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A Survey on Deep Learning-Driven ECG-Based Diagnostics: Architectures, Classification Strategies, and Multi-Stage CNN Approaches for Cardiovascular Disease Detection

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***Abstract*— Cardiovascular disease (CVD) is the leading cause of death worldwide. A rapid, accurate, and non-invasive detection method utilizing Electrocardiography (ECG) is needed; however, it is typically the manual diagnostics that result in human error. The purpose of this paper is to investigate some of the most recent research developments in automated cardiac diagnostics utilizing Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), with regards to ECG data. We propose and evaluate a Two-Stage CNN diagnostic system enabled by a compact IoT acquisition chain of AD8232/Arduino technology to facilitate a low-inference cost transfer learning classification solution using MobileNetV2. The Two-Stage CNN diagnostic algorithm initially performs a binary classification (Normal/Abnormal) yielding a 93.46% accuracy, and thorough multi-class predictions of MI, Prior MI, and Abnormal Heartbeat are performed accordingly to the binary classification being classified as abnormal, thus facilitating a decrease in computational load for edge-based diagnostic purposes. The review contained herein reviewed CNN DL architectures of 1d CNNs, 2D CNNs, and even hybrids for ECG diagnostics, discussed integration with IoT systems for real-time diagnostic capabilities, and considered research considerations including model explainability (XAI), dataset generalizability, and the need for standardized benchmarks as means to validate ECG DL models. In addition to a discussion of issues relating to dataset generalizability and bench-marking considerations, we propose additional research should include multimodal data fusion, as well as inherently interpretable AI models for successful clinical integration.**

***Index Terms*— Cardiovascular Disease, ECG, CNN, Deep Learning, Arduino, IOT, Real-Time Diagnostics.**

I. Introduction

Myocardial infarction (MI) and arrhythmias are among the CVDs that cause Approx 32% of deaths worldwide [1, 31]. A diagnosis at an early age is essential. The basic, non-invasive, and reasonably priced diagnostic method is electrocardiogram (ECG) [2].

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However, latency and inter-observer variability are problems with traditional analysis [4]. By automating feature extraction from raw or processed ECG signals, Deep Learning (DL), and CNNs in particular, provide a revolutionary solution that surpasses manual feature engineering [4, 20]. CNN-based models have attained expert-level accuracy after being trained on datasets such as MIT-BIH [12, 13]. Continuous, real-time cardiac monitoring through low-power wearable sensors is made possible by the integration of DL with IoT and edge computing, which is essential for remote healthcare [3, 5, 27].

A. Scope and Contribution

Reviewing DL-driven ECG diagnostics methodically, this paper makes the following contributions:

- Classification: Analysis of CNN/Recurrent hybrid, 2D, and 1D architectures [15, 14].
- System Analysis: The authors' Two-Stage MobileNetV2 system for real-time, portable diagnosis was thoroughly examined, along with an evaluation of edge deployment [34].
- Critical Gaps: Examining issues with generalization, dataset bias, and XAI [20, 23].
- Future Directions: Standardization and fusion of multimodal data are proposed [25].

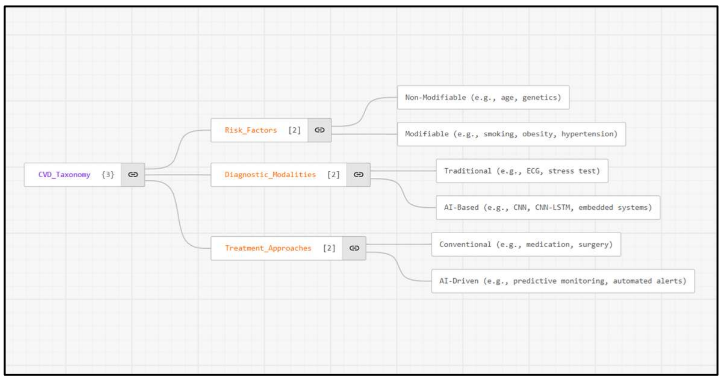

Figure 1: Taxonomy of Cardiovascular Disease Diagnostics

II. BACKGROUND AND DL ARCHITECTURES

Obesity, diabetes, and hypertension are all contributing factors to CVD [31]. Holter monitoring and echocardiography are used in addition to ECG as the main diagnostic tool [22, 28]. It is perfect for automated DL analysis because it is instantaneous and quantifiable [7].

