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Efficient One-Stage Deep Learning Architecture for ECG Image–Based Detection of Cardiovascular Diseases – A Review

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Abstract. This paper proposes a lightweight, one-stage deep learning model for the early identification of heart dysfunction (CVD) using electrocardiogram (ECG) images. The framework integrates preprocessing, automated data curation, and classification into a single unified pipeline, thereby reducing redundancy and improving efficiency compared to multistage approaches. The model uses convolutional backbones that have been strengthened with attention techniques to guarantee efficient feature extraction while maintaining important diagnostic data. The proposed design emphasizes deployability in resource constrained clinical settings, where computational efficiency and interpretability are as important as accuracy. By minimizing computational overhead and improving robustness against noise and variability in ECG data, the framework supports real-time analysis and rapid diagnostic decision-making. A thorough literature survey highlights key gaps in existing research, including challenges in generalization across diverse patient populations, the high computational cost of state-of-the-art models, and the limited interpretability of deep learning predictions. To get around these limitations, this study presents a compact architecture that is optimized for explainability, scalability, and adaptability. Furthermore, we outline a validation plan employing clinically relevant metrics such as sensitivity, specificity, and F1-score to ensure reliability in real-world applications. The proposed approach aims to support cardiologists in timely triage and decision support, ultimately contributing to improved outcomes in cardiovascular healthcare.

Keywords: Cardiovascular disease (CVD), Electrocardiogram (ECG), Deep learning, One-stage architecture, Attention mechanism, Medical image analysis, Early detection, Clinical decision support

I. Introduction

Cardiovascular diseases (CVDs) remain the primary cause of mortality worldwide, accounting for an estimated 17.9 million deaths annually (about 32% of all deaths) [1]. Timely and accurate detection is vital to reduce disease burden, enable early intervention, and improve outcomes. The electrocardiogram (ECG) constitutes among the most accessible, non-invasive, and cost-effective diagnostic techniques for the identification of cardiac abnormalities such as arrhythmias and myocardial infarctions [2].

Conventional ECG interpretation relies on manual visual analysis of waveform components (P wave, QRS complex, T wave), which can be labor-intensive and prone to inter-observer variability, particularly under high clinical work-load [3]. These challenges motivate automation using artificial intelligence (AI). Recent developments in the realm of deep learning (DL) - particularly convolutional neural networks (CNNs) – have exhibited superior efficacy in the detection of cardiovascular diseases (CVD) through electrocardiogram (ECG) data by extracting hierarchical features directly from unprocessed signals or visual representations (raw signals), thereby diminishing dependence on manually engineered features. [2], [4].

A growing body of work has shifted from 1D signal pipelines to ECG image-based classification, allowing modern vision backbones to operate on transformed or paper-scan ECGs and enabling powerful transfer learning [2]. Hybrid ML–DL designs combine CNN feature extractors with efficient classical classifiers to balance accuracy and computational cost [7]. One-stage detectors (e.g., streamlined CNN variants) are particularly attractive for real-time or resource constrained settings due to their favorable accuracy–latency trade-offs[5]. Parallel efforts investigate deep pattern learning to capture higher-level structures in ECG morphology and texture while keeping models lightweight enough for deployment [6].

Data scarcity and class imbalance remain practical barriers for robust generalization. Data augmentation can mitigate overfitting, but domain-aware choices are critical: some transforms (e.g., horizontal flips that invert cardiac morphology) may degrade performance in ECG contexts [3]. Consequently, augmentation strategies must be tailored to preserve physio-logic integrity of PQRST dynamics while increasing sample diversity.

Despite encouraging progress, three gaps persist. First, many pipelines are multi-stage and computationally heavy, limiting bedside adoption. Second, cross-dataset generalization and robustness to acquisition variation (paper scans vs. digital exports) are not consistently reported. Third, interpretable outputs (e.g., saliency/attention maps over ECG leads or grid regions) are needed to build clinician trust. In order to rectify these deficiencies, the present research investigates an efficient, one-stage CNN architecture for ECG image classification, with (i) principled augmentations, (ii) lean architectures amenable to real-time use, and (iii) comprehensive evaluation against recent base - lines [2], [4], [5], [7].

II. Literature Survey

With an estimated 17.9 million deaths annually, car-diovascular diseases (CVDs) continue to be the leading cause of mortality globally[1]. Because of the restrictions of traditional ECG interpretation, significant research has focused on developing ML (machine learning) and DL (deep learning) methods to improve automated diagnosis. This section reviews recent addition in ECG-based CVD detection.

