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AI in Contemporary Healthcare: Practical Implementation Obstacles, Ethical Integration, and an ECG Arrhythmia Case Analysis

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Abstract

Artificial intelligence has quickly grown within healthcare, encompassing domains such as medical imaging, disease forecasting, clinical documentation, drug discovery and operational management. Even if things are improving, the transition from controlled research settings to real-world clinical use remains stagnant. A common theme in recent literature is that high accuracy in test conditions does not consistently signify readiness for practical implementation. Barriers, including system interoperability, clinical trust, regulatory pathways, and ethical accountability, persist in its adoption. This paper reviews Ai driven healthcare research published from 2020 to 2025, highlighting the gap between reported innovation and practical application. To find sources, we used peer-reviewed databases, institutional reports, and policy papers. After screening for relevance, a carefully chosen group was looked at in detail, with a focus on the application domain, the evaluation method, readiness for deployment, and the reported limitations. The findings confirm that the majority of published research emphasizes benchmark performance, relegating deployment conditions to a secondary status. This paper presents a structured framework for responsible AI integration, comprising four interrelated pillars: technical reliability, interpretability and ethical design, regulatory and validation alignment, and clinical workflow compatibility. The framework is analyzed via an ECG arrhythmia classification case study utilizing a multi-scale residual network with a three-channel enriched input that integrates dual-lead ECG morphology and a distinct RR-interval signal. The case illustrates that benchmark success and clinical readiness are interconnected yet distinct. This study's limitations encompass reliance on secondary sources and variability in reporting standards among the reviewed works.

Keywords: *Artificial Intelligence in Healthcare, Responsible AI Integration, Clinical Deployment, Explainable AI, ECG Arrhythmia Detection, Multi-Scale Residual Networks.*

1. Introduction

Artificial intelligence is becoming a key area of innovation in healthcare, with extended uses in fields such as medical imaging, predicting patient's outcomes, managing records, drug development, and hospital operations (Jiang et al, 2025 & Esteva et al, 2019). Progress in machine learning and deep learning has delivered clear advantages, particularly in identifying patterns, supporting clinical decisions, and enhancing predictive accuracy. However, translating these developments into real world clinical practice remains challenging and uncertain. A recurring issue is the strong focus on performance matrices like accuracy, sensitivity, and specificity, while comparatively less attention is paid to factors affecting real-world implementation. Challenges such as system interoperability, variation in data across institutions, regulatory constraints, clinical acceptance, and ethical handling of patient data continue to slow down widespread adoption (Wang et al., 2020). Hence, it is observed that many models that show promising results in a controlled environment do not show similar results in a realistic environment (Jiang et al., 2025). The gap between these two aspects is particularly evident in the analysis of physiological signals. The electrocardiogram (ECG) is one of the fundamental tools in cardiology, allowing for the analysis of cardiac electrical activity without the need for invasive procedures and the detection of rhythm abnormalities like arrhythmias (Kachuee et al., 2018). The interpretation of the ECG is labor-intensive and prone to inter-observer variability, especially in cases of continuous or ambulatory monitoring (Kachuee et al., 2018). This has led to the increasing focus on the use of machine learning and deep learning techniques for the detection of arrhythmias (Zhang et al., 2022). Convolutional and residual network architectures have yielded promising performance for ECG-based arrhythmia classification tasks (Zhang et al., 2022; Yildirim, 2018). However, the nature of ECG signals has also made them notoriously difficult to model, with inter-patient differences, noise, and the simultaneous presence of significant clinical features across multiple time scales (Zhang et al., 2023a). The problem of severe class imbalance, where the number of normal beats may outstrip the number of beats for the less common forms of arrhythmia by more than 100 to 1, also makes the training and evaluation of such models problematic (Zhang et al., 2022). These features make the application of ECG-based arrhythmia detection an interesting case for understanding the challenges associated with the adoption of healthcare AI. A model may perform well on a standard benchmark but not be ready for deployment, as the latter also depends on robustness, interpretability, cross-validation, and compatibility with existing workflows (Jiang et al., 2025). In this context, the present paper will adopt the following twofold strategy. Firstly, it will survey the latest healthcare AI literature, with particular emphasis on the gap between development and application. Secondly, it will propose a structured approach for the responsible integration of AI, with particular reference to the dimensions of technical reliability, interpretability, and ethics, regulatory and validation, and clinical workflow integration. The proposed approach will be illustrated through an ECG arrhythmia classification problem, solved via a multi-scale residual network with three-channel enriched input. The paper has three major contributions. First, it identifies the common limitations in the healthcare AI literature in the context of deployment readiness. Second, it proposes a structured four-component integration framework applicable to all healthcare AI domains. Third, it demonstrates the application of these factors through the context of the ECG arrhythmia classification problem.

