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CAN WE TEACH A MACHINE TO BE A CARDIOLOGIST?

Outline

- Introduction
  - Project Aims and Motivation
  - Background
  - Project Methodology
- Method
  - Data Pre-Processing
  - Feature Extraction
  - Machine Learning Classification
- Results
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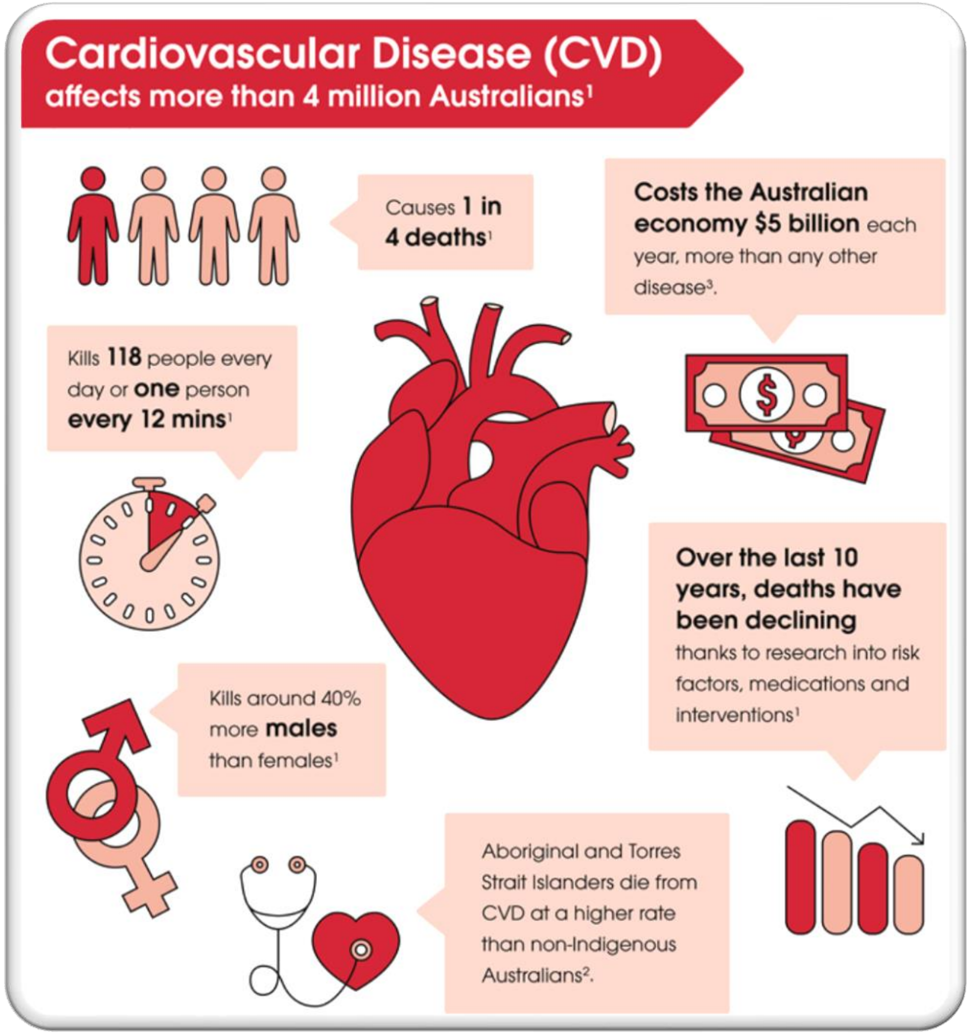
  - Comparison with Literature
- Conclusion

Introduction

The Big Picture

- Among Australia's leading health problems
  - 1 in 6 live with CVD
  - Causes 1 in 4 deaths
- Often preventable with lifestyle changes
- Hence, important to diagnose early and accurately



Source: https://www.heartfoundation.org.au/activities-finding-or-opinion/key-stats-cardiovascular-disease

Project Aim

- Find good method of classifying heart conditions
  - Data pre-processing
  - Machine learning (ML) to classify
- Experiment with different methods
- Summarise findings

Image source: https://www.firstbeat.com/en/blog/what-is-heart-rate-variability-hrv/

Electrocardiograms

- Electrical signal produced by the heart
- Important in diagnosing heart disease
- Easily collected → place electrodes on skin
- Can be processed like any other digital signal

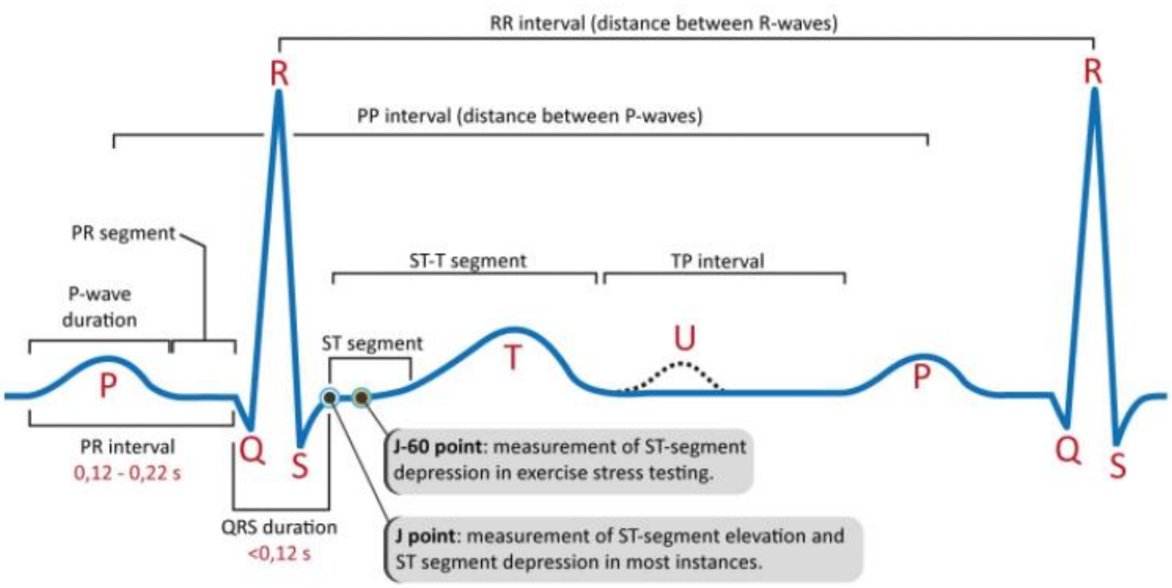
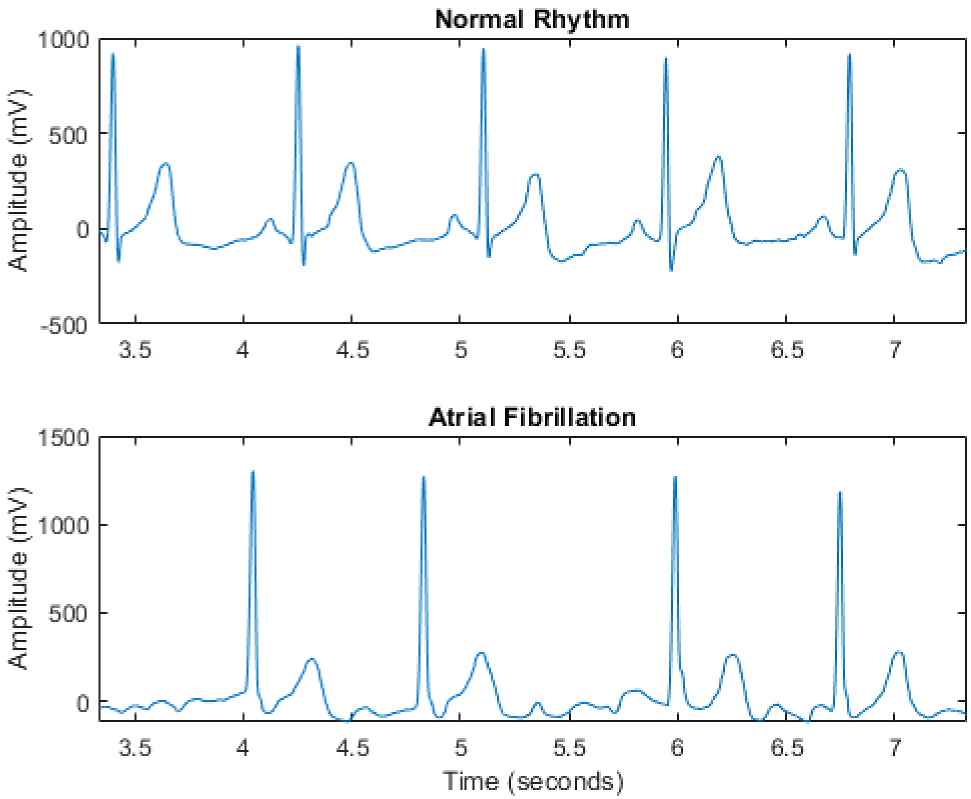


