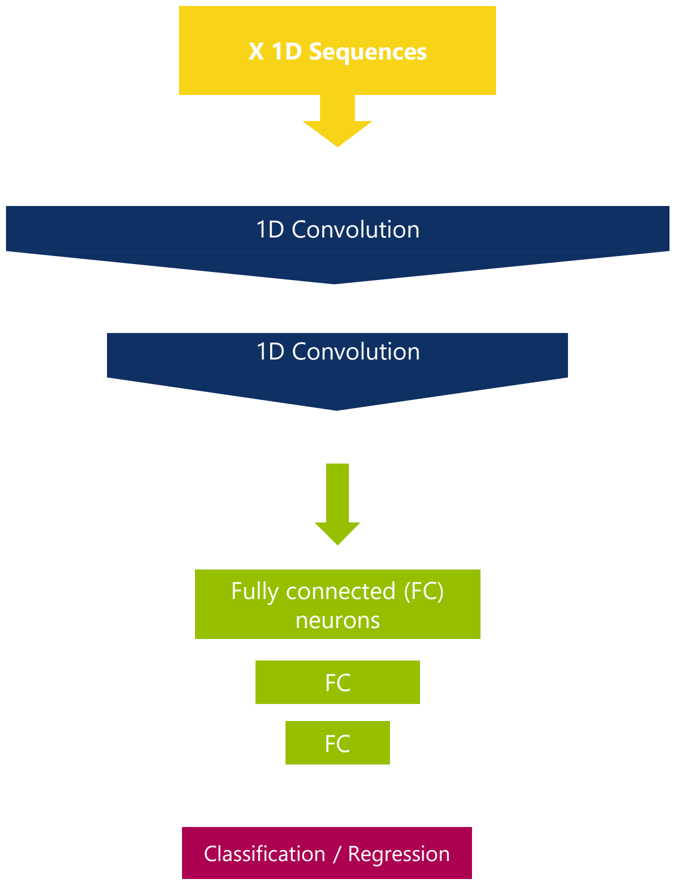
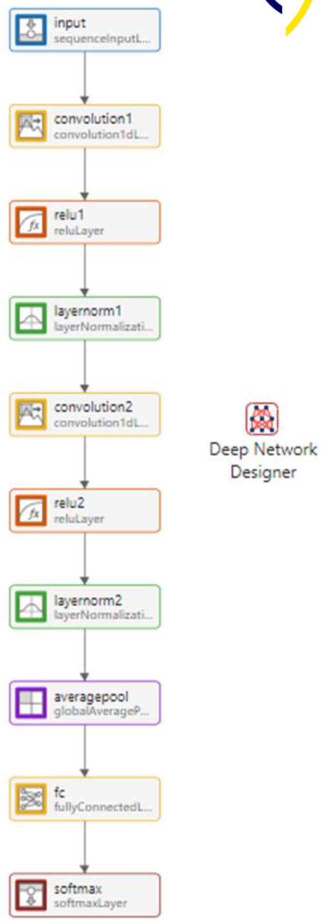
Final Approach – Deep Learning

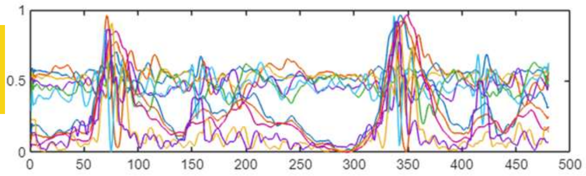




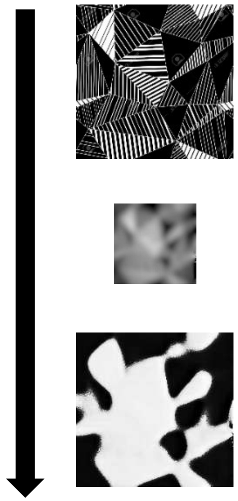


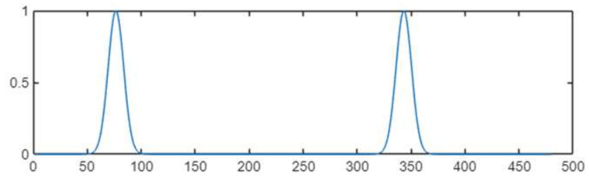
Final Approach – Deep Learning

11 Channels Sequence



3 **S**eismo**C**ardio**G**rams (x, y, z)
3 **G**yro**C**ardio**G**rams (x, y, z)
5 engineered signal combinations





