

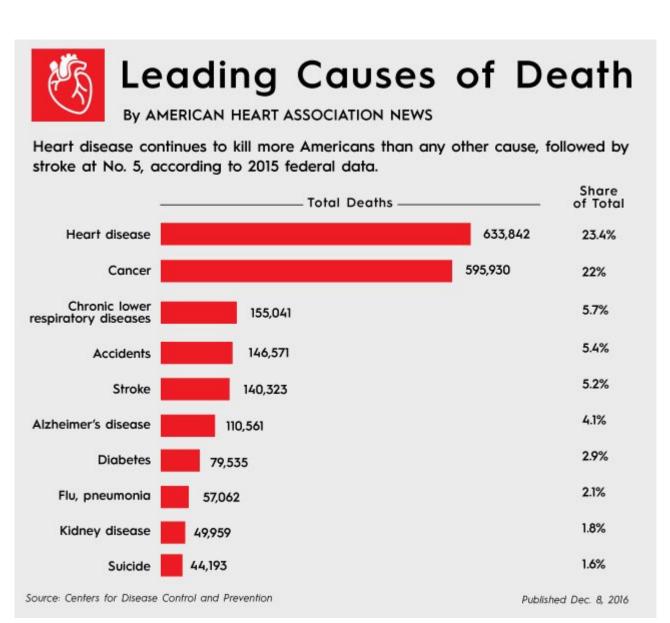


Smart medical IoT

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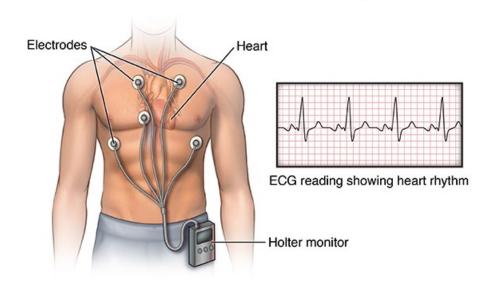
MOTIVATION: Heart disease and unsatisfied treatment

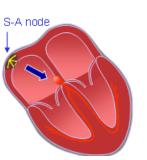
- Heart diseases are the number 1 killer in the western world.
- Up to date, there is not satisfactory drug treatments.
- "No change in the number of deaths attributed to heart failure has been observed between 1995 and 2011."



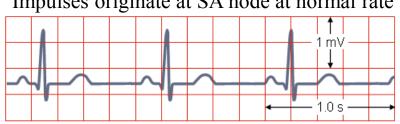
How are cardiac diseases diagnosed today?

Holter monitor with ECG reading

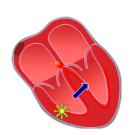




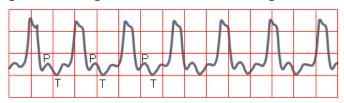
Normal sinus rhythm Impulses originate at SA node at normal rate



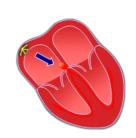
All complexes normal, evenly spaced, Rate 60-100/min



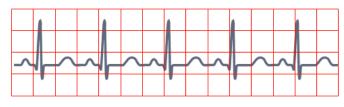
Ventricular tachycardia
Impulses originate at ventricular pacemaker



Wide ventricular complexes. Rate>120/min



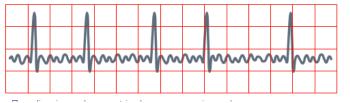
Sinus tachycardia Impulses originate at S-A node at rapid rate



All complexes normal, evenly spaced. Rate >100/min

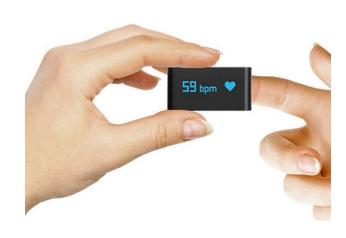


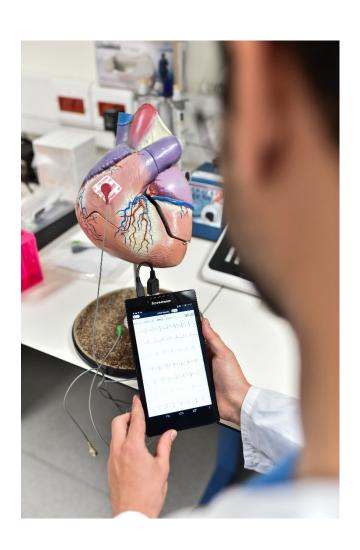
Atrial Fibrillation
Impulses have chaotic, random pathways in atria