Image source: https://ecgwaves.com/course/the-ecg-book/

Atrial Fibrillation

- Atria contract rapidly
- P-wave replaced with disorderly tremor waves
- Variable heart rate
- Characterised by palpitations, shortness of breath and chest pain
- Incidence increases with age



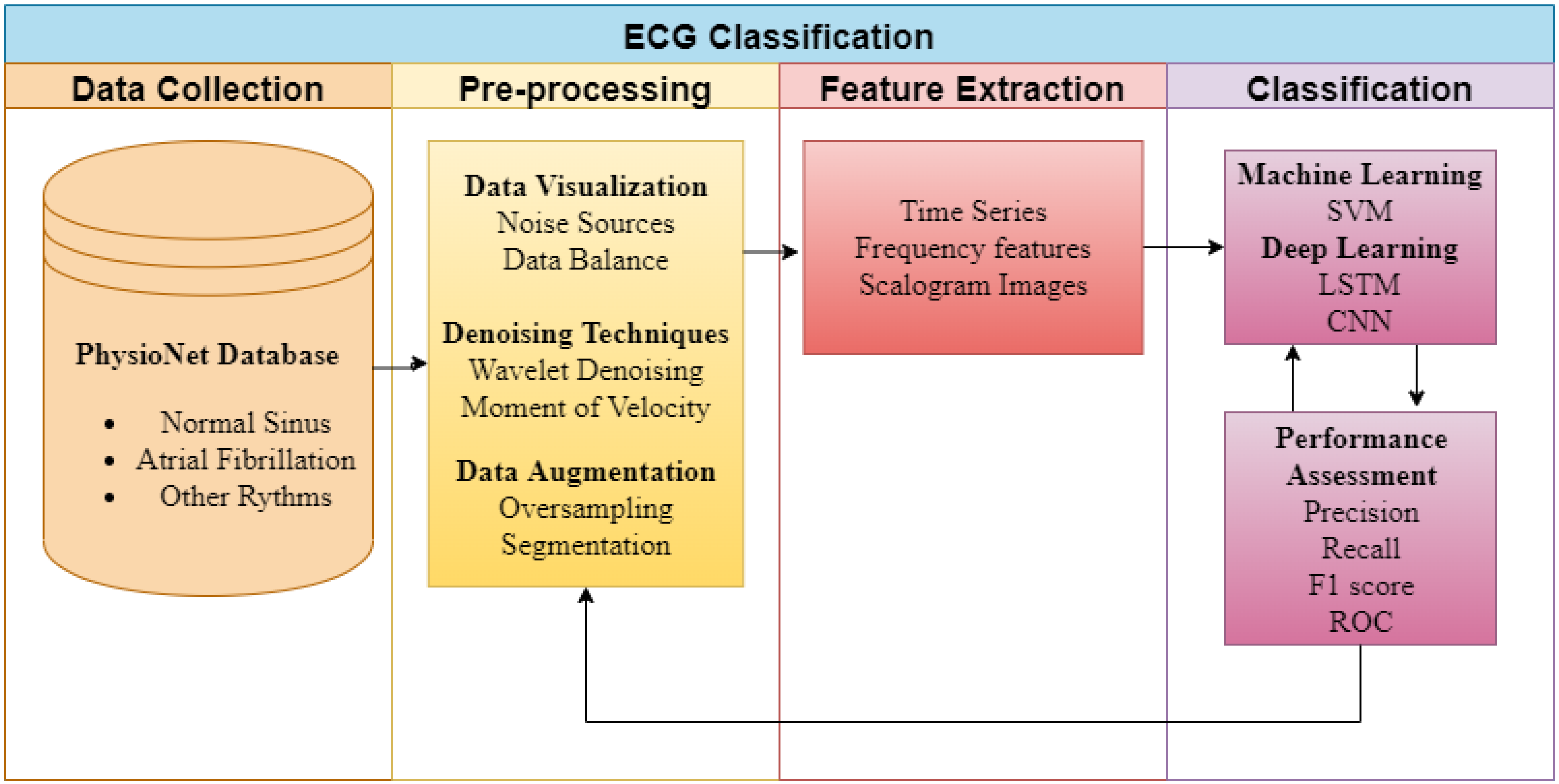
ECG data source: https://www.physionet.org/content/challenge-2017/1.0.0/

Background on Machine Learning

- Application of AI
- Algorithms:
  - Parse data
  - Learn from it
  - Make informed decisions
- Split data: training and test sets

