IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 11 September 2024, accepted 24 October 2024, date of publication 28 October 2024, date of current version 11 November 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3487013

RESEARCH ARTICLE

Systematic Comparison of ECG Delineation Algorithm Performance on Smartwatch Data

KATHARINA M. JAEGER[1], MICHAEL NISSEN[1], MADELEINE FLAUCHER[1], LUISA GRAF[1], JOANA JOANIDOPOULOS[1], LARS ANNEKEN[2], HANNA HUEBNER[3,4,5,6], CHLOË GOOSSENS[3,4,5,6], ADRIANA TITZMANN[3,4,5,6], CONSTANZA PONTONES[3,4,5,6], PETER A. FASCHING[3,4,5,6], MATTHIAS W. BECKMANN[3,4,5,6], BJOERN M. ESKOFIER[1,7], (Senior Member, IEEE), AND HEIKE LEUTHEUSER[1]

[1]Department Artificial Intelligence in Biomedical Engineering, Friedrich-Alexander-Universität Erlangen–Nürnberg, 91052 Erlangen, Germany
[2]Department of Medicine 2-Cardiology and Angiology, Friedrich-Alexander-Universität Erlangen-Nürnberg, 91054 Erlangen, Germany
[3]Department of Gynecology and Obstetrics, Uniklinikum Erlangen, Friedrich-Universität Erlangen-Nürnberg, 91054 Erlangen, Germany
[4]Comprehensive Cancer Center Erlangen-EMN (CCC ER-EMN), 91054 Erlangen, Germany
[5]Comprehensive Cancer Center Alliance WERA (CCC WERA), 91054 Erlangen, Germany
[6]Bavarian Cancer Research Center (BZKF), 91052 Erlangen, Germany
[7]Translational Digital Health Group, Institute of AI for Health, Helmholtz Zentrum München—German Research Center for Environmental Health, 85764 Neuherberg, Germany

Corresponding author: Katharina M. Jaeger (katharina.jaeger@fau.de)

This work was supported by the Federal Ministry of Health on the Basis of a Decision by the German Bundestag under Grant ZMVI1-2519DAT400.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the ethics committee of the Friedrich-Alexander-Universität Erlangen-Nürnberg under Application No. 22-237-S and 530_20B.

ABSTRACT Cardiovascular diseases are the leading cause of global mortality, necessitating early detection and continuous monitoring for timely interventions. Smartwatches with electrocardiogram (ECG) recording capabilities enable real-time, at-home cardiac monitoring. Specific ECG characteristics can provide insights into cardiovascular diseases. The delineation of ECGs, which is the identification of fiducial points (such as onsets, offsets, and peaks), is a time-consuming task. Automated ECG delineation can enhance this process, but existing research comparing available algorithms is limited. Furthermore, to the best of our knowledge, none have addressed single-lead ECGs from smartwatches, which can be noisy and unfiltered. Thus, this study evaluates the best-performing open-source algorithm for single-lead and smartwatch ECG data. We used two public datasets (Lobachevsky University Database, QT Database) and two smartwatch datasets (SmartHeartWatch Dataset, SMART Start Dataset) including two devices (Apple Watch, Withings ScanWatch). Algorithms from three toolkits (NeuroKit, ECGKit, ECGdeli) were assessed based on the time deviation between algorithm outputs and reference annotations, sensitivity, true positives, and false negatives. Results were further evaluated against the Common Standards for Quantitative Electrocardiography (CSE) recommendations. ECGdeli outperformed the other algorithms. For QRS on- and offset, ECGkit shows comparable sensitivity, but otherwise lower scores. NeuroKit consistently shows lower sensitivity across all four data sets, however, the temporal deviation between detected point and reference was higher. Overall, sensitivity scores were higher for Apple Watch data compared to Withings ScanWatch data. This study demonstrates that segmentation algorithms are applicable to single-lead smartwatch ECG data, with ECGdeli being the most stable overall, and NeuroKit recommended for scenarios prioritizing the temporal accuracy of detected points.

INDEX TERMS Cardiovascular diseases, mobile health, ECG segmentation, wearable devices.

I. INTRODUCTION

Cardiovascular diseases are the leading cause of global mortality, with their prevalence having doubled over the

The associate editor coordinating the review of this manuscript and approving it for publication was Angelo Trotta.

past three decades [1]. This growing burden underscores the need for effective strategies to manage risk factors and improve cardiovascular health. Early detection and continuous monitoring of cardiac conditions are crucial for timely interventions, which can significantly improve patient outcomes [2], [3].

Specific characteristics of the electrocardiogram (ECG) can provide insights into the condition and prognosis of heart failure patients. A prolonged QRS complex is associated with poorer outcomes [4]. Prolonged QT and QTc duration are predictors of cardiac arrest and sudden death [5], [6]. Changes in T-wave morphology are also predictive of mortality in heart failure patients [7]. Traditional ECG monitoring methods in clinical settings offer valuable diagnostic and prognostic information. However, these methods are often limited to scheduled appointments and brief recording periods, which can miss transient or asymptomatic cardiac events outside these windows.

Smartwatches with ECG monitoring capabilities have emerged as useful, non-invasive tools that complement routine clinical care by offering real-time, continuous cardiac health monitoring [8], [9], [10], [11], [12]. These devices allow patients to take measurements from home, providing flexibility and enabling long-term use. This facilitates new insights into cardiac health, such as understanding disease progression, gaining better insights into medication efficacy, and identifying patterns that may predict acute events. Many smartwatches already feature certified algorithms for detecting atrial fibrillation. Perez et al. showed that the use of smartwatches for continuous heart rate monitoring resulted in the detection of atrial fibrillation in a significant number of participants, which enabled early medical intervention and improved patient outcomes [8]. Initial validation studies to capture important clinical parameters have shown promising results [13], [14], [15], [16], [17], [18], [19]. However, the full potential of smartwatch ECGs is far from being fully exploited.

To ensure that smartwatches can provide reliable cardiac monitoring, it is essential to accurately extract clinically relevant information from recorded ECG data. Automated ECG feature extraction requires sophisticated algorithms and signal processing techniques. This process involves careful signal segmentation and determining fiducial points that mark the onsets, offsets, and peaks of each ECG waveform, a task known as ECG delineation. Manual annotation by cardiologists is time-consuming and impractical for large-scale, continuous monitoring. Further, automatic protocols for ECG annotation can save a considerable amount of time with similar clinical endpoints compared to manual annotation carried out by expert operators, as the work by Jauregui et al. shows [20].

Existing work on ECG delineation focuses on processing traditional 12-channel ECGs obtained through standard clinical equipment [21], [22], [23], [24]. However, ECGs used in a traditional clinical setting differ significantly from smartwatch ECGs. Smartwatch ECGs use only one lead instead of twelve, use different electrode types and involve different recording settings and environments, as users might often be on the move. Further, the smartwatch ECGs undergo pre-filtering, which differs across different devices, and recordings are often performed by laymen without medical training. Given these differences, the question arises whether the established ECG delineation algorithms perform equally well on smartwatch ECG data.

To the best of our knowledge, the performance of ECG delineation algorithms on data obtained from smartwatches has not yet been investigated. With the increasing adoption of smartwatches for health monitoring, this gap highlights an urgent need to evaluate and adapt these algorithms for accurate and reliable use with smartwatch ECG data.

Therefore, the objectives of this work are to: i) determine the best-performing open-source algorithm for delineating ECGs from smartwatch data, ii) evaluate its performance in identifying key fiducial points, and iii) assess how well it performs across various smartwatch models. We base our analysis on four datasets, including two public open-source ECG datasets and two smartwatch datasets recorded by us. Our study evaluated two commonly used smartwatches with ECG functionality and involved a diverse user collective. An overview of this work is shown in Figure 1.

II. DATA SETS

An overview of the characteristics of all datasets included in this study is shown in Table 1.

A. PUBLIC OPEN-SOURCE ECG DATASETS

1) LOBACHEVSKY UNIVERSITY DATABASE

The Lobachevsky University Database (LUDB) [25] was published in 2020 and serves as an open tool for the validation of ECG delineation algorithms. It contains 200 12-lead ECG recordings with a length of 10 seconds each and a sampling frequency of 500 Hz. A variety of different morphologies are represented. For our experiments, we only use lead I as it is most similar to smartwatch ECGs.