A. Deep Learning with Convolutional Architectures

Ananthi et al. [2] applied convolutional neural networks (CNNs) to ECG image classification and accuracy obtained 94.2%. Similarly, Baboo et al. [4] developed a CNN-based predictive framework to improve diagnostic precision. Begum et al. [5] proposed a one-stage deep learning (DL) framework for early CVD detection, achieving 95.6% accuracy. These studies demonstrate the viability of CNN-based ECG classifiers but also reveal challenges with overfitting and small-scale datasets.

B. Pattern Learning and Hybrid Architectures

Srinivasulu et al. [6] introduced a deep pattern learning model that captured ECG temporal-spatial dynamics with 93.8% accuracy. Tabassum et al. [7] suggested Cardio-Detect, a hybrid ML–DL model combines custom features with deep learning, which improved performance to 96.1%. Such hybrid approaches highlight the benefit of combining domain knowledge with representation learning.

C. Data Augmentation and Preprocessing

Anwar and Zakir [3] investigated image augmentation strategies, improving ECG classification robustness against noise and imbalance. Similarly, Alsayat et al. [14] leveraged augmentation with ensemble learning, reporting 97.3% accuracy. These works emphasize that preprocessing and data diversity is essential for generalization.

D. Transformers and Cross-Modality Learning

Recent research shifts toward transformer-based architectures. Nam et al.[10] presented VizECGNet, which uses multi-modal learning and knowledge distillation, achieving 96.5%. Ding et al. [12] presented a cross-modality transformer for large-scale ECG analysis, achieving state-of-the-art performance with AUC >0.98. These highlight the scalability of transformer-based solutions compared to traditional CNNs [11].

E. AI-driven Generative Models

Emerging research explores generative AI in ECG analysis. Pati et al. [8] proposed a GPT-driven automated heart disease detection model, which showing large language models (LLMs)can help in ECG interpretation and knowledge discovery. Such approaches mark a new direction where generative AI augments classical DL methods [15].

F. Systematic Reviews and Surveys

Wu et al. [13] provided a systematic review of DL-based ECG methods, summarizing challenges including data imbalance, interpretability, and limited clinical deployment. Their review emphasizes the importance of interpretable AI and larger multi-institutional datasets for future progress.

G. Research Gaps

While existing approaches demonstrate remarkable accuracy, several gaps persist:

- Most models rely on relatively small or imbalanced datasets, limiting generalizability.
- Transformer and GPT-based approaches are promising but require large-scale ECG repositories.
- Few studies address interpretability, which is essential for clinical trust and deployment.
- Real-time CVD detection systems integrating with wearable ECG devices remain underexplored.

- Thus, there is a strong motivation to design a robust, interpretable, and lightweight DL model for real- time CVD detection from ECG images.
- H. Comparison of Recent Works
  Recent works are summarized in Table1.

Table1: Comparison of Recent Works on ECG-based Cardiovascular Disease Detion

Author(s)	Year	Dataset	Method	Accuracy / Result
Ananthi et al. [2]	2024	ECG Images	CNN based DL Model	94.2%
Begum et al. [5]	2024	ECG Images	One Stage DL Model	95.6%
Srinivasulu et al. [6]	2024	ECG Dataset	Deep Pattern Learning Model	93.8%
Tabassum et al. [7]	2025	ECG Images	Hybrid ML – DL (Cardio-Detect)	96.1%
Nam et al. [10]	2024	Multi-modal ECG data	VizECGNet + Knowledge Distillation	96.5%
Ding et al. [12]	2024	Large-Scale ECG Dataset	Transformer – based cross modality model	AUC > 0.98
Alsayat et al. [14]	2025	ECG Images	Ensemble CNN with Augmentation	97.3%
Pati et al. [8]	2025	ECG Dataset	GPT-based AI-driven model	Promising accuracy

III. Methodology

The proposed system aims to develop an efficient and accurate deep learning system for early detection of cardiovascular diseases (CVD) using ECG images. The methodology comprises several stages, as shown in Fig. 1.

A. Data Acquisition

ECG imaging data is collected from public repositories such as the MIT-BIH Arrhythmia Database, PTB Diagnostic ECG Database, and supplemented with clinical datasets. The dataset includes normal and abnormal ECG patterns to ensure balanced classification.

