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AN INTERPRETABLE ECG-BASED APPROACH FOR DETECTING HEMODYNAMICALLY SIGNIFICANT ARRHYTHMIAS USING LIGHTWEIGHT MACHINE LEARNING MODELS

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The object of this study is the diagnostic process of patients with suspected hemodynamically significant arrhythmia in emergency and telemedicine settings, where rapid and interpretable decision support is required. The problem addressed is the limited access to echocardiographic assessment in emergency and resource-constrained environments, where interpretable and computationally efficient alternatives are urgently needed, particularly for mobile and field-deployed applications.

The main results show that machine learning models, such as XGBoost, achieved strong diagnostic performance (F1-score = 0.84, AUC = 0.91), while rule-based classifiers provided clinically interpretable accuracy. These results enabled partial compensation for the absence of echocardiography and contributed to reliable triage in acute and time-sensitive settings.

This effectiveness stems from key features of the method: reliance on interpretable ECG features (tQRS, tRR, HR, and EF derived from tQRS/tRR) and low computational complexity, setting it apart from more opaque deep learning methods. The results are explained by the strong correlation between these features and both electrical and mechanical heart function, enabling hemodynamic assessment without imaging. This supports clinical trust in the algorithm's outputs.

The proposed approach is applicable in primary screening, emergency triage, telemedicine, and remote monitoring, combining accuracy with explainability and autonomy from imaging tools. Therefore, research on interpretable ECG-based detection of hemodynamically significant arrhythmias remains highly relevant, especially in settings lacking access to specialized diagnostics

Keywords: ECG-based EF estimation, ejection fraction, machine learning, ECG classification, tQRS/tRR ratio

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1. Introduction

The use of electrocardiographic (ECG) data for automated cardiovascular assessment has seen significant growth in recent years, largely driven by advancements in artificial intelligence and biomedical signal processing. Among various cardiac conditions, particular emphasis has been placed on identifying hemodynamically significant arrhythmias (HSA) – rhythmic disturbances that compromise the heart's ability to pump effectively, thereby reducing tissue perfusion [1, 2].

Key indicators of compromised hemodynamic function typically include an ejection fraction (EF) below 0.5, prolonged QRS complex durations exceeding 120 milliseconds, and atypical heart rate values (less than 40 bpm or more than 130 bpm).

Although echocardiography remains the gold standard for evaluating EF and overall cardiac function, its practicality is often limited in settings such as pre-hospital care, emergency response, telemedicine, and remote or under-resourced regions. This has increased interest in alternative diagnostic approaches that are non-imaging based and compatible with portable or wearable platforms, with ECG being particularly attractive due to its accessibility and cost-effectiveness [3].

Deep learning models, such as convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), have demonstrated promising results in arrhythmia classification. However, their clinical utility is hindered by issues like lack of transparency, high computational demands, and dependence on large, annotated datasets. These drawbacks are especially problematic in scenarios requiring rapid, interpretable, and resource-efficient solutions [4, 5].

Therefore, studies that are devoted to the development of interpretable and computationally efficient methods for detecting hemodynamically significant arrhythmias from standard ECG signals are of high scientific relevance. They address the persisting gap between black-box deep learning approaches and the urgent clinical demand for transparent, physiologically grounded, and resource-efficient diagnostic tools that can be deployed in emergency, telemedicine, and resource-limited settings.

2. Literature review and problem statement

Several studies have explored the use of deep learning models for arrhythmia detection from ECG data. The paper [1] demonstrates that deep neural networks trained on large ECG datasets can detect arrhythmias with cardiologist-level accuracy. It is shown that such models perform well in outpatient monitoring. But there are still unresolved questions related to their clinical deployment, particularly due to their black-box nature and lack of interpretability. The reasons include the opacity of model decisions, dependence on large labeled datasets, and high computational cost, which makes their use in real-time and low-resource settings impractical. An option to overcome these difficulties can be the use of lightweight and physiologically interpretable ECG features integrated into rule-based or hybrid diagnostic systems.

