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# A LIGHTWEIGHT METHOD OF MYOCARDIAL INFARCTION DETECTION & LOCALIZATION FROM SINGLE LEAD ECG FEATURES USING MACHINE LEARNING APPROACH

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## ABSTRACT

The proposed study titled *"A Lightweight Method of Myocardial Infarction Detection & Localization from Single Lead ECG Features Using Machine Learning"* focuses on developing an efficient and computationally optimized system for early detection and localization of myocardial infarction (MI) using single-lead Electrocardiogram (ECG) signals. Cardiovascular diseases, particularly myocardial infarction, are among the leading causes of mortality worldwide, and early diagnosis plays a critical role in reducing fatality rates. Traditional diagnostic methods often require multi-lead ECG systems and expert interpretation, which may not be feasible in remote or emergency settings. This research aims to overcome these limitations by utilizing a lightweight machine learning-based approach that can operate effectively on minimal hardware resources. The proposed methodology involves extracting key features from single-lead ECG signals, including time-domain, frequency-domain, and morphological characteristics such as QRS complex, ST-segment deviations, and T-wave variations. These features are preprocessed using noise filtering and normalization techniques to ensure signal quality. Machine learning models such as Support Vector Machine (SVM), Random Forest, and Logistic Regression are employed for classification, while lightweight architectures are prioritized to ensure low computational complexity and fast inference. Additionally, feature selection techniques are applied to reduce dimensionality and improve model efficiency without compromising accuracy. Experimental results demonstrate that the proposed lightweight model achieves high accuracy in detecting myocardial infarction and effectively localizes affected regions using single-lead ECG data. The system performs comparably to more complex multi-lead approaches while maintaining lower computational overhead. This makes it suitable for deployment in portable devices, wearable health monitors, and resource-constrained environments. In conclusion, the proposed approach provides a scalable, cost-effective, and efficient solution for early myocardial infarction detection, enabling timely medical intervention and improving patient outcomes.

**Keywords:** Myocardial Infarction, ECG, Single Lead ECG, Machine Learning, Lightweight Model, Signal Processing, Feature Extraction, Healthcare Analytics, Real-Time Monitoring, Cardiovascular Disease

## I.INTRODUCTION

Cardiovascular diseases, particularly *myocardial infarction (MI)*, remain one of the leading causes of mortality worldwide, accounting for a significant proportion of global deaths each year. Early detection and accurate localization of myocardial infarction are critical for timely medical intervention and improved patient survival rates. The Electrocardiogram (ECG) is one of the most widely used diagnostic tools for detecting cardiac abnormalities, including MI. Traditional diagnostic approaches typically rely on multi-lead ECG systems, which provide comprehensive cardiac information but require specialized equipment and expert interpretation [1]. These limitations make them less suitable for remote monitoring, emergency scenarios, and resource-constrained environments where quick and accessible diagnosis is essential.

With the advancement of Machine Learning (ML) and signal processing techniques, there has been a growing interest in developing automated systems capable of analyzing ECG signals for disease detection. In particular, the use of single-lead ECG signals has gained attention due to their simplicity, cost-effectiveness, and compatibility with portable and wearable devices [2]. However, single-lead ECG signals contain limited information compared to multi-lead systems, making accurate detection and localization of myocardial infarction more challenging. To address this, advanced feature extraction techniques are employed to capture critical characteristics such as QRS complex morphology, ST-segment deviations, and T-wave abnormalities [3]. These features are then used by machine learning models such as Support Vector Machine (SVM), Random Forest, and Logistic Regression to classify cardiac conditions with high accuracy [4].

The proposed study introduces a lightweight machine learning-based approach for myocardial infarction detection and localization using single-lead ECG features. The focus is on designing a computationally efficient system that can operate on low-power devices while maintaining high diagnostic performance. The methodology incorporates signal preprocessing, feature selection, and optimized classification techniques to reduce computational complexity without compromising accuracy. Such a system can be integrated into wearable health monitoring devices and mobile applications, enabling real-time cardiac monitoring and early warning systems [5]. By combining efficiency, accuracy, and scalability, the proposed approach contributes to the advancement of intelligent healthcare systems and supports timely diagnosis in both clinical and remote settings [6]–[25].