2. Literature Review

Recent literature has reaffirmed the rapid progress of AI in healthcare, including its applications in diagnosis, risk stratification, treatment planning, remote monitoring, workflow, and administrative tasks, with notable advancements in the application of AI[1] to image analysis and data-based clinical decision support tools (Faiyazuddin et al., 2025; Habehh & Gohel, 2021). However, a notable feature of the literature is that the progress of algorithms has outstripped the implementation of the technology, with the difficulties of workflow, regulation, and clinician trust being discussed far less than the performance[2] of the algorithms (Faiyazuddin et al., 2025). The overall machine learning literature follows a similar trend. While the applications have expanded to include electronic health records, images, anomalies, and decision support, the reviews all highlight the risks to be addressed with regard to ethics, logistics[3], and feasibility (Habehh & Gohel, 2021). The machine learning community has largely outgrown the consideration of accuracy as a viable adoption metric. A model that performs well on a classification[4] task under highly controlled circumstances can be of no use in a clinical setting due to its underlying data assumptions, preprocessing requirements, or violation of clinical workflow (Faiyazuddin et al., 2025; Habehh & Gohel, 2021). This concern challenge is extended to clinical language processing. The research on health NLP has shown that narrative clinical text and hospital documents are considered. The research on health NLP has shown that narrative clinical text includes diagnoses, treatment notes[5], prescriptions, and discharge summaries and that this text contains useful information for research and decision support (Hao et al., 2021). To extract this information reliably, there are domain-specific approaches that are sensitive to clinical time structures and based on healthcare practice rather than language modeling (Hao et al., 2021). This is relevant to the present study because it supports one of the fundamental principles: for all domains of healthcare AI, how useful a system is is just as relevant to how well it fits clinical data and practice as how good its underlying model is. In this setting, ECG-based arrhythmia classification is a promising space to analyze the adoption gap phenomenon. EC[6] is one of the most popular approaches for cardiac monitoring, and the use of deep learning for arrhythmia detection has seen a major surge in the past ten years (Ansari et al., 2023). A review of the literature from 2017 to 2023 shows the high performance of deep learning models for classification tasks, including the use of convolutional, recurrent, and transformer-based models (Ansari et al., 2023). However, the review also points out the lack of uniformity in the results, which makes it difficult to compare the results of different studies, thereby limiting the overall applicability of the results (Ansari et al., 2023). One of the most important trends in recent ECG-related neural network studies has been the shift towards multi-scale representation learning. This is because ECGs carry important[7] features over a wide range of time scales, ranging from sharp QRS complexes to slower T waves and ST segments. This makes the use of a single kernel inherently limited. This was addressed by Zhang et al. (2023a), who used a multi-scale residual neural network and data fusion. This study has had a significant influence on this work but also points out one of the main differences: the addition of the RR interval channel, which provides information[8] at the rhythm level, not available in any multi-scale approach (Alsaleem et al., 2022). Another trend deals with the increased input context, especially the rhythm context. The earlier approaches were based on manually engineering the RR and QRS features. Several works have demonstrated the failure of these approaches when the engineering of the features was incomplete (Alsaleem et al., 2022). Recent approaches aim to reintroduce the rhythm context into the learned features. The implication for our work is straightforward. The restriction to local waveform morphology[9] simply ignores the information for which the RR interval channel was explicitly designed. Thirdly, there is a third category of recent papers that focus on interpretability and trustworthiness. With ECG models close to practical application, it is no longer sufficient that they are accurate. Overfitting risks, computational costs, and decision-making processes are all issues that need to be addressed in order to facilitate adoption, as noted by Talukder et al. (2025). Explainability is quickly becoming an accepted minimum requirement in clinical settings. The current study does not yet fulfill this requirement, as will be discussed. Taken as a whole, the research advances on three fronts simultaneously which are improved predictive performance[10], richer input representations, and increased accountability. Yet the correlation between benchmark outcomes and clinical applicability remains unresolved. Broad healthcare AI reviews highlight ongoing issues related to governance, integration, and long term validation (Faiyazuddin et al, 2025) while ECG specific studies indicate that even advanced architectures rely extensively on controlled datasets and experimental evaluation settings (Ansari et al, 2023; Talukder et al, 2025). ECG arrhythmia classification is therefore an appropriate domain through which to assess responsible AI integration as it is technically advanced, clinically significant, and representative of the broader deployment challenge. For the purpose of this paper[11], the literature examined has established two key conclusions. First, it has established the need to develop a framework that extends beyond accuracy in the assessment of healthcare AI. Second, it has confirmed ECG-based detection of arrhythmia as an actual and relevant case through which to apply this framework. While the literature reviewed has not suggested that performing well is irrelevant, it has consistently shown that doing so is only one aspect of a longer process that must also consider reliability, interpretability, cross-validation, and workflow compatibility (Ansari et al., 2023; Faiyazuddin et al., 2025; Talukder et al., 2025).

