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Cardiovascular Disease Detection in ECG images using CNN - MobilNet Model

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ABSTRACT

As cardiovascular diseases (CVDs) persist as the world's leading cause of death, a timely and precise diagnosis is crucial. Using electrocardiogram (ECG) measurements, which provide crucial information in this respect, automating the recognition of cardiac disorders has shown enormous promise thanks to neural network methods. The use of a Convolutional Neural Network, also based on the MobileNet model, for identifying the presence of cardiovascular abnormalities from ECG pictures, is looked at in this work. The MobilNet model, well-known for its efficiency and portability, is used to extract high-dimensional features. This makes it possible to classify ECG patterns associated with various heart conditions accurately. When contrasted with conventional techniques, findings from experiments suggest that the recommended approach has been effective in achieving excellent accuracy and adaptability. The proposed approach could assist healthcare professionals in quickly and accurately diagnosing patients, ultimately leading to better patient outcomes.

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1.0 INTRODUCTION

Cardiovascular diseases (CVDs) account for a significant portion of morbidity and mortality globally, highlighting the demand for efficient diagnostic methods. Electrocardiogram (ECG) analysis is essential for detecting cardiac issues since it provides real-time insights into heart function. Clinicians must painstakingly analyse ECGs to interpret them, which may be complex and vulnerable to mistakes. Convolutional neural systems (CNNs), a machine learning algorithm, have become popular for automated ECG categorisation to deal with these problems.

This work recognises heart disease in ECG pictures using the MobilNet theory, a lightweight CNN architecture designed for mobile and integrated sensory workloads. Because they significantly reduce computational costs while maintaining high accuracy, MobilNet's depth-wise separable convolutions are perfect for real-time medical applications. Our recommended approach intends to increase the accuracy of diagnosis and the success rate of ECG monitoring by utilising advanced feature extraction competencies.

The rest of the paper is structured into three main sections: Section III presents the method used. In contrast, Section II quantifies the pertinent research, including the structure of the model and data preparation.

1.1 Basic Concepts

- *Machine Learning:* The study associated with creating models and methods that let computers operate, learn from data, or forecast outcomes without explicit programming is known as machine learning. Algorithmic learning algorithms are crucial to interpreting various medical data in the healthcare setting, including identifying cardiovascular ailments, to aid in diagnosis, prognosis, and treatment determinations.
- *Deep Learning:* Deep neural networks investigate and learn from data using artificial neural networks. Jobs requiring complex feature extraction and pattern recognition are particularly well-suited for them. Deep learning models are valuable resources for early recognition and management of cardiovascular conditions, which might lead to better patient treatment and safer treatment methods.
- *CNN:* CNN stands for convolutional neural network. It is an artificial neural network made especially for handling and interpreting visual input, such as pictures. In a variety of computer vision tasks, CNNs have proven remarkably effective. CNNs have the potential to automatically extract hierarchical features from images and handle complex visual data, which makes them useful for the detection of cardiovascular disease.
- *MobilNet:* MobilNet is a deep learning model intended for embedded and mobile vision applications that is both portable and efficient. It significantly reduces figuring out cost despite retaining superior precision by utilising depth-wise separable convolutions. Unlike traditional CNN designs, MobilNet minimises the total quantity of parameters and processes by converting standard convolutions into depth-wise and pointwise convolutions. As a result, it functions well for real-time processing in circumstances with limited horsepower, such as mobile devices and medical applications.
- *Gridline Removal:* The technique of removing gridlines or other grid artefacts from an image is known as Gridline removal. In image processing, gridlines refer to undesired patterns, like lines or grids, that arise in images due to different factors such as interference, printing, or scanning. Techniques for removing gridlines from images are used to improve their visual quality by eliminating these unwanted grid patterns. The aim is to create a cleaner and more precise image to facilitate better analysis or presentation.