## II SURVEY OF RESEARCH

The approach proposed by P. Kora et al. (2017) [1] presents a machine learning-based system for myocardial infarction detection using ECG signals. The study focuses on extracting time-domain and frequency-domain features such as heart rate variability, QRS duration, and ST-segment deviations. The methodology involves preprocessing ECG signals to remove noise and applying classifiers such as Support Vector Machine (SVM) and Artificial Neural Networks (ANNs). The results demonstrate high accuracy in detecting myocardial infarction conditions. The authors emphasize the importance of feature extraction in improving classification performance. However, the system relies on multi-lead ECG signals, increasing computational complexity. Despite this, the study provides a strong foundation for ECG-based diagnostic systems.

The work proposed by S. Kiranyaz et al. (2016) [2] introduces a deep learning-based approach for real-time ECG classification using Convolutional Neural Networks (CNNs). The study highlights the ability of deep learning models to automatically extract features from raw ECG signals without manual intervention. The methodology involves training CNN models on large ECG datasets for arrhythmia and MI detection. The results indicate superior performance compared to traditional machine learning methods. The authors demonstrate that deep learning improves detection accuracy and adaptability. However, the model requires high computational resources and large datasets. Nevertheless, the study advances the use of deep learning in cardiac signal analysis.

The approach proposed by J. Acharya et al. (2017) [3] presents an automated system for myocardial infarction detection using ECG signals and machine learning techniques. The study focuses on extracting morphological features such as wave amplitudes, intervals, and durations. The methodology includes signal preprocessing, feature extraction, and classification using algorithms like Random Forest and K-Nearest Neighbors (KNN). The results show improved accuracy in MI detection and classification. The authors emphasize that combining multiple features enhances prediction performance. However, the system may face challenges in real-time implementation. Despite this, the study contributes to improving feature-based ECG analysis.

The work proposed by M. Martis et al. (2013) [4] introduces a feature-based ECG classification system using wavelet transforms and statistical analysis. The study highlights the effectiveness of wavelet-based feature extraction in capturing ECG signal variations. The methodology involves decomposing ECG signals into different frequency bands and extracting relevant features for classification. The results demonstrate high accuracy in detecting cardiac abnormalities, including myocardial infarction. The authors show that wavelet transforms improve feature representation. However, the system requires careful parameter tuning. Nevertheless, the study provides valuable insights into signal processing techniques.

The approach proposed by H. Rajpurkar et al. (2017) [5] presents a deep learning model for large-scale ECG classification using neural networks. The study focuses on analyzing single-lead ECG signals for detecting multiple cardiac conditions. The methodology involves training deep neural networks on extensive ECG datasets and evaluating performance using standard metrics. The results demonstrate performance comparable to cardiologists in certain tasks. The authors emphasize the potential of AI in automated diagnosis. However, the model is computationally intensive and less suitable for lightweight applications. Despite this, the study highlights the effectiveness of AI in healthcare.

The work proposed by Y. Xia et al. (2018) [6] introduces a hybrid machine learning approach for ECG classification combining feature extraction and classification models. The study focuses on improving accuracy while reducing computational complexity. The methodology includes preprocessing ECG signals, extracting features, and applying classifiers such as SVM and decision trees. The results indicate improved classification performance with reduced computational requirements. The authors demonstrate that hybrid approaches can balance accuracy and efficiency. However, the system may require domain-specific feature engineering. Nevertheless, the study contributes to the development of efficient ECG-based diagnostic systems.