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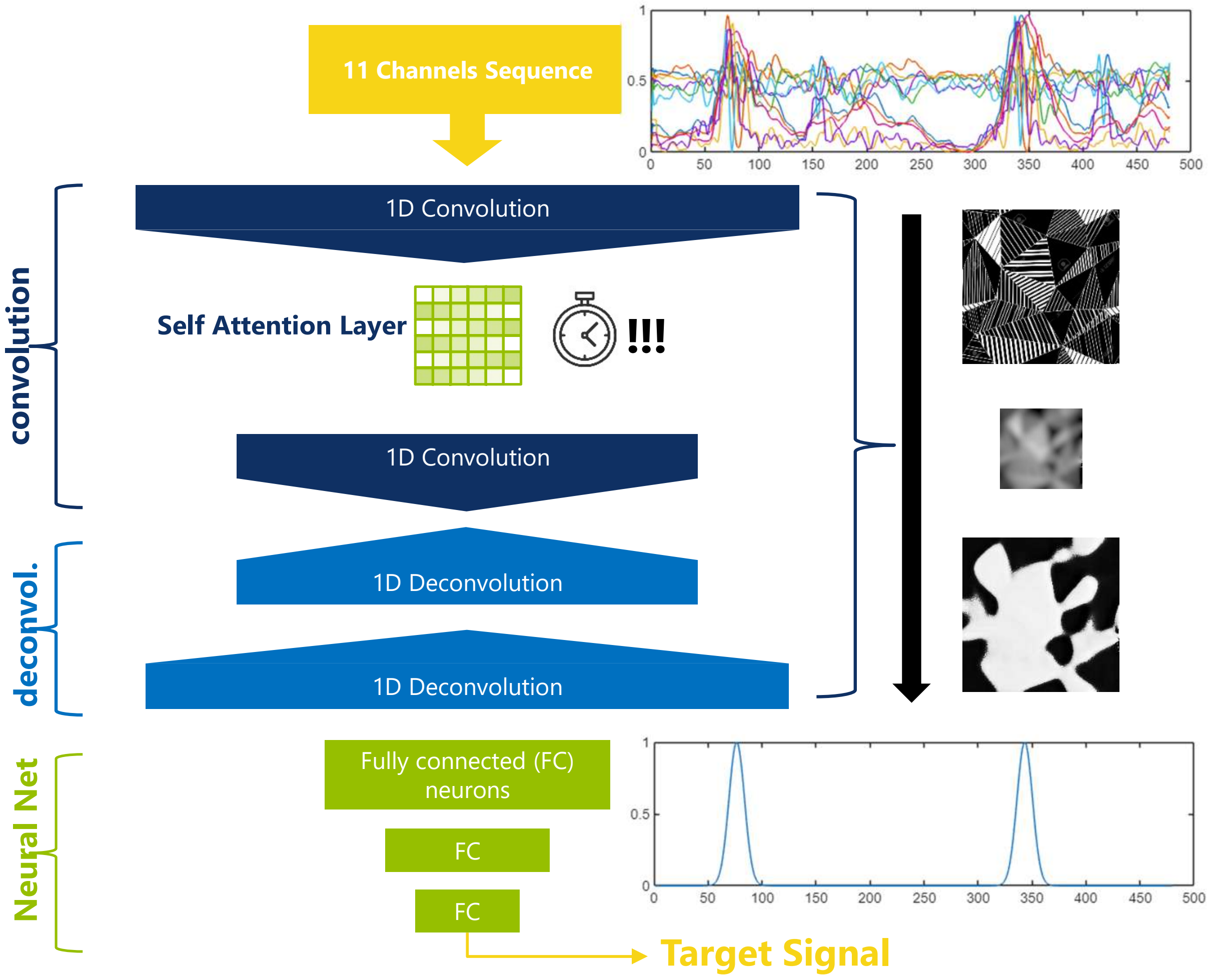