2) QT DATABASE

The QT database (QTDB) [26] was introduced in 1997, and it comprises 105 recordings that last for 15 minutes each, taken from two different leads. The sampling frequency for the recordings is 250 Hz, and it covers a wide variety of morphologies.

B. SMARTWATCH DATASETS

The smartwatch datasets included in this study contain data recorded with the Apple Watch Series 7 (Apple Inc., USA) and the Withings ScanWatch (Withings SA, France). The Apple Watch ECG app has FDA clearance, and the Withings ScanWatch has reviewed medical certification in Europe and FDA clearance in the United States. We are not aware of any public datasets containing smartwatch recorded data.

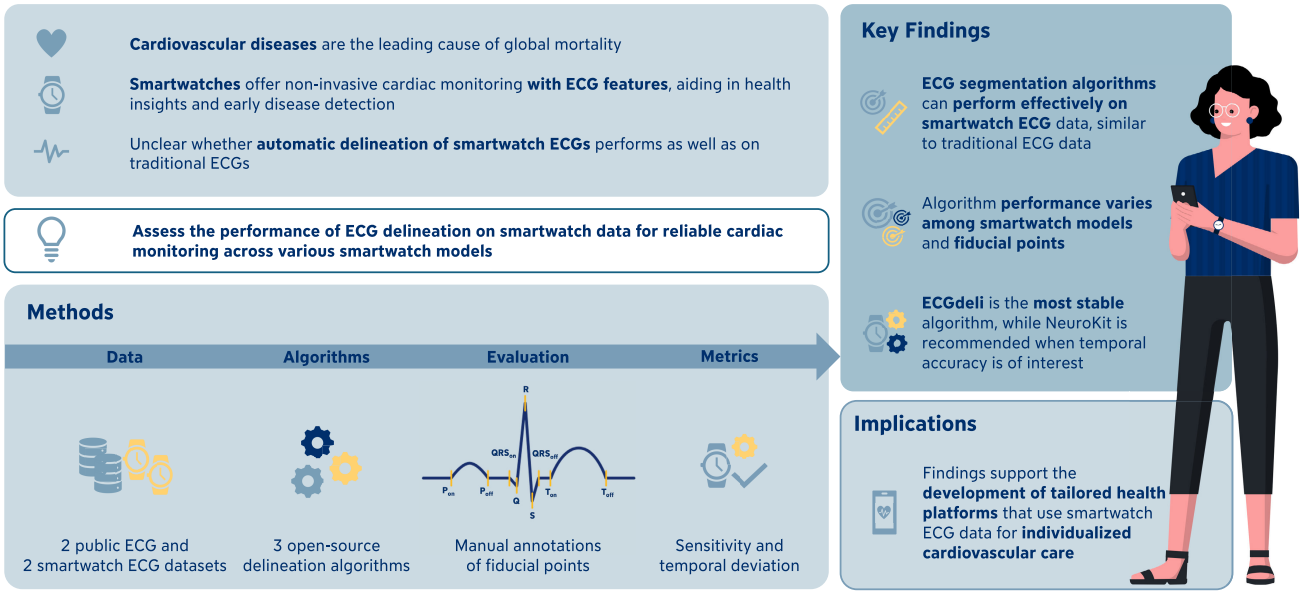


FIGURE 1. Visual abstract showing the main motivation and objective, methods, key findings, and implications of our study.

TABLE 1. Characteristics of the datasets, that are used in this study. The datasets include public datasets containing traditional ECG signals and datasets containing ECGs recorded with smartwatches.

	Year	Number of signals	Signal length	ECG type	Sampling frequency
Lubachevsky University Database (LUDB) [25]	2020	200	10 s	12-channel ECG	500 Hz
QT Database (QTDB) [26]	1997	105	15 min	2-channel ECG	250 Hz
SmartHeartWatch	2022	96	30 s – 50 s	1-channel ECG (Withings ScanWatch / Apple Watch)	300 Hz / 512 Hz
SMART Start	2023	28	30 s – 50 s	1-channel ECG (Withings ScanWatch)	300 Hz

1) SMARTHEARTWATCH DATASET

Data for the SmartHeartWatch study were collected between August and October 2022 at the Machine Learning and Data Analytics Lab of the Friedrich-Alexander Universität Erlangen–Nürnberg, Germany. Participants were asked to self-record an ECG with two different smartwatches in a resting phase as well as in a recovery phase after physical activity. Participants included a healthy group and a group of people with heart failure. The study protocol was approved by the responsible ethics committee (vote number 22-237-S). Participants included in the study were required to be at least 22 years old, capable of completing all study phases as self-assessed, and provide written informed consent. For the healthy group, exclusion criteria included the presence of electrical implants, poor skin integrity in areas where smartwatches were to be applied, diagnosed heart failure or other heart diseases, and pregnancy or breastfeeding. Participants with heart failure were excluded if they had a pacemaker, defibrillator, or other electrical implants, poor skin integrity in relevant areas, or were pregnant or breastfeeding. In total, for each participant four smartwatch ECG recordings were obtained: two with the Apple Watch Series 7 and two with the Withings ScanWatch.

A total of 26 participants, comprising 70 % (n=18) without any known cardiac conditions and 30 % (n=8) with a diagnosis of heart failure (HF), were enrolled in the study. The mean age of the healthy participants was 56 ± 20 years, with 61 % (n=11) females included in this group. The participants with diagnosed heart failure had a mean age of 69 ± 9 years, and among them, 50 % (n=4) were female. During data acquisition, the smartwatches detected atrial fibrillation in eight recordings from two healthy and two participants with HF. These recordings were excluded from the dataset. In total 96 recordings from 25 participants were included in the final dataset. In this study, we did not evaluate differences among resting and recovery phases or between healthy and heart failure participants.

2) SMART START DATASET

The SMART Start dataset originates from a study including pregnant women who were equipped with a Withings ScanWatch, enabling them to conduct measurements at home

independently throughout their pregnancy. The study was conducted at the Department of Gynaecology and Obstetrics, Uniklinikum Erlangen, starting in December 2022. Data was collected using the Carecentive framework for mobile health-powered trials.[1] The study included pregnant women between the ages of 18 and 50 who were between 8+0 to 23+6 weeks pregnant and had given written informed consent. Women with electrical implants were excluded, as were those with poor skin integrity on the wrist or a wrist circumference greater than 20 cm. The study received approval by the responsible ethics committee (530_20*B*). As the data collection is still ongoing at the time of analysis, only a subset has been used, the cutoff date was October 18, 2023. The subset comprises only participants who used the smartwatch during the study period. For each participant, a single ECG recording was selected. To maintain a manageable labeling workload, a random subset was generated from the available data. The resulting dataset consists of 28 participants with an average age of 34 ± 4 years and an average gestational age of 23 ± 7 weeks (mean $\pm$ standard deviation).

C. REFERENCE ANNOTATIONS

1) PUBLIC ECG DATASETS

The LUDB and QTDB datasets contain manual annotations for the on- and offsets of the P-wave, T-wave, and QRS-complex.

2) SMARTWATCH DATASETS

Reference annotation of fiducial points, including on- and offsets of P-wave and T-wave, as well as Q/R/S-peak locations, were conducted by two independent ECG signal processing experts. The SMART Start dataset additionally contains annotations for QRS on- and offset. The annotation process adhered to established cardiologist guidelines and was facilitated using the MaD GUI [27], a dedicated labeling interface.

Figure 2 shows exemplarily the fiducial point locations for an ECG cycle. The fiducial points comprise P-wave: P_{on}, P_{off}, QRS complex: QRS_{on}, Q, R, S, QRS_{off}, and T-wave: T_{on}, T_{off}.

III. METHODS

A. DELINEATION ALGORITHMS

For our experiments, we included the ECG delineation algorithms from the toolboxes NeuroKit,[2] ECGkit,[3] and ECGdeli.[4] All three algorithms provide the source code and extract all of the following features: onset and offsets of P-wave (P_{on}, P_{off}), T-wave (T_{on}, T_{off}) and QRS-complex (QRS_{on}, QRS_{off}), as well as the peaks of the QRS-complex (Q, R, S). We chose these fiducial points as they are available for all algorithms and can be used to compute clinically relevant cardiac features. The ECG delineation algorithms in the Python toolbox NeuroKit [28] and in the Matlab toolbox ECGkit implement the approach by Martinez et al. [29]. The ECG delineation algorithm in the Matlab toolbox ECGdeli is based on the paper by Pilia et al. [30]. All three algorithm implementations are wavelet-based. We chose to evaluate only open-source algorithms to ensure transparency and reproducibility, as their source code is publicly accessible and allows for independent verification of the results. Additionally, open-source algorithms benefit from continuous community-driven improvements and offer flexibility to adapt the code to specific research needs.

