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AUTOMATED CLASSIFICATION OF HEMODYNAMICALLY SIGNIFICANT ARRHYTHMIAS BASED ON ECG FEATURES

Annotation: *This paper presents an automated method for the classification of hemodynamically significant arrhythmias (HSA) based solely on electrocardiographic (ECG) features, without the use of additional imaging diagnostic techniques. The proposed approach relies on key ECG parameters, including QRS complex duration, RR intervals, and heart rate (HR). The study is based on data from the open-access MIT-BIH Arrhythmia Database, which contains multiple types of cardiac rhythm disturbances. A comparative analysis of arrhythmia classes was conducted, leading to the identification of diagnostically significant predictors associated with hemodynamic instability. Logical decision rules and a decision tree model were developed to enable automatic recognition of HSA and clinical risk stratification. The proposed algorithm demonstrates high interpretability and practical applicability for real-time monitoring systems. The results confirm that ECG-based features alone can be effectively used for preliminary detection of dangerous arrhythmias. The developed approach is especially valuable for telemedicine systems and healthcare facilities with limited access to expensive diagnostic equipment.*

Key words: *ECG, arrhythmia, hemodynamically significant arrhythmia (HSA), QRS complex, RR intervals, heart rate, MIT-BIH, automated diagnosis.*

Introduction

Cardiac arrhythmias are disturbances in the regular electrical activity of the myocardium that can lead to significant alterations in systemic hemodynamics. Among these, particular attention is given to hemodynamically significant arrhythmias (HSA), which are associated with reduced tissue perfusion, hypotension, syncope, and, in some cases, an increased risk of fatal outcomes.

Modern approaches to assessing HSA typically involve the use of imaging-based diagnostic tools – particularly echocardiography, which allows for the evaluation of ejection fraction and volumetric characteristics of the left ventricle. However, in settings with limited access to expensive hardware - especially at the outpatient level or within telemedicine systems – there is a growing need for alternative, less resource-intensive diagnostic methods.

Electrocardiography (ECG) remains the most accessible and widely used method for the primary diagnosis of heart diseases. ECG signals provide a range of parameters that reflect the electrical activity of the heart, including the QRS complex duration, RR intervals, and heart rate (HR). According to several studies, these parameters can serve as surrogate markers of the functional state of the cardiovascular system [2, 3, 10].

Hemodynamically significant arrhythmia (HSA) is a type of cardiac rhythm disturbance that leads to reduced tissue perfusion and may result in loss of consciousness, hypotension, ischemia, and other severe consequences. Current diagnostic methods for HSA typically involve costly and labor-intensive procedures, including echocardiography. This study proposes an approach to evaluating HSA based solely on ECG features [1, 2], such as QRS complex duration, RR intervals, and heart rate (HR). The primary objective is to automate preliminary diagnosis using open-access data and simple physiological criteria.

Materials and methods

This study implements a step-by-step approach aimed at developing an interpretable and technically feasible algorithm for recognizing hemodynamically significant arrhythmias (HSA) based on electrocardiographic data. The process begins with the selection of initial data and the classification of arrhythmia types. Key diagnostic features are then extracted and subjected to quantitative analysis. Logical rules are formulated, followed by validation using a decision tree model. This approach allows for a justified integration of clinically significant parameters with their application in engineering-based diagnostic systems.

The study utilizes the open-access MIT-BIH Arrhythmia Dataset, which includes five primary types of cardiac rhythms: normal rhythm, supraventricular ectopic beat, ventricular ectopic beat, fusion of ventricular and supraventricular activity, and other arrhythmias. Signal classification is visualized (see Figure 1), and the averaged parameters are presented in Table 1.