- *Thresholding:* Thresholding is a fundamental technique in image processing that involves setting an intensity threshold and using that threshold to transform an image into a binary (black and white) image. Pixels below the threshold are set to a different colour, usually black, whereas pixels with intensities above the threshold are set to one colour, usually white. This helps draw attention to particular details or objects in a picture by setting them apart from the surrounding area. Thresholding is frequently used to segment images and make additional.
- *Gaussian Filtering:* Gaussian filtering is a common image processing method for noise reduction and smoothing. It operates by applying a Gaussian filter kernel to an image, emphasising pixels at the centre and gradually decreasing the influence of pixels farther away. This weighted averaging effectively blurs the image, reducing high-frequency noise and fine details. The Gaussian filter is beneficial because it preserves edges and important image structures while removing noise.
- *Contour Extraction:* One of the basic image processing techniques is contour extraction, which recognises and extracts an object's boundaries from an image. It involves detecting continuous curves that define the edges or outlines of distinct regions with similar properties, such as intensity or colour. Contour extraction in ECG images helps identify the shape and patterns of the electrical functioning inside the heart, enhancing cardiovascular disease detection.
- *Evaluation Parameters:* Evaluation parameters evaluate the machine learning model's efficiency. Below are the evaluation criteria used in the study, along with their formulas.

  a) *Accuracy:* Accuracy is the most commonly employed performance statistic in machine learning and categorisation applications. The accuracy can be expressed as the number of properly designated predictions divided by the total number of predictions.

  $$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

  b) *Precision:* Precision is an index used to quantify the precision of upbeat tracks performed.

  $$\text{Precision} = \frac{TP}{TP + FP}$$

  c) *Recall:* The fullness of favourable judgments is gauged by recall.

  $$\text{Recall} = \frac{TP}{TP + FN}$$

  d) *F1 Score:* This measure, identified as the F1 score, balances recall and reliability by merging them into a single number.

  $$\text{F1 Score} = 2 \supset \frac{Precision \supset \text{Recall}}{Precision + Recall}$$

  e) *Confusion Matrix:* A confusion matrix is a chart showing a classification model's efficiency. The film provides a summary of the model's accuracy and error types.

  f) *AUC-ROC:* By analysing the area under the contour of the ROC visualisation, the AUC-ROC gauge estimates the model's capacity to discriminate between classes.

  g) *Specificity:* A measure of efficiency labelled specificity evaluates how a model determines adverse examples.

  $$\text{Specificity} = \frac{TN}{TN + FP}$$

1.2 Motivation

Globally, cardiovascular disease is among the most prevalent causes of mortality. Quick recognition of cardiovascular disease can aid in prompt patient diagnosis and care, hence lowering the illness's morbidity and death rate.

1.3 Problem Statement

As cardiovascular diseases (CVDs) continue to be listed among the leading causes of premature death worldwide, immediate and precise testing is vital. Manually interpreting ECG readings is a common component of traditional diagnostic techniques, although it may be laborious and prone to human error. The present research aims to use deep learning techniques, namely a Convolutional Neural Network (CNN) with the MobilNet model, to identify cardiovascular diseases from ECG readings automatically. The proposed method improves efficiency, accuracy, and accessibility in healthcare scenarios.

1.4 Scope

Establishing a computerised way to identify cardiovascular diseases from ECG measurements. Using a CNN-based MobilNet model to extract aspects and categorise ECG data effectively.

1.5 Objectives

The primary objectives are:

- To generate and implement a CNN-MobilNet-inspired deep learning technique for evaluating ECG images.
- To preprocess ECG pictures in order to improve features and reduce noise.
- To use an organised set of cardiovascular illnesses to train the model.
- Standard categorisation measures should be used to review the simulation results.

1.6 Advantages

- The methodology implemented by CNN-MobilNet improves classification accuracy by efficiently capturing complex patterns in Cardiac pictures.
- MobilNet's lightweight design guarantees quicker deployment and processing on devices with limited resources.
- Reduces human error by eliminating the demand for manual ECG interpretation.
- Remote evaluations may be included in telemedicine systems.
- Lessens the need for costly diagnostic equipment and skilled cardiologists.
- Improves patient outcomes by allowing prompt identification and alarms.

2.0 LITERATURE SURVEY

A description of the many studies in the literature that are mentioned is given in this section.

The methodology in (Rath *et al.,* 2022) described that the objective is to detect cardiovascular disease from the ECG signal. The datasets used are MIT-BIH and PTB-ECG. Four ECG readings are analysed using deep learning procedures to detect heart illness. The model with the most remarkable overall performance is merged using an ensemble method known as majority voting. To determine each model's performance on the different datasets, the F1-score and AUC are used as performance metrics. In order to help distant patients, the developed model can also be used with cloud computing and IOT platforms. Larger and unbalanced datasets must be used to validate the proposed model.