Baseline irregular, ventricular response irregular

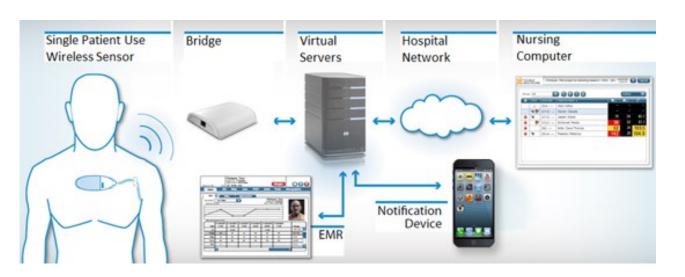
Future cardiac diseases detection







Medical IoT description in the internet

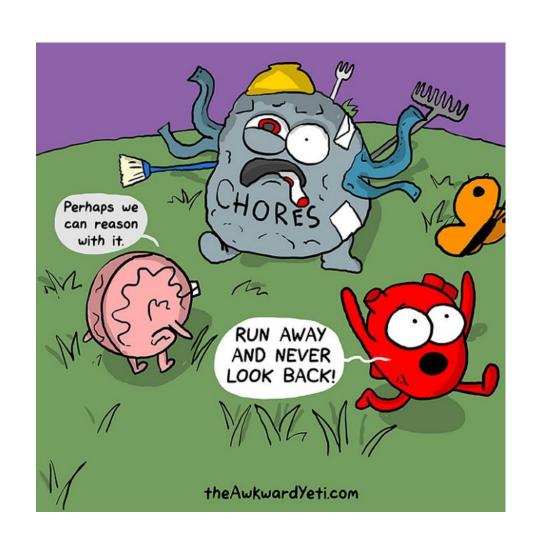








Making smart IoT



AF increases stroke incidence



9.7MEuropeans diagnosed with AF



2.7-3.3%

Prevalence of AF in 2030 in EU

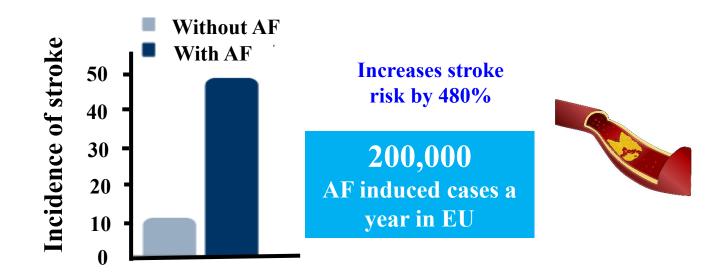


€10 billion

Annual direct-cost
in EU

Center of Health Protection 2016

Zoni-Berisso et al. Clin Epidemiol 2014

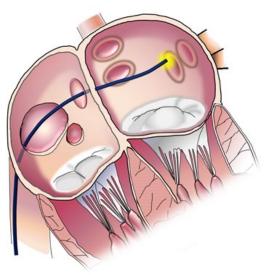


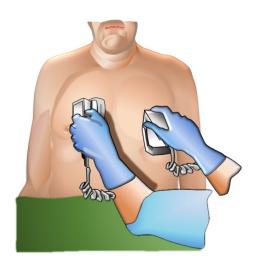
Existing treatments for AF are limited in their outcome

Catheter ablation

Cardioversion

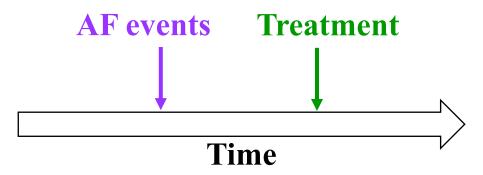
Drug treatments



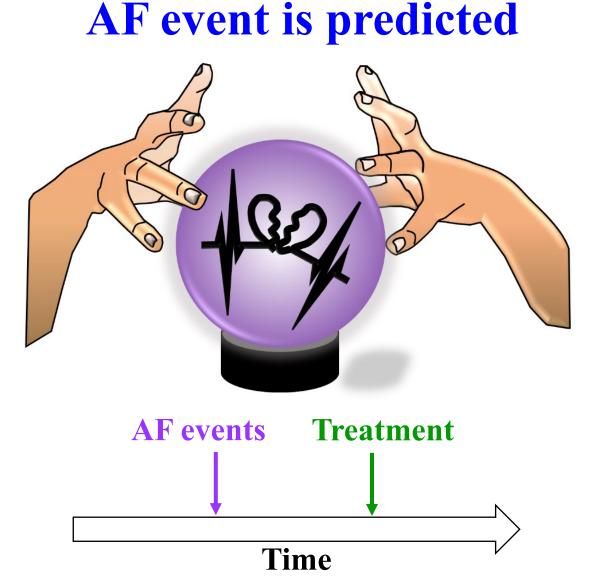




- 30% are repeated procedure
- 25% of the procedures have less than 15% success

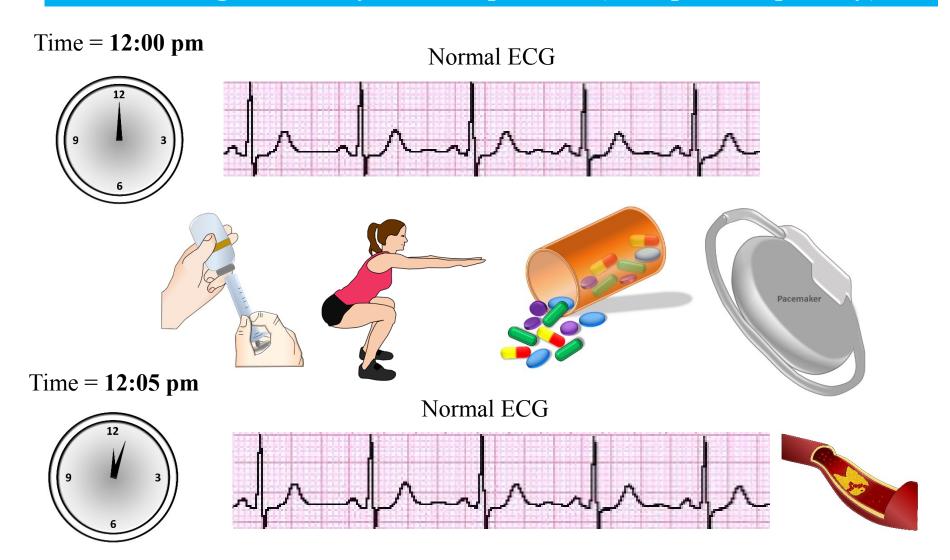


Mindset Change: Treat AF associated effects when

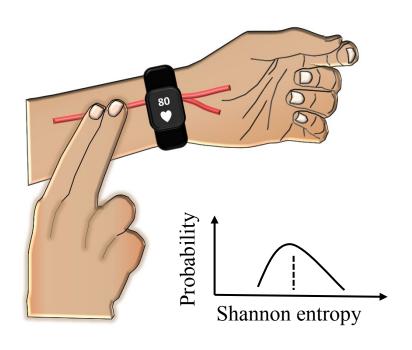


Timing is everything: Eliminating AF events and their side effects

User target: Paroxysmal AF patients (2-3 episodes per day)



Beat to beat variability changes before AF event



Submitted patent: Yaniv Y. Early prediction and detection of arrhythmogenic events #1863

Vaziri, S. M et al. Circulation, 1994. Bettoni, M et al. Circulation, 2002. Shin, D. G. et al. Circ J, 2006.

