심전도 분석 연구를 위한 MUSE Data 활용법

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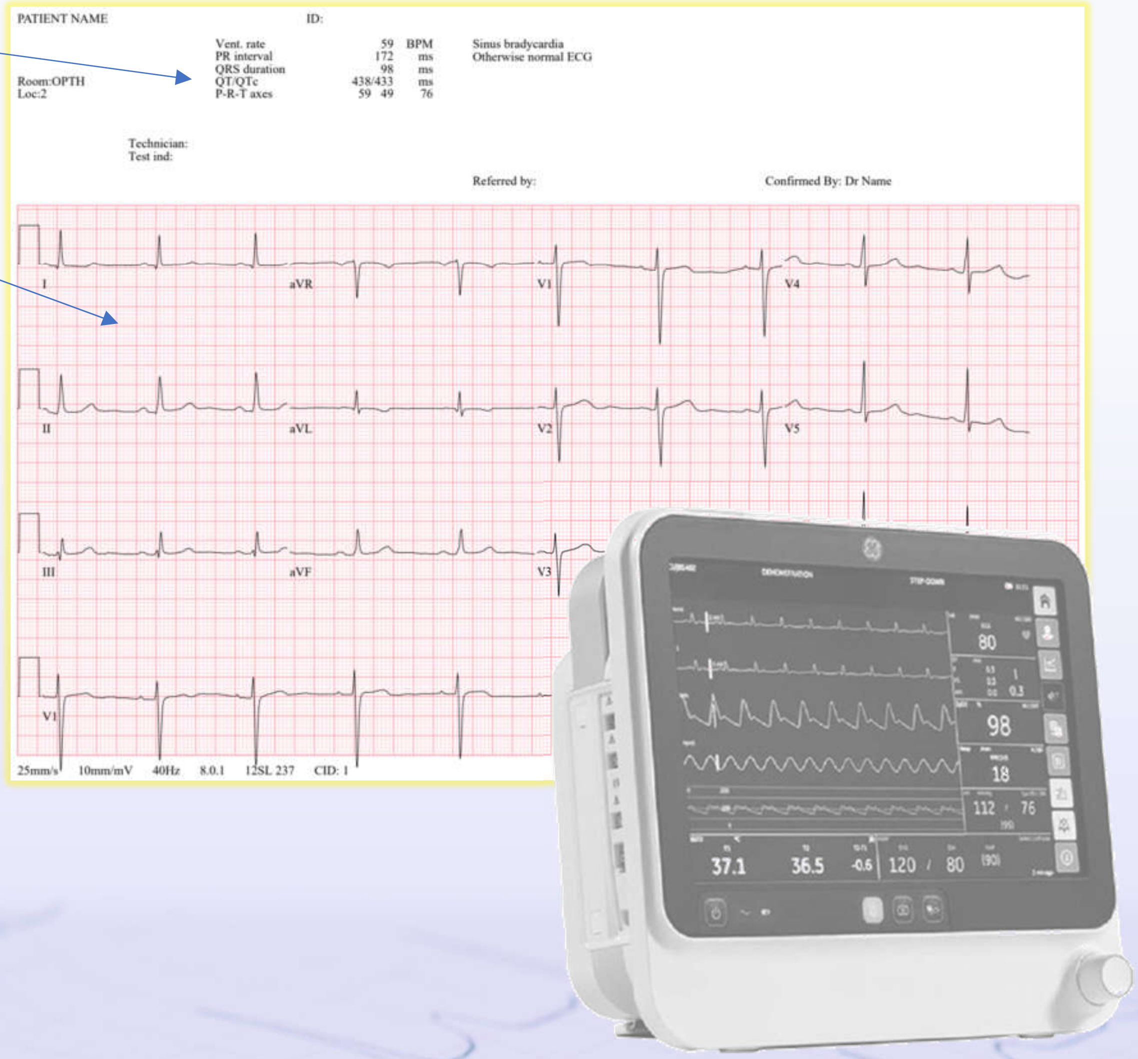
- 약물 효과 및 부작용 탐지
- 임상 위험도 예측 모델 개발

Conflict of interest

BUDON
› Bottom up Data |
evidnet

목차

- ECG parameter를 이용한 연구
- 12 lead ECG waveform 기반 연구
  - Paroxysmal Afib
  - MI detection with wearable device
- ECG 데이터 수집 및 활용 방법
- Q&A



ECG parameter를 이용한 연구

THE IMPACT OF DRUG-INDUCED QT INTERVAL PROLONGATION ON DRUG DISCOVERY AND DEVELOPMENT

Bernard Fermini and Anthony A. Fossa

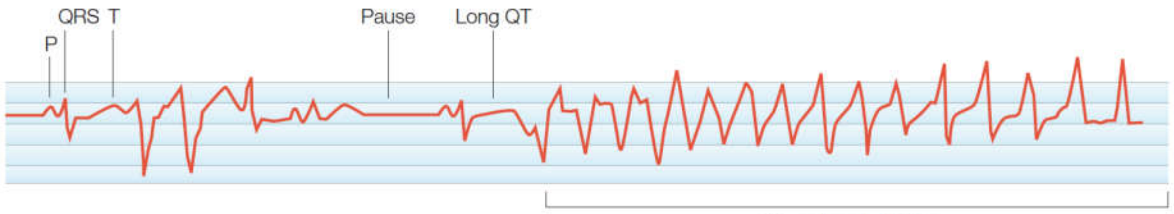


Figure 3 | **Electrocardiogram of Torsades de Pointes.** Torsades de Pointes is characterized by an abnormally prolonged QT interval,

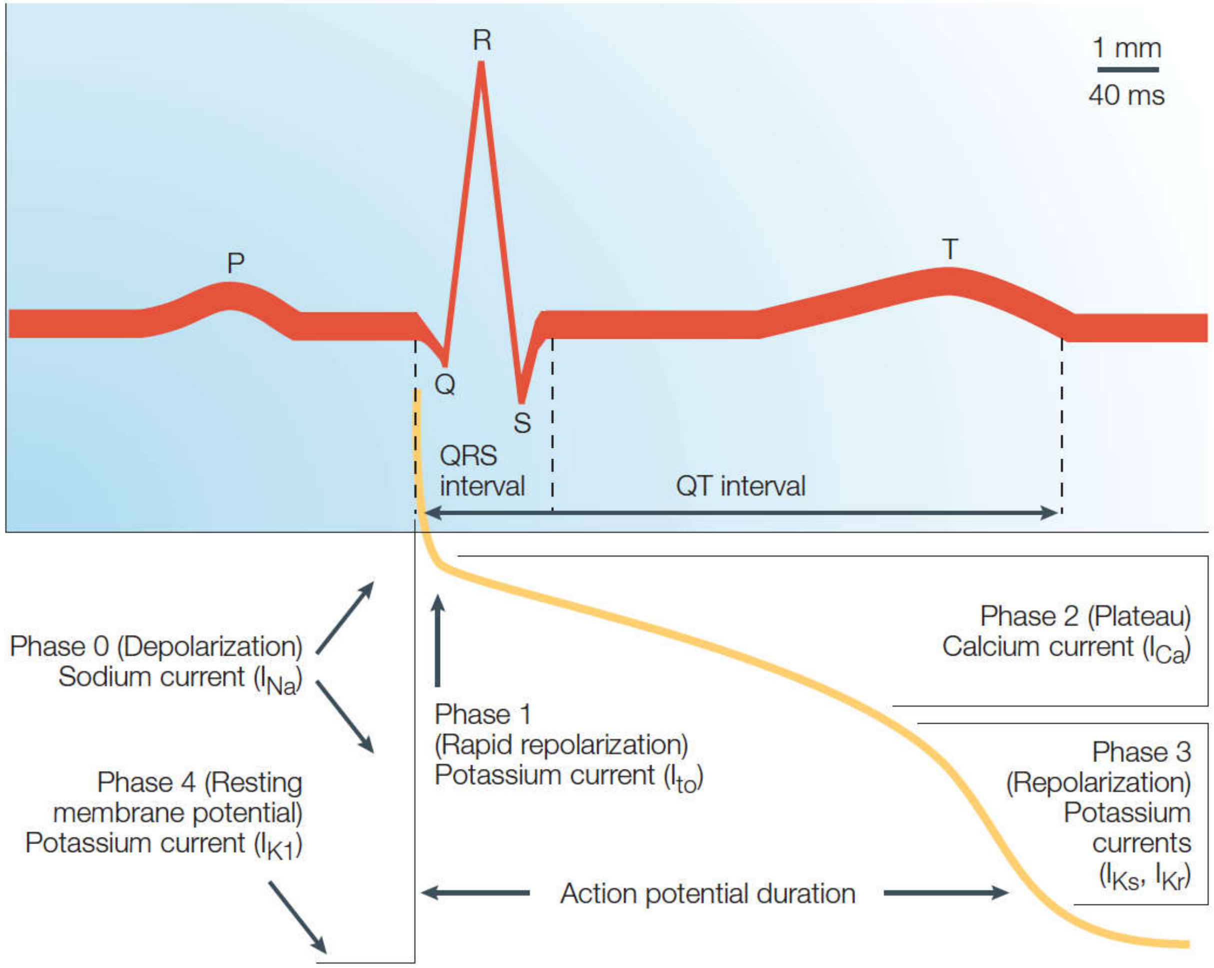
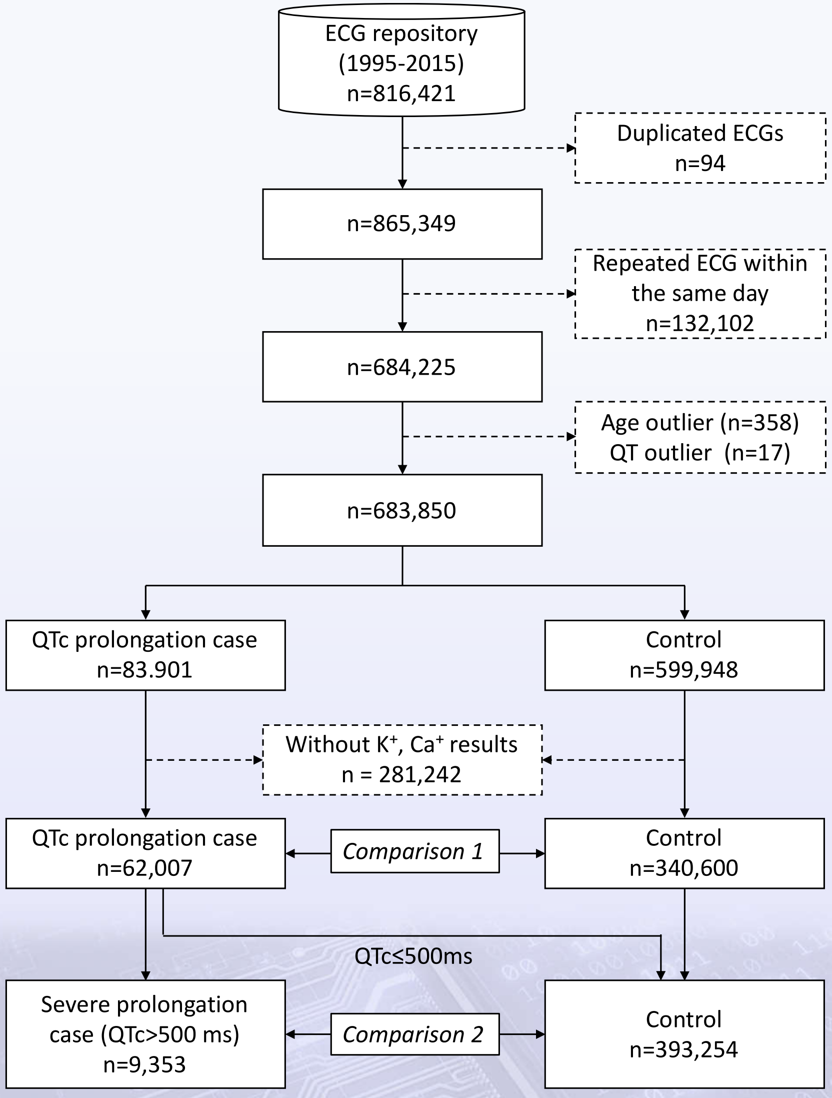
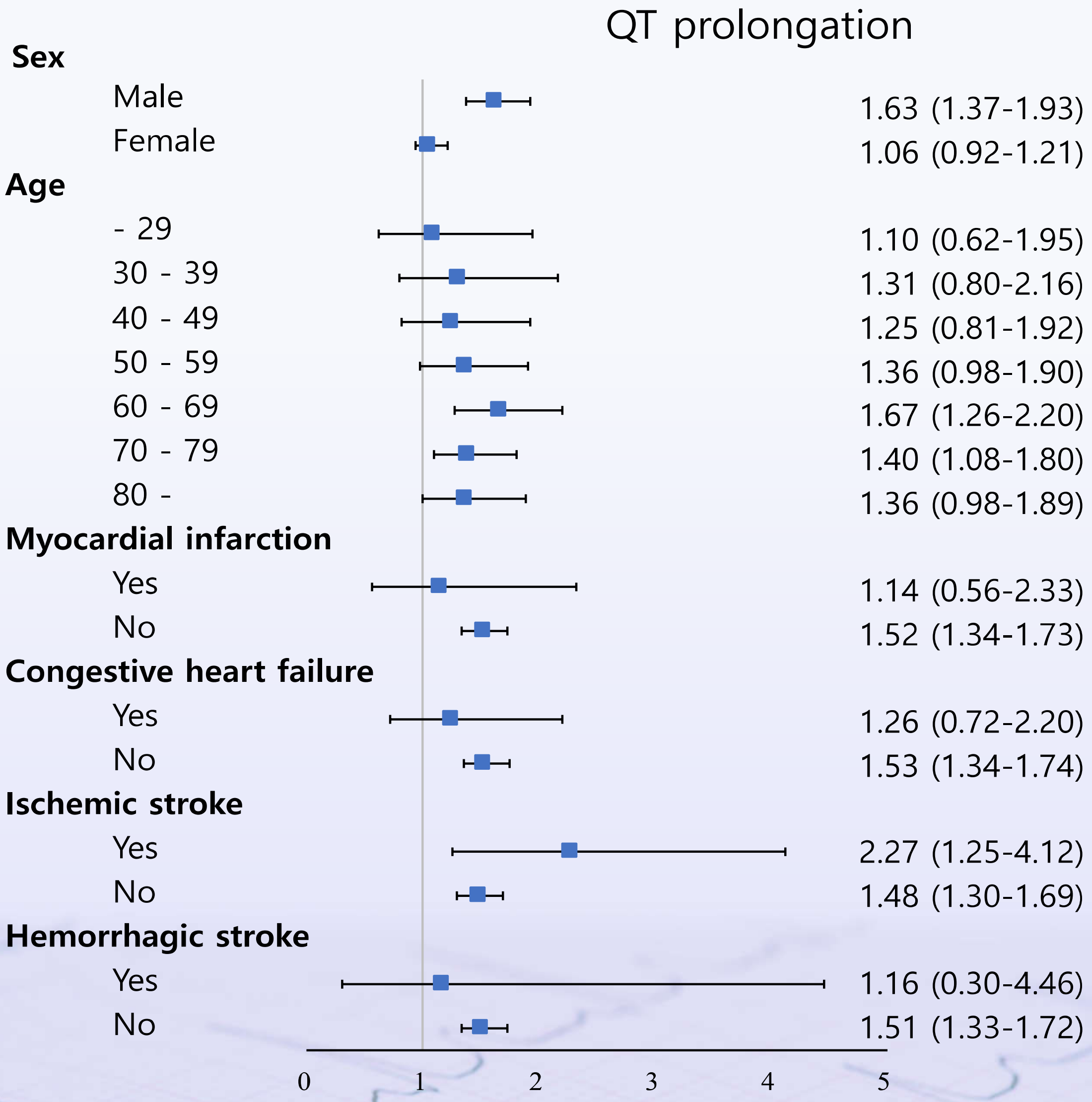


Figure 1 | **Temporal correlation between action potential duration and the QT interval on the surface ECG.** The surface electrocardiogram (ECG), which provides information on the

Fermini B, Fossa AA. The impact of drug-induced QT interval prolongation on drug discovery and development. Nat Rev Drug Discov. 2003 Jun;2(6):439-47. doi: 10.1038/nrd1108.