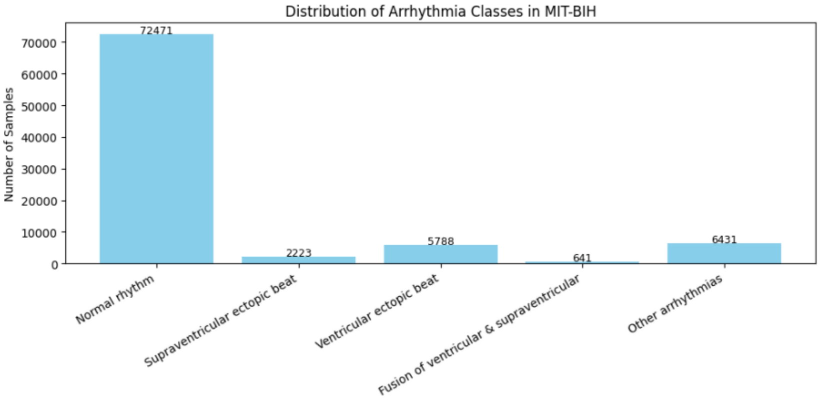

Figure 1 – Distribution of arrhythmia classes in the MIT-BIH dataset

Table 1 – Average ECG Feature Values by Arrhythmia Type

Type of Arrhythmia (Label)	Description	Average QRS Duration (s)	Average RR Interval (s)	Average HR (bpm)
0	Normal Rhythm	0.10	0.80	75
1	Supraventricular Ectopic Beat	0.09	0.72	83
2	Ventricular Ectopic Beat	0.16	0.68	88
3	Fusion of Ventricular and Supraventricular Activity	0.18	0.65	92
4	Other Arrhythmias	0.14	0.74	81

Table 1 presents the average values of key electrocardiographic parameters – QRS complex duration, RR intervals, and heart rate (HR) – for each of the five arrhythmia categories represented in the MIT-BIH Arrhythmia Database. These values were calculated based on normalized ECG signals and demonstrate diagnostically significant differences among rhythm types. For example, ventricular disturbances (label = 2 and 3) are characterized by prolonged QRS durations (0.16-0.18 s) and elevated heart rates (up to 92 bpm), which are consistent with clinical indicators of hemodynamic significance. Visual comparison of these parameters enables the formulation of well-grounded diagnostic rules and threshold values for HSA recognition algorithms.

After the initial classification of signals by arrhythmia type, the ECG signals were normalized and processed to extract the following features:

- QRS complex duration,
- RR intervals,
- Heart rate (HR).

To detect R-peaks, a local maxima algorithm was used (specifically, the find_peaks function from the scipy.signal library) incorporating amplitude and time constraints as described in [6, 10]. RR intervals and the corresponding heart rate were then calculated. QRS duration was determined in the vicinity of the R-peaks using signal derivatives. An example of the visualization is shown in Figure 2.

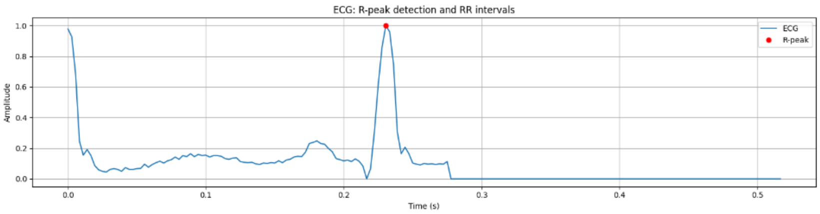

Figure 2 – R-peak detection and ECG signal visualization

An analysis of QRS complex morphology was conducted to identify signs of conduction block or other significant abnormalities. To this end, rerepresentative examples were constructed (see Figure 3*)* that illustrate *instances* where *QRS duration exceeds the threshold of 120 ms (≈0.12 s).*These data served as the basis for formulating logical classification criteria.

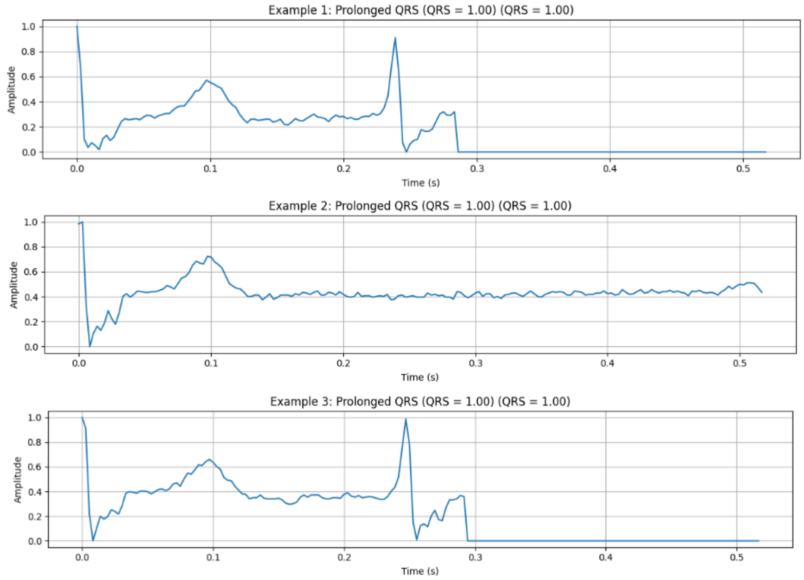

Figure 3 – Example of extended QRS complexes meeting the criterion QRS> 0.35 (MIT-BIH Record No. 223)