The paper [3] demonstrates the diagnostic potential of AI-enabled ECG for screening left ventricular dysfunction, showing that artificial intelligence can detect impaired contractility with high sensitivity. However, the study does not explore the physiological basis of the ECG features used, limiting clinical interpretability. This lack of transparency makes the system difficult to validate in diverse populations or under emergency conditions. One of the unresolved questions is how to achieve robust explainability while maintaining diagnostic performance. The approach relies on large annotated datasets, which are rarely available in low-resource environments.

The paper [2] describes a deep neural network for 12-lead ECG diagnosis trained on a large Brazilian dataset. It is shown that the model outperforms conventional classifiers in detecting multiple cardiac pathologies. Yet, the unresolved question concerns the explainability of the predictions, which are hard to verify in clinical terms. The reason is the complexity of the architecture and lack of insight into which features influence the output. While the authors propose a visualization scheme, it remains insufficient for interpretability in emergency care.

The paper [4] proposes a deep learning framework for ECG arrhythmia classification using a hybrid CNN-LSTM model. By integrating convolutional layers for morphological feature extraction with recurrent layers for temporal sequence modeling, the study demonstrates improved accuracy in classifying arrhythmias compared to conventional approaches. However, the research does not address whether the detected rhythm abnormalities correspond to functional impairments such as reduced ejection fraction or inadequate perfusion, limiting its clinical applicability. The model remains a statistical classifier of rhythm patterns without linking outputs to hemodynamic consequences, which restricts its value in emergency or triage settings. Another unresolved question is the generalizability of this approach, since performance was tested only on well-annotated benchmark datasets. The dependence on curated data poses challenges for real-world implementation in resource-limited contexts, where noisy and incomplete ECG signals are common.

The paper [6] presents a lightweight hybrid CNN-LSTM architecture for ECG-based arrhythmia detection. The model is designed to balance diagnostic accuracy with computational efficiency, making it suitable for portable or wearable monitoring systems. The authors demonstrate that convolutional layers effectively capture morphological features of ECG signals, while LSTM units model temporal dependencies, resulting in reliable arrhythmia classification. However, the study does not assess clinical endpoints such as the hemodynamic significance of detected arrhythmias or their correlation with patient outcomes, which limits medical interpretability. Another limitation is the reliance on controlled datasets, where signal noise and variability are minimal compared to real-world conditions. An unresolved question concerns whether such lightweight architectures can sustain accuracy under diverse patient populations and emergency scenarios.

The paper [5] investigates the use of AI models for predicting complications after myocardial infarction using 12-lead ECG data. It is shown that AI can identify subtle prognostic markers often missed by physicians. Yet, the approach is hindered by the requirement for extensive, high-quality labeled datasets. The diagnostic mechanism also lacks transparency, raising concerns about reliability in acute care scenarios. The key limitation is the absence of interpretable physiological rules that would make such predictions clinically trustworthy. This makes the case for developing logic-based algorithms using clearly defined ECG parameters.

The study [7] addresses the issue of ECG signal quality by developing a machine learning classifier for segmenting low- and high-quality ECG intervals. It is shown that classification performance improves when poor-quality signals are excluded. However, the authors do not evaluate how signal quality affects the extraction of physiological indicators like heart rate or ejection fraction. The unresolved problem is whether downstream diagnostic models retain validity under variable signal conditions. This reinforces the importance of building systems that not only assess signal quality but also maintain physiological interpretability across varying input reliability.

The paper [8] focuses on the automated detection of tachycardia episodes using convolutional neural networks. It is shown that CNNs achieve high performance in identifying abnormal heart rhythms. However, the study does not assess the physiological impact of detected arrhythmias – for example, whether a specific tachycardia episode leads to reduced cardiac output or ejection fraction. The key limitation is the absence of criteria for hemodynamic significance, which are crucial for prioritizing urgent cases in clinical workflows. This highlights the need for models that incorporate clinically meaningful thresholds, such as EF < 0.5 or HR extremes, into their decision logic.

