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EXPLAINABLE AI BASED ARRHYTMIA MONITORING SYSTEM

PARIMALA M[1], VIGNESHWAR P[2], SAYOOJ KUMAR VS[3], SABARI KANNAN R[4], VISHWA RC[5]

Assistant Professor, Department of Artificial Intelligence and Data Science, Dhanalakshmi Srinivasan Engineering College (Autonomous), Perambalur[1]

Student, Department of Artificial Intelligence and Data Science, Dhanalakshmi Srinivasan Engineering College (Autonomous), Perambalur[2,3,4,5]

Abstract: Cardiovascular diseases are a major global health concern, creating a need for intelligent and realtime cardiac monitoring systems. Conventional electrocardiogram (ECG) analysis often depends on specialists and may not provide immediate support in emergency or remote settings. This paper presents CardioSense AI, an explainable real-time ECG monitoring platform that combines embedded sensing, deep learning, automated reporting, and a hospital-grade dashboard for rapid rhythm assessment. The system uses an AD8232 sensor with an ESP32 microcontroller for live ECG acquisition. A one-dimensional convolutional neural network (1D-CNN) directly classifies ECG signals into Normal Rhythm, Bradycardia, Tachycardia, and PVC-type Arrhythmia. To improve transparency, Grad-CAM based Explainable AI (XAI) highlights waveform regions influencing the model prediction. The platform also provides live ECG streaming, alerts, confidence indicators, and simulation support using the MIT-BIH Arrhythmia Database. In addition, an automated report generation module enables downloadable clinical summaries after each session. Experimental results show that the proposed system achieves effective real-time classification with interpretability and practical usability. CardioSense AI offers a scalable solution for telecardiology, bedside monitoring, and preventive healthcare applications.

I.INTRODUCTION

Cardiovascular diseases (CVDs) are among the leading causes of death worldwide, making early detection and continuous monitoring of heart conditions increasingly important. Disorders such as tachycardia, bradycardia, arrhythmias, and premature ventricular contractions (PVCs) can lead to severe complications if not identified at an early stage. The electrocardiogram (ECG) is one of the most widely used non-invasive diagnostic tools for monitoring the electrical activity of the heart and detecting such abnormalities. Traditional ECG interpretation is usually performed by trained medical professionals. Although effective, manual analysis can be time-consuming and may not always be available in emergency or remote healthcare environments. In many cases, conventional ECG devices only display signals without providing intelligent diagnostic support. This creates the need for automated and real-time ECG monitoring systems that can assist both clinicians and patients. Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have significantly improved biomedical signal analysis. In particular, one-dimensional Convolutional Neural Networks (1D-CNNs) have shown strong performance in ECG classification by automatically learning meaningful waveform features directly from raw signals. These models reduce the need for manual feature extraction and enable fast and accurate diagnosis. To address existing limitations, this paper proposes CardioSense AI, an explainable real-time ECG monitoring system integrated with embedded hardware and a hospital-grade dashboard.

The system uses an AD8232 ECG sensor connected to an ESP32 microcontroller for live ECG signal acquisition. A trained deep learning model directly classifies ECG signals into four categories: Normal Rhythm, Bradycardia, Tachycardia, and PVC-type Arrhythmia.To improve transparency and trust, the proposed system incorporates Explainable Artificial Intelligence (XAI) using Grad-CAM, which highlights the ECG waveform regions influencing the model's decision. The platform also provides a live dashboard for waveform visualization, alerts, downloadable reports, and confidence indicators. In addition, a simulation mode using the MIT-BIH Arrhythmia Database is included for testing and validation. The proposed CardioSense AI system aims to provide a low-cost, intelligent, and practical solution for telecardiology, bedside monitoring, preventive healthcare, and real-time cardiac screening.

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II.LITERATURE SURVEY

Jun et al. proposed a two-dimensional Convolutional Neural Network (2D-CNN) for ECG arrhythmia classification by converting ECG beats into grayscale images. Their model was evaluated on the MIT-BIH Arrhythmia Database and achieved an average accuracy of 99.05%, demonstrating the strong capability of CNNs in extracting ECG features automatically.

