# Heart Disease Prediction Using EfficientNet-B0: A Deep Learning-Based ECG Image Analysis Approach

**Prabakaran S.[1*], Kavitha E.[2], Anusha R.[3], Arun Prasad S.[4]**

[1,3]Research Scholar, [2]Assistant Professor (Sl.Gr), University College of Engineering Villupuram, (A Constituent College of Anna University, Chennai), India.

[4]Assistant Professor, Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), St. Anne's College of Engineering and Technology, Panruti, India.

**E-mail:** [1*]ucevpraba@gmail.com, [2]ekavitharesearch1@gmail.com, [3]anusharamadoss93@gmail.com, [4]arunucev@gmail.com

## Abstract

Autonomous Electrocardiogram (ECG) image classification contributes to the effective detection of cardiac abnormalities and decrease the reliance on manual interpretations. This research study integrates transfer learning and EfficientNet-B0 architecture for the classification of four-class ECG images. In the pre-trained model, the open-source ECG images are pre-processed via image size adjustment, tensor conversion, and channel wise normalization. EfficientNet-B0 architecture combined with the weights obtained via ImageNet training was fine-tuned by enabling a task specific classifier with four output classes and training with cross-entropy loss function and Adam optimizer. The model performance analysis is done in terms of accuracy, precision, recall, F1-score, and confusion matrix analysis. The resultant ECG image classification corresponds to the accuracy of 99.61%. The class-level performance demonstrates high model prediction results. Moreover, the proposed framework performs efficient classification and visualization of individual ECG images.

**Keywords:** EfficientNet-B0, Cardiovascular Disease, Deep Learning, ECG Image Classification, Electrocardiogram, Transfer Learning.

*** Corresponding Author**



*DOI: https://doi.org/10.36548/jucct.2026.3.003*

Extended version of article received from 6th **International Conference on Artificial Intelligence, 6G Communications and Network Technologies 2026**

*Received: 09.05.2026, received in revised form: 14.06.2026, accepted: 04.07.2026, published: 13.07.2026*

## 1. Introduction

Cardiovascular diseases (CVDs) are considered as one of the serious global health problems with high mortality rates. One of the commonly used approaches for the measurement of cardiac electrical activity is electrocardiography (ECG), which gives information about heart rhythm and abnormalities; however, the interpretation of ECG depends on the clinical experience. The use of artificial intelligence (AI) automates the process of ECG analysis with the help of computer-assisted decision-making. The CNNs can detect hierarchical features of ECG images, thereby enabling an analysis of waveforms and rhythm characteristics related to different types of heart diseases.

An efficientNet-b0 based transfer learning architecture is considered in this study to classify the ECG images into four different classes. The ECG images are pre-processed before transferring the data to classifier, where the steps performed include resizing, conversion into tensors, and normalization, followed by data augmentation. The classification layer includes the classifier that has been trained using cross-entropy loss and Adam optimizer. Moreover, the proposed framework infers new ECG images after uploading it into the integrated pipeline for ECG image pre-processing, classification, and visualization of prediction.

The rest of the paper is structured as follows: Section 2 provides for a literature review on the implementation of deep learning in cardiovascular and ECG image analysis; Section 3 describes the proposed approach, starting from data collection and pre-processing, through initialization and EfficientNet-B0 fine-tuning; Section 4 shows the experimental results with the discussion on classification performance metrics, confusion matrix, and ROC analysis; and Section 5 concludes the research study.

## 2. Literature Review

In recent times, artificial intelligence, machine learning and deep learning technologies are widely utilized in cardiovascular disease prediction and clinical decision support systems. Ramesh and Lakshmanna [1] have suggested a novel hybrid deep learning approach with a neural fuzzy inference system for early prediction and prevention of coronary heart disease, showing the possible combination of predictive learning with intelligent decision support techniques. Oyewola et al. [2] have studied ensemble optimization and deep learning approaches to cardiovascular disease diagnosis, highlighting the importance of model integration and optimization in enhancing the predictive capacity of the model. In the same way, Almazroi et al. [5] have developed a new deep learning clinical decision support system for heart disease prediction, and Almulihi et al. [6] have designed an ensemble framework with hybrid deep learning for early prediction. Also, Dubey et al. [7] have studied an optimization-based deep learning approach for heart disease classification, and Omankwu et al. [8] have analysed the use of deep neural network in cardiovascular disease prediction.

Deep learning plays a major role in enhancing the ECG-based predictions and risk assessments. Mayourian et al. [3] proposed an artificial intelligence integrated advanced ECG system capable of predicting mortality in children and adult patients with congenital heart diseases. This work demonstrates the prognostic capacity of deep learning when directly applied to the ECG data. The focus of the research was on the mortality risk prediction rather than multi-class disease classification with good discrimination observed for five years of mortality prediction. Kaur et al. [4] considered different attributes such as race, sex, and age differences in ECG deep learning models for performing heart failure prediction. This study highlights the need to consider not only the accuracy of the model but also its fairness on different demographic groups. Researchers have also focused on a more extensive view on the application of deep learning in medicine, medical imaging, IoT-based medical informatics, and smart healthcare [9], [10], [12].

