

ECG Interpretation in Natural Language from Derived Metrics Through API Invocation [†]

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Abstract

The existing portable ECG systems are reliable for continuous monitoring, but they provide output in numerical values and in binary alarms. Herein, a single-lead non-invasive cardiac monitoring system named ‘CorSeg’ is presented, where AI-driven natural language feedback has been integrated. Additionally, HRV features, including RMSSD and SDNN, have been derived from five minutes of ECG recording. The metrics such as RR intervals, HR, and HRV features are combined with contextual data to form a local summary and to feed the AI model (GPT-4.1-Nano) through API invocation. The experiment has been performed with a FLUKE ECG simulator and with limited volunteers to observe the AI feedback.

Keywords: electrocardiogram (ECG); heart rate variability (HRV); Artificial Intelligence (AI); ECG interpretation in natural language; Premature Ventricular Contractions (PVCs); wearable ECG

1. Introduction

Cardiovascular disease is a major health concern globally, where Sudden Cardiac Arrest (SCA) is usually caused by the electrical malfunction of the heart [1]. An electrocardiogram (ECG) is a method to identify heart abnormalities, where the ECG analysis is carried out by a medically graded ECG system, such as the traditional 12-lead ECG and Holter monitor [2]. As the ECG system requires an expert to operate and interpret the data, non-expert users need a user-friendly ECG system that can be used for continuous monitoring of their heart. Recent studies show that there are numerous wearable ECG systems that exist, such as the Apple Watch, Fitbit Sense, and Cardia Mobile, which can be used in non-clinical settings for personal monitoring [3]. These ECG systems are capable of real-time monitoring that provides limited and specialized metrics data. As a result, the output metrics of the ECG system are difficult to understand by non-expert users. Recent advancements in Artificial Intelligence (AI) have gained attention for implementing AI models such as Large Language Models (LLMs) through Application Programming Interface (API) invocation to interpret data in natural language [4,5].

In this paper, an API invocation approach has been utilized to process the numeric output of the system into understandable output in natural language. Additionally, the Heart Rate Variability (HRV) feature has been integrated with the existing CorSeg system. The numeric output has been obtained to form a local summary of results by analyzing



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several metrics such as RR intervals, Heart Rate (HR) estimation, Root Mean Square of Successive Differences (RMSSD), and Standard Deviation of Normal-to-Normal Intervals (SDNN). The local summary is then fed to the GPT-4.1-Nano model through API invocation to interpret the summary in natural language with an explanation. The results from the FLUKE ECG simulator and from the multiple volunteers will help biomedical engineers to develop and integrate more advanced AI-based systems to interpret the ECG data.

2. Materials and Methods

Processing of ECG outcomes in natural language was obtained through a three-stage approach, such as data acquisition, processing, and AI implementation.

2.1. CorSeg ECG and Data Acquisition

The CorSeg [6] is a cross-platform-supported portable ECG system depicted in Figure 1a–c that was designed for monitoring heart activity in non-clinical settings where the system can collect raw ECG signals with a maximum sampling rate of 1 kHz. The system consists of hardware and software, where the hardware includes the ESP32-PICO-K-D4 microcontroller (Espressif Systems, Shanghai, China), the LSM9D1 motion sensor (STMicroelectronics, Geneva, Switzerland), and the AD8232 ECG sensor module (Analog Devices, Wilmington, MA, USA) for initial ECG processing and transmitting the timestamp and voltage of the ECG signal [7]. The acquired sensor's data transmission was performed via built-in Bluetooth, based on the asynchronous method to avoid freezing the mobile application. Herein, the CorSeg ECG system was used to collect raw ECG data from the FLUKE ECG simulator (Fluke Corporation, Everett, WA, USA), where ECG data was also acquired from selected volunteers with three hydrogel-based wet electrodes at a sampling rate of 500 Hz.