3. Proposed Framework for Responsible AI Integration in Healthcare

The reviewed literature suggests that there is a lack of balance, whereby advancements in algorithmic capability have been greater than those in the conditions for practical deployment. While there have been improvements in the performance of various tasks, this has not been matched in terms of deployment (Faiyazuddin et al., 2025; Habehh & Gohel, 2021). Some of the reasons for this include heterogeneity in data, lack of interoperability, and lack of clarity regarding model outputs and regulatory pathways (Hao et al., 2021). The assessment of AI systems based on performance is not sufficient to evaluate them for practical deployment. What is required is a more structured approach, which considers technical performance as well as operational feasibility as evaluation criteria from the outset. In the work, the readiness for deployment is included as part of the design of the system, as opposed to a final evaluation criterion. The framework proposed here offers evaluation criteria for whether the AI system is likely to perform well in clinical settings, without requiring new architectures to be developed. The intention is to add to the evaluation process[12], which already exists, by highlighting criteria that have a more direct impact on usability. The proposed framework is based on four interrelated components: technical reliability, interpretability and ethical considerations, regulatory and validation alignment, and clinical workflow integration. These components are not necessarily linear steps. Rather, they are overlapping considerations that are interrelated and interact throughout the development and deployment life cycle of an AI system. A weakness in one of these components can limit usability regardless of performance in other components. Technical reliability refers to the ability to maintain stable and in line performance across a variety of diverse and imperfect conditions. Clinical data is heterogeneous across patients, acquisition methods, and institutional settings, and even models trained on limited datasets may fail to generalise effectively (Habehh & Gohel, 2021). For ECG signals, heterogeneity arises from patient specific morphologies, signal noise, and feature distribution across different temporal scales. Observations on ECG classification tasks have highlighted that for effective architectures, it is important to successfully combine information related to local features and global rhythms within ECG signals (Ansari et al., 2023), and this has been achieved through multi scale and residual learning approaches (Zhang et al, 2023a). Within this framework, technical reliability is not only associated with benchmark level performance but also with robustness across varying data conditions, including managing class imbalance and signal noise. Interpretability is an essential pre-requisite for clinical adoption. Clinical decisions are not only associated with accountability; which black box approaches are incapable of fulfilling. A model may be perfectly correct, yet its outputs will not be accepted if the decision-making process is not interpretable (Talukder et al., 2025). Recent approaches in ECG analysis are moving towards the integration of explainability tools such as attribution maps, SHAP values, and feature visualization, making the decision-making process auditable (Talukder et al., 2025). Ethical considerations are an integral part of the decision-making process. As Shown in Figure 1[13 – 15].

