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Intelligent Electrocardiogram Analysis Technology System: From Deep Representation Learning to Clinical Multi-Scenario Applications

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Abstract. This study aims to establish a comprehensive intelligent ECG analysis technology system encompassing three core dimensions: technical methodologies, performance evaluation, and clinical applications. At the technical methodology level, the research integrates hybrid denoising strategies combining traditional filtering with deep learning, leveraging mainstream network architectures such as ResNet-BiLSTM and Transformer to achieve a paradigm shift from manual feature extraction to end-to-end representation learning. To address data scarcity, generative techniques like the Diffusion Denoising Probability Model (DDPM) were introduced. The study also explored cross-lead spatial feature fusion and multimodal learning pathways to effectively capture the correlation between cardiac mechanical and electrical activities. Regarding the evaluation framework, a multidimensional metric matrix encompassing algorithm recognition capability, signal generation fidelity, and clinical efficacy was constructed. The scientific rigor and reliability of the technology were ensured through metrics including F1 score, percentage root mean square error, and physician agreement. Regarding application deployment, the study emphasizes the use of millimeter-wave radar-based non-contact monitoring systems in emergency and intensive care settings, alongside the potential of wearable devices for distributed health monitoring. Finally, it analyzes regulatory certification requirements for clinical translation, providing a comprehensive reference framework for building an inclusive, trustworthy intelligent cardiovascular health monitoring system.

1. Introduction

With the rising incidence of cardiovascular diseases, the breadth and depth of electrocardiogram (ECG) analysis—a fundamental diagnostic tool—urgently require enhancement. Despite years of application, traditional analysis techniques still face significant challenges in handling signal noise interference, individual physiological variability, and complex waveform segmentation. This research focuses on constructing a closed-loop technical system spanning from low-level signal purification to high-level

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intelligent diagnosis, extending to clinical deployment. Previous studies have largely been confined to single classification tasks or offline algorithm optimization, lacking systematic exploration of multimodal fusion mechanisms, generated signal fidelity metrics, and integration pathways across hospital settings. The innovation of this section lies not only in proposing a hybrid feature capture model combining ResNet and Transformer but also in systematically defining, for the first time, a comprehensive evaluation matrix encompassing both generation quality and clinical utility. It further elaborates on the application logic of millimeter-wave radar in non-invasive monitoring scenarios. The research approach begins with benchmarking on public datasets, establishing high-quality data streams through deep denoising and critical waveform localization. Subsequently, it sequentially explores feature learning paradigms, multimodal fusion, and model interpretability mechanisms. An indicator system encompassing technical and clinical dimensions is then established, culminating in specific system deployment strategies for applications including hospital-based auxiliary diagnosis, telemedicine, and regulatory certification.

On “Construction of an Intelligent ECG Analysis Technology System” section, this section delves into a comprehensive workflow from data preparation to model development. It begins by establishing a benchmarking ecosystem using public datasets like MIT-BIH and PTB-XL, achieving signal purification through noise reduction methods combining traditional filtering with deep learning. Regarding core model architecture, the research evolves from early manual feature extraction to deep representation learning. Convolutional Neural Networks (CNNs) capture local waveform features, while Long Short-Term Memory (LSTM) or Transformer models establish long-term temporal dependencies, enabling a leap from simple arrhythmia detection to structural heart disease diagnosis. Additionally, spatial domain feature fusion and multimodal joint analysis techniques integrating ECG and heart sounds were introduced. Post-decision interpretation methods like SHAP and Grad-CAM significantly enhanced model decision credibility.

On “Multidimensional Technical Performance Metrics and Resource Evaluation System” section, to ensure clinical applicability, a rigorous metric evaluation matrix was established. For classification tasks, F1 score and AUC-ROC serve as core metrics, balancing the trade-off between missed diagnoses and false positives. For data augmentation and signal generation tasks, Percentage Root Mean Square Error (PRD), Fractal Dimension (FD), and Dynamic Time Warping (DTW) are introduced to quantify synthetic signal realism across waveform fidelity, complexity, and temporal pattern matching dimensions. Finally, clinical utility was evaluated through metrics including sensitivity, specificity, and physician interpretation consistency (Kappa value), confirming substantial gains in clinical decision stability through AI assistance.