Yıldırım et al. introduced a one-dimensional CNN (1D-CNN) model for classifying long-duration ECG segments into 17 rhythm classes. Instead of analyzing individual beats, the proposed method used 10-second ECG fragments, reducing repeated beat-level classification and improving real-time feasibility. The model achieved an overall accuracy of 91.33% and was recommended for mobile and telemedicine applications.

Alamatsaz et al. developed a lightweight hybrid CNN-LSTM model for ECG-based arrhythmia detection. Their architecture combined CNN layers for morphological feature extraction and LSTM layers for temporal sequence learning. Tested on MIT-BIH and PhysioNet datasets, the model achieved 98.24% accuracy, showing the effectiveness of hybrid deep learning frameworks for real-time systems.

Xiao et al. presented a systematic review of deep learning methods for ECG arrhythmia classification. Their study analyzed hundreds of research papers and found that CNN-based models were the most commonly used architectures. The review highlighted challenges such as dataset bias, lack of inter-patient validation, and limited explainability in many proposed systems.

Ansari et al. reviewed the progress of deep learning for ECG arrhythmia detection from 2017 to 2023. The authors compared CNNs, recurrent neural networks (RNNs), transformers, and hybrid models, concluding that deep learning approaches significantly outperform traditional machine learning methods. They also emphasized that future ECG AI systems should include transparency through Explainable AI techniques.

Daduvy et al. proposed a Multi-Scale Convolutional LSTM Dense Network (MS-CLDNet) for robust arrhythmia classification. Their work focused on solving class imbalance and noise sensitivity issues commonly present in ECG datasets. Experimental results showed improved performance, especially for minority arrhythmia classes.

Rajpurkar et al. introduced Cardiologist-Level Arrhythmia Detection with Deep Neural Networks, one of the most influential ECG AI studies. Using a large single-lead ECG dataset, the deep CNN model achieved performance comparable to board-certified cardiologists in detecting multiple arrhythmias. This study demonstrated the real clinical potential of deep learning in ECG diagnosis.

Hannun et al. developed a deep neural network for detecting arrhythmias from ambulatory ECG recordings. Their model was trained on a large dataset and showed high sensitivity and specificity across several rhythm classes.
The study emphasized the usefulness of wearable AI-assisted monitoring systems.

Kiranyaz et al. proposed a patient-specific 1D-CNN architecture for real-time ECG classification. Their approach adapted the model for individual patient characteristics and achieved high accuracy with low computational complexity, making it suitable for embedded and portable healthcare devices.

Acharya et al. designed a deep CNN model for automatic myocardial infarction and arrhythmia classification using ECG signals. Their work demonstrated that deep learning can successfully identify multiple cardiac abnormalities without handcrafted features.

Oh et al. introduced an attention-based recurrent neural network for arrhythmia detection from ECG signals. By incorporating attention mechanisms, the model improved interpretability and focused on important temporal waveform regions, which is valuable for explainable healthcare systems.

III. HARDWARE AND SYSTEM DESIGN

The proposed CardioSense AI system is designed as an intelligent real-time cardiac monitoring platform that integrates biomedical sensing, embedded processing, deep learning inference, explainable AI, and a hospital-grade dashboard. The architecture follows a layered model consisting of signal acquisition, preprocessing, decisionmaking, visualization, and report generation, enabling low-latency and accurate ECG analysis.

