

Cardio Vision - Innovating Healthcare for Well Being Through Cardio Vascular Disease Detection

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Abstract -Cardiovascular diseases remain one of the leading causes of mortality worldwide, making early and accurate diagnosis a critical requirement in modern healthcare. Electrocardiograms (ECGs) are extensively used for monitoring heart activity due to their non-invasive nature, affordability, and ability to reveal vital cardiac abnormalities. However, manual interpretation of ECG recordings is a challenging and time-consuming process that relies heavily on clinical expertise and is prone to subjective variations.

With the increasing availability of digital ECG data, automated analysis techniques have gained significant attention as a means to support clinicians in decision-making. In this work, a hybrid image-based ECG classification framework is proposed that combines the representation learning capability of deep learning models with the efficiency of machine learning classifiers. ECG images are processed using convolutional neural networks to automatically extract meaningful visual features that capture essential waveform characteristics related to cardiac conditions.

The extracted features are subsequently classified into four clinically relevant categories: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal heart rhythm. This multi-class formulation reflects realistic diagnostic scenarios encountered in clinical practice. The proposed approach aims to reduce dependency on manual interpretation, improve consistency in diagnosis, and enable faster identification of cardiac abnormalities.

Key Words: Electrocardiogram (ECG), ECG Image Classification, Cardiovascular Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Machine Learning, Hybrid Classification Model, Medical Image Analysis, Automated Diagnosis

1. INTRODUCTION

Cardiovascular diseases (CVDs) continue to pose a serious global health concern, accounting for nearly 17.9 million deaths each year, which is approximately 32% of total worldwide mortality [1]. A large share of these deaths results from myocardial infarction and other cardiac abnormalities, underscoring the importance of early detection and timely medical intervention [4]. Modern lifestyle factors such as physical inactivity, increased stress, and aging populations have further contributed to the rising incidence of heart-related conditions, placing a growing burden on healthcare systems. Consequently, there is a strong need for accurate, efficient, and automated diagnostic tools that can assist clinicians in making reliable decisions.

The electrocardiogram (ECG) remains one of the most commonly used diagnostic techniques for assessing cardiac health due to its non-invasive nature, low cost, and ability to record the heart's electrical activity in real time [5]. ECG signals provide critical information about heart rhythm, conduction disorders, and myocardial damage. However, traditional ECG interpretation relies heavily on the experience of trained cardiologists, making the process time-consuming and susceptible to subjective judgment and human error, particularly in high-volume clinical settings [4]. In some cases, subtle abnormalities in ECG waveforms may be overlooked, leading to delayed or inaccurate diagnoses.

To overcome these limitations, automated ECG analysis using machine learning (ML) and deep learning (DL) techniques has gained significant attention. Conventional ML-based methods depend on handcrafted features such as heart rate variability and frequency-domain characteristics, which require extensive preprocessing and expert knowledge [5]. These approaches often struggle to capture the complex and non-linear patterns present in ECG signals. In contrast, deep learning models, especially Convolutional Neural Networks (CNNs), are capable of automatically learning meaningful and hierarchical features directly from ECG signals or images, eliminating the need for manual feature extraction [1][10].

Recent progress in transfer learning has further improved ECG-based diagnostic systems. Pre-trained CNN models such as VGG16, ResNet50, and InceptionV3 enable efficient feature extraction while significantly reducing training time and computational requirements [2][6]. Several studies have demonstrated improved accuracy in detecting myocardial infarction and cardiac arrhythmias using these models [3][8][11]. Despite these advancements, challenges such as limited generalization, high computational demands, and lack of interpretability still remain [13]. To address these issues, this work proposes CardioVision, a hybrid ECG image-based framework that combines deep learning for feature extraction with traditional machine learning classifiers, aiming to accurately identify multiple cardiac conditions while ensuring robustness, efficiency, and clinical reliability [7][12].

2. Literature Survey

Early studies on automated ECG analysis primarily relied on traditional signal processing and classical machine learning techniques. These approaches focused on extracting handcrafted features such as RR intervals, QRS complex duration, ST-segment deviations, and frequency-domain characteristics from ECG signals. The extracted features were then classified using algorithms like Support Vector

Machines, k-Nearest Neighbors, and Random Forests. While these methods achieved reasonable accuracy, their performance was highly dependent on feature quality and often degraded in the presence of noise and patient-specific variability [5].

To improve reliability, researchers proposed hybrid frameworks that combined preprocessing techniques such as filtering and normalization with machine learning classifiers. These methods enhanced robustness across datasets but still relied heavily on manual feature engineering. As a result, they struggled to capture subtle morphological variations in ECG waveforms that are critical for identifying complex cardiac conditions [5].