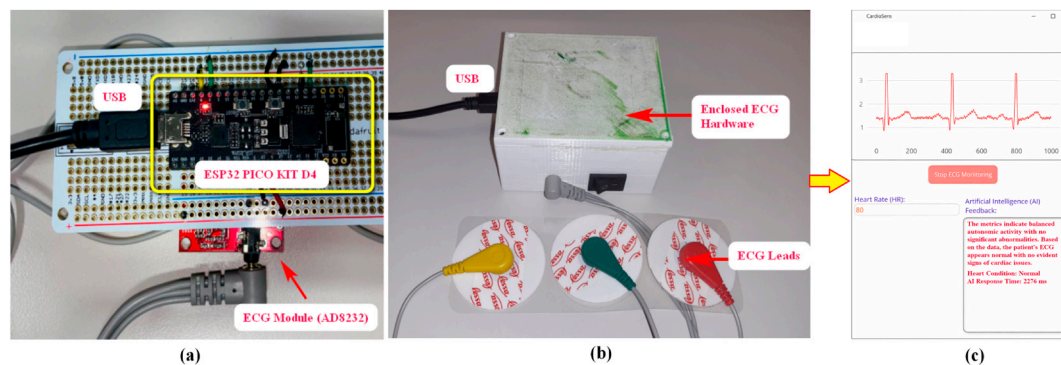


Figure 1. CorSeg ECG System. (a) Open view of the custom-designed ECG Circuitry. (b) Circuitry enclosed within its housing. (c) Outlook of developed ECG software.

2.2. ECG Processing

At this stage, the software developed by using visual studio 2022 (Microsoft Corporation, Redmond, WA, USA) received the timestamps and voltage data over Bluetooth from the hardware and initiated ECG signal filtering by using Dynamic Simple Moving Average (DSMA). The DSMA used the motion sensor's feedback to adapt the window size dynamically so that the ECG signal can be smoother and more responsive throughout the ECG recording. The DSMA can be represented by the following Equation (1):

$$Fs[n] = \frac{1}{N} \sum_{k=0}^{N-1} S(n-k) \left[\text{where } N = 5 + 15 \times \frac{\sqrt{a_x^2 + a_y^2 + a_z^2} - g}{\max(\sqrt{a_x^2 + a_y^2 + a_z^2} - g)} \right] \quad (1)$$

where $F_s[n]$ presents the smooth version of the input ECG. Later, this filtered ECG was utilized to detect R-peaks and measure the RR intervals. For that, an adaptive threshold value was calculated to detect R-peak by the following Equation (2).

$$P_{th}[n] = 0.70 \times \max_{n-4999 \leq k \leq n} F_s[k] \quad (2)$$

The $P_{th}[n]$ represents the adaptive threshold values where the value was computed as 70% of the maximum ECG signal amplitude throughout the sliding window of 5000 most recent samples. Afterward, the R-peak was detected when the smoothed signal amplitude exceeded the threshold value, where the time difference between two successive R-peaks was recorded, which is demonstrated by Equation (3).

$$RR_i = R_{i+1} - R_i, [\text{when } F_s[n] > P_{th}[n] \Rightarrow n = R_i] \quad (3)$$

Subsequently, the heart rate was calculated based on the obtained RR intervals by using Equation (4).

$$HR = \frac{60,000}{RR_i} \text{BPM} \quad (4)$$

Additionally, the extraction of the HRV features was performed based on the RR intervals of the 5 min ECG recording. The RMSSD and SDNN were calculated to identify the short-term and overall variability [8] using Equation (5) and Equation (6), respectively.

$$RMSSD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \quad (5)$$

$$SDNN = \sqrt{\frac{1}{N} \sum_{i=1}^N (RR_i - \overline{RR})^2} \text{ where } \overline{RR} = \frac{1}{N} \sum_{i=1}^N RR_i \quad (6)$$

Finally, the local summary was produced based on the derived HRV features, including RMSSD and SDNN, and with measured parameters such as HR and RR intervals, as shown in Figure 2. To ensure the robustness of the summary, minimize random errors and large deviations of the derived data. Descriptive statistics such as median, interquartile range (IQR), minimum, maximum, and mean were also computed.

