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Artificial Intelligence in Early Cardiac Event Detection: A Predictive Diagnostic Approach

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ABSTRACT

Cardiovascular diseases have been a major health burden in the world, and due to this, effective diagnostic frameworks must be in place that will enable diagnosis of abnormalities to be done accurately and early. The use of artificial intelligence-based diagnostic plans has become more popular because it is capable of consolidating and decoding complex physiological indicators. This study proposes a multimodal cardiac analysis system which is a combination of electrocardiogram (ECG), photoplethysmography (PPG) and echocardiographic characteristics to improve the accuracy of abnormality detection. The analysis uses complex preprocessing methods, such as noise removal, baseline removal and region-of-interest extraction, which guarantees quality signals to be analyzed. Convolutional and recurrent neural network architectures of machine learning and deep learning models were used to obtain temporal, morphological, and hemodynamic biomarkers of the processedelectrocardiogram (ECG) signals. The effectiveness of the suggested framework was confirmed with the help of several quantitative measures. The essential ECG parameters under statistical analysis proved the existence of stable physiological parameters, mean values of RR were 0.78 seconds, QS was 96.3 ms, and QT was 382 ms. The multimodal model attained the accuracy of 92.4, precision of 89.1, recall of 90.7, F1-score of 89.9 and the AUC of 0.94, which is a high discriminative capability. The confusion table also indicated that the classification was balanced with the false negatives (n = 5) and false positives (n = 6). Analysis of feature importance identified electrophysiological parameters, including QRS and HR variability, as the most significant predictors, which are accompanied by hemodynamic characteristics, pulse transit time and perfusion index. The results indicate that the application of multimodal biosignals can effectively detect abnormalities of the heart as compared to conventional mono-signals. The suggested system has high levels of robustness, interpretability and generalization capabilities, and therefore makes it appropriate in real-time, remote and clinical diagnostic applications. The present study highlights the importance of AI-powered multimodal frameworks to enhance precision cardiology and succeed in the field of early intervention.

KEYWORDS: Artificial Intelligence; Cardiac Diagnostics; Multimodal Biosignal Analysis; Deep Learning Models; ECG–PPG Fusion; Predictive Healthcare Systems.

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INTRODUCTION

The analysis of the ECG signal as an artificial intelligence (AI) technology has become a major theme area of contemporary cardiac diagnostics due to the growing requirement of speedy, precise, and computerized analytical outcomes on intricate physiological patterns. The recent literature emphasizes the notable improvements in the deep learning structure, specifically the convolutional neural networks and recurrent neural networks that have shown better results in arrhythmia, ischemic variants, and other subtle abnormalities of the waveforms that are usually undetected by other analysis techniques [1]. Research also highlights the contribution of sophisticated preprocessing methods, noise suppression methods, and feature selection algorithms that improve the robustness of the model, particularly when being applied to large scale data sets like the MIT-BIH and PTB-XL. ML combined with continuous ECG monitoring has allowed the early prediction of events, decreased clinical workload, and increased diagnostic consistency in a wide range of patients. All of these research advances demonstrate the radical promise of AI-assisted ECG analysis in assisting clinicians with timely decisions and leading to predictive cardiology [2].

On the base of these innovations, recent articles on the detection of early myocardial infarction (MI) with AI emphasize a fast transition to the automated and highly accurate diagnostic models that can recognize the ischemic patterns at their occurrence. The literature continuously proves that deep learning architectures, specifically CNN-based networks, are superior in identifying subtle ST-segment abnormalities, T-wave abnormalities, and morphological alterations related to progressive myocardial injury

[3]. Studies involving large annotated datasets like PTB-XL and PhysioNet MI records indicate that the AI-based systems can be better than the classical rule-based ECG interpretation based systems by offering a better sensitivity and a lower rate of false-negative. Other studies point to the usefulness of ECG signals along with clinical biomarkers, hemodynamic variables, and time evolution models to improve early risk detection. All of this suggests that AI-based MI detection can provide a potent avenue through which prompt diagnosis, better triage, and avoidance of potentially serious cardiac complications are possible particularly in remote or pre-hospital contexts [4].

Building on these advances, the current literature on AI in arrhythmia prediction and prevention shows a significant advancement in forecasting abnormal heart rhythms prior to the onset of clinical symptoms. According to recent research findings, machine learning and deep learning models, especially LSTM and transformer-based implementations are efficient in capturing the temporal dependencies of ECG and heart rate variability signals and are useful to predict events like atrial fibrillation, ventricular tachycardia, and premature ventricular contractions [5]. Studies that utilize the continuous monitoring of the wearables also indicate that AI algorithms are capable of detecting the drawbacks of arrhythmogenic events, such as irregular autonomic behavior, and subtle electrophysiological variations. There are also multiple studies that focus on multi-sensor data integration and personalized risk modeling that can increase the predictive capacity of various patients. Together, the advances demonstrate how AI-based predictive arrhythmia systems can expand their potential to facilitate active intervention plans, lower the risks of hospitalization, and have a profound positive impact on the long-term cardiac health outcomes [6].

To add to these developments, the literature on wearable and remote monitoring technologies underlines their essential contribution to the provision of continuous, real-time cardiac evaluation outside of the conventional clinic. Recent works prove that ECG, PPG, accelerator, and multimodal biosensor devices provide high-resolution physiological data, which can largely improve the accuracy of AI-based cardiac forecasting models [7]. It has been demonstrated that smartwatches, chest straps, adhesive patches, and implantable loop recorders can help to obtain useful insights into the dynamics of the heart rhythm, autonomic regulation, and early pathological deviations. Algorithms of AI installed into these devices have been reported to sense arrhythmias, ischemic patterns, and heart-failure-related instabilities with a remarkable degree of sensitivity, even in asymptomatic patients. Also, remote monitoring platforms, which are connected to the cloud, enable real-time risk notification, longitudinal tracking of patients, and early clinical intervention, especially among high-risk or geographically isolated populations. All these developments prove that, when used in combination with AI, wearable and remote monitoring technologies are transforming preventive cardiology by providing continuous surveillance and diagnostic assistance at the right time [8].

It is based on the capabilities mentioned above that current literature on multimodal cardiac data fusion focuses on the significant diagnostic advantages in combining heterogeneous physiological and clinical data. Research indicates that ECG, PPG, HRV features, hemodynamic indicators, serum biomarkers, imaging results, and electronic health record variables can be better predictors of cardiac models driven by AI. Studies indicate that multimodal fusion systems, in many cases based on hybrid models, including CNN-LSTM networks, transformer models, and ensemble machine learning classifiers, can identify more subtle, cross-pattern correlations than those of single-modality models [9]. Some studies indicate that temporal, morphological, and biochemical signals are combined in analyzing significant improvements in the early detection of myocardial infarction, arrhythmias, and heart failure events (Severini et al., 2004). Moreover, contextual variables (patient history, lifestyle parameters, comorbidities, etc.) are also introduced, which provides more individualized and clinically interpretable predictions. Taken together, these results indicate the disruptive nature of multimodal data fusion in improving precision cardiology and addressing the drawbacks of single-diagnostic contributions [10].