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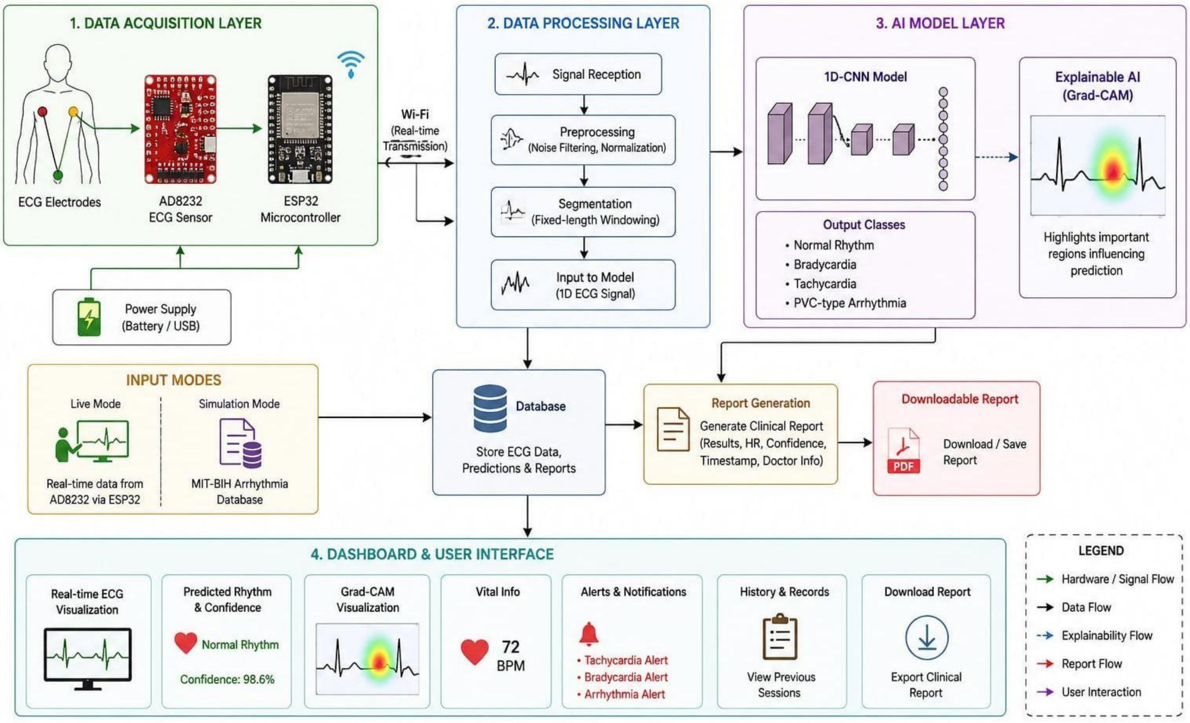

Figure 1: System Architecture

A. Overall System Model

The complete system can be represented as:

$$Y = f(X; \theta)$$

where:

- X represents the ECG input signal acquired from hardware sensors
- θ denotes the trained deep learning model parameters
- Y is the final output containing rhythm classification, heart rate status, alerts, and explainability results.

This formulation combines sensing, AI prediction, and clinical decision support in one unified framework.

B. Hardware Layer

The hardware unit consists of:

- **AD8232 ECG Sensor** for capturing heart electrical signals
- **ESP32 Microcontroller** for signal acquisition and communication
- **Electrodes (RA, LA, RL)** for body signal collection
- USB / Battery power supply for portability

The ESP32 digitizes analog ECG signals and transmits them to the dashboard through serial communication.

Sampling frequency:

$$f_s = 250Hz$$

Sampling interval:

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$$T_s = \frac{1}{f_s} = 0.004s$$

Thus, one ECG sample is acquired every 4 ms

C. Signal Preprocessing Layer

Raw ECG data often contains motion artifacts, baseline drift, and electrical noise. Therefore preprocessing is applied.

Mean Removal

$$x'(n) = x(n) - \mu$$

where:

$$\mu = \frac{1}{N} \sum_{n=1}^{N} x(n)$$

Normalization

$$x_{norm}(n) = \frac{x(n) - \mu}{\sigma}$$

Median Filtering

$$y(n) = median[x(n-k), \ldots, x(n+k)]$$

This improves signal quality before feeding into AI model.

D. AI Prediction Layer

A trained 1D Convolutional Neural Network (1D-CNN) directly classifies ECG waveform into:

- Normal Rhythm
- Bradycardia
- Tachycardia
- PVC Arrhythmia

Input shape:

$$Input = (300 \times 1)$$

Prediction:

$$\hat{y} = argmax(P(y \mid x))$$

where $P(y \mid x)$ is softmax probability.

