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ECG Signal Classification Using Fine-Tuned MobileNetV2 for Cardiovascular Disease Detection

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Abstract- Cardiovascular disease, otherwise referred to as heart disease, represents one of the most common and fatal illnesses that entails injuring the heart as well as the blood vessels. These, in turn, can cause a range of complications such as myocardial ischemia, for instance, coronary artery disease, or heart failure. The appropriate and timely identification of heart conditions. Clinical practice is determined by the relevance of the illness. The sickness known as heart disease, also known as cardiovascular disease, is common and, sadly, harmful. This condition deals with the morbidity and mortality associated with the heart and blood vessels. This can cause numerous issues such as myocardial ischemia, coronary heart problems and heart failure. A timely and correct identification of heart ailments. clinical practice is guided by the relevance of the disease. Being able to identify those at risk allows for preventative measures, preventative actions, and individualized treatment plans to lessen the negative effects and slow the disease's course. The identification of cardiac disease has seen significant growth in recent years. major improvements as a result of the incorporation of the complex. Technology and methods based on computation. Among them is the machine. predictive modeling, data mining methods, and learning algorithms frameworks that make extensive use of physiological and clinical data information.

Index Terms- Cardiovascular disease, Electrocardiogram (ECG), Vision Transformers (ViTs), Neural networks, and Machine learning in healthcare.

I. INTRODUCTION

Cardiovascular diseases are one of the prime problems of the present century. The only reliable, non-invasive screening test available for heart disease remains ECG. It consumes a lot of time to interpret and has only professional understanding. The creation of a new technique for the early detection of an illness raises a new standard and efficacy in medical care [1]. Heart disease is one of the most common and severe medical conditions due to the damage that this condition causes in the heart and blood arteries, bringing about such adverse consequences as myocardial infarction, heart failure, and coronary artery disease[7]. Hence, one of the exigencies of clinical practice is to make a diagnosis of heart disease within the constraints of time and with precision. Purpose of clinical practice is also to make timely and accurate diagnosis of heart disease. Early recognition and targeted at-risk patient intervention make possible the timely application of appropriate curative measures, preventive measures, and tailored interventions to reduce disease progression and adverse complications. Twente years ago the art of heart diseases detection has come a long way mostly due to the technological and scientific development that has taken place. This includes the use of data analytics, these form machine learning and predictive modeling approximations to enhance diagnosis and risk stratification processes with extensive clinical and physiological data.In this paper, we suggest the detection of heart disease using ECG images by employing state-of-the-art technologies in the form of vision transformer models [2].

The ECG test is an experiment conducted on a screen to diagnose heart problems. This research proposal presents an automated strategy for the recognition of cardiac disease using a combination of multi-field extraction and the nonlinear analysis of data derived from an ECG. This research work aims to develop a model for future ECG analysis and symptom-based detection-based cardiac vascular disease diagnosis [3].

II. RELATED WORK

This part discusses the characteristics of the ECG to include P wave, QRS wave, ST segment, and T wave trace in the healthy individual.

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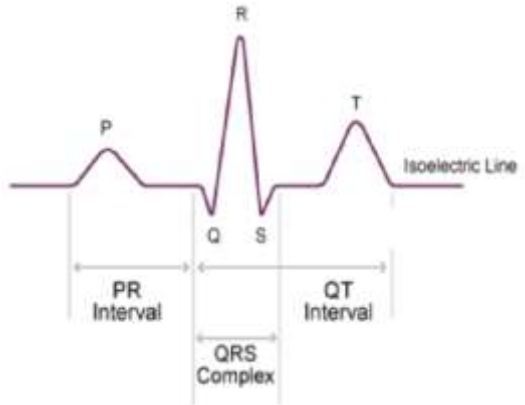
P wave depicts atrial depolarization in an ECG. There is an upright wave in leads I, aVF, V3-V6. It usually does not exceed 0.11sec. There is a positive P wave in leads I, II, aVF and V4-V6. Conversely, the P wave in V1 and V3 leads is usually diphasic while negative in aVR. A normal atrial activity is when a P-wave is smooth and not peaked or notched.[5][4].

The PR interval, refers to the time the electrical impulse takes to travel from the atria to the ventricles. By default, the period should take between 0.12 to 0.20 seconds. hence, indicating excellent communication between the upper and the lower chambers of the heart[5].