B. EVALUATION CRITERIA

As evaluation metrics, we calculated the error as the deviation between the algorithm output and reference annotations in milliseconds (ms) as mean (μ) and standard deviation (σ) over all events in the respective dataset. We considered a difference greater than 120 ms as misdetection and did not include these events in the error detection, as suggested by Beraza and Romero [21]. Sensitivity (Se) was calculated to interpret the number of misdetections. We did not evaluate Positive Predictive Value (PPV) and F1-score, as for LUDB and QTDB, not every heartbeat was annotated, and we, therefore, cannot evaluate false positives.

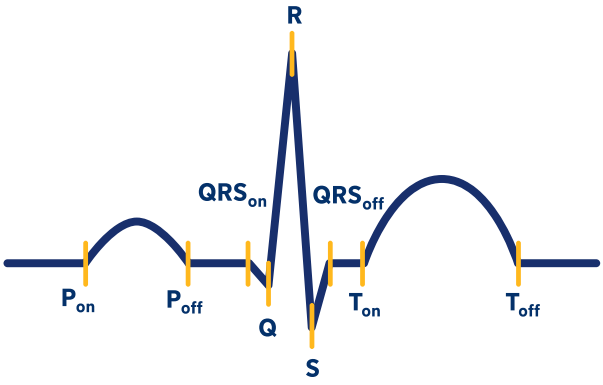


FIGURE 2. Location of fiducial points, including onset and offsets of P-wave (P_{on}, P_{off}), T-wave (T_{on}, T_{off}) and QRS-complex (QRS_{on}, QRS_{off}), as well as the peaks of the QRS-complex (Q, R, S).

TABLE 2. Acceptable deviations in ms for fiducial point delineation according to the CSE working party [31].

	P_{on}	P_{off}	QRS_{on}	QRS_{off}	T_{off}
$\sigma_{acceptable}$ in ms	10.2	12.7	6.5	11.6	30.6

We, further, evaluated the results of the delineation algorithms for each fiducial point with respect to acceptable deviations according to the recommendations by the Common Standards for Quantitative Electrocardiography (CSE) working party [31], as also performed in comparable studies [21], [22]. The values for acceptable deviations are shown in Table 2.

[1] https://carecentive.net/
[2] https://github.com/neuropsychology/NeuroKit
[3] https://ecg-kit.readthedocs.io/en/master/index.html
[4] https://github.com/KIT-IBT/ECGdeli

TABLE 3. Results for delineation algorithms on public ECG datasets and smartwatch datasets. Public datasets: Lobachevsky University Database (LUDB) [26], QT database (QTDB) [25] and their combination (LUDB+QTDB); Smartwatch datasets: SmartHeartWatch, SMART Start, and their combination (SmartHeartWatch+SMART Start). Results are reported in Sensitivity (Se) in %, deviation ($\mu \pm \sigma$) in ms, and the number of True Positives (TP) and False Negatives (FN). Delineation results are shown for the fiducial points on- and offset of P-waves (P_{on} and P_{off}), T-waves (T_{on} and T_{off}) and QRS-complex (QRS_{on} and QRS_{off}) as well as Q/R/S-peak locations (Q, R, S). For each fiducial point, the highest Se among the algorithms is highlighted in bold. A dash (-) indicates that no annotations were available for specific fiducial points in the corresponding dataset.

			P_{on}	P_{off}	QRS_{on}	Q	R	S	QRS_{off}	T_{on}	T_{off}
QTDB	ECGdeli	Se (%)	**98.18**	**98.34**	**99.91**	-	**99.86**	-	98.70	**89.02**	**91.61**
		$\mu \pm \sigma$ (ms)	-6.22 ± 30.09	17.22 ± 25.21	-7.67 ± 21.59	-	-3.72 ± 14.20	-	11.08 ± 29.19	-4.12 ± 41.94	3.19 ± 39.38
		TP	3136	3141	3525	-	3523	-	3482	1257	3245
		FN	58	53	3	-	5	-	46	155	297
	ECGkit	Se (%)	87.41	91.11	99.72	-	97.59	-	**99.55**	71.53	79.08
		$\mu \pm \sigma$ (ms)	3.95 ± 27.23	-3.07 ± 23.01	10.65 ± 15.88	-	-7.22 ± 18.32	-	2.95 ± 19.39	-4.73 ± 43.06	3.33 ± 31.29
		TP	2792	2910	3518	-	3443	-	3512	1010	2801
		FN	402	284	10	-	85	-	16	402	741
	NeuroKit	Se (%)	96.34	94.27	90.45	-	98.41	-	82.20	67.00	66.80
		$\mu \pm \sigma$ (ms)	25.97 ± 33.65	-18.83 ± 31.63	-24.92 ± 40.64	-	-11.65 ± 19.54	-	-6.62 ± 28.08	23.22 ± 61.50	-21.64 ± 33.91
		TP	3077	3011	3191	-	3472	-	2900	946	2366
		FN	117	183	337	-	56	-	628	466	1176
LUDB	ECGdeli	Se (%)	**98.5**	**99.21**	99.34	-	**99.29**	-	**99.40**	**96.41**	**92.81**
		$\mu \pm \sigma$ (ms)	-18.16 ± 28.21	21.26 ± 15.39	-11.53 ± 13.58	-	4.19 ± 10.42	-	17.40 ± 20.62	-9.04 ± 34.62	10.44 ± 28.17
		TP	1381	1390	1817	-	1816	-	1818	1583	1524
		FN	20	11	12	-	13	-	11	59	118
	ECGkit	Se (%)	88.15	91.79	**99.56**	-	99.18	-	98.80	89.10	88.55
		$\mu \pm \sigma$ (ms)	-10.86 ± 24.09	-8.07 ± 19.52	4.70 ± 14.71	-	1.90 ± 13.0	-	-2.52 ± 15.38	-11.60 ± 25.0	3.84 ± 25.48
		TP	1235	1286	1821	-	1814	-	1807	1463	1454
		FN	166	115	8	-	15	-	22	179	188
	NeuroKit	Se (%)	97.86	93.72	95.63	-	98.74	-	94.59	86.36	72.47
		$\mu \pm \sigma$ (ms)	11.02 ± 35.03	-22.37 ± 35.08	-6.44 ± 23.92	-	0.41 ± 12.59	-	-3.91 ± 22.40	24.35 ± 57.30	-17.75 ± 28.93
		TP	1371	1313	1749	-	1806	-	1730	1418	1190
		FN	30	88	80	-	23	-	99	224	452
SmartHeartWatch	ECGdeli	Se (%)	**93.97**	**96.7**	-	**98.38**	**98.11**	**98.44**	-	**96.81**	**95.72**
		$\mu \pm \sigma$ (ms)	-9.90 ± 44.07	20.17 ± 27.62	-	13.94 ± 20.45	15.72 ± 19.61	15.77 ± 25.19	-	-5.12 ± 32.84	11.60 ± 31.49
		TP	2480	2552	-	3101	3111	3102	-	2849	2817
		FN	159	87	-	51	60	49		94	126
	ECGkit	Se (%)	69.27	72.30	-	45.53	96.25	63.92	-	72.38	70.51
		$\mu \pm \sigma$ (ms)	-8.64 ± 41.55	-16.22 ± 31.47	-	8.14 ± 15.52	6.69 ± 18.43	3.03 ± 26.10	-	-5.20 ± 36.9	-6.09 ± 37.12
		TP	1828	1908	-	1435	3052	2014	-	2130	2075
		FN	811	731	-	1717	119	1137	-	813	868
	NeuroKit	Se (%)	82.76	81.02	-	92.93	97.26	92.8	-	90.49	90.01
		$\mu \pm \sigma$ (ms)	15.50 ± 36.62	-16.56 ± 27.78	-	-7.66 ± 17.13	-1.75 ± 9.34	2.54 ± 26.87	-	37.65 ± 33.62	-23.94 ± 24.90
		TP	2184	2138	-	2929	3084	2924	-	2663	2649
		FN	455	501	-	223	87	227	-	280	294
SMART Start	ECGdeli	Se (%)	88.95	**97.81**	**99.64**	**99.73**	**99.82**	**99.64**	**99.55**	**95.46**	**97.73**
		$\mu \pm \sigma$ (ms)	-25.14 ± 53.09	17.73 ± 27.2	4.94 ± 24.03	7.72 ± 18.31	3.13 ± 4.02	1.26 ± 12.75	-4.62 ± 21.67	33.62 ± 38.95	-7.51 ± 33.99
		TP	974	1071	1107	1109	1109	1106	1096	1052	1077
		FN	121	24	4	3	2	4	5	50	25
	ECGkit	Se (%)	68.40	74.25	96.94	44.60	98.29	60.45	95.73	85.57	81.58
		$\mu \pm \sigma$ (ms)	-4.79 ± 37.86	-15.29 ± 28.77	19.22 ± 29.16	-0.54 ± 7.95	-0.84 ± 10.08	-1.21 ± 15.73	-20.99 ± 28.72	17.88 ± 39.22	-1.54 ± 32.61
		TP	749	813	1077	496	1092	671	1054	943	899
		FN	346	282	34	616	19	439	47	159	203
	NeuroKit	Se (%)	**90.14**	95.07	93.70	95.86	99.28	95.86	98.55	79.76	97.1
		$\mu \pm \sigma$ (ms)	31.96 ± 30.84	-16.19 ± 28.59	-8.71 ± 27.86	-9.69 ± 21.23	-0.06 ± 6.47	2.87 ± 14.01	-15.39 ± 19.55	70.01 ± 33.12	-33.97 ± 28.34
		TP	987	1041	1041	1066	1103	1064	1085	879	1070
		FN	108	54	70	46	8	46	16	223	32
QTDB + LUDB	ECGdeli	Se (%)	**98.30**	**98.61**	**99.72**	-	**99.66**	-	98.94	**92.99**	**91.99**
		$\mu \pm \sigma$ (ms)	-9.94 ± 30.02	18.46 ± 22.73	-8.98 ± 19.33	-	-1.03 ± 13.57	-	13.25 ± 26.73	-6.86 ± 38.11	5.51 ± 36.33
		TP	4517	4531	5342	-	5339	-	5300	2840	4769
		FN	78	64	15	-	18	-	57	214	415
	ECGkit	Se (%)	87.64	91.32	99.66	-	98.13	-	**99.29**	80.98	82.08
		$\mu \pm \sigma$ (ms)	-0.59 ± 27.18	4.6 ± 22.12	8.62 ± 15.75	-	-4.08 ± 17.23	-	1.09 ± 18.31	-8.79 ± 33.74	3.50 ± 29.43
		TP	4027	4196	5339	-	5257	-	5319	2473	4255
		FN	568	399	18	-	100	-	38	581	929
	NeuroKit	Se (%)	96.80	94.10	92.22	-	98.53	-	86.43	77.41	68.60
		$\mu \pm \sigma$ (ms)	21.36 ± 34.77	-19.91 ± 32.76	-18.38 ± 36.71	-	-7.53 ± 18.39	-	-5.60 ± 26.13	23.90 ± 59.02	-20.34 ± 32.38
		TP	4448	4324	4940	-	5278	-	4630	2364	3556
		FN	147	271	417	-	79	-	727	690	1628
SmartHeartWatch + SMART Start	ECGdeli	Se (%)	**92.50**	**97.03**	-	**98.73**	**98.55**	**98.76**	-	**96.44**	**96.27**
		$\mu \pm \sigma$ (ms)	-14.20 ± 47.29	19.45 ± 27.52	-	12.30 ± 20.1	12.41 ± 17.84	11.96 ± 23.48	-	5.32 ± 38.63	6.32 ± 33.32
		TP	3454	3623	-	4210	4220	4208	-	3901	3894
		FN	280	111	-	54	62	53	-	144	151
	ECGkit	Se (%)	69.01	72.87	-	45.29	96.78	63.01	-	75.97	73.52
		$\mu \pm \sigma$ (ms)	-7.52 ± 40.55	-15.94 ± 30.69	-	5.91 ± 14.48	4.71 ± 16.97	1.97 ± 24.0	-	1.88 ± 39.1	-4.72 ± 35.88
		TP	2577	2721	-	1931	4144	2685	-	3073	2974
		FN	1157	1013	-	2333	138	1576	-	972	1071
	NeuroKit	Se (%)	84.92	85.14	-	93.69	97.78	93.59	-	87.56	91.94
		$\mu \pm \sigma$ (ms)	20.62 ± 35.74	-16.44 ± 28.05	-	-8.20 ± 18.34	-1.30 ± 8.71	2.63 ± 24.12	-	45.68 ± 36.3	-26.82 ± 26.33
		TP	3171	3179	-	3995	4187	3988	-	3542	3719
		FN	563	555	-	269	95	273	-	503	326