3 **S**eismo**C**ardio**G**rams (x, y, z)
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5 engineered signal combinations

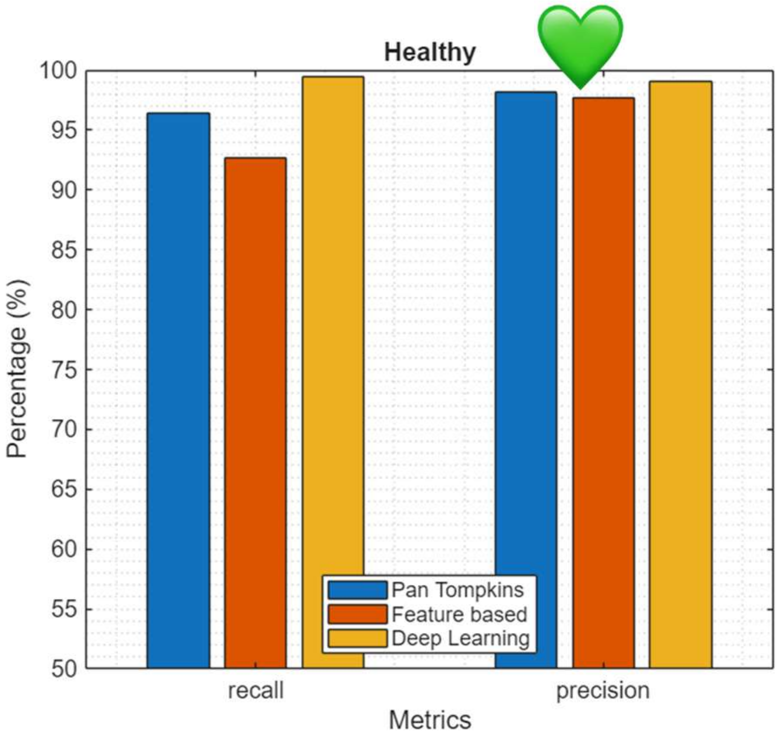
Encoder – Decoder Architecture

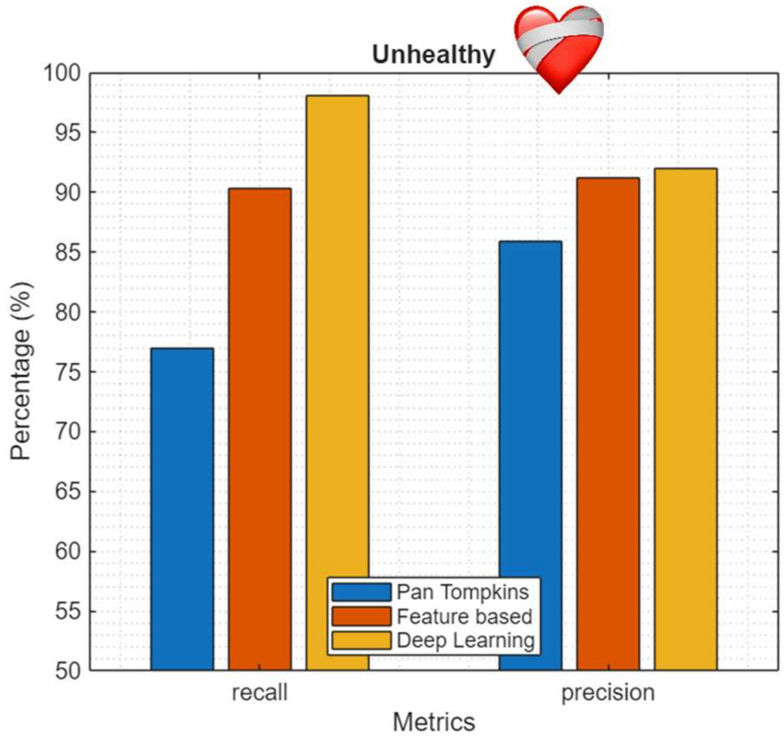
- Feature encoder by convolution
- Feature decoder by deconvolution restores temporal structure → smooth and spatially coherent features
- Features that do not contribute to correct target signal tend to be washed out → **acts like non-linear denoising**

Attention Layers as core improvement!