Ventricular depolarization occurs during the QRS complex, which should last less than 0.12 seconds[11]. The amplitude is over 0.5 mV in at least one of the standard leads and more than 1.0 mV in at least one precordial lead, with an upper normal limit of 2.5–3.0 mV. Small septal Q waves may also be considered as within normal limits in leads I, aVL, V5, and V6 if its measurement is less than or equal to 0.04 seconds and the amplitude is less than one-third of the R wave amplitude in the same lead. From V1 up to V6, R waves become taller while S waves become smaller. R waves and S waves are roughly equal in leads V3 or V4. It represents the transitional zone [4][5].

The ST segment in a normal ECG is usually isoelectric, sloping upwards into the T-wave. In some precordial leads, small amounts of elevation up to 2.0 mm are considered normal, but depression of more than 0.5 mm in any lead is abnormal.

The T-wave reflects ventricular repolarization and, in at least five of the limb leads, should point in the same direction as the QRS complex. It typically is rounded and asymmetrical, with a smooth rising phase that peaks and then slopes down more rapidly In V2-V6, a T-wave is upright; in aVR, it is



inverted[12]. In V3 and V4, it must be at least 0.2 mV, and in V5 and V6, it must be at least 0.1 mV. [5].

Fig 1: The classical ECG curve with its common Waveforms [4].

The entire duration of ventricular depolarization and repolarization is measured by the QT interval. In men, the normal QT interval is 0.40 seconds or less, while in women, it should not exceed 0.44 seconds. This interval is critical for assessing the heart's electrical stability[5].

Studies involving the use of various techniques for heart disease detection, specifically through the analysis of ECG images, have shown the importance of machine learning (ML) and deep learning (DL) models. They enhance the overall heart diagnosis and treatment process through the use of certain algorithms. One of the difficulties that comes with heart disease detection is the issue of imbalanced datasets, as it tends to bias the outcome and ultimately affect the performance of the model. Therefore, considerable efforts have been made in formulating deep learning and machine learning models, one of which includes GANs. This artificial intelligence model helps to synthesizes other forms of data in order to fill the gap within the training set reducing chances of overfitting in the training set and enhancing deeper detection. For instance, a structure where GAN architecture is combined with LSTM has outperformed the conventional models[2].In recent years, a number of other studies have improved upon this by designing systems which are able to analyze different ECG formats and achieve a very high level of accuracy in the diagnosis of heart diseases. Hybrid diagnostic systems based on CNNs have achieved over 96% of accuracy. Modern developments, for example, vision transformer models, have also been successful in classifying an ECG signal. Notably, these developments demonstrate the increasing significance of DL and ML in the enhancement of heart disease detection systems.

III. LITERATURE SURVEY

In recent years, deep learning models have been shown to be particularly successful in the area of Convolutional Neural Networks that can automatically learn complex patterns in the medical image processing domain. CNNs are excellent for feature extraction for medical data such as ECG signals that play a critical role in diagnosing cardiovascular diseases[8].The structure is especially useful for applications such as MobileNet and improved MobileNetV2 efficient and lightweight, in real-time diagnostic systems[9][10].Normalization, filtering, and segmenting are other preprocessing techniques, which are crucial for signal quality and accuracy in the model's identification of disease markers[11].

Ensemble learning techniques further increase the reliability and robustness of a diagnostic system. The bagging or voting classifier harnesses diversity between models by combining

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their predictions to further increase generalization[12].The ensemble approaches improve the detection of complex patterns in ECG signals while controlling false positives and negatives false positives and negatives[13].High sensitivity and specificity are crucial for proper medical diagnosis, especially in cardiovascular anomalies[14].It relies on the strengths of MobileNetV2, data segmentation, preprocessing, and ensemble methods for the contribution toward developing an accurate and efficient cardiovascular disease detection system[15].

IV. METHODLOGY

The proposed MobileNet architecture model followed by ensemble classifier for combining the classification models even get more accuracy

- Importing an ECG image dataset and performing normalization and preprocessing.
- Using the suggested MobileNetV2 Architecture, features are extracted from the picture.
- Integration of traditional machine learning methods with several classification layers, such as the softmax layer.
- Using ensemble learning to increase accuracy and predictions.
- Cardiovascular disease prediction with increased accuracy using the trained model.

1. Importing ECG Image Dataset and Perform Preprocessing and Normalization

Dimension Standardization: ECG images can have different sizes when they are imported. Resizing is done to provide consistency and compliance with the model architecture (e.g., MobileNet). Standard measurements are 227x227x3 pixels. Here, '227x227' represents the height and width in pixels, and '3' represents the RGB (red, green, and blue) color channels that are commonly included in colorful images.