E. Heart Rate Estimation

R-peaks are detected from ECG waveform. If RR interval is:

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$$RR = t_{n+1} - t_n$$

Then:

$$BPM = \frac{60}{RR}$$

Clinical interpretation:

- Bradycardia:

$$BPM < 60$$

- Normal Rate:

$$60 \leq BPM \leq 100$$

- Tachycardia:

$$BPM > 100$$

F. Explainable AI Layer

To improve trust and interpretability, **Grad-CAM** is applied to highlight waveform regions influencing the prediction.

$$\alpha_k = \frac{1}{Z} \sum_i \frac{\partial y^c}{\partial A_i^k}$$

$$L_{GradCAM} = ReLU\left(\sum \alpha_k A_k\right)$$

This generates a heatmap overlay on the ECG signal for visual explanation.

G. System Objective Function

The overall objective is to maximize prediction reliability while minimizing delay:

$$max(Accuracy + Explainability + Reliability) - \lambda Latency$$

This ensures high-speed and accurate real-time monitoring.

H. Overall Workflow

$$Electrodes \rightarrow AD8232 \rightarrow ESP32 \rightarrow Preprocessing \rightarrow CNNModel \rightarrow XAI \rightarrow Dashboard \rightarrow Report$$

IV. METHODOLOGY

A. Operational Workflow

The system operates in two selectable modes:

- **Live Mode** – acquires real-time ECG signals using the AD8232 sensor and ESP32 hardware.
- **Demo Mode** – uses pre-recorded signals from the MIT-BIH Arrhythmia Database for simulation and testing.

After mode selection, incoming ECG data is streamed into the monitoring engine for continuous analysis.

B. Sliding Window Analysis

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Instead of processing the entire signal at once, ECG data is divided into fixed windows for rapid prediction. Each window contains a short duration of waveform samples, enabling low-latency diagnosis and smoother realtime visualization.

If $x(n)$ is the incoming signal, then each analysis block is:

$$W_i = [x(i), x(i+1), x(i+2), \ldots, x(i+N)]$$

where N is the selected window size.

This method reduces memory load and improves real-time performance.

C. Intelligent Classification Engine

Each ECG window is passed through the trained deep learning network. The classifier directly determines whether the rhythm belongs to:

- Normal Rhythm
- Bradycardia
- Tachycardia
- PVC Arrhythmia

The predicted output is selected using:

$$Class = \arg\max(P_1, P_2, P_3, P_4)$$

where P_i are probability scores of each class.

To improve reliability, repeated predictions are aggregated before displaying the final decision.

D. Decision Stabilization Logic

Single-window predictions may fluctuate due to transient noise. Therefore, the system uses majority voting across multiple recent windows.

$$Final = mode(C_1, C_2, C_3, \ldots, C_k)$$

where C_k are recent predictions.

This improves consistency and reduces false alarms.

E. Explainable AI Strategy

The proposed CardioSense AI system integrates Explainable Artificial Intelligence (XAI) to improve transparency and trust in automated ECG diagnosis. A Grad-CAM based visualization technique is employed to identify the portions of the ECG waveform that most strongly influenced the model's decision. Clinically relevant regions such as abnormal peaks, irregular RR intervals, widened QRS complexes, or premature beats are emphasized through a heatmap overlay. This highlighted visualization is directly superimposed on the live ECG waveform so that users and clinicians can easily interpret the reasoning behind the classification result. In addition, confidence values are displayed to indicate the certainty level of the predicted output.

F. Frequency Domain Analysis

In addition to time-domain waveform interpretation, the system performs frequency-domain analysis using Fast Fourier Transform (FFT). The spectral transformation is expressed as:

$$X(f) = \sum x(n) e^{-j2\pi f n}$$

This module converts ECG signals into their frequency components and helps identify dominant rhythm frequencies, periodic irregularities, motion artifacts, and overall signal energy distribution. The dashboard displays this information through spectral heatmaps and frequency intensity plots, providing an additional layer of diagnostic insight.

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I. Smart Alert Generation

To enhance real-time clinical usefulness, the system incorporates an intelligent alert mechanism that continuously monitors the ECG signal and model predictions. Alerts are automatically generated when sustained tachycardia, bradycardia, PVC events, poor signal quality, or sensor disconnection are detected. Critical abnormalities activate blinking visual indicators and optional audible alarms similar to ICU monitoring systems.
This ensures that urgent cardiac events are immediately brought to the user's attention.

