Grenze International Journal of Engineering and Technology, January Issue

CARDIO ALERT: Proactive Heart Attack Monitoring using Sensors and AI Algorithms

Anjana Krishna V R[1], Anugraha M[2], Arjun CA[3], Bewan Patric[4] and Dhanya S[5]
[1]UG Scholars, FISAT, Cochin, India
[2-5]Dept. of ECE, FISAT, Cochin, India

Abstract— **This study introduces an efficient heart attack detection system that combines ECG monitoring and pulse rate sensors to enhance diagnostic accuracy. Leveraging data from both sources, the system applies machine learning algorithms—including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF)—to classify ECG patterns into normal and myocardial infarction categories. Additionally, an ensemble model integrating these algorithms was developed to further improve prediction performance. The ensemble approach captures complementary strengths from each classifier, resulting in robust and reliable classification outcomes in both training and testing stages. Future implementation of this model on a wearable device aligned with the Internet of Medical Things (IoMT) could enable real-time, continuous health monitoring, providing early alerts for heart attack symptoms and enhancing patient outcomes through proactive care and reduced need for hospital visits. This work demonstrates the potential of machine learning and IoMT-enabled wearables to advance cardiovascular monitoring and support critical, timely interventions**

Index Terms— **Heart attack prediction, Random Forest, KNearest Neighbors, SVM,Machine learning.**

I. Introduction

The identification of heart attacks in younger individuals has become an increasingly important focus within the medical community, as cardiovascular diseases, once thought to primarily affect older adults, are now being detected more frequently among younger populations. A heart attack, medically referred to as myocardial infarction, occurs when the blood supply to a section of the heart muscle is obstructed, leading to tissue damage. In younger demographics, heart attacks are often linked to underlying conditions such as congenital heart defects, high cholesterol levels, smoking, obesity, or the use of certain drugs. Prompt recognition of cardiac events in youth is critical, as symptoms may differ significantly from those experienced by older patients. While chest pain remains a hallmark symptom in adults, younger individuals may present more subtle signs, including shortness of breath, fatigue, or discomfort in the jaw, neck, or arms. Recent advancements in artificial intelligence (AI) and machine learning (ML) have opened new avenues for enhancing the accuracy and efficiency of cardiac diagnostics. These technologies enable the automated analysis of complex ECG waveforms and pulse rate patterns, supporting early and accurate detection of myocardial infarction with minimal reliance on manual interpretation. The integration of a pulse rate sensor alongside ECG monitoring further improves diagnostic accuracy by providing complementary physiological insights, such as real-time heart rate variability and circulatory response.

Grenze ID: 01.GIJET.12.1.588

This dual-sensor approach enhances the system's ability to recognize abnormal cardiac events, particularly in ambiguous or early-stage cases. In this work, we propose the development of an embedded system that integrates both ECG and pulse rate sensors to facilitate continuous monitoring, early detection, and timely alerting of potential heart attacks. Designed to be compact, portable, and suitable for wearable deployment, the system aims to empower individuals—especially those at higher risk—with proactive cardiac health monitoring, even outside of clinical settings. The remainder of this paper is organized as follows: Section II reviews relevant literature and recent advancements in ECG-based heart attack detection. Section III outlines the methodology used for system design, sensor integration, classification using ensemble machine learning. Section IV presents the experimental results, performance analysis, and discussion. Finally, Section V concludes the study and suggests potential directions for future work, including clinical validation and real-time deployment enhancements.

