Clinical feasibility and reliability of automated cardiac interval assessment from smartwatch ECG in lung cancer patients

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Abstract

Cancer therapies may induce cardiovascular complications, including atrial fibrillation (AF) and conduction abnormalities, highlighting the need for continuous cardiac monitoring. This study presents a deep learning framework for automated estimation of PR and corrected QT (QTc) intervals from single-lead smartwatch ECG recordings in lung cancer patients. Daily ECG recordings acquired over 12 weeks from 40 patients were analyzed using a U-Net–based segmentation model and compared with the NeuroKit2 algorithm. Preliminary validation on paired smartwatch and standard 12-lead ECG recordings demonstrated lower mean absolute errors for both PR (14.3 ms vs 24.5 ms) and QTc (13.6 ms vs 19.1 ms) cardiac time intervals (CTIs) estimation. These results support the feasibility of accurate CTIs assessment from wearable ECG devices and highlight their potential for scalable remote cardiotoxicity monitoring in oncology populations.

1. Introduction

Cancer remains a major global health challenge, with approximately 20 million new cases diagnosed worldwide in 2022. Among all malignancies, lung cancer is the most frequently diagnosed, accounting for nearly 2.5 million new cases and representing approximately 12.4% of all cancers globally [1]. Although advances in cancer therapies have significantly improved patient survival, treatments such as chemotherapy and radiotherapy may induce cardiovascular complications, including arrhythmias and electrophysiological disturbances [2]. Atrial fibrillation (AF) is commonly observed in oncological patients [3] and has been associated with adverse clinical outcomes and increased mortality [4]. Because AF may remain asymptomatic for long periods, continuous monitoring is crucial to enable early detection and timely clinical intervention.

The electrocardiogram (ECG) is the gold standard for the assessment of cardiac rhythm and conduction abnormalities. While 12-lead ECG recordings are routinely acquired in clinical settings, recent technological advances have enabled the widespread adoption of wearable devices capable of recording single-lead ECG signals. These devices allow frequent and non-invasive monitoring outside the hospital environment, supporting long-term assessment of patients during cancer treatment [5]. Furthermore, wearables are increasingly recognized by cardio-oncology specialists as valuable tools for rhythm surveillance and remote patient management [6].

Although wearable ECG monitoring has largely focused on automated AF detection, rhythm classification alone does not fully characterize treatment-related electrophysiological changes. Cardiac time intervals (CTIs), such as the PR and corrected QT (QTc) intervals, provide complementary information on atrioventricular conduction and ventricular repolarization. Their longitudinal assessment may therefore extend wearable monitoring beyond AF screening, enabling the identification of conduction or repolarization abnormalities potentially associated with cardiotoxicity.

Despite this potential clinical value, limited evidence is available regarding the reliability of CTI measurements derived from smartwatch ECG recordings. Most existing studies focus on end-to-end deep learning approaches for AF detection or prediction, often providing limited interpretability. To address this gap, we propose a deep learning framework based on U-Net segmentation for the automated estimation of PR and QTc intervals from smartwatch recordings acquired in lung cancer patients. The proposed approach aims to provide an accurate and clinically interpretable solution for remote cardiotoxicity monitoring in oncology populations.

2. Materials

The dataset was collected in collaboration with the Cardiology Department of the *Unidade Local de Saúde Gaia-Espinho* (ULSGE, Portugal) and included 40 lung cancer patients (30% female, 70% male; age range 42–80 years) undergoing oncological treatment. The cohort presented a heterogeneous clinical profile in terms of disease stage and treatment regimens, reflecting a real-world cardio-oncology population. Only two patients developed an AF episode during the monitoring period. Each participant was provided with a Samsung Galaxy Watch5 and asked to acquire single-lead ECG recordings at least once per day for a 12-week period. The resulting dataset comprised 6,273 single-lead ECG recordings, each approximately 30 s long and sampled at 500 Hz.

