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Is it possible to predict a cardiac arrest? AI close to clinical decision practice

March 3, 2021

CACHET spring seminar

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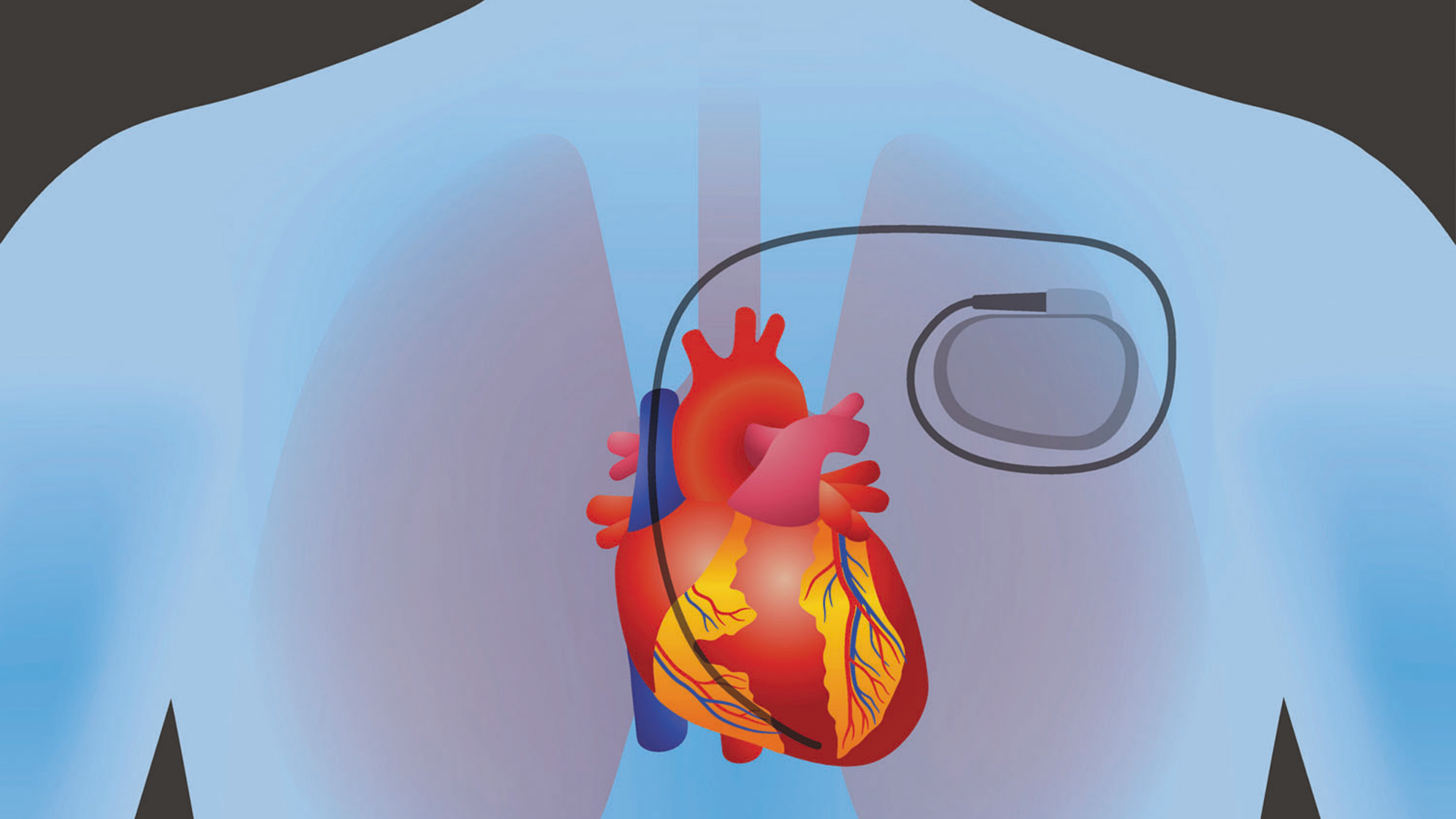
Region H Rigshospitalet · Vital Beats · University of Copenhagen · data-pitch INNOVATION PROGRAMME



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Remote Monitoring:
Transmission of ICD/pacemaker data


PATS

Technicians' & physicians' needs

Support for prioritisation (Tecnicians)

- Pritoritisation (5 min)
- Prepare handover to physician

Support for decision-making (Physicians)

- Reaching a decision (20 min)
- Information overload

Andersen, T. O. et al. (2019). Unpacking telemonitoring work: Workload and telephone calls to patients in implanted cardiac device care. *International journal of medical informatics*, *129*, 381-387.

