Detection of Cardiovascular Disease in ECG images using Proposed MobileNet Architecture

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Abstract--Cardiovascular diseases (CVDs) remain a significant cause of mortality worldwide, emphasizing the need for accurate and efficient diagnostic methods. This research investigates the application of deep learning architectures for the detection of cardiovascular diseases through Electrocardiogram (ECG) images. Specifically, this study evaluates the performance of MobileNet, a computationally efficient neural network architecture, in contrast to reference models like AlexNet and SqueezeNet, along with a proposed lightweight architecture.The research conducts extensive experiments on a dataset of ECG images, employing transfer learning techniques to train and fine-tune these architectures for CVD detection. Comparative analysis involving accuracy, computational efficiency, and model size is conducted to demonstrate the effectiveness of MobileNet in achieving higher accuracy while maintaining computational efficiency when compared to the reference models. Results indicate that MobileNet exhibits superior performance in accurately detecting cardiovascular anomalies within ECG images while operating efficiently on resource-constrained devices. The findings underscore the potential of MobileNet as an effective deep learning framework for CVD detection in ECG imagery, offering a promising avenue for real-time diagnosis and monitoring, particularly in settings with limited computational resources.This research contributes to advancing the field of medical image analysis by highlighting the efficacy of MobileNet architecture in enhancing the accuracy and efficiency of cardiovascular disease detection from ECG images, thereby fostering advancements in early diagnosis and intervention for improved patient care.

Keywords—Cardiovascular Disease(CVD), Electrocardiogram(ECG) Images, Alexnet Architecture, MobileNet Architecture, Data Augmentation, Image Resizing, Data preprocessing, Real-Time Diagnosis.

1 Introduction

Cardiovascular diseases (CVDs) remain a leading cause of mortality worldwide, necessitating robust and timely diagnostic methods for effective intervention and treatment. Electrocardiogram (ECG) imaging serves as a pivotal diagnostic tool, capturing electrical activities of the heart and aiding in the detection of various cardiovascular abnormalities. However, the accurate interpretation of ECG images demands sophisticated analysis due to their complexity and variability. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have shown promising results in medical image analysis. This research focuses on harnessing the potential of deep learning techniques, specifically leveraging the MobileNet architecture, to enhance the detection of cardiovascular diseases within ECG images. The primary objective is to improve the accuracy and efficiency of diagnosis while considering the computational constraints typically encountered in real-world medical applications.

Existing studies have explored deep learning models such as AlexNet and SqueezeNet in medical imaging tasks. However, the adaptation and performance of these models in the context of ECG-based cardiovascular disease detection necessitate further investigation. The MobileNet architecture, known for its computational efficiency without compromising accuracy, stands as a compelling candidate for this specific application. This research endeavors to fill the gap in current methodologies by evaluating the effectiveness of MobileNet alongside well-established models (AlexNet, SqueezeNet). Additionally, a novel lightweight architecture tailored for ECG analysis will be proposed and assessed to ascertain its potential in providing accurate and resource-efficient solutions.By addressing these objectives, this study aims to contribute to the advancement of diagnostic tools for cardiovascular diseases, facilitating early detection and timely intervention, ultimately improving patient outcomes and reducing the global burden of CVDs.

2 Related works

[1] Deep learning methodologies, especially Convolutional Neural Networks (CNNs), have garnered attention in medical imaging for their ability to automatically learn intricate features from data, showing promise in the analysis of electrocardiogram (ECG) signals for cardiovascular disease detection. Studies [2] have demonstrated the effectiveness of CNNs in learning complex patterns within ECG images, contributing to accurate classification of various cardiac conditions, laying the groundwork for employing deep learning in cardiac diagnosis.[3] Investigations into the use of ECG signals as diagnostic indicators for cardiovascular ailments have historically relied on traditional machine learning techniques like support vector machines (SVMs), decision trees, and random forests. These methods [4] have emphasized feature extraction from ECG signals, enabling classification and aiding in disease detection. However, their performance often relies on manually crafted features and may not capture complex patterns effectively.