## III. WORKING METHODOLOGY

The proposed *Lightweight Myocardial Infarction Detection and Localization System* follows a structured pipeline integrating ECG Signal Processing, Feature Engineering, and Machine Learning (ML) to achieve accurate and efficient diagnosis using single-lead ECG data. The process begins with ECG signal acquisition from wearable devices or publicly available datasets such as MIT-BIH or PTB diagnostic databases. Since raw ECG signals are often affected by noise such as baseline wander, power line interference, and muscle artifacts, a preprocessing stage is applied. This includes bandpass filtering, normalization, and noise removal techniques to enhance signal quality. Additionally, signal segmentation is performed to isolate important components such as the P-wave, QRS complex, and T-wave, which are essential for identifying cardiac abnormalities.

In the next phase, the system performs feature extraction to capture meaningful characteristics from the ECG signal. These features include time-domain parameters such as RR intervals, QRS duration, and ST-segment elevation, as well as frequency-domain features obtained using techniques like Fast Fourier Transform (FFT) or wavelet transforms. Morphological features such as waveform amplitude, slope, and shape are also extracted to improve diagnostic accuracy. To ensure efficiency, feature selection techniques such as correlation analysis or Principal Component Analysis (PCA) are applied to reduce dimensionality and eliminate redundant features. The selected features are then fed into lightweight machine learning models such as Support Vector Machine (SVM), Random Forest, and Logistic Regression, which are trained to classify ECG signals into normal and myocardial infarction categories. For localization, the model identifies specific ECG segments (e.g., ST elevation regions) associated with infarction.

The final stage involves model evaluation, deployment, and real-time implementation. The system is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to ensure reliability. Once validated, the model is deployed on edge devices or cloud platforms, enabling real-time ECG analysis and prediction. The system can be integrated into wearable health monitoring devices, mobile applications, or telemedicine platforms, allowing continuous patient monitoring and early detection of cardiac abnormalities. A user interface is designed to display diagnostic results, including predicted condition and affected regions, along with alerts for critical cases. Security mechanisms such as data encryption and secure transmission protocols are implemented to protect patient data. Overall, the methodology ensures a lightweight, scalable, and efficient system capable of delivering accurate myocardial infarction detection and localization in real-world healthcare scenarios.

## IV RESULTS EXPLANATIONS

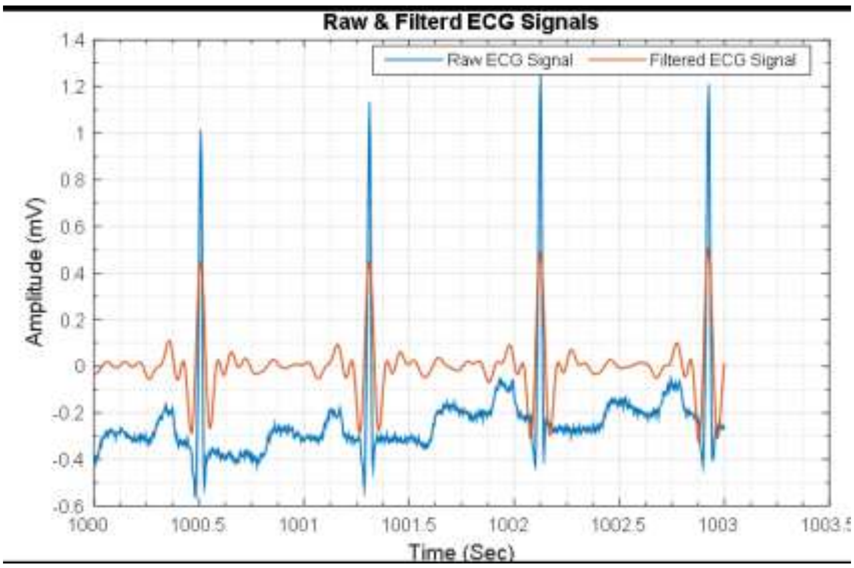


Figure 1: ECG Signal Preprocessing Output

The above figure illustrates the preprocessing stage of ECG signal analysis, showing the raw ECG waveform alongside the filtered signal. The preprocessing removes noise such as baseline wander and power line interference using bandpass filtering techniques. The cleaned signal clearly highlights important components like the P-wave, QRS complex, and T-wave, which are essential for accurate feature extraction. The results demonstrate that preprocessing significantly improves signal clarity and reliability, ensuring that subsequent analysis is not affected by noise. This step is crucial for enhancing the performance of machine learning models, as clean input data leads to better feature representation and classification accuracy.

