ADHVARA: Multiple Cardiovascular Disease Detection from ECG Signals using CNN

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***Abstract*—In the context of the leading causes of mortality worldwide, cardiovascular disease stands prominent. Detection in the incubation stage is essential for effective intervention. This study aims to improve the classification accuracy of electrocardiogram (ECG) signals into four different cardiac conditions using machine learning techniques. ECG signals are converted to images and pre-processed before being classified. Preprocessing involves reshaping and standardising an image into a particular format. The proposed solution uses pre-trained models like ResNet-18, VGG-16, EfficientNet-B0, MobileNetV3-Large, and GoogLeNet to detect patterns in data and trains accordingly. The dataset is classified into 4 categories (abnormal heartbeat, normal heartbeat, history of myocardial infarction, and myocardial infarction). Each category is labelled before it's fed to the model for training. This research involves the digital classification of ECG signals and assorting the best CNN model with higher accuracy.**

***Index Terms*—CNN -Convolution Neural Network, ECG -Electrocardiogram EfficientNet-B0, MobileNetV3-Large and GoogLeNet**

I. Introduction

The diagnosis of cardiovascular diseases is a crucial aspect of health care. Any delays in the process might lead to fatal conditions. Our model helps in preventing such scenarios by detecting the abnormalities in the electrocardiogram signals and predicting the disease using various machine learning techniques. The raw ECG signals contain various other noises caused by respiration, sweating, body movements, and electromagnetic fields of devices. The dimensions of these datasets are also not standardized. In order to obtain optimal images for training the model, applying transforms plays a major role. Transforms help in resizing the images into equal dimensions and converting these images into numerical values and normalising them.

Post-transformation, labelling of the dataset into four different categories, namely normal, abnormal, myocardial infarction, and signals containing history of the disease, is performed. Once the data is preprocessed into the required format, the ResNet-18 model is trained with this dataset. ResNet18 is a pretrained model based on a convolutional neural network that consists of 18 layers for image classification purposes. This trained model is then tested and evaluated based on F1-score, recall, and accuracy metrics for the improvement of the performance of the model. This model can further be implemented in wearable devices like smartwatches and T-shirts for early diagnosis, which helps in reducing risk factors and preventing serious health conditions.

II. Related Works

The raw ECG dataset consists of various noises, such as baseline wander and powerline interference, which need to be removed for easy analysis. The preprocessing of the data is done by using techniques such as noise removal, such as SMA methods and notch filters. The LSTM model, which is based on a residual neural network, is very efficient in capturing the relationships between sequential data and is used for ECG forecasting. This model is then evaluated using the RMSE method for better performance [1]. The implementation of AI and ML in the field of health care has improved the diagnosis of cardiovascular diseases by a large extent. Machine learning models are used in training the machine with the available dataset, based on which future predictions can be made. The machine learning algorithms can identify and learn the patterns in the ECG data and classify the test data into required categories [2]. The R-peak is an important feature of the ECG signals that aids in determining the features in the datasets. Extraction of this R-peak can be done by applying preprocessing techniques like noise reduction and segmentation and feeding these processed signals into a model containing a 1-D convolutional neural network, which helps in the feature extraction process. This model is evaluated using a custom accuracy metric for determining the difference between the predicted output and the actual output

[3].

Once the preprocessing of the data is performed, it has to be transformed into required dimensions, which results in equal analysis on each dataset. Applying transformation techniques like Gaussian filters and hue transforms on the ECG datasets has proven very effective in ensuring consistency in all the required dimensions [4].The image classification process involves extracting the necessary features in the datasets and recognising the patterns involved in them. The ResNet 18 model integrated with CNN for better performance has around 96.5 percent accuracy in multiclass classification of the data. ResNet has additional normalisation and activation layers for improved feature extraction. Integration of CNN results in more layers to the ResNet model, resulting in extracting multiple features from the same input data [5].