While considerable advances have been made, current works mostly concentrate on structured clinical data, unidimensional ECG signals, prediction of mortality risk, hybrid deep learning architectures, or complex ensemble models [1] - [8]. Simultaneously, only a minimal research effort has been done on utilizing lightweight transfer learning for multi-class classification of two-dimensional ECG images. The high prevalence of heart disease makes research in the field of AI-powered ECG analysis mostly relevant [11]. For this reason, the current study examines the efficiency of using a pretrained EfficientNet-B0 architecture for multi-class classification of ECG images. In contrast to the current mortality risk prediction systems based on ECG analysis, the proposed system classifies two-dimensional ECG images into several diagnostic classes using pre-processing, transfer learning, and classification.

## 3. Proposed Methodology

This research work proposes a deep learning-based system for multi-class classification of ECG images with the help of a pretrained EfficientNet-B0 model. In particular, the proposed system categorizes ECG images into four classes: Normal, Abnormal Heartbeat, Myocardial Infarction (MI), and History of MI. The collected ECG images [13] are sorted in folders according to their respective classes and loaded via the ImageFolder utility of PyTorch. Before the training procedure starts, all images are resized into 224×224 pixels, transformed into tensors and normalized according to the channels of the pretrained model. Figure 1 presents the entire workflow of the proposed system.

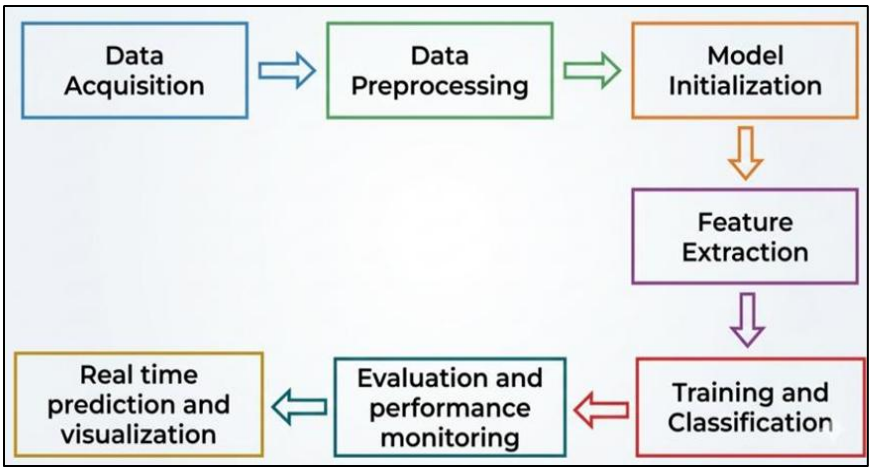


**Figure 1.** Overall workflow of the proposed multi-class ECG image classification

Classification architecture utilizes EfficientNet-B0, which is pretrained on ImageNet and fine-tuned for the task of four-category ECG classification via transfer learning. Original classification layer is substituted by a problem-oriented fully connected layer that has four output nodes corresponding to each disease class. Pre-processed ECG images are then fed through the network architecture EfficientNet-B0 in order to learn the visual features related to waveform morphology and unique image features for each class. Network parameters are trained using the Adam optimizer, and the objective function is defined by the multi-class cross-entropy loss. The loss and accuracy are used for tracking the model performance during the training phase, while the testing on unseen ECG images is done using accuracy, precision, recall, F1-score, confusion matrix, and one-vs-rest ROC-AUC analyses.

### 3.1 Data Collection

ECG image dataset that was utilized in this study comes from the ECG Image Dataset [13]. This dataset is used to train the model to perform multi-class ECG image classification and has four classes: Myocardial Infarction (MI), Abnormal Heartbeat, History of MI, and Normal. Examples of images from these classes are shown in Figure 2 to Figure 5.