In addition to smartwatch recordings, standard 12-lead ECGs were acquired in the hospital at baseline and at the end of the 12-week monitoring period using Mortara 350 or Mortara 250c systems. The CTIs automatically provided by the Mortara devices were used as reference measurements for population-level comparisons. Furthermore, for four patients, additional 12-lead ECG recordings were acquired immediately after the corresponding smartwatch recordings. These temporally matched smartwatch–12-lead ECG pairs were used for external validation of the proposed framework. The study was conducted according to the approved ethical protocol (code 83-2024-1), and all participants provided written informed consent.

3. Methods

3.1. ECG Preprocessing

Selected ECG recordings were standardized using z-score normalization and subsequently filtered to improve signal quality. To ensure adequate signal quality, the first 5 s of each recording were discarded to remove acquisition artifacts. The remaining signal was divided into consecutive 15 s windows and evaluated using the power-based signal quality index (pSQI) [7]. For each recording, the window with the highest pSQI value was selected for subsequent analysis.

A 50 Hz notch filter was applied to remove power-line interference, followed by a sixth-order Butterworth bandpass filter (0.5–100 Hz) and median removal to reduce baseline offset. The resulting signals were used as input for both the proposed framework and NeuroKit2 [8].

3.2. U-Net-Based ECG Segmentation

A U-Net architecture was employed to perform beat-by-beat ECG segmentation. Prior to segmentation, four time-domain signal representations were extracted from each recording: Hilbert envelope, Shannon energy envelope, homomorphic envelope, and smoothed envelope. These features enhance relevant signal characteristics while reducing noise.

The extracted features were downsampled to 50 Hz, combined into a four-channel representation, and divided into overlapping patches of 64 samples. The resulting patches were provided as input to a U-Net model, previously trained on the LUDB dataset [9].

The network generated sample-wise probability maps for four classes: ‘baseline’, ‘P wave’, ‘QRS complex’, and ‘T wave’. Following segmentation, R-peaks were detected from the preprocessed ECG signals using the ASI segmenter implemented in BioSPPy [10]. BioSPPy was preferred over NeuroKit2 because it provided more reliable R-peak detection and reduced the risk of missed beats.

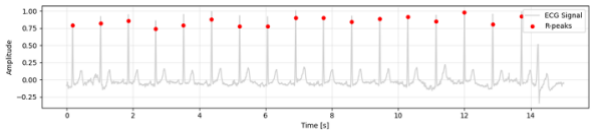

Figure 1. R-peaks detection using BioSPPy.

For each detected R-peak, a heartbeat window was defined using the median RR interval, where RR represents the temporal distance between two consecutive R peaks.

$$[\, W_{i,start} = R_i - 0.4\, x\, median(RR),$$
$$W_{i,end} = R_i + 0.6\, x\, median(RR)\,].$$

The asymmetric window was designed to include both the preceding P wave and the subsequent T wave within the same cardiac cycle. Segmented events were then assigned to the corresponding heartbeat windows, and only physiologically valid beats were retained according to the following criteria:

- exactly one R-peak within the heartbeat window;
- at least two QRS samples detected by the segmentation model;
- the R-peak located between the segmented QRS boundaries.

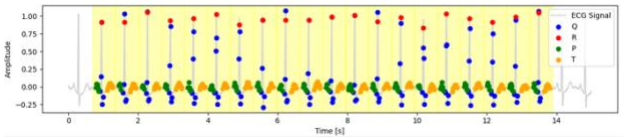

Figure 2. Example of filtered beats. The yellow background highlights valid beats. The Q samples represent the QRS label predicted by the U-Net.

For each valid beat, the PR interval was computed as the time difference between P-wave onset min(P), and QRS onset min(QRS), while the QT interval was measured from QRS onset min(QRS), to T-wave offset max(T).

PR = min(QRS) −min(P)

QT = max(T) −min(Q)

The corrected QT interval (QTc) was subsequently calculated using Fridericia's formula: $QT_c = \frac{QT}{\sqrt[3]{RR}}$. Finally, beat-level measurements were averaged to obtain a single PR, QT and QTc estimate for each ECG recording.

4. Results

After applying the proposed framework to the entire dataset, the obtained results were analyzed from two complementary perspectives. First, the performance of the method was evaluated by comparing the estimated CTIs with those obtained using NeuroKit2. Second, a validation and longitudinal analysis was performed to investigate the behavior of CTIs throughout the 12-week monitoring period.