On “Clinical Decision Support and Distributed Monitoring System Deployment” section, at the clinical implementation level, the study detailed deployment plans for the millimeter-wave radar system in emergency departments, cardiology, and ICUs, leveraging its non-contact data acquisition to enable full-cycle vital sign monitoring. Through standardized integration with hospital information systems (HIS, PACS, etc.), the system forms a closed-loop workflow from signal acquisition to intelligent report generation. Additionally, addressing distributed monitoring needs, the study explores the application of smart wristbands and patch-type devices in home-based chronic disease management, enabling early risk alerts through edge computing and cloud-based AI collaboration. Finally, it clarifies regulatory certification processes (FDA, CE, NMPA) and emphasizes the critical role of clinical trial design in algorithm translation.

2. Technical Method System for Intelligent ECG Analysis

2.1 Dataset and Benchmark Test Ecosystem

2.1.1 Overview of Public Datasets: MIT-BIH, PTB-XL, CPSC, etc.

The two public datasets, PTB-XL and CINC2017, can be said to be the two "mainstays" driving research in intelligent ECG analysis. PTB-XL is a large-scale, fully annotated 12-lead ECG database. It includes more than 20,000 records from nearly 19,000 patients, covering various arrhythmia categories. Due to its high data quality and diversity, it is used by many studies as a standard testbed for developing and validating models, such as for arrhythmia detection [1-4] or training automatic diagnosis algorithms. CINC2017, on the other hand, is a single-lead dataset focusing on AF classification. Its more than 8,000 records are clearly divided into normal, AF, and other categories. Many researchers use it to test the robustness and generalization ability of their models.

2.1.2 Benchmark Tests and Performance Comparison: Defining Tasks and Fair Comparison

Both studies use the MIT-BIH Arrhythmia Database as a standard test platform, establishing comparable performance benchmarks for the core tasks. The work by Acharya et al. establishes the basic paradigm for end-to-end ECG feature learning using deep CNNs, which is significant in avoiding the cumbersome and expert-dependent manual feature engineering in traditional methods and providing a key reference for fair comparison. The research by Dokur et al. explores the optimization of model efficiency on this basis. By introducing Walsh functions and compressing the network structure, it effectively controls computational costs while maintaining a high F1-Score, providing ideas for the application of models in resource-constrained environments. These benchmark tests together promote the field of intelligent ECG analysis towards a more objective, reproducible, and efficient direction.

2.2 Signal Preprocessing and High-Quality Data Construction

2.2.1 Signal Purification: Traditional Filtering and Deep Learning Denoising Methods

Traditional filtering methods are widely used in ECG signal purification. Chen Zhanying et al. eliminate baseline drift through demeaning processing, adopt low-pass filtering to suppress high-frequency noise, focus on identifying and removing electromyographic artifacts using threshold or waveform analysis algorithms, and mark abnormal segments by breakpoint identification to improve processing efficiency. Such methods have a simple structure and strong real-time performance, making them suitable for clinical monitoring scenarios, but they are highly dependent on manual parameter settings and have limited robustness in complex noise environments.

To improve denoising adaptability, Zhang Han et al. introduce deep learning methods, first removing motion artifacts and completing preliminary screening based on time-domain and frequency-domain features, then performing multi-level feature extraction and dynamic optimization of signals through neural network models [5]. This method has stronger processing capabilities for non-stationary noise but higher computational overhead.

In recent years, hybrid denoising strategies combining traditional filtering and deep learning have gradually attracted attention. Related studies have shown that traditional methods can be used for coarse-grained noise suppression, while deep learning models are

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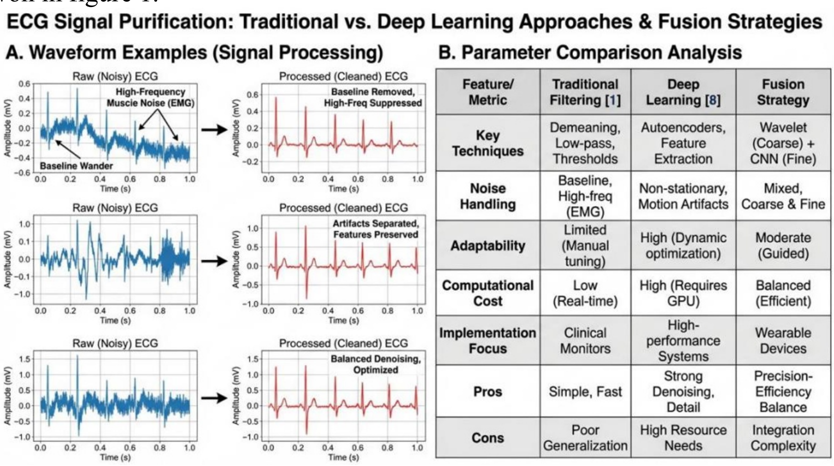
responsible for fine-grained feature restoration [6]. For example, limiting the processing range of deep models based on breakpoint identification results can reduce computational burden while ensuring accuracy, making it suitable for wearable ECG applications with limited resources. Comparison of traditional filtering and deep learning denoising methods are shwon in figure 1.