ICD/Pacemaker remote monitoring

6.000 clinics world wide

4M patients with ICD/pacemaker

Typical large clinic

- **3.000 patients**
- **14.000 transmissions per year**
- **40% require clinical decision-making***

*Ricci, R. et al. (2014). Manpower and Outpatient Clinic Workload for Remote Monitoring of Patients with Cardiac Implantable Electronic Devices. *Journal of cardiovascular electrophysiology*, 25(11), 1216-1223.

Support clinical decisions:

What if we could predict the risk of arhythmias in the near future?

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4 day risk prediction using ICD data?

ESC European Society of Cardiology
Europace (2018) **0**, 1–7
doi:10.1093/europace/euy257

CLINICAL RESEARCH

Predicting electrical storms by remote monitoring of implantable cardioverter-defibrillator patients using machine learning

Saeed Shakibfar[1], Oswin Krause[1], Casper Lund-Andersen[2], Alfonso Aranda[3], Jonas Moll[1], Tariq Osman Andersen[1], Jesper Hastrup Svendsen[2,4], Helen Høgh Petersen[2†], and Christian Igel[1]*

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Received 9 July 2018; editorial decision 6 October 2018; accepted 10 October 2018

Aims Electrical storm (ES) is a serious arrhythmic syndrome that is characterized by recurrent episodes of ventricular arrhythmias. Electrical storm is associated with increased mortality and morbidity despite the use of implantable cardioverter-defibrillators (ICDs). Predicting ES could be essential; however, models for predicting this event have never been developed. The goal of this study was to construct and validate machine learning models to predict ES based on daily ICD remote monitoring summaries.

Methods and results Daily ICD summaries from 19 935 patients were used to construct and evaluate two models [logistic regression (LR) and random forest (RF)] for predicting the short-term risk of ES. The models were evaluated on the parts of the data not used for model development. Random forest performed significantly better than LR ($P < 0.01$), achieving a test accuracy of 0.96 and an area under the curve (AUC) of 0.80 (vs. an accuracy of 0.96 and an AUC of 0.75). The percentage of ventricular pacing and the daytime activity were the most relevant variables in the RF model.

Conclusion The use of large-scale machine learning showed that daily summaries of ICD measurements in the absence of clinical information can predict the short-term risk of ES.

Keywords Machine learning • Electrical storm • Prediction • Implantable cardioverter-defibrillators • Ventricular arrhythmia • Random forest

Table 3 Accuracies, AUC values, and sensitivities at 0.9 and 0.99 specificity

	Logistic regression	Random forest
Accuracy	0.96	0.96
AUC	0.75	0.80
Sensitivity at 0.9 specificity	0.53	0.61
Sensitivity at 0.99 specificity	0.37	0.39

AUC, area under the curve.

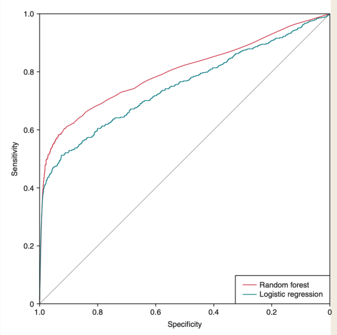

Figure 2 ROC curves for predicting ES. ES, electrical storm; ROC, receiver operating characteristic.

It works!

But, too many false positives in clinical practice

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AI/ML in health works (in the lab)

npj Digital Medicine www.nature.com/npjdigitalmed

ARTICLE OPEN

Deep learning algorithm predicts diabetic retinopathy progression in individual patients

Filippo Arcadu[1,2], Fethallah Benmansour[1,2], Andreas Maunz[1,2], Jeff Willis[3,4], Zdenka Haskova[3,4,7*] and Marco Prunotto[2,5,6,7*]