ECG parameter를 이용한 연구





Choi Y, Lim HS, Chung D, Choi JG, **Yoon D**. Risk Evaluation of Azithromycin-Induced QT Prolongation in Real-World Practice. Biomed Res Int. 2018 Oct 14

ECG parameter를 이용한 연구

Computational Medical Informatics

TITLE	CITED BY	YEAR
Risk evaluation of azithromycin-induced QT prolongation in real-world practice Y Choi, HS Lim, D Chung, J Choi, D Yoon BioMed research international 2018	97	2018

The NEW ENGLAND JOURNAL of MEDICINE

ORIGINAL ARTICLE

Azithromycin and the Risk of Cardiovascular Death

Wayne A. Ray, Ph.D., Katherine T. Murray, M.D., Kathi Hall, B.S., Patrick G. Arbogast, Ph.D., and C. Michael Stein, M.B., Ch.B.

ABSTRACT

BACKGROUND

Although several macrolide antibiotics are proarrhythmic and as[...] creased risk of sudden cardiac death, azithromycin is thought to have minin[...] diotoxicity. However, published reports of arrhythmias suggest that azithr[...] may increase the risk of cardiovascular death.

METHODS

We studied a Tennessee Medicaid cohort designed to detect an increased risk of death related to short-term cardiac effects of medication, excluding patients with serious noncardiovascular illness and person-time during and shortly after hospitalization. The cohort included patients who took azithromycin (347,795 prescriptions), propensity-score–matched persons who took no antibiotics (1,391,180 control periods), and patients who took amoxicillin (1,348,672 prescriptions), ciprofloxacin (264,626 prescriptions), or levofloxacin (193,906 prescriptions).

NEJM (2012)

Research Article

Risk Evaluation of Azithromycin-Induced QT Prolongation in Real-World Practice

Young Choi[1,2] Hong-Seok Lim,[3] Dahee Chung,[1] Jung-gu Choi,[1] and Dukyong Yoon[1]

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Academic Editor: Robin Vos

Background. Azithromycin exposure has been reported to increase the risk of QT prolongation and cardio[...] death. How[...] findings on the association between azithromycin and cardiovascular death are controversial, and azithromycin is still used in actual practice. Additionally, quantitative assessments of risk have not been performed, including the risk of QT prolongation [...]hen patients are exposed to azithromycin in a real-world clinical setting. Therefore, in this study, we aimed to evaluate the risk of [...]ure to azithromycin on QT prolongation in a real-world clinical setting using a 21-year medical history database of a tertiary [...]al institution. *Methods.* We analyzed the electrocardiogram results and relevant electronic health records of 402,607 subjects [...] tertiary teaching hospital in Korea from 1996 to 2015. To evaluate the risk of QT prolongation of azithromycin, we [...]se-control analysis using amoxicillin for comparison. Multiple logistic regression analysis was performed to correc[...] accompanying drugs, and disease. *Results.* The odds ratio (OR) for QT prolongation (QTc>450 ms in male and >460 [...] on azithromycin exposure was 1.40 (95% confidence interval [CI], 1.23-1.59), and the OR for severe QT prolongation ([...] was 1.43 (95% CI, 1.13-1.82). On the other hand, the ORs on exposure to amoxicillin were 1.06 (95% CI, 0.97-1.15) and [...] 0.70-1.09). In a subgroup analysis, the risk of QT prolongation in patients aged between 60 and 80 years was signifi[...] when they are exposed to azithromycin. *Conclusions.* The risk of QT prolongation was increased when patients, pa[...] elderly aged 60-79 years, were exposed to azithromycin. Therefore, clinicians should pay exercise caution using azi[...] consider using other antibiotics, such as amoxicillin, instead of azithromycin.

Choi et al. (2018)

JACC (2020)

LEADERSHIP PAGE

Considerations for Drug Interactions on QTc Interval in Exploratory COVID-19 Treatment

Dan M. Roden, MDCM, *Interim Division Chief, Division of Cardiovascular Medicine, Vanderbilt University School of Medicine*
Robert A. Harrington, MD, *President of the American Heart Association*
Athena Poppas, MD, *President of the [...]can College of Cardiology*
Andrea M. Russo, MD, *President of th[...] Rhythm Society*

scientific reports

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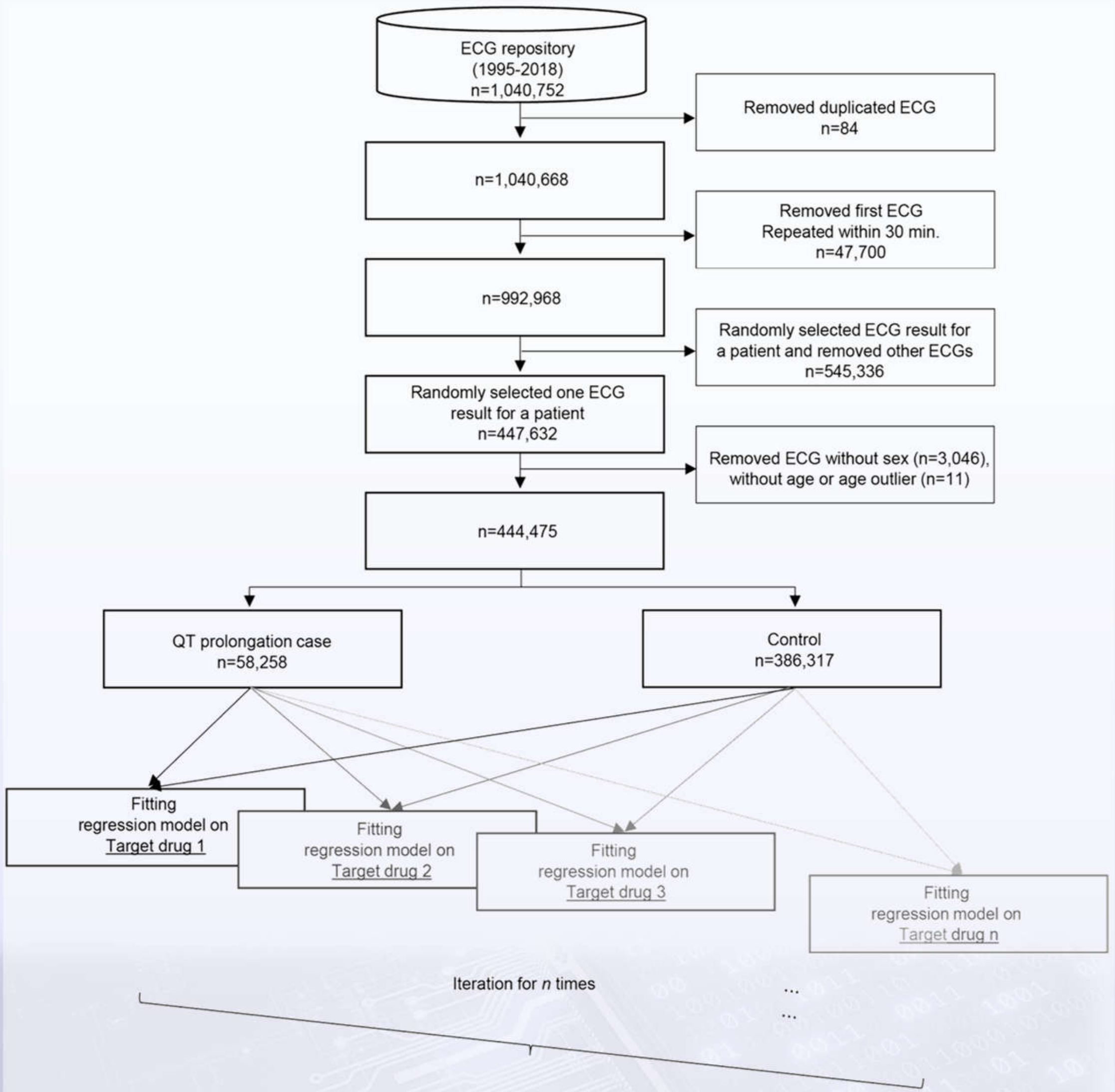
OPEN

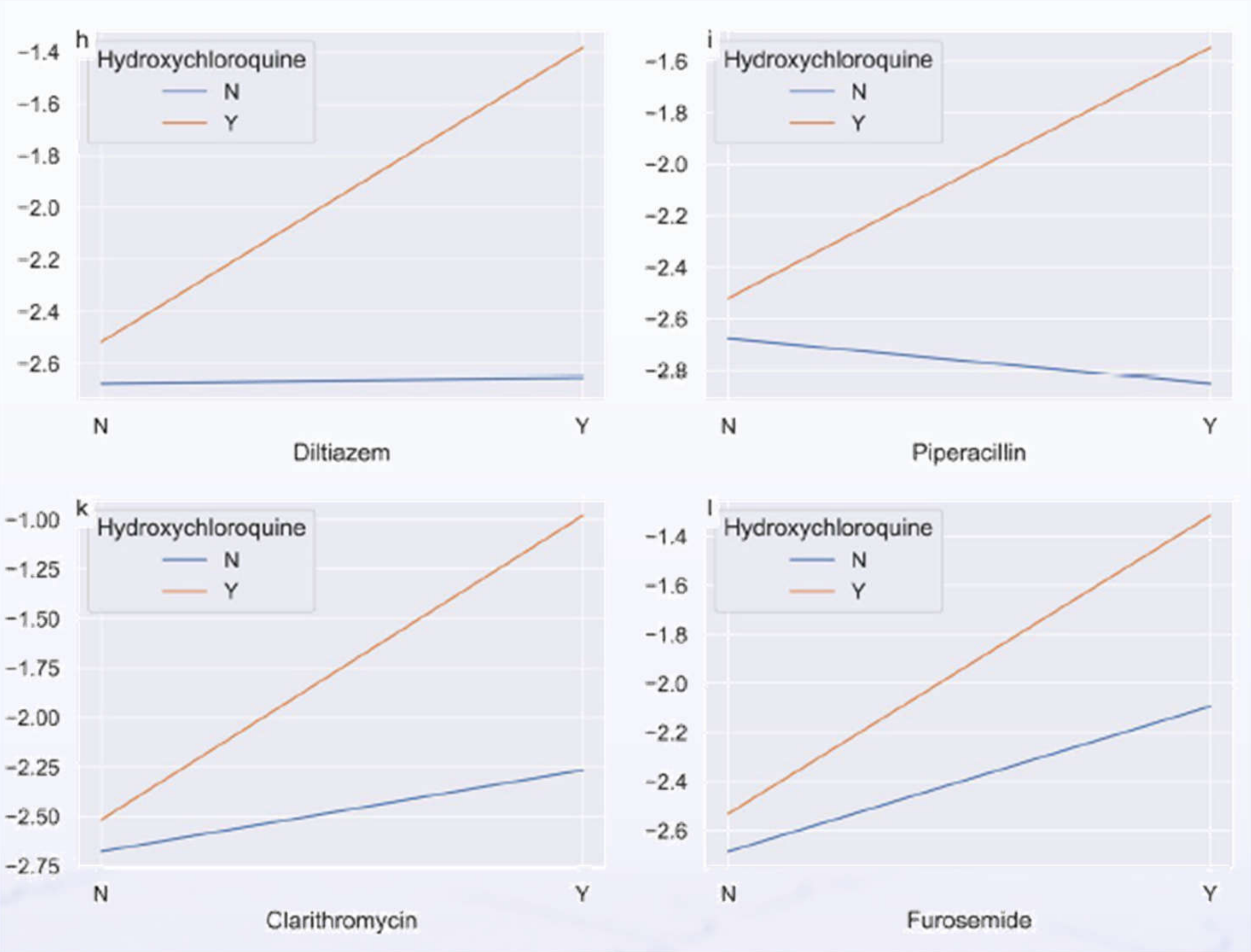
Risk of QT prolongation through drug interactions between hydroxychloroquine and concomitant drugs prescribed in real world practice

Byung Jin Choi[1,6], Yeryung Koo[1,6], Tae Young Kim[1], Wou Young Chung[2], Yun Jung Jung[2], Ji Eun Park[2], Hong-Seok Lim[3], Bumhee Park[1,4] & Dukyong Yoon[1,5]

Choi et al. (2021)