II. Related Works

T. DivyaSree et.al in [1], presents an efficient approach to monitoring cardiac activity through the AD8232 chip. This technology captures and processes the heart's electrical signals to track heart rate and detect abnormalities. The paper highlights potential applications in remote patient monitoring and early detection of cardiac issues. The AD8232 chip offers several advantages, such as compact size, high performance, ease of integration, and cost-effectiveness, making it suitable for portable healthcare devices and heart attack detection systems. Arun Prasath et.al in [2], explores the use of IoT (Internet of Things) technology to create a system for heart rate monitoring using pulse sensor. The system utilizes cloud computing for data storage, processing, and analysis, making it scalable and accessible. The authors highlight the future potential for wearable devices that provide continuous monitoring, as well as the integration of telemedicine platforms for remote consultations and diagnoses. Key advantages of this system include early detection of cardiac abnormalities and an alert mechanism designed to notify emergency services promptly. In [3], Srinivasa Reddy Dasarapalli et.al focuses on utilizing signal processing techniques to extract features from ECG signals, followed by machine learning algorithms for accurate diagnosis. The future scope of this research includes developing real-time detection systems and exploring artificial intelligence integration for wearable devices that provide continuous monitoring. This system offers several advantages, including improved efficiency, enhanced accessibility, and robust performance in diagnosing heart disorders. Gnaneswari G. et.al in [4] highlights the use of data analytics and machine learning applications in healthcare to enhance heart disease diagnosis. The paper explores the future scope of developing real-time monitoring devices that enable early detection and timely intervention. Additionally, the author discusses the potential for improving predictive models to provide accurate and timely heart attack predictions. Key advantages of this approach include early prediction of heart attacks, reduced healthcare costs, and improved accessibility to healthcare services. The studies conducted in [5], details the potential of deep learnng techniques in diagnosing cardiovascular diseases (CVDs) such as congestive heart failure (CHF), coronary artery disease (CAD), and myocardial infarction (MI) using electrocardiogram (ECG) signals and echocardiogram (ECHO) images, with high accuracy and reliability. An open-source algorithm for classifying ECG images using a fine-tuned InceptionV3 model was adopted in [6]. In [7], a system is designed to monitor a person's heartbeat and send alerts if the heartbeat crosses the set limit, aiming to detect heart attacks, utilizing a heartbeat sensor, microcontroller, and GSM. The study conducted in [8] is an initial trial of a three-lead wearable electrocardiogram (ECG) monitoring device during a full marathon, demonstrating its potential for preventing sudden cardiac arrest during short-term exercise and homebased cardiac rehabilitation.In [9] the paper proposed M2ECG, a deep learning-based method to estimate ECG signals from wearable mechanocardiogram (MCG) data, enabling continuous and non-invasive heart monitoring.In [10] This involves developing a wearable multi-sensor system capable of realtime cardiovascular health monitoring by integrating multiple biosignals for early detection of cardiac abnormalities. Uchiyama et al. [11] proposed a deep learning-based approach using an end-to-end convolutional neural network on 12-lead ECG image data from the PTB Diagnostic ECG Database, achieving an impressive accuracy of 99.82% in detecting myocardial infarction. While this method sets a high performance benchmark, it involves considerable computational overhead due to the complexity of deep learning architectures. Likith Reddy et al.'s interpretable multi-channel model (IMLE-Net)[12] achieved a macro ROC-AUC of 0.9216 on PTB-XL with explainable features learned across beat, rhythm, and channel levels. Another recent study employing a hybrid CNN-VAE model[13] reported a 98.51% accuracy with 97.95% F1-score across PTB-XL's 23 classes. Although these models demonstrate superior performance over traditional ensemble methods, their computational demands are considerable, motivating our choice of a lighter ensemble approach that maintains competitive accuracy with significantly lower complexity. We utilize different learning algorithms such as k-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest, which have been widely recognized for their effectiveness in classification tasks. These algorithms are applied to datasets containing two distinct classes: normal and abnormal, where the abnormal class includes cases of myocardial infarction and other heart-related issues. By comparing the performance of these algorithms, we aim to identify the most suitable model for early detection of heart abnormalities. Our approach involves integrating various sensors to collect real-time ECG data, which is then processed and analysed using the aforementioned learning models. The goal is to predict the onset of heart conditions, providing timely alerts that could potentially save lives. This paper presents a comprehensive comparison of these algorithms, discussing their strengths and limitations in the context of ECG signal analysis, and highlights the potential for different learning methods to revolutionize the field of cardiac health monitoring. Our ensemble-based method (KNN, SVM, RF) aims to achieve competitive accuracy with significantly reduced computational cost, making it more suitable for resource-constrained and realtime applications.

