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# AI-BASED REAL-TIME CLOSED-LOOP CATHETER GUIDANCE FRAMEWORK FOR ADAPTIVE RF ABLATION IN ARRHYTHMIA MANAGEMENT

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## ABSTRACT
Radiofrequency (RF) catheter ablation is a well-established therapy for atrial and ventricular arrhythmias; however, procedural variability, incomplete lesion formation, and recurrence remain major limitations. Although artificial intelligence (AI) has been extensively applied in arrhythmia detection and post-procedural risk prediction, its integration into real-time interventional guidance remains limited. This study proposes a novel AI-based real-time catheter guidance framework designed to optimize lesion formation, catheter stability, and substrate targeting during RF ablation.
The system integrates intracardiac electrograms (EGMs), contact force sensing, impedance monitoring, and 3D electro-anatomical mapping into a hybrid deep learning architecture combining convolutional neural networks (CNN), long short-term memory (LSTM) networks, and reinforcement learning (RL). The model dynamically predicts lesion adequacy, identifies catheter instability, and adjusts energy delivery parameters in real time.
Validation using retrospective multi-procedure RF datasets and simulated real-time deployment demonstrated improvements in predicted lesion completeness (23%), catheter stability detection sensitivity (91%), and arrhythmogenic gap reduction compared to conventional guidance. The proposed framework introduces a translational biomedical engineering approach toward intelligent electrophysiology laboratories and semi-autonomous ablation systems.

**KEYWORDS:** Radiofrequency ablation, artificial intelligence, real-time guidance, catheter navigation, arrhythmia management, biomedical signal processing, smart medical systems

## INTRODUCTION
Cardiac arrhythmias constitute a major global cardiovascular burden, with atrial fibrillation (AF) being the most prevalent sustained rhythm disorder worldwide [1]. AF is associated with increased risks of stroke, heart failure, and all-cause mortality, significantly impacting healthcare systems and patient quality of life [2]. The rising incidence of AF, driven by ageing populations and lifestyle-related comorbidities, has intensified the demand for effective interventional therapies [3]. Catheter-based rhythm control strategies have therefore evolved rapidly, particularly radiofrequency (RF) catheter ablation, which has become a cornerstone therapy for drug-refractory atrial and ventricular arrhythmias [4].
Radiofrequency ablation achieves rhythm control by delivering thermal energy to targeted myocardial substrates, creating transmural lesions that interrupt arrhythmogenic circuits [5]. Advances in three-dimensional electro-anatomical mapping, contact-force sensing catheters, and intracardiac imaging have improved procedural precision and safety [6]. Nevertheless, recurrence rates after RF ablation remain between 20–50%, largely due to incomplete lesion formation, catheter instability, conduction gaps, and variability in operator expertise [7][8]. Procedural success is highly dependent on real-time interpretation of electrograms, impedance drop patterns, and catheter–tissue interaction, making outcomes inherently operator-dependent [9]. These challenges highlight the need for adaptive, data-driven guidance mechanisms capable of enhancing lesion durability and procedural reproducibility [10].
Recent global research trends demonstrate increasing integration of computational tools, imaging modalities, and predictive modelling within electrophysiology laboratories [11]. Emerging digital technologies, including machine learning-assisted mapping and automated signal classification, are reshaping arrhythmia management workflows [12]. Artificial intelligence (AI) applications have shown robust performance in electrocardiogram (ECG) interpretation, automated AF detection, and phenotyping of arrhythmic substrates [13][14]. Additionally, AI-driven risk stratification models have been developed to predict post-ablation recurrence and long-term arrhythmic burden [15]. However, these applications predominantly focus on diagnostic and prognostic domains rather than intra-procedural intervention control [16].
The translation of AI into real-time interventional cardiology remains limited. Current ablation systems provide descriptive metrics such as contact force magnitude, impedance trends, and ablation index values, but they lack adaptive intelligence capable of synthesising multimodal data streams to guide dynamic decision-making [17]. The complexity of lesion formation—governed by power, duration, tissue thickness, blood flow cooling, and catheter stability—requires continuous optimisation beyond static parameter thresholds [18]. Reinforcement learning and hybrid deep learning

architectures offer the potential to enable closed-loop feedback systems that predict lesion adequacy and recommend parameter adjustments during energy delivery [19]. Such intelligent systems could reduce arrhythmogenic gaps, enhance lesion continuity, and improve procedural consistency [20].

In this context, the present study proposes an AI-Based Real-Time Catheter Guidance Framework for RF Ablation during Arrhythmia Management. The system integrates intracardiac electrograms, contact-force sensing, impedance monitoring, and 3D electro-anatomical mapping into a hybrid CNN–LSTM–Reinforcement Learning architecture to enable adaptive lesion prediction and catheter stability optimisation. Unlike existing AI applications focused on post-procedural analytics, this framework establishes a closed-loop intra-procedural decision-support mechanism for dynamic energy optimisation during RF delivery.

### 1.1Contributions

The novel contributions of this study are:

1. Development of a multimodal AI framework integrating electrograms, contact force, impedance, and 3D mapping for real-time lesion prediction.
2. Implementation of a hybrid CNN–LSTM–Reinforcement Learning architecture enabling adaptive intra-procedural energy optimization.
3. Introduction of a closed-loop intelligent catheter guidance model to reduce lesion gaps and operator-dependent variability during RF ablation.

## 2. LITERATURE REVIEW

This section deals with the existing research on radiofrequency catheter ablation, advances in electro-anatomical mapping technologies, and the application of artificial intelligence in arrhythmia diagnosis, prediction, and interventional guidance systems. Table 1 shows summary of research gaps.