ECG parameter를 이용한 연구

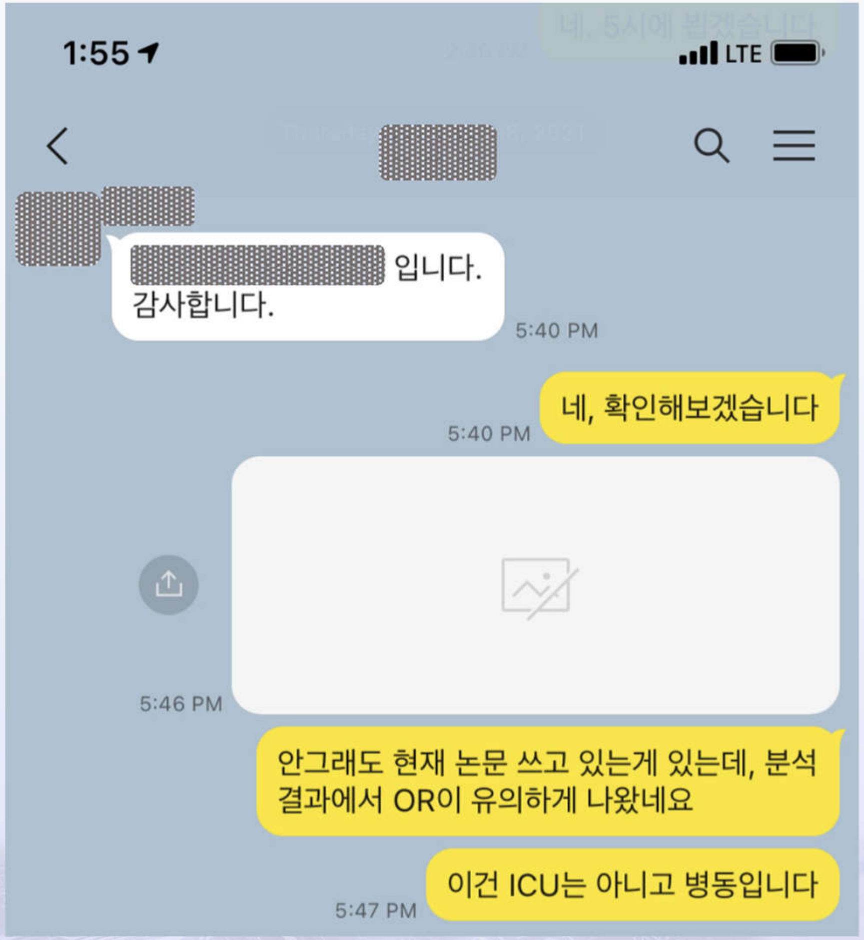


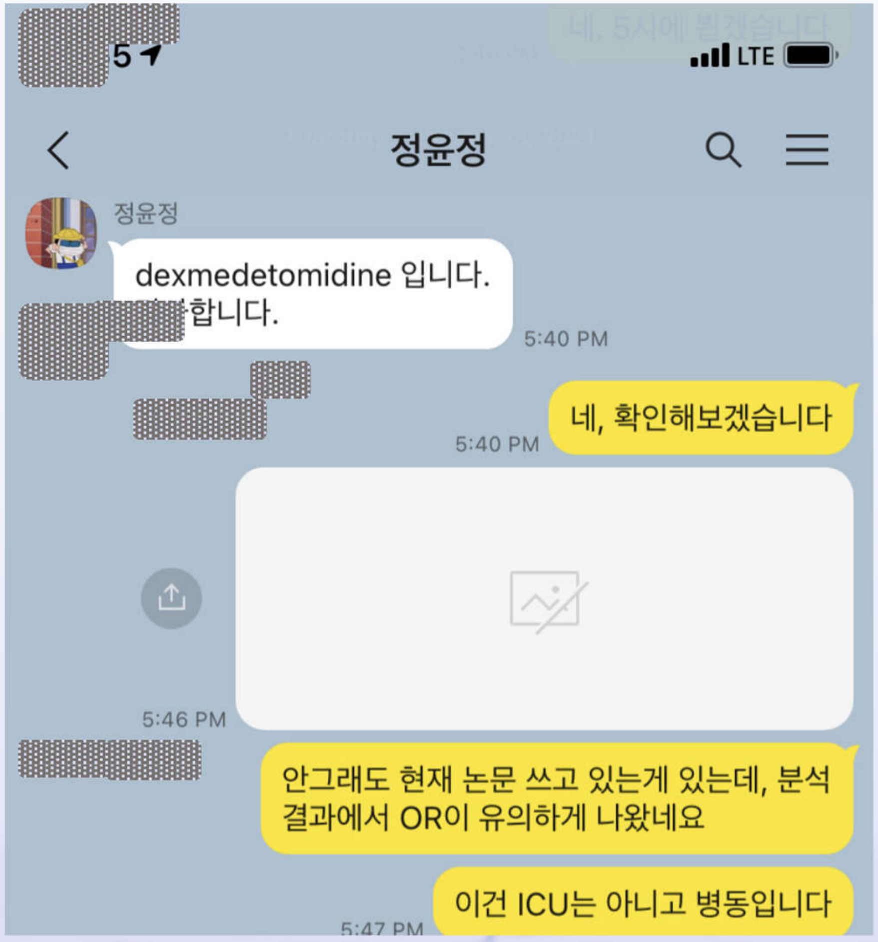


Choi BJ, Koo Y, Kim TY, Chung WY, Jung YJ, Park JE, Lim HS, Park B, <u>**Yoon**</u> D. Risk of QT prolongation through drug interactions between hydroxychloroquine and concomitant drugs prescribed in real world practice. Sci Rep. 2021 Mar 25;11(1):6918.

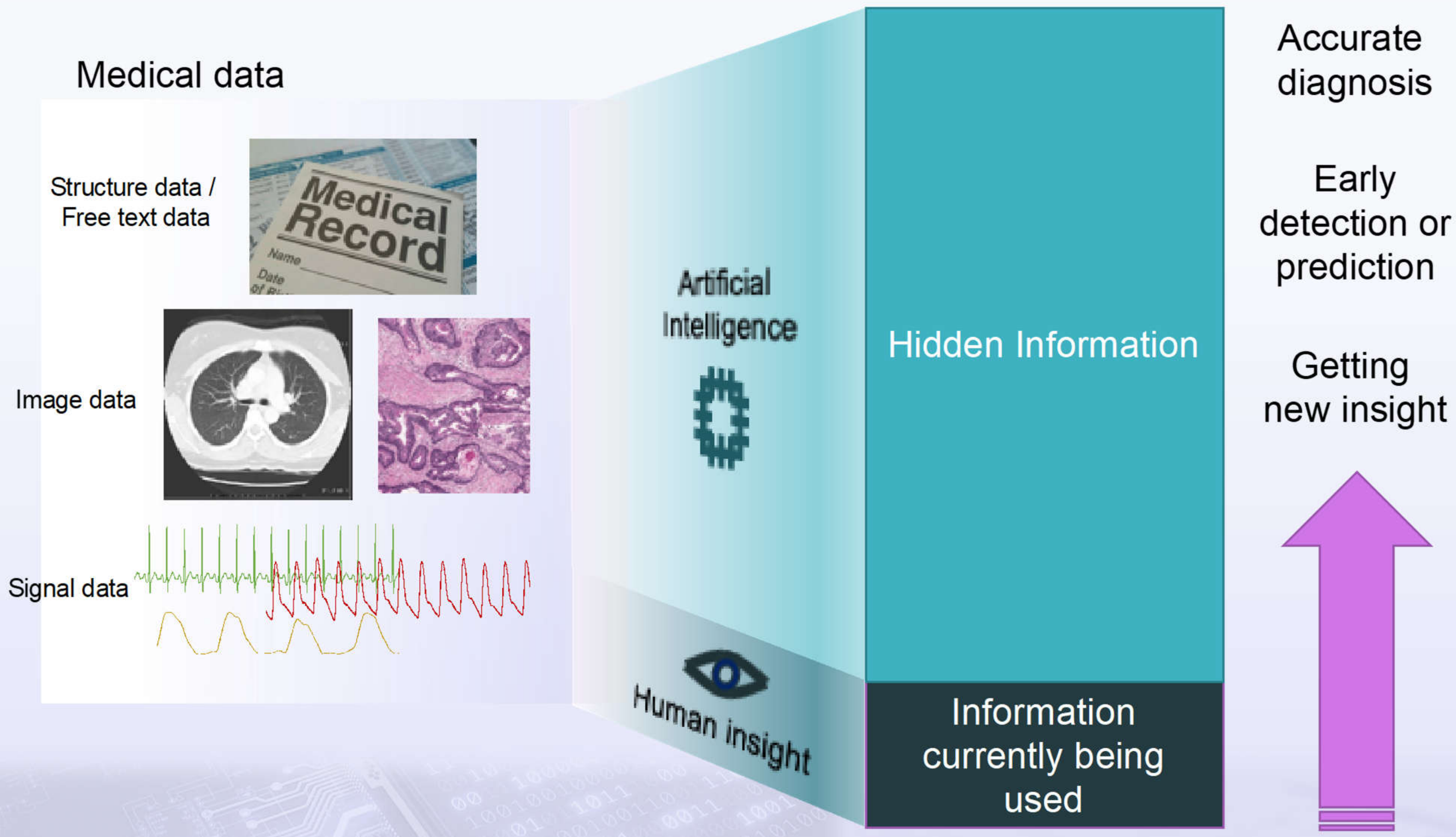
ECG parameter를 이용한 연구

Computational Medical Informatics





12 lead ECG waveform 기반 연구



Arrhythmia classification
Atrial fibrillation
Contractile dysfunction
Heart failure
Mortality

Diabetes mellitus
Hypoglycemia
Hyperkalemia

....

- <u>**Yoon D**</u>[§¶], Jang JH, Choi BJ, Kim TY, Han CH. Discovering hidden information in biosignals from patients by artificial intelligence. *Korean J Anesthesiol*. 2020 Jan 16

ECG & Deep learning

Europace (2021) **00**, 1–13
doi:10.1093/europace/euaa377

ESC
European Society of Cardiology

REVIEW

Deep learning and the electrocardiogram: review of the current state-of-the-art

Sulaiman Somani [1], Adam J. Russak [1,2], Felix Richter [1], Shan Zhao [1,3], Akhil Vaid[1], Fayzan Chaudhry[1,4], Jessica K. De Freitas [1,4], Nidhi Naik [1], Riccardo Miotto [1,4], Girish N. Nadkarni[1,2,5], Jagat Narula[6,7], Edgar Argulian[6,7], and Benjamin S. Glicksberg [14,*]

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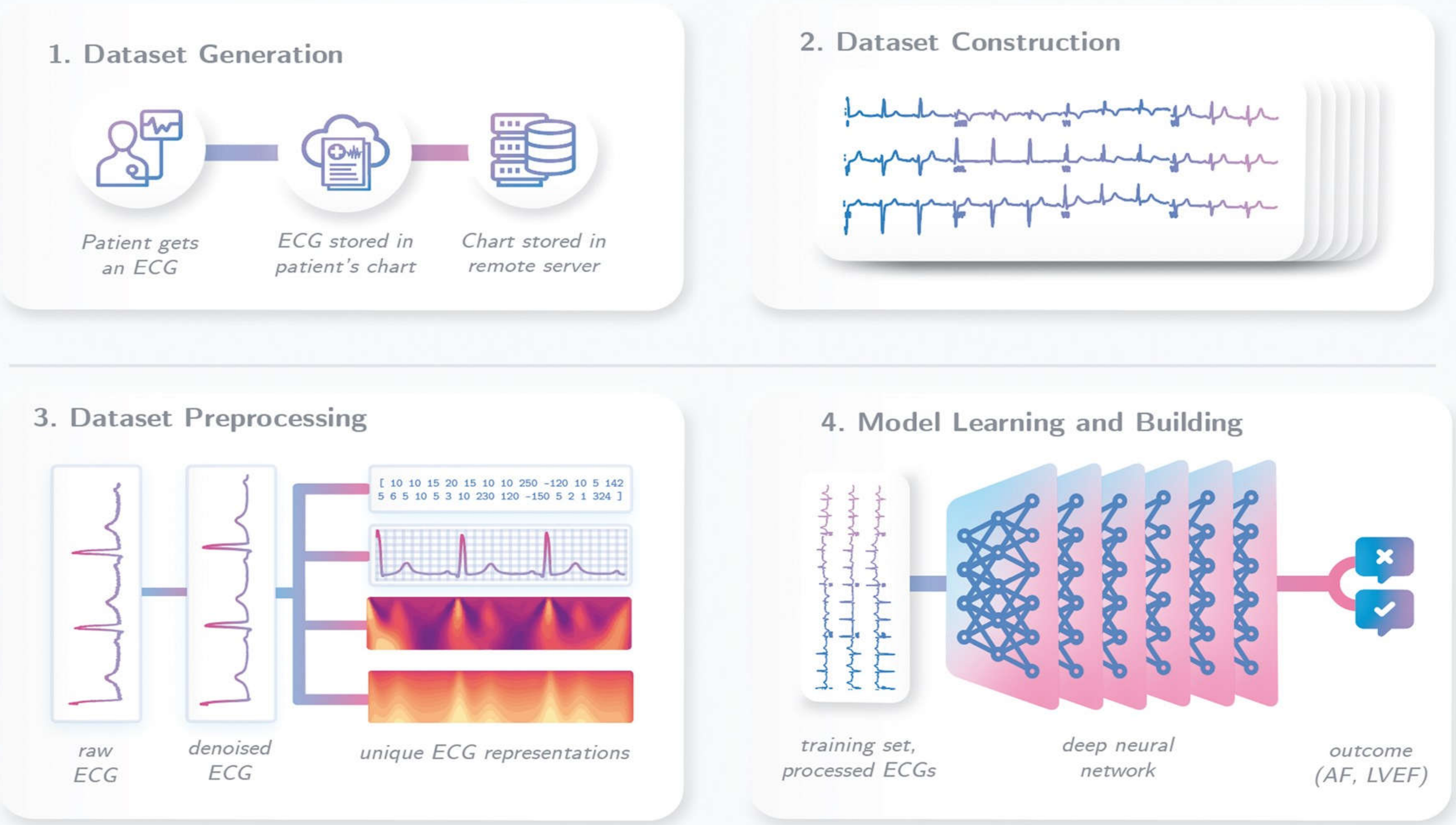

1. Dataset Generation
Patient gets an ECG
ECG stored in patient's chart
Chart stored in remote server
2. Dataset Construction
3. Dataset Preprocessing
[10 10 15 20 15 10 10 250 -120 10 5 142
5 6 5 10 5 3 10 230 120 -150 5 2 1 324]
raw ECG
denoised ECG
unique ECG representations
4. Model Learning and Building
training set, processed ECGs
deep neural network
outcome (AF, LVEF)

