Původní sdělení | Original research article

Artificial intelligence in resting ECG: Higher accuracy in the interpretation of rhythm abnormalities

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SOUHRN

Úvod: Cílem této studie je vyhodnocení výkonu nově vyvinutého rytmového modelu určeného pro interpretaci EKG a založeného na umělé inteligenci (AI-ECGRM) v binární klasifikaci mezi sinusovým rytmem a arytmiemi.
Metody: Interpretace EKG záznamů generované pomocí AI-ECGRM byly v rámci studie porovnány s diagnostickými závěry zkušeného kardiologa. Metodou použitou ke klasifikaci dat byla matice záměn, přičemž vyhodnocení zahrnuje senzitivitu, specificitu, pozitivní prediktivní hodnotu a negativní prediktivní hodnotu.
Výsledky: Testovací datová sada obsahuje 1 491 náhodně vybraných EKG záznamů (průměrný věk 65 ± 21 let; 54 % žen). Pro danou datovou sadu čítala diagnostika kardiologa 1 271 záznamů se závěrem sinusový rytmus a 220 záznamů se závěrem arytmie. Oproti tomu interpretace generovaná pomocí AI-ECGRM čítala 1 169 záznamů se závěrem sinusový rytmus a 322 záznamů se závěrem arytmie. Senzitivita a specificita AI-ECGRM byla 94 % a 91 %. Pozitivní prediktivní hodnota byla 64 %. Negativní prediktivní hodnota dosáhla 99 %, což značí velmi nízkou pravděpodobnost vynechání potenciální patologie.
Závěr: Výsledky ukazují na účinnost nově vyvinutého AI-ECGRM pro rozlišení záznamů se sinusovým rytmem a arytmií. Navíc metoda vykazuje vysokou negativní prediktivní hodnotu blížící se 100 %.
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ABSTRACT

Objective: This study aimed to evaluate the performance of a developed novel AI-based ECG rhythm model (AI-ECGRM) in binary classification between sinus rhythm and arrhythmias.
Methods: The interpretations generated by the AI-ECGRM were compared to the diagnostic conclusions made by cardiologists. The confusion matrix was used to verify the AI-ECGRM's sensitivity, specificity, positive predictive value, and negative predictive value.
Results: The testing dataset included 1,491 randomly selected ECGs (mean age 65±21 years; 54% female). Out of the testing dataset, the highly advanced cardiologists diagnosed 1,271 ECGs as sinus rhythm and 220 as arrhythmia. The AI-ECGRM labelled 1,169 as sinus rhythm and 322 as arrhythmia out of the same ECGs. The sensitivity and specificity of the model were 94% and 91%, respectively. The positive predictive value was 64%. The negative predictive value was 99%, indicating a very low probability of missing any potential pathology.
Conclusion: The results demonstrated the efficacy of the developed AI-ECGRM in accurately discriminating between ECGs exhibiting normal sinus rhythm and those indicating cardiac arrhythmias. Moreover, the AI-ECGRM exhibited an exceptional negative predictive value, approaching 100%.

Keywords:
Arrhythmia
Artificial intelligence
Cardiovascular diseases
ECG interpretation
Resting ECG
Sinus rhythm

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Introduction

Over the past decades, cardiovascular diseases have consistently remained the leading causes of mortality worldwide, and unfortunately, their prevalence continues to rise.[1–3] Cardiac arrhythmias often serve as the initial signs of clinically silent cardiovascular conditions and are associated with increased morbidity and mortality in numerous cases.[4–6] The electrocardiogram (ECG) is a fundamental diagnostic tool for detecting arrhythmias (ARs). While not recommended for routine health check-ups in otherwise healthy individuals, the reality is quite different.[7,8] Primary care professionals and non-cardiologist professionals routinely perform ECG examinations as part of their daily practice, leading to a significant number of false positive misinterpretations of the ECGs.[9–11] This situation not only places a burden on cardiologists but also results in increased healthcare costs.[12] Moreover, overlooking the presence of ARs due to false negative ECG interpretations exposes patients to the risk of AR related complications such as ischemic stroke, heart failure progression, or sudden cardiac death. Consequently, there is a need for new approaches to support non-cardiologist professionals in making accurate diagnostic conclusions.