The paper [9] outlines the hemodynamic consequences of arrhythmias based on experimental physiological data. It is shown that certain types of arrhythmias can significantly reduce stroke volume and tissue perfusion, with EF and HR being strong indicators. However, these findings were established under controlled laboratory conditions and are not integrated into automated diagnostic tools. The gap lies in the translation of these physiological insights into practical, algorithmic criteria for real-time ECG analysis. This justifies the development of computational systems that can identify HSA events using clinically grounded logic derived from established hemodynamic markers.

The paper [10] explores the use of deep convolutional neural networks for the automated detection of myocardial infarction based on ECG signals. It is shown that CNNs can automatically extract morphological features and achieve higher diagnostic accuracy than traditional approaches that rely on handcrafted signal descriptors. However, the study does not address the interpretability of the model outputs, making it difficult to understand which ECG characteristics indicate ischemic injury or infarction. This lack of physiological transparency limits clinical acceptance and practical deployment. Another limitation is the strong dependence on well-annotated datasets, which may not reflect the variability of real-world ECG recordings. The unresolved question is how to integrate deep learning models into clinical workflows while maintaining both diagnostic accuracy and physiological validity.

Although recent advances in deep learning have improved automated arrhythmia detection from ECG data, key scientific challenges remain. Most existing models lack physiological interpretability and clinical transparency, limiting their use in medical decision-making. They often rely on large labeled datasets and require significant computational resources, making them impractical for emergency or mobile applications. Furthermore, few approaches incorporate clinically validated thresholds such as ejection fraction (EF) and heart rate (HR), which are essential for evaluating hemodynamic impact. While ECG-derived surrogates for EF have been proposed, their integration into real-time diagnostic systems is limited, and the balance between accuracy and interpretability remains poorly explored.

Taken together, the reviewed studies reveal a persistent gap in the development of diagnostic systems that combine clinical interpretability, low computational complexity, and hemodynamic relevance when detecting arrhythmias from ECG data.

3. The aim and objectives of the study

The aim of this study is to propose and substantiate an interpretable ECG-based approach for detecting hemodynamically significant arrhythmias using physiologically meaningful features (tQRS, tRR, HR, EF) and lightweight classification models. This will allow enables reliable and explainable triage of patients in emergency, telemedicine, and resource-limited settings without reliance on echocardiography.

To achieve this aim, the following objectives are accomplished:

– to prepare and segment ECG data into fixed-length windows suitable for model training and evaluation;

– to extract interpretable physiological features (tQRS, tRR, HR, EF) and define threshold-based criteria for HSA;

– to evaluate the diagnostic performance and interpretability of the rule-based classifier in comparison with machine learning models;

– to validate the physiological plausibility of the ECG-derived ejection fraction proxy EF as a diagnostic indicator for hemodynamically significant arrhythmia.

4. Materials and methods

The object of this study is the diagnostic process of patients with suspected hemodynamically significant arrhythmia in emergency and telemedicine settings, where rapid and interpretable decision support is required.

This study is based on the hypothesis that a combination of physiologically meaningful ECG features and lightweight classification models – such as rule-based logic and simple machine learning techniques – can provide a reliable and interpretable method for detecting hemodynamically significant arrhythmias (HSA) [11–14]. Unlike deep neural networks, the proposed approach does not require large volumes of training data or high computational power. Instead, it emphasizes clinical transparency and alignment with physiological principles. The study assumes that the tQRS/tRR ratio is a physiologically valid surrogate for ejection fraction, as supported by prior literature. Simplifications include the exclusive use of four features (tQRS, tRR, HR, and EF), the adoption of fixed clinical thresholds (e.g., EF < 0.5, tQRS > 120 ms), and the use of data from a single annotated dataset (MIT-BIH), without incorporating variability from additional populations or leads [15–17].

