決生斷死--人工智慧
在心臟循環學的應用

蔡維中.高醫心臟內科
Wei-Chung Tsai, MD, FHRS
Kaohsiung Medical University, Taiwan
2020 @ KMUH

1

Disclosures

- **WC. Tsai:** None

2

學習目標

- 數位化、智慧醫療
- 人工智慧應用在心臟學
- 高醫的人工智慧醫療發展

3

Old school vs Now 過去與現在

Modified from Leslie Saxon`s presentation in HRS 2019

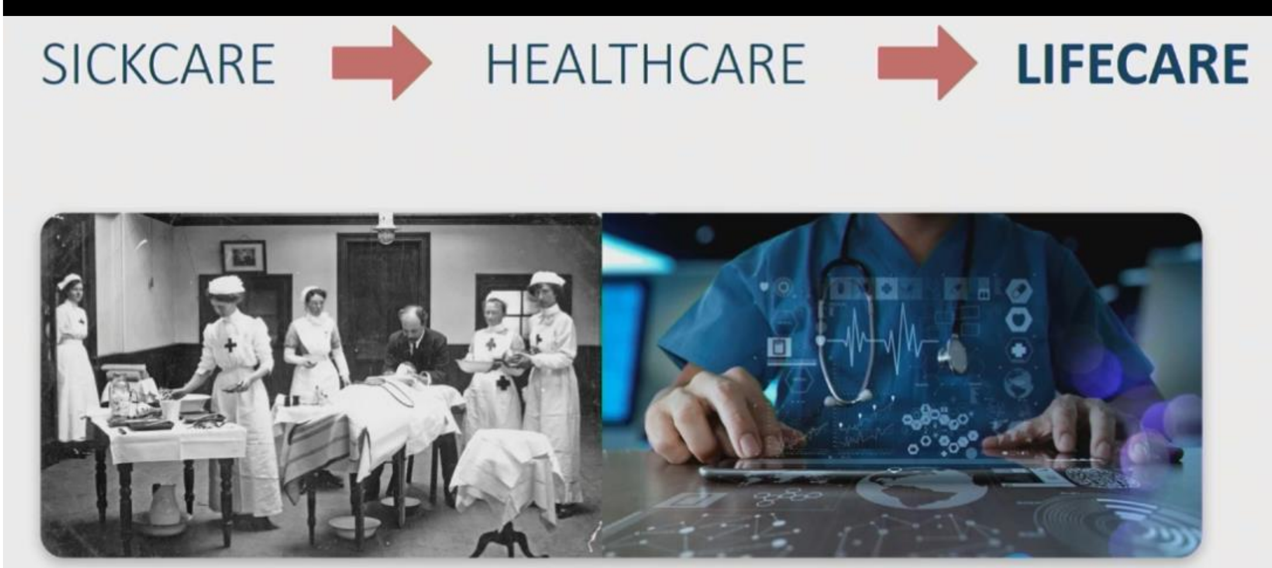
4

Incredible speed of change 劇變

Modified from Leslie Saxon`s presentation in HRS 2019

5

Care of Life 生命照顧



Modified from Leslie Saxon`s presentation in HRS 2019

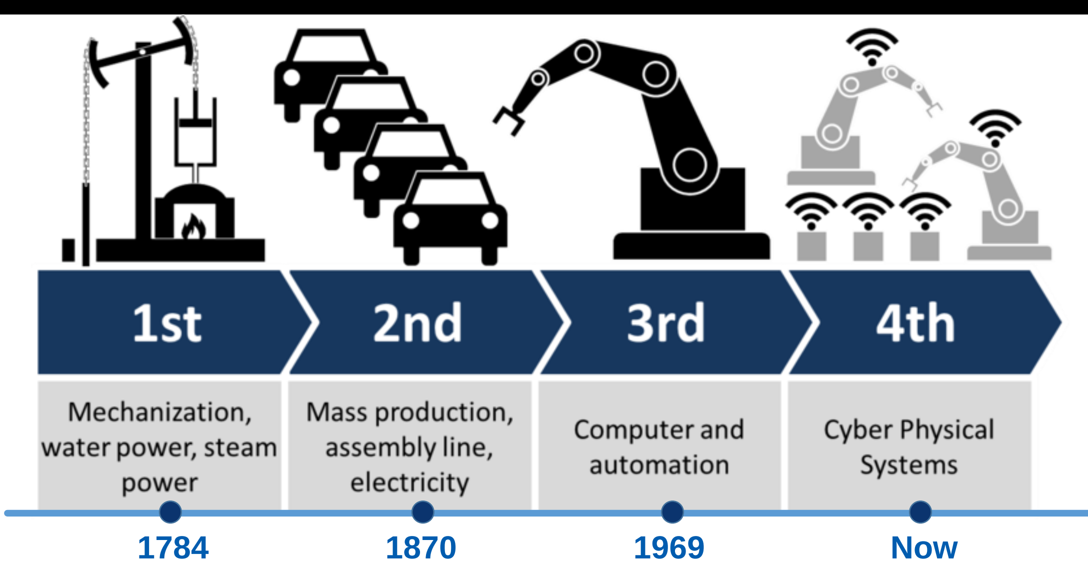
6

Traditional vs Digital Health傳統vs 數位

Modified from Leslie Saxon`s presentation in HRS 2019

7

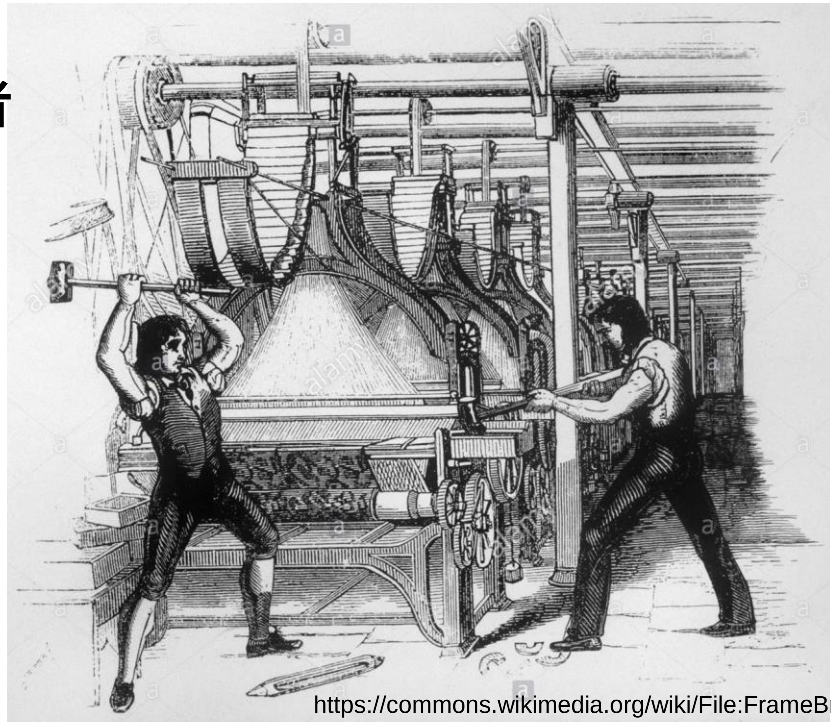
The Four Industrial Revolutions 工業革命



https://www.industryleadersmagazine.com/ready-fourth-industrial-revolution/

8

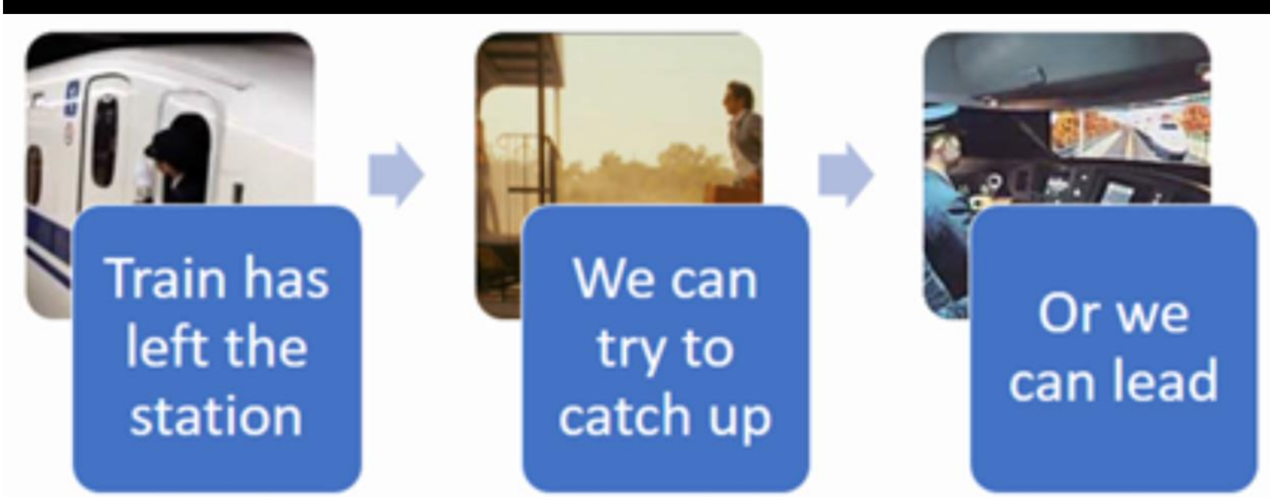
Luddite
盧德主義者



https://commons.wikimedia.org/wiki/File:FrameBreaking-1812.jpg

9

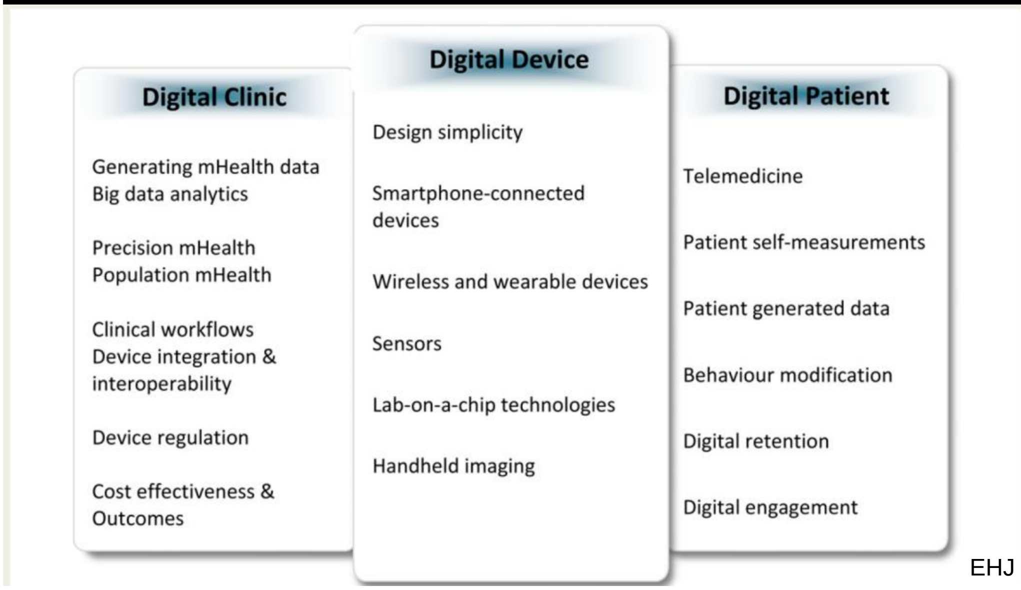
Artificial Intelligence (AI) 人工智慧



Modified from David Scheer`s presentation in HRS 2019

10

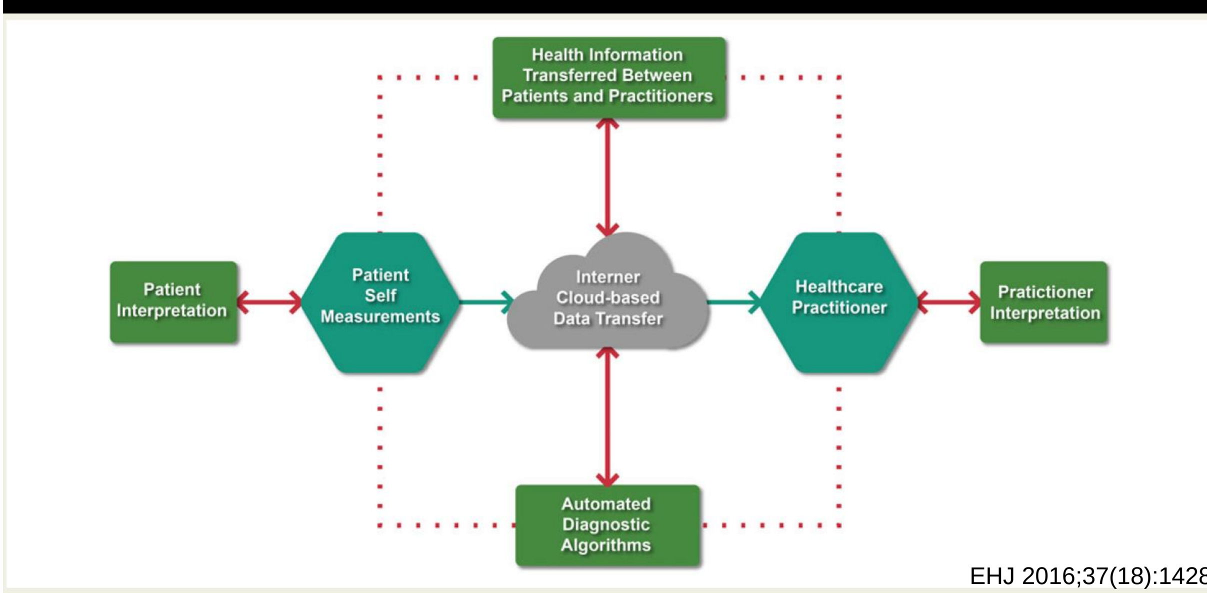
Mobile technology & digitization of healthcare 行動技術與數位健康照護



EHJ 2016;37(18):1428-1438

11

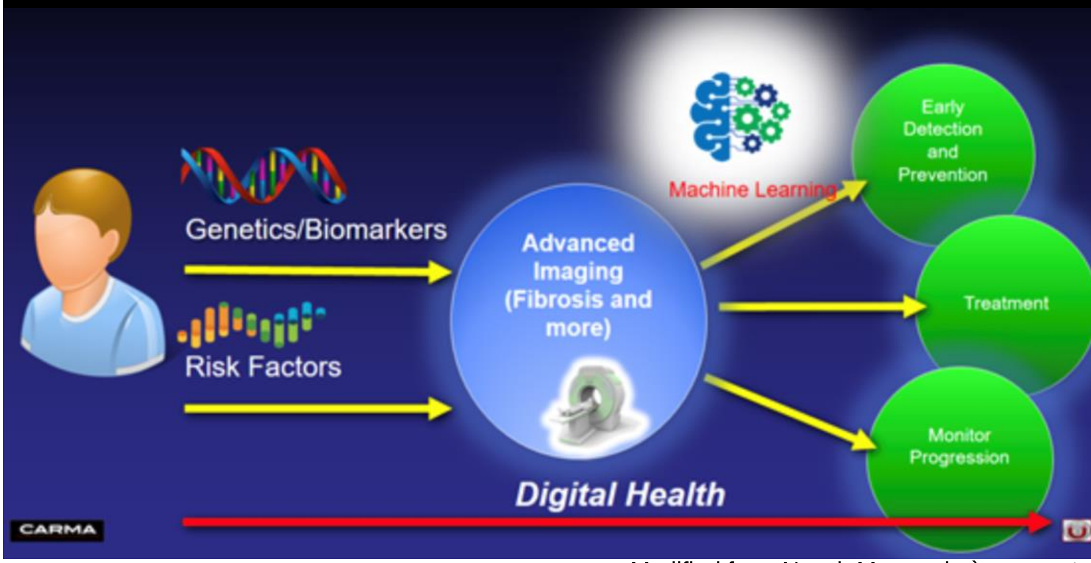
Mobile technology & digitization of healthcare 行動技術與數位健康照護