The global burden of diabetic retinopathy (DR) continues to worsen and DR remains a leading cause of vision loss worldwide. Here, we describe an algorithm to predict DR progression by means of deep learning (DL), using as input color fundus photographs (CFPs) acquired at a single visit from a patient with DR. The proposed DL models were designed to predict future DR progression, defined as 2-step worsening on the Early Treatment Diabetic Retinopathy Diabetic Retinopathy Severity Scale, and were trained against DR severity scores assessed after 6, 12, and 24 months from the baseline visit by masked, well-trained, human reading center graders. The performance of one of these models (prediction at month 12) resulted in an area under the curve equal to 0.79. Interestingly, our results highlight the importance of the predictive signal located in the peripheral retinal fields, not routinely collected for DR assessments, and the importance of microvascular abnormalities. Our findings show the feasibility of predicting future DR progression by leveraging CFPs of a patient acquired at a single visit. Upon further development on larger and more diverse datasets, such an algorithm could enable early diagnosis and referral to a retina specialist for more frequent monitoring and even consideration of early intervention. Moreover, it could also improve patient recruitment for clinical trials targeting DR.

npj Digital Medicine (2019)2:92 ; https://doi.org/10.1038/s41746-019-0172-3

INTRODUCTION

Vision loss due to diabetic eye disease is on the rise and it is expected to reach epidemic proportions globally in the next few decades. In 2017, ~425 million people worldwide had diabetes, and this number is estimated to increase to 642 million by 2040.[1] Diabetic retinopathy (DR) is the most common and insidious

The purpose of this work was to go beyond the use of DL for DR diagnostics[15–17,19] and to assess the feasibility of developing DCNNs operating on 7-field CFPs that can predict the future threat of significant DR worsening at a patient level over a span of 2 years after the baseline visit.

To achieve that, our DCNNs have been trained on high-

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ELSEVIER

Early detection of sepsis utilizing deep learning on electronic health record event sequences

Simon Meyer Lauritsen[a,b,*], Mads Ellersgaard Kalør[a], Emil Lund Kongsgaard[a], Katrine Meyer Lauritsen[b,e], Marianne Johansson Jørgensen[d], Jeppe Lange[b,d], Bo Thiesson[a,c]

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ARTICLE INFO

Keywords:
Sepsis
Clinical decision support systems
Machine learning
Medical informatics
Early diagnosis
Electronic health records

ABSTRACT

Background: The timeliness of detection of a sepsis incidence in progress is a crucial factor in the outcome for the patient. Machine learning models built from data in electronic health records can be used as an effective tool for improving this timeliness, but so far, the potential for clinical implementations has been largely limited to studies in intensive care units. This study will employ a richer data set that will expand the applicability of these models beyond intensive care units. Furthermore, we will circumvent several important limitations that have been found in the literature: (1) Model evaluations neglect the clinical consequences of a decision to start, or not start, an intervention for sepsis. (2) Models are evaluated shortly before sepsis onset without considering interventions already initiated. (3) Machine learning models are built on a restricted set of clinical parameters, which are not necessarily measured in all departments. (4) Model performance is limited by current knowledge