To increase the amount of data for the analysis, we additionally evaluated the algorithms on the combination of the smartwatch ECG data sets (SmartHeartWatch + SMART Start) and the combination of the two publicly available ECG datasets (QTDB + LUDB).

IV. RESULTS

A. BENCHMARK ECG DELINEATION ALGORITHMS

Table 3 shows the delineation results for the public ECG datasets QTDB and LUDB, as well as for the smartwatch datasets SmartHeartWatch and SMART Start. The results are

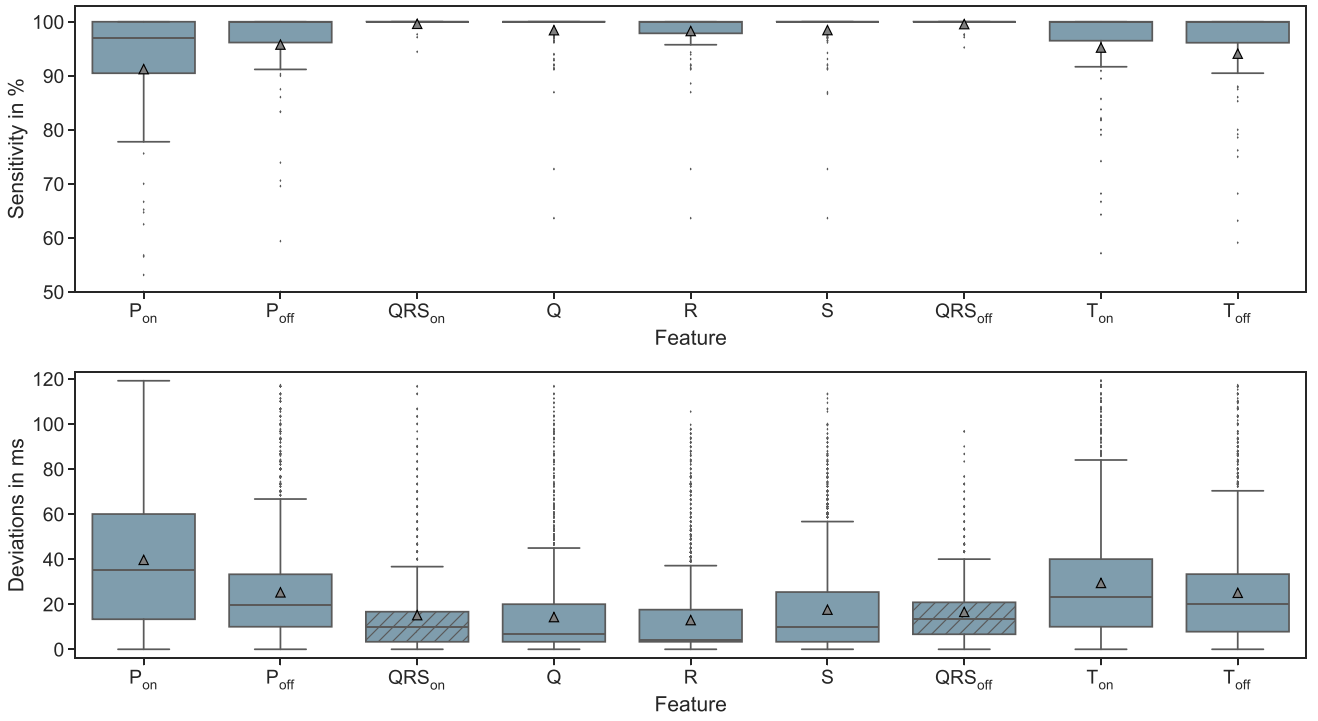


FIGURE 3. Boxplots showing sensitivity in % and deviation in ms of ECG delineation using ECGdeli algorithm on SmartHeartWatch and SMART Start datasets. Fiducial points include on- and offset of P-waves (P_{on}, P_{off}) and T-waves (T_{on}, T_{off}), and Q/R/S-peak locations (Q, R, S) (solid color). Additionally, results for on- and offset of the QRS-complex (QRS_{on}, QRS_{off}) are shown, but only on the SMART Start dataset (dashed color). Only true positive detections are considered within this plot. The horizontal bars represent the median sensitivity, diamonds (⋄) indicate outliers. The boxes represent the interquartile range, and the vertical lines extend to the furthest observation that is not considered an outlier, i. e., that is at most 1.5 times the interquartile range from the top or bottom of the box. Triangles (△) represent the mean.

displayed as Se in %, deviation from the ground truth in ms ($\mu \pm \sigma$) and the number of true positives (TP) and false negatives (FN).