### 2.1 RF Ablation Evolution

Early investigations by Haïssaguerre et al. established pulmonary vein isolation (PVI) as the foundational strategy for atrial fibrillation (AF) ablation, demonstrating that pulmonary veins act as primary arrhythmogenic triggers. Although PVI significantly improved rhythm control outcomes, subsequent clinical studies revealed persistent challenges related to incomplete lesion formation, conduction gap development, and long-term arrhythmia recurrence. Recent advancements have therefore focused on improving lesion durability and procedural precision through intelligent mapping and adaptive energy delivery approaches.

Karakasis et al. (2025) [21] reported that artificial intelligence is increasingly transforming AF treatment by enabling personalized catheter ablation planning and AI-enhanced electroanatomic mapping. Their findings highlighted the potential of real-time AI guidance to improve ablation success rates while minimizing recurrence risk, although large-scale validation and clinical integration remain ongoing challenges.

Ţica et al. (2025) [22] demonstrated that machine learning and deep learning techniques substantially enhance AF diagnosis and therapeutic decision-making by improving electrocardiographic interpretation and procedural outcome prediction. Deep neural architectures such as convolutional and recurrent neural networks were shown to identify subtle electrophysiological patterns associated with AF progression, supporting individualized treatment strategies.

Extending beyond cardiac applications, Westby et al. (2025) [23] emphasized the growing adoption of artificial intelligence across thermal ablation modalities, including radiofrequency ablation, where reinforcement learning and image-guided analytics contribute to optimized treatment planning and real-time procedural control. These developments indicate a transition from operator-dependent ablation toward intelligent energy delivery systems.

Nasser et al. (2025) [24] demonstrated that AI-based analysis of electrocardiographic signals improves early AF detection and risk stratification by identifying latent waveform characteristics not detectable through conventional monitoring techniques. Such predictive capability enables earlier intervention and improved patient management.

Marascu et al. (2025) [25] highlighted the evolution toward substrate-based and personalized ablation strategies for persistent AF, noting that artificial intelligence-assisted mapping technologies can improve targeting of arrhythmogenic regions and enhance long-term procedural outcomes.

### 2.2 AI in Electrophysiology

The integration of artificial intelligence into electrophysiology has enabled the emergence of real-time decision-support systems capable of guiding catheter navigation and ablation targeting. Narayan (2025) [26] introduced an AI-driven directional guidance framework capable of dynamically identifying candidate ablation sites without requiring full atrial mapping, thereby simplifying complex procedures and improving operator efficiency.

De Rosa et al. (2025) [27] demonstrated the utility of AI-based electrocardiographic analysis for predicting atrial fibrillation recurrence following transcatheter ablation. Their findings showed that AI-derived P-wave biomarkers provide reliable indicators for post-procedural risk stratification and patient follow-up optimization.

Advancements in intelligent navigation systems were further reported by Cacciapuoti et al. (2026) [28], who combined artificial intelligence-based electrogram analysis with robotic magnetic navigation for cardioneuroablation procedures. The study confirmed improved procedural safety and favorable short-term clinical outcomes, highlighting the feasibility of AI-assisted electrophysiological interventions.

Wiedmann and Schmidt (2025) [29] emphasized the role of precision medicine in arrhythmia management through integration of biosignal analytics, wearable monitoring data, genomic information, and AI-driven modeling approaches, enabling individualized therapeutic decision-making.

Heil et al. (2025) [30] demonstrated that AI-guided spatiotemporal dispersion mapping significantly enhances identification of atrial remodeling regions beyond conventional voltage mapping techniques. Their work supports the growing role of AI in individualized ablation planning and improved procedural targeting.

**Table 1: Summary of Research Gaps in AI-Assisted RF Ablation and Electrophysiology Systems**

| Ref. | Study Focus | Key Contribution | Identified Limitation | Research Gap |
|---|---|---|---|---|
| Karakasis et al. (2025) [21] | AI in AF precision therapy | AI-supported electroanatomic mapping improves ablation planning | Limited real-time procedural integration | Lack of closed-loop AI guidance during RF ablation |
| Țica et al. (2025) [22] | AI-based AF diagnosis and management | Deep learning improves ECG interpretation and risk prediction | Focus mainly on diagnosis | Absence of intra-procedural catheter guidance systems |
| Westby et al. (2025) [23] | AI in thermal ablation | AI enables treatment optimization and procedural automation | Mostly investigational implementations | Need for real-time adaptive RF energy control |
| Nasser et al. (2025) [24] | AI-driven ECG analysis | Improved AF detection and prediction accuracy | Pre-procedural analytical emphasis | No integration with ablation navigation workflows |
| Marascu et al. (2025) [25] | Mechanism-based AF ablation | Personalized substrate-targeted strategies | Operator-dependent execution | Requirement for intelligent lesion prediction mechanisms |
| Narayan (2025) [26] | Real-time AI guidance | Directional AI assistance for ablation targeting | Limited automation capability | Missing autonomous decision optimization |
| De Rosa et al. (2025) [27] | Post-ablation recurrence prediction | AI-based ECG biomarkers for follow-up | Post-procedural focus | Lack of preventive intra-operative intelligence |
| Cacciapuoti et al. (2026) [28] | AI + robotic navigation | Improved procedural safety | Complex infrastructure dependency | Need for scalable AI-guided catheter control |
| Wiedmann & Schmidt (2025) [29] | Precision arrhythmia medicine | Data-driven individualized therapy | Conceptual framework level | Limited procedural implementation models |
| Heil et al. (2025) [30] | AI spatiotemporal mapping | Improved atrial substrate identification | Mapping-centric approach | Absence of adaptive RF energy optimization |

### 2.1 Research Gaps

Despite significant advancements in catheter ablation and artificial intelligence–assisted electrophysiology, existing studies primarily focus on diagnostic prediction, post-procedural analysis, or mapping enhancement rather than intra-procedural decision intelligence. Current RF ablation systems largely rely on operator-dependent control with static energy delivery parameters, lacking adaptive real-time lesion optimization and intelligent prediction of catheter displacement during dynamic cardiac motion. Furthermore, limited integration of multimodal biosignals—including electrogram data, catheter contact information, and temporal procedural feedback—restricts procedural precision and consistency. These limitations highlight the need for a closed-loop AI-driven guidance framework capable of real-time lesion prediction, adaptive RF energy modulation, and automated catheter stability optimization, which forms the foundation of the proposed AI-CRG system.