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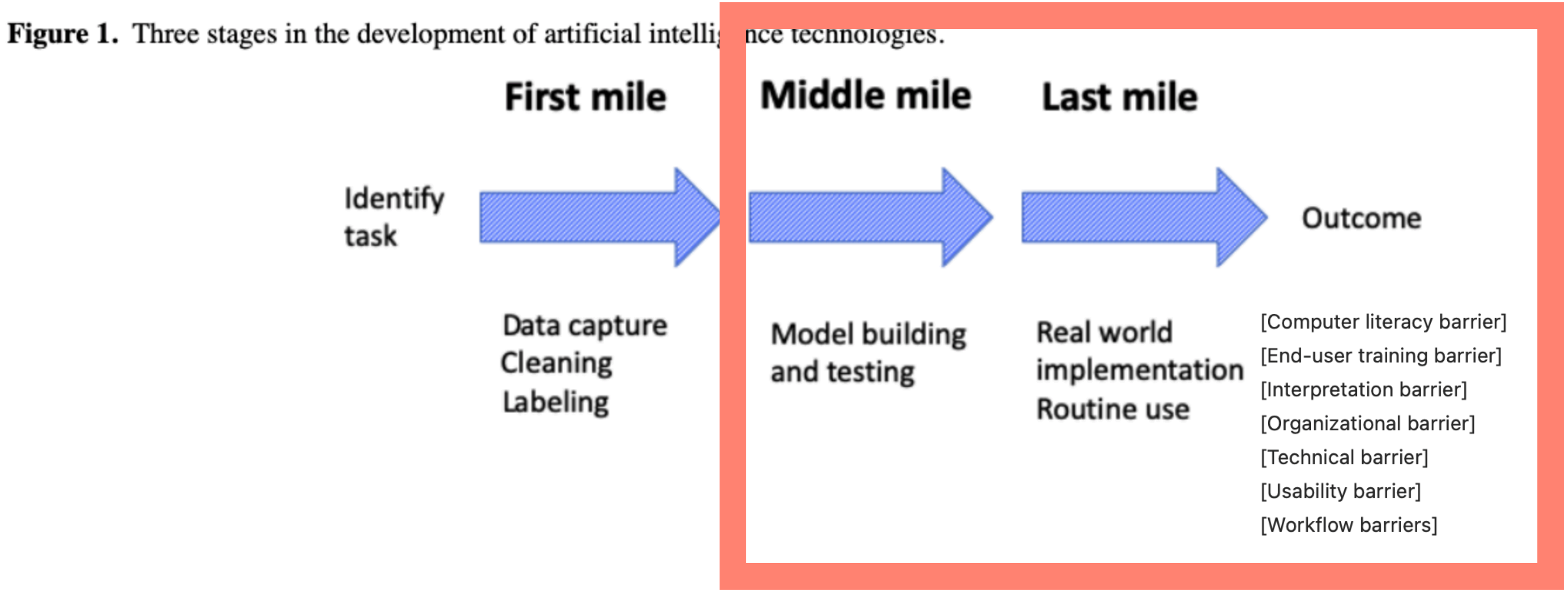
"The Last Mile": Where AI Meets Reality



Coiera, E. (2019). The last mile: where artificial intelligence meets reality. *Journal of medical Internet research*, 21(11), e16323.

Google Brain: AI-tool in the wild

Predicting Diabetic Retinopathy

Deep-learning tool tested in 11 clinics in Thailand

Socio-technical challenges with AI-tool in real life

- Busy screening procedures
- Poor lightning conditions resulted in poor predictions
- Internet speed: 60-90 seconds to upload
- Accuracy and patient burden: 50% opt out because of referral to other clinic (not all patients have cars)

Beede, E. et al. (2020). A Human-Centered Evaluation of a Deep Learning System Deployed in Clinics for the Detection of Diabetic Retinopathy. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1-12).*al of medical informatics*, *129*, 381-387.

Risk of ventricular fibrillations or tachycardia within 30 days

1

❌ Alarm Raised

2

44.0% chance of ventricular tachycardia or fibrillation within 30 days

Observations increasing likelihood of arrhythmia:

observations
ventricular tachycardia episodes in zone 1 previous week

Observations decreasing likelihood of arrhythmia:

observations
no electrical storm on day
no ventricular tachycardia episodes in zone 1 on day
no atps on day
no ventricular tachycardia episodes in zone 1 previous day
no ventricular tachycardia episodes previous week