Normalization: The purpose of normalization is to scale the pixel values within a given range, usually between 0 and 1 or -1 and 1. The pixel values are scaled between a specified range or the mean is subtracted and divided by the standard deviation.

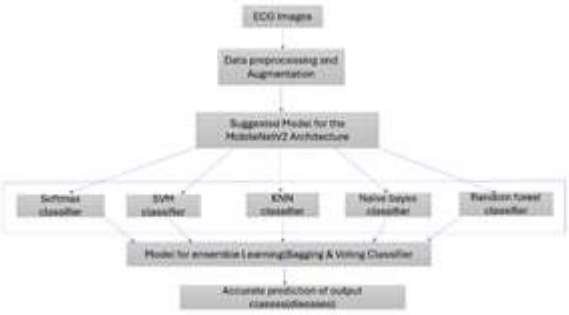

Fig 2 Proposed MobileNetV2 Architecture Model

Diverse Transformations: The size and diversity of the dataset are increased using a variety of augmentation strategies, which helps to improve the model's generalization capacity and avoid overfitting. Some common transformations include:

Rotation: Rotating the images by a specific angle (such as 90 or 180 degrees) may add variants.

Filp: 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: Changing an image's contrast or brightness.

Random cropping: Removing arbitrary cropping or sections from the images.

Normalization Formula: Usually, the normalization formula uses the min-max normalization approach to scale the pixel values X between 0 and 1:

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

Augmentation Transformations: As mentioned above, the above transformations involve applying functions or procedures onto images so that randomness can be added even if they don't have an exact mathematical definition. For example, methods or classes that enable one to define parameters of transformations say rotation, flipping or zooming, are typically in use in codes or libraries such as TensorFlow or Keras to make augmentation. Such transformations are randomly applied on images during training, to provide augmentations of the data. Combined, such methods add diversity to the dataset, but aid in enabling the model to learn strong patterns and features, meaning enhanced performance from the model not only at the time of training but also while making predictions on new ECG s

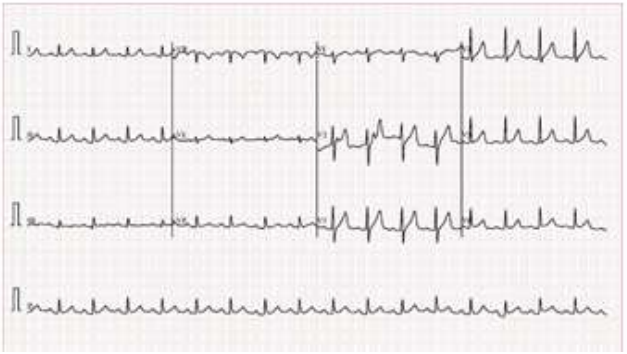

Fig 3 ECG Image Dataset after preprocessing

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2 feature Extraction from ECG Images using MobileNetV2 Architecture

The depthwise separable convolutional layer consists of two layers. The first one is called the depthwise convolution and the second one is known as the pointwise convolution. If the two-step convolution is considered as two layers, then MobileNetV2 will have a total of 28 layers. Then the 4.2 million parameters of a normal MobileNetV2 can be reduced even more if we use it carefully by setting appropriate width multiplier hyperparameter. The input image is of size 224 × 224 × 3.

MobileNetV2 incorporates the architecture of the convolutional neural network for reducing computational complexity efficiently and has been well designed to obtain features; it is particularly great for using within highly constrained environments in terms of computational resources, such as mobile and embedded systems due to the use of depthwise separable convolutions in image feature extraction.

Components of MobileNetV2 Architecture

Depthwise Convolution: A standard convolutional layer carries out a huge computational budget because filters are convolved with the input volume for every channel. Depthwise separable convolutions split up the process into depthwise convolution and pointwise convolution. This approach performs convolutions separately with all the channels of the input for each channel. It generates a set of feature maps by applying one single filter with respect to all the input channels. Applying filters to individual channels rather than all channels at once significantly reduces computing complexity.

Pointwise Convolution: The pointwise convolutions use 1x1 convolutions after the depthwise convolution. The output of the depthwise convolution is combined and transformed by using the 1x1 filters. Since it combines information from multiple channels, the pointwise convolutions help the network detect subtle patterns.

Batch Normalization: The second method that is going to be used to improve the training process of a deep neural network is batch normalization. This method normalizes every input entering the layer; each input gets a standard deviation of about one and a mean close to zero. As before described, this normalization helps in reducing the internal covariate shift, hence stabilizing and quickening the training.