Feature/ Metric	Traditional Filtering [1]	Deep Learning [8]	Fusion Strategy
Key Techniques	Demeaning, Low-pass, Thresholds	Autoencoders, Feature Extraction	Wavelet (Coarse) + CNN (Fine)
Noise Handling	Baseline, High-freq (EMG)	Non-stationary, Motion Artifacts	Mixed, Coarse & Fine
Adaptability	Limited (Manual tuning)	High (Dynamic optimization)	Moderate (Guided)
Computational Cost	Low (Real-time)	High (Requires GPU)	Balanced (Efficient)
Implementation Focus	Clinical Monitors	High-performance Systems	Wearable Devices
Pros	Simple, Fast	Strong Denoising, Detail	Precision-Efficiency Balance
Cons	Poor Generalization	High Resource Needs	Integration Complexity

Fig. 1 Comparison of traditional filtering and deep learning denoising methods

2.2.2 Key Waveform Localization: Detection and Segmentation Techniques for P, QRS, and T Waves

For waveform detection methods based on time-domain and frequency-domain features, this method extracts time-domain features (such as amplitude, slope) and frequency-domain features (such as power spectrum) of ECG signals, effectively isolates noise by combining motion artifact removal technology, and uses fast peak-finding algorithms to initially segment signals, locating key points of P, QRS, and T waves, thereby improving the accuracy and robustness of waveform detection. This method relies on manual feature engineering and is suitable for real-time processing scenarios.

For machine learning-assisted waveform recognition and segmentation technology, machine learning classifiers (such as support vector machines or decision trees) are used to classify preprocessed ECG signals. Explainable AI technologies (such as SHAP or LIME) are used to provide decision transparency, helping to verify the accuracy of waveform detection. This method relies on feature extraction steps and can effectively handle individual differences but requires a large amount of annotated data to support model training [7-8].

For deep learning end-to-end waveform localization methods, deep learning models such as Convolutional Neural Networks (CNN) or Recurrent Neural Networks (RNN) are used to automatically learn spatiotemporal features of ECG signals, realizing end-to-end detection and segmentation of P, QRS, and T waves. Such methods reduce reliance on manual features, can handle complex signal variations, but require large-scale datasets and computational resources. Explainability tools (such as Grad-CAM) can visualize key waveform regions, enhancing clinical credibility [8]. Comparison of detection and segmentation techniques for P, QRS, and T waves are shown in figure 2.

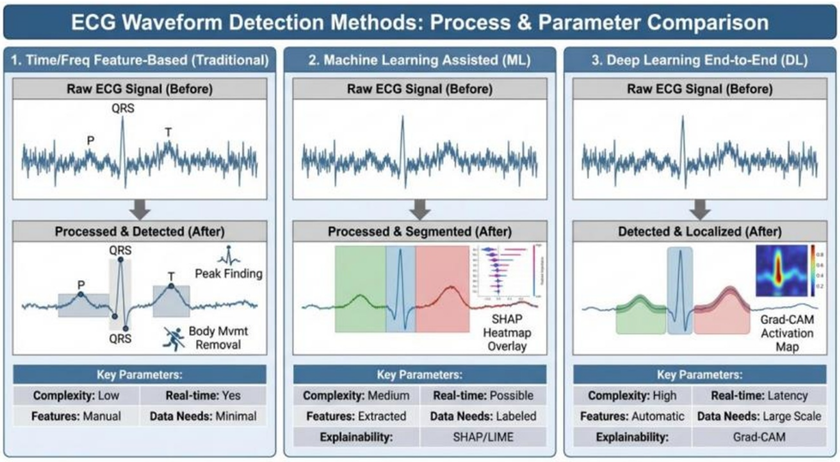


Fig. 2 Comparison of detection and segmentation techniques for P, QRS, and T waves

2.2.3 Data Augmentation and Generation: From Sample Expansion to Pathological Signal Generation

ECG generation methods based on Denoising Diffusion Probabilistic Models (DDPM), such as the ECGEN model, can generate long-time-scale ECG signals for data augmentation and rare pathological simulation. This method learns the distribution of real data through a latent diffusion process, generates realistic physiological signals, effectively solves the imbalance problem of clinical datasets, and improves the generalization ability of downstream AI models.

