Rendering 1:

Context:

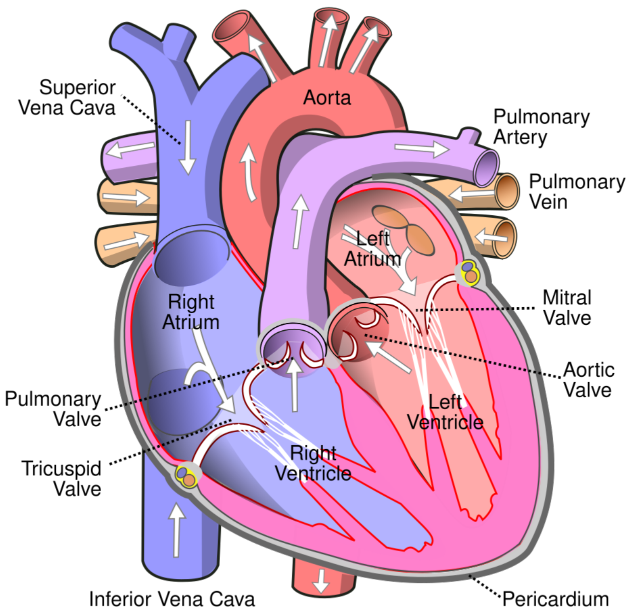
- Heart responsible for blood circulation through the whole body [3] [5]
- Worldwide: cardiovascular diseases are leading cause of mortality [1] [6]
- Well-known problem: arrhythmia/cardiac irregularities -> early diagnosis and prevention of cardiovascular diseases if detected is possible [3] [6]
- Change from regular pattern can be sign for myocardial infarction (MI) [4]

- arrhythmias: irregular heartbeat [3] [6], different types [1]
- myocardial infarction: heart attack [6] -> When blood flows to the heart is blocked

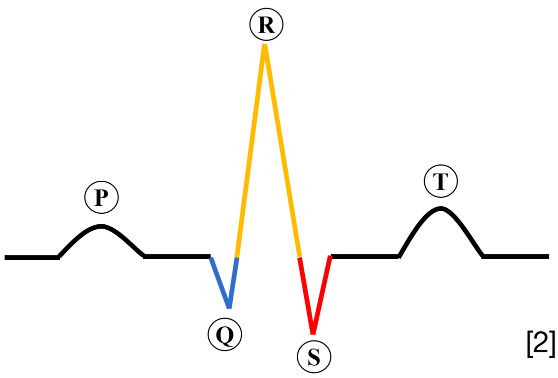
ECG:

- Electrocardiogram [4] [5]
- Time-series [1] [5]
- Non-invasive recording of electrical activity of the heart [2] [4] [5] [6]
- Monitor functionality of heart [1]
- Signal: wave -> shows each heartbeat's rhythm and strength [2]
- consists of 5 parts: [2] [4] [5] [6]
  - P: atrial contraction, small increase (round)
  - Q/R/S: ventricular contraction
    - Q: small decrease
    - R: big increase
    - S: small decrease
  - T: ventricular relaxation, small increase but bigger than P

- Benchmark approach for detection of cardiac anomalies like arrhythmia [6]
- Difficulty: detect and categorise different waveforms in a big amount of data -> use deep learning to detect anomalies [1] [6]
- Use ML or DL techniques to standardise and automate analysis -> improve patient outcomes [6]