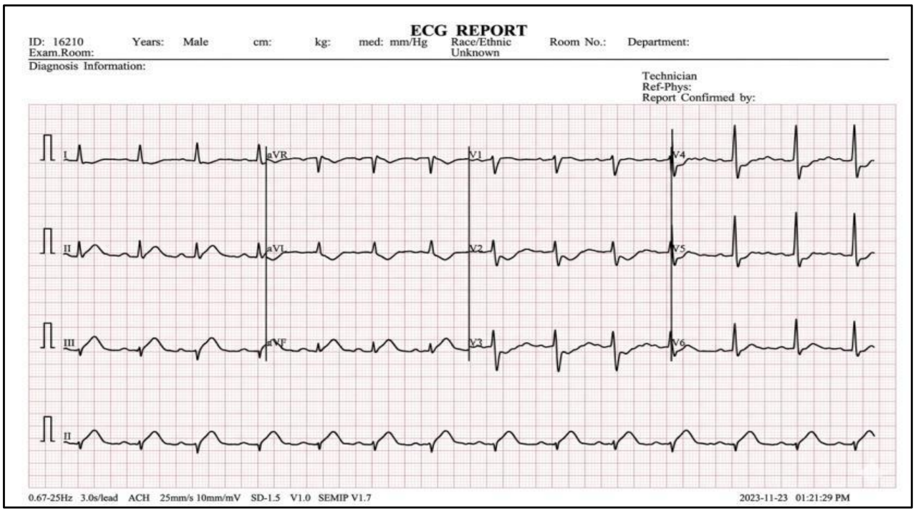


**Figure 2.** ECG image of a myocardial infarction case

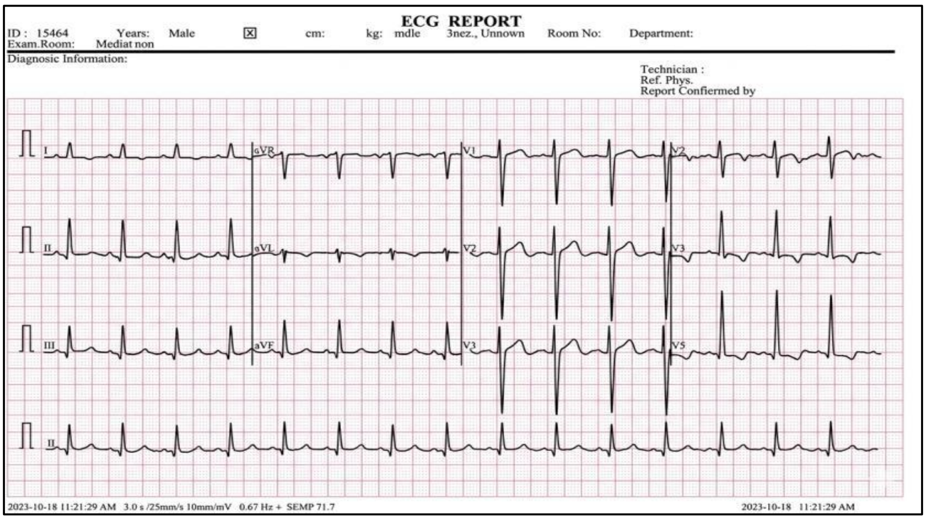


**Figure 3.** ECG image of an abnormal heartbeat case

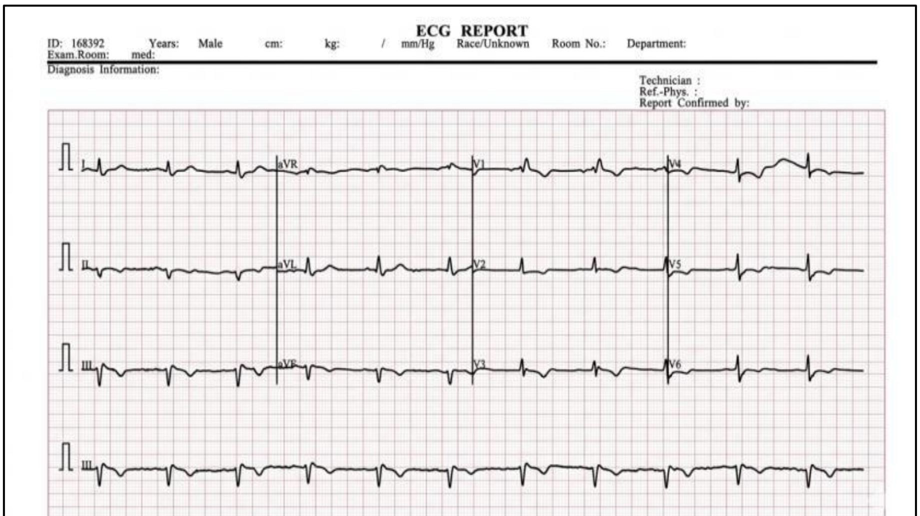


**Figure 4.** ECG image of a patient with a history of myocardial infarction

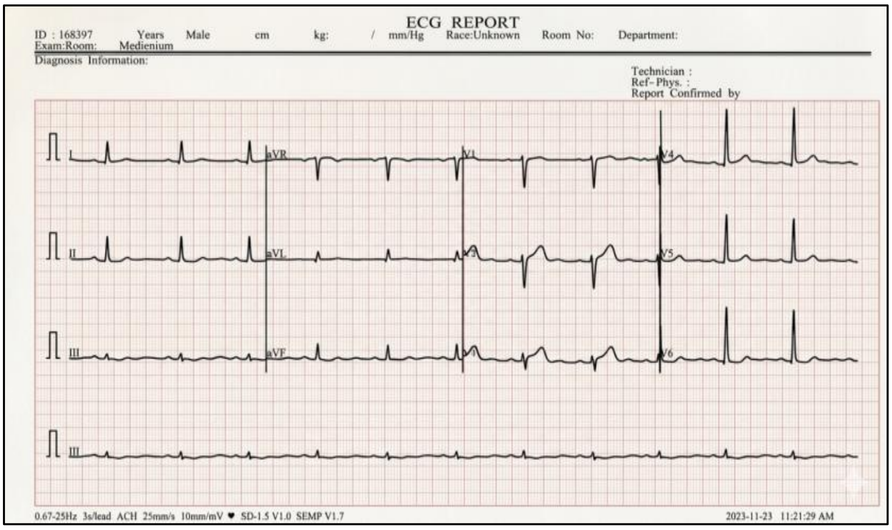


**Figure 5.** ECG image of a normal case

The data is then classified under class-specific folders such that each ECG image can be mapped to its corresponding diagnostic label. Under the adopted architecture, the data was fed to the training process through loading the images using the ImageFolder module from the PyTorch library, which automatically creates the pair of image and labels according to the folder structure and indexes them as integers per class.

### 3.2 Image Preprocessing

Image pre-processing module converts the ECG images to the input format required for EfficientNet-B0 model. The pre-processing steps that have been implemented include the steps of resizing, converting the images to tensors, and perform channel normalization.

#### 3.2.1 Image Resizing

Each ECG image is resized to the input resolution required by EfficientNet-B0:

$$I_r = \text{Resize}(I, 224, 224)$$

where $I$ denotes the original ECG image and $I_r$denotes the resized image with dimensions $224 \times 224$pixels. This operation ensures that every sample has a consistent spatial size before being passed to the network.

#### 3.2.2 Tensor Conversion

After resizing, each ECG image is converted into a PyTorch tensor. For an 8-bit image, the conversion scales each pixel value from $[0, 255]$to $[0, 1]$:

$$X_{c,h,w} = \frac{I_r(h, w, c)}{255}$$

where $c$ represents the color channel and $h, w$ represent the spatial coordinates. The resulting input tensor has the form:

$$X \in \mathbb{R}^{3\times224\times224}$$

This formula is more specific than the generic statement ToTensor(Ioriginal) because it directly describes the numerical transformation performed on the ECG image.

### 3.2.3 Channel-Wise Normalization

The tensor is normalized using the channel statistics associated with ImageNet-pretrained models:

$$\hat{X}_c = \frac{X_c - \mu_c}{\sigma_c}$$