The MIT-BIH Arrhythmia Database from PhysioNet was selected due to its widespread use in validation of ECG classification models and its detailed expert annotations. This dataset includes 48 ECG recordings, each obtained from a unique subject (except one), captured via two leads over approximately 30-minute sessions. The recordings were sampled at 360 Hz and manually annotated by experienced cardiologists [18, 19]. Raw ECG signals were normalized and segmented into fixed-size windows of 188 samples, comprising 187 data points and a single corresponding label. Only segments containing normal or arrhythmic activity were retained for analysis. Basic noise filtering techniques were applied to minimize interference from baseline wander and motion artifacts. Compared to dynamic R-peak-based windowing used in earlier studies, the fixed-length segmentation minimized errors from missed or noisy R-peaks and allowed consistent feature extraction for real-time or wearable applications.

From each ECG window, four physiologically relevant features were extracted: QRS complex duration (tQRS), interval between successive R-waves (tRR), heart rate (HR, derived as the inverse of tRR), and an ejection fraction surrogate (EF = tQRS / tRR). The choice of these features was motivated by their strong physiological relevance, their link to ventricular conduction and pump function, and their prior use in cardiological modeling [20–23]. Based on these features, a transparent rule-based classifier was designed using simple binary thresholds (Table 1). A segment was labeled as HSA-positive if any of the thresholds were exceeded, allowing interpretable real-time diagnosis.

Table 1

Diagnostic thresholds used in the rule-based classifier [20]

Feature	Threshold	Clinical interpretation
HR	< 40 or > 130 bpm	Bradycardia or tachycardia
tQRS	> 120 ms	Intraventricular conduction delay
EF	< 0.5	Reduced ejection fraction
tQRS/tRR	> 0.3	Empirically derived threshold for abnormal EF

These thresholds were selected based on established clinical guidelines (e.g., AHA/ACC criteria), published diagnostic frameworks, and prior models for ECG-based EF estimation. The rule-based classifier was directly implemented without model training, enabling immediate clinical use in low-resource environments while maintaining full interpretability.

To complement the rule-based system, lightweight supervised machine learning models were developed, including logistic regression, random forest, and gradient boosting (XGBoost). These algorithms were chosen due to their suitability for small tabular datasets and widespread use in biomedical classification tasks [24, 25]. To mitigate class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied, generating synthetic samples of underrepresented HSA cases to improve generalization. The dataset was divided into training and test subsets (mitbih_train.csv and mitbih_test.csv), and evaluation was carried out on the held-out test set.

Model performance was assessed using standard classification metrics: accuracy, recall, specificity, F1-score, and ROC-AUC [26, 27]. Feature importance analysis was performed for tree-based models to ensure that predictions aligned with physiological reasoning. All development and evaluation were conducted in Python 3.10 using scikit-learn, XGBoost, pandas, and imbalanced-learn on a standard workstation without GPU acceleration [28].

The resulting hybrid diagnostic framework thus combined fully interpretable rule-based logic with machine learning models capable of capturing non-linear feature interactions. This dual approach provided both transparency and higher predictive capacity, emphasizing practical deployment for emergency care, telemedicine, and resource-limited clinical environments.

5. Results of evaluation of interpretable electrocardiogram features and diagnostic models for hemodynamically significant arrhythmia detection

5. 1. ECG segmentation and feature extraction for hemodynamically significant arrhythmia detection

Analysis of the derived ejection fraction (EF) distribution across the dataset (Fig. 1) revealed two distinct clusters: one corresponding to normal cardiac function with mean EF values around 0.65, and another representing pathological cases with EF values below the clinical threshold of 0.5. This separation demonstrates that the ECG-derived surrogate of EF effectively reflects ventricular performance and can distinguish between preserved and impaired hemodynamic states.