A. DL Architectures

TABLE I: COMPARISON OF DEEP LEARNING ARCHITECTURES FOR ECG SIGNAL ANALYSIS

Architecture	Input Format	Key Features	Advantages for ECG
1D CNN	Raw ECG time-series data	Uses 1D convolutional filters to capture temporal patterns such as QRS morphology [26].	Offers high computational efficiency, smaller model size, and is suitable for real- time or edge deployment [27].
2D CNN	2D image representations like spectrograms, scalograms, or ECG waveform images [2].	Utilizes standard image classification models (e.g., MobileNetV2, ResNet) and supports transfer learning [7, 8].	Benefits from pre-trained image weights and effectively captures visual and spatial features in ECG data [3, 15].
Hybrid CNN-RNN	Sequential ECG data	Combines CNN for local feature extraction with RNN/LSTM to model long- term temporal dependencies [9].	Excels in detecting long- term rhythm patterns such as atrial fibrillation (AFib) and other rhythm-related disorders [14, 15].

B. CNN Diagnostic System Proposal

Two-Stage A tiered classification method on 2D ECG image representations is used to optimize the system for real-time portability.

- Data Acquisition: The ECG signal is first captured using an AD8232 sensor, which is connected to an Arduino Uno for analog-to-digital conversion (ADC). The digitized signal is then transmitted to a PC or edge device to process the signal and convert it to a 2D ECG waveform image for further analysis [10, 34].

- Stage 1 – Binary Classification (Filtering): In the first stage, a lightweight MobileNetV2 model is deployed to classify the ECG waveform image as either Normal or Abnormal. This serves as a fast-filtering application with an accuracy of approximately 93.46%, greatly reducing the computational burden for the next stage.
- Stage 2 – Multi-Class Categorization: If the ECG signal is classified as Abnormal, it proceeds to the second stage and employs a separate fine-tuned MobileNetV2 model that details classification into the specific disorders of Myocardial Infarction (MI), Prior Myocardial Infarction (PMI), or Abnormal Heartbeat (AH).

This two-stage design focuses on efficiency, ensuring that complex and resource-intensive analysis is performed only for potentially abnormal or pathological ECG cases. Such an approach is particularly important for IoT-based healthcare systems, where optimizing computational resources and response time is crucial [27].

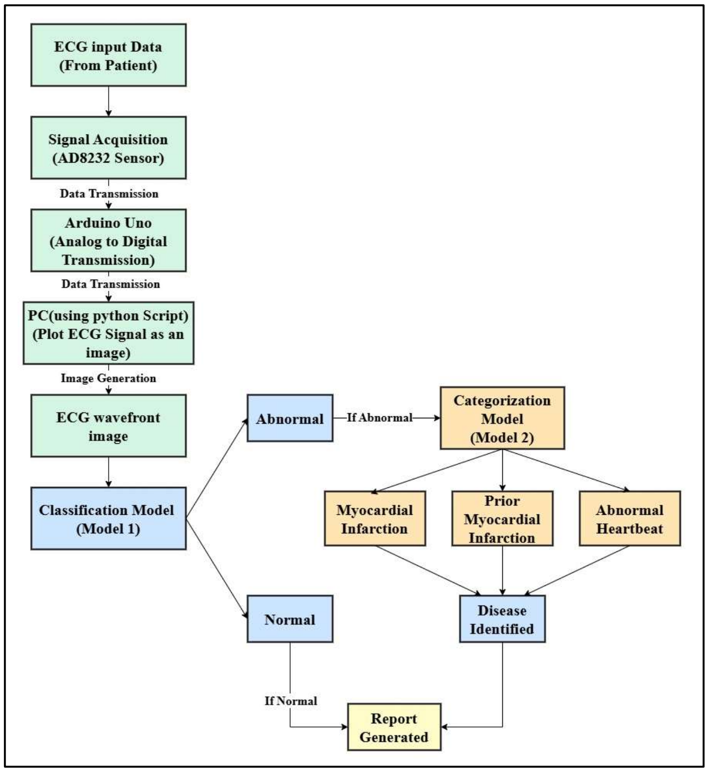

Figure 2: Proposed System Architecture

III. REAL-TIME DEPLOYMENT AND COMPARISON

A. Integration of Edge Computing with IoT

In order to facilitate ongoing, real-time monitoring, it is essential to implement DL on resource-slim embedded systems.