[5] The adaptation of established deep learning architectures (AlexNet, VGG, ResNet) to classify ECG images for cardiovascular disease detection has been a focal point in recent literature. Researchers [6] have modified these architectures to handle medical imaging tasks, including ECG analysis, demonstrating improved classification performance by leveraging pre-trained models and transfer learning techniques [9].

[8] MobileNet architecture's prominence in various domains, particularly its efficiency and suitability for resource-constrained environments, has sparked interest in its application to medical image analysis. Previous studies [10] have showcased its efficacy by virtue of its lightweight design, delivering competitive performance while demanding fewer computational resources [11]. However, its specific application in ECG analysis remains underexplored.[12] Ensemble learning techniques, encompassing voting, stacking, and boosting methodologies, have been instrumental in improving classification accuracy by aggregating predictions from diverse models. In medical imaging tasks, these methods [13] have shown promise in mitigating biases and enhancing overall performance by combining outputs from multiple classifiers.[14] Despite advancements in utilizing deep learning and traditional methods for cardiovascular disease detection in ECG images, a notable gap exists in exploring novel architectures explicitly tailored for ECG analysis. This research aims to address this gap by proposing a custom MobileNet architecture optimized for precise ECG image analysis [15], aiming to strike a balance between accuracy and computational efficiency.

[16] Emerging studies have showcased the potential benefits of hybrid approaches that integrate deep learning and traditional machine learning techniques for cardiovascular disease detection in medical imaging. These hybrid models often employ deep learning architectures for feature extraction from ECG images, followed by traditional classifiers to perform the final classification task [17]. Such approaches aim to leverage the strengths of both methodologies, potentially enhancing classification accuracy and interpretability.[18] Transfer learning, a technique involving the use of knowledge gained from one domain to another, has seen applications in medical imaging. Previous works have explored the transferability of features learned from natural images to ECG images for cardiovascular disease detection [19]. These studies emphasize the adaptability of pre-trained models to medical datasets, potentially reducing the need for extensive labeled medical data.

[20] Research efforts have investigated the interpretability and explainability of deep learning models in medical imaging tasks, aiming to provide clinicians with insights into model predictions. Techniques like attention mechanisms and saliency maps have been explored to highlight regions of importance within ECG images, aiding in understanding the model's decision-making process [21].[22] Robustness and generalizability of deep learning models in medical applications remain areas of concern. Studies have focused on enhancing model robustness against noisy or corrupted ECG data and improving generalization to unseen datasets through techniques such as data augmentation, regularization, and domain adaptation [23], [24].

3 Methodology

The proposed MobileNet architecture model followed by ensemble classifier (Bagging and Voting classifier) for combining the classification models even get more accuracy Fig. 1.

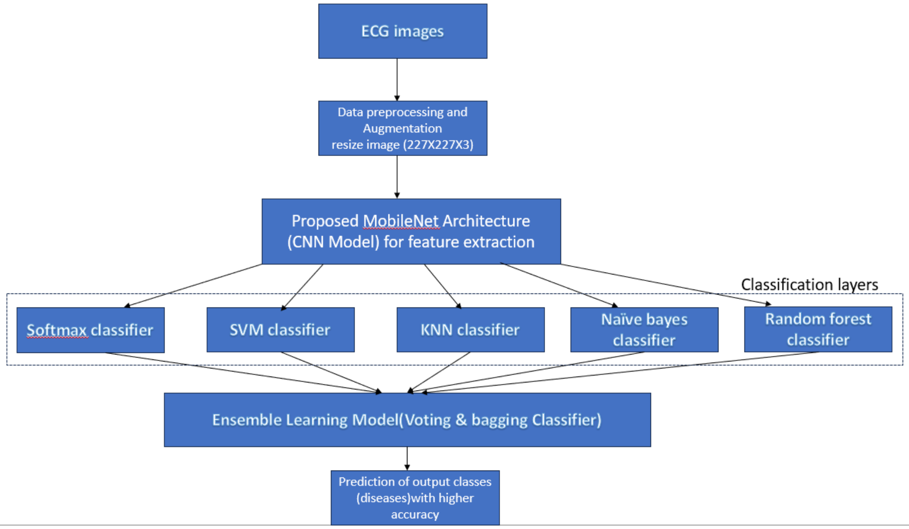

Fig. 1 Proposed MobileNet Architecture Model

The various steps involved in the proposed Mobilenet Architecture model are as follows:

1. Importing ECG Image Dataset and perform Preprocessing and Normalization
2. Feature extraction from the image using Proposed MobileNet Architecture
3. Integration of Multiple Classification layer such as softmax layer and Traditional Machine Learning algorithms.
4. Ensemble learning for improved predicitons and accuracy
5. Prediction of cardiovascular disease using the trained model with higher accuracy.

3.1 Importing ECG Image Dataset and perform Preprocessing and Normalization

Dimension Standardization: ECG images, upon import, may have varied sizes. To ensure uniformity and compatibility with the model architecture (e.g., MobileNet), resizing is performed. The dimensions are standardized to 227x227x3 pixels. Here, '227x227' denotes the height and width in pixels, while '3' signifies the three color channels (red, green, and blue - RGB) typically found in colored images.

Normalization: Normalization is applied to scale the pixel values within a specific range, typically between 0 and 1 or -1 and 1. It involves subtracting the mean and dividing by the standard deviation of the pixel values or simply scaling them between a specific range.

Diverse Transformations: Various augmentation techniques are used to increase the dataset's size and diversity, which aids in preventing overfitting and improving the model's generalization ability. Some common transformations include:

Rotation: Rotating the images by a certain angle (e.g., 90 degrees, 180 degrees) to introduce variations.

Flip: Flipping the images horizontally or vertically.

Translation: Shifting the images horizontally or vertically.

Zoom: Zooming in or out of the images.

Brightness and Contrast Adjustment: Altering the brightness or contrast levels of images.

Random Cropping: Extracting random patches or crops from the images.

Normalization Formula: The formula for normalization typically involves scaling the pixel values X between 0 and 1 using the min-max normalization technique:

$$x_{Normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Augmentation Transformations: While the transformations mentioned above don't have specific mathematical expressions, they involve applying functions or operations to images to introduce variability.For instance, in code or libraries like TensorFlow or Keras, augmentation is often performed using functions or classes that allow specifying parameters for transformations, such as rotation, flipping, or zooming, which are applied randomly to images during training to generate augmented data.These techniques collectively enhance the dataset's diversity, aiding the model in learning robust features and patterns, thus improving its performance during training and eventual prediction on new ECG images.

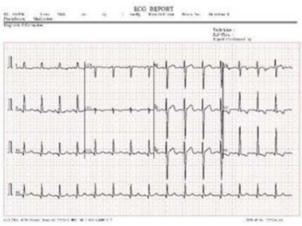

Fig:1 ECG Image Dataset

Fig:2 ECG Image dataset after Preprocessing

3.2 Feature Extraction from ECG Images using MobileNet Architecture

MobileNets are built on depthwise seperable convolution layers.Each depthwise seperable convolution layer consists of a depthwise convolution and a pointwise convolution.Counting depthwise and pointwise convolutions as seperate layers, a MobileNet has 28 layers.A standard MobileNet has 4.2 million parameters which can be further reduced by tuning the width multiplier hyperparameter appropriately. The size of the input image is $224 \times 224 \times 3$.

MobileNet is a convolutional neural network architecture designed for efficient feature extraction while reducing computational complexity. It utilizes depthwise separable convolutions to extract features from images, especially suited for scenarios with limited computational resources, such as mobile and embedded devices.