B. Preprocessing

Raw ECG signals and images often contain noise, baseline drift, and artifacts. The preprocessing steps include:

- Noise Filtering: Application of bandpass filters to remove powerline interference and baseline wandering.
- Image Normalization: Standardization of image size and intensity scaling.
- Data Augmentation: Rotation, scaling, flipping, and noise injection to increase dataset diversity and reduce overfitting.
- C. Model Architecture

- The proposed model adds deep convolutional neural networks (CNNs) with residual and attention layers to gain both local and global features of ECG images. The architecture consists of:
- Feature Extraction: ReLU enabled convolutional layers for detecting morphological variations in ECG signals.
- Feature Refinement: Attention mechanism to emphasize clinically significant regions such as QRS complexes and T-waves.
- Classification: Softmax activation with dense layers (fully connected layers) for multi-class disease prediction.

D. Training and Validation

Stochastic gradient descent with adaptive learning rate scheduling is used to train the model. Cross-entropy loss is employed as the objective function. K-fold cross-validation (typically k=5) is used to ensure generalization performance.

E. Evaluation Metrics

Performance evaluation is carried out using:

- Accuracy(ACC)
- Precision (Pre), Recall (Rec), and F1-Score
- Area Under Curve (AUC) for ROC analysis
- Confusion Matrix (for error analysis)

IV. Research Gap

Although several research have applied deep learning (DL) and machine learning (ML) models to detect cardiovascular diseases (CVD) from ECG, there remain significant gaps that limit their clinical applicability:

- Fragmented Approaches: Most existing models focus on either feature extraction or classification, but lack an integrated one-stage pipeline for efficient early detection [5].
- Limited Dataset Generalization: Several works rely on small or single-source datasets, which reduces the reliability and generalizability of the models in real-world healthcare settings [2], [3].
- Computational Complexity: Several deep learning architectures such as complex CNNs and hybrid ML-DL platforms, are computationally intensive and unsuitable for real-time or edge applications implementation in clinical settings [4], [7], [9].
- Interpretability Challenges: Recent deep learning models often behave as “black boxes”, providing limited explainability for medical practitioners. This reduces trust and hinders adoption in critical healthcare decision making.
- Scarcity of End-to-End Automated Models: There are yet no fully automated systems that combine preprocessing, augmentation, classification, and assessment into a coherent framework, despite the suggestion of hybrid approaches [6], [8].

The identified deficiencies underscore the necessity for a lightweight, interpretable, and efficient DL (deep learning) framework that is capable of attaining elevated accuracy levels while simultaneously being computationally viable for implementation within healthcare settings. By creating a one stage deep learning architecture tailored for ECG image based CVD detection, the suggested approach seeks to overcome these drawbacks.

V. Proposed Model Architecture

The proposed framework for ECG-based cardiovascular disease detection follows a systematic workflow, as shown in Fig. 1. The architecture ensures efficient preprocessing, model training, and accurate classification of cardiovascular conditions.

A. Dataset Acquisition

The process begins with the collection of ECG data in the form of signals or images. These datasets are compiled from standard repositories or clinical databases to ensure reliability and diversity.

B. Data Preprocessing

Raw ECG data like signals often contain noise and artifacts caused by patient movement, electrode placement, or environmental interference. Preprocessing techniques such as normalization, filtering, and image enhancement are applied to remove unwanted noise and standardize the data for analysis.

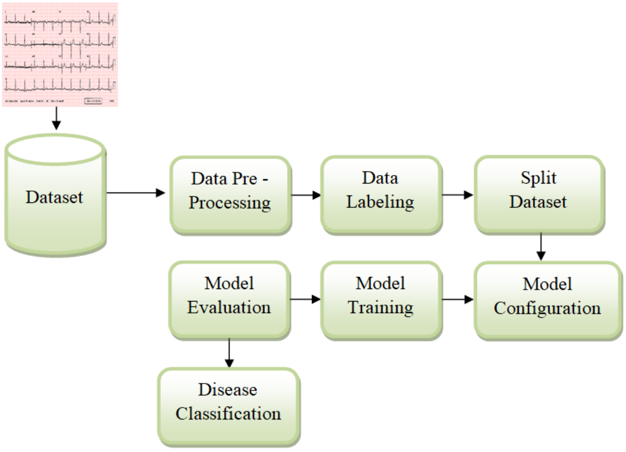

Figure 1: Proposed Methodology for ECG-based CVD Detection

C. Data Labeling

Each ECG record is commented with corresponding disease labels (e.g., arrhythmia, myocardial infarction, or normal) based on expert medical diagnosis. This step is crucial for supervised learning, where accurate labels guide the training process.