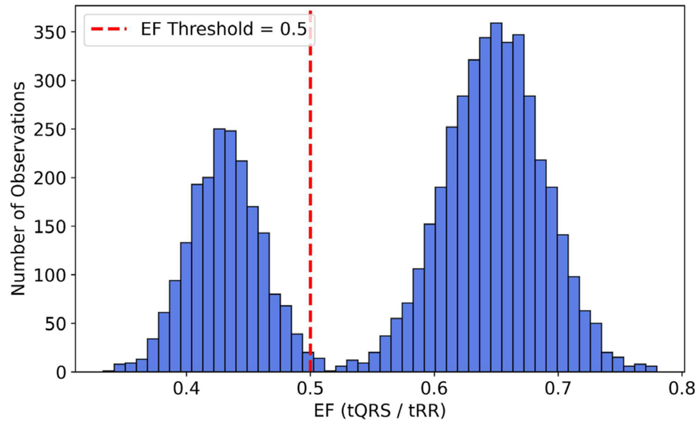

Fig. 1. Distribution of ejection fraction in the sample

Further examination of the relationship between EF and the tQRS/tRR ratio (Fig. 2) showed a near-linear correlation consistent with established physiological models. A diagnostic cutoff was identified at approximately tQRS/tRR ≈ 0.36, which corresponded to EF < 0.5, confirming its discriminative value as a marker of hemodynamic compromise.

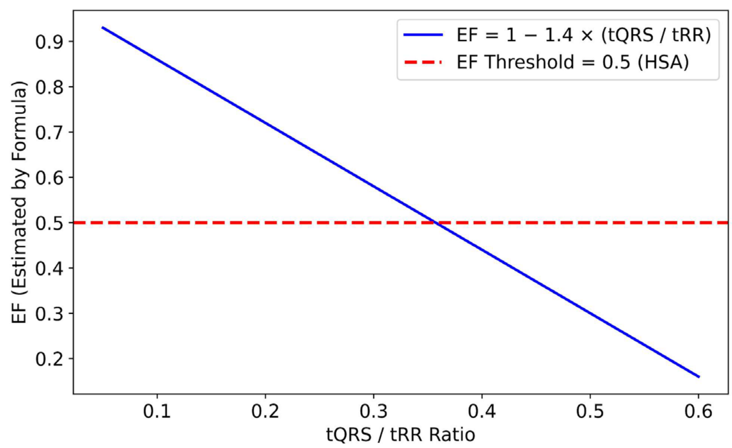

Fig. 2. Relationship between ejection fraction and TQRS/TRR ratio

These findings indicate that simple, interpretable ECG-derived features capture clinically meaningful patterns of cardiac dysfunction [29]. By aligning with physiological reasoning and clinical expectations, they provide a solid foundation for the subsequent development of both rule-based and machine learning models for hemodynamically significant arrhythmia detection.

5. 2. Extraction of interpretable features and development of rule-based classifier for hemodynamically significant arrhythmia detection

The rule-based classifier demonstrated reliable diagnostic performance on the test dataset, achieving an F1-score of 0.76, recall of 0.79, and accuracy of 0.86. These results confirm that even a simple set of interpretable ECG-based thresholds can provide clinically meaningful sensitivity to hemodynamic compromise.

The confusion matrix (Fig. 3) illustrates the distribution of true positives, true negatives, false positives, and false negatives.

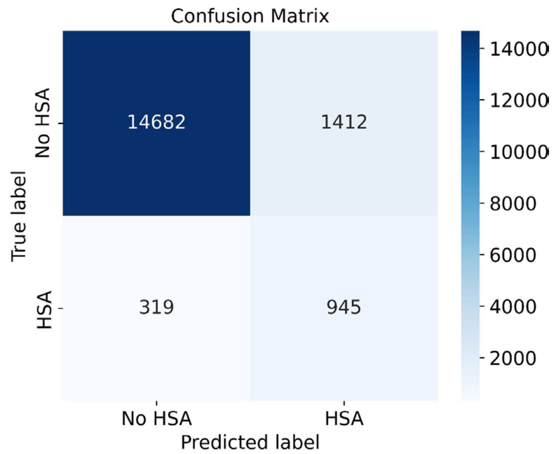

Fig. 3. Confusion matrix of the rule-based classifier for hemodynamically significant arrhythmia detection

The model maintained a favorable balance between sensitivity and specificity, while ensuring that each diagnostic decision could be transparently explained in terms of underlying physiological parameters [30].