Table 2 **Applications of ECGs using deep learning**

Citation	Category	Prediction task	Dataset	Number of ECGs	Number of patients	Architecture
Parvaneh *et al.* [13] (2018)	Arrhythmias	Atrial fibrillation	CINC 2017	12 186	12 186	CNN + RNN
Xiong *et al.* (2018) [77]	Arrhythmias	Arrhythmia	CINC 2017	12 186	12 186	CNN
Ribeiro *et al.* (2019) [43]	Arrhythmias	Arrhythmia	Telehealth network of Minas Gerais	1 558 415	1 558 415	Ensemble (CNN, DNN)
Attia *et al.*[26]	Arrhythmias	Paroxysmal AF	Mayo Clinic	649 931	180 922	CNN + GBM
Wang *et al.* (2019)[78]	Arrhythmias	Arrhythmia	CCDB	193 690	193 690	CNN
Hannun *et al.*[42]	Arrhythmias	Arrhythmia	iRhythm	91 232	53 549	CNN
Brisk *et al.* (2019)[79]	Arrhythmias	Arrhythmia	CINC 2017	12 186	12 186	CNN
Wasserlauf *et al.*[49]	Arrhythmias	Atrial fibrillation	CINC 2017	7500	7500	CNN + LSTM + SVM
Ivanovic *et al.* (2019)[80]	Arrhythmias	Atrial fibrillation	Serbia	1097	1097	CNN
Smith *et al.*[44]	Arrhythmias	Arrhythmia	Cardiolog	1473	1473	CNN
Mousavi *et al.* (2020) [80]	Arrhythmias	Arrhythmia	CINC 2015	1250	1250	CNN (DDDN)
Van de Leur *et al.*[45]	Arrhythmias	Arrhythmia triage in the ED	University Medical Center Utrecht	336 835	142 040	Residual CNN
Oster *et al.* (2020)[81]	Arrhythmias	Atrial fibrillation	UK Biobank	77 202	75 778	CNN
Wang *et al.*[27]	Arrhythmias	Arrhythmia	Tianchi competition	20 036	20 036	CNN/HMM + GBM
Chen *et al.* (2020)[82]	Arrhythmias	Arrhythmia	CPSC2018	6877	6877	CNN + GBM
Cai *et al.*[50]	Arrhythmias	Atrial fibrillation	Chinese PLA General Hospital, wearable ECGs, CPSC2018	16 557	11 994	CNN
Tison *et al.*[54]	Cardiomyopathy	Heart failure, PAH, MVP	UCSF	36 186	36 186	Ensemble (CNN, DNN)
Kwon *et al.*[61]	Cardiomyopathy	Heart failure	Mediplex Sejong Hospital	55 163	22 765	CNN
Attia *et al.* [59]	Cardiomyopathy	Heart failure	Mayo Clinic	3 874	3 874	CNN + LSTM + SVM
Attia *et al.* [57]	Cardiomyopathy	Heart failure	Mayo Clinic	97 829	97 829	CNN
Kwon *et al.* [56]	Cardiomyopathy	Left ventricular hypertrophy	Sejong General Hospital, Mediplex Sejong Hospital; Korea	21 286	21 286	CNN
Yoon *et al.* (2019)[83]	Extracardiac	Noise detection	Ajou University Hospital; Korea	3000	3000	CNN
Ko *et al.*[55]	Cardiomyopathy	Hypertrophic cardiomyopathy	Mayo Clinic	67 001	67 001	CNN + RNN
Attia *et al.*[67]	Extracardiac	Age, Sex	Mayo Clinic	774 783	774 783	CNN
Galloway *et al.*[65]	Extracardiac	Hyperkalaemia	Mayo Clinic	1 638 546	449 380	CNN
Lin *et al.*[66]	Extracardiac	Hyperkalaemia	Tri-Service General Hospital; Taiwan	66 321	40 180	CNN
Wang *et al.*[27]	Extracardiac	Pre-diabetes	Beijing, China	2914	2914	CNN
Noseworthy *et al.*[60]	Extracardiac	Racial Bias	Mayo Clinic	97 829	97 829	CNN
Raghunath *et al.*[68]	Extracardiac	Mortality	Geisinger Hospital System	1 338 576	422 311	CNN
Kwon *et al.*[53]	Extracardiac	Pulmonary hypertension	Sejong General Hospital, Mediplex Sejong Hospital; Korea	59 844	23 376	CNN
Han *et al.*[75]	Extracardiac	Noise, Adversarial attack	CINC 2017	12 186	12 186	CNN
Tadesse *et al.*[62]	Ischaemia	Myocardial infarction (STEMI, NSTEMI)	GGH	21 241	21 241	CNN
Kwon *et al.*[52]	Valvulopathy	Aortic stenosis	Sejong General Hospital, Mediplex Sejong Hospital; Korea	39 371	39 371	CNN
Kwon *et al.*[53]	Valvulopathy	Mitral regurgitation	Sejong General Hospital, Mediplex Sejong Hospital; Korea	70 709	38 241	CNN + RNN

This table highlights the 31 applications found during the literature search for ECG analysis, with information about the dataset source, sample size (by unique ECGs and unique patients) present for training and testing, task at hand, and neural network architecture used. Because these studies do not use the same metrics or the same validation protocol to evaluate each model's performance and because the authors firmly believe that comparison of models is tenuous without greater context beyond what this table can provide, these measures have been omitted from being reported in the table.
CNN, convolutional neural network; ECGs, electrocardiograms; LSTM, long–short-term memory; RNN, recurrent neural network.

Computational Medical Informatics

Paroxysmal Afib

An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction

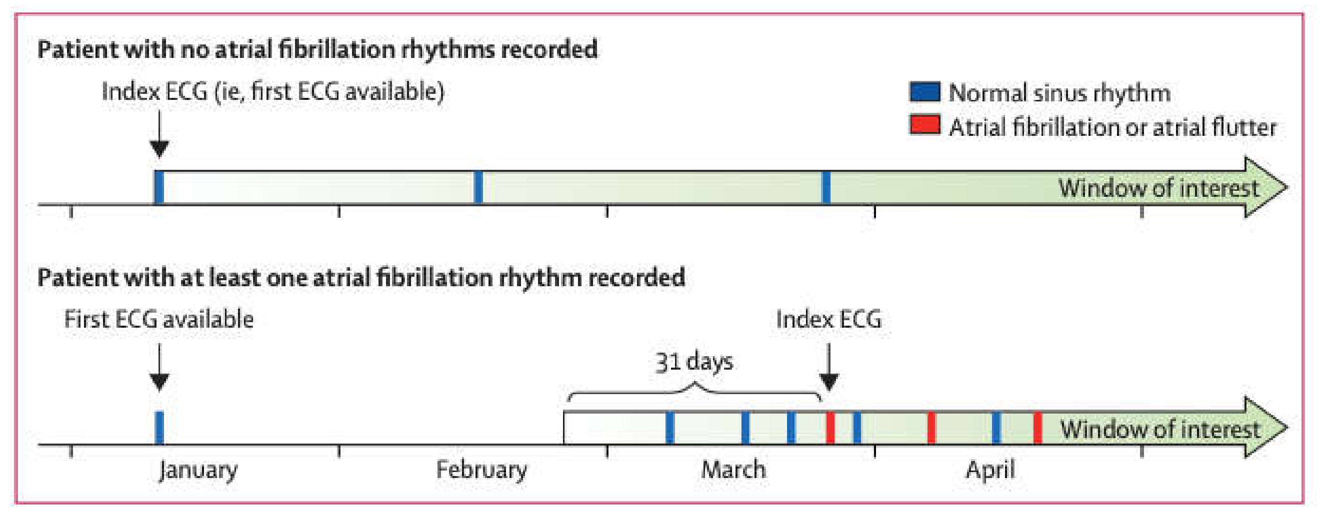
Zachi I Attia, Peter A Noseworthy*, Francisco Lopez-Jimenez, Samuel J Asirvatham, Abhishek J Deshmukh, Bernard J Gersh, Rickey E Carter, Xiaoxi Yao, Alejandro A Rabinstein, Brad J Erickson, Suraj Kapa, Paul A Friedman*

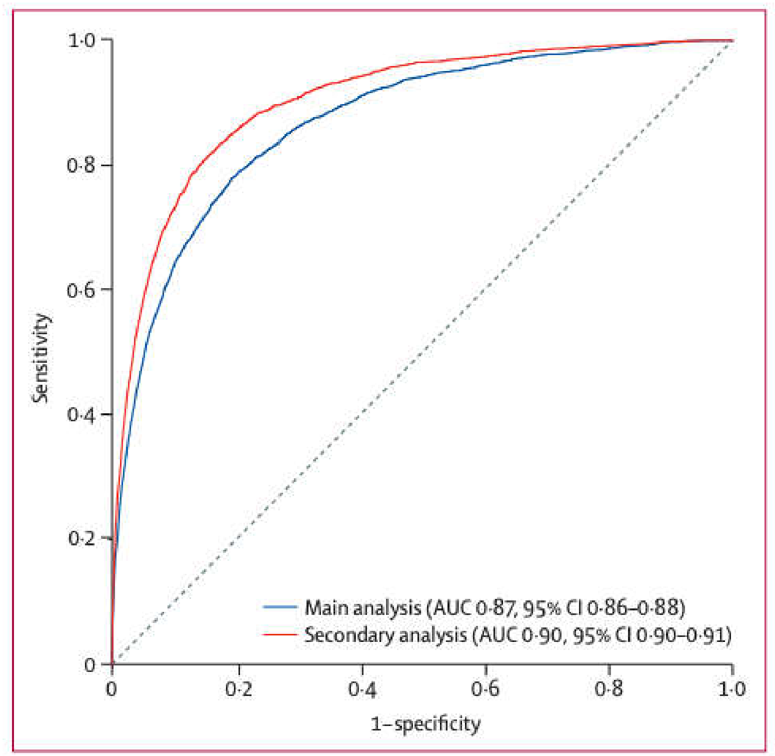
Summary

Background Atrial fibrillation is frequently asymptomatic and thus underdetected but is associated with stroke, heart failure, and death. Existing screening methods require prolonged monitoring and are limited by cost and low yield. We aimed to develop a rapid, inexpensive, point-of-care means of identifying patients with atrial fibrillation using machine learning.

Lancet 2019; 394: 8

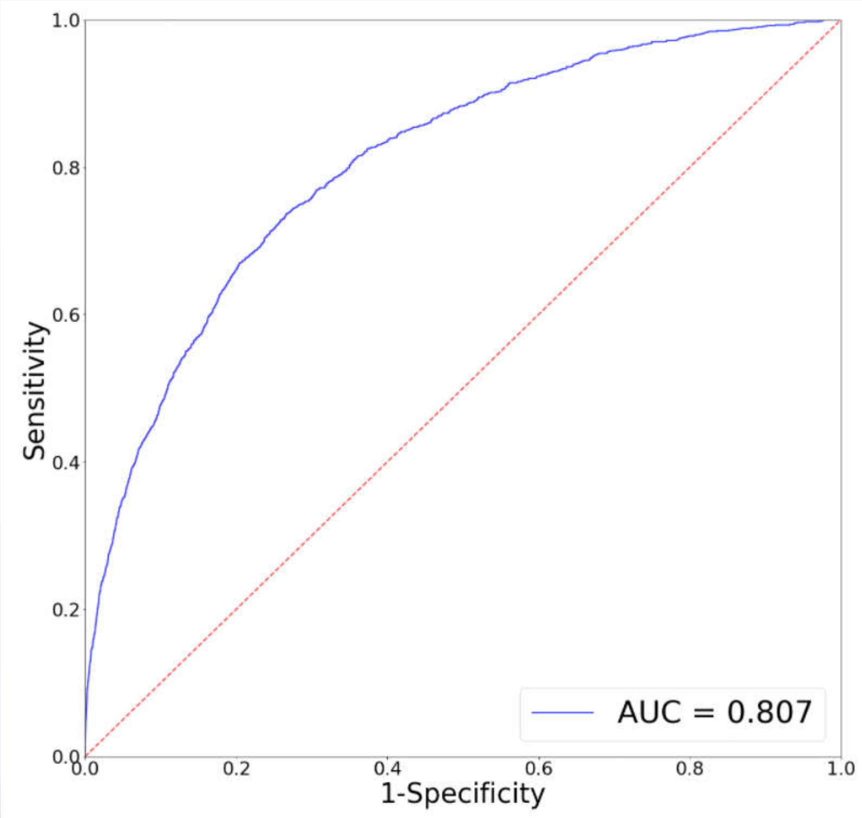
Published Online
August 1, 2019





Paroxysmal Afib

ESC Heart & Stroke 2021



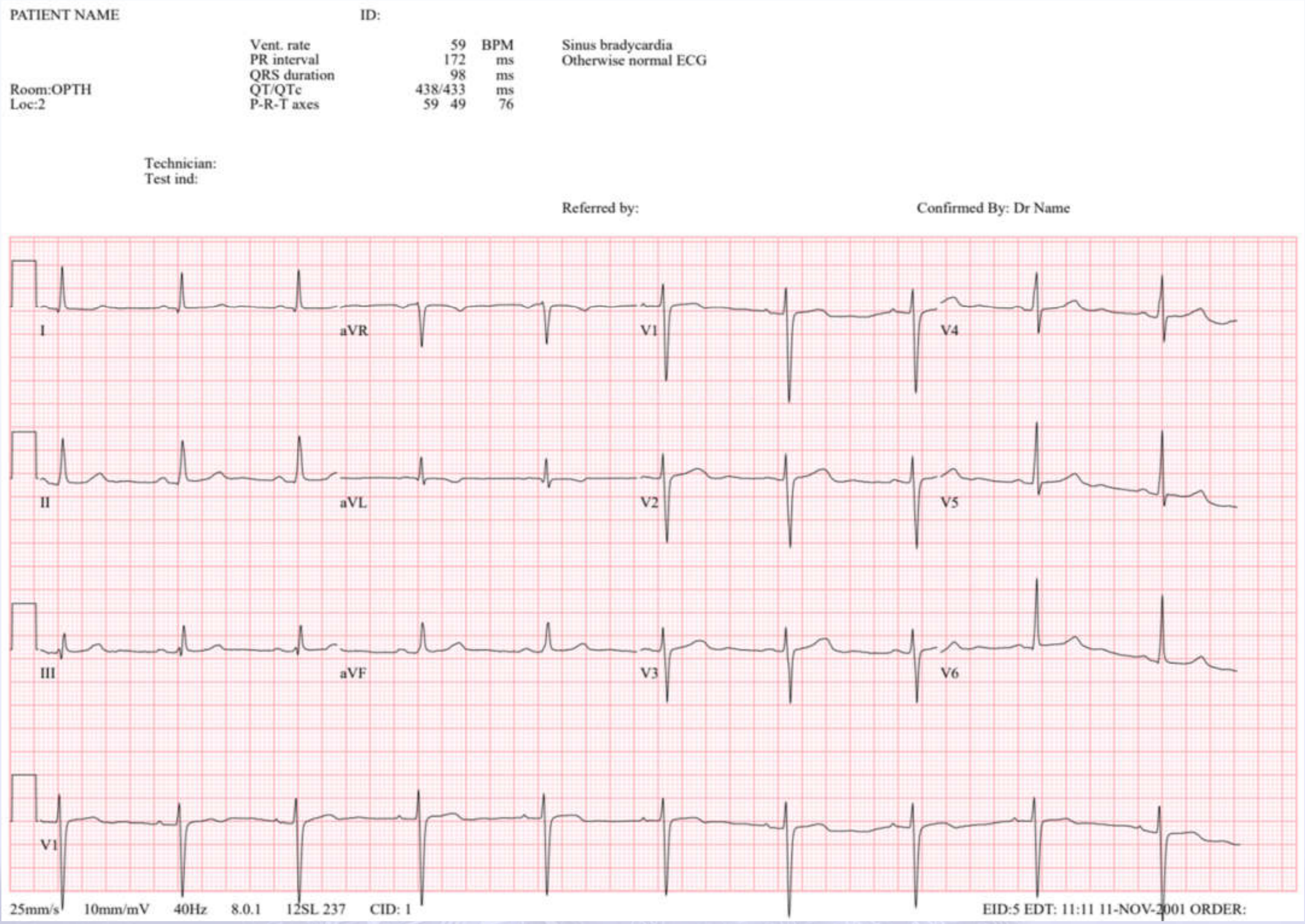
ROC curve for AI-enabled ECG algorithm for the test set

