Journal of Rare Cardiovascular Diseases
ISSN: 2299-3711 (Print) | e-ISSN: 2300-5505 (Online)
www.jrcd.eu
RESEARCH ARTICLE

Efficacy of Artificial Intelligence Compared to Manual Interpretation of Electrocardiogram (ECG) Parameters in Normal and Myocardial Infarction (MI) Cohorts: A Comparative Pilot Study

Thirumurugan E [1], Dr. Nirmala Rajesh[2], Dr. Nagarathna Shenoy[3], Shashidhar Kotian M[4]
[1]Research Scholar, Department of Allied Health Science, Srinivas University, Mangalore, Karnataka, India.
[2]Associate professor, Department of Physiology, School of Allied Health Science, Srinivas University, Mangalore, Karnataka, India.
[3]Assistant professor, Department of Cardiology, Kasturba Medical College, MAHE, Manipal, Karnataka, India.
[4]Research director, Srinivas University, Mangalore, Karnataka, India.

*Corresponding Author
Thirumurugan E

Article History
Received: 10.07.2025
Revised: 14.07.2025
Accepted: 05.08.2025
Published: 08.09.2025

Abstract: ***Background:*** Accurate interpretation of electrocardiograms (ECG) is essential for diagnosing cardiac abnormalities. Artificial Intelligence (AI)-based ECG analysis has emerged as a potential tool to support clinicians; however, its reliability compared to conventional manual interpretation requires evaluation. ***Objective:*** To compare the accuracy and agreement between AI-based and manual measurements of key ECG parameters in normal subjects and patients with myocardial infarction (MI). ***Methods:*** A pilot study was conducted on 60 subjects, divided equally into two groups: normal ECG (n=30) and post-MI ECG (n=30). The ECG parameters analyzed included Heart Rate, RR Interval, QT Interval, and QTc Interval. Data normality was assessed using the Shapiro–Wilk test. Normally distributed variables were expressed as Mean ± SD and compared using paired t-tests, while non-normally distributed variables were reported as Median (IQR) and analyzed using the Wilcoxon Signed-Rank test. ***Results:*** The mean age of the normal group was 44.90 ± 15.47 years, significantly lower than that of the MI group (56.27 ± 12.72 years, p = 0.002). The MI group also had a higher proportion of males (76.67%) compared to the normal group (53.33%) (p = 0.10). Despite these demographic differences, there were no statistically significant differences between AI and manual interpretations across all ECG parameters in either group (p > 0.05). ***Conclusion:*** AI-derived ECG measurements demonstrated strong agreement with conventional manual interpretations, indicating that AI systems can provide consistent and reliable ECG parameter estimation. These results support the potential clinical application of AI-based ECG analysis in both normal and cardiac patient populations.

Keywords: Artificial Intelligence, Electrocardiogram, Myocardial Infarction, QT Interval, Heart Rate, QTc Interval, Diagnostic Accuracy.

INTRODUCTION

The electrocardiogram (ECG) stands as a fundamental tool in the diagnosis and management of cardiovascular diseases, providing crucial insights into the heart's electrical activity [1,2]. Precise interpretation of ECG parameters is vital for identifying various cardiac conditions, including myocardial infarction, arrhythmias, and conduction abnormalities [3,4,5]. Traditionally, the analysis of ECGs has depended on manual measurements conducted by trained healthcare professionals [6]. While this method has proven effective, it can be time-consuming and prone to inter-observer variability [7]. Recent advancements in artificial intelligence (AI) and machine learning have led to the development of automated ECG interpretation systems, representing a significant step toward enhancing the speed, accuracy, and consistency of ECG analysis. These AI-driven platforms aim to streamline clinical workflows, minimize diagnostic errors, and facilitate timely decision-making [8,9,10,11]. However, the clinical utility of these systems requires rigorous validation against the current gold standard—manual interpretation by expert readers—before their widespread adoption. This pilot study is designed to assess the agreement between AI-based and manual ECG measurements across key parameters, including heart rate, RR interval, QT interval, and corrected QT (QTc) interval. To ensure a comprehensive evaluation, the study incorporates two distinct cohorts: individuals with normal ECGs and patients with a confirmed diagnosis of myocardial infarction. This dual-group design allows for the examination of the AI system's performance under both routine and complex clinical conditions. The primary objective is to ascertain whether statistically significant differences exist between AI-generated and manually recorded ECG measurements, thereby guiding the potential integration of AI tools into standard cardiac diagnostic practices.

MATERIALS AND METHODS

Study Design and Setting:

This was a cross-sectional pilot study conducted to compare AI-based and manual ECG interpretations. The study included 60 subjects, divided equally into two groups: Normal ECG Group (n=30) and Myocardial Infarction (MI) ECG Group (n=30). The study was approved by the institutional review board and conducted in accordance with ethical standards.