https://en.wikipedia.org/wiki/Heart#/media/

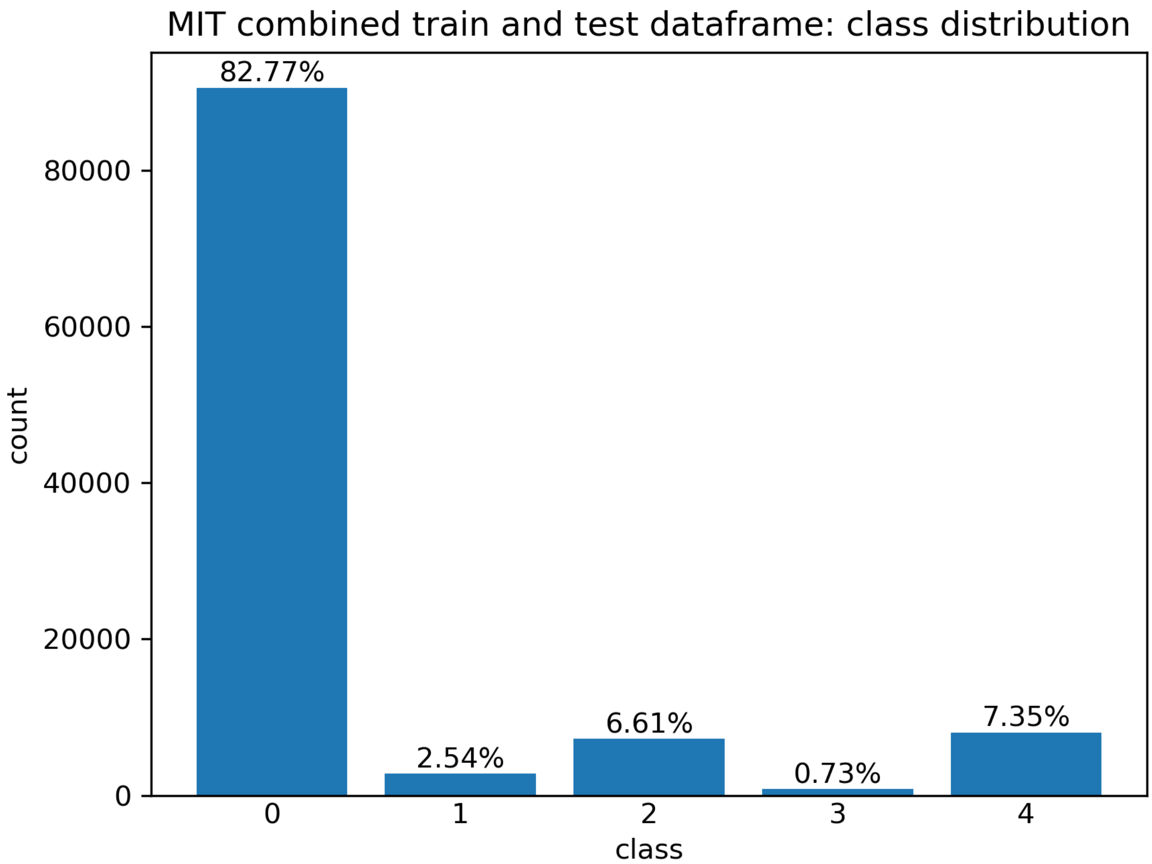


[2]

<u>Definition of the problem:</u>
- **supervised problem**: labeled data
- **Classification** problem: first arrhythmia 5 classes, second transfer learning MI 2 classes

<u>2 preprocessed datasets:</u> [1]
- 188 columns -> time points, final column: classification result
- Each row represents one 1.2 heartbeats