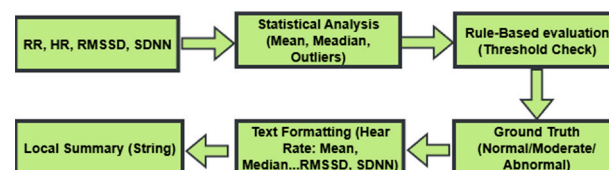


Figure 2. Workflow of derived metrics to local summary text generation.

2.3. Integration of GPT-4.1-Nano AI Model with the Software

To enable the ECG interpretation, the GPT-4.1-Nano AI model was integrated with the software. Figure 3 presents the ECG local summary to the AI interpretation processing pipeline. Herein, a ChatGPT API (OpenAI, San Francisco, CA, USA) was used to access the GPT-4.1-Nano model remotely, and thus, the computation load at the software end of the CorSeg system was reduced. The GPT-4.1-Nano was chosen due to its attractive features, such as computational efficiency and low-latency text generation, which enable real-time interpretation of the produced summary [9]. Due to its design architecture, the model can summarize data, interpret numeric values, and perform advanced reasoning with human-understandable explanations. The interpretation of the local summary involved four steps:

input structure, prompt construction, API invocation, and output. The input data was structured by combining the local summary with the contextual data, such as subject age, sex, and eating habits, for the purpose of reasoning by the AI model. The prompt was performed with a dynamic predefined prompt template where ECG sampling frequency and recording duration were merged with the structured data. Afterward, the prompt was sent to the GPT-4.1-Nano model via the API invocation through an asynchronous method to avoid unnecessary interruptions, such as freezing the software. According to the prompt instruction, the AI model generated the final output with an explanation and indicated heart conditions as normal, moderate, and abnormal.



Figure 3. Workflow of the local summary to AI Feedback.

3. Results and Discussion

Experiments, including simulated ones with a FLUKE ECG simulator and volunteer tests, were conducted in a laboratory environment. Four records of 5 min ECGs were analyzed and observed through AI, where rec-1, rec-3, and rec-4 were obtained from volunteers and rec-2 was obtained from a FLUKE ECG simulator (settings: ventricular arrhythmias -PVCs at 12 beats per minute). Figure 4 represents the histogram and Poincaré graphs of all sets of records. In Figure 4a, the RR intervals are clustered around 780–820 ms, where the RR interval distribution has moderate spread, indicating moderate HRV. Contrary to this, the Poincaré shows a compact elliptical cluster aligned along the identical line, indicating a strong correlation between the RR intervals. Both graphs suggest balanced autonomic activity of the heart. In Figure 4b, a large deviation of RR intervals is observed between 750 ms and 1500 ms, which indicates a strong bimodal distribution.