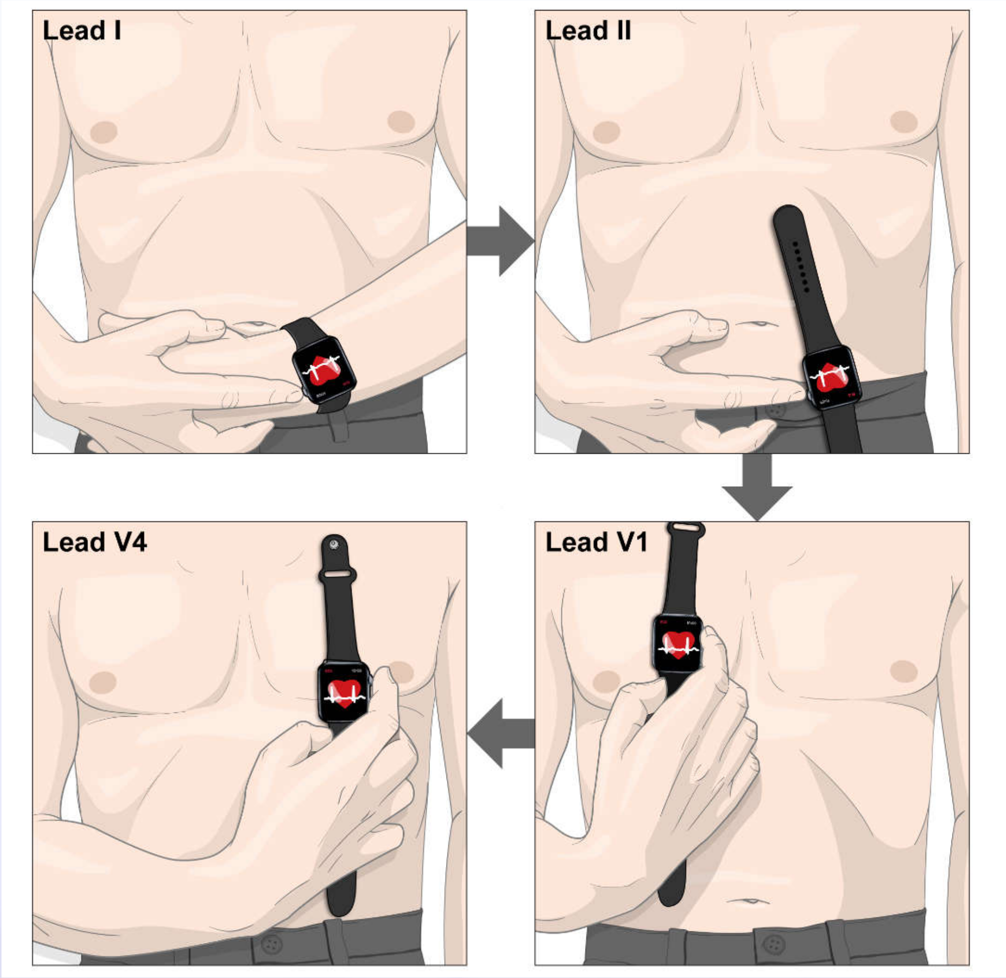
- Dependent variables: AI model inference outputs (continuous or binary form)
- Predictor variables: Age, sex, TOAST classification (LAA, SAO, cryptogenic or test dataset)

Table 2. Logistic regression results

Variable	β (SE)	OR	p value
Age	0.0608 (0.0006)	1.067	<0.001
Male	0.4973 (0.0158)	1.644	<0.001
cryptogenic	0.5807 (0.2448)	1.787	0.018
LAA	0.3390 (0.1721)	1.404	0.049
SAO	0.2792 (0.1654)	1.322	0.091

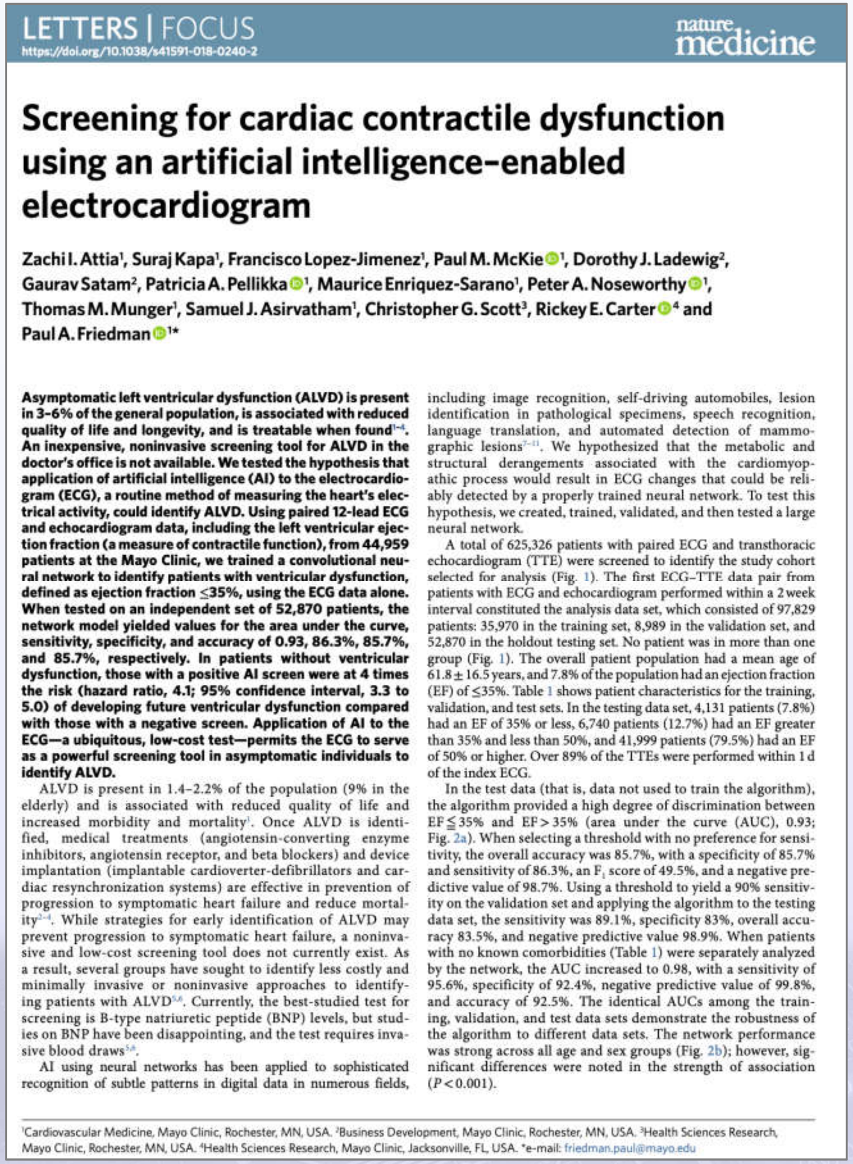
MI detection with wearable device





- CH Han, BT Lee, HS Lim, JH Jang, Y Lee, **D Yoon*** Artificial intelligence for automated detection of acute myocardial infarction using asynchronous ECG signals—a preview of implementing artificial intelligence with multichannel ECG obtained by smartwatches: Retrospective study. JMIR (accepted)

Cardiac contractile dysfunction


LETTERS | FOCUS
https://doi.org/10.1038/s41591-018-0240-2
nature medicine

Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram

Zachi I. Attia[1], Suraj Kapa[1], Francisco Lopez-Jimenez[1], Paul M. McKie[1], Dorothy J. Ladewig[2], Gaurav Satam[2], Patricia A. Pellikka[1], Maurice Enriquez-Sarano[1], Peter A. Noseworthy[1], Thomas M. Munger[1], Samuel J. Asirvatham[1], Christopher G. Scott[3], Rickey E. Carter[4] and Paul A. Friedman[1]*

Asymptomatic left ventricular dysfunction (ALVD) is present in 3–6% of the general population, is associated with reduced quality of life and longevity, and is treatable when found[1–4]. An inexpensive, noninvasive screening tool for ALVD in the doctor's office is not available. We tested the hypothesis that application of artificial intelligence (AI) to the electrocardiogram (ECG), a routine method of measuring the heart's electrical activity, could identify ALVD. Using paired 12-lead ECG and echocardiogram data, including the left ventricular ejection fraction (a measure of contractile function), from 44,959 patients at the Mayo Clinic, we trained a convolutional neural network to identify patients with ventricular dysfunction, defined as ejection fraction ≤35%, using the ECG data alone. When tested on an independent set of 52,870 patients, the network model yielded values for the area under the curve, sensitivity, specificity, and accuracy of 0.93, 86.3%, 85.7%, and 85.7%, respectively. In patients without ventricular dysfunction, those with a positive AI screen were at 4 times the risk (hazard ratio, 4.1; 95% confidence interval, 3.3 to 5.0) of developing future ventricular dysfunction compared with those with a negative screen. Application of AI to the ECG—a ubiquitous, low-cost test—permits the ECG to serve as a powerful screening tool in asymptomatic individuals to identify ALVD.

ALVD is present in 1.4–2.2% of the population (9% in the elderly) and is associated with reduced quality of life and increased morbidity and mortality[1]. Once ALVD is identified, medical treatments (angiotensin-converting enzyme inhibitors, angiotensin receptor, and beta blockers) and device implantation (implantable cardioverter-defibrillators and cardiac resynchronization systems) are effective in prevention of progression to symptomatic heart failure and reduce mortality[2–4]. While strategies for early identification of ALVD may prevent progression to symptomatic heart failure, a noninvasive and low-cost screening tool does not currently exist. As a result, several groups have sought to identify less costly and minimally invasive or noninvasive approaches to identifying patients with ALVD[5,6]. Currently, the best-studied test for screening is B-type natriuretic peptide (BNP) levels, but studies on BNP have been disappointing, and the test requires invasive blood draws[5,6].

AI using neural networks has been applied to sophisticated recognition of subtle patterns in digital data in numerous fields, including image recognition, self-driving automobiles, lesion identification in pathological specimens, speech recognition, language translation, and automated detection of mammographic lesions[7–11]. We hypothesized that the metabolic and structural derangements associated with the cardiomyopathic process would result in ECG changes that could be reliably detected by a properly trained neural network. To test this hypothesis, we created, trained, validated, and then tested a large neural network.

A total of 625,326 patients with paired ECG and transthoracic echocardiogram (TTE) were screened to identify the study cohort selected for analysis (Fig. 1). The first ECG–TTE data pair from patients with ECG and echocardiogram performed within a 2 week interval constituted the analysis data set, which consisted of 97,829 patients: 35,970 in the training set, 8,989 in the validation set, and 52,870 in the holdout testing set. No patient was in more than one group (Fig. 1). The overall patient population had a mean age of 61.8 ± 16.5 years, and 7.8% of the population had an ejection fraction (EF) of ≤35%. Table 1 shows patient characteristics for the training, validation, and test sets. In the testing data set, 4,131 patients (7.8%) had an EF of 35% or less, 6,740 patients (12.7%) had an EF greater than 35% and less than 50%, and 41,999 patients (79.5%) had an EF of 50% or higher. Over 89% of the TTEs were performed within 1 d of the index ECG.

In the test data (that is, data not used to train the algorithm), the algorithm provided a high degree of discrimination between EF ≦ 35% and EF > 35% (area under the curve (AUC), 0.93; Fig. 2a). When selecting a threshold with no preference for sensitivity, the overall accuracy was 85.7%, with a specificity of 85.7% and sensitivity of 86.3%, an F_1 score of 49.5%, and a negative predictive value of 98.7%. Using a threshold to yield a 90% sensitivity on the validation set and applying the algorithm to the testing data set, the sensitivity was 89.1%, specificity 83%, overall accuracy 83.5%, and negative predictive value 98.9%. When patients with no known comorbidities (Table 1) were separately analyzed by the network, the AUC increased to 0.98, with a sensitivity of 95.6%, specificity of 92.4%, negative predictive value of 99.8%, and accuracy of 92.5%. The identical AUCs among the training, validation, and test data sets demonstrate the robustness of the algorithm to different data sets. The network performance was strong across all age and sex groups (Fig. 2b); however, significant differences were noted in the strength of association ($P < 0.001$).

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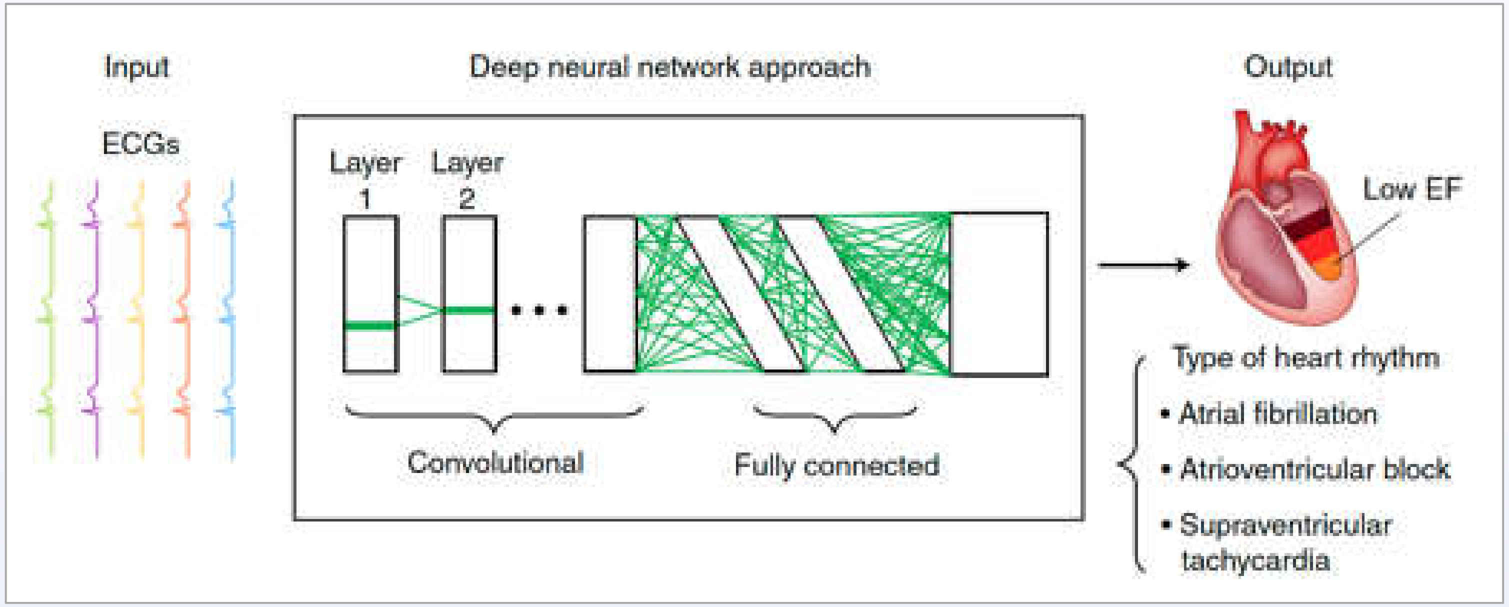

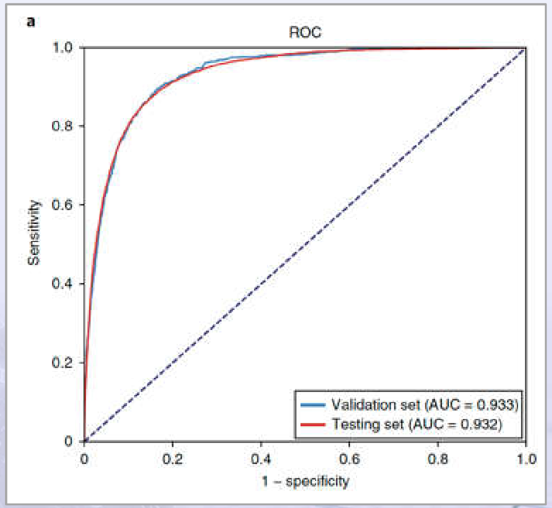

Attia ZI, Kapa S, Lopez-Jimenez F, McKie PM, Ladewig DJ, Satam G, et al. Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram. Nat Med 2019; 25: 70-4.