EHJ 2016;37(18):1428-1438

12

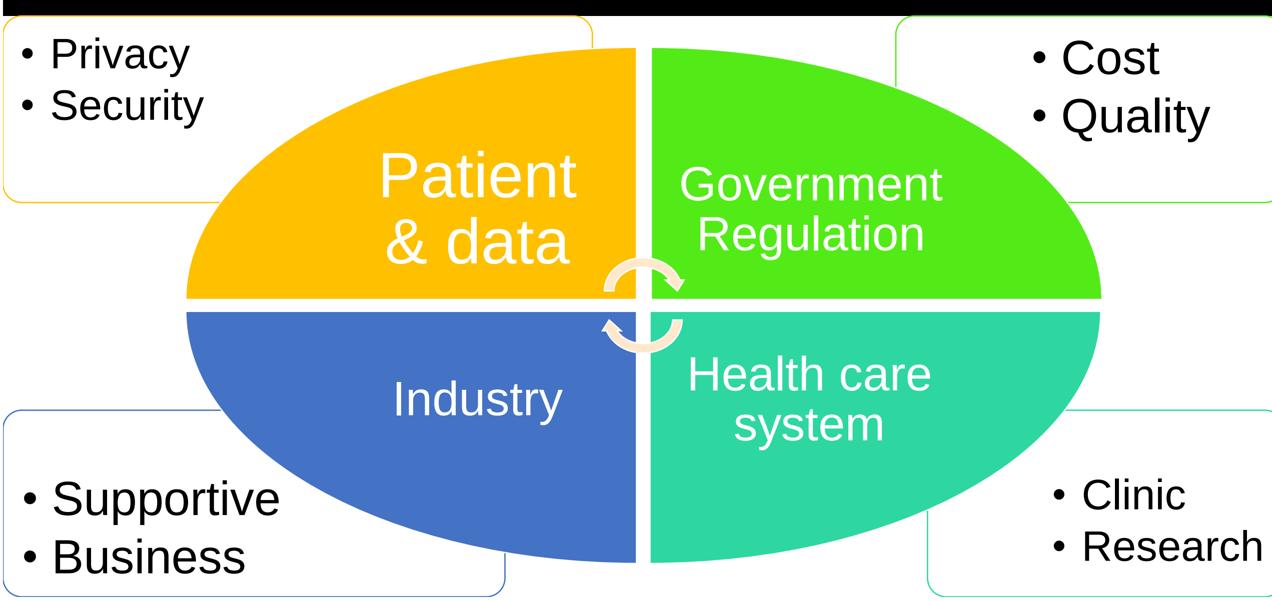
Personalized Path in managing Arrhythmia 個人化路徑處理心律不整



Modified from Nassir Marrouche`s presentation in HRS 2019

13

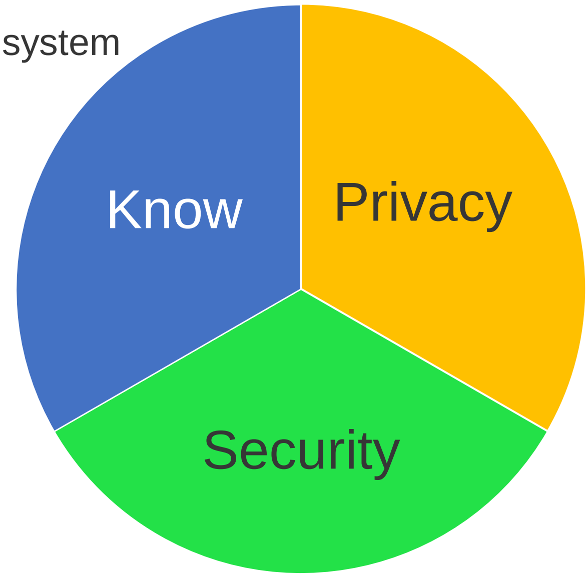
AI, we must lead!



14

Patient Perspective 病人的觀點

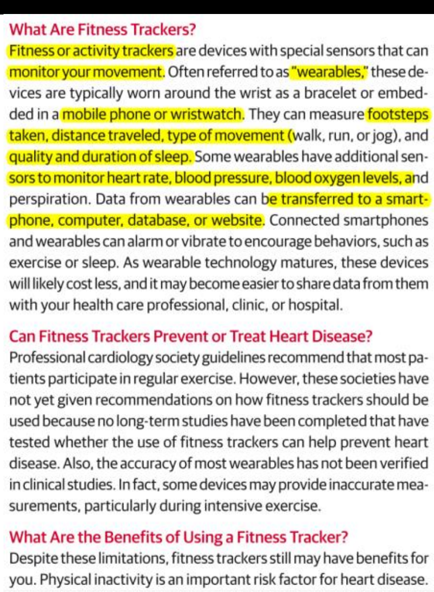
- Want regular updated from health care system
- Want access to data via EMR portal
- Want basic information of their CIED
- Consumer devices to help diagnosis



Cardiovascular Implantable Electronic Device (CIED)
Electronic medical record （EMR）

15

Wearable Fitness Trackers and Heart Disease 穿戴式瘦身追蹤器與心臟疾病



What Are Fitness Trackers?
Fitness or activity trackers are devices with special sensors that can monitor your movement. Often referred to as "wearables," these devices are typically worn around the wrist as a bracelet or embedded in a mobile phone or wristwatch. They can measure footsteps taken, distance traveled, type of movement (walk, run, or jog), and quality and duration of sleep. Some wearables have additional sensors to monitor heart rate, blood pressure, blood oxygen levels, and perspiration. Data from wearables can be transferred to a smartphone, computer, database, or website. Connected smartphones and wearables can alarm or vibrate to encourage behaviors, such as exercise or sleep. As wearable technology matures, these devices will likely cost less, and it may become easier to share data from them with your health care professional, clinic, or hospital.

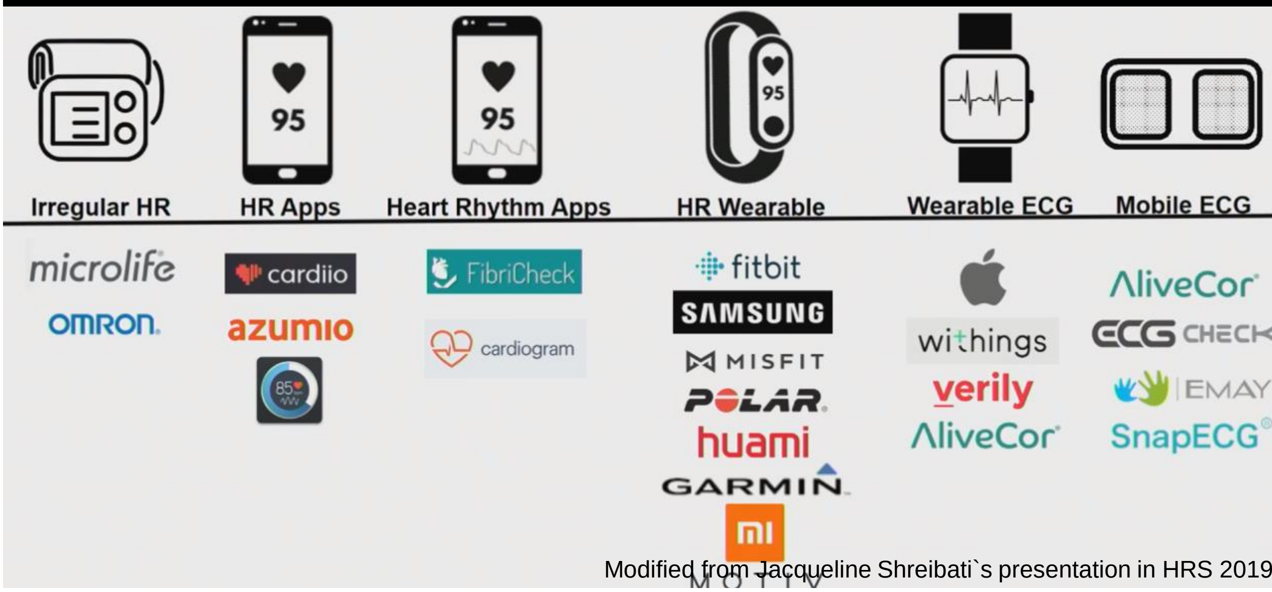
Can Fitness Trackers Prevent or Treat Heart Disease?
Professional cardiology society guidelines recommend that most patients participate in regular exercise. However, these societies have not yet given recommendations on how fitness trackers should be used because no long-term studies have been completed that have tested whether the use of fitness trackers can help prevent heart disease. Also, the accuracy of most wearables has not been verified in clinical studies. In fact, some devices may provide inaccurate measurements, particularly during intensive exercise.

What Are the Benefits of Using a Fitness Tracker?
Despite these limitations, fitness trackers still may have benefits for you. Physical inactivity is an important risk factor for heart disease.

JAMA Cardiol. 2016;1(2):239.

16

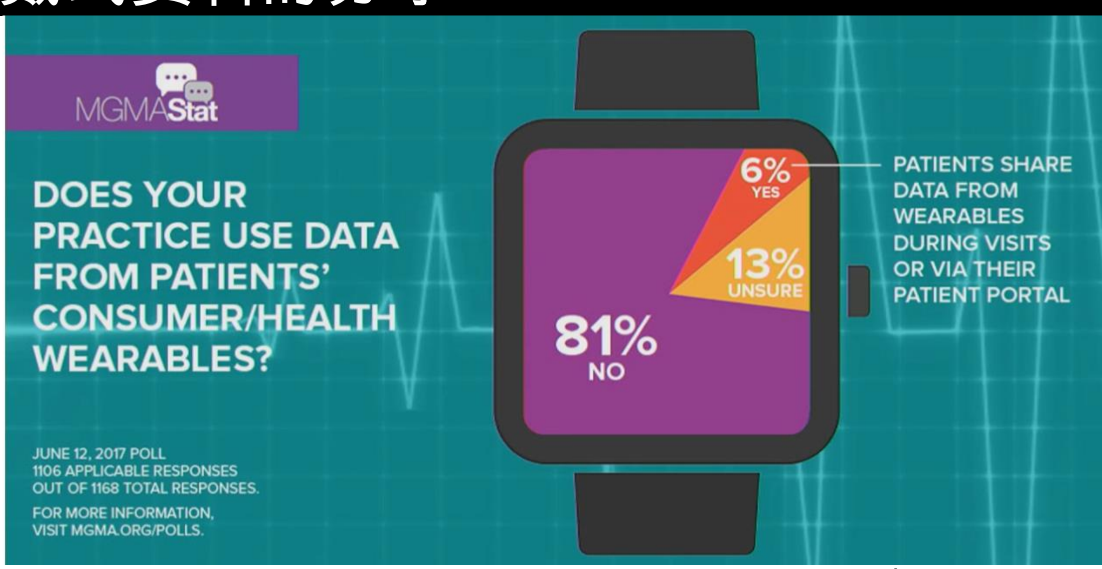
Digital Health Tools for Arrhythmia identification
用來偵測心律不整的數位化健康工具



Modified from Jacqueline Shreibati`s presentation in HRS 2019

17

Wearables data sharing
穿戴式資料的分享



Modified from David Scheer`s presentation in HRS 2019

18

Step Back and Ask

- What?
- Where?

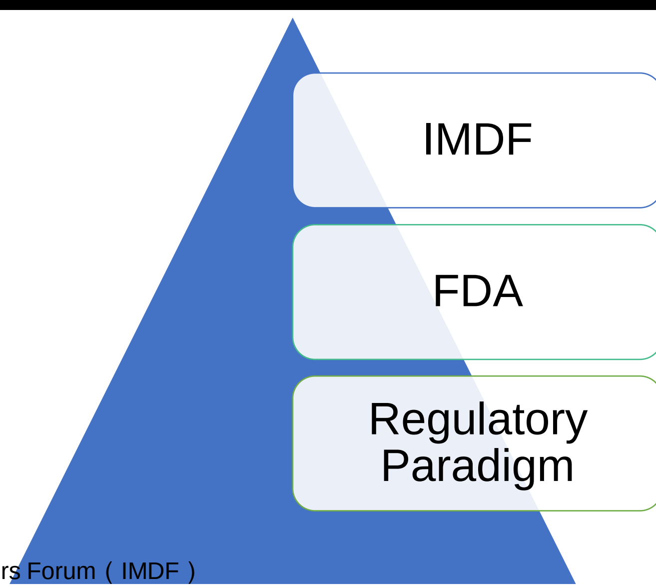
- Regulated by FDA?
- Should I Trust?

- Interpret?
- Useful?

19

Government Perspective 政府觀點

- Reduce inefficiencies
- Improve access
- Reduce cost
- Increase quality
- Engage patients



International Medical Device Regulators Forum（IMDF）

20

FDA – Digital health

Read Our Digital Health Innovation Action Plan

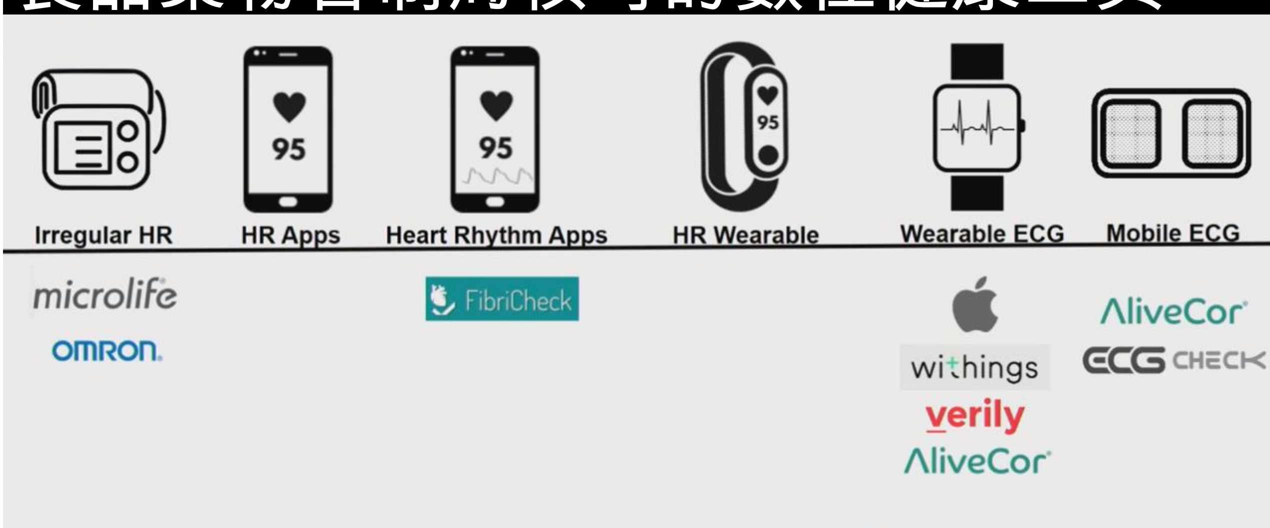
The Digital Health Innovation Action Plan outlines our efforts to reimagine the FDA's approach to ensuring all Americans have timely access to high-quality, safe and effective digital health products. As part of this plan, we committed to several key goals, including increasing the number and expertise of digital health staff at the FDA, launching the digital health software precertification pilot program ("Pre-Cert") and issuing guidance to modernize our policies.

Commissioner's Statement: Advancing new digital health policies to encourage innovation, bring efficiency and modernization to regulation

https://www.fda.gov/medical-devices/digital-health

21

Digital Health Tools : FDA-Cleared 食品藥物管制局核可的數位健康工具



Modified from Jacqueline Shreibati`s presentation in HRS 2019

22

Devices of AI 相關的裝置

CIED

Wearables
Medical grade

Wearables
Consumer Devices

23

Atrial Fibrillation — ❤ 118 BPM Average

This ECG shows signs of AFib.

If this is an unexpected result, you should talk to your doctor.

24

Rhythm Abnormalities & Wearable Devices 心律失常與穿戴式裝置

ATRIAL FIBRILLATION (AF)

An AF alert could be a false positive from irregular rhythm detection by the photoplethysmographic (PPG) sensor

- ☐ Confirm rhythm with electrocardiogram (ECG) to rule out ectopic rhythms or variable atrioventricular nodal conduction
  This may involve ambulatory ECG monitoring
- ☐ Consider risk factors for thromboembolism and risks vs benefits of anticoagulation
- ☐ Evaluate for structural heart disease
- ☐ Determine optimal strategy of rate vs rhythm control depending on patient's symptoms
- ☐ Consider referral for further management if indicated

TACHYCARDIA

Beware of inaccurate measurements due to limitations of the PPG-based sensor

- ☐ Assess if heart rate is appropriate (ie, related to stress, anxiety, pain, infection, dehydration, pregnancy, or medication) or inappropriate and if proportional to baseline physical conditioning
- ☐ Assess symptoms and evaluate for structural heart disease
- ☐ Consider referral for further management if indicated

BRADYCARDIA

Chronotropic incompetence does not trigger a notification

- ☐ Determine if bradycardia is primary or secondary (ie, related to medication, hypothyroidism, or infection)

If bradycardia is detected at rest

- ☐ Confirm with ECG
- ☐ Evaluate heart rate acceleration with exercise
- ☐ Assess for symptoms that correlate with bradycardia (ie, syncope, presyncope, or exertional tolerance)
  - ☐ If symptoms ▸ Consider referral for pacemaker
  - ☐ If no symptoms ▸ Consider ambulatory ECG monitoring; consider exercise treadmill test to unmask chronotropic incompetence

Confirm by ECG or ambulatory ECG monitoring!