The emergence of deep learning marked a significant advancement in ECG-based diagnosis. Convolutional Neural Networks (CNNs) enabled automatic feature extraction directly from ECG signals and images, eliminating the need for handcrafted features. A seminal study demonstrated that deep CNNs could effectively detect myocardial infarction by learning discriminative spatial and temporal patterns from ECG data, significantly outperforming traditional approaches [1]. This work highlighted the capability of deep models to identify minor waveform distortions that are difficult to detect manually.

Subsequent research extended CNN-based models to multi-class and beat-level ECG classification tasks. Deep neural network architectures were shown to capture complex morphological patterns across different cardiac conditions, achieving high sensitivity and specificity [11]. These findings established CNNs as a reliable foundation for automated ECG interpretation in clinical environments.

Another important research direction focused on patient-specific and real-time ECG analysis. Adaptive one-dimensional CNN models were introduced to continuously learn from incoming ECG data, allowing the system to adjust to individual cardiac patterns without extensive retraining [4]. Such adaptability proved particularly valuable for wearable devices and continuous monitoring systems, where ECG characteristics can vary significantly over time.

Arrhythmia detection also received significant attention in the literature. Studies employing deep learning-based monitoring systems combined convolutional and recurrent architectures to capture both spatial waveform characteristics and temporal dependencies across heartbeats [10]. These approaches demonstrated improved detection accuracy and scalability for long-term ECG monitoring applications [8].

With the growing adoption of transfer learning, researchers leveraged pre-trained deep models to address the challenge of limited labeled ECG data. Lightweight architectures, such as MobileNet-based models, were shown to provide a good balance between classification accuracy and computational efficiency, making them suitable for deployment in resource-constrained clinical environments [3].

Recent studies have emphasized the importance of multi-class ECG classification and clinical relevance. Unlike binary classification systems, multi-class frameworks enable differentiation between normal rhythms, myocardial infarction, and other abnormalities, reflecting real-world

diagnostic scenarios [12]. Additionally, multimodal approaches that integrate ECG data with clinical parameters have shown improved diagnostic performance and interpretability [12].

Despite these advancements, challenges such as limited generalization, high computational demand, and lack of explainability remain. Many deep learning models perform well on benchmark datasets but struggle to adapt to diverse patient populations and acquisition conditions [4]. These limitations motivate the need for efficient hybrid systems that combine deep learning-based feature extraction with interpretable machine learning classifiers, forming the foundation for the proposed approach in this work.

3. METHODOLOGY

The proposed CardioVision system follows a structured and systematic methodology to automatically detect cardiovascular diseases from electrocardiogram (ECG) images using a hybrid deep learning and machine learning approach. The methodology is designed to enhance diagnostic accuracy while maintaining computational efficiency and interpretability. ECG images corresponding to different cardiac conditions are processed through multiple stages, including dataset collection, feature extraction using deep learning models, training and testing, and final disease classification. By combining the strengths of convolutional neural networks and traditional machine learning classifiers, the proposed framework ensures robust and reliable detection of cardiac abnormalities suitable for clinical applications.

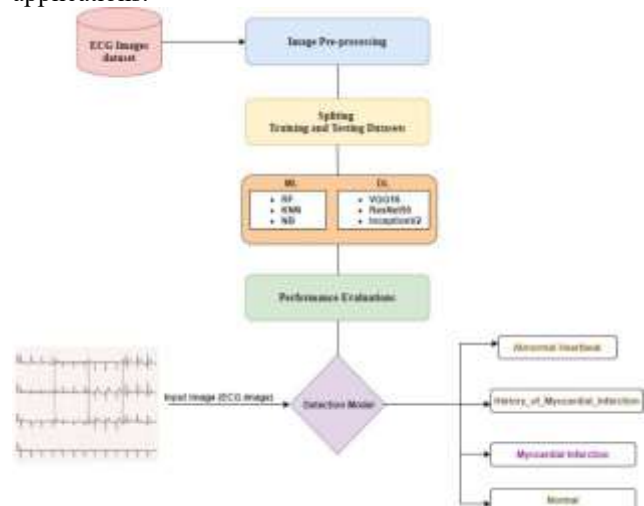


Fig -1: Proposed Architecture

This system architecture (Fig-1) illustrates the proposed Cardio Vision framework for automated ECG image classification. The pipeline begins with ECG image acquisition and preprocessing, followed by splitting the dataset into training and testing sets. Deep learning models extract discriminative features from ECG images, which are further classified using machine learning techniques. Finally, the detection model categorizes the input ECG into clinically relevant classes, and performance is evaluated to assess diagnostic effectiveness.

3.1 Dataset Collection

The dataset used in this study consists of ECG images collected from publicly available online repositories. These images represent four distinct cardiac conditions: Abnormal Heartbeat, History of Myocardial Infarction, Myocardial Infarction, and Normal. Each class exhibits unique waveform characteristics and rhythm patterns that reflect different cardiac activities. The dataset is examined for quality, diversity, and class distribution to ensure effective learning. This diverse collection of ECG images forms the foundation for training and evaluating the CardioVision system, enabling it to accurately distinguish between normal and abnormal cardiac conditions.

