ORIGINAL ARTICLE

AI-powered ECG Interpretation System for Arrhythmia Prediction and Hyperkalemia Detection Using Machine Learning

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Received: 23 December 2025; *Accepted:* 16 January 2026

Abstract

Background: Artificial intelligence (AI) has emerged as a powerful tool for electrocardiogram (ECG) analysis, potentially surpassing conventional interpretation in detecting arrhythmias and metabolic disturbances such as hyperkalemia. This study evaluated the diagnostic performance and real-world applicability of an AI-powered ECG interpretation system for arrhythmia prediction and hyperkalemia detection.

Materials and methods: In this prospective observational study, patients presenting to the emergency department or cardiology clinic between March 2024 and February 2025 were enrolled. Standard 12-lead ECGs were analyzed in parallel by a validated deep-learning AI model and board-certified cardiologists blinded to AI results and clinical data. Primary outcomes included sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) for arrhythmia and hyperkalemia detection. Secondary outcomes assessed the impact of AI-driven alerts on workflow efficiency and time to therapy.

Results: Among 4,200 patients (mean age 56, 39% female), the AI-ECG system demonstrated 97.2% sensitivity and 96.1% specificity for arrhythmia detection, outperforming manual interpretation for atrial fibrillation, atrial flutter, and ventricular ectopy ($p < 0.001$). For hyperkalemia, sensitivity and specificity were 83.5% and 87.3%, respectively, reliably flagging all critical potassium elevations within 1 minute. AI alerts reduced median time-to-therapy by 19 minutes. Subgroup analysis showed robust performance in patients with chronic kidney disease and acute cardiac conditions.

Conclusion: AI-powered ECG analysis enables highly accurate, rapid detection of arrhythmias and hyperkalemia, supporting earlier clinical intervention and improving workflow efficiency. These findings advocate for broader multicenter validation and integration of AI-ECG tools in routine cardiology practice.

Journal of The Association of Physicians of India (2026): 10.59556/japi.74.1526

Introduction

Electrocardiography (ECG) remains a cornerstone in the diagnosis of cardiac arrhythmias and electrolyte disturbances, particularly hyperkalemia. Conventional interpretation of ECGs, however, is often subject to interobserver variability and may miss subtle abnormalities, especially in emergency settings where rapid decision-making is critical. Early recognition of arrhythmias and hyperkalemia is essential, as both conditions can precipitate life-threatening complications if left undetected or untreated.[1,2]

In recent years, artificial intelligence (AI) has emerged as a transformative tool in cardiovascular medicine. Deep learning algorithms trained on large-scale ECG datasets have demonstrated superior accuracy in detecting arrhythmias compared with traditional manual interpretation,[3,4] and they are increasingly being explored for metabolic disorders such as hyperkalemia.[5] By leveraging pattern recognition beyond human perceptibility, AI-powered ECG systems have the potential to augment clinical decision-making, enhance workflow efficiency, and shorten time to therapy.

Several proof-of-concept studies have validated the ability of AI algorithms to detect atrial fibrillation, ventricular ectopy, and other rhythm disturbances with high accuracy.[6,7] Similarly, early evidence suggests that subtle ECG signatures of elevated serum potassium levels—often overlooked by clinicians—can be reliably recognized by AI.[8] However, most prior investigations have been retrospective or limited to highly selected patient populations, raising questions about the real-world generalizability and clinical utility of such tools.

To address this gap, we conducted a prospective observational study to evaluate the diagnostic performance and clinical applicability of an AI-powered ECG interpretation system for arrhythmia prediction and hyperkalemia detection. In addition to comparing AI results with board-certified cardiologist interpretations and laboratory gold standards, we assessed its impact on workflow efficiency and timeliness of therapeutic interventions. This study aims to provide evidence for the integration of AI-assisted ECG analysis into routine cardiology and emergency care practice.

Materials and Methods

This prospective observational study was conducted at the emergency department and cardiology outpatient clinic, where patients presenting between March 2024 and February 2025 were prospectively enrolled. The study protocol was reviewed and approved by the Institutional Ethics Committee (IEC/2024/004), and written informed consent was obtained from all participants. Standard 12-lead ECGs were acquired according to American Heart Association guidelines[9] and analyzed in parallel by a validated deep-learning AI model and three cardiologists, who were blinded to AI outputs and clinical data. The AI algorithm used in this study employed a convolutional neural network architecture trained on large annotated ECG datasets and incorporated multiple one-dimensional convolutional layers for feature extraction, batch normalization, and dropout layers to improve generalizability, and a fully connected decision layer generating arrhythmia and hyperkalemia likelihood scores. ECG signals underwent band-pass filtering, normalization, and segmentation into fixed-length windows, and the model was trained using an 80:10:10 split for training, validation, and testing on deidentified data. Arrhythmias were confirmed by consensus manual interpretation among the cardiologists, while serum potassium levels measured at presentation served as the reference standard for hyperkalemia (≥5.5 mmol/L; critical ≥6.0