III. METHODOLOGY

The methodology for ECG signal classification involves multiple stages, beginning with data preprocessing, where ECG data is collected from publicly available datasets and segmented into two classes: normal and abnormal (myocardial infarction). Data cleaning is conducted to address missing values, outliers, and inconsistencies, thereby ensuring that the dataset is organized and trustworthy. Feature extraction is then carried out using signal processing techniques to identify key ECG characteristics such as heart rate, peak amplitudes, QRS complex intervals, and waveform morphology, which are essential for accurate classification. Machine learning models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF), are employed to classify ECG signals. KNN, a non-parametric algorithm, categorizes data based on the similarity of data points, with the optimal value of K determined to balance accuracy and computational efficiency. SVM, a supervised learning algorithm, utilizes a radial basis function (RBF) kernel to handle non-linear ECG data separation, making it effective for detecting heart abnormalities. Random Forest, an ensemble of decision trees, aggregates results from multiple trees to enhance classification robustness and reduce the risk of overfitting. To further improve accuracy and reliability, an ensemble learning approach is implemented by combining KNN, SVM, and RF using techniques such as soft voting and stacking. This integration leverages the strengths of each model, enhancing adaptability to varying ECG signal patterns and reducing misclassification rates. The models are then evaluated using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to assess their effectiveness. By following this structured approach, the methodology ensures an efficient and reliable classification of ECG signals, contributing to improved detection of myocardial infarction and better healthcare outcomes.

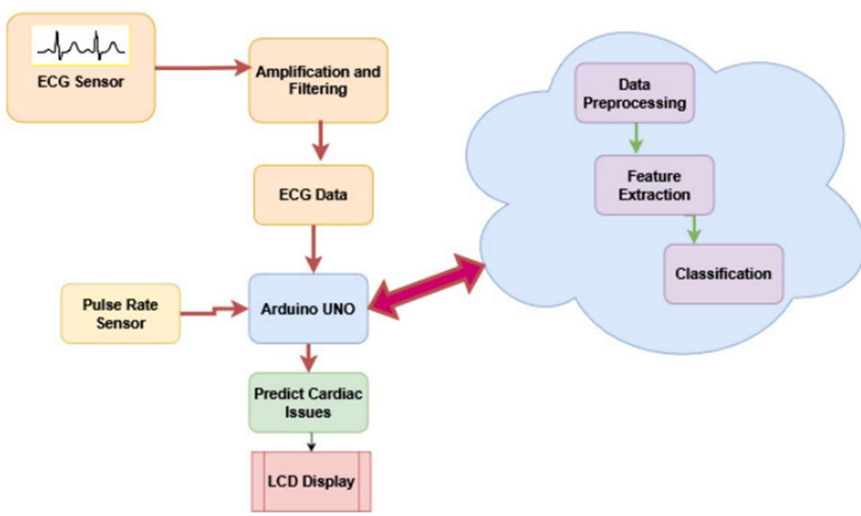

Fig. 1. Block diagram for ECG Monitoring system.

The AD8232 is a compact ECG sensor widely utilized for monitoring heart activity, particularly in portable devices. In a standard three-lead configuration, the electrodes are connected to the right arm, left arm, and right leg, with the final lead serving as a reference ground. This setup minimizes distortion, providing a clearer representation of the heart's electrical activity. This sensor incorporates instrumentation amplifiers designed to enhance the available ECG signals while employing filters to eliminate extraneous noise, resulting in clean and interpretable ECG data for subsequent analysis. For the AD8232, heart rate measurement is linked to the assessment of the R-wave within the QRS complex. The calculation of heart rate can be executed efficiently by determining the intervals between R-wave peaks, using the formula: Heart Rate (bpm) = 60 / Average R-R interval (in seconds). This capability allows for real-time heart rate monitoring, which is advantageous from both clinical and personal health management perspectives. An individual's heart function can be tracked using an ECG, which allows for the determination of how the heart muscles contract and relax. When looking at an electrocardiogram, three essential waves can be noted: atrial depolarization is captured by the P-wave, ventricular depolarization is marked by the QRS complex, and the Twave shows the process of their repolarization.

For most ECG readings, the measured amplitude ranges between 0.5 mV and 3mV, with a frequency range of 0.05Hz to 100Hz. To enhance reliability in heart attack detection, a pulse rate sensor is employed alongside ECG monitoring. The AD8232 ECG sensor is a compact and efficient module designed to monitor the electrical activity of the heart, referred to as an electrocardiogram (ECG). It detects the heart's subtle electrical signals via three electrodes placed on the body. These signals are subsequently amplified and filtered to eliminate any noise, resulting in a precise analog ECG output. This sensor is frequently utilized in health monitoring and diagnostic equipment due to its ability to deliver accurate and comprehensive information regarding heart function. Its small form factor and low power requirements render it ideal for wearable technology and ongoing heart monitoring applications.