Chesnokov, Y. V. Artif Intell Med, 2008.

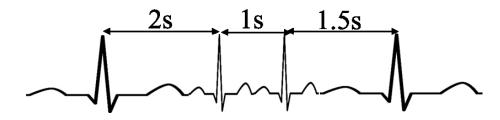
Mohebbi, M. & Ghassemian, H. Comput Methods Programs Biomed, 2012.

Seaborn, G. E. et al. Ann Noninvasive Electrocardiol, 2014.

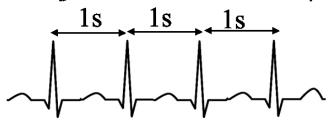
Intermediate heart rate variability



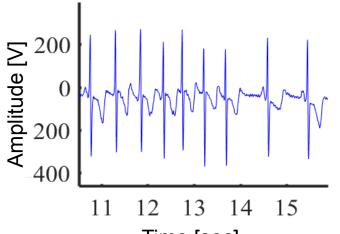
<u>High</u> heart rate variability (AF patients)

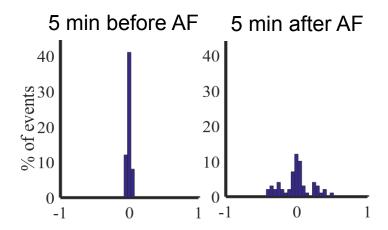


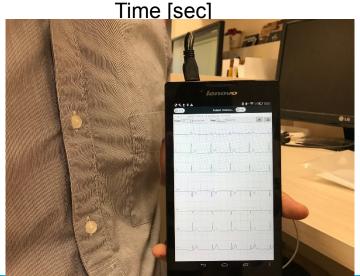
Reduced heart rate variability (just before AF event)

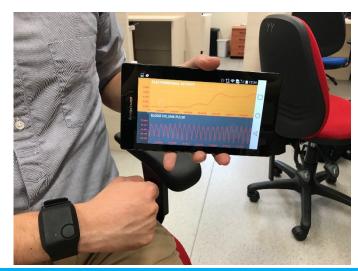


Predicting AF events







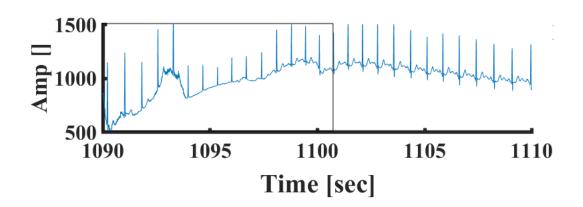


Challenge: Designing a patient-tailored wearable device based on real time heart rate variability analysis that can predict AF events with low false-negative and false-positive alerts

Challenges for IoT solution

Challenge 1:

Limited automated detection of R peaks (QRS)



Challenge 3: Automated diagnosis



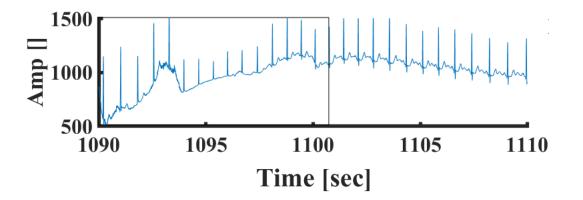
Challenge 2: Embedding complex algorithms on mobile devices