Further analysis can be done by comparing image-based classification and signal-based classification deep learning models for 2D image transformation of the ECG signals. Comparison between 1D and 2D signal representation resulted in better performance by the 1D transformation. Multimodal fusion, which is the combination of different modalities, was also used to improve the modal performance by using multilabel ECG signals rather than multiple representations of the data, which resulted in 74 percent accuracy in the classification of the images [6]. Convolutional neural networks have been the most efficient model in image classification since they automatically extract the features from the input data. The integration of different other models along with CNN improves the results exponentially. This model uses a residual network with three residual blocks containing multiple convolution layers, along with a classification block for classification of one-dimensional ECG signal data. This results in the automatic extraction of important features from the input data. By selecting a batch size of 32 with 50 epochs, this model achieved a highest accuracy of 99.5 percent and an average accuracy of 98 percent. On using 10 coefficients of variation, the model achieves over 92 percent accuracy when tested using accuracy, precision, recall, and F1-score evaluation metrics. Hence, CNN proves to be a very efficient model when integrated with residual blocks [7].

However, there are numerous other models for the same purpose. EfficientNet is another deep learning model that scales the given input into standard dimensions used for classification purposes. The model used combines an efficient net for feature extraction and a prediction block for classifying the images into different labels. The efficient net block is based on 16 repetitions of MobileNet, which is a computer vision model with enhanced image classification capabilities. This helps in multiple feature extraction for large datasets. The prediction block classified the data based on the features extracted into 24 different classes, each with different labels. These labels were again fed to the model as training data, and the original labels were used for the other datasets. Finally the model was evaluated by the Adam optimiser, which obtained 91.5 percent accuracy [8]. There are also comparisons performed on different CNN models, namely AlexNet, GoogLeNet, and SqueezeNet. AlexNet is a deep learning model used for multiple-class classification that consists of convolution layers and rectified linear units for classifying non-linear data. GoogLeNet is used to capture data with a large scalability. The model includes a continuous wavelet transform for representing the given ECG signals in two dimensions. When evaluated, it achieved an accuracy of 97.8, 97.78, and 97.2 percent for the models, respectively, in the classification process [9].

III. Methodology

This process begins with gathering a dataset from Mendeley Data containing classified ECG images. Followed by data pre-processing, this involves normalising and standardising data. The dataset is labelled into four categories. After labelling, the dataset is combined and divided into training and testing datasets with a ratio of 80:20. The training data is fed into various pre-trained models to compute the best model. During the training phase, the model can improve its performance by using a cross-entropy loss function and be optimised using the Adam optimizer. Based on evaluation metrics like recall, precision, and accuracy, a model's performance is determined.

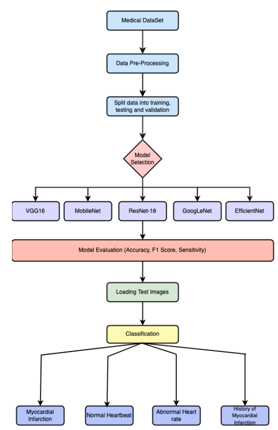

Fig. 1. Work flow of ADHVARA

A. Dataset

This study focuses on ECG signals only, not on other parameters like blood pressure or haemoglobin level. Data should be independent of additional features, so we opted for the ECG Images dataset of Cardiac Patients from Chandramma Dayananda Sagar Institute of Medical Education and Research. This dataset has four categories of ECG signals: abnormal heartbeat, normal heartbeat, history of myocardial infarction, and myocardial infarction. All images in the dataset have a consistent size and high resolution, which facilitated a straightforward data pre-processing process.