ECGdeli achieves the highest Se for the on- and offset of P- and T-waves on the public ECG datasets (LUDB, QTDB). For QRS_{on} and QRS_{off}, ECGkit achieves a comparable Se. ECGdeli performs best on all fiducial points for the smartwatch datasets (SmartHeartWatch, SMART Start), except for P_{on} on the SMART Start dataset, where NeuroKit performs best. In all other cases, NeuroKit consistently has a lower Se for all the points on any of the four investigated datasets.

For the following analysis, we concentrate on ECGdeli, which performed best among the investigated algorithms.

B. FIDUCIAL POINT ANALYSIS FOR ECG DELINEATION ON SMARTWATCH DATA

Figure 3 shows the Se in % and the deviation in ms of ECGdeli algorithm for all investigated fiducial points. QRS_{on} and QRS_{off} is evaluated on the SMART Start dataset only, whereas the results for all other fiducial points comprise data from SMART Start and SmartHeartWatch datasets.

ECGdeli achieves a Se over 90% for all fiducial points. The QRS-complex shows the lowest errors, with the points Q, R, S, as well as QRS_{on} and QRS_{off}, exhibiting high Se and a low mean deviation. In contrast, P_{on} is segmented with the lowest Se and the highest deviation. Detailed results can be seen in Table 3.

C. DELINEATION OF DIFFERENT SMARTWATCH TYPES

Figure 4 shows the delineation performance using the ECGdeli algorithm for Apple Watch and Withings ScanWatch recordings. The Se of delineating the Apple Watch using ECGdeli is generally higher for all fiducial points compared to the Withings ScanWatch. Especially for the QRS-complex, ECGdeli hardly misses any peaks on the Apple Watch. There is a slightly higher deviation for the QRS-complex on the Apple Watch. For P-wave and T-wave, the deviations are comparable between Apple Watch and ScanWatch. Example signals for the Apple Watch and Withings ScanWatch including fiducial point locations determined by ECGdeli and corresponding reference annotations are shown in Figure 5.

Detailed delineation results for all three algorithms are attached in the supplementary material.

V. DISCUSSION

In this study, we evaluated the performance of automatic delineation algorithms for ECGs on smartwatch data. We benchmarked three open-source algorithms using four datasets. Two of these datasets consist of smartwatch ECGs collected from a diverse user group. Our results show

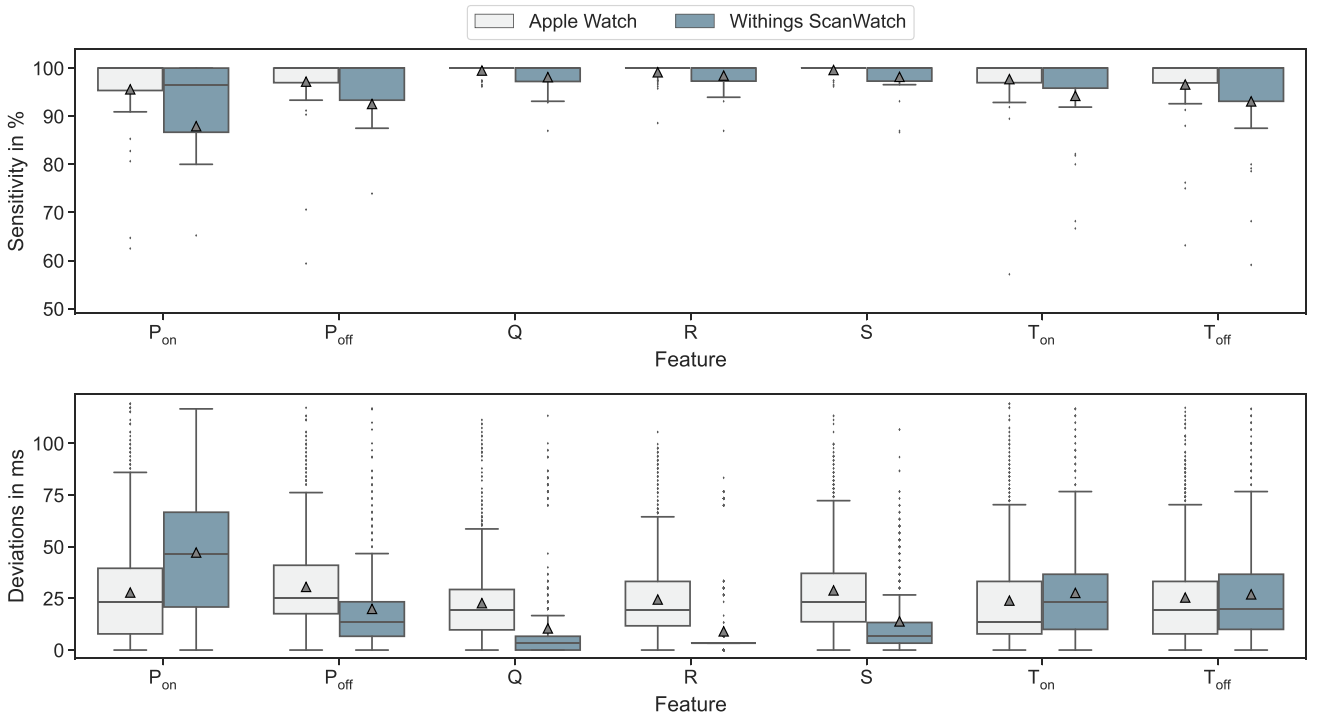


FIGURE 4. Boxplots showing the sensitivity in % and deviations in ms of ECG delineation using ECGdeli algorithm on the SmartHeartWatch dataset for Apple Watch and Withings ScanWatch. Delineation was performed for on- and offset of P-waves (P_{on}, P_{off}) and T-waves (T_{on}, T_{off}), and Q/R/S-peak locations (Q, R, S). Only true positive detections are considered within this plot. The horizontal bars represent the median sensitivity, diamonds (⋄) indicate outliers. The boxes represent the interquartile range, and the vertical lines extend to the furthest observation that is not considered an outlier, i. e., that is at most 1.5 times the interquartile range from the top or bottom of the box. Triangles (△) represent the mean.

that delineation performance is consistent across all four datasets, although the performance varies among different fiducial points. ECGdeli is the most stable performing algorithm for smartwatch data, whereas NeuroKit exhibited higher temporal accuracy in detecting fiducial points, despite recognizing fewer points correctly overall.

There are differences between the watches: the ECGdeli algorithm identifies P-waves more accurately on the Apple Watch. While more points are detected correctly with the Apple Watch, the overall deviation is higher compared to the ScanWatch. Figure 5 illustrates the differences in signal quality: the Apple Watch produces a cleaner ECG signal, whereas the Withings ScanWatch appears to contain high frequency noise. We used the signals in their raw format without applying any preprocessing algorithms. Both manufacturers do not disclose details regarding the internal preprocessing of the signals. For our analysis, we focused on the raw signals provided by the watches to ensure comparability and universal applicability.

The strengths of our study include a diverse user group and its evaluation across two leading smartwatch models.

When comparing the mean deviation of the ECGdeli algorithm on smartwatch data with normal deviations resulting from inter-observer differences (see Table 2), the limits for QRS_{on}, QRS_{off}, and T_{off} are within the range, while for P_{on} and P_{off}, they are outside the range of acceptable values.

We achieve comparable results to existing algorithm benchmarks on conventional ECG datasets [21], [24]. Additionally, our implementation of ECGdeli shows similar results to the original publication by Pilia et al. [30]. Compared to the results reported by Beraza and Romero [21], we found discrepancies in the performance of ECGkit on QTDB, especially for the T-wave. However, our benchmarking approach differed slightly. We focused only on lead I, unlike their study, which considered two leads.