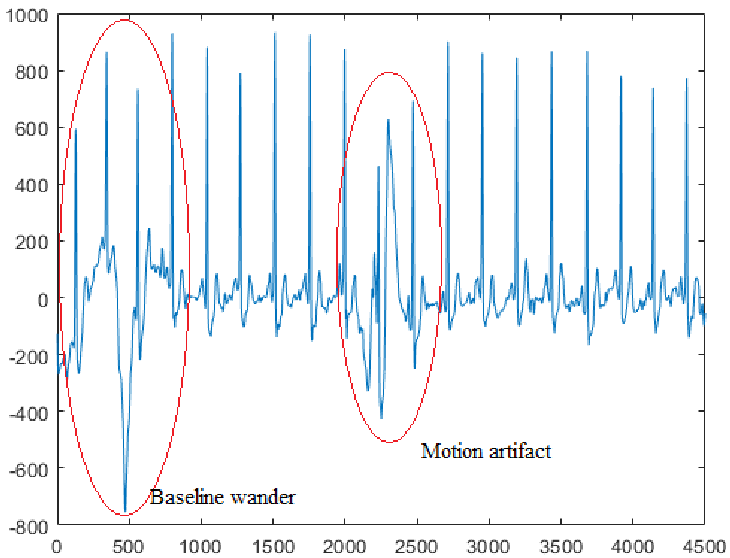
Source: https://hbr.org/2020/05/harnessing-artificial-intelligence

Project Methodology

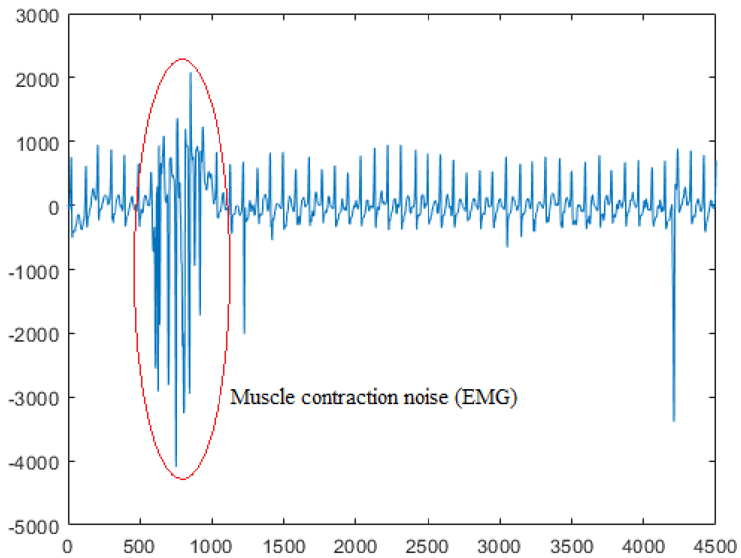


Pre-Processing and Feature Extraction

ECG Noise



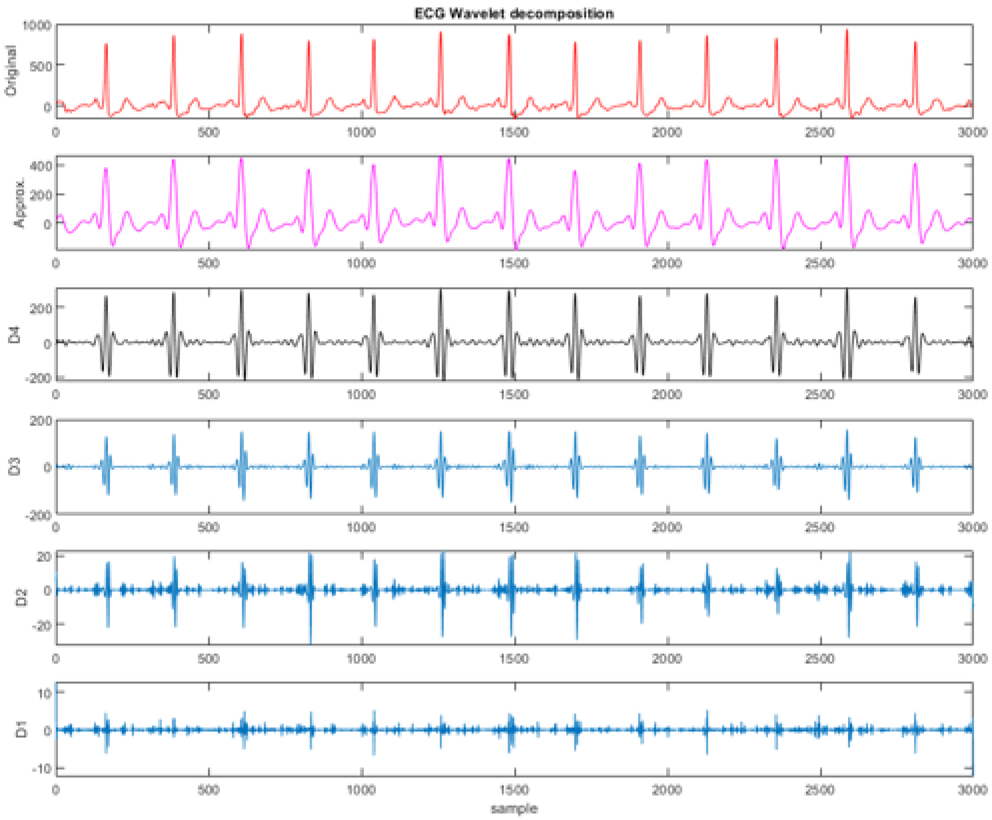
Baseline wander and motion artifact



Muscle contraction

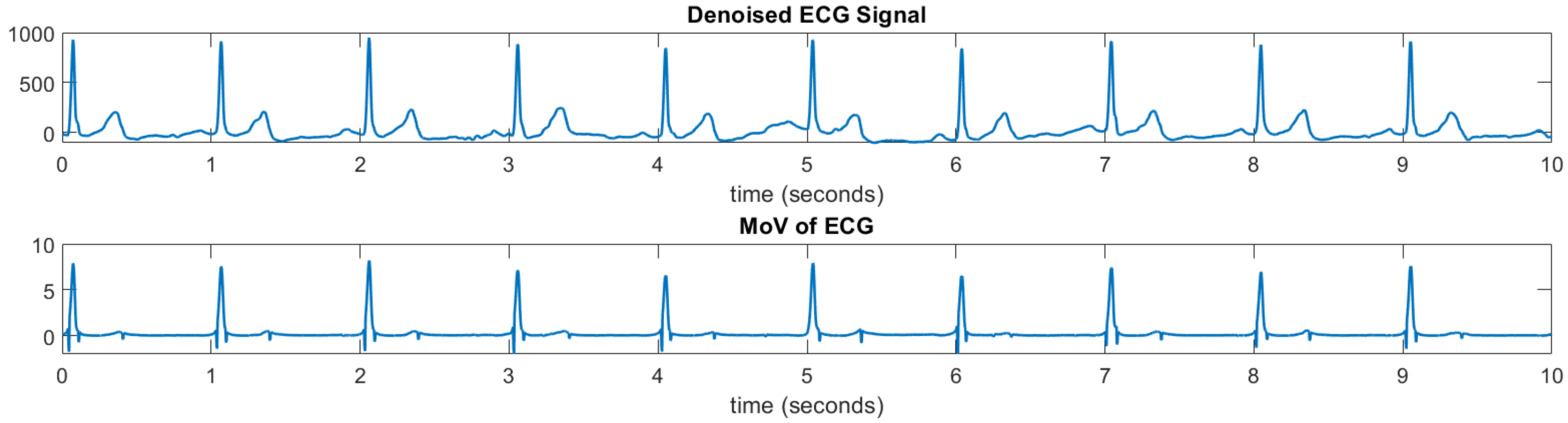
Wavelet Denoising

- Wavelets form orthonormal basis
  - Similar to sinusoids in Fourier analysis
- Can decompose signals
  - Denoise by applying threshold to coefficients
  - Separate signal and noise in ECGs better than sinusoids
- Time-frequency representation of signal