This level of explainability is particularly valuable in emergency medicine, telehealth, and rural screening scenarios, where clinician trust and rapid triage are critical. Although the classifier is less flexible than data-driven models, its transparency and computational efficiency make it a practical baseline solution for detecting hemodynamically significant arrhythmias in real-world low-resource environments.

5. 3. Comparative evaluation of machine learning and rule-based models

Machine learning models trained on the interpretable ECG-derived features (tQRS, tRR, HR, EF) demonstrated superior diagnostic performance compared to the rule-based classifier. Among the evaluated classifiers, XGBoost achieved the best overall results, with an accuracy of 0.907, recall of 0.87, F1-score of 0.84, and AUC of 0.91 (Table 2).

Table 2

Classification metrics of the XGBoost model for HSA detection

Metric	Value
Accuracy	0.907
Precision	0.733
Recall	0.87
F1-score	0.84
AUC	0.91

The receiver operating characteristic curve (Fig. 4) further illustrates the strong predictive ability of XGBoost, showing clear separation between positive and negative cases of HSA.

Compared to the rule-based classifier (F1-score = 0.76), the machine learning models – particularly XGBoost – provided higher precision and overall predictive power. Importantly, feature importance analysis revealed that tQRS and EF contributed most significantly to model predictions, supporting their clinical relevance and confirming consistency with physiological rationale.

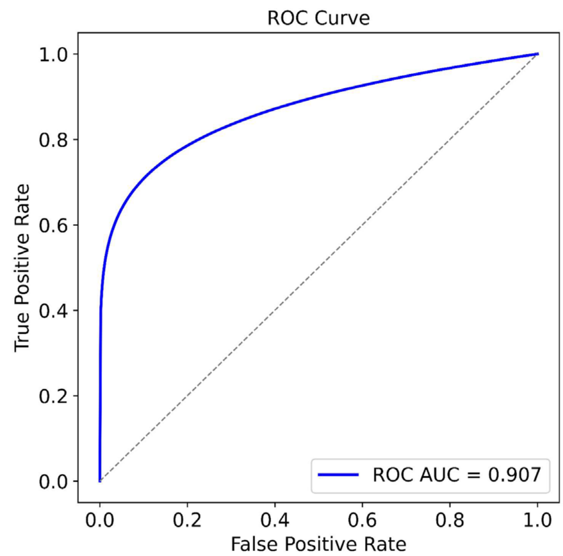

Fig. 4. Receiver operating characteristic curve for the extreme gradient boosting model

These findings indicate that while the rule-based system offers full interpretability, its diagnostic capacity is limited relative to machine learning models. In contrast, XGBoost balances strong predictive performance with partial interpretability, making it a promising option for automated HSA detection in clinical and prehospital contexts.

5. 4. Validation of the physiological formula for ejection fraction estimation

In this study, the statistical behavior and clinical consistency of two ECG-based formulas for estimating ejection fraction (EF) were analyzed using surface ECG data. Specifically, the ratio of QRS complex duration (tQRS) to the R-R interval (tRR) was evaluated as a non-invasive surrogate for cardiac performance, intended as a potential substitute for echocardiographic measurements in contexts where imaging is not feasible.

Two formulas were analyzed: a reference model expressed as $EF = 1 - 1.4 * (tQRS / tRR)$, and a simplified version, $EF = tQRS / tRR$, introduced to improve interpretability and facilitate implementation within rule-based classification.