The conventional interpretation of the ECG done by computer started back in the 1950s, but the results are still not satisfactory to fully realize its potential in clinical practice.[13] In recent years, the medical field has increasingly embraced the implementation of artificial intelligence (AI) in diagnostic devices, and cardiology has been at the forefront of this trend.[14,15] AI, with its ability to simulate human thinking processes, is emerging as a valuable tool in the evaluation of ECGs.[16] Given that AI is a relatively new technology for ECG interpretation, it is essential to continue its development, conduct further research, and explore its potential from various perspectives.

To enhance and expand the concept of automated ECG interpretation and support non-cardiologist professionals, we have developed and tested a novel AI-based ECG rhythm model (AI-ECGRM). Our objective is to create a reliable and innovative tool for ECG interpretation that can be seamlessly integrated into daily clinical practice. This study aimed to assess the performance of the developed AI-ECGRM in the binary classification of ECGs, specifically distinguishing between sinus rhythm (SR) and ARs.

Materials and methods

Study design

We conducted a comparative study to assess the performance of the developed AI-ECGRM in binary classification between normal SR and ARs. The interpretations generated by the AI-ECGRM were compared to the diagnostic conclusions made by cardiologists. A confusion matrix, which allowed for measuring the sensitivity (SE), specificity (SP), positive predictive value (PPV), and negative predictive value (NPV) of the AI-ECGRM, was used to evaluate the performance.

AI-ECGRM description

The AI-ECGRM was specifically developed and trained to interpret 10-second recordings of 12-lead resting ECGs and to identify normal SR and various cardiac ARs. The ECG data from the dataset serves as input for the AI-ECGRM. The initial preprocessing stage involves filtering and noise reduction using the ECG device's built-in algorithms while baseline wandering is eliminated. Furthermore, the device extracts ECG features such as heart rate, R-peak positions, QRS width, J-point position, and more. The noise-free data is then converted into an image-like representation called a relief map, incorporating information from all 12 leads. Additionally, the ECG features are transformed into a Poincaré graph, from which a Poincaré vector is derived. These image-like ECG representations, Poincaré vectors, and other features are utilized as inputs for training the AI-ECGRM. The AI-ECGRM is designed to differentiate between normal SR and various ARs, including atrial fibrillation (AF), ventricular rhythm, supraventricular rhythm, narrow complex tachycardia, wide complex tachycardia, and other abnormal rhythms influenced by heart ectopy and other factors. BTL Industries Ltd. developed the AI-ECGRM, integrated into the BTL 4 and BTL 8 resting ECG devices, the BTL CONNECTin clinical information system, and the BTL CardioPoint unified software solution for comprehensive cardiopulmonary functional analysis.

To develop and internally validate the AI-ECGRM, a training dataset was compiled. This dataset comprised ECGs obtained from emergency rooms in Czech hospitals (with diagnoses assigned by hospital cardiologists) and publicly available ECGs with diagnoses assigned by cardiologists (published by Shaoxing People's Hospital and Ningbo First Hospital in collaboration with PhysioNet/CinC Challenge 2021).[17] The dataset was expanded to include additional rare diagnoses collected from hospitals in the Czech Republic. ECGs were excluded based on several criteria, including patient age under 18 years, presence of a pacemaker, noisy or missing ECG signals, and unassigned diagnoses.

The final dataset was randomly divided into two groups: training the AI-ECGRM (80% of the ECGs) and internal testing (20% of the ECGs). The diagnoses distribution in both groups was balanced. The cardiologists' diagnostic conclusions served as the reference standard for comparison. The AI-ECGRM was trained and internally validated using this dataset to accurately differentiate between normal SR and ARs (Fig. 1).