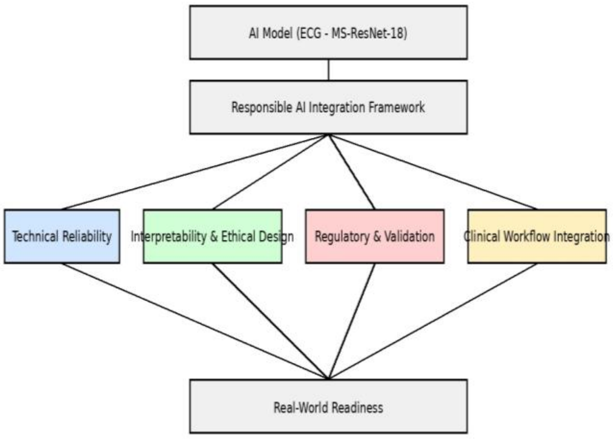

Figure 1 **Proposed Framework**

Fairness towards all patient groups, data ethics, and the presentation of uncertainty are not add-ons but integral components of the decision-making approach (Faiyazuddin et al., 2025). Regulatory and validation alignment is concerned with the evidence necessary for clinical deployment. Most published works use internal splits on one data set only, and this restricts how broadly the results can be generalized (Ansari et al., 2023). Clinical dependencies involve validating on external datasets, following standardised protocols and conducting prospective evaluation. Regulators require documented evidence of safety, consistency, and reproducibility. Without this, technically sound models remain confined within research settings. The framework, therefore, highlights approaches that reflect real-world use on diverse datasets, reproducibility, and transparent reporting of performance and failure modes. On the other hand, clinical workflow integration refers to the ease with which the AI system can be incorporated into the existing healthcare workflow. Even well validated and accurate models can fail to deploy if they pose a substantial workflow disruption, additional cognitive burden, or infrastructure changes that the clinical setting is unable to support (Hao et al., 2021). Healthcare practice is curated along temporal limits, professional status and procedural norms. The new AI system must be integrated within this system and not vice versa. For ECG monitoring in particular, this entails "near real-time processing," "compatibility with existing monitoring equipment," and "results that can be immediately understood and used." Computational costs and unclear results can be obstacles to practical application regardless of performance metrics. These four components, therefore, outline the circumstances under which the transition from research to practice for the AI system becomes viable. The literature, as a whole, has largely focused on each of the components individually, with the technical performance of the system being the focal point of the majority of the research (Faiyazuddin et al., 2025; Ansari et al., 2023). The framework, therefore, seeks to bring all the components together to form a singular evaluative framework for the viability of healthcare-based AI systems. In this paper, the framework is applied to the evaluation of an ECG arrhythmia classifier using the multi-scale residual structure with three-channel enriched inputs. while the objective is not to assert clinical readiness, it is to demonstrate what an extensive evaluation process appears like in practice. This shifts the discussion from accuracy to robustness, interpretability, scope, and compatibility.

4. Results and Discussion

4.1.Experimental Setup and Hyperparameters

All experiments are performed using an NVIDIA GPU-enabled system and PyTorch. The best model checkpoint is based on peak validation accuracy. The final results are obtained by loading the best checkpoint and testing on the held-out set using TTA and tuned thresholds. Table I shows the important hyperparameters.

Table 1 Hyperparameters

Hyperparameter	Value
Segment length	512 samples (1.42s)
Input channels	3 (Lead I, Lead II, RR)
Batch size	64
Epochs	50
LR warmup	5 epochs
Learning rate	1×10^{-3} (AdamW)
Weight decay	1×10^{-4}
Focal Loss γ	3.0
Dropout	0.4
TTA passes	5

4.2.Training Dynamics

Figure 2 shows the training and validation loss and accuracy graphs for 50 epochs. It can be seen that the training loss steadily and monotonically decreases and approaches zero by epoch 50. The accuracy for the validation set has high variance in the initial epochs (epochs 1 to 20), which is natural due to Weighted Random Sampler. This is because the class distribution in the training set will be significantly different from that in the validation set. This will result in high variance in the accuracy for the validation set before the model is able to learn discriminative features. From epoch 20 onwards, the accuracy for the validation set steadily and consistently improves and reaches 98.28% by epoch 47. The point at which the training loss and validation loss start to diverge (training loss being zero and validation loss increasing from epoch 35) is due to mild overfitting. As shown in Figure 2.

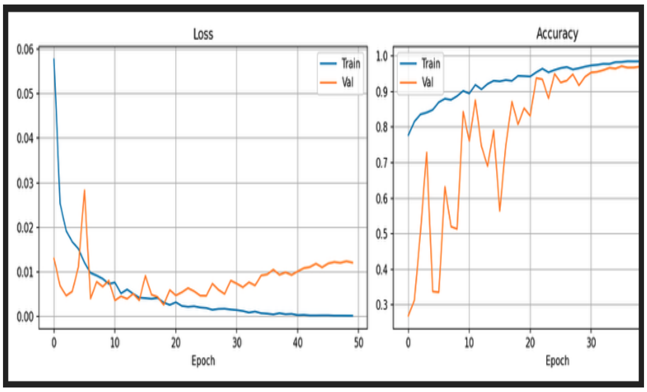

Figure 2 **Training and validation loss (left) and accuracy (right) over 50 epochs. Validation instability in early epochs is attributable to the Weighted Random Sampler distribution shift**

4.3.Quantitative Classification Results

The precision, recall, and F1-score per class on the held-out set (16,407 segments) under the tuned threshold prediction using TTA are shown in Table 2. Threshold calibration achieves a significant increase in overall accuracy from 97.26% (argmax) to 99.18%, and the largest gains are observed for the minority classes, thereby validating the effectiveness of post-hoc threshold optimisation for imbalanced classification tasks. As shown in Table 2.