Malakouti (2023) described that based on ECG, heart disease is classified using the recommended approach. The suggested model uses Linear Discriminant Analysis, Random Forest, Gaussian NB, Dummy Classifier and Logistic Regression models for machine learning. The MIT-BIH Arrhythmia Database and the Physio Net PTB Diagnostic Electrocardiography Database are the datasets used in the proposed model. A 10-fold cross-validation is used as the validation measure once the model has been trained. The suggested model's evaluation criteria are AUC-ROC, Precision, and Recall. Ten-fold cross-validation assisted the suggested model in resolving the overfitting issue. For the suggested model, the PTB Diagnostic Electrocardiography Database was unsuitable.

The methodology in (Alqahtani *et al.,* 2022) described that the objective is to detect cardiovascular disease. The dataset used is the Cardiovascular Disease Dataset from Kaggle. The Machine Learning models used are XGBoost, KNN, and DT. Deep Learning models used are DNN and KDNN. RF Feature Selection approach is used as a Feature Extraction technique. Pearson's Coefficient is used as an approach for Correlation Analysis. The proposed model used an ensemble model of machine learning algorithms, which allowed the algorithms to demonstrate increased accuracy. The proposed model mentions that deep learning models did not perform well due to limited data.

The methodology in (Yoon and Kang, 2023) described that the proposed model is used with the ECG to 12-lead electrocardiogram (ECG) database, gathered by Shaoxing People's Hospital and Chapman University, is the dataset utilised. The stacking ensemble method's base learner was the ResNet-50 model. By merging the predictions of the base learners, SVM, RF, LR and XGBoost are utilised as meta learners. The multimodality approach gave a more complete picture of the patient's condition, which may have resulted in more precise diagnoses. Overfitting resulted from improper regularisation of the ensemble method.

The methodology in (Abubaker and Babayiğit, 2022) described the objective of using deep learning and machine learning methods for detecting cardiovascular illness in ECG pictures. The transfer learning strategy was examined using AlexNet and SqueezeNet, two low-scale pretrained deep neural networks. Like the max-pooling layer, a pooling layer might downsample the feature map to reduce the computational cost. The dataset contains 928 unique patient records broken down into four classes. Performance analysis employed F1 score, recall, accuracy, and precision. Information loss may occur from cropping the ECG images, which include header and footer data. The final layers must be replaced to adapt the SqueezeNet and AlexNet models to the new task.

The methodology in (Rath *et al.,* 2021) described the objective of using deep learning methods to identify heart illness in imbalanced ECG data. The Generative Adversarial Network model generates and uses additional fake data to detect imbalanced data. When detecting heart illness, the ensemble version of the GAN-LSTM model performed better than the other. The PTB-ECG and MITBIH arrhythmia databases include the ECG signals of many patients. Several ensemble models have been developed to find arrhythmias in various ECG signals. It is possible to identify arrhythmia from the ECG data using the GAN model. A loss of important data could arise from undersampling the majority class, which might impact how well the model generalises to actual situations.

The methodology in (Khan *et al.,* 2021) described the objective of using deep neural networks to classify cardiac disorders through electrocardiogram sensing. An architecture based on SSD MobileNet V2 was used to detect CVD. Subject-matter experts manually collected and annotated 11,148 typical 12-lead ECG images from medical institutions. The four primary cardiac abnormalities were the focus of the investigation. Shown higher accuracy in tasks requiring classification and detection utilising a single lead-based ECG picture compared to traditional 12-lead ECG images, and created a productive automated model to identify cardiac conditions from electrocardiograms. TensorFlow API and Google Colab are used to implement the model. SSD MobileNet V2 allowed for a significantly faster analysis of the ECG time-series data with signal leads.

The methodology in (Haleem *et al.,* 2021) described the objective of detecting cardiovascular disease for time-adaptive ECG. Suggested a multiclass algorithm with two stages. The first step determines the number of adaptive beats over time by automatically segmenting the ECG using a sequential deep learning architecture. Time-adaptive CNN is used for first-stage ECG beats over multiple time intervals, forming the basis of a second stage. To create two-dimensional images from ECG beats, apply the Short-Time Fourier Transform. The models were trained using data from the MIT/BIH-PhysioNet databases. The main characteristics are identified by extracting the unique ECG beats using an automated ECG segmentation method. Z-score normalisation was used to standardise to a unit variance and a zero mean. A variety of arrhythmias that are included in the dataset have not been thoroughly examined.