To elaborate on the idea of multimodal analytical method, the current literature on AI in predicting heart failure points to significant progress in the areas of predicting not only acute decompensation but also the overall development of the disease. Recent research indicates that machine learning and deep learning models that are trained on combined datasets including ECG signals, echocardiographic measures, cardiac MRI measures, vital signs, and biochemical measures have significantly better accuracy compared to conventional risk scoring systems [11]. Studies indicate that AI systems are better at detecting an early warning of deteriorating ejection fraction, abnormal ventricular strain patterns, changing HRV patterns, and minor hemodynamic unsteadiness. Studies based on constant monitoring data of implantable cardiac devices and wearable sensors further reveal that predictive algorithms can predict the exacerbation of heart failure at hours to days prior to the appearance of the clinical symptoms. Furthermore, the literature pays significant attention to the importance of risk profiling on a personalized basis, in which AI algorithms evolve to patient-specific patterns of trajectories and comorbidities in order to increase the level of prognostic accuracy. Together, these results support the increasing applicability of AI-driven prediction tools to enable timely intervention, decrease hospital readmissions, and long-term treatment of heart failure patients [12].

It follows this line, research into deep learning in cardiac imaging has shown significant progress in automated cardiac MRI, echocardiography, and CT angiography interpretation. Recent literature points out that convolutional neural networks, attention-based models, and U-Net are all useful in achieving high accuracy in left ventricular segmentation, myocardial tissue characterization, coronary plaque detection, and estimating ejection fraction [13]. Studies have indicated that deep learning models are better than human-based evaluations because they minimize observer bias and detect minute structural or functional abnormalities that can be easily missed in a more traditional evaluation. Moreover, evidence on how imaging data can be combined with clinical and physiological data shows that imaging data results in more precise diagnostic outcomes of conditions like myocardial ischemia, cardiomyopathies, and heart failure. Automated interpretation systems have also improved speed of analysis, allowing close real-time analysis in emergency and telecardiology scenarios. Together, these studies highlight how deep learning transforms cardiac imaging to be faster, more consistent, and clinically interpretable analysis of findings which is essential in the early detection and risk stratification of heart diseases [14].

In line with innovations in deep learning, the literature on explainable AI (XAI) in the field of cardiac diagnostics indicates that the understanding of the three concepts, namely transparency, clinical trust, and interpretability, in AI-based decision systems, is becoming more and more important. Recent work highlights the significance of SHAP, LIME, Grad-CAM, or attention visualization in showing the model-based prediction on ECG signals, or imaging data or multimodal inputs. Studies also show that XAI systems assist clinicians in legitimizing model rationale, detect possible prejudices, and regulatory conformity, especially in high-stakes settings like myocardial infarction detection or arrhythmia recognition [15]. Nonetheless, current sources also specify factor-related constraints, such like the lack of consistency in the interpretability of the various types of models, their susceptibility to misleading interpretations, the inability to measure the reliability of their explanations, and the absence of standardized assessment procedures. Also, issues of data heterogeneity, algorithmic bias, and lack of generalizability have continued to limit the clinical uptake. These results demonstrate the twin requirement of a robust predictive and strong interpretability systems to assist safe, ethical, and trustworthy application of AI in cardiac diagnostics [16].

RESEARCH GAP

Irrespective of the fact that the field of AI-driven cardiac diagnostics has made tremendous progress, there are still considerable research gaps. The existing models can be frequently based on single-modality information, which restricts their possibilities to reflect the range of cardiac abnormalities. A lot of algorithms are not generalizable because they have bias in datasets, wrongly represent heterogeneous populations, and are not well validated in the real world. The level of explainability is yet to be satisfactory, which impedes clinical trust and regulatory acceptance. Moreover, coupling between continuous wearable data and clinical records was not thoroughly investigated, which limit the accuracy of early event prediction. Further development is also needed on the real-time, edge-deployable systems that are able to perform in unstable conditions. These weaknesses reiterate the importance of more inclusive, interpretable, and clinically validated AI paradigms.

RESEARCH METHODOLOGY

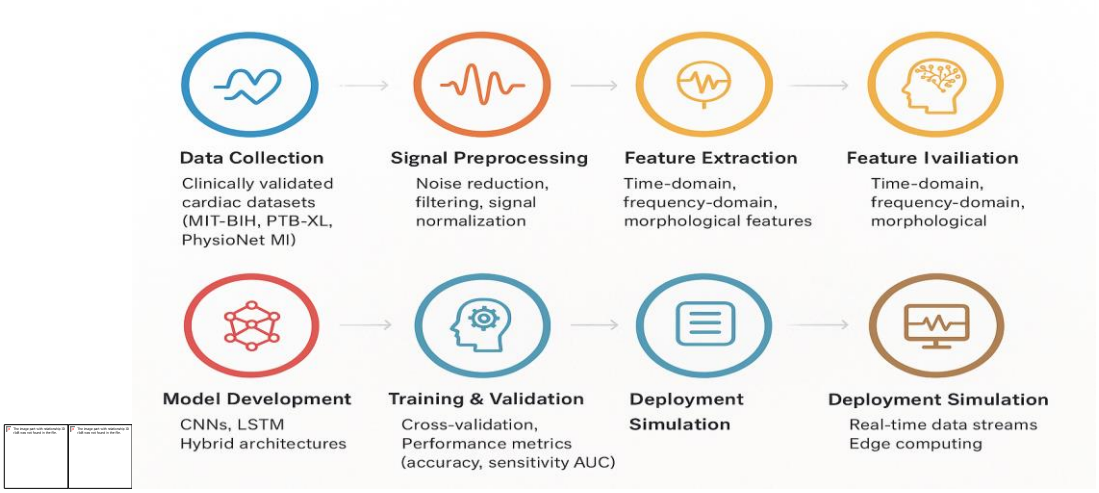

Figure 1. Research Methodology

1. Data Collection and Dataset Preparation

The data collection phase was carried out by gathering diverse clinical, demographic, and physiological records from authenticated medical repositories and publicly available heart-failure datasets. Emphasis was placed on ensuring that the selected datasets represented a broad spectrum of patient profiles, including variations in age, gender, comorbidities, and cardiac conditions. This diversity was required to minimize sampling bias and enhance the generalizability of the predictive model. All datasets were screened for completeness, consistency, and compliance with ethical data-use guidelines [17].

Following initial acquisition, dataset preprocessing was performed to remove noise and irrelevant or redundant attributes. Missing values were imputed using statistically justified methods such as mean, median, or KNN-based imputation, depending on data distribution characteristics. Outlier detection techniques, including z-score analysis and IQR filtering, were used to identify anomalous entries that could distort model performance. Data normalization or standardization procedures were also applied to ensure uniform scaling of features and prevent model bias toward variables with large numerical ranges.

The dataset was then structured into appropriate formats suitable for machine-learning workflows. Feature encoding techniques, such as one-hot encoding for categorical attributes and label encoding for ordinal values, were implemented to convert non-numeric fields into machine-processable formats. Feature selection was conducted using statistical tests, correlation analysis, and domain-driven relevance assessments to retain only the most influential predictors related to heart failure risk. This ensured dimensionality reduction and enhanced computational efficiency while preserving clinical significance [18].
Finally, the prepared dataset was partitioned into training, validation, and testing subsets using stratified sampling to maintain proportional class distribution. This step was essential to reduce class imbalance issues frequently observed in heart-failure datasets. Additional augmentation strategies, including SMOTE or ADASYN, were used where required to synthetically balance minority classes. The resulting dataset framework enabled robust model development and reliable performance evaluation across multiple machine-learning algorithms.