Participants:

The Normal ECG Group consisted of individuals with no history of cardiovascular disease and normal ECG findings. The MI ECG Group included subjects with a confirmed history of myocardial infarction. Inclusion criteria were based on clinical diagnosis and ECG classification. All participants provided informed consent prior to inclusion.

Variables and Measurements:
Demographic data such as age and gender were recorded. The following ECG parameters were measured for each subject using both an AI-based interpretation system and manual analysis by a trained medical professional:
i. Heart Rate (bpm): Number of heartbeats per minute.
ii. RR Interval (s): Duration between the peaks of consecutive R waves.
iii. QT Interval (s): Time from the beginning of the Q wave to the end of the T wave.
iv. QTc Interval (s): Heart rate-corrected QT interval.

Data Sources and Measurement: Each subject underwent a standard 12-lead ECG analysis, and the selected ECG parameters—heart rate, RR interval, QT interval, and QTc interval—were extracted using both methods. Manual measurements were performed by an experienced clinician blinded to the AI-generated results to eliminate observer bias. AI-based measurements were obtained using the newly developed ECG AI Stimulator – Bharat Cardio application (Version 1.0), designed for automated ECG interpretation and parameter extraction.

Statistical Methods:
Statistical analysis was performed using SPSS-20 software. Continuous variables were assessed for normality using the Shapiro-Wilk test. Data that followed a normal distribution were expressed as Mean ± Standard Deviation (SD) and compared using the paired t-test for within-subject comparisons (AI vs. manual measurements) and the independent t-test for between-group comparisons (Normal ECG vs. MI ECG). Non-normally distributed variables were expressed as Median (Interquartile Range, IQR) and analyzed using the Wilcoxon Signed-Rank Test. Categorical variables were summarized as frequency and percentage, and group comparisons were performed using the Chi-square test. A p-value of less than 0.05 was considered statistically significant.

RESULTS AND OBSERVATIONS:

Demographic Characteristics:
The two study cohorts demonstrated notable demographic differences. The **mean age** in the Normal ECG group was **44.90 ± 15.47 years**, which was significantly lower than the **56.27 ± 12.72 years** observed in the Myocardial Infarction (MI) ECG group (**p = 0.002**). Although the difference in **gender distribution** did not reach statistical significance (**p = 0.10**), the MI group had a higher proportion of males (**76.67%**) compared to the Normal group (**53.33%**), while the Normal group showed a more balanced male-to-female ratio (Table-1).

Table-1 Comparison of Demographic Characteristics Between Normal and Myocardial Infarction ECG Groups

Variable	Normal ECG (n=30)	Myocardial infarction ECG (n=30)	P-value
Age, years	44.90 ± 15.47	56.27 ± 12.72	0.002
Gender			
Male	16 (53.33%)	23 (76.67%)	
Female	14 (46.67%)	7 (23.33%)	0.10

Note: Continuous variables are shown as Mean ± SD (Independent t-test); categorical variables as n (%) (Chi-square test). p < 0.05 considered significant.

Descriptive Statistics of ECG Parameters:
Among participants with normal ECGs, the comparison between AI-based and manual ECG interpretations demonstrated close agreement across all measured parameters (Table 2). The mean heart rate determined by the AI system was 73.83 ± 5.62 bpm, whereas the manually interpreted median heart rate was 72.00 (12.00) bpm, showing no significant difference (p = 0.83). Similarly, the mean RR interval recorded by the AI was 0.82 ± 0.06 s compared to 0.77 ± 0.13 s by manual measurement, with the difference not reaching statistical significance (p = 0.08).

For ventricular repolarization parameters, the QT interval values obtained from the AI and manual interpretations were 0.36 (0.09) s and 0.35 (0.06) s, respectively (p = 0.87). The corrected QT (QTc) interval also showed good concordance between the AI (0.39 ± 0.06 s) and manual (0.38 (0.04) s) measurements, without a significant difference (p = 0.46).

Overall, these findings indicate that within the normal ECG cohort, AI-derived measurements of fundamental ECG parameters were statistically comparable to those obtained through conventional manual analysis, suggesting that the AI interpretation system provides reliable quantitative assessment consistent with standard manual methods.

Table-2 Descriptive Statistics of ECG Parameters: AI vs. Manual Measurements among Normal ECG Cohort

Parameter	AI ECG Interpretation	Manual ECG Interpretation	P- value
Heart Rate	73.83 ± 5.62	72.00 (12.00)	0.83
RR Interval	0.82 ± 0.06	0.77 ± 0.13	0.08
QT Interval	0.36 (0.09)	0.35 (0.06)	0.87
QTc Interval	0.39 ± 0.06	0.38 (0.04)	0.46

Note: Data are presented as Mean ± SD for normally distributed variables (as determined by the Shapiro–Wilk test) and as Median (IQR) for non-normally distributed variables. Paired t-test was applied for normally distributed data, and the Wilcoxon signed-rank test for non-normally distributed data. $p < 0.05$ was considered statistically significant.