This work has several limitations. First, annotations for QRS_{on} and QRS_{off} are available only for one of two smartwatch datasets, which may limit the generalizability of these findings. Compared to other benchmarking studies, we used only a small selection of algorithms, as our focus was on open-source implementations, which ensure greater transparency and reproducibility of results. Furthermore, the studies on smartwatch data involved a small sample size, which may impact the robustness and applicability of the results.

Existing studies have demonstrated the utility of smartwatches in managing various conditions, including heart failure [12], [19], cardiac rhythm safety in medication treatment [10] or monitoring congenital heart disease in children [14]. The findings of our underlying study, which confirm the feasibility of automatic segmentation using smartwatches, can be leveraged to develop mobile health

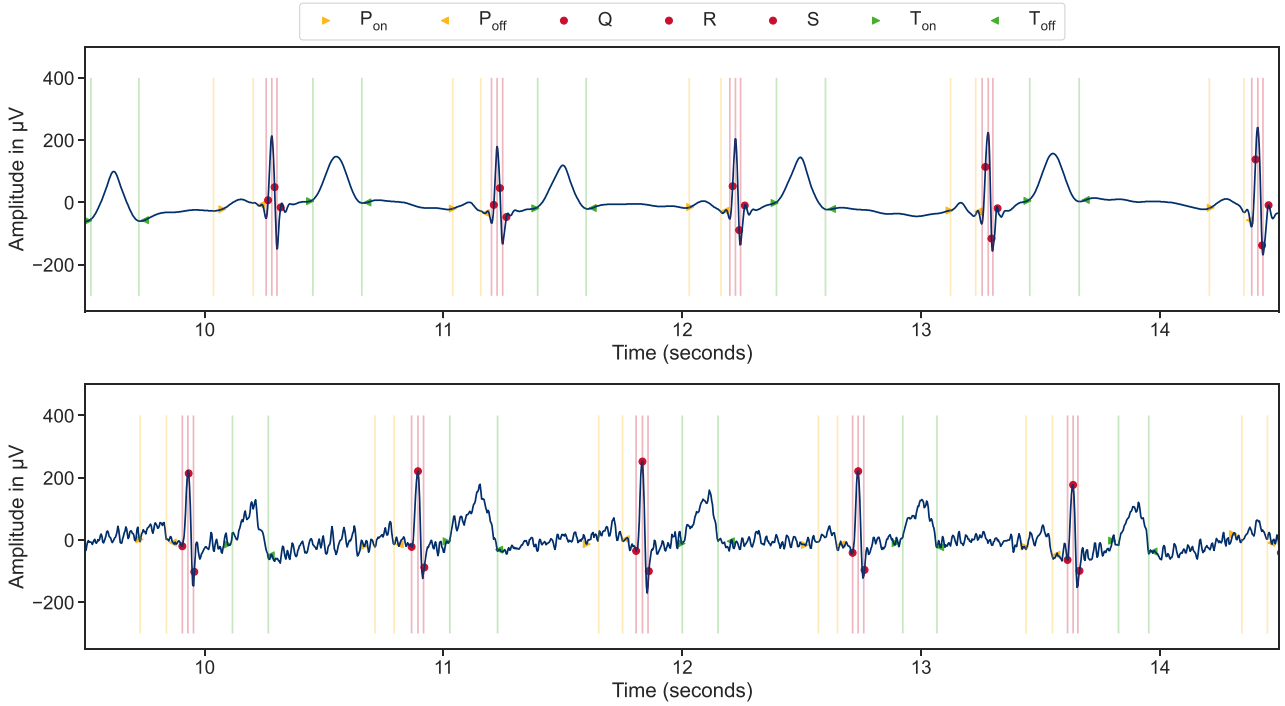


FIGURE 5. Example signal of an ECG recorded with the Apple Watch (upper plot) and Withings ScanWatch (lower plot) from the same participant (SmartHeartWatch, age: 52, sex: female, condition: healthy, phase: resting). Yellow markers correspond to P-waves, red to QRS-complex, green to T-waves. The symbol ▷ corresponds to the onset of a wave, ∘ corresponds to the wave peak, ◁ corresponds to the offset of a wave. The vertical lines indicate reference annotations.

solutions/digital health platforms for these cardiovascular conditions.

For future studies, we recommend selecting the algorithm based on the specific application and deciding whether to prioritize high accuracy or a high detection rate, and ensuring that it suits the particular smartwatch being used.

VI. CONCLUSION AND OUTLOOK

We demonstrate the feasibility of segmentation algorithms for ECG data generated by smartwatches, paving the way for further studies on smartwatch-based heart disease monitoring. We conclude that open-source ECG segmentation algorithms perform equally well on smartwatch ECG data compared to traditional ECG data. Specifically, ECGdeli proved to be the most stable algorithm overall, while NeuroKit is recommended when temporal accuracy of detected points is of interest.

Future work should focus on clinical validation of these algorithms for specific cardiovascular disease markers. Our heterogeneous findings indicate that the functionality of automatic delineation algorithms should be further tested across multiple smartwatch models to ensure broader applicability and reliability.

ACKNOWLEDGMENT

Katharina M. Jaeger analyzed the data, created all figures, and drafted the article. Michael Nissen, Madeleine Flaucher, and Heike Leutheuser assisted in interpreting the results and writing the article. Lars Anneken provided clinical expertise and assisted in data annotation. Bjoern M. Eskofier, Heike Leutheuser, Matthias W. Beckmann, Peter A. Fasching, and Hanna Huebner supervised the project and provided resources. Michael Nissen, Luisa Graf, Hanna Huebner, Chloë Goossens, Adriana Titzmann, and Constanza Pontones supported in study conception, management, patient recruitment, and investigation. Joana Joanidopoulos assisted in data annotation. All authors commented, critically reviewed, and approved the final article.

REFERENCES

[1] G. A. Roth et al., "Global burden of cardiovascular diseases and risk factors, 1990–2019: Update from the GBD 2019 study," *J. Amer. College Cardiol.*, vol. 76, no. 25, pp. 2982–3021, Dec. 2020.

[2] M. Arrigo, M. Jessup, W. Mullens, N. Reza, A. M. Shah, K. Sliwa, and A. Mebazaa, "Acute heart failure," *Nature Rev. Disease Primers*, vol. 6, no. 1, pp. 1–15, Mar. 2020.

[3] W. T. Abraham, P. B. Adamson, R. C. Bourge, M. F. Aaron, M. R. Costanzo, L. W. Stevenson, W. Strickland, S. Neelagaru, N. Raval, S. Krueger, S. Weiner, D. Shavelle, B. Jeffries, and J. S. Yadav, "Wireless pulmonary artery haemodynamic monitoring in chronic heart failure: A randomised controlled trial," *Lancet*, vol. 377, no. 9766, pp. 658–666, Feb. 2011.

[4] A. Kashani and S. S. Barold, "Significance of QRS complex duration in patients with heart failure," *J. Amer. College Cardiol.*, vol. 46, no. 12, pp. 2183–2192, Dec. 2005.

[5] E. Watanabe, T. Arakawa, T. Uchiyama, M. Tong, K. Yasui, H. Takeuchi, T. Terasawa, I. Kodama, and H. Hishida, "Prognostic significance of circadian variability of RR and QT intervals and QT dynamicity in patients with chronic heart failure," *Heart Rhythm*, vol. 4, no. 8, pp. 999–1005, Aug. 2007.

[6] P. Arsenos, K. A. Gatzoulis, A. Laina, I. Doundoulakis, S. Soulaidopoulos, A. Kordalis, G. Oikonomou, K. Triantafyllou, N. Fragakis, V. Vasilikos, and K. Tsioufis, "QT interval extracted from 30-minute short resting Holter ECG recordings predicts mortality in heart failure," *J. Electrocardiol.*, vol. 72, pp. 109–114, May 2022.

[7] J. L. Isaksen, J. Ghouse, C. Graff, M. S. Olesen, A. G. Holst, A. Pietersen, J. B. Nielsen, M. W. Skov, and J. K. Kanters, "Electrocardiographic T-wave morphology and risk of mortality," *Int. J. Cardiol.*, vol. 328, pp. 199–205, Apr. 2021.