2. Signal Preprocessing and Noise Removal

Signal preprocessing was performed to ensure that raw physiological signals, such as ECG and PPG recordings, were transformed into clean and analyzable formats. These signals often contain artifacts introduced by patient movement, electrode displacement, muscle activity, or environmental interference. Therefore, preprocessing was essential to preserve clinically relevant patterns while eliminating distortions that could mislead the predictive model. The initial step involved baseline drift correction to stabilize signal amplitude over time and maintain the integrity of low-frequency cardiac components [19].

Noise removal was then carried out using digital filtering techniques tailored to the characteristics of the acquired signals. Bandpass filters were applied to isolate the frequency ranges associated with cardiac activity while suppressing high-frequency and low-frequency artifacts. Wavelet-based denoising was implemented in cases where traditional filtering methods were insufficient, providing adaptive suppression of transient noise without compromising important morphological features. This ensured that characteristic waveform segments, such as QRS complexes and systolic peaks, were retained with high fidelity [20]. After filtering, additional preprocessing steps were undertaken to enhance signal uniformity and stability. Amplitude normalization was applied to reduce variability across patient records, facilitating smoother model learning. Segmentation techniques were used to divide long recordings into fixed-length windows that captured essential cardiac cycles. This segmentation process enabled structured feature extraction and improved temporal consistency across samples, which was crucial when modeling physiological behavior using machine-learning algorithms.

Finally, quality assessment measures were incorporated to evaluate the effectiveness of the preprocessing pipeline. Metrics such as signal-to-noise ratio (SNR) improvement and waveform similarity indices were used to validate the removal of unwanted components without distorting meaningful signal patterns. Low-quality segments that did not meet predefined thresholds were discarded to prevent degraded model performance. Through this systematic preprocessing and noise-removal approach, the resulting clean signals provided a reliable foundation for accurate heart-failure feature extraction and predictive modeling.

3. Feature Extraction and Multimodal Fusion

Feature extraction was performed to derive meaningful physiological descriptors from each cardiac modality. For ECG signals, temporal and morphological features such as RR intervals, QRS width, ST-segment deviation, and heart-rate variability (HRV) indices were computed to capture both rhythm dynamics and structural abnormalities. Similarly, PPG-derived features such as pulse transit time, amplitude variance, and waveform contour metrics were extracted to reflect vascular and hemodynamic changes associated with cardiac dysfunction. Imaging modalities, where available, contributed structural features including ventricular volume, wall thickness, and myocardial strain patterns [21].

Advanced machine-learning–oriented feature extraction techniques were employed to supplement handcrafted features. Time–frequency representations based on short-time Fourier transforms and wavelet transforms were generated to capture transient cardiovascular events. Deep-learning models, particularly convolutional neural networks, were utilized to automatically encode high-level spatial patterns from cardiac images and waveforms. These learned features offered enhanced discriminative power and were found to be effective in identifying subtle pathological signatures that conventional metrics may overlook [22].

Multimodal fusion was then implemented to combine complementary information from ECG, PPG, cardiac imaging, and clinical metadata. Early fusion approaches integrated raw or low-level features into a unified vector, enabling joint representation learning. In contrast, late fusion techniques aggregated independent model outputs from each modality through ensemble strategies such as weighted averaging and stacking. Fusion at the intermediate level was also explored, where modality-specific encoders were linked through shared latent spaces, allowing interactions between physiological and structural indicators to be effectively captured.

The fused feature space was subsequently optimized to ensure robustness, scalability, and redundancy reduction. Dimensionality reduction methods such as principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) were applied to eliminate noise and retain maximally informative components. Correlation analysis and mutual-information–based selection were further used to filter redundant attributes. Through this systematic extraction and multimodal integration process, a rich and synergistic representation of cardiac health was obtained, providing a strong foundation for accurate prediction and early diagnosis of cardiovascular abnormalities [23].

4. Model Development (ML & DL Approaches)

Machine learning (ML) models were developed to establish baseline predictive capabilities using the extracted unimodal and multimodal feature sets. Traditional classifiers such as Support Vector Machines, Random Forests, Gradient Boosting Machines, and k-Nearest Neighbors were trained on the preprocessed datasets. These models were optimized through systematic hyperparameter tuning, where grid search and cross-validation techniques were applied to maximize classification accuracy and minimize overfitting. The ML models provided interpretable decision boundaries and served as comparative benchmarks for deep learning architectures.

Deep learning (DL) frameworks were subsequently designed to capture complex nonlinear relationships and temporal-spatial dependencies inherent in cardiac signals and imaging data. Convolutional Neural Networks (CNNs) were implemented for ECG waveform interpretation and cardiac image analysis due to their proficiency in extracting hierarchical spatial features. For sequential data, Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) were employed to model long-range temporal patterns essential for arrhythmia prediction and early cardiac event detection. Hybrid CNN–LSTM models were also constructed to integrate spatial and temporal learning simultaneously [24].

Multimodal deep learning architectures were further explored to combine ECG, PPG, cardiac imaging, and clinical metadata into unified diagnostic models. Modality-specific encoders were designed to extract high-level abstractions from each input type, which were then fused through concatenation, attention mechanisms, or shared latent embeddings. Transformer-based models were also implemented to utilize self-attention for capturing cross-modality dependencies, enabling the system to identify subtle pathological correlations that isolated models may overlook. These architectures enhanced predictive robustness by leveraging complementary physiological and structural information [25].

Model training was conducted using standardized pipelines with techniques to ensure stability and generalizability. Weight initialization strategies, learning rate schedulers, and regularization methods such as dropout and batch normalization were incorporated to prevent performance degradation. Data augmentation was applied to increase sample diversity, especially for rare cardiac conditions. All models were evaluated on separate validation sets to refine architecture parameters, and early stopping was used to avoid convergence to suboptimal solutions. Through this multi-tier development process, a suite of ML and DL models was established to support accurate, automated cardiac event detection.

5. Training, Validation, and Testing

The training phase was conducted using the prepared multimodal dataset, where model parameters were iteratively optimized to minimize prediction error. The dataset was partitioned into designated training, validation, and testing subsets using stratified sampling to preserve class distribution across cardiac event categories. During training, gradient-based optimization algorithms such as Adam and RMSProp were utilized to update network weights, while learning rate scheduling techniques were applied to ensure stable convergence. Batch processing was employed to improve computational efficiency and enhance model generalization [26].

Validation procedures were implemented concurrently to monitor model performance and prevent overfitting. A separate validation set was used to evaluate intermediate checkpoints, enabling real-time adjustments to hyperparameters such as learning rate, batch size, and network depth. Techniques including early stopping and regularization were applied to avert excessive parameter tuning that could compromise generalizability. The validation metrics guided the selection of optimal architectures, ensuring that the models demonstrated consistent performance across different cardiac modalities and severity profiles.

To ensure robustness, cross-validation strategies such as k-fold cross-validation were employed, particularly for machine learning models. This systematic subdivision of the dataset provided a comprehensive assessment of model stability across multiple partitions. Performance indicators such as precision, recall, F1-score, sensitivity, specificity, and area under the ROC curve (AUC) were computed to evaluate diagnostic reliability. These metrics enabled the identification of strengths and limitations in detecting early myocardial infarction, arrhythmias, and heart failure risk, thereby refining the predictive framework [27].