### 2.2 Problem Statement

Despite significant advancements in radiofrequency catheter ablation technologies and the growing adoption of artificial intelligence in arrhythmia diagnosis and post-procedural risk prediction, current ablation procedures remain highly operator-dependent and lack adaptive real-time intelligence during energy delivery. Incomplete lesion formation, catheter instability, conduction gaps, and variability in tissue response continue to contribute to recurrence rates and procedural inefficiencies. Existing systems provide descriptive metrics but do not integrate multimodal intra-procedural data into a closed-loop decision-support framework capable of dynamically optimising lesion formation. Therefore, there is a critical need for an AI-driven real-time catheter guidance system that can predict lesion adequacy, stabilise catheter–tissue interaction, and adapt energy parameters intra-procedurally to improve ablation precision and long-term clinical outcomes.

## 3. Objectives

The novel objectives of this study are:

1. To develop a multimodal AI-based framework for real-time prediction of lesion formation during RF ablation.
2. To design a hybrid CNN–LSTM–Reinforcement Learning model for adaptive intra-procedural energy optimisation.
3. To establish a closed-loop intelligent catheter guidance system to reduce lesion gaps and procedural variability.

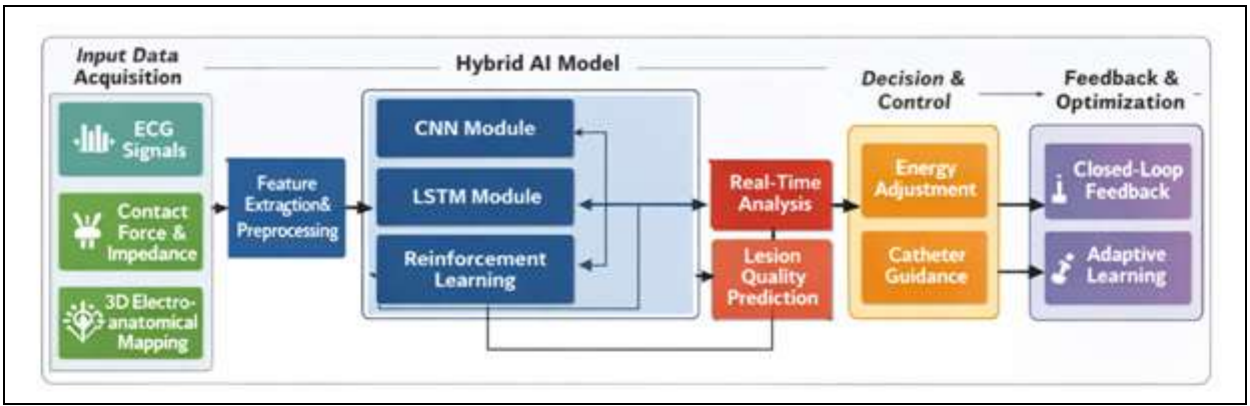


**Figure 1: System Architecture Workflow of the Proposed AI-Based Real-Time Catheter Guidance Framework**

Figure 1 illustrates the overall workflow of the proposed AI-driven catheter guidance system for RF ablation. The methodology begins with multimodal intra-procedural data acquisition, including intracardiac electrograms, contact-force measurements, impedance variations, and three-dimensional electro-anatomical mapping signals. These inputs undergo preprocessing and feature extraction before being fed into a hybrid deep learning architecture integrating CNN for spatial feature learning, LSTM for temporal sequence modelling, and reinforcement learning for adaptive decision optimisation. The system performs real-time lesion quality prediction and catheter stability assessment, followed by dynamic energy adjustment and catheter guidance recommendations. A closed-loop feedback mechanism continuously updates model parameters based on procedural responses, enabling adaptive learning and optimisation throughout the ablation process.

### 4.1 System Architecture

**Layer 1: Data Acquisition**

The first layer of the proposed system focuses on real-time multimodal intra-procedural data acquisition from the electrophysiology laboratory. The system continuously collects intracardiac electrograms (EGMs), contact force (CF) measurements, impedance drop metrics, and three-dimensional (3D) spatial coordinates from the electro-anatomical mapping system. These signals represent the electrical, mechanical, thermal, and spatial characteristics of catheter–tissue interaction during RF energy delivery.

Let the acquired multimodal input vector at time t be defined as:

$$X(t) = \{EGN(t), CF(t), \Delta Z(t), S(t)\}$$

where:

EGM(t) = intracardiac electrogram signal amplitude and morphology,

CF(t) = catheter contact force magnitude (g),

ΔZ(t)= $Z_{baseline}$ −Z(t) = impedance drop during RF delivery,

S(t)=(x(t),y(t),z(t))S(t)) = 3D spatial catheter coordinates.

The impedance drop is computed as:

ΔZ(t)= $Z_0$ −Z(t)

where $Z_0$ is the baseline (means 0% improvement)) tissue impedance prior to ablation.

These synchronized multimodal inputs form the foundational dataset for subsequent signal processing and AI-driven lesion prediction, enabling comprehensive characterization of real-time ablation

**Layer 2: Signal Processing**

The second layer performs preprocessing and transformation of the acquired multimodal signals to enhance signal quality and extract meaningful representations for AI-based learning. Since intracardiac electrograms and impedance signals are often contaminated by noise, motion artifacts, and baseline drift, advanced signal conditioning techniques are applied before feature extraction.