This dual approach leverages ECG data to monitor electrical heart activity, while the pulse rate sensor provides real-time information on blood flow and heart rate variability. By integrating data from both sources, the detection system can identify irregular patterns more accurately, offering a more comprehensive view of cardiac health and improving early detection rates.

Algorithm**:** Heart Attack prediction using various algorithm

Initialization**:**

Load ECG datasets

Preprocessing:

The ECG data is sourced from datasets that are publicly available, and where it is split into "normal" and "abnormal" (myocardial infarction) classes, and suitable for cleaning and accuracy purposes. In order to classify the data, the signal processing methods are then used to extract the relevant features; heart rate, peak amplitude and QRS intervals.

Model Training using KNN**:**

KNN is a basic, non-parametric algorithm that classifies data by similarity. KNN can handle small datasets fairly well and since it is memorization-based, on a large dataset it can be very slow. Classification accuracy in KNN depends on an appropriate selection of K value.

Model Training using SVM**:**

SVM is a supervised algorithm that employs an RBF(radial basis function) kernel to distinguish non-linear ECG data by searching for an optimal hyperplane. SVM performs adequately in both binary and high-dimensional classifications but must be carefully adjusted to avoid overfitting when it encounters data with noise.

Model Training using Random Forest:

Random Forest (RF) is an ensemble method that builds multiple decision trees from random data subsets of the training dataset and then uses majority voting to classify an ECG. It has shown high accuracy, robustness, and it is better than using a single decision tree, but its interpretability is less than that of other, simpler models.

Model Training using Ensemble method:

Ensemble methods involve combining multiple base models to achieve improved predictive performance over individual models. The effectiveness of ensemble methods is, in part, a function of the diversity between the models and utilizes techniques such as majority voting for classification and averaging for regression.

Evaluation:

Compute Accuracy, Precision, Recall, and F1-score.

Output**:**

Display predicted rating and success category.

IV. RESULTS AND DISCUSSION

The PTBDB ECG dataset available on Kaggle [14], serves as a valuable resource for identifying patients involved in heartattack research conducted by my organization. This dataset is primarily categorized into two classes: normal and myocardial infarction. It is further segmented into training datasets and test samples, each containing ECG data labeled accordingly. The study population comprises 8,405 cases of myocardial infarction and 3,238 normal cases, which are utilized to train a machine learning model aimed at differentiating between heart attacks and normal heart conditions. Additionally, the test set includes 2,101 cases of myocardial infarction and 808 normal cases, providing a means to evaluate the model's predictive accuracy on previously unseen data. Both datasets are skewed towards myocardial infarction cases, aligning with the study's objective of developing an automated diagnostic system based on ECG signals. In this research, we concentrated on identifying irregularities in cardiac activity by utilizing data from heart rate sensors and ECG signals, which were analyzed through various machine learning techniques. Initially, the output from the heart rate sensor was examined against a predetermined threshold to identify potential heart irregularities, such as arrhythmias or abnormal heart rhythms. This initial analysis enabled us to highlight any atypical heart rates that might suggest an underlying cardiac condition. Subsequently, the ECG signals were evaluated using three distinct machine learning algorithms: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest. Each algorithm was employed to classify the ECG data and assess the risk of a heart attack or the presence of abnormal heart function.

To evaluate the efficacy of these algorithms, we employed a range of assessment metrics, including accuracy, precision, recall, F1 score, and the area under the ROC curve (AUC). Confusion matrices were created to illustrate the true positives, false positives, true negatives, and false negatives for each classifier, offering a comprehensive view of the classification performance of each algorithm. ROC curves were utilized to analyze the balance between sensitivity and specificity for each model, while precision-recall curves provided additional insights into the relationship between precision (the ratio of true positives to the total number of positive predictions) and recall (the ratio of true positives to the total number of actual positives). These metrics are crucial for comprehending not only the accuracy of the models but also their ability to maintain a balance between precision and recall, particularly in medical diagnostics where false negatives can lead to serious repercussions.