One-year mortality

LETTERS
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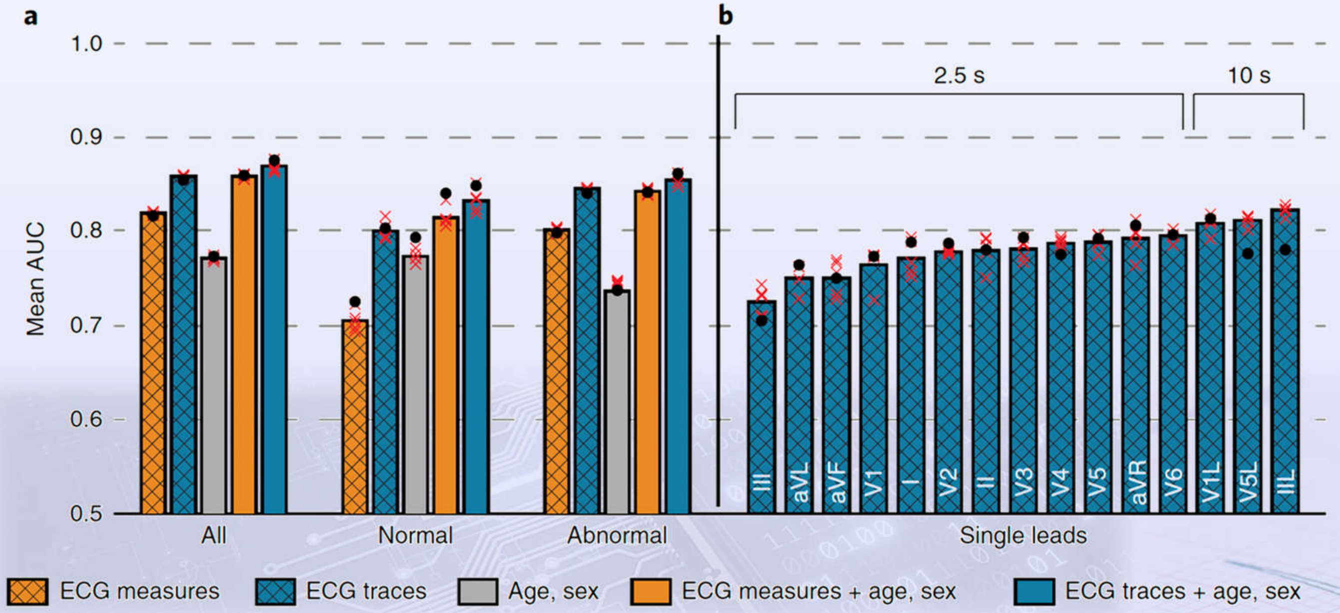
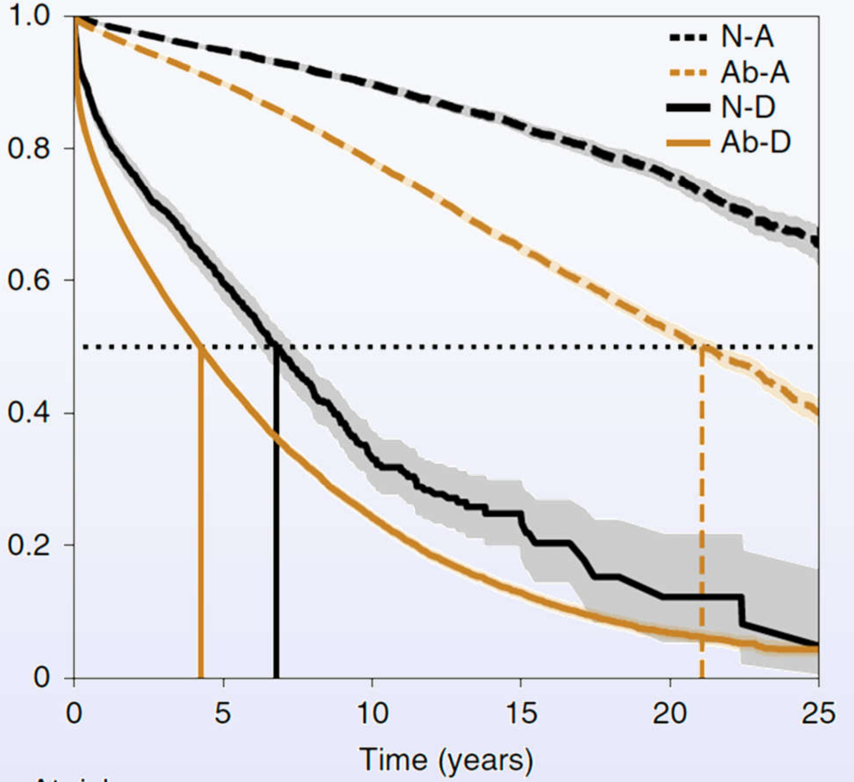
nature medicine
Check for updates
NATURE MEDICINE | VOL 26 | JUNE 2020 | 886-891 | www.nature.com/naturemedicine

Prediction of mortality from 12-lead electrocardiogram voltage data using a deep neural network

Sushravya Raghunath[1], Alvaro E. Ulloa Cerna[1], Linyuan Jing[1], David P. vanMaanen[1], Joshua Stough[1,2], Dustin N. Hartzel[3], Joseph B. Leader[3], H. Lester Kirchner[4], Martin C. Stumpe[5], Ashraf Hafez[5], Arun Nemani[5], Tanner Carbonati[5], Kipp W. Johnson[5], Katelyn Young[6], Christopher W. Good[7], John M. Pfeifer[8], Aalpen A. Patel[9], Brian P. Delisle[10], Amro Alsaid[7], Dominik Beer[7], Christopher M. Haggerty[1,7,11] and Brandon K. Fornwalt[1,7,9,11] ✉





At risk

78,084	17,618	5,906	2,361	1,051	276
144,378	37,786	14,596	5,028	1,723	336
4,361	527	89	17	4	2
56,441	7,708	1,915	476	124	24

hypoglycemia & ECG Morphology

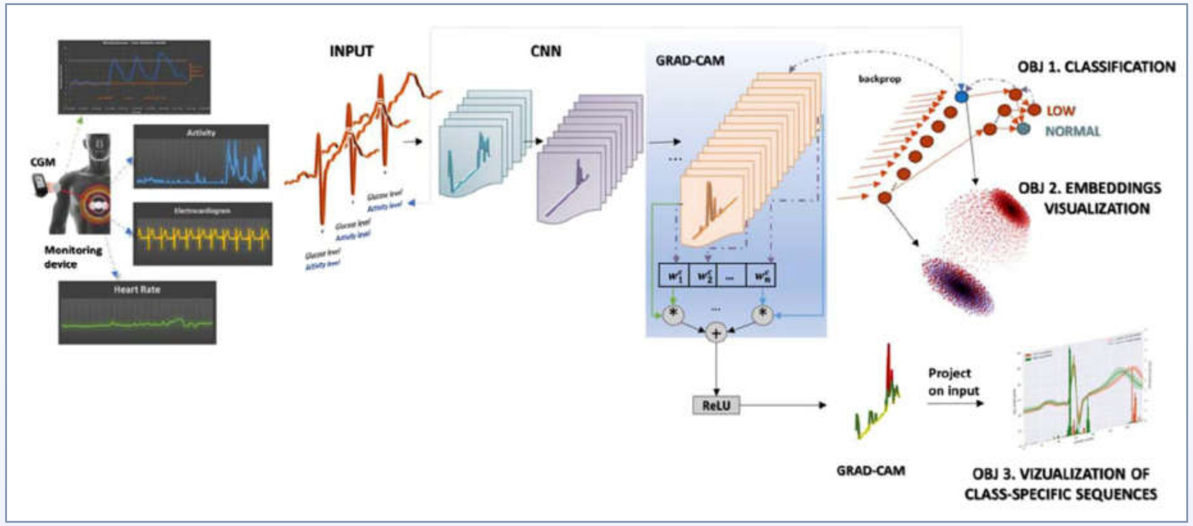
SCIENTIFIC REPORTS
natureresearch

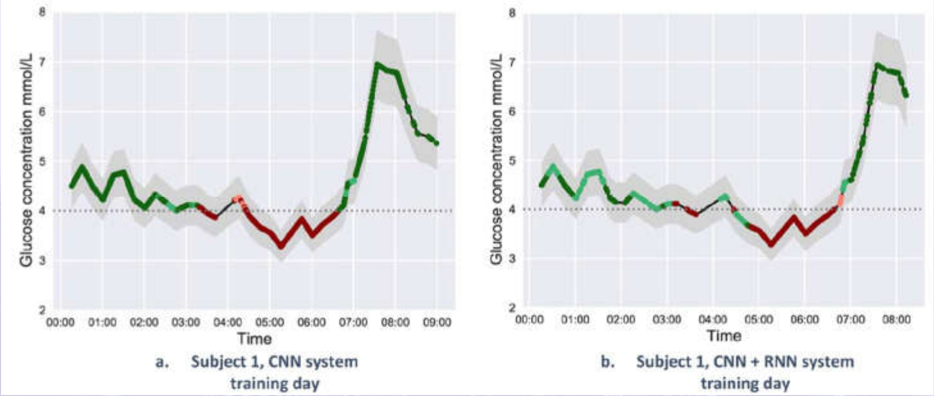
OPEN

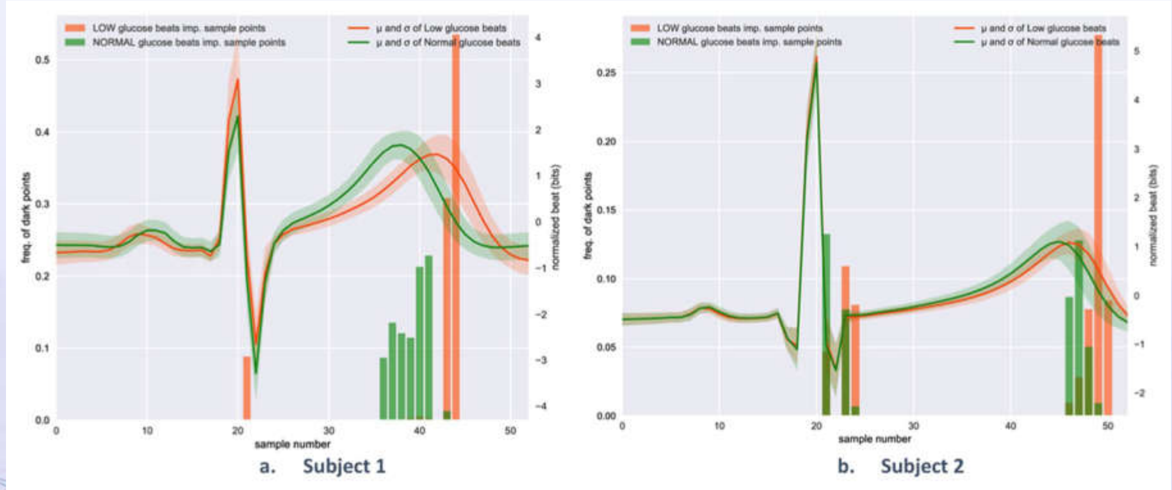
Precision Medicine and Artificial Intelligence: A Pilot Study on Deep Learning for Hypoglycemic Events Detection based on ECG

Mihaela Porumb[1], Saverio Stranges[2,3,4], Antonio Pescapè[5] & Leandro Pecchia[1*]