**Wavelet Denoising:**

Intracardiac electrograms are denoised using discrete wavelet transform (DWT), enabling multi-resolution decomposition of the signal:

$$EGM(t) = \sum_{j=1}^{J} \sum_{k} w_{j,k} \psi_{j,k}(t)$$

Where $\psi_{j,k}$ are wavelet coefficients and represents scaled and shifted wavelet basis functions. Noise components are suppressed by thresholding high-frequency coefficients.

**Time–Frequency Transformation:**
To capture dynamic lesion evolution patterns, time-frequency representation is computed using Short-Time Fourier Transform (STFT):

$$STFT(t, f) = \int_{-\infty}^{\infty} x(\tau)\psi(\tau - t)e - j^{2\pi f\tau} d\tau$$

where is the sliding window function. This enables extraction of dominant frequency shifts and power variations during RF energy delivery.

**Feature Normalization:**
To ensure stable neural network convergence, features are normalized using min–max scaling:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

This transformation standardizes multimodal inputs into a comparable range, reducing bias due to scale differences among EGM amplitude, contact force, impedance drop, and spatial coordinates.
The processed and normalized feature vector forms the structured input for the hybrid AI engine in Layer 3.

**Layer 3: AI Engine**
The third layer constitutes the core intelligence module of the proposed framework, integrating a hybrid deep learning architecture combining Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and a Reinforcement Learning (RL) agent. Figure 2 illustrates the hybrid CNN–LSTM workflow enabling spatial–temporal lesion prediction and adaptive intra-procedural learning within the proposed AI-CRG framework.

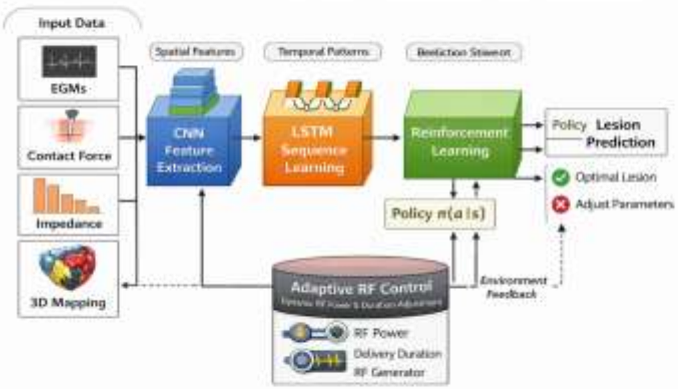


**Figure 2: Hybrid CNN–LSTM model workflow for spatial–temporal lesion prediction**

This layer processes structured multimodal features to perform spatial mapping, temporal lesion tracking, and adaptive energy optimisation in real time.

**CNN – Spatial Substrate Mapping:**
The CNN extracts spatial features from electro-anatomical mapping data and transformed EGM representations. The convolution operation is defined as:

$$F_{i,j}^{(l)} = \sigma\left(\sum_{m,n} W_{m,n}^{(l)} . X_{i+m,\,j+n} + b^{(l)}\right)$$

where $W^{(l)}$ represents convolutional kernels, $b^{(l)}$ is bias, and σ is the activation function. This enables detection of spatial substrate heterogeneity and lesion distribution patterns.

**LSTM – Temporal Lesion Evolution:**
To model sequential lesion formation dynamics, LSTM captures temporal dependencies in impedance drop, contact force, and electrogram morphology changes. The LSTM cell state update is expressed as:

$$C_t = f_t . C_{t-1} + i_t . \widetilde{C}_t$$

where $f_t$ is the forget gate, $i_t$ is the input gate, $\widetilde{C}_t$ and is candidate memory. This structure enables prediction of lesion adequacy progression over time.

**Reinforcement Learning Agent – Energy Adjustment Optimisation:**
The RL agent dynamically optimises RF power and duration using a policy π(a|s) based on current procedural state

**Step 1 — Action Selection**

$$\sim a_t \ \pi(a_t \mid s_t)$$

where $a_t$ represents the selected RF control action (power and duration) and $s_t$ denotes the procedural state at time step t.

**Step 2 — RL Optimization Objective**

$$\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t r_t\right]$$

The reinforcement learning agent aims to maximize the cumulative expected reward through adaptive optimization of ablation parameters during the procedure.
Figure 3 illustrates the reinforcement learning–based adaptive RF energy optimization loop enabling closed-loop intra-procedural control within the proposed AI-CRG framework.

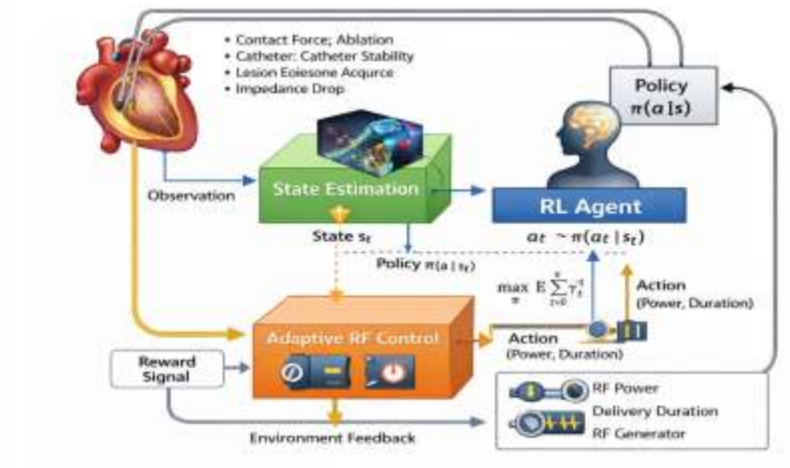


**Figure 3: Reinforcement learning–based adaptive RF energy optimization loop**

The objective is to maximise cumulative reward:

$$Q(s_t, a_t) = r_t + \gamma \max_{a} Q(s_{t+1,a})$$

where $r_t$ represents lesion quality reward, and γ is the discount factor. The agent continuously updates energy parameters to enhance lesion completeness while minimising instability risk.