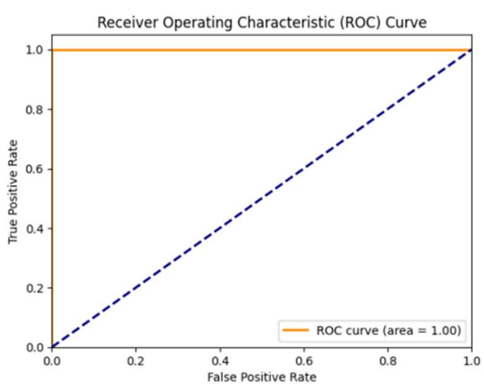

Fig. 2. Training ROC curve using Ensemble Method

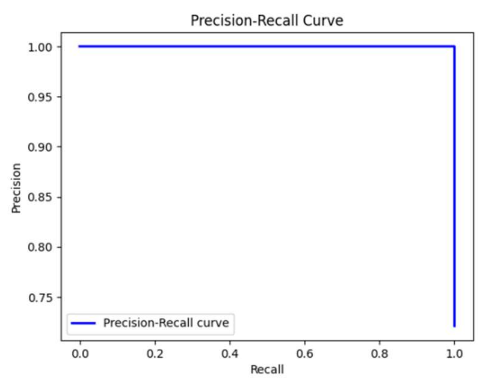

Fig. 3. Precision curve for Ensemble Method

To further enhance prediction accuracy, the KNN, SVM, and Random Forest (RF) algorithms are combined in an ensemble classifier approach. By leveraging the strengths of each method, the ensemble model compensates for individual weaknesses and delivers more robust results. The KNN provides local neighborhood insights, SVM contributes strong boundary-based classification, and RF adds the advantage of aggregating multiple decision trees to minimize overfitting and improve generalization. Figures 2 to 6 illustrate the performance of the ensemble method: Figure 2 shows the training ROC curve, Figure 3 presents the precision curve, Figure 4 displays the confusion matrix, Figure 5 illustrates the recall curve, and Figure 6 shows the F1-score curve. These figures collectively demonstrate that the ensemble classifier achieves higher accuracy, sensitivity, and specificity compared to any single algorithm by integrating diverse patterns and reducing the impact of individual model biases, ultimately leading to more reliable and consistent classification results across both training and testing sets.

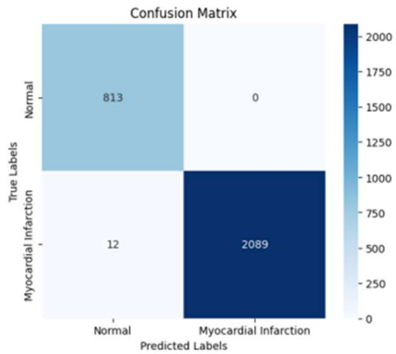

Fig. 4. Confusion matrix for ensemble method

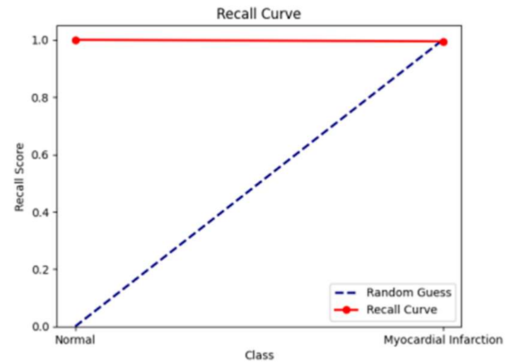

Fig. 5. Recall curve for ensemble method

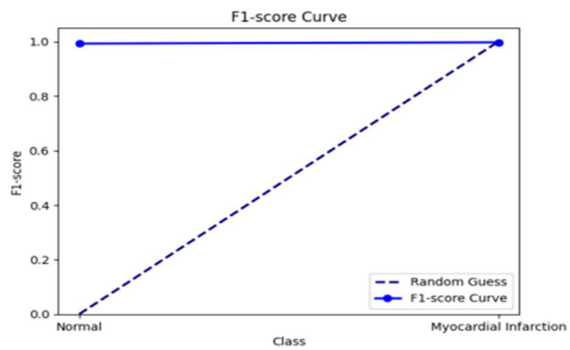

Fig. 6. F1-Score of Ensemble method

TABLE I: PERFORMANCE METRICS OBTAINED FOR DIFFERENT METHODS

Model	Accuracy	Precision	Recall	F1 Score
KNN	0.61	1.00	0.46	0.63
SVM	0.99	0.99	0.99	0.99
Random Forest	0.97	1.00	0.96	0.98
Ensemble method	0.99	0.99	0.99	0.99