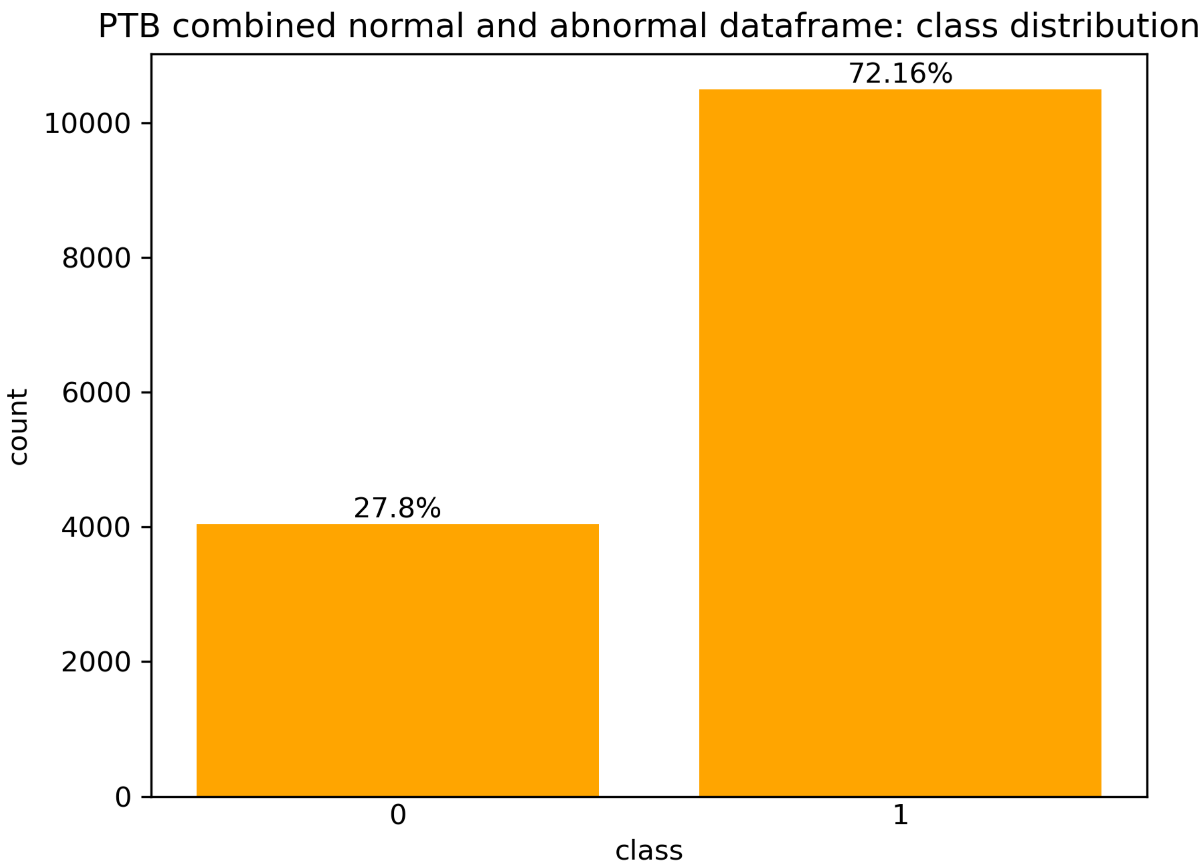
- MIT-BIH Arrhythmia database: most used dataset for detecting and classifying arrhythmia [6]
  - Recordings from 47 different subjects
  - Each beat classified by at least 2 cardiologists
  - **5 categories:** 0: normal N, 1: atrial premature S, 2: premature ventricular contraction V, 3: fusion ventricular and normal F, 4: not classifiable/fusion of paced and normal Q -> broad variety of different arrhythmia types (see overview example plots for each class on p. 3)
  - **109446 samples in total** -> train 80%, test: 20% [1]
  - **Numerical, normalised and preprocessed data, no missing values, no duplicates**
  - **Imbalanced** classes (see plot on p. 2):
    - 0: 82.8%, 1: 2.5%, 2: 6.6%, 3: 0.7%, 4: 7.3%
    - For training procedure, **data augmentation** is necessary to balance classes, like in [1] to **prevent model bias toward class 0**
    - Especially class 3 is underrepresented (less than 1%).
    - Test to validate observation: scipy.stats chisquare test
      - H0: balanced class distribution -> each class identical frequency: 109446 rows/5 classes = 21889.2
      - H1: unbalanced class distribution
      - p-val: 0 -> $p < 0.05$ -> H0 is rejected, H1: unbalanced class distribution present




MIT cl. 0 example
MIT cl. 1 example
MIT cl. 2 example
MIT cl. 3 example
MIT cl. 4 example
PTB cl. 0 example
PTB cl. 1 example
amplitude
time
0.0 0.2 0.4 0.6 0.8 1.0
0 25 50 75 100 125 150 175

- PTB Diagnostic ECG database:
  - Recordings from 290 subjects: 148 MI, 53 healthy, 90 diagnosed with 7 different diseases
  - Here: MI and normal datasets (see overview example plots for each class on p. 3)
  - **14552 samples in total** -> train 80%, test: 20%
  - **Numerical, normalised and preprocessed data, no missing values, duplicates** (6 in abnormal dataset, 1 in normal dataset -> delete, so 14545 rows)
  - **Imbalanced** classes (see plot on p. 4):
    - 1/MI: 72.2%, 0/normal: 27.8%
    - For training procedure, **data augmentation** is necessary to balance classes, like in [1] to **prevent model bias towards class 1**
    - Test to validate observation: scipy.stats chisquare test
      - H0: balanced class distribution -> each class identical frequency: 14545 rows/2 classes = 7272.5
      - H1: unbalanced class distribution
      - p-val: 0 -> $p < 0.05$ -> H0 is rejected, H1: unbalanced class distribution present
  - broad variety of different ECG signals that indicate MI (see overview example plots for each class on p. 3)