http://techno-adviser.blogspot.co.il

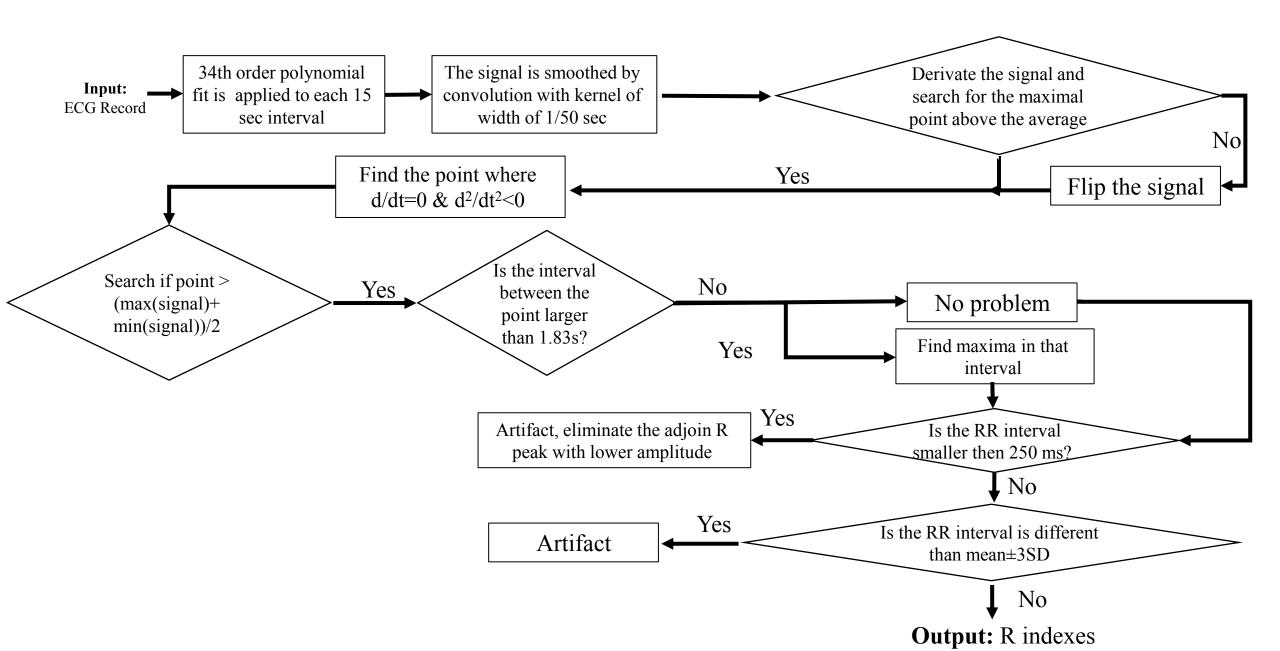
https://www.infineon.com

Aim 1

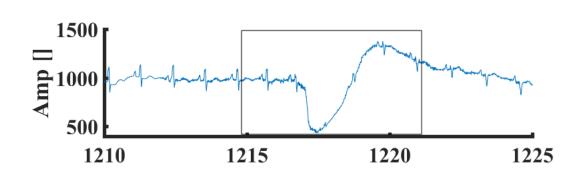


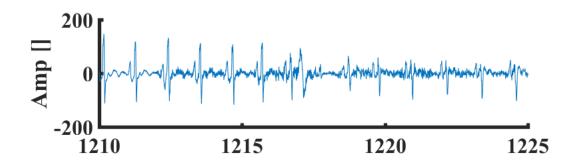
To develop a robust R-peak detector for low quality ECG of patients with cardiac diseases.