with

$$\mu = (0.485, 0.456, 0.406)$$

and

$$\sigma = (0.229, 0.224, 0.225)$$

for the red, green, and blue channels, respectively. The normalized tensor $\hat{X}$ is used as input to EfficientNet-B0.

## 3.3 EfficientNet-B0 Model Initialization

The Model Initialization Module utilizes an existing EfficientNet-B0 network and trains it for classifying four types of ECG images. The model is initialized using ImageNet pre-trained weights to enable feature extraction and establish a learned visual representation.

The initial EfficientNet-B0 classifier was designed to classify 1000 ImageNet classes. Hence, the final classification layer is modified by adding a new fully connected layer with four outputs:

$$o = Wz + b,\ W \in \mathbb{R}^{4\times d},\ b \in \mathbb{R}^4$$

Where, $z \in \mathbb{R}^d$ is the feature vector generated by the EfficientNet-B0 backbone and $o \in \mathbb{R}^4$ contains one logit for each ECG category.

### 3.4 Feature Extraction

The feature extraction module employs the EfficientNet-B0 backbone, which is already trained to convert each normalized ECG image into a feature vector. In contrast to defining every convolution using the general CNN equation, the proposed method allows for representing the implemented as:

$$z = f_{\text{EffNet-B0}}(\hat{X}; \theta_f)$$

Where, $\hat{X} \in \mathbb{R}^{3\times224\times224}$ shows the normalized ECG image, $f_{\text{EffNet-B0}}$ denotes the EfficientNet-B0 feature-extraction backbone, $\theta_f$ represents its parameters, and $z$ denotes the extracted feature vector supplied to the task-specific classifier.

### 3.5 ECG Classification and Model Training

The extracted feature vector is passed to the four-output classification layer:

$$o = Wz + b$$

Where,

$$o = [o_1, o_2, o_3, o_4]$$

represents the logits associated with the four ECG categories:

1. Normal
2. Abnormal Heartbeat
3. Myocardial Infarction
4. History of Myocardial Infarction

For inference and probability-based evaluation, the logits are converted into class probabilities using:

$$p_k = \frac{\exp(o_k)}{\sum_{j=1}^{4} \exp(o_j)},\ k \in \{1, 2, 3, 4\}$$

Where, $p_k$ denotes the predicted probability of the $k$-th ECG category.