Testing dataset

The testing dataset aimed to make an external validation of the AI-ECGRM and to determine its SE, SP, PPV, and NPV of the labelling of the ECGs in comparison to the cardiologists' diagnostic conclusions of the same input data (Fig. 1). Both the cardiologist and the AI-ECGRM had the same baseline: the ECGs were anonymized with no assigned diagnosis nor patient information, the cardiologist did not see the patient since that was not possible for the AI-ECGRM either, and the counterparties did not know the other party's evaluations. The cardiologists' evaluations of the ECGs were assessed in two steps. First, the ECGs were evaluated by a cardiologist (1- to 3-year prac-

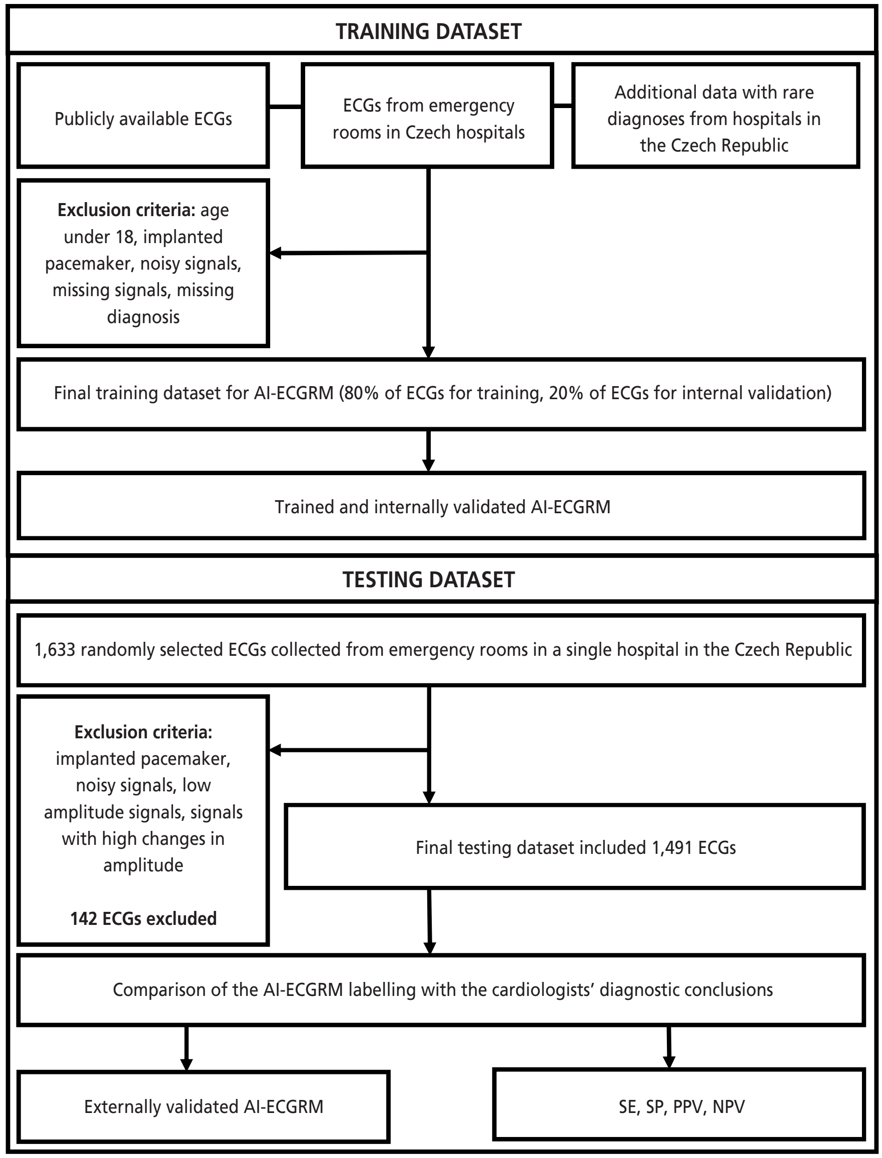

Fig. 1 – Study flow chart.

tice with ECG evaluation). Next, the diagnostic conclusions were confirmed by a cardiologist consultant (an experienced electrophysiologist) of the 2nd Department of Internal Cardiovascular Medicine, General University Hospital in Prague.