As shown in Fig. 1, the distribution of EF values across the dataset exhibited a clear bimodal pattern. One cluster centered around a physiologically normal value of ~ 0.65, while the second comprised EF values below 0.5 – commonly indicative of reduced ventricular output. This differentiation supports the feasibility of using ECG-derived EF as a proxy for cardiac function.

Importantly, it is possible to identify a diagnostic threshold for hemodynamic compromise based on the simplified EF expression. Segments with $tQRS / tRR > 0.36$ consistently corresponded to EF values below 0.5, a clinically recognized marker of reduced ventricular output. This threshold was derived empirically from the bimodal EF distribution (Fig. 1) and was further supported by the near-linear correlation observed in Fig. 2. This decision boundary provides a physiologically interpretable rule for detecting potential hemodynamic insufficiency using ECG-derived parameters.

To further validate the approach, a correlation analysis between EF and the simplified tQRS / tRR ratio was performed (Fig. 2), revealing a near-linear relationship. This relationship substantiates the underlying mathematical logic of the formula and enabled the identification of a decision boundary: segments with tQRS / tRR > 0.36 were consistently associated with EF < 0.5, signifying potential hemodynamic compromise.

This finding highlights the practical value of estimating EF from ECG parameters in a physiologically consistent manner. While this technique cannot replace imaging in precise diagnostics, it offers a viable screening method – particularly useful in prehospital, telehealth, or resource-limited settings. As part of a scalable, interpretable framework, this methodology aligns with current AI-driven trends in cardiology aimed at expanding early detection capabilities beyond conventional hospital infrastructure.

6. Discussion of results and clinical interpretation of the proposed HSA detection method

The segmentation of ECG signals into fixed-length 188-sample windows enabled consistent extraction of physiologically meaningful features across all records. This design preserved temporal integrity and facilitated reproducible feature computation. As illustrated in Fig. 1, the derived ejection fraction (EF) distribution exhibited clear separation between normal and pathological clusters, demonstrating that segmentation was sufficient to preserve physiologically relevant variability. In contrast to prior work such as [3], where dynamic R-peak-based windowing introduced errors in noisy arrhythmic signals, the fixed-window approach minimized dependence on precise peak detection. This makes the method particularly advantageous for real-time analysis in wearable and prehospital systems, where robustness and low latency are essential.

The rule-based classifier, grounded in established clinical thresholds for QRS duration, heart rate, and EF, provided transparent diagnostic logic. Its performance, with an F1-score of 0.76 and accuracy of 0.86 (Fig. 3), confirms that interpretable rules can achieve clinically acceptable sensitivity to hemodynamic compromise. Unlike deep CNN approaches [1] that achieved higher raw accuracy but offered limited interpretability, the present framework ensures that each decision is directly tied to physiological markers. This transparency is especially relevant for triage in low-resource environments, where clinician trust depends on clear diagnostic reasoning.

Machine learning classifiers trained on the same interpretable feature set demonstrated higher predictive capacity. Among them, XGBoost achieved the best balance of sensitivity and precision (F1-score = 0.84, AUC = 0.91; Table 2, Fig. 4). The improvement over the rule-based model is explained by its ability to capture non-linear interactions among features while still preserving partial interpretability through feature importance analysis. In contrast to complex CNN or LSTM architectures reported in [3] and [5], which require large datasets and significant computational resources, the lightweight boosting approach retained feasibility for mobile deployment. Thus, the combination of interpretability and high diagnostic performance represents a step toward clinically usable decision support.

Validation of the ECG-derived surrogate for ejection fraction provided additional physiological grounding. The analysis of EF values (Fig. 1, 2) revealed a bimodal distribution with a cutoff at tQRS / tRR > 0.36, reliably separating normal from compromised cardiac function. This observation corroborates the patented model EF = 1 – 1.4(tQRS / tRR) while offering a simplified surrogate more suitable for real-time classification. In contrast to [2], where EF estimation was suggested but not validated within an automated detection pipeline, the present results confirm its diagnostic plausibility and integrate it into a classification framework. This contributes a novel link between electrical and mechanical cardiac parameters, enabling hemodynamic risk stratification without echocardiography.