### 3.5.1 Training Objective

As the task contains four mutually exclusive diagnostic classes, the model is trained using multi-class cross-entropy loss. For a mini-batch containing $B$ECG images, the loss is:

$$\mathcal{L} = -\frac{1}{B}\sum_{n=1}^{B}\log\left(\frac{\exp\left(o_{n,y_n}\right)}{\sum_{j=1}^{4}\exp\left(o_{n,j}\right)}\right)$$

Where, $B$is the mini-batch size, $y_n$is the ground-truth class index of sample $n$, $o_{n,y_n}$is the logit assigned to the correct class, and $o_{n,j}$is the logit for class $j$.

### 3.5.2 Parameter Optimization

The model parameters are optimized and updated using the Adam optimizer. Instead of incorrectly representing Adam as ordinary gradient descent, the update is written as:

$$g_t = \nabla_\theta \mathcal{L}_t$$
$$m_t = \beta_1 m_{t-1} + (1-\beta_1)g_t$$
$$v_t = \beta_2 v_{t-1} + (1-\beta_2)g_t^2$$

with bias correction:

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t},\ \hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

and parameter update:

$$\theta_t = \theta_{t-1} - \alpha\frac{\widehat{m}_t}{\sqrt{\hat{v}_t}+\varepsilon}$$

Where, $\alpha$represents the learning rate, $g_t$denotes the gradient at iteration $t$, and $m_t$and $v_t$are the first- and second-moment estimates.

## 3.6 Evaluation and Performance Monitoring

After training, the model is evaluated on ECG images. The predicted class for sample $n$is obtained from the largest output logit:

$$\hat{y}_n = \arg\max_{k \in \{1,2,3,4\}} o_{n,k}$$

Overall, the classification accuracy is calculated as:

$$\text{Accuracy} = \frac{1}{N} \sum_{n=1}^{N} \mathbb{1}(\hat{y}_n = y_n)$$

Where, $N$ shows the total number of evaluated ECG images and $\mathbb{1}(\cdot)$equals 1 when the prediction is correct and 0 otherwise.

For each ECG class $k$, precision and recall are computed as:

$$\text{Precision}_k = \frac{TP_k}{TP_k + FP_k}$$

$$\text{Recall}_k = \frac{TP_k}{TP_k + FN_k}$$

and the class-wise F1-score is:

$$F1_k = 2\frac{\text{Precision}_k \text{Recall}_k}{\text{Precision}_k + \text{Recall}_k}$$

Where, $TP_k$, $FP_k$, and $FN_k$denote the true-positive, false-positive, and false-negative counts for class $k$, respectively. A confusion matrix is additionally used to examine class-specific prediction errors.

### 3.7 Real-Time Prediction and Visualization

The Single-Image Prediction Module applies the trained EfficientNet-B0 model to a newly uploaded ECG image. After preprocessing, the image is expanded with a batch dimension:

$$X_{\text{test}} \in \mathbb{R}^{1 \times 3 \times 224 \times 224}$$

The trained model produces four logits:

$$o = f(X_{\text{test}}; \theta) \in \mathbb{R}^4$$

The final predicted ECG category is:

$$\hat{y} = \arg \max_{k \in \{1,2,3,4\}} o_k$$

If class probabilities are required for display, they are calculated as:

$$p_k = \frac{\exp(o_k)}{\sum_{j=1}^{4} \exp\left(o_j\right)}$$

The predicted class label is then displayed together with the uploaded ECG image using Matplotlib.

## 4. Results and Discussion

EfficientNet-B0 model-based architecture was tested on four-class ECG image classification that included Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, and Normal ECG Images. The primary experimental settings are summarized in Table 1.

**Table 1.** Experimental parameters of the ECG classification framework

| Parameter | Specification |
|---|---|
| Dataset | ECG Image Dataset [13] |
| Input Data Type | 2D ECG images |
| Number of Classes | 4 |
| Model Architecture | EfficientNet-B0 |
| Input Image Size | 224 × 224 pixels* |
| Input Channels | 3 (RGB) |
| Tensor Pixel Range | [0, 1] |
| Normalization Mean | [0.485, 0.456, 0.406] |
| Normalization Standard Deviation | [0.229, 0.224, 0.225] |
| Optimizer | Adam |
| Evaluation Samples | 772 images |
| Implementation Framework | PyTorch |
| Visualization Tool | Matplotlib |

In total, 772 ECG images were used to test the model. Input examples are shown in Figure 6. Figure 7 presents an example of the dataset loading and batch processing used.