Statistics

To determine the values of SE, SP, PPV, and NPV for the AI-ECGRM, we utilized a confusion matrix.[18] In this evaluation, we employed the statistical program "R" (version 3.0.2). The cardiologists' diagnostic conclusions were considered the reference standard for further assessment. When diagnosed by the cardiologists, the presence of normal SR or the presence of pathology other than the mentioned ARs was regarded as a negative test result, while the presence of the mentioned ARs was considered a positive test result. The AI-ECGRM classifies instances either as the mentioned ARs (considered a positive result) or as normal SR (considered a negative result).

Results

The testing dataset comprised 1,633 randomly selected ECGs, each unique ECG and none included in the training dataset. The ECGs were collected from emergency rooms in a single hospital in the Czech Republic. Based on the criteria outlined in Table 1, 142 ECGs were excluded from the dataset. Consequently, the final testing dataset consisted of 1,491 ECGs, with a mean age of 65±21 years and 54% of the participants being female.

Cardiologists diagnosed 1,271 as normal SR and 220 as AR among the ECGs in the final testing dataset. The AI-ECGRM labelled 1,169 ECGs as normal SR and 322 as AR. Subsequently, a comparison was made between the AI-ECGRM's labelling and the diagnostic conclusions from the cardiologists.

The comparison between the AI-ECGRM results and the cardiologists' diagnostic conclusions yielded the following results. Out of the analyzed ECGs, 207 were true

Table 1 – Exclusion criteria for testing dataset, expressed as n (%)

Exclusion criteria	ECGs excluded (n = 142)
Implanted pacemaker	6 (4.2%)
Noisy ECGs	105 (73.9%)
Low amplitude ECGs	2 (1.4%)
ECGs with high changes in amplitude (caused by external conditions, *e.g.* electrode movement)	29 (20.4%)

Table 2 – The labelling from the AI-ECGRM compared with the diagnostic conclusions from the cardiologists in the confusion matrix, expressed as n

	Diagnostic conclusions from the cardiologists	
Labelling from the AI-ECGRM	Positive (n = 220)	Negative (n = 1,271)
Positive (n = 322)	TP (n = 207)	FP (n = 115)
Negative (n = 1,169)	FN (n = 13)	TN (n = 1,156)

Table 3 – Results, expressed as %

SE	SP	PPV	NPV
94%	91%	64%	99%

positive (TP), indicating that the AI-ECGRM correctly processed AR in accordance with the cardiologists' diagnoses. Additionally, 1,156 ECGs were true negative (TN), where both the AI-ECGRM and the cardiologists' conclusions agreed that these ECGs displayed normal SR. However, there were 115 false positive (FP) in which the AI-ECGRM labelling contradicted the cardiologists' diagnostic conclusions. Despite being diagnosed as normal SR by cardiologists, the AI-ECGRM incorrectly labelled these ECGs as ARs. Furthermore, there were 13 false negative (FN) where the AI-ECGRM labelling contradicted the cardiologists' diagnoses. In these cases, the AI-ECGRM incorrectly labelled the ECGs as normal SR while the cardiologists diagnosed them as ARs (Table 2 for a comprehensive summary of the results.).

The AI-ECGRM demonstrated a SE of 94% in correctly identifying patients with ARs. It exhibited an SP of 91% in correctly identifying patients with normal SR. The PPV, which represents the probability that the ECGs labelled as ARs were indeed ARs, was 64%. Notably, the high proportion of FP was primarily due to ECGs with pathologies other than ARs. The NPV, which indicates the probability of correctly labelled SR, was 99% (Table 3).

Discussion

In this study, we conducted an evaluation of the effectiveness of the developed AI-ECGRM. What sets this AI-ECGRM apart is its utilization of a relief map in conjunction with additional ECG features, such as heart rate, R-peak positions, QRS width, and J-point position, as inputs for the AI. This approach closely mimics the decision-making process of expert cardiologists, allowing the AI-ECGRM to engage in data evaluation from a similar starting point.