G. Report Generation

After completion of a monitoring session, the system automatically generates a downloadable clinical report summarizing the analysis. The report contains diagnosis results, heart rate statistics, confidence scores, ECG waveform snapshots, explainability visualizations, spectral findings, and timestamped session information. This feature is useful for medical documentation, remote consultations, and long-term patient record management.

H. User Interface Design

The dashboard is developed using hospital-grade visualization principles to provide an intuitive and professional monitoring environment. It uses a dark high-contrast theme for prolonged viewing, animated real-time ECG waveform display, modular diagnostic panels, alert indicators, and live status updates. The user interface is optimized for bedside monitoring, telemedicine applications, and preventive healthcare environments where clarity and rapid decision support are essential.

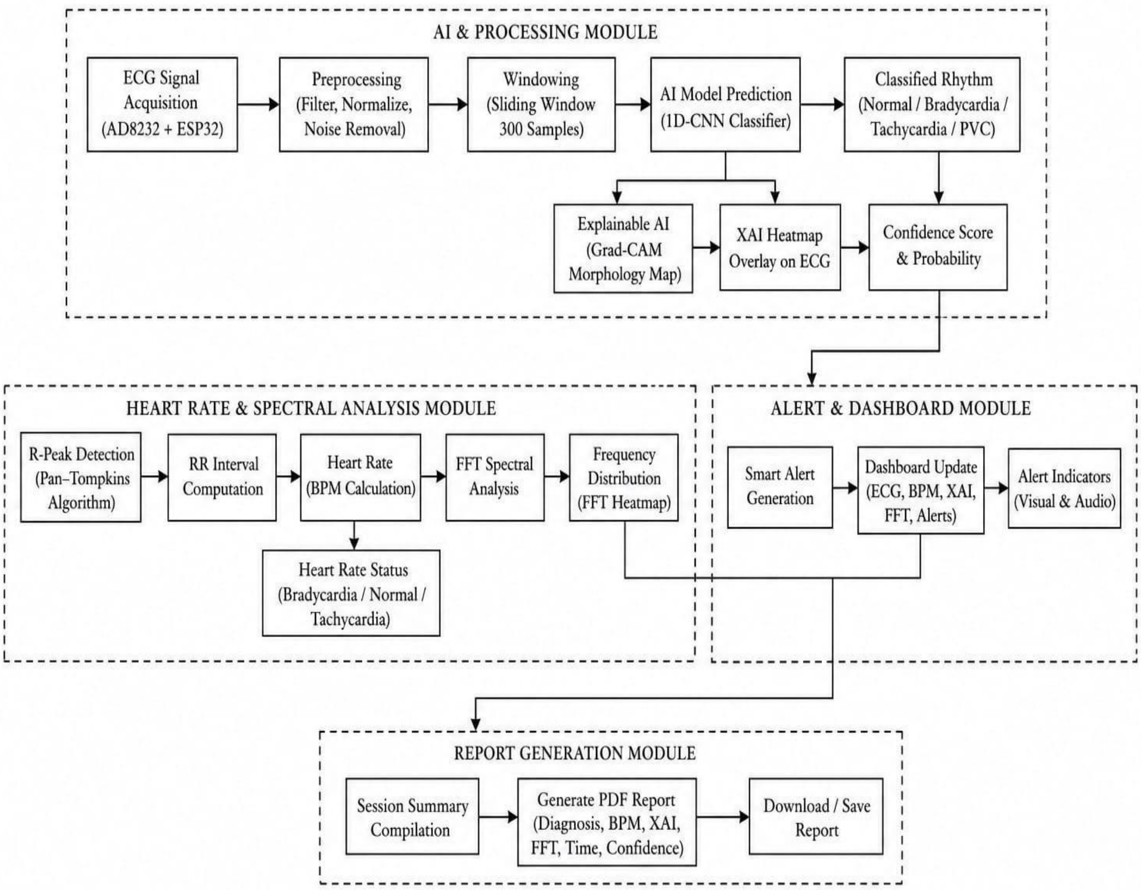

Figure 2: Activity diagram

V. RESULTS AND DISCUSSION

The developed CardioSense AI system was successfully implemented and evaluated in both Demo Mode using the MIT-BIH Arrhythmia Database and Live Mode using the AD8232 ECG sensor integrated with ESP32 hardware. Experimental

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testing confirms that the proposed platform can perform real-time ECG acquisition, rhythm classification, explainable AI visualization, spectral interpretation, and intelligent dashboard monitoring.