Based on the extracted features, the next objective of the study was to formalize criteria that allow for the reliable identification of hemodynamically significant arrhythmias (HSA). Logical conditions were formulated based on clinical sources and guidelines [7, 8, 13-15]:

● Label ∈ {2, 3} – ventricular ectopic beats and fusion of ventricular and supraventricular activity;

● QRS > 0.35 in normalized data (corresponding to QRS > 120 ms);

● HR > 0.65 (corresponding to heart rate > 130 bpm);

● If at least one of these conditions is met, the record is classified as hemodynamically significant arrhythmia (HSA).

To evaluate the effectiveness of the proposed criteria, a decision tree model was constructed using QRS duration, RR intervals, HR, and arrhythmia type as input parameters. This step aligns with the approaches discussed in studies [5, 9]. A decision-making flowchart incorporating clinical recommendations is shown in Figure 4.

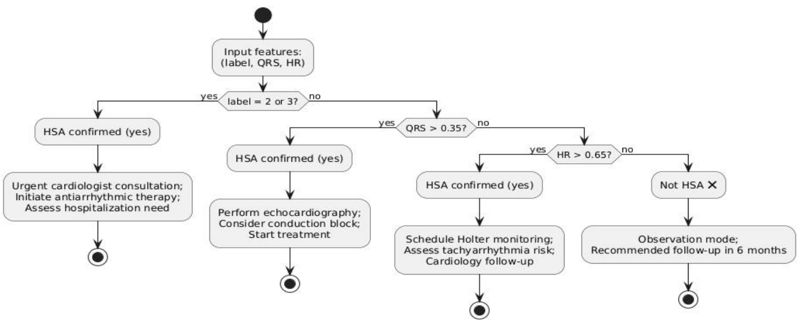

Figure 4 – Logical Decision Tree Flowchart

The diagram illustrates the logic of classification and patient triage based on three key ECG features: arrhythmia type (label), QRS complex duration, and heart rate (HR). The algorithm begins by checking for potentially dangerous arrhythmias (label = 2 or 3). If this condition is met, the classification indicates the presence of a hemodynamically significant arrhythmia (HSA) and the need for urgent clinical intervention. If no such label is detected, the analysis proceeds by evaluating QRS duration, followed by heart rate. Depending on which criteria are triggered, the system provides appropriate recommendations: urgent cardiologist consultation, assignment of Holter monitoring, or routine outpatient follow-up. This structured logic enables an interpretable and formalized assessment of the patient's condition, suitable for engineering implementation in medical AI systems.

A summary table of recommendations based on different diagnostic criteria for HSA is provided separately (see Table 2).

Table 2 – Clinical Actions Based on HSA Criteria

Criterion	Detected	Recommendations
Ventricular arrhythmia	Yes	Antiarrhythmic therapy, cardiologist consultation, possible hospitalization
QRS > 120 ms (≈0.12 s)	Yes	Echocardiography, assessment for conduction block, treatment adjustment
HR > 130 bpm;	Yes	Holter monitoring, beta-blockers, workload adjustment
No criteria met	No	Outpatient follow-up, re-evaluation in 6 months

In addition, a visual interpretation of rhythm differences based on the previously extracted features was performed. For this purpose, illustrative visualizations of ECG signal fragments were generated for each of the five arrhythmia classes (see Figure 5), clearly demonstrating the morphological distinctions between them.