The primary outcome of this study revealed that the developed AI-ECGRM achieved a near-perfect NPV of almost 100%. This exceptional performance demonstrates the high accuracy and reliability of the AI-ECGRM in ruling out pathology. These findings highlight the tremendous potential of AI in ECG evaluation and indicate that further development and testing of this technology is a promising pathway to pursue.

Results evaluation

The high NPV of 99% demonstrates the reliability of the AI-ECGRM, indicating a very low probability of missing any potential pathology. In this study, only 13 cases out of 1,169 (1% of cases) were incorrectly labelled by the AI-ECGRM. Considering the potential for misinterpretation of ECGs by non-cardiologist professionals, the AI-ECGRM's quality becomes a significant advantage.

Upon further analysis of the 13 ECGs labelled as FN by the AI-ECGRM, we identified several potential confounders contributing to these misclassifications. In 4 ECGs, the FN labelling originated from the incorrect interpretation of noise or artifacts presented in the recordings (Fig. 2). To minimize the risk of FN labelling, it is crucial to strictly exclude noisy ECGs from the analysis conducted by the AI-ECGRM. In 2 ECGs, the misinterpretation of the P wave originating from the sinus node was the cause of FN labelling (Fig. 3). This situation typically represents abnormal atrial activation, often benign when asymptomatic. Although missing this condition usually does not lead to serious adverse events, it is still essential to consider it in the interpretation. For 4 ECGs, the cause of FN labelling was the interpretation of sporadic sinus beats that were interpolated between paroxysms of arrhythmias (Fig. 4). While such occurrences are rare, they can have potentially severe implications if AF is overlooked, as it may fail to initiate anticoagulation therapy. Two ECGs presented ambiguous interpretations and may ultimately be classified as normal SR after thorough evaluation. However, one ECG met the exclusion criteria due to an implanted pacemaker and should have been excluded from the dataset to avoid inaccuracies. These findings highlight the importance of addressing and minimizing confounders to improve the accuracy of the AI-ECGRM in differentiating between normal SR and ARs.

The PPV of 64% observed in this study reflects the primary focus of the AI-ECGRM on distinguishing between SR and various types of ARs. However, it should be noted that specific morphological pathologies of the heart, which are not true ARs, were incorrectly labelled as ARs (Fig. 5). Additionally, there may have been cases where the AI-ECGRM identified subtle or borderline changes of unknown clinical significance, such as sinus tachycardia, as abnormal, while cardiologists interpreted them as normal, leading to an increased number of FP results.

Regarding the FP results, it is crucial to consider the potential implications of over-diagnosing patients with conditions that may have no significant impact on their lives if they would not have otherwise been aware of them. This poses challenges from a personal perspective and places a burden on the healthcare system, both in terms of financial and human resources.[19] It is crucial to