3

Stage 1: Understanding needs & co-design solutions

Fieldwork study

Co-design workshops

Design sessions

Stage 2: Development of AI-algorithm

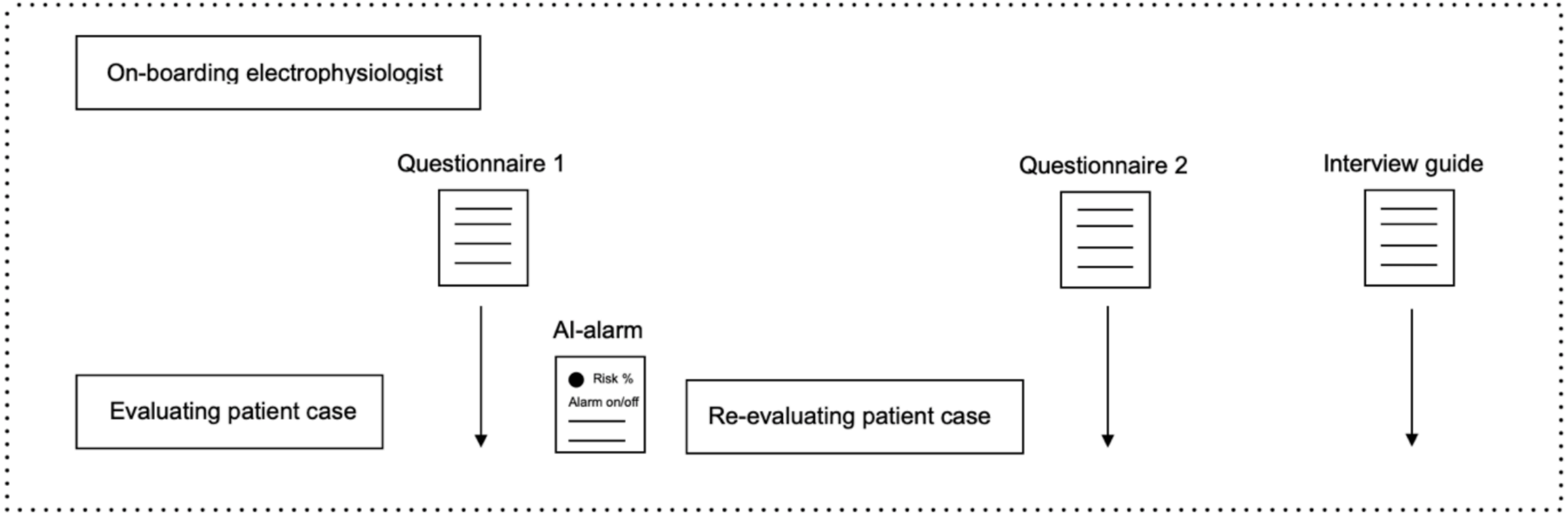
Data collection (ICD)

Data pre-processing

Feature selection

Supervised machine learning

Stage 3: Near-live feasibility study



AI-tool

1251 patients (2015-2019)
11921 transmissions, 74,149 arrhythmia episodes
Random forest & LIME XAI
Tested on 2,342 of the 11,921 transmissions
Accuracy: 0.96
Positive predictive value: 0.67
Negative predictive value of 0.97
Threshold for alarm: 0.28

Near-live case study

5 patient cases
7 electrophysiologists
12.5 hrs video analysed using grounded theory

Feasibility of AI-tool in clinical practice?

Does the AI-alarm Support Clinical Decision-Making?

- Change action
- Visualization
- Reduce time

Overall feasibility

- Acceptability
- Adoption
- Demand
- Implementation

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Table 2. The effect of the alarm on electrophysiologists' decision-making: questionnaire answers

Question	Answer	Number of answers	Number of answers in %	Case 1	Case 2	Case 3	Case 6	Case 7
1) The AI-alarm makes me change my decision on clinical action								
	Yes	1	3%	14%	0%	0%	0%	0%
	No	33	97%	86%	100%	100%	100%	100%
2) The AI-alarm supported my decision-making								
	Strongly disagree/disagree	8	24%	29%	14%	0%	43%	29%
	Neither agree nor disagree	3	9%	14%	0%	0%	14%	14%
	Agree/ Strongly agree	23	68%	57%	86%	100%	43%	57%
3) The AI-alarm's visualization of parameters supported my decision making								
	Strongly disagree/disagree	10	29%	43%	14%	17%	43%	29%
	Neither agree nor disagree	3	9%	14%	14%	14%	14%	14%
	Agree/ Strongly agree	21	62%	43%	86%	83%	43%	57%
4) The AI-alarm can help me reach a decision faster								
	Strongly disagree/disagree	12	35%	57%	29%	17%	29%	43%
	Neither agree nor disagree	4	12%	14%	0%	0%	43%	0%
	Agree/ Strongly agree	18	53%	29%	71%	83%	29%	57%

Beyond accuracy: context dependencies

Physician: The AI-tool's prediction is something that might make me react a little more aggressively. If our patient schedule is fully booked, both today and tomorrow, and the day after tomorrow, but on Friday we have time. Then I kind of have to make a trade-off.

Workflow effects: delegation to technicians

Physician: Physicians don't bother to hear about it if it is below a certain percentage. You might well imagine that introducing this alarm will support handling low-risk transmissions

Trust established in use

Physician: Just like with all other new technology based on machine learning: the first two months I sit and read through to see what I have, but in month three, I will look at the output alone. Because - then I trust that it has pulled out what is appropriate, and then it starts saving me all the work I did in the beginning

Human-AI collaboration: second opinion

Physician: We have a lot of patients who suddenly have a lot of VT, and they are very interesting, because if you have some doubt about really stepping in – I could well imagine that you might want to lean on the algorithm's advice

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Next steps

- Prospective study
- Activity & arrhythmia?