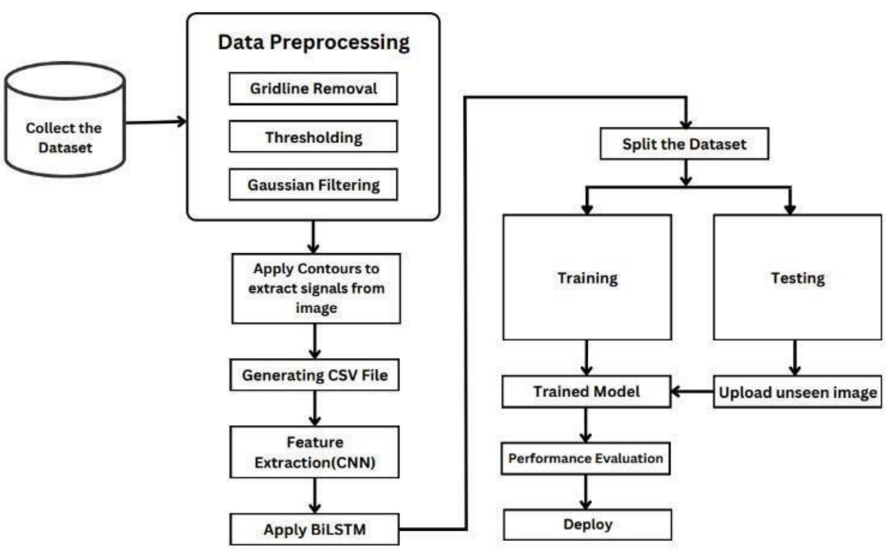
3.0 PROPOSED SYSTEM

3.1 Architecture

The project's architecture is intended to identify cardiovascular illness in ECG pictures.

Figure 1

Proposed System Architecture of the Cardiovascular Disease Detection Model



To enhance the quality of mobile processing, ECG pictures are prepped for analysis using Gaussian filtering, thresholding, and gridline removal. Contours are used to extract the key ECG signals from the preprocessed pictures to concentrate on pertinent information for practical mobile analysis. The main modification emphasises using MobileNet in the feature extraction phase because of its effectiveness on mobile devices.

The advantages of MobileNet for mobile deployment (speed, power consumption) are highlighted in the explanation. Instead of using a traditional CNN for feature extraction, MobileNet, an efficient and flexible CNN, is used. This decision is essential for deployment on mobile devices with limited resources, as it allows quicker processing and less battery usage. A collection of ECG pictures is used to train the MobileNet-based model using various techniques. Performance is determined to guarantee precision and dependability for mobile-based early detection. By deploying the trained MobileNet model on mobile devices, users may input unseen ECG pictures for quick, on-the-go analysis and perhaps early heart abnormality identification.

3.2 Methodology

The study has many modules, including Dataset Gathering and Preparation, Augmented Data, feature extraction using MobilNet, Fully Connected Layers for Classification, Training, and Performance assessment.

1) *Dataset Gathering and Preparation:* ECG image collections are gathered from clinical databases or publicly accessible sources. Preprocessing includes grayscale conversion, eliminating noise, picture scaling, and normalisation to improve model performance.
2) *Augmenting Data:* In addition to the methods already discussed, think about using time warping to gently compress or lengthen the ECG waveform along the time axis to simulate changes in heart rate or recording speed. Amplitude scaling, which randomly varies the total signal level, is another helpful technique. Investigate using artificial artifacts that mimic actual ECG noise, such as baseline wander or muscular tremors, to make the model more resilient by making it learn to disregard unimportant disruptions. Lastly, combining augmentations — applying a mix of these methods at random—can provide training examples that are much more difficult and varied.
3) *Extraction of Features using MobilNet:* MobilNet CNN layers are used for feature extraction, which makes it perfect for situations with limited resources. In order to efficiently extract hierarchical characteristics from the source ECG pictures, this design usually comprises a sequence of separate convolutional blocks followed by pooling layers. MobileNet's lightweight design enables lower model sizes and quicker training durations, making it easier to deploy on edge devices for real-time cardiac monitoring. Additionally, even when using a little amount of ECG data, its well-defined structure and the availability of pre-trained weights on big datasets like ImageNet allow for efficient transfer learning for ECG analysis tasks. To classify the collected characteristics into various cardiovascular disease groups, they are run through thick layers using activation functions as ReLU and Softmax.
4) *Using Fully Connected Layers for Classification:* The gathered features are classified into different cardiovascular disease categories using fully connected layers run through thick layers using activation functions such as ReLU and Softmax.
5) *Training and Optimising Models:* The model is trained using a categorical cross-entropy loss function and the Adam optimiser. Strategies involving dropout regularisation and early halting are used to avoid overfitting.
6) *Assessment of Performance:* Reliability, accuracy, recall, F1-score, and AUC-ROC on a separate test set are used to evaluate how well the trained model detects cardiovascular diseases from ECG images.