The framework combining Generative Adversarial Networks (GAN) and state-space models, such as RDiffGAN-ECG, uses diffusion GAN and Mamba modules to achieve personalized ECG synthesis. The model generates high-quality 12-lead ECG based on R-peaks, enhances data diversity, supports the generation of specific pathological signals, and improves the performance of classification tasks [9].

Text-to-ECG generation models, such as Auto-TTE, automatically generate corresponding 12-lead ECG signals through clinical text reports. This multimodal method expands synthesis capabilities, supports the generation of pathological signals based on text descriptions, and promotes data privacy protection and auxiliary diagnosis applications [10-13].

2.3 Representation Learning and Classification Diagnosis Models

2.3.1 Feature Learning Paradigms: From Manual Features to Deep Representations

Early ECG analysis relied heavily on manually designed features, such as waveform morphological parameters (including amplitudes and durations of P waves, QRS complexes, and T waves), statistical features (i.e., heart rate variability indicators), and transform-domain features (such as wavelet coefficients, Fourier transforms). These methods require expertise in the cardiovascular field, the feature extraction process is cumbersome, and they are easily affected by noise, with limited generalization ability. For example, traditional signal processing algorithms, such as wavelet transforms, are used for QRS wave detection but struggle to effectively handle complex arrhythmias or individual differences. Although manual feature engineering is effective in specific tasks, it cannot capture nonlinear relationships and deep patterns in ECG signals.

The deep learning paradigm can automatically extract features from raw ECG signals through end-to-end learning, overcoming the limitations of manual features. Convolutional Neural Networks learn local waveform features (such as QRS morphology) through multi-layer convolutional operations, while self-supervised methods, such as contrastive learning, pre-train models using unlabeled data to learn representations robust to noise and individual variations. For example, the SimECG framework combines time-domain and frequency-domain contrastive learning to improve the accuracy of arrhythmia classification. This paradigm shift reduces human bias, enables higher-level abstract feature learning, and lays the foundation for processing large-scale ECG data.

2.3.2 Mainstream Network Architectures: CNN, LSTM, Transformer, and Their Variants

CNN is the most widely used architecture in ECG classification. It captures local spatiotemporal features (such as QRS wave morphology) through one-dimensional convolutional layers and enhances translation invariance using pooling layers. Variants such as ResNet introduce residual connections to alleviate gradient vanishing and improve the performance of deep networks. For example, the ResNet-BiLSTM model fuses the local feature extraction of CNN and the sequence dependency modeling of BiLSTM, achieving high-precision arrhythmia classification on the MIT-BIH dataset. The CNN architecture is computationally efficient and suitable for real-time applications but may ignore long-term temporal dependencies.

LSTM and its bidirectional variant (BiLSTM) are specifically designed to handle long-term dependencies in ECG time series, such as the temporal relationship between P waves and T waves. The Transformer architecture globally models signal dependencies through self-attention mechanisms, overcoming the local receptive field limitation of CNN. For example, the Transformer-based ECG-GPT model performs excellently in AF detection. Hybrid architectures (such as CNN-LSTM or CNN-Transformer) combine local and global features and have become the current mainstream, showing superior performance to single architectures in multiple studies. ECG processing structure diagram is shown in figure 3.