During evaluation, the trained AI model classified four major categories: Normal Rhythm, Bradycardia, Tachycardia, and Arrhythmia (PVC/abnormal rhythm). The confusion matrix obtained from testing demonstrates excellent performance, where all 200 test samples were correctly classified. Each class contained 50 samples, and no misclassification was observed between categories. This indicates strong separability of the learned ECG features and stable model generalization under the tested dataset.

The classification report further validates the effectiveness of the model. Precision, recall, and F1-score for all four classes were equal to 1.00, while the overall accuracy reached 100% across 200 samples. These metrics confirm that the model accurately identifies both normal and abnormal rhythm patterns without false positives or false negatives in the evaluation set.

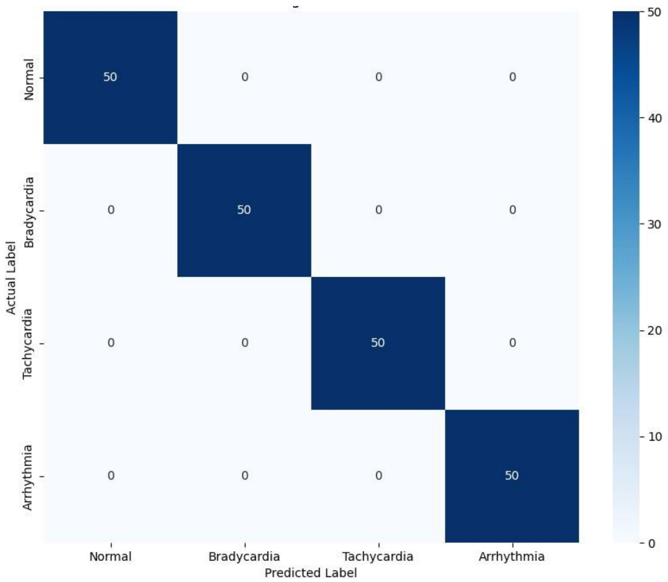

Figure 3 : Confusion Matrix

In **Demo Mode**, the dashboard successfully simulated different ECG conditions. Normal rhythm displayed regular RR intervals, bradycardia showed slower heart rate patterns, tachycardia produced rapid repeated complexes, and arrhythmia demonstrated irregular waveform morphology. The system dynamically updated the diagnosis panel and status indicators according to the selected condition.

In **Live Mode**, real-time ECG signals captured from the AD8232 sensor were transmitted through the ESP32 serial interface with low latency. The waveform was continuously plotted on the dashboard, and heart rate estimation remained stable under normal signal acquisition conditions. Hardware connection indicators, COMport communication, and live monitoring status were also verified successfully.

The Explainable AI module generated Grad-CAM based attention maps highlighting ECG waveform regions that most influenced the AI decision. For arrhythmic conditions, attention regions were concentrated around abnormal peaks, widened QRS complexes, or irregular intervals. This improves interpretability and provides user confidence in automated diagnosis.

The FFT spectral analysis module further transformed ECG signals into frequency-domain representations. Distinct spectral differences were observed among classes. Tachycardia cases produced higher dominant frequencies, bradycardia showed lower frequency peaks, and arrhythmia cases demonstrated irregular energy dispersion. This confirms the usefulness of spectral analysis as an additional validation layer.

The hospital-grade dashboard interface operated effectively as an ICU-inspired monitoring console with modules for waveform display, diagnosis, XAI interpretation, spectral plots, hardware status, and report generation. Visual alerts were triggered automatically for abnormal rhythms, while normal rhythm states were shown with green safe indicators. Overall, the results demonstrate that **CardioSense AI** provides a reliable and low-cost intelligent ECG monitoring solution with excellent classification accuracy, explainability, and real-time usability. The system is highly suitable for

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hospital bedside monitoring, telemedicine, home healthcare, and preventive cardiac screening. Future work may include cloud integration, wearable ECG devices, multi-lead acquisition, and larger real-world clinical validation datasets.