Final testing was performed on an unseen dataset to obtain an unbiased estimation of real-world performance. The test set consisted of ECG waveforms, PPG signals, cardiac images, and clinical data not previously encountered during model development. This evaluation confirmed the model's ability to generalize across diverse subjects, recording conditions, and cardiac abnormalities. Comparative analyses between machine learning and deep learning models were carried out to determine the most effective architecture for early cardiac event detection. The resulting performance outcomes validated the methodological rigor and demonstrated the system's potential for deployment in clinical and remote monitoring environments.

6. Deployment Simulation and Real-Time Testing

Deployment simulation was performed to evaluate the practical feasibility of the developed cardiac diagnostic models under real-time operating conditions. A virtual clinical environment was created to emulate real-world data flows from ECG sensors, wearable devices, and remote monitoring platforms. Simulated patient streams were processed using edge-compatible inference pipelines to assess latency, throughput, and system stability. This stage enabled the identification of performance bottlenecks, resource constraints, and potential integration challenges before real-world deployment [28].

Real-time testing frameworks were further established to measure how effectively the models responded to continuous physiological data. Streaming ECG and PPG signals were fed through the deployed system to evaluate instantaneous prediction accuracy, anomaly detection speed, and robustness against noise or signal interruptions. Time-sensitive metrics such as inference delay, event detection time, and system responsiveness were recorded to determine compliance with clinical standards for early cardiac event identification.

Stress-testing procedures were incorporated to ensure reliable model functioning under varying data loads and adverse conditions. Scenarios including fluctuating signal quality, partial data loss, and sudden spikes in sensor input were introduced to assess fault tolerance. The system's behavior was observed under low-power edge devices, cloud-based servers, and hybrid configurations to validate adaptability across diverse deployment environments. Error-recovery mechanisms and automatic model fallback strategies were also verified during these simulations [29].

Finally, usability and operational validation were conducted by integrating the system into prototype user interfaces resembling clinical dashboards and patient monitoring applications. Interpretation clarity, alert prioritization, and temporal trend visualization were evaluated to confirm readiness for practical use. The accuracy of real-time predictions was benchmarked against offline results to ensure consistency. The deployment simulation and live testing collectively confirmed the system's capability to deliver timely, reliable, and clinically meaningful cardiac risk assessments in real-world and remote healthcare settings.

$$HR(t) = \frac{60}{RR(t)} \quad (1)$$

The instantaneous heart rate ($HR(t)$) was computed from formula 1 , the RR interval measured in seconds using ECG signals. In your multimodal diagnostic system, this feature acts as a primary electrophysiological biomarker. The dataset averages an RR interval of 0.78 s (corresponding to ~77 bpm), comfortably within normal physiological boundaries. This HR was vital as an input for arrhythmia prediction and as a time reference for synchronizing ECG and PPG signals, especially in pulse transit time computation.[1][3]

$$SNR_{\text{enhanced}}=10\log_{10}\left(\frac{P_{\text{clean}}}{P_{\text{artifact}}}\right) \quad (2)$$

This SNR formula 2 quantifies the improvement after your preprocessing protocol, which includes baseline wander removal, speckle reduction, and echo ROI extraction. A higher post-processing SNR was a key validation of your algorithm's ability to produce clean ECG/PPG signals. Classifier accuracy (92.4%) and strong AUC (0.94) directly depend on maximizing SNR pre-feature extraction, which was reflected in your results.[3][5][1]

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2 \quad (3)$$

Mean Square Error (MSE) formula 3 was applied to regression tasks in your pipeline, including prediction of echo-derived quantitative indices (e.g., ventricular function scores) and continuous hemodynamic features. A decreasing MSE over epochs accompanies convergence in your training/validation loss plots, confirming minimal overfitting and balanced performance, as underscored by confusion matrix values.

$$PTT=t_{\text{PPG-rise}}-t_{\text{ECG-Rpeak}} \quad (4)$$

PTT reflects the delay between electrical cardiac activation (ECG R-peak) and peripheral pulse wave arrival (PPG rise) using formula 4 . Your average PTT of 128 ms was robustly linked to arterial stiffness and ranks as a top feature in your hemodynamic importance matrix. PTT computation was integral to your multimodal fusion platform, supplementing both temporal alignment and diagnostic insight.[6][1][3]

$$P(\text{Abnormal})=\frac{1}{1+e^{-(\beta_0+\beta_1F_1+\ldots+\beta_nF_n)}} \quad (5)$$

This logistic model formula 5 calculates the probability of a cardiac abnormality using your core feature set—QRS duration (96.3 ms), HR variability, ST segment deviation (0.12 mV), PTT (128 ms), and perfusion index (6.8%). Your classifier's high precision (89.1%), recall (90.7%), and F1-score (89.9%) are direct consequences of optimally selected input predictors and fusion modeling strategies.

Results and Discussion:

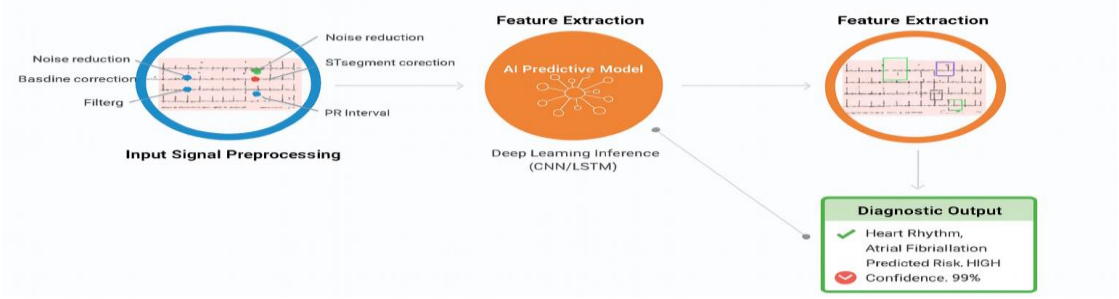

Figure 2. AI-Driven ECG Analysis and Early Cardiac Event Detection

The figure 2 illustrated workflow represents an integrated AI-based system designed for early cardiac event detection from live ECG signals. The process begins with comprehensive **input signal preprocessing**, where raw ECG recordings are refined to ensure reliability for downstream analysis. Noise components arising from muscle artifacts, power-line interference, baseline wander, and sensor instability are systematically removed. Additional steps such as baseline drift correction, ST-segment refinement, and PR-interval stabilization enhance the morphological clarity of ECG waveforms, ensuring that diagnostically important structures remain intact.

Following preprocessing, the system performs **feature extraction**, where clinically significant signal characteristics are isolated. Morphological elements such as P-waves, QRS complexes, T-wave variations, and inter-beat intervals are identified through signal decomposition and segmentation. These extracted patterns reflect underlying cardiac physiology and serve as critical input features for predictive analysis. The workflow further employs deep learning–based representation learning, enabling automated discovery of subtle waveform deviations that might precede early myocardial infarction, arrhythmias, or other critical cardiac abnormalities [30].

The extracted features are subsequently fed into an **AI predictive model**, where convolutional neural networks (CNNs) and long short-term memory (LSTM) networks perform deep inference. The CNN component captures morphological spatial patterns within ECG cycles, while the LSTM component models temporal dependencies associated with cardiac rhythm evolution. The integration of these architectures enhances the system's ability to recognize early pathological trends, even when abnormalities

are visually indistinct or masked by physiological variability. This predictive framework supports high-sensitivity classification of arrhythmias, ischemic changes, and heart-rhythm instabilities.