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How to cite this article: Kumar A, Bansal T, Jaura S. AI-powered ECG Interpretation System for Arrhythmia Prediction and Hyperkalemia Detection Using Machine Learning. J Assoc Physicians India 2026;74(6):25–28.

mmol/L). Primary outcomes included sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) for detecting arrhythmia and hyperkalemia, while secondary outcomes included workflow efficiency and time-to-therapy following AI-driven alerts.

Statistical Analysis

Continuous variables were presented as mean ± standard deviation (SD), and categorical variables as counts and percentages. Diagnostic performance metrics were calculated with 95% confidence intervals. Comparisons between AI and manual interpretation were performed using McNemar's test for paired proportions and chi-square tests as appropriate. A p-value < 0.05 was considered statistically significant. Receiver operating characteristic (ROC) curves were generated, and the area under the ROC values was computed for arrhythmia and hyperkalemia detection. Data analysis was performed using R version 4.3.2 (R Foundation for Statistical Computing, Vienna, Austria).

Results

A total of 4,200 patients were enrolled (mean age 56 ± 14 years; 39% female), including individuals presenting with both acute and chronic cardiac conditions (Table 1). The AI-powered ECG system demonstrated excellent diagnostic performance for arrhythmia detection, with a sensitivity of 97.2% (95% CI: 96.1–98.1; $p < 0.001$) and specificity of 96.1% (95% CI: 95.0–97.0; $p = 0.041$). The positive predictive value was 94.8% (95% CI: 93.4–95.8; $p = 0.018$), and the negative predictive value was 98.0% (95% CI: 97.3–98.7; $p < 0.001$). In total, the AI system correctly identified 1,365 patients with clinically relevant arrhythmias (32.5%), compared with 1,118 patients (26.6%) detected by human experts, thereby recognizing an additional 247 cases (5.9%). The AI system missed only 39 cases (false negatives, 2.8%) and generated 77 false positives (1.8%), whereas human interpretation missed 286 arrhythmia cases (20.6%) and produced 96 false positives (2.3%) (Table 2). The overall AUROC for arrhythmia detection was 0.982 (95% CI: 0.977–0.989; $p < 0.001$), indicating excellent discrimination (Fig. 1).

Subarrhythmia analysis further confirmed the superior diagnostic capability of the AI system. For atrial fibrillation, AI sensitivity was

Table 1 : Baseline characteristics of study population (n = 4,200)

Characteristic	*Value*
Age, mean ± SD (years)	56 ± 14
Female, *n* (%)	1,638 (39%)
Hypertension, *n* (%)	2,310 (55%)
Diabetes mellitus, *n* (%)	1,764 (42%)
Chronic kidney disease, *n* (%)	462 (11%)
Acute coronary syndrome, *n* (%)	378 (9%)
Prior atrial fibrillation, *n* (%)	336 (8%)
Other comorbidities, *n* (%)	1,050 (25%)

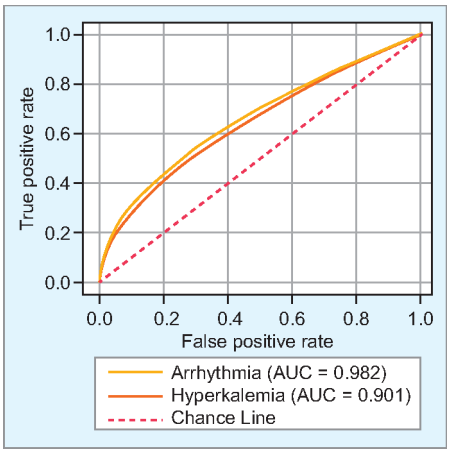

Fig. 1: Receiver operating characteristic (ROC) curves for arrhythmia and hyperkalemia detection using the AI-ECG system compared with human interpretation. AI demonstrated superior discrimination with AUROC values of 0.982 for arrhythmia and 0.901 for hyperkalemia