[8] M. V. Perez et al., "Large-scale assessment of a smartwatch to identify atrial fibrillation," *New England J. Med.*, vol. 381, no. 20, pp. 1909–1917, Nov. 2019.

[9] M. Nasarre, M. Strik, F. D. Ramirez, S. Buliard, H. Marchand, S. Abu-Alrub, S. Ploux, M. Haïssaguerre, and P. Bordachar, "Using a smartwatch electrocardiogram to detect abnormalities associated with sudden cardiac arrest in young adults," *EP Europace*, vol. 24, no. 3, pp. 406–412, Mar. 2022.

[10] B. Maille, M. Wilkin, M. Million, N. Rességuier, F. Franceschi, L. Koutbi-Franceschi, J. Hourdain, E. Martinez, M. Zabern, C. Gardella, H. Tissot-Dupont, J. P. Singh, J.-C. Deharo, and L. Fiorina, "Smartwatch electrocardiogram and artificial intelligence for assessing cardiac-rhythm safety of drug therapy in the COVID-19 pandemic. The QT-logs study," *Int. J. Cardiol.*, vol. 331, pp. 333–339, May 2021.

[11] C. O. Avila, "Novel use of apple watch 4 to obtain 3-lead electrocardiogram and detect cardiac ischemia," *Permanente J.*, vol. 23, pp. 19–25, Jun. 2019.

[12] A. Singhal and M. R. Cowie, "The role of wearables in heart failure," *Current Heart Failure Rep.*, vol. 17, no. 4, pp. 125–132, Aug. 2020.

[13] T. Caillol, M. Strik, F. D. Ramirez, S. Abu-Alrub, H. Marchand, S. Buliard, N. Welte, S. Ploux, M. Haïssaguerre, and P. Bordachar, "Accuracy of a smartwatch-derived ECG for diagnosing bradyarrhythmias, tachyarrhythmias, and cardiac ischemia," *Circulat., Arrhythmia Electrophysiol.*, vol. 14, no. 1, Jan. 2021, Art. no. e009260.

[14] M. Kobel, P. Kalden, A. Michaelis, F. Markel, S. Mensch, M. Weidenbach, F. T. Riede, F. Löffelbein, A. Bollmann, A. S. Shamloo, I. Dähnert, R. A. Gebauer, and C. Paech, "Accuracy of the apple watch iECG in children with and without congenital heart disease," *Pediatric Cardiol.*, vol. 43, no. 1, pp. 191–196, Jan. 2022.

[15] D. Mannhart, E. Hennings, M. Lischer, C. Vernier, J. Du Fay de Lavallaz, S. Knecht, B. Schaer, S. Osswald, M. Kühne, C. Sticherling, and P. Badertscher, "Clinical validation of automated corrected QT-interval measurements from a single lead electrocardiogram using a novel smartwatch," *Frontiers Cardiovascular Med.*, vol. 9, Jun. 2022, Art. no. 906079.

[16] N. Saghir, A. Aggarwal, N. Soneji, V. Valencia, G. Rodgers, and T. Kurian, "A comparison of manual electrocardiographic interval and waveform analysis in lead 1 of 12-lead ECG and apple watch ECG: A validation study," *Cardiovascular Digit. Health J.*, vol. 1, no. 1, pp. 30–36, Jul. 2020.

[17] C. A. M. Spaccarotella, S. Migliarino, A. Mongiardo, J. Sabatino, G. Santarpia, S. De Rosa, A. Curcio, and C. Indolfi, "Measurement of the QT interval using the apple watch," *Sci. Rep.*, vol. 11, no. 1, p. 10817, May 2021.

[18] N. Sprenger, A. S. Shamloo, J. Schäfer, S. Burkhardt, K. Mouratis, G. Hindricks, A. Bollmann, and A. Arya, "Feasibility and reliability of smartwatch to obtain precordial lead electrocardiogram recordings," *Sensors*, vol. 22, no. 3, p. 1217, Feb. 2022.

[19] M. Strik, T. Caillol, F. D. Ramirez, S. Abu-Alrub, H. Marchand, N. Welte, P. Ritter, M. Haïssaguerre, S. Ploux, and P. Bordachar, "Validating QT-interval measurement using the apple watch ECG to enable remote monitoring during the COVID-19 pandemic," *Circulation*, vol. 142, no. 4, pp. 416–418, Jul. 2020.

[20] B. Jáuregui, J. Fernández-Armenta, J. Acosta, D. Penela, C. Terés, A. Ordóñez, D. Soto-Iglesias, E. Silva, A. Chauca, J. M. Carreño, C. Scherer, A. Pedrote, and A. Berruezo, "MANual vs. automatic local activation time annotation for guiding premature ventricular complex ablation procedures (MANIaC-PVC study)," *EP Europace*, vol. 23, no. 8, pp. 1285–1294, Aug. 2021.

[21] I. Beraza and I. Romero, "Comparative study of algorithms for ECG segmentation," *Biomed. Signal Process. Control*, vol. 34, pp. 166–173, Apr. 2017.

[22] G. Chen, M. Chen, J. Zhang, L. Zhang, and C. Pang, "A crucial wave detection and delineation method for twelve-lead ECG signals," *IEEE Access*, vol. 8, pp. 10707–10717, 2020.

[23] G. Jimenez-Perez, A. Alcaine, and O. Camara, "Delineation of the electrocardiogram with a mixed-quality-annotations dataset using convolutional neural networks," *Sci. Rep.*, vol. 11, no. 1, p. 863, Jan. 2021.

[24] A. I. Kalyakulina, I. I. Yusipov, V. A. Moskalenko, A. V. Nikolskiy, A. A. Kozlov, N. Y. Zolotykh, and M. V. Ivanchenko, "Finding morphology points of electrocardiographic-signal waves using wavelet analysis," *Radiophys. Quantum Electron.*, vol. 61, nos. 8–9, pp. 689–703, Jan. 2019.

[25] A. I. Kalyakulina, I. I. Yusipov, V. A. Moskalenko, A. V. Nikolskiy, K. A. Kosonogov, G. V. Osipov, N. Yu. Zolotykh, and M. V. Ivanchenko, "LUDB: A new open-access validation tool for electrocardiogram delineation algorithms," *IEEE Access*, vol. 8, pp. 186181–186190, 2020.

[26] P. Laguna, R. G. Mark, A. Goldberg, and G. B. Moody, "A database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG," in *Proc. Comput. Cardiol.*, 1997, pp. 673–676.

[27] M. Ollenschläger, A. Küderle, W. Mehringer, A.-K. Seifer, J. Winkler, H. Gaßner, F. Kluge, and B. M. Eskofier, "MaD GUI: An open-source Python package for annotation and analysis of time-series data," *Sensors*, vol. 22, no. 15, p. 5849, Aug. 2022.

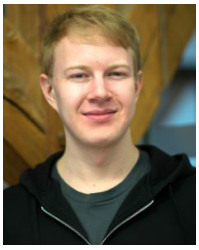
[28] D. Makowski, T. Pham, Z. J. Lau, J. C. Brammer, F. Lespinasse, H. Pham, C. Schölzel, and S. H. A. Chen, "NeuroKit2: A Python toolbox for neurophysiological signal processing," *Behav. Res. Methods*, vol. 53, no. 4, pp. 1689–1696, Aug. 2021.

[29] J. P. Martinez, R. Almeida, S. Olmos, A. P. Rocha, and P. Laguna, "A wavelet-based ECG delineator: Evaluation on standard databases," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 4, pp. 570–581, Apr. 2004.

[30] N. Pilia, C. Nagel, G. Lenis, S. Becker, O. Dössel, and A. Loewe, "ECGdeli—An open source ECG delineation toolbox for MATLAB," *SoftwareX*, vol. 13, Jan. 2021, Art. no. 100639.

[31] The CSE Working Party, "Recommendations for measurement standards in quantitative electrocardiography," *Eur. Heart J.*, vol. 6, no. 10, pp. 815–825, Oct. 1985.

KATHARINA M. JAEGER received the master's degree in medical engineering (specializing in signal processing and machine learning) from the Friedrich-Alexander-Universität Erlangen–Nürnberg (FAU), Germany, where she is currently pursuing the Ph.D. degree with the Machine Learning and Data Analytics Laboratory. She is involved in several interdisciplinary projects, including the SMART Start Project, which aims to integrate innovative technologies into prenatal care to improve health outcomes for mothers and newborns. In addition, she contributes to the teaching and mentoring of students in the field of biomedical signal processing. Her research focuses primarily on developing algorithms for health informatics, particularly in wearable technology and biomedical data analysis.