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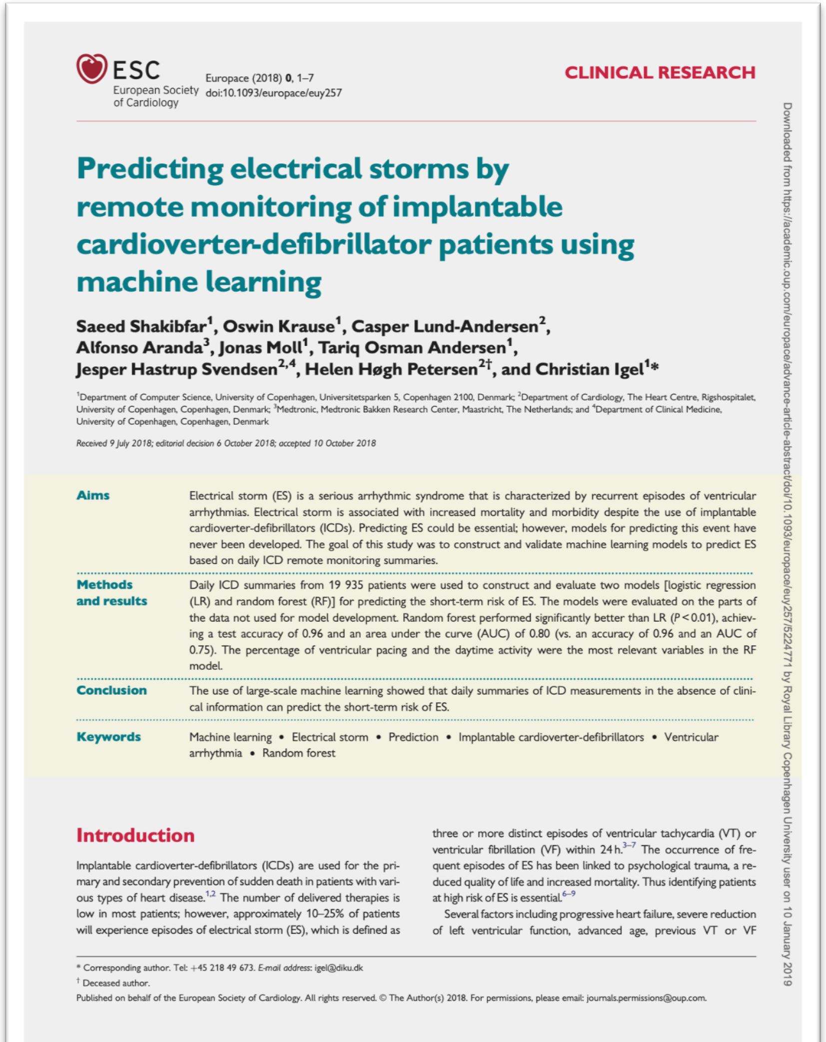
Activity as predictor



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[1]Department of Computer Science, University of Copenhagen, Universitetsparken 5, Copenhagen 2100, Denmark; [2]Department of Cardiology, The Heart Centre, Rigshospitalet, University of Copenhagen, Copenhagen, Denmark; [3]Medtronic, Medtronic Bakken Research Center, Maastricht, The Netherlands; and [4]Department of Clinical Medicine, University of Copenhagen, Copenhagen, Denmark

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Introduction

Implantable cardioverter-defibrillators (ICDs) are used for the primary and secondary prevention of sudden death in patients with various types of heart disease.[1,2] The number of delivered therapies is low in most patients; however, approximately 10–25% of patients will experience episodes of electrical storm (ES), which is defined as three or more distinct episodes of ventricular tachycardia (VT) or ventricular fibrillation (VF) within 24 h.[3–7] The occurrence of frequent episodes of ES has been linked to psychological trauma, a reduced quality of life and increased mortality. Thus identifying patients at high risk of ES is essential.[6–9]

Several factors including progressive heart failure, severe reduction of left ventricular function, advanced age, previous VT or VF