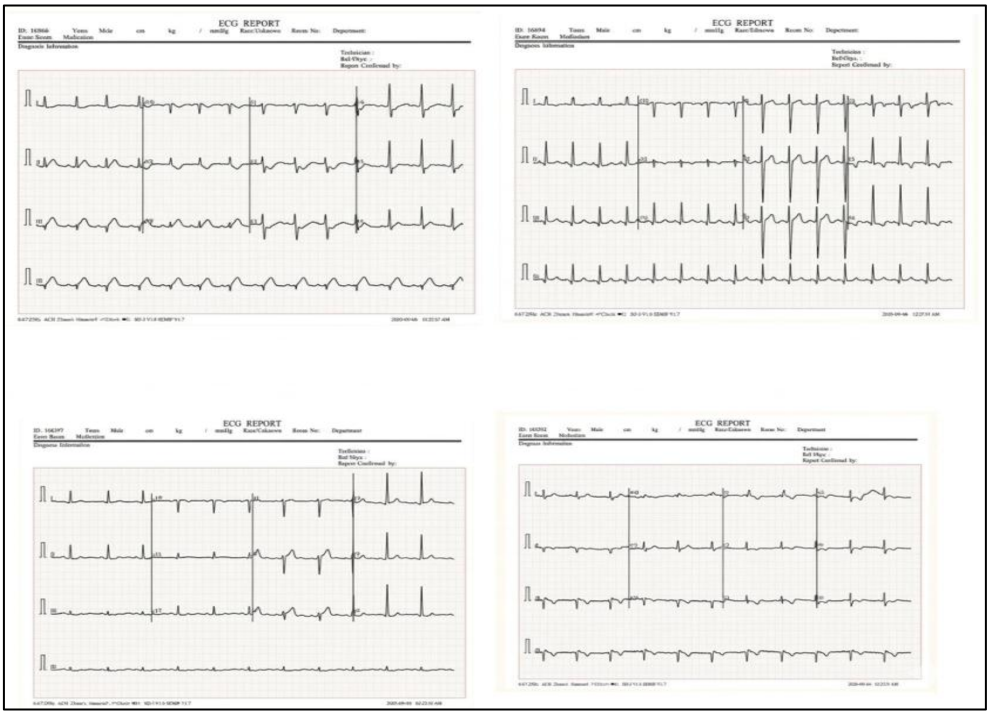


**Figure 6.** Input ECG images from the four diagnostic categories

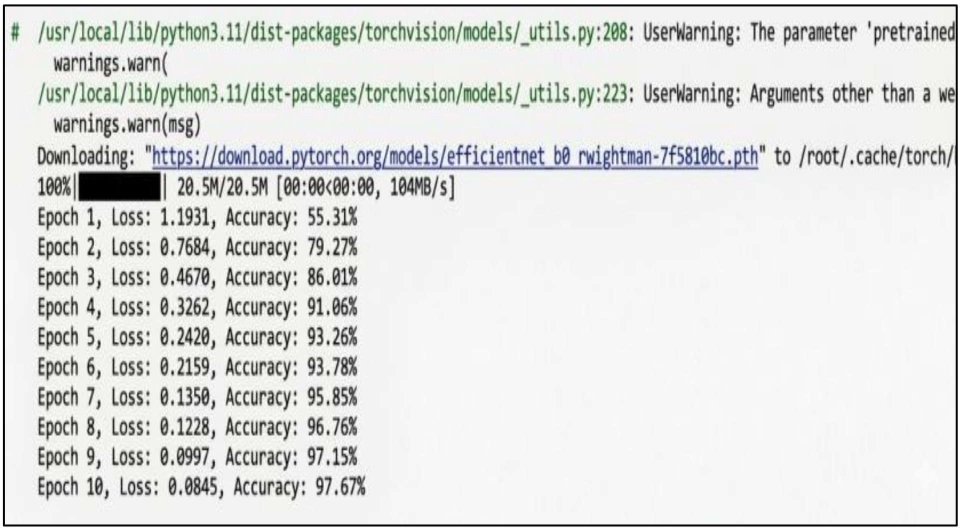


**Figure 7.** ECG dataset loading and model training progress

**Table 2.** Classification performance of the EfficientNet-B0 model

| ECG Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Myocardial Infarction | 1 | 1 | 1 | 200 |
| History of MI | 0.99 | 1 | 1 | 172 |

| | | | | |
|---|---|---|---|---|
| Abnormal Heartbeat | 1 | 0.99 | 0.99 | 200 |
| Normal | 1 | 1 | 1 | 200 |
| Accuracy - 0.9961 | | | | 772 |

Table 2 shows the classification accuracy of the suggested EfficientNet-B0 algorithm for the four categories of ECG classification. The proposed solution managed to classify 769 out of 772 test images, thus providing 99.61% accuracy. The near-perfect precision, recall, and F1-score scores have been obtained for all four classes except for the Abnormal Heartbeat one.