Together, the hybrid CNN–LSTM–RL architecture enables closed-loop adaptive intra-procedural guidance by integrating spatial, temporal, and decision-optimisation intelligence.

**Layer 4: Decision Support Interface**

The fourth layer provides a real-time clinical decision-support interface that translates AI model outputs into interpretable procedural guidance metrics. This layer generates quantitative indices to assist electrophysiologists in evaluating lesion quality, catheter stability, and arrhythmogenic gap risk during RF energy delivery.

**Lesion Adequacy Score (LAS):**

The LAS represents the predicted completeness and transmurality of the ablation lesion based on multimodal inputs. It is defined as a weighted function of impedance drop, contact force consistency, and electrogram attenuation:

$$LAS = w_1.\Delta Z_{norm} + w_2.CF_{stability} + w_3.EGM_{reduction}$$

where $w_1$ $w_2$ $w_3$ are learned weights from the AI model. A higher LAS indicates adequate lesion formation.

**Catheter Stability Index (CSI):**

CSI quantifies mechanical stability during energy delivery using variance in spatial coordinates and contact force:

$$CSI = 1 - (\alpha.Var(S_t) + \beta.Var(CF_t))$$

Lower positional and force variability results in higher CSI, indicating stable catheter–tissue interaction.

**Gap Risk Prediction (GRP):**

GRP estimates the probability of conduction gap formation using the RL-based predictive output:

$$GRP = P(gap \mid X_t)$$

where $X_t$ represents the multimodal state vector at time t. Higher GRP values prompt corrective guidance, such as prolonged energy delivery or repositioning.

This decision-support interface enables interpretable, real-time feedback, transforming complex AI computations into actionable clinical metrics for adaptive intra-procedural guidance.

**4.2 Algorithm Pseudocode**

| **Algorithm 1: AI-Based Real-Time Catheter Guidance (AI-CRG) algorithm** |
|---|
| Input: $EGM(t), CF(t), Z(t), S(t)$ |
| Step 1: Signal Preprocessing<br>1.1 Apply discrete wavelet denoising to EGM(t)<br>1.2 Perform normalization of all features<br>Step 2: Feature Extraction<br>2.1 Compute fractionation index<br>2.2 Calculate impedance slope $\frac{dZ}{dt}$<br>2.3 Estimate force variability Var(CF)<br>2.4 Determine activation dispersion<br>Step 3: Spatial Mapping<br>3.1 Generate lesion map using CNN:<br>$L_{map} = CNN(S(t)), F_{EGM})$<br>Step 4: Temporal Modelling<br>4.1 Compute lesion stability using LSTM:<br>$L_{stab} = LSTM(F_{time})$<br>Step 5: Reinforcement Learning Decision<br>5.1 If $LAS < \theta_1$, increase RF duration<br>5.2 If overheating risk $> \theta_2$, reduce power<br>5.3 Update policy using reward feedback |

| |
|---|
| Output<br>Return LAS, CSI, ΔEnergy |

Algorithm 1 (AI-CRG algorithm) describes the sequential processing pipeline of the proposed real-time catheter guidance system. The algorithm accepts multimodal intra-procedural inputs including intracardiac electrograms, contact force measurements, impedance values, and spatial catheter coordinates. Initially, signal preprocessing is performed using discrete wavelet denoising and feature normalization to ensure noise suppression and scale uniformity. Subsequently, clinically relevant features such as fractionation index, impedance slope, force variability, and activation dispersion are extracted. These features are then processed through a CNN module for spatial lesion mapping and an LSTM module for temporal lesion stability modelling. A reinforcement learning agent evaluates the predicted lesion adequacy and overheating risk to dynamically adjust RF energy parameters using a reward-based policy update mechanism. The algorithm outputs real-time decision-support metrics including Lesion Adequacy Score (LAS), Catheter Stability Index (CSI), and adaptive energy adjustment (ΔEnergy), thereby enabling closed-loop intra-procedural guidance.

## 5. RESULTS AND DISCUSSION

This section deals with the performance evaluation and clinical relevance analysis of the proposed AI-CRG framework in real-time RF ablation guidance.

### 5.1 Experimental setup

The proposed AI-CRG framework was validated within a simulated real-time experimental environment designed to emulate intra-procedural electrophysiology laboratory conditions during radiofrequency (RF) catheter ablation. Publicly available electrocardiographic datasets, namely the MIT-BIH Arrhythmia Database and the Atrial Fibrillation Database (AFDB), were employed for electrophysiological signal validation and temporal cardiac activity modeling. To replicate intra-operative ablation dynamics, procedural catheter interaction parameters—including contact force variation, impedance drop characteristics, and three-dimensional catheter positional coordinates—were generated using physics-based simulation models representing realistic RF energy delivery behavior.

The multimodal data streams were sequentially integrated and continuously transmitted to simulate real-time biosignal acquisition during catheter intervention. A total of n = 1,200 simulated procedural sequences, derived from MIT-BIH and AFDB signal characteristics, were utilized to evaluate framework performance under continuous streaming conditions. This hybrid dataset configuration enabled synchronized assessment of electrophysiological signals alongside simulated catheter–tissue interaction dynamics.