- Lets the model look at multiple time steps simultaneously
- **“which time points matter most?”**
- No recurrence → faster!

Final Approach – Deep Learning





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Conclusions

Rule based signal processing methods reach their limits

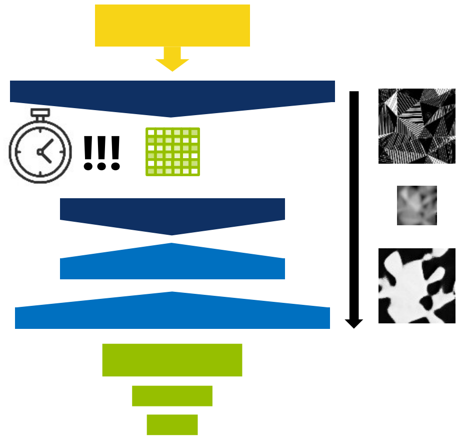
- Pan Tomkins algorithm works well for healthy signals
- But performance decreases significantly for complex pathological signals

Feature-based Machine Learning improves for unhealthy

- Well engineered features reduce false positives in pathological signals
- But reduced accuracy for healthy signals

Deep Learning enables reliable heart beat annotation

- 1 D CNN encoder-decoder architecture with attention increased prediction accuracy
- Best performance for healthy and pathological heart beat annotations
- <u>Robustness through learned temporal context</u>
- Same architecture might be applicable to other quasi-periodic signals



Sources

MATLAB Tool Boxes:

- Signal Processing Toolbox
- Statistics and Machine Learning Toolbox
- Deep Learning Toolbox

Data used for Training:

- 29 healthy people: IEEE Sensors Journal 2019, 19, 1 (DOI: 10.1109/JSEN.2018.2874706)
- 100 unhealthy people: Front. Physiol. 2021, 12 (DOI: 10.3389/fphys.2021.750221)
- Deep Learning architecture inspiration: Computation in Cardiology Conference 2024 – Hands on Tutorials: Deep Learning for Biomedical Signal Processing: ECG Reconstruction

Further Reading:

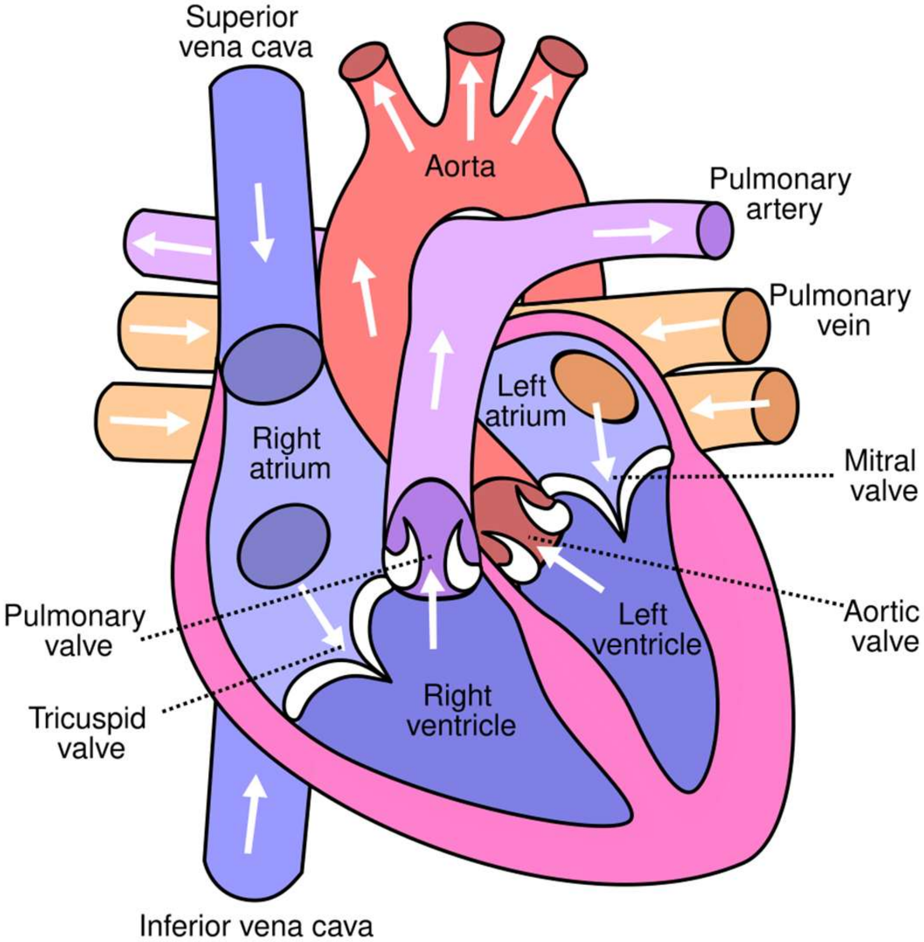
- "A review of Deep Learning for Biomedical Signals: Current Applications, Advancements, Future Prospects, Interpretation, and Challenges"; Computers, Materials & Continua 2025, 83 (3), 3753 (DOI: 10.32604/cmc.2025.063643)