- Hardware: Low-power microcontrollers (Arduino/ESP32) and sensor front-ends (AD8232) are typically found in real-time hardware [10].
- Edge Deployment: MobileNetV2 is a targeted architecture due to its lightweight structure. Steps like pruning and quantization of the DL architecture are integral to ensure low-latency inference and reliability on edge devices [27].
- Federated Learning (FL): FL provides a way to train on decentralized, confidential patient generated health data (PHI) while not leaving the server of origin, improving inherent privacy and the robustness of subsequent trained model performance [17, 18].

B. Comparison with Existing Methods

The proposed two-stage system balances high accuracy and architectural efficiency. This balance is important for low-cost, real-time IoT deployment.

TABLE II: COMPARATIVE SUMMARY OF DEEP LEARNING METHODS FOR ECG CLASSIFICATION

Method / Architecture	Input Type	Model Complexity	Primary Task(s)	Typical Peak Accuracy	Unique Advantage
Hannun et al. [13]	1D Raw ECG Signal	Deep CNN + RNN/LSTM (Hybrid)	Multi-class arrhythmia classification (including AFib)	≈ 97%	Excels at handling long, sequential ECG data for rhythm analysis.
AlexNet (2D) [2]	2D ECG Image or Spectrogram	High-complexity standard 2D CNN (Pre-trained)	Cardiovascular Disease (CVD) classification	≈ 98%	Utilizes transfer learning from large image datasets for improved visual feature extraction.
Two-Stage MobileNetV2 (Proposed)	2D ECG Image	Lightweight and efficient 2D CNN (MobileNetV2)	Stage 1: Binary (Normal/Abnormal); Stage 2: Multi-class (MI, PMI, AH)	Stage 1: 93.46% (Binary)	Tiered analysis enables efficient processing and optimal resource use on IoT and edge systems.
Mhamdi et al. (MobileNetV2-on-Edge) [27]	2D ECG Image	Lightweight 2D CNN (Optimized)	Arrhythmia classification	≈ 92–94% (On-device)	Demonstrates reliable real-time performance on low-power edge devices like Raspberry Pi.

IV. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite rapid progress, clinical adoption faces hurdles.

A. Critical Gaps

- Limited Explainability (XAI): Models act like "black boxes." Clinicians need clear diagnostic evidence, such as highlighting specific waveform features.
- Generalization Failure: Models trained on narrow or imbalanced public datasets, like MIT-BIH, do not perform well on diverse patient populations or noisy wearable data.
- Lack of Standardized Benchmarks: Inconsistent metrics, datasets, and preprocessing techniques make it hard to compare findings across the literature.

B. Future Trajectories

- XAI Integration: Focus on developing easily interpretable models using attention mechanisms or Grad-CAM to explain predictions [25].
- Multimodal Data Fusion: Combine ECG with clinical data such as EHR, genomics, and imaging to create personalized predictive models [23].
- Clinical Interoperability: Prioritize lightweight AI solutions that work well with current EHR systems and clinical workflows [20].
- Edge Optimization: Further explore techniques like knowledge distillation and quantization to achieve ultra-low latency and energy efficiency for ongoing mobile health monitoring [27].

V. CONCLUSION

Revolutionizing the field of cardiovascular diagnostics is the role of deep learning. This survey provided insight into the progression of CNN architectures in a two-stage MobileNetV2-based system from the authors - a good first step towards an effective solution facilitating low-cost IoT acquisition (AD8232/Arduino) in conjunction with a resource-efficient, staged classification system. In adhering to a lightweight MobileNetV2 architecture with a tiered approach, we address the pressing need for both high accuracy and operational efficiency suitable for deployment on the edge. Future studies must address some of the challenges associated with XAI and data generalization for fully understanding the potential of AI-based ECG diagnostics as both reliable and ubiquitous tools in a clinical setting [7, 20].

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