JAMA. 2019;321(11):1098-1099

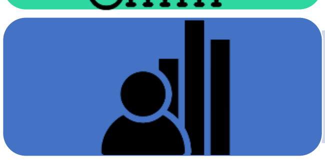
25

Health Care System Perspective 健康照護系統的觀點

- CIED
- Remote

- New Medical devices
- New Consumer devices

- Big data



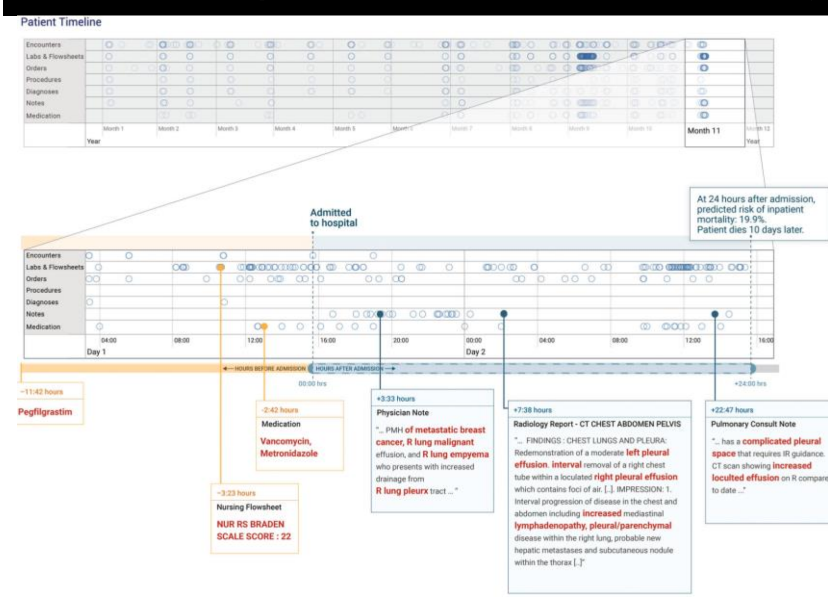
- Research

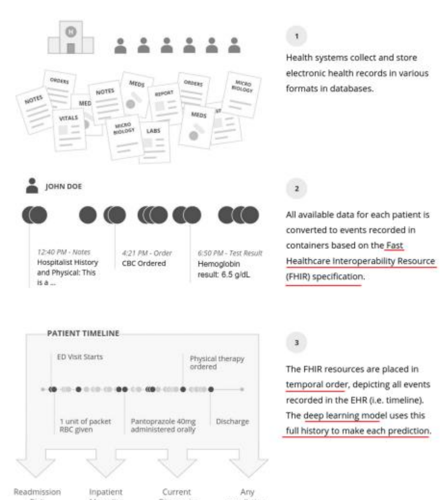
26

Big data & Electronic health records (EHR)

27

Scalable and accurate deep learning with EHR 以深度學習來對電子病歷紀錄做解讀

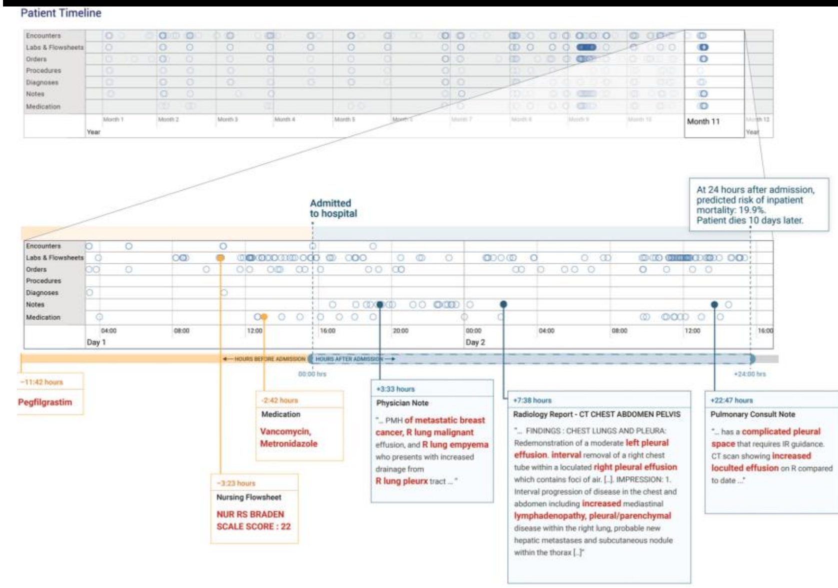


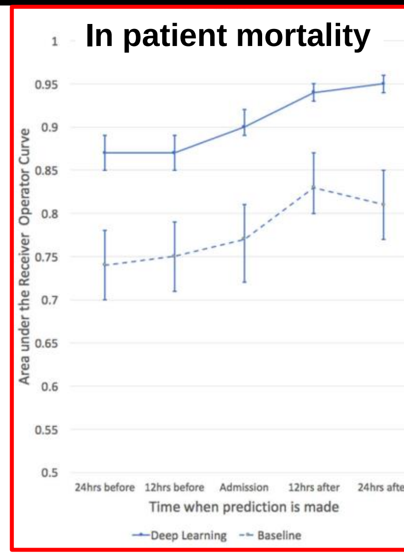


npj Digital Medicine 2018;1:18

28

Scalable and accurate deep learning with EHR
以深度學習來對電子病歷紀錄做解讀





npj Digital Medicine 2018;1:18

29

AI + new Devices

30

Mobile technology & digitization of healthcare
行動技術與數位健康照護

Study	Study size	Study population	Digital health technology intervention group	Comparator	Outcomes	Salient findings
Heart failure						
Koehler et al.[42] TIM-HF Randomized trial Germany	710	Ambulatory class II–III HF patients with ejection fraction ≤35%	Weight scale, blood pressure, and single lead ECG	Usual care	Composite outcome of hospital admission for HF and/or all-cause mortality at 24 months	No significant difference in outcomes of mortality or HF hospitalization [(15 vs. 17%) hazard ratio 0.89 (95% CI 0.67–1.19, $P = 0.44$)]
Weintraub et al.[41] SPAN-CHF II Randomized trial USA	188	Symptomatic HF patients with a prior hospitalization within 2 weeks	Weight scale, blood pressure, and heart rate monitor	Usual care	HF readmission at 3 months	At 3 months, telemedicine interventions were associated with a reduction in HF readmission [(10 vs. 19%) hazard ratio 0.50 (95% CI 0.25–0.99, $P = 0.05$)]
Cardiac surgery						
Arrhythmia						
Barrett et al.[71] Prospective observational USA	146	Patients referred cardiac arrhythmia management	Zio Patch wireless telemetry monitor	Simultaneous Holter monitor	Comparison of the arrhythmia detection over the total wear time	Zio Patch detected significantly more events over the total wear time compared with Holter monitoring (96 vs. 61 events, $P < 0.001$)
Lowres et al.[72] SEARCH-AF Prospective observational Australia	1000	Patients aged 65 or greater screened for the presence of an atrial arrhythmia	AliveCor smartphone iECG	–	Prevalence of newly diagnosed atrial fibrillation	Smartphone rhythm screening by pharmacists demonstrated a 7% prevalence and a 1.5% incidence of newly diagnosed atrial fibrillation in a community cohort of elderly patients
Coronary heart disease						
Chow et al.[33] TEXT ME Randomized trial Australia	710	Adult patients with coronary heart disease established by a prior history of a myocardial infarction or angiographically proven	Text messaging to promote tobacco abstinence, healthy eating, and maintaining physical activity	Usual care	6-month LDL-C levels, systolic blood pressure, body mass index, physical activity, and smoking status	At 6 months, text messaging was associated with a lower LDL-C (−5 mg/dL), a greater reduction in systolic blood pressure (−7.6 mmHg), a lower body mass index (−1.3), increases in physical activity (+2.93 metabolic equivalents), and a significant reduction in smoking (26 vs. 44%) compared with controls

EHJ 2016;37(18):1428-1438

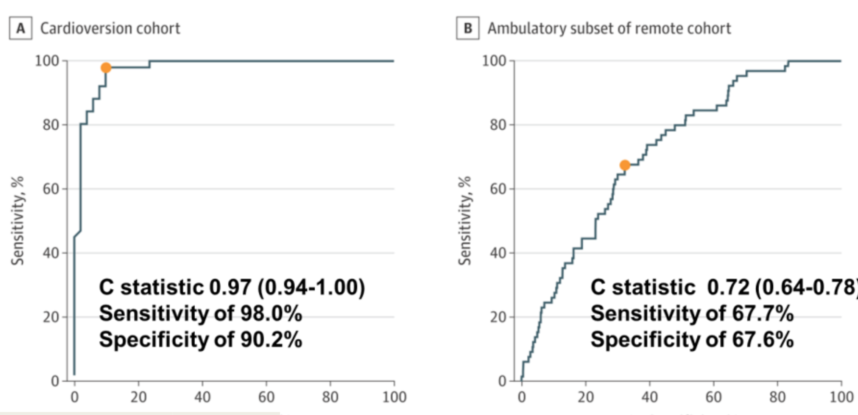
31

Using smart watch and AI to detect AF
使用智慧手錶與人工智慧來偵測心房顫動

Photoplethysmography

DNN, heuristic pretraining

Figure 2. Accuracy of Detecting Atrial Fibrillation in the Cardioversion Cohort



Cohort	PPV	NPV	AUC
Cardioversion cohort (sedentary)	90.9	97.8	0.97
Subset of remote cohort (ambulatory)	7.9	98.1	0.72

JAMA Cardiol. 2018;3(5):409-416

32

Results of a Large-scale, App-based Study to Identify Atrial Fibrillation Using a Smartwatch:

The Apple Heart Study

Mintu Turakhia MD MAS and Marco Perez MD
on behalf of the Apple Heart Study Investigators

NCT # 03335800

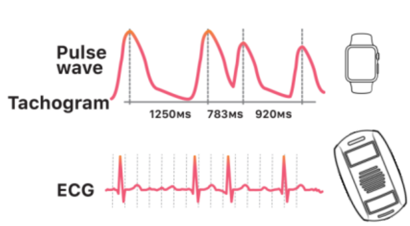
Stanford MEDICINE

Am Heart J. 2019;207:66-75

33

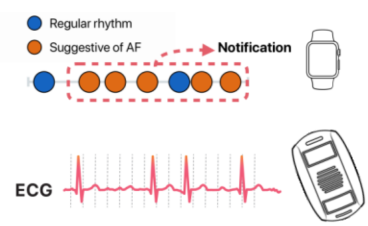
Positive Predictive Values

Irregular Tachograms



	Afib on ECG Patch	Positive Tachograms	PPV* (97.5% CI)
Overall	1,489	2,089	0.71 (0.69–0.74)
Age ≥ 65	548	914	0.60 (0.56 – 0.64)

Irregular Pulse Notifications



	Afib on ECG Patch	Positive Notifications	PPV (95% CI)
Overall	72	86	0.84 (0.76–0.92)
Age ≥ 65	25	32	0.78 (0.64 – 0.92)

34

Conclusions

Study w/ Novel Virtual Design
419,297 in 8 months

Proportion Notified low
Overall: 0.52% (0.49-0.54)

ECG patch 13 days after
34% had Afib

Positive predictive value
Tachogram: 0.71 (0.69-0.74)
Notification: 0.84 (0.76-0.92)

57% Notified (surveyed)
Contacted Non-Study Provider

Exposure to the
app was safe

35

The NEW ENGLAND JOURNAL of MEDICINE

ORIGINAL ARTICLE

Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation

Marco V. Perez, M.D., Kenneth W. Mahaffey, M.D., Haley Hedlin, Ph.D., John S. Rumsfeld, M.D., Ph.D., Ariadna Garcia, M.S., Todd Ferris, M.D., Vidhya Balasubramanian, M.S., Andrea M. Russo, M.D., Amol Rajmane, M.D., Lauren Cheung, M.D., Grace Hung, M.S., Justin Lee, M.P.H., Peter Kowey, M.D., Nisha Talati, M.B.A., Divya Nag, Santosh E. Gummidipundi, M.S., Alexis Beatty, M.D., M.A.S., Mellanie True Hills, B.S., Sumbul Desai, M.D., Christopher B. Granger, M.D., Manisha Desai, Ph.D., and Mintu P. Turakhia, M.D., M.A.S., for the Apple Heart Study Investigators*

BACKGROUND

Optical sensors on wearable devices can detect irregular pulses. The ability of a smartwatch application (app) to identify atrial fibrillation during typical use is unknown.

METHODS

Participants without atrial fibrillation (as reported by the participants themselves) used a smartphone (Apple iPhone) app to consent to monitoring. If a smartwatch-based irregular pulse notification algorithm identified possible atrial fibrillation, a telemedicine visit was initiated and an electrocardiography (ECG) patch was mailed to the participant, to be worn for up to 7 days. Surveys were administered 90 days after notification of the irregular pulse and at the end of the study. The main objectives were to estimate the proportion of notified participants with atrial fibrillation shown on an ECG patch and the positive predictive value of irregular pulse intervals with a targeted confidence interval width of 0.10.

RESULTS

We recruited 419,297 participants over 8 months. Over a median of 117 days of monitoring, 2161 participants (0.52%) received notifications of irregular pulse. Among the 450 participants who returned ECG patches containing data that could be analyzed — which had been applied, on average, 13 days after notification — atrial fibrillation was present in 34% (97.5% confidence interval [CI], 29 to 39) overall and in 35% (97.5% CI, 27 to 43) of participants 65 years of age or older. Among participants who were notified of an irregular pulse, the positive predictive value was 0.84 (95% CI, 0.76 to 0.92) for observing atrial fibrillation on the ECG simultaneously with a subsequent irregular pulse notification and 0.71 (97.5% CI, 0.69 to 0.74) for observing atrial fibrillation on the ECG simultaneously with a subsequent irregular tachogram. Of 1376 notified participants who returned a 90-day survey, 57% contacted health care providers outside the study. There were no reports of serious app-related adverse events.

CONCLUSIONS

The probability of receiving an irregular pulse notification was low. Among participants who received notification of an irregular pulse, 34% had atrial fibrillation on subsequent ECG patch readings and 84% of notifications were concordant with atrial fibrillation. This siteless (no on-site visits were required for the participants), pragmatic study design provides a foundation for large-scale pragmatic studies in which outcomes or adherence can be reliably assessed with user-owned devices. (Funded by Apple; Apple Heart Study ClinicalTrials.gov number, NCT03335800.)

N Engl J Med 2019;381:1909-17.

36

Cardiologist-level arrhythmia detection and classification in ambulatory ECG using DNN

Table 1 | Diagnostic performance of the DNN and averaged individual cardiologists compared to the cardiologist committee consensus ($n = 328$)

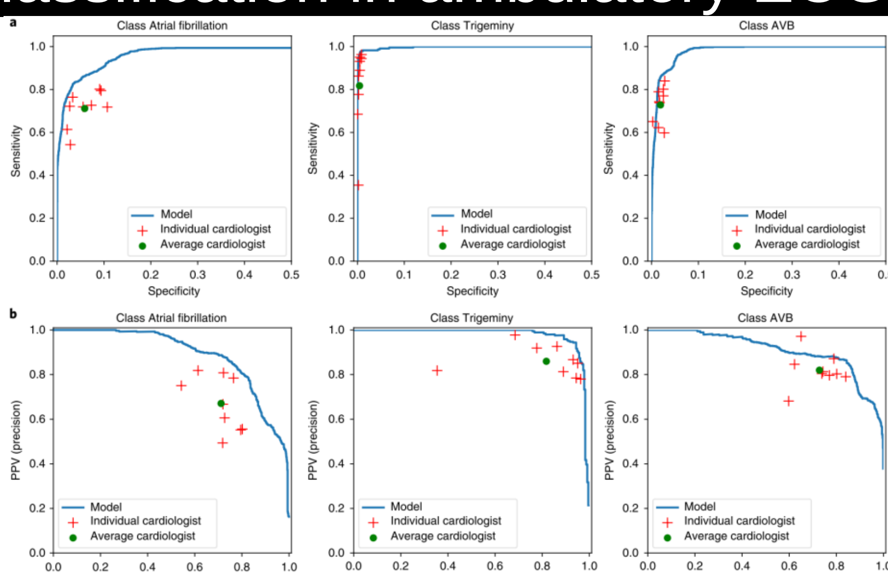
	Algorithm AUC (95% CI)[a]		Algorithm F_1[b]		Average cardiologist F_1	
	Sequence[a]	Set[b]	Sequence	Set	Sequence	Set
Atrial fibrillation and flutter	0.973 (0.966–0.980)	0.965 (0.932–0.998)	0.801	0.831	0.677	0.686
AVB	0.988 (0.983–0.993)	0.981 (0.953–1.000)	0.828	0.808	0.772	0.761
Bigeminy	0.997 (0.991–1.000)	0.996 (0.976–1.000)	0.847	0.870	0.842	0.853
EAR	0.913 (0.889–0.937)	0.940 (0.870–1.000)	0.541	0.596	0.482	0.536
IVR	0.995 (0.989–1.000)	0.987 (0.959–1.000)	0.761	0.818	0.632	0.720
Junctional rhythm	0.987 (0.980–0.993)	0.979 (0.946–1.000)	0.664	0.789	0.692	0.679
Noise	0.981 (0.973–0.989)	0.947 (0.898–0.996)	0.844	0.761	0.768	0.685
Sinus rhythm	0.975 (0.971–0.979)	0.987 (0.976–0.998)	0.887	0.933	0.852	0.910
SVT	0.973 (0.960–0.985)	0.953 (0.903–1.000)	0.488	0.693	0.451	0.564
Trigeminy	0.998 (0.995–1.000)	0.997 (0.979–1.000)	0.907	0.864	0.842	0.812
Ventricular tachycardia	0.995 (0.980–1.000)	0.980 (0.934–1.000)	0.541	0.681	0.566	0.769
Wenckebach	0.978 (0.967–0.989)	0.977 (0.938–1.000)	0.702	0.780	0.591	0.738
Frequency-weighted average	0.978	0.977	0.807	$\boxed{0.837}$	0.75[illegible]	$> \boxed{0.780}$