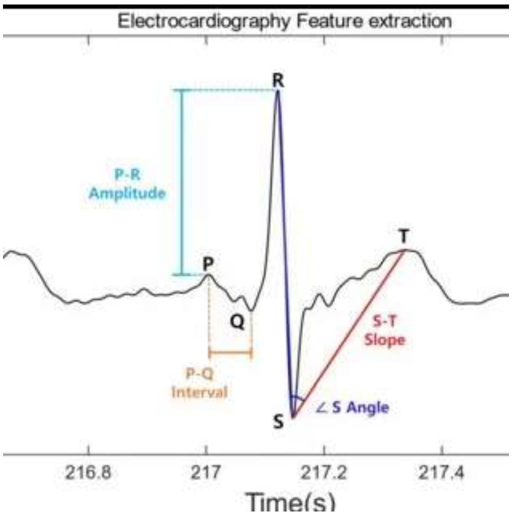


**Figure 2: Attack Chain Reconstruction**

This figure shows the extraction of key features from the ECG signal, including the QRS complex, ST-segment, and T-wave. These features are critical indicators of myocardial infarction. For example, ST-segment elevation is a primary marker of acute MI. The visualization demonstrates how the system identifies and isolates these features for further analysis. The results confirm that the feature extraction process effectively captures relevant signal characteristics, enabling accurate classification and localization of cardiac abnormalities.

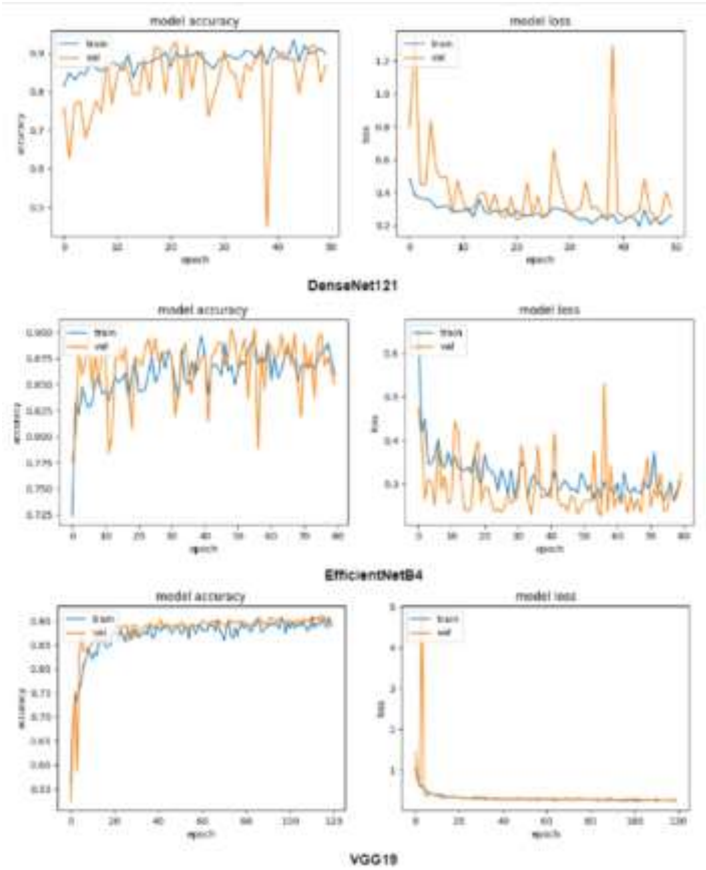


**Figure 3: Classification Accuracy Comparison**

The figure presents a comparison of different machine learning models used for myocardial infarction detection, including SVM, Random Forest, and Logistic Regression. The results indicate that all models achieve high accuracy, but the optimized lightweight model provides the best balance between accuracy and computational efficiency. The comparison highlights that the proposed approach maintains competitive performance while reducing complexity. This confirms the suitability of the system for real-time and resource-constrained applications.