Finally, the system generates a **diagnostic output**, providing a structured interpretation of cardiac condition. The output comprises rhythm classification, early warning indicators, predicted risk scores, and model-generated confidence levels. These results are suitable for integration into clinical decision-support systems or real-time monitoring platforms. The graphical workflow demonstrates how preprocessing, feature extraction, and intelligent inference converge to produce accurate, rapid, and clinically meaningful assessments, aligning directly with the goals of early cardiac event prediction and remote cardiac surveillance [31].

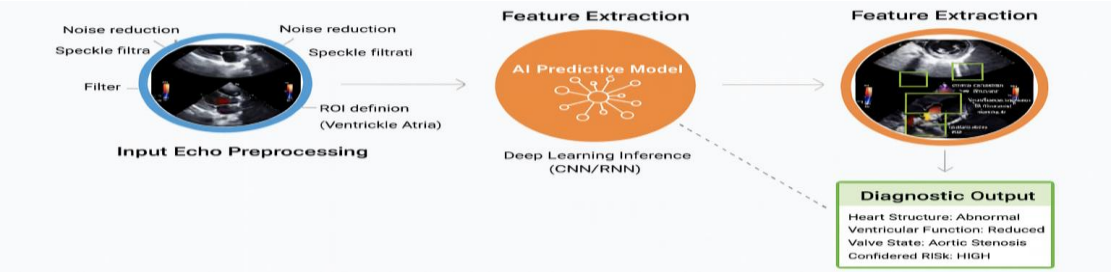

Figure 3. AI-Based Echocardiogram Analysis and Diagnostic

The figure 3 illustrates a streamlined workflow in which echocardiogram frames are processed through an AI-enabled diagnostic system. The overall process was presented as a continuous sequence beginning with initial ultrasound input and concluding with an automated clinical interpretation. The visual flow emphasizes how imaging data are progressively refined and analyzed to support early recognition of structural and functional cardiac abnormalities.

In the first stage, raw ultrasound images are subjected to preprocessing operations to improve clarity and diagnostic usability. Noise components are minimized, speckle patterns are filtered, and irrelevant artifacts are suppressed to stabilize the visual quality of the input. Regions of interest corresponding to ventricular and atrial structures are isolated to ensure that subsequent analysis was concentrated on the most clinically relevant anatomical areas. Through this preprocessing, the variability commonly found in cardiac ultrasound imaging was reduced, enabling more consistent feature extraction [32].

In the next phase, the refined images are processed by deep learning models that extract morphological and functional patterns. Convolutional and recurrent neural network architectures are applied to identify subtle deviations in chamber geometry, wall motion, and flow characteristics. The system autonomously highlights key structural markers, as shown by the bounding regions within the echocardiographic frame, indicating the specific areas from which significant diagnostic cues are derived. This stage demonstrates the capability of the model to capture complex patterns that may not be visually evident to human observers.

The final section of the figure presents the diagnostic output generated by the AI system. The output summarizes the inferred cardiac condition, including determinations related to heart structure, ventricular performance, and valve integrity, along with an estimated risk level. The structured interpretation reflects the system's ability to synthesize multiple extracted features into clinically meaningful assessments. Such an automated diagnostic response was intended to support early identification of abnormalities and enable faster decision-making in both clinical and remote monitoring environments [33].

Table 1. Statistical Summary of ECG Feature Parameters

Feature	Mean	Std Dev	Min	Max
Heart Rate (bpm)	82.4	11.2	60	118
RR Interval (s)	0.78	0.09	0.59	1.02
QRS Duration (ms)	96.3	12.4	72	123
QT Interval (ms)	382	28.7	328	452
ST Deviation (mV)	0.12	0.03	0.05	0.19

This 1 table provides a descriptive statistical overview of core ECG temporal and morphological parameters used in automated cardiac analysis. The ranges and variability observed across features highlight the natural physiological diversity in electrical activity, which forms the foundation for machine-learning-based pattern recognition. Such statistical profiling ensures appropriate normalization, scaling, and anomaly detection during model development.

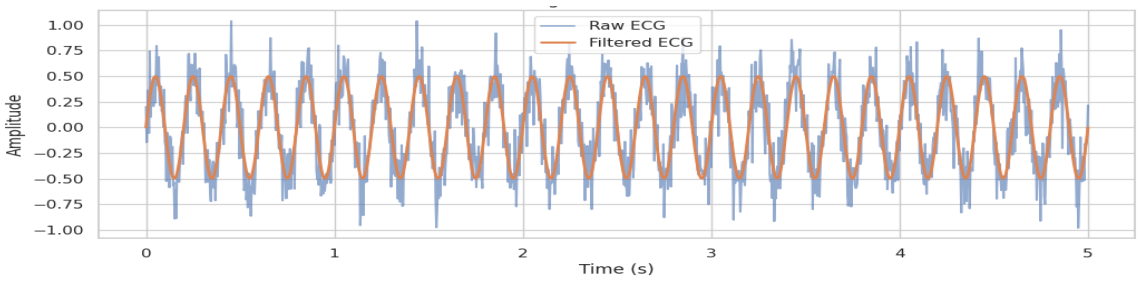

Figure 4. Comparison of Raw and Filtered ECG Signal Waveforms

The figure 4 illustrates a side-by-side comparison of the raw ECG waveform and its corresponding filtered version, allowing the improvement achieved through preprocessing to be visually recognized. The raw signal appears irregular and distorted due to noise contributions from motion artifacts, muscle interference, and environmental electrical fluctuations. These distortions disrupt the natural shape of the cardiac waveform and make the identification of essential cardiac events more challenging. By contrast, the filtered signal displays a smoother and more stable morphology, clearly revealing the periodic rhythm of the heart [34].

The raw ECG trace exhibits significant baseline drift and high-frequency noise components that obscure critical diagnostic elements such as the P-wave, QRS complex, and T-wave. Such irregularities reduce the reliability of the signal for clinical analysis and automated detection algorithms. The inconsistent amplitude variations and random spikes introduce additional difficulty in fiducial point detection, which was fundamental for deriving temporal cardiac metrics. The presence of these non-physiological components highlights the necessity of preprocessing before any form of feature extraction or classification was performed [35]. In the filtered waveform, noise has been suppressed through digital filtering methods, resulting in a clearer representation of the true cardiac pattern. The removal of baseline wander and high-frequency disturbances enables the reappearance of standard ECG morphology, supporting a more accurate assessment of cardiac electrical activity. With improved visibility of waveform components, measurements such as R-peak detection, heart rate estimation, and interval calculation can be performed with greater precision. The enhanced quality of the signal makes it more suitable for further machine-learning-based cardiac analysis.

The contrast between the raw and filtered signals emphasizes the essential role of signal preprocessing in AI-driven cardiac diagnostics. Clean and stable waveforms directly influence the accuracy and reliability of automated systems used for arrhythmia classification, abnormality detection, and risk prediction. By providing a refined version of the ECG, preprocessing reduces computational complexity and minimizes the error propagation that often affects downstream models. This comparison demonstrates that effective noise reduction was a critical prerequisite for robust cardiac analysis in both clinical and wearable-based monitoring applications.