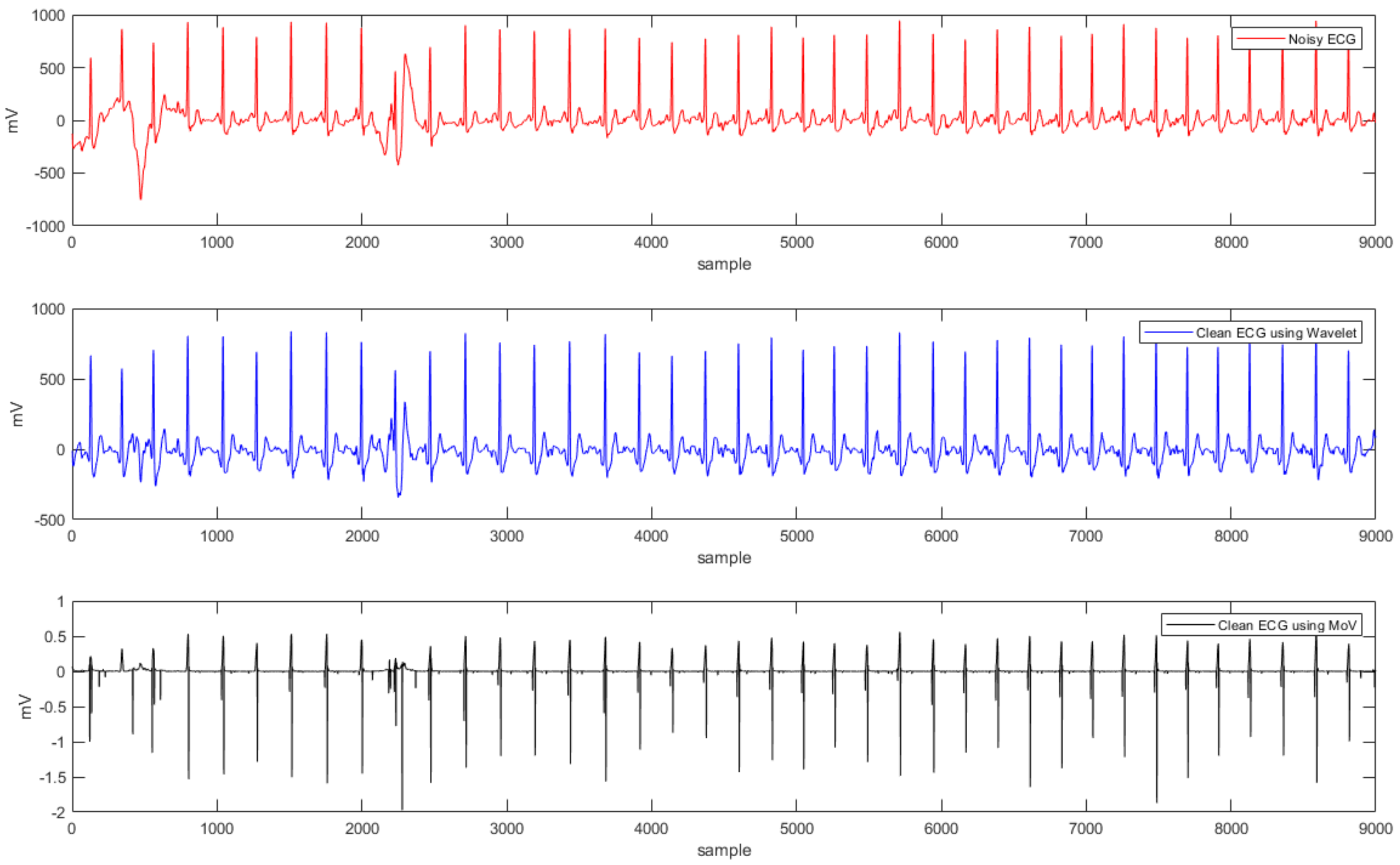


Moment of Velocity

- Like “instantaneous frequency” (IF) of a signal
- But more robust to noise than IF
- Found it highlighted QRS complex, but obscured other features
  - Hence poor results

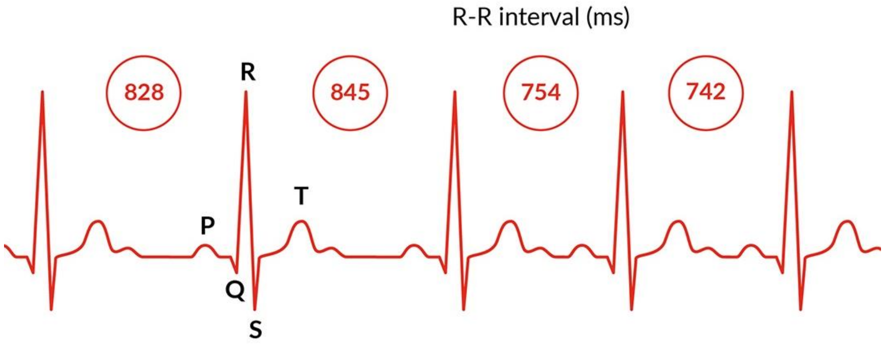


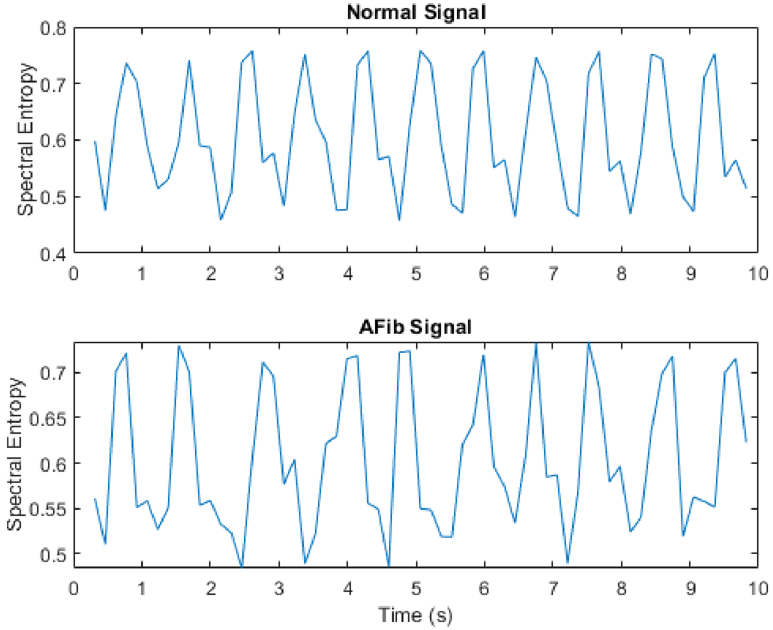
Pre-processing Results



Feature Extraction

- Time domain
  - Heart rate variability
- Frequency domain
  - Instantaneous frequency
  - Spectral entropy
- Time-frequency domain
  - Scalogram
- Others
  - Statistical features, signal quality, etc.