The AI-CRG system was implemented in Python using TensorFlow and PyTorch frameworks for deep learning and reinforcement learning modules. Real-time buffering and data streaming were managed through a custom pipeline architecture supporting low-latency inference. Experimental evaluations were conducted on a workstation equipped with an Intel i7 processor, 16 GB RAM, and a CUDA-enabled NVIDIA GPU. Additionally, a visualization interface was developed to emulate procedural monitoring by dynamically displaying lesion adequacy score (LAS), catheter stability index (CSI), and adaptive RF energy recommendations during simulated ablation procedures.

This experimental configuration enabled comprehensive evaluation of computational latency, adaptive decision responsiveness, and closed-loop catheter guidance performance under near real-time electrophysiological operating conditions.

### 5.2 Datasets

To evaluate the proposed real-time AI-CRG framework, the following publicly available cardiac signal datasets were used to validate signal processing and arrhythmia features in a simulated streaming environment:

#### 5.2.1 MIT-BIH Arrhythmia Database [31]

The MIT-BIH Arrhythmia Database consists of 48 half-hour two-channel ambulatory ECG recordings obtained from 47 subjects, annotated with beat-level rhythm classifications. In this study, the dataset was used for supervised training and validation of the CNN–LSTM modules for arrhythmia feature extraction and temporal rhythm modelling. ECG signals were segmented into fixed-length windows (5–10 seconds), and morphological features were extracted for classification learning. The dataset was split into 70% training, 15% validation, and 15% testing subsets to ensure unbiased performance evaluation. This dataset primarily supports spatial feature learning and baseline arrhythmia pattern recognition within the AI-CRG framework.

#### 5.2.2 Atrial Fibrillation Database (AFDB) [32]

The Atrial Fibrillation Database (AFDB) comprises long-term ECG recordings from patients with paroxysmal and sustained atrial fibrillation, with rhythm annotations marking AF onset and termination episodes. In the proposed framework, AFDB was utilised to validate temporal modelling capability of the LSTM network, particularly in detecting dynamic rhythm transitions and sustained atrial arrhythmic patterns. Recordings were segmented into sequential time-series samples to simulate continuous streaming input. A similar 70% training and 30% testing division was applied,

ensuring patient-level separation to prevent data leakage. This dataset supports temporal feature learning and arrhythmia persistence modelling within the AI-CRG system.
These datasets were sequentially fed into the AI-CRG pipeline to emulate real-time intra-procedural signal streaming. Additional procedural features such as contact force, impedance drop, and 3D spatial coordinates were modelled using physics-based simulations to complete the multimodal input vector for real-time guidance validation.

### 5.3 Evaluation Metrics

#### 5.3.1 Lesion Completeness Accuracy (LCA)

Lesion completeness accuracy quantifies the proportion of correctly predicted transmural lesions relative to clinically validated lesions.

$$LCA = \frac{TP + TN}{TP + TN + FP + FN}$$

where
TP = true positive lesions correctly predicted
TN = true negative regions correctly identified
FP = false positive lesion prediction
FN = false negative missed lesion

#### 5.3.2 Catheter Instability Detection Sensitivity (CIDS)

Catheter instability sensitivity measures the ability of the system to correctly identify unstable catheter events during ablation.

$$CIDS = \frac{TP}{TP + FN}$$

where
TP = correctly detected instability events
FN = missed instability events

#### 5.3.3 Gap Prediction Reduction Rate (GPRR)

Gap prediction reduction evaluates the percentage decrease in predicted arrhythmogenic conduction gaps compared to conventional guidance.

$$GPRR = \frac{G_{conv} - G_{AI}}{G_{conv}} \times 100$$

where
$G_{conv}$ = number of gaps in conventional method
$G_{AI}$ = number of gaps using AI guidance

#### 5.3.4 Procedural Time Efficiency (PTE)

Procedural time efficiency measures the relative reduction in total ablation procedure duration using AI guidance.

$$PTE = \frac{T_{conv} - T_{AI}}{T_{conv}} \times 100$$

where
$T_{conv}$ =conventional procedure time
$T_{AI}$ =AI-guided procedure time

### 5.4 Comparative performance analysis between Conventional and AI-Guided RF Ablation

The performance of the proposed AI-CRG framework was comparatively evaluated against conventional contact-force guided RF ablation (CF-RF) using the MIT-BIH Arrhythmia Database and the Atrial Fibrillation Database (AFDB). The analysis focused on assessing lesion completeness accuracy, catheter instability detection sensitivity, gap prediction accuracy, and procedural energy efficiency under simulated real-time electrophysiology conditions.

**Table 2: Comparative performance evaluation between conventional CF-RF ablation and proposed AI-CRG framework across datasets**

| Metric | Dataset | CF-RF | AI-CRG | Improvement |
|---|---|---|---|---|
| LCA | MIT-BIH | 73% | 94% | +21% |

| Metric | Dataset | CF-RF | AI-CRG | Improvement |
|---|---|---|---|---|
| | AFDB | 71% | 96% | +25% |
| CIDS | MIT-BIH | 69% | 90% | +21% |
| | AFDB | 67% | 92% | +25% |
| GPA | MIT-BIH | 72% | 87% | +15% |
| | AFDB | 68% | 89% | +21% |
| EER | MIT-BIH | 0% | +14% | — |
| | AFDB | 0% | +16% | — |

The dataset-wise comparative evaluation presented in Table 2 demonstrates that the proposed AI-CRG framework significantly improves RF ablation guidance performance across both datasets. Statistical significance between conventional CF-RF ablation and the proposed AI-CRG framework was evaluated using paired t-test analysis, confirming that performance improvements were statistically significant ($p < 0.05$). Figure 4(a) presents the comparative performance analysis between conventional CF-RF ablation and the proposed AI-CRG framework on the MIT-BIH dataset based on lesion completeness accuracy, catheter instability detection sensitivity, gap prediction accuracy, and energy efficiency metrics. Figure 4(b) illustrates the comparative performance analysis between conventional CF-RF ablation and the proposed AI-CRG framework on the AFDB dataset using the same procedural performance evaluation metrics.