Results 1-The R peak detector algorithm

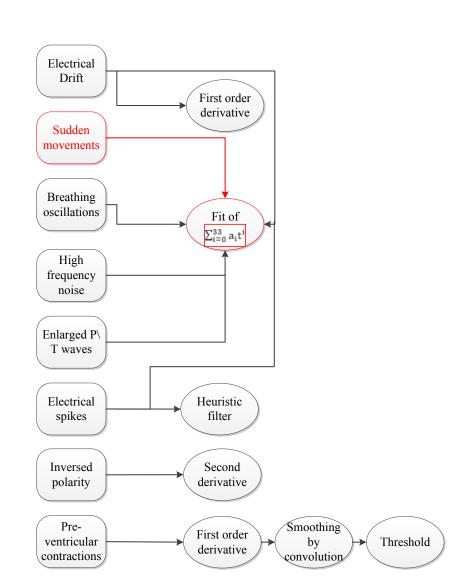


Results 1: Detecting the R interval in the presence of sudden patient movement

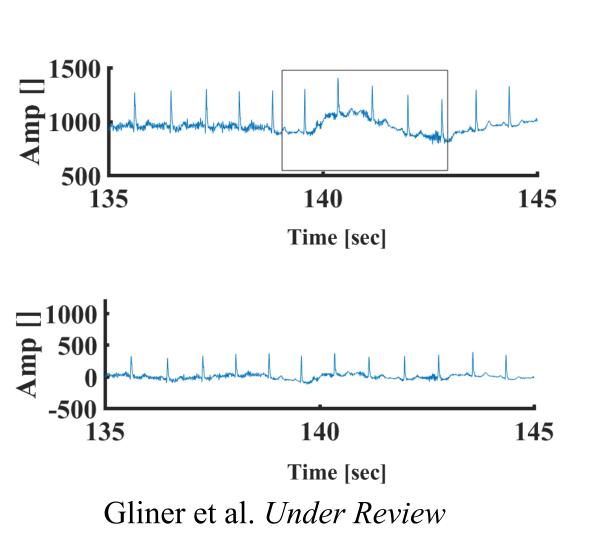


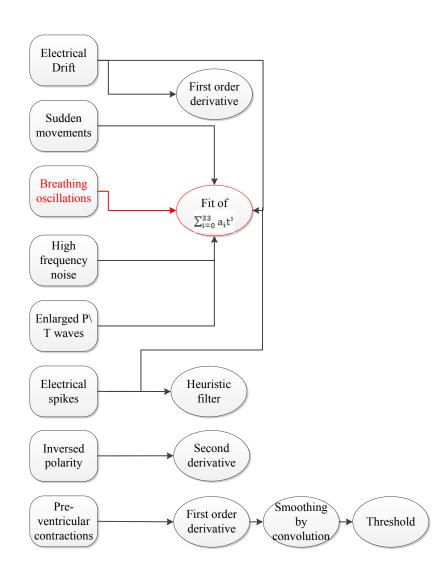


Gliner et al. *Under Review*

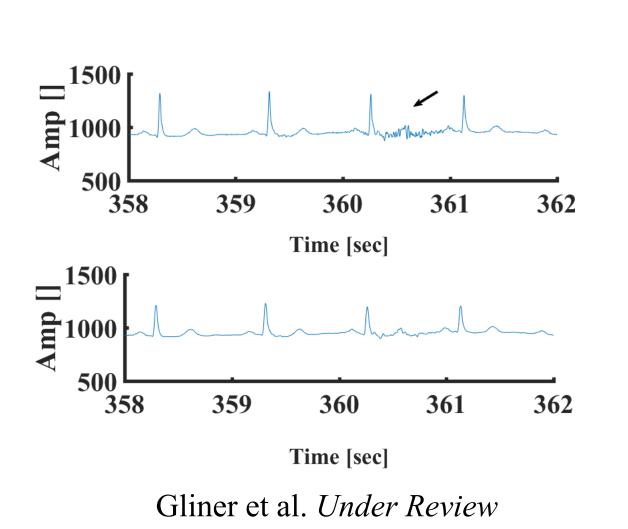


Results 1: Decoding the R interval in the presence of breathing oscillations



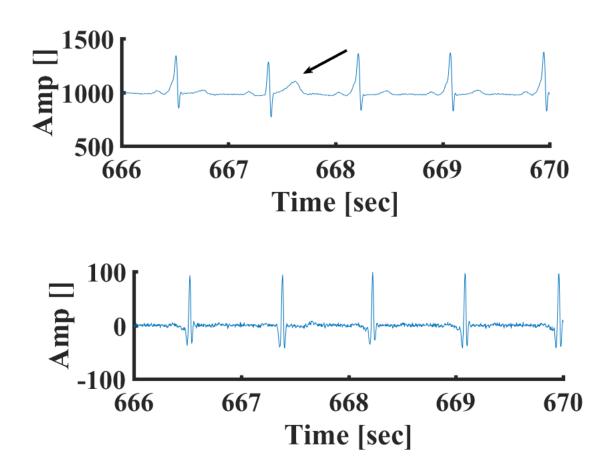


Results 1: Detecting the R peak in the presence of high frequency environmental noise

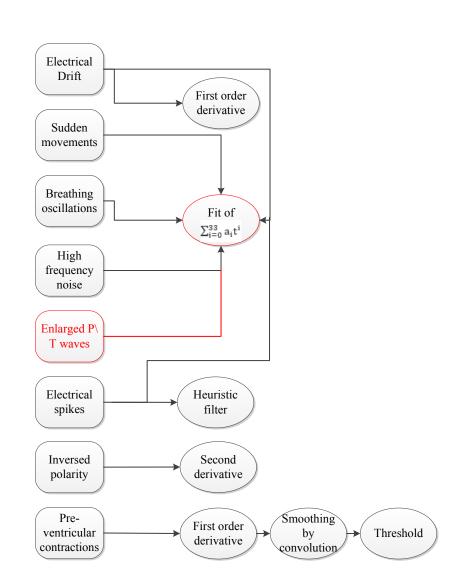


Electrical Drift First order derivative Sudden movements Breathing oscillations Fit of $\sum_{i=0}^{33} a_i t^i$ High frequency noise Enlarged P\ T waves Electrical Heuristic spikes Second Inversed derivative polarity Pre-Smoothing First order ventricular Threshold derivative contractions convolution

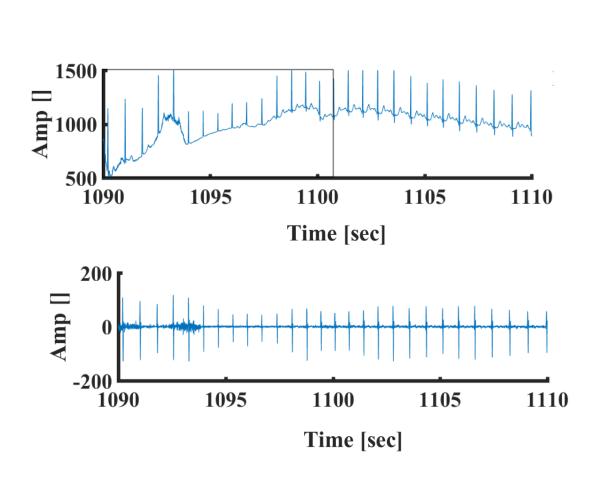
Results 1: Detecting the R peak in the presence of enlarged P or T waves



Gliner et al. *Under Review*



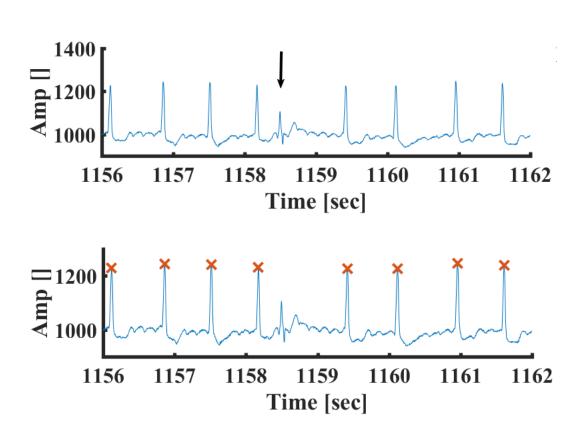
Results 1: Detecting the R peak in the presence of electrical drift

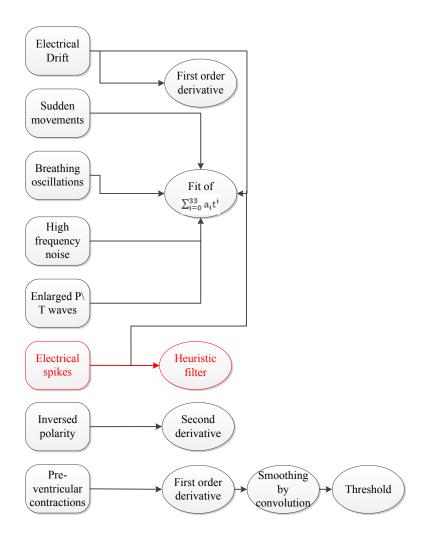


Electrical Drift First order derivative Sudden movements Breathing oscillations Fit of $\sum_{i=0}^{33} a_i t^i$ High frequency noise Enlarged P T waves Heuristic Electrical spikes filter Second Inversed polarity derivative Pre-Smoothing First order ventricular Threshold derivative contractions convolution