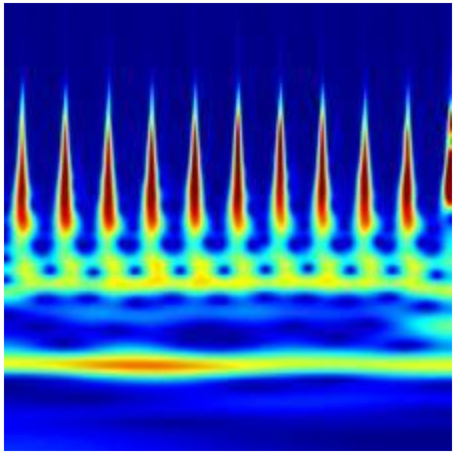




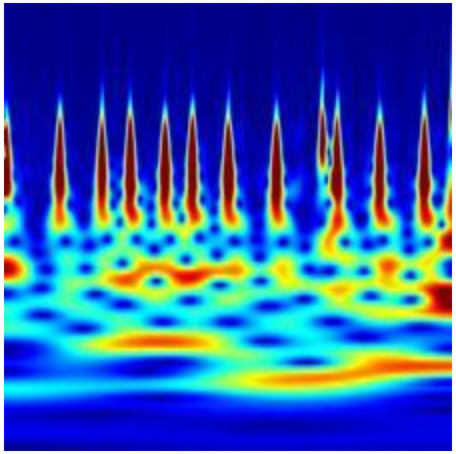
HRV image from: https://www.firstbeat.com/en/blog/what-is-heart-rate-variability-hrv/

Scalograms

- Graphical time-frequency signal representation
  - Relatively regular for normal ECGs
  - And strong response around 1 Hz
  - Irregular pattern for abnormal conditions
- Images good for CNNs
- No manual feature extraction required



Normal Signal

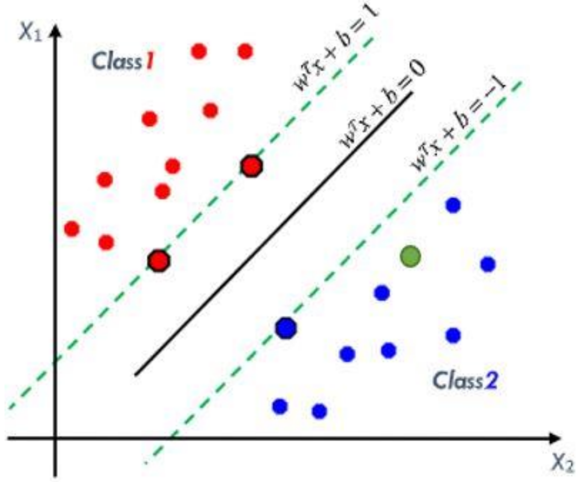


AF Signal

Machine Learning Classification

Support Vector Machines

- Class separation based on feature extracted
- Well-demonstrated for ECG classification
- Features used:
  - Heart rate variability (HVR)
  - Multi-type features



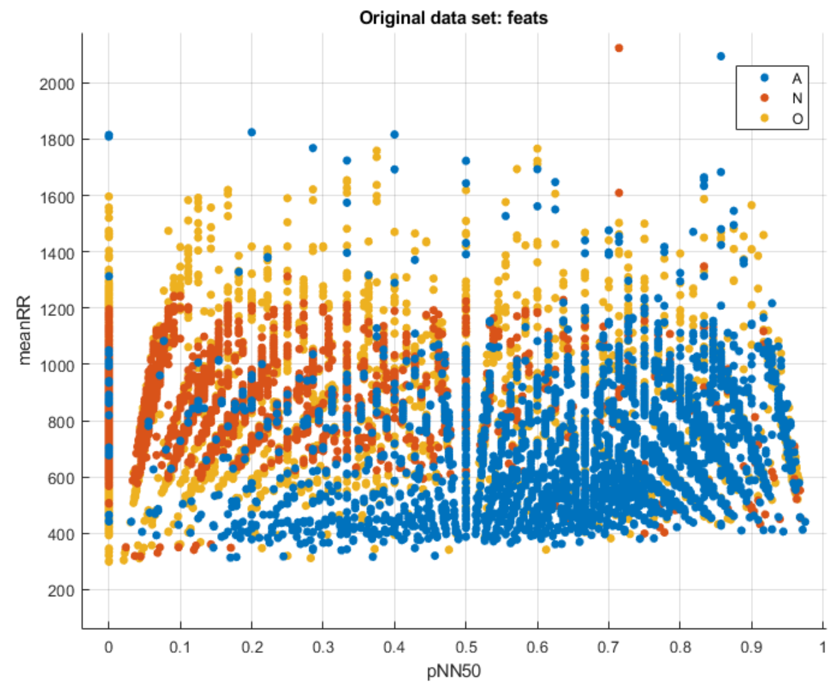
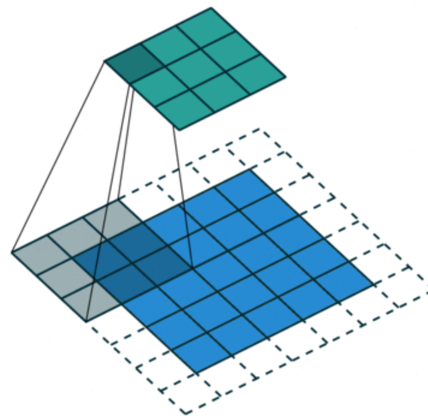


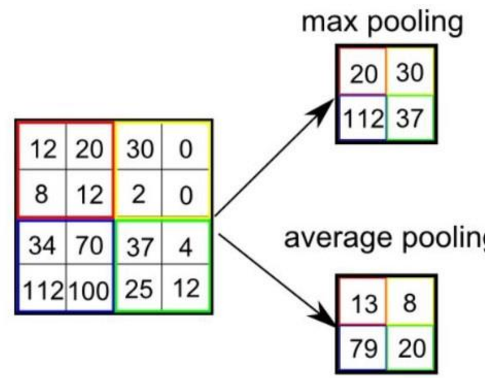
Image adapted from: https://www.sciencedirect.com/science/article/pii/B9780128113189000272