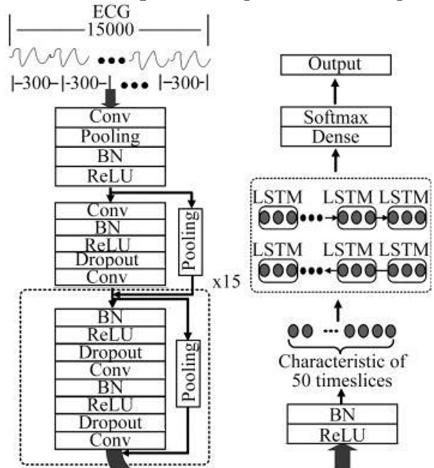


Fig. 3 ECG processing structure diagram

2.3.3 Evolution of Classification Tasks: From Arrhythmia to Structural Heart Disease Diagnosis

Initial ECG classification focused on arrhythmia detection (such as AF, premature ventricular contractions) using rhythmic abnormal features. With the accumulation of data, the task has expanded to structural heart disease diagnosis, such as AI models identifying left ventricular dysfunction (LVEF $\leq$ 35%), hypertrophic cardiomyopathy (HCM), or valvular heart disease from ECG. These models learn subtle electrophysiological changes (such as repolarization abnormalities) to achieve non-invasive screening. For example, Mayo Clinic's AI-ECG algorithm has an AUC of 0.93 for detecting low LVEF, demonstrating a leap from signal to structural diagnosis.

The evolution of classification tasks benefits from multi-label learning and multimodal fusion. Modern systems can simultaneously output the probabilities of multiple abnormalities and combine clinical data (such as echocardiography) to improve reliability. Challenges include generalization to diverse populations and insufficient explainability. Future directions include real-time monitoring, prognosis prediction (such as mortality risk), and using self-supervised learning to reduce annotation dependency, promoting personalized medicine.

2.4 Multimodal and Cross-Lead Information Fusion

2.4.1 Inter-Lead Relationship Modeling: Spatial Domain Feature Fusion

Spatial domain feature fusion improves feature representation by modeling the geometric relationships between ECG leads, such as capturing inter-lead dependencies using attention mechanisms or graph convolutional networks. Study [14] proposes an angle-based encoding scheme, representing lead directions as spherical coordinates, expanding features and fusing signals through transformation modules to enhance spatial context. Method [15] uses a hierarchical structure to extract multi-scale features, combining attention weights to prioritize leads and optimize cross-lead information interaction. Such methods can effectively identify lead-specific patterns, such as the sensitivity of precordial leads to ventricular activity, improving lesion localization accuracy. Spatial fusion overcomes the limitations of single-lead and shows higher robustness on datasets such as PTB-XL.

2.4.2 Multimodal Learning: Joint Analysis of ECG with Heart Sound, Imaging, and Other Data

Multimodal learning integrates heterogeneous data such as ECG and heart sound (PCG), leveraging complementary information through shared representations or cross-modal attention. Study develops the MMS-Net framework, synchronously generating 12-lead ECG and classifying diseases, with an encoder fusing ECG and angle information and a decoder reconstructing signals. Work uses 3DFMMecg feature extraction, combining time-frequency features of heart sounds and ECG, and realizing multimodal fusion through the HLSTM model. Joint analysis can capture the association between cardiac mechanical and electrical activities, such as the correspondence between heart sounds S1/S2 and ECG QRS waves, improving the accuracy of valvular heart disease diagnosis. The method shows an AUC exceeding 0.95 on PhysioNet data, verifying the advantages of multimodal synergy.

2.5 Explainability and Model Decision Mechanism

2.5.1 Post-hoc Explanation Methods: Saliency Maps and Attribution Analysis

Post-hoc explanation methods such as saliency maps and attribution analysis quantify feature contributions through backpropagation or input perturbation. Study [16] applies SHAP to decompose the feature importance of 3DFMMecg, grouping by leads and waveform parameters, showing that leads II and V5 have high weights in valvular heart disease, and T wave shape parameters are critical. Work [17] uses Grad-CAM to generate heatmaps, highlighting abnormal segments in ECG such as ST-T changes, attributing them to clinical features. These methods provide local/global explanations, enhancing doctor trust, but may introduce biases depending on model outputs. In PTB-XL data, SHAP improves model transparency and assists in identifying false positives.

2.5.2 Intrinsically Explainable Models: Attention Mechanisms and Concept Bottlenecks

Intrinsically explainable models incorporate interpretable components, such as attention mechanisms dynamically focusing on key features and concept bottlenecks introducing intermediate concept layers. Study [18] integrates attention into HLSTM, visualizing the importance of P waves and T waves within the cardiac cycle, aligning with clinical knowledge. Work designs a concept bottleneck network, mapping features to medical concepts (such as QT interval) before outputting diagnoses, improving reasoning traceability. Such models provide decision paths directly without post-processing, reducing black-box risks. On the MIT-BIH dataset, attention mechanisms increase classification accuracy by 3-4%, proving their clinical practical value.