Chisquare test:
https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.chisquare.html
https://en.wikipedia.org/wiki/Goodness_of_fit
- categorical variable: classes
- H0: Expected distribution: balanced, each class has the same frequency
- p-val < 0.05: H0 is rejected

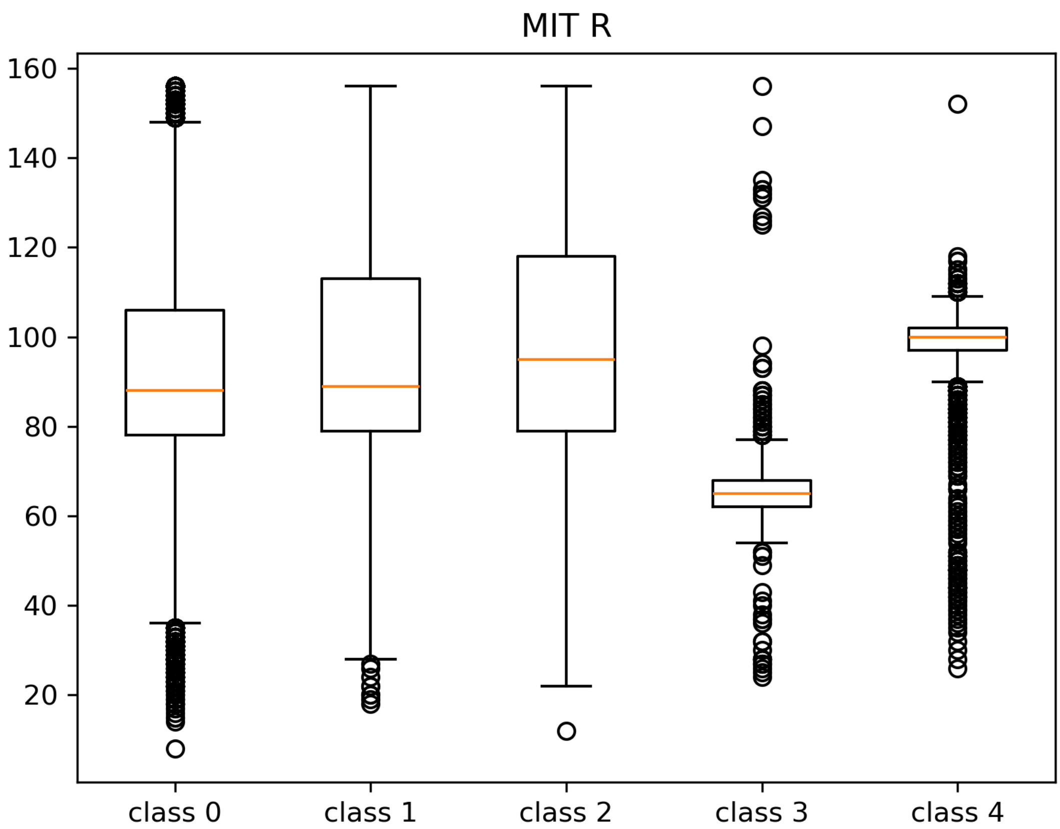


Preprocessing procedure in [1]:
- extraction of single beats from longer ECG data
- Split ECG signals into 10s windows -> select one window
- Amplitude normalisation between 0 and 1
- Find all local maximums
- Find R peaks
- Find median of R-R peak time (time of one heart beat) -> T
- Select signal part with length 1.2T for each R peak to include all phases of the heartbeat
- Adding zeroes to produce signals of equal length to generate input for DL technique