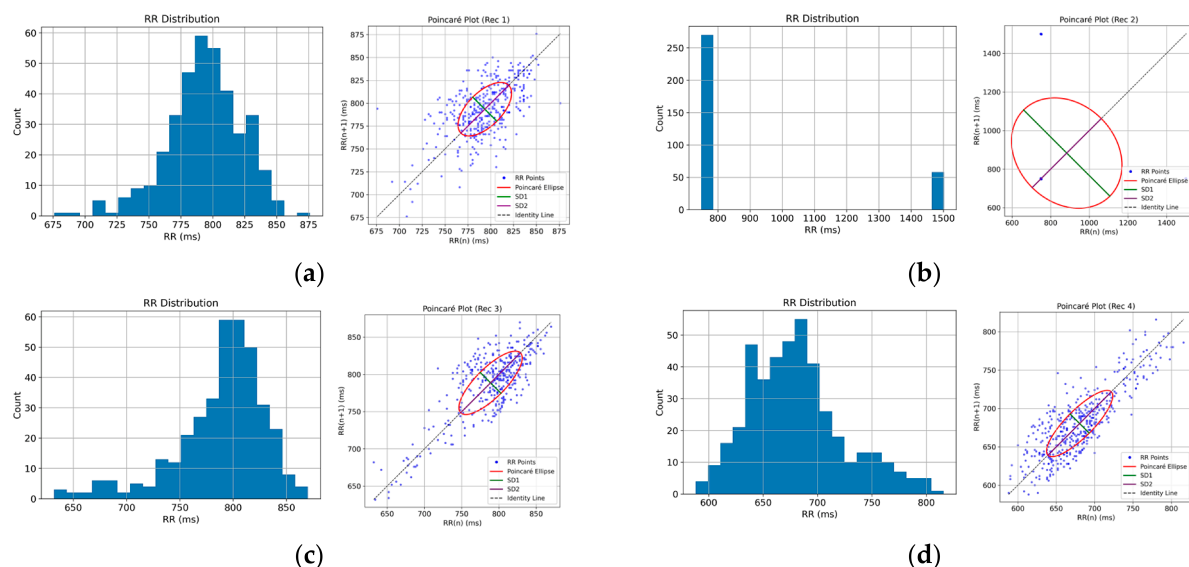


Figure 4. (a) Histogram and Poincaré graphs for rec-1; (b) histogram and Poincaré graphs for rec-2; (c) histogram and Poincaré graphs for rec-3; (d) histogram and Poincaré graphs for rec-4.

The Poincaré shows that the RR intervals are inconsistent and the RR interval points are not clustered, whereas both graphs suggest that the heart rhythm pattern is not normal, as expected. In Figure 4c, the histogram shows RR intervals spread widely, indicating high variability, whereas the Poincaré shows a broader elliptical shape than the rec-1. Both graphs indicate the heart is healthy with dynamic HRV, which is due to the volunteers' test

being performed in a resting condition. Finally, Figure 4d shows that the RR intervals are moderately spread around 750–800 ms, where the Poincaré shows the reduced beat-to-beat variability. Both graphs indicate a normal heart rhythm with reduced HRV as expected for the moderate workout during the test.

Table 1 demonstrates the metrics derived from the records along with ground truth and AI feedback, where the ground truth was classified as normal/abnormal by focusing on an overall pattern of HRV features (SDNN and RMSSD) and the HR distribution characteristics (median, mean, IQR, and HR ranges). Rec-1 presents sitting-state data where SDNN is 29.26, and RMSSD is 26.34, which indicates relaxation and a normal heart rhythm. The AI provided feedback on heart activity as normal, which was similar to the ground truth, with a response latency of 2276 ms. Rec-2 is related to the mimic signal of Premature Ventricular Contractions (PVCs), which is reflected by highly concentrated heart rate values at 80 BPM with skewed distribution and the SDNN (286.64 ms), RMSSD (447.70 ms), and large deviation of the HR. The ground truth condition for the record obtained was abnormal, whereas the AI feedback was also abnormal, as expected. Rec-3 was also classified as normal according to the ground truth and the AI feedback. Rec-4 was obtained in a squatting condition, which was reflected by the SDNN (43.04 ms) and RMSSD (25.07), indicating moderate variability. The AI response latency ranged from 2128 ms to 2518 ms with an overall variation of 390 ms. However, a sample of extended AI feedback has been shown in Figure 1c.

Table 1. Summarization of the records along with metric and AI feedback.