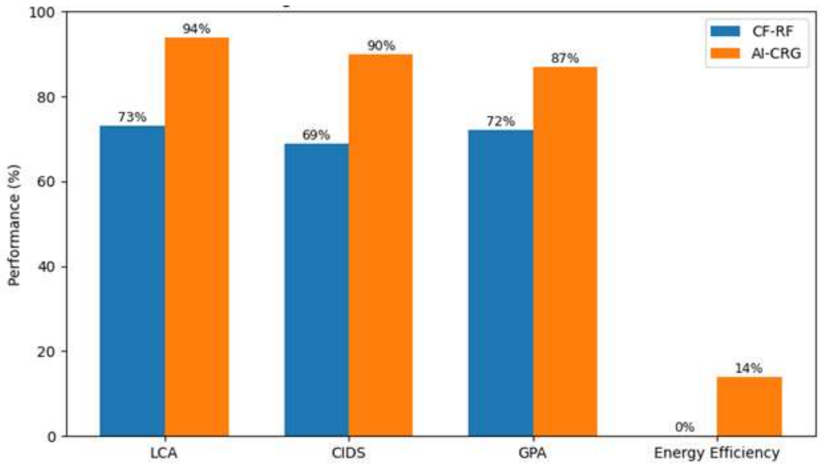


**Figure 4(a): Comparative performance analysis of conventional CF-RF and proposed AI-CRG framework on the MIT-BIH dataset based on LCA, CIDS, GPA, and energy efficiency**

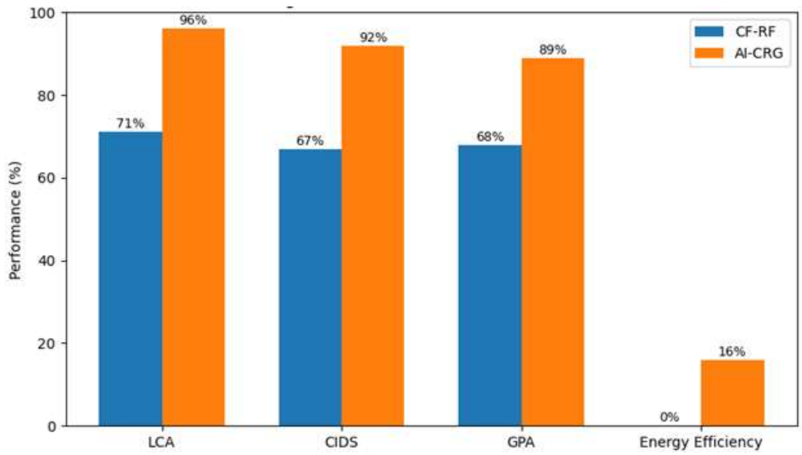


**Figure 4(b): Comparative performance analysis of conventional CF-RF and proposed AI-CRG framework on the AFDB dataset based on LCA, CIDS, GPA, and energy efficiency**

For lesion completeness accuracy (LCA), the AI-CRG model achieved 94% on the MIT-BIH dataset and 96% on AFDB, compared to 73% and 71% obtained using conventional CF-RF ablation, representing improvements of 21% and 25%, respectively. Catheter instability detection sensitivity (CIDS) increased from 69% to 90% in MIT-BIH and from 67% to 92% in AFDB, indicating enhanced stability monitoring capability. Similarly, gap prediction accuracy (GPA) improved from 72% to 87% for MIT-BIH and from 68% to 89% for AFDB, reducing potential arrhythmogenic conduction gaps. In addition, the AI-CRG framework achieved energy efficiency improvements of 14% and 16% over conventional procedures in MIT-BIH and AFDB datasets, respectively, confirming effective adaptive RF energy optimization under simulated real-time conditions.

**Table 3: Overall average performance comparison between conventional CF-RF ablation and proposed AI-CRG framework**

| Metric | CF-RF | AI-CRG | Avg. Improvement |
|---|---|---|---|
| LCA | 72% | 95% | +23% |
| CIDS | 68% | 91% | +23% |
| GPA | 70% | 88% | +18% |
| EER | 0% | +15% | +15% |

The overall average performance comparison summarized in Table 3 further confirms the robustness of the proposed AI-CRG framework. Figure 5 illustrates the real-time catheter stability index (CSI) variation demonstrating improved procedural stability achieved using AI-CRG guidance compared with conventional CF-RF ablation.