DNN

Nat Med. 2019;25(1):65-69

37

Cardiologist-level arrhythmia detection and classification in ambulatory ECG using DNN



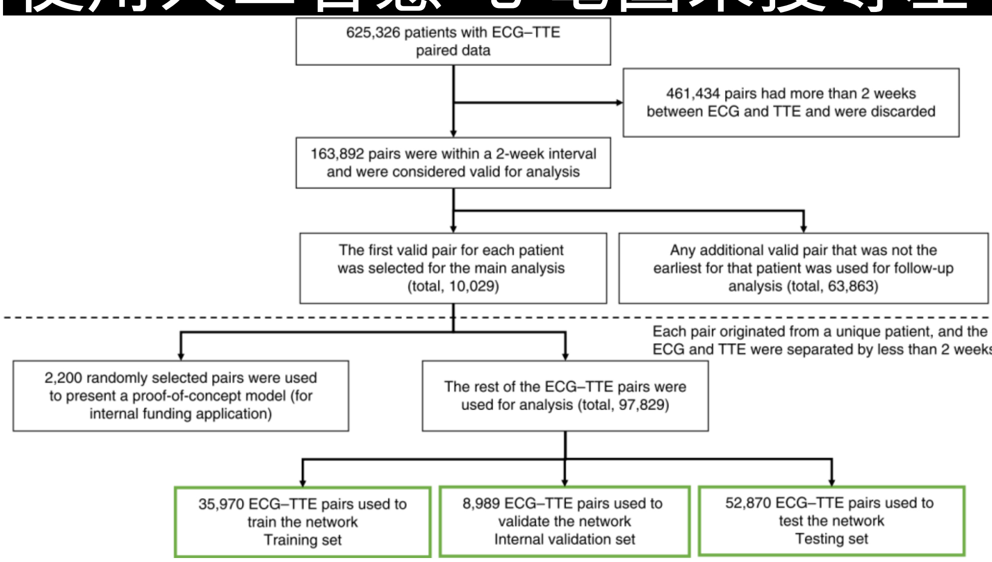
Nat Med. 2019;25(1):65-69

38

AI +
old Devices

39

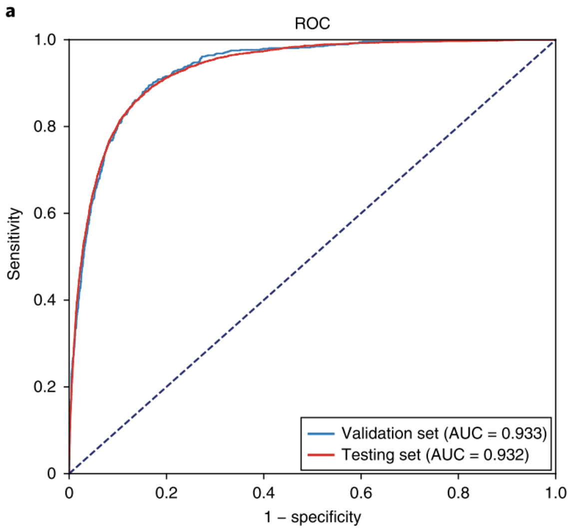
Using AI-ECG to screen LV dysfunction
使用人工智慧-心電圖來搜尋左心室失常



Nat Med. 2019;25(1):70-74

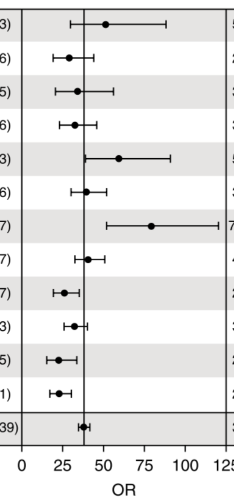
40

Using AI-ECG to screen LV dysfunction
使用人工智慧-心電圖來搜尋左心室失常



b

Group	Sensitivity	Specificity	OR (95% CI)
Female <40	74 (53/72)	95 (2,895/3,053)	51.11 (29.55–88.41)
Male <40	72 (86/120)	92 (2,405/2,616)	28.83 (18.92–43.93)
Female 40–49	74 (63/85)	92 (2,300/2,495)	33.78 (20.35–56.07)
Male 40–49	80 (178/223)	89 (2,491/2,796)	32.31 (22.81–45.75)
Female 50–59	85 (150/177)	91 (3,286/3,593)	59.46 (38.83–91.06)
Male 50–59	86 (390/455)	87 (4,440/5,116)	39.41 (29.94–51.87)
Female 60–69	90 (235/260)	89 (4,207/4,707)	79.09 (51.83–120.69)
Male 60–69	89 (722/815)	84 (5,762/6,867)	40.48 (32.32–50.71)
Female 70–79	80 (228/284)	86 (4,230/4,897)	25.82 (19.06–34.98)
Male 70–79	90 (843/936)	78 (5,014/6,433)	32.03 (25.65–40.00)
Female ≥80	84 (156/186)	81 (2,350/2,895)	22.42 (15.00–33.50)
Male ≥80	89 (463/518)	73 (2,382/3,271)	22.56 (16.88–30.14)
Overall	86 (3,567/4,131)	86 (41,762/48,739)	37.86 (34.52–41.52)

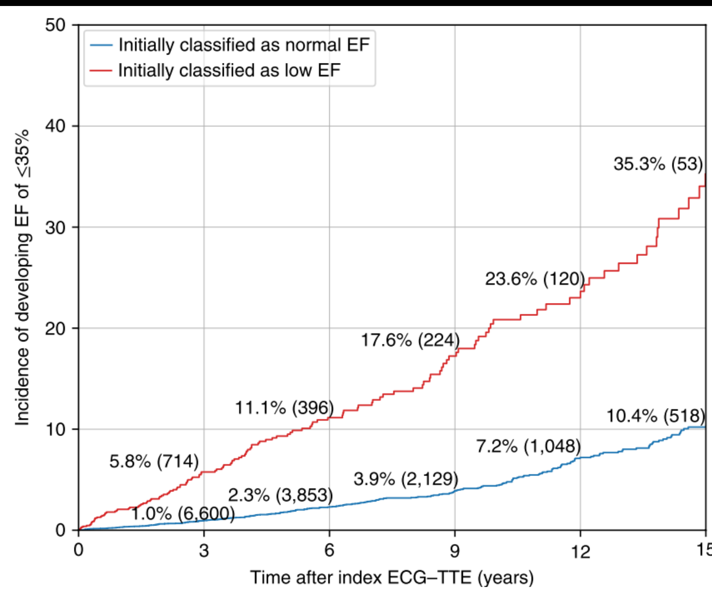


CNN

Nat Med. 2019;25(1):70-74

41

Using AI-ECG to screen LV dysfunction
使用人工智慧-心電圖來搜尋左心室失常



Nat Med. 2019;25(1):70-74

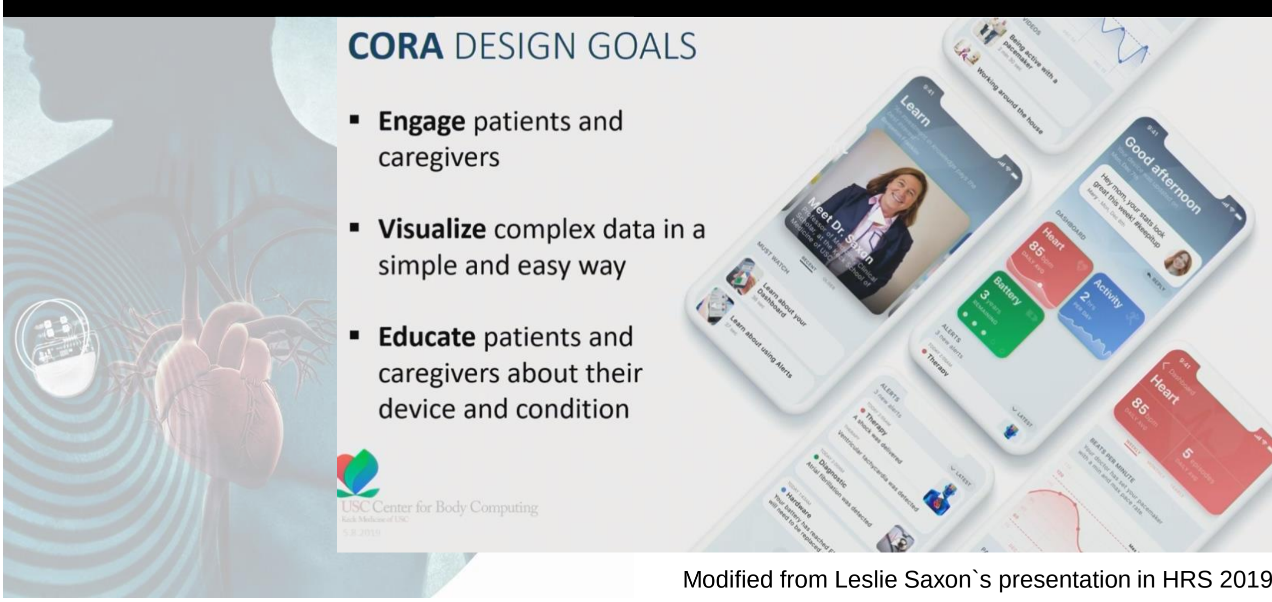
42

Industry Perspective 產業的觀點

- Supportive
- Changing relationships
  - Remote CIED
  - New devices
- Regulatory requirements
- Business model

43

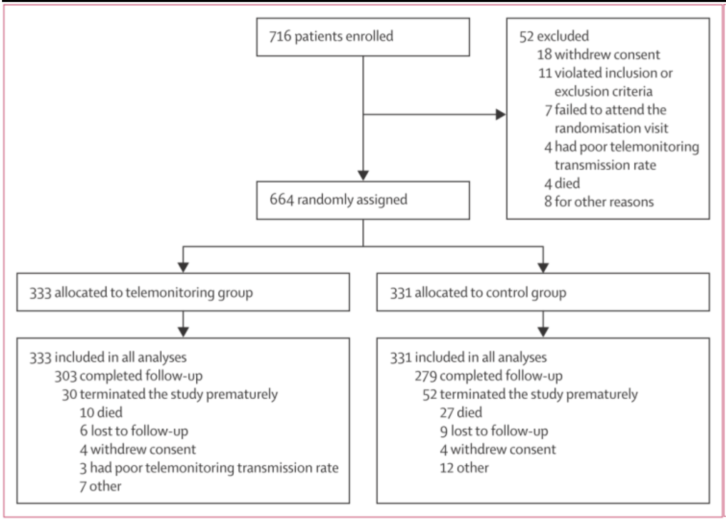
CORA

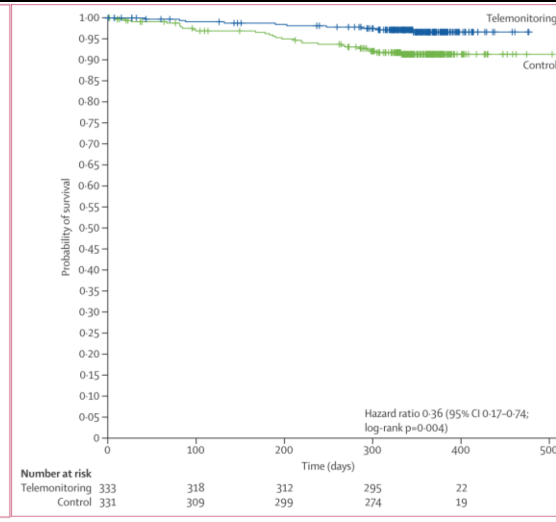


Modified from Leslie Saxon`s presentation in HRS 2019

44

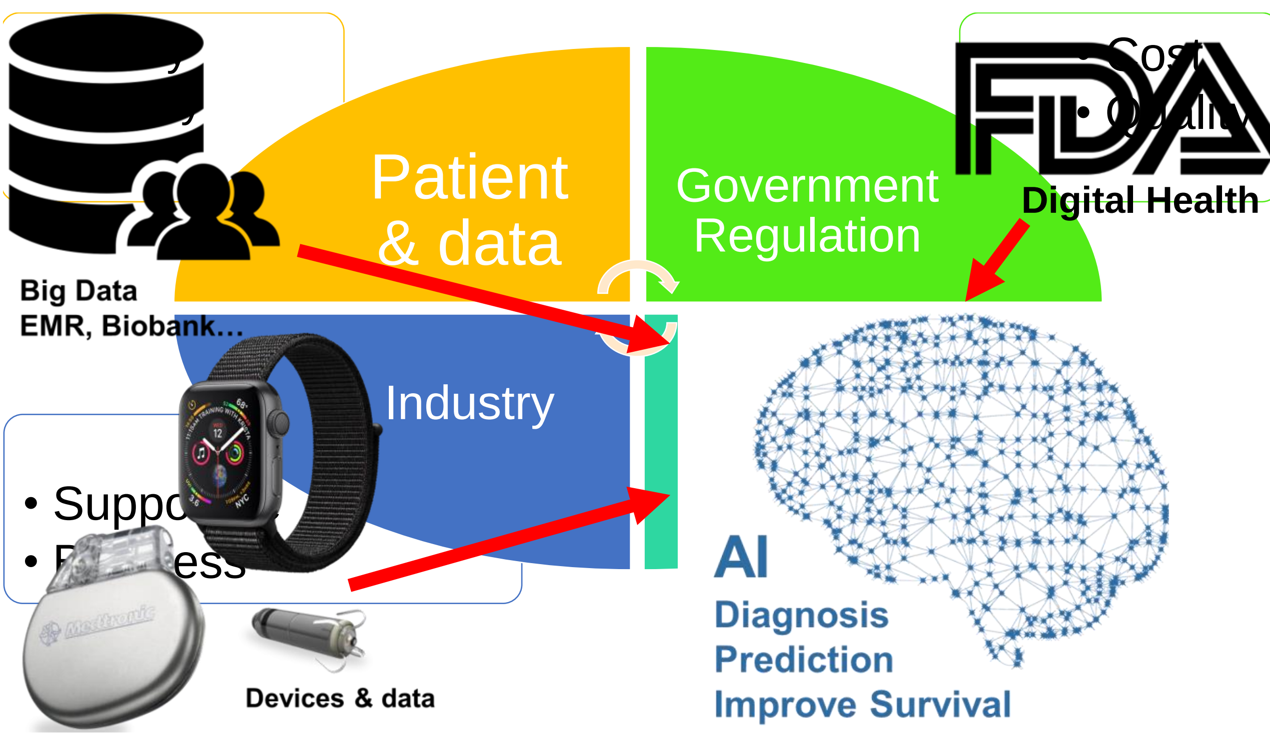
Implant-based multiparameter telemonitoring of patients with heart failure (IN-TIME)





Lancet. 2014;384(9943):583-590

45



46

47

Prediction of cardiac arrest by machine learning 以機器學習來預測心跳休止

Table 1 Modified early warning score

Score	Respiratory rate (breaths/minute)	Heart rate (beats/minute)	Systolic blood pressure (mmHg)	Temperature (°C)	AVPU
3	-	-	≤ 70	-	-
2	≤ 8	≤ 40	71 to 80	≤ 35	-
1	-	41 to 50	81 to 100	35.1 to 36	-
0	9 to 14	51 to 100	101 to 199	36.1 to 38	Alert
1	15 to 20	101 to 110	-	38.1 to 38.5	Reacting to voice
2	21 to 29	111 to 129	≥ 200	≥ 38.6	Reacting to pain
3	> 29	> 129	-	-	Unresponsive

AVPU, A for 'alert', V for 'reacting to vocal stimuli', P for 'reacting to pain', U for 'unconscious'.