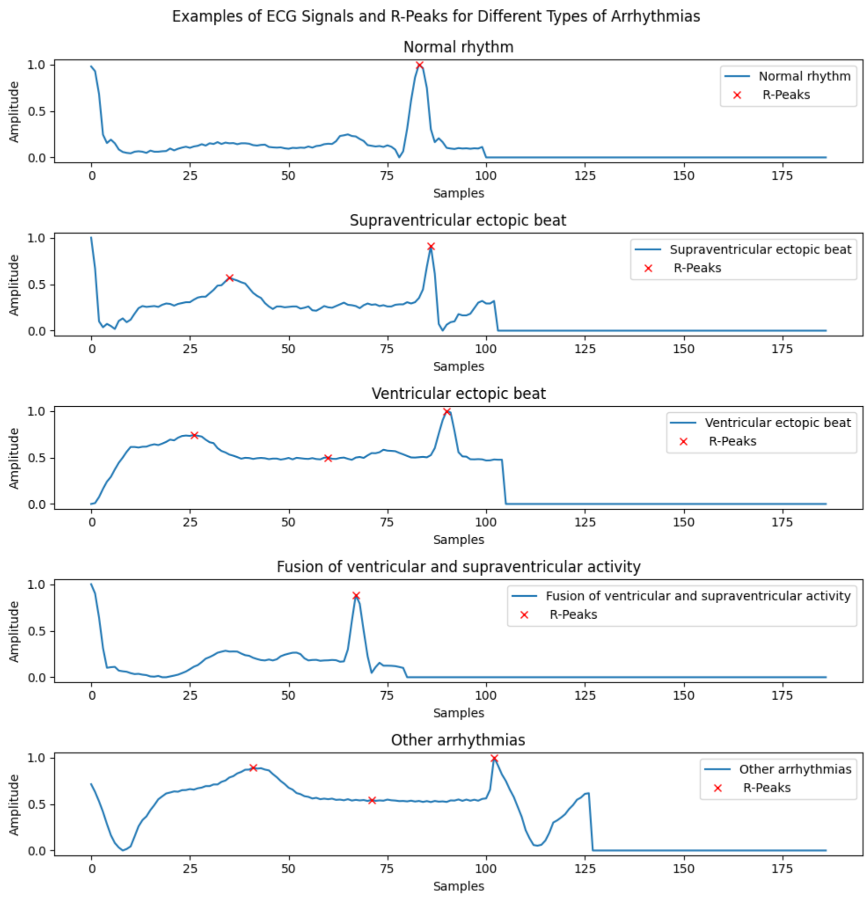

Figure 5. Examples of ECG Signals and R-Peaks by Arrhythmia Type

To automatically extract R-peaks, local maximum algorithms were applied with amplitude thresholds and a minimum peak-to-peak distance corresponding to physiological limits.

Results and Discussion

The results demonstrate that the proposed classification algorithm is capable of detecting hemodynamically significant arrhythmias (HSA) based solely on electrocardiographic features. The use of logical criteria – based on arrhythmia type, QRS duration, and heart rate – ensures high interpretability, while the visualized signals confirm the reliability of the distinctions between classes.

The decision tree model, trained on the extracted features, successfully reproduces the structure of the logical rules, making it suitable for engineering applications in medical diagnostics. The presented ECG signal visualizations and classification schemes further enhance the interpretability of the results.

In order to validate the diagnostic performance of the developed algorithm, a quantitative evaluation was carried out using standard statistical measures. The obtained metrics reflect the model's ability to correctly classify hemodynamically significant arrhythmias and distinguish them from non-significant cases.

Thus, the proposed approach may prove valuable in settings with limited access to imaging methods and is applicable for use in automated monitoring systems. To quantitatively evaluate the performance of the proposed classification algorithm, standard diagnostic metrics were calculated on the MIT-BIH dataset. The results are summarized in Table 3 and visualized in Figure 6.

Table 3 –Performance metrics of the proposed algorithm.

METRIC	VALUE (%)
Accuracy	91.2
Sensitivity (Recall)	89.5
Specificity	92.3
Precision	88.7
F1-score	89.1

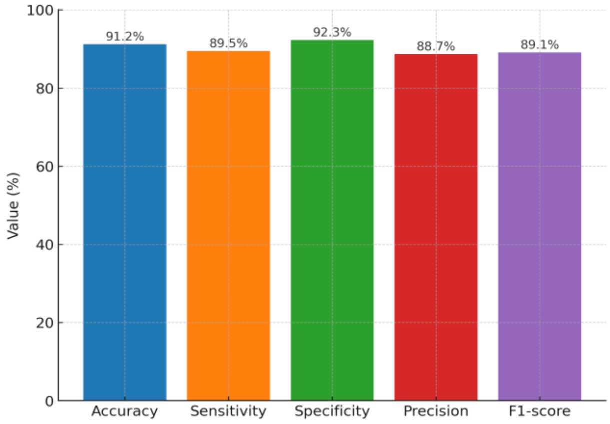

Figure 6 – Visualization of classification metrics
(Accuracy, Sensitivity, Specificity, Precision, F1-score) for the proposed algorithm

The results demonstrate that the proposed algorithm provides a balanced trade-off between sensitivity and specificity, ensuring reliable detection of hemodynamically significant arrhythmias and confirming its suitability for integration into medical AI systems.