4.0 RESULTS AND DISCUSSIONS

This investigation uses the evaluation parameters for the AdaBoost, Gradient Boost, MobileNetV2, InceptionV3, Naive Bayes, ResNet50, and Logistic Regression algorithms.

Table 1

The Performance Metrics for the Algorithms Used in the Proposed System

	Accuracy	Precision	Recall	F1 Score	Specificity
AdaBoost	0.52	0.58	0.52	0.47	0.76
Gradient Boost	0.88	0.90	0.88	0.85	0.92
MobileNetV2	0.92	0.93	0.92	0.90	0.94
InceptionV3	0.69	0.70	0.69	0.67	0.82
Naive Bayes	0.54	0.46	0.54	0.49	0.78
ResNet50	0.86	0.87	0.86	0.86	0.89
Logistic Regression	0.69	0.56	0.69	0.61	0.81

Figure 2

AdaBoost Confusion Matrix of the Model

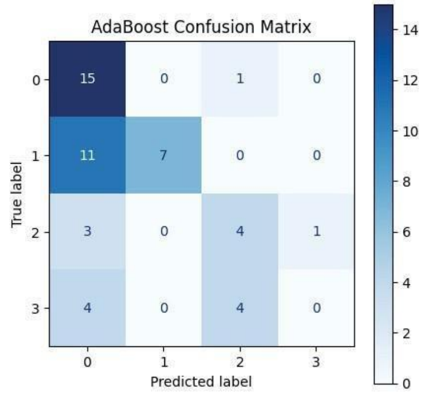


Figure 2 displays the confusion matrix for the AdaBoost Model.

Figure 3

Gradient Boost Model's Confusion Matrix

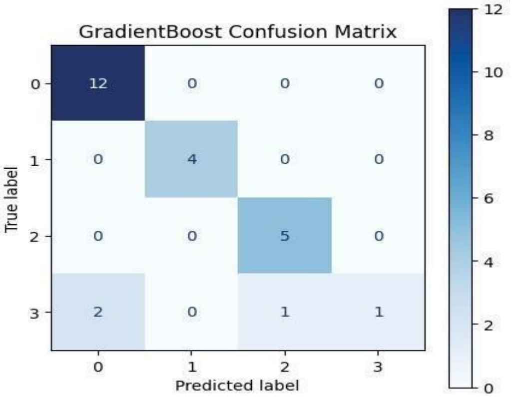


Figure 3 exhibits the confusion matrix for the Gradient Boost Model.

Figure 4

MobileNetV2 Model's Confusion Matrix

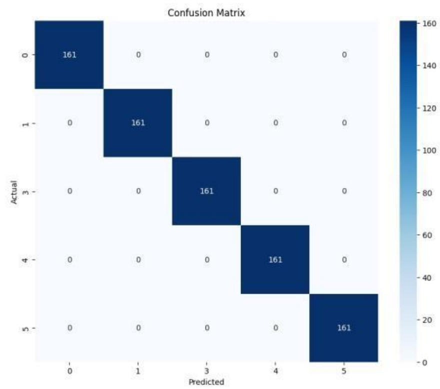


Figure 4 demonstrates the confusion array for the MobileNetV2 Mode.

Figure 5

InceptionV3 Model's Confusion Matrix

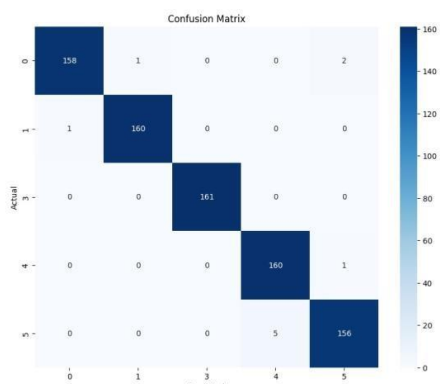


Figure 5 exhibits the confusion matrix associated with the InceptionV3 Model.