Crit Care. 2012 Jun 21;16(3):R108

48

Prediction of cardiac arrest by machine learning 以機器學習來預測心跳休止

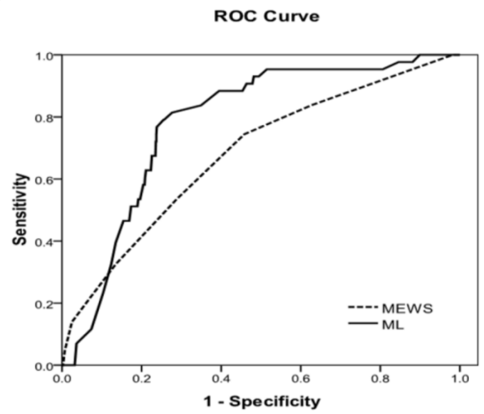


Figure 2 Machine learning score and modified early warning score predicting cardiac arrest within 72 hours. Receiver operating characteristics (ROC) curve analysis of the machine learning (ML) score and the modified early warning score (MEWS) in predicting cardiac arrest within 72 hours.

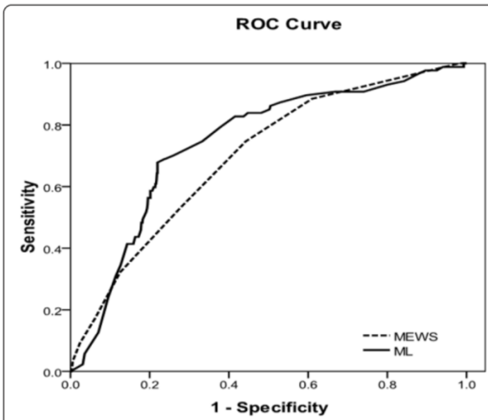


Figure 3 Machine learning score and modified early warning score predicting death within 72 hours. Receiver operating characteristics (ROC) curve analysis of machine learning (ML) score and the modified early warning score (MEWS) in predicting death after admission.

-- ML --

SVM

Age

HRV

Vital signs

Cardiac arrest within 72 hours

Death after admission

Crit Care. 2012 Jun 21;16(3):R108

49

Prediction of cardiac arrest by machine learning 以機器學習來預測心跳休止

Table 4 Discriminatory values of the machine learning score and the modified early warning score

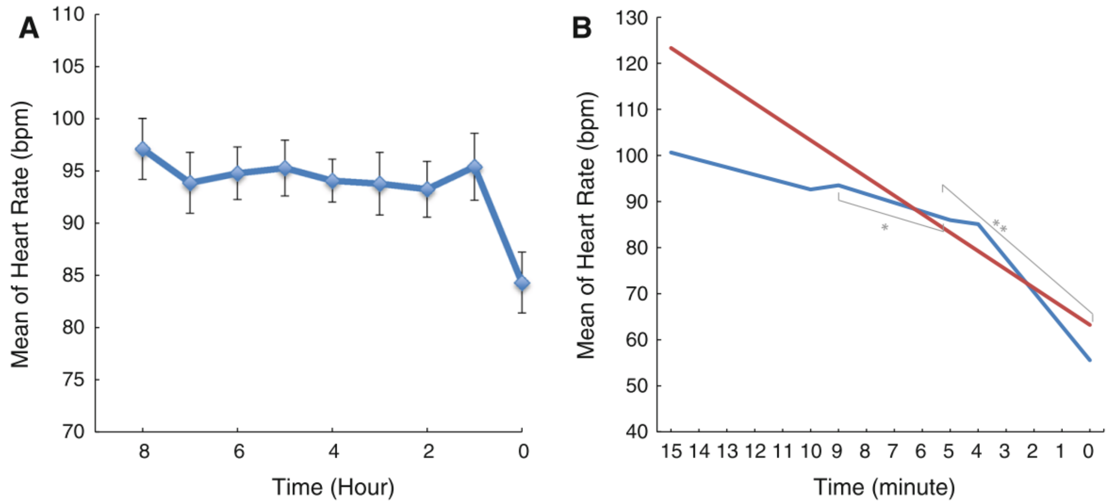
Variable	ML score (95% CI)[a]	MEWS (95% CI)[b]	Difference (95% CI for difference)[c]	*P* value
Cardiac arrest within 72 hours after presentation				
Area under ROC curve	0.781	0.680	0.101 (0.006 to 0.197)	0.037
Sensitivity	81.4	74.4	7.0 (-11.1 to 21.9)	0.581
Specificity	72.3	54.2	18.1 (14.3 to 22.0)	< 0.001
Positive predictive value	12.5 (9.0 to 17.1)	7.4 (5.3 to 10.3)		< 0.001
Negative predicting value	98.8 (97.5 to 99.4)	97.8 (95.9 to 98.8)		0.133
Likelihood ratio (+)[d]	2.94 (2.46 to 3.52)	1.62 (1.34 to 1.96)		
Death after admission[e]				
Area under ROC curve	0.741	0.693	0.048 (-0.023 to 0.119)	0.185
Sensitivity	69.8	74.4	-4.7 (-16.7 to 7.4)	0.572
Specificity	73.9	55.7	18.2 (14.3 to 22.2)	< 0.001
Positive predictive value	21.5 (16.9 to 26.9)	14.7 (11.5 to 18.4)		< 0.001
Negative predicting value	96.0 (94.1 to 97.3)	95.5 (93.2 to 97.1)		0.608
Likelihood ratio (+)[d]	2.67 (2.23 to 3.20)	1.68 (1.45 to 1.94)		

CI, confidence interval; MEWS, modified early warning score; ML, machine learning; ROC, receiver operating characteristic. [a]A cutoff value of 60 and above was used for the ML score. [b]A cutoff value of 3 and above was used for the MEWS. [c]The 95% confidence interval for the difference between the ML score and the MEWS for each diagnostic statistic was calculated, except for positive predictive value, negative predictive value, and likelihood ratio (+) that are not well established. [d]Likelihood ratio of a positive test. [e]In-hospital death during current admission. 95% confidence interval or statistical test not computed because the method is not well established for the diagnostic statistics concerned.

Crit Care. 2012 Jun 21;16(3):R108

50

ECG prior to in-hospital cardiac arrest 在院心跳休止前的心電圖變化



J Clin Monit Comput (2015) 29:385–392

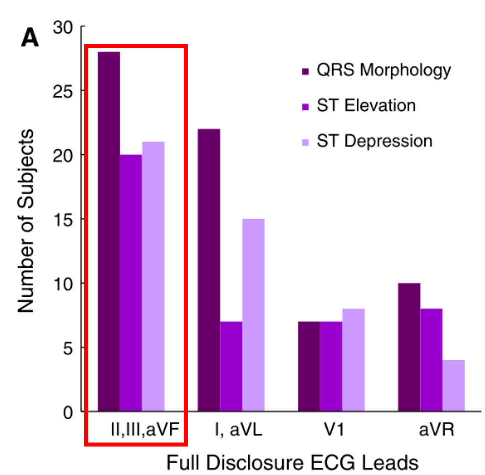
51

ECG prior to in-hospital cardiac arrest 在院心跳休止前的心電圖變化

Table 2 Distribution of QRS morphology and ST segment changes prior to cardiac arrest

	Initial rhythms: asystole (n = 15)	Initial rhythms: PEA (n = 24)	Initial rhythms of asystole and PEA	*p* value*
QRS morphology (%)	12 (80)	9 (38)	21 (54)	0.01
ST elevation (%)	11 (73)	9 (38)	20 (51)	0.02
ST depression (%)	10 (67)	13 (54)	23 (59)	0.44
ST elevation or depression (%)	10 (67)	8 (33)	18 (46)	0.04

* Chi-square was performed to detect significant differences between PEA and asystole groups ($p < 0.05$)



J Clin Monit Comput (2015) 29:385–392

52

Deep Learning for SCA Detection in AED 搭配深度學習的自動體外心臟去顫器來偵測猝死

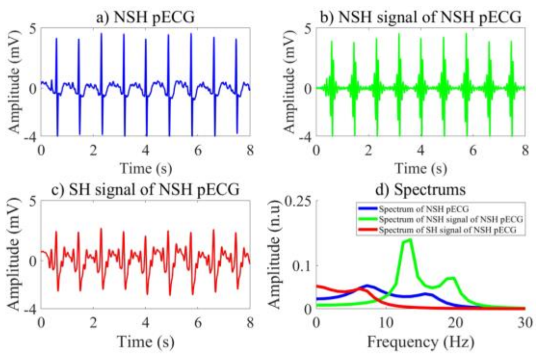


Figure 2. Input channels and their spectrums of the CNN for NSH pECG.

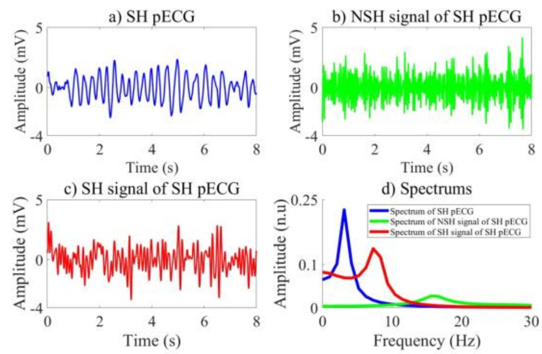


Figure 3. Input channels and their spectrums of the CNN for SH pECG.

Sci Rep. 2018 Nov 21;8(1):17196

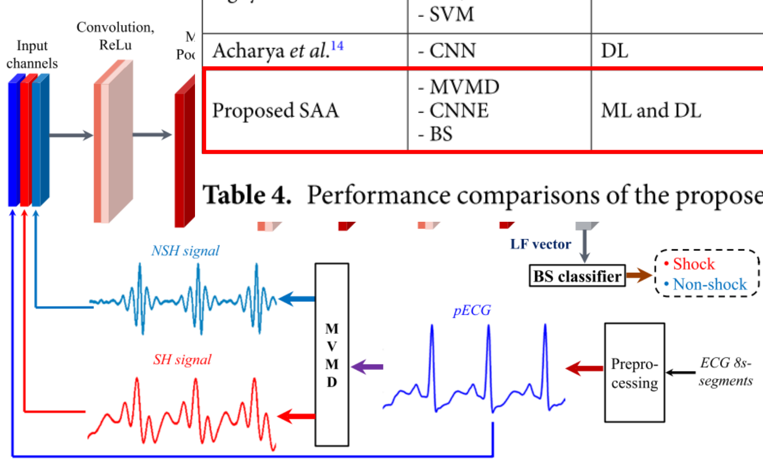
53

Deep Learning for SCA Detection in AED 搭配深度學習的自動體外心臟去顫器來偵測猝死

Table 3. The selectec

Ref.	Appoaches	Type of method	Segment	Ac (%)	Se (%)	Sp (%)
Nguyen *et al.*[8]	- MVMD - GA, SFFS - SVM	ML	8 s	99.00	97.36	99.16
Acharya *et al.*[14]	- CNN	DL	2 s	93.18	95.32	91.04
Proposed SAA	- MVMD - CNNE - BS	ML and DL	8 s	99.26	97.07	99.44

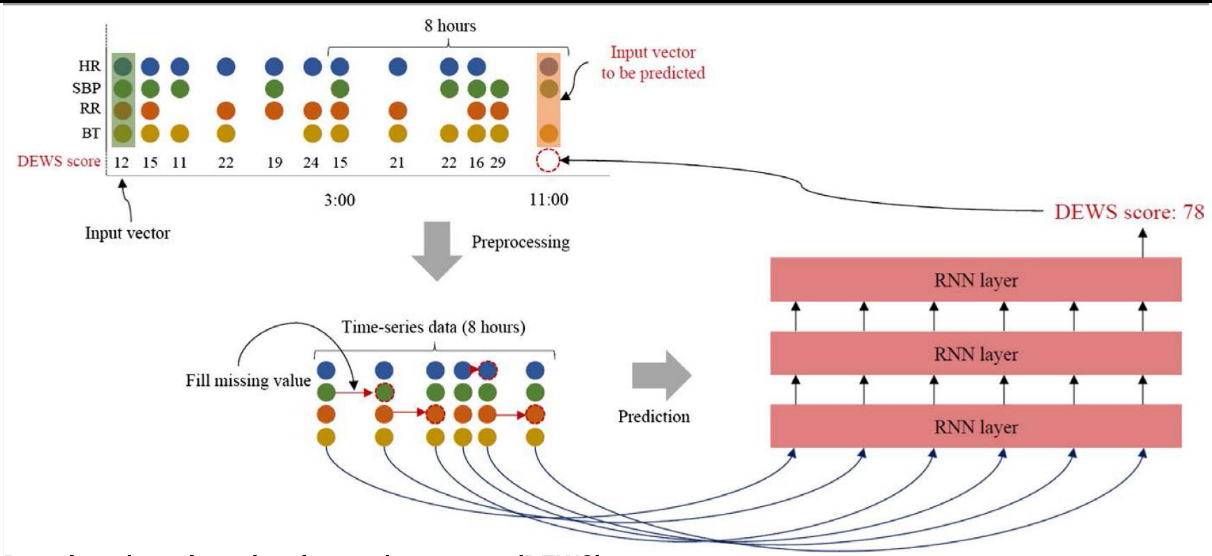
Table 4. Performance comparisons of the proposed method to existing algorithms.



Sci Rep. 2018 Nov 21;8(1):17196

54

An Algorithm Based on Deep Learning for Predicting In-Hospital Cardiac Arrest



Deep learning – based early warning system (DEWS)

J Am Heart Assoc. 2018 Jun 26;7(13)

55

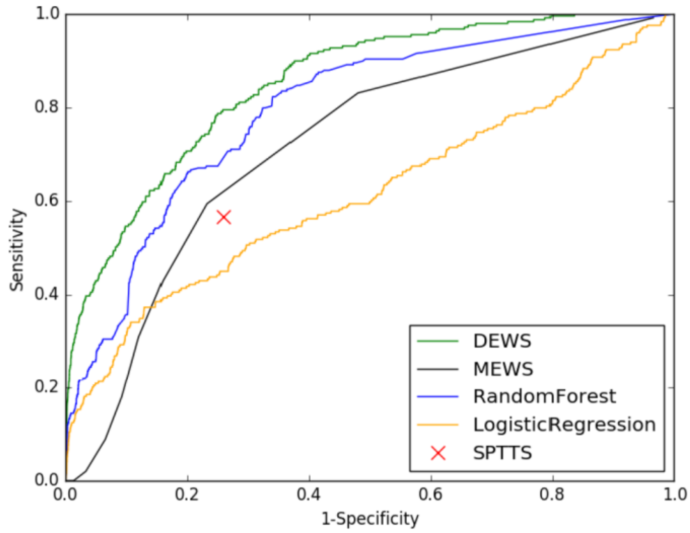
An Algorithm Based on Deep Learning for Predicting In-Hospital Cardiac Arrest

	Hospital A				Hospital B			
	AUROC	**(95% CI)**	**AUPRC**	**(95% CI)**	**AUROC**	**(95% CI)**	**AUPRC**	**(95% CI)**
Predicting cardiac arrest								
DEWS	0.850	(0.847-0.853)	0.044	(0.040-0.046)	0.837	(0.829-0.857)	0.239	(0.219-0.257)
MEWS	0.603	(0.603-0.603)	0.003	(0.003-0.003)	0.765	(0.765-0.765)	0.028	(0.028-0.028)
Random Forest	0.780	(0.776-0.787)	0.014	(0.012-0.014)	0.823	(0.812-0.828)	0.203	(0.184-0.218)
Logistic Regression	0.613	(0.607-0.620)	0.007	(0.006-0.007)	0.780	(0.767-0.795)	0.057	(0.051-0.061)
Predicting death without attempted resuscitation								
DEWS	0.926	(0.925-0.929)	0.188	(0.180-0.194)	0.911	(0.910-0.922)	0.221	(0.210-0.229)
MEWS	0.815	(0.815-0.815)	0.032	(0.032-0.032)	0.894	(0.894-0.894)	0.172	(0.172-0.172)
Random Forest	0.910	(0.908-0.913)	0.065	(0.061-0.068)	0.910	(0.908-0.911)	0.150	(0.141-0.160)
Logistic Regression	0.655	(0.650-0.661)	0.020	(0.019-0.020)	0.806	(0.802-0.812)	0.112	(0.105-0.118)

J Am Heart Assoc. 2018 Jun 26;7(13)

56

An Algorithm Based on Deep Learning for Predicting In-Hospital Cardiac Arrest

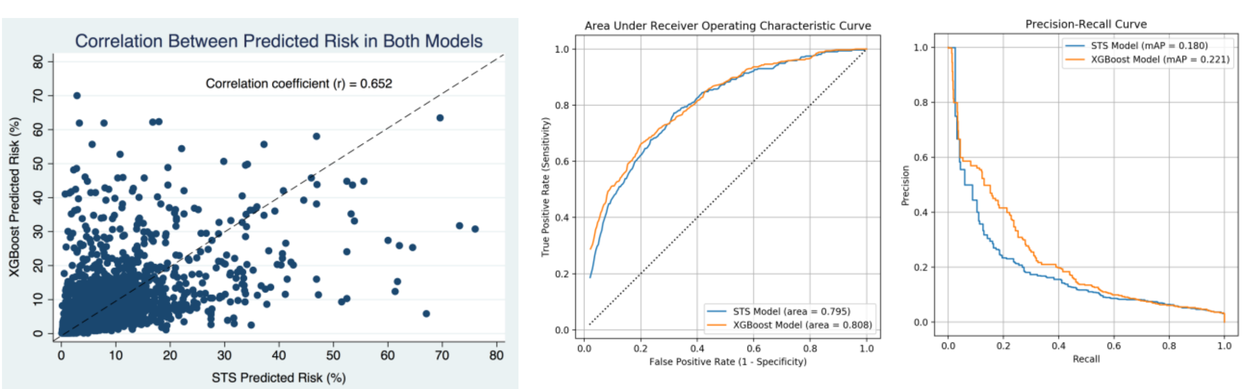


Receiver operating characteristic curve for predicting In-hospital cardiac arrest in hospital A

J Am Heart Assoc. 2018 Jun 26;7(13)

57

Machine Learning Algorithm in Estimating Mortality Risk in Cardiac Surgery.