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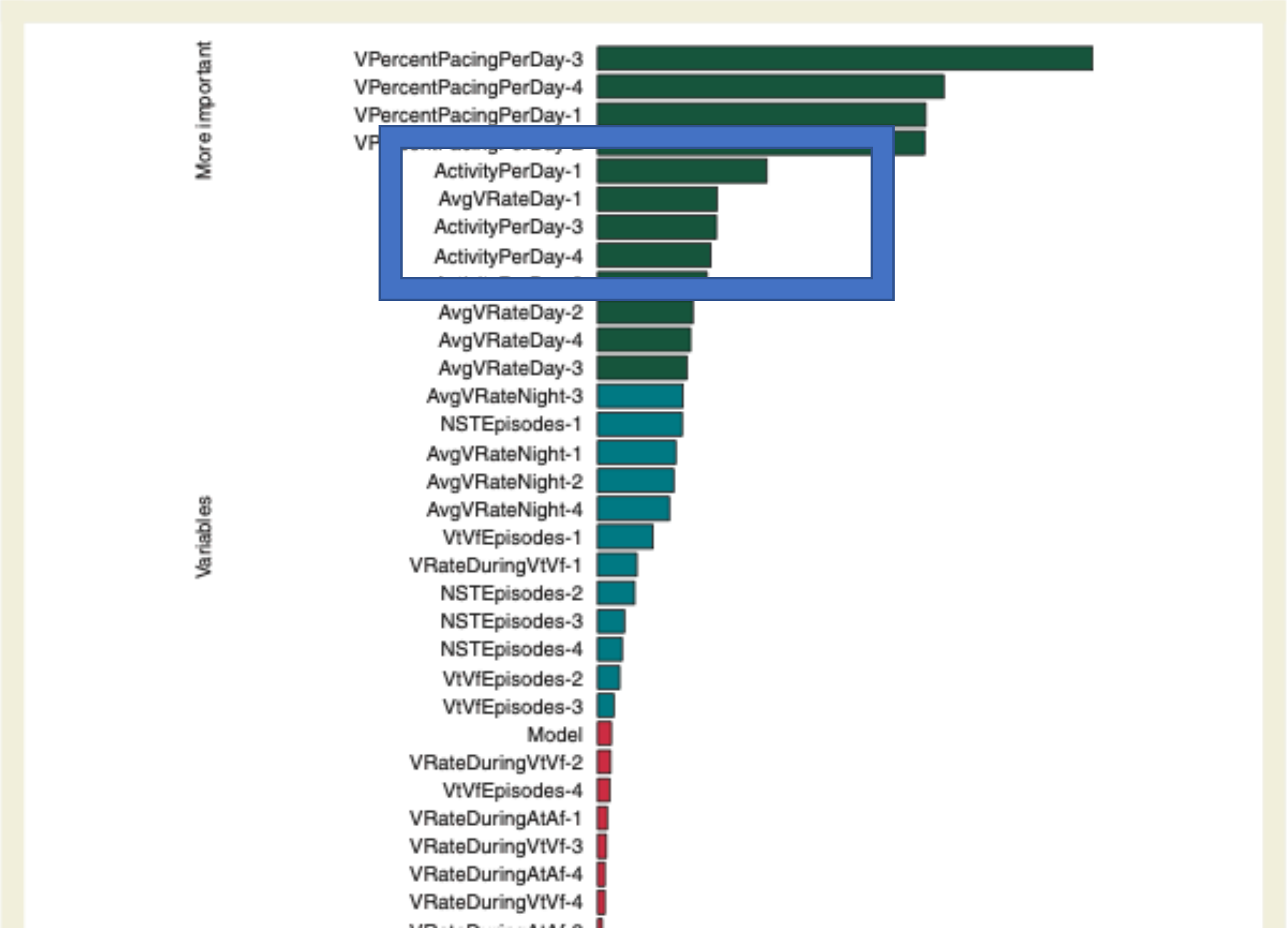
† Deceased author.



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SafeHeart project (Eurostars 2020-2023)

Patient-Generated Health Data
Symptoms, Activity, Biometric, Behaviour

Medication Profile
Dosage, Side-Effects Kind, Compliance

Cardiac Implantable Electronic Device
ECG, Arrhythmias, Biometrics

National Health Registry
Diagnoses, Admissions, Procedures

Electronic Medical Record
Medication, Notes, Test results

Amsterdam UMC University Medical Centers
REGION H Rigshospitalet
Vital Beats
Activinsights

Questions?

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Workshop at CHI 2021: Realizing AI in healthcare: Challenges appearing in the wild
http://bit.ly/RealizingAIinHealthcareWS