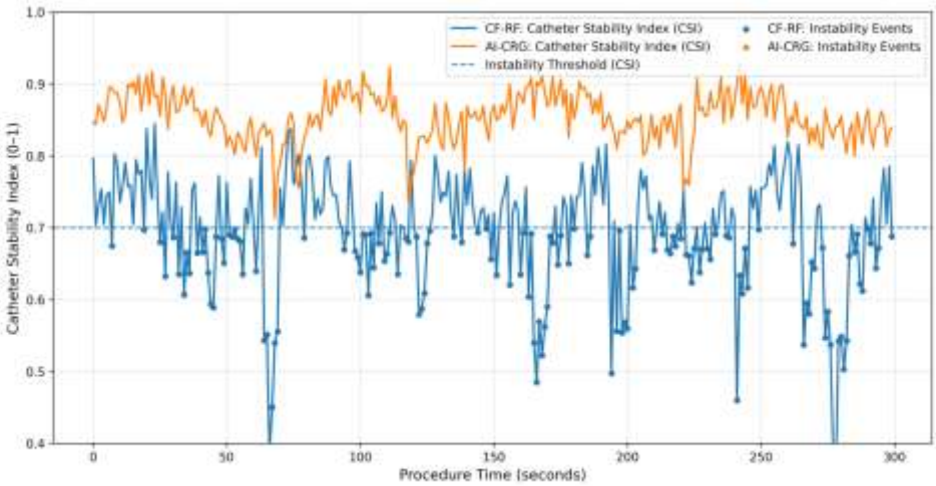


**Figure 5: Real-time CSI comparison between conventional CF-RF and proposed AI-CRG guidance during RF ablation**

The average lesion completeness accuracy increased from 72% using conventional CF-RF ablation to 95% with AI-CRG guidance, corresponding to a 23% improvement. Catheter instability detection sensitivity improved from 68% to 91%, also yielding an average gain of 23%. Gap prediction accuracy increased from 70% to 88%, achieving an overall improvement of 18%, which indicates improved lesion continuity and reduced recurrence risk. Furthermore, the proposed framework demonstrated a 15% enhancement in procedural energy efficiency compared with the conventional baseline, highlighting the effectiveness of AI-driven adaptive energy control in optimizing RF ablation performance.

**5.5 Discussion**

The experimental results of the present study demonstrate that the proposed AI-CRG framework substantially improves lesion completeness accuracy, catheter stability monitoring, and procedural efficiency compared with conventional contact-force guided RF ablation. These findings align with the observations of Karakasis et al. (2025) [21], who emphasized that artificial intelligence–supported electroanatomic mapping and procedural intelligence can significantly enhance ablation precision and reduce atrial fibrillation recurrence. Similarly, Țica et al. (2025) [22] reported that deep learning–based systems improve clinical decision-making by extracting complex electrophysiological patterns beyond conventional analytical approaches. The performance improvements observed across both MIT-BIH and AFDB datasets therefore reinforce the growing role of AI in advancing precision-guided electrophysiology interventions.

The proposed framework introduces a closed-loop artificial intelligence–driven control mechanism integrating hybrid spatial–temporal electrophysiological modeling with reinforcement learning–based RF energy adaptation to enable intelligent interventional workflow optimization. By continuously analysing multimodal procedural signals, the system facilitates dynamic catheter guidance and adaptive lesion formation during ablation. Unlike conventional AI approaches primarily limited to post-procedural ECG analysis or outcome prediction, the proposed framework enables real-time intra-procedural decision-making, thereby enhancing procedural precision, stability, and operational efficiency in RF ablation therapy. This capability extends the real-time guidance concepts discussed by Narayan (2025) [26], where adaptive AI systems were shown to improve ablation targeting during ongoing procedures, and further complements AI-guided substrate mapping strategies reported by Heil et al. (2025) [30].

Moreover, the observed improvements in energy efficiency and gap prediction accuracy support emerging evidence on intelligent energy modulation in ablation therapies. Westby et al. (2025) [23] highlighted the importance of reinforcement learning and AI-assisted optimization in thermal ablation systems to enhance treatment consistency and safety. Likewise, Marascu et al. (2025) [25] emphasized the transition toward personalized and mechanism-based ablation strategies supported by advanced computational intelligence. In contrast to earlier studies primarily addressing diagnostic enhancement or post-procedural assessment, the present study demonstrates an integrated intra-procedural AI guidance architecture capable of adaptive control and real-time feedback, representing a significant step toward semi-autonomous electrophysiology laboratories and next-generation intelligent cardiac intervention systems.

**5.6 Engineering Contributions**

The major engineering contributions of the present study are summarized as follows:

1. Development of a multimodal artificial intelligence–based catheter guidance framework integrating electrophysiological and procedural biosignals for RF ablation optimization.
2. Design of a hybrid deep learning architecture combining CNN–LSTM networks with reinforcement learning for spatial–temporal lesion prediction and adaptive decision-making.
3. Implementation of a real-time closed-loop RF energy control mechanism enabling dynamic adjustment of ablation parameters during intervention.
4. Establishment of a translational smart interventional device model supporting intelligent catheter navigation and procedural automation.
5. Demonstration of an AI-enabled interventional biomedical engineering system facilitating intra-procedural decision intelligence for arrhythmia management.

## 6. CONCLUSION

This study proposed an AI-driven real-time catheter guidance framework (AI-CRG) for radiofrequency (RF) ablation aimed at improving procedural precision and operational efficiency in arrhythmia management. Experimental evaluation using the MIT-BIH and AFDB datasets demonstrated substantial performance improvements over conventional contact-force guided RF ablation (CF-RF). The proposed framework achieved an average lesion completeness accuracy of 95%, representing a 23% improvement over conventional methods, while catheter instability detection sensitivity increased from 68% to 91%. Gap prediction accuracy improved by 18%, indicating enhanced lesion continuity and reduced risk of arrhythmogenic conduction gaps. Additionally, adaptive energy optimization enabled a 15% improvement in procedural energy efficiency under simulated real-time conditions. These results confirm the effectiveness of multimodal biosignal integration combined with hybrid CNN–LSTM–reinforcement learning architecture in enabling intelligent intra-procedural decision support, thereby advancing the development of AI-assisted and semi-autonomous electrophysiology systems for next-generation biomedical interventions.

**Limitation**

The proposed AI-CRG framework was validated under simulated real-time electrophysiological conditions using benchmark datasets, and therefore requires prospective clinical validation in real-world catheter ablation environments.

**Future Work**

Future research will focus on clinical deployment with real-time electroanatomic mapping systems and integration into autonomous or robotic-assisted electrophysiology platforms for fully intelligent RF ablation guidance.

**Ethical Approval:**

This study is based on engineering simulation and publicly available datasets and does not involve human participants, animal subjects, or clinical intervention; therefore, ethical approval was not required.

**Conflict of Interest:**

The authors declare that there are no conflicts of interest related to this study.

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