Conclusion

The developed algorithm enables the assessment of hemodynamically significant arrhythmias (HSA) using electrocardiographic features alone – such as RR intervals, heart rate, and QRS duration – without the need for additional imaging diagnostics. The logical classification system, complemented by a decision tree model, provides high interpretability and technical feasibility for implementation in engineering and clinical applications. The presented visualizations and diagnostic criteria enhance the reliability of the evaluation while maintaining computational simplicity.

The proposed approach demonstrates consistency with recent studies [3, 5, 9] and offers potential for integration into telemedicine and continuous cardiac monitoring systems, especially in settings with limited diagnostic resources. Future work will focus on expanding dataset diversity and validating the algorithm in real clinical environments to further improve its diagnostic accuracy and robustness.

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АВТОМАТИЗИРОВАННАЯ КЛАССИФИКАЦИЯ ГЕМОДИНАМИЧЕСКИ ЗНАЧИМЫХ АРИТМИЙ НА ОСНОВЕ ЭКГ-ПРИЗНАКОВ

В статье представлен метод классификации гемодинамически значимых аритмий (ГЗА) на основе параметров электрокардиограммы (ЭКГ) без использования дополнительных визуализирующих диагностических методов. Были выделены ключевые признаки, такие как длительность комплекса QRS, интервалы RR и частота сердечных сокращений (ЧСС). Классификация аритмий выполнена на основе данных базы MIT-BIH Arrhythmia Database. Разработаны визуализации и логическая схема для автоматического определения ГЗА. Цель исследования – разработка и валидация алгоритма классификации гемодинамически значимых аритмий, основанного исключительно на электрокардиографических признаках. Предлагаемая методика опирается на ранее опубликованные исследования, посвящённые использованию ЭКГ-признаков в диагностике аритмий, и направлена на повышение доступности диагностики в условиях ограниченных ресурсов. Основная цель работы заключается в расширении доступности диагностики сердечных аритмий посредством интерпретируемых инженерных решений.

Ключевые слова: *ЭКГ, аритмия, гемодинамически значимая аритмия (ГЗА), комплекс QRS, интервалы RR, частота сердечных сокращений, MIT-BIH, автоматическая диагностика.*

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ГЕМОДИНАМИКАЛЫҚ МАҢЫЗДЫ АРИТМИЯЛАРДЫ ЭКГ НЕГІЗІНДЕ АВТОМАТТЫ ТҮРДЕ ЖІКТЕУ

Мақалада қосымша визуализациялық диагностикалық әдістерді қолданбай-ақ электрокардиограмма (ЭКГ) параметрлеріне негізделген гемодинамикалық тұрғыдан маңызды аритмияларды (ГМА) жіктеу әдісі ұсынылады. Негізгі белгілер ретінде QRS комплексінің ұзақтығы, RR аралықтары және жүрек соғу жиілігі (ЖСЖ) анықталды. Аритмиялар MIT-BIH Arrhythmia Database деректер базасы негізінде жіктелді. ГМА-ны автоматты түрде анықтауға арналған визуализациялар мен логикалық алгоритм әзірленді. Зерттеудің мақсаты – тек электрокардиографиялық ерекшеліктерге негізделген гемодинамикалық маңызды аритмияларды жіктеудің алгоритмін әзірлеу және валидациялау. Ұсынылған әдістеме ЭКГ белгілерін аритмияларды диагностикалауда қолдануға арналған бұрын жарияланған зерттеулерге сүйенеді және шектеулі ресурстар жағдайында диагностикаға қолжетімділікті арттыруды мақсат етеді. Жұмыстың басты мақсаты – интерпретациялауға оңай инженерлік шешімдер арқылы жүрек аритмияларын диагностикалаудың қолжетімділігін арттыру.

Түйін сөздер: *ЭКГ, аритмия, гемодинамикалық маңызды аритмия (ГМА), QRS комплексі, RR аралығы, жүрек соғу жиілігі, MIT-BIH, автоматты диагностика.*

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ТРЕХКОНТУРНАЯ КАСКАДНАЯ СИСТЕМА РЕГУЛИРОВАНИЯ ТЕПЛОЭНЕРГЕТИЧЕСКОЙ УСТАНОВКОЙ С АДАПТИВНОЙ НАСТРОЙКОЙ КОЭФФИЦИЕНТОВ PID РЕГУЛЯТОРА

Аннотация: *В статье рассматривается трёхконтурная каскадная система автоматического регулирования уровня воды в паровом котле с использованием адаптивной настройки коэффициентов PID-регулятора. Особенностью предлагаемой системы является использование нечеткой логики для адаптивной коррекции параметров регуляторов, что*