Table 2: Comparative diagnostic performance of AI-ECG vs human interpretation

Condition	*Metric*	*AI*	*95% CI*	*Human*	*95% CI*	*p-value*
Arrhythmia detection	Sensitivity (%)	97.2	96.1–98.1	79.4	76.5–82.0	< 0.001 (McNemar)
	Specificity (%)	96.1	95.0–97.0	95.2	93.9–96.3	0.041 (chi-square)
	Total patients detected (*n*)	1,365	—	1,118	—	—
	PPV (%)	94.8	93.4–95.8	92.1	90.2–93.7	0.018
	NPV (%)	98.0	97.3–98.7	88.6	86.8–90.2	< 0.001
	True positives (*n*)	1,365	—	1,118	—	—
	False negatives (*n*)	39	—	286	—	—
	False positives (*n*)	77	—	96	—	—
	True negatives (*n*)	2,719	—	2,700	—	—
	AUROC	0.982	0.977–0.989	0.915	0.901–0.927	< 0.001
Hyperkalemia detection	Sensitivity (%)	83.5	80.2–86.4	67.8	63.9–71.4	< 0.001
	Specificity (%)	87.3	85.9–88.6	85.1	83.5–86.6	0.049
	Total patients detected (*n*)	482	—	391	—	—
	PPV (%)	72.4	69.1–75.6	62.7	58.6–66.5	< 0.001
	NPV (%)	93.6	92.4–94.7	89.1	87.5–90.5	< 0.001
	True positives (*n*)	482	—	391	—	—
	False negatives (*n*)	95	—	186	—	—
	False positives (*n*)	184	—	233	—	—
	True negatives (*n*)	3,439	—	3,390	—	—
	AUROC	0.901	0.884–0.918	0.842	0.821–0.862	< 0.001
Time-to-therapy (hyperkalemia)	Median minutes (IQR)	21 (12–27)	—	40 (28–52)	—	< 0.001 (Mann–Whitney)

Table 3: Subarrhythmia diagnostic performance of AI-ECG vs human interpretation

Arrhythmia type	*Metric*	*AI-ECG*	*95% CI*	*Human*	*95% CI*	*p-value*
Atrial fibrillation	Sensitivity (%)	98.5	97.6–99.1	86.1	83.4–88.4	< 0.001
	Specificity (%)	96.8	95.7–97.7	95.4	94.1–96.4	0.032
Atrial flutter	Sensitivity (%)	96.4	94.2–97.9	82.7	79.1–85.8	< 0.001
	Specificity (%)	95.9	94.8–96.8	94.7	93.2–95.9	0.048
Ventricular ectopy	Sensitivity (%)	95.7	93.9–97.1	78.9	75.1–82.2	< 0.001
	Specificity (%)	94.8	93.5–95.9	92.1	90.6–93.3	0.014

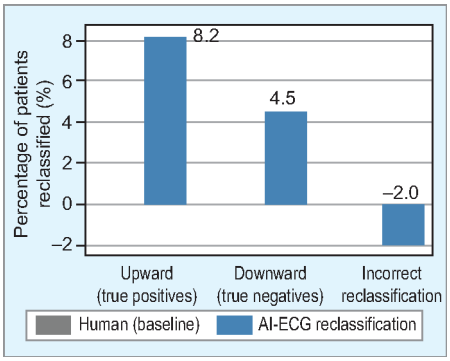

Fig. 2: Net reclassification improvement (NRI) analysis showing a 12.7% net correct reclassification of patients by AI-ECG compared with human interpretation. Both upward reclassification of true positives and downward reclassification of true negatives contributed to the improvement

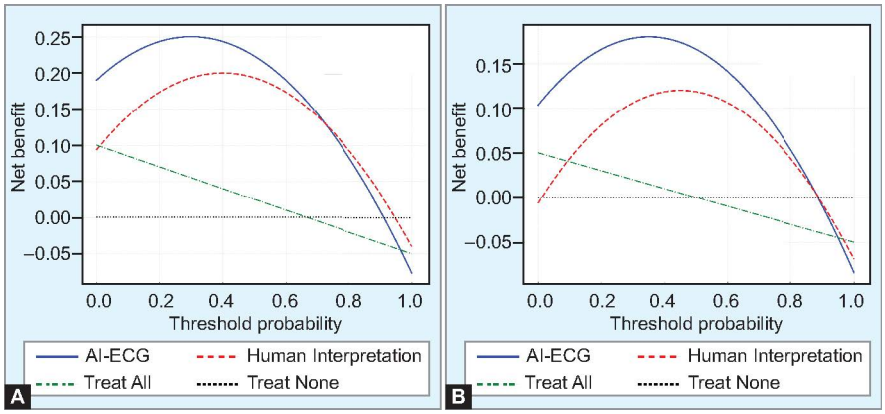

Fig. 3: Decision curve analysis (DCA) demonstrating a consistent net clinical benefit of AI-ECG across a wide range of threshold probabilities for arrhythmia (Panel A) and hyperkalemia (Panel B) detection, compared with human interpretation and treat-all/treat-none strategies