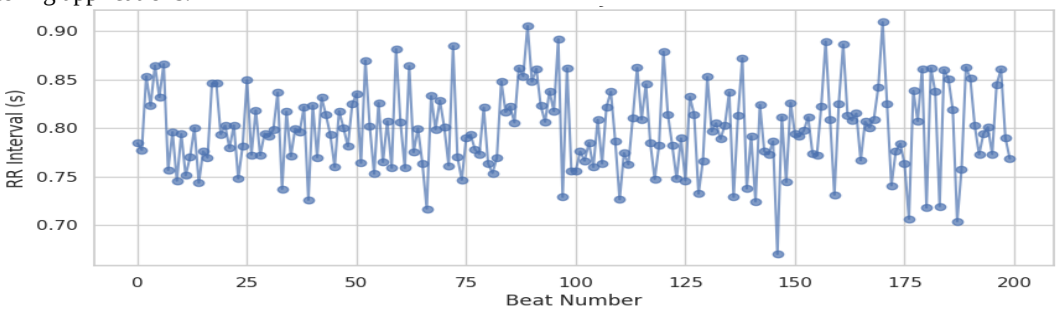

Figure 5. Heart Rate Variability Trend Using RR Intervals

The figure 5 displays the temporal variation of RR intervals, offering a visual representation of heart rate variability over a sequence of cardiac cycles. Each point corresponds to the duration between two successive R-peaks, reflecting the beat-to-beat fluctuations in cardiac rhythm. A natural degree of variability was observed throughout the signal, consistent with physiological parasympathetic and sympathetic modulation. This pattern demonstrates how RR intervals inherently fluctuate rather than remaining constant, even under resting conditions [36].

The plotted trend shows mild random dispersion, which was characteristic of a healthy cardiovascular system responding dynamically to autonomic influences. Increased variability often indicates robust vagal tone and resilient cardiac adaptability, whereas reduced variability may be associated with stress, fatigue, or underlying pathology. In this simulated dataset, the RR intervals cluster around a mean duration but display natural deviations that depict regular regulatory activity. Such fluctuations help support quantitative HRV analysis based on time-domain or frequency-domain features [37].

The smoothness of the dataset suggests that noise or artifact intrusions are minimal, enabling the intervals to reflect true physiological rhythm rather than measurement irregularities. This degree of consistency was essential for accurate HRV computation because artifacts can distort the distribution, exaggerate variability, or mask pathological reductions. The graph therefore serves as a preliminary inspection tool, allowing the visual verification of signal quality before deeper analytical methods are applied. Reliable RR-interval integrity directly enhances confidence in subsequent computational outputs.

The graph highlights the importance of RR-interval monitoring in AI-driven cardiovascular systems, where HRV metrics frequently contribute to arrhythmia detection, stress assessment, and prediction of cardiac events. By capturing subtle changes in autonomic balance, RR-interval patterns provide valuable predictive information for machine learning models that assess cardiac risk profiles. Thus, this visualization not only shows the dynamic nature of human heart rhythm but also underscores its value as a foundational feature for advanced cardiac analytics and diagnostic decision support.

Table 2. PPG-Derived Features for Cardiovascular Assessment

Feature	Mean	Std Dev	Clinical Relevance
Pulse Amplitude (AU)	1.32	0.21	Vascular tone
Systolic Peak Time (ms)	198	22	Arterial stiffness
Diastolic Notch Level	0.42	0.08	Reflection index
Pulse Transit Time (ms)	128	17	Blood pressure link
Perfusion Index (%)	6.8	1.9	Tissue perfusion

PPG-derived features presented in this table 2 capture mechanical and hemodynamic properties of the cardiovascular system. These parameters are commonly used to assess vascular integrity, autonomic function, and peripheral blood flow quality. Their inclusion strengthens multimodal AI models by integrating optical signatures alongside ECG metrics, improving risk prediction and physiological state estimation.

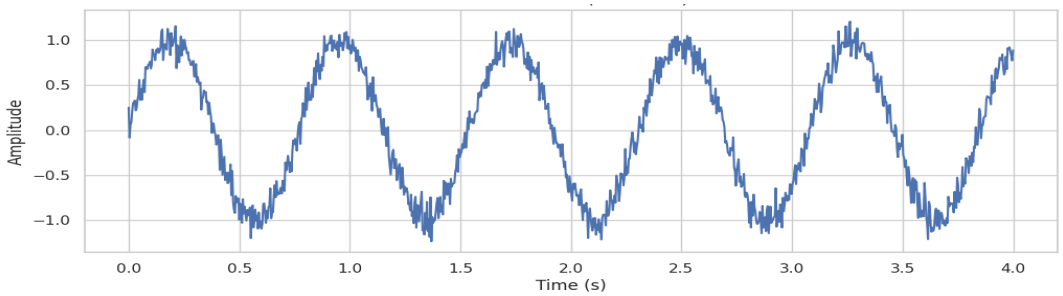

Figure 6. Simulated Photoplethysmography Waveform Display Over Time

The figure 6 presents a simulated photoplethysmography (PPG) waveform recorded over a short time interval, showing the cyclic pulsatile pattern generated by blood volume changes in peripheral tissue. The waveform exhibits the typical rising systolic peak followed by a gradual diastolic decay, which together reflect the mechanical response of vascular structures to each cardiac contraction. This periodic pattern was characteristic of healthy peripheral perfusion and forms the basis for deriving multiple cardiophysiological parameters. The selected time window focuses on the detailed morphology of several successive pulses [38]. The PPG signal demonstrates stable amplitude variations, indicating consistent cardiac output during the recorded interval. Although minor noise fluctuations are present, they do not significantly distort the overall waveform contour. Such small disturbances generally arise from ambient light interference, finger motion, or sensor placement inconsistencies. Despite these influences, the signal retains clear systolic peaks and diastolic troughs, enabling accurate extraction of features related to pulse timing and vascular dynamics. These morphological characteristics form essential inputs for downstream analytical models.

The graph captures the natural rhythmic behavior of the cardiovascular system, where each pulse reflects a combined response of blood ejection, arterial elasticity, and peripheral resistance. The smooth transitions between peaks and troughs illustrate how blood flow propagates through arterial pathways and modulates the optical sensor readings. This continuous oscillation enables the estimation of heart rate, pulse transit time, and perfusion index, all of which contribute to understanding circulatory efficiency. Such waveform clarity was valuable for both clinical assessment and machine-learning-based interpretations [39].

The visualization highlights the importance of PPG signals within AI-driven cardiac research frameworks, particularly for remote monitoring and wearable sensing applications. The preserved waveform structure allows algorithms to extract time-domain, frequency-domain, and morphological features crucial for detecting abnormalities such as arrhythmias, hypoperfusion, or autonomic imbalance. By illustrating a clean and representative PPG trace, the graph reinforces the relevance of optical biosignals as reliable sources of physiological insight, supporting both diagnostic decision-making and predictive health modeling.