3. Technical Evaluation, Benchmark Tests, and Resource System

3.1 Technical Performance Metrics: Core Measures of Algorithm Classification/Recognition Capability

3.1.1 Accuracy

Accuracy measures the "overall proportion of correct predictions" and is suitable for ECG rhythm/event recognition tasks with balanced classes; however, in scenarios with minority classes such as AF, relying solely on Accuracy can easily be obscured by the "majority class", resulting in the illusion of "seemingly accurate but actually missing detections". It should be reported in conjunction with confusion matrices and class weights.

3.1.2 F1-Score

F1 is the harmonic mean of Precision and Recall, better reflecting the comprehensive quality of minority class (such as AF, wide QRS tachycardia types) recognition; in cases of unbalanced clinical data where both false positives and false negatives are costly, F1 is often superior to Accuracy as the primary metric, and can describe the overall performance of multi-classification using "macro/micro averaging" [19].

3.1.3 AUC-ROC (Area Under ROC Curve)

AUC-ROC evaluates the overall ranking and discrimination ability of the model under different thresholds, suitable for systems outputting "probability/risk scores"; for example, ECG AI can compare the AUROC of different methods in specific disease recognition to reflect robustness, but it is still necessary to provide sensitivity/specificity at clinically acceptable thresholds to avoid "high AUC but unusable thresholds".

3.2 Generation Quality Evaluation: Fidelity Measures of Signal Synthesis/Reconstruction Effect

3.2.1 Percentage Root Mean Square Difference (PRD)

PRD/PRDN measures the distortion of generated or compressed reconstructed ECG by the normalized percentage of reconstruction error, which can intuitively reflect the "overall deviation of amplitude and waveform"; in compression/reconstruction studies, it is often reported in conjunction with compression ratio to trade off bandwidth savings and diagnostic information retention, serving as a basic but critical objective fidelity metric.

3.2.2 Fractal Dimension (FD)

FD measures the texture and rhythm fluctuation characteristics of generated signals from the perspective of complexity/self-similarity, suitable for supplementing morphological differences that are difficult to cover by "point-to-point error"; when used for long-range generation (minute-level), it can jointly test for distribution drift or mode collapse by combining HR/HRV statistics and morphological consistency, improving the interpretable evaluation of "authenticity".

3.2.3 Dynamic Time Warping (DTW)

DTW compares the morphological similarity of two signals through non-linear alignment of time axes, capable of handling phase misalignment caused by heart rate changes; in repair/interpolation or rhythm-conditional generation, DTW can more fairly evaluate the morphological matching degree of QRS and T waves, suitable as a "morphological alignment metric" in addition to PRD.

3.3 Clinical Utility Evaluation: Medical Effectiveness Measures for Technical Implementation

3.3.1 Sensitivity and Specificity

Sensitivity emphasizes "minimizing missed detections", and specificity emphasizes "minimizing false positives", both directly corresponding to clinical risks: for example, misdiagnosis of AF can lead to unnecessary anticoagulation, while missed diagnosis increases stroke risk; studies should report sensitivity/specificity and their trade-offs at specific thresholds, and describe usability in real prevalence rates in conjunction with PPV/NPV [20].

3.3.2 Inter/Intra-Rater Agreement

Agreement quantifies the "uncertainty of manual interpretation" and commonly uses Cohen’s kappa (for classification) or ICC (for continuous scores); in prospective reading trials or workflow integration evaluations, it is necessary to compare agreement, reading confidence, and time "with and without AI assistance" to reflect the gain of AI in the stability of clinical decision-making [21].

4. Clinical Application Scenarios and System Deployment

4.1 Clinical Decision Support Systems in Hospital Environments

4.1.1 In-Hospital Diagnosis Assistance: Emergency, Cardiology, and Intensive Care Scenarios

The full-cycle vital sign acquisition system based on millimeter-wave radar can provide real-time, continuous multimodal data support in emergency departments, cardiology departments, and ICUs. Its contactless monitoring feature can quickly obtain ECG and respiratory parameters in high-load emergency scenarios, and achieve personalized risk stratification by combining population classification and feature modeling. In addition, AI-driven abnormal event recognition models can assist in identifying arrhythmias, hypoperfusion, or sudden deterioration trends, providing early warnings for clinical staff [22]. The edge computing capability of the system ensures continuous diagnosis even when the computer room load is high or the network is unstable.