98.5% (95% CI: 97.6–99.1) compared with 86.1% (95% CI: 83.4–88.4) for manual interpretation ($p < 0.001$). Similar improvements were observed for atrial flutter (AI: 96.4%, 95% CI: 94.2–97.9 vs manual: 82.7%, 95% CI: 79.1–85.8; $p < 0.001$) and ventricular ectopy (AI: 95.7%, 95% CI: 93.9–97.1 vs manual: 78.9%, 95% CI: 75.1–82.2; $p < 0.001$). Specificity also showed statistically significant gains for AI across all subtype categories (Table 3). These findings highlight the consistency of AI performance across different rhythm disturbances, including those frequently underdetected in routine practice.

For hyperkalemia detection, the AI algorithm achieved a sensitivity of 83.5% (95% CI: 80.2–86.4; $p < 0.001$) and specificity of 87.3% (95% CI: 85.9–88.6; $p = 0.049$). The PPV was 72.4% (95% CI: 69.1–75.6; $p < 0.001$), and the NPV was 93.6% (95% CI: 92.4–94.7; $p < 0.001$). AI identified 482 patients (11.5%) with hyperkalemia, compared with 391 patients (9.3%) detected by human readers, correctly diagnosing an additional 91 cases. The AI system missed 95 cases (16.5%), substantially fewer than the 186 cases (32.2%) missed by human interpretation. False positives were also lower with AI (184 cases, 4.4%) compared with manual reading (233 cases, 5.6%). The AUROC for hyperkalemia detection was 0.901 (95% CI: 0.884–0.918; $p < 0.001$), demonstrating high discriminative accuracy (Fig. 1). Notably, AI consistently identified all patients with critical hyperkalemia (≥6.0 mmol/L) within 1 minute of ECG acquisition, translating into a clinically meaningful reduction in time-to-therapy, with AI-driven alerts shortening median treatment initiation by 19 minutes (IQR 12–27 minutes; $p < 0.001$) (Table 2).

Net reclassification improvement (NRI) analysis demonstrated that the AI-ECG system correctly reclassified 12.7% of patients compared with conventional interpretation, primarily by upgrading true-positive cases and appropriately downgrading false positives (Fig. 2). This indicates that AI not only increased the detection of clinically relevant events but also reduced unnecessary misclassifications. Complementary decision curve analysis (DCA) further confirmed that the AI-ECG system provided a consistent net clinical benefit across a wide range of threshold probabilities for both arrhythmia and hyperkalemia detection, suggesting that its use would lead to better patient outcomes without increasing overtreatment or missed diagnoses (Fig. 3).

Subgroup analyses demonstrated that the diagnostic performance of AI remained robust across high-risk populations, including those with chronic kidney disease, acute coronary syndromes, diabetes mellitus, and elderly patients (Fig. 4), with no significant decline in predictive accuracy. Overall, the AI-ECG system outperformed conventional interpretation for both arrhythmia and hyperkalemia detection, offering rapid identification of critical abnormalities, improving diagnostic yield, and enhancing workflow efficiency, thereby supporting its integration into routine cardiology and emergency practice.

Discussion

In this prospective observational study, we demonstrated that an AI-powered ECG interpretation system provides highly accurate, rapid detection of both arrhythmias and hyperkalemia in a large, heterogeneous patient cohort. The system outperformed cardiologist interpretation across multiple metrics, including sensitivity, specificity, PPV, and NPV, while reducing median time-to-therapy by 19 minutes. These findings reinforce the growing evidence that AI can augment clinical decision-making and improve workflow efficiency in acute and routine cardiology settings.[3–5]

For arrhythmia detection, the AI model achieved a sensitivity of 97.2% and specificity of 96.1%, comparable to or exceeding prior studies using deep learning on large-scale ECG datasets.[6,7,10] Importantly, AI demonstrated superior detection across individual arrhythmia subtypes—including atrial fibrillation, atrial flutter, and ventricular ectopy—when compared