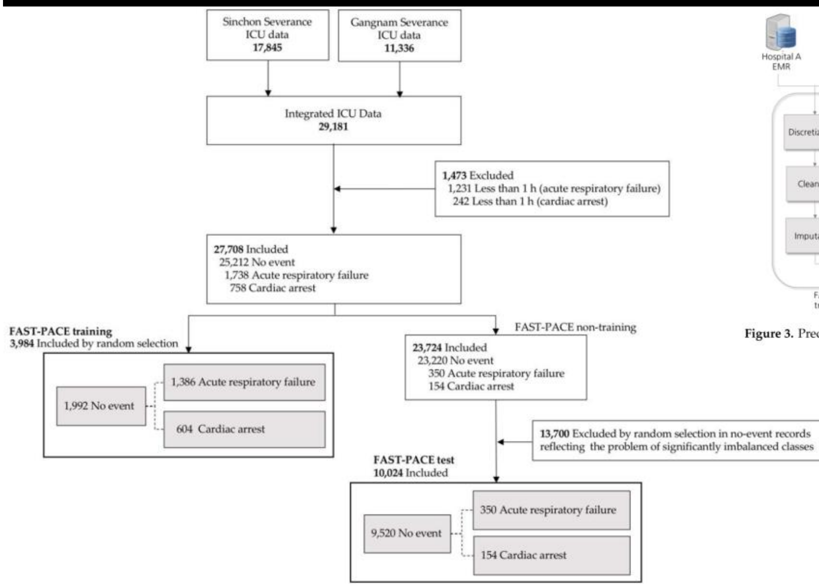


XGBoost

Ann Thorac Surg. 2019 Nov 7. pii: S0003-4975(19)31620-0

58

Predicting Cardiac Arrest and Respiratory Failure Using AI with Simple Trajectories of Patient Data.



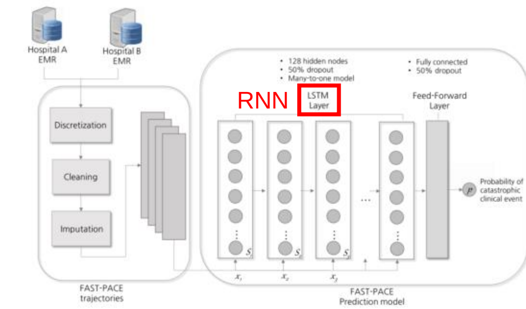


Figure 3. Prediction model design. LSTM = long short-term memory; x = input; S = memory cell.

J Clin Med. 2019 Aug 29;8(9)

59

Predicting Cardiac Arrest and Respiratory Failure Using AI with Simple Trajectories of Patient Data.

Table 1. List of features.

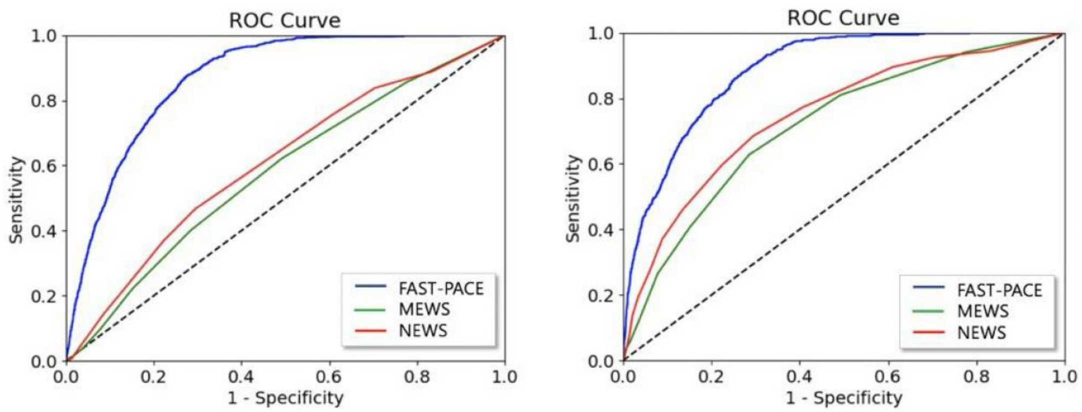
Category	Feature	Data Type	Range	Missing (%)
Vital	Pulse rate (bpm)	continuous	0–300	11.46
Sign	Systolic BP (mmHg)	continuous	0–300	7.78
	Diastolic BP (mmHg)	continuous	0–300	6.81
	Respiratory rate (breaths/min)	continuous	0–150	12.76
	SpO_2 (%)	continuous	0–100	24.01
	Body temperature (°C)	continuous	2–45	14.36
History	Treatment history † (yes or no)	categorical	0, 1	
Operation ‡	ASA classification	continuous	1–6	
	History of recent surgery (yes or no)	categorical	0, 1	

† Treatment history: any pharmacological treatment or additional oxygen supply that could affect the vital signs at the time of measurement; ‡ Operation: major surgery within one week of event occurrence.

J Clin Med. 2019 Aug 29;8(9)

60

Predicting Cardiac Arrest and Respiratory Failure Using AI with Simple Trajectories of Patient Data.



(a) **Acute Respiratory failure** (b) **Cardiac Arrest**

Figure 5. AUROC of FAST-PACE, MEWS, and NEWS predicting (**a**) acute respiratory failure and (**b**) cardiac arrest within 6 h.

J Clin Med. 2019 Aug 29;8(9)

61

AI predicts MI and cardiac death based on clinical risk, CAC, and EAT

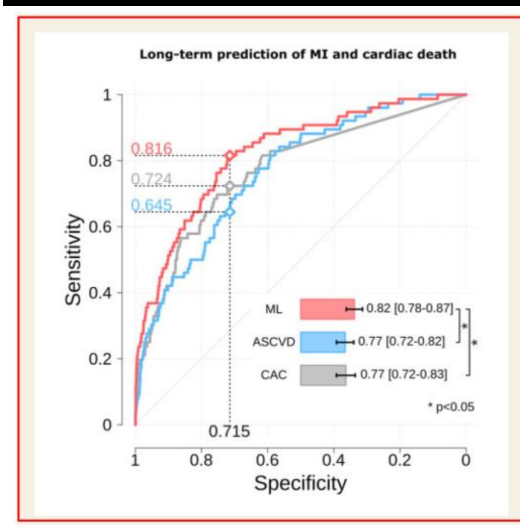


Table 2 **Multivariable Cox regression for event prediction**

	HR (95% CI)	*P*-value
High ML	2.94 (1.39–6.31)	**0.005**
Log2 (CAC score)	1.16 (1.06–1.27)	**0.001**
ASCVD risk score (%)	1.04 (1.01–1.06)	**0.001**
Log2 (EAT volume)	1.43 (0.94–2.16)	0.095
Age (years)	1.01 (0.98–1.04)	0.670
Gender (male)	0.96 (0.58–1.60)	0.885

CNN + XGBoost
+ Repeated cross-validation

Coronary artery calcium (CAC)
epicardial adipose tissue (EAT)

Cardiovasc Res. 2019 Dec 19. pii: cvz321

62

AI predicts MI and cardiac death based on clinical risk, CAC, and EAT

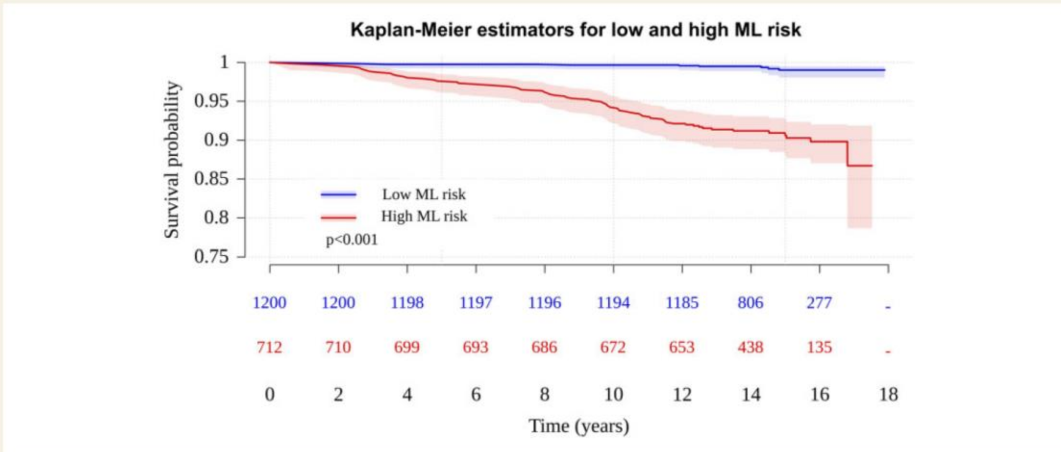


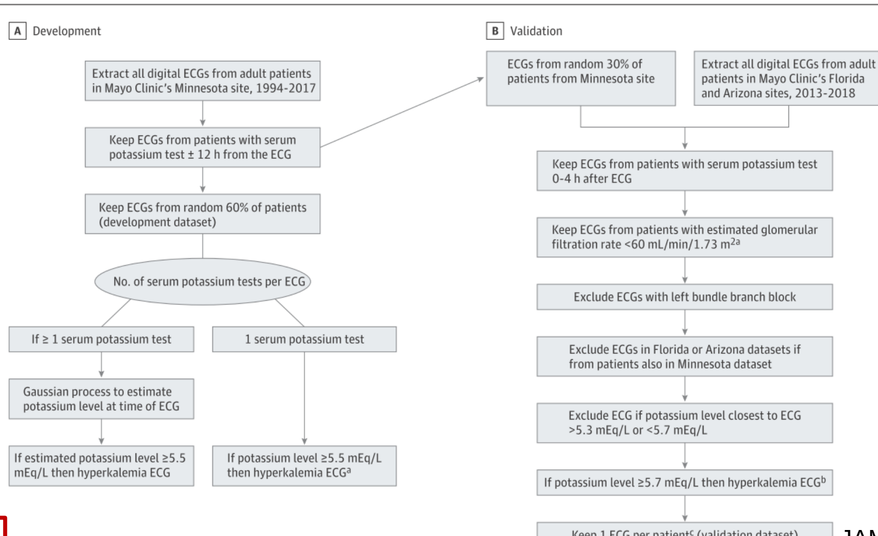
Figure 4 Kaplan–Meier estimator for population (*N* = 1912) with low (blue) and high machine learning risk (red).

Cardiovasc Res. 2019 Dec 19. pii: cvz321

63

AI for screen hyperkalemia 以人工智慧來篩檢高血鉀

Figure 1. Development and Validation Data Sets Generation and Electrocardiogram (ECG) Labeling of Hyperkalemia



CNN

JAMA Cardiol. 2019;4(5):428-436.

64

AI for screen hyperkalemia
以人工智慧來篩檢高血鉀

Table 2. Validation Data Set Performance for Hyperkalemia From 2 and 4 Leads of the ECG

	Value (95% CI)			
	2-Lead ECG[a]		4-Lead ECG[b]	
Validation Data Set	Sensitivity = Specificity	High Sensitivity[c]	Sensitivity = Specificity	High Sensitivity
Minnesota (n = 50 099)				
AUC	0.883 (0.873-0.893)	0.883 (0.873-0.893)	0.901 (0.892-0.911)	0.901 (0.892-0.911)
Sensitivity, %	79.9 (77.6-82.0)	90.2 (88.4-91.7)	81.3 (79.0-83.4)	89.3 (87.5-91.0)
Specificity, %	81.3 (80.9-81.6)	63.2 (62.7-63.6)	84.2 (83.9-84.5)	70.0 (69.6-70.4)
NPV, %	99.4 (99.3-99.4)	99.6 (99.5-99.7)	99.4 (99.3-99.5)	99.6 (99.5-99.7)
PPV, %	10.1 (9.5-10.7)	6.0 (5.7-6.4)	11.9 (11.2-12.6)	7.2 (6.8-7.7)
Florida (n = 6011)				
AUC	0.860 (0.837-0.883)	0.860 (0.837-0.883)	0.885 (0.863-0.907)	0.885 (0.863-0.907)
Sensitivity, %	80.5 (75.4-84.9)	91.3 (87.4-94.3)	84.0 (79.2-88.0)	92.3 (88.6-95.1)
Specificity, %	75.2 (74.0-76.3)	54.7 (53.4-56.0)	77.1 (75.8-78.0)	60.5 (59.2-61.7)
NPV, %	98.7 (98.3-99.0)	99.2 (98.8-99.5)	99.0 (98.6-99.2)	99.4 (99.0-99.6)
PPV, %	14.0 (12.3-15.7)	9.2 (8.1-10.3)	15.4 (13.7-17.3)	10.5 (9.3-11.7)
Arizona (n = 5855)				
AUC	0.853 (0.830-0.877)	0.853 (0.830-0.877)	0.880 (0.860-0.901)	0.880 (0.860-0.901)
Sensitivity, %	[illegible]	[illegible]	[illegible]	[illegible]
Specificity, %	75.3 (74.1-76.4)	55.0 (53.7-56.3)	77.0 (75.9-78.1)	60.3 (59.0-61.6)
NPV, %	98.6 (98.2-98.9)	99.0 (98.6-99.3)	98.9 (98.6-99.2)	99.4 (99.1-99.6)
PPV, %	13.3 (11.6-15.0)	8.7 (7.7-9.8)	14.8 (13.0-16.7)	10.1 (9.0-11.4)

4-lead ECG is better than 2-lead ECG

JAMA Cardiol. 2019;4(5):428-436.

65

中山高醫 AI 合作計畫

66

國立中山大學與高雄醫學大學
108 年度合作研究計畫申請書

一、基本資料： 申請編號：

計畫類型□整合型 ■個人型 **申請經費： 50 萬元**

計畫名稱	中文	使用人工智慧來預測重大心臟不良事件，以醫院基礎的研究					
	英文	Using AI to predict MACE (Major Adverse Cardiac Event), a hospital-based study					
計畫重點說明	首次申請合作研究計畫						
研究主題	□醫藥化學 ■臨床醫學 □醫療器材	□藥理毒理學 □新藥開發 □醫療管理	□環境醫學 □醫學工程 □人文科學	□轉譯醫學 □音樂治療 □其他			
總計畫主持人姓名	蔡維中	職稱	助理教授	學校	高雄醫學大學		
各子計畫名稱		計畫主持人		計畫共同主持人			
子計畫一（個人型計畫）	使用人工智慧來預測重大心臟不良事件，以醫院基礎的研究	姓名/職稱	蔡維中/助理教授、主治醫師	姓名/職稱	李錫智/教授		
		學校/系所	高雄醫學大學/醫學系	學校/系所	中山大學/電機工程學系		

67

高醫中山合作 AI 團隊成員

類 別	姓 名	現 職	在本計畫內擔任之具體工作性質、項目及範圍
主持人	林宗憲	高醫心臟內科主任	研究計畫之整體設計、規劃及學術技術指導
共同主持人	李錫智	中山大學教授	研究計畫之整體設計、規劃及學術技術指導
共同主持人	蔡維中	高醫心臟內科主治醫師	研究計畫之整體設計、規劃及學術技術指導及撰寫論文報告
共同主持人	黃天祈	高醫心臟內科主治醫師	研究計畫之整體設計、規劃及學術技術指導及撰寫論文報告
共同主持人	陳崇鈺	高醫藥研所助理教授	研究計畫之整體設計、規劃及學術技術指導
研究人員	林彥廷	中山大學碩士班學生	參考資料收集、演算法設計、程式開發、建檔及撰寫論文報告。
研究人員	陳俊諺	中山大學碩士班學生	參考資料收集、演算法設計、程式開發、實驗數據分析與建檔。
研究人員	洪晟維	中山大學碩士班學生	參考資料收集、演算法設計、程式開發、實驗數據分析與建檔。
研究人員	劉宜學	高醫心臟內科總醫師	研究計畫之整體設計、規劃及學術技術指導
研究人員	莊富鈞	專任助理	協助執行行政工作、個案收集、庶務
研究人員	李晏姍	兼任助理	協助執行行政工作、個案收集、庶務
研究人員	劉襲明	高醫後醫系學生	協助心電圖、個案及臨床病歷的收集
研究人員	程牧宭	高醫護理系學生	協助心電圖、個案及臨床病歷的收集