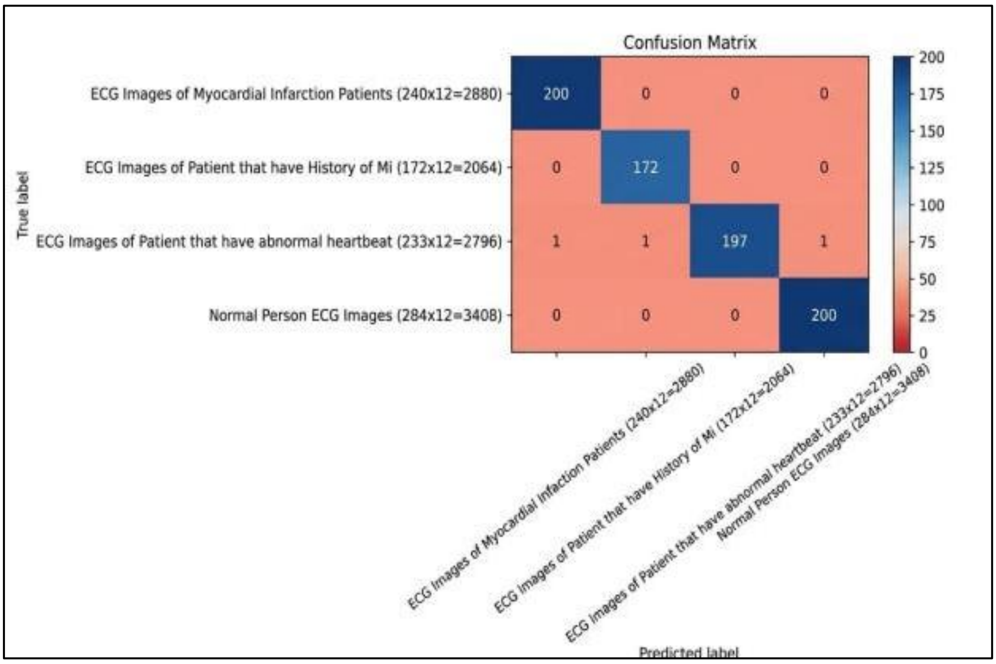


**Figure 8.** Confusion matrix of the proposed EfficientNet-B0 model

As seen from the confusion matrix shown in Figure 8, an analysis of the classification errors is provided. All the 200 Myocardial Infarction instances, 172 History of MI instances, as well as 200 Normal instances have been correctly classified. Out of the 200 Abnormal Heartbeat instances, only 197 were accurately classified, while the remaining three were placed into different classes.

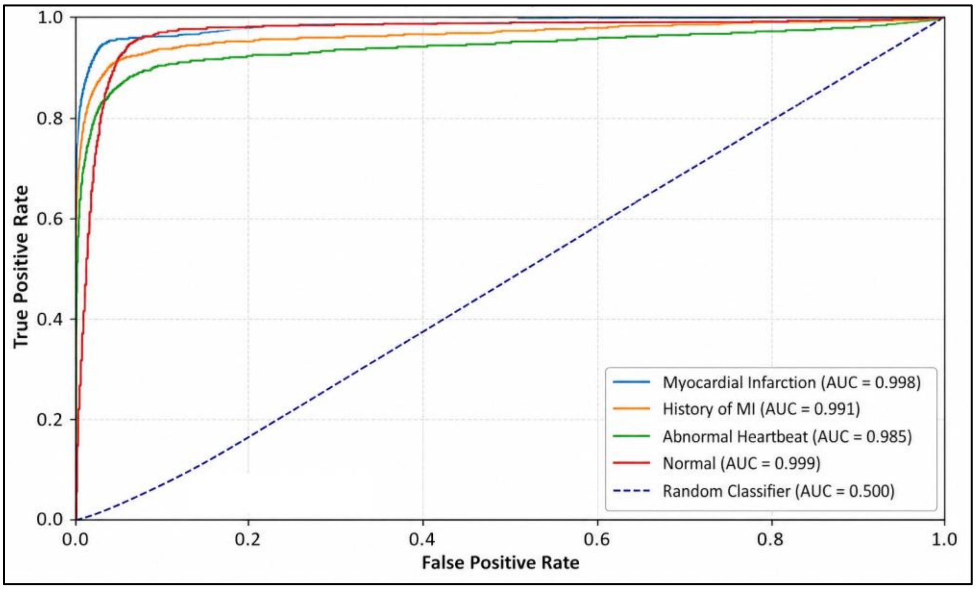


**Figure 9.** ROC curves of the proposed EfficientNet-B0 model

Moreover, the class-wise discrimination ability of the suggested EfficientNet-B0 framework is tested by the ROC-AUC test shown in Figure 9 by changing the decision thresholds. The obtained AUC scores for the classes are the following: 0.998 for Myocardial Infarction, 0.991 for History of MI, 0.985 for Abnormal Heartbeat, and 0.999 for Normal ECG images, wherein the relatively lower AUC score for Abnormal Heartbeat is related to the class with which the classification errors occurred. Along with the overall 99.61% accuracy, perfect class-wise precision, recall, and F1-scores, as well as confusion matrix scores, the ROC-AUC scores suggest good performance of the tested framework. However, additional research should be done to validate the framework externally.