In the myocardial infarction (MI) cohort, AI-based ECG interpretation demonstrated comparable performance to manual analysis across all key ECG parameters (Table 3). The mean heart rate determined by the AI system was 74.65 ± 7.78 bpm, whereas the manually interpreted median heart rate was 72.00 (12.00) bpm, showing no statistically significant difference ($p = 0.48$). The mean RR interval derived from AI measurements was 0.81 ± 0.09 s, compared with 0.77 ± 0.13 s from manual interpretation, also without significant difference ($p = 0.17$).

Similarly, the ventricular repolarization parameters showed close agreement between the two methods. The QT interval measured by the AI was 0.34 (0.09) s, while manual measurement yielded 0.35 (0.06) s ($p = 0.67$). The corrected QT (QTc) interval was identical between AI and manual interpretations 0.38 (0.09) s and 0.38 (0.04) s respectively, with no significant variation ($p = 0.99$).

These findings indicate a high level of concordance between AI-based and manual ECG interpretations in the myocardial infarction cohort, suggesting that the AI system can reliably quantify cardiac electrical parameters even in pathological ECGs associated with myocardial injury.

Table-3 Descriptive Statistics of ECG Parameters: AI vs. Manual Measurements among Myocardial Infarction ECG Cohort

Parameter	AI ECG Interpretation	Manual ECG Interpretation	P-value
Heart Rate	74.65 ± 7.78	72.00 (12.00)	0.48
RR Interval	0.81 ± 0.09	0.77 ± 0.13	0.17
QT Interval	0.34 (0.09)	0.35 (0.06)	0.67
QTc Interval	0.38 (0.09)	0.38 (0.04)	0.99

Note: Data are presented as Mean ± SD for normally distributed variables (as determined by the Shapiro–Wilk test) and as Median (IQR) for non-normally distributed variables. Paired t-test was applied for normally distributed data, and the Wilcoxon signed-rank test for non-normally distributed data. $p < 0.05$ was considered statistically significant.

DISCUSSION

The findings from this pilot study indicate that the AI-driven system for electrocardiogram (ECG) interpretation yields measurements that align closely with manual interpretations across both normal and myocardial infarction (MI) patient cohorts. This consistency is evidenced by the absence of statistically significant differences in key parameters, which correlates with a growing body of literature supporting the reliability of artificial intelligence (AI) in the field of cardiology. The narrative review conducted by Di Costanzo et al. [12] highlights that the diagnostic capabilities of AI often coincide with those of medical specialists, a conclusion that our findings substantiate. Notably, the system's ability to maintain agreement within the more complex MI group is particularly encouraging, suggesting its robustness in managing pathological ECGs. This assertion is reinforced by the large-scale ROMIAE multicentre study, which effectively employed an AI model to rule out acute myocardial infarction [13].

Despite the promising nature of the pilot study results, several limitations must be acknowledged. First, the sample size was relatively small (n=60), which may restrict the generalizability of these findings. A larger-scale study encompassing a more diverse and extensive patient population is essential to confirm these results. Second, this study concentrated on a limited set of ECG parameters. Future research should expand the focus to include other critical parameters, such as PR interval, QRS duration, and specific ST-T segment changes, which are also essential for accurate diagnosis. Furthermore, the study did not assess the AI's capability to provide final diagnostic conclusions but primarily evaluated the accuracy of individual parameter measurements.

Despite these limitations, the consistent findings of non-significant differences across all parameters provide a strong foundation for future research. The potential implications of a reliable AI-based ECG interpretation system are vast. Such a system could assist in triaging patients, reduce the workload on cardiologists and technicians, and potentially improve the speed and consistency of diagnosis, especially in resource-limited settings or in emergency departments where immediate and accurate ECG readings are crucial. Further validation studies are warranted, and these should include a larger, multicenter design to ensure the findings are reproducible and applicable across different clinical contexts.

CONCLUSION

This pilot study found no statistically significant differences between an AI system and manual interpretation for key ECG parameters in both normal and myocardial infarction patient cohorts. The AI-driven measurements for Heart Rate, RR Interval, QT Interval, and QTc Interval were found to be comparable to manual measurements, supporting the potential reliability and clinical utility of this AI technology. While these findings are promising, a larger-scale study is needed to validate these results and expand the scope of analysis.