Convolutional Neural Networks

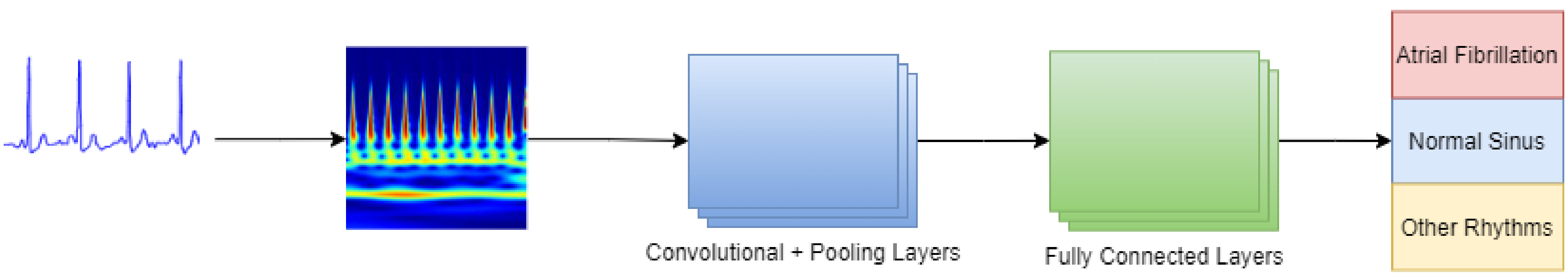
- Good for images classification
- No need for manual feature extraction



Convolution Layer

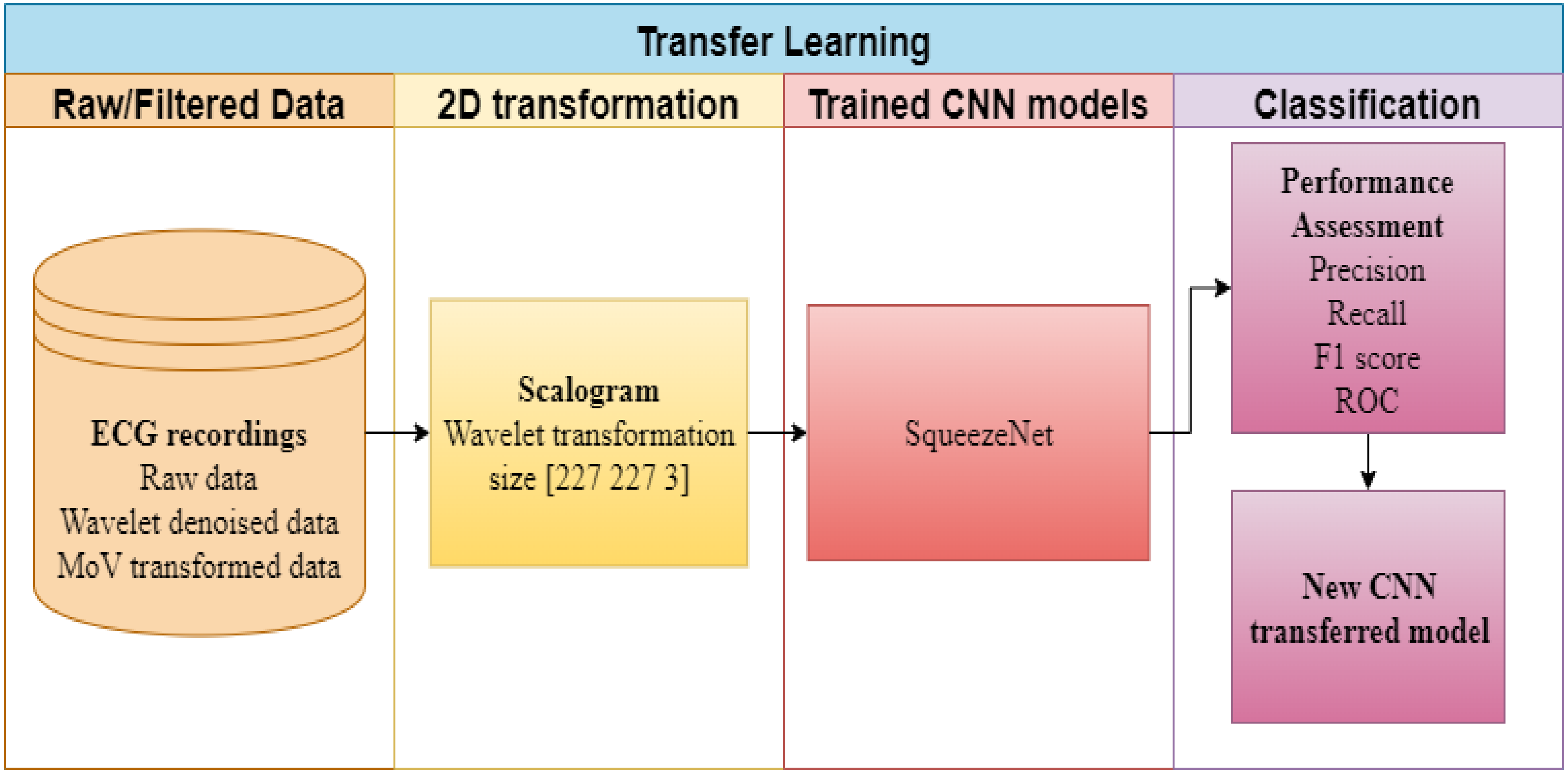


Pooling Layer



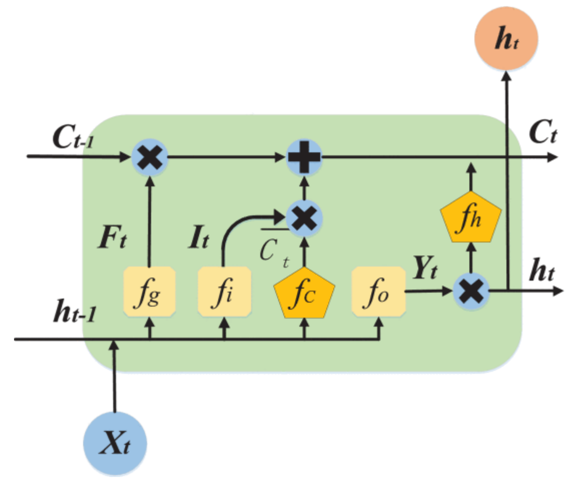
Convolution graphics source: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Transfer Learning



Long-Short Term Memory Networks

- RNN well-suited to time-series data
- Have ability to keep or forget information
- Features improve performance
  - Used IF and entropy
  - Not the best choice
- BiLSTM