Detailed Explanation of Layers in MobileNetV2:

Input Layer: The input image data is sent to this layer. The input layer receives the processed ECG images after they have been preprocessed and resized to a standard size (such as 227x227x3).

Convolution Layers (depthwise Separable Convolution): MobileNetV2 uses depthwise separable convolutions a lot. which consists of:

Depthwise Convolutional Layer: uses 3x3 filters to carry out independent convolutions for each channel of the input picture. Each channel's unique properties are extracted.

Pointwise Convolutional Layer: Combines and refines the retrieved features across channels using 1x1 convolutions after the depthwise convolution. It facilitates the conversion and blending of data from many sources.

Feature Extraction Process: During this process of passing the input image through these convolutional layers, the network comes up with the patterns and features of various sizes as well as at different complexity levels. Subsequently, each of these convolutional layer's extracts progressively higher-level abstraction information from the input image.

Batch Normalization Layers: Each convolutional process is followed by batch normalization. By standardizing each layer's output, it guarantees steady and quick convergence throughout training.

Pooling Layers(Optional): Pooling layers Such as average pooling or max pooling, are sometimes inserted between convolutional layers in some versions of MobileNet. The pooling layer downsamples the spatial dimensions of feature maps, thereby preserving significant information and thus saving computations. Fully Connected Layer for Classification:

The feature maps that result from multiple convolutional and pooling layers are flattened at the end of the architecture. These are passed through fully connected layers, which map the high-level features that the preceding layers extracted after interpreting them to the classification classes.

Feature Extraction Process

Such filters in the layers of convolution process the input image at each level, extracting some information ranging from simple edges and textures to more complex forms and patterns. These layers consist of such filters that are adopted to carry out convolutions so as to extract various information about the input image.

As the image data proceeds through successive layers, higher-level characteristics, including object forms or classification-relevant elements, such as in this case, cardiovascular disease-related features for ECG images, are retrieved. More abstract and indicative of the underlying patterns that characterize an image, the acquired characteristics become.

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Movement towards Classification
As the recovered characteristics move level by level, they transform and condense into high-level representations. These representations are passed into the final fully connected layers for classification to interpret and map the learnt information into proper classes or categories (e.g., cardiovascular disease in different variants). Finally, based on the learning parameters of the model and the features extracted using it, the output of the final classification layer gives the projected class probabilities or labels for the input ECG image. Conclusion Conclusion In a nutshell, with regards to the general architecture method, the Convolutional, Batch normalization, and the fully connected layers gradually apply hierarchical features extraction from the input ECG images that are gradually transformed into representations used for proper classification of cardiovascular condition.

3. Integration of Multiple Classification Layers
After feature extraction, several classifiers are added to the MobileNetV2 architecture in order to include many classification layers. In order to make predictions of classes or labels for ECG images, each classifier uses the features gathered by MobileNetV2, explained as follows:

Feature Extraction using MobileNetV2: As outlined earlier, it is the MobileNetV2 architecture that captures representative and hierarchical characteristics from input ECG images. These characteristics cover patterns informative of cardiovascular illness learnt and encoded across many layers of the network.

Extension with Multiple Classification Techniques: The extracted feature is fed as inputs to several classifiers after the feature extraction stage. In order to complete the final classification, these classifiers have been incorporated into the final layers of the network. The various classifiers include:

1.Softmax Classifier: Softmax, a popular method for multi-class classification, gives each class a probability and determines which class has the highest chance.

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

Support Vector Machines (SVM): SVMs' decision function in binary classification divides classes by identifying the hyperplane with the biggest margin.

For linear separable class

$$f(x) = sign(W.X + b)$$

For non-linear SVMs separates, the expression entails mapping the input characteristics into higher-dimensional spaces using kernel functions (such as polynomial and radial basis function, or RBF).

K-Nearest Neighbors(KNN): The value of k nearest neighbors chooses the majority class of the k nearest neighbors in the feature space to make predictions. The classification is chosen by a simple majority vote among the k neighbors.

Native Bayes Classifier: Using Bayes' theorem and the premise that characteristics are independent of class, Naive Bayes forecasts class probabilities.

$$p\left(y/x\right) = \frac{p(y)\ X\ p\left(x/y\right)}{p(x)}$$

Decision Trees: In order to make decisions, decision trees divide the feature space recursively according to the values of the features.