SCIENTIFIC REPORTS | (2020) 10:170 | https://doi.org/10.1038/s41598-019-56927-5





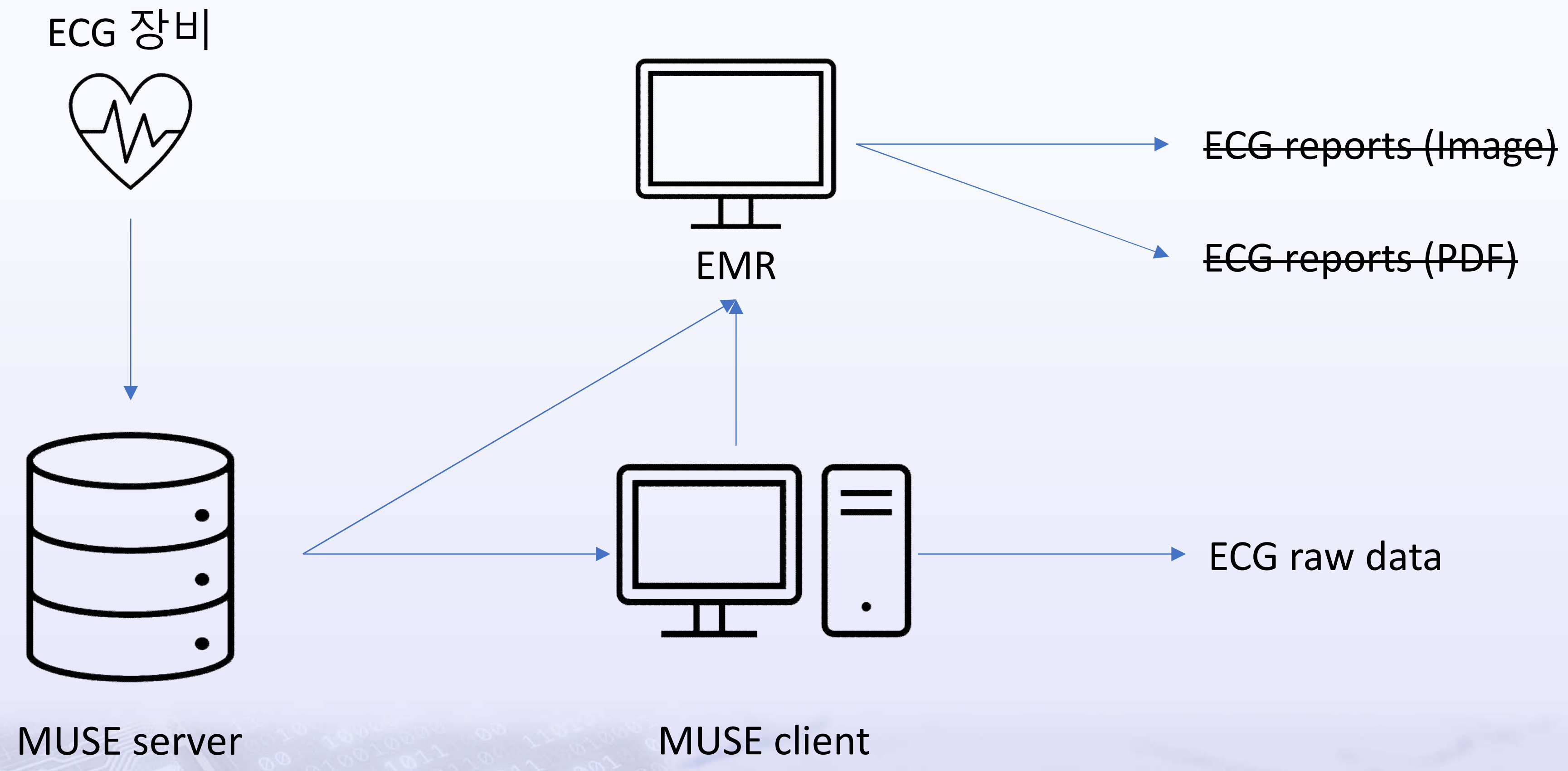


진행중인 연구 in CMI

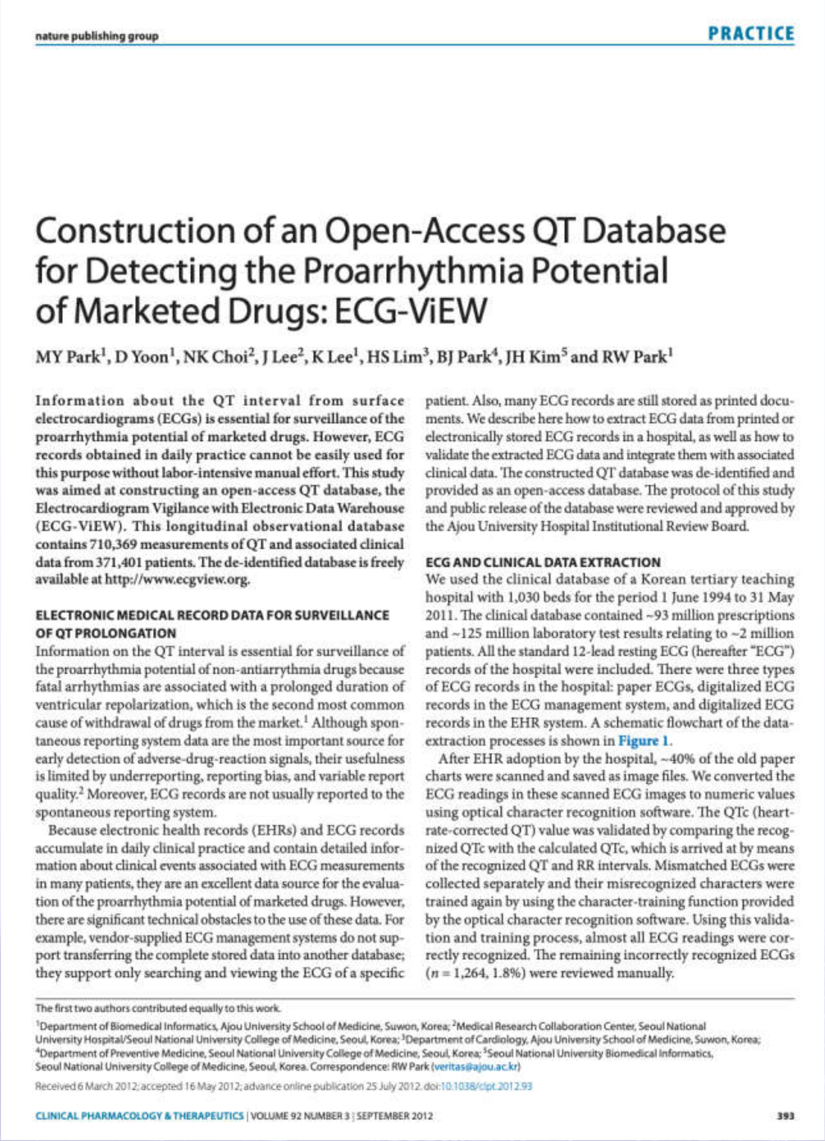
- 12 lead ECG
  - CACS
  - Afib related disease/treatment
  - hyperkalemia
  - …

- ECG + other biosignal in ICU
  - Delirium
  - Weaning
  - Bleeding
  - Respiratory failure
  - Renal failure
  - …

ECG 데이터 수집 및 활용 방법



ECG 데이터 수집 및 활용 방법 (~2012)



nature publishing group

PRACTICE

Construction of an Open-Access QT Database for Detecting the Proarrhythmia Potential of Marketed Drugs: ECG-ViEW

MY Park[1], D Yoon[1], NK Choi[2], J Lee[2], K Lee[1], HS Lim[3], BJ Park[4], JH Kim[5] and RW Park[1]

Information about the QT interval from surface electrocardiograms (ECGs) is essential for surveillance of the proarrhythmia potential of marketed drugs. However, ECG records obtained in daily practice cannot be easily used for this purpose without labor-intensive manual effort. This study was aimed at constructing an open-access QT database, the Electrocardiogram Vigilance with Electronic Data Warehouse (ECG-ViEW). This longitudinal observational database contains 710,369 measurements of QT and associated clinical data from 371,401 patients. The de-identified database is freely available at http://www.ecgview.org.

ELECTRONIC MEDICAL RECORD DATA FOR SURVEILLANCE OF QT PROLONGATION

Information on the QT interval is essential for surveillance of the proarrhythmia potential of non-antiarrythmia drugs because fatal arrhythmias are associated with a prolonged duration of ventricular repolarization, which is the second most common cause of withdrawal of drugs from the market.[1] Although spontaneous reporting system data are the most important source for early detection of adverse-drug-reaction signals, their usefulness is limited by underreporting, reporting bias, and variable report quality.[2] Moreover, ECG records are not usually reported to the spontaneous reporting system.

Because electronic health records (EHRs) and ECG records accumulate in daily clinical practice and contain detailed information about clinical events associated with ECG measurements in many patients, they are an excellent data source for the evaluation of the proarrhythmia potential of marketed drugs. However, there are significant technical obstacles to the use of these data. For example, vendor-supplied ECG management systems do not support transferring the complete stored data into another database; they support only searching and viewing the ECG of a specific patient. Also, many ECG records are still stored as printed documents. We describe here how to extract ECG data from printed or electronically stored ECG records in a hospital, as well as how to validate the extracted ECG data and integrate them with associated clinical data. The constructed QT database was de-identified and provided as an open-access database. The protocol of this study and public release of the database were reviewed and approved by the Ajou University Hospital Institutional Review Board.

ECG AND CLINICAL DATA EXTRACTION

We used the clinical database of a Korean tertiary teaching hospital with 1,030 beds for the period 1 June 1994 to 31 May 2011. The clinical database contained ~93 million prescriptions and ~125 million laboratory test results relating to ~2 million patients. All the standard 12-lead resting ECG (hereafter "ECG") records of the hospital were included. There were three types of ECG records in the hospital: paper ECGs, digitalized ECG records in the ECG management system, and digitalized ECG records in the EHR system. A schematic flowchart of the data-extraction processes is shown in Figure 1.

After EHR adoption by the hospital, ~40% of the old paper charts were scanned and saved as image files. We converted the ECG readings in these scanned ECG images to numeric values using optical character recognition software. The QTc (heart-rate-corrected QT) value was validated by comparing the recognized QTc with the calculated QTc, which is arrived at by means of the recognized QT and RR intervals. Mismatched ECGs were collected separately and their misrecognized characters were trained again by using the character-training function provided by the optical character recognition software. Using this validation and training process, almost all ECG readings were correctly recognized. The remaining incorrectly recognized ECGs (n = 1,264, 1.8%) were reviewed manually.

The first two authors contributed equally to this work.

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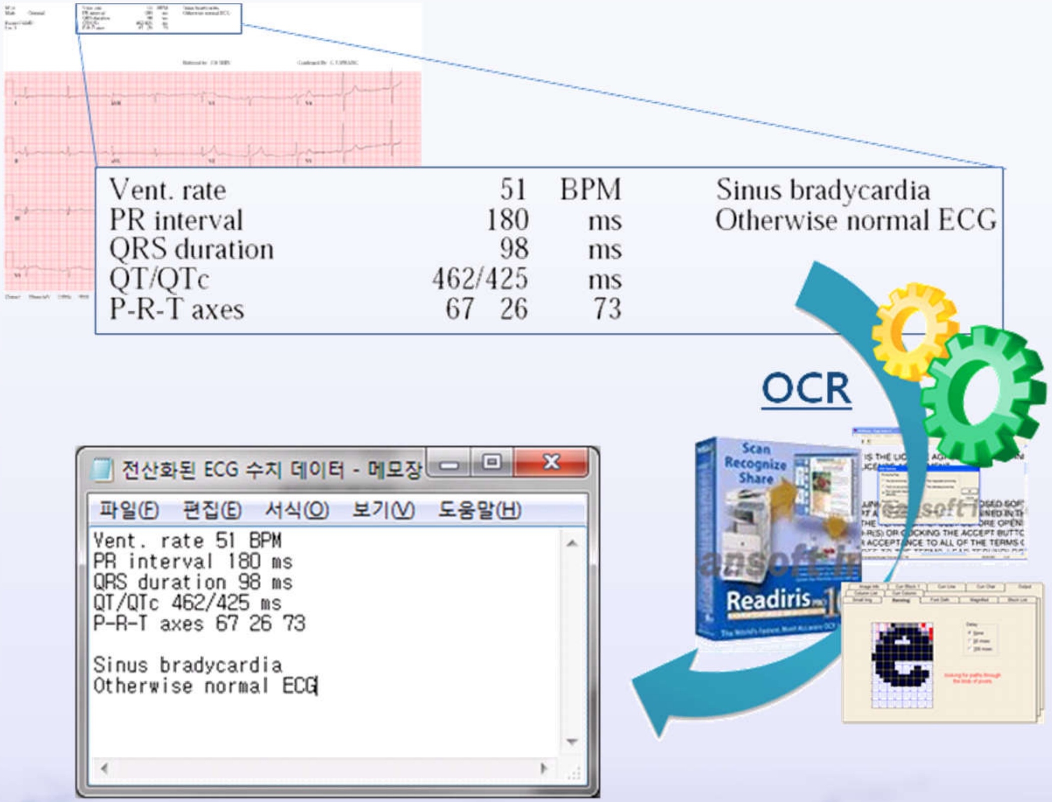
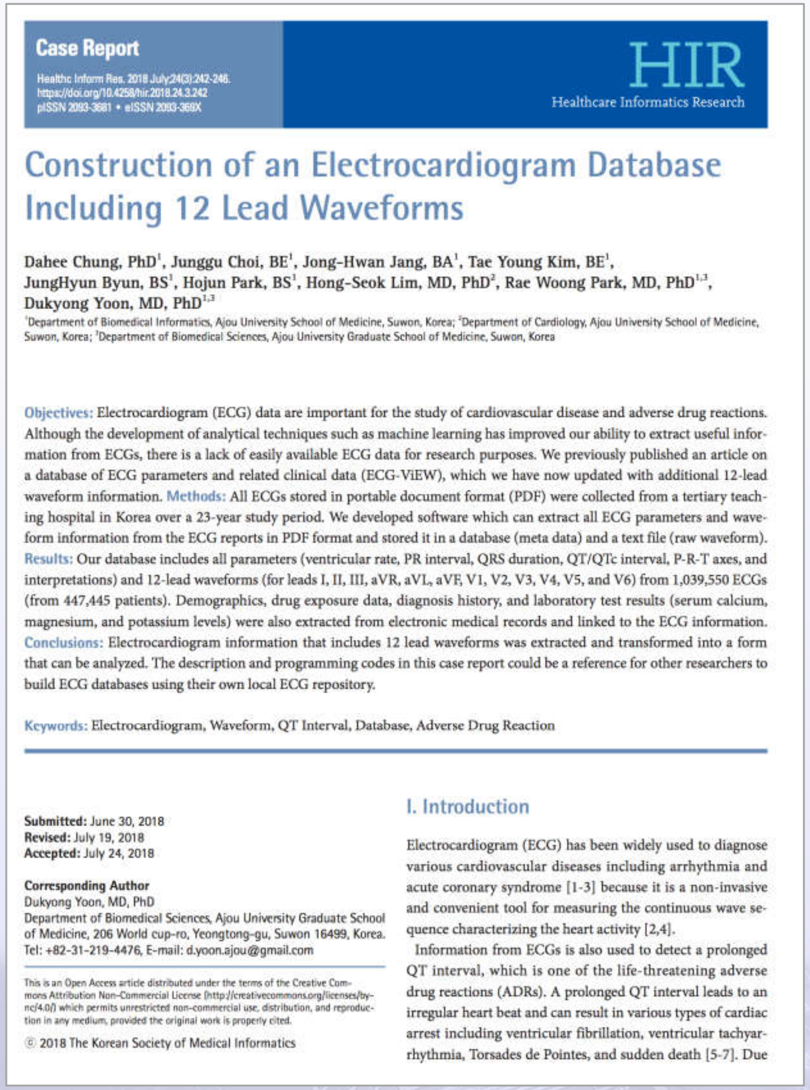
CLINICAL PHARMACOLOGY & THERAPEUTICS | VOLUME 92 NUMBER 3 | SEPTEMBER 2012 393



Park MY, Yoon D, Choi NK, Lee J, Lee K, Lim HS, Park BJ, Kim JH, Park RW. Construction of an open-access QT database for detecting the proarrhythmia potential of marketed drugs: ECG-ViEW. Clin Pharmacol Ther. 2012 Sep;92(3):393-6.