Table 2 **Per-Class Results on MIT-BIH ,Test Set(Tuned Thresholds + TTA) TTA)**

Class	Prec.	Recall	F1	n
Normal (N)	0.9937	0.9970	0.9953	13,584
Supravent. (S)	0.9592	0.9017	0.9295	417
Ventricular (V)	0.9860	0.9770	0.9815	1,085
Fusion (F)	0.8678	0.8750	0.8714	120
Unknown (Q)	0.9983	0.9892	0.9937	1,201
Weighted Avg	0.9917	0.9918	0.9917	16,407

The normalised confusion matrix in Figure 3 also provides further insight into the error characteristics. Normal beats are classified with near-perfect recall of 0.997. Ventricular beats have 0.977 recall, with approximately 1% of the samples being incorrectly classified as Normal. Supraventricular beats have 0.902 recall, with 10% of the samples being confused with Normal. This has been well documented and is due to the well-known problem of the morphological similarity between certain supraventricular ectopic beats and sinus rhythm with aberrant conduction. The Fusion beats have the poorest performance, with recall of 0.875 and F1 of 0.871, which is consistent with the inherently ambiguous nature of this beat type, being the superposition of Normal and Ventricular beats. The Unknown/Paced beats are classified with 0.989 recall. As shown in Figure 3.

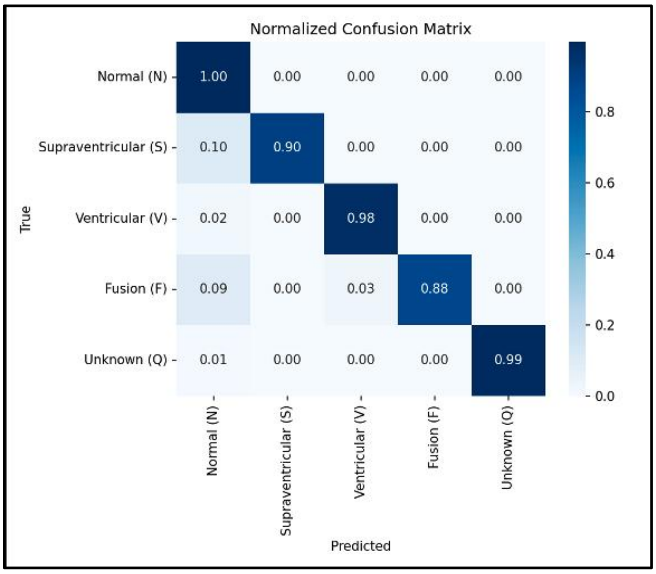

Figure 3 **Normalised confusion matrix on the MIT-BIH test set (16,407 segments). Off-diagonal entries represent misclassification rates**

4.4.Comparison with Prior Work

In Table III, context is provided for the results of the proposed MS-ResNet-18 in comparison to representative previous methods using the same MIT-BIH database and five-class AAMI EC57 classification scheme. The proposed method attains the best classification accuracy and has fewer parameters than deep learning methods based on ResNet architectures. As Shown in Table 3.

Table 3 Comparison with Prior Approaches on MIT-BIH (5-class AAMI EC57)

Method	Acc.	Params	Input
SVM + features	~93–95%	<1K	RR + morphology
1D ResNet-18	~97–98%	~11M	Raw ECG
Stanford ResNet-34	~98%	~22M	Raw ECG
CNN-LSTM	~97–98%	~5–8M	Raw ECG
MS-ResNet-18 (Ours)	99.18%	7.36M	L-I + L-II + RR