TABLE II: PERFORMANCE COMPARISON WITH EXISTING WORKS

Ref paper and Algorithm	Accuracy	Precision	Recall	F1 Score
[15] K-NN	99.74	-	-	99.20
[16] Random Forest	98.00	-	-	-
[17] Ensemble method	98.70	99.00	98.40	-
Our Method	99.00	99.00	99.00	99.00

Table I provides a comparative evaluation of the three algorithms based on the previously discussed performance metrics. Both SVM and the ensemble classifier, which integrates KNN, SVM, and Random Forest, demonstrated superior performance across all metrics, with notable improvements in accuracy, sensitivity, and specificity. This integration yields the highest performance, suggesting the ensemble approach as the optimal choice for reliable classification in this context. To make a final decision, the ECG results are evaluated alongside the pulse rate sensor output. By combining these two sources, the system can assess both electrical heart activity and blood flow characteristics, enhancing the accuracy and reliability of cardiac health monitoring. This integrated approach helps in identifying subtle indicators of irregularities, providing a more comprehensive analysis for effective heart attack detection.

Table II summarizes the performance metrics of selected machine learning algorithms from the referred works identified through the literature review process. These studies were assessed based on their effectiveness in ECG-based cardiac abnormality detection. In particular, the reported results for the K-Nearest Neighbors (K-NN) algorithm showed an accuracy of 99.74% and an F1 Score of 99.20%, serving as strong evidence of its reliability in classification. The ensemble (stacked) method also demonstrated high performance, with an accuracy of 98.70%, balanced with a precision of 99.00% and a recall of 98.40%. On the other hand, the Random Forest method achieved a decent accuracy of 98.00%, though it lacked detailed performance metrics in the referred work. Based on the findings of these studies and their reported metrics, it is evident that the development of a proposed systemic model for ECG signal classification can be strongly supported and justified.

V. Conclusion and Future Scope

In this work, we developed an ensemble-based machine learning model integrating K-Nearest Neighbors, Support Vector Machine, and Random Forest to classify ECG images into two categories: normal and myocardial infarction. The model displayed strong performance, achieving notable accuracy during both training and testing phases. By combining the strengths of these classifiers, the ensemble approach enhances the model's robustness and reliability—key attributes when handling sensitive medical data. This integration enables the model to make more accurate predictions, which is crucial in medical contexts where precision directly impacts patient outcomes. Looking ahead, an exciting avenue for future development involves integrating this ML model into a wearable device capable of continuous real-time ECG monitoring. Such a device could record ECG signals constantly, using the trained model to identify early warning signs of potential abnormalities and alert users to patterns that may indicate heart attack symptoms. This system could alert both the patient and healthcare providers for timely intervention, ultimately enhancing response times and potentially saving lives. This vision aligns with the Internet of Medical Things (IoMT), offering a long-term, non-invasive, and portable solution for cardiovascular monitoring. By enabling seamless, continuous monitoring outside clinical settings, this wearable could enhance early detection, reduce hospital visits, and empower proactive health management. The deployment of this machine learning model on a wearable device would represent a significant step forward in accessible and effective cardiac care.

References

[1] Srinivasa Reddy Dasarapalli; Ramesh Kumar Panneerselvam; Sainadh Annavarapu; KrishnaTeja,Reddy Gopireddy (2023). Three-Lead ECG and Heartrate Variability Using AD8232. IEEE Access, 10, 3168161. doi:10.1109/ICCCNT56998.2023.10306769

[2] T. Arun Prasath; M. Mohamed Arif et.al., " IOT based heart attack detection and heart rate monitoring system".2023 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA) Year: 2023 — Conference Paper — Publisher: IEEE.