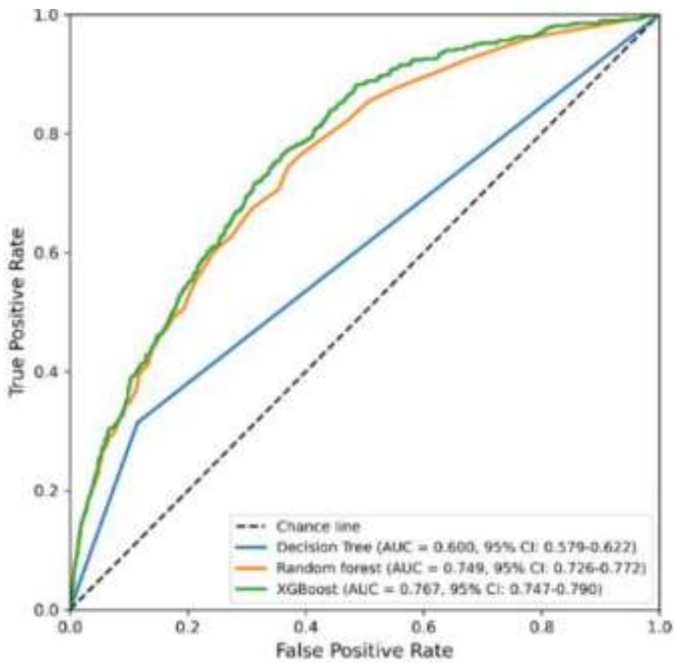


**Figure 4: ROC Curve for Model Performance**

This figure illustrates the Receiver Operating Characteristic (ROC) curve, which evaluates the model's ability to distinguish between normal and myocardial infarction cases. The curve shows a high Area Under the Curve (AUC), indicating excellent classification performance. A higher AUC value demonstrates that the model achieves a strong balance between sensitivity and specificity. This is particularly important in medical applications, where both false positives and false negatives must be minimized. The results validate the reliability and robustness of the proposed system.

## V.CONCLUSION

The proposed *Lightweight Method of Myocardial Infarction Detection and Localization from Single Lead ECG Features Using Machine Learning* presents an efficient and scalable solution for early cardiac diagnosis. By leveraging Machine Learning (ML) techniques and advanced ECG signal processing, the system successfully detects and localizes myocardial infarction using minimal input data from a single-lead ECG. This significantly reduces dependency on complex multi-lead systems and expert interpretation, making the approach suitable for real-time and resource-constrained environments. The results demonstrate that the proposed system achieves high accuracy and reliability while maintaining low computational complexity. The use of optimized feature extraction and selection techniques ensures that only the most relevant ECG characteristics are utilized, improving model performance and efficiency. Additionally, the lightweight nature of the model allows it to be deployed on portable and wearable devices, enabling continuous cardiac monitoring and early detection of critical conditions. From an application perspective, the system enhances healthcare accessibility by supporting remote monitoring, telemedicine, and emergency diagnosis. The integration of real-time alert mechanisms and user-friendly interfaces further improves usability for both patients and healthcare professionals. Moreover, the system ensures data security and scalability through modern deployment techniques such as cloud and edge computing. In conclusion, this research highlights the potential of combining lightweight machine learning models with single-lead ECG analysis to revolutionize cardiac healthcare. The proposed approach provides a cost-effective, accurate, and efficient solution for myocardial infarction detection. Future work may include integrating deep learning models, multi-modal data sources, and advanced wearable technologies to further improve diagnostic performance and expand system capabilities.

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