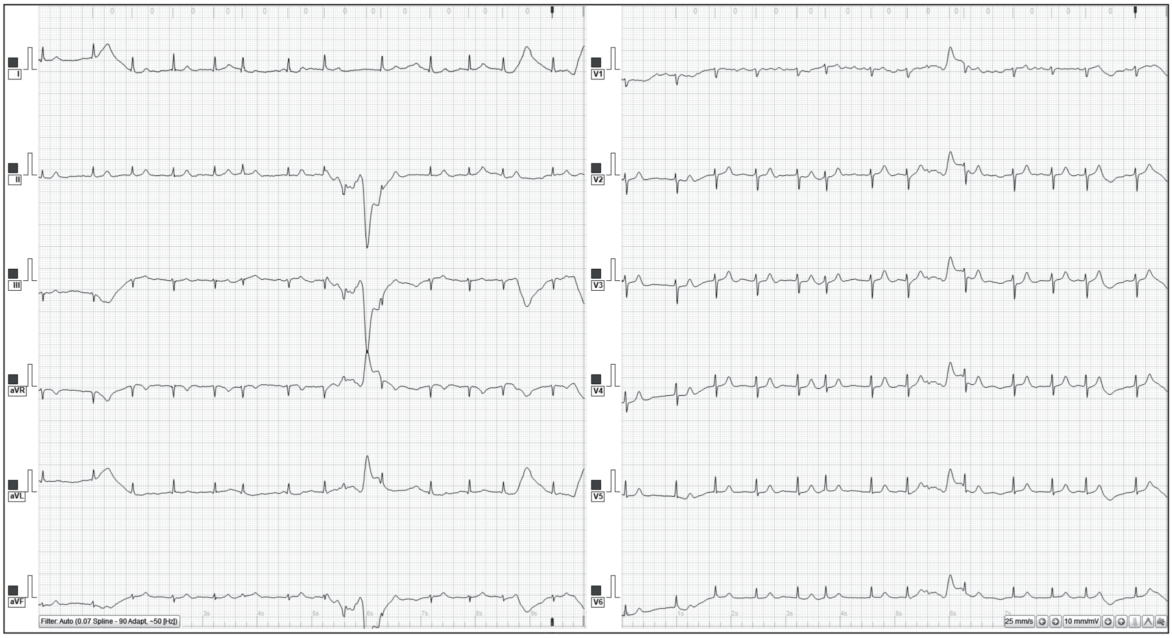

Fig. 2 – Example of FN result originating from wrongly interpreted noise or artefacts, AF.

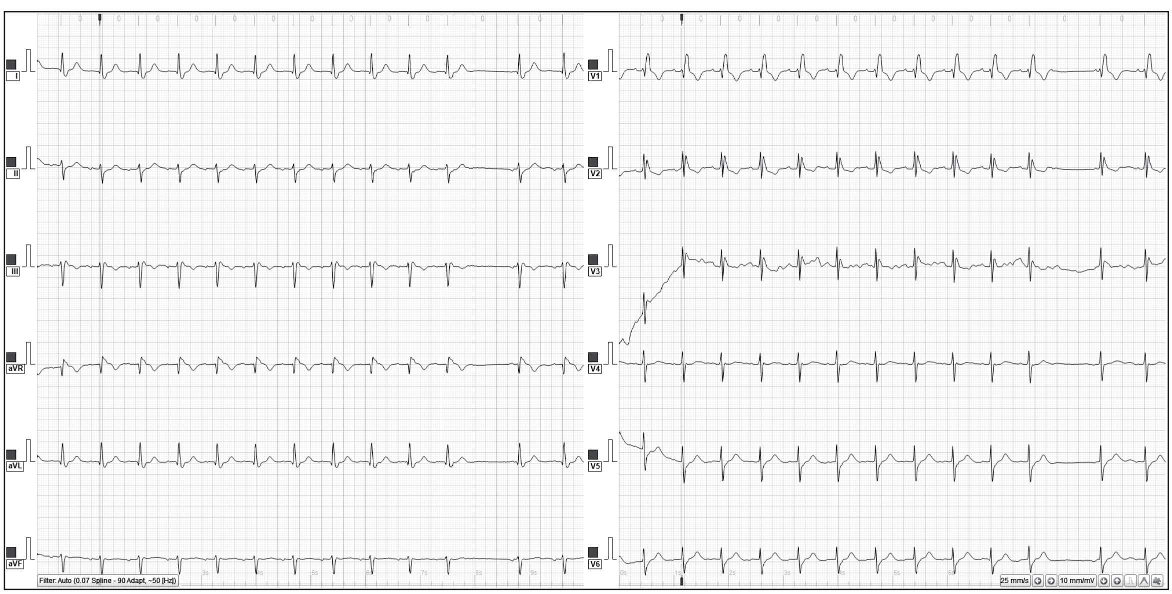

Fig. 3 – Example of FN result originating from wrongful interpretation of the P wave as SR.

carefully balance the contribution of newly developed diagnostic methods with their practical impact, an aspect that should be considered in future research.

In this study, the cardiologists' diagnostic conclusions were regarded as the reference standard for training and testing the AI-ECGRM. However, it is essential to acknowledge that the cardiologists themselves could have been mistaken in their interpretations, as evidenced by the two ECGs mentioned with ambiguous interpretations during the evaluation of the results. Although cardiologists generally exhibit higher accuracy in ECG evaluation than non-cardiologist professionals, errors are still possible.[20] Furthermore, it is worth noting that the comprehensive ECG evaluation conducted in this study does not necessarily reflect the routine practices followed in clinical settings.