Get in touch if you have any questions or would like to work with us on deep learning solutions!

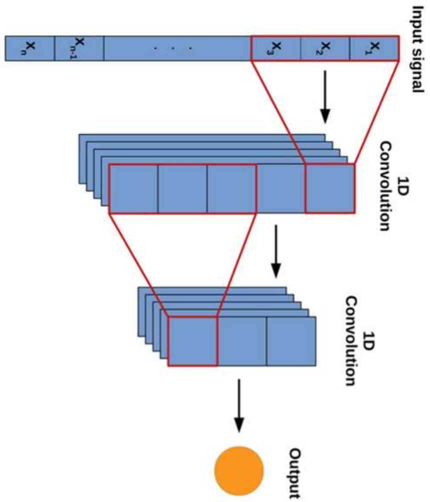
Thank you for your Attention!

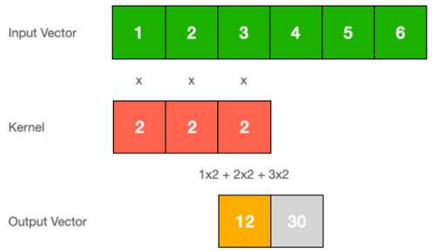
Supplementing Informations

Illustration of the human heart



Descriptive Examples for convolution





Stride

nn.Conv1d(in_channels=1, out_channels=1,
 kernel_size=3, stride=3,
 bias=False
)