4.1. Validation on Paired Smartwatch and 12-Lead ECG Recordings

The proposed framework was compared with NeuroKit2 using four smartwatch–12-lead ECG pairs acquired in close temporal proximity. Mean absolute error (MAE) was computed between smartwatch-derived and reference 12-lead ECG intervals. To estimate reference intervals from the 12-lead ECGs, lead V1 was used for PR interval calculation because of its favorable P-wave visibility, whereas lead V5 was selected for QT interval measurement. QTc values were then computed using Fridericia's correction formula, with RR intervals averaged across all leads.

Table 1 reports the corresponding interval values obtained from single-lead (SL) and 12-lead (12L) ECG recordings. The estimated CTIs from the smartwatch recordings showed good agreement with those obtained from the 12-lead reference ECG. When the PR interval is reported as NaN, the network was unable to identify a P wave within the corresponding recording.

The proposed method achieved lower estimation errors than NeuroKit2 for both PR and QTc intervals. The PR interval MAE decreased from 24.5 ms to 14.3 ms, while QTc interval MAE decreased from 19.1 ms to 13.6 ms.

Table 1. Validation of CTIs between SL and 12L ECG signals were acquired immediately afterwards, in four patients. PR, QT, and QTc intervals are reported in milliseconds (ms).

Patient	PR (ms)		QT (ms)		QTc (ms)	
	SL	12L	SL	12L	SL	12L
P1	113	125	342	356	372	387
P2	NaN	111	321	322	364	394
P3	142	114	379	380	387	392
P4	123	120	384	384	411	414

Although this analysis was limited to four paired recordings, the results suggest that the proposed beat-by-beat segmentation framework provides more accurate CTIs estimation when temporally matched reference recordings are available.

4.2. Population-Level Analysis

To evaluate performance across the entire study cohort, smartwatch-derived intervals were compared with the closest available 12-lead ECG measurements for each patient. In this setting, recordings were not necessarily acquired on the same day, introducing physiological variability unrelated to the estimation method.

For the PR interval, NeuroKit2 achieved a higher correlation with the reference values ($r = 0.539$) than the proposed model ($r = 0.205$). In contrast, the proposed framework provided better QTc estimation, showing both lower MAE (19.97 ms vs. 31.0 ms) and higher correlation ($r = 0.467$ vs. 0.344).

These findings indicate that performance depends on the interval considered. While NeuroKit2 performed better for PR estimation, the proposed framework achieved superior QTc estimation, suggesting that the beat-by-beat segmentation approach may be particularly effective for QTc assessment from smartwatch ECG recordings. Overall, neither method consistently outperformed the other when evaluated against the reference CTIs automatically provided by the hospital ECG systems.

4.2. Longitudinal Analysis

A longitudinal analysis was subsequently performed on all smartwatch recordings collected during the 90-day monitoring period. Visual inspection of PR and QTc trajectories did not reveal consistent increasing or decreasing trends across patients. PR values were generally distributed between 80 and 180 ms, whereas QTc values ranged between 300 and 450 ms. To quantify temporal variability, a beat-by-beat statistical analysis was performed. Most recordings did not exhibit significant temporal changes: 79.7% of signals showed no significant variation in PR interval, while 96.4% showed no significant variation in QTc interval. The percentages of significant increases and decreases were low and approximately balanced, indicating overall stability of both intervals. Finally, statistically significant changes between the beginning and the end of the monitoring period were assessed for each patient using a t-test. Significant changes were observed only in isolated cases, confirming that CTIs remained generally stable over time within this cohort.