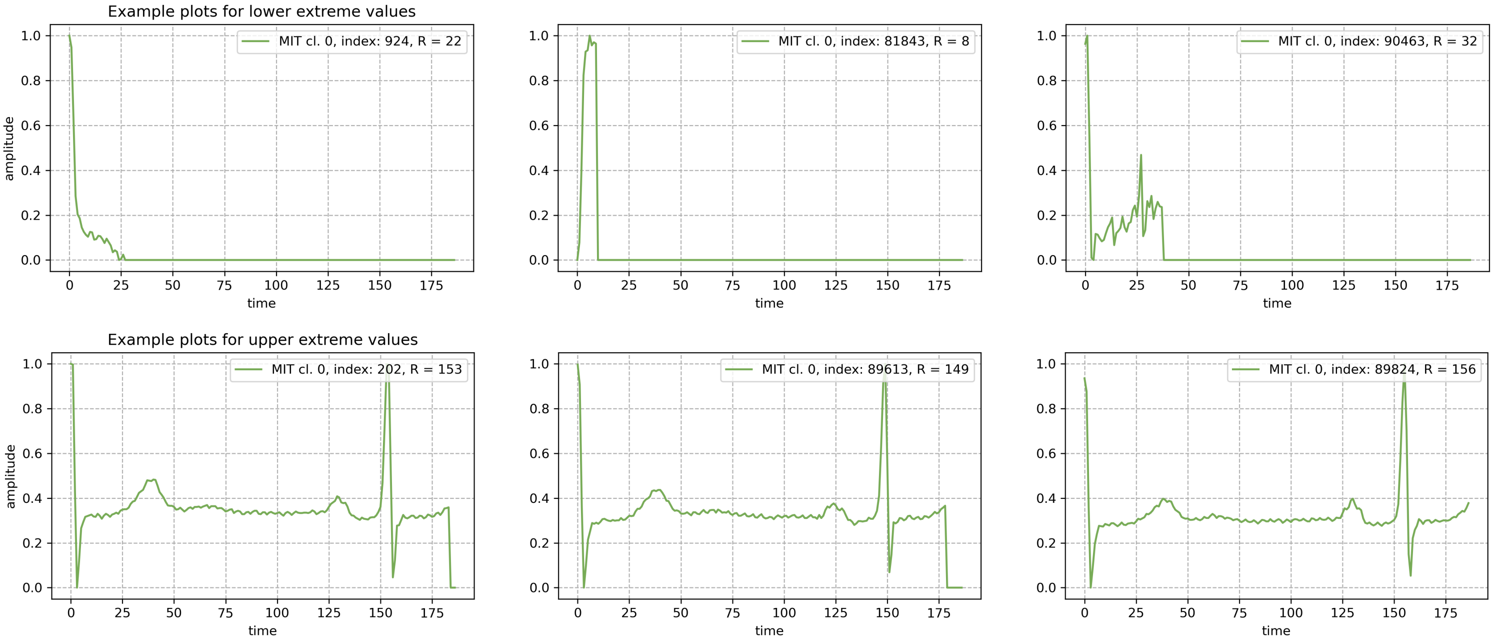
RR distance:
- duration of heartbeat
- Each row shows data of 1.2R, padded with zeros -> possible to extract R by identifying index at start of zero padding and dividing index by 1.2
- **Calculate R for each heartbeat of each class, identification of extreme values, analysis of corresponding ECG data**

- MIT:

class	Mean R	Median R	Lower extreme values	Upper extreme values
0	92	88	0.5%	1.0%
1	95	89	0.3%	0.0%
2	98	95	0.1%	0.0%
3	65	65	3.5%	6.2%
4	99	100	5.1%	0.5%