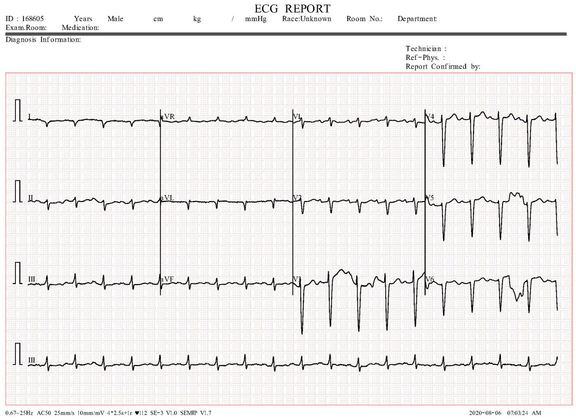

Fig. 2. Abnormal ECG signal

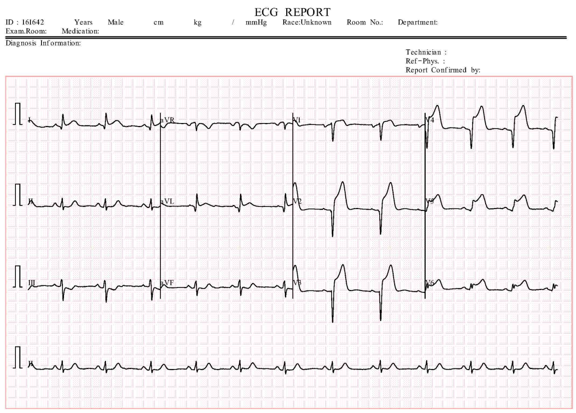

Fig. 3. Myocardial Infarction ECG Signal

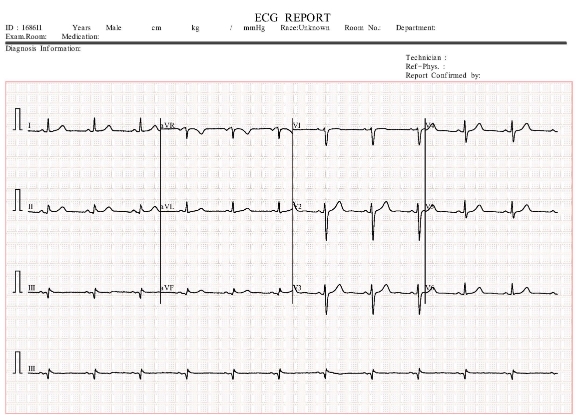

Fig. 4. Normal ECG Signal

B. Data pre-processing

The pre-processing pipeline for the dataset included resizing all images to standard input dimensions. Followed by converting images to PyTorch tensors for compatibility and normalising pixel values to the range [-1, 1] using a mean and standard deviation of [0.5, 0.5, 0.5]. These steps were implemented using the transforms library in PyTorch to ensure consistent input formatting, stabilise model training, and improve convergence during training. ECG images were labelled according to their respective categories to clearly indicate the class to which each image belongs. This labelling ensures accurate classification and facilitates the training and evaluation of the model.

C. Test-Train-Validation Split

In this step, ECG images from the four categories were combined and then split into training and testing sets in 80:20 ratio. The training set is used to teach the model to recognize patterns in the ECG signals, while the testing set, which contains ECG images not seen by the model during training, is used to evaluate its ability to generalize and accurately classify new data.

D. Model development

Multiple models are trained and evaluated to achieve better accuracy and performance. The following models are used to classify ECG images.

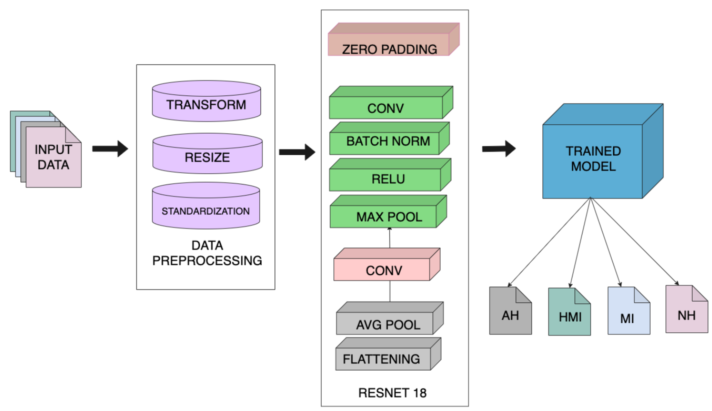

Fig. 5. Model architecture

1) EfficientNet-B0: EfficientNet is capable of providing high accuracy and better computational efficiency. This model can work on a large dataset and works well even if noise exists in the dataset. The time-sensitivity of EfficientNet leads to the analysis of micro-scale features in ECG signals.

2) MobileNetV3-Large: MobileNet is a lightweight model with less latency, which can reduce the duration of model training. The convolution layer is split into depth-wise and point-wise for better performance. Depth-wise, a filter is applied to individual pixels in the image, and point-wise, all values are summed up.

3) GoogLeNet: The GoogLeNet model is based on inception architecture, in which hidden layers can use multiple filters without alteration in the depth of the neural network. In this model, larger layers are replaced with smaller individual layers for easy propagation of data in the hidden layer, due to this model's efficiency is increased.