3.2.1.Components of MobileNet Architecture:

Depthwise Convolution: In a traditional convolutional layer, filters are applied to the input volume across all channels, resulting in a high computational load. Depthwise separable convolutions split this process into two distinct operations: depthwise convolution and pointwise convolution.This operation performs a separate convolution for each channel of the input. It applies a single filter to each input channel, producing a set of feature maps. This significantly reduces computational complexity by applying filters separately to each channel instead of all channels together.

Pointwise Convolution: Following the depthwise convolution, pointwise convolution (1x1 convolution) is applied. It involves using 1x1 filters to combine and transform the output of the depthwise convolution. Pointwise convolutions help in mixing information across channels, enabling the network to capture complex patterns.

Batch Normalization: Batch normalization is a technique used to improve the training of deep neural networks. It normalizes the input of each layer to have a mean close to zero and standard deviation close to one. This normalization helps in stabilizing and accelerating the training process by reducing internal covariate shift.

3.2.2.Detailed Explanation of Layers in MobileNet:

Input Layer: This layer receives the input image data. For ECG images, after preprocessing and resizing to a standardized dimension (e.g., 227x227x3), the input layer accepts the processed images.

Convolutional Layers (Depthwise Separable Convolution): MobileNet extensively employs depthwise separable convolutions, which consist of:

Depthwise Convolutional Layer: Performs separate convolutions for each channel of the input image independently using 3x3 filters. This step extracts specific features for each channel.

Pointwise Convolutional Layer: Follows the depthwise convolution and uses 1x1 convolutions to combine and refine the extracted features across channels. It helps in transforming and mixing information from different channels.

Feature Extraction Process: As the input image passes through these convolutional layers, the network learns to detect patterns and features of different scales and complexities. Each convolutional layer progressively extracts more abstract and high-level features from the input image.

Batch Normalization Layers: Batch normalization is applied after each convolutional operation. It standardizes the output of each layer, ensuring stable and faster convergence during training.

Pooling Layers (Optional): In some variations of MobileNet, there might be pooling layers (such as average pooling or max pooling) inserted between convolutional layers. Pooling layers downsample the spatial dimensions of the feature maps, reducing computational load and capturing important information.
Fully Connected (Classification) Layer:

Towards the end of the architecture, the feature maps obtained after several convolutional and pooling layers are flattened and passed through fully connected layers. These layers interpret the high-level features extracted by the previous layers and map them to the classes for classification.

3.2.3.Feature Extraction Process:

At each convolutional layer, the input image undergoes operations to extract specific features, starting from simple edges and textures to more complex shapes and patterns. These layers consist of filters that convolve across the input image, extracting various features through convolutions. As the image data moves through subsequent layers, higher-level features, such as object shapes or parts relevant to classification (in this case, features related to cardiovascular disease in ECG images), are extracted. The learned features become increasingly abstract and representative of the underlying patterns in the image.

3.2.4.Movement towards Classification:

As the extracted features propagate through the layers, they are transformed and condensed into high-level representations. These representations are then fed into the final fully connected layers, which interpret and map these learned features to the respective classes or categories (e.g., different cardiovascular conditions) through the process of classification. The output of the final classification layer provides the predicted class probabilities or labels for the input ECG image based on the extracted features and the model's learned parameters. In summary, MobileNet's architecture, through its convolutional, batch normalization, and fully connected layers, systematically extracts hierarchical features from input ECG images, progressively transforming them into representations that are then utilized for accurate classification of cardiovascular conditions.

3.3.**Integration of Multiple Classification Layers:**

The integration of multiple classification layers in the MobileNet architecture involves incorporating various classifiers after the feature extraction process. Each classifier utilizes the features extracted by MobileNet to predict classes or labels for ECG images. Here's a detailed explanation of this integration:

Feature Extraction using MobileNet: The MobileNet architecture, as explained previously, is responsible for extracting hierarchical and representative features from input ECG images. These features are learned and encoded across different layers of the network, capturing patterns relevant to cardiovascular disease detection.