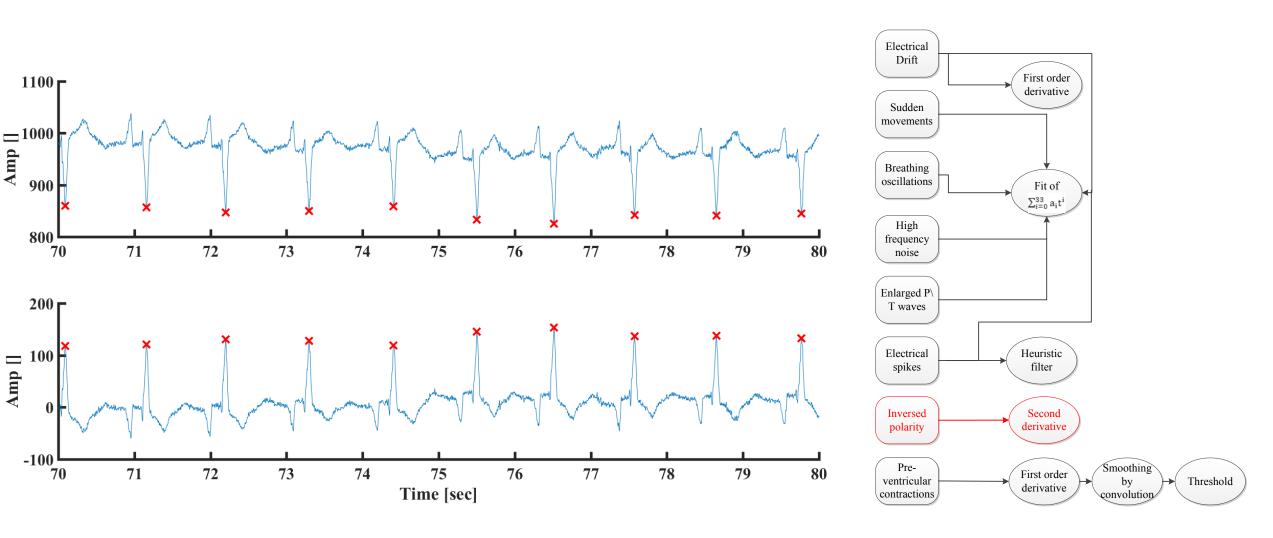
Gliner et al. *Under Review*

Results 1: Detecting the R peak in the presence of electrical spikes



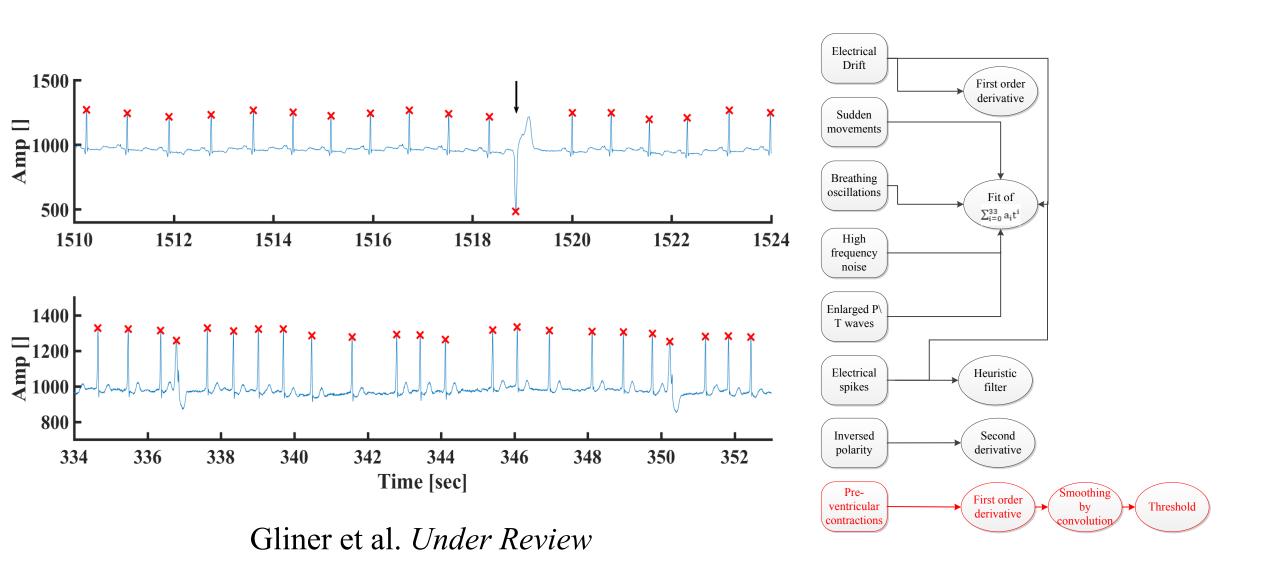


Results 1: Detecting the R peak with reverse ECG polarity



Gliner et al. *Under Review*

Results 1: Detecting the R peak in the presence of premature ventricular contraction



Results 1: Peak detector performance

Non-AF (%)	gqrs algorithm	Pan et al.	Behar et al.	Current algorithm
False negative	0.15	0.49	0.47	0.14
False positive	0.39	0.33	1.19	0.28
Positive prediction	99.6	99.7	98.8	99.7

AF	gqrs	Pan et al.	Behar et	Current
(%)	algorithm	algorithm	al.	algorithm
			algorithm	
False negative	0.42	0.72	2.09	0.34
False positive	0.79	0.67	5.45	0.25
Positive prediction	99.2	99.3	95.7	99.7