5. Discussion and Conclusion

The present study demonstrates the feasibility of

estimating clinically relevant CTIs from smartwatch-derived single-lead ECG recordings using a deep learning based beat-by-beat segmentation framework. By combining ECG feature extraction, U-Net segmentation, and post-processing of cardiac events, the proposed approach enables transparent and clinically interpretable estimation of PR and QTc intervals. Compared with NeuroKit2, the framework achieved lower estimation errors for both intervals when evaluated on temporally matched smartwatch and 12-lead ECG recordings, suggesting that deep learning based segmentation can improve the reliability of interval extraction from wearable ECG signals, even under real-world acquisition conditions characterized by variable signal quality. Unlike many end-to-end artificial intelligence models developed for AF detection, the proposed method provides clinically meaningful biomarkers that can be directly interpreted by healthcare professionals, potentially facilitating the integration of wearable ECG monitoring into routine cardio-oncology practice. Nevertheless, some limitations should be acknowledged. Only two patients developed AF during the monitoring period, limiting the possibility of investigating associations between interval changes and arrhythmic events, while external validation was performed on a limited number of temporally matched recordings. Future studies involving larger cohorts and additional synchronized smartwatch–12-lead ECG acquisitions are therefore required to further validate the proposed methodology and assess its clinical utility. Overall, these results support the potential of wearable ECG devices combined with deep learning techniques for continuous remote cardiac monitoring and provide a foundation for future investigations in cardio-oncology populations.

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References

[1] Freddie Bray, Mathieu Laversanne, Hyuna Sung, Jacques Ferlay, Re becca L Siegel, Isabelle Soerjomataram, and Ahmedin Jemal. Global cancer statistics 2022: Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians, 74(3):229–263, 2024.

[2] Federico Viganego, Robin Singh, and Michael G Fradley. Arrhyth mias and other electrophysiology issues in cancer patients receiving chemotherapy or radiation. Current cardiology reports, 18(6):52, 2016.

[3] Michał Gawlik, Jakub Michal Zimodro, Aleksandra Gąsecka, 98 8| BIBLIOGRAPHY Krzysztof J Filipiak, and Sebastian Szmit. Cardiac arrhythmias in oncological patients—epidemiology, risk factors, and management within the context of the new esc 2022 guidelines. Current Oncology Reports, 25(10):1107–1115, 2023.

[4] Robert Monsour, Angie Seo, Nicholas Wilcox, and Michael G Fradley. Diagnosis and management of atrial arrhythmias in cancer patients. Current Cardiology Reports, 27(1):103, 2025.

[5] Suranga Seneviratne, Yining Hu, Tham Nguyen, Guohao Lan, Sara Khalifa, Kanchana Thilakarathna, Mahbub Hassan, and Aruna Seneviratne. A survey of wearable devices and challenges. IEEE Communications Surveys & Tutorials, 19(4):2573–2620, 2017.

[6] Giuseppe Boriani, Jacopo F Imberti, Riccardo Asteggiano, Pietro Ameri, Davide A Mei, Michał Farkowski, Julian Chun, Josè Luis Merino, Teresa Lopez-Fernandez, and Alexander R Lyon. Mobile/wearable digital devices for care of active cancer patients: a survey from the esc council of cardio-oncology. European Heart Journal-Digital Health, 6(2):162–169, 2025.

[7] Zhao Z, Zhang Y**,** SQI Quality Evaluation Mechanism of Single-Lead ECG Signal Based on Simple Heuristic Fusion and Fuzzy Comprehensive Evaluation. *Front Physiol.* 2018;9:727.

[8] Dominique Makowski, Tam Pham, Zen J Lau, Jan C Bram mer, François Lespinasse, Hung Pham, Christopher Schölzel, and SH Annabel Chen. Neurokit2: A python toolbox for neurophysiological signal processing. Behavior research methods, 53(4):1689–1696, 2021.

[9] Alena Kalyakulina, Igor Yusipov, Viktor Moskalenko, Alexan der Nikolskiy, Konstantin Kosonogov, Nikolai Zolotykh, and Mikhail Ivanchenko. Lobachevsky university electrocardiography database. Type: Dataset. Available online: https://physionet. org/content/ludb/1.0. 0/(accessed on 10 July 2021), 2020.

[10] BioSPPy Developers. BioSPPy Signals ECG Module Documentation. URL https://biosppy.readthedocs.io/en/stable/biosppy.signals.html#module-biosppy.signals.ecg. Accessed: 2026.

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