Random Forest Classifier: An ensemble of decision trees is called Random Forest. The class prediction is obtained by combining the predictions from a set of decision trees and either voting or averaging (naturally, the latter only applies to Regression Trees). The building and structure of the nodes of the decision, that are the leaves, are specific formulas for Decision Trees and Random Forests depending on the splitting criteria and tree-growing techniques used (for example, Gini impurity, entropy). Note that these are just a level higher descriptions of the basic concepts behind each classifier. The details of implementations, together with the parameter tuning and optimization techniques, would differ depending upon the libraries or frameworks that are used, including possibly scikit-learn for Python.

Advantages of Integration
Variability in Classification Methods: Combining several classifiers enables utilizing the advantages of various classification techniques, including both linear and non-linear approaches.

Robustness and Ensemble Learning: Combining different classifiers reduces the biases and mistakes of each model, which may improve the predictions' overall accuracy and robustness.

Examining Various Decision Boundaries: Diverse viewpoints on the classification job may result from the distinct ways in which each classifier defines decision limits in the feature space.

4. Ensemble Learning for Improved Predictions: To further strengthen the accuracy of the predictions from the different layers in classification, ensemble learning techniques are

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employed: bagging and voting classifiers. In this context, bagging trains various models with different subsets of a dataset and combines them for final classification. Voting classifiers attempt to introduce overall accuracy by taking output from different classifiers in an endeavour to produce the most probable class for each ECG image.

5. Proposed Algorithm
Input: ECG image dataset.
Output: predicted class for test ECG images.

Import and preprocess the ECG Image dataset, Resize the image to standardized dimensions (227x227x3 pixels) and Apply data augmentation techniques.

Performs convolutions on all channels of the input feature map separately to ensure that every channel has its own distinct feature extraction process.

Each depthwise convolution is followed by the insertion of a 1×1 pointwise convolution, which helps in effective merging and reshapingof features formed per channel.

In order to stabilize training more efficiently, batch normalization is performed after every convolutional layer.
d. For every batch:

- Non-linearity is introduced through the use of a ReLU activation layer.
- A ReLU activated depthwise separable convolution block is constructed next.
- The last part of the process involves compressing the output by means of the convolutional layer that transforms the spatial configurations into a single vector.
- Last step involved in the processing of the information is assigning the obtained features into certain classes or probabilities.

V.EXPERIMENTAL RESULTS

Once our model was trained, we created an eco-friendly website and included the model. The test findings are as

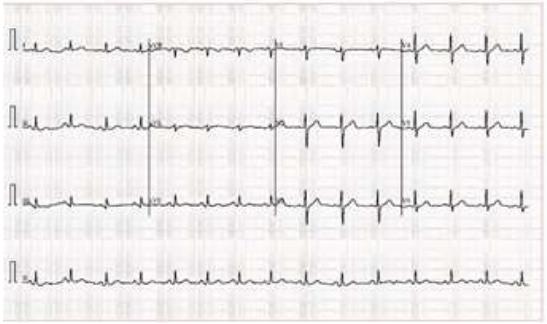

Fig 5: Ecg Image of Abnormal Heartbeat(Hb)

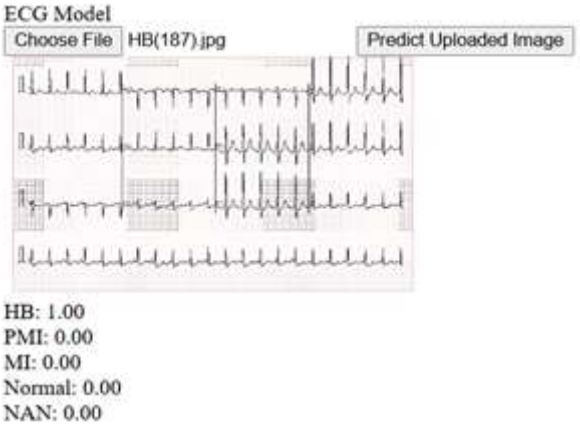

Fig 6: The Output Class Predicated of the Image

follows, and the forecasts are accurate.