Total (%)	gqrs algorithm	Pan et al. algorithm	Behar et al.	Current algorithm
False negative	0.30	0.30	1.21	0.24
False positive	0.62	0.62	3.91	0.27
Positive prediction	99.4	99.4	97.2	99.7

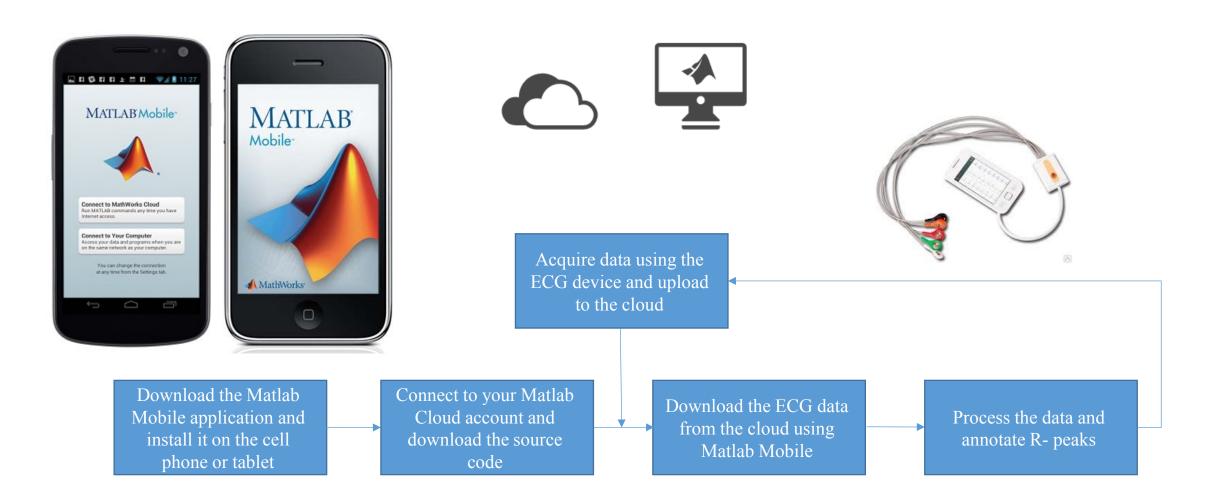
Aim 2



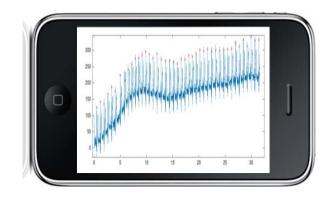
http://techno-adviser.blogspot.co.il

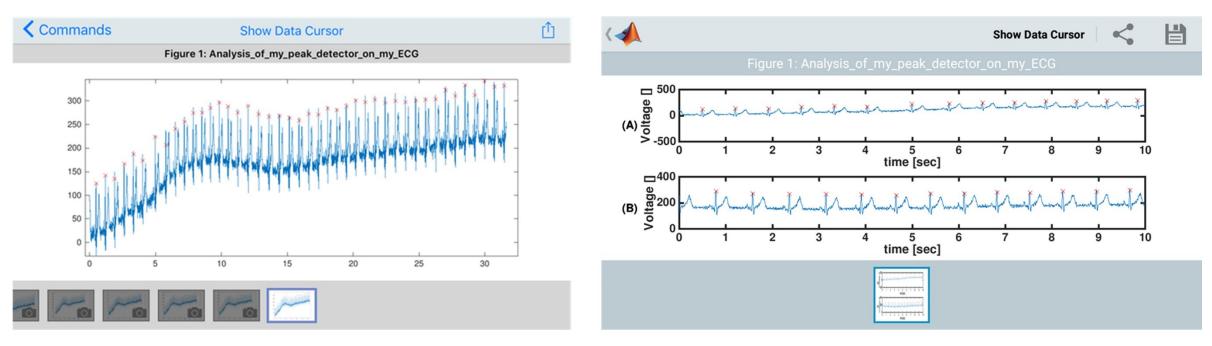
Embedding complex algorithms on mobile devices.