Further perspectives and related research

In this study, we developed an AI-ECGRM specifically designed to distinguish between normal SR and ARs. The primary objective of this study was to assess the effectiveness of the AI-ECGRM in labelling and differentiating ARs from normal SR in a general context. However, there is further scope to explore the effectiveness of the AI-ECGRM in labelling and distinguishing between specific types of ARs, which could be the focus of future research.

Moreover, there is an opportunity for the AI-ECGRM to be further developed by expanding its labelling capabili-

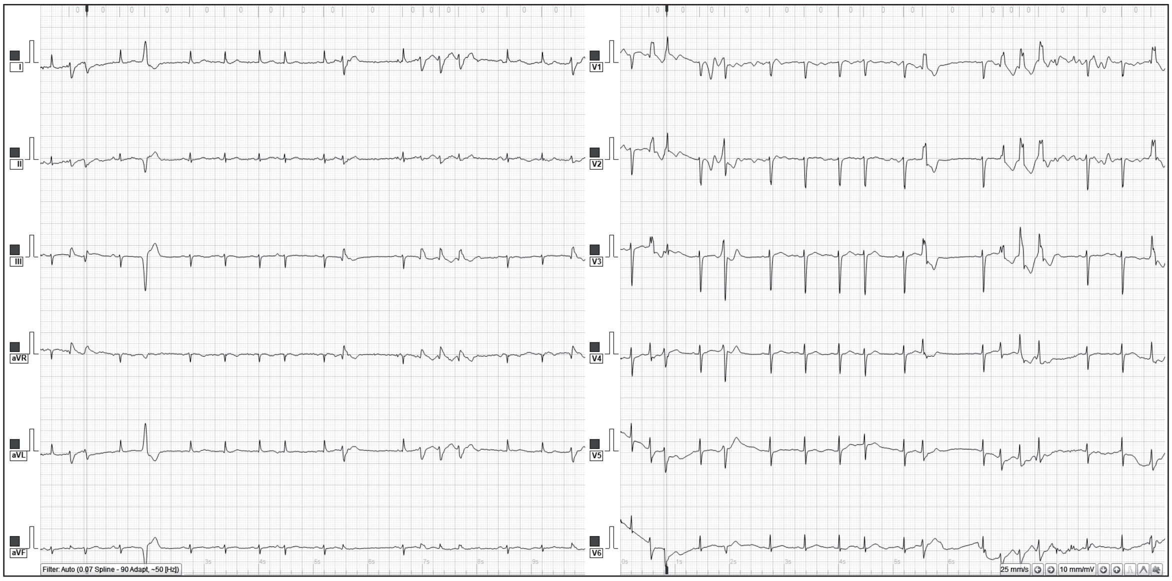

Fig. 4 – Example of FN result originating from prioritizing the sections of the ECG with SR above pathological sections in evaluation.