Figure 6

Naïve Bayes Model's Confusion Matrix

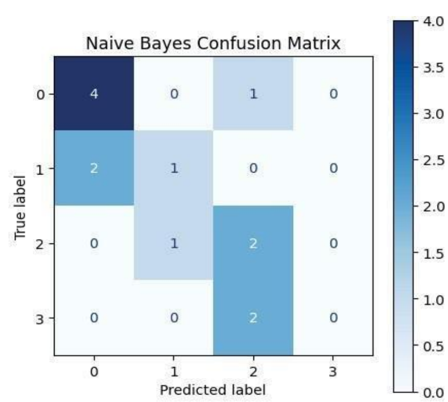
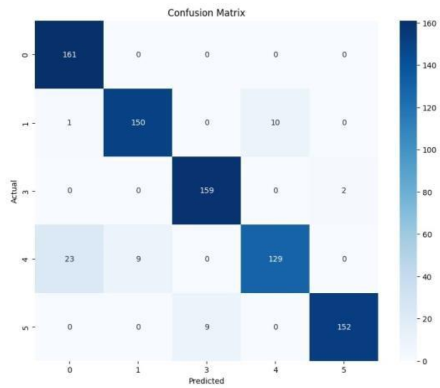


Figure 6 displays the confusion matrix for the Naive Bayes Model.

Figure 7

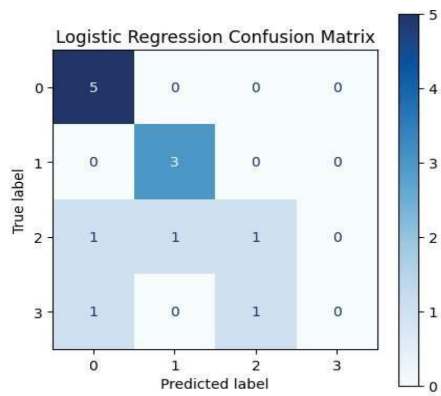
ResNet50 Model's Confusion Matrix



The confusion matrix for the RestNet50 Model is shown in Figure 7.

Figure 8

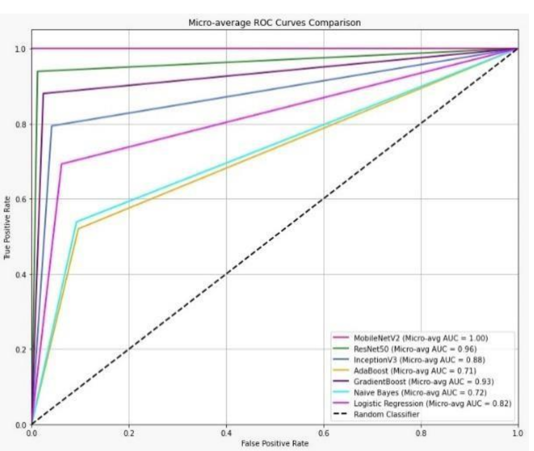
Logistic Regression Model's Confusion Matrix



The matrix of misinformation of the logistic regression study model is shown in Figure 8.

Figure 9

Micro-average ROC Curves of Different Models



The Micro-average ROC curves of AdaBoost, Gradient Boost, InceptionV3, RestNet50, Naive Bayes, MobileNetV2, and Figure 9 display models of logistic regression.

5.0 CONCLUSION AND FUTURE WORK

To sum up, the MobileNetV2 model shows a convincing method for detecting cardiovascular illness using ECG pictures. Through crucial phases, including data pretreatment and feature extraction, this research demonstrates how well a lightweight CNN architecture analyses and classifies ECG data. The use of MobileNetV2, which is optimised for mobile and embedded vision, demonstrates how resource-efficient deep learning methods may identify diseases with noteworthy accuracy and dependability, giving medical personnel a helpful tool, particularly in environments with limited resources.

A few areas need to be investigated for future development. First, the quality of retrieved features can be further improved by optimising preprocessing processes specific to MobileNetV2's input needs. Second, the model's performance and sensitivity to important ECG patterns may be improved by examining other MobileNet family variants, fine-tuning techniques, or including attention processes. Adding larger and more diverse collections to the training dataset would provide a more reliable and generalisable model that can be used to treat a greater variety of cardiovascular conditions.

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