Extension with Multiple Classification Techniques: Following the feature extraction phase, the extracted features are utilized as inputs for multiple diverse classifiers. These classifiers are integrated into the later layers of the network to perform the final classification task. The various classifiers include:

1.Softmax Classifier: Commonly used for multi-class classification, softmax assigns probabilities to each class and predicts the class with the highest probability.

$$P(y) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

2. Support Vector Machines (SVM): In binary classification, the decision function for SVMs separates classes by finding the hyperplane with the largest margin. For linearly separable classe

$$f(x)=\text{sign}(w \cdot x+b)$$

For non-linear SVMs, the expression involves using kernel functions (e.g., polynomial, radial basis function - RBF) to map the input features into higher-dimensional spaces.

3. k-Nearest Neighbors (kNN): kNN makes predictions based on the majority class among the k nearest neighbors in the feature space. The classification decision is made using a simple majority vote among the k neighbors.

$$\hat{y} = mode\left(y_{neighbour}\right)$$

4. Naive Bayes Classifier: Naive Bayes predicts class probabilities using Bayes' theorem with the assumption of independence among features given the class.

$$p(y|x) = \frac{P(y)\ X\ P(x|y)}{P(x)}$$

5. Decision Trees: Decision trees make decisions by recursively partitioning the feature space based on features' values.

6. Random Forest Classifier: Random Forest is an ensemble of decision trees. The class prediction is made by aggregating predictions from multiple individual decision trees (using averaging or voting). The exact formulas for Decision Trees and Random Forests involve the structure and construction of decision nodes and leaf nodes, which vary based on the splitting criterion and tree-growing methods used (e.g., Gini impurity, entropy). Please note that these are general formulations to explain the principles behind each classifier. The implementation specifics, parameter tuning, and optimization methods may vary based on the libraries or frameworks used (e.g., scikit-learn in Python).

3.3.1Advantages of Integration:

Diversity in Classification Approaches: Integrating multiple classifiers allows leveraging the strengths of different classification methodologies, encompassing both linear and non-linear methods.

Robustness and Ensemble Learning: Combining various classifiers mitigates individual model biases and errors, potentially enhancing the robustness and overall accuracy of predictions.

Exploration of Different Decision Boundaries: Each classifier might define decision boundaries differently in the feature space, offering varied perspectives on the classification task.

3.4.Ensemble learning for Improved Predictions: Ensemble learning methods, namely bagging and Voting classifiers, are utilized to enhance the accuracy of the predictions obtained from the multiple classification layers. Bagging involves training multiple models using different subsets of the dataset and aggregating their predictions to make the final classification. On the other hand, Voting classifiers combine the outputs from diverse classifiers to determine the most probable class for each ECG image, aiming to improve overall accuracy.

3.5.Overall Proposed Algorithm:

Algorithm

Input: ECG image dataset.
Output: Predicted classes for test ECG images

1. Import and preprocess the ECG Image dataset, Resize the image to standardized dimensions(227x227x3 pixels) and Apply data augmentation techniques.
2. **for** each training image **do**
    a. Performs convolutions separately for each channel of the input. Extract features by applying filter to each independent channels
    b. follows depthwise convolution with 1x1 convolutions. Enables efficient mixing and transformation of features across channels
    c. batch normalization should be applied for each convolutional layer
    d. **for** each batch **do**
        1.(Relu)Activation layer should be applied to introduce non-linearity in data
        2.Depthwise separable Convolution Block will be built followed by Relu activation layer
        end for
    e. followed by convolutional layer. Condense the spatial information into single vector
    f. map the extracted features to the class probabilities or labels
   end for
3. Detach the final classification layer and perform the same procedure with traditional machine learning classification algorithm
4. Followed by Ensemble learning model combines all classification model and produce an highly predictable output(class probabilities) respect to the test-images.