3.2 Model Architecture

The CardioVision framework adopts a hybrid model architecture that integrates deep learning and machine learning techniques for ECG image analysis. Pre-trained convolutional neural network (CNN) models such as VGG16, ResNet50, and InceptionV3 are employed for feature extraction using transfer learning. These models capture hierarchical and discriminative features from ECG images, including waveform morphology, rhythm variations, and subtle abnormalities in P, QRS, and T waves. The extracted deep features are then passed to machine learning classifiers for final classification. This hybrid architecture combines the powerful representation learning capability of deep networks with the efficiency and interpretability of classical classifiers, resulting in improved diagnostic performance.

3.3 Training and Testing

Once the ECG dataset is pre-processed, it is divided into training and testing subsets to ensure effective learning and reliable evaluation. The training set is used to optimize the model by learning discriminative ECG features through deep learning-based feature extraction and machine learning-based classification. During this phase, the model parameters are adjusted to capture important waveform characteristics associated with different cardiac conditions. The testing set consists of previously unseen ECG images and is used to evaluate the model's performance and generalization capability. This balanced data split helps prevent overfitting and ensures that the trained model can accurately classify ECG images under real-world clinical conditions.

3.4 Algorithms Used

The CardioVision system employs a combination of deep learning and machine learning algorithms to achieve accurate ECG classification. Deep learning models, specifically VGG16, ResNet50, and InceptionV3, are used for automated feature extraction from ECG images, capturing both fine-grained waveform details and global structural patterns. These extracted features are then classified using machine learning algorithms such as Random Forest, K-Nearest Neighbors, and Naïve Bayes. Random Forest provides robust ensemble-based predictions, K-Nearest Neighbors classifies ECG samples based on feature similarity, and Naïve Bayes offers fast probabilistic classification. The integration of these algorithms ensures a balanced trade-off between accuracy,

efficiency, and interpretability in cardiovascular disease detection.

4. RESULTS

The performance of the proposed system was evaluated using standard measures such as accuracy, precision, recall, and F1-score for all four heart condition classes. Fig -2 presents a comparative evaluation of different deep learning and machine learning hybrid models, including Random Forest, K-Nearest Neighbors, and Naïve Bayes combined with deep learning-based feature extraction. Among these, the Random Forest-based hybrid model achieved the best overall performance, demonstrating stable and balanced results across all categories. The results indicate that deep learning models effectively capture important ECG image features, while the choice of classifier plays a key role in final predictions. Overall, the hybrid approach improves accuracy and reliability, making it suitable for multi-class ECG image classification.

DL & ML Models Evaluations

DL Model	ML Model	Accuracy	Precision	Recall	F1 Score
VGG16	RF	88.0	88.0	88.0	88.0
VGG16	KNN	85.8943621389178	85.8943621389178	85.8943621389178	85.8943621389178
VGG16	NB	86.1788647329185	86.1788647329185	86.1788647329185	86.1788647329185
ResNet50	RF	88.0	88.0	88.0	88.0
ResNet50	KNN	76.8547329183887	76.8547329183887	76.8547329183887	76.8547329183887
ResNet50	NB	81.3380348913885	81.3380348913885	81.3380348913885	81.3380348913885
InceptionV3	RF	88.0	88.0	88.0	88.0
InceptionV3	KNN	76.3782768783787	76.3782768783787	76.3782768783787	76.3782768783787
InceptionV3	NB	88.30841182283378	88.30841182283378	88.30841182283378	88.30841182283378

Fig -2: DL&ML Models Evaluations

4. CONCLUSIONS

CardioVision successfully demonstrates an effective and reliable approach for the automated detection and classification of cardiovascular abnormalities using ECG images by integrating deep learning and traditional machine learning techniques. The preprocessing stage played a vital role in enhancing the quality and consistency of ECG images, which in turn improved the accuracy and stability of feature extraction. Deep learning models based on convolutional neural network architectures effectively learned complex spatial and morphological patterns present in ECG signals, capturing subtle waveform variations associated with different cardiac conditions. These extracted features were then utilized by machine learning classifiers to establish clear and reliable decision boundaries, leading to accurate classification outcomes. The system achieved consistent performance across multiple cardiac categories, highlighting its potential to assist medical professionals in timely and informed diagnostic decision-making. Furthermore, the integration of the trained models into a user-friendly web-based interface improved system accessibility and practical usability in clinical settings. Overall, the experimental results validate that the proposed hybrid CardioVision framework can serve as a dependable and efficient decision-support tool for the early detection and classification of heart disorders.

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