[3] Thunga Divya Sree; Raveena Manasi B; Vemuri Sai Rutwik; Thumma Sagar Sahith Reddy; Siddharth Battacharya; Rajesh Kumar M,"Pattern Recognition of ECG Signal to Detect Heart Disorders". 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society Year: 2007 — Conference Paper — Publisher: IEEE

[4] Chusak Thanawattano;Ronachai Pongthornseri;Songphon Dumnin,"Wearable wireless ECG sensor with cross-platform realtime monitoring". 2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences Year: 2012 — Conference Paper — Publisher: IEEE

[5] R. Elshafey, R. Hamila, and F. Bensaali, "Deep learning-based approaches for myocardial infarction detection: A comprehensive review of recent advances and emerging challenges," Medicine in Novel Technology and Devices, vol. 23, Art. no. 100322, doi: 10.1016/j.medntd.2024.100322.

[6] A. M. Gitau, V. Ruto, Y. Njathi, L. Mugambi, V. A. Sitati, and A. Kaburia, "Automated ECG Image Classification with InceptionV3," in Computing in Cardiology 2024, vol. 51, pp. 1–4, Sept. 2024, doi: 10.22489/CinC.2024.498.

[7] A. Patil, S. Sutar, and I. Malwade, "IOT Based Heart Attack Detection and Heart Rate Monitor," Int. J. Res. Appl. Sci. Eng. Technol., vol. 11, no. 6, pp. 430–433, Jun. 2023. [Online]. Available: https://www.ijraset.com.

[8] K. Hirai, N. Sakano, S. Oozawa, D. Ousaka, Y. Kuroko, and S. Kasahara, "Initial trial of three-lead wearable electrocardiogram monitoring in a full marathon," Prog. Pediatr. Cardiol., vol. 69, 2023, Art. no. 101597, doi: 10.1016/j.ppedcard.2023.101597.

[9] A.Tapotee, S.Pal, and A.Ray, "M2ECG: Wearable Mechanocardiograms to Electrocardiogram Estimation Using Deep Learning," IEEE Access, vol. 12, pp. 9000–9012, 2024, doi:10.1109/ACCESS.2024.3353463.

[10] G.J. Garcia, K.Gao, and H.J. Kim, "A Wearable Multi-Sensor System for Real-Time Monitoring of Cardiovascular Health," IEEE J. Biomed. Health Inform., early access, 2023, doi:10.1109/JBHI.2023.3256984.

[11] Uchiyama R, Okada Y, Kakizaki R, Tomioka S. End-to-End Convolutional Neural Network Model to Detect and Localize Myocardial Infarction Using 12-Lead ECG Images without Preprocessing. Bioengineering (Basel). 2022 Sep 1;9(9):430. doi: 10.3390/bioengineering9090430. PMID: 36134976; PMCID: PMC9495488.
[12] L. Reddy, R. Reddy, A. Dandu, M. Mohammed, and K. B. Madhavi, "IMLE-Net: Interpretable Multi-Level and Multi-Channel Deep Neural Network for Electrocardiogram Classification," *arXiv preprint*, arXiv:2204.05116, 2022. [Online]. Available: https://arxiv.org/abs/2204.05116 .
[13] Immaculate Joy Selvam, Moorthi Madhavan, Senthil Kumar Kumarasamy, Detection and classification of electrocardiography using hybrid deep learning models, Hellenic Journal of Cardiology, Volume 81, January–February 2025, Pages 75-84, https://doi.org/10.1016/j.hjc.2024.08.011
[14] https:// https://www.kaggle.com/datasets/harimrai/ptbdb-ecg
[15] M. Anwar, M. Islam, M. A. Rahman, and M. A. H. Akhand, "Lightweight Myocardial Infarction Detection and Localization Using Single-Lead ECG on Low-Power Edge Devices,"IEEE Sensors Letters, vol. 8, no. 3, pp. 1–4, Feb. 2024.DOI: 10.1109/LSENS.2024.3357649.
[16] A. Jahnavi, A. B. Chava, and G. V. Kumari,"Automated Screening of Myocardial Infarction Using Morphology-Based Features From Derived ECG Leads,"in Proc. IEEE EMBC, Jul. 2023, pp. 1–4. DOI: 10.1109/EMBC40787.2023.10342862.
[17] A. Aziz, A. Shahid, and H. Ali,"Spectral Texture-Based ECG Feature Extraction for Detecting Myocardial Infarction Using Machine Learning,"in 2023 6th International Conference on Computing, Communication and Digital Technologies (CCODE), 2023, pp. 879–883.DOI: 10.1109/CCODE56898.2023.10177890