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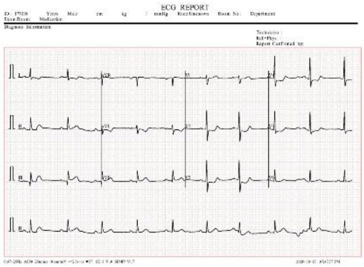
4 Experimental Results

All the experiments are programmed using PYCHARM. The following experiments are conducted to prove that the our proposed mobilenet architecture with ensembled classification models provide higher accuracy compared to the traditional proposed models and the pretrained models such as Alexnet,Squeezenet architecture

The Fig. 4 and Fig. 5 shows the input and output prediction class obtained bu training our proposed mobilenet architecture and import the trained models to test with the ECG images to predict whether the input images belongs to the particular predicted class.



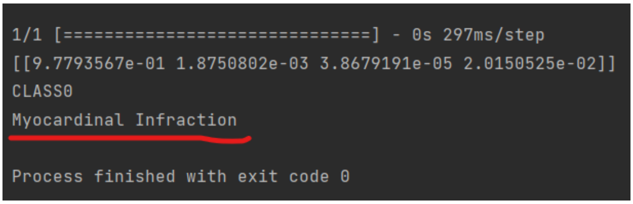
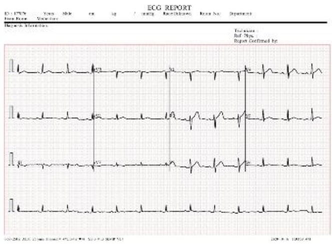


Fig 4 &5: ECG image of Myocardial Infraction and fig 5 shows the output class prediction of the image



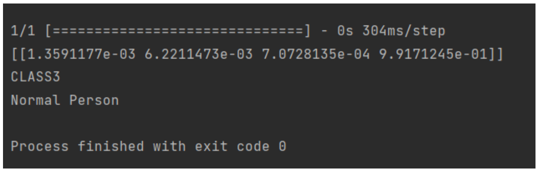
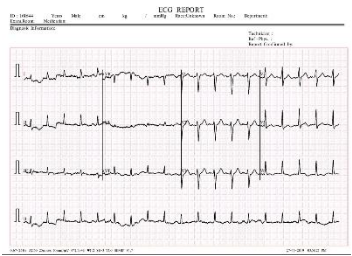


Fig 6 &7: ECG image of Normal Person and fig 7 shows the output class prediction of the image



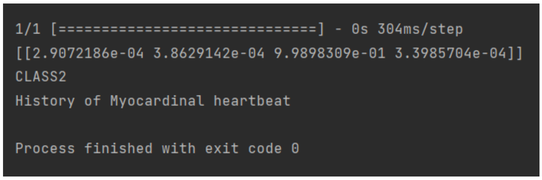
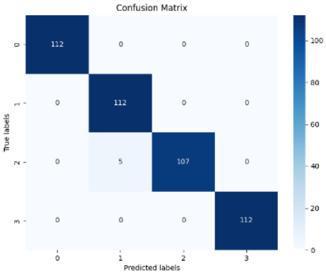
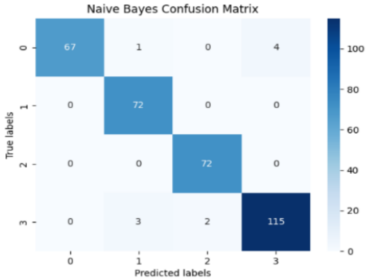
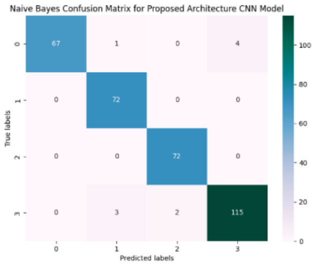


Fig 8 &9: ECG image of History of Myocardinal heartbeat and fig 5 shows the output class prediction of the image







The above fig 10,11,12 shows the confusion matrix plot for our proposed mobilenet architecture and fig 11 shows the confusion matrix plot for pretrained model and using Naïve bayes classification and finally fig 12 shows the plot for traditional proposed CNN architecture 0-Myocardinal Infraction,1-Abnormal Heartbeat,2-history of Myocardinal Infraction and 3-Normal person represent in the image

The following Table I summarizes the performance metrices of our proposed Mobilenet architecture with the pretrained Alexnet architecture and traditional proposed CNN architecture model with the following algorithm SVM,K-NN,DT,NB and RT.