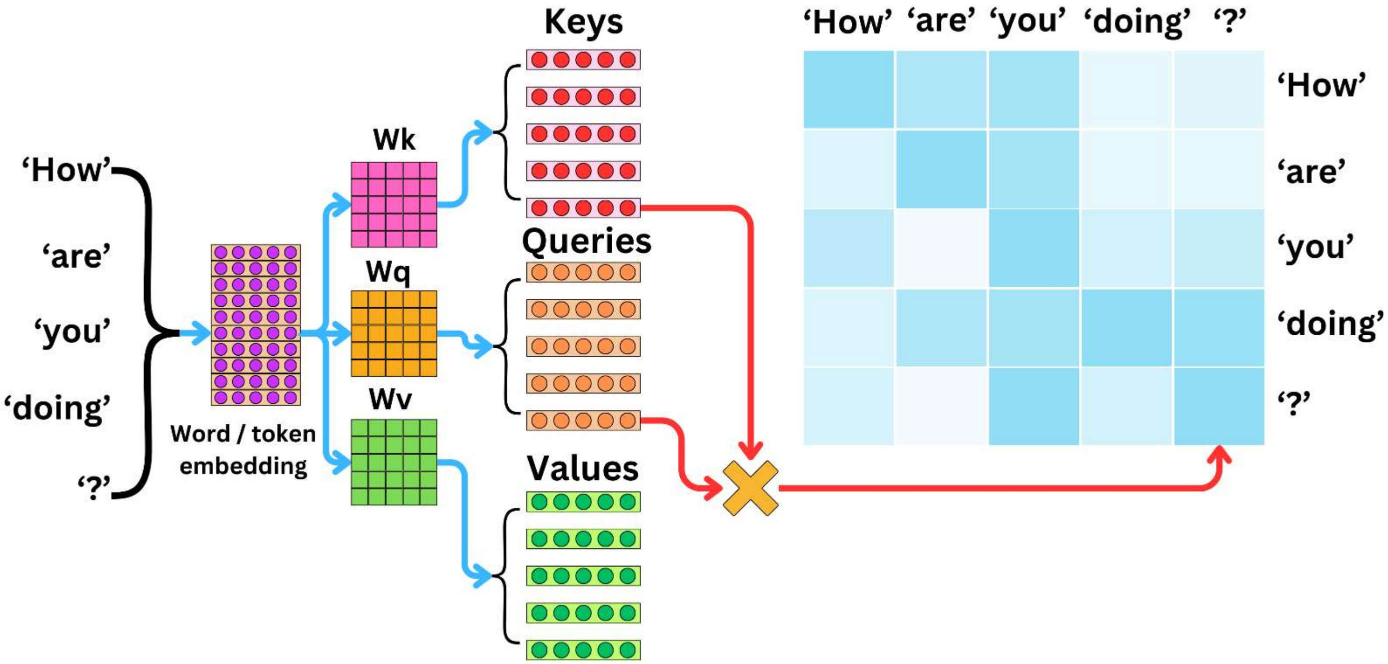
Size

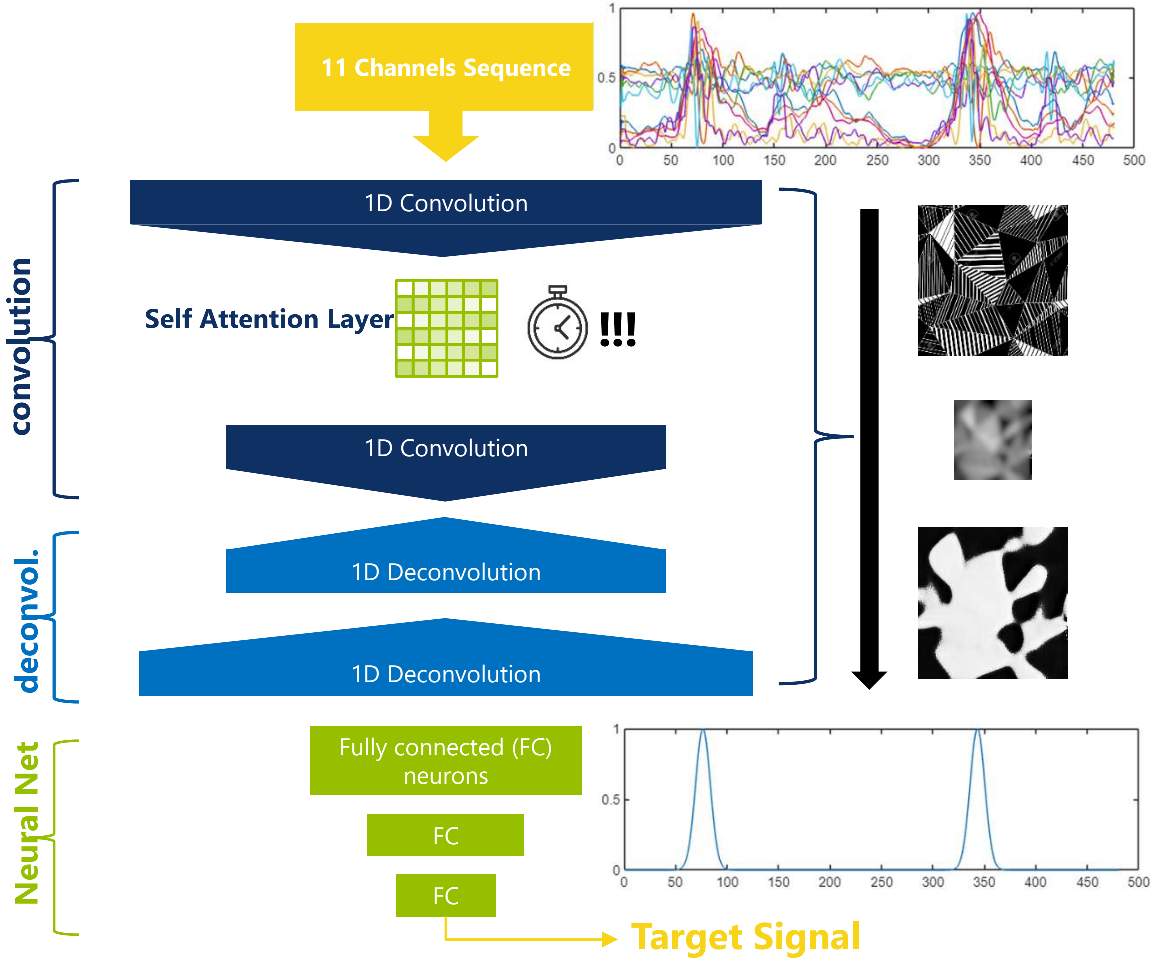
$$L_{out} = \left\lfloor \frac{L_{in} + 2 \times \text{padding} - \text{dilation} \times (\text{kernel\_size} - 1) - 1}{\text{stride}} + 1 \right\rfloor$$