MICHAEL NISSEN received the B.Sc. degree in information systems and the M.Sc. degree in computer science from Friedrich-Alexander-Universität Erlangen–Nürnberg (FAU), in 2016 and 2020, respectively, where he is currently pursuing the Ph.D. degree with the Machine Learning and Data Analytics Laboratory (MaD Lab). He is a Research Associate with MaD Lab, FAU. His research interests include digital health, virtual clinical trials, biomedical signal analysis, and human–computer interaction. Furthermore, he offers freelance consultant services in digital health, web development, and e-commerce.

MADELEINE FLAUCHER received the bachelor's degree in biomedical engineering from Ostbayerische Technische Hochschule Regensburg, in 2018, and the master's degree in medical engineering from the Friedrich-Alexander-Universität Erlangen–Nürnberg (FAU), in February 2021, where she is currently pursuing the Ph.D. degree with the Machine Learning and Data Analytics Laboratory. Her master's thesis was on smartphone-based colorimetric analysis for prenatal care. She has been a Researcher with the Machine Learning and Data Analytics Laboratory, FAU, since April 2021. Her research interests include digital health, mobile health applications, and data analytics in biomedical engineering.

LUISA GRAF received the B.Sc. degree in medical engineering and the M.Sc. degree in medical engineering with a focus on medical electronics from Friedrich-Alexander-Universität Erlangen–Nürnberg, Erlangen, Germany, in 2020 and 2022, respectively. Throughout her academic journey, her primary focus has been on the exploration of biosignal analysis and the application of wearable technology for data collection.

JOANA JOANIDOPOULOS is currently pursuing the B.Sc. degree in medical engineering with Machine Learning and Data Analytics Lab, Friedrich-Alexander-Universität Erlangen–Nürnberg, Erlangen, Germany. Her Bachelor's thesis is on performing an analysis of segmentation algorithms for smartwatch-based ECG monitoring. She is with the Digital Orchestration and Engineering Department, Siemens Healthineers Erlangen. Her research interests include wearable medical diagnostic devices, medical data analytics, and the application of artificial intelligence in medical use cases.

LARS ANNEKEN received the medical degree (Hons.) from Goethe University, Frankfurt, in 2009. He has extensive experience in cardiology. Since 2022, he has been leading the EP-Department, Universitätsklinikum Erlangen, Germany. He is currently a Senior Physician the Department of Medicine 2-Cardiology and Angiology, Uniklinikum Erlangen, Germany. He has contributed to multiple peer-reviewed publications and presentations at international conferences. In addition, he has conducted research abroad, including with Montreal Heart Institute, Canada.

HANNA HUEBNER received the Ph.D. degree in molecular medicine, with extensive experience in digital and classical biomarker research for precision medicine. She is currently the Leader of the Digital and Personalized Medicine Research Group, Women's Clinic, Uniklinikum Erlangen, Germany. Her work primarily focuses on personalized care based on innovative digital and minimal invasive biosample solutions to improve patient outcomes. She is actively involved in several pioneering projects, including the SMART Start Project, the digiOnko Project, and the MIDIA-Hub Initiative.

CHLOË GOOSSENS received the master's degree in biomedical sciences from Hasselt University, Belgium, and the Ph.D. degree in biomedical sciences from KU Leuven, Belgium, where she conducted research in intensive care medicine. She is currently a Research Assistant with the Department of Gynecology and Obstetrics, Uniklinikum Erlangen, Germany. Following her postdoctoral work in the same field, she joined Uniklinikum Erlangen, in 2021. Since then, she has been working in the field of women's health, focusing on personalized and digital medicine and applying her experience from both preclinical and clinical studies.

ADRIANA TITZMANN studied medicine with the Friedrich-Alexander-Universität Erlangen–Nürnberg (FAU). She is currently a Medical Doctor with the Department of Gynecology and Obstetrics, Uniklinikum Erlangen. She is part of the SMART Start Research Group, which focuses on digitalization in obstetrics.

CONSTANZA PONTONES received the Ph.D. degree in medicine. She primarily works in the field of prenatal diagnostics and obstetrics. She is currently the Deputy Senior Physician with the Department of Gynecology and Obstetrics, Uniklinikum, Erlangen, Germany. Her research focuses on the improvement of prenatal care. She is involved in the SMART Start Project, in which she was responsible for patient recruitment, study realization, and data analysis.

PETER A. FASCHING received the M.D. degree. After completing medical school in Cologne, in 1999, he was with the University Hospital Düsseldorf, Germany, and the David Geffen School of Medicine, University of California at Los Angeles. In 2020, he joined the Board of Directors of Translational Research in Oncology (TRIO), the not-for-profit clinical research organization formerly known as BCIRG. He is currently an Associate Professor of gynecology and obstetrics and translational medicine with the Friedrich-Alexander-Universität Erlangen–Nüremberg and the National Center for Tumor Diseases WERA, Erlangen, Germany. He is also the Head of the Clinical Trials Unit, Women's Clinic, University Hospital Erlangen, and the Coordinator of the Breast Cancer Center and the Gynecological Oncology Center. He is also the President of the German Breast Cancer Study Group AGO-B e.V. Over the past five years, he has published more than 800 peer-reviewed articles, which have appeared in the *Annals of Oncology*, *New England Journal of Medicine*, *Nature*, *Nature Genetics*, *Lancet Oncology*, *Journal of Clinical Oncology*, and the *Journal of the National Cancer Institute*. His research interests include cancer prevention, target discovery, big data, and digital medicine. He was awarded to be a member of the German National Academy of Sciences Leopoldina. He has won numerous awards, including the Florence Nightingale Award from the German Society of Breast Diseases, preceded by the Gunter Baster Innovation Award from the German Society of Gynecology and Obstetrics. He is rated as a Clarivate Highly Cited Researcher.

MATTHIAS W. BECKMANN is currently the Director of the Department of Gynecology and Obstetrics, Friedrich-Alexander-Universität Erlangen–Nüremberg, Erlangen; the Director of the Comprehensive Cancer Center Erlangen-EMN, Erlangen; and the Vice Director of the CCC Alliance Würzburg, Erlangen, Regensburg, Augsburg (WERA)/National Center of Tumor disease (NCT). His research interests include integration into clinical practice of discoveries in molecular genetics like genetics and predisposition for cancer (personalized medicine supported by digital medicine approach) and healthcare research for the integration of guidelines, respectively quality indicators into certified structural units. He is a member of the Board of Directors of the Bavarian Center for Cancer Research (BZKF). He is the Chairperson of the DKGs Certification Commission for Genital Cancer Center and the Guideline Commission (DGGG).

BJOERN M. ESKOFIER (Senior Member, IEEE) received the degree in electrical engineering from the Friedrich-Alexander-Universität Erlangen–Nürnberg (FAU), Erlangen, Germany, in 2006, and the Ph.D. degree in biomechanics from the University of Calgary, Calgary, AB, Canada. Since April 2023, he has been an Associate Principal Investigator and the Leader of the Research Group Translational Digital Health, Helmholtz Zentrum Munich. He currently heads the Machine Learning and Data Analytics (MaD) Laboratory, FAU. He is also the Founding Spokesperson of FAU's Department of Artificial Intelligence in Biomedical Engineering and the German Ministry of Economic Affairs and Climate Action GAIA-X Usecase Project TEAM-X. He is the Co-Spokesperson of the German Research Foundation Collaborative Research Center EmpkinS. He was a recipient of several medical-technical research awards, including the Curious Minds Award in Life Sciences by Manager Magazin and Merck, in 2021.

HEIKE LEUTHEUSER received the Diploma (Dipl.-Phys. Univ.) degree in physics with an emphasis on medicine, in 2011, and the Ph.D. degree for her research on wearable computing applications in eHealth from the Friedrich-Alexander-Universität Erlangen–Nürnberg (FAU), Erlangen, Germany, in 2019. In 2016, she was a Visiting Student Researcher with Stanford University, Stanford, CA, USA. From 2022 to 2023, she was a Postdoctoral Researcher with the Institute for Machine Learning, ETH Zürich, Switzerland. Since 2022, she has been leading the Research Group "Digital Health-Biosignals," Machine Learning and Data Analytics Laboratory, FAU. Her research interests include biomedical time series analysis, wearable health monitoring, and machine learning for time series.