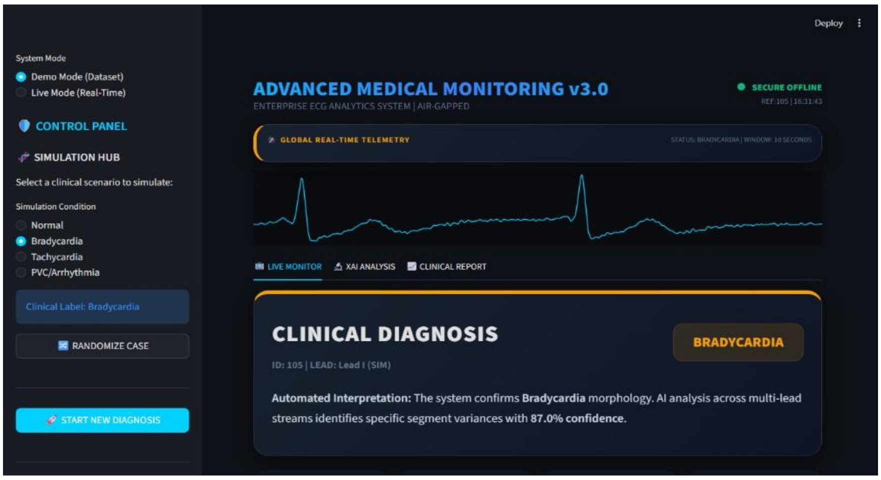

Figure 4 : Dashboard output showing bradycardia detection in demo mode

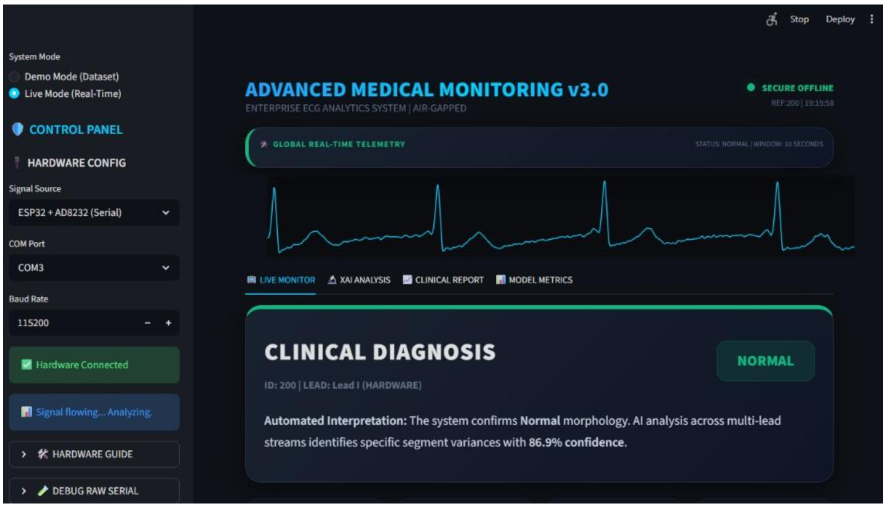

Figure 5 : Dashboard output showing normal detection in live mode

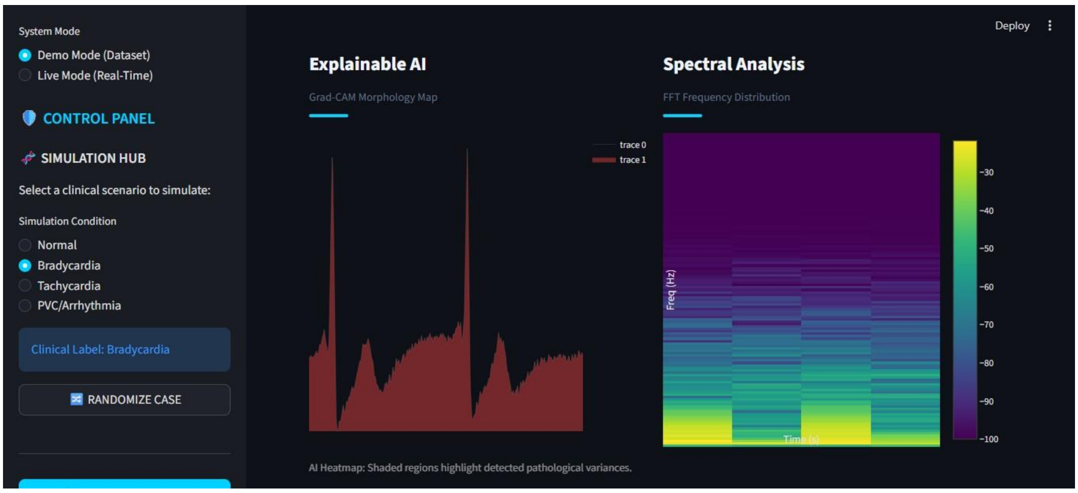

Figure 6 : Dashboard output showing Xai graph for bradycardia

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VI CONCLUSION

This work presented CardioSense AI, an intelligent real-time ECG monitoring and classification system designed for early cardiac abnormality detection using deep learning and embedded hardware integration. The proposed system combines the AD8232 ECG sensor, ESP32 microcontroller, and a trained AI model to continuously acquire and analyze ECG signals through both live monitoring and dataset-based simulation modes. Unlike conventional monitoring systems that only display raw waveforms, the developed platform provides automated rhythm interpretation by directly classifying signals into Normal Rhythm, Bradycardia, Tachycardia, and Arrhythmia categories. The system also integrates advanced features such as Explainable AI (Grad-CAM visualization), FFTbased spectral analysis, real-time BPM estimation, ICU-style alert mechanisms, and downloadable clinical report generation through a hospital-grade dashboard interface. Experimental evaluation demonstrated excellent model performance, achieving 100% classification accuracy on the tested dataset with high precision, recall, and F1score across all classes.

The developed framework offers a low-cost, portable, and user-friendly solution for smart cardiac surveillance in hospitals, rural clinics, home monitoring, and telemedicine applications. By combining accurate diagnosis with transparent AI explanations and real-time visualization, CardioSense AI can support faster clinical decisionmaking and preventive healthcare management.

VII FUTURE SCOPE

The proposed CardioSense AI system demonstrates strong potential for expansion into advanced healthcare applications. Several future improvements can further enhance the system's clinical usefulness, scalability, and intelligence.