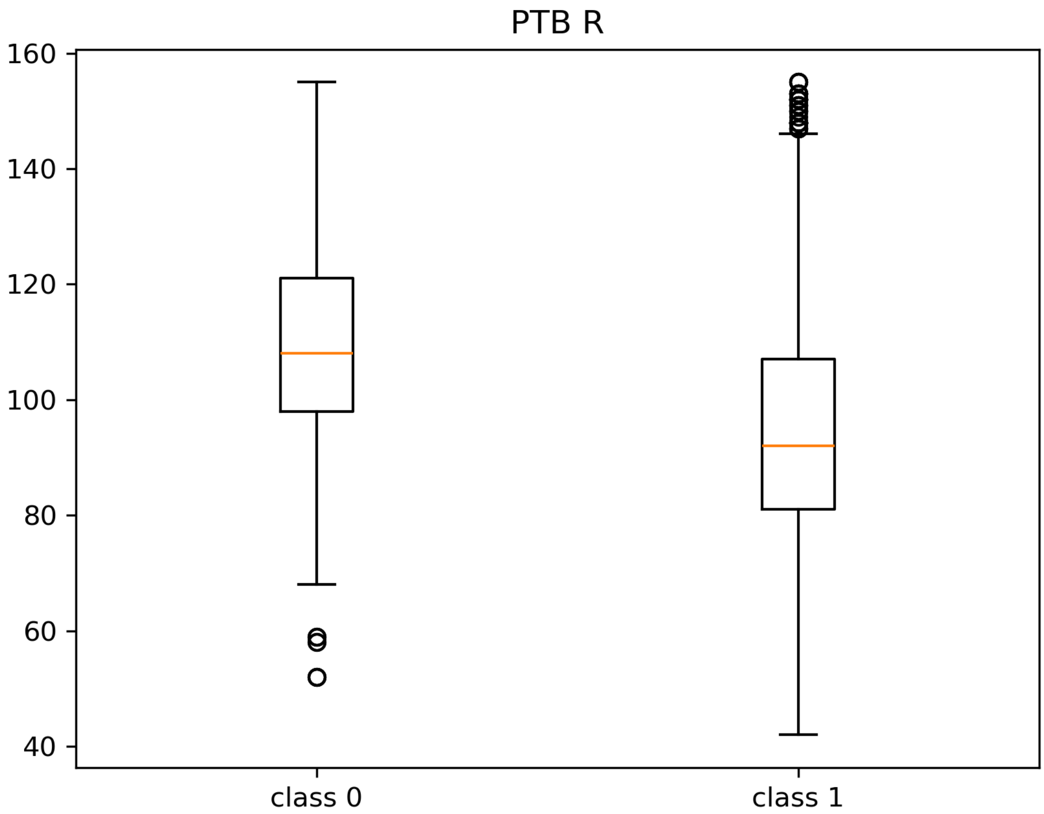


- class 0:
  - **ECG data of example lower extreme values for R look NOT normal (see upper row in plot on p. 6) -> could be a classification mistake?**
  - For upper extreme values ECG data seems to be okay (see lower row in plot on p. 6)
- For other classes it is hard to say if ECG data of extreme values for R look unnormal, because it is arrhythmia data -> could be due to disease
- Class 3/4: high amount of extreme values for R

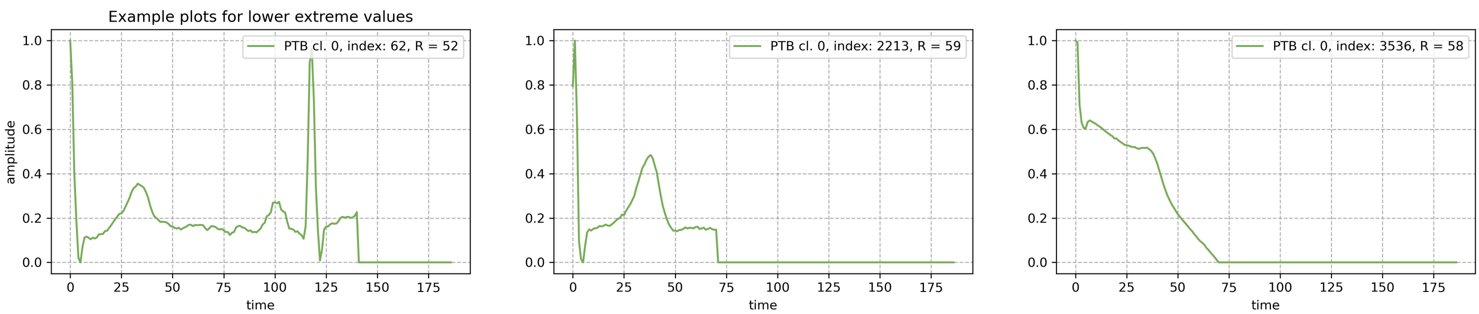


- PTB:

class	Mean R	median R	Lower extreme values	Upper extreme values
0	109	108	0.2%	0.0%
1	94	92	0.0%	0.6%