Results 2: Mobile system



Results 2: Peak detection on mobile phones





Gliner et al. *Under Review*

Aim 3



https://www.infineon.com

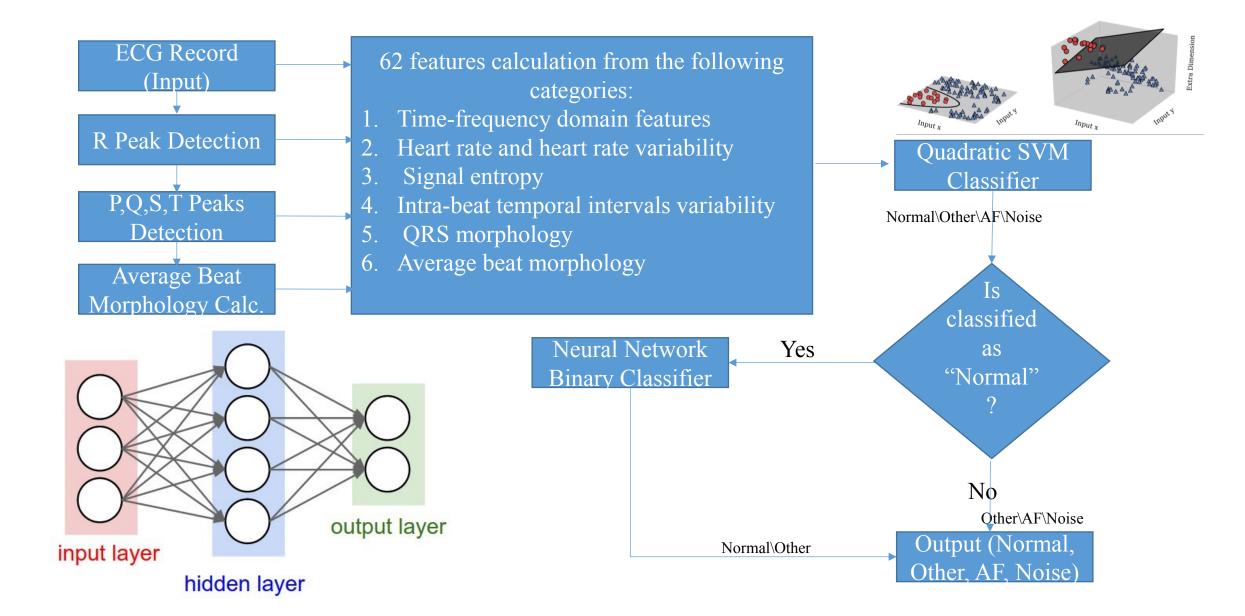
Automated diagnosis

Aim 3- Database

∧liveCo

- 2 datasets: a training set of 8,528 single lead ECG recordings from 9s to just over 60s and a test set containing 3,658 ECG recordings of similar length.
- All recordings consisted of one bipolar channel recorded by an AliveCordevice.
- The data was sampled at 300 Hz and filtered by a band pass filter in the device itself.
- The training set data was annotated by a cardiologist to one of the four types: normal (\sim 59.5% of the recordings), AF (\sim 10% of the recordings), other rhythm (\sim 30% of the recordings), and noisy (\sim 0.5% of the recordings).
- 10 trials on the hidden set were allowed

Results 3: Learning strategy and algorithm



Aim 3 Results: CinC 2017 challenge classifier results

Cross-validation matrix on the training set:

Ours	Normal	AF	Other	Noise
Normal	4772	9	244	4
AF	17	650	70	0
Other	455	51	1960	10
Noise	35	5	21	225

Results on the hidden set:

Normal rhythm:

AF rhythm:

Other rhythm:

$$F_{1n} = \frac{2N_n}{\sum N + \sum n}$$

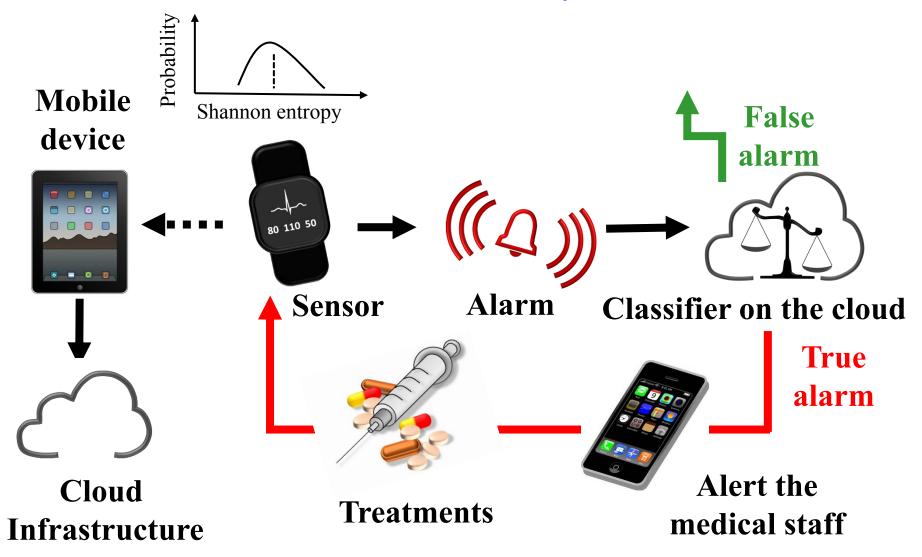
$$F_{1a} = \frac{2A_a}{\sum A + \sum a}$$

$$F_{1o} = \frac{2O_o}{\sum O + \sum o}$$

	F ₁
Normal	0.9
AF	0.81
Other	0.7
Total	0.8

$$F_1 = \frac{F_{1n} + F_{1a} + F_{1o}}{3}$$

Summary



Acknowledgments

Bioelectric and Bioenergetic System Lab

- Joachim Behar, PhD
- •Limor Arbel Ganon, BSc
- •Vadim Gliner, BSc
- •David Kamoun, BSc
- •Joseph M. Leichner, BSC
- •Savyon Mazgaoker, BSc
- •Noa Kirschner Peretz, MSc
- •Aviv Rosenberg, BSc
- •Sofia Segal, MSc
- •Ido Weiser Bitoun, BSc
- •Daphna Marbach, MSc

Mobile Health Lab/PhysioZoo

- •Alexandra Alexandrovich, PhD
- •Eugene Konyukhov, MD
- •Ori Shemla



Collaborators

- •Prof. Ana M. Gomez, Inserm, France
- •Dr. Kenta Tsutsui, NIA/NIH, US
- Prof. Edward G. Lakatta, NIA/NIH, US
- •Prof. Shi-Qiang Wang, Beijing University, China
- •Prof. Jin Zhang, UCSD, US
- •Jose Jalife, UM, US















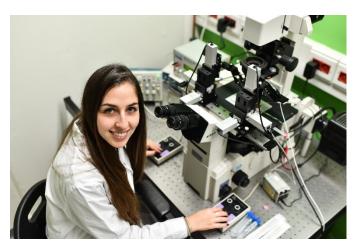
Thanks for your attention!













Questions?