68

科技部計畫

69

目前成果

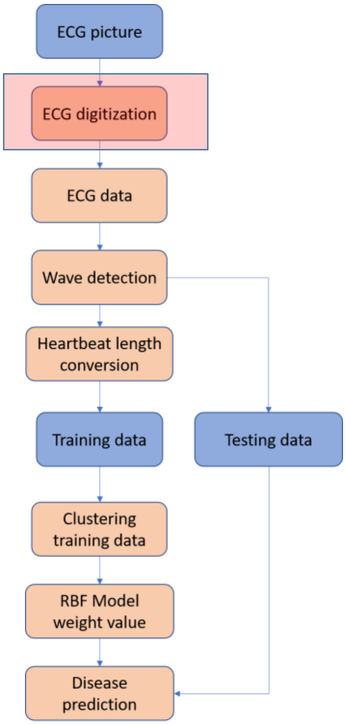
- 機器學習應用於心電圖心跳模式之分類研究

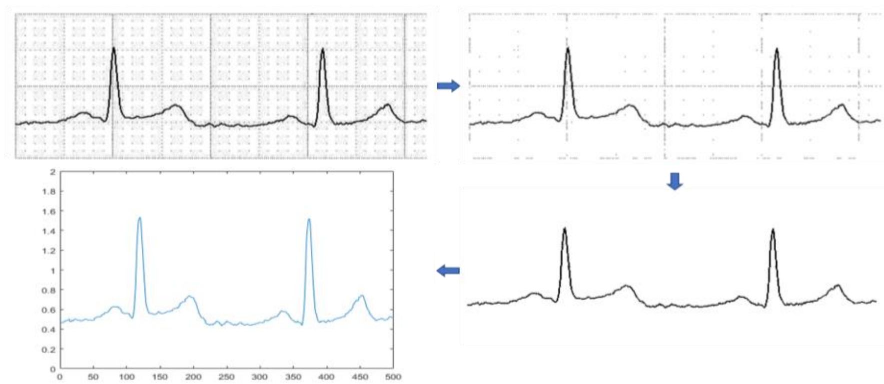
  Applying Machine Learning on Classification of Electrocardiogram Heartbeat Patterns

- Dataset
  - MIT-BIH arrhythmia database
  - KMUH ECG data

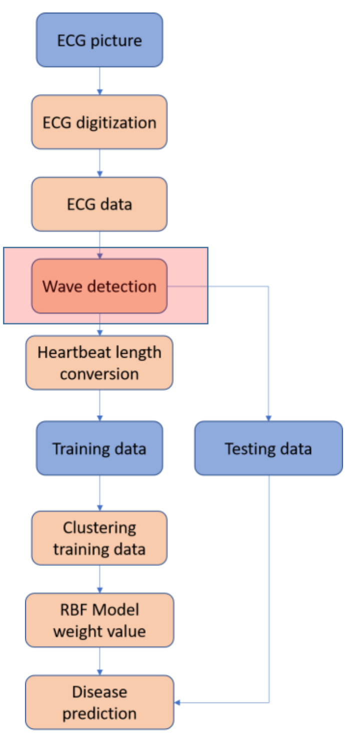
AAMI	MIT-BIH
N	N, L, R
S	e, j, A, a, J, S
V	V, E
F	F
Q	/, f, Q

70

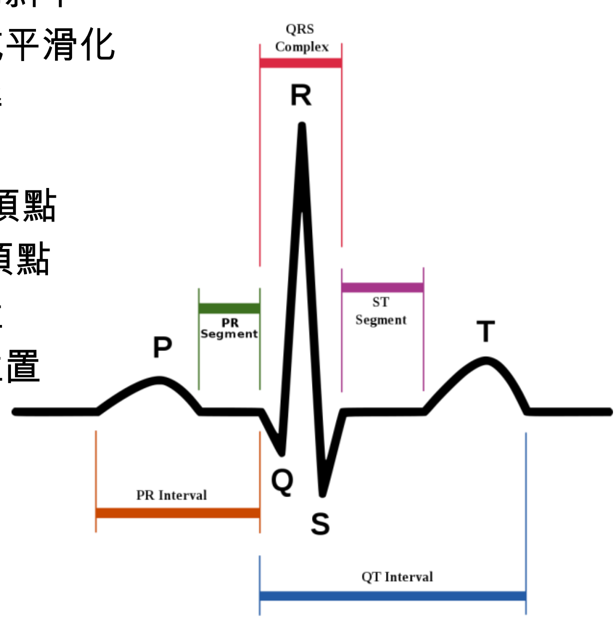




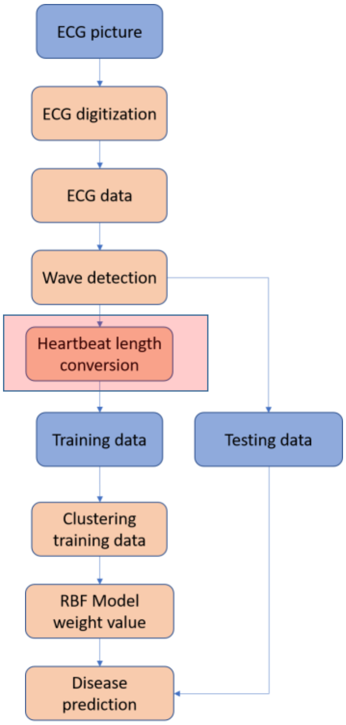
71



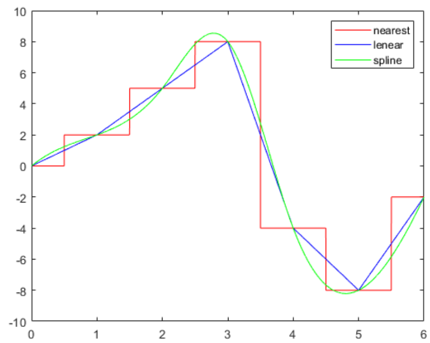
1. 計算點與點間斜率
2. 波形線條區域平滑化
3. 重新計算斜率
4. 偵測R波頂點
5. 偵測Q及S波頂點
6. 偵測P及T波頂點
7. 修正頂點位置
8. 尋找基準線位置

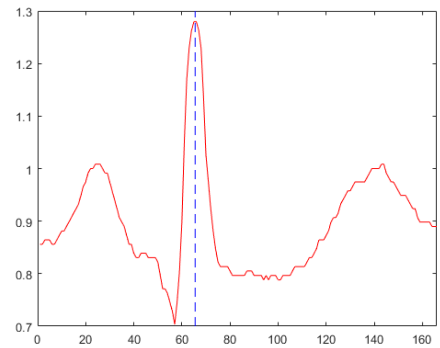


72

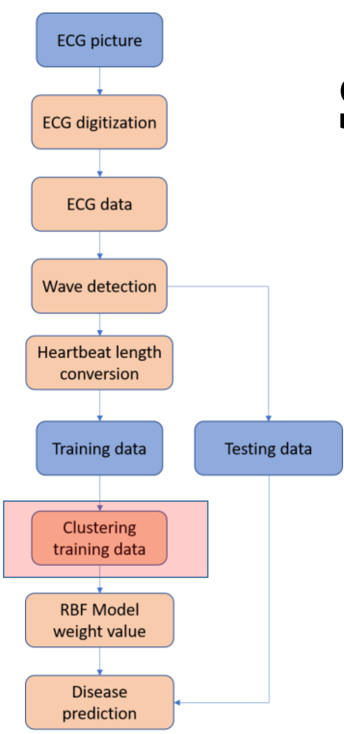


1. Nearest：鄰近點內插法
2. Linear：線性內插法
3. Spline：三次樣條數據內插法





73



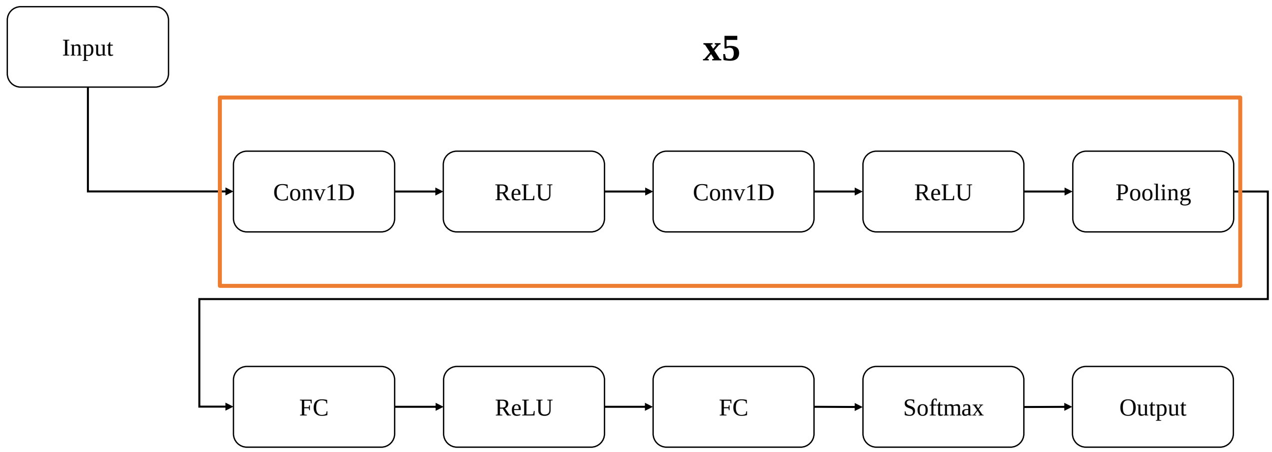
SCC-I clustering

- 透過SCC-I的分群，得到每個群的中心點及偏差值，能夠將較相似形狀的波歸為同一群，藉此將其所代表的資訊做一個切割，將結果作為RBF隱藏層的參數使用。

$$
\begin{aligned}
F_j(\mathbf{x}) &= \frac{G_j(\mathbf{x})}{\sum_{i=1}^{J} G_i(\mathbf{x})}, \\
G_i(\mathbf{x}) &= \prod_{k=1}^{n} \exp\left[-\left(\frac{x_k - c_{i,k}}{v_{i,k}}\right)^2\right]
\end{aligned}
$$

74

深度學習模型



卷積神經網路(Convolutional Neural Networks, CNN)

75

性能評估指標

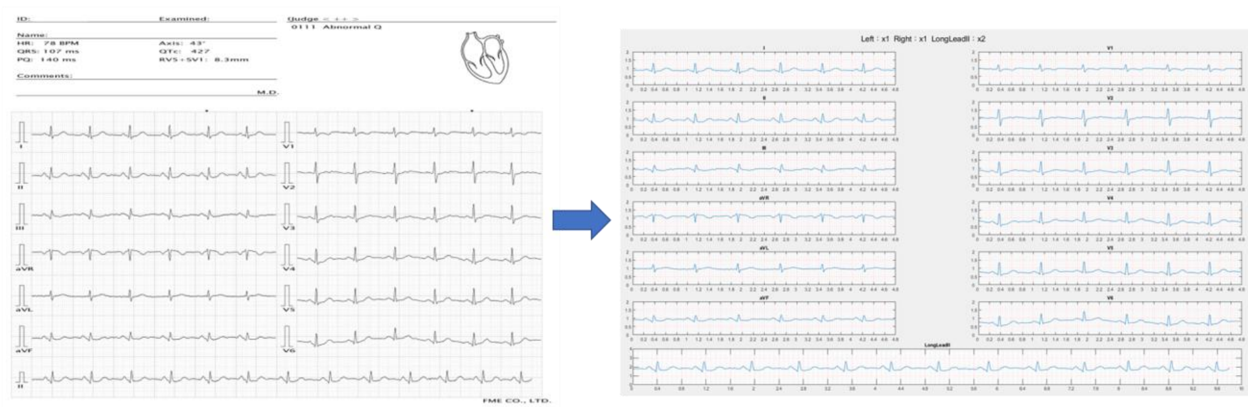
$$\text{Sensitivity (Se)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Positive predictivity } (\text{P}^{+}) = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{F} - measure = \frac{2 \times \text{P}^{+} \times Se}{\text{P}^{+} + Se}$$