## 5. Conclusion

In this research, a transfer learning approach using EfficientNet-B0 has been developed for the classification of ECG images in four different classes, namely: Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, and Normal. In this approach, the image processing and ImageNet pre-trained EfficientNet-B0 have been combined with task-specific classification layer. After employing cross-entropy loss and Adam as optimization method, the classifier was able to reach a total accuracy rate of 99.61%. Confusion matrix revealed that there was no problem in the classification of myocardial infarction, history of mi, and normal, but three abnormal heartbeat images were falsely classified. These results showed that the EfficientNet-B0 could be employed for automatic classification of ECG images; nevertheless, the ROC-AUC needs to be validated because the current curves do not coincide with the classification performance.

## References

[1] Ramesh, B., and Kuruva Lakshmanna. "A Novel Early Detection and Prevention of Coronary Heart Disease Framework Using Hybrid Deep Learning Model and Neural Fuzzy Inference System." IEEE Access 2024, vol. 12, 26683-26695.

[2] Oyewola, David Opeoluwa, Emmanuel Gbenga Dada, and Sanjay Misra. "Diagnosis of Cardiovascular Diseases by Ensemble Optimization Deep Learning Techniques." International Journal of Healthcare Information Systems and Informatics (IJHISI) 2024, vol. 19, no. 1, 1-21.

[3] Mayourian, Joshua, Amr El-Bokl, Platon Lukyanenko, William G. La Cava, Tal Geva, Anne Marie Valente, John K. Triedman, and Sunil J. Ghelani. "Electrocardiogram-Based Deep Learning to Predict Mortality in Paediatric and Adult Congenital Heart Disease." European Heart Journal 2025, vol. 46, no. 9, 856-868.

[4] Kaur, Dhamanpreet, J. Weston Hughes, Albert J. Rogers, Guson Kang, Sanjiv M. Narayan, Euan A. Ashley, and Marco V. Perez. "Race, Sex, and Age Disparities in the Performance of ECG Deep Learning Models Predicting Heart Failure." Circulation: Heart Failure 2024, vol. 17, no. 1, e010879.

[5] Almazroi, Abdulwahab Ali, Eman A. Aldhahri, Saba Bashir, and Sufyan Ashfaq. "A Clinical Decision Support System for Heart Disease Prediction Using Deep Learning." IEEE Access 2023, vol. 11, 61646-61659.

[6] Almulihi, Ahmed, Hager Saleh, Ali Mohamed Hussien, Sherif Mostafa, Shaker El-Sappagh, Khaled Alnowaiser, Abdelmgeid A. Ali, and Moatamad Refaat Hassan. "Ensemble Learning Based on Hybrid Deep Learning Model for Heart Disease Early Prediction." Diagnostics 2022, vol. 12, no. 12, 3215.

[7] Dubey, Animesh Kumar, Amit Kumar Sinhal, and Richa Sharma. "Heart Disease Classification Through Crow Intelligence Optimization-Based Deep Learning Approach." International Journal of Information Technology 2024, vol. 16, no. 3, 1815-1830.

[8] Omankwu, Obinnaya CB, M. C. Okoronkwo, and Chigbundu Kanu. "Cardiovascular (Heart) Diseases Prediction Using Deep Learning Neural Network Model." NIPES-Journal of Science and Technology Research 2024, vol. 6, no. 1.

[9] Zhang, Huanhuan, and Yufei Qie. "Applying Deep Learning to Medical Imaging: A Review." Applied Sciences 2023, vol. 13, no. 18, 10521.

[10] Amiri, Zahra, Arash Heidari, Nima Jafari Navimipour, Mansour Esmaeilpour, and Yalda Yazdani. "The Deep Learning Applications in IoT-Based Bio-And Medical Informatics: A Systematic Literature Review." Neural Computing and Applications 2024, vol. 36, no. 11, 5757-5797.

[11] Martin, Seth S., Aaron W. Aday, Norrina B. Allen, Zaid I. Almarzooq, Cheryl AM Anderson, Pankaj Arora, Christy L. Avery "2025 Heart Disease and Stroke Statistics: A Report of US And Global Data from the American Heart Association." Circulation 2025, vol. 151, no. 8, e41-e660.

[12] Rahman, Anichur, Tanoy Debnath, Dipanjali Kundu, Md Saikat Islam Khan, Airin Afroj Aishi, Sadia Sazzad, Mohammad Sayduzzaman, and Shahab S. Band. "Machine Learning and Deep Learning-Based Approach in Smart Healthcare: Recent Advances, Applications, Challenges and Opportunities." AIMS public health 2024, vol. 11, no. 1, 58.

[13] ECG Image [Dataset] - https://www.kaggle.com/datasets/kanishkarathore1604/ecg-image