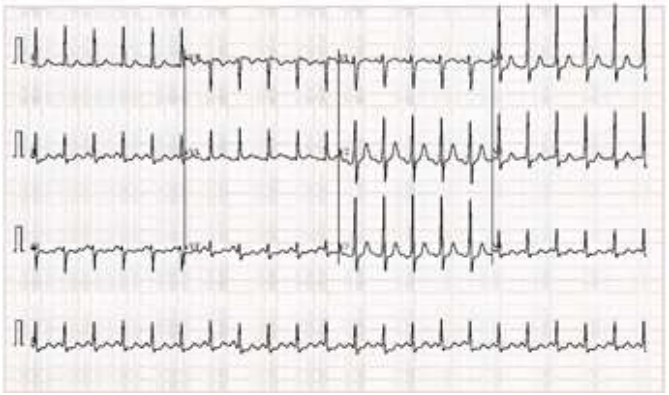

Fig 7: Ecg Image of Normal Person

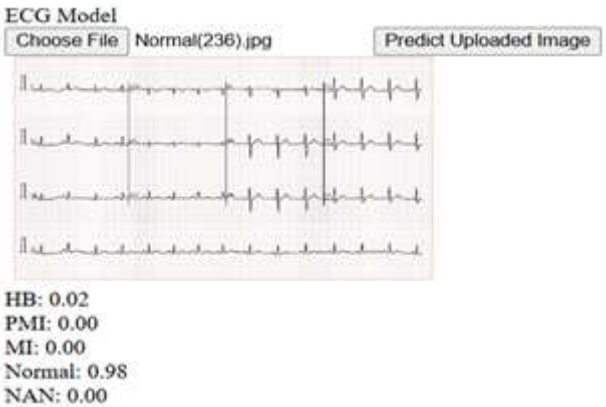

Fig 8: Shows The Output Class Predicated of the Image.

The performance metrics of the proposed Mobilenet architecture, the pretrained Alexnet architecture, and the conventionally offered CNN architecture model of algorithms SVM, K-NN, DT, NB, and RT are presented here in Table I below.

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Models	Algorithm	Recall	f1-Score	Precision	Accuracy
Alexnet-pretrained model	NB	0.8936	0.8893	0.8991	89.36%
	RF	0.9702	0.9810	0.9681	92.69%
	SVM	0.9612	0.9602	0.9609	96.02%
	K-NN	0.7872	0.7714	0.8247	78.72%
	DT	0.9621	0.9691	0.9732	78.69%
Conventional suggested architecture (CNN)	NB	0.9809	0.9789	0.9705	98.01%
	RF	0.9708	0.9709	0.9671	97.11 %
	SVM	0.9721	0.9682	0.9729	97.21%
	K-NN	0.8721	0.8702	0.8698	87.21%
	DT	0.9621	0.9701	0.9689	96.11%
MobileNet Architecture	NB	0.9775	0.9087	0.9717	94.71%
	RF	0.9557	0.9609	0.9589	89.89%
	SVM	0.8801	0.8903	0.8789	88.21%
	K-NN	0.8589	0.8552	0.8501	85.01%
	DT	0.9498	0,9501	0.9431	94.31
	Softmax	0.9668	0.9606	0.9686	96.88%
	Ensembled	0.9886	0.9698	0.9779	97.98%

Among the three model architectures MobileNet architecturewon with the best performance, mainly using the ensembled approach at a precision of 97.98%. Softmax also did good in accuracy at 96.88%. Excellent results were shown by MobileNet for all algorithms used. Accuracy at 94.71 was produced by Naive Bayes, and at 94.31, Decision Tree. Although AlexNet and traditional CNN performed competitively with the others, mostly with Naive Bayes and SVM, the consistent performance of MobileNet outperformed the others, and was thus the best choice for this classification task concerning its average accuracy, recall, precision, and F1 score[17].

VI. CONCLUSION

In conclusion, the fine-tuned MobileNetV2 model is very promising to be utilized for the detection of cardiovascular disease in images of ECG. Depthwise separable convolutions are employed in the MobileNetV2 architecture to feature extraction in a more powerful but efficient manner that encapsulates all the significant information from the ECG signal used to identify cardiovascular anomalies. This model learns its representations hierarchically; thus, it is able to learn low-level and high-level features that are vital to the correct classification of the disease-related patterns. Integrating all the classification techniques along with ensemble methods further enhance the accuracy and reliability of this model in the robust identification of cardiovascular anomalies. Combining this with MobileNetV2's streamlined feature extraction, this ensemble classifier seems quite promising in the domain of automation of cardiovascular disease diagnosis.

Future work will focus on developing an interactive front-end that will facilitate the real-time analysis of the ECG with the model. Moreover, additional classes of diseases will be integrated to enhance the range of diagnosis that the model can deliver and hence the utility of the model in the clinic.

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