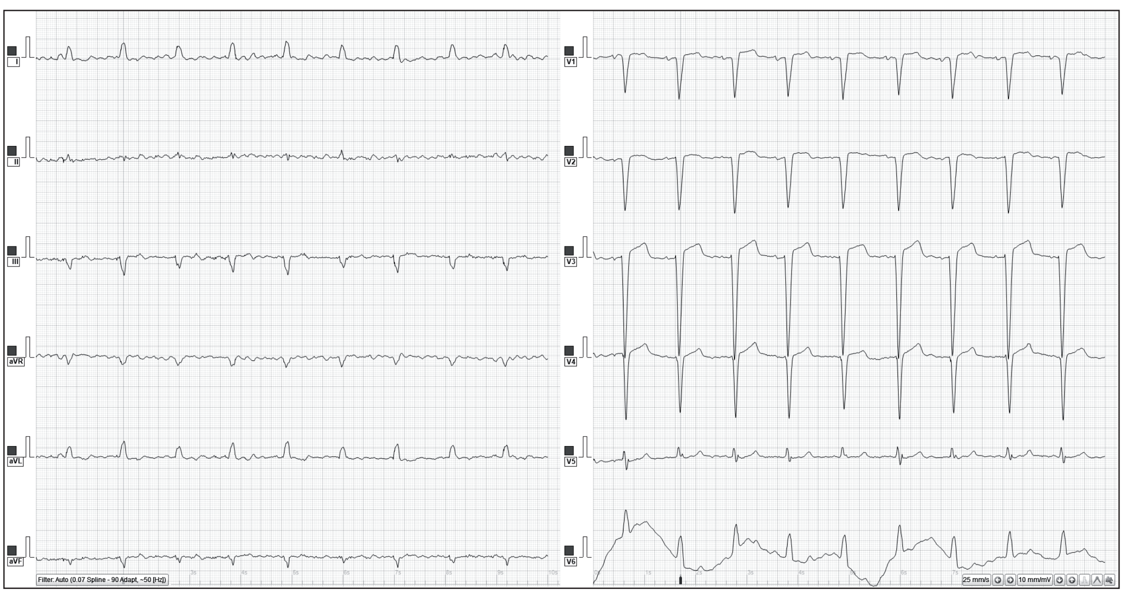

Fig. 5 – Example of FP result (labelled by the AI-ECGRM) showing SR and noise in limb leads, wider QRS complex, intraventricular conduction disturbance with secondary repolarization changes.

ties to include morphological abnormalities of the heart. It would introduce a more complex task for the AI-ECGRM in providing accurate labels. Exploring this aspect would contribute to the overall improvement and advancement of the AI-ECGRM.

It is important to note that this study is not the first exploration of AI-based ECG evaluation, as previous studies have already investigated various aspects of AI in this field. Some of these studies focused on AI's role in detecting heart failure with preserved ejection fraction, paroxysmal supraventricular tachycardia, or identifying patients with AF.[21–24] The existence of a considerable body of research with positive outcomes regarding AI's performance suggests its promising potential as a valuable tool in ECG evaluation.

By building upon the existing knowledge and positive results from previous studies and addressing the opportunities for further development and exploration mentioned above, we can continue to advance the field of AI-driven ECG interpretation and harness its potential for improved diagnostic accuracy and patient care.

Limitations

One limitation of our study, which is also applicable to automated evaluation methods in general, is the need for actual patient data. While this provides a pristine baseline for data evaluation, devoid of patient-specific factors and distractions, it does not replicate the real-world clinical scenario. In clinical practice, ECGs are routinely assessed with the patient's clinical profile, symptoms, and other diagnostic information, including laboratory tests and cardiac imaging. These additional pieces of information contribute to the final interpretation of the ECG.

Furthermore, there are additional limitations in our study. Most patients included in the study were older; therefore, the AI-ECGRM's applicability to younger populations is not reflected in our results. Additionally, the results cannot be extrapolated to patients with permanent pacing, as the AI-ECGRM was not explicitly trained or validated for this subgroup.

Conclusion

The results demonstrated the efficacy of the developed AI-ECGRM in accurately discriminating between ECGs exhibiting normal SR and those indicating cardiac ARs. Moreover, the AI-ECGRM exhibited an exceptional NPV, approaching 100%.

Conflict of interest

VC and LP are employees of BTL Industries Ltd. SH is an independent specialist having a contract with BTL Industries Ltd. He supervises the team composed of the rest of the authors. The products to be declared (developed and marketed) are resting ECG devices BTL 4 and BTL 8, the BTL CONNECTin, and the BTL CardioPoint.

Funding

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Ethical statement

The study followed good clinical practice and adhered to the principles outlined in the Declaration of Helsinki. Approval for the study was obtained from the Ethics Committee of the General University Hospital in Prague (5/23 S). Since fully anonymized ECGs were used, the Ethics Committee did not require informed patient consent.

Author contributions

SH took care of the scientific integrity of the work and editing of the manuscript. VC and LP provided technical support and technical descriptions. BS, MV, JH, MZ, LM, KK, NK, JCL, MD, and JM were involved in annotating the underlying data and in making its comprehensive evaluation and analysis. All the authors approved the final version of the article.

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