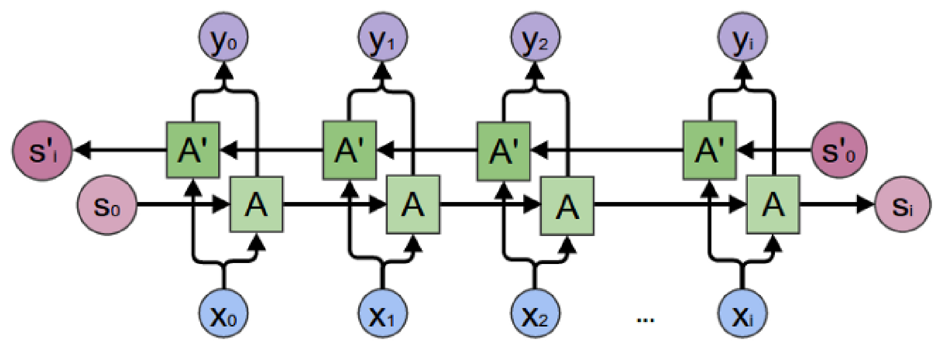


Image sources: (top) https://towardsdatascience.com
(bottom) https://medium.com/

Results

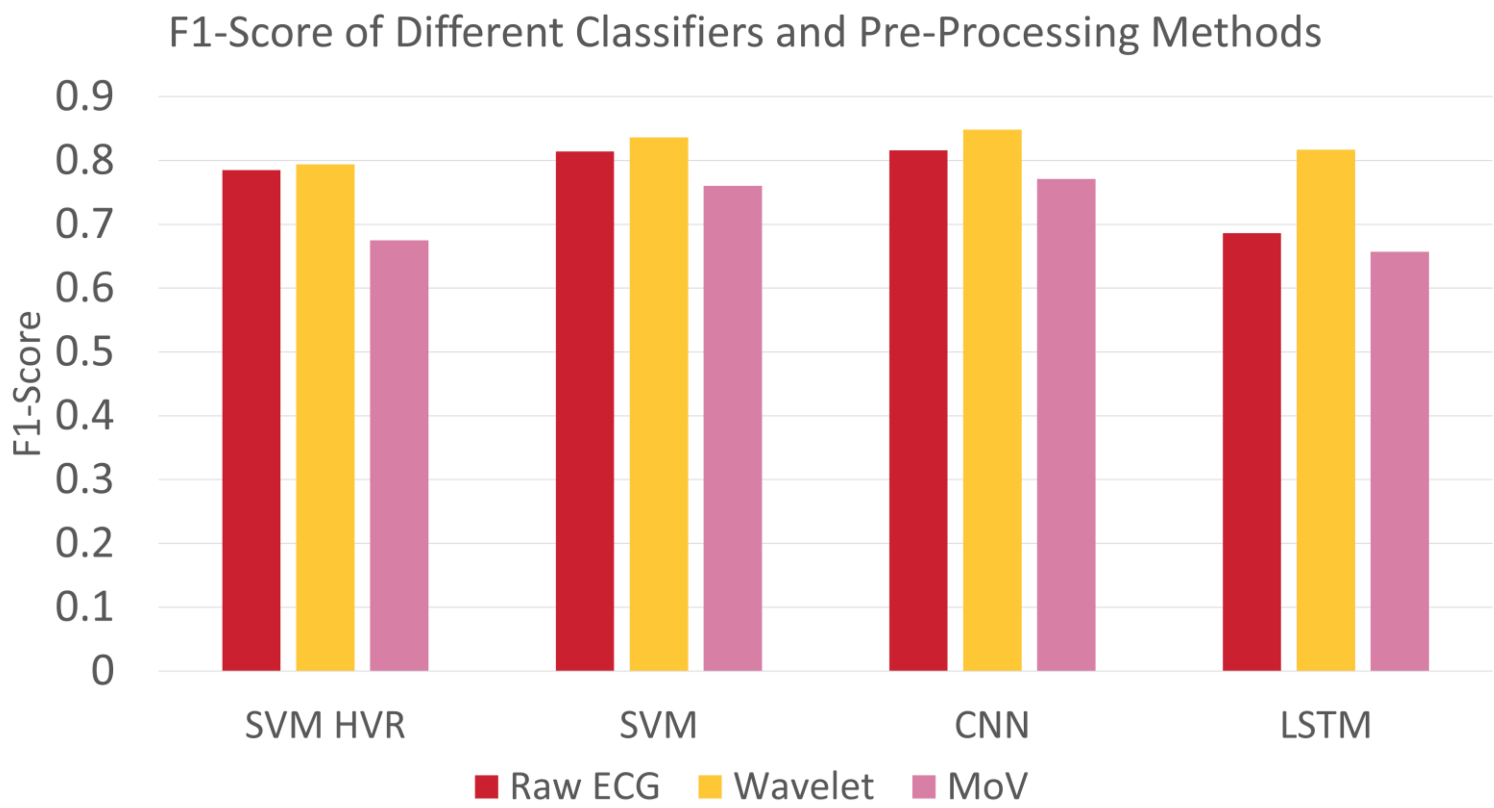
Classifier Performance

- Accuracy can be misleading
- Used F1-Score instead
  - Geometric mean of precision and recall
  - Better measure of performance

Actual class	Predicted class: Normal	Predicted class: Abnormal	
Normal	998	0	100%
Abnormal	2	0	0%
	99.8%	0%	

Accuracy: 99.8%
Precision: (99.8% + 0%)/2 = 49.9%
Recall: (100% + 0%)/2 = 50%
F1-Score: 49.9%

Comparison of Methods



Comparison to Literature

Author	Pre-processing	Features	ML Classifier	F1-Score
M. Rashed-Al-Mahfuz et al.	Segmentation and CWT	Scalogram	CNN	99.9%
S. Saadatnejad et al.	Wavelet transform	RR interval	LSTM network	95.5%
S. Celin and K. Vasanth	Bandpass filter	Time-domain	SVM	85.7%
M. Kropf et al.	Feature-detection algorithms	QRS detection, time-domain	Random forest	81.0%
T. Wang et al.	Filtering, CWT, segmentation	Scalogram	CNN	68.8%
Our results	**Wavelet denoising**	**Time-domain**	**SVM**	**79.3%**
Our results	**Wavelet denoising**	**Scalogram**	**CNN**	**84.8%**

Conclusions: so, can we teach a machine to be a cardiologist?

- Yes!
  - ML can accurately identify heart conditions
  - Our results demonstrate this
  - Fine-tuning could improve results
- Possible future work
  - More appropriate pre-processing, feature extraction and classification techniques
  - Better combination of these
  - Extend to other heart conditions
  - Apply in hospital settings or in wearable devices, etc.

Thankyou!

Any questions?

SUB CRUCE LUMEN

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Moment of Velocity

- The Hilbert Transform of a function of time is another function of time with different shape
- Given as:

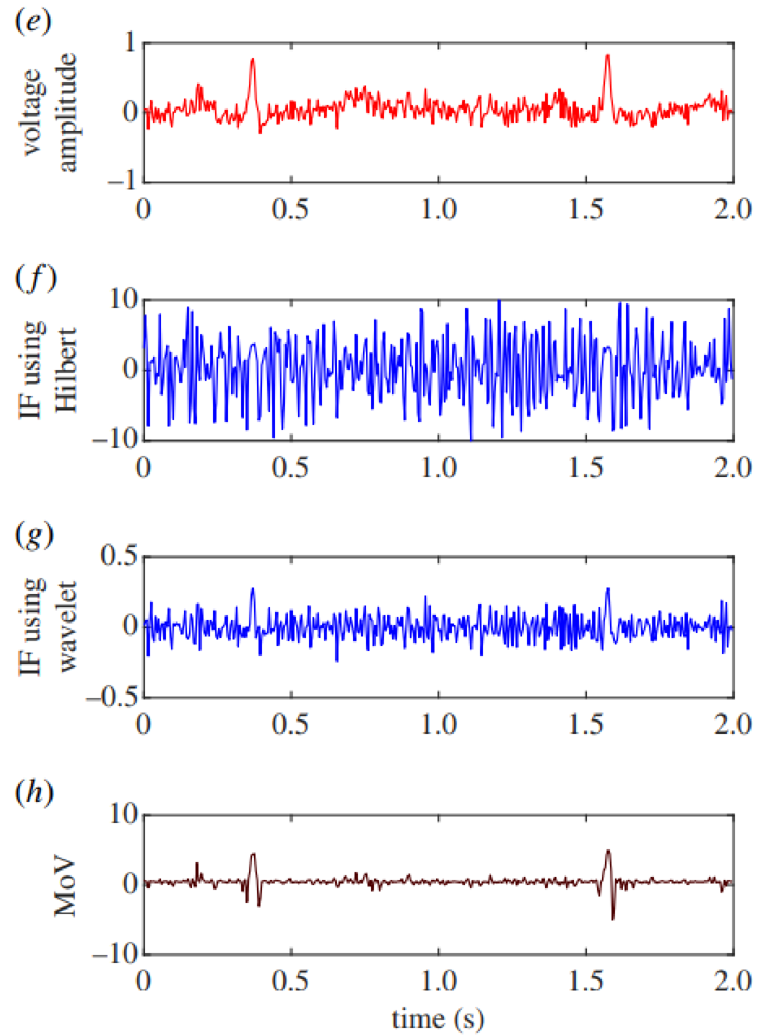
$$y(t) = \mathrm{H}[x(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau}\,\mathrm{d}\tau.$$

- Instantaneous frequency:

$$f(t) = \frac{1}{2\pi}\frac{\mathrm{d}}{\mathrm{d}t}\left[\arctan\left(\frac{\mathrm{H}[x(t)]}{x(t)}\right)\right]$$
$$= \frac{x(t)(\mathrm{dH}[x(t)]/\mathrm{d}t) - \mathrm{H}[x(t)](\mathrm{d}x(t)/\mathrm{d}t)}{x(t)^2 + \mathrm{H}[x(t)]^2}$$

- MoV:

$$= x(t)\frac{\mathrm{dH}[x(t)]}{\mathrm{d}t} - \mathrm{H}[x(t)]\frac{\mathrm{d}x(t)}{\mathrm{d}t}$$



Source: https://royalsocietypublishing.org/doi/pdf/10.1098/rsos.182001

SVM - HVR

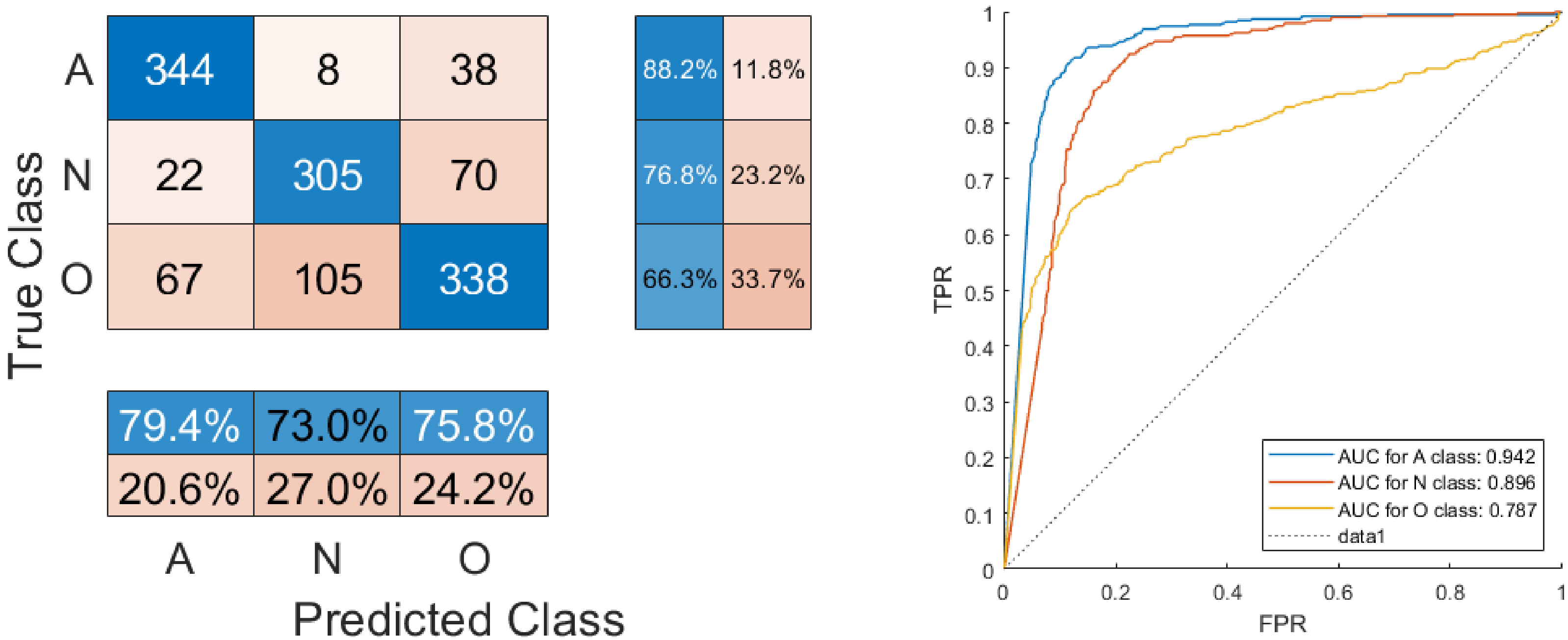
Feature	Meaning	Unit
Heart rate	The number of heart beats per minute	bpm
Mean Interval	The mean value of beat-to-beat intervals	ms
SDNN	Standard deviation of beat-to-beat intervals	ms
SDSD	standard deviation of difference beat-to-beat intervals	ms
RMSSD	root mean square of beat-to-beat intervals	ms
NN50	the number of intervals that greater than 50 ms	du
pNN50	the percentage of intervals that greater than 50 ms	%
NN20	the number of intervals that greater than 20 ms	du
pNN20	the percentage of intervals that greater than 20 ms	%
ShE	shannon entropy of heart beats	du

SVM – Multi-type Features

Type	Features	Number
Time Domain	SDNN, RMSSD, NNx	8
Frequency Domain	LF power, HF power, LF/HF	8
Non-linear Features	SampEn, ApEn, Poincaré plot, Recurrence Quantification Analysis	95
Signal Quality	bSQI, iSQI, kSQI, rSQI	36
Morphological Features	P-wave power, T-wave power, QT interval	22
	total	169

Tool provided by F. Andreotti: https://github.com/fernandoandreotti/cinc-challenge2017

SVM 169-Dimension Results



(a) Confusion matrix

(b) ROC