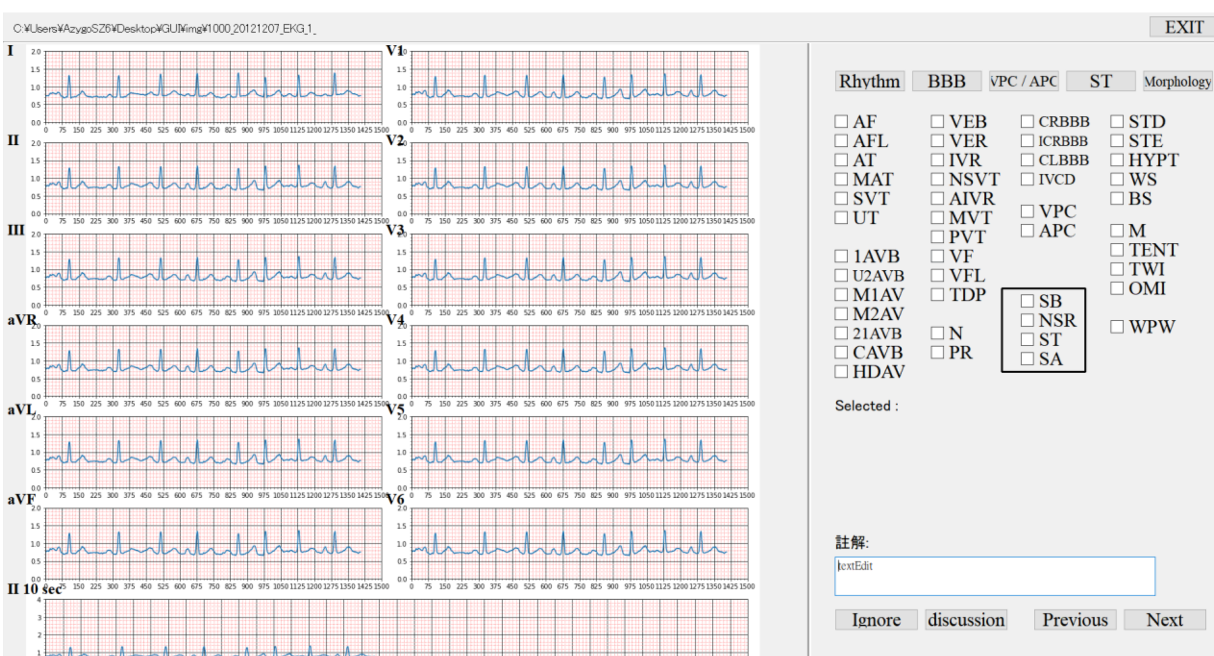
76



2.57MB

17 kb

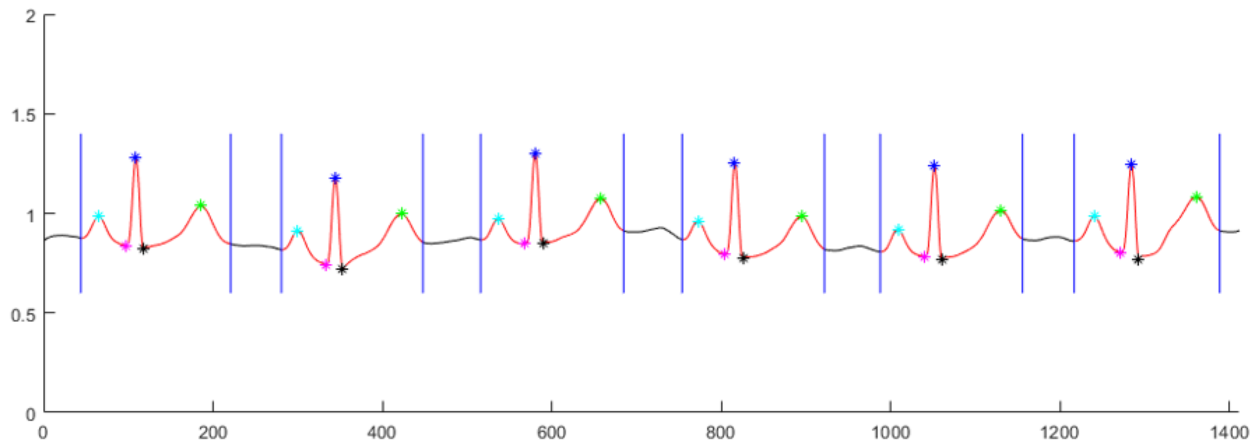
77



去識別化！ 檔案縮小僅 0.7%！ Labeling 程式！

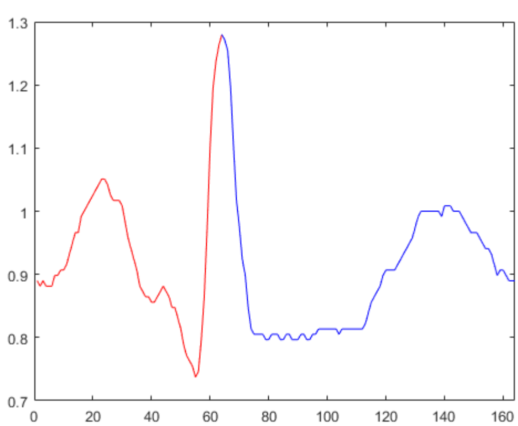
78

心電圖波形識別

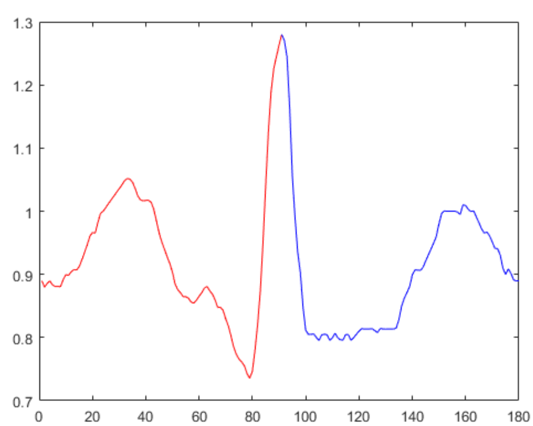


79

心電圖波形內差



原始：166 pixel



內插後：180 pixel

80

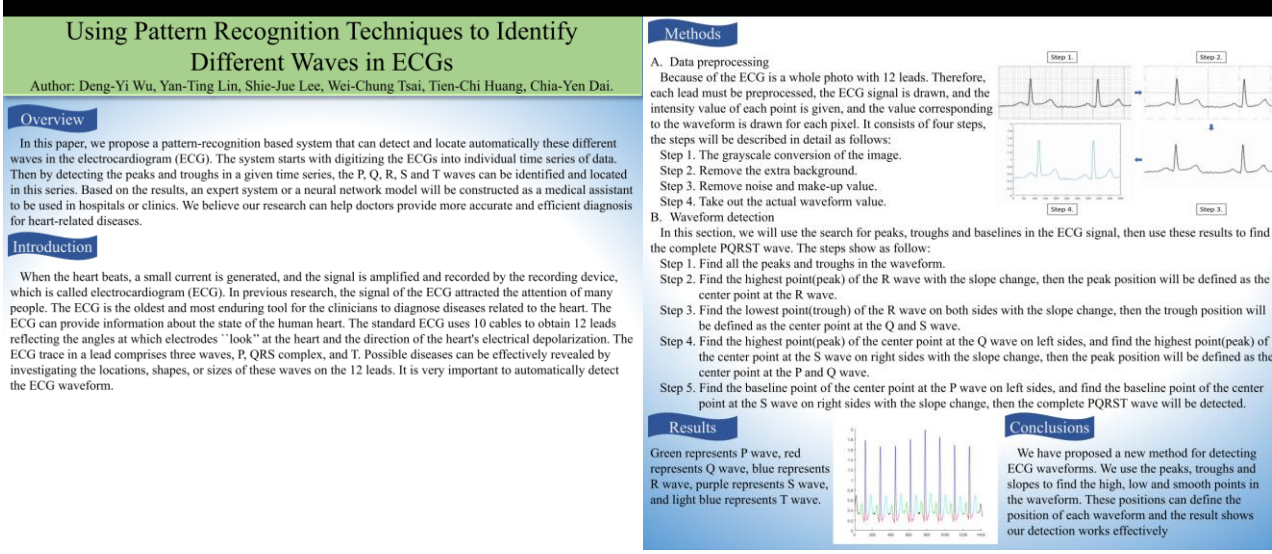
診斷預測準確度

Type	Accuracy	P^+	Se	F-measure
Our method	**0.8454**	**0.8405**	0.9277	**0.8819**
SVM-linear	0.7965	0.8226	0.8540	0.8380
SVM-RBF	0.7268	0.6946	**0.9981**	0.8192
KNN	0.7750	0.8102	0.8380	0.8239

- 心電圖心跳偵測及分類方法
- 內插法將資料轉換為相同維度
- 解決訓練模型時，輸入須為相同維度的問題

81

目前發表 poster@ WCRAI 2019



Using Pattern Recognition Techniques to Identify Different Waves in ECGs

Author: Deng-Yi Wu, Yan-Ting Lin, Shie-Jue Lee, Wei-Chung Tsai, Tien-Chi Huang, Chia-Yen Dai.

Overview

In this paper, we propose a pattern-recognition based system that can detect and locate automatically these different waves in the electrocardiogram (ECG). The system starts with digitizing the ECGs into individual time series of data. Then by detecting the peaks and troughs in a given time series, the P, Q, R, S and T waves can be identified and located in this series. Based on the results, an expert system or a neural network model will be constructed as a medical assistant to be used in hospitals or clinics. We believe our research can help doctors provide more accurate and efficient diagnosis for heart-related diseases.

Introduction

When the heart beats, a small current is generated, and the signal is amplified and recorded by the recording device, which is called electrocardiogram (ECG). In previous research, the signal of the ECG attracted the attention of many people. The ECG is the oldest and most enduring tool for the clinicians to diagnose diseases related to the heart. The ECG can provide information about the state of the human heart. The standard ECG uses 10 cables to obtain 12 leads reflecting the angles at which electrodes ``look'' at the heart and the direction of the heart's electrical depolarization. The ECG trace in a lead comprises three waves, P, QRS complex, and T. Possible diseases can be effectively revealed by investigating the locations, shapes, or sizes of these waves on the 12 leads. It is very important to automatically detect the ECG waveform.

Methods

A. Data preprocessing

Because of the ECG is a whole photo with 12 leads. Therefore, each lead must be preprocessed, the ECG signal is drawn, and the intensity value of each point is given, and the value corresponding to the waveform is drawn for each pixel. It consists of four steps, the steps will be described in detail as follows:

Step 1. The grayscale conversion of the image.
Step 2. Remove the extra background.
Step 3. Remove noise and make-up value.
Step 4. Take out the actual waveform value.

Step 1. Step 2. Step 3. Step 4.

B. Waveform detection

In this section, we will use the search for peaks, troughs and baselines in the ECG signal, then use these results to find the complete PQRST wave. The steps show as follow:

Step 1. Find all the peaks and troughs in the waveform.
Step 2. Find the highest point(peak) of the R wave with the slope change, then the peak position will be defined as the center point at the R wave.
Step 3. Find the lowest point(trough) of the R wave on both sides with the slope change, then the trough position will be defined as the center point at the Q and S wave.
Step 4. Find the highest point(peak) of the center point at the Q wave on left sides, and find the highest point(peak) of the center point at the S wave on right sides with the slope change, then the peak position will be defined as the center point at the P and Q wave.
Step 5. Find the baseline point of the center point at the P wave on left sides, and find the baseline point of the center point at the S wave on right sides with the slope change, then the complete PQRST wave will be detected.

Results

Green represents P wave, red represents Q wave, blue represents R wave, purple represents S wave, and light blue represents T wave.

Conclusions

We have proposed a new method for detecting ECG waveforms. We use the peaks, troughs and slopes to find the high, low and smooth points in the waveform. These positions can define the position of each waveform and the result shows our detection works effectively

82

目前發表 – Conference paper

2019 12th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)

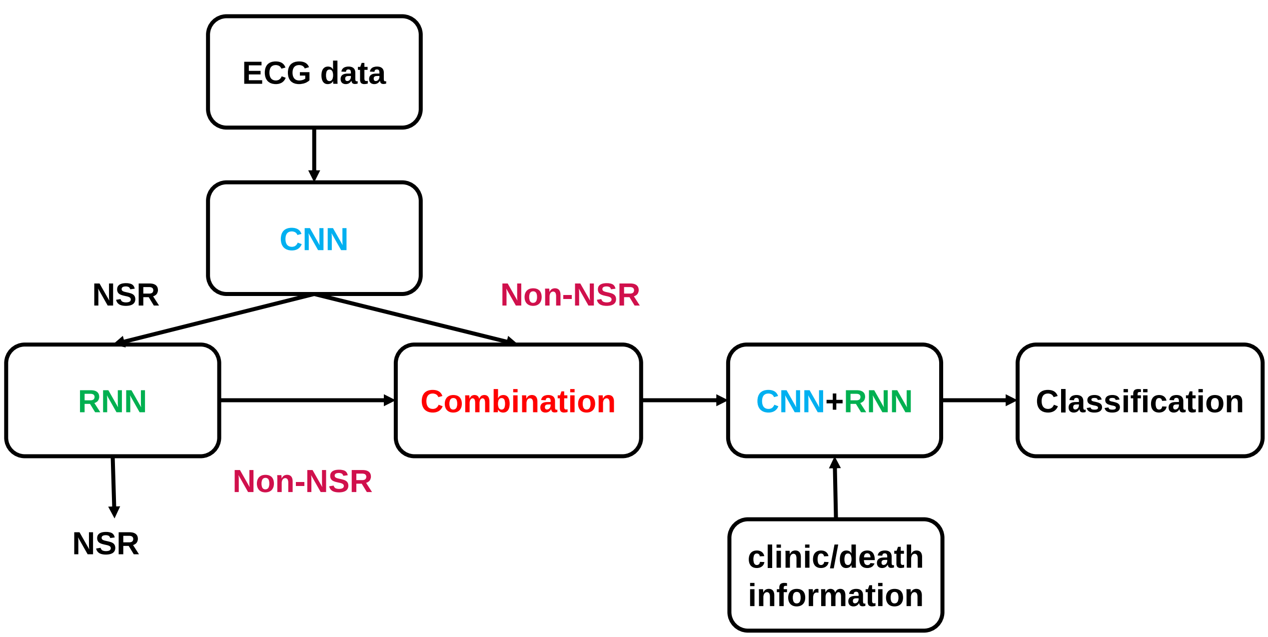
Constructing RBF Networks for Classifying ECG Heartbeat Patterns

Deng-Yi Wu[1], Yan-Ting Lin[1], Shie-Jue Lee[2], Wei-Chung Tsai[3], Tien-Chi Huang[3], Chia-Yen Dai[3]

[1]Department of Electrical Engineering, National Sun Yat-Sen University, Kaohsiung, Taiwan
[2]Intelligent Electronic Commerce Research Center, National Sun Yat-Sen University, Kaohsiung, Taiwan
[3]Department of Internal Medicine, Kaohsiung Medical University, Kaohsiung, Taiwan

CISP-BMEI 2019

83



84

85

HFrEF + VT

OHCA

AMI + VT

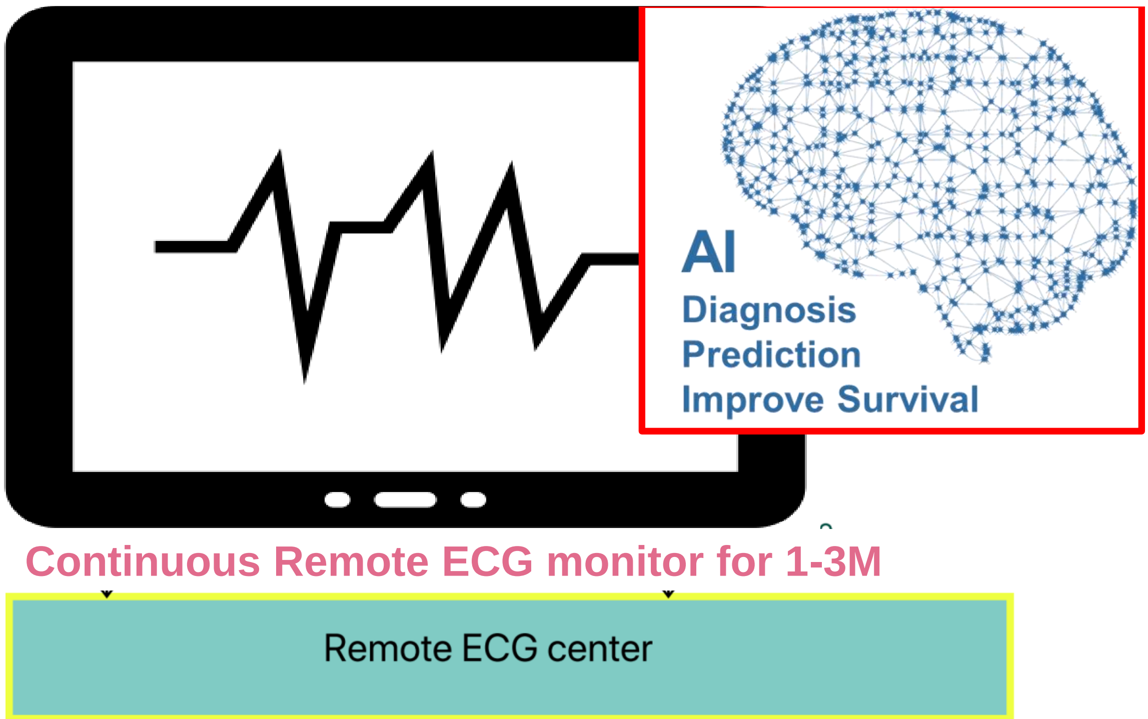
CCU + Remote ECG

CV + Remote ECG

Discharge

Remote ECG center

86



87

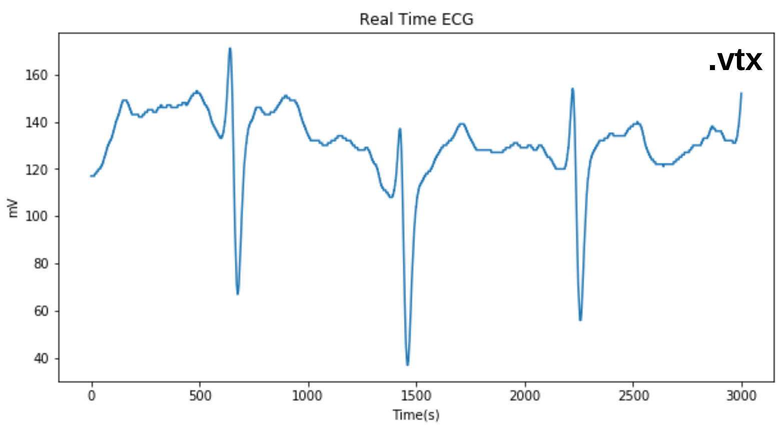
心肌梗塞後高危險族群的中長期24小時心電圖監控

KMUH Medical AI 子計畫
2018～2020

88

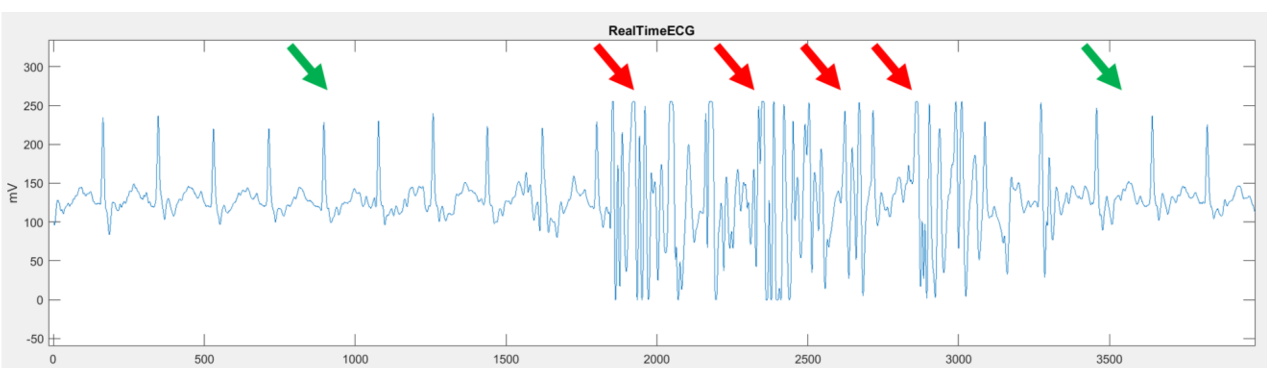
BST-VT2000 訊號分析

- 副檔名：『.vts』&『.vtx』
- 檔案編碼：Hex 16進制 Raw data
- 檔頭 Header：200 bytes
- Amplitude：0~255 (9.7 mV)
- ECG data：
  - .vts：Sample rate = 300Hz
  - .vtx：Sample rate = 1200Hz



89

CCU無線ECG系統擷取心律不整



90

Summary 摘要

- Digital health in cardiology
- AI enhance lifecare in cardiology
  - To predict mortality and morbidity!
  - To make precision medicine possible!

91

Acknowledgement

- KMU
  - 許博翔 • 賴文德
  - 李智雄 • 王國禎
  - 李香君 • 林宗憲
  - 許柏超 • 黃天祈
  - 劉宜學 • 程牧宥
- NSYSU
  - 李錫智 • 林彥廷
  - 陳俊諺 • 洪晟維

92

Thank you for your attention!

蔡維中 k920265@gap.kmu.edu.tw

93