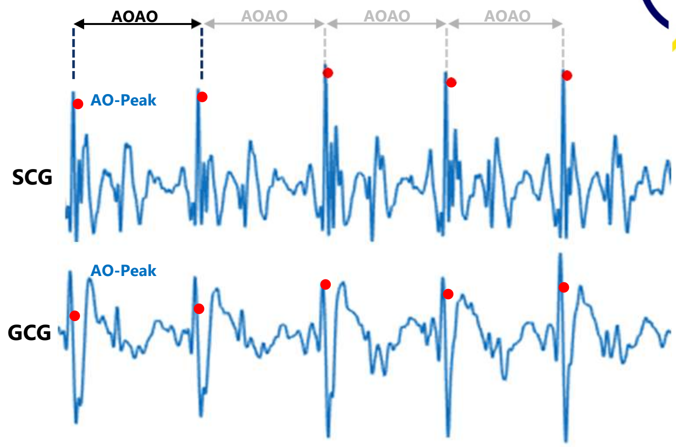
$$2 = \frac{6 + (2 * 0) - 1 * (3 - 1) - 1}{3} + 1$$

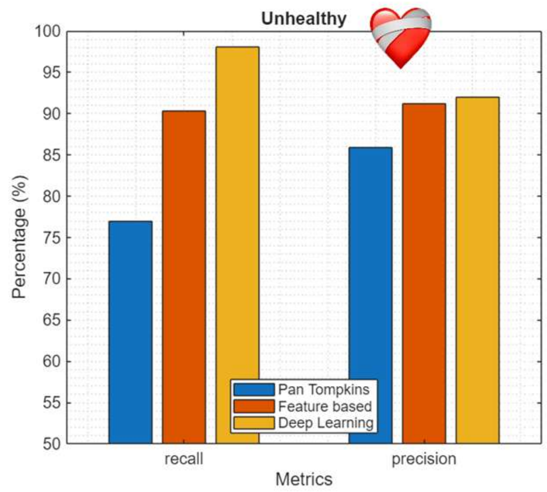
jinglescode.github.io

Dexcriptive example of Self Attention




11 Channels Sequence
convolution
1D Convolution
Self Attention Layer
!!!
1D Convolution
deconvol.
1D Deconvolution
1D Deconvolution
Neural Net
Fully connected (FC) neurons
FC
FC
Target Signal


AOAO
AOAO
AOAO
AOAO
AO-Peak
SCG
AO-Peak
GCG


Unhealthy
Percentage (%)
Pan Tompkins
Feature based
Deep Learning
recall
precision
Metrics