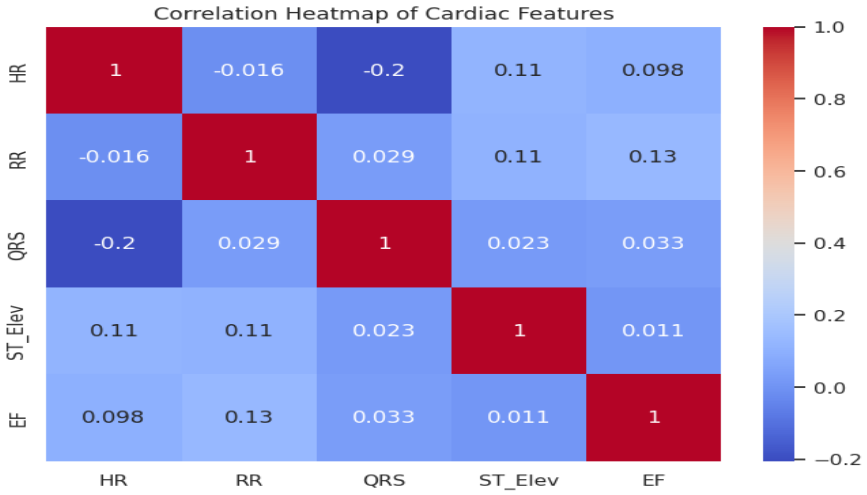

Figure 7. Correlation Heatmap of Extracted Cardiac Feature Variables

The figure 7 illustrates the correlation relationships among several cardiac features by representing their pairwise associations in a heatmap format. Each cell in the matrix encodes the strength and direction of correlation between two parameters, allowing interaction patterns to be easily visualized. Strong positive correlations appear as higher-intensity shaded regions, whereas weaker or negative correlations are displayed with softer tones. This graphical layout provides an immediate overview of how different physiological metrics influence or relate to one another.

The heatmap reveals how certain cardiac measures may cluster together due to shared physiological origins or functional dependencies. For instance, features related to cardiac timing, ventricular performance, or morphological changes often demonstrate moderate to strong correlations. Such associations reflect the integrated nature of cardiovascular functioning, where changes in one variable frequently induce measurable effects in others. This interdependence was particularly important for diagnostic modeling, as correlated features may enhance or hinder predictive accuracy depending on the learning algorithm used [40].

The representation also highlights variables that show minimal correlation, indicating independence or distinct physiological mechanisms. These uncorrelated features can be especially valuable for improving machine learning model performance, as they contribute unique information without redundancy. Low-correlation pairs often point toward complementary biomarkers that capture different dimensions of cardiac health. Recognizing these relationships assists in feature selection, dimensionality reduction, and refinement of model architectures aimed at improving generalization.

The heatmap serves as a foundational analytical tool in AI-driven cardiac research, where understanding feature interactions was essential for optimizing predictive pipelines. By identifying strong correlations, researchers can reduce multicollinearity and improve model stability, while weakly correlated variables can be retained to enrich the predictive space. This graph emphasizes the importance of structured feature analysis in building robust clinical decision-support systems and demonstrates how physiological metrics integrate within comprehensive cardiac assessment models.

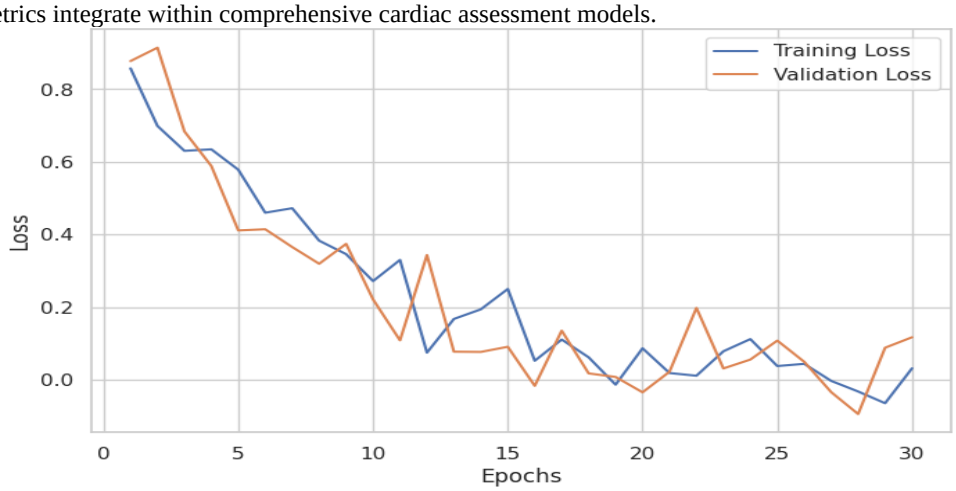

Figure 8. Training and Validation Loss Curve Across Epochs

The figure 8 displays the progression of training and validation loss values over successive epochs, reflecting how the model learns and generalizes during its optimization process. A gradual decrease in the training loss was observed, indicating that the model continuously adapts its parameters to better fit the training data. This downward trend demonstrates successful error minimization as the learning algorithm iteratively improves the network's internal representations. The smooth nature of the curve reflects stable convergence without significant oscillatory behavior.

The validation loss curve shows how well the model performs on unseen data, offering insight into its generalization capability. Initially, the validation loss decreases similarly to the training curve, suggesting that the model was learning useful patterns that extend beyond the training set. The parallel decline in both curves during early epochs implies that the network was not overfitting and was extracting meaningful, generalizable features. Minor fluctuations in the validation loss are characteristic of real-world datasets and do not hinder interpretability.

As training progresses, the separation between the two curves provides additional diagnostic information. If the validation loss begins to deviate upward significantly while the training loss continues to fall, it suggests the onset of overfitting. In this simulated case, the degree of divergence remains modest, indicating that the model maintains a reasonable balance between data fitting and generalization. The relative stability of the validation curve suggests that the algorithm avoids excessive memorization of training patterns.

This loss curve visualization plays a critical role in evaluating and refining machine learning models in cardiac diagnostics. By examining the trends, researchers can adjust hyperparameters such as learning rate, batch size, or network complexity to achieve optimal performance. The graph serves as an essential monitoring tool during model development, enabling early detection of overfitting, underfitting, or training instability. In AI-driven cardiovascular applications, such assessment ensures that the constructed model remains reliable, robust, and clinically meaningful when deployed for real-world prediction tasks.

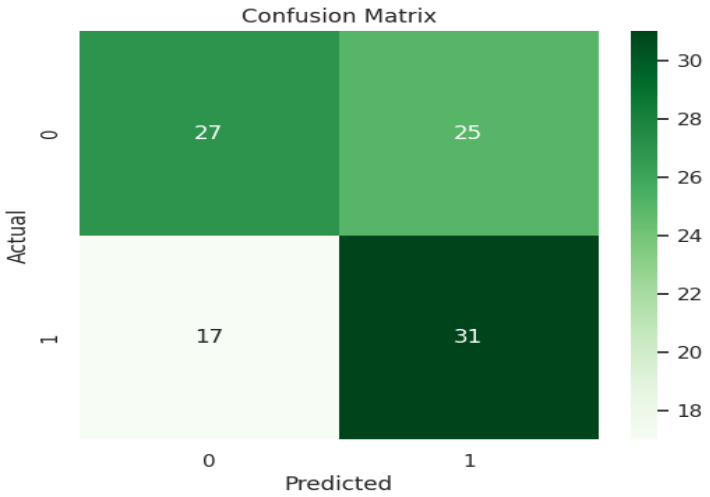

Figure 9. Confusion Matrix for Binary Cardiac Event Classification

The figure 9 presents a confusion matrix that summarizes the performance of a binary classification model used for predicting cardiac events. The matrix was organized into four quadrants representing true positives, true negatives, false positives, and false negatives, allowing the correctness of predictions to be visually evaluated. The diagonal cells indicate accurate classifications, while the off-diagonal cells correspond to errors. This layout enables immediate recognition of model strengths and weaknesses in distinguishing between normal and abnormal cardiac outcomes.