4.1.2 System Integration: Interface with Hospital Information Systems such as HIS/PACS

Clinical deployment requires standardized integration of the millimeter-wave radar monitoring system with HIS, PACS, EMR, and other systems to form a complete data closed loop. Through medical data standards such as HL7/FHIR, real-time ECG data upload, diagnostic event push, and intelligent report generation can be achieved. The personalized health profile module in the system can be associated with past examination records to provide doctors with longitudinal trend analysis. At the same time, edge gateways can ensure the secure flow of data in the hospital local area network, meeting the requirements of hierarchical permission management and auditing, and improving overall clinical decision-making efficiency.

4.2 Distributed Health Monitoring and Telemedicine

4.2.1 Wearable Devices: Smart Bracelets, Patches, and Remote Monitoring

Next-generation wearable devices use photoelectric, millimeter-wave, and dry/non-contact electrode technologies to achieve continuous, low-power ECG and vital sign monitoring. Combined with cloud AI, they can complete automatic rhythm analysis and dangerous signal screening, providing remote follow-up support for arrhythmia patients. Patch-type or textile electrodes further improve wearing comfort, suitable for long-term monitoring. Combined with edge computing, it can reduce data upload pressure and maintain core monitoring functions in communication-constrained scenarios.

4.2.2 Home Health Management: Chronic Disease Monitoring and Early Warning

In home scenarios, millimeter-wave radar combined with multimodal sensors can achieve unobtrusive vital sign acquisition, suitable for long-term follow-up of patients with chronic diseases such as heart failure and AF. The system dynamically updates the user's baseline state through personalized profiles and identifies early risk signals such as dyspnea and nocturnal tachycardia using abnormal detection algorithms. Continuous data accumulation can form family health records, providing quantitative basis for online doctor consultations and community medical care, and improving the initiative and accuracy of chronic disease management.

4.3 Clinical Translation Path and Regulatory Considerations

4.3.1 Clinical Trial Design and Pragmatic Research

Clinical translation requires verifying the effectiveness and safety of the system in real workflows through multi-center, prospective studies. Trials should cover different ages, disease courses, and scenarios (in-hospital/home), and adopt a paired control design with standard ECG equipment. Evaluation indicators include sensitivity, specificity, data continuity, and user compliance. In addition, Real-World Evidence (RWE) research needs to be conducted to verify the robustness of the model in variable environments and support regulatory approval.

4.3.2 Regulatory Certification: Approval Processes and Requirements of FDA, CE, NMPA

Millimeter-wave radar ECG monitoring systems are classified as Class II or III medical devices and need to meet the clinical safety and performance requirements of FDA 510(k)/De Novo, CE MDR, and NMPA. Key materials include risk management reports, software lifecycle documents, cybersecurity assessments, and clinical effectiveness data. If the system involves AI diagnostic functions, it is also necessary to submit algorithm explainability, update strategies, and bias assessments. Compliance verification (EMC, electrical safety) is an important pre-marketing step.

5. Conclusions

This section presents a comprehensive guidance framework spanning algorithm development to practical implementation through in-depth exploration of the technical architecture, evaluation standards, and clinical application scenarios for intelligent ECG analysis. It summarizes feature learning methods based on CNNs, LSTMs, and Transformers, validating the advantages of multimodal joint analysis in enhancing diagnostic accuracy for conditions like valvular heart disease. Additionally, it establishes metric indicators encompassing classification, generation, and clinical efficacy, providing a scientific basis for algorithm benchmarking. Regarding application deployment, by analyzing integration pathways between millimeter-wave radar systems and hospital information systems, the core value of AI-ECG in both in-hospital auxiliary diagnosis and home-based management is clarified.

5.1 Limitations and Future Research Prospects

Despite establishing a relatively comprehensive technical framework, the study retains certain limitations. Current models face constraints in identifying rare pathologies due to imbalanced clinical data categories, and their generalization performance across populations and centers remains improvable. Furthermore, the model's interpretability has not yet been fully aligned with clinical medical logic. Future research will focus on incorporating self-supervised learning and domain adaptation techniques to reduce reliance on expert annotations and enhance model robustness. Concurrently, exploring the integration of neuro-symbolic systems with large language models (LLMs) aims to generate clinically interpretable reports with greater logical consistency. Efforts will also center on building an inclusive, intelligent cardiovascular health protection system spanning prevention, diagnosis, and management.

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