The first major scope is the integration of cloud-based remote monitoring, where ECG data and diagnosis reports can be securely transmitted to hospitals or doctors in real time. This would enable continuous supervision of patients from home and support telemedicine services.

The system can also be upgraded into a wearable portable device by replacing wired electrodes with compact wireless sensors and battery-powered embedded hardware. Such a design would allow continuous ambulatory monitoring during daily activities.

Another important future enhancement is multi-lead ECG acquisition. Currently, the prototype focuses on singlelead monitoring, but integrating 3-lead or 12-lead ECG systems would improve diagnostic capability for complex cardiac conditions such as myocardial infarction, ischemia, and conduction disorders.

The AI engine can be further improved using advanced deep learning architectures such as LSTM networks, Transformers, or hybrid CNN-attention models for higher robustness and early-stage anomaly detection. Training with larger real-world hospital datasets would also improve generalization performance.

Future versions may include personalized health analytics, where the system learns a patient's baseline rhythm and detects subtle deviations over time. This would be valuable for preventive cardiology and chronic disease management.

The Explainable AI module can be expanded with SHAP, LIME, and saliency mapping techniques to provide richer interpretation for clinicians and increase trust in automated diagnosis.

Additional features such as voice alerts, emergency SMS notifications, ambulance alerts, medicine reminders, and doctor appointment scheduling can transform the platform into a complete smart healthcare assistant.

Integration with mobile applications and IoT ecosystems would allow patients to access reports, alerts, and health trends directly from smartphones.

Overall, CardioSense AI has significant future scope as a next-generation intelligent cardiac monitoring platform suitable for hospitals, home healthcare, rural medical centers, and smart city healthcare infrastructure.

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