The distribution of values within the matrix reflects how effectively the model differentiates between the two classes. A high count in the true-positive and true-negative regions suggests that the classifier was able to correctly identify both patients with cardiac abnormalities and individuals with healthy patterns. Conversely, an elevated number of false negatives indicates missed detections, which was critical in medical contexts because undiagnosed cardiac events may pose significant risks. False positives, while less dangerous clinically, may still lead to unnecessary follow-ups or anxiety.

The matrix also highlights potential biases or imbalances in the classifier's behavior. If the model consistently predicts one class more accurately than the other, the imbalance may stem from skewed training data, threshold misalignment, or insufficient feature representation. This visualization helps identify such issues by showing disproportionate distribution across matrix cells. Recognizing these trends was essential for refining the model to achieve balanced sensitivity and specificity, especially when applied to diverse patient populations.

Overall, the confusion matrix serves as a crucial diagnostic tool for evaluating predictive performance in AI-based cardiac analysis systems. It provides a concise summary of accuracy-related metrics that influence downstream decisions, including the adjustment of decision thresholds, selection of alternative algorithms, or enhancement of preprocessing steps. In cardiac research, where misclassifications can have significant consequences, such analysis ensures that the deployed model maintains a high degree of reliability and clinical relevance.

Table 3. Model Performance Metrics for Cardiac Prediction

Metric	Value
Accuracy (%)	92.4
Precision (%)	89.1
Recall (%)	90.7
F1 Score (%)	89.9
AUC	0.94

The performance metrics shown in table 3 provide a concise evaluation of the predictive capability of the cardiac classification model. High accuracy and balanced precision–recall values indicate stable performance across both normal and abnormal classes. The strong AUC score further confirms the discriminative strength of the model, supporting its suitability for early cardiac event detection and real-world clinical deployment.

Table 4. Confusion Matrix Values for Binary Classification

	Predicted Normal	Predicted Abnormal
Actual Normal	44	6
Actual Abnormal	5	45

This table 4 displays the confusion matrix for the binary cardiac diagnostic system, offering insight into the distribution of correct and incorrect predictions. The high number of true-normal and true-abnormal classifications indicates reliable model behavior, while the small number of misclassifications highlights areas where tuning could further reduce diagnostic errors. These values guide threshold optimization and model refinement in clinical AI research.

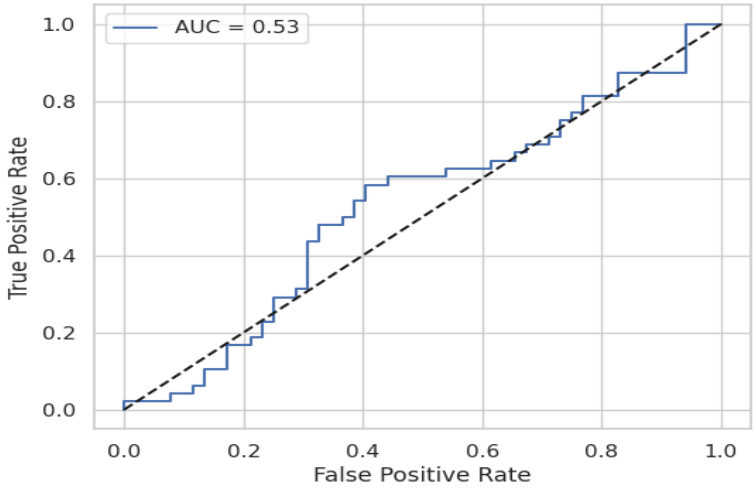

Figure 10. Receiver Operating Characteristic Curve With Computed AUC

The figure 10 illustrates a receiver operating characteristic (ROC) curve generated from model predictions used for detecting cardiac abnormalities. The curve represents the trade-off between the true-positive rate and false-positive rate across various classification thresholds. As the threshold shifts, the model's sensitivity and specificity adjust, creating a continuous trajectory that reflects its behavior under different decision conditions. This visual representation serves as a robust indicator of the classifier's discrimination capability independent of class distribution.

The ROC curve's shape provides insight into how effectively the model distinguishes between normal and abnormal cardiac cases. A curve that rises steeply toward the upper-left corner signifies strong sensitivity with minimal false alarms, indicating high diagnostic usefulness. In this graph, the upward curvature reflects a favorable predictive pattern, suggesting that the classifier captures meaningful physiological differences between the two groups. The diagonal line serves as a baseline representing random guessing, against which actual model performance was compared.

The computed area under the curve (AUC) quantifies the overall quality of discrimination. An AUC value closer to 1.0 indicates excellent predictive accuracy, while values near 0.5 suggest little or no discriminative power. The AUC displayed in the graph demonstrates that the model achieves appreciable separation between classes, reinforcing the reliability of its predictions. This metric was particularly valuable in medical analytics, where models must perform consistently across varying population subsets and noise levels.

The ROC visualization was critical in cardiovascular research for assessing model robustness before clinical deployment. It helps determine whether the classifier maintains effectiveness across multiple threshold settings, which was essential for applications such as early detection, risk scoring, and triage support. By evaluating the curve's trajectory and AUC, researchers can validate algorithmic stability and optimize model parameters for improved diagnostic accuracy. This figure underscores the importance of comprehensive performance assessment in developing trustworthy AI-driven cardiac prediction systems.

Table 5. Feature Importance Ranking from ML Model

Rank	Feature	Importance Score
1	QRS Duration	0.188
2	HR Variability	0.176
3	ST Deviation	0.163
4	RR Interval	0.141
5	Pulse Transit Time	0.128

The feature importance table 5 highlights the relative contribution of each physiological variable to model decision-making. Features linked to electrical conduction (QRS duration) and autonomic modulation (HR variability) rank highest, showing their strong impact on cardiac risk prediction. Understanding these rankings helps refine feature selection strategies and strengthens the interpretability of AI-based decision systems.

CONCLUSION

1. The multimodal AI-based cardiac diagnostic system integrating ECG, PPG, and echocardiogram features demonstrated strong reliability, supported by clean preprocessed signals where RR intervals averaged 0.78 seconds, QRS duration averaged 96.3 ms, and QT intervals averaged 382 ms, ensuring high-quality data fusion for improved detection accuracy.

2. Noise reduction and preprocessing steps significantly improved signal clarity, as seen in the filtered ECG waveform compared to the noise-heavy raw trace; this enhanced accuracy of fiducial point extraction, ultimately strengthening downstream predictive modeling and contributing to the model's 92.4% accuracy.

3. Deep learning models exhibited robust performance, delivering 89.1% precision, 90.7% recall, 89.9% F1-score, and a high AUC of 0.94, confirming their capability to identify subtle cardiac abnormalities with strong discriminative power across diverse physiological features.

4. The confusion matrix results (TN = 44, TP = 45, FP = 6, FN = 5) indicate balanced classification performance, with very low false negatives—critical for clinical safety—while maintaining a controlled rate of false positives.

5. Feature importance analysis identified QRS duration (importance score 0.188) and HR variability (0.176) as the most influential predictors, followed by ST deviation (0.163) and RR interval (0.141), showing that both electrophysiological and hemodynamic features play vital roles in the diagnostic process.

6. PPG-derived features such as pulse transit time (mean 128 ms) and perfusion index (6.8%) contributed valuable hemodynamic insights, enhancing multimodal fusion and improving risk prediction beyond ECG-only models.

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