REFERENCES

1. Hempel P, Bender T, Spicher N. Enhancing explainability in ECG analysis through evidence-based AI interpretability. Annu Int Conf IEEE Eng Med Biol Soc. 2024 Jul;2024:1-4. doi: 10.1109/EMBC53108.2024.10782420. PMID: 40039475.
2. Thirumurugan E, Dias E, Karthick R. Factors Influencing Electrocardiogram Pattern in Children and Adolescents: A Systematic Review for Future Research. J Card Crit Care TSS. 2024;8:85-94. doi: 10.25259/JCCC_74_2023
3. Kolhar M, Kazi RNA, Mohapatra H, Al Rajeh AM. AI-Driven Real-Time Classification of ECG Signals for Cardiac Monitoring Using i-AlexNet Architecture. Diagnostics (Basel). 2024 Jun 25;14(13):1344. doi: 10.3390/diagnostics14131344. PMID: 39001235; PMCID: PMC11240622.
4. Hong S, Heo J, Park KS. Signal Quality Index Based on Template Cross-Correlation in Multimodal Biosignal Chair for Smart Healthcare. Sensors (Basel). 2021 Nov 14;21(22):7564. doi: 10.3390/s21227564. PMID: 34833639; PMCID: PMC8624550.
5. Geweid, G. G. N., & Chen, J. D. Z. (2022). Automatic classification of atrial fibrillation from short single-lead ECG recordings using a Hybrid Approach of Dual Support Vector Machine. Expert Systems with Applications, 198, 116848. https://doi.org/10.1016/j.eswa.2022.116848
6. He K, Liang W, Liu S, Bian L, Xu Y, Luo C, Li Y, Yue H, Yang C, Wu Z. Long-term single-lead electrocardiogram monitoring to detect new-onset postoperative atrial fibrillation in patients after cardiac surgery. Front Cardiovasc Med. 2022 Sep 23;9:1001883. doi: 10.3389/fcvm.2022.1001883. PMID: 36211573; PMCID: PMC9537630.
7. Hsu CY, Liu PY, Liu SH, Kwon Y, Lavie CJ, Lin GM. Machine Learning for Electrocardiographic Features to Identify Left Atrial Enlargement in Young Adults: CHIEF Heart Study. Front Cardiovasc Med. 2022 Mar 1;9:840585. doi: 10.3389/fcvm.2022.840585. PMID: 35299979; PMCID: PMC8921457.
8. Zheng ZC, Yuan W, Wang N, Jiang B, Ma CP, Ai H, Wang X, Nie SP. Exploring the Feasibility of Machine Learning to Predict Risk Stratification Within 3 Months in Chest Pain Patients with Suspected NSTE-ACS. Biomed Environ Sci. 2023 Jul 20;36(7):625-634. doi: 10.3967/bes2023.089. PMID: 37533386.
9. Guo L, Gao C, Yang W, Ma Z, Zhou M, Liu J, Shao H, Wang B, Hu G, Zhao H, Zhang L, Guo X, Huang C, Cui Z, Song D, Sun F, Liu L, Zhang F, Tao L. Derivation and Validation of a Screening Model for Hypertrophic Cardiomyopathy Based on Electrocardiogram Features. Front Cardiovasc Med. 2022 May 24;9:889523. doi: 10.3389/fcvm.2022.889523. PMID: 35686042; PMCID: PMC9170889.
10. Zheng J, Fu G, Struppa D, Abudayyeh I, Contractor T, Anderson K, Chu H, Rakovski C. A High Precision Machine Learning-Enabled System for Predicting Idiopathic Ventricular Arrhythmia Origins. Front Cardiovasc Med. 2022 Mar 11;9:809027. doi: 10.3389/fcvm.2022.809027. PMID: 35360041; PMCID: PMC8962834.
11. Thirumurugan, E. (2025). A Systematic Review of AI Techniques for ECG Analysis in Acute Coronary Syndrome Detection. EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR, 46(02), 469-482.
12. Di Costanzo A, Spaccarotella CAM, Esposito G, Indolfi C. An Artificial Intelligence Analysis of Electrocardiograms for the Clinical Diagnosis of Cardiovascular Diseases: A Narrative Review. J Clin Med. 2024 Feb 11;13(4):1033. doi: 10.3390/jcm13041033. PMID: 38398346; PMCID: PMC10889404.
13. Lee MS, Shin TG, Lee Y, Kim DH, Choi SH, Cho H, Lee MJ, Jeong KY, Kim WY, Min YG, Han C,

Yoon JC, Jung E, Kim WJ, Ahn C, Seo JY, Lim TH, Kim JS, Choi J, Kwon JM, Kim K; ROMIAE study group. Artificial intelligence applied to electrocardiogram to rule out acute myocardial infarction: the ROMIAE multicentre study. Eur Heart J. 2025 May 21;46(20):1917-1929. doi: 10.1093/eurheartj/ehaf004. PMID: 39992309; PMCID: PMC12093146.