- class 0:
  - **Some ECG data of example lower extreme values for R look NOT normal (see plot on p. 7) -> could be a classification mistake?**
- For other class it is hard to say if ECG data of extreme values for R look unnormal, because it is MI data -> could be due to disease



Compare R data of different classes:

- is the data significantly different when comparing different classes? -> should be different because different classes correspond to normal and ECG data from different arrhythmia types or MI

- statistical test: Kruskal Wallis -> each class has a different amount of data
  - check if R data is significantly different ($p < 0.05$) for:
    - MIT class 0 vs MIT class 1 -> yes
    - MIT class 0 vs MIT class 2 -> yes
    - MIT class 0 vs MIT class 3 -> yes
    - MIT class 0 vs MIT class 4 -> yes
    - MIT class 1 vs MIT class 2 -> yes
    - MIT class 1 vs MIT class 3 -> yes
    - MIT class 1 vs MIT class 4 -> yes
    - MIT class 2 vs MIT class 3 -> yes
    - MIT class 2 vs MIT class 4 -> yes
    - MIT class 3 vs MIT class 4 -> yes
    - MIT class 0 vs PTB class 1 -> yes
    - MIT class 1 vs PTB class 1 -> NO (maybe the kind of arrhythmia from the MIT dataset has similar characteristics with MI)
    - MIT class 2 vs PTB class 1 -> yes
    - MIT class 3 vs PTB class 1 -> yes
    - MIT class 4 vs PTB class 1 -> yes
    - PTB class 0 vs PTB class 0 -> yes

  - check if R data is NOT significantly different ($p > 0.05$) for:
    - MIT class 0 vs PTB class 0 (because with transfer learning it should be possible to classify PTB class 0 correctly) -> NO => maybe extreme values for MIT dataset are problematic

Kruskal Wallis test:

https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.kruskal.html

https://de.wikipedia.org/wiki/Kruskal-Wallis-Test

- Groups do not have to be the same size
- H0: population median is equal for all groups
- p-val < 0.05: H0 is rejected

LATER:

Training: [1]

- First:
  - Arrhythmia classification on MIT dataset -> 5 classes
  - Start with easy models, test hyper parameters, later DL
- Second:
  - use first model as base for training of MI classifier with PTB data (80% training, 20% test, transfer learning) -> 2 classes
- Important: data augmentation to balance classes
- Data augmentation: create more samples from existing samples to generate more samples of underrepresented classes (oversampling, undersampling…)
- Generate results comparable to [1] (see more publications with comparable training for comparison of results and context)

Metrics:

Accuracy: proportion of total predictions the model correctly predicted
(TP+TN) / (TP+TN+FP+FN))

Sensitivity/Recall: proportion of actual positives correctly predicted by the model
TP/(TP+FN)
- reflects reliability in detecting arrhythmias or MI

Specificity: proportion of real negatives that are correctly predicted
TN/(TN+FP)
- ability of model to prevent incorrect diagnoses

Precision: of all positive predictions, how many were actually positive
TP/(TP+FP)

F1 Score: high F1 means that precision and recall are high, low F1 means that one or both are low
2*((Precision * Recall)/(Precision + Recall))

Results [1]:

- Arrhythmia detection:
  - More than 93% average accuracy
- MI detection:
  - more than 95% accuracy
  - more than 95% precision
  - more than 95% recall

Results [6]:

- over 96% accuracy, sensitivity, specificity, F1 score in arrhythmia detection

Results project:

- should be better than 93% accuracy, sensitivity, specificity, F1 score in arrhythmia detection
- Should at least generate 95% accuracy, precision, recall in MI detection
- Comparison with other publications

- [1]: ECG Heartbeat Classification: A Deep Transferable Representation
- [2]: Electrocardiogram Heartbeat Classification for Arrhythmias and Myocardial Infarction
- [3]: Classification and Detection of ECG Arrhythmia and Myocardial Infarction Using Deep Learning: A Review
- [4]: https://www.analyticsvidhya.com/blog/2021/07/artificial-neural-network-simplified-with-1-d-ecg-biomedical-data/
- [5]: https://www.datasci.com/solutions/cardiovascular/ecg-research
- [6]: Deep learning for ECG Arrhythmia detection and classification: an overview of progress for period 2017-2023