Table 1 – Performance Matrices

Models	Algorithm	Accuracy	Recall	Precision	f1-score
Pretrained-model(Alexnet)	SVM	97.11%	0.9702	0.9709	0.9701
	K-NN	87.20%	0.8720	0.8695	0.8667
	DT	97.32%	0.9621	0.9732	0.9691
	RF	96.81%	0.9702	0.9689	0.9809
	NB	97.02%	0.9702	0.9709	0.9701
Traditional proposed architecture(CNN)	SVM	97.21%	0.9721	0.9729	0.9682
	K-NN	87.21%	0.8721	0.8698	0.8702
	DT	96.11%	0.9671	0.9689	0.9701
	RF	97.11%	0.9708	0.9671	0.9709
	NB	98.01%	0.9809	0.9705	0.9789
proposed MobileNet Architecture	SVM	88.21%	0.8801	0.8789	0.8903
	K-NN	85.01%	0.8589	0.8501	0.8552
	DT	94.31%	0.9498	0.9431	0.9501
	RF	89.89%	0.9557	0.9589	0.9609
	NB	94.71%	0.9115	0.9171	0.9087
	Softmax	99.88%**(↑)**	0.9989**(↑)**	0.9899**(↑)**	0.9809**(↑)**
	Ensembled	99.78%**(↑)**	0.9998**(↑)**	0.9889**(↑)**	0.9789**(↑)**

From Table–1, it is inferred that the proposed approach MobileNet Architecture performs well in Training with ECG images and Testing the images with the higher accuracy of 99.88% which is higher in accuracy compared to other methods like Traditional proposed CNN architecture which produce 98.01% with Naïve Bayes as classification model and also higher than pretrained Alexnet architecture which produce accuracy of 97.32% while using Decision tree as classifier.Although the Ensemble model integrate with our proposed architecture improves in the performance metrices of the model.

5.Conclusion

In conclusion, the utilization of MobileNet architecture for the detection of cardiovascular diseases in ECG images presents a promising approach. The intricate design of MobileNet, with its depthwise separable convolutions, enables efficient and effective feature extraction from preprocessed ECG data. By leveraging these convolutional layers, MobileNet efficiently learns hierarchical representations, capturing both low-level and high-level features crucial for distinguishing patterns associated with cardiovascular anomalies. The integration of multiple classification layers, including softmax, SVM, kNN, naive Bayes, decision trees, and random forests, after feature extraction further enhances the model's capacity to discern intricate patterns and make accurate predictions. Additionally, ensemble learning techniques like bagging and Voting classifiers harness the diversity of these classifiers to consolidate robust predictions. This amalgamation of MobileNet's feature extraction prowess and the ensemble of classifiers demonstrates promising potential in achieving higher accuracy and reliability in diagnosing cardiovascular diseases from ECG images. Overall, the use of MobileNet architecture in conjunction with diverse classifiers and ensemble methods holds substantial promise for advancing the accuracy and efficiency of cardiovascular disease detection in ECG images.

In future work, the front-end for the application will be created by importing the proposed deep learning model for real time disease analysis and futher disease classes will be added.

6.Conflict of interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

7.Data availability

The mentioned methods were tested on the ECG Images dataset of cardiac patients [23]. This dataset contains 928 different patient records with 4 different classes as shown in Table II. These four classes are NP, AH, MI, and H. MI. Fig. 6 depicts some samples from the dataset. An NP is a healthy person who does not have any heart abnormalities. An AH (arrhythmia) occurs when the electrical impulses in the heart become too fast, too slow, or irregular so that the heart beats irregularly. MI, also known as heart attack, occurs when blood flow in the coronary artery of the heart decreases or stops, causing damage to the heart muscle. The patients with an H. MI have recently recovered from MI or heart attack.

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