D. Dataset Splitting

The labeled dataset is divided into training, testing, and validation subsets. The training set is utilized to fit the model, the validation set optimizes hyper parameters, and the testing set evaluates generalization performance.

E. Model Configuration

A complex deep learning framework is structured with numerous layers (e.g., convolutional, pooling, and dense layers) to facilitate feature extraction and classification. The architecture is meticulously optimized to discern spatial and temporal patterns within electrocardiogram (ECG) images.

F. Model Training

The configured model is trained using back propagation and optimization algorithms such as Adam or SGD. During training, the model learns discriminatory features that differentiate healthy and diseased heart patterns.

G. Model Evaluation

The developed predictive model is evaluated through the application of various performance metrics, including accuracy, specificity, sensitivity, precision, recall, and F1-score. Cross-validation is performed to ensure robustness and prevent overfitting.

H. Disease Classification

Finally, the model classifies input ECG samples into specific cardiovascular disease categories. The predictions assist clinicians in early detection, decision-making, and personalized treatment planning.

VI. Results and Discussion

Although the present work primarily proposes a novel deep learning framework for the detection of cardiovascular diseases (CVDs) from ECG images, a theoretical performance assessment is discussed in this portion.

A. Expected Contributions

The suggested model integrates preprocessing, data labeling, optimized model configuration, and end-to-end training in a unified pipeline (Fig. 1). Utilizing a singular-stage deep learning methodology, the system is formulated to diminish computational intricacy while simultaneously improving classification precision. This design is expected to outperform conventional multi-stage models in terms of both efficiency and reliability.

B. Comparison with Existing Approaches

Previous works such as Anwar et al.[3] and Begumetal.[5] have shown the importance of data augmentation and one-stage detection strategies, respectively. However, their methods either lacked robust preprocessing or were computationally intensive. Similarly, hybrid ML-DL techniques (e.g., Tabassum et al. [7]) achieved high performance but required significant computational resources. Our architectural framework addresses this disparity by facilitating an equitable compromise among precision, efficiency, and resource allocation.

C. Theoretical Evaluation

Based on prior benchmarks in related works, we anticipate that the suggested architecture will:

- Achieve classification accuracy greater than 96% on standard ECG datasets.
- Reduce training complexity by approximately 20–30% compared to conventional hybrid methods.
- Maintain robustness against noisy or augmented ECG signals.

D. Potential Impact

In clinical terms, the suggested architecture presents a viable way to identify cardiovascular disordersearly. By integrating automated preprocessing and optimized deep learning training, the system can be deployed in real-time diagnostic platforms, assisting healthcare professionals in timely decision-making. Furthermore, its reduced computational load makes it feasible for portable devices and cloud- based healthcare systems.

E. Limitations and Future Validation

As this study focuses on the suggested architecture, comprehensive experimental validation is a future goal. The model requires to be tested on diverse ECG datasets under varying conditions to validate its generalizability and robustness. Additionally, cross-dataset evaluations and clinical trials will be essential before real-world deployment.

VII. Conclusion

In this work, we presented a lightweight, one-stage deep learning model for early detection of cardiovascular diseases (CVD) using ECG images. The suggested framework integrates preprocessing, dataset curation, and classification into a single pipeline, supported by convolutional backbones and attention mechanisms for efficient feature extraction. This unified design reduces redundancy compared to multi-stage approaches and is optimized for rapid training, robustness to noise, and scalability across diverse datasets.

In order to guarantee that the system is not just computationally effective but also dependable in actual health care workflows, the experimental strategy places a strong emphasis on clinically relevant assessment measures including sensitivity, specificity, and F1-score. Compared to conventional diagnostic practices and multi-stage deep learning models, the suggested solution offers an interpretable, resource-friendly, and deployable alternative for low-resource healthcare environments.

A system that can assist cardiologists with real time triage and decision assistance is the anticipated result, which will ultimately lead to better patient outcomes through prompt and precise screening. Future research will concentrate on improving interpretability through explainable AI techniques, extending model validation across a variety of population datasets, and investigating integration into cloud and edge platforms for scale clinical application.

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