ECG 데이터 수집 및 활용 방법 (~2018)



Case Report

Healthc Inform Res. 2018 July;24(3):242-246.
https://doi.org/10.4258/hir.2018.24.3.242
pISSN 2093-3681 • eISSN 2093-369X

HIR
Healthcare Informatics Research

Construction of an Electrocardiogram Database Including 12 Lead Waveforms

Dahee Chung, PhD[1], Junggu Choi, BE[1], Jong-Hwan Jang, BA[1], Tae Young Kim, BE[1], JungHyun Byun, BS[1], Hojun Park, BS[1], Hong-Seok Lim, MD, PhD[2], Rae Woong Park, MD, PhD[1,3], Dukyong Yoon, MD, PhD[1,3]

[1]Department of Biomedical Informatics, Ajou University School of Medicine, Suwon, Korea; [2]Department of Cardiology, Ajou University School of Medicine, Suwon, Korea; [3]Department of Biomedical Sciences, Ajou University Graduate School of Medicine, Suwon, Korea

Objectives: Electrocardiogram (ECG) data are important for the study of cardiovascular disease and adverse drug reactions. Although the development of analytical techniques such as machine learning has improved our ability to extract useful information from ECGs, there is a lack of easily available ECG data for research purposes. We previously published an article on a database of ECG parameters and related clinical data (ECG-ViEW), which we have now updated with additional 12-lead waveform information. Methods: All ECGs stored in portable document format (PDF) were collected from a tertiary teaching hospital in Korea over a 23-year study period. We developed software which can extract all ECG parameters and waveform information from the ECG reports in PDF format and stored it in a database (meta data) and a text file (raw waveform). Results: Our database includes all parameters (ventricular rate, PR interval, QRS duration, QT/QTc interval, P-R-T axes, and interpretations) and 12-lead waveforms (for leads I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6) from 1,039,550 ECGs (from 447,445 patients). Demographics, drug exposure data, diagnosis history, and laboratory test results (serum calcium, magnesium, and potassium levels) were also extracted from electronic medical records and linked to the ECG information. Conclusions: Electrocardiogram information that includes 12 lead waveforms was extracted and transformed into a form that can be analyzed. The description and programming codes in this case report could be a reference for other researchers to build ECG databases using their own local ECG repository.

Keywords: Electrocardiogram, Waveform, QT Interval, Database, Adverse Drug Reaction

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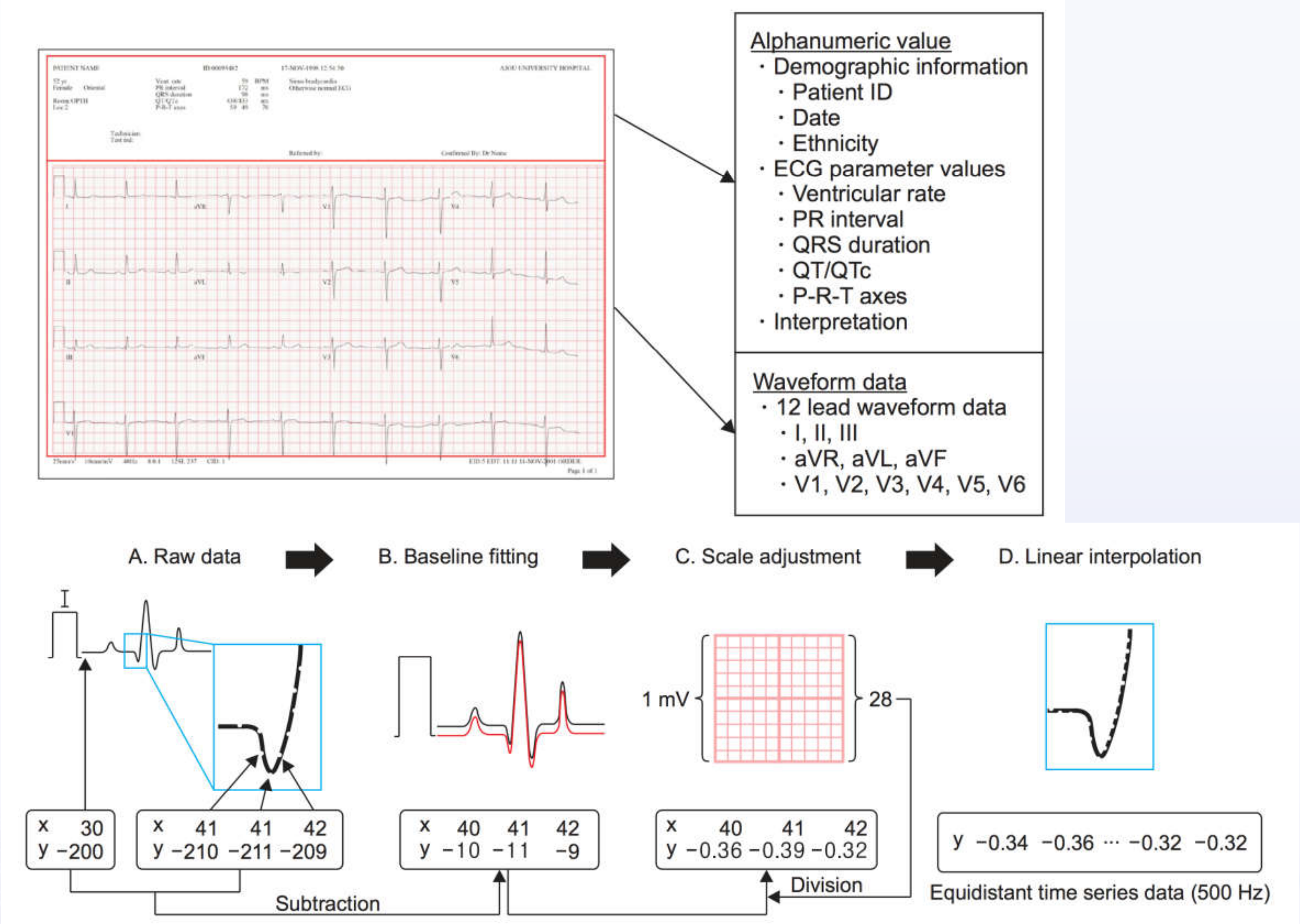
I. Introduction

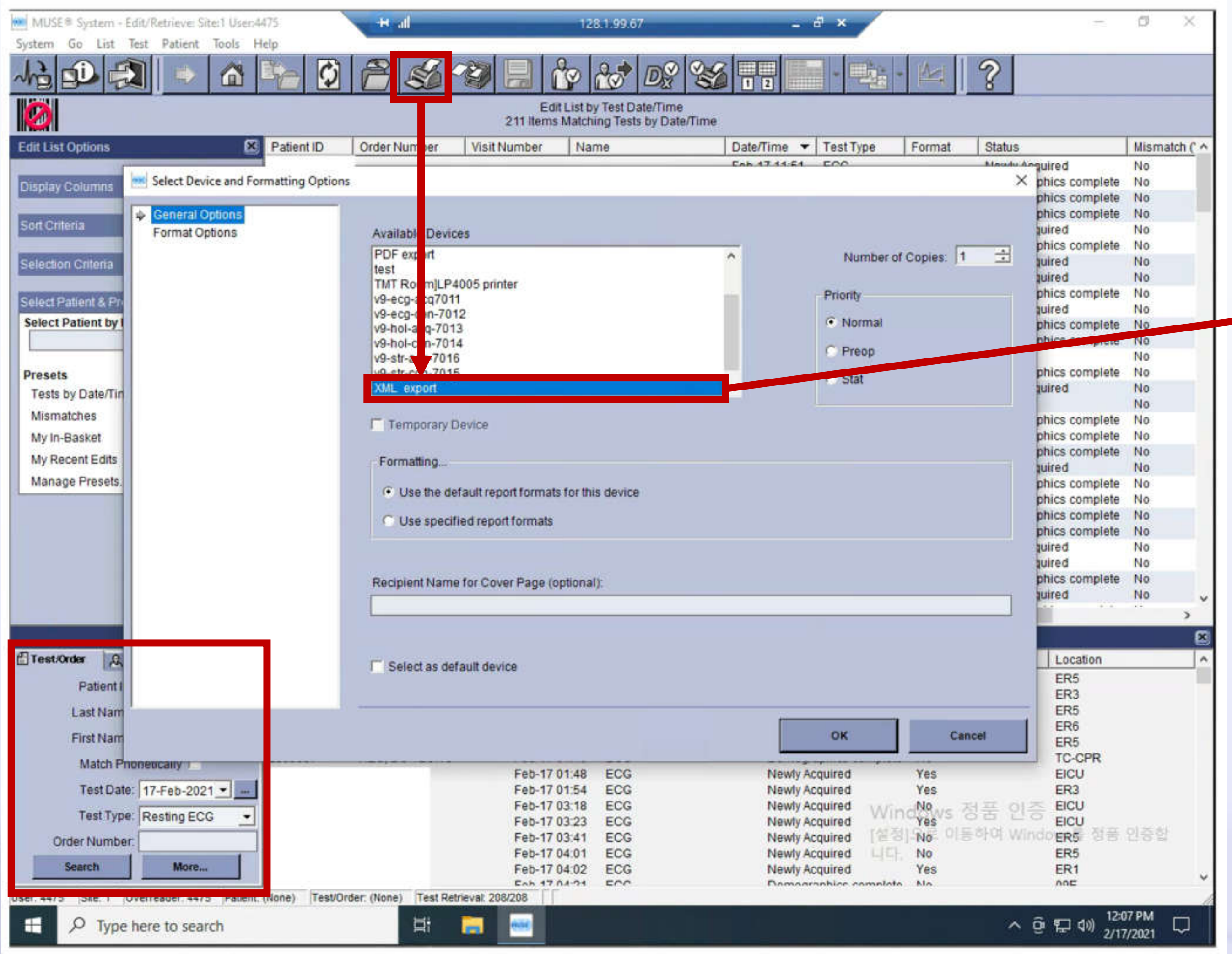
Electrocardiogram (ECG) has been widely used to diagnose various cardiovascular diseases including arrhythmia and acute coronary syndrome [1-3] because it is a non-invasive and convenient tool for measuring the continuous wave sequence characterizing the heart activity [2,4].

Information from ECGs is also used to detect a prolonged QT interval, which is one of the life-threatening adverse drug reactions (ADRs). A prolonged QT interval leads to an irregular heart beat and can result in various types of cardiac arrest including ventricular fibrillation, ventricular tachyarrhythmia, Torsades de Pointes, and sudden death [5-7]. Due



Chung D, Choi J, Jang JH, Kim TY, Byun J, Park H, Lim HS, Park RW, Yoon D. Construction of an Electrocardiogram Database Including 12 Lead Waveforms. Healthc Inform Res. 2018 Jul;24(3):242-246.

ECG 데이터 수집 및 활용 방법 (2019~)



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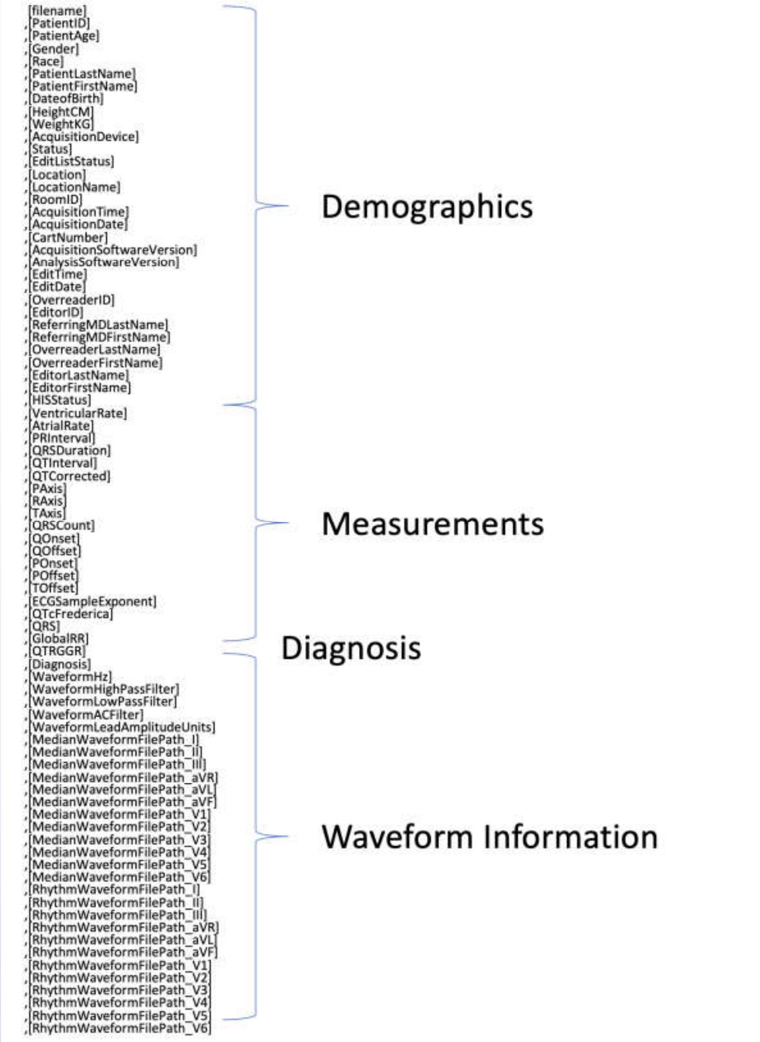

ECG **데이터 수집 및 활용 방법** (2019~)

Computational Medical Informatics

- 2가지 허들
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    - 120만건 데이터를 수집하려면? (최소 600번)
  - 데이터 파싱/디코딩

GE


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Philips


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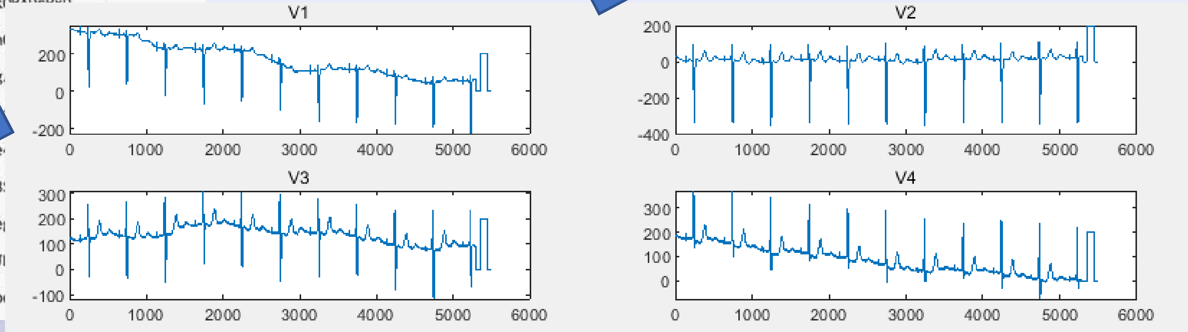

QnA

Computational Medical Informatics

BUDon

› Bottom up Data |

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김태영


구예령


강소라


김소연


박태준


김형준


정의진


장수경