The findings demonstrate that computationally efficient and physiologically interpretable methods can detect hemodynamically significant arrhythmias without reliance on echocardiography. Robust segmentation preserved meaningful signal variability, rule-based thresholds provided clinical transparency, machine learning models enhanced predictive performance, and validation of the EF surrogate confirmed physiological plausibility. Altogether, the results show that accurate and explainable detection of HSA is feasible in emergency, telemedicine, and resource-limited conditions.

Despite its strengths, the study has several limitations. First, the validation was restricted to a single dataset the MIT-BIH Arrhythmia Database – which may not generalize to broader populations with varying demographics or comorbidities. The accuracy of extracted features such as tQRS and tRR also depends heavily on signal quality and segmentation precision. Noisy or artifact-laden recordings can introduce measurement errors that degrade model performance.

Another limitation lies in the use of fixed decision thresholds. While clinically justified, such thresholds may not capture inter-individual variability in cardiac physiology. Future iterations of the model should explore adaptive thresholding via unsupervised clustering or meta-learning. Furthermore, the current classification pipeline analyzes each ECG window independently, neglecting temporal context. Incorporating sequential models like LSTMs or transformers could improve robustness by modeling arrhythmic patterns over time.

From a technical standpoint, real-world deployment may require additional validation across various sampling rates, devices, and preprocessing pipelines. The model also lacks uncertainty quantification, which could be addressed using Bayesian approaches or conformal prediction to support clinical decision-making in borderline cases.

Finally, future work should align ECG-derived estimates with echocardiographic ground truth, enhancing the physiological fidelity of EF estimation and enabling better calibration. Embedding the method into wearable diagnostic platforms may also involve addressing hardware constraints, power consumption, and noise resilience.

7. Conclusion

1. The extraction of physiologically interpretable ECG features was achieved and successfully validated, confirming their relevance to hemodynamic compromise. Specifically, the surrogate measure of ejection fraction (EF = tQRS / tRR) exhibited a bimodal distribution, where normal values were centered around 0.65 and pathological values fell below 0.5. A clinically meaningful decision threshold at tQRS / tRR = 0.36

was identified, supporting the feasibility of using surface ECG-derived metrics for functional cardiac evaluation without the need for imaging.

2. A rule-based model was developed using binary thresholds for heart rate, QRS duration, and EF. This simple classifier achieved an F1-score of 0.76, recall of 0.79, and accuracy of 0.86. Despite its simplicity, the model is fully interpretable and easy to implement, making it suitable for real-time screening and telehealth applications, especially in low-resource environments or areas without access to echocardiography.

3. Machine learning classifiers trained on the same set of features outperformed the rule-based approach. The XGBoost model achieved an accuracy of 0.907, F1-score of 0.84, and AUC of 0.91. It also maintained strong sensitivity (recall = 0.87) and showed resilience to class imbalance, managed through the application of SMOTE. Although more complex, the machine learning approach offered at least partial interpretability via feature importance analysis, while delivering stronger predictive performance than the rule-based logic.

4. Analysis of ECG segments from the MIT-BIH dataset confirmed the physiological validity of the patented EF estimation formula ($EF = 1 - 1.4 \times tQRS / tRR$). The near-linear correlation observed between EF and the tQRS/tRR ratio supports the use of this relationship as a quantitative indicator of hemodynamic significance. This non-invasive estimation of cardiac function, integrated into the classification framework, presents a promising step toward the development of scalable and interpretable arrhythmia detection tools for both clinical and remote monitoring settings.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

All data used in this study are publicly available, including the MIT-BIH Arrhythmia Database (PhysioNet). Additional materials may be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that artificial intelligence technologies were used exclusively for assisting in the search and formatting of bibliographic references. No AI tools were applied in generating the scientific content, data analysis, results, or conclusions of the present work.

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