4) VGG-16: VGG-16 has a combination of convolution, dense, and max-pooling layers. It has multiple hyperparameters, due to which low features in ECG signals are computed.

5) Resnet-18: The ResNet-18 model architecture has 18 residual layers that can overcome vanishing gradient issues in neural networks. Residual layers help in skipping certain intermediate layers, due to which the input remains almost the same throughout the model. It is best to analyse both long-term and short-term features, as ECG signals contain minute variations this feature can capture it.

E. Optimization and Entropy

To improve the accuracy and performance of our model, we have used the Adam optimizer, as this can overcome sparse gradient issues. It helps the model to converge at a faster rate. All hyperparameters are fine-tuned by using this optimizer. This study focuses on multi-class classification, and predicting dissimilarities among them is important. This is achieved using a cross-entropy loss function.

IV. Results and Discussion

a) Result: The primary goal of this research was to evaluate the performance of deep learning models for detecting cardiovascular diseases from ECG signal images. Among ResNet-18, VGG-16, EfficientNet-B0, MobileNetV3-Large, and GoogLeNet, ResNet-18 demonstrated the best accuracy at 99.73 percentage This highlights its robustness in image-based classification, particularly in precision-critical medical diagnostics.

ResNet-18's residual connections effectively address the vanishing gradient problem, enabling superior feature extraction and classification compared to other models. While models like GoogLeNet and EfficientNet-B0 showed efficiency, they lacked the same level of accuracy. MobileNetV3-Large offered speed and lightweight deployment but prioritized efficiency over precision.

TABLE I
Table of Results

Model	Metrics			
	Precision	***Accuracy***	***Recall***	***F1-score***
VGG-16	0.7534	0.7534	0.7534	0.75
MobileNetV3-Large	0.9542	0.9542	0.9542	0.95
EfficientNet-B0	0.9623	0.9623	0.9623	0.96
GoogLeNet	0.9717	0.9717	0.9717	0.97
ResNet18	0.9973	0.9973	0.9973	0.99

The deployment of ResNet-18 in a web application makes it accessible for real-time ECG anomaly detection, especially valuable in resource-limited settings. These findings emphasize the importance of model selection tailored to specific datasets and applications. Future efforts could enhance performance by diversifying the dataset and optimizing models for real-time and resource-constrained environments.

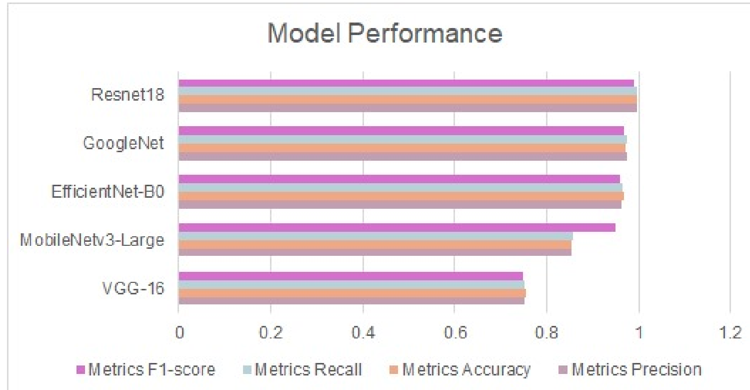

Fig. 6. Model performance

V. Conclusion and Scope for Future Enhancement

a) Conclusion: In the digital era, our main focus is on making ECG reports easily accessible at our fingertips. To achieve this, we have implemented a model on our website that allows users to upload images of their ECG signals and receive their report. This approach not only reduces the possibility of human error but also automates the healthcare process. After experimenting with multiple CNN models, we conclude that the ResNet-18 model has higher accuracy compared to other CNN models with an accuracy of 0.9973.

b) Scope for Future Enhancement: This research serves as a stepping stone for ECG signal feature extraction using CNN. Along with detecting cardiovascular diseases, the generation of missing leads can be developed. Generally, ECG contains missing leads due to errors during the extraction of ECG signals, factors such as sweating, body movements, and air gaps between the electrode and body. To overcome such a situation, lead generation is required. Once lead is generated, it can be fed to this model for diagnosis. In wearable technologies such as smartwatches and smart rings, this can be modified to detect real-time ECG leads.

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