5. Discussion

The model achieves high classification performance on the MIT-BIH dataset, with the accuracy increasing from 97.26% with standard argmax prediction to 99.18% with per-class threshold calibration and test-time augmentation. The performance increase for the minority classes aligns with the literature, which has demonstrated the effectiveness of post-hoc thresholding approaches in compensating for the problem of class imbalance in ECG classification tasks (Zhang et al., 2022). Error analysis from the confusion matrix shows that most misclassifications involve classes with overlapping signal morphology. The 10% confusion between Supraventricular and Normal beats reflects a well-documented separability challenge when classification is restricted to short temporal windows, particularly when rhythm context is limited (Ansari et al., 2023). Fusion beat performance, while lowest across the five classes, is expected given the inherently composite morphology of these beats and their sparse representation in the training data (Ansari et al., 2023). The architectural choices are also contributing factors to these results. The parallel structure of the convolutional branches in each residual block of the model enables the model to capture both the detailed QRS characteristics and the broader T-wave and ST-segment characteristics simultaneously, which is not feasible with single-receptive-field models (Zhang et al., 2023a). The residual skip connections facilitate the maintenance of gradient flow and the use of deeper feature hierarchies without optimisation degradation (He et al., 2016). The inclusion of the explicit RR-interval input channel also provides rhythm-level context, which is not present in the morphology-only approaches, and this is supported by the improved sensitivity to arrhythmias when timing characteristics are used in conjunction with morphology (Alsaleem et al., 2022). The evaluation is based on one dataset only, and this limits any conclusions that can be drawn on the process of generalization. Variability in patients, noise associated with devices, and acquisition variability from different clinical sites are known to cause degradations in system performance. Validation is required on multiple datasets before any assessment of generalization can be performed. The results should be considered specific to the dataset and not universally applicable (Ansari et al., 2023). With respect to interpretability, the current model does not include any explicit mechanisms for this. While the structured three-channel inputs and threshold-calibrated outputs allow for some degree of control over the decision boundaries, the feature representations are currently opaque to clinical inspection. As highlighted by Talukder et al. (2025), this is a recognized limitation for clinical models, which require the capability to examine the reasoning behind each individual prediction for verification and trust. The use of the AAMI EC57 classification system enables comparability with other published studies, thereby partially addressing the requirement of alignment with regulatory and validation standards. However, internal evaluation of the dataset is inadequate to achieve regulatory approval. Readiness for deployment requires external validation, extensive testing in real world settings, and documentation of performance across different patient demographics (Faiyazuddin et al, 2025). Regarding clinical workflow integration, the 7.36M parameter architecture and fixed length segment processing are advantageous characteristics for embedded monitoring applications. However, for practical implementation, further assessment of inference latency, hardware compatibility, and output presentation will be required. The literature has consistently identified workflow misalignment as a primary barrier to the adoption of AI in healthcare (Hao et al, 2021), which remains an unresolved issue for the current system. If evaluated based on all four components of the framework, the model can be described as technically robust but not yet prepared for deployment. This positions the study in alignment with the broader literature on AI in healthcare, where high performance under controlled conditions is necessary but not sufficient for deployment (Faiyazuddin et al, 2025; Ansari et al, 2023).

Conclusion

In this paper, the disparity between the performance of AI in healthcare research and the requirements for its application in the real world has been explored. From the literature review, it can be concluded that the recent studies have shown impressive performance on various tasks, but the important factors for its application have still not received due attention. Accuracy alone does not make AI suitable for application. In order to bridge the gap, the paper proposed the four-component framework for the integration of responsible AI, which includes technical reliability, interpretability and ethical design, regulatory and validation alignment, and clinical workflow integration. The proposed framework is not meant to replace the existing evaluation approaches but to complement them with the operational and institutional aspects that make it possible for the system to go from the lab to the clinic. The framework is implemented through an ECG arrhythmia classification case study using a multi-scale residual network named MS-ResNet-18, which includes a three-channel enriched input feature combining dual-lead ECG and an explicit RR interval feature. The model reaches 99.18% accuracy on the MIT-BIH test set with tuned thresholds and possesses superior detection capability for clinically critical classes of arrhythmia. However, upon analysis of this framework, it is evident that single-dataset evaluation, lack of interpretability, and untested workflow integration pose important readiness gaps. While not necessarily deficiencies within the model, they speak to the state at which this type of research currently is. The study also supports the need for the evaluation of healthcare AI to extend beyond its technical performance to its reliability, transparency, and integration. The proposed framework can be used for this evaluation and can be reused for other healthcare AI domains besides ECG classification. Future directions include multi-dataset validation to assess cross-population generalisation, integration of attribution-based explainability methods such as Grad-CAM adapted to one-dimensional signals, and evaluation of the system under real-time monitoring conditions. Each of these would move the work closer to the deployment pathway and address the limitations identified through the framework analysis.

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