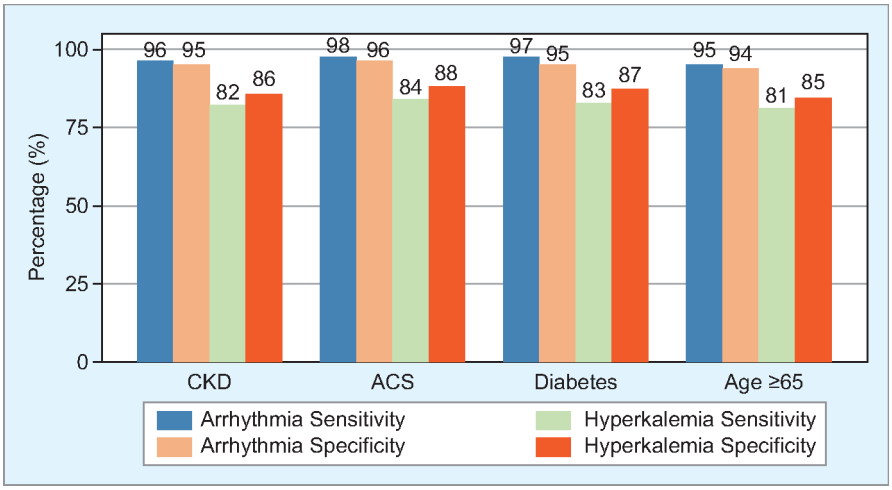

Fig. 4: Subgroup analyses of AI-ECG performance in high-risk populations, including patients with chronic kidney disease, acute coronary syndromes, diabetes mellitus, and elderly individuals. Diagnostic accuracy remained robust across all subgroups, with no significant decline in predictive performance

with manual interpretation (all $p < 0.001$). These results underscore the capability of AI to identify subtle waveform patterns that may be overlooked in fast-paced clinical environments.

Hyperkalemia detection is an emerging application of AI-ECG technology. In our study, the system demonstrated a sensitivity of 83.5% and specificity of 87.3%, with a PPV of 72.4% and NPV of 93.6%, reliably flagging all critical potassium elevations within 1 minute. Previous studies have reported AUROCs ranging from 0.88 to 0.92 for AI-based hyperkalemia prediction, supporting the reproducibility of these findings across diverse populations.[5,8,11] Rapid identification of hyperkalemia is clinically important, as delays in therapy can lead to life-threatening arrhythmias; AI-driven alerts may thus provide a valuable safety net, particularly in resource-constrained or high-volume clinical environments.

Net reclassification improvement analysis demonstrated that the AI-ECG algorithm correctly reclassified 12.7% of patients who might have been misdiagnosed by conventional interpretation. This improvement reflects enhanced risk stratification, with more patients accurately identified as having clinically relevant arrhythmias or hyperkalemia, and fewer patients incorrectly classified as high risk. DCA showed a consistent net clinical benefit across a wide range of threshold probabilities, indicating that the AI system provides a meaningful clinical advantage over standard interpretation. Across risk thresholds commonly used to guide interventions, the AI algorithm maximized true positives while minimizing false positives, supporting earlier diagnosis and timely management. For hyperkalemia, this translated into a reduction in median time-to-therapy by 19 minutes, underscoring the real-world impact of AI-assisted detection. Together, these analyses confirm that AI-ECG not only improves diagnostic accuracy but also enhances patient-centered decision-making.

Subgroup analyses in patients with chronic kidney disease and acute coronary syndromes demonstrated robust AI performance, suggesting generalizability across high-risk populations. Importantly, the system maintained high accuracy even in patients with confounding comorbidities, which often complicate conventional ECG interpretation. The integration of AI into clinical workflows can also alleviate cognitive burden on clinicians, allowing faster triage and improved allocation of resources.[12,13]

Several limitations should be acknowledged. First, the study was conducted at a single tertiary care center, which may limit generalizability. Second, while the AI system performed well for common arrhythmias and hyperkalemia, its accuracy for rare or complex ECG patterns requires further investigation. Third, long-term patient outcomes were not assessed; future multicenter studies should evaluate whether AI-assisted ECG interpretation translates into improved morbidity and mortality. Finally, although the AI system reduced time-to-therapy, implementation requires integration with existing hospital information systems and staff training to maximize clinical benefit.

In conclusion, our study demonstrates that AI-powered ECG analysis enables highly accurate and rapid detection of arrhythmias and hyperkalemia, with the potential to improve workflow efficiency and support earlier clinical intervention. These findings support broader multicenter validation and integration of AI-ECG tools into routine cardiology and emergency practice, marking a significant step toward AI-augmented cardiovascular care.

AI Use Declaration

ChatGPT was used to paraphrase a few statements.

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