Record ID	Condition	HR (Median)	HR (IQR)	HR (Min–Max)	HR (Mean)	SDNN (ms)	RMSSD (ms)	Local Summary (Overall)	GPT Feedback (Overall)	Latency (ms)
Rec-1	Sitting	75.0	73.0–77.0	68–89	75.4	29.26	26.34	Normal	Normal	2276
Rec-2	Simulator	80.0	80.0–80.0	40–80	72.9	286.64	447.70	Abnormal	Abnormal	2257
Rec-3	Standing	75.0	73.0–77.0	69–95	76.0	42.33	27.98	Normal	Normal	2518
Rec-4	Squatting	89.0	85.0–92.0	73–102	88.3	43.04	25.07	Normal	Normal	2128

4. Conclusions and Future Work

The paper presented an extended version of a non-invasive cardiovascular monitoring system called “CorSeg”, where AI-based ECG interpretation through API invocation and HRV features were integrated. The ability to interpret ECG data with explanations in natural language made the system unique from the mentioned devices. The experiment was performed with a FLUKE ECG simulator and with limited volunteers, where four sets of 5 min ECGs were obtained at a sampling frequency of 500 Hz. The CorSeg system merged all the derived metrics, such as HR, RR intervals, and HRV metrics, with contextual data, such as subject age, sex, and eating habits, to form a local summary. The local summary was then fed to the GPT-4.1-Nano AI model via API invocation. It was found that all responses generated by AI matched the ground truth in finalizing the heart condition, where the response latency varied from 2128 ms to 2518 ms. Though the system provides expected AI feedback, an extended study on risk management of hallucination by AI and justification of DSMA parameters is necessary. Future work will focus on detailed analysis of DSMA against classical filters, the potential risk of hallucination by the AI model, and testing the system on a more diverse population.

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References

1. Umair, M.K.; Waheed, R.; Abrar, M.F.; Ali, S.; Lee, I.E.; Jan, S.; Shaheen, F. Time series electrocardiography (ECG) data for early prediction of cardiac arrest. *Sci. Rep.* **2026**, *16*, 9761. [[CrossRef](#)] [[PubMed](#)]
2. Da Silva e Silva, M.R.H.; de Sousa, D.R.T.; Ortiz, J.V.; Monteiro, M.M.; Brandão, A.R.J.; Silva e Silva, M.R.; Smith-Doria, S.; Cavalcante, M.S.M.; Couceiro, K.N.; Arêas, G.P.T.; et al. Evaluation of the autonomic nervous system in autochthonous patients from Amazon with acute Chagas disease treated with benznidazole. *PLoS Negl. Trop. Dis.* **2026**, *20*, e0014022. [[CrossRef](#)]
3. Khan, B.; Khalid, R.T.; Masrur, M.H.; Awais, M.; Khan, B.; Khoo, B.L. Next-generation wearable ECG systems: Soft materials, AI integration, and personalized healthcare applications. *Chem. Eng. J.* **2025**, *525*, 170117. [[CrossRef](#)]
4. Baydili, İ.; Tasci, B.; Tasci, G. Artificial intelligence in psychiatry: A review of biological and behavioral data analyses. *Diagnostics* **2025**, *15*, 434. [[CrossRef](#)] [[PubMed](#)]
5. Bandlamudi, J.; Chaudhuri, R.; Gantayat, N.; Mukherjee, K.; Agarwal, P.; Sindhgatta, R.; Mehta, S. A framework for testing and adapting REST APIs as LLM tools. *arXiv* **2025**, arXiv:2504.15546.
6. Miah, M.R.; Postolache, O.A. A non-invasive cross-platform supported pocket ECG device for heart monitoring. In Proceedings of the 2025 Third International Conference on Industry 4.0 Technology (I4Tech), Pune, India, 18–20 September 2025.
7. Miah, M.R.; Postolache, O.A. Performance evaluation of a wearable CorSeg ECG system with MIT-BIH arrhythmia database. In Proceedings of the 2026 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Montevideo, Uruguay, 7–10 April 2026.
8. Schneider, M.; Rominger, C.; Schwerdtfeger, A.R. Associations between positive affect and heart rate variability: A systematic review. *Curr. Cardiol. Rep.* **2025**, *27*, 148. [[CrossRef](#)] [[PubMed](#)]
9. Introducing GPT-4.1 in the API. Available online: <https://openai.